Radiance Data Assimilation

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for

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DTC GSI Tutorial

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Outline

• Introduction
• Different types of satellite data.
• Basic Concepts for Assimilating Observations from Passive Nadir Sounders
• Assimilating satellite radiances.
  – Data assimilation equation
  – Quality control and Observation Errors.
  – Bias correction.
  – Thinning
  – Monitoring.
• Some Comments on Cloudy Radiances.
• Final Comments
Introduction

• Satellites instruments do not directly measure the atmospheric state.
• Instead they measure radiation emitted by and/or transmitted by the atmosphere.
• This presentation describes the relationship between the atmospheric state and the observed radiation. And how the information contained therein is exploited through assimilation into the NWP model.
Different Types of Satellite Data
Meterological Satellite Constellation (from WMO)
Different Types of Satellite Data

- **Active** (bouncing a signal off something)
  - Wind Lidar
  - SAR
  - Cloud radar
  - Scatterometry
Different Types of Satellite Data

- **Occultation** (signal passing through the atmosphere)
  - HALOE
  - SAGE
  - SCIAMACHY
Different Types of Satellite Data

- **Passive** (receiving radiative signal from source)
  - Visible Instruments
  - IR Instruments
  - Microwave Instruments
Passive Instruments

• This talk will focus on passive infrared and microwave instruments as they are the most common and biggest contributors to Numerical Weather Prediction
Geometry: Limb v/s Nadir Sounding

• **Limb sounding:** Viewing the Earth’s atmosphere *tangentially*
  – Higher *vertical* resolution
  – Lower *horizontal* resolution
  – Most often used for observing the stratosphere and above
  – GPSRO
    • most commonly used
Geometry: Limb v/s Nadir Sounding

- **Nadir sounding:** Viewing towards the Earth’s surface
  - Lower *vertical* resolution
  - Higher *horizontal* resolution
  - Most often used in NWP
Basic Concepts for Assimilating Observations from Passive Nadir Sounders
Taking advantage of the frequency dependent atmospheric absorption

- The atmosphere is variously opaque and transparent to electromagnetic radiation depending on the wavelength.
- We take advantage of this, plus the fact that at longer wavelengths we can observe thermal emission from the atmosphere itself to infer information on the atmosphere’s temperature and humidity profile.
Atmospheric Opacity in the Microwave Spectrum
An Infrared Spectrum

Dashed lines are Planck curves for 200K-300K at 20K intervals

Radiance ($\text{mW/cm}^2/\text{sr/cm}^{-1}$)

Wavenumber (cm$^{-1}$)
An Infrared Spectrum - converted into Brightness Temperature

- **CO$_2$**
- **H$_2$O**
- **O$_3$**

**Wavelength (µm)**

**Brightness Temperature (K)**

- **Shortwave window** (with solar contribution)
- **Longwave window**
IASI v/s HIRS: The Thermal Infrared
The temperature profile is the most important factor for determining the radiance observation. The vertical distribution of emitting v/s absorbing gases also impacts observations.

First step is to determine temperature profile. To do this, we need to choose frequencies where we know the absorption profiles already.

We choose gases with a constant distribution to do this.

For the infrared we use CO\textsubscript{2}.

For the microwave we use O\textsubscript{2}.

These are hence known as temperature sounding bands.

But all bands are sensitive to temperature, often – as in the case of H\textsubscript{2}O – with sharper Jacobians.

Once we have a good temperature profile we can use that to infer molecular abundances of variable species using appropriate frequencies.

This is actually performed simultaneously with the temperature estimation when we do data assimilation.
Illustration of Jacobian or Weighting Function
MetOp-A HIRS/4 \[ \frac{dT_B}{dT} \]
MetOp-A IASI [ $dT_B/dT$ ]
MetOp-A AMSU-A [ $dT_B/dT$ ]
MetOp-A HIRS/4 $\left[ \frac{dT_B}{d\ln(H_2O)} \right]$
MetOp-A IASI \[ \frac{dT_B}{d\ln(H_2O)} \]
MetOp-A AMSU-A \[ \frac{dT_B}{d\ln(H_2O)} \]
MetOp-A HIRS/4 \[ \frac{dT_B}{d\ln(O_3)} \]
Obtaining vertical profiles

- The Jacobian's give the sensitivity to the vertical profiles of temperature / gases / clouds etc.

- If we sum the contribution of each channel, we can get a very accurate estimate of the mean atmospheric temperature albeit with very low vertical resolution.

- If we take differences between each of the channels we can infer the profile with high vertical resolution, but the result will be very noisy estimate.

- When we assimilate the radiance observations we are effectively producing a minimum variance solution to the problem: which is a compromise between these two extremes.
Forward Models

• To exploit these radiances, it is important to have an accurate way of simulating them from the atmospheric state.

