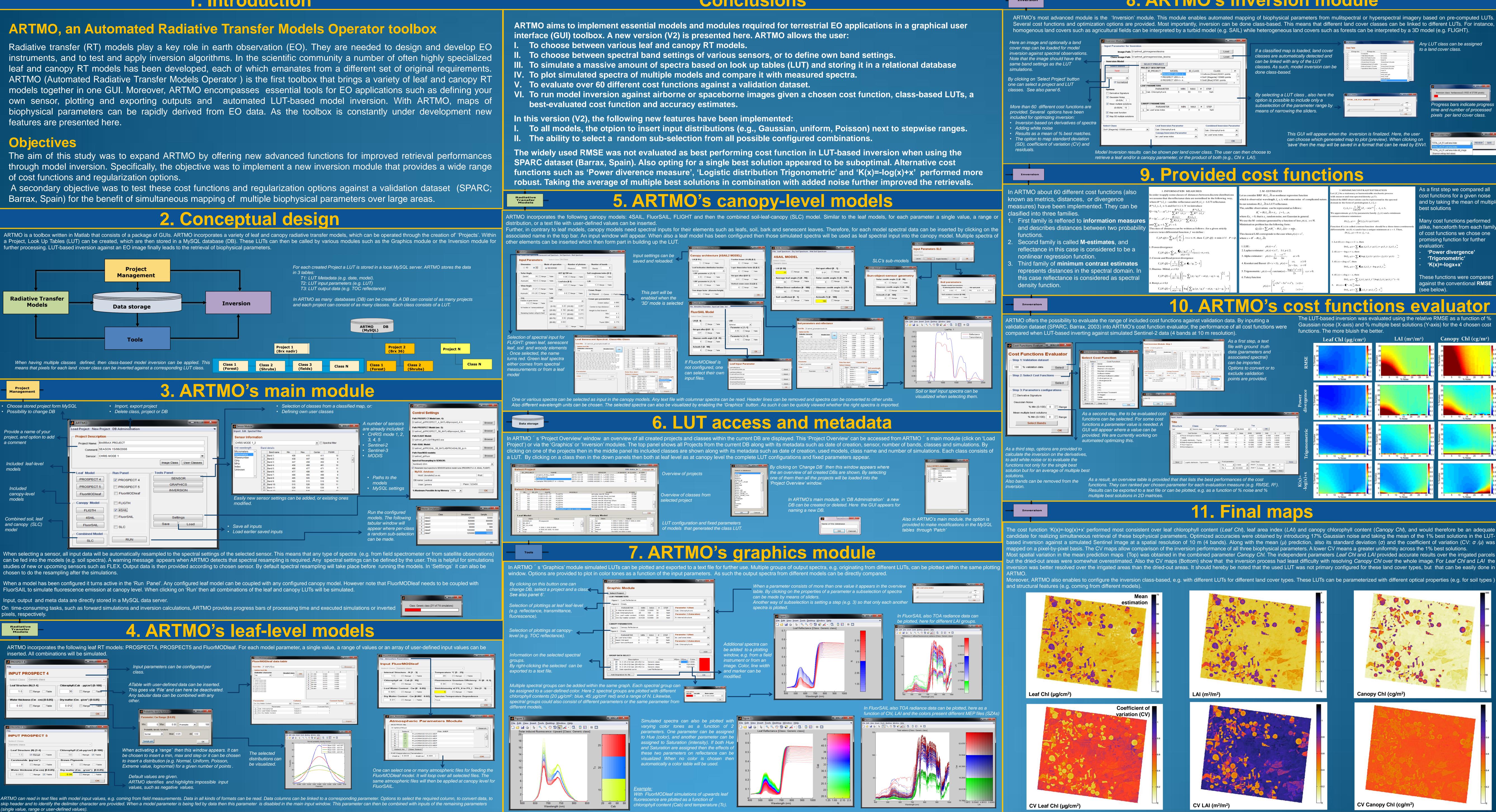


# Using the ARTMO toolbox for automated retrieval of biophysical parameters through radiative transfer model inversion: Optimizing LUT-based inversion J. Verrelst<sup>a</sup>, J.P. Rivera<sup>a</sup>, G. Leonenko<sup>b</sup>, L. Alonso<sup>a</sup> & J. Moreno<sup>a</sup>

