Practical use of EO-LDAS: application to agricultural monitoring

J Gómez-Dans

National Centre for Earth Observation (NCEO)
Department of Geography
University College London

Caveat emptor!

I have biases. I try not to make them too obvious, but...

- I have a strong bias towards the land surface
- I have a strong bias towards optical EO

However! you can have this discussion for other components of the Earth System, and other remote sensing domains!

Acknowledgments: Nicola Pounder, the rest of the UCL team, ESA & NCEO

What do *you* want out of EO data?

- EO has the potential to provide monitoring capabilities:
  - Lots of things: Carbon *and* water fluxes, land use, . . .
  - Globally, but at fine spatial detail
  - All the time, and for long time periods
- But there's some effort to go from "EO data" $\Rightarrow$ "product"

An example: What you want

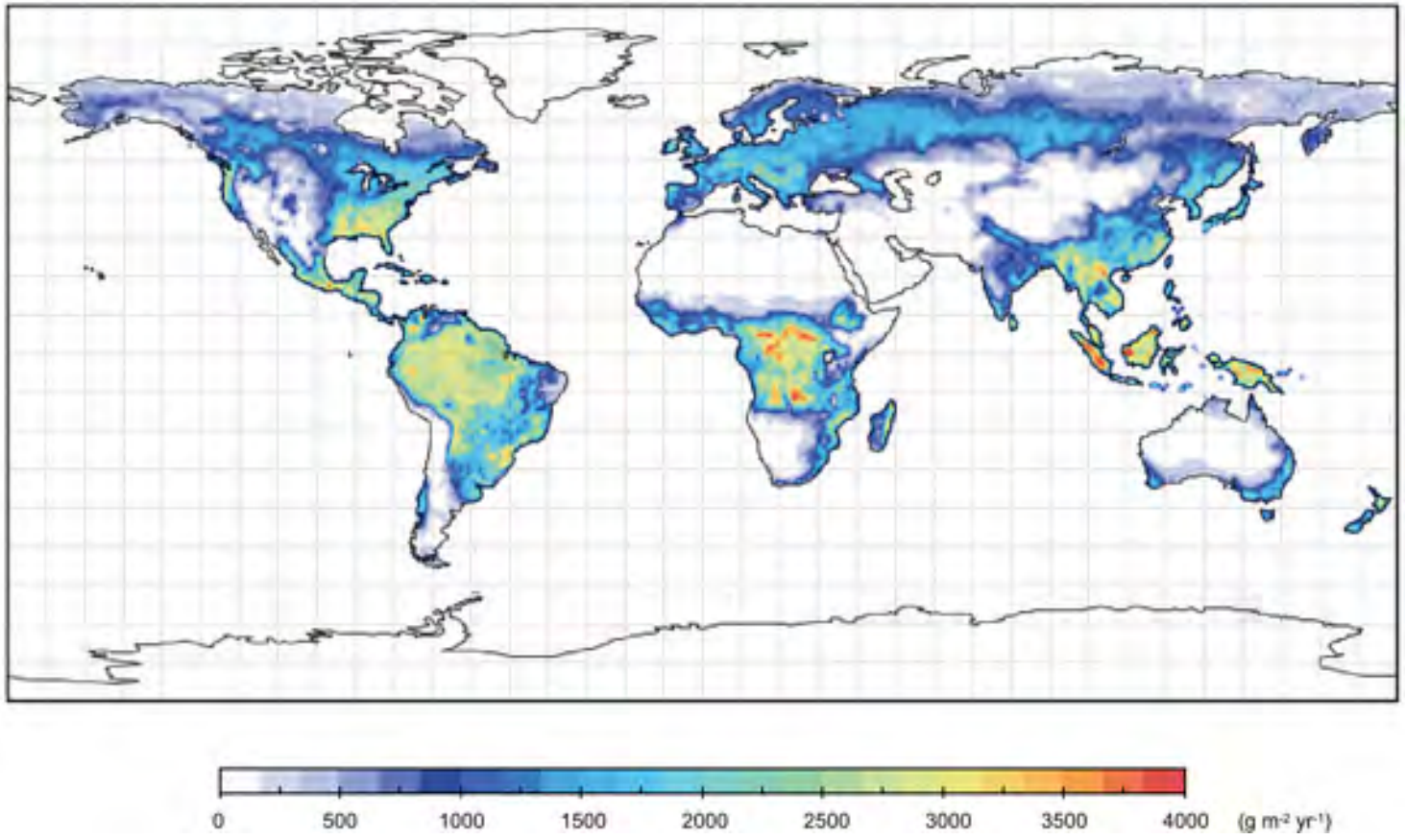


Figure: Global GPP (Global Primary Productivity) Source

An example: What you get

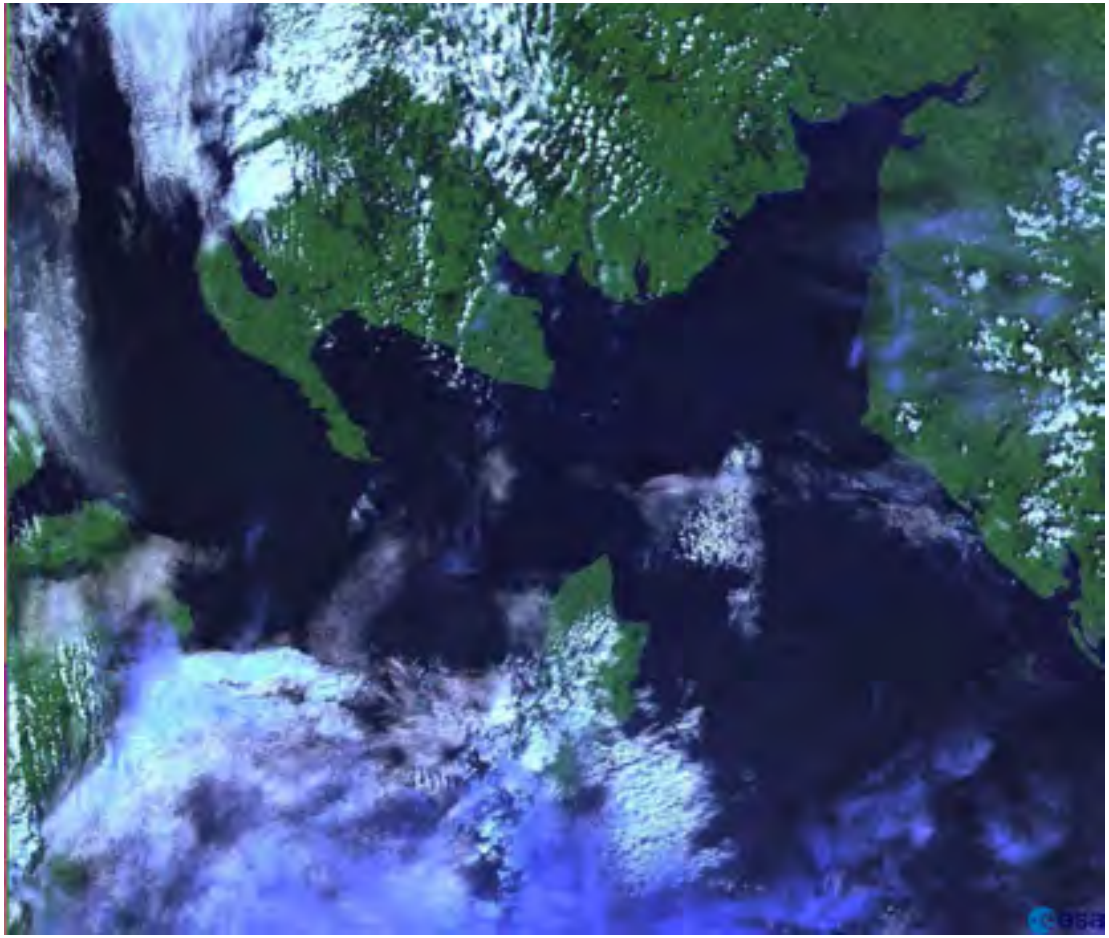


Figure: RGB composite ETM+7 Source

The dichotomy...