• Line-by-line (LBL) models use state-of-the-art spectroscopic databases to make these calculations at high spectral resolution.

• These monochromatic calculations are then combined using the instruments’ spectral response functions (ISRFs) to simulate what the instrument observes.

• This can be very slow. Too slow for operational radiance assimilation.
Fast Forward Models

- To allow radiances to be operationally assimilated, fast radiative transfer models, which use regression schemes to simulate the output from LBL models, have been produced.

- The two main fast models used operationally in NWP centers are RTTOV (developed by the EUMETSAT NWPSAF) and CRTM (JCSDA).

- The errors in the fast model are not usually a significant component of the total error budget (at least for clear atmosphere).

- Most importantly, fast models allow the Jacobians (and the model adjoint) to be calculated efficiently.
Radiative Transfer models also need to know the surface emissivity

- Over ocean we usually have models, e.g.
  - ISEM (infrared)
  - FASTEM (microwave)
- Over land we often use atlases, either of the emissivity's themselves or of the land type.
- Emissivity's can also be retrieved from the observations themselves.
Surface Emissivity : Infrared
Surface Emissivity: Microwave

Emissivity over the ocean are very low in the microwave.
Assimilating satellite radiances

Data Assimilation Equation
Basic analysis problem

\[ J = J_b + J_o + J_c \]

\[ J = \frac{1}{2} [x - x_b]^T B^{-1} [x - x_b] + \frac{1}{2} [H(x) - y]^T R^{-1} [H(x) - y] + J_c \]

Penalty = Fit to background + Fit to observations + Constraints

\( x \) = Analysis ; \( x_b \) = Background

\( \delta x = x - x_b \) = Analysis increment

\( B \) = Background Error Covariance

\( H \) = (Nonlinear) Forward Model ; \( H \) = Linearized about \( x_b \)

\( y \) = Observations ; \( d = y - Hx_b \) = Observation Innovation

\( R = E + F \) = Instrument Error + Representativeness Error = Observation Error

\( J_c \) = Constraint terms
The basic analysis problem is given by:

$$J = J_b + J_o + J_c$$

where

$$J = \frac{1}{2} \left[ x - x_b \right]^T B^{-1} \left[ x - x_b \right] + \frac{1}{2} \left[ H(x) - y \right]^T R^{-1} \left[ H(x) - y \right] + J_c$$

The penalty consists of three parts:

- **Fit to background:**
  \[ J_b = \frac{1}{2} \left[ x - x_b \right]^T B^{-1} \left[ x - x_b \right] \]

- **Fit to observations:**
  \[ J_o = \frac{1}{2} \left[ H(x) - y \right]^T R^{-1} \left[ H(x) - y \right] \]

- **Constraints:**
  \[ J_c \]

The difference between the observations and the background transformed into model space, the first guess departure, is an important measure. It is often the basis of quality control procedures.

- **x = Analysis:**
  The difference between the observations and the background transformed into model space, the first guess departure, is an important measure. It is often the basis of quality control procedures.

- **δx = x − x_b:**
  The difference between the observations and the background transformed into model space, the first guess departure, is an important measure. It is often the basis of quality control procedures.

- **B = Background:**
  Model space, the first guess departure, is an important measure. It is often the basis of quality control procedures.

- **H = (Nonlinear) Forward Model:**
  Model space, the first guess departure, is an important measure. It is often the basis of quality control procedures.

- **y = Observations:**
  Observations. The difference between the observations and the background transformed into model space, the first guess departure, is an important measure. It is often the basis of quality control procedures.

- **R = E + F = Instrument Error + Representativeness Error:**
  Observation Error

- **J_c = Constraint terms:**
  Constraint terms
Assimilating satellite radiances

Quality Control
Quality Control Procedures

• The quality control step may be the most important aspect of satellite data assimilation.
• Data which has gross errors or which cannot be properly simulated by forward model must be removed.
• Most problems with satellite data come from 4 sources:
  – Instrument problems.
  – Clouds and precipitation simulation errors.
  – Surface emissivity simulation errors.
  – Processing errors (e.g., wrong height assignment, incorrect tracking, etc…).
Quality Control Procedures

• **IR cannot** see through most clouds.
  – Cloud height difficult to determine – especially with mixed FOVs.
  – Since deep layers not many channels completely above clouds.
• Microwave impacted by clouds and precipitation but signal is smaller from thinner clouds.
• Poor knowledge of surface emissivity and temperature characteristics for land / snow / ice.
  – Also makes detection of clouds / precipitation more difficult over these surfaces.
• **Asymmetric** error distribution due to clouds and processing errors.
Effect of Cloud on IR Spectrum

