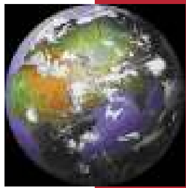
Hyperspectral retrieval of biophysical variables through inversion of radiative transfer models

Solving the ill-posed inverse problem



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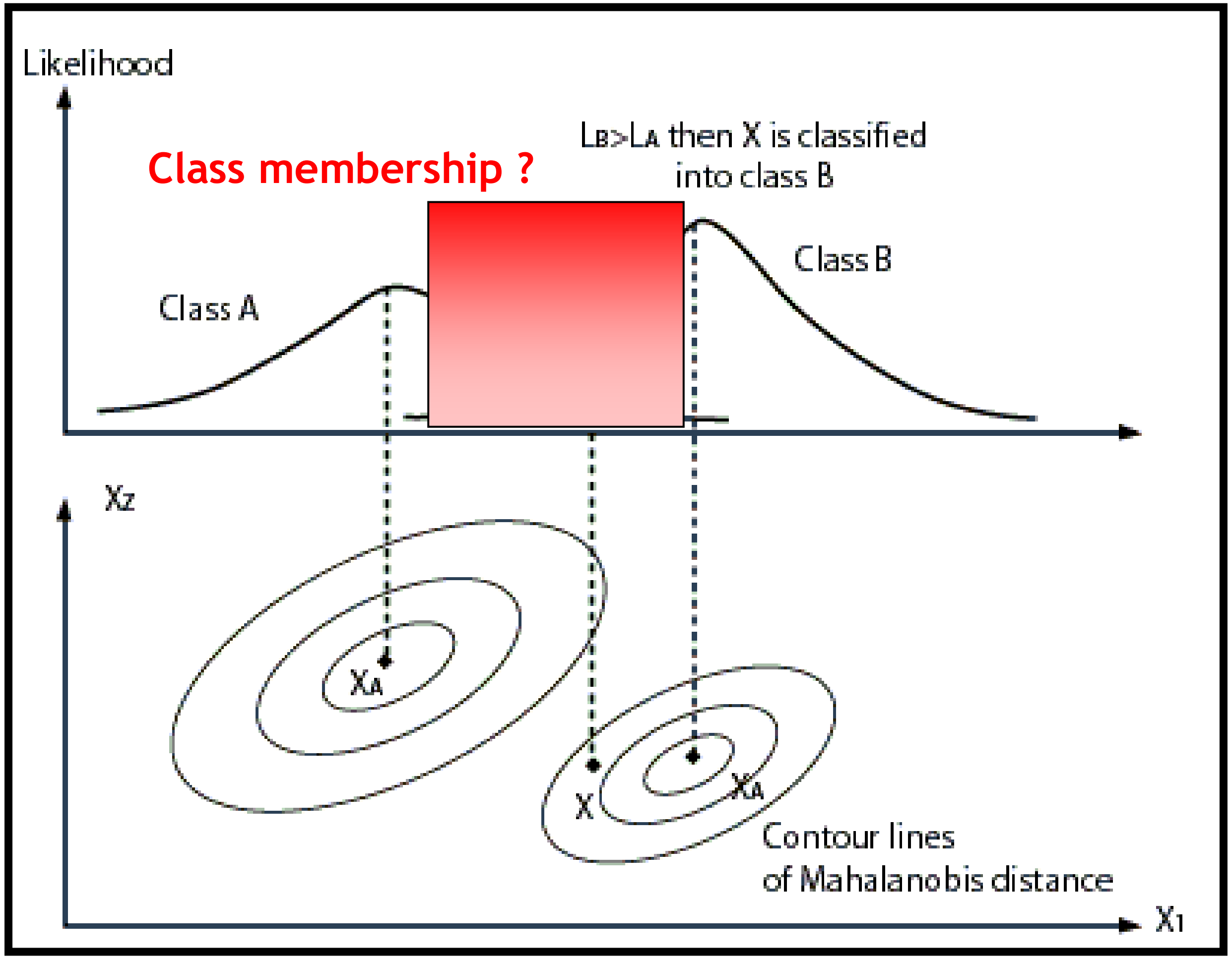
What is "ill-posed inverse problem"?

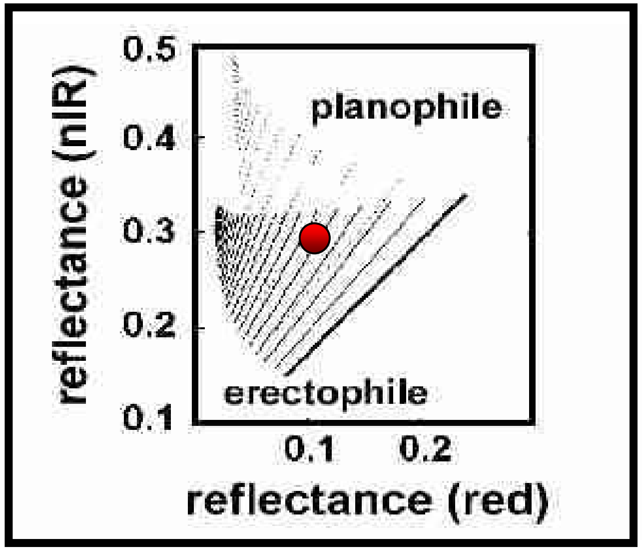
- Categorical variables



Overlap of land cover classes in a 2-dimensional feature space (source: web)

What is "ill-posed inverse problem"?

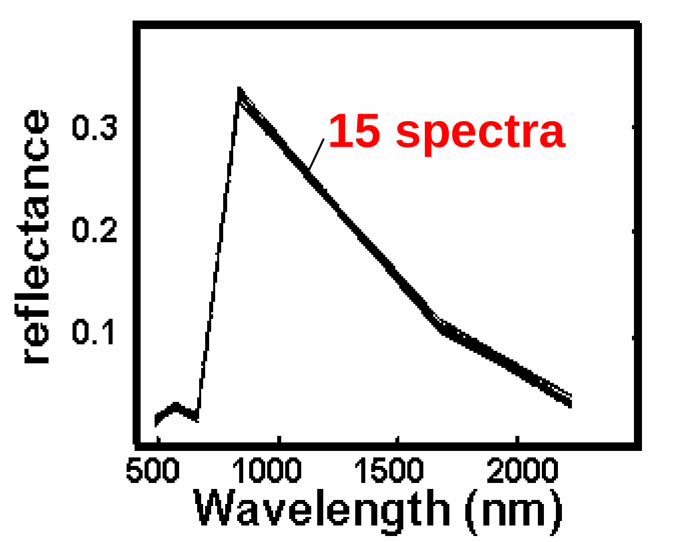
- Continuous variables



The ill-posed inverse problem illustrated in the red-nIR feature space. LAI-isolines range from 0 (bare soil) to LAI=5 in steps of 0.5 (SAILH+PROSPECT simulations) (Atzberger, 2004)

What is "ill-posed inverse problem"?

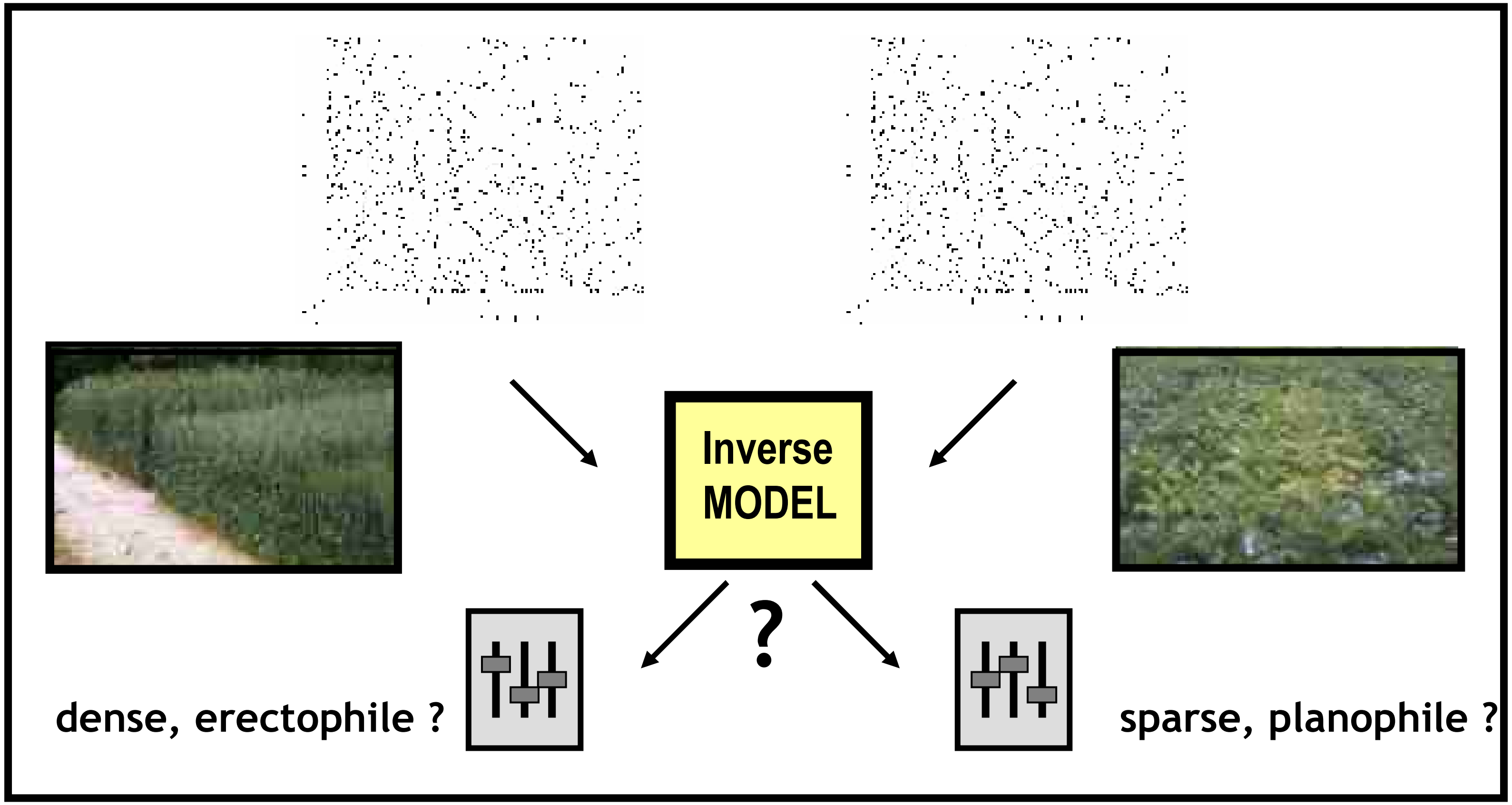
- Continuous variables



The ill-posed inverse problem illustrated for a Landsat-TM sensor. 15 different parameter combinations lead to ± similar canopy reflectance spectra (SAILH+PROSPECT simulations) (Atzberger, 2003)

What is "ill-posed inverse problem"?