Application requirements

- **Vegetation productivity [kg]**
- **Biomass [kg]**
- **Burned biomass [kg]**
- **Evapotranspiration [$W \cdot m^{-2}$]**

EO measurements

- **Reflectance**
- **Brigthness temperature**
- **Radiance[$W \cdot sr{-}1 \cdot m^{-2} \cdot Hz^{-1}$]**
- **Backscatter[σ_0]**

Fundamental challenge $\Rightarrow$ EO data is **an indirect measurement!**

$\Rightarrow$ EO data need Interpretation

The virtual constellation concept

Monitoring a process of interest with a single sensor is typically difficult

- Sensors are built as a compromise with different users, so design typically optimal only for a few applications.
- Continuous monitoring hampered by clouds, orbits, . . .
- Different sensors have different sensitivity to different parameters
- Different sensors also have different “nuisance” processes to worry about

So we need a framework to consistently interpret observations from different sensors.

Two “schools” for EO interpretation

Empirical/*Inductive* Usually based on correlations between obs & “ground truth” measurements.

Physical/*Deductive* (Usually) based on physical models that describe eg radiation-soil-canopy interactions.

Two “schools” for EO interpretation

Empirical/*Inductive* Usually based on correlations between obs & “ground truth” measurements.

Physical/*Deductive* (Usually) based on physical models that describe eg radiation-soil-canopy interactions.

Bottom line

Empirical approach ✗ are easy, but hardly robust.

- Really hard to extend to multi-sensor schemes

Physical-approach ✓ encompasses our knowledge about physics, sensor characteristics, etc.

- ✗ Usually requires loads of ancillary data
- ✓ But you can also stand on the shoulders of giants!

The forward problem

- A model $\mathcal{H}$ describes the effect of the land surface in the measurements ($\vec{R}$)
  - Typically, model based on radiative transfer theory
  - e.g. the amount of vegetation changes $\Rightarrow$ reflectance changes
  - We define the state vector $\vec{x}$ as a set of land surface parameters that describe the land surface
- Mathematically

$$\vec{x} \xrightarrow{\mathcal{H}} \vec{R}$$

- i.e. if state vector is known, then we can predict observations
- Usually, we have observations and want to know the state!

The inverse problem

- The inverse problem is what we're interested in
- A statistical model that describes the observations could be

$$\vec{R} = \mathcal{H}(\vec{x}) + \nu$$

- ν is additive random noise (assume Gaussian $\mathcal{N}(0, \mathbf{C}_{obs})$
- So a solution is a state vector that results in a prediction that goes through the observations, or

$$\left|\left|\mathcal{H}(\vec{x}) - \vec{R}\right|\right|^2 \leqslant \nu$$

- If $\nu > 0$, then we have infinite solutions

An example

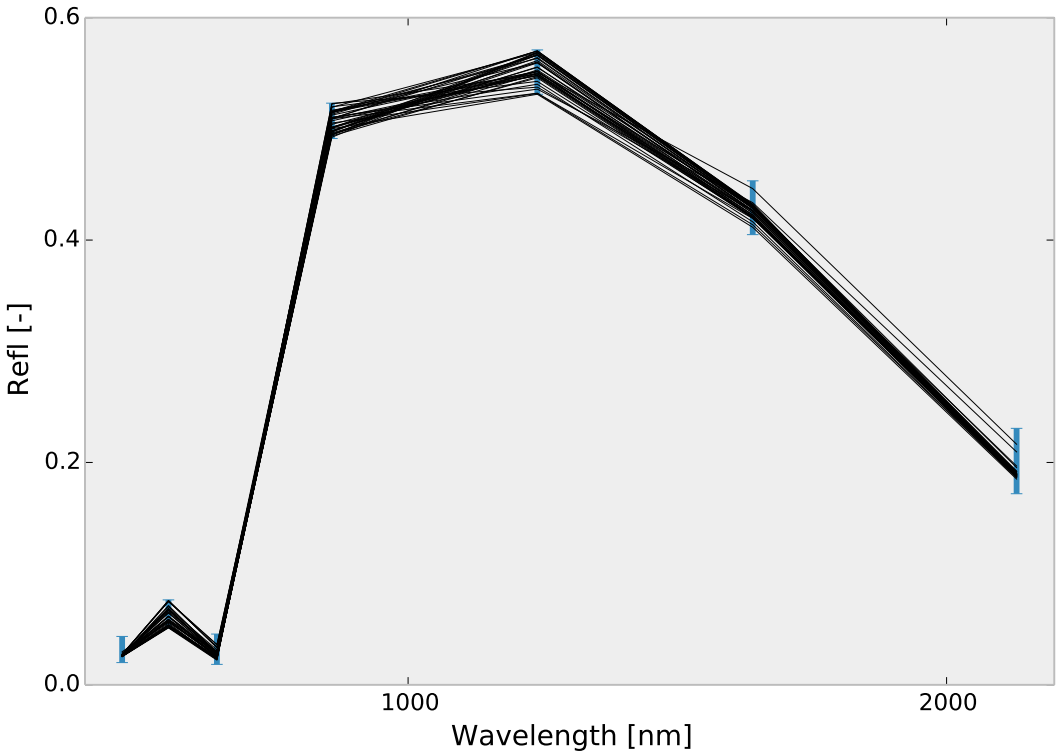
The setup

- Landsat TM spectral/angular sampling
- Green canopy. LAI 4.2
- e.g. lush & green wheat crop
- Noise: typical/optimistic

An example

The setup

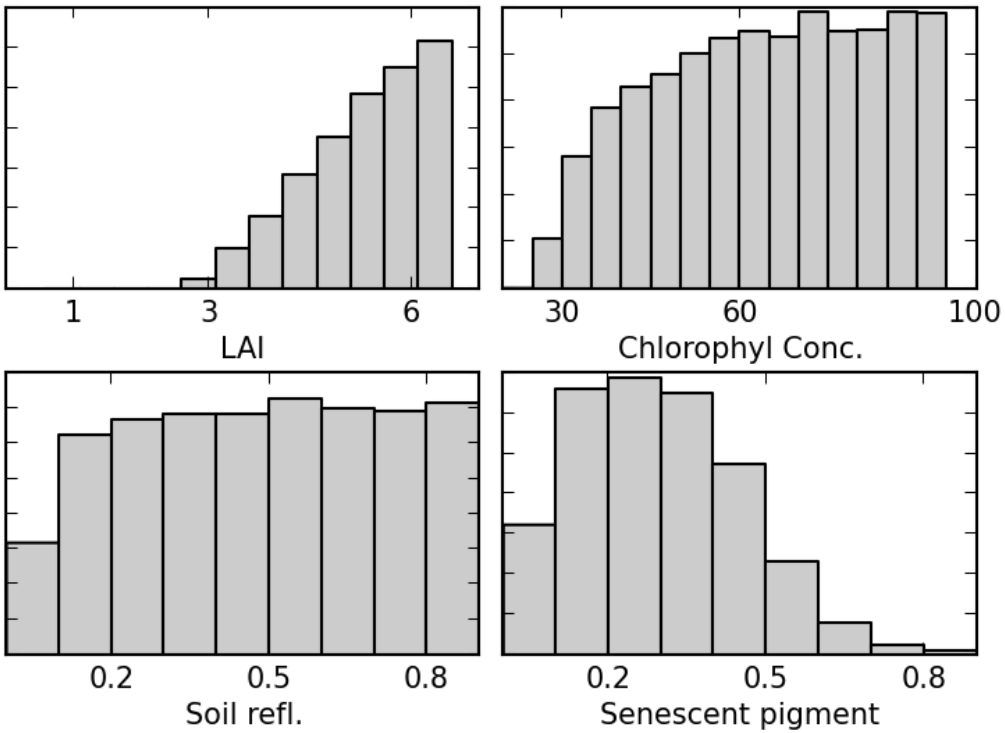
- Landsat TM spectral/angular sampling
- Green canopy. LAI 4.2
- e.g. lush & green wheat crop
- Noise: typical/optimistic



