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Correction of surface reflectance retrieval in the tree shadow by machine learning

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Contents

Introduction

Reflectance retrieval applications

Developpement of high spatial resolution imaging spectroscopy allows one to retrieve accurate values of surface reflectance, with applications in :

- Land cover mapping
- Vegetation and cultures monitoring
- Characterization of impervious surfaces condition in urban areas

Introduction
Reflectance retrieval applications

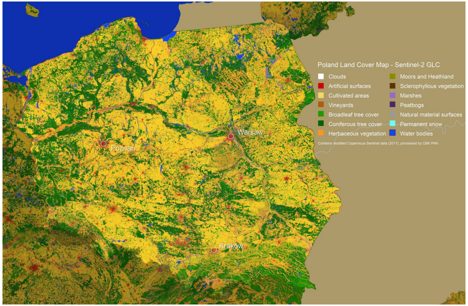


Figure – Land cover map, © ESA

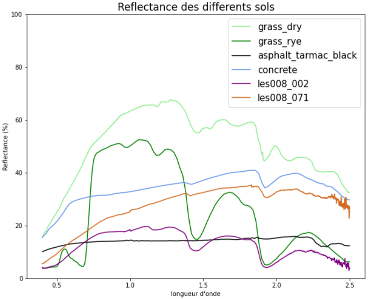


Figure – Soils reflectances

Introduction

Treatment of shadows

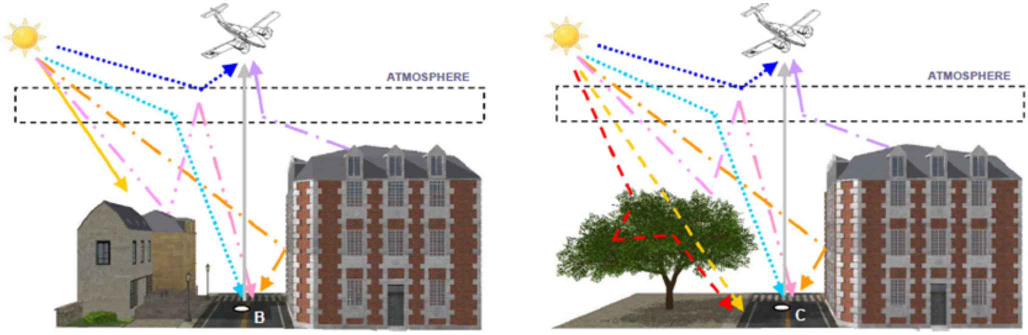


Figure – Taxonomy of the radiative transfer components for an urban scene in a building and in a tree shadow.

Introduction

Treatment of shadows

- 3D atmospheric correction models manage opaque object
- Need to properly account for irradiance transmitted and scattered through semi transparent media as tree crowns

Correction of reflectance retrieval in ICARE-VEG :

$$\rho_{ICV}(C,\lambda) = \frac{R_{dir}(\lambda)}{I_{tot}^{IC}(\lambda)} \times \frac{\pi}{T_{dir}(\lambda)} = \frac{R_{sensor} - R_{env} - R_{atm}}{I_{trans} + I_{diff} + I_{refl} + I_{coupl}} \times \frac{\pi}{T_{dir}} \qquad (1)$$

$$= \frac{\rho_{IC}(C,\lambda)}{1+\beta(C,\lambda)} \qquad (2)$$

with a correction factor $\beta(C,\lambda)$ defined by :

$$\beta(C,\lambda) = \frac{I_{trans}}{I_{tot}^{IC}} = \frac{I_{trans}^{dir} + I_{trans}^{diff}}{I_{tot}^{IC}} \qquad (3)$$

Introduction
Shadow dependencies

The irradiance in the tree shadow depends on many parameters that could be divided in 3 general parts :

1. 15 Scene parameters
   - Tree structural parameters : tree height, trunk height, crown form and diameter.
   - Leaf distribution : LAI (Leaf Area Index), porosity, Leaf angle distribution (LAD).
   - Leaf optical properties due to chemical traits : chlorophyll, carotenoid, water thickness, dry mater content.
   - Environment parameters : soil, slope, aerosol.
   - Illumination condition : sun zenithal angle.
2. Spatial parameters : position of the pixel in the shadow.
3. Spectral parameter : spectral band considered.

