Application of Inverse Methods to Atmospheric Remote Sensing

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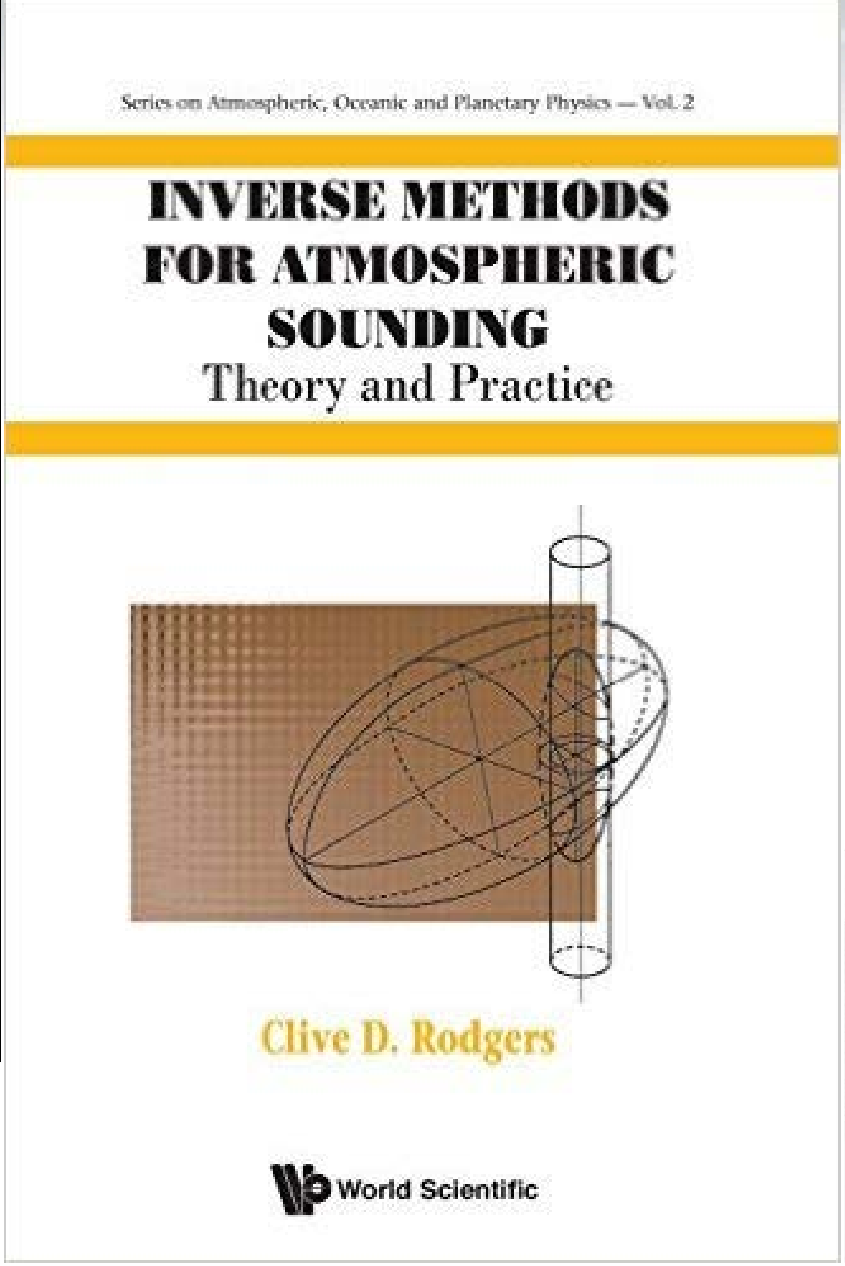
Patriarch of Atmospheric Trace Gas Retrievals

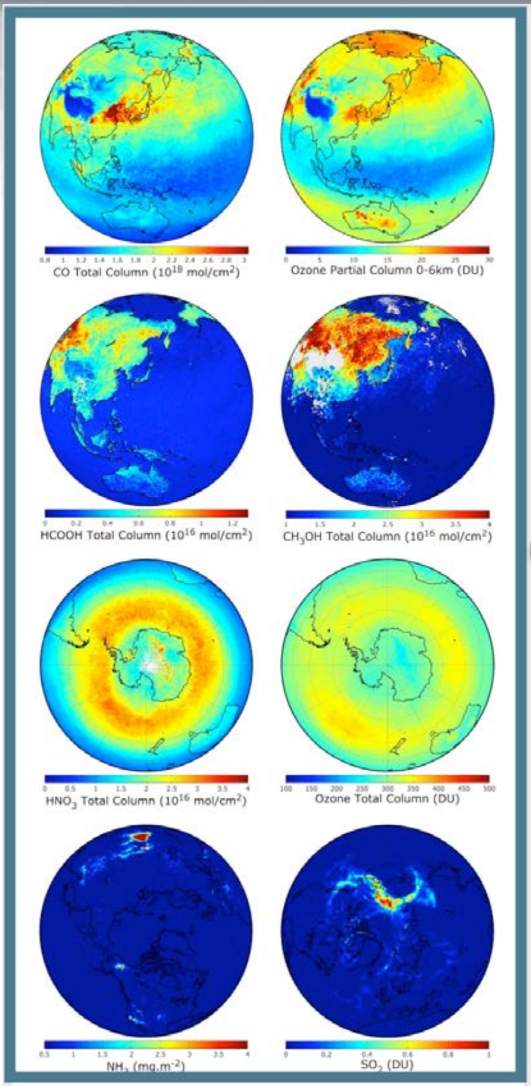
Dr. Clive D. Rodgers (Oxford University Emeritus) has had an indelible impact on atmospheric retrievals.

He brought estimation theory from statistics and electrical engineering into the trace gas remote sensing community.

Most modern trace gas satellite retrieval algorithms utilize this theory, e.g. TES, MOPITT, IASI, OMI, MLS, etc.

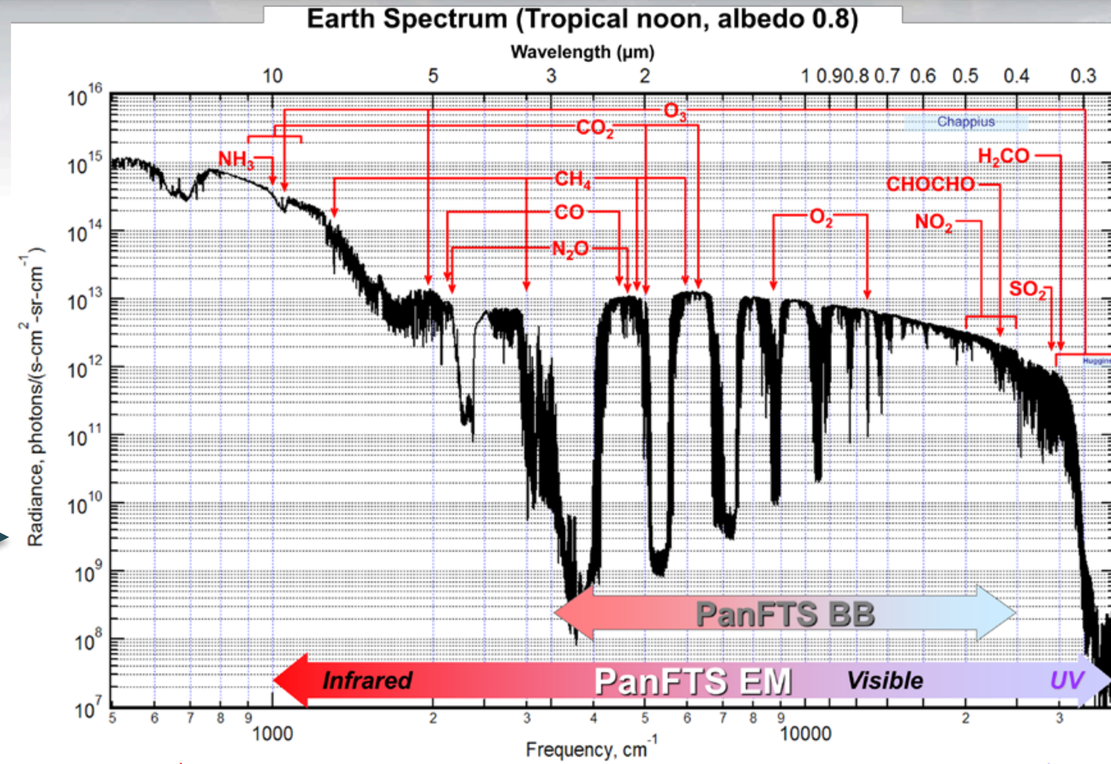


Remote sensing of the atmosphere



Clerbaux *et al*

Radiative Transfer



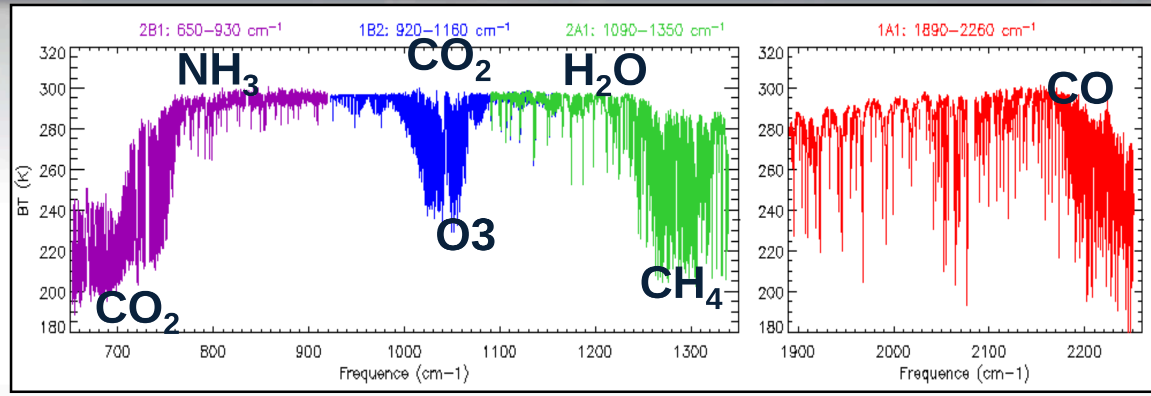
Atmospheric remote sensing is based upon radiative transfer, which quantifies the molecular absorption and scattering of electromagnetic radiation at different wavelengths through the atmosphere.

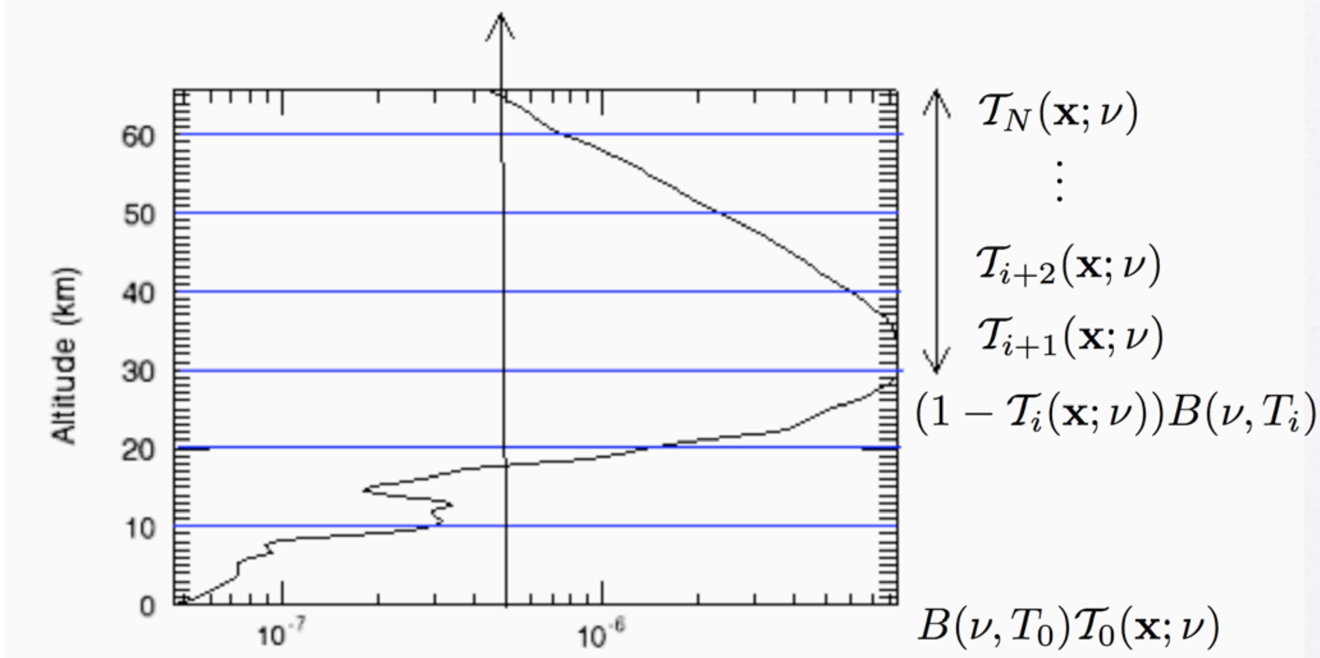
Radiation Transfer: thermal infrared

In the nadir (down-looking) thermal infrared, gases absorb and emit spectral radiation (wavelength-dependent ***v***).

The radiation that is emitted to space is the sum of the transmittance ***T*** and the Planck emission ***B*** at layer *i* and temperature T_i.

The layer transmittance is a function of optical depths, which are defined in terms of gas aborption, κ^j, and gas amount $\mathbf{x}^j$.