No Cloud

Mid-Level Cloud

High Opaque Cloud

H₂O

CO₂

O₃

Noise
Cloud Detection in the GSI

- Assume the cloud is a single layer at pressure $P_c$ and with unit emissivity and coverage within the FOV, $N_c$.
- Cloud fraction: $0 \leq N_c \leq 1$
- $P_c$ is below the tropopause and above the ground
- Find $P_c$ and $N_c$ so that the RMS deviation, $J(N_c, P_c)$, of the calculated cloud from the model (over a number of channels) is minimized.
- Remove all channels that would be radiatively affected by this cloud.

\[ R_{\text{cld}}(\nu, P_c) = N_c R_{\text{overcast}}(\nu, P_c) + (1 - N_c) R_{\text{clear}}(\nu, P_c) \]

\[ J(N_c, P_c) = \sum_{\nu} \left( \frac{R_{\text{cld}}(\nu, P_c) - R_{\text{obs}}(\nu)}{\sigma(\nu)} \right)^2 \]

- $\sigma(\nu)$ is the assumed observation error for channel $\nu$. This calculation should be done in radiance space, and not in brightness temperature space.
Observational Errors

• Observation errors specified based on instrument errors and statistics
• Generally for satellite data, variances are specified a bit large since the correlated errors (from RT and instrument errors) are not well known.
• Observation errors are also generally specified as being uncorrelated spectrally, but efforts are being made to determine the off-diagonal components of the observation error covariance matrix.
### Satinfo File

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- **Use Channel?**
- **Assigned**
- **Maximum allowed FG Departure** (after bias correction)
- **Observation Error**
Assimilating satellite radiances

Bias Correction
Bias Correction

• The differences between simulated and observed observations can show significant biases.

• The source of the bias can come from:
  – Inadequacies in the characterization of the instruments.
  – Deficiencies in the forward models.
  – Errors in processing data.
  – Biases in the background.

• Except when the bias is due to the background, we would like to remove these biases.
Bias Correction

• Currently bias correction only applied to a few data sets:
  – Radiances
  – Radiosonde data (radiation correction and moisture)
  – Aircraft data
• For radiances, biases can be much larger than signal
• Essential to bias correct the data
• NCEP uses a variational bias correction scheme (other centers are similar) using atmospheric air mass and scan angle predictors
Scan dependent biases for AMSU

platform: amsua
region: global
variable: observed-simulated (without bias correction) (K)
valid: 00Z20FEB2001 00Z22MAR2001

channel 5

channel 6

channel 7

channel 8

satellite zenith angle (degrees)
Satellite radiance observations

Bias correction

• Air mass prediction equation for bias – *variational* bias correction
  – Add to control vector (analysis variables $x_{n+i}$)
    
    where $\text{Total bias correction} = \sum_{i=1}^{n_p} x_{n+i} p_i$
  – Predictors ($p_i$) for each channel
    • mean
    • path length (local zenith angle determined)
    • integrated lapse rate
    • (integrated lapse rate)$^2$
    • cloud liquid water
    • Fourth-order polynomial of scan-angle
    • Surface emissivity predictor
    • Latitude dependent bias for SSMI/S
NOAA 18 AMSU-A
No Bias Correction

channel 7
χ 0.3765
f 54.94 GHz
λ 5456.89 μm
avg: 1.837
sdv: 0.369

channel 8
χ 0.3955
f 55.50 GHz
λ 5401.64 μm
avg: 1.263
sdv: 0.505
NOAA 18 AMSU-A
With Bias Corrected

channel 7
\( \chi = 0.3765 \)
\( f = 54.94 \text{ GHz} \)
\( \lambda = 5456.69 \text{ \(\mu\)m} \)

avg: -0.022
sdv: 0.200

channel 8
\( \chi = 0.3955 \)
\( f = 55.50 \text{ GHz} \)
\( \lambda = 5401.64 \text{ \(\mu\)m} \)

avg: -0.026
sdv: 0.222
Observation - Background Histogram

DMSP15  July2004 : 1month

before bias correction
after bias correction
Application of NWP Bias Correction for SSMIS F18

Using Met Office SSMIS Bias Correction Predictors

O-B Before Bias Correction

O-B After Bias Correction

O-B Before Bias Correction

O-B After Bias Correction

Using Met Office SSMIS Bias Correction Predictors

Unbias & Bias Corrected O-B

Dsc

Asc

Global

Dsc

Asc

Global

Ascending Node

Descending Node

Latitude
Bias Correction and QC Interact

Bias Correction
Observations are bias-corrected after quality control

Quality Control
Quality control usually uses bias-corrected observations
Assimilating satellite radiances

