An Earth Observation Land Data Assimilation System

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Outline

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What we want

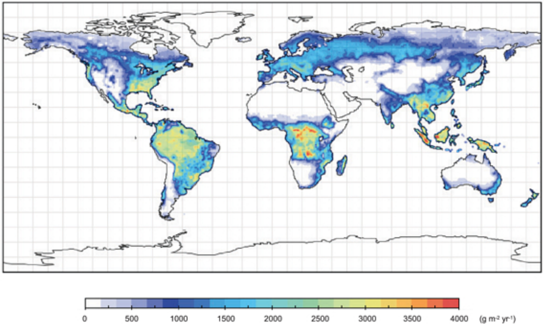

Figure: Global GPP map Source

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What we get

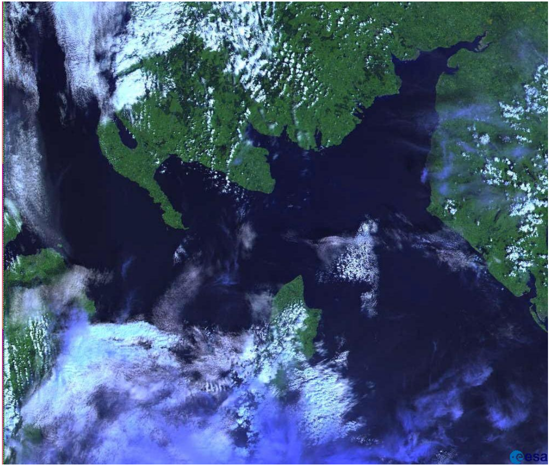

Figure: RGB composite ETM+7 Source

EO: A timely global picture of the land surface?

Remote Sensing problem to estimate parameters that describe the state of the land surface/vegetation

Challenges
- We might not observe the land surface (clouds! satellite scheduling)
- Sensors measure state of the surface indirectly $\rightsquigarrow$ signal interpretation
- In general, we might not be very sensitive to what we want to measure/monitor.

Interpreting EO signals

There are a two main approaches to interpreting EO data:

- **Empirical** Usually based on correlations between Veg Indices and "ground truth" measurements.
- **Physical** (Usually) based on radiative transfer models that describe radiation-soil-canopy interactions.

Bottom line

- **Empirical approaches ✗** are easy, but hardly robust.
- **RT approach ✓** encompass our knowledge about physics, sensor characteristics, etc.

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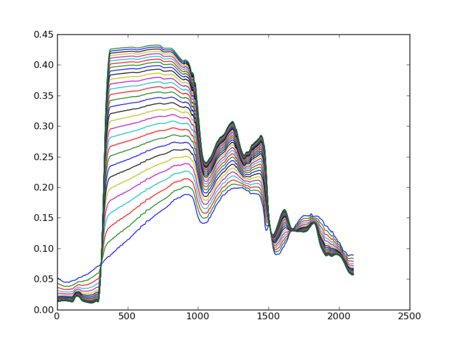
The forward problem: Example

The forward problem is to simulate the observations **y** knowing the state of the land surface, **x**

Example

Assume that we sweep LAI from 0.2 to 5 $m^2 m^{-2}$, keeping other parameters in the state (Chlorophyll, soil refl., etc) constant



The inverse problem

In fact, get observations of eg reflectance or radiance and want to infer states or parameters:
Usually estimate the state using least squares:

$$\min_{\mathbf{x}} \frac{||\mathbf{y} - H(\mathbf{x})||^2}{\sigma^2} \tag{1}$$

Ill-posed problems

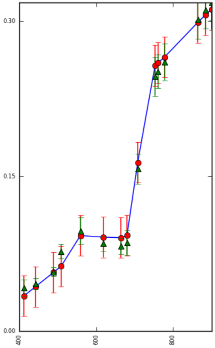
However, the inverse problem is often ill-posed:

- There might not be enough information in the observations to infer the state
- equivalently, the sensitivity of the obsrevations w.r.t state might be poor
- we have noise!

In other words, there might be many combinations of states that fit the data reasonably well.

An ill-posed problem

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



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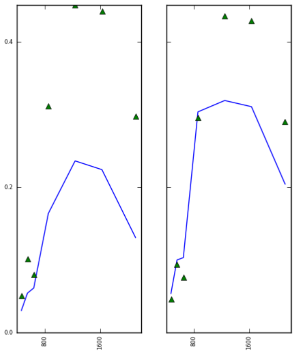

Inversion and Bayes' Rule

Consider probabilities $p(\mathbf{x})$ rather than $\mathbf{x}$ Use Bayes' Rule to combine obsrevations and other relevant info

- Consistent treatment of uncertainty
- Include vague (or not so vague) prior knowledge to constrain the problem.
- Combination of fit to the data and prior knowledge

We knew it before we started

We always have prior information. This can be of many forms:

- Previous observations and/or climatologies
- Land surface or veg models
- Similar experiments
- "Expert knowledge" *("my mate reckons that...")*

Note that ideas like *"the evolution of this parameter is smooth"* also count as prior info!