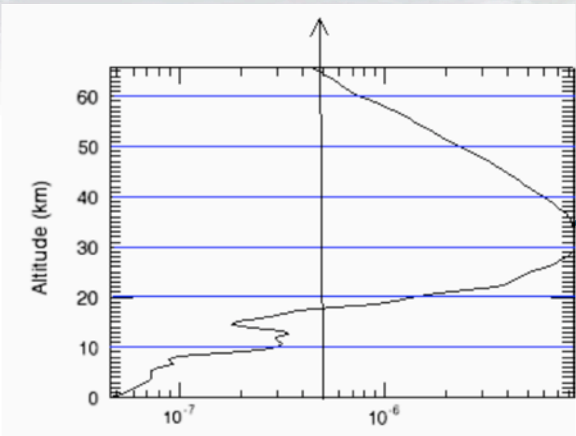


$$F(\mathbf{x};\nu) = B(\nu,T_0)\mathcal{T}_0(\mathbf{x};\nu) + \sum_{i=1}^{N}(1-\mathcal{T}_i(\mathbf{x};\nu))B(\nu,T_i)\prod_{l=i+1}^{N}\mathcal{T}_l(\mathbf{x};\nu)$$

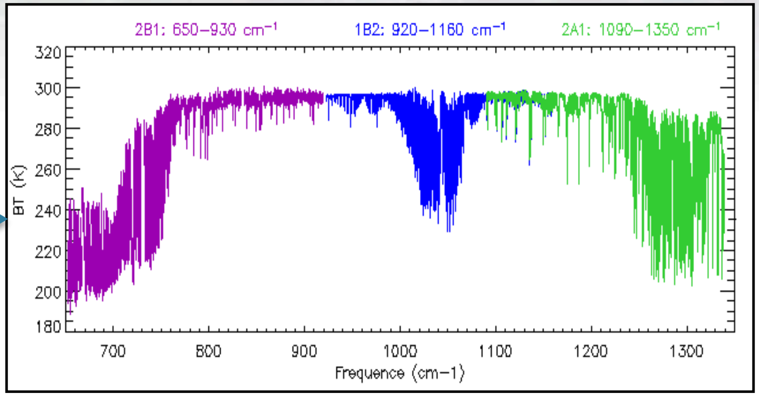
$$\text{where}\quad \mathcal{T}_i(\mathbf{x};\nu) = \exp\left[-\sum_{j=1}^{P}\kappa_i^j(\nu)\mathbf{x}_i^j\right]$$

Setting the stage: from physics to math

The Forward Problem

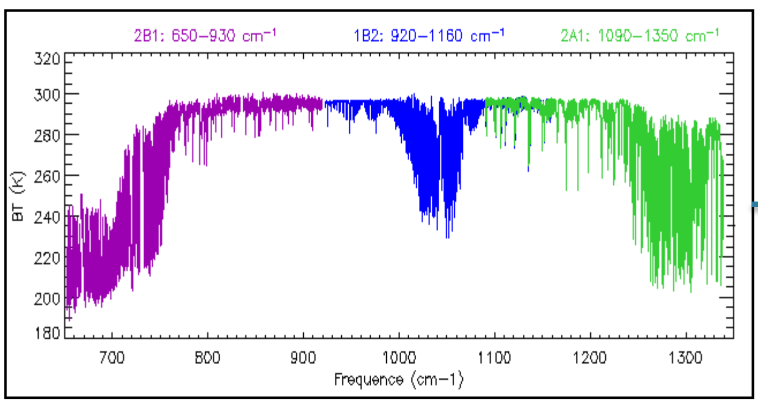


Equation of radiative transfer

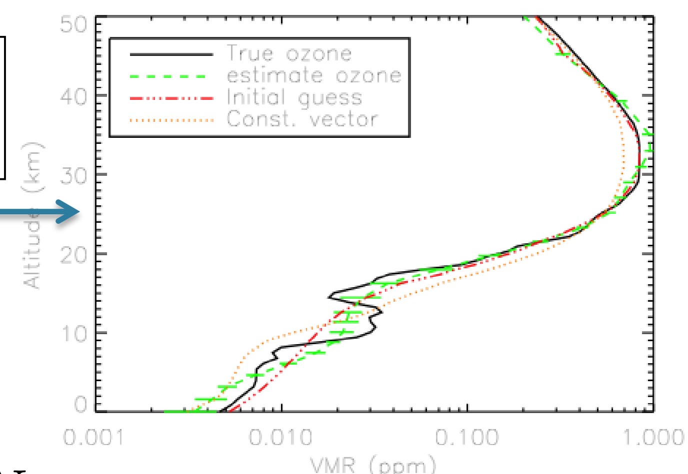


$$\mathbf{x} \in \mathbb{R}^N \qquad \mathbf{F}(\mathbf{x}) : \mathbb{R}^N \rightarrow \mathbb{R}^M$$

The Inverse Problem



Inverse model of radiative transfer



$$\mathbf{y} \in \mathbb{R}^M \qquad \mathbf{R}(\mathbf{y}) : \mathbb{R}^M \rightarrow \mathbb{R}^N \qquad \hat{\mathbf{x}} \in \mathbb{R}^N$$

Posing your problem

- An inverse problem is the inference of parameters (or functions) of a system given observables of that system.
  - How do I infer the vertical distribution of ozone given observations of infrared spectral radiances?
- Inverse problems are frequently *ill-posed*

The notion of ill-posed problems is attributed to J. Hadamard through the definition of a well-posed problem:

1. A solution exists
2. The solution is unique
3. The solution depends continuously on the data

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SUR LES PROBLEMES AUX DERIVEES PARTIELLES ET LEUR SIGNIFICATION PHYSIQUE.

PAR M. JACQUES HADAMARD.

"La physique ne nous donne pas seulement l'occasion de résoudre des problèmes . . . . elle nous fait pressentir la solution."—*Poincaré.*

qu'ils correspondent ou non à une donnée physique.

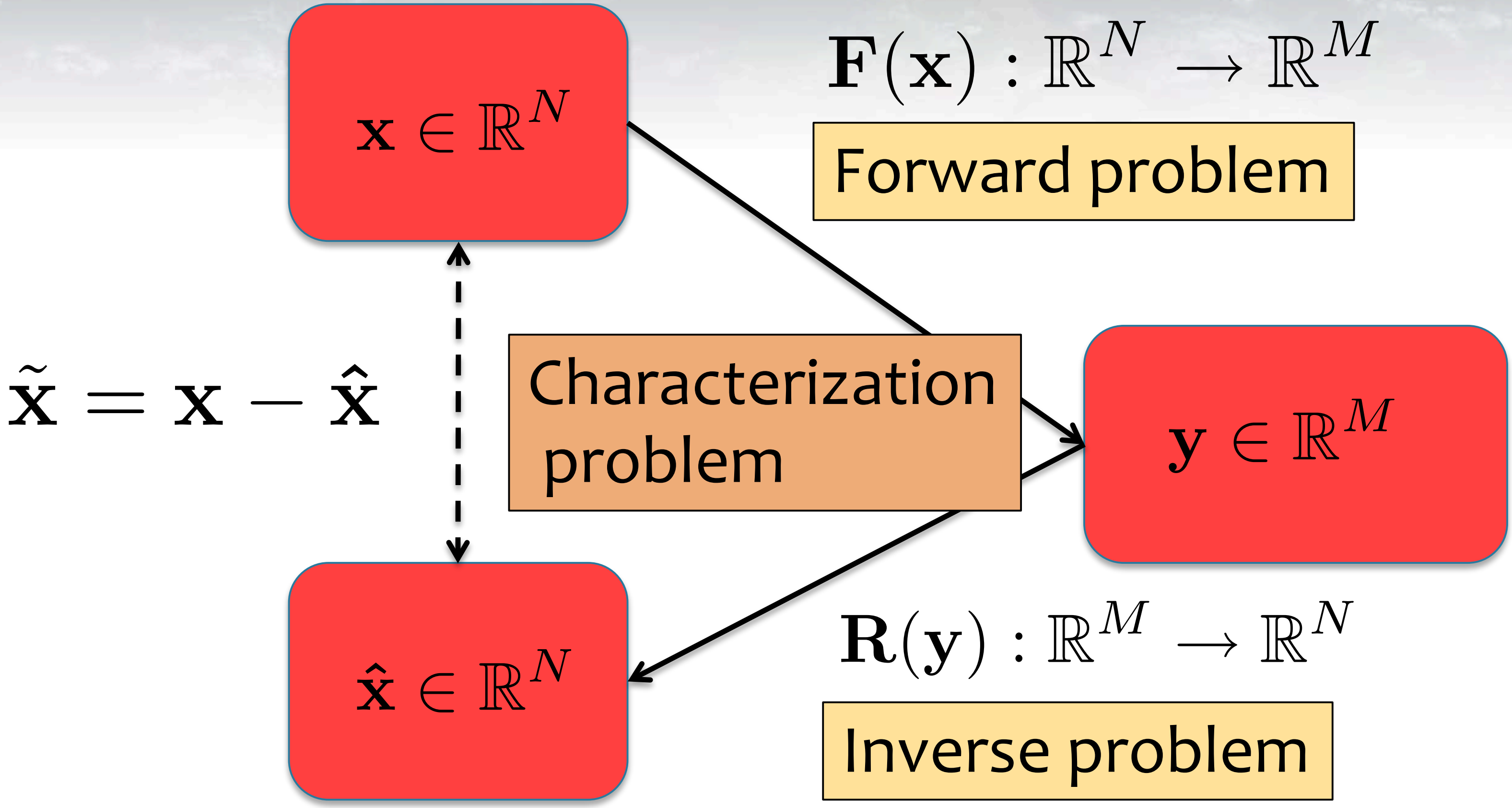
Relativement à l'équation de Laplace

$$\text{(A)} \qquad \frac{\delta^2 u}{\delta x^2} + \frac{\delta^2 u}{\delta y^2} + \frac{\delta^2 u}{\delta z^2} = 0,$$

c'est le problème de Dirichlet (ou l'un de ses analogues) qui se présente dans les ap-

Goal of inverse methods is to develop *regularization approaches that transform an ill-posed problem to a well-posed problem.*

Tripartite Challenge



The retrieval problem can decomposed into 3 components:

1. Forward Problem: What is the relationship between what can be measured and what we want to know?
2. Inverse Problem: How to determine what I want to know given what can be measured.
3. What is the relationship between what has been estimated ("retrieved") with what I want to know?

The Forward Model

Everything is blurry: the additive noise model

$$\mathbf{y} = \mathbf{F}(\mathbf{x}) + \mathbf{n}$$

- **y** what you measure.
- **F** is the forward model
- **x** is the *state vector* (what you want to know)
- **n** is the noise vector (the precision of your measurement)

Inverse methods hinge upon an understanding of the functional properties of **F** and *a priori* knowledge of **x** and **n**

$$\hat{\mathbf{x}} = \mathbf{R}(\mathbf{y})$$

How to be sensitive: the Jacobian

We start by representing the equation of radiative transfer as a vector valued non-linear function:

$$\mathbf{F}(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) \\ f_2(\mathbf{x}) \\ \vdots \\ f_M(\mathbf{x}) \end{bmatrix} \qquad f_m(\mathbf{x}) : \mathbb{R}^N \to \mathbb{R}$$

We will focus on the Taylor series expansion of the forward model

$$\mathbf{F}(\mathbf{x} + \delta\mathbf{x}) \approx \mathbf{F}(\mathbf{x}) + \nabla\mathbf{F}(\mathbf{x})\delta\mathbf{x}$$

For linear problems, ∇**F** does not depend on **x**. For, nonlinear problems it does.

How to be sensitive: the Jacobian

The Jacobian can be written more explicitly as

$$\nabla \mathbf{F}(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_N} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_2}{\partial x_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_M}{\partial x_1} & \frac{\partial f_M}{\partial x_2} & \cdots & \frac{\partial f_M}{\partial x_N} \end{bmatrix}$$

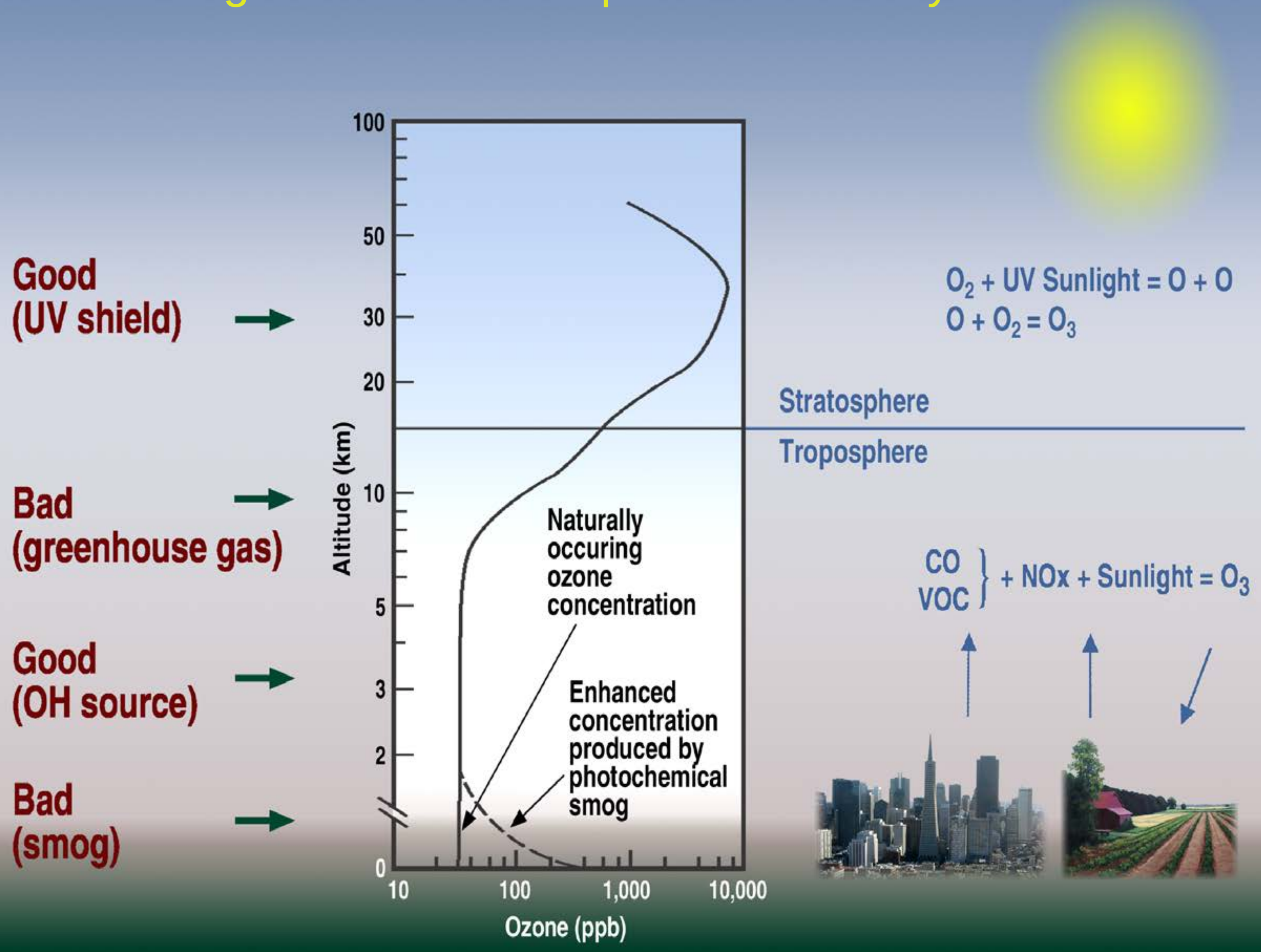
where $x_n = [\mathbf{x}]_n$ for compactness, we' ll redefine the Jacobian as

$$\nabla \mathbf{F}(\mathbf{x}) = \mathbf{K}_{\mathbf{x}} = \mathbf{K}(\mathbf{x})$$

The Jacobian describes how much an observable will change if the state changes.

