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Information retrieval by explicit inversion

Michel M. Verstraete
Frascati, 1 August 2006

Outline

1. How good are BRF models?
2. Principles of model inversion in a remote sensing context
3. Look-Up Tables (LUT) approach
4. Applications
5. Exploiting RPV

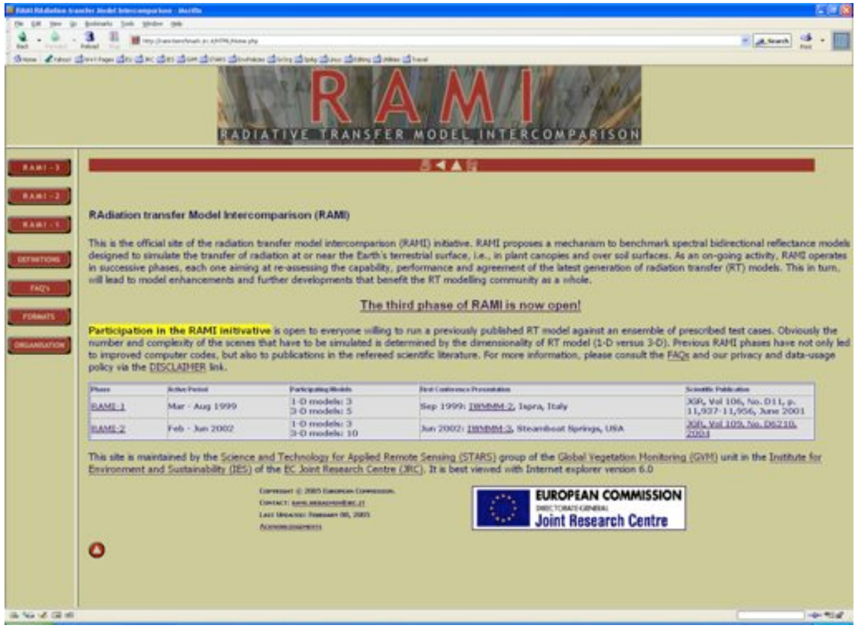
Radiative Transfer Model Intercomparison

- Phase 1: March to August 1999
- Reference: Pinty et al. (2001) 'Radiation Transfer Model Intercomparison (RAMI) Exercise', *Journal of Geophysical Research*, **106**, 11,937-11,956.

- Phase 2: February to June 2002
- Reference: Pinty et al. (2004) 'RAdiation transfer Model Intercomparison (RAMI) exercise: Results from the second phase', *Journal of Geophysical Research*, **109**, D06210 10.1029/2003JD004252.

- Phase 3: Mars to December 2005 (paper submitted)

- Home, protocols and results: http://rami-benchmark.jrc.it/



Motivations for RT model evaluation

- Radiation Transfer (RT) models constitute an essential component for the quantitative interpretation of remote sensing data
- The accuracy and reliability of the solutions to the inverse problems are determined by the performance of both the RT models and the remote sensing instruments
- The increase in data accuracy and BRF sampling of current RS instruments will be better exploited if the uncertainties of the RT models are decreased
- The establishment of a consensus on standards among the surface BRF community should form the basis for its credibility with respect to other scientific communities as well as decision and policy makers

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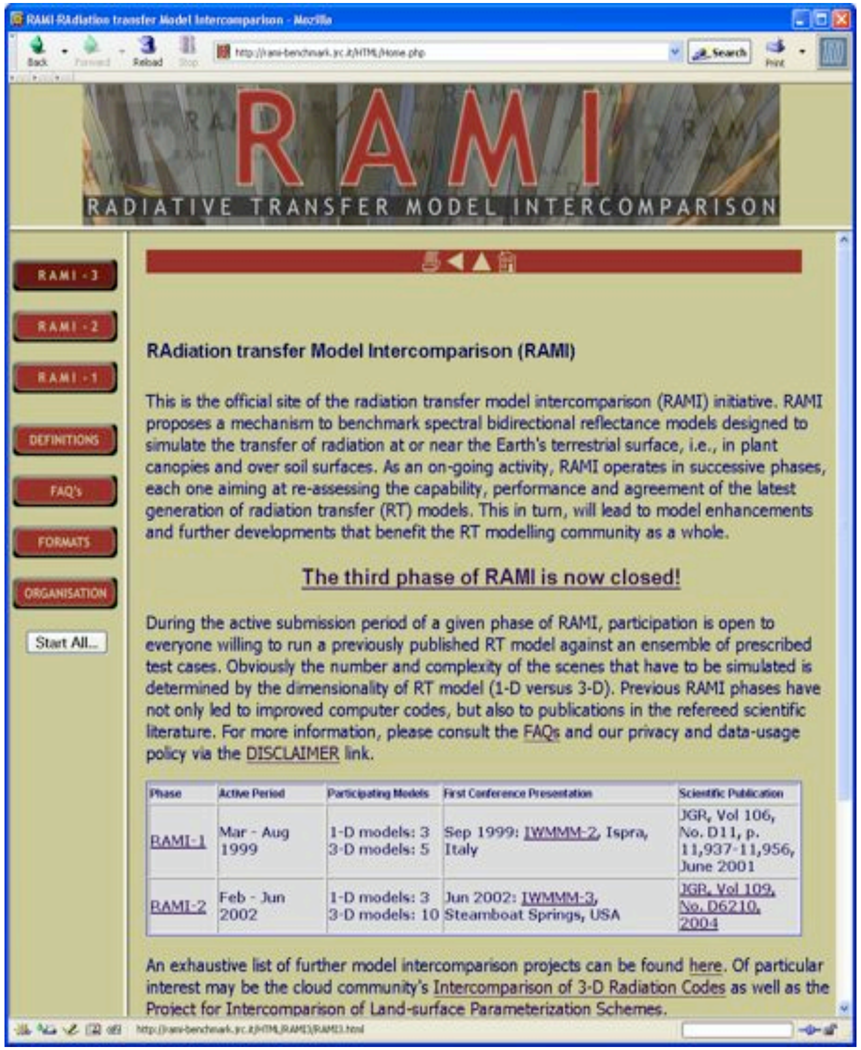
RAMI benchmarking