An example

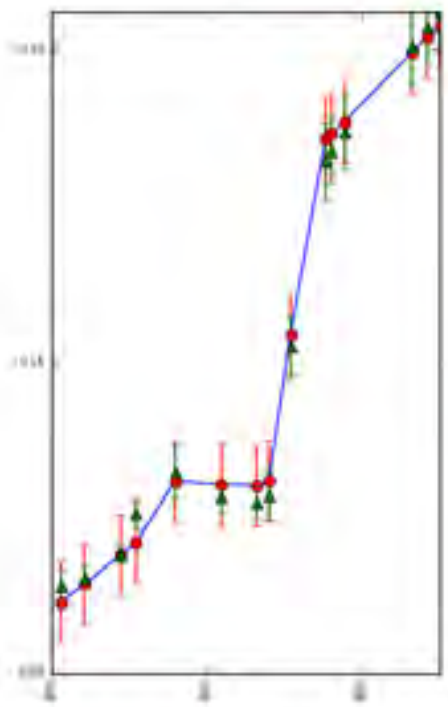
The setup

- Landsat TM spectral/angular sampling
- Green canopy. LAI 4.2
- e.g. lush & green wheat crop
- Noise: typical/optimistic



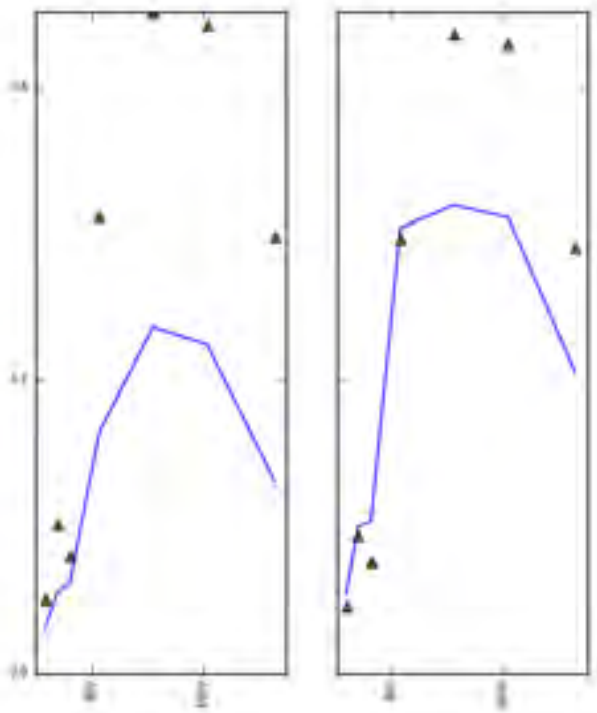
An ill-posed problem

1. Invert RT model for MERIS observations of a field



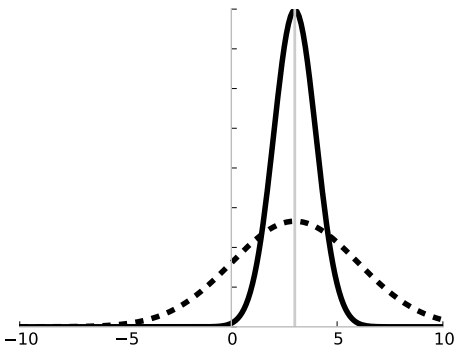
An ill-posed problem

1. Invert RT model for MERIS observations of a field
2. Predict surf refl for MODIS observations of same field



Probability

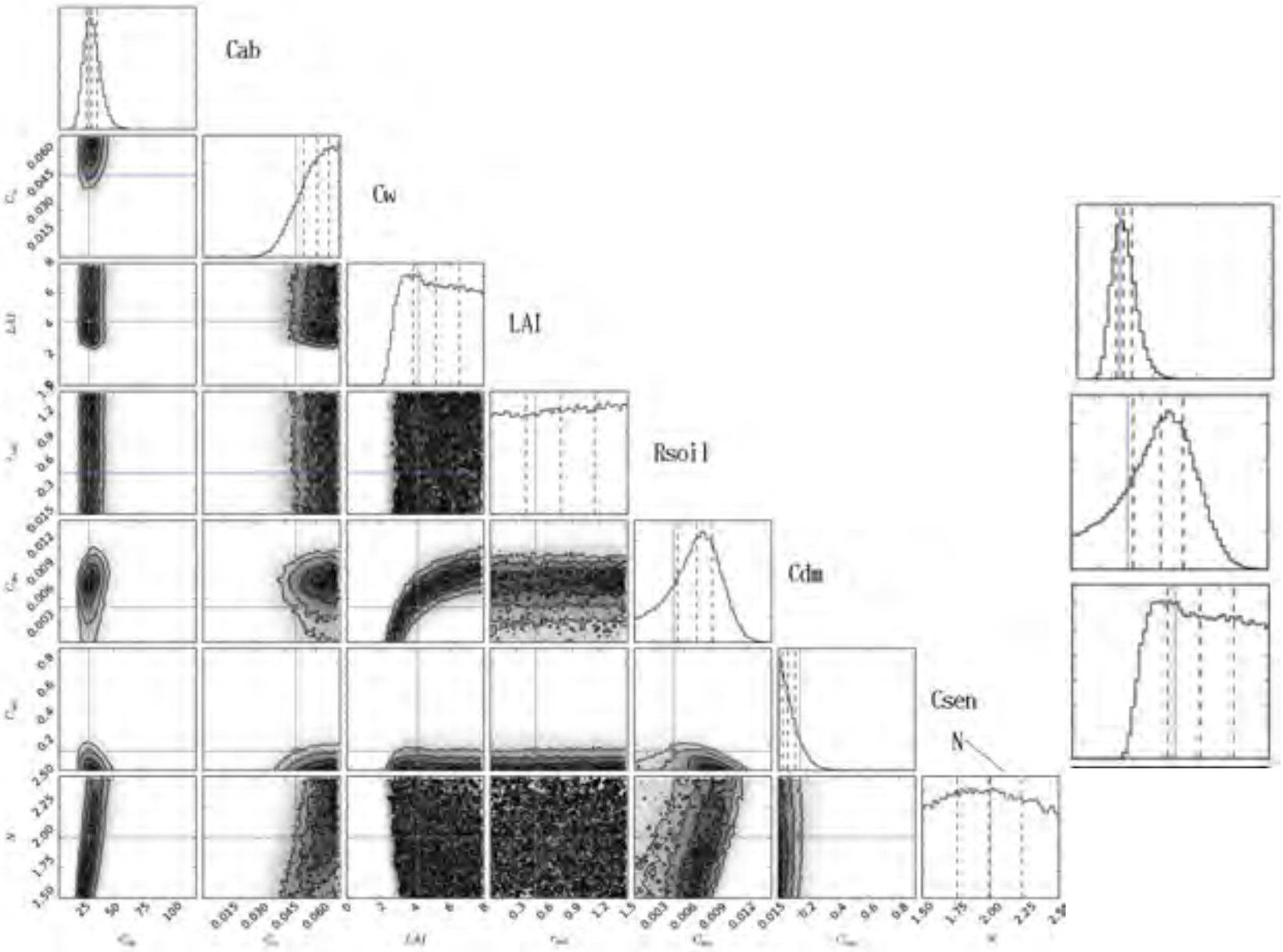
- Can't avoid ill posedness, so embrace it!!
- Assume we no longer have discrete parameters, but parameter distributions.
- The param distribution encompasses our current belief in the value of the parameter.



Our problem is now how to express $p(\vec{\mathbf{x}}|\vec{\mathbf{R}})$, the probability of the state $\vec{\mathbf{x}}$ conditioned on the observations, $\vec{\mathbf{R}}$.

$\Rightarrow$ Use Bayes' Rule!

An S2/MSI posterior pdf



A priori distribution

- Any prior knowledge is feasible!
- The challenge is the ability to encode it in a pdf
- Typically, we might have some idea of e.g. parameter boundaries, or typical values
- However, we should also consider models as priors
- After all, a model gives a prediction of the observations

A bit about models

Statistical A “black box” “harvested” from observations as an input/output map ping

Process-based A combination of mechanistic descriptions of processes and their int eractions.

In practice, most practical models are a pragmatic blend of both types.