Test case: ozone

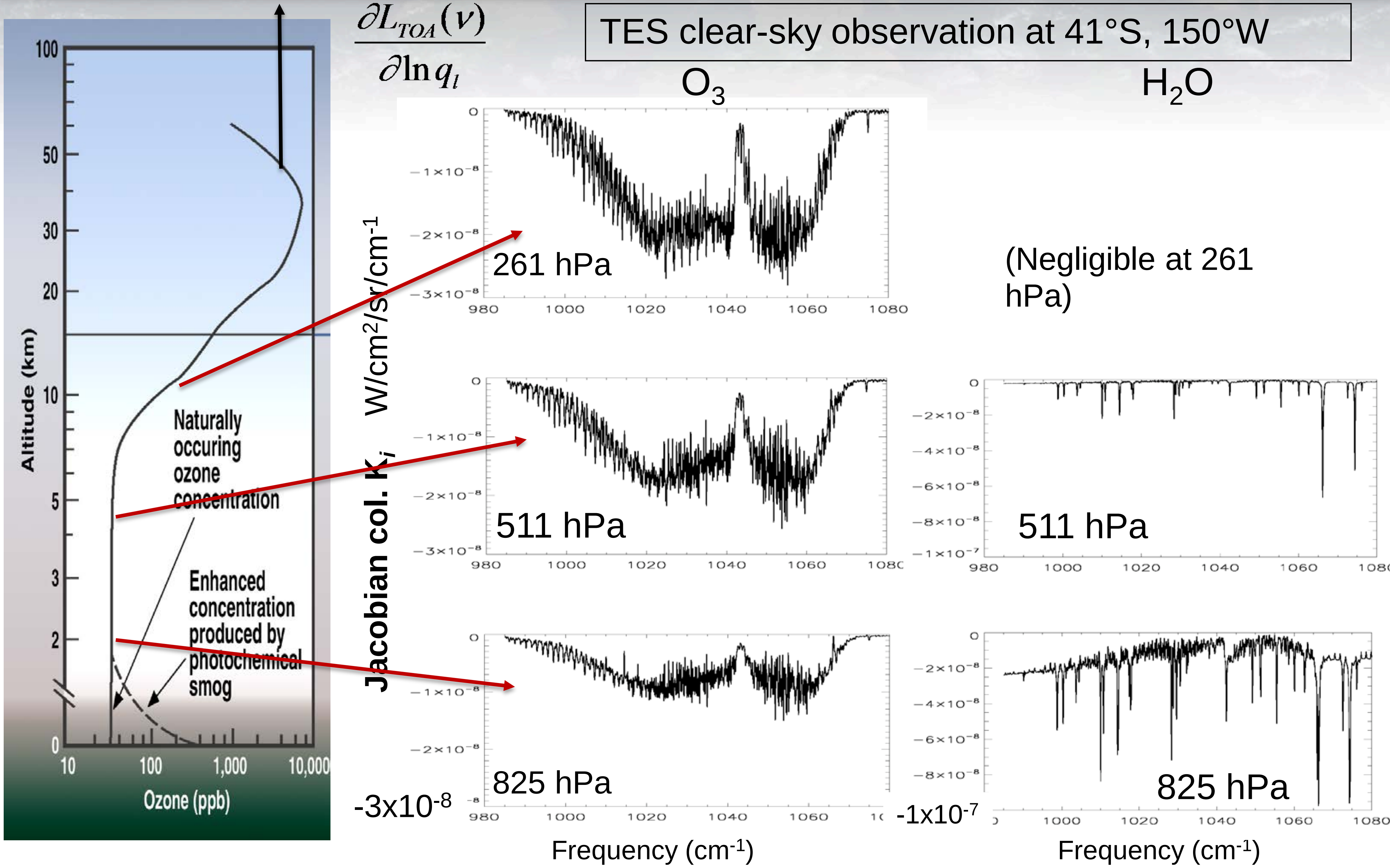
Characterization of the vertical distribution of ozone is critical to understanding its role in atmospheric chemistry and climate



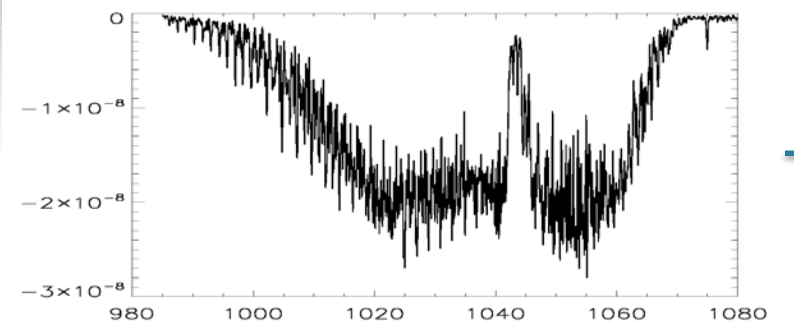
Jacobians and the greenhouse gas effect

$$\frac{\partial L_{TOA}(\nu)}{\partial \ln q_l}$$

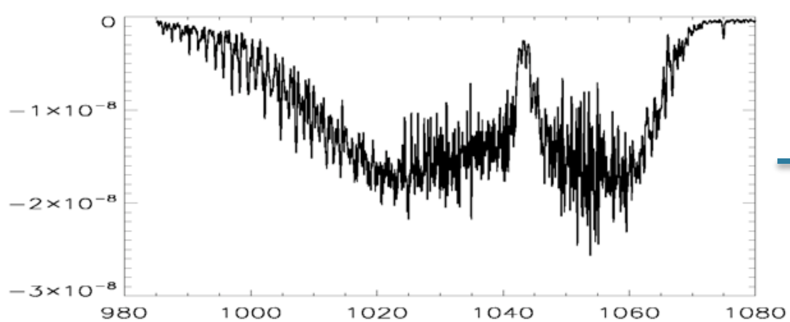
TES clear-sky observation at 41°S, 150°W



Filling the columns



$$\nabla \mathbf{F}(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_N} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_2}{\partial x_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_M}{\partial x_1} & \frac{\partial f_M}{\partial x_2} & \cdots & \frac{\partial f_M}{\partial x_N} \end{bmatrix}$$



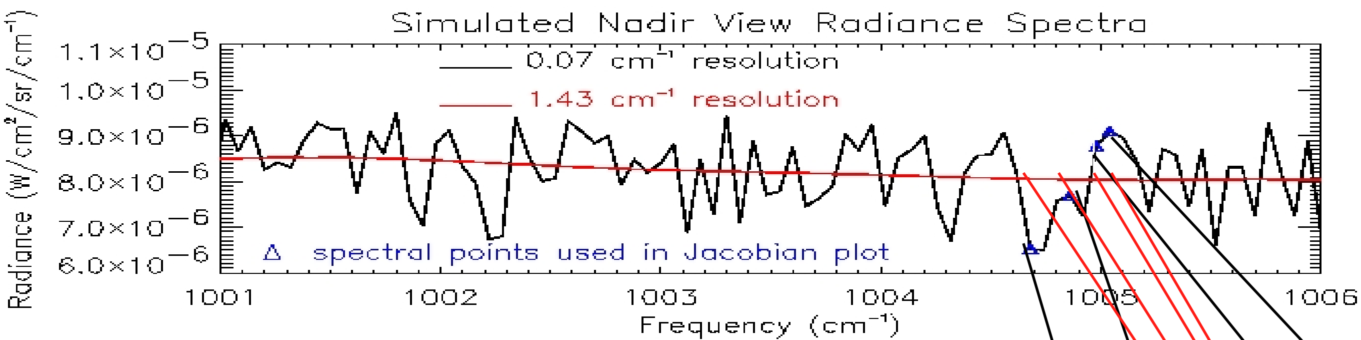
The columns of the Jacobian define the sensitivity of the radiances to ozone at a *specific* altitude

Where is it?
Spectral resolution impacts vertical resolution.

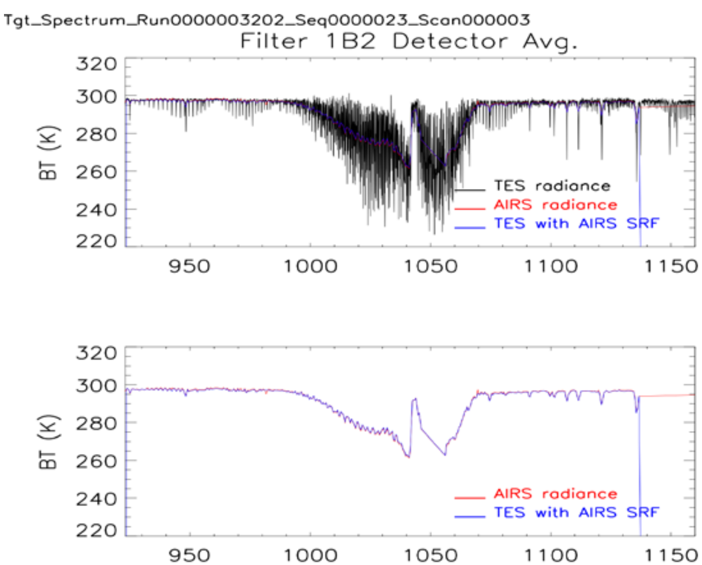
In the thermal infrared,
vertical resolution is obtained by exploiting
the pressure dependence of spectral lines

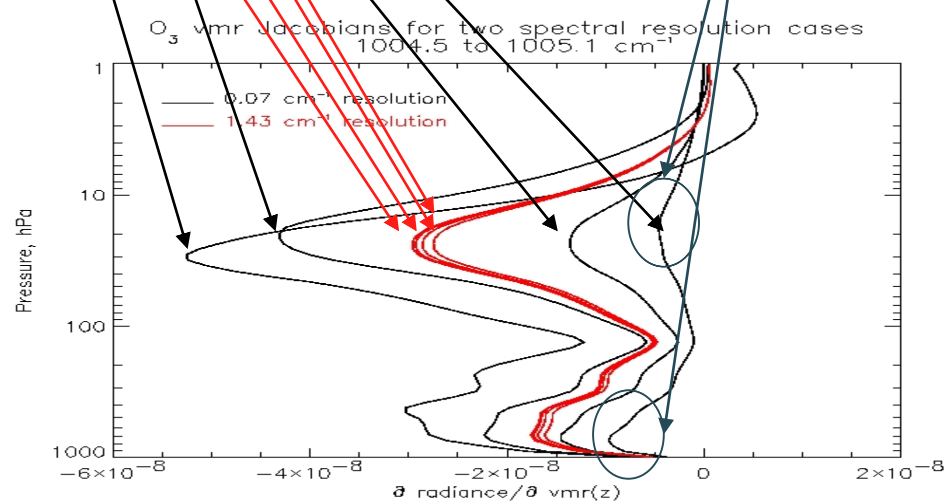
At a spectral resolution of 1.43 cm^{-1}, the spectral radiances respond *in the same way* to changes to the vertical distribution of ozone

At a spectral resolution of 0.07 cm^{-1}, the spectral radiances respond differently to changes in the vertical distribution of ozone.

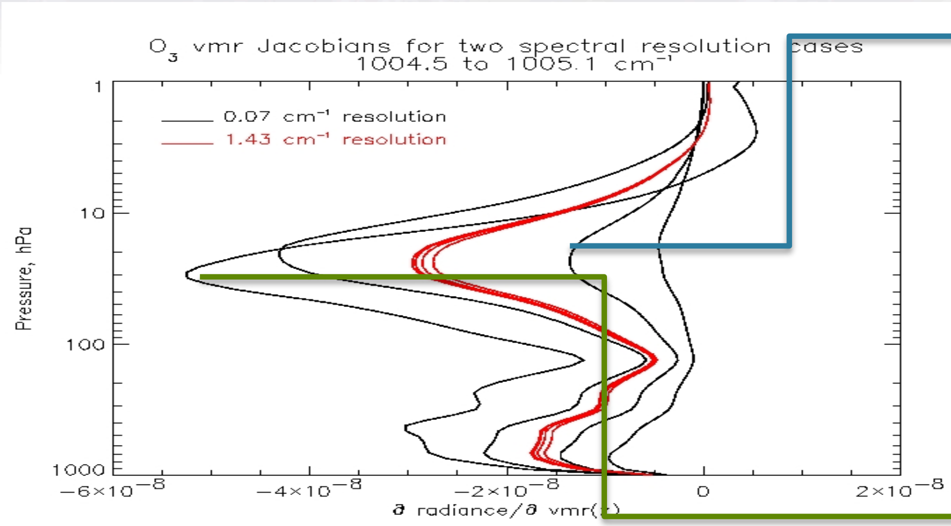


The spectral wings of the ozone lines have greater sensitivity to the lower troposphere than the stratosphere





Filling the rows



$$\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_N} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_2}{\partial x_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_M}{\partial x_1} & \frac{\partial f_M}{\partial x_2} & \cdots & \frac{\partial f_M}{\partial x_N} \end{bmatrix}$$

The rows of the Jacobian define the sensitivity of a *specific* radiance to ozone for each altitude.

The Inverse Problem

How often does that happen? From physics to statistics.

Let's say that we made some guess, $\mathbf{x}_0$, about ozone at a particular place, e.g., Boulder. What would we see at the instrument?

$$\mathbf{y} - \mathbf{F}(\mathbf{x_0}) \approx \mathbf{K}(\mathbf{x} - \mathbf{x_0}) + \mathbf{n}$$

We know about the sensitivities, **K**

To determine **x**, we need to know something about **x** and **n**

If we can statistically characterize **x** and **y** in general, we can estimate **x** in particular given a measurement **y.**

Bayes' Theorem

We want to know the probability of the atmospheric state **x**, e.g., ozone, *given* a measurement **y**, e.g., radiances: $p(\mathbf{x}|\mathbf{y})$ How do we calculate it?