Purpose:

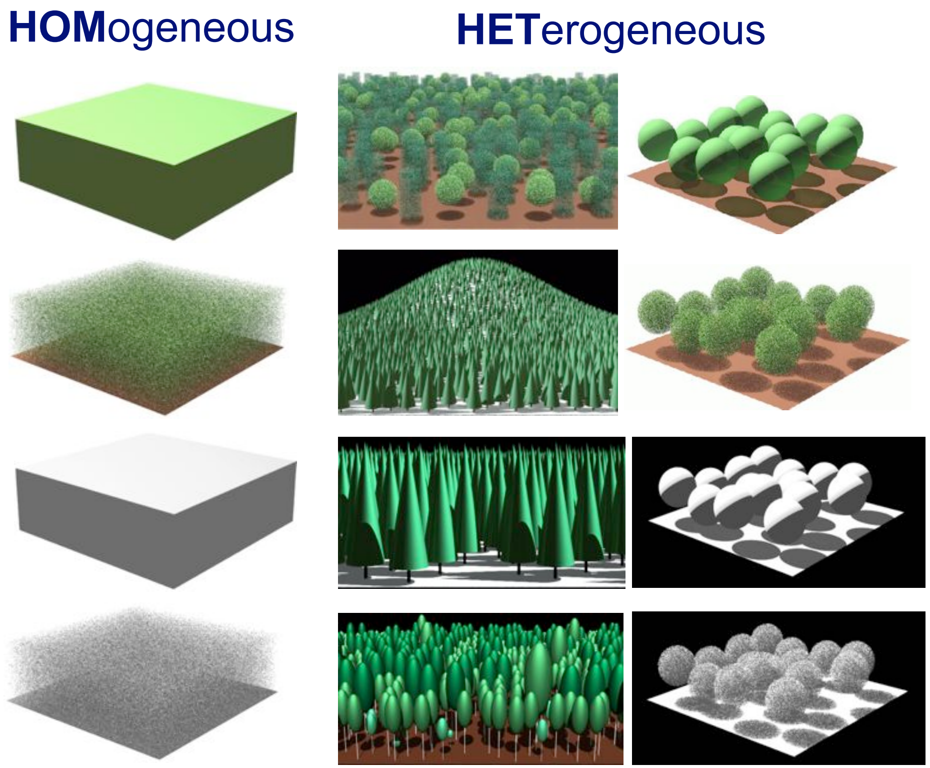
- act as **common platform** for intercomparison
- document **discrepancies** between or **uncertainties and errors** within models
- establish a model intercomparison **protocol**
- foster scientific **debate**

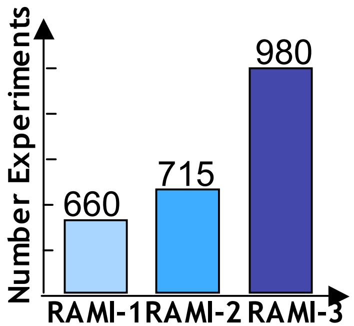


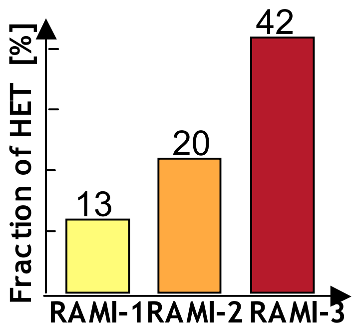
Ref: http://rami-benchmark.jrc.it/.

RAMI evolution

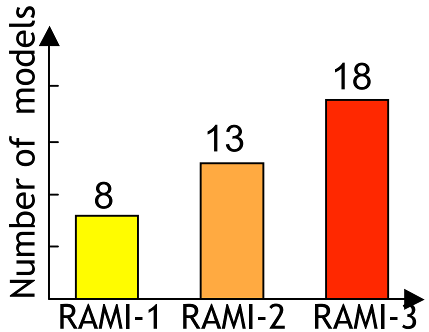
- **RAMI-1** (1999):
  - § Turbid medium and discrete
  - § Solar domain + purist corner
- **RAMI-2** (2002):
  - § Topography + true "zoom-in"
- **RAMI-3** (2005):
  - § Birch and conifer scene (GO models)
  - § Heterogeneous purist corner
  - § Local transmission and horizontal flux measurements