- Continuous variables



If different model parameters lead to similar spectral signatures, it is also difficult to retrieve the correct vegetation characteristics from measured spectra

Outline of the presentation

Problem description

- Terminology - Radiative transfer models

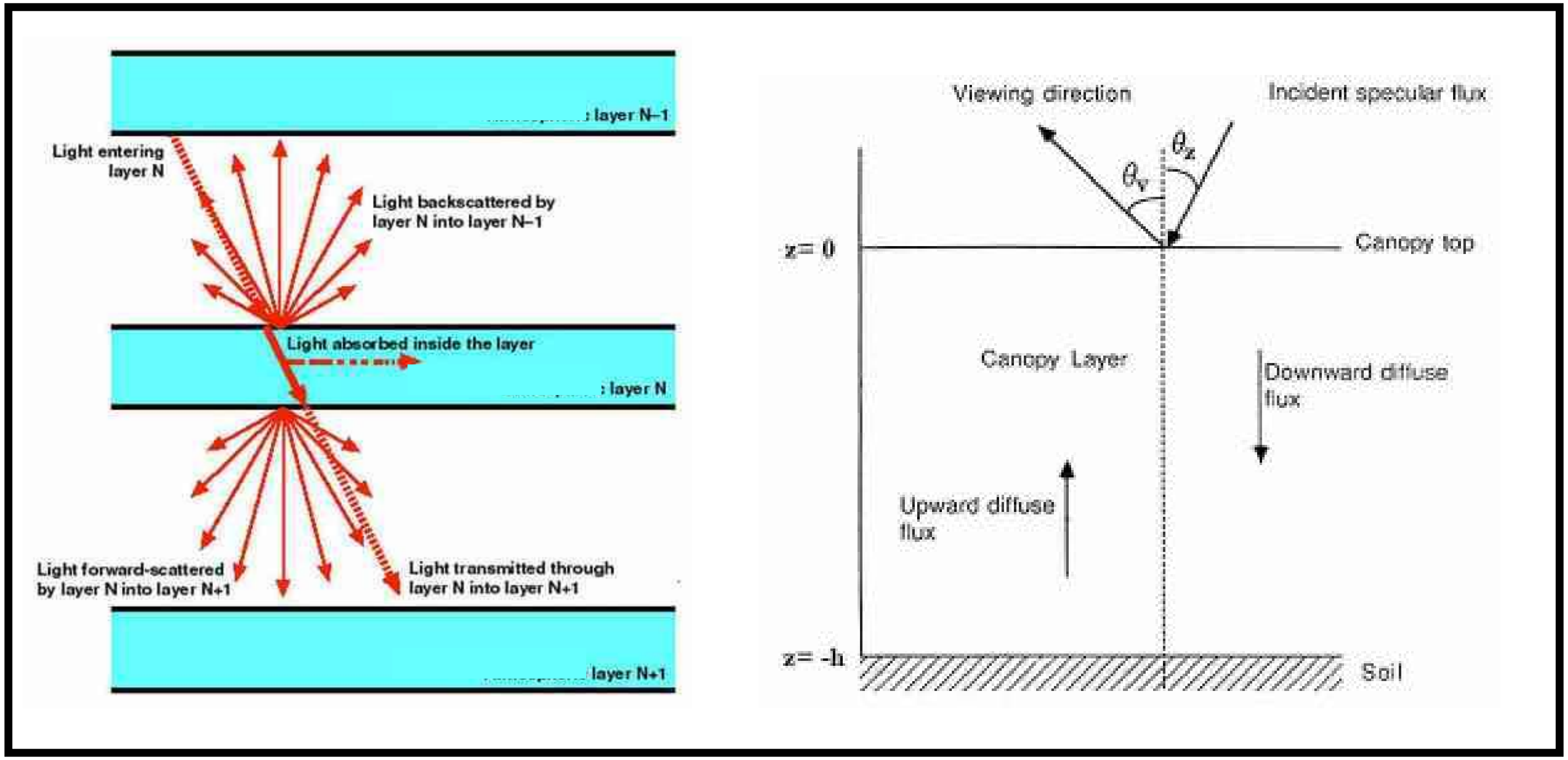


Illustration of radiative transfer models. The scattering and absorption of EMR is modelled by applying physical principles. From given canopy characteristics, the TOC reflectance is simulated. No analytical solution for the inverse problem exist (source: web)

Problem description

- Terminology - Radiative transfer models

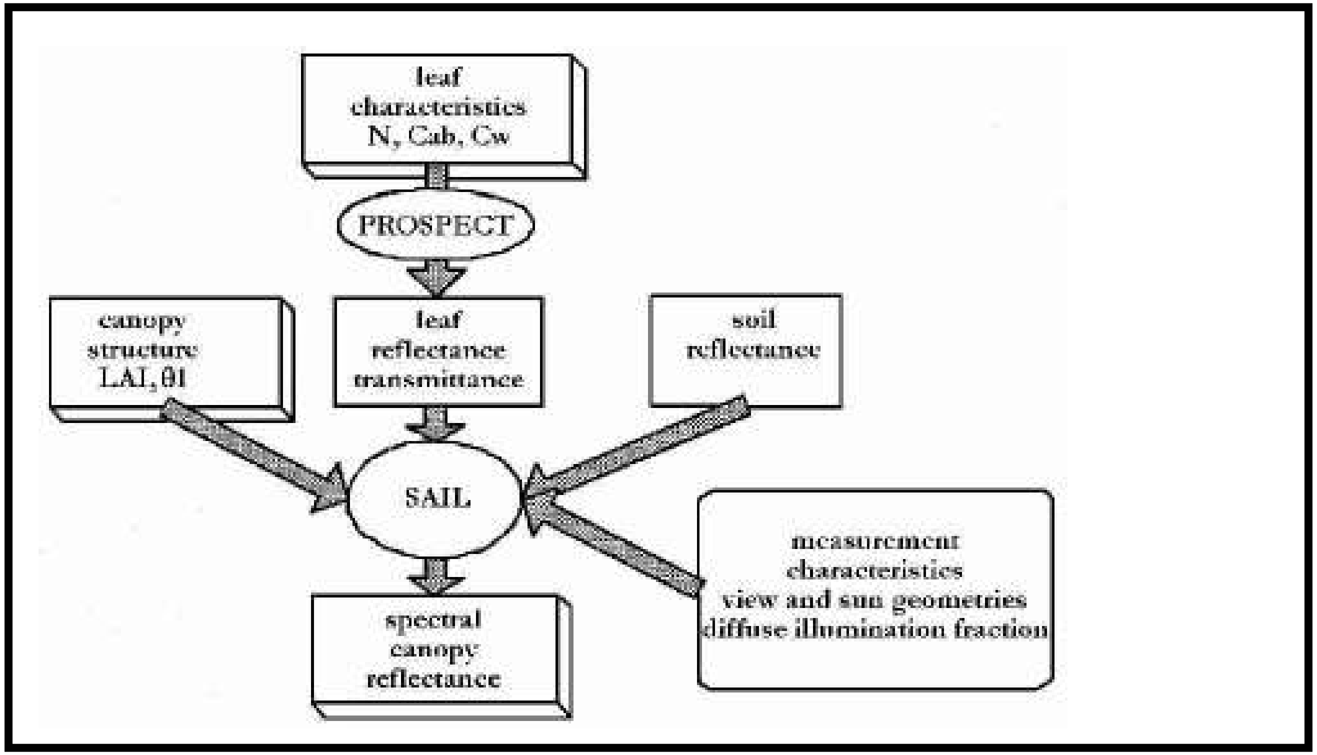


Illustration of the coupled SAILH+PROSPECT radiative transfer model for plant canopies. The entire wavelength range (400-2500 nm) is modelled using only a few parameters (from Jacquemoud, 1993)

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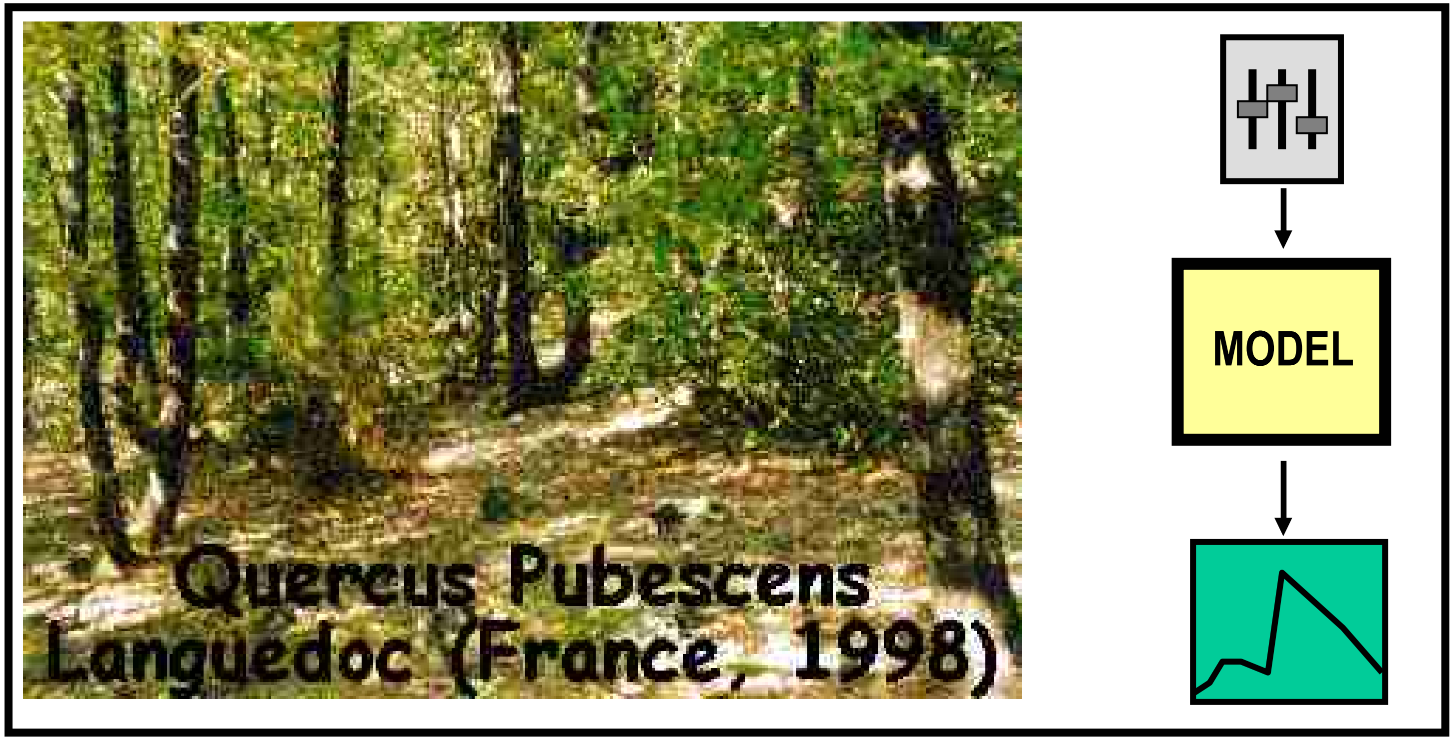
Problem description