Model type	**Statistical**	**Process-based**
Pros	Easy. Uncertainty formalism	Wider range of validity
Cons	Limited validity	Missing processes

Some of the problems with “models”

- Parameters may be based on a few studies
- Drivers (meteo data) may have large uncertainties
- The model might have missing or incorrect descriptions of processes that are important
- The interfacing between processes might be poor (eg spatial/temporal scales etc)
- ✗ It’s hard to quantify how much uncertainty goes into each of these boxes.
- In the view of all the above, we should have methods allow some moderation of the influence of models!

A variational DA framework: `eoldas_ng`

- Remember variational DA?
- Assumptions:
  - Gaussian statistics
  - Linear (or weakly non-linear) models
- Problem is minimisation of a cost function
- Quite efficient using gradient descent methods
- A framework for EO data interpretation $\Rightarrow$ `eoldas_ng`

Weak constraint assimilation

Define a cost function $J(\vec{\mathbf{x}})$ to minimise:

$$J(\vec{\mathbf{x}}) = J_{prior}(\vec{\mathbf{x}}) + J_{obs}(\vec{\mathbf{x}}) + J_{model}(\vec{\mathbf{x}}) \tag{1}$$

Prior Penalisation for departure of the model state from its *a priori* distribution.

$$J_{prior}(\vec{\mathbf{x}}) = \frac{1}{2}[\vec{\mathbf{x}} - \vec{\mathbf{x}}_{prior}]^T \mathbf{C}_{prior}^{-1}[\vec{\mathbf{x}} - \vec{\mathbf{x}}_{prior}] \tag{2}$$

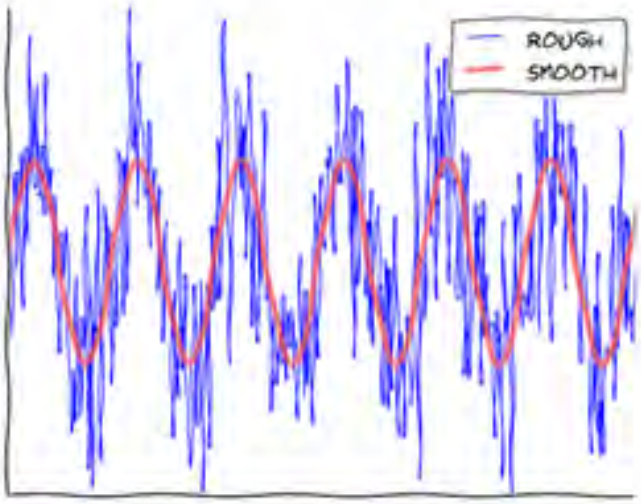
Observation Penalisation associated with differences between the observed ($\vec{R}$) and predicted magnitudes (e.g. reflectances) using the observation operator $\mathcal{H}$

$$J_{obs}(\vec{\mathbf{x}}) = \frac{1}{2}[\vec{R} - \mathcal{H}(\vec{\mathbf{x}})]^T \mathbf{C}_{obs}^{-1}[\vec{R} - \mathcal{H}(\vec{\mathbf{x}})] \tag{3}$$

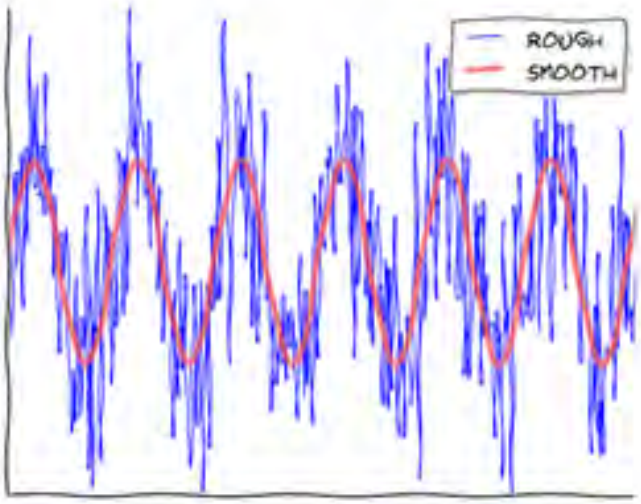
Dynamic model Penalisation for departure of the model state from that predicted by an underlying process model $\mathcal{M}$

$$J_{model}(\vec{\mathbf{x}}) = \frac{1}{2}[\vec{\mathbf{x}} - \mathcal{M}(\vec{\mathbf{x}})]^T \mathbf{C}_{model}^{-1}[\vec{\mathbf{x}} - \mathcal{M}(\vec{\mathbf{x}})] \tag{4}$$

Regularisation (penalise non-smooth solutions)



Regularisation (penalise non-smooth solutions)



- Lots of history in image processing ($\Rightarrow$ Markov Random Fields)
- Assume evolution of a parameter is smooth, but enforce weakly
  - e.g. first order difference are zero mean gaussian distributed
  - Width of distribution $\Rightarrow$ Degree of belief in smoothness
- Can also use other models (e.g. double logistic for LAI...) weakly

The dynamic model

$$J_{model} \rightsquigarrow \frac{1}{2}[\Delta\vec{\mathbf{x}}]^T \mathbf{C}_{model}^{-1}[\Delta\vec{\mathbf{x}}], \quad \Delta = \begin{pmatrix} 1 & -1 & 0 & \cdots & 0 \\ 0 & 1 & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \cdots & -1 \end{pmatrix} \tag{5}$$

- But... what's the value for $\mathbf{C}_{model}$?
- Use generalised cross validation to find out it's value

Shortcomings of using physical models

- Radiative Transfer models as observation operators issues:
  1. Speedof RT models
  2. Requirement of e.g. adjoint code
  3. Large problems (e.g. lots of pixels) require lots of iterations of minimise

Shortcomings of using physical models

- Radiative Transfer models as observation operators issues:
  1. Speedof RT models
  2. Requirement of e.g. adjoint code
  3. Large problems (e.g. lots of pixels) require lots of iterations of minimise
- Partial solution: Gaussian Process emulators
  - Very fast approximations to the full model
  - Good for non-linear models
  - Easy to train (typically 100 model runs)
  - Easy to calculate first and second order derivatives
  - Provide an estimate of approximation uncertainty
  - Able to work with single band or full spectrum