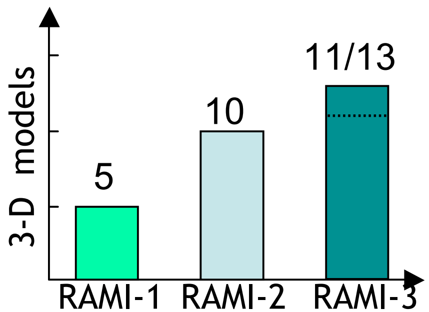






3-D models
1-D models
new in RAMI-3





MODEL NAME	PARTICIPANT	AFFILIATION
ACRM	A. Kuusk	Tartu Observatory,Estonia
DART	J.P. Gastellu, E.Martin	CESBIO, France
drat	M. Disney, P. Lewis	UCL, UK
FLIGHT	P. North	Univ. Swansea, UK
frat	P. Lewis, M. Disney	UCL, UK
FRT	M. Möttus, A. Kuusk	Tartu Observatory,Estonia
Hyemalis	R. Ruiloba	NOVELTIS, France
MAC	R. Fernandes	CCRS, Canada
mbrf	W. Qin	NASA GFSC, USA
RGM	D. Xie, W. Qin	Beijing N. Univ., China
Rayspread	T. Lavergne	JRC, Italy
raytran	T. Lavergne	JRC,Italy
SAIL++	W. Verhoef	NLR, Netherlands
½ discret	N. Gobron	JRC, Italy
Sprint3	R. Thompson	Cox, USA
4SAIL2	W. Verhoef	NLR, Netherlands
5scale	N. Rochdie, R. Fernandes	CCRS, Canada
2stream	B. Pinty, T. Lavergne	JRC, Italy

Measurement types

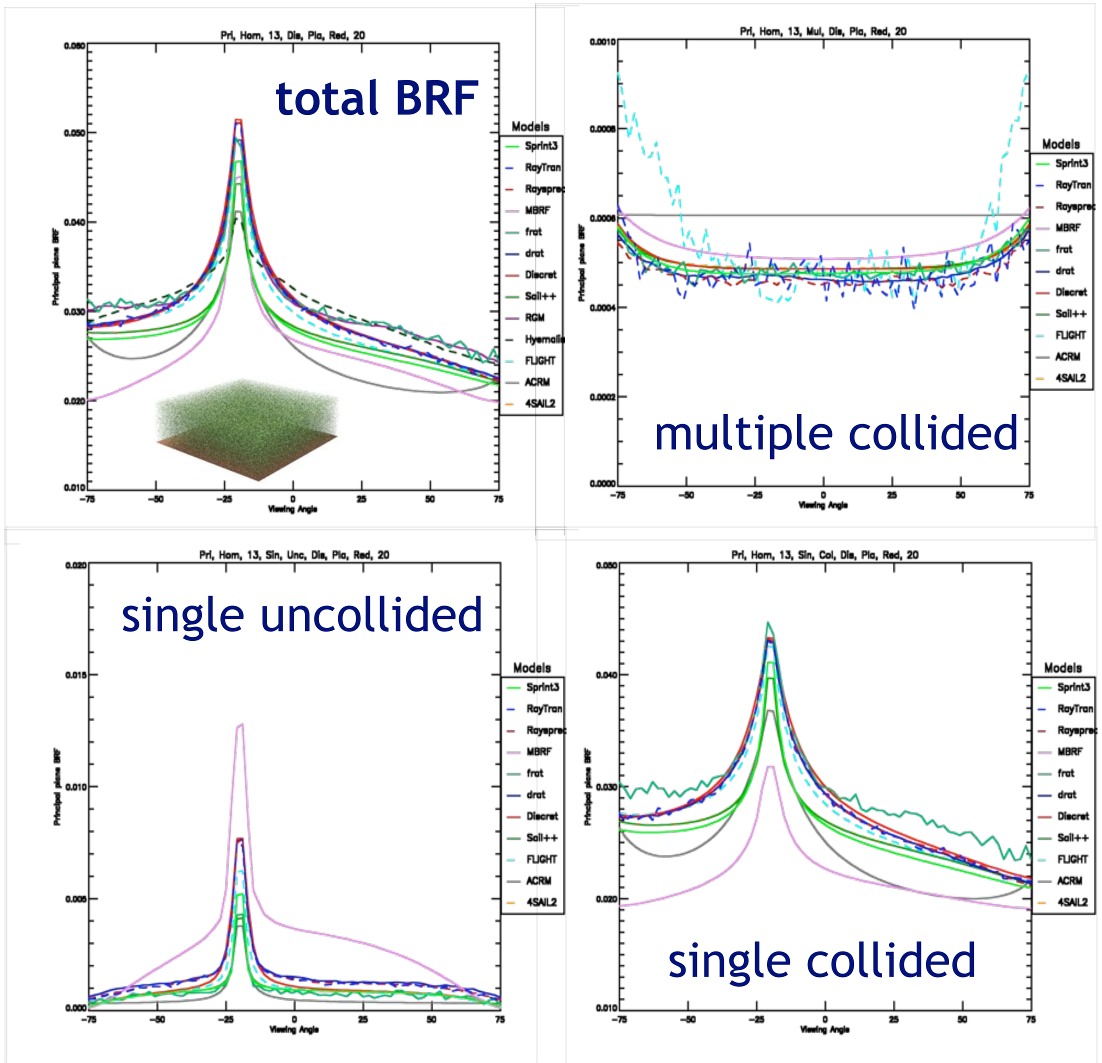
Measurements include

Flux **quantities:**

- Albedo
- Transmission
- Absorption

BRF quantities:

- Total BRF (PP+OP)
- BRF components
  - -multiple collided
  - -single uncollided (hit soil only once)
  - -single collided (hit leaves only once)



RT model intercomparison caveats

- In general, there is **no absolute 'truth' available!** Model results cannot be evaluated against some reference standard.

- Laboratory data are difficult to use as reference standard due to incomplete knowledge of the exact illumination, measurement, as well as (structural and spectral) target properties.

but

- Model results can be compared ***against each other*** to document their relative differences.

- Model results can be compared over ***ensembles*** of test scenarios to establish trends/behaviours in their performance.

- Careful inspection/verification of an ensemble of model results may lead to the establishment of the "***most credible solutions***" as a surrogate for the "truth".