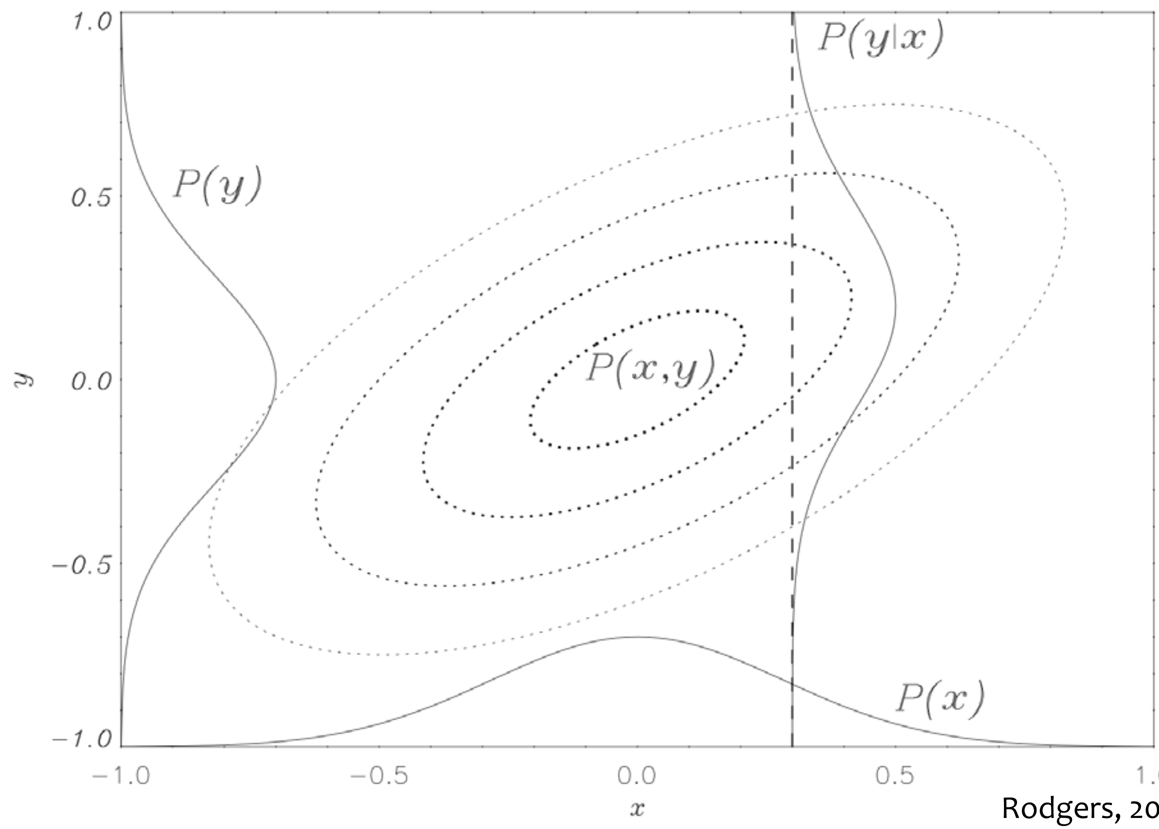
Start with the joint probability distribution function (pdf): $p(\mathbf{x}, \mathbf{y})$

The conditional pdf is:

$$p(\mathbf{y}|\mathbf{x}) \triangleq \frac{p(\mathbf{x}, \mathbf{y})}{p(\mathbf{x})}$$

The marginal distribution is

$$p(\mathbf{x}) = \int p(\mathbf{x}, \mathbf{y}) d\mathbf{y}$$



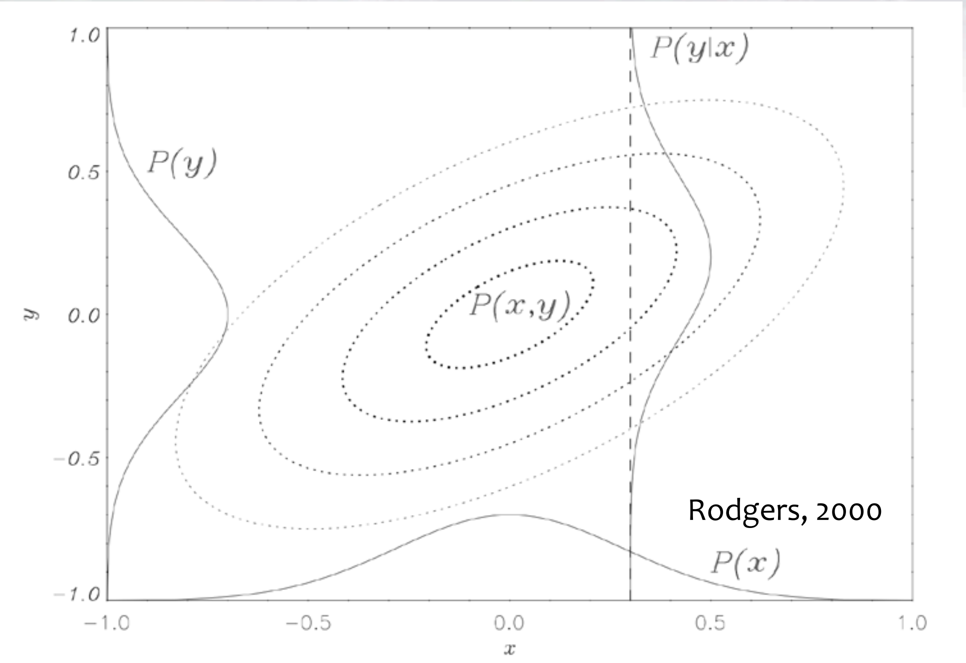
Rodgers, 2000

Bayes' Theorem

The joint pdf can be written two ways:

$$p(\mathbf{y},\mathbf{x}) = p(\mathbf{y}|\mathbf{x})p(\mathbf{x})$$

$$p(\mathbf{x},\mathbf{y}) = p(\mathbf{x}|\mathbf{y})p(\mathbf{y})$$



Substituting these into the conditional pdf leads to *a posteriori distribution* from the Bayes' Theorem:

$$p(\mathbf{x}|\mathbf{y}) = \frac{p(\mathbf{y}|\mathbf{x})p(\mathbf{x})}{p(\mathbf{y})}$$

Let's break it down:

$p(\mathbf{x})$ *A priori* knowledge of the state

$p(\mathbf{y}|\mathbf{x})$ Observation *given* knowledge of the state (data distribution)

$p(\mathbf{y})$ Marginal distribution. Need integration of the joint pdf

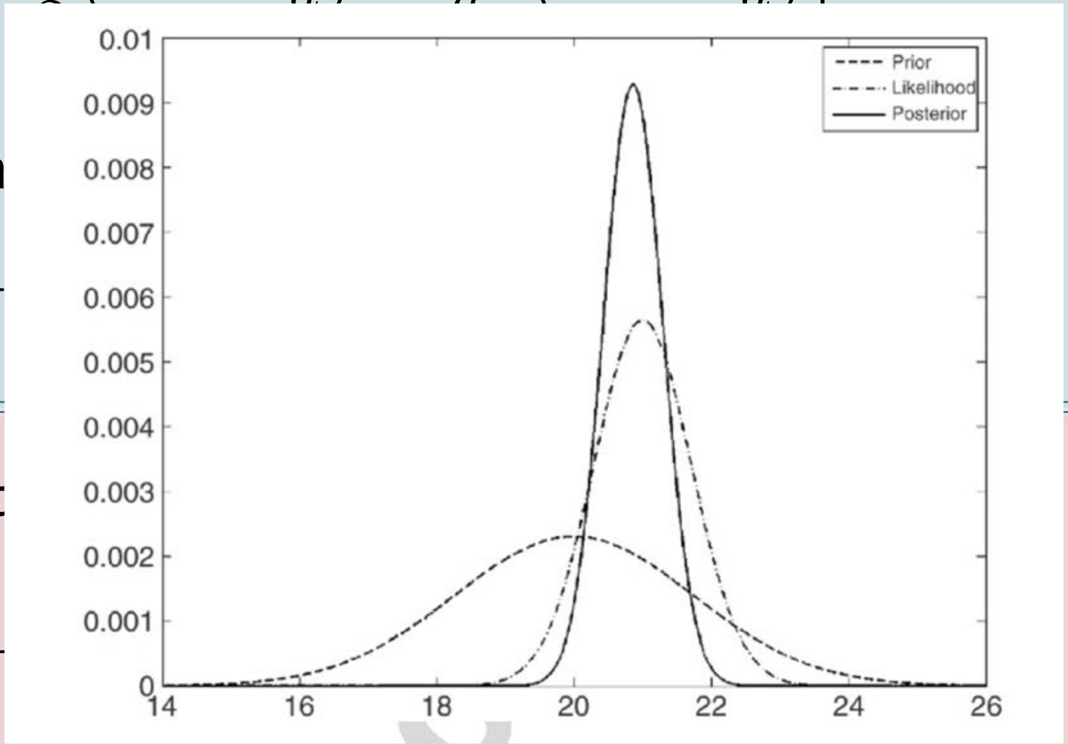
The Multivariate Gaussian case

The ***prior*** distribution is

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{n/2}|\mathbf{S}_a|^{1/2}} \exp\left[-\frac{1}{2}(\mathbf{x}-\mathbf{x}_a)^\top \mathbf{S}_a^{-1}(\mathbf{x}-\mathbf{x}_a)\right]$$

The prior mean and covariance can

$$E[\mathbf{x}] = \mathbf{x}_a \qquad E[(\mathbf{x}-\mathbf{x}_a)(\mathbf{x} -$$



The ***data*** distribution is defined in t

$$p(\mathbf{y}|\mathbf{x}) = \frac{1}{(2\pi)^{n/2}|\mathbf{S}_n|^{1/2}} \exp\Bigg[$$

The data mean and covariance can be defined as

$$E[\mathbf{n}] = \bar{\mathbf{n}} = \mathbf{0} \qquad E[(\mathbf{n}-\bar{\mathbf{n}})(\mathbf{n}-\bar{\mathbf{n}})^\top] = \mathbf{S}_n$$

The data model assumes measurement noise statistics are known

Climbing the hill: MAP solution

Algebraic manipulation:

$$\ln p(\mathbf{x}|\mathbf{y}) \propto \ln p(\mathbf{y}|\mathbf{x}) + \ln p(\mathbf{x}) + \mathrm{const}$$

In practice p(**y**) can ignored for the purposes of estimating **x**

$$\ln p(\mathbf{x}|\mathbf{y}) \propto \|\mathbf{y} - \mathbf{F}(\mathbf{x})\|^2_{\mathbf{S}_n^{-1}} + \|\mathbf{x} - \mathbf{x}_a\|^2_{\mathbf{S}_a^{-1}}$$

$p(\mathbf{x}|\mathbf{y})$ is the sum of Gaussians—and also a Gaussian—and has a maximum: The most probable value of **x** given **y**.

The Maximum A Posteriori (MAP) solution is consequently found from

$$\frac{dp(\mathbf{x}|\mathbf{y})}{d\mathbf{x}}|_{\mathbf{x}=\hat{\mathbf{x}}} = \mathbf{0} \qquad \hat{\mathbf{x}} = \int \mathbf{x}p(\mathbf{x}|\mathbf{y})d\mathbf{x}$$

The MAP solution can be written as a numerical problem:

$$\min_{\mathbf{x}} \left\{ (\mathbf{y} - \mathbf{F}(\mathbf{x}))^\top \mathbf{S}_n^{-1} (\mathbf{y} - \mathbf{F}(\mathbf{x})) + (\mathbf{x} - \mathbf{x}_a)^\top \mathbf{S}_a^{-1} (\mathbf{x} - \mathbf{x}_a) \right\}$$

The geometry of Bayes

Bayes Theorem provides a statistical justification for the least squares problem

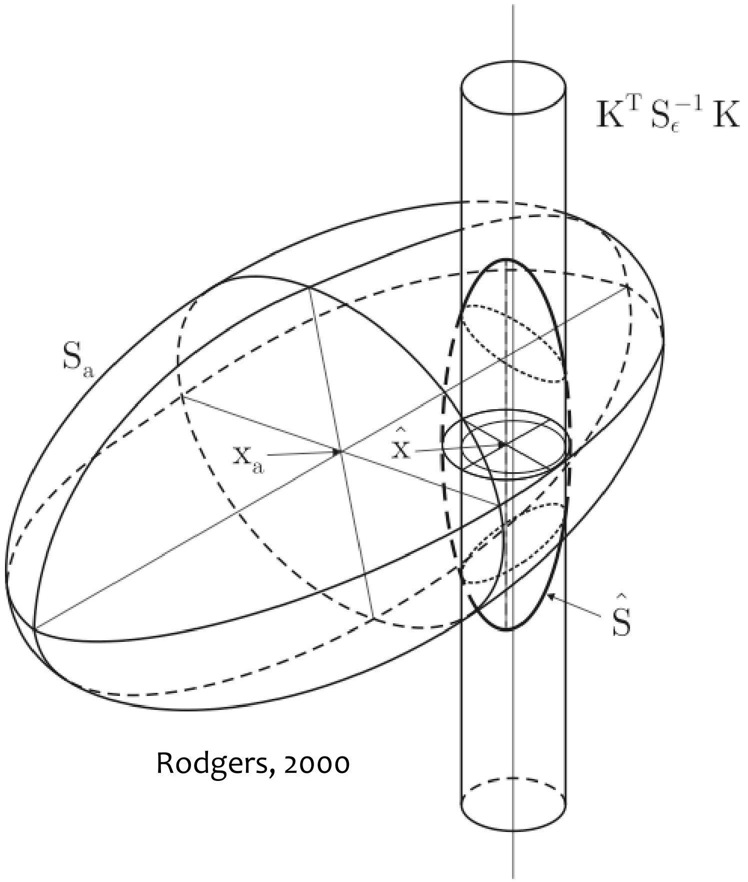
$$\min_{\mathbf{x}} \left\{ (\mathbf{y} - \mathbf{F}(\mathbf{x}))^\top \mathbf{S}_n^{-1} (\mathbf{y} - \mathbf{F}(\mathbf{x})) + (\mathbf{x} - \mathbf{x}_a)^\top \mathbf{S}_a^{-1} (\mathbf{x} - \mathbf{x}_a) \right\}$$

$$\hat{\mathbf{x}} = \mathbf{x}_a + (\mathbf{K}^\top \mathbf{S}_n^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \mathbf{K}^\top \mathbf{S}_n^{-1} (\mathbf{y} - \mathbf{F}(\mathbf{x}_a))$$

$$\hat{\mathbf{S}} = (\mathbf{K}^\top \mathbf{S}_n^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1}$$

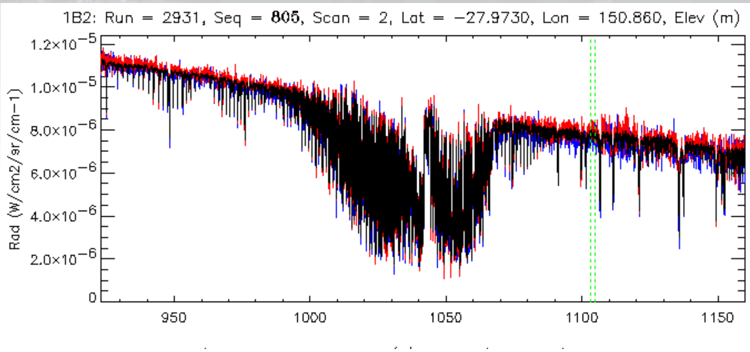
Example: Let $\mathbf{x} \in \mathbb{R}^3$ $\mathbf{y} \in \mathbb{R}^2$

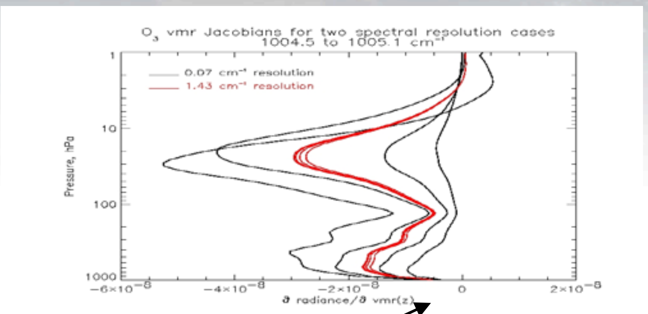
- Large ellipsoid is a contour of the prior pdf
- Cylinder is a contour of the pdf of the state given only the measurement
- Small ellipsoid is a contour of the posterior pdf:



Rodgers, 2000

The optimal estimate





Observed radiances

Jacobian

noise

$$\mathbf{y} - \mathbf{F}(\mathbf{x}_a) \approx \mathbf{K}(\mathbf{x} - \mathbf{x}_a) + \mathbf{n}$$

Forward model

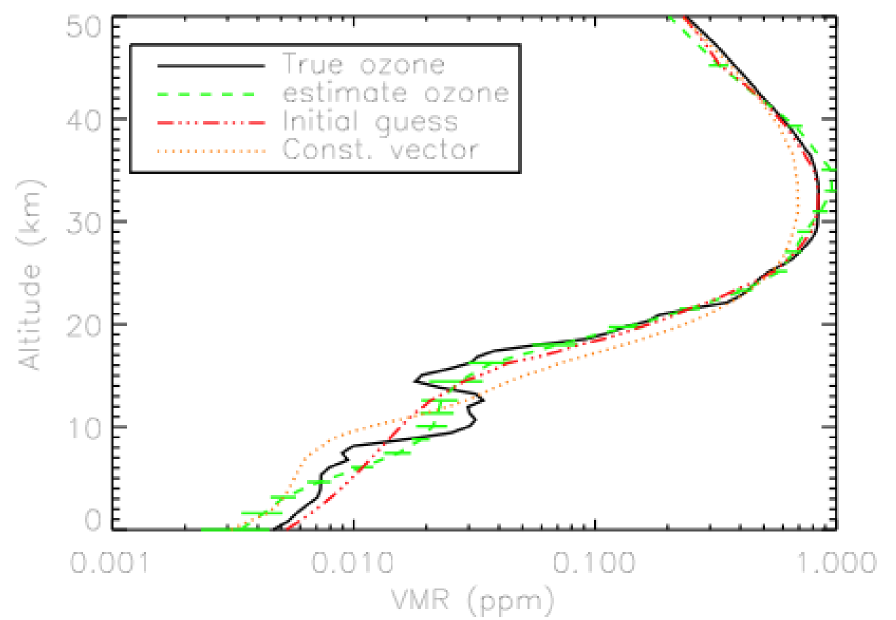
True profile

A priori profile

$$\hat{\mathbf{x}} = \mathbf{x}_a + (\mathbf{K}^\top \mathbf{S}_n^{-1}\mathbf{K} + \mathbf{S}_a^{-1})^{-1}\mathbf{K}^\top \mathbf{S}_n^{-1}(\mathbf{y} - \mathbf{F}(\mathbf{x}_a))$$

The optimal estimate is a balance between what the data can tell us about the state and what we already know about it.
How do we characterize the balance?