### **1. Introduction**



PROSPECT 4     Input parameters can be configured per class     Input parameters can be configured per class.     Input parameters can be configured.     Input parameters can be combined with any other.     Input parameters can be combined with any other.	ODleaf data table         Image: Constraint of the second sec
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er thickness (Cw - cm) [0-0.05] Dry matter (Cm - g/cm <sup>2</sup> ) [0-0.05] Other.	Parameter         Column 3         •         1         Add           Parameter         Column 1         Convert Fact         1         Add           :: Chlorophyll ab         Column 1         1
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OK Probability density function Parameter: Cw Range: [0.0.05] Min: 0 Max: 0.05 # samples ● 100 Probability density functions Normal ● Mean 0.025 std 0.02	: Leaf Water Content Column 2 1
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Probability density functions	
Probability density functions	Import
UT PROSPECT 5	J Figures
	File Edit View Insert Iools Desktop Window Help 💽
Class	Normal probability density function
f Structure (N) [1-4]Chlorophyll (Cab µg/cm) [0-100] When activating a 'range' then this window appears. It can	
1.5 Range Table 50 Range Table be chosen to insert a min, max and step or it can be chosen The s	elected 40-
otenoids (ug/cm²) Brown Pigments to insert a distribution (e.g. Normal Uniform Poisson distrib	utions can
0       Range       Table       Extreme value, lognormal) for a given number of points .       be vis	ualized.
er thickness (Cw-cm) [0-0.05] _ Dry matter (Cm - g/cm²) [0-0.05]	20-
Default values are given.	
ARTMO identifies and highlights impossible input values, such as negative values.	10

<sup>a</sup>: Image Processing Laboratory (IPL), University of Valencia, Spain <sup>b</sup>: College of Science, Swansea University, Wales UK.

### Conclusions

### Inversion

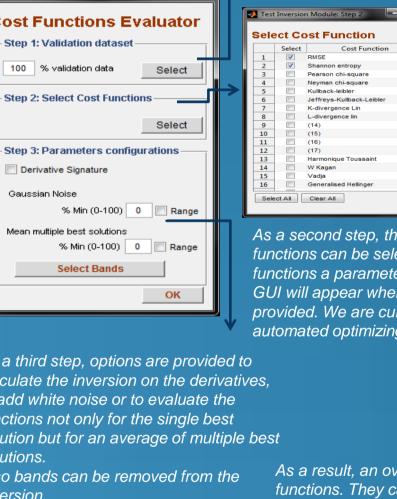
Note that the image should have the

lasses. See also panel 6.

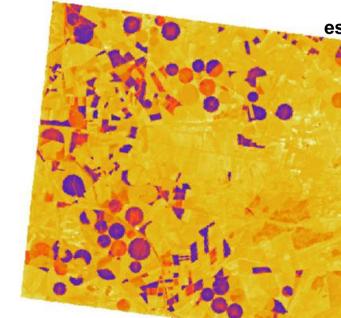
- cluded for optimizing inversion:
- Results as a mean of % best matches The option to map standard deviation
- (SD), coefficient of variation (CV residuals.