Relative intercomparison (1)

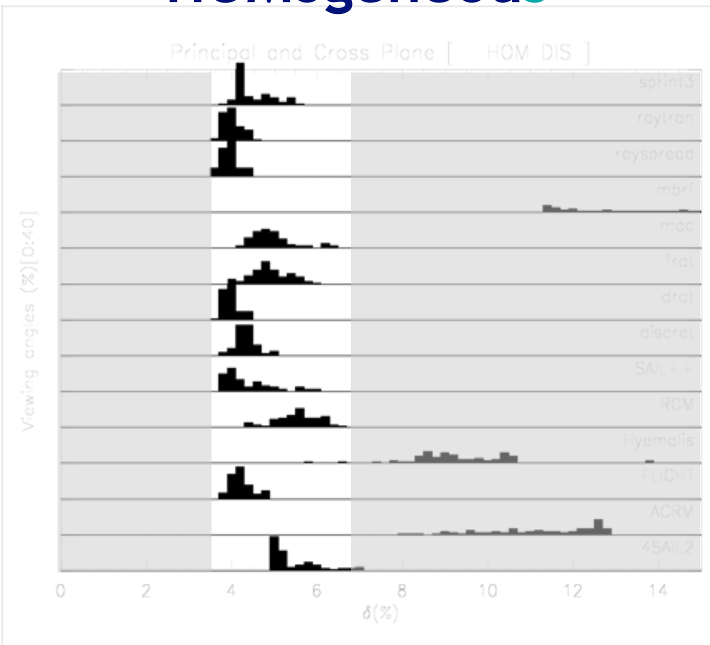
Model to ensemble differences:

$$\delta\left(\theta_v,\theta_0,\lambda,\zeta\right)_{c\leftrightarrow\langle m\rangle} = \frac{200}{N_{\text{models}}} \sum_{m=1;m\neq c}^{N_{\text{models}}} \frac{\left|\rho_c\left(\theta_v,\theta_i,\lambda,\zeta\right)-\rho_m\left(\theta_v,\theta_i,\lambda,\zeta\right)\right|}{\left|\rho_c\left(\theta_v,\theta_i,\lambda,\zeta\right)+\rho_m\left(\theta_v,\theta_i,\lambda,\zeta\right)\right|}\ [\%]$$

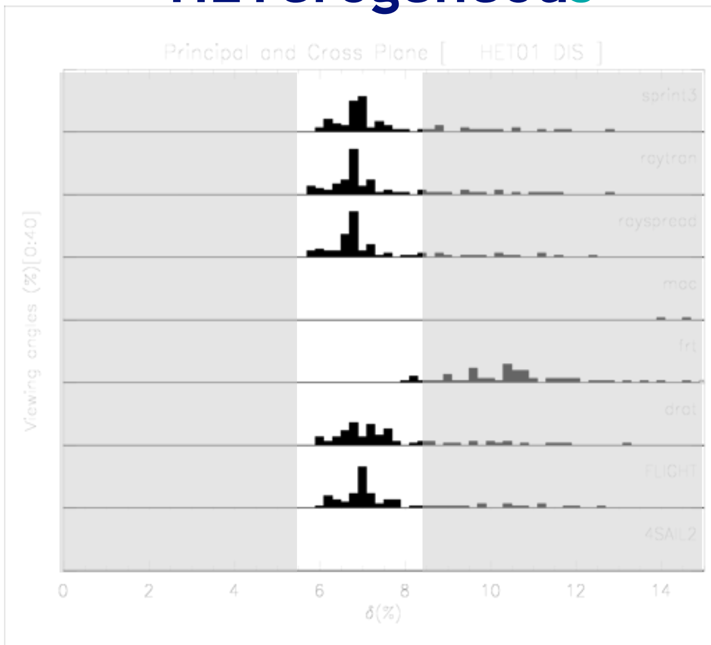
Repeat for all available viewing, illumination, spectral, and structure conditions.

→ Make histogram of $\delta\left(\theta_v,\theta_0,\lambda,\zeta\right)_{c\leftrightarrow\langle m\rangle}$ values

HOMogeneous



HETerogeneous



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Relative intercomparison (2)

Model to ensemble differences:

$$\delta\left(\theta_v,\theta_0,\lambda,\zeta\right)_{c\leftrightarrow\langle m\rangle} = \frac{200}{N_{\text{models}}} \sum_{m=1;m\neq c}^{N_{\text{models}}} \frac{\left|\rho_c\left(\theta_v,\theta_i,\lambda,\zeta\right)-\rho_m\left(\theta_v,\theta_i,\lambda,\zeta\right)\right|}{\left|\rho_c\left(\theta_v,\theta_i,\lambda,\zeta\right)+\rho_m\left(\theta_v,\theta_i,\lambda,\zeta\right)\right|}\ [\%]$$

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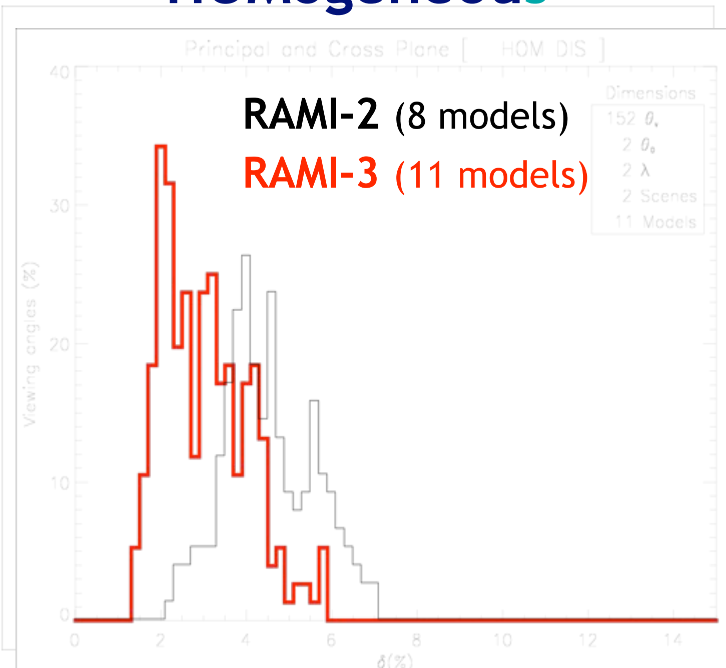