Goals

The main goal of our study is to **build a metamodel predicting the correction factor β accounting for scene parameters (1), and both spatial (2) and spectral (3) parameters**

To do so, our roadmap is the following :

1. Build a space filling design of experiment.
2. Carry out 3D physical simulations with radiative transfer code DART.
3. Build a first metamodel.
4. Conduct a sensibility analysis.
5. Build a second metamodel taking into account only influent variables.

Design of Experiment

Probabilistic modelling : Input variables densities

- 11 quantitatives and 4 qualitatives variables
- Transformations to have independent variables

Tree dimensions distributions : tree height, trunk height and crown diameter fitted with openTURNS.

<u>OT Tools :</u> **ot.KernelSmoothing()**, **ot.FittingTest.BIC()**

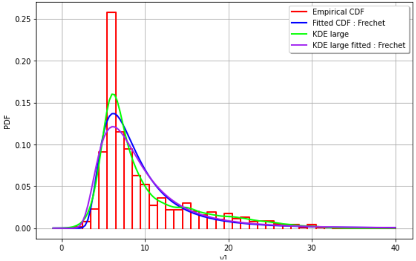


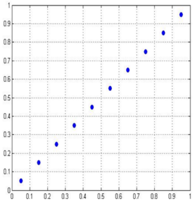
Figure – Probability density function (PDF) for tree height (Lyon metropolitan area database)

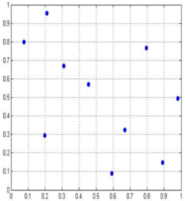
Design of Experiment

Latin hypercube sampling (LHS)

To build our design of experiment we chose to use the LHS (Latin hypercube sampling) method. Let $X = (x_1, ..., x_n)$ be a random uniform vector with independent copula. This way of sampling allows one to distribute N sample points and consists of :

1. Dividing each variable range in N equals intervals.
2. Choosing sampling points ensuring that in any axis-aligned hyperplane there is only one point.





Design of Experiment

LHS Optimization

Criterions : Let $X = (x^{(i)})_{1 \leq i \leq N}$ be a set of N sampling points.

1. Centered L^2 discrepancy (C2) :

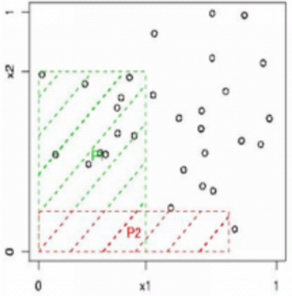
$$D_N(X) = \sup_{B \in J} \left| \frac{A(B,X)}{N} - \lambda(B) \right|$$

2. MinDist :

$$\phi(X) = \min_{ij} \left\| x^{(i)} - x^{(j)} \right\|_2$$

3. PhiP :

$$\phi_p(X) = \left(\sum_{1 \leq i < j \leq N} \left\| x^{(i)} - x^{(j)} \right\|_2^p \right)^{\frac{1}{p}} \underset{p \to +\infty}{\longrightarrow} \phi(X)$$



Design of Experiment

LHS Optimization

Optimization methods :

1. Monte-Carlo : Generate n LHS designs and choose the optimal one according to the previously chosen criterion.
2. Simulated Annealing LHS : A new design is obtained by swapping one coordinate between 2 sampling points. This new design is conserved or not with the probability :

$$max\left(1, \exp\left(-\frac{\phi(X_n) - \phi(X_{n+1})}{T_n}\right)\right)$$

   Where ϕ is the criterion previously chosen and $(T_i)_i$ a temperature profile.
   Then, we repeat this process in an iterative way.

OT Tool : **ot.SimulatedAnnealingLHS** and **ot.LHSExperiment**
==> Space filling LHS with **5000 points for 15 input variables**

Design of Experiment

DART Simulations

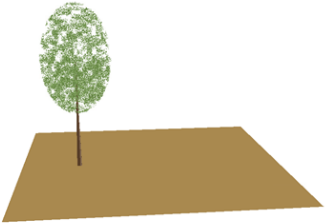


Figure – 3D DART scene

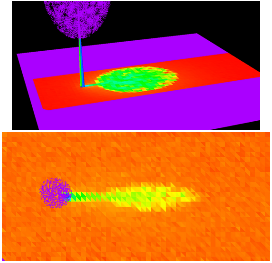


Figure – Radiative budget for 1 spectral band

DART : Discrete Anisotropic Radiative Transfer (DART 5) for Modeling Airborne and Satellite Spectroradiometer and LIDAR Acquisitions of Natural and Urban Landscapes. Jean-Philippe Gastellu-Etchegorry et al, Remote Sensing 2015