The challenge is to translate prior knowledge into prior distributions.

Fitting the data

The least squares concept is useful if data are Gaussian.

$$p(\mathbf{y}|\mathbf{x}) = \frac{1}{2\pi^{k/2}|\mathbf{C}_{obs}|^{1/2}} \exp\left[-\frac{1}{2}\left\{H(\mathbf{x})-\mathbf{y}\right\}^{T}\mathbf{C}_{obs}^{-1}\left\{H(\mathbf{x})-\mathbf{y}\right\}\right] \quad (2)$$

- Eg mismatch metric for state translated into observations $H(\mathbf{x})$ and observations $\mathbf{y}$, moderated by the observational uncertainty, $\mathbf{C}_{obs}$
- Can also include error in H
- Other models are available if the observations are not Gaussian.

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Introduction

The **EOLDAS project** is funded by ESA as part of the **Support to Science Element (STSE)** of the Earth observation Envelope Programme.

The aims of the projects are:

- To develop and document a generic data assimilation scheme to assist the retrieval of geophysical parameters from medium resolution optical EO data
- To develop a prototype software package implementing selected aspects of the scheme
- To validate the prototype using multi-sensor EO data and field measurements

The project is led by the UK **National Centre for Earth Observation (NCEO)** with a team that includes:

- **University College London**
- **The University of Reading**
- The European Commision's **Joint Research Center**
- **Friederich Schiller Universität Jena**
- **FastOpt GMbH**
- **Assimila**

Figure: From http //jgomezdans.github.com/eoldas_release/

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What does EOLDAS do?

EOLDAS allows the user to define a cost function $J(\mathbf{x})$, and it minimises it

- We prescribe a dynamic model for advancing the state from one time step to the next, $\mathcal{M}$
- We assume that all statistics are Gaussian
- We work in the optical domain using a radiative transfer model.
  - ... Although you could work in other domains using the appropriate observation operator
- ✗ We usually require partial derivatives of the ObsOper & DynModels

Solving the Bayesian DA problem (I)

Define

$$J(\mathbf{x}) = J_{prior}(\mathbf{x}) + J_{obs}(\mathbf{x}) + J_{model}(\mathbf{x}) \tag{3}$$

Prior Departure of state from prior

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

Observation Departure of state from observations

$$J_{obs}(\mathbf{x}) = \frac{1}{2}[\mathbf{y} - \mathcal{H}(\mathbf{x})]^T \mathbf{C}_{obs}^{-1} [\mathbf{y} - \mathcal{H}(\mathbf{x})] \tag{5}$$

Dynamic model Departure of state from dynamic process model $\mathcal{M}$

$$J_{model}(\mathbf{x}) = \frac{1}{2}[\mathbf{x} - \mathcal{M}(\mathbf{x})]^T \mathbf{C}_{model}^{-1} [\mathbf{x} - \mathcal{M}(\mathbf{x})] \tag{6}$$

The dynamic model $\mathcal{M} = \mathbf{Ax} + \mathbf{b}$

- **A** can be seen as the derivative of any process model at **x**, and **b** is then a process model bias term. This opens the possibility of using e.g., biophysical models such as e.g. DALEC as a weak constraint.
- An important set of process models are first and second order difference constraints. These constraints emphasise a smooth evolution of the spatial or temporal parameter trajectory.
- Viewing this form of solution as a combination of state variable estimation and filtering
- We demonstrate that this simple model can be extremely useful in reducing uncertainty.

Outline

1. Introduction: The Remote Sensing Problem
2. Inverse problems & Data Assimiation
3. EOLDAS
4. Examples
   - NDVI filter
   - SENTINEL2
   - Spatial aspects
5. Conclusions

Simplest DA case

The data Consider a univariate time series, e.g. NDVI

- Noisy!
- Gappy!