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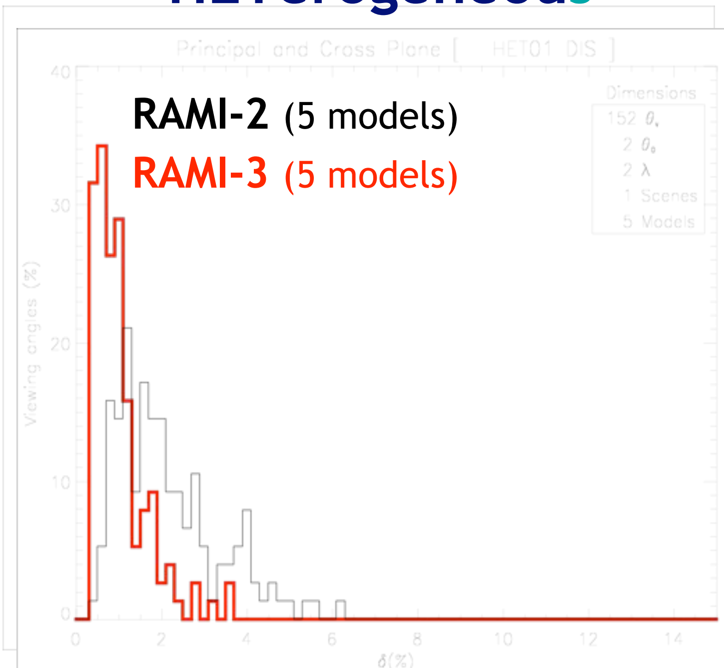

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Relative intercomparison (3)

Use χ^2 metric to identify how close RT models are to a credible BRF solution:

$$\chi^2(\lambda) = \frac{1}{N-1} \sum_{i=1}^{N_{\theta_0}} \sum_{s=1}^{N_{scenes}} \sum_{j=1}^{N_{\theta_v}} \frac{\left[\rho(i,s,j;\lambda) - \rho_{credible}(i,s,j;\lambda)\right]^2}{\sigma^2(i;\lambda)}$$

Credible BRF solution is derived from 3D Monte Carlo models:

$$\rho_{credible}(i,s,j;\lambda) = \langle \rho_{3D}(i,s,j;\lambda) \rangle$$

Simulation error is fraction *f* of credible BRF solution:

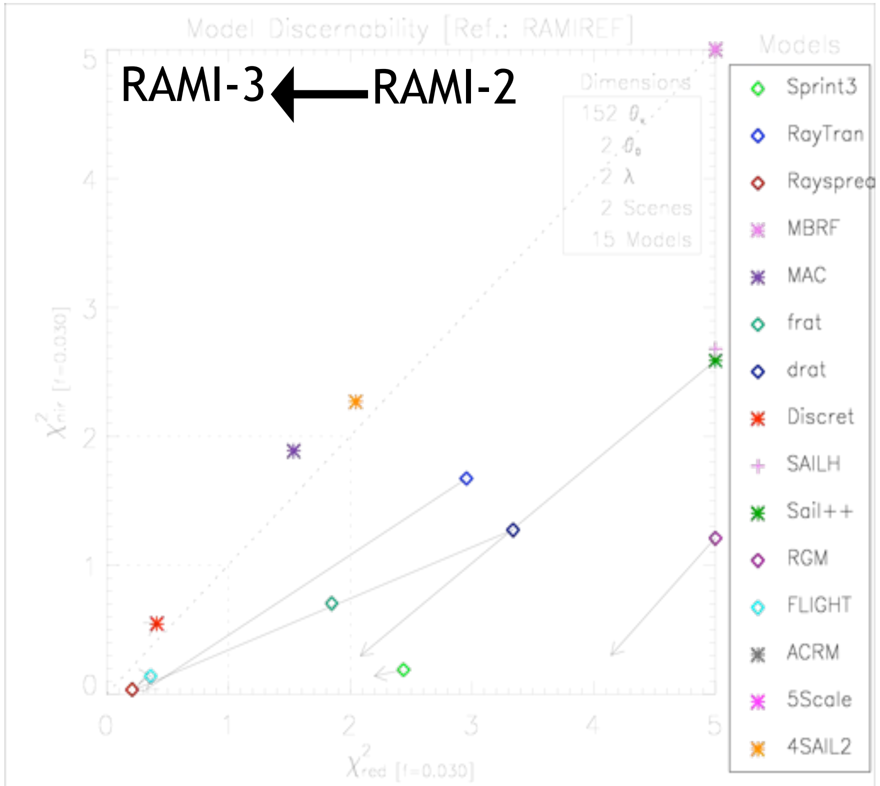
$$\sigma(i,\lambda) = f \langle \rho_{3D}(i,s,j;\lambda) \rangle$$

Models with $X^2 \leq 1$ are indiscernible from the $\rho_{credible}$ to within *f*