Mean transmittance metamodel

Gaussian process regression

Let $f : x \mapsto f(x)$ be the function representing the tree crown transmittance. We want to estimate it by a gaussian process :

$$f \sim \mu + Z \tag{4}$$

with :

$$\mu(x) = \sum_i \beta_i F_i(x) \quad \text{the deterministic part, with a chosen functional basis } (F_i)_i \tag{5}$$

$$Z \sim \mathcal{GP}(0, k(.,.)) \quad \text{with } k(.,.) = \sigma^2 cov(.,.) \text{ the kernel} \tag{6}$$

Thus, we construct a surrogate model :

$$f(x) = \mu(x) + Z(x) \sim \mathcal{N}(\mu(x), \sigma^2) \tag{7}$$

Mean transmittance metamodel

Gaussian process regression

Basis : Constant
Covariance model : Matern 5/2
Nugget factor : 0.01

RMSE : 0.06044
R2 : 0.894313

OT Tool : **ot.KrigingAlgorithm**

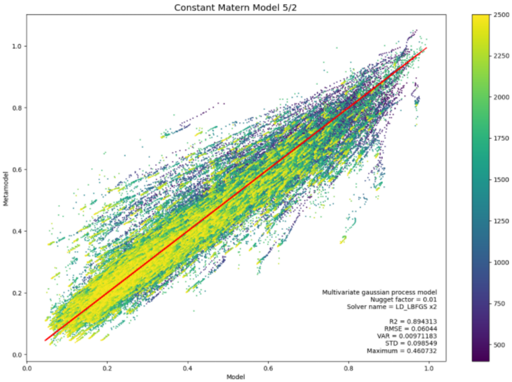


Figure – Validation graph of a metamodel trained on 1050 data

Mean transmittance metamodel
Gaussian process regression

We tried to choose different lambdas and to fit a multivariate GP, but it's really long
==>1 metamodel / output

Overall good results $R2 \sim 0.9$ for 1050 train data and 3950 test data, some less accurate prediction. Next steps :

- Analyze these cases
- Sensitivity Analysis to fix the non influent input and build another space filling design
- We also want to reduce the dimension, as we have $\sim$ 100 spectral output => 1D Karhunen-Loève

Mean transmittance metamodel
Sensitivity analysis

Let's consider $Y = f(X)$ as a random vector, we consider the following decomposition :

$$Y = f(X) = f_0 + \sum_i f_i(X_i) + \sum_{i,j} f_{ij}(X_i, X_j) + \ldots + f_{123\ldots n}(X_1, X_2, \ldots, X_n) \tag{8}$$

$$\begin{aligned} f_0 &= E[Y] \\ f_i(x_i) &= E[Y|X_i = x_i] - f_0 \\ f_{ij}(x_i, x_j) &= E[Y|X_i = x_i, X_j = x_j] - f_0 - f_i(x_i) - f_j(x_j) \end{aligned}$$

We aim to use this decomposition to explain Y variance :

$$V(Y) = \sum_i V(f_i(X_i)) + \sum_{i,j} V(f_{ij}(X_i, X_j)) + \ldots + V(f_{123\ldots n}(X_1, X_2, \ldots, X_n)) \tag{9}$$

Mean transmittance metamodel

Sensitivity analysis

Then we can define Sobol's indices (first and second orders here) :

$$S_i = \frac{V(f_i(X_i))}{V(Y)} = \frac{V(E[Y|X_i = x_i])}{V[Y]} \tag{10}$$

$$S_{ij} = \frac{V(f_ij(X_i, X_j))}{V(Y)} = \tag{11}$$

And also total Sobol indices :

$$S_i^{tot} = 1 - S_{\bar{i}} = 1 - \frac{V(E(Y|X_{\bar{i}}))}{E(Y)} \tag{12}$$

<u>OT Tools :</u> **ot.SobolIndicesExperiment**, **ot.SaltelliSensitivityAlgorithm**