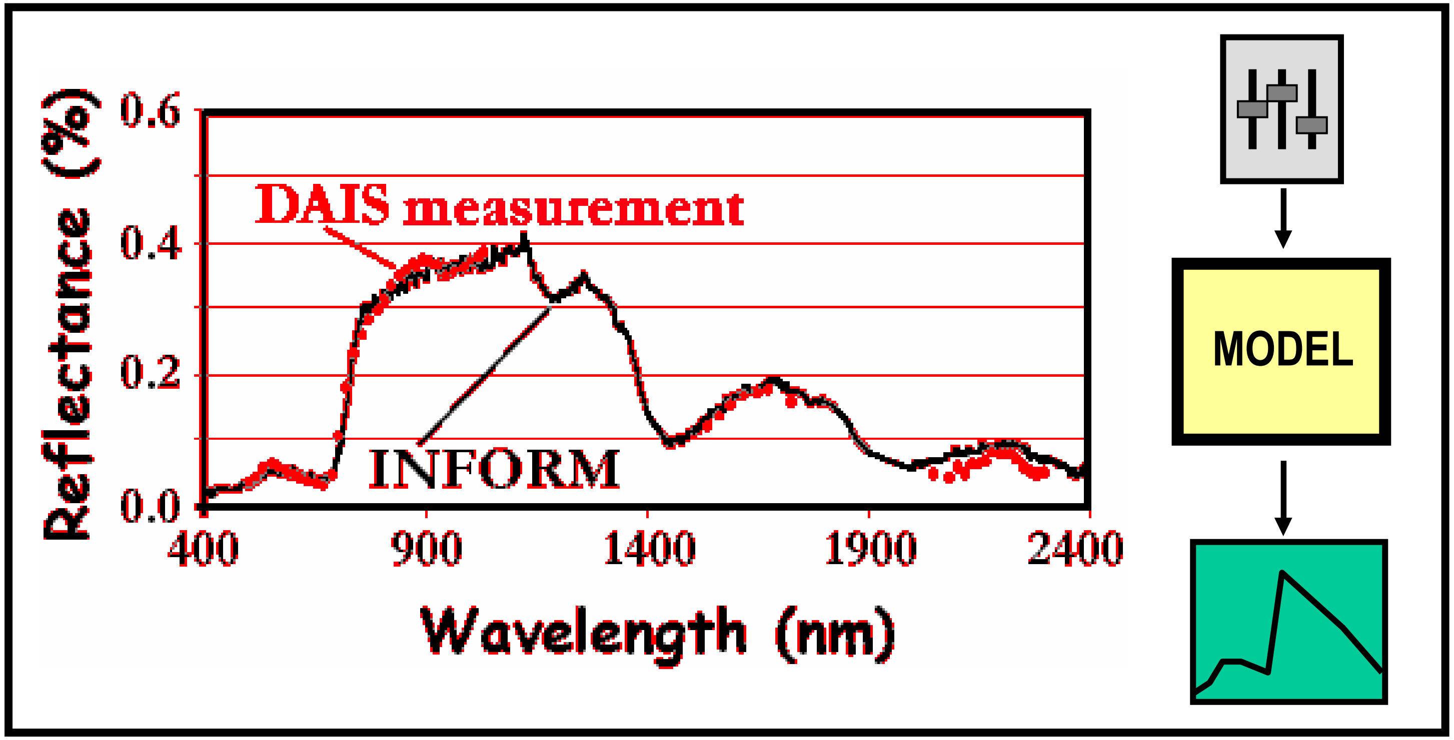
- Terminology - Forward modelling



Forward modelling: Input of measured canopy biophysical characteristics into the radiative transfer model to simulate the spectral properties of the canopy

Problem description

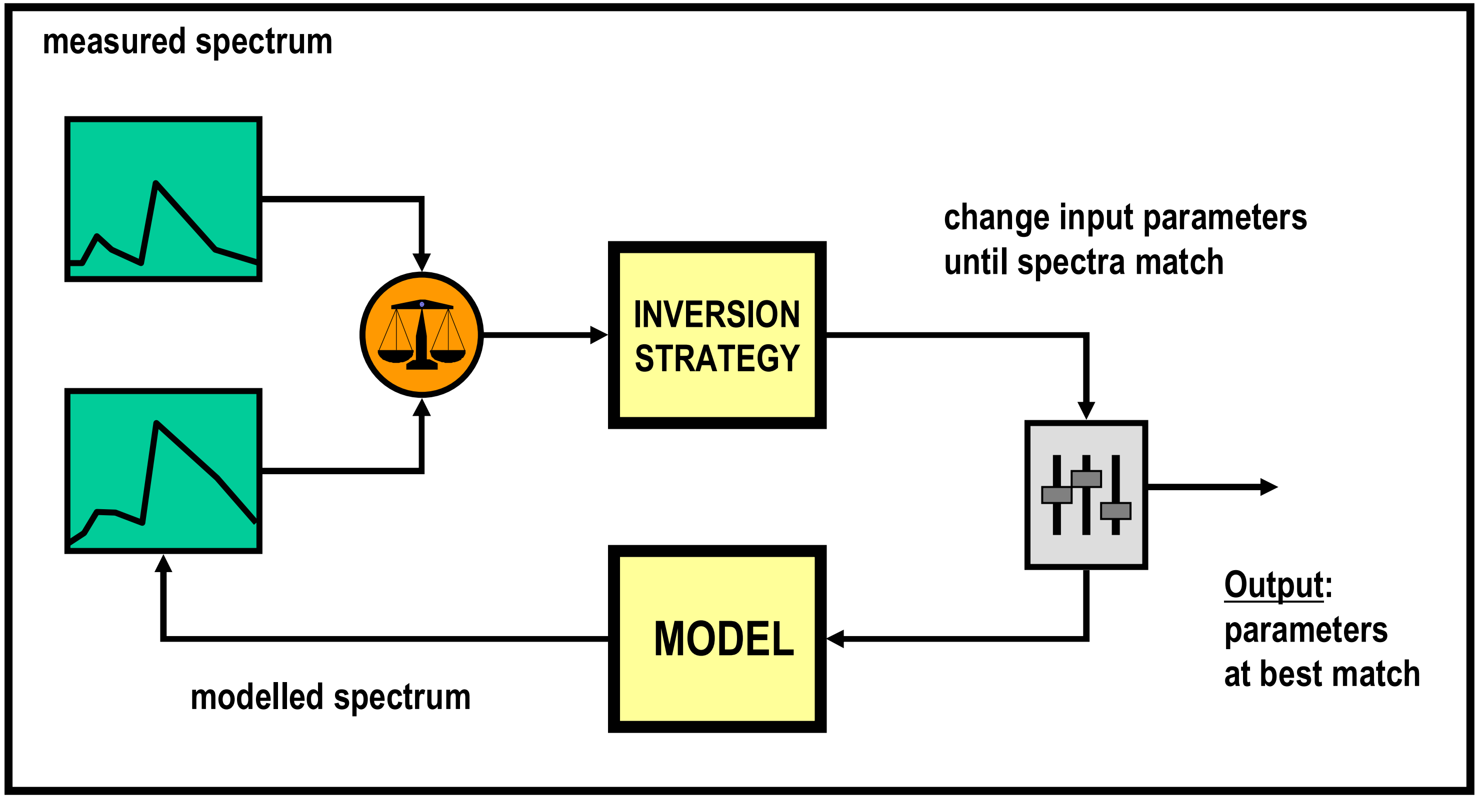
- Terminology - Forward modelling



Forward modelling: Input of measured canopy biophysical characteristics to simulate spectral properties of an oak canopy - Comparison with measured spectra (DAIS-7915) (Atzberger, 1999)

Problem description

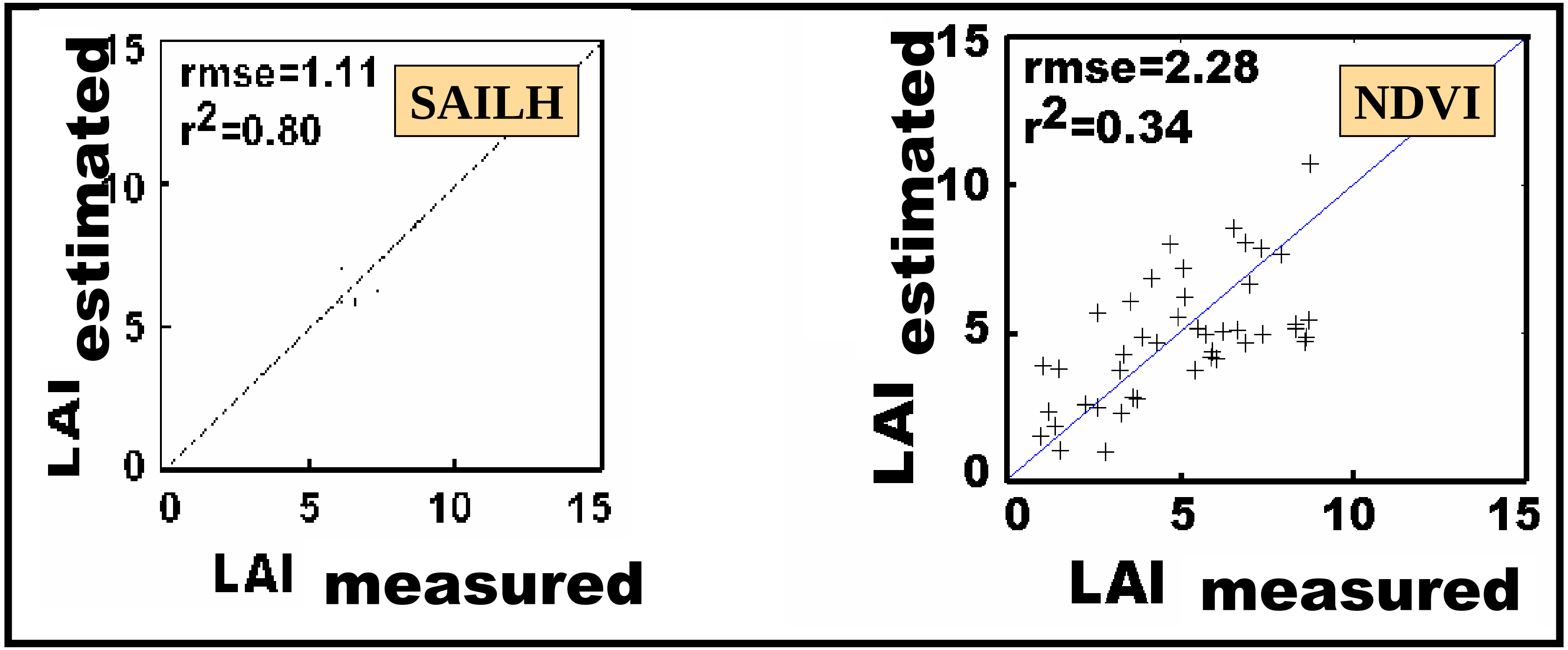
- Terminology - Inverse modelling



Model inversion by matching of measured and modelled spectra (from Verhoef & Bach, 2003)