Emulation (I): PROSPECT+SAIL

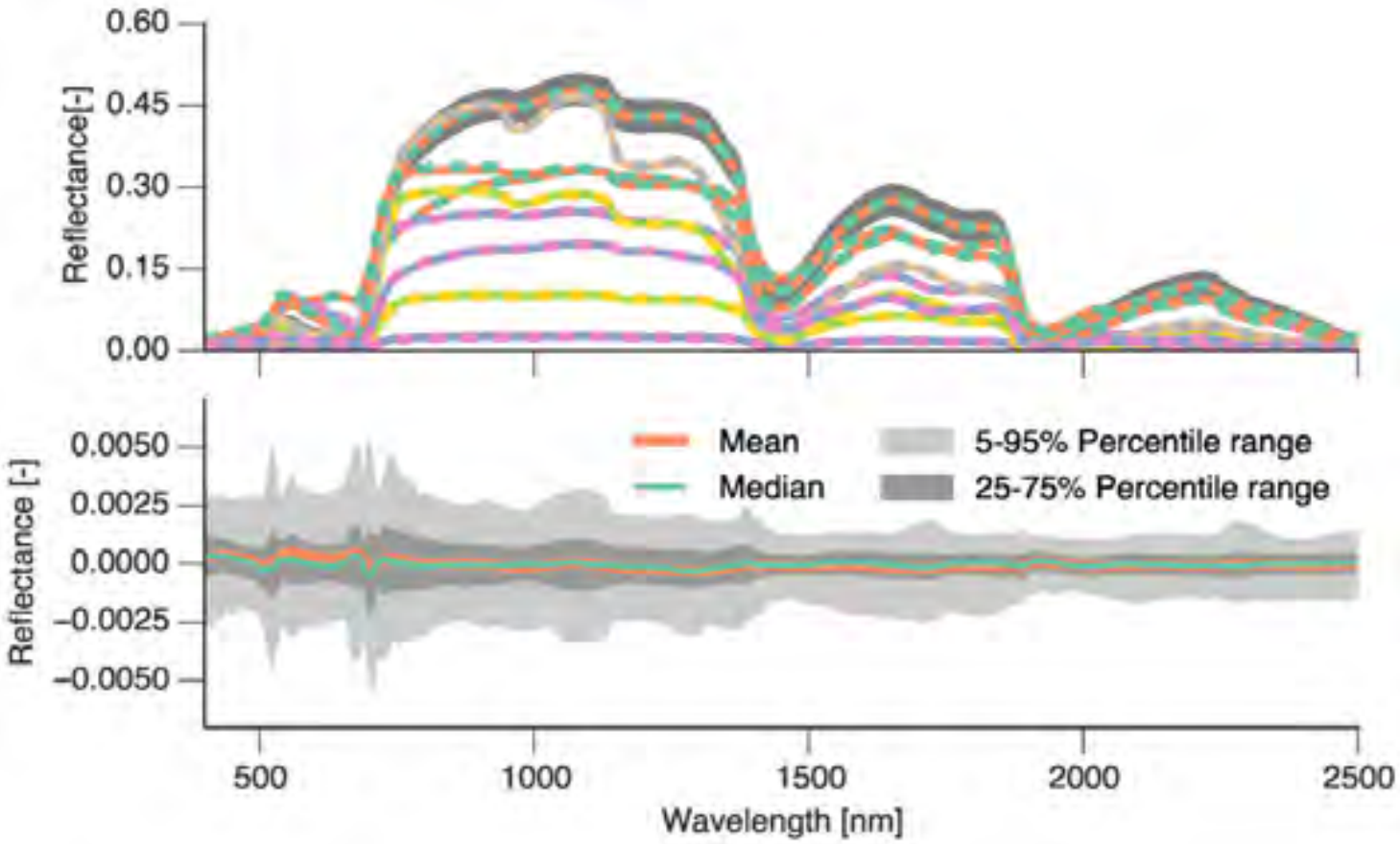


Figure: Gómez-Dans *et al.*, (2016), Rem Sens

Emulation (II): 6S+PROSPECT+SAIL

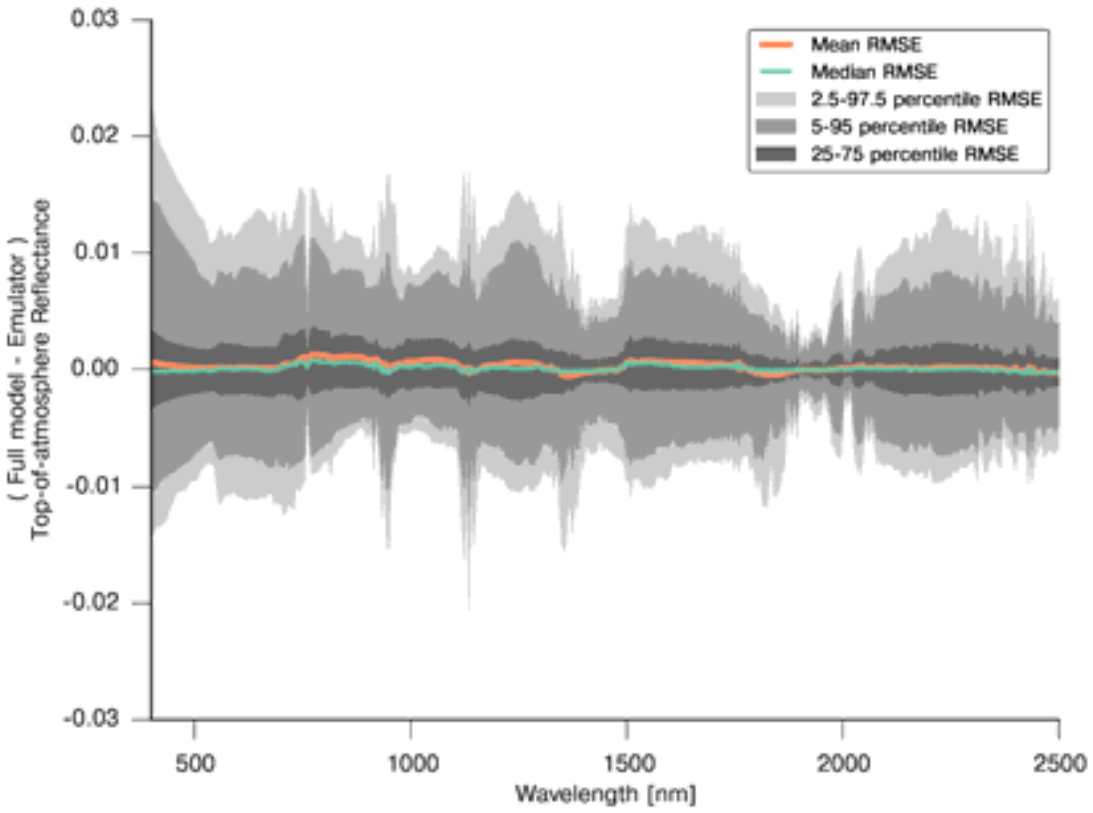


Figure: Gómez-Dans *et al.*, (2016), Rem Sens

Emulation (III): PROSPECT+SAIL, Gradient

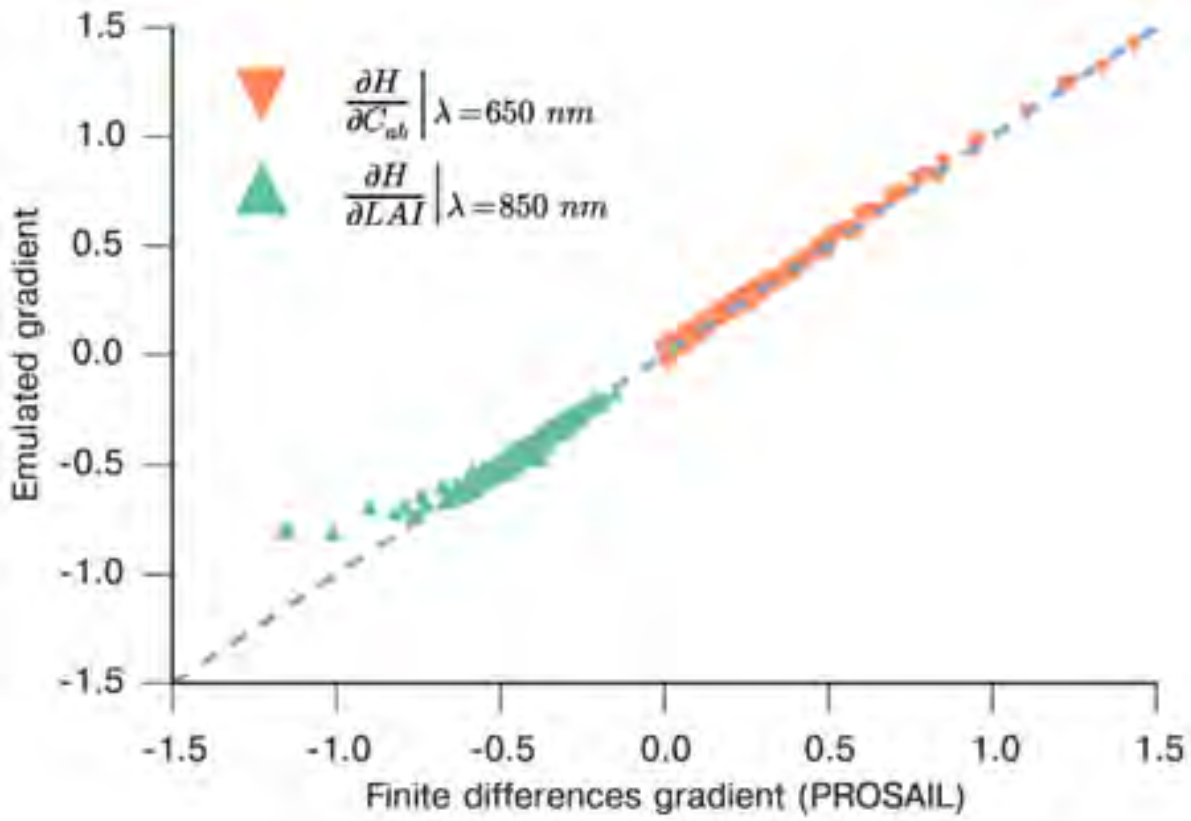


Figure: Gómez-Dans *et al.*, (2016), Rem Sens

How does all this work together?