can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be interpreted by a turbid model (e.g. SAIL) while heterogeneous land covers such as forests can be in Here an image and optionally a land a classified map is loaded, land cove inversion against spectral observation sses are automatically detected and same band settings as the LUT classes. As such. model inversion o PROJECT DESCRIPTION simulations. done class-based. By clicking on 'Select Project' button one can select a project and LUT n is possible to include only a pselection of the parameter range b More than 60 different cost functions are MIN MAX # STEP neans of narrowing the sliders. rovided. Several options have been Inversion based on derivatives of spec Adding white noise 9. Provided cost functions Inversion As a first step we compared all n ARTMO about 60 different cost functions (also Subha ior a given noise nown as metrics, distances, or divergence bserved at wavelength  $\lambda_i \in \Lambda$  with some noise of complicated na the BRF observations can be represented in the spectra and by taking the mean of multiple  $\operatorname{R}^*(\lambda_i)$  - satellite reflectance and  $R_i(\lambda_i)$  - LUT reflectance otations  $R(\lambda_i, \overline{\vartheta})$  is LUT reflectance. in in the form of periodogram  $I_n(\lambda_k)$ neasures) have been implemented. They can be  $I_n(\lambda_k) = \frac{1}{2\pi n} \left| \sum_{j=1}^N (Z_j - m) e^{ij\lambda_k} \right|^2, \quad \lambda_k \in \Lambda.$ best solutions satellite observations can be represented as follows  $(\mathbf{q}_1^*,\ldots,\mathbf{q}_n^*) = \frac{R^*(\lambda_1)}{\sum R^*(\lambda_2)},\ldots,\frac{R^*(\lambda_N)}{\sum R^*(\lambda_N)}$  $R_{j}^{*} = R(\lambda_{j}, \overline{\mathcal{P}}) + \varepsilon_{j}, \quad j = 1, ..., n,$ clasified into three families. proximate  $g(\lambda)$  by parametric family  $f_{\theta}(\lambda)$  and a minimum  $\varepsilon E \varepsilon_i = 0$ , that is  $\varepsilon_i$  random noise, not Gaussian in general estimator minimizes  $(\mathbf{p}_1^{i},\ldots,\mathbf{p}_n^{i}) = \frac{K_i(\lambda_1)}{\sum R_i(\lambda_1)},\ldots,\frac{K_i(\lambda_N)}{\sum R_i(\lambda_N)}$ First family is reffered to information measures use the M - estimates generated by a function of loss  $\rho(x)$ ,  $x \in \Re$ . Many cost functions performed  $D(f_{\theta},g) = \int K\{f_{\theta}(\lambda)/g(\lambda)\}d\lambda.$ n problem has the following form: on K(x) is called contrast function should be a three times cont alike, henceforth from each fami and describes distances between two probability ass of distances can be written as follows : for a given strictly  $Q_n(\overline{\eta}) = \sum \rho(R_j^* - R(\lambda_j, \overline{\eta})) - > \min_n.$ tiable on  $(0, \infty)$  and it has a unique minimum at x = 1. The twice differential function f we define :  $D(f_{\theta},g) = 0 \Leftrightarrow f_{\theta} = g.$ of cost functions we chose one lassical LSE corresponds to the case when  $\rho(x) = x$ functions.  $\Gamma_{\rm f}[P,Q] = \sum_{i=1}^{n} q_i f\left(\frac{p_i^{\prime}}{q}\right), \ 1 \le i \le N, \ \text{then } \Gamma_{\rm f}[P,Q] \to \min i \ {\rm ff} \ P$ here  $x = R^* - R(\lambda_1, \overline{9})$ . romising function for further Second family is called **M-estimates**, and t  $K(x) = \log x + 1/x$ , then evaluation:  $D(f_{\theta},g) = \sum \left( \int g(f_{\theta}(\lambda_j) / g(\lambda_j) + g(\lambda_j) / f_{\theta}(\lambda_j) \right)^{-1}$  $\rho(x) = x^2$ . reflectance in this case is considered to be a Laplace estimater :  $\rho(x) = |x|^p$ ,  $1 \le p \le 2$  $\Gamma_{\rm f}[P,Q] = \sum_{l=1}^{n} p_l \frac{(p_l/q_l)^a - 1}{a(a+1)}, a \in (-\infty, +\infty).$  $(x) = -\log x + x$ , then 'Power divergence' Alpha estimator:  $\rho(x) = \frac{1}{2\alpha} - \frac{-e^{-\alpha x}}{2\alpha}, \qquad \alpha > 0.$ nonlinear regression function.  $D(f_{\theta}, g) = \sum \langle \langle \log(f_{\theta}(\lambda) / g(\lambda) + f_{\theta}(\lambda) / g(\lambda) \rangle \rangle$ sie and Read power divergence **Frigonometric** 4. Koenker and Basset (0 < c < 1),  $\rho(x) = \begin{cases} cx, & x \ge 0\\ (c-1)x, & x < 0 \end{cases}$  $x = (\log x)^2$ , then Third family of **minimum contrast estimates**  $\Gamma_{\rm f}[P,Q] = \left(\frac{1}{a+1}\right) \sum_{l=1}^n p_l \, \boldsymbol{\phi}_l \, / \, q_l \stackrel{\text{\tiny{T}}}{=} -1$ 'K(x)=-logx+x'  $D(f_{\theta},g) = \sum \mathbf{\Phi}g(f_{\theta}(\lambda_j) - \log g(\lambda_j))$ ma - Mittal,  $a \neq 0,1$ represents distances in the spectral domain. In Trigonometric:  $\rho(x) = \nu \left[ x \arctan(sx) - \frac{\log(s^2x^2 + 1)}{2} \right], \quad s, \nu > 0.$  $\Gamma_{t}[P,Q] = \left(\frac{1}{(b-1)}\right) \left[1 + \sum_{i=1}^{n} (p_{i}/q_{i})^{a} - a(p_{i}-q_{i}) - q_{i}\right]^{a-1} - 1$  $x = x \log x - x$ , then this case reflectance is considered as spectral lese functions were compared  $\mathbf{D}(\mathbf{f}_{\theta}, g) = \sum f_{\theta}(\lambda_j) g(\lambda_j)^{-1} \{ \log(f_{\theta}(\lambda_j) g(\lambda_j)^{-1}) - 1 \}$ against the conventional RMSE  $\frac{c}{c}(3x^2-3x^4+x^6), |x| \le c$ density function.  $K(x) = \left( \left( \frac{\alpha}{2} - 1 \right)^{2} \right)$  then  $\Gamma_{\rm f}[P,Q] = \left(\frac{1}{a(a-1)}\right) \log\left(\sum_{l=1}^{n} q_l(p_l/q_l)^a - a(p_l-q_l) - q_l\right) + 1$  $\mathbf{D}(\mathbf{f}_{\theta},g) = \sum_{i} \left[ f_{\theta}(\lambda_{i}) / g(\lambda_{i}) \right]^{2} - 1$ (see below). **10. ARTMO's cost functions evaluator** Inversion RTMO offers the possibility to evaluate the range of included cost functions against validation data. By inputting a Gaussian noise (X-axis) and % multiple best solutions (Y-axis) for the 4 chosen cost alidation dataset (SPARC, Barrax, 2003) into ARTMO's cost function evaluator, the performance of all cost functions were functions. The more bluish the better ompared when LUT-based inverting against simulated Sentinel-2 data (4 bands at 10 m resolution). Leaf Chl (µg/cm²)  $LAI (m^2/m^2)$  Canopy Chl (cg/m<sup>2</sup>) s a first step, a text tions Evaluat... le with ground truth Module: Step 2 ata (parameters and ost Functions Evaluato sociated spectral) Step 1: Validation dataset – an be imported. 00 % validation data Selec ptions to convert or to xclude validation Step 2: Select Cost Functions oints are provided Step 3: Parameters configurations (14) — 🗆 🗪 Derivative Signature Generalised Hellinger ∋aussian Noise % Min (0-100) lean multiple best solution s a second step, the to be evaluated % Min (0-100) 0 Select Bands tions a parameter value is needed. A ▼ RELRMSE ▼ I will appear where a value can be 
 Cost function
 Param. a
 Param. b
 # samples
 % LUT
 Noise
 RMSE
 %RMSE
 MAE
 R