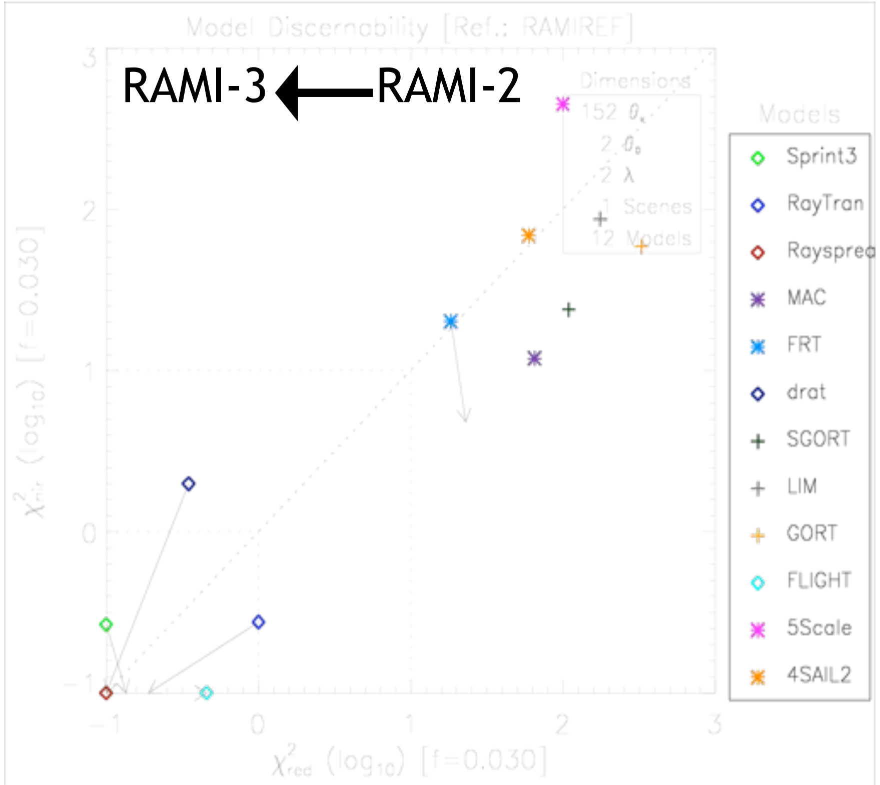
Relative intercomparison (4)

Discrete

Homogeneous



Heterogeneous



X^2 uses σ=0.03<BRF>$_{3D}$

Model performance improved from RAMI-2 to RAMI-3!

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Measurement interpretation

- A model representing a measurement expresses the dependency of this measurement with respect to the relevant variables:

$$z = f(s_1, s_2, \ldots, s_M)$$

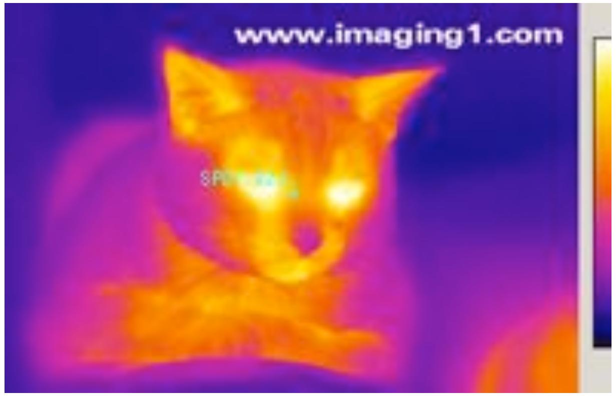
- where s_m are the state variables of the system (here: target, environment, source of radiation, sensor)
- In principle, if the model is correct and if the values of all state variables s_m are known, such a model can accurately simulate the observation (direct problem)
- In practice, a quantity z^* is measured, and one seeks information on the state variables s_m (inverse problem)
- If a single state variable accounts for the physics of the measurement, the problem can be solved accurately (analytically or numerically):

$$z = f(s) \Rightarrow z^* = f(s^*) + \varepsilon \Rightarrow s^* = f^{-1}(z^*; \varepsilon)$$

- where s^* is the estimate of the state variable retrieved from the measurement z^*, and ϵ stands for the error of measurement.
- In general, more than one state variable is required to describe the physics of the problem. The solution of the inverse problem then requires multiple equations and therefore multiple measurements.

Example: Thermal IR

- As a simple initial example, consider the following thermal image, where each pixel corresponds to a measurement of the emission intensity in the infrared spectral domain:



The measured intensity *I* (in W m^{-2}) can be estimated with the formula:

$$I = \sigma T^4$$

where σ stands for the Stefan-Boltzmann constant and *T* (in K) is the temperature of the target (the only state variable in this case).

- To the extent the assumed model (*f*) is correct, the temperature of the target can be estimated as follows:

$$T = (I / \sigma)^{1/4}$$

- However, if the target is not a perfect blackbody, it will emit with a spectrally-variable emissivity ϵ and the model (*f*) becomes:

$$I = \varepsilon \sigma T^4$$

- Because the system now has two state variables (ϵ and *T*), there is an infinite number of couples of values (solutions) that could satisfactorily 'explain' the measured intensity *I*.

Problem terminology

- A problem is said to be well-posed if it meets the following criteria, set by Hadamard (1902):
  - § For each set of data, there exists a solution
  - § The solution is unique
  - § The solution depends continuously on the data

- Inverse problems are usually ill-posed, because they tend to allow multiple solutions.

- In addition, a problem is well-conditioned if small variations in the input data induce small variations in the output. This is often estimated with the condition number of the problem, defined as the maximum value of the ratio of the relative errors in the solution to the relative error in the data, over the problem domain.