The estimate is sensitive to the ozone plume but does not completely capture it.
How do we characterize the resolution of the estimate?



Characterization

The Third Pillar: Characterization

A powerful part of this methodology is the characterization of the estimate relative to the true state.

Consider the approximation

$$\mathbf{y} - \mathbf{F}(\mathbf{x}_a) \approx \mathbf{K}(\mathbf{x} - \mathbf{x}_a) + \mathbf{n}$$ substitute into the estimate

$$\hat{\mathbf{x}} = \mathbf{x}_a + (\mathbf{K}^\top \mathbf{S}_n^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \mathbf{K}^\top \mathbf{S}_n^{-1} (\mathbf{K}(\mathbf{x} - \mathbf{x}_a) + \mathbf{n})$$

$$\boxed{\hat{\mathbf{x}} = \mathbf{x}_a + \mathbf{A}(\mathbf{x} - \mathbf{x}_a) + \mathbf{G}\mathbf{n}}$$

Gain matrix

$$\mathbf{G} = \frac{\partial \hat{\mathbf{x}}}{\partial \mathbf{F}} = (\mathbf{K}^\top \mathbf{S}_n^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \mathbf{K}^\top \mathbf{S}_n^{-1}$$

Averaging kernel matrix

$$\mathbf{A} = \frac{\partial \hat{\mathbf{x}}}{\partial \mathbf{x}} = \mathbf{G}\mathbf{K}$$

The optimal estimate (retrieval) is related to the true (but unknown state) by the averaging kernel matrix.

Averaging Kernel

The averaging kernel matrix, **A**, is one of the most important characterizations of the estimate

$$\mathbf{A} = \frac{\partial \hat{\mathbf{x}}}{\partial \mathbf{x}} = \mathbf{GK}$$

The averaging kernel matrix describes the change in the estimate due to the change in the true state. This relationship can be further described by looking at the rows and columns of **A** with respect to the estimate.

Averaging kernel

$$\frac{\partial \hat{x}_i}{\partial \mathbf{x}} = \langle \mathbf{a}_{i,*}, \delta \mathbf{x} \rangle$$

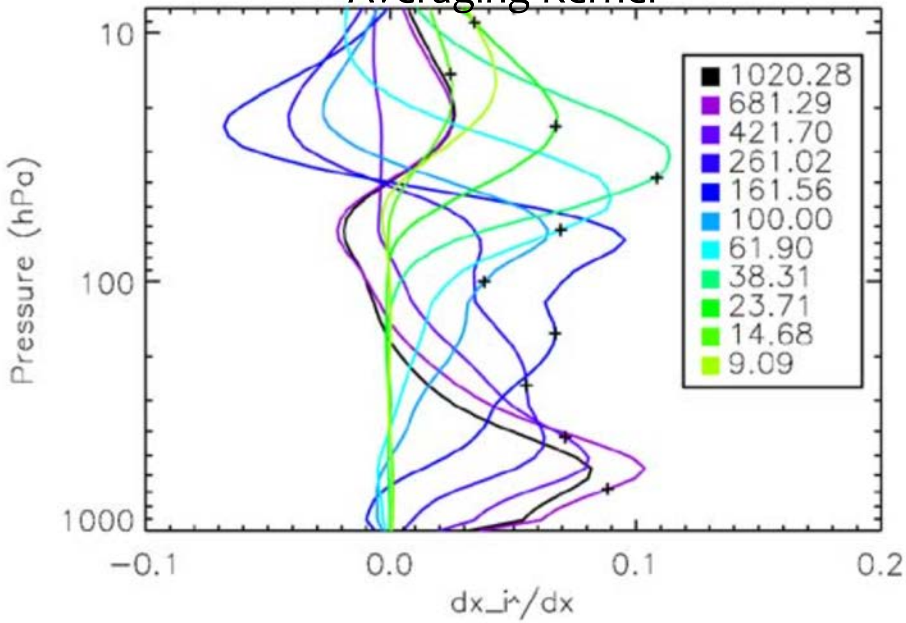
Impulse response

$$\frac{\partial \hat{\mathbf{x}}}{\partial x_i} = \delta x_i \mathbf{a}_{*,i}$$

Averaging Kernel Matrix

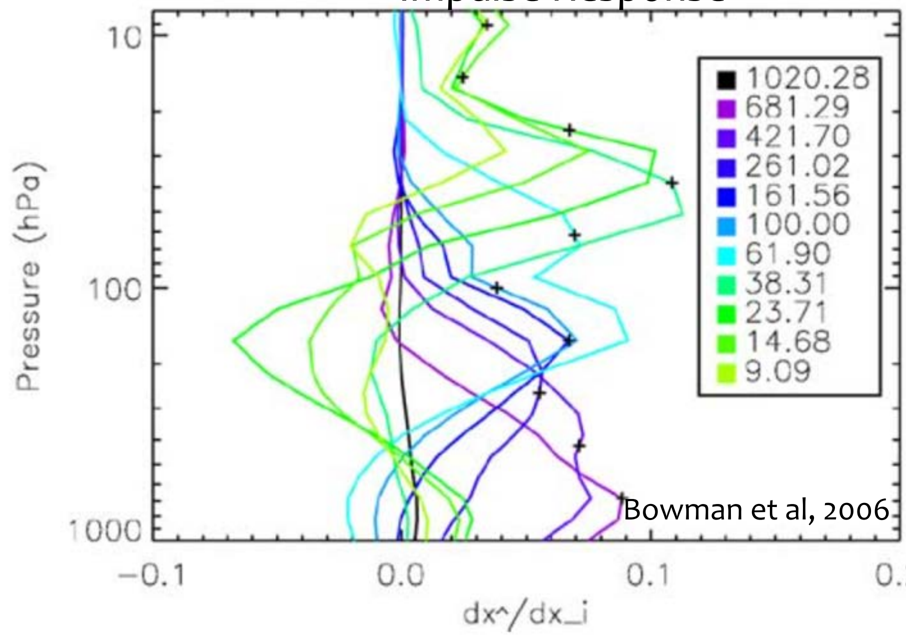
The averaging kernel and the impulse response provide complimentary information about the estimate.

Averaging Kernel



$$\frac{\partial \hat{x}_i}{\partial \mathbf{x}} = \langle \mathbf{a}_{i,*}, \delta \mathbf{x} \rangle$$

Impulse Response



$$\frac{\partial \hat{\mathbf{x}}}{\partial x_i} = \delta x_i \mathbf{a}_{*,i}$$

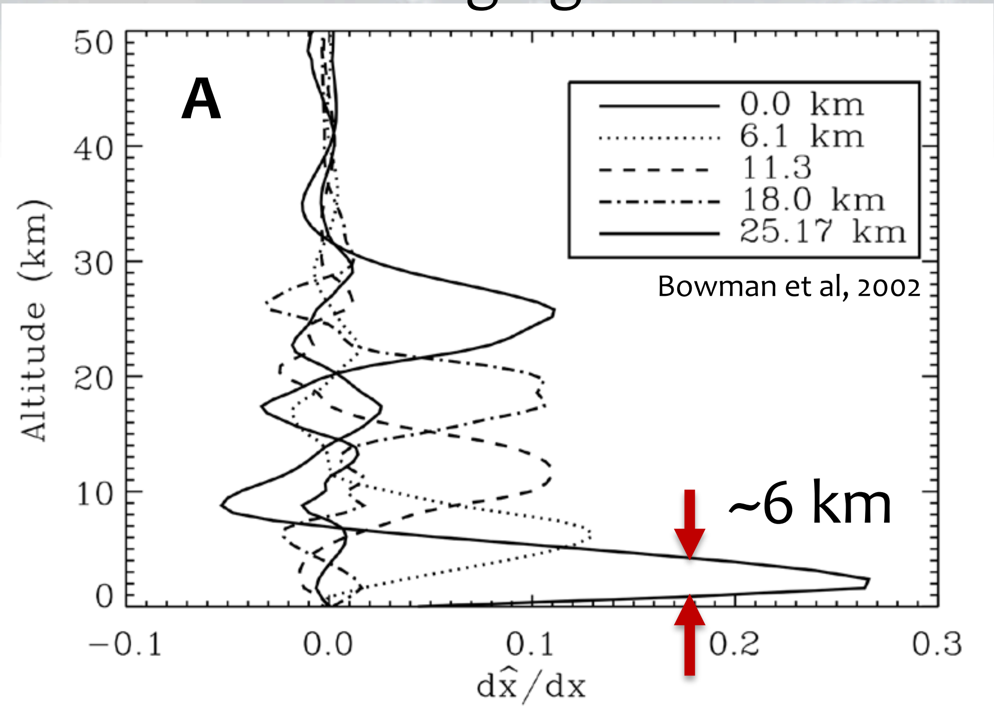
The averaging kernel describes how the true state changes the estimate at a particular altitude, $\hat{x}_i$, whereas the impulse response describes how the entire estimate changes to the true state a particular altitude, x_i.

Where is it? Resolution

The averaging kernel provides a means of defining the vertical *resolution* of the estimate, i.e., how well can the estimate (ozone) at one altitude be distinguished from another?

The resolution can be calculated from full-width half height.

Averaging kernel



A more robust, but more abstract definition of resolution is the degrees of freedom for signal (dofs), which is the trace of the averaging kernel matrix:

$$\boxed{\mathrm{dofs} = \mathrm{Trace}(\mathbf{A})}$$

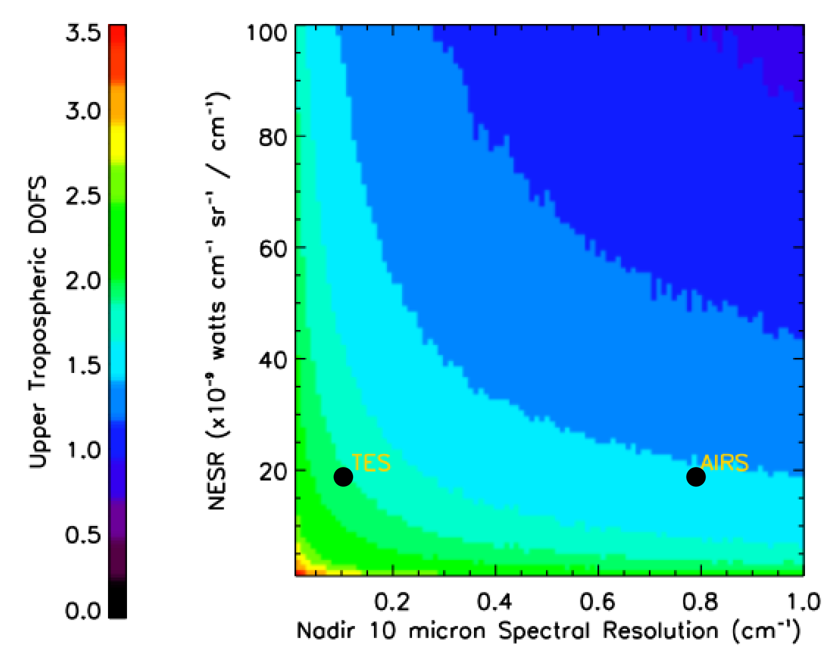
The dofs provides a measure of the independent information that can be determined from an estimate. It can be calculated over subsets of the atmospheric state

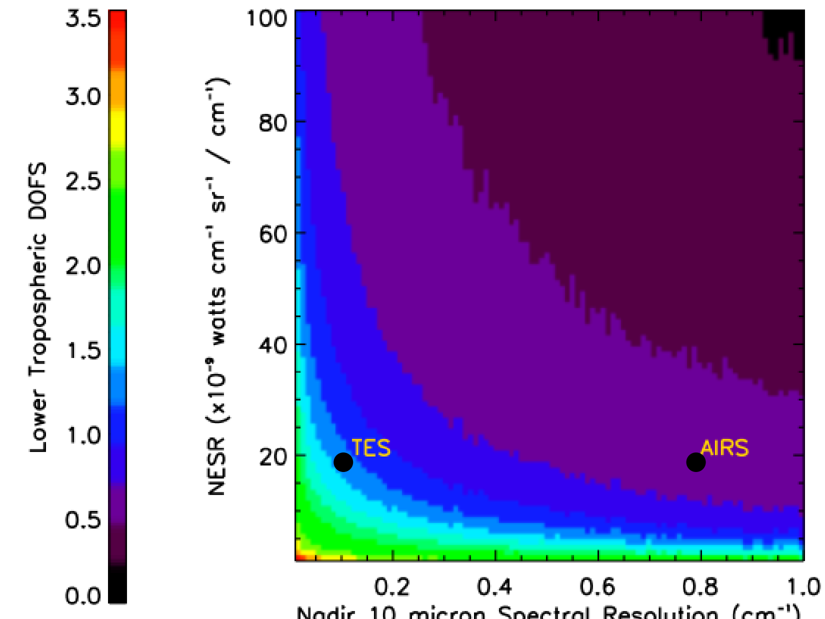
The what and where of vertical resolution

The averaging kernel is a function of the sensitivity, which includes spectral resolution, precision, the inherent variability of the atmospheric state.