Problem description

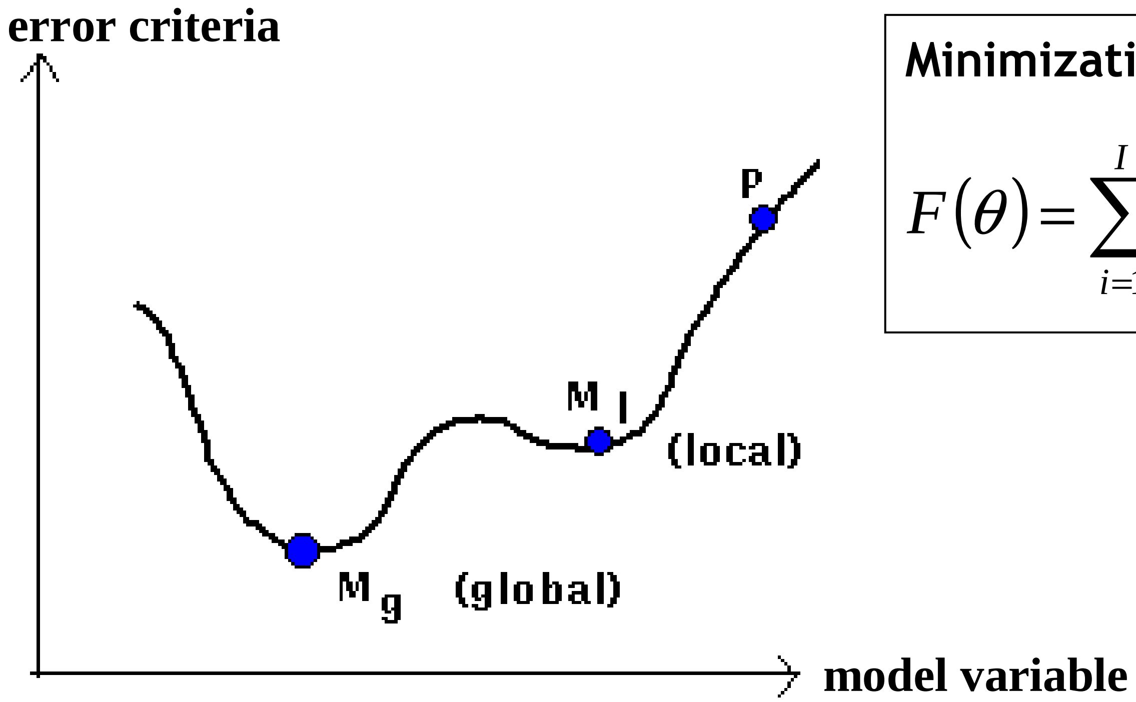
- Terminology - Inverse modelling



LAI retrieval through inversion of SAILH+PROSPECT radiative transfer model (left) compared to traditional NDVI (right) (Atzberger et al., 2004)

Problem description

- Terminology - Numerical inversion



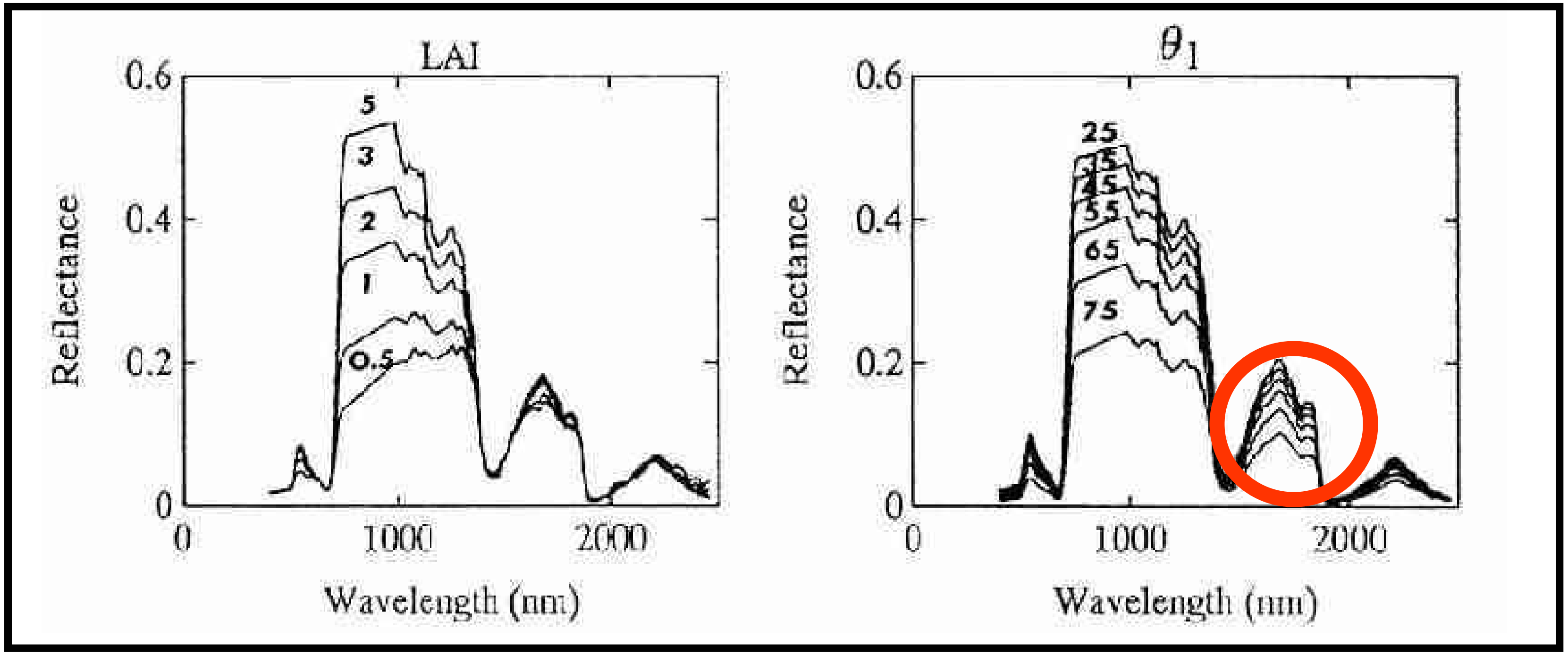
Minimization with Simplex

$$F(\theta) = \sum_{i=1}^{I} \left(\frac{\rho_i - M_i(\theta)}{\sigma_i} \right)^2$$

Illustration of error criteria, initial guess, global and local minima. Starting from an initial guess (P), the search algorithm tries to find the model variable(s) leading to the smallest error (Mg) between measured and simulated reflectance. The search algorithm may get trapped in a local minima (Ml) and never reaches the global minima (Mg) (source: web)

Problem description

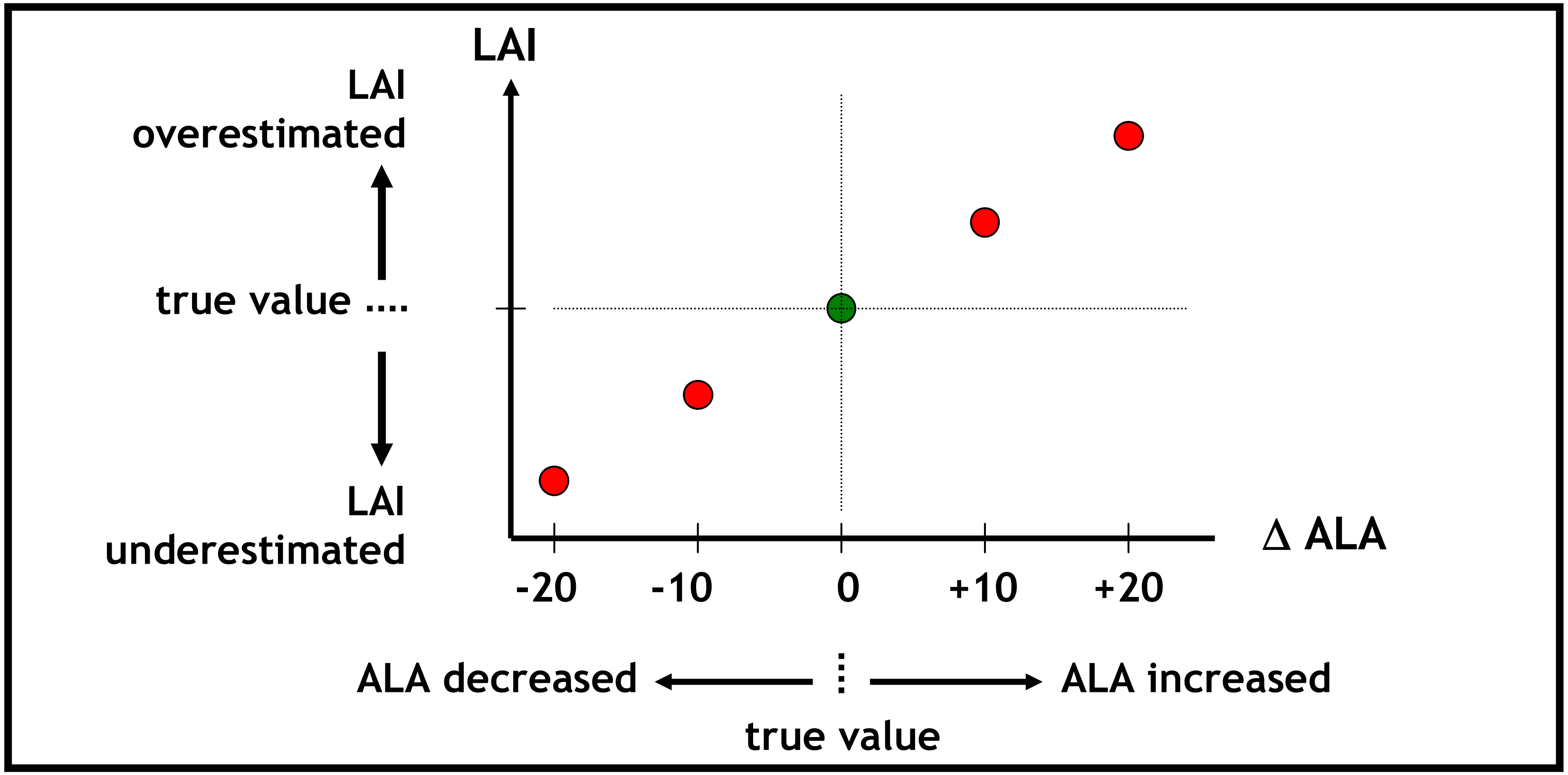
- Reasons for the ill-posed inverse problem



Model simulations reveal that LAI (left) and average leaf angle (ALA) (right) have more or less similar effects on simulated canopy reflectance (from Jacquemoud et al., 1995)