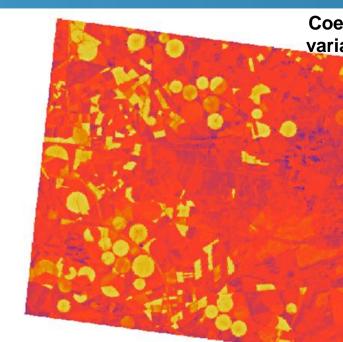
 tower divergence measure
 20
 0
 1000
 1
 15
 8.4323
 0.1986
 6.7985
 0.864
 ded. We are currently working on tomated optimizing this. ogistic distribution - Trgono... 20.1000 40. leta-Divergence (Itakura-Sai... 0 49 K(x)=x(log(x))-x 0 0 30000 30 9 14.5275 0.2911 12.3383 a third step, options are provided to culate the inversion on the derivatives 10 15 20 25 % Noise 5 10 15 20 25 o add white noise or to evaluate the a v 0.0000 v Axis X % Samples v min 0 Axis X % Samples v min 0 Axis Y % Noise v 11 Settings Draw nctions not only for the single best lution but for an average of multiple besi As a result, an overview table is provided that that lists the best performances of the cost Iso bands can be removed from the unctions. They can ranked per chosen parameter for each evaluation measure (e.g. RMSE, R<sup>2</sup>). Results can be exported to a text file or can be plotted, e.g. as a function of % noise and % *multiple best solutions in 2D matrices.* 11. Final maps Inversion



ARTMO. and structural features (e.g. coming from different models).