Different instrument designs can achieve resolution at different altitudes by making trade-offs such as spectral resolution and precision.

Sensitivity to ozone in the lower most troposphere requires much higher spectral resolution than the upper troposphere.





Courtesy J. Worden

The many flavors of error

The total error can be split into two useful terms: $\hat{\mathbf{S}} = (\mathbf{K}^\top \mathbf{S}_n^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1}$
smoothing and measurement error

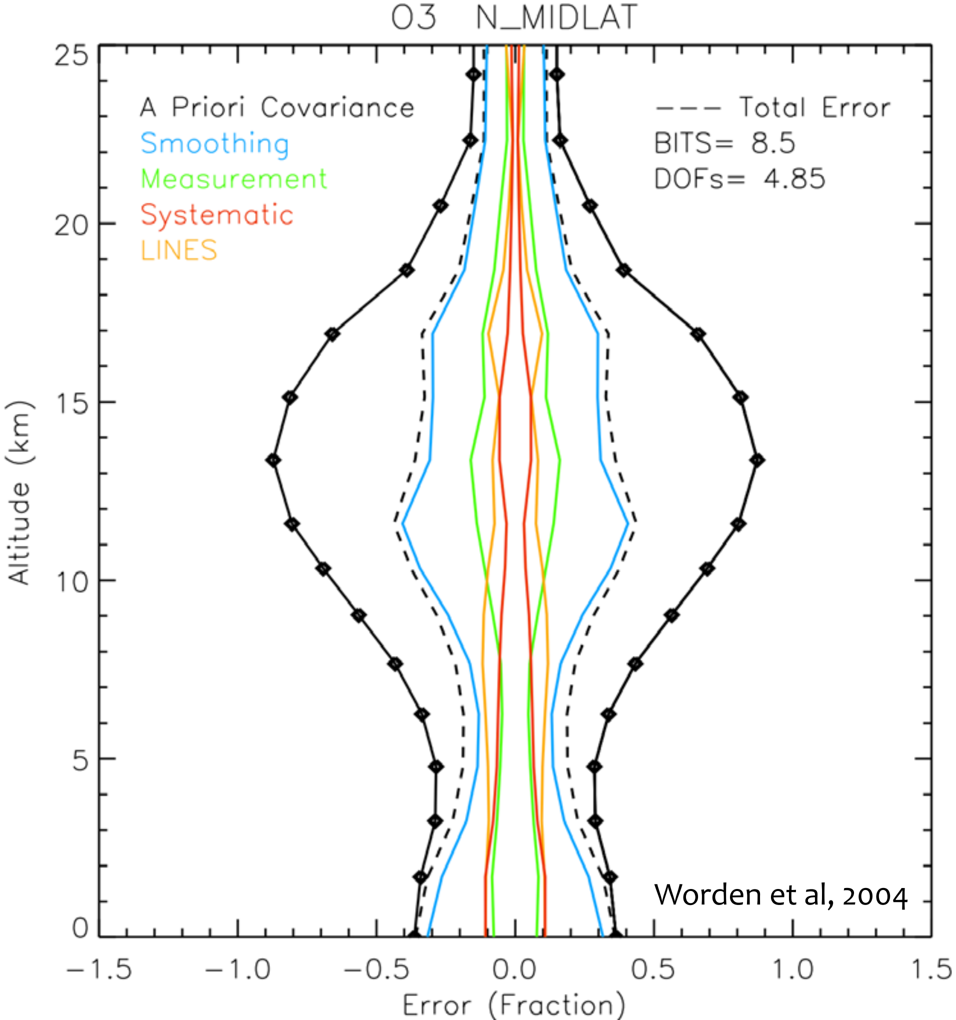
$$\hat{\mathbf{S}} = (\mathbf{I} - \mathbf{A})\mathbf{S}_a(\mathbf{I} - \mathbf{A})^\top + \mathbf{G}\mathbf{S}_n\mathbf{G}^\top$$

Smoothing error — measurement error

<u>Smoothing error:</u> error in the estimate from the lack of resolution (as defined by the averaging kernel).

Note that the smoothing error is dependent on the variability of the state: CO2 will be different than O3.

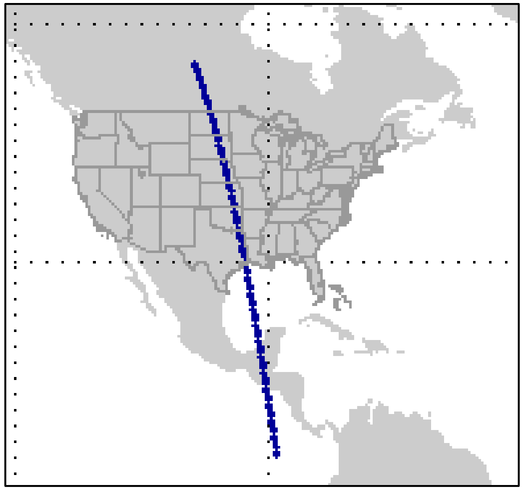
<u>Measurement error:</u> error from random noise.

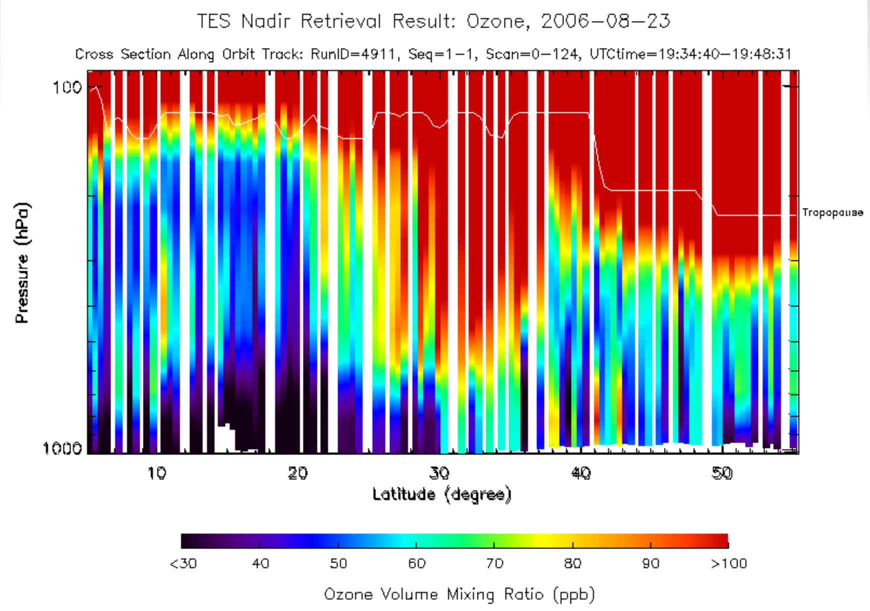


Putting it together

TES observations during the NOAA TEXAQS 2006 campaign

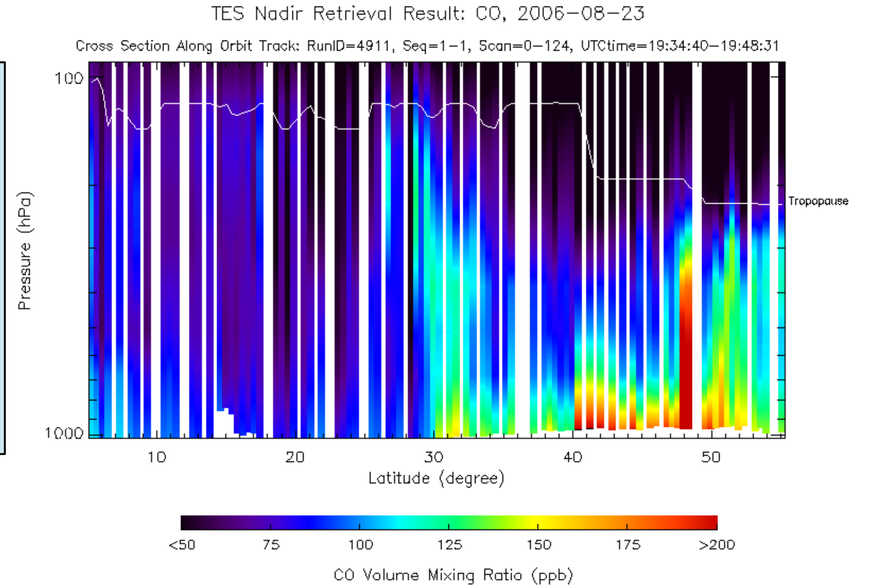
http://tes.jpl.nasa.gov/TexAQS_2006/browse_run4911.html





TES retrievals of elevated ozone and CO are seen near Houston on Aug 23rd, 2006.

How do we characterize this retrievals?

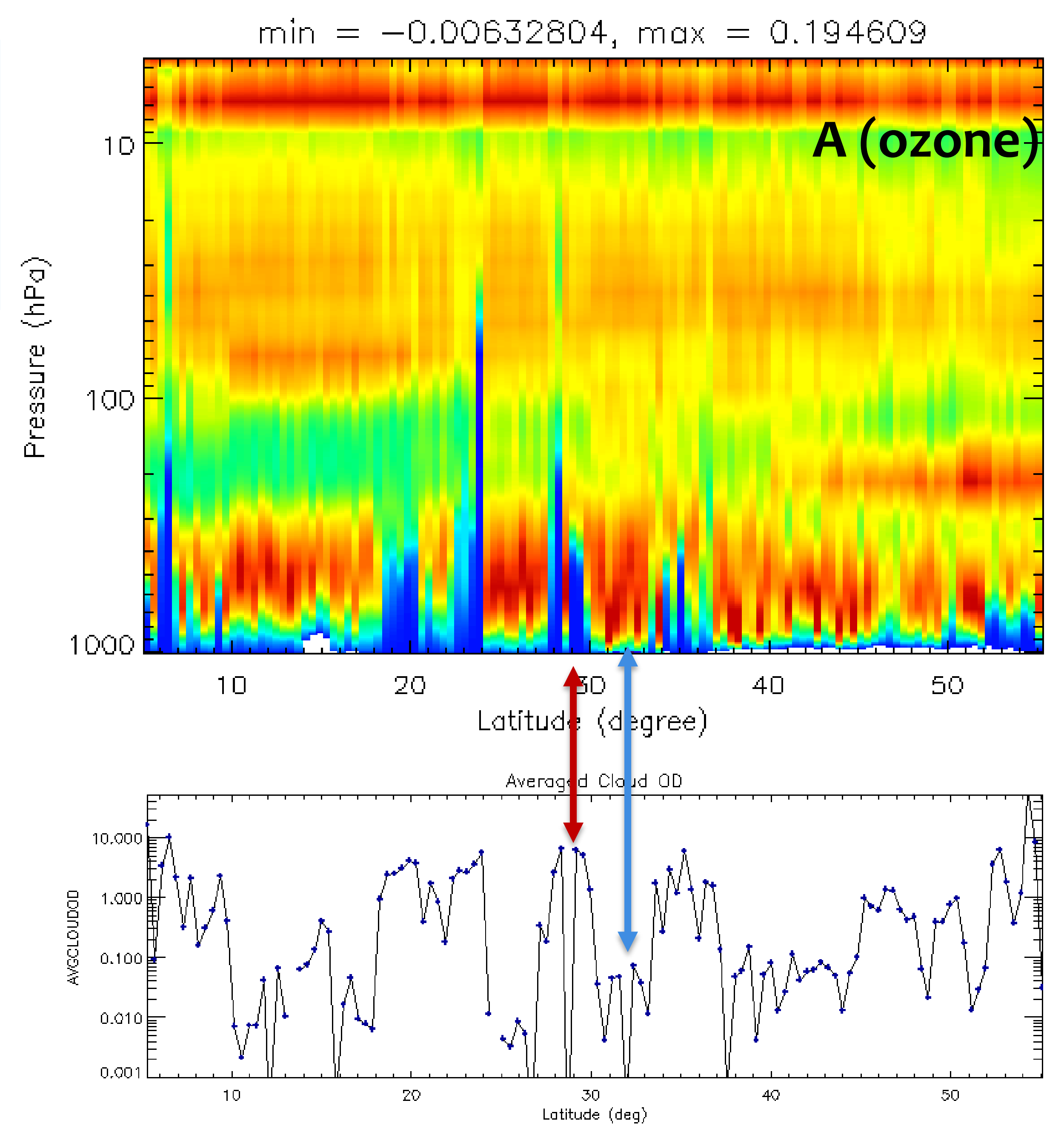


A Cloudy View

The primary driver of sensitivity for thermal instruments is surface temperature and clouds.

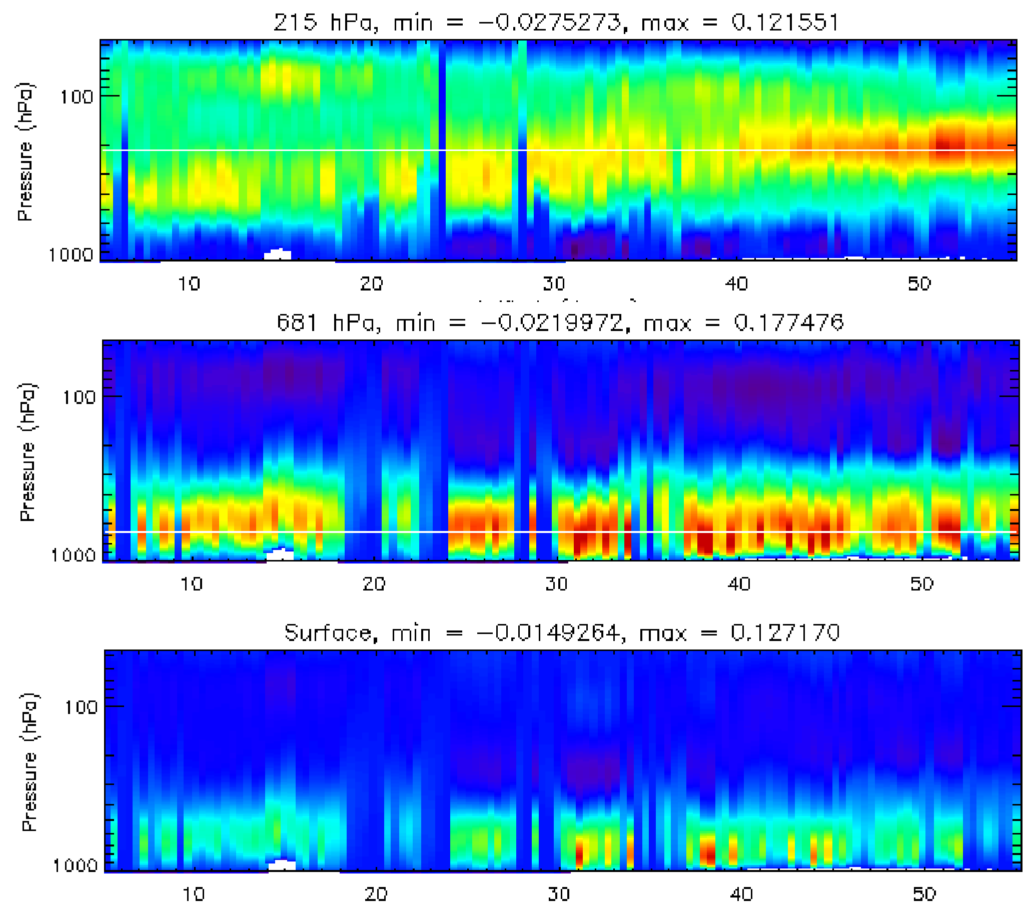
The TES-retrieved cloud optical depth is high off the coast of Texas
but low directly on land.