Problem description

- Assessing the ill-posed inverse problem

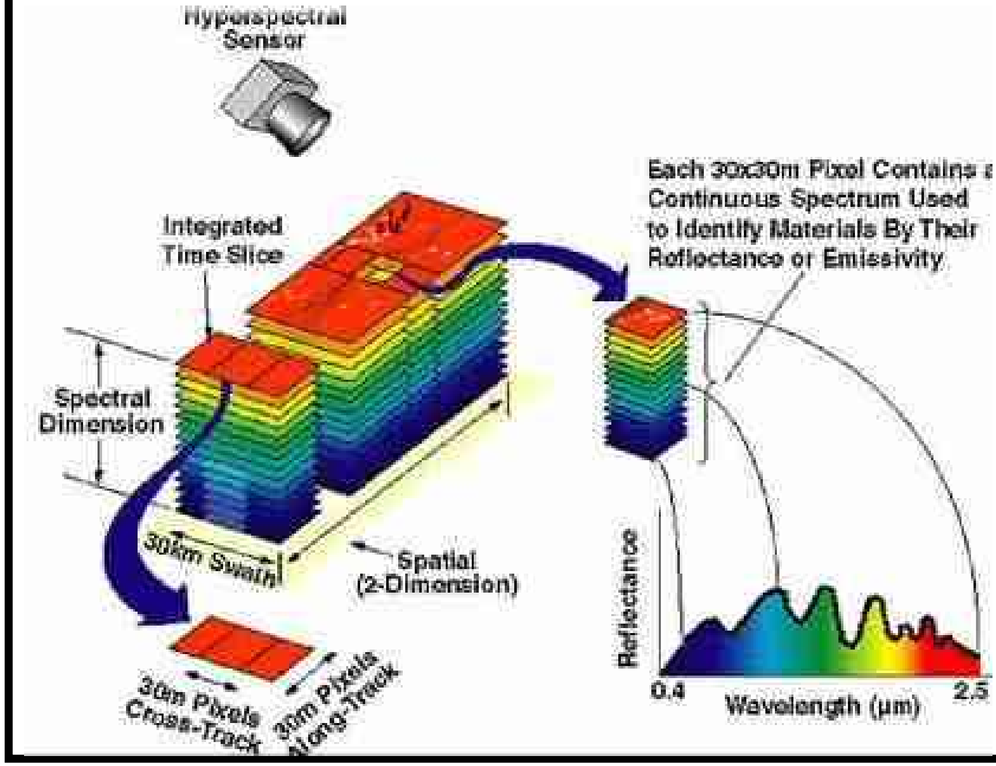


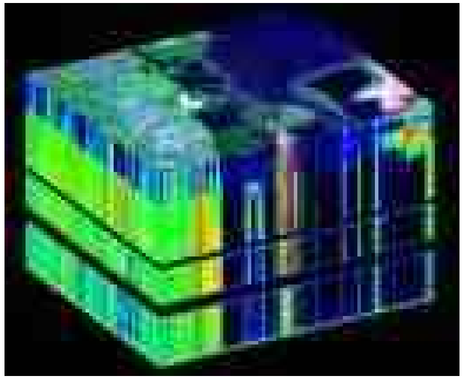
The ill-posed inverse problem can be easily assessed. A spectrum is simulated and then inverted, while fixing one model parameter (here: ALA) to a false value (here: ALA + Δ ALA). If the solution is ill-posed, the wrong model parameter will be compensated by another parameter (here: LAI), whereas the residual errors remain low.

Strategies for solving the ill-posed inverse problem

Strategies for solving the problem

- Sensor improvements

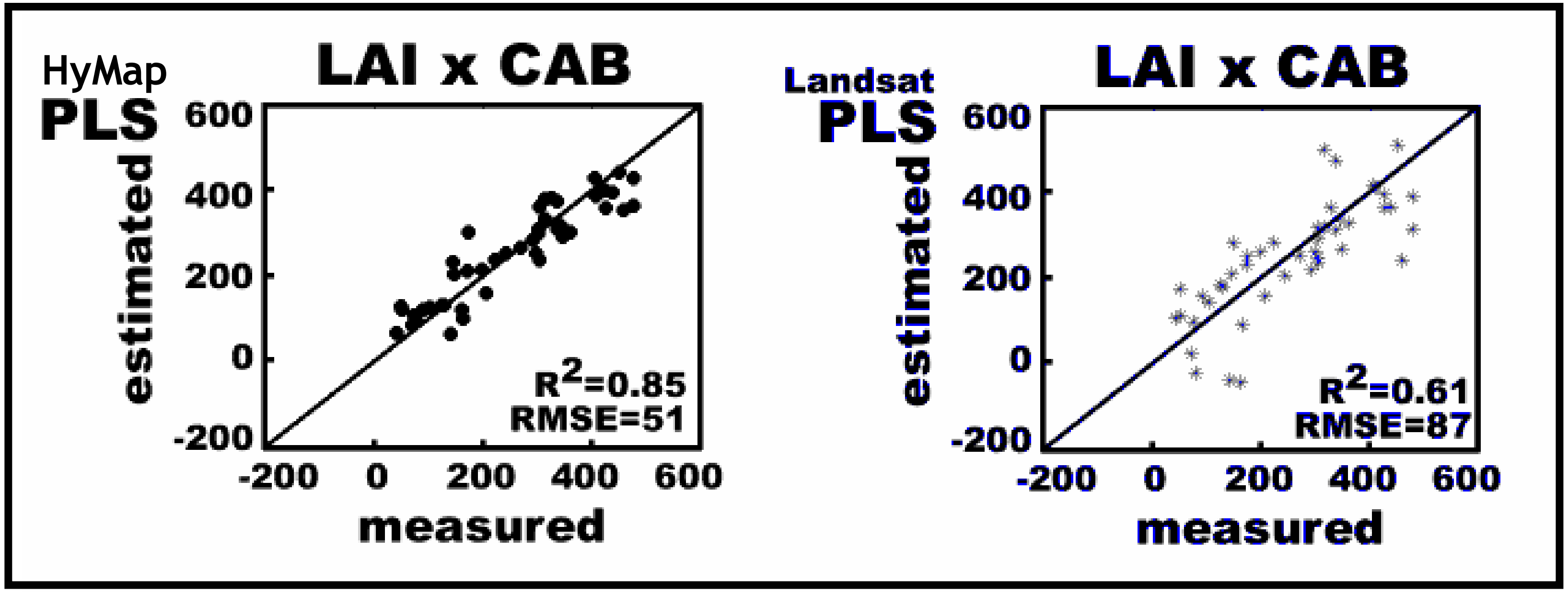




By mapping the Earth surface in many continuous spectral bands, a better inversion of radiative transfer models can be achieved (source: web)

Strategies for solving the problem

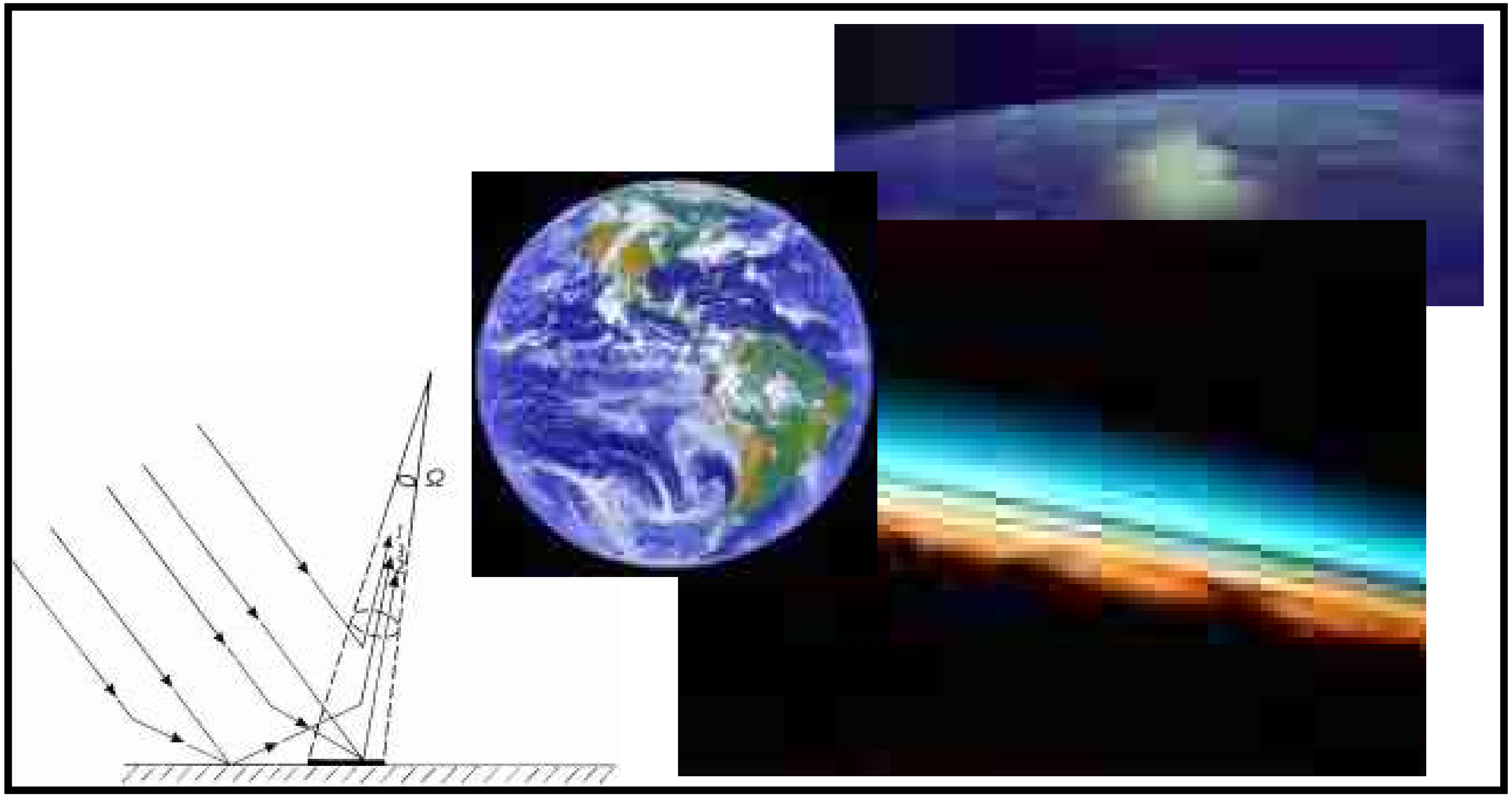
- Sensor improvements



Field experiments reveal that canopy integrated chlorophyll content (LAI x CAB) is better retrieved (PLS regression) using hyperspectral information (left) compared to multi-spectral information (right) (Atzberger et al., 2004)

Strategies for solving the problem

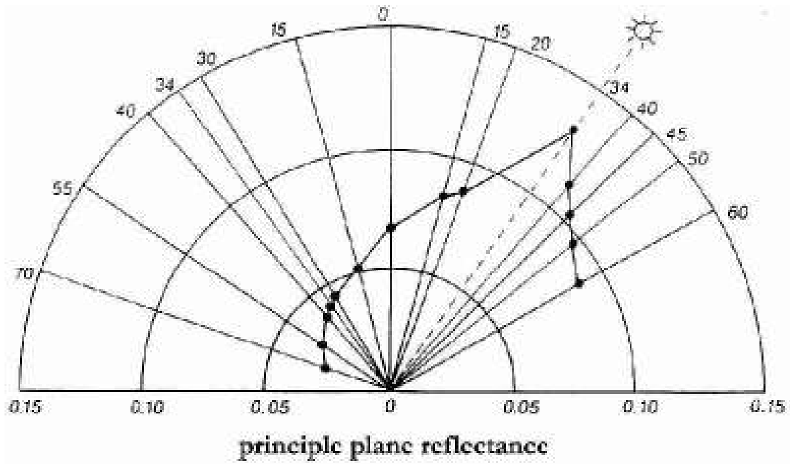
- Sensor improvements

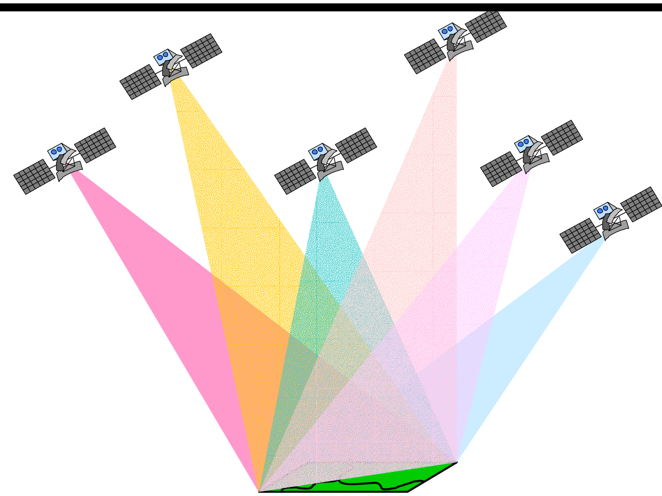


The better the radiometric quality of the spectral signature (SNR, calibration, atmospheric correction), the higher the accuracy of the retrieval of biophysical variables (source: web)