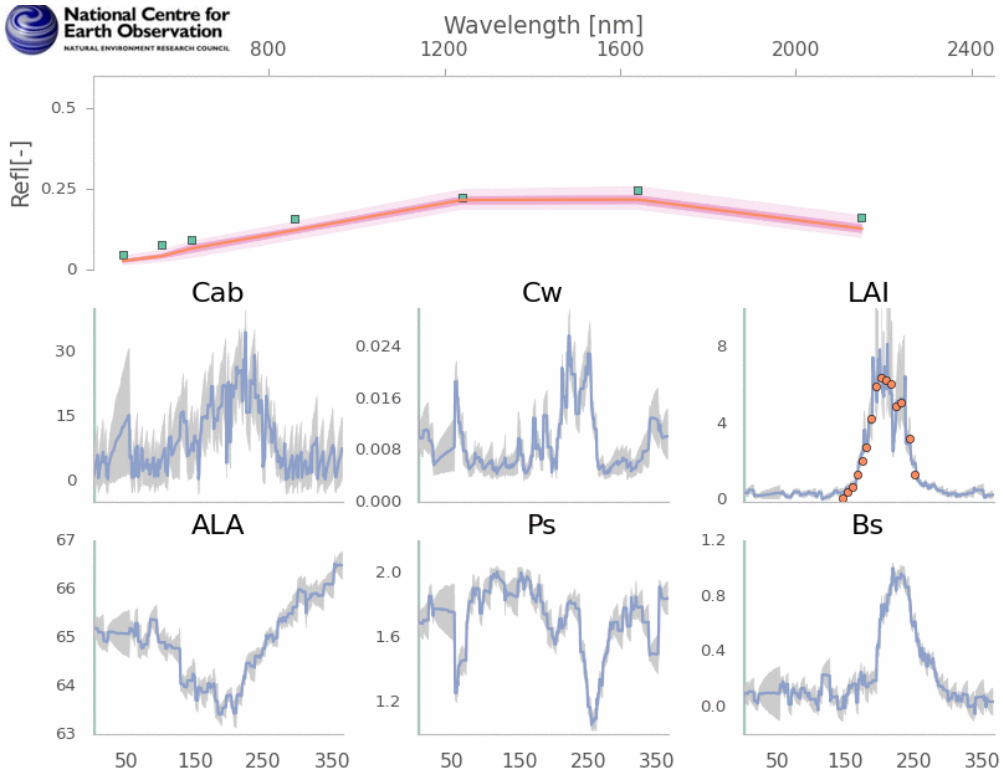
Let's consider how the vegetation evolves over a year in a maize field in Illinois.

- We will use MODIS daily surface reflectance
- We will interpret the MODIS data using the PROSAIL RT model
- We will use emulators to access its gradient etc.
- We will assume that parameters change smoothly (regularisation), so our model is