Leaf Chl (µg/cm<sup>2</sup>)



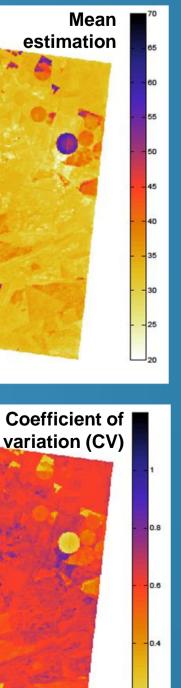
CV Leaf Chl (µg/cm<sup>2</sup>)

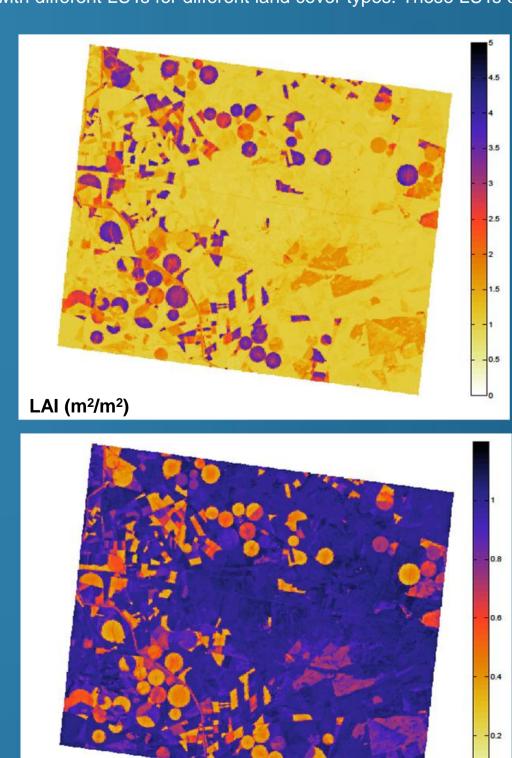


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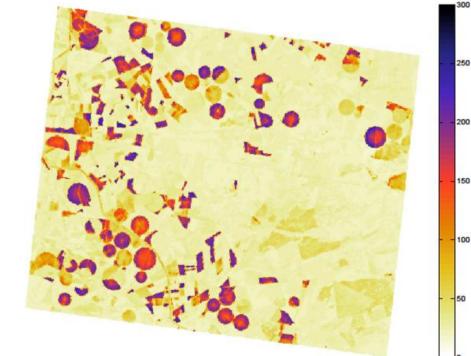
## **8. ARTMO's inversion module**

ne cost function 'K(x)=-log(x)+x' performed most consistent over leaf chlorophyll content (Leaf Chl), leaf area index (LAI) and canopy chlorophyll content (Canopy Chl), and would therefore be an adequate andidate for realizing simultaneous retrieval of these biophysical parameters. Optimized accuracies were obtained by introducing 17% Gaussian noise and taking the mean of the 1% best solutions in the LUTsed inversion against a simulated Sentinel image at a spatial resolution of 10 m (4 bands). Along with the mean ( $\mu$ ) prediction, also its standard deviation ( $\sigma$ ) and the coefficient of variation (CV:  $\sigma / \mu$ ) was napped on a pixel-by-pixel basis. The CV maps allow comparison of the inversion performance of all three biophysical parameters. A lower CV means a greater uniformity across the 1% best solutions. Most spatial variation in the mean prediction maps (Top) was obtained in the combined parameter Canopy Chl. The independent parameters Leaf Chl and LAI provided accurate results over the irrigated parcels but the dried-out areas were somewhat overestimated. Also the CV maps (Bottom) show that the inversion process had least difficulty with resolving Canopy ChI over the whole image. For Leaf ChI and LAI the Moreover, ARTMO also enables to configure the inversion class-based, e.g. with different LUTs for different land cover types. These LUTs can be parameterized with different optical properties (e.g. for soil types)

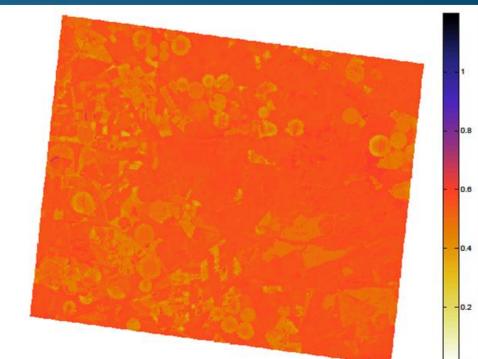




CV LAI (m<sup>2</sup>/m<sup>2</sup>)



Canopy Chl (cg/m<sup>2</sup>)



CV Canopy Chl (cg/m<sup>2</sup>)