DA solution

- Set an uninformative prior $\rightsquigarrow x \sim \mathcal{U}(-1, 1)$
- Let the dynamic model be $x^{t+1} = x^t + \epsilon$ (1st order differntial operator)
- Set boundary conditions for dynamic model: periodic
- Assume Gaussian iid noise

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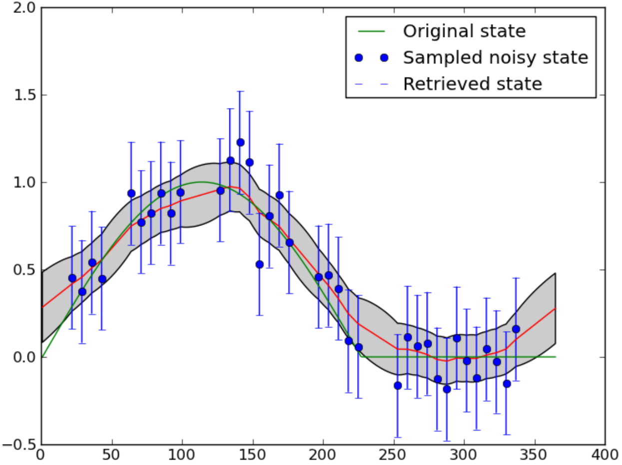
Univariate timeseries DA results



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Simulating the performance of SENTINEL-2

- 13 spectral bands VNIR + SWIR with spatial resolutions of 10, 20 and 60m.
- Approximate Sentinel-2 MSI acquisition geometry:
  - $1\times$ sample every 5 days ($\sim$ 73 per year).
  - Solar zenith angle correspoding to 10:30AM local time at $50^\circ N$
  - Random relative azimuth and random view zenith between 0 and 15°
- Effect of missing observations due to cloud, snow, etc.
- Surface reflectance uncertainty prescribed to be similar to MODIS.

The state vector

Table: The EOLDAS state vector

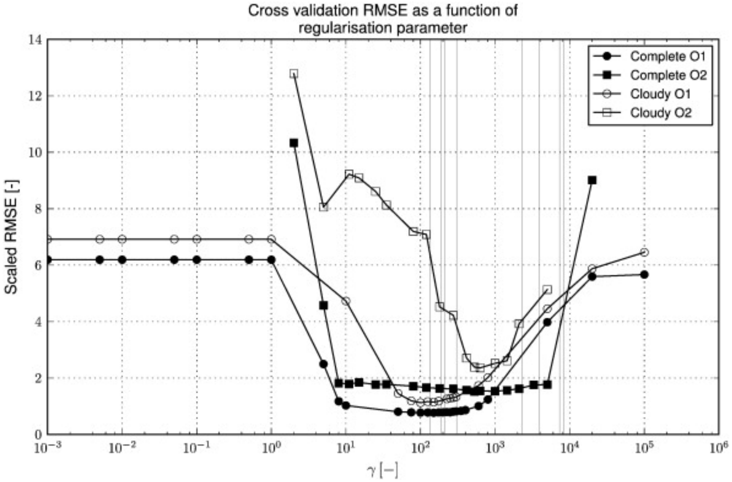
#	Name	Symbol	Units	Default	Max	Min	Transformation
1✓	Leaf Area Index	LAI	None	3	0.01	10	$\exp(-LAI/2)$
2	Canopy height	xh	m	5	0.1	5	-
3	Leaf radius	xr	m	0.01	-0.001	0.1	-
4✓	Chlorophyll a,b	Cab	gcm^{-2}	40	0	200	$\exp(-Cab/100)$
5	Carotenoids	Car	gcm^{-2}	0	0	200	$\exp(-Car/100)$
6✓	Leaf water	Cw	cm^{-1}	0.01	0.00001	0.1	$\exp(-50Cw)$
7✓	Dry matter	Cm	gcm^{-2}	0.007	0.00001	0.01	$\exp(-100Cm)$
8✓	Leaf layers	N	None	1.0	1	2.5	-
9✓	Soil PC 1	s1	None	0.2	0.05	0.4	-
10	Soil PC 2	s2	None	0	-0.1	0.1	-
11	Soil PC 3	s3	None	0	-0.05	0.05	-
12	Soil PC 4	s4	None	0	-0.03	0.03	-
13	Leaf Angle Dist	LAD	5	Discrete	-	-	