$$LAI_{tomorrow} = LAI_{today} + \nu$$

- We will also add some non-polemic prior distributions as priors

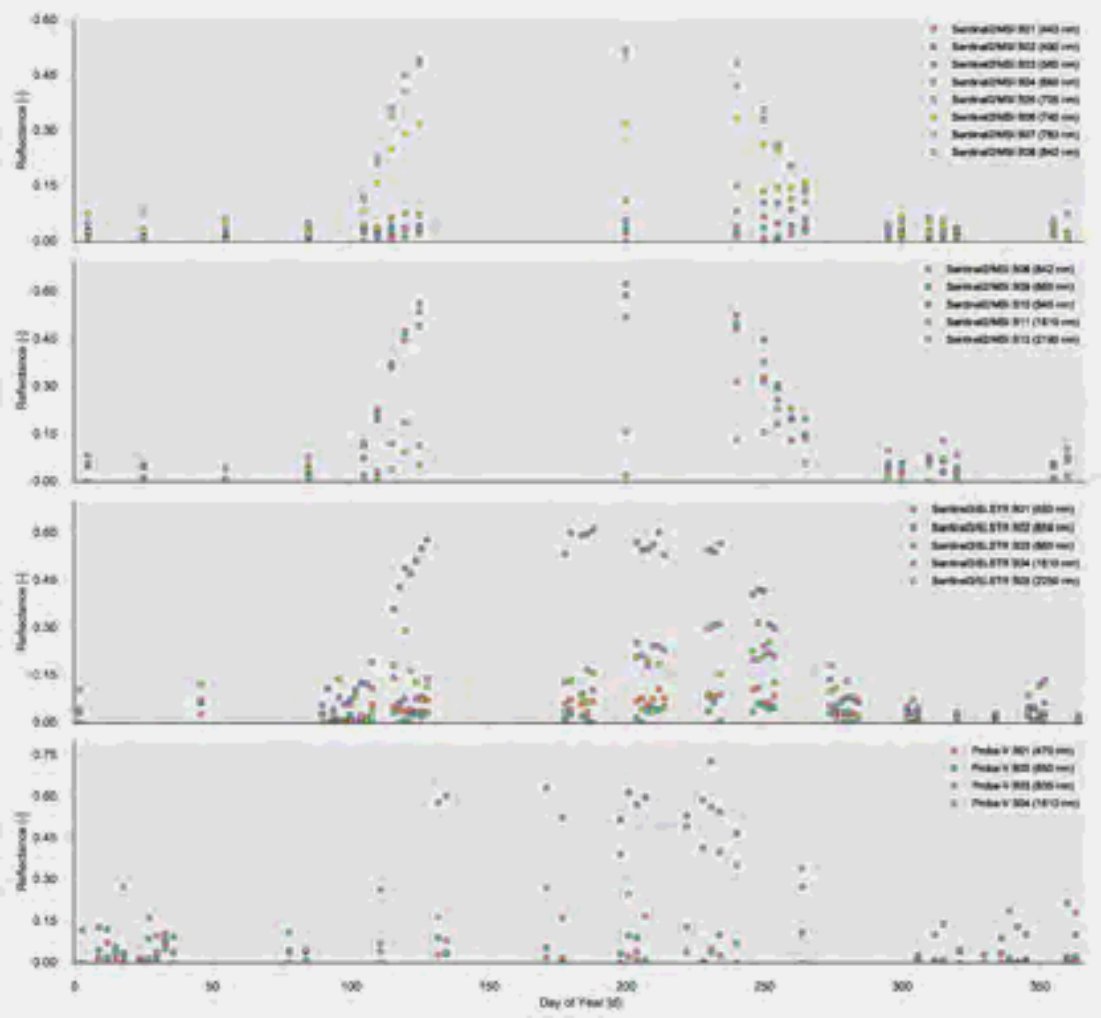
An example using MODIS data: Bondville



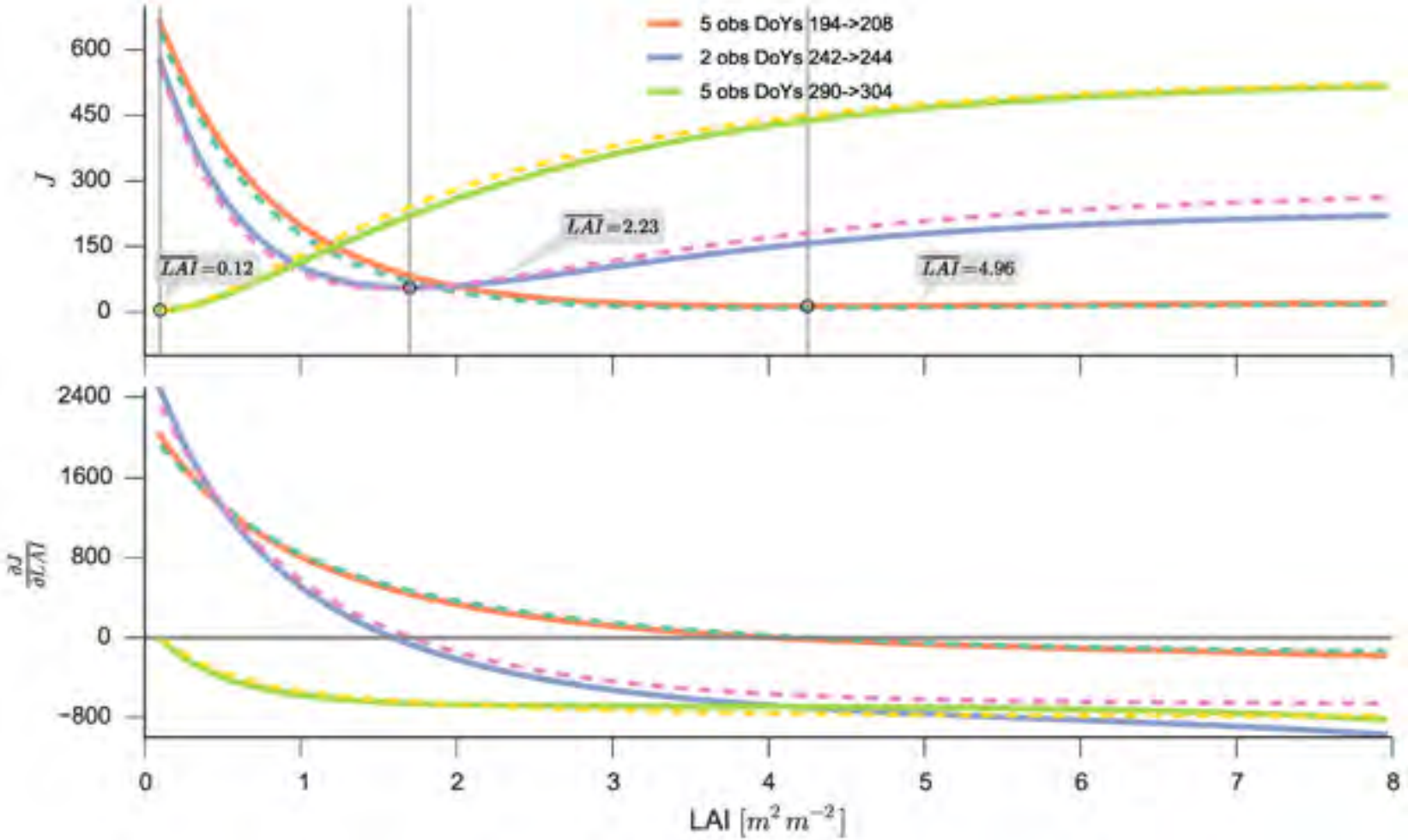
Putting it all together: “Sentinel” example

- Sentinel2 + S3/SLSTR + ProbaV time series
- Using PROSAIL RT model through emulators
- Using temporal regularisation
- Solution using gradient descent
- Solved using `eoldas_ng` package

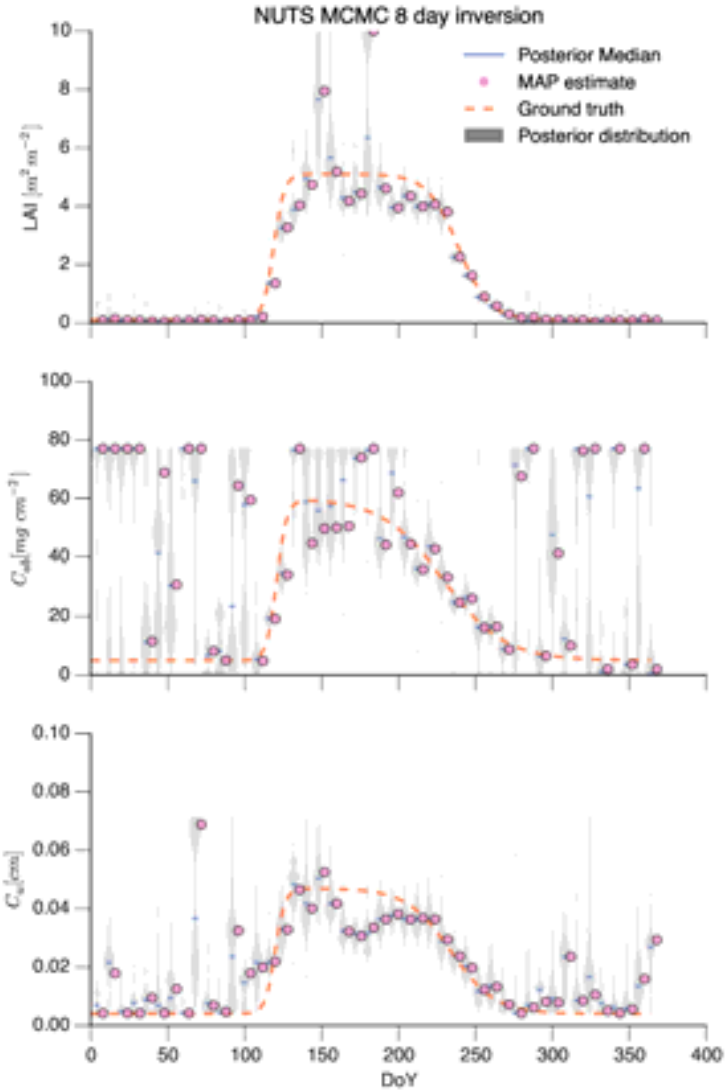
The data



How does the cost function look like?



Windowed inversion: invert all observations in 8 days



Putting it all together: “Sentinel” example

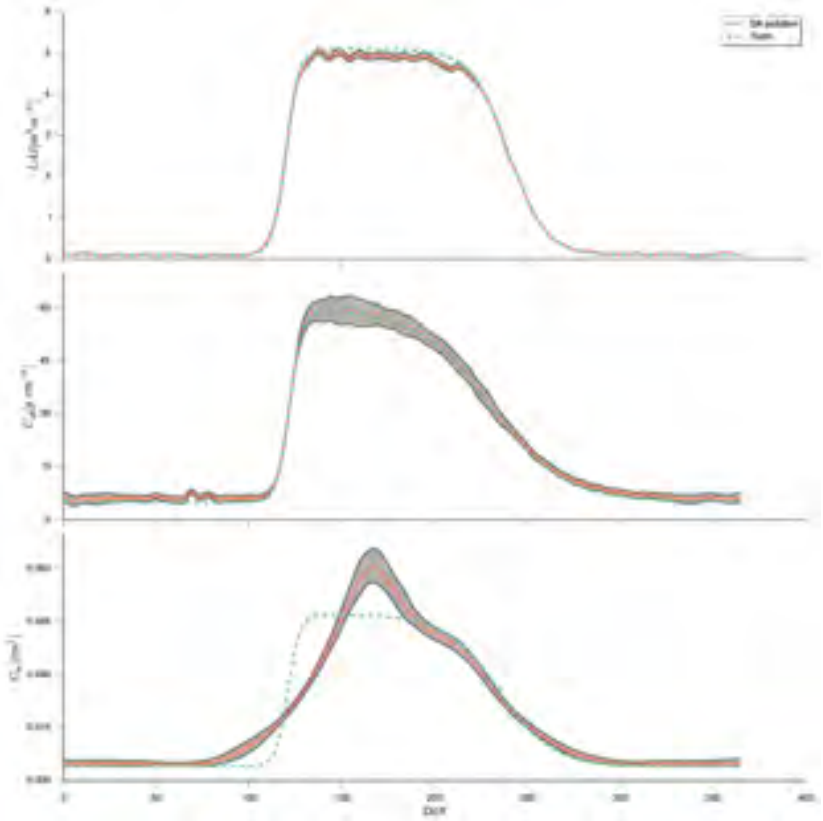
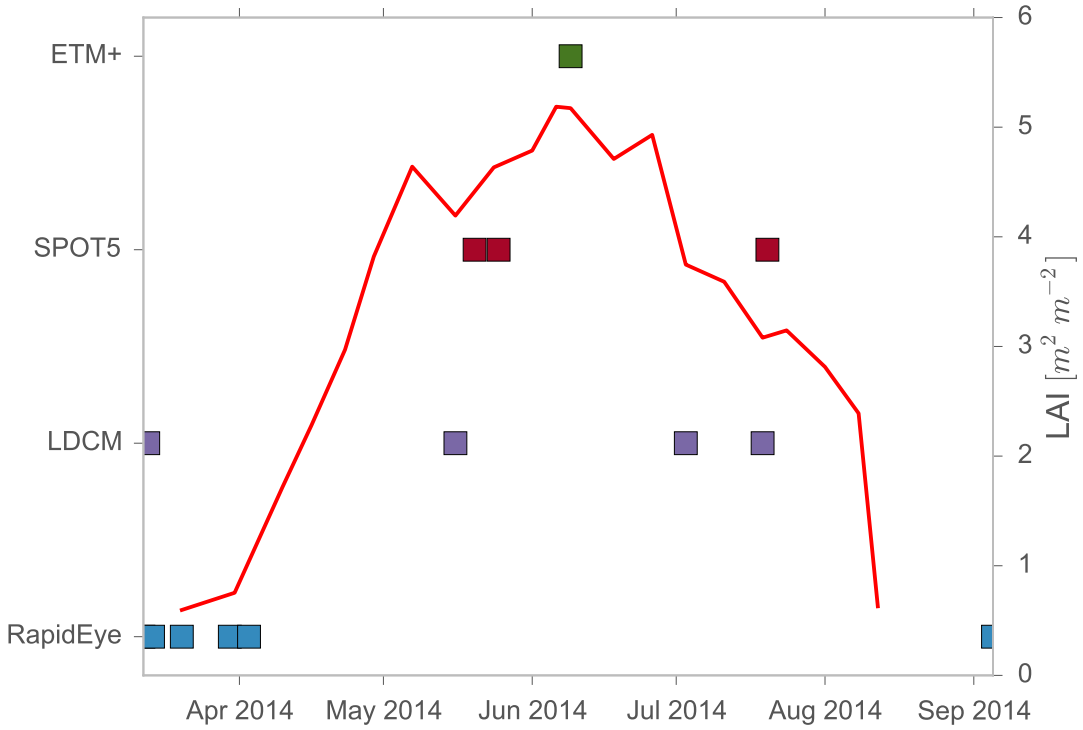