The diagonal of the ozone averaging kernel shows high sensitivity in the lower troposphere.

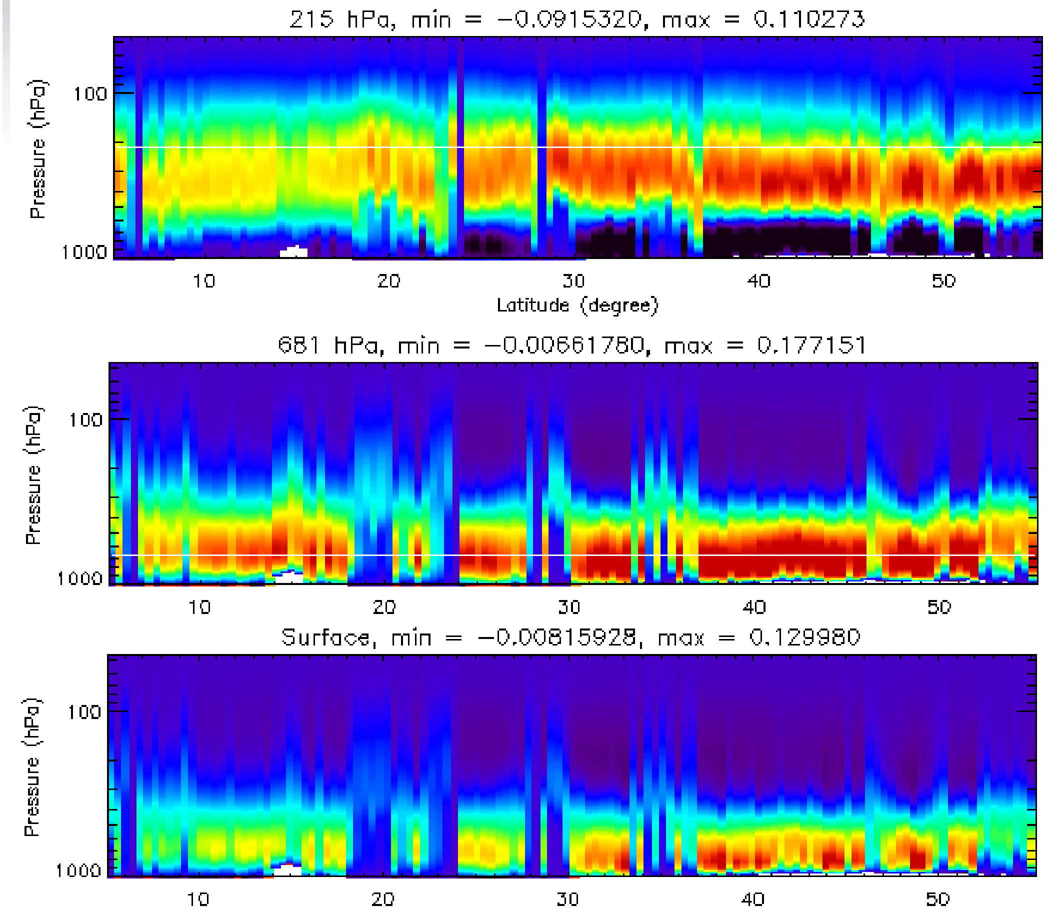


Where is the pollution?

O3 AK



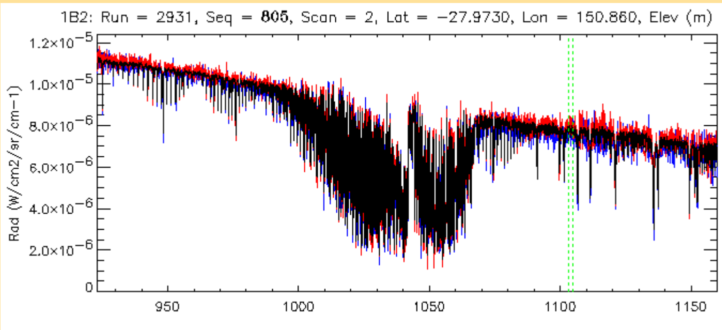
CO AK



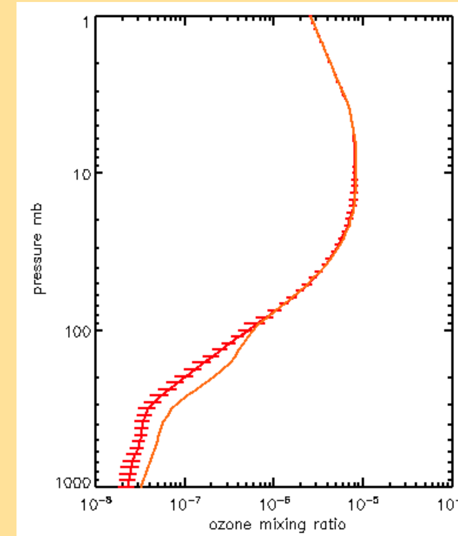
- O3 and CO between the surface and 680 hPa and 18-20N is driven by the a priori.
- At 680 hPa, the retrievals are influenced by the true atmosphere from near surface to about 300 hPa.
- Poleward of 40N, upper tropospheric O3 sensitivity at 215 hPa increases because of decreasing tropopause height.

Observation operators:

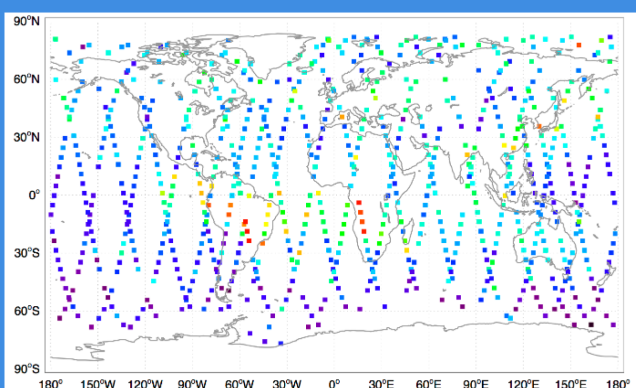
connecting measurements to assimilation



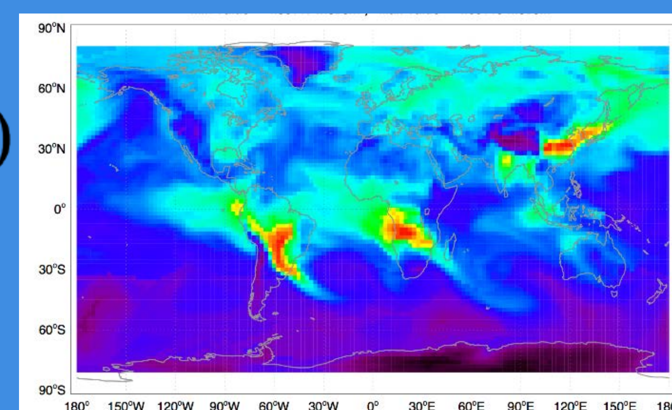
$$\|\mathbf{y}-\mathbf{F}(\mathbf{x}_a)\|^2_{\mathbf{S}_n^{-1}} + \|\mathbf{x}-\mathbf{x}_a\|^2_{\mathbf{S}_a^{-1}}$$



$$\hat{\mathbf{x}} = \mathbf{x}_a + \mathbf{A}(\mathbf{x}-\mathbf{x}_a) + \mathbf{G}\mathbf{n}$$



$$\mathbf{H}_i(\bullet) = \mathbf{x}_a + \mathbf{A}_i(\bullet - \mathbf{x}_a)$$



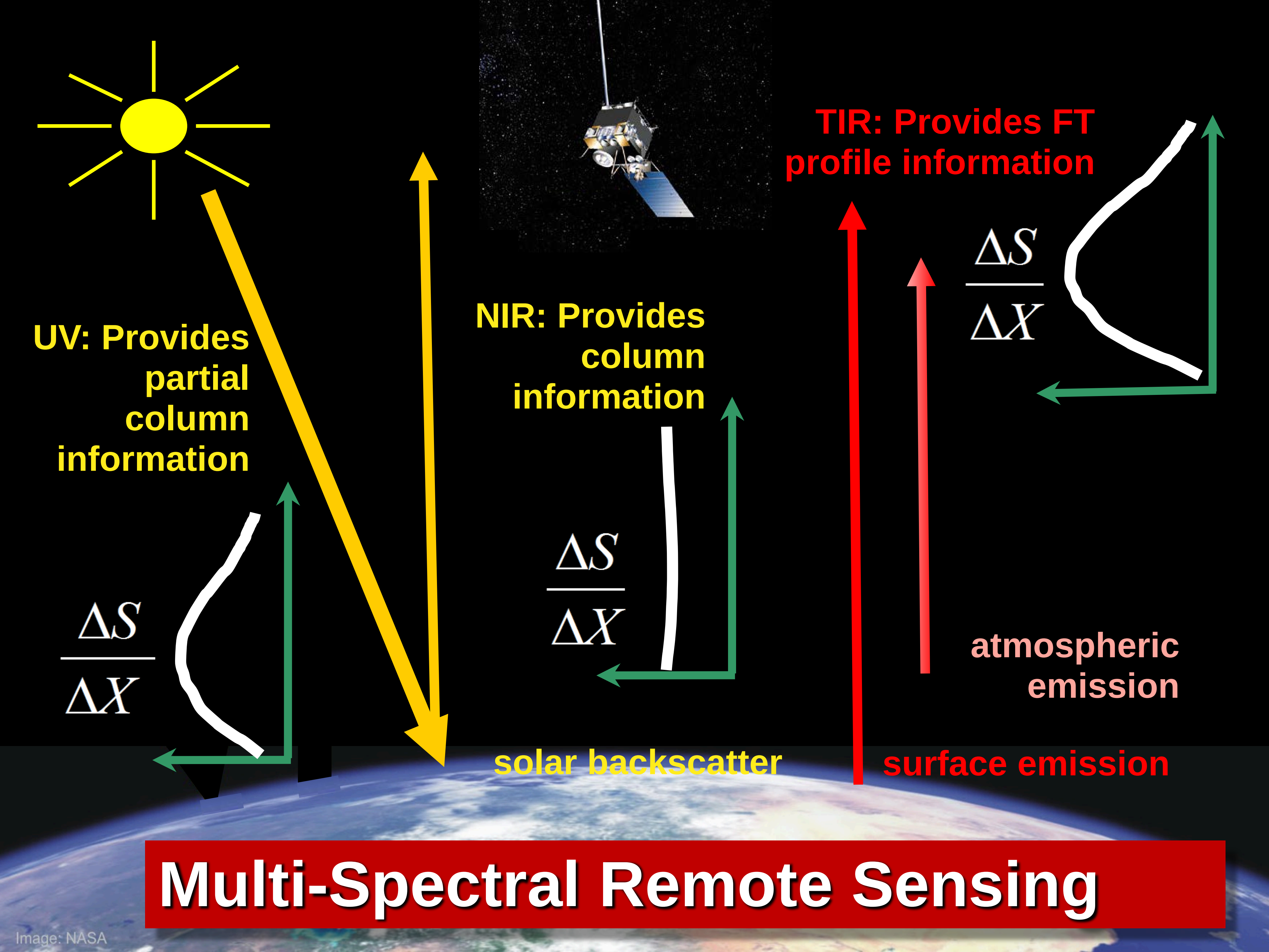
$$\sum_i \|\hat{\mathbf{x}}_i - \mathbf{H}_i(\mathbf{x})\|^2_{(\mathbf{G}_i\mathbf{S}_n^i\mathbf{G}_i^T)^{-1}} + \|\mathbf{x}_0-\mathbf{x}_B\|^2_{\mathbf{B}^{-1}}$$

Conclusions/Future Directions

- Atmospheric trace gas retrievals are built on 3 pillars:
  - Forward Model (atmospheric radiative transfer)
  - Inverse Model (optimal estimation)
  - Characterization/Error Analysis (averaging kernels, dofs, etc.)
- Observation operators-–constructed from averaging kernels—are powerful tools to compare remote sensing estimates to other data, e.g., sondes, and to assimilation systems
- Non-Gaussian, non-linear approaches, e.g., Markov Chain Monte Carlo (MCMC), will become increasingly important.

