Course outline, objectives, workload, projects, expectations

Introductions

Remote Sensing Overview

Elements of a remote sensing observing system
1. platform (satellite, surface, etc)
2. experimental design - forward problem
3. retrieval components - inversion/estimation

http://reef.atmos.colostate.edu/~odell/at652/
Why remote sensing?

Much of the atmosphere is inaccessible to routine in situ measurements

→ Only way to provide large enough sample to provide a large-scale view of the Earth system is from space

AVHRR SST anomalies Nov 96,97
Related Classes

• **AT721 – Advanced Techniques in Radiative Transfer**  
  Spring 2014, O’Dell  
  Will focus on RT techniques in various parts of the spectrum, with application primarily to remote sensing but also energy budget. Bulk of the class is a single large application-based project of the student’s choice.

• **AT752 – Inverse methods in the atmospheric sciences (Fall 2014, O’Dell)**  
  Fall 2014, O’Dell  
  Provides an introduction to inverse modeling, with application to modern retrieval theory, flux inversions, and data assimilation.

• **AT737 – Satellite Observations**  
  Spring 2015?, VonderHaar  
  Satellite measurements; basic orbits and observing systems; applications of remote sensing and imaging to investigations of atmospheric processes.
UCAR Comet Lectures

We will occasionally draw on lecture material from the UCAR Comet “MetEd” series, either in place of class or out of class.
What is remote sensing?

“The observation of radiation* that interacted with a remote object or collection of objects”

• Does not mean satellites specifically! (surface, balloon-borne, etc can also count)
• Usually it is the amount of radiation that matters, but sometimes timing is also used (e.g. radar & lidar)

* Some don’t use radiation (e.g. GRACE uses gravity field)
Properties of the earth system that are subject to remote sensing

- **Temperature**: land surface, ocean surface, atmospheric profile (troposphere & stratosphere)

- **Gases**: water vapor, ozone, CO₂, methane, oxygen, NO₂, CO, BrO, D₂O, ... (integrated & profile info)

- **Clouds**: Optical depth, cloud profile, particle sizes, ice vs. liquid (phase), cloud fraction

- **Aerosols**: Types (sulfates, sea salt, dust, smoke, organics, black carbon), optical depth, height

- **Surface features**: surface height, ocean winds, vegetation properties, ocean color, sea ice, snow cover.
Applications?
Applications?

- Weather prediction (data assimilation)
- Climate state observations (e.g. clouds, sea ice loss)
- Climate Model validation/comparisons
- Air quality state / forecasts
- Solar power forecasts
- Carbon cycle
- Hydrology/water cycle
- Biogeochemical modeling
Example: Data assimilation for NWP

<table>
<thead>
<tr>
<th>Terrestrial based</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface synoptic and ships</td>
<td>31,497</td>
</tr>
<tr>
<td>Data buoys, drifting and moored</td>
<td>8,694</td>
</tr>
<tr>
<td>Aircraft</td>
<td>52,557</td>
</tr>
<tr>
<td>Radio sonde</td>
<td>645</td>
</tr>
<tr>
<td>Balloon winds</td>
<td>1,452</td>
</tr>
<tr>
<td><strong>Total terrestrial</strong></td>
<td>94,845</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Space based</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud motion winds</td>
<td>262,132</td>
</tr>
<tr>
<td>Surface winds - Scatterometer</td>
<td>505,140</td>
</tr>
<tr>
<td>Microwave - temperature and water vapour</td>
<td>799,644</td>
</tr>
<tr>
<td>Infra-red clear sky temperature and water vapour</td>
<td>611,839</td>
</tr>
<tr>
<td><strong>Total space based</strong></td>
<td>1,730,253</td>
</tr>
<tr>
<td><strong>Total all data</strong></td>
<td>1,825,098</td>
</tr>
</tbody>
</table>

ECMWF assimilated data breakdown
“Golden Age of Remote Sensing”