- Inverse problems may also be ill-conditioned if solutions are very sensitive to or change abruptly with small changes in the input data.

Ref: J. Hadamard. Sur les problèmes aux dérivées partielles et leur signification physique. Bull. Univ. of Princeton, p. 49-52, 1902.

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Inversion caveats

Gathering multiple measurements is useless if

- additional measurements involve new state variables and therefore new models:

$$z_1^* = f_1(s_1^1, s_2^1, \ldots, s_M^1) + \varepsilon_1$$
$$z_2^* = f_2(s_1^2, s_2^2, \ldots, s_M^2) + \varepsilon_2$$
$$\vdots$$
$$z_K^* = f_K(s_1^K, s_2^K, \ldots, s_M^K) + \varepsilon_K$$

- the target system changes between successive observations (different values of the state variables):

$$z_1^* = f(s_1^1, s_2^1, \ldots, s_M^1) + \varepsilon_1$$
$$z_2^* = f(s_1^2, s_2^2, \ldots, s_M^2) + \varepsilon_2$$
$$\vdots$$
$$z_K^* = f(s_1^K, s_2^K, \ldots, s_M^K) + \varepsilon_K$$

- or if identical measurements are simply repeated:

$$z_1^* = f(s_1, s_2, \ldots, s_M) + \varepsilon_1$$
$$z_2^* = f(s_1, s_2, \ldots, s_M) + \varepsilon_2$$
$$\vdots$$
$$z_K^* = f(s_1, s_2, \ldots, s_M) + \varepsilon_K$$

Role of independent variables

- To acquire more information on an invariant system, it is necessary to gather different measurements by changing one (or more) variable other than the state variables. The measurement model then becomes:

$$z = f(x_1, x_2, \cdots, x_N; s_1, s_2, \cdots, s_M)$$

where the independent variables x_i describe the changing conditions of observations. Their values are known at the time of the measurement.

- If the system of interest can be observed in more than one way, multiple independent variables may be defined.
- In the case of remote sensing, space and time naturally refer to different targets, while wavelength, the geometry of illumination and observation, and the polarization of the radiation are useful independent variables.
- Multiple measurements may thus be acquired under different conditions of observation:

$$z_1^* = f(x_1^1, x_2^1, \cdots, x_N^1; s_1, s_2, \cdots, s_M) + \varepsilon_1$$
$$z_2^* = f(x_1^2, x_2^2, \cdots, x_N^2; s_1, s_2, \cdots, s_M) + \varepsilon_2$$
$$\cdots$$
$$z_K^* = f(x_1^K, x_2^K, \cdots, x_N^K; s_1, s_2, \cdots, s_M) + \varepsilon_K$$

Model inversion (1)

- In general, a system of *K* equations with *M* state variables cannot be solved analytically or numerically to retrieve a unique exact solution.
- To derive reliable and accurate information on the properties of a target from remote observations,
  - if $K<M$, the system is under-determined.
  - if $K=M$, measurement errors may prevent the identification of the exact solution.
  - if $K>M$, the system is over-determined.
- Instead of looking for the correct solution, (i.e., the values of the state variables s_m which do verify this system of equations), we try to find an optimal solution, which best accounts for the observed variability in the measurements, despite the noise, model limitations and incomplete sampling.
- A quality criterion is thus needed. For instance, we will try to minimize an expression such as

$$\delta^2 = \sum_{k=1}^{K} \left[z_k^* - f(x_1, x_2, \ldots, x_N; s_1, s_2, \ldots, s_M) \right]^2$$

Model inversion (2)

- Practical (conceptual) procedure:
  1. select arbitrary initial guess values of the state variables s_m,
  2. use the known values of the independent variables x_n,
  3. simulate the measurements in direct mode: $z=f(x_n,s_m)$,
  4. compute the corresponding figure of merit function δ^2. If δ^2 is low enough, stop and consider the current values of s_m as the best estimates of the state variables. Otherwise, modify the values of s_m in some rational way and iterate from 2.
- When is δ^2 small enough?
  - § If $\delta^2 >> \epsilon^2$, a significant fraction of the variance in the measured data cannot be accounted for by the model,
  - § If $\delta^2 << \epsilon^2$, the model may be trying to interpret measurement noise.
- How are the next values of s_m selected?
- Alternative approaches:
  - § Quasi-Newton, genetic algorithms
  - § Adjoint models, Kalman filters, assimilation methods
  - § Look Up Tables (LUT)

Notes on inversion procedures

- The essence of an inversion procedure conceptually reduces to a minimization problem
- The performance of an inversion algorithm is directly linked to the way the model parameter space is searched to locate the optimal solution
- Quasi-Newton methods, Adjoint models, Genetic Algorithms and other procedures are particular tools to implement this search; they compete on accuracy, speed, algorithmic complexity (derivatives or model values only), and reliability
- The complexity of the model, the efficiency of the inversion procedure, and the speed of computation critically control the applicability of a model/inversion procedure in an operational context
- The interpretation of a data set by inversion requires a model describing how measurements depend on the selected independent variable(s), and the inversion process generates a new data set that is independent of the independent variable(s) used in the process

Inversion caveats (1)

- Most inversion problems accept multiple solutions: solution space, probable solutions, most representative solution
- Probable solutions may depend on the initial guess, choice of δ^2 function and computational accuracy
- More (larger K) and better measurements (lower ϵ) tend to reduce the set of probable solutions (constraints)
- More complex models (larger M) expand the solution space and may increase the set of probable solutions
- Solutions for which $\delta^2 < \epsilon^2$ are indistinguishable on the basis of available empirical evidence: multiple solutions may be equally acceptable
- Iterative algorithms may be expensive operationally