The dynamic model

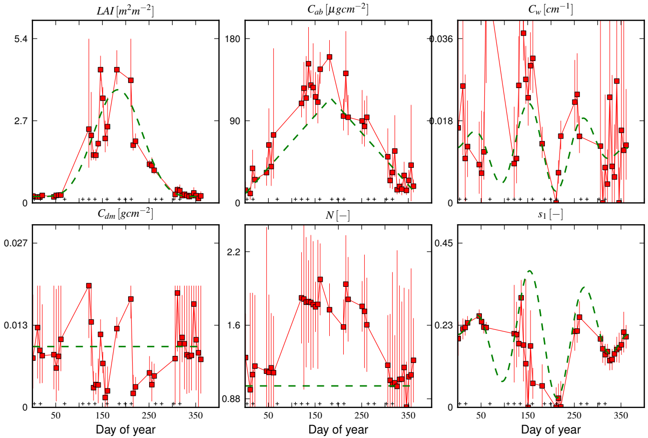
$$J_{model} \rightsquigarrow \frac{1}{2}[\Delta \mathbf{x}]^T \mathbf{C}_{model}^{-1}[\Delta \mathbf{x}], \quad \Delta = \begin{pmatrix} 1 & -1 & 0 & \cdots & 0 \\ 0 & 1 & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \cdots & -1 \end{pmatrix} \tag{7}$$

- But... what's the value for $\mathbf{C}_{model}$?
- Assume $\mathbf{C}_{model} = \gamma \mathbf{I}$
- Use generalised cross validation to find out it's value:
    1. Set one value of γ
    2. Solve the DA problem
    3. Assume we have observations from another sensor (maybe low information content)
    4. Try to predict the observations from our inferred state.
    5. Goto (1)
    6. Select lowest difference between predictions and observations.