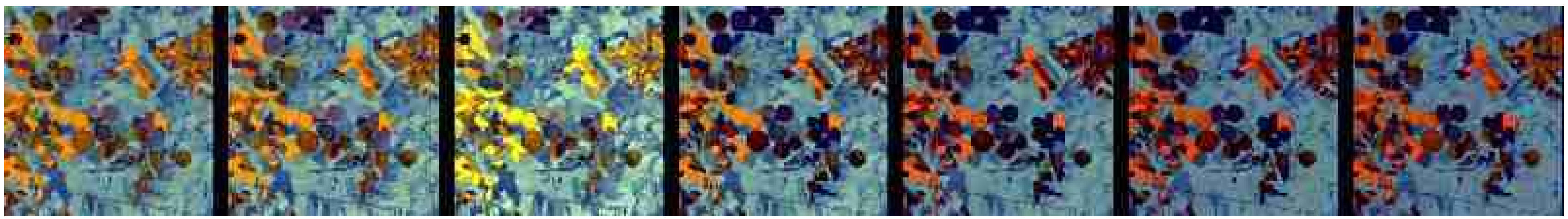
Strategies for solving the problem

- Increasing the dimensionality of the data





-60° -45° hot spot nadir view +22° +45° +60°

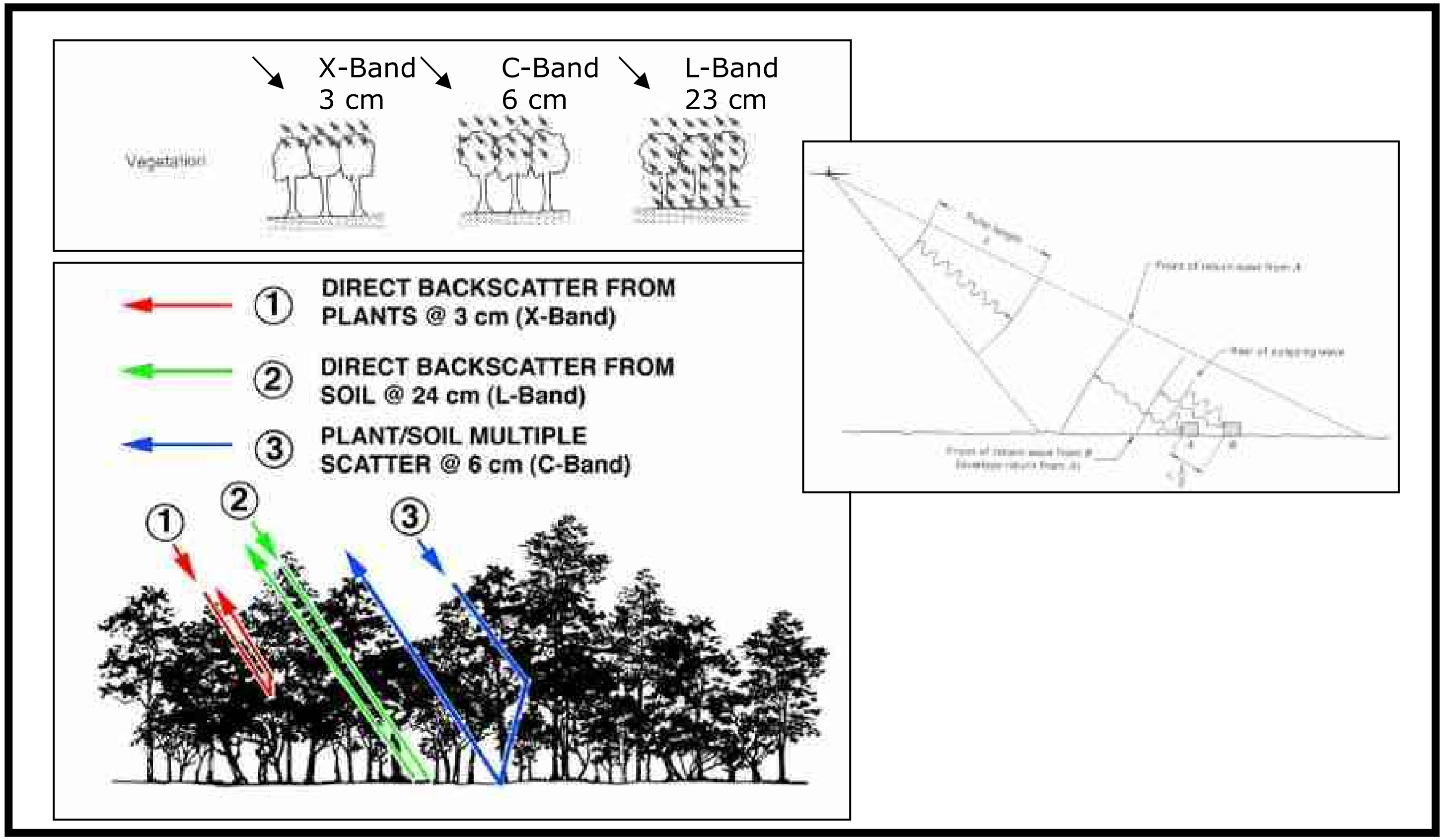


660 nm, 730 nm, 840 nm

The ill-posed problem can be considerably reduced by increasing the dimensionality of the data set – here: combining spectral and directional data (source: web)

Strategies for solving the problem

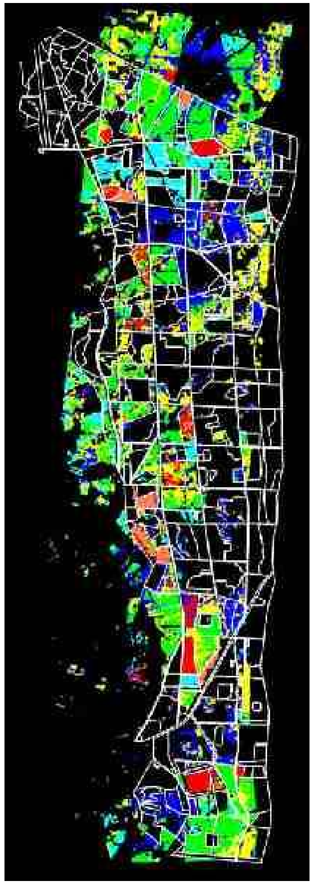
- Increasing the dimensionality of the data



The ill-posed problem can be considerably reduced by increasing the dimensionality of the data set – here: by combining optical and microwave data sets (source: web)

Strategies for solving the problem

- Including (external) prior information



$$F(\theta) = \quad + \quad$$

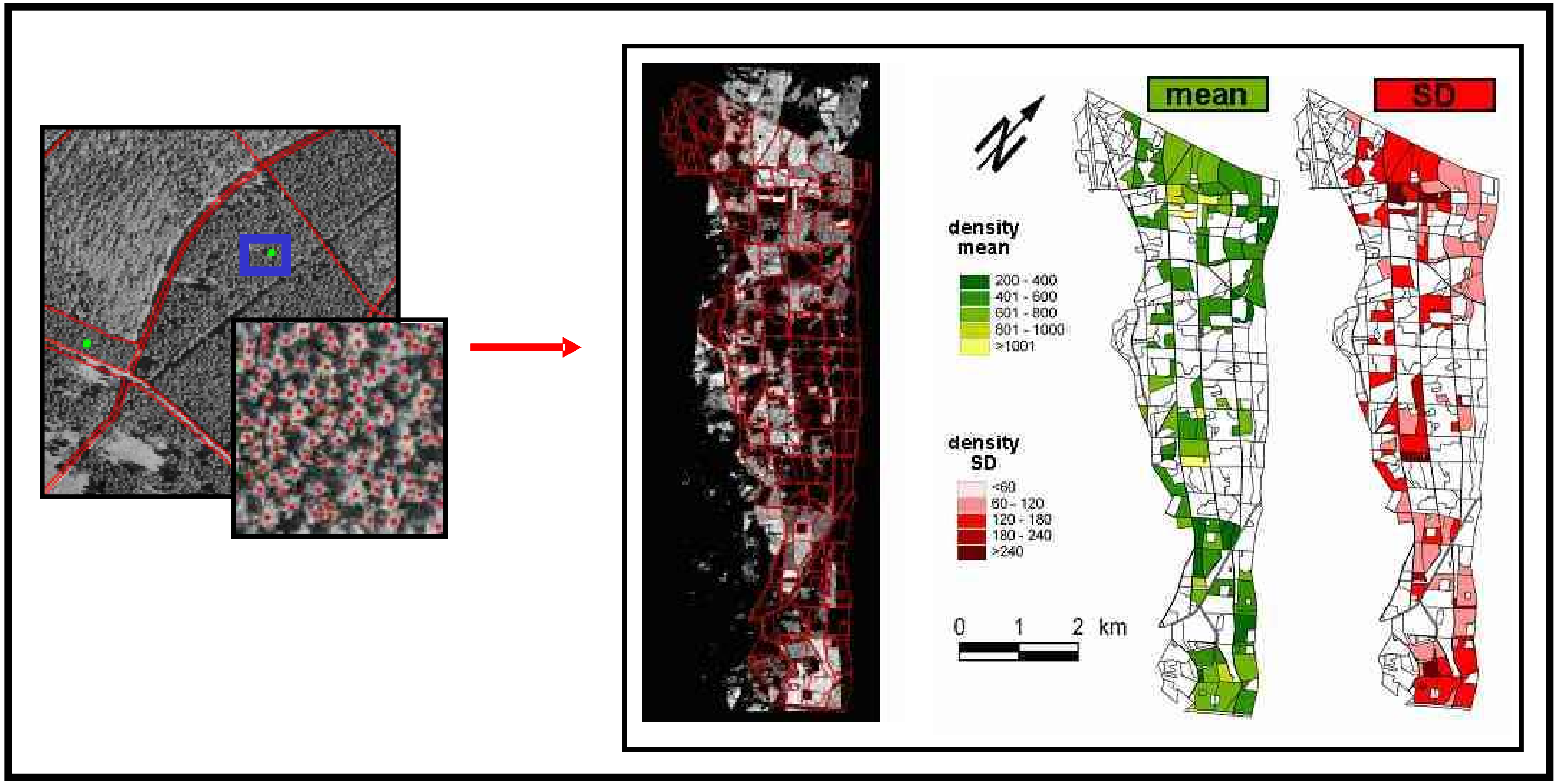
spectral info

prior info

The error surface can be better reshaped and restricted, if externally derived prior information is available (e.g. land cover classification yielding information on plant architecture) (Schlerf, Atzberger & Hill, 2002)