Mean transmittance metamodel

Sensitivity analysis

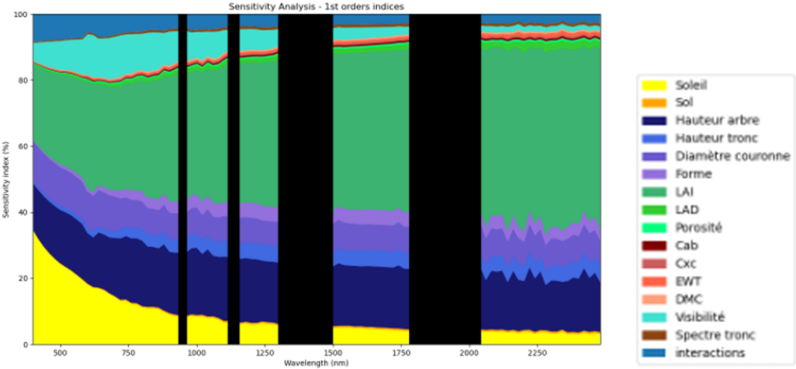


Figure – Sensitivity Analysis performed on previous metamodel using Sobol Indices

Mean transmittance metamodel

Sensitivity analysis

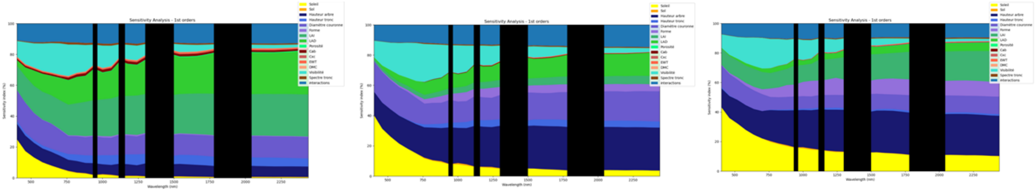


Figure – Sensitivity Analysis for different LAI ranges : $0.5 \leq LAI \leq 2$ (left), $2 \leq LAI \leq 3.5$ (center) and $3.5 \leq LAI \leq 8$ (right)

Karhunen-Loève decomposition 1D

We consider a second order stochastic process $X(t, \omega)$ and I a bounded subset of $\mathbb{R}^d$
Under some hypothesis, we can write a finite approximation of $X(t, \omega)$ in $L_2(\mathbb{R}, \Omega)$:

$$\forall t \in I, \quad X(t, \omega) = \sum_{\alpha \geq 1} \sqrt{\lambda_\alpha} \xi_\alpha(\omega) \phi_\alpha(t) \tag{13}$$

Where $(\lambda_\alpha)_{\alpha \geq 1}$ are the eigenvalues and $(\phi_\alpha)_{\alpha \geq 1}$ the eigenfunctions of the second kind Fredholm equation and :

$$\xi_\alpha(\omega) = \frac{1}{\sqrt{\lambda_\alpha}} \int_I X(t, \omega) \phi_\alpha(t) dt \tag{14}$$

It's then possible to truncate the decomposition to the most significant eigenvalues to get a finite decomposition ==> **Dimension reduction**

Karhunen-Loève decomposition 1D

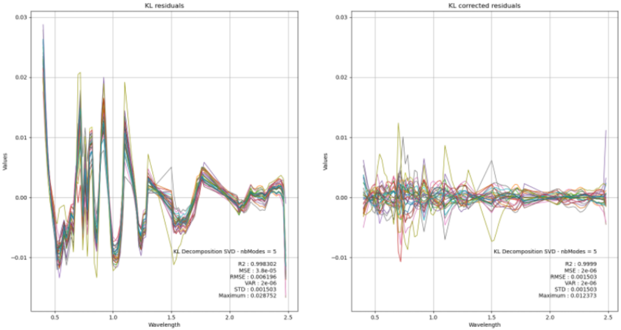


Figure – Karhunen-Loeve decomposition residuals with 5 modes, with only 50 test runs

RMSE : 0.001503
MaxError : 0.012373

OT Tools :
ot.KarhunenLoeveSVDAlgorithm
ot.KarhunenLoeveValidation

Karhunen-Loève decomposition 1D

Optimal number of modes

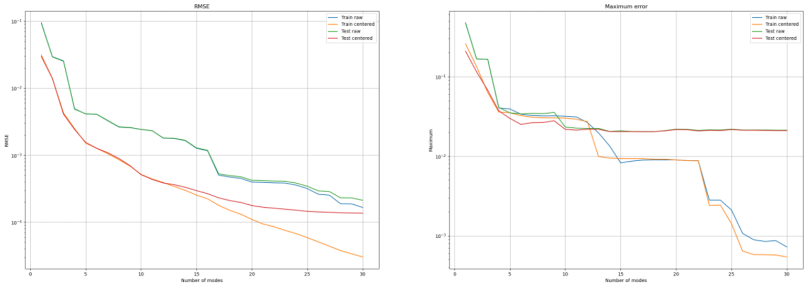


Figure – Benchmark results for KL decomposition from 1 up to 30 modes - Ntrain = 1500 - Ntest = 1500