NASA’s A-Train
Example: Monitoring of Atmospheric Composition & Climate (MACC) at ECMWF

In Focus: Aerosol radiative forcing products

June 2013  MACC-II scientists have estimated the impact of man-made atmospheric aerosols on climate, finding that they offset up to a third of the warming due to greenhouse gases. Read the full article.
Forecast of Aerosols Optical Depth

Monday 26 August 2013 00UTC MACC Forecast t+003 VT: Monday 26 August 2013 03UTC
Dust Aerosols Optical Depth at 550 nm

Map showing the distribution of aerosols optical depth around the world with a concentration in the Middle East and North Africa region.
Carbon Monoxide Forecast

Thursday 15 August 2013 00UTC MACC-TM5 Forecast t+006 VT: Thursday 15 August 2013 06UTC
Total Column Carbon Monoxide [ 10^18 molecules / cm2 ]
“Cloud Streets” over near Greenland from MODIS
Monitoring Climate Change:
Stratospheric cooling & tropospheric warming with microwave O$_2$
A puzzle?


a) TLS V032: Lower Stratosphere Temperature Anomaly Trends: All Months
GLS Trend = -0.0305 °K per year

b) TLS V032: Lower Stratosphere Temperature Anomaly Trends:
Non Volcanic Months (SATO < 0.01)
GLS Trend = -0.0242 °K per year

c) Stratospheric Aerosol Optical Thickness - SATO
No published SATO data after 12/99

D Kelly O'Day - http://chartsgraphs.wordpress.com 02/01/2011
There are multiple aspects to remote sensing:

- **Platform** (aircraft, satellite, balloon, ground-based) – this dictates the time/space sampling characteristics & errors

- **Source of EM Radiation**

- **Radiation interaction mechanism**

- **Forward and inverse models** - this defines the physical and system errors (user in principle has more control over this facet of the system)
Observing Platforms

- Ground-based: Radiometers, sunphotometers, lidar, radar, doppler wind arrays. Local but good time coverage.

- Aircraft: local-to-regional spatial, limited time coverage (measurement campaigns)

- Satellite (orbit determines spatial & temporal coverage)
Substantial influence on sampling - e.g. synoptic like versus asynoptic
Figure 1.7 Oblique orbiting (near-polar orbiting) satellites: Sun-synchronous orbits (each 3 hours)
Figure 1.8 Example of geostationary satellite coverage.

Figure 1.9 U.S. geostationary satellites: GOES
HEO Example: PCW-PHEMOS from Environment Canada

- Polar Communications and Weather (PCW) mission (2017): 2 operational met satellites in Highly Elliptical Orbit (HEO) for quasi-geostationary observations along with a communications package
- Polar Highly Elliptical Molniya Orbit Science (PHEMOS) suite of imaging spectrometers
- Weather Climate and Air quality (WCA) option is now entering phase-A study (see talk by J.C. McConnell on Thursday)
- Quasi-continuous coverage of GHGs over the high latitudes (~40-90°N) using TIR+NIR would help constrain GHG sources/sinks at fine temporal scales

Trischenko & Garand (2011)

Courtesy Ray Nassar
Source of Radiation

**PASSIVE**
- Sunlight (UV, Vis, Near IR): May be scattered (by atmospheric constituents or surface) or absorbed.
- Thermal Emission (Thermal IR, microwave, radio)

**ACTIVE**
- Radar (radio & microwave), GPS (radio)
- Lidar (visible and near-infrared)
Radiation Interactions

• **Extinction**
  • Radiation removed from some background source (typically the sun or a laser)
  • Can be removed because of scattering, absorption, or both

• **Emission**
  • Adds radiation to a beam because of THERMAL EMISSION (thermal IR & microwave only)

• **Scattering**
  • Adds radiation to a beam
  • From clouds, aerosols, or surface.
  • Affects solar & thermal
  • Passive or active
Experimental Design

Based on some sort of relation defined by a physical process:

(a) extinction – aerosol OD, TCCON CO2, occultation
(b) emission - atmospheric sounding, precipitation,..
(c) scattering - passive, cloud aerosol, ozone,..
- active, radar & lidar
The Observing System Transfer Function

Key parameters & steps:
- Measurement, \( y(t) \) and error \( \varepsilon_y \)
- Model \( f \) & its error \( \varepsilon_f \)
- Model parameters \( b \) and errors
- Constraint parameters \( c \)
The Retrieval Problem

Forward Problem (real)
\[ y = F(x) + \varepsilon_y \]
y = measurement
\( F = \) Nature’s forward model
\( x = \) parameter desired
\( \varepsilon_y = \) error in measurement (noise, calibration error, …)

Often the relation between the measurement \( y \) and the parameter of interest \( x \) is not entirely understood
\[ y = f(\hat{x}, b) + \varepsilon_y + \varepsilon_f \]

Inverse Problem
\[ \hat{x} = I(y, b) \]
\( b = \) ‘model’ parameters that facilitate evaluation of \( f \)
\( \varepsilon_f = \) error of model
**PROBLEM:**

The performance of the ‘system’ is affected by the performance of the individual parts. Examples of issues:

(i) Properly formed forward models – [e.g. Z-R relationships, poorly formed forward model without an understanding of what establishes the links between the observable y(Z) and the retrieved parameter X(R) ]

(ii) Need for prior constraints – temperature inversion problem

(iii) Poorly formed inverse model: simple regressions or neural network systems might not produce useful errors
Inversion versus estimation - radar/rainfall example

Radar-rainfall relationship

\[ Z = AR^b \]

‘Inversion’

\[ R = (Z/A)^{1/b} \]

but......

A and b are not-unique and vary from rain-type to rain-type implicitly involving some sort of ‘cloud’ model

Stephens, 1994
Non-uniqueness and Instability

Estimation

Cost Function: \( \Phi = M [y-f(x)] \)

‘metric’ of length (e.g. least squares)

Unconstrained

Constrained \( \Phi = M [y-f(x)] + C(x) \)

Solution space non-unique

C(x)= initial or \textit{a priori} constraint
Non-uniqueness and instability: example from emission

Physically:

Weighting functions that substantially overlap

\[ I(0) = \int B(z')W(0,z')dz' \]

- Will generally not yield unique solution in the presence of instrument noise & finite # of channels

Figure 1.3 (a) Schematic diagram for a satellite-based atmospheric temperature profile measurement. The contribution to the radiation measured at the selected wavelength arises from a discrete level. (b) A version of the contribution function of Fig. 1.3a corresponding to a more practical case where the measured radiation originates from a range of different levels in unequal proportions (from Twomey, 1977).
Results from temperature retrieval project

Weighting Functions from a theoretical instrument

Noiseless Retrieval

Realistic noise, proper noise model

Realistic noise, assumed noiseless
Information Content: The example of IR-based retrieval of water vapor

Metric of how much a priori constraint contribute to the retrieval

A→0, all a priori, no measurement
A→1, no a priori, all measurement
Change Calibration (i.e. measurement error by 100%)

Largest impact where measurements contribute most
Forward Problem (applied)

\[ y = f(\hat{x}, \hat{b}) + \varepsilon_y + \varepsilon_f \]

- \( f \) = our depiction of the forward model
- \( \hat{x}, \hat{b} \) = estimates of \( x, y \)
- \( \varepsilon_f = F(x, b) - f(\hat{x}, \hat{b}) + \frac{\partial f}{\partial b}(\hat{b} - b) \),
  = error in forward model

Radiative transfer model (most common)
Radiation + physical model
Radiation model + NWP (radiance assimilation)

For the most challenging problems we encounter, it is generally true that the largest uncertainty arise from forward model errors. If you see error estimates on products that exclude these errors – then you ought to be suspicious – really suspicious.
Geostationary allows us to see cloud mov