Strategies for solving the problem

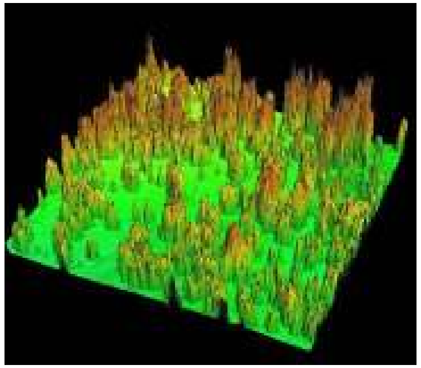
- Including (external) prior information

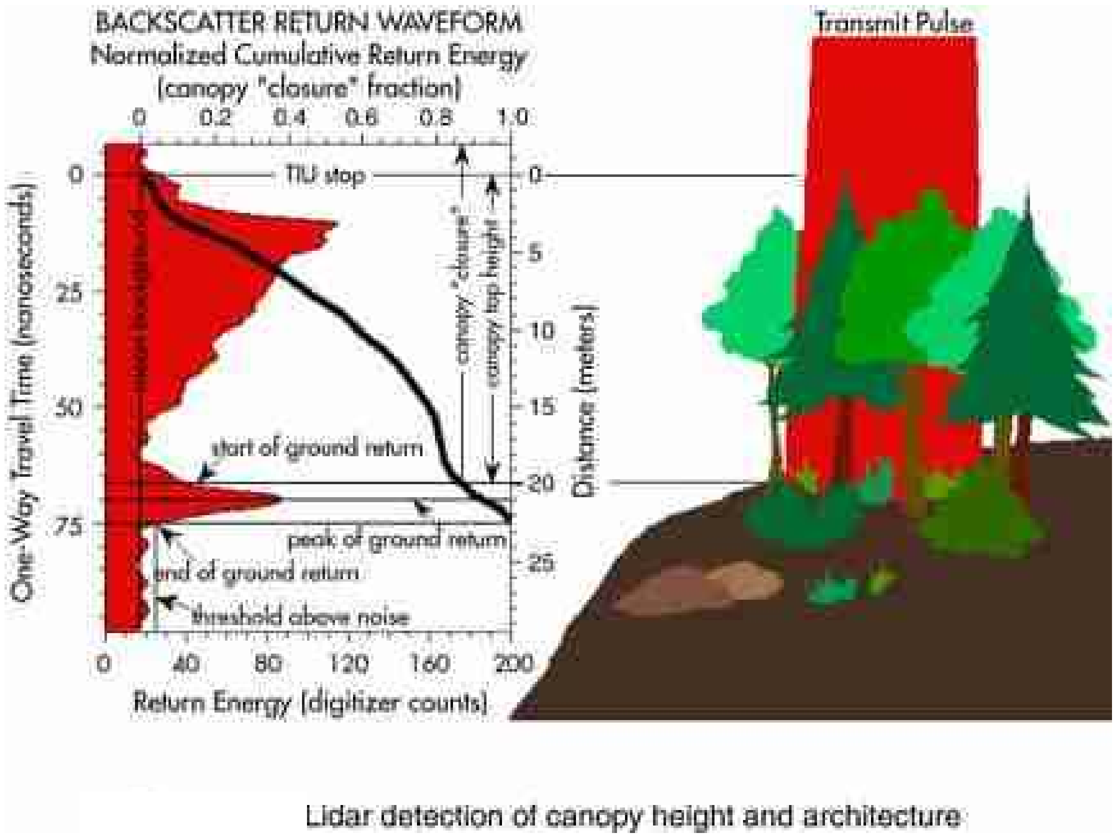


The number of variables to be retrieved can be reduced if some variables can be mapped from other EO data (e.g. stem density derived from BW orthophotos) (Atzberger & Schlerf, 2002)

Strategies for solving the problem

- Including (external) prior information

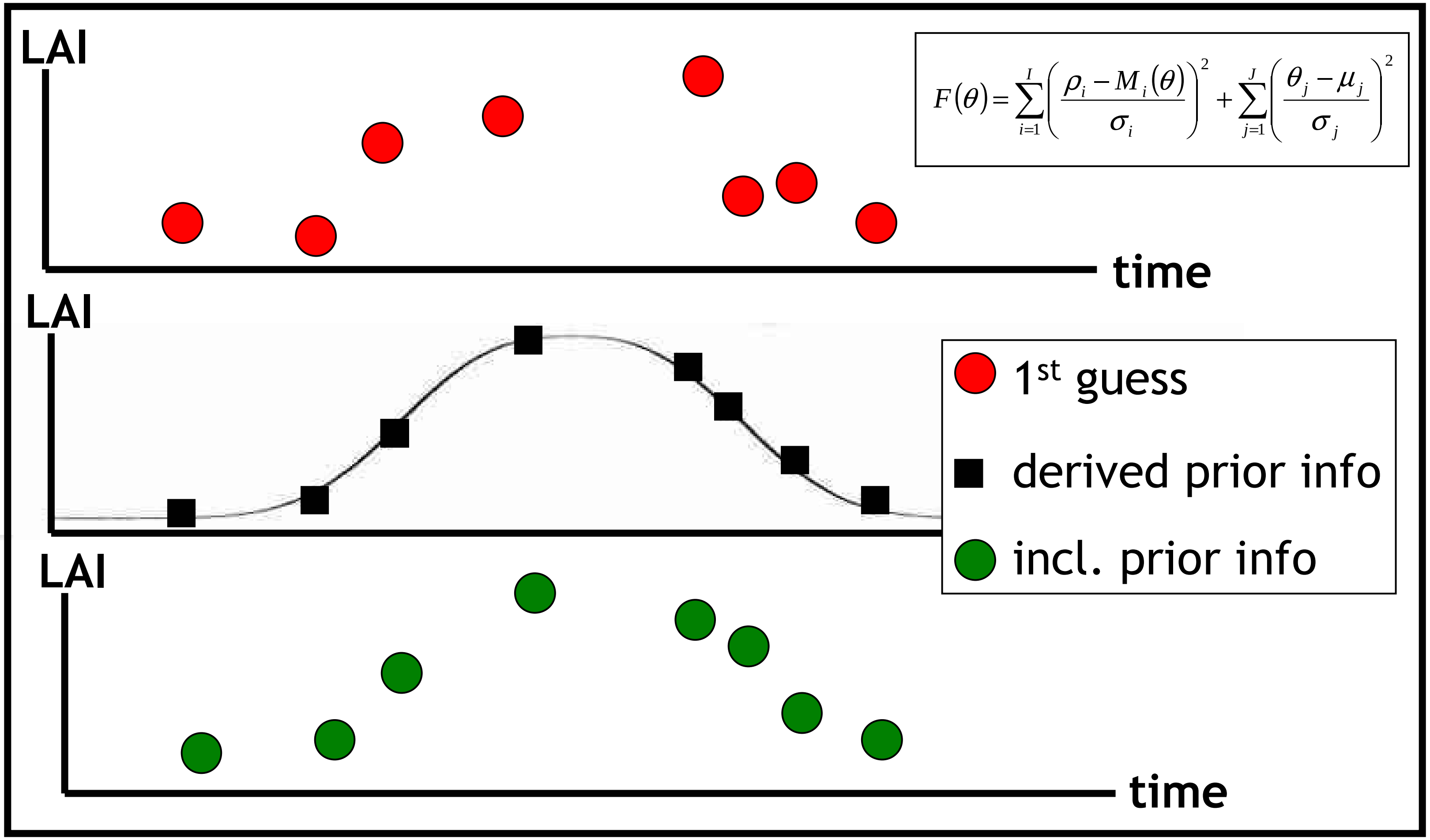




The number of variables to be retrieved can be reduced if some variables can be mapped from other EO data (e.g. canopy height and architecture from LIDAR measurements) (source: web)

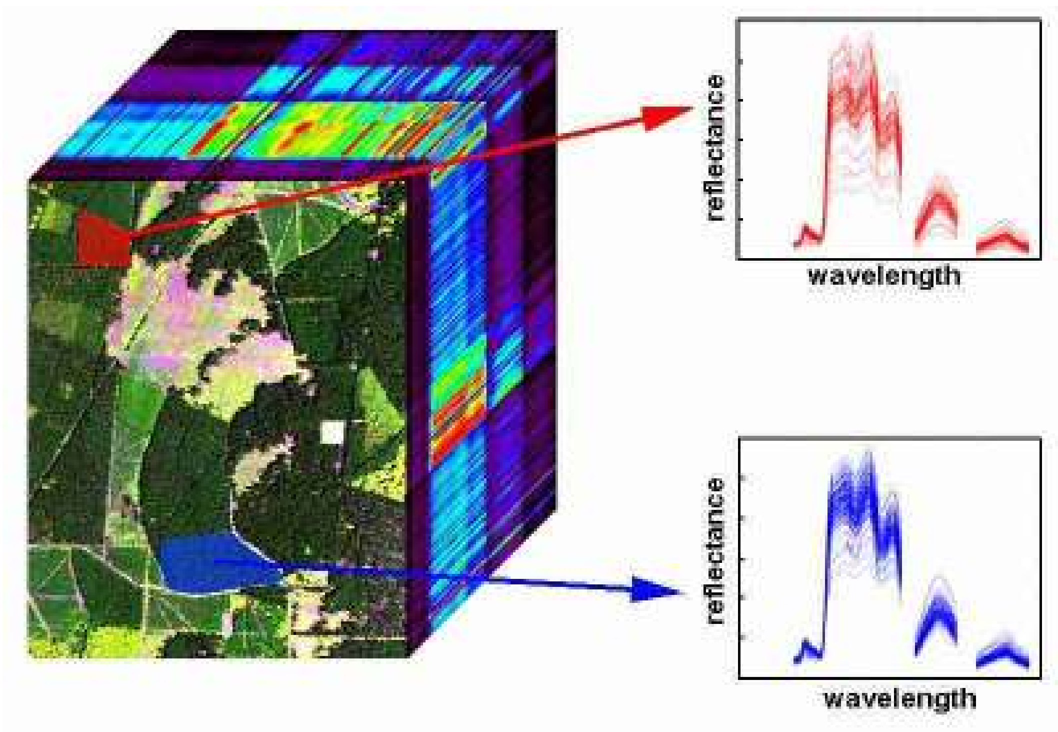
Strategies for solving the problem

- Exploiting the temporal consistency



Strategies for solving the problem

- Exploiting the spatial consistency



Principle of the object-based approach for solving the ill-posed inverse problem. Image objects (e.g. agricultural fields) have unknown leaf architectures. However, it can be assumed that the leaf architecture within a given image object is more or less similar. This leads to distinctive spectral clusters (Atzberger, 2004)

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Strategies for solving the problem