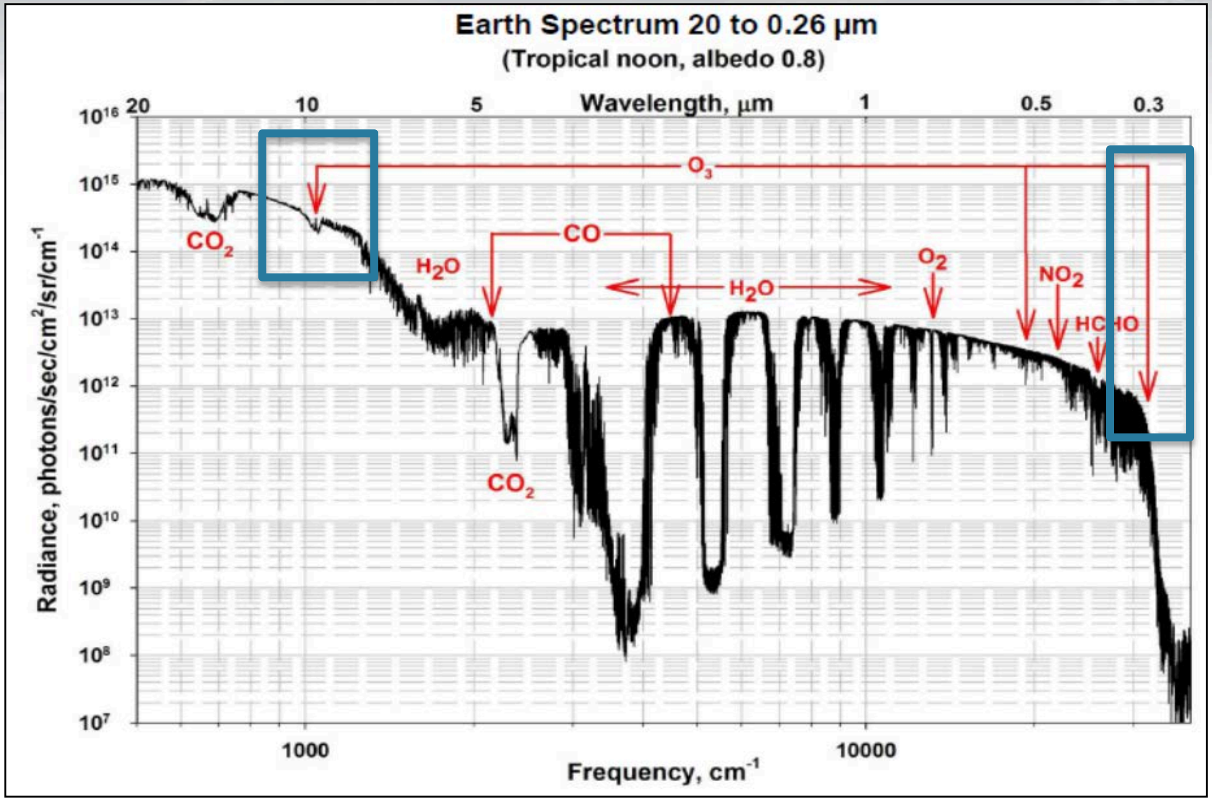
Backup

BACKUP


TIR: Provides FT profile information
UV: Provides partial column information
NIR: Provides column information
$\frac{\Delta S}{\Delta X}$
$\frac{\Delta S}{\Delta X}$
$\frac{\Delta S}{\Delta X}$
atmospheric emission
solar backscatter
surface emission
Multi-Spectral Remote Sensing
Image: NASA

Two eyes are better than one: IR and UV

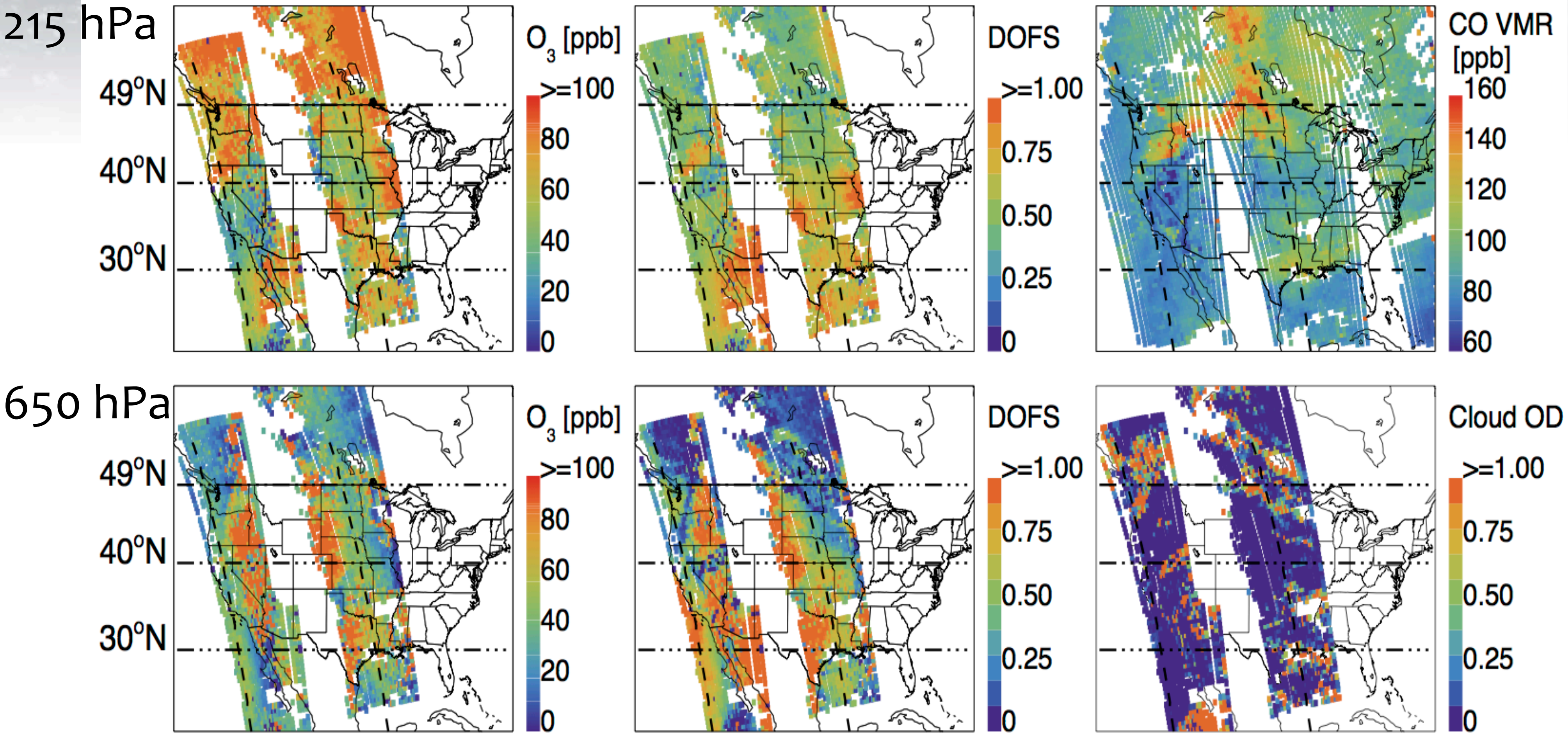
IR
ATMOS
CLAES
HALOE
IMG
MIPAS
TES
AIRS
ACE-FTS
IASI
CrIS



UV
TOMS
SAGE
SBUV
SOLCE
OSIRIS
SCIAMACHY
OMI
GOME
GOME-2

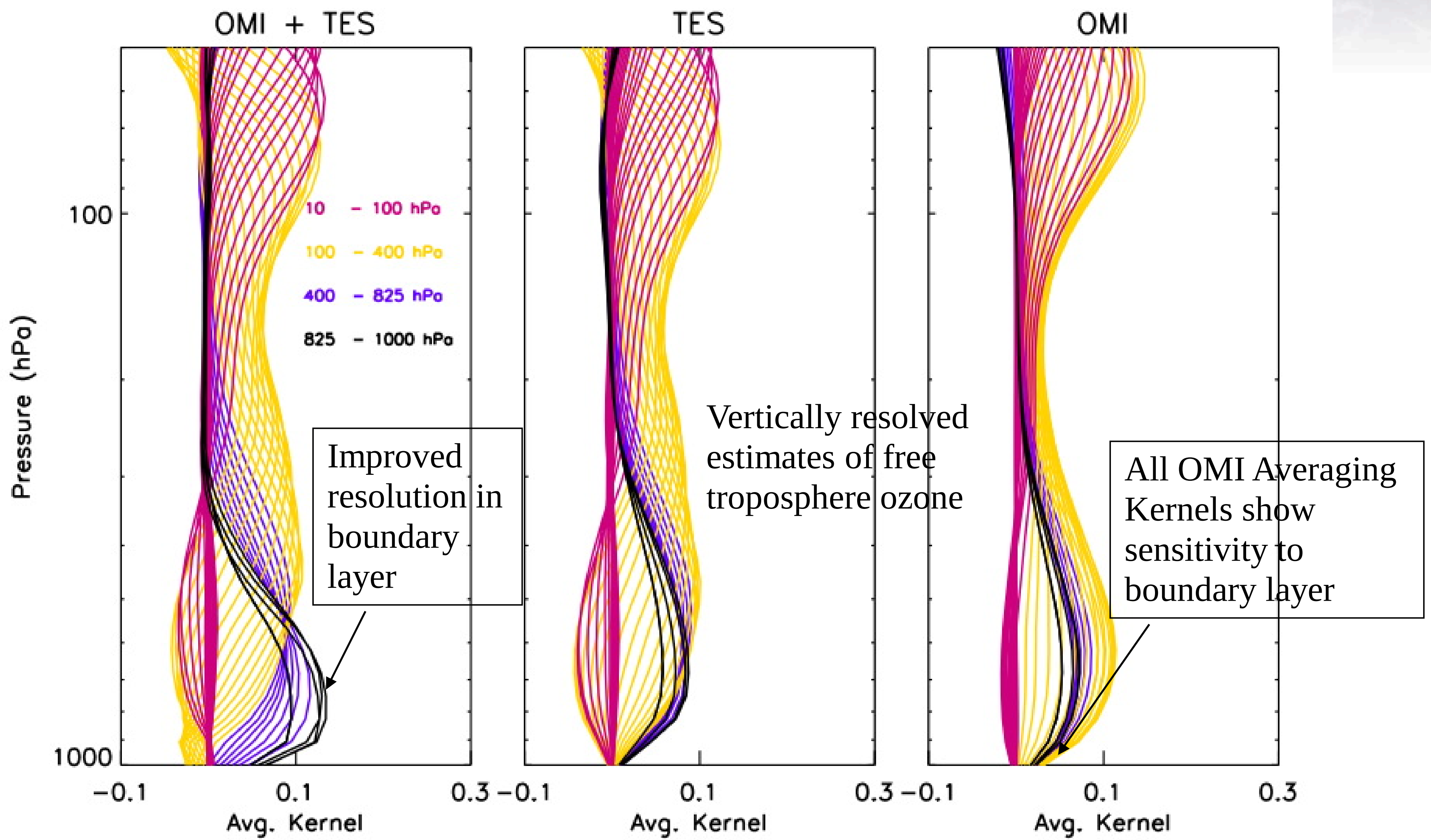
UV and IR measurements provide complimentary sensitivity to ozone. Worden et al, GRL, 2007 and Landgraff and Hasekamp, JGR, 2007 showed the feasibility of estimating boundary layer ozone. Fu et al, ACP, 2013 and Cuesta et al, ACP, 2013 have demonstrated the potential for TES and IASI.

AIRS/OMI--Aug 23rd, 2006



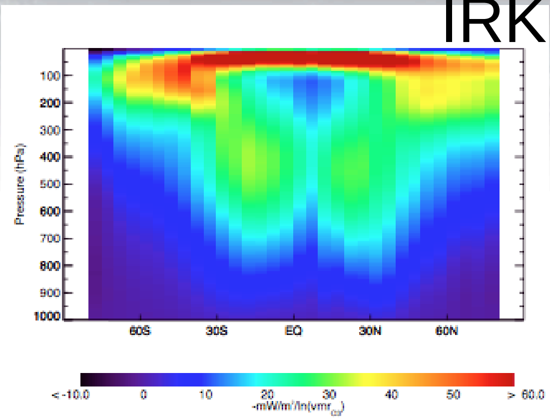
- The TES optimal estimation retrieval algorithm was applied to the combination of AIRS and OMI radiances to infer O3 and CO.
- Elevated CO and O3 in Pacific NW associated with biomass burning.
- DOFS show skill in separating upper and lower troposphere.
- DOFS and Cloud OD show the British Columbia obscured by clouds
- Elevated Texan LT ozone associated with agricultural burning and antrhopogenic emissions

Diagnosis of synthetic retrievals



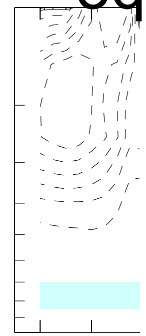
OLR bias in chemistry-climate models

IRK(z)



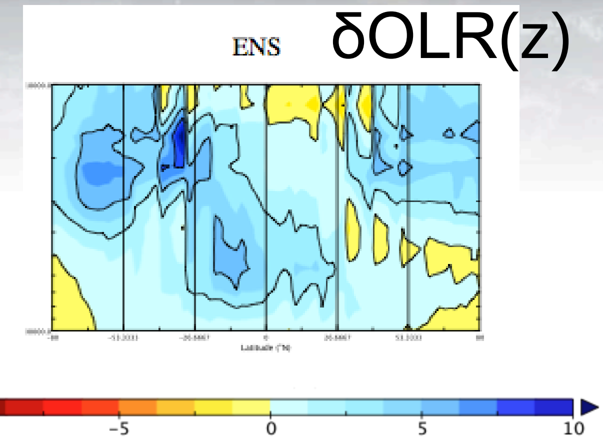
▯

δq(z)

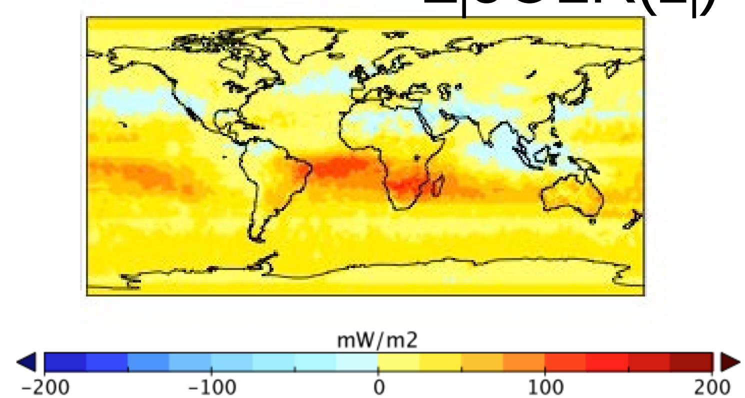


=

ENS δOLR(z)

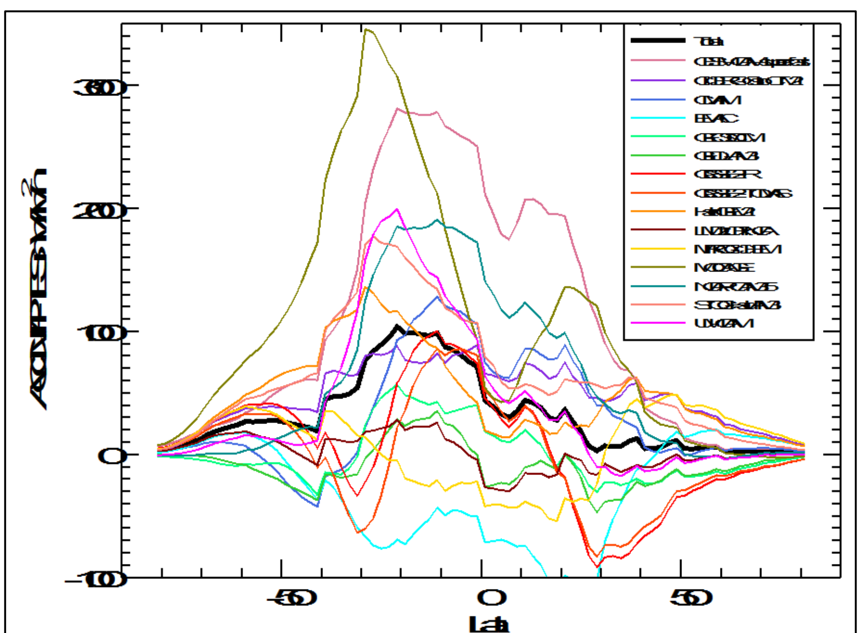


mWm^{-2} $\Sigma_i \delta OLR(z_i)$



ZM ozone vs TES / ppbv (acchist; 2000 slice mean)

The Atmospheric Chemistry-Climate Model Intercomparison Project (**ACCMIP**) estimated historic radiative forcing (RF) and future response using consistent emissions for the IPCC 5th assessment. (Lamarque et al, 2013)



Bowman *et al*, 2013

In the tropics, discrepancies lead to over 300 mWm^{-2} for individual models and up to 100 mWm^{-2} for the ACCMIP ensemble.