Karhunen-Loève decomposition 1D

Optimal number of modes

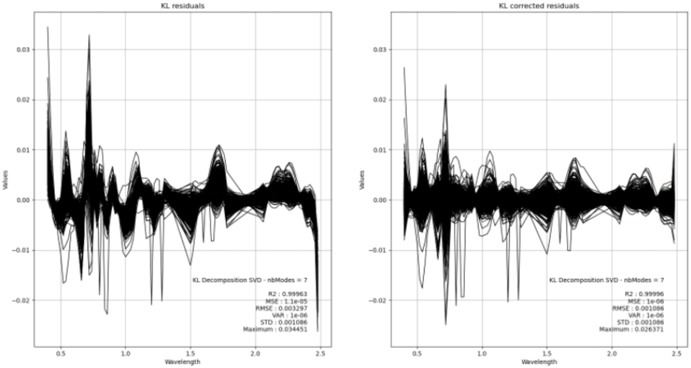


Figure – results for KL decomposition with 7 modes - Ntrain = 1500 - Ntest = 1500

Karhunen-Loève decomposition 2D

Meshing problem

Performing a 2D Karhunen-Loève decomposition for the spatial component is more tricky :

1. Different dimensions for different scenes ==> Different meshes
2. P1 Interpolation to get a common mesh
3. Flattening of the 2D scene

Karhunen-Loève decomposition 2D

First attempts

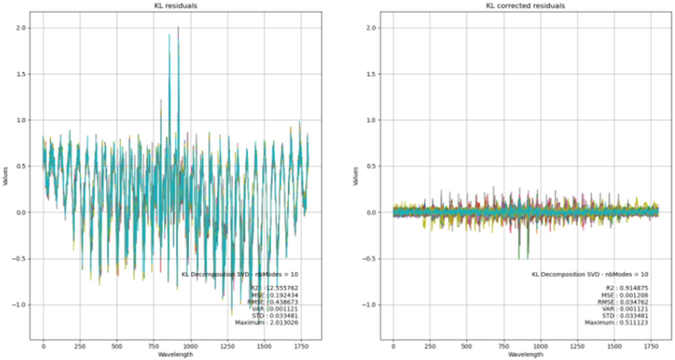


Figure – results for KL 2D decomposition with 10 modes - Ntrain = 1500 - Ntest = 1500

Karhunen-Loève decomposition 2D

First attempts

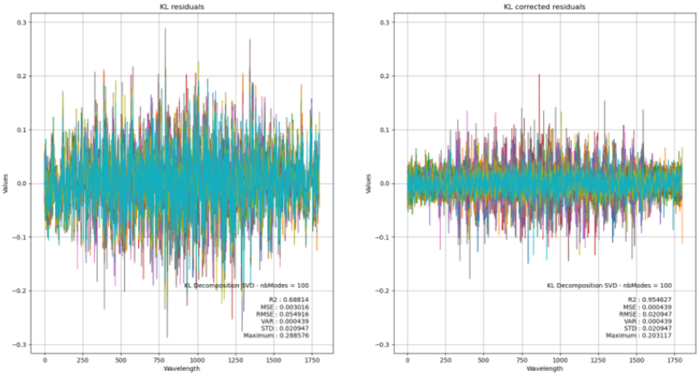


Figure – results for KL 2D decomposition with 100 modes - Ntrain = 1500 - Ntest = 1500

Conclusion and outlook

- First use of openTURNS, GP and Sobol indices for this application.
- First study fully conducted with openTURNS and no R at all.
- Promising first results

Now we have to :

- Perform 2D KL for different crown shapes (Warping depending on the form)
- Try to do a 3D KL decompostion, spectral+spatial
- Fix non influent variables and build a better metamodel (try also PCE)
- Find a way to take into account real trees, with complex shapes

Thanks for your attention !

Questions ?

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