- Exploiting the spatial consistency

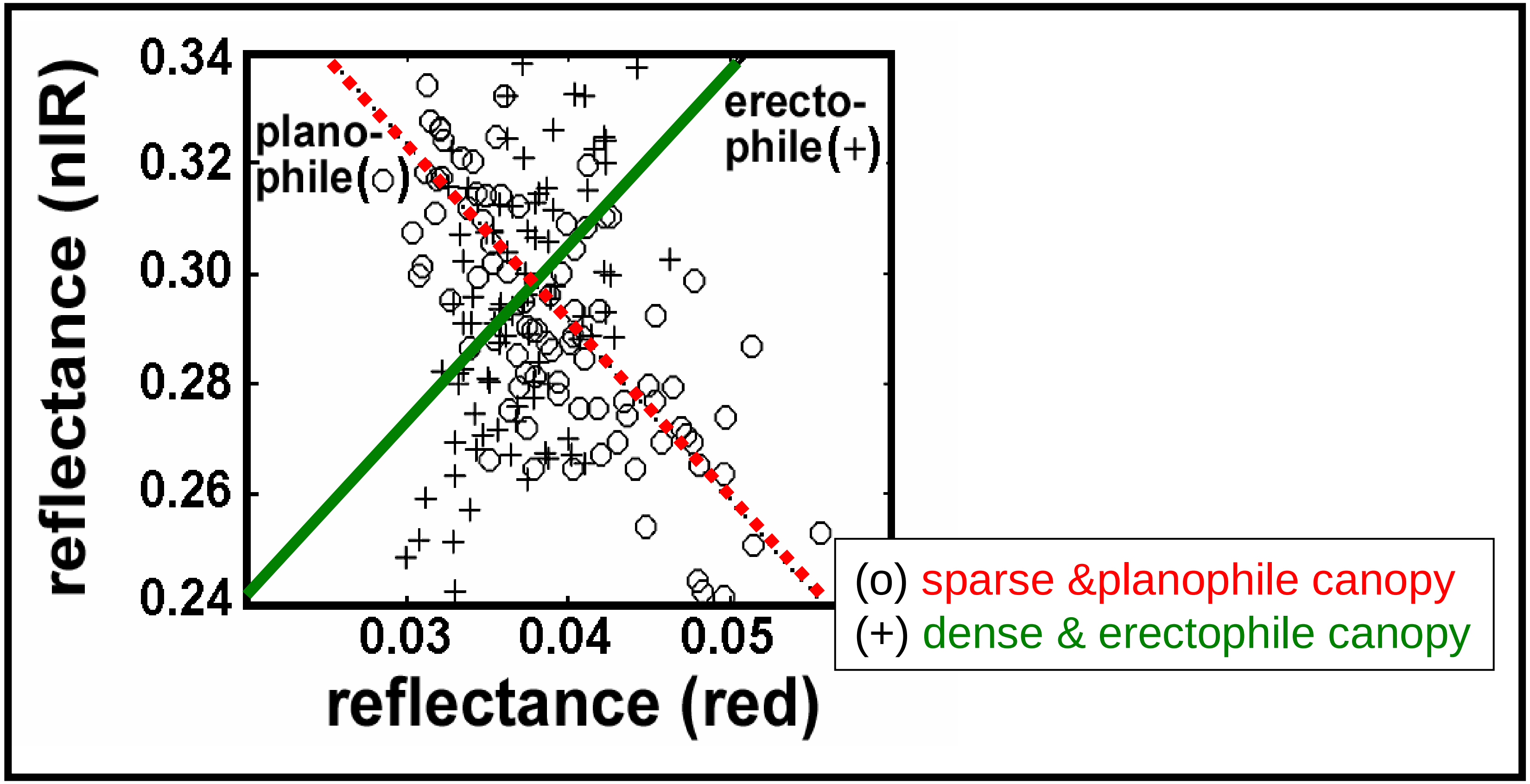
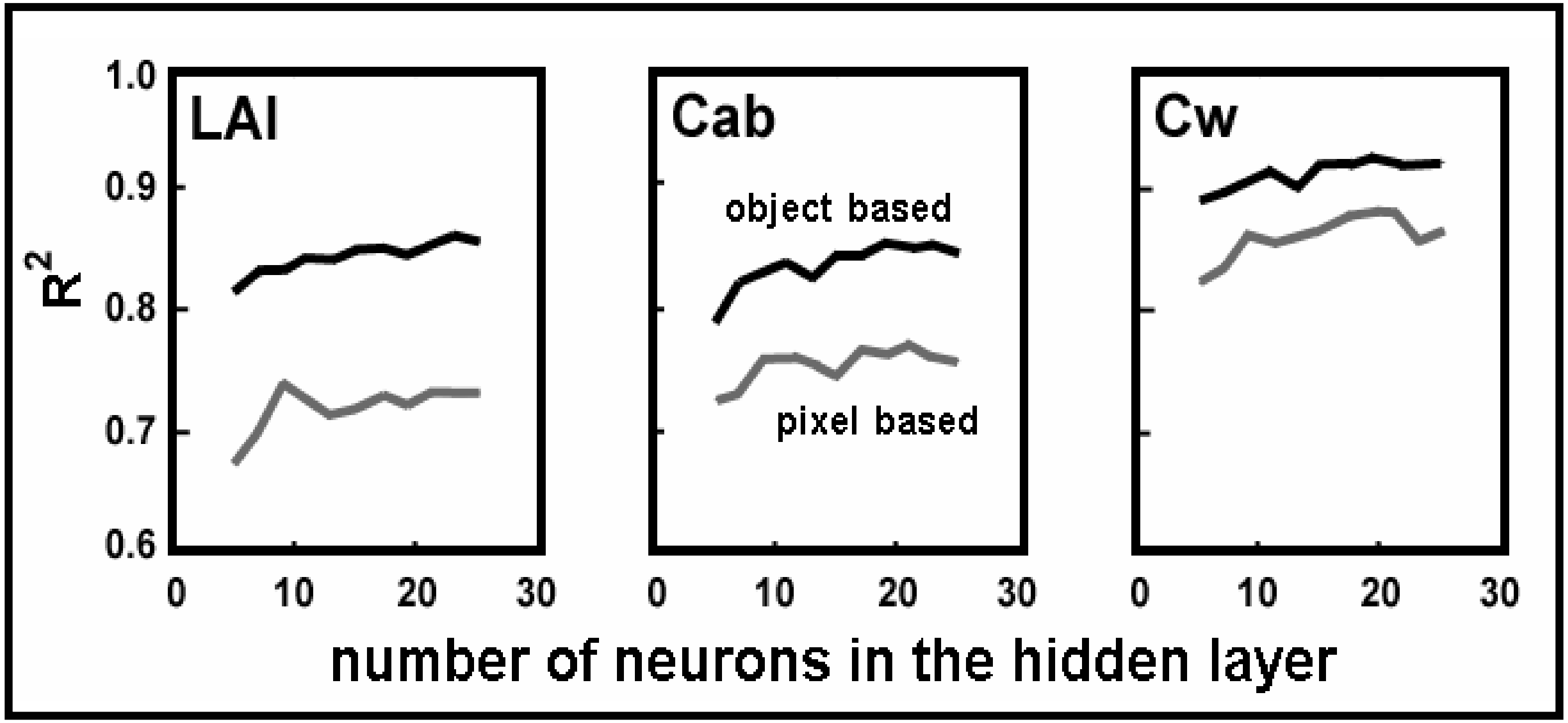


Illustration of the genesis of distinctive spectral clusters in the red-nIR feature space (Atzberger, 2004)

Strategies for solving the problem

- Exploiting the spatial consistency

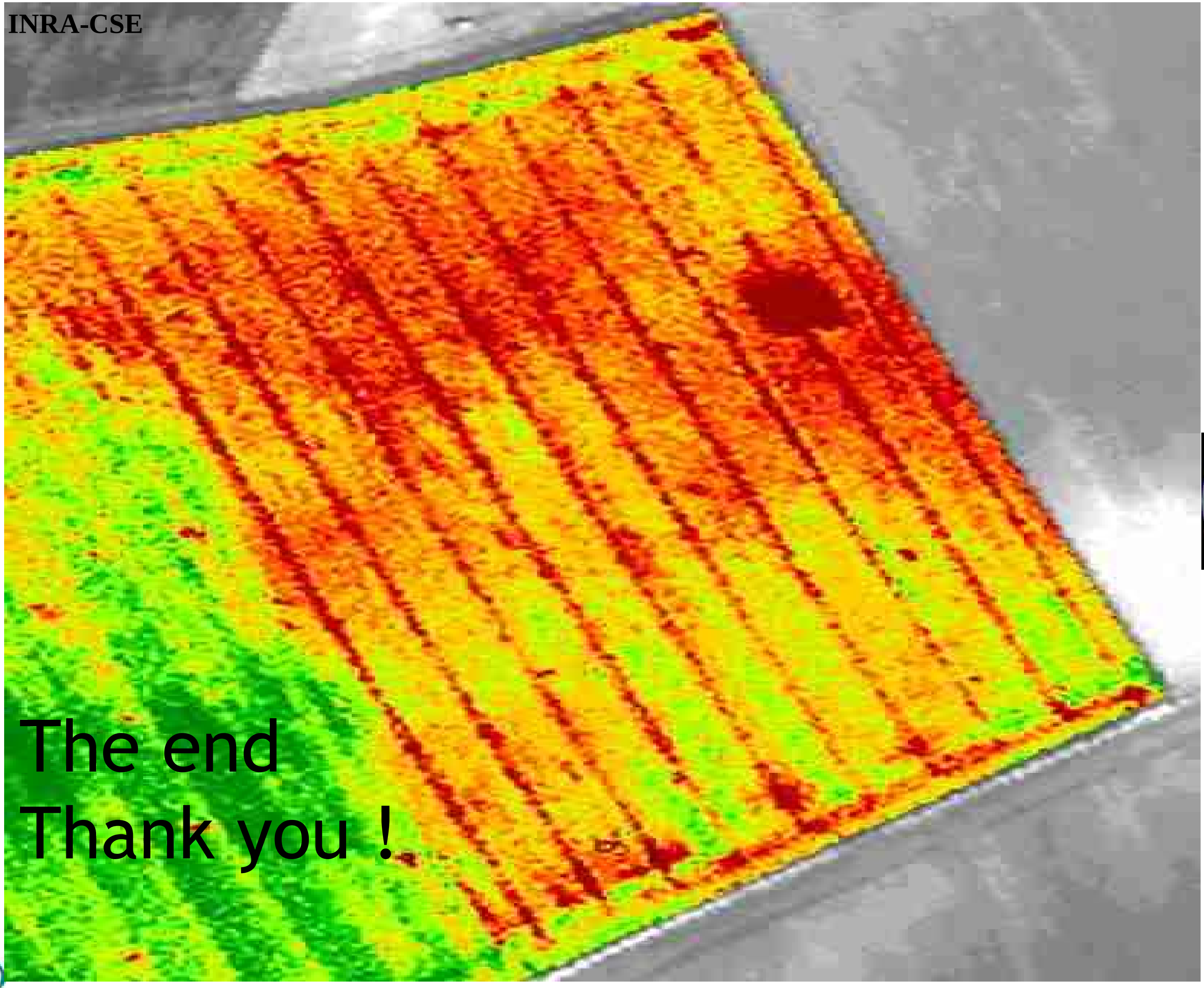


Coefficient of determination (R2) between true and retrieved canopy variables as a function of the number of neurons in the hidden layer for the object based model inversion (black line) and the traditional inversion (gray line) (Atzberger, 2004)

Conclusions

Conclusions

- Accuracy of RTM of uppermost importance
- Combined RTM have high potential
- External prior information very useful
- Temporal & spatial consistency should be taken into account



The end
Thank you !