Figure: Gómez-Dans *et al.*, (2016), Rem Sens

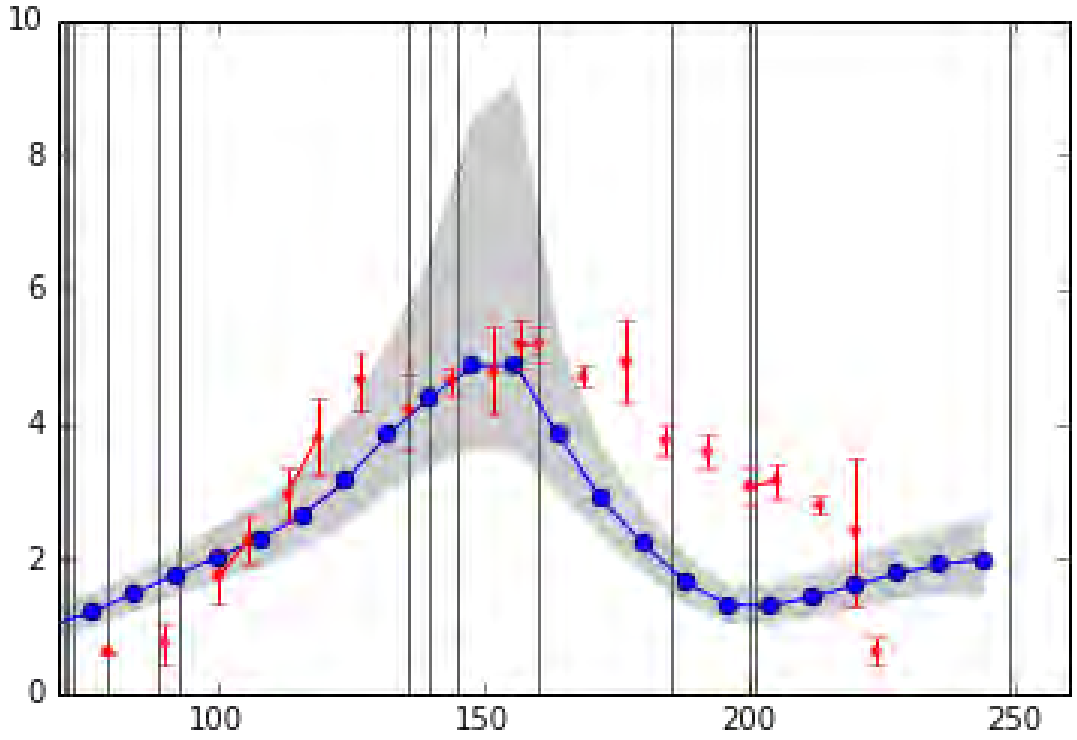
Multi-sensor capabilities

- Collaboration with Sina Truckenbrodt (Uni Jena, Germany)
- Gebesee agricultural site in Thüringen (Germany). Part of FLUXNET
- Winter wheat field



- Mix'n'match of optical sensors
- Typical pattern for a cloudy area
- A reasonable first test case

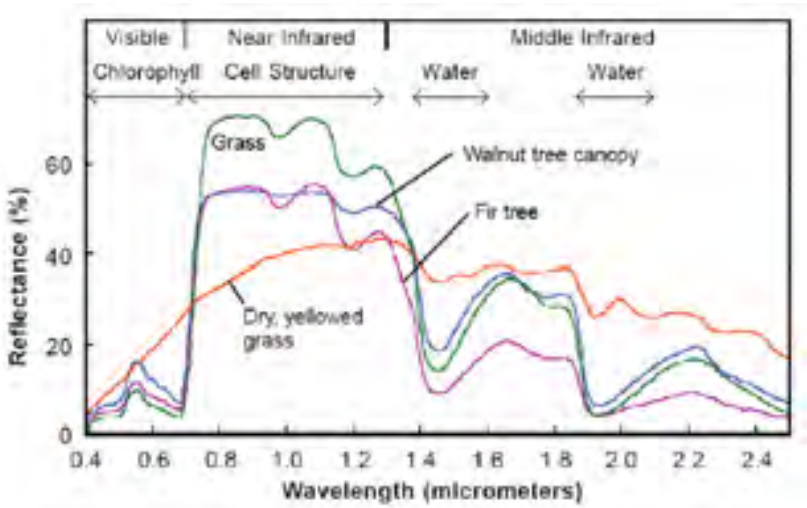
Just solving for LAI...



- Only attempting LAI + regularisation
- Pattern is sensible up to DoY ~170
- $DoY > 170 \rightarrow$ canopy senescence, not yet taken into account

Can we explain the LAI trajectory?

- The reflectance due to the canopy is to do with vegetation optical depth (VOD)
- Broadly, VOD controlled by
  - the amount of leaf area (LAI) and
  - the optical properties of the leaves



  - LAI and leaf optical properties compensate each other
- Posterior covariance matrix, parameters would be anticorrelated

Effective parameters

In the previous example, we made assumptions about our problem (we assumed the leaves were healthy and green)

- If the assumptions in the model aren't met, the parameters are wrong
- Remember, we are estimating the *a posteriori* distribution: $p(\vec{x}|\vec{R}, I)$
- I above means "any other bit of information we have used"
- This includes assumptions about vegetation structure (e.g. clumping)
- So the parameters can become "effective"
- In some applications, you can have an effective parameter and still be useful.

Final remarks

- Physical models allow one to explain a lot of the processes that give rise to the obesrvations
- These processes and the parameters that control them are usually what you want for applications
- The inverse problem results in a non-unique solution due to the limit in information content in the observations
- A Bayesian framework (DA) allows you to:
  - Supplement the observations with prior information (distributions, models, . . .)
  - Blend different observational streams consistently
  - Get a grasp on uncertainty
- Beware of assumptions in your models! Do they meet reality?
- Today's practical hopefully demonstrates this!