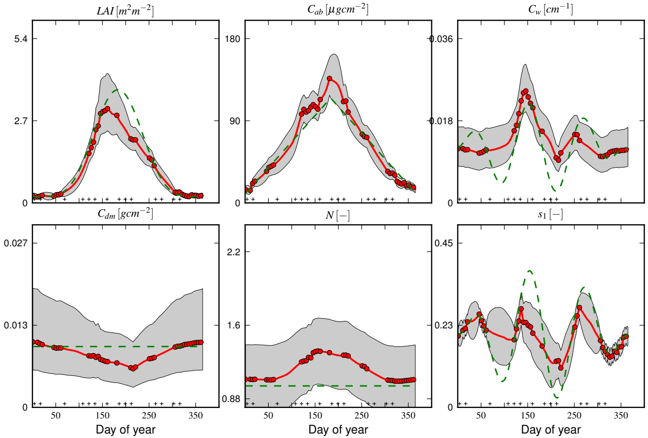
GCV assuming a SPOT/VGT sensor



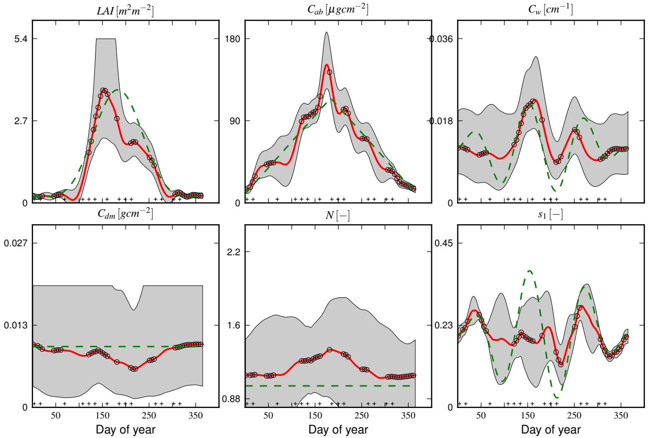
Inverting single observations



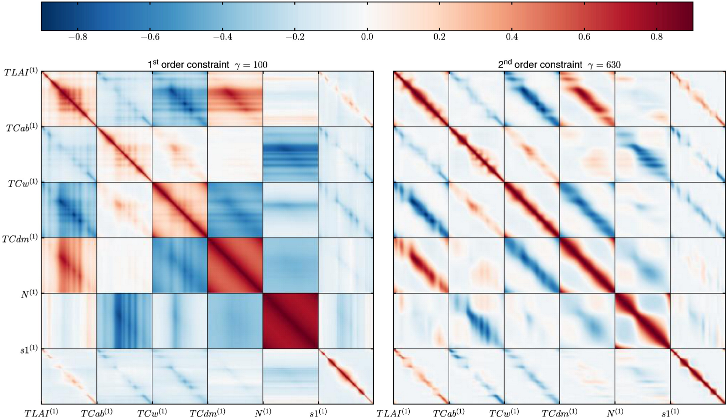
First order differential constraint



Second order differntial constraint



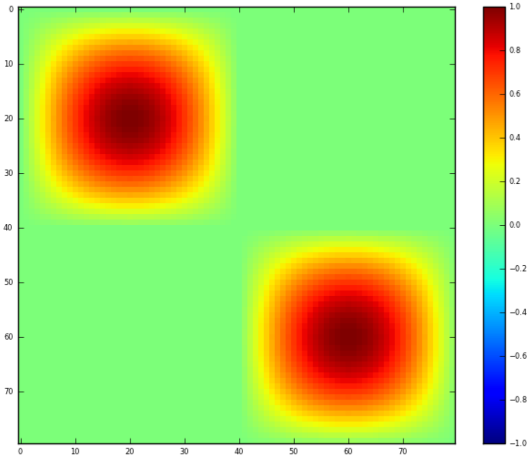
Posterior correlation matrices



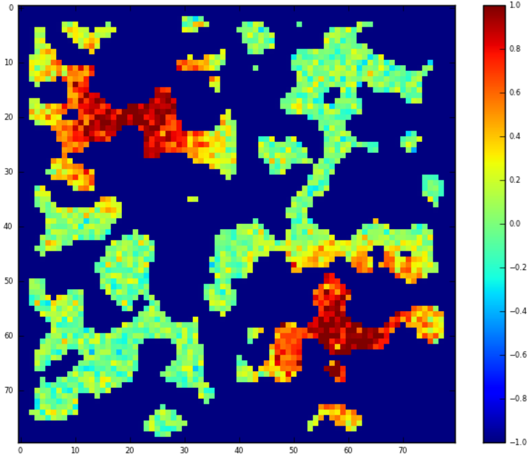
Space is the new time

- ✓ A dynamic model that penalises non-smooth trajectories can also be applied to space
- ✓ In general, spatial/temporal smoothness makes sense,
- ✓ We can also combine data across different spatial resolutions/scales
- ✓ We still get full uncertainty treatment
- ✓ Quite trivial to expand to a full spatio-temporal problem
- ✗ It is computationally very challenging (high memory requirements)
- ✗ In some cases, space/time discontinuities will need to be accounted for

Blending different resolutions



Blending different resolutions



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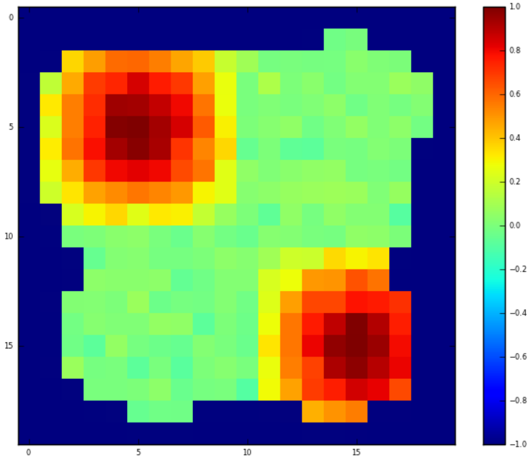

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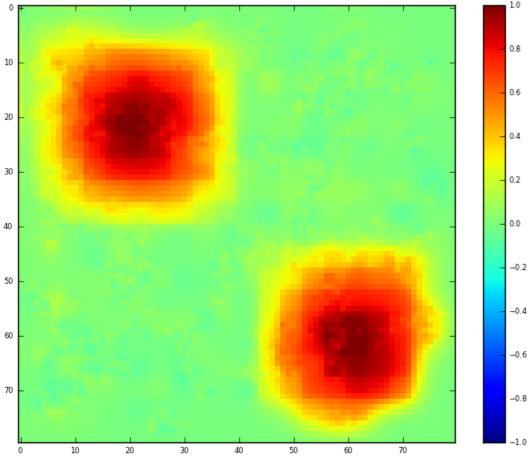

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Final remarks (I)

- DA blends all sorts of observations with prior knowledge
- Critical in an age of consistent multi-sensor datasets (Essential Climate Variables)

... and “convoys”, “trains“

- It allows the best interpretation of the data using sound physical principles.
- The inferences are traceable, and there’s extensive uncertainty information.
- Prior information can come from many places: vague knowledge, models, etc.
- Drawbacks:
  - Steep learning curve
  - Relatively complex problems
  - Computationally very demanding
- We hope that EOLDAS can be used as a learning & prototyping tool

Final remarks (II)

- Weak constraint concept is very powerful
- We can use simple “regularisation” models to improve retrievals greatly
- Or we could use DGVMs/LSMs
- Only tested using Optical data, but microwave and thermal could be done

References

EOLDAS code & users’ guide Available online @ `http://jgomezdans.github.com/eoldas_release`

EOLDAS paper Lewis et al., 2012, Rem Sens Env

Community We are happy to discuss with you ideas on how to improve & use the code!

Thanks

- To Guido, for having hosted me at VU.
- To the Erasmus staff training grants, for supporting this visit.