Thinning
Thinning or Superobbing

- **Thinning**
  - Reducing spatial or spectral resolution by selecting a reduced set of locations or channels.
  - Can include “intelligent thinning” to use better observation.
- **Superobbing**
  - Reducing spatial or spectral resolution by combining locations or channels.
  - Can reduce noise.
  - Includes reconstructed radiances.
  - Can include higher moments contained in data [Purser et al., 2010](#).
  - Can be done with obs or departures, but should be done after QC.
- Both can be used to address 3 problems:
  - Redundancy in data.
  - Reduce correlated error.
  - Reduce computational expense.
Five Order of Magnitude Increases in Satellite Data Over Fifteen Years (2000-2015)

Received = All observations received operationally from providers
Selected = Observations selected as suitable for use
Assimilated = Observations actually used by models
Assimilating satellite radiances

Data Monitoring
Data Monitoring

- It is essential to have good data monitoring.
- Usually the NWP centers see problems with instruments prior to notification by provider (Met Office especially).
- The data monitoring can also show problems with assimilation systems.
- Needs to be ongoing/real time.
- Monitoring reports from most major NWP centers at: http://research.metoffice.gov.uk/research/interproj/nwpsaf/monitoring.html
Quality Monitoring of Satellite Data

AIRS Channel 453 26 March 2007

platform: airs.049
region: global (180W-180E, 90S-90N)
variable: ges (w/o bias cor) - obs (K)
valid: 00Z 11 MAR 2007 to 00Z 10 APR 2007

channel 375
\( \lambda = 0.3328 \) GHz
\( \lambda = 13.17 \) \( \mu \)m
avg: -1.254
sdv: 1.010

channel 453
\( \lambda = 0.8282 \) GHz
\( \lambda = 18.61 \) \( \mu \)m
avg: -0.688
sdv: 1.247
CHANNEL 453
**IS NOT** ASSIMILATED

channel 479
\( \lambda = 0.2532 \) GHz
\( \lambda = 12.48 \) \( \mu \)m
avg: -0.678
sdv: 0.910

channel 484
\( \lambda = 0.2982 \) GHz
\( \lambda = 12.43 \) \( \mu \)m
avg: -0.714
sdv: 0.927

Increase in SD
Fits to Guess
Initial Problem

When we stopped assimilating
Initial “fix” to instrument
Some Comments on Cloudy Radiances
Cloudy Radiances

• Most of the above discussion concerns the assimilation of radiances unaffected by cloud.

• Currently we are not operationally assimilating cloudy radiances but the GSI contains experimental code for assimilating such radiances in the microwave.

• The next few slides discuss why clouds are both important and difficult for data assimilation…

• …and discusses one aspect of the modifications we are making to assimilate them
Why are clouds important?

• A decade ago almost all assimilation of satellite radiances assumed the scene was clear of clouds.
• Clouds were considered a source of noise that needed to be removed or corrected for.
• This is not because clouds were not important but because they were difficult.
• By ignoring regions affected by cloud we are not considering some meteorological very important areas.
• By selectively assimilating clear radiances we may be biasing the model (representivity issues).
Clouds can be spatially complex

Often we assume a cloud looks like this…

…when they can really look like this

Spatial structure can be below the resolution of the observation, the model or both
Clouds can be radiatively complex

- The complexity of the impact of clouds on observed spectra varies greatly with type of cloud and spectral region.
- If clouds are transmissive they will tend to have spectrally varying absorption – and hence emission – which depends on phase (water or ice), crystal habit and particle size distribution.
- Scattering from cloud and precipitation particles can by very significant – tends to lower the observed brightness temperature.
Clouds can introduce non-linearities

• The radiative signal from clouds is often large and very non-linear so the tangent-linear assumption used in variational data assimilation may not hold.
• Quality control that minimizes the impact of this non-linearity is required.
Clouds need to be consistent with temperature and humidity fields

• Adding clouds to the analysis without ensuring a consistent humidity and temperature profile can be problematic.
  – For example a cloud added into a dry atmosphere will tend to be removed by the model.
Final Comments
Overall Comments

• Satellite data must be treated carefully.
• Important to be aware of instrument characteristics before attempting to use data.
• No current component of observing system is used “perfectly” or “as well as possible”.
• Computational expense plays important role in design of system.
Useful References

Auligne T.; McNally A. P.; Dee D. P., 207: Adaptive bias correction for satellite data in a numerical weather prediction system, QJRMS, 133, 631-642.


Dee, D. P. , Uppala S., 2009: Variational Bias correction of satellite radiance data in the ERA-Interim reanalysis, QJRMS, 135, 1830-1841.


RTTOV homepage: http://research.metoffice.gov.uk/research/interproj/nwpsaf/rtm/

http://www.ecmwf.int/newsevents/training/rcourse_notes/DATA_ASSIMILATION/REMOTE_SENSING

References – Cloud Assimilation