Inversion caveats (2)

- Results may be sensitive to initial guess values of s_m (local minima)
  - Repeat the inversion starting from other initial conditions (e.g., Genetic Algorithms)
- Results may be sensitive to numerical accuracy
  - Use double or quadruple precision (on the computer)
- Results may be sensitive to the exit criterion (number of iterations, lack of further progress, error or exception condition detection)
  - Test different criteria
- Models with more state variables better 'fit' the data but generate more possible solutions
  - Limit the number of state variables to be estimated simultaneously
- Repeated model value and model derivative computations in real-time may lead to very large computing requirements
  - Investigate alternative approaches and trade-offs

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Look Up Table (LUT) approach (1)

- An alternative to the dynamic iterative search for an optimized solution is
  - to pre-compute once and for all the set of all possible measurements associated with all conceivable target systems of interest and conditions of observation: {x} and {s} → database (LUT) of simulated z
  - to solve the inverse problem by searching for the best match between the string of measurements and the entries of such a LUT for identical values of the independent variables: {x} and actual z^* → most likely {s}

- The LUT pre-defines (and therefore limits a priori) the solutions which can be found, but it guarantees that at least one solution will always be found

- The LUT approach always yields a ranked set of possible solutions, and makes their non-uniqueness explicit

- One advantage is to allow a significant fraction of all computations to be made in advance, but the decrease in real-time floating point calculations is traded-off against increased memory requirements of the LUT

Look Up Table (LUT) approach (2)

- The discretization of the LUT with respect to independent and dependent variables is crucial:
  - simulating conditions that never occur imposes useless computing beforehand and unnecessary searches during the inversion process.
  - too high a discretization may lead to the frequent identification of multiple solutions.
  - the level of discretization may be expanded or reduced to provide better accuracy where needed or to avoid almost equivalent solutions.

- More realistic or complex algorithms (in particular coupled models) may be used to generate the LUT than with more traditional approaches.

- The failure to match a set of measurements with any entry in the LUT may indicate that the observed system does not correspond to any of the ones assumed during the creation of the LUT, and may serve to discriminate undesirable situations (e.g., the presence of clouds in the case of a retrieval of surface properties). Alternatively, additional geophysical situations can be included in the LUT.

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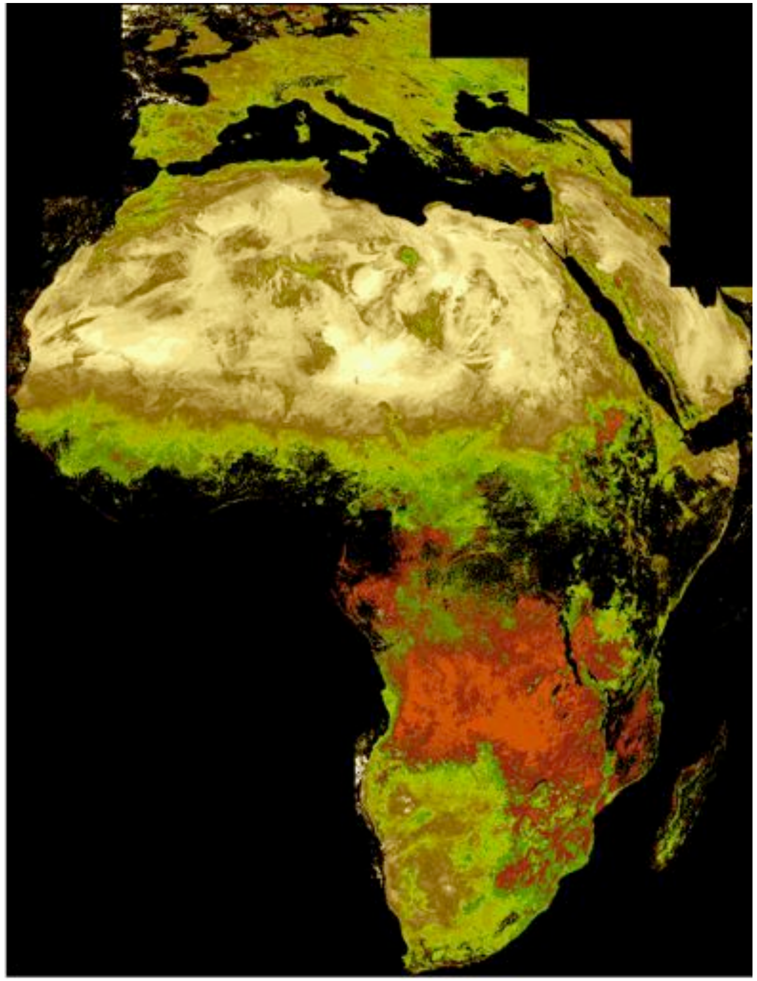
Example 1: Estimating surface albedo

- Application to Meteosat:
  - simulate the ToA BRF that should be measured by this sensor for a large variety of soil, vegetation and atmospheric conditions, as well as for typical geometries of illuminations and observation during the day
  - for each actual measurement string and associated independent variables, search the LUT (database) for the closest match
  - assign the geophysical properties of that simulation to the corresponding location



Meteosat-5, 1-20 June 1996 composite, θ_s=30°

Ref: Pinty, B., F. Roveda, M. M. Verstraete, N. Gobron, Y. Govaerts, J. V. Martonchik, D. Diner and R. Kahn (2000) 'Surface Albedo Retrieval from METEOSAT. Part 1: Theory and Part 2: Application', *Journal of Geophysical Research*, **105**, 18,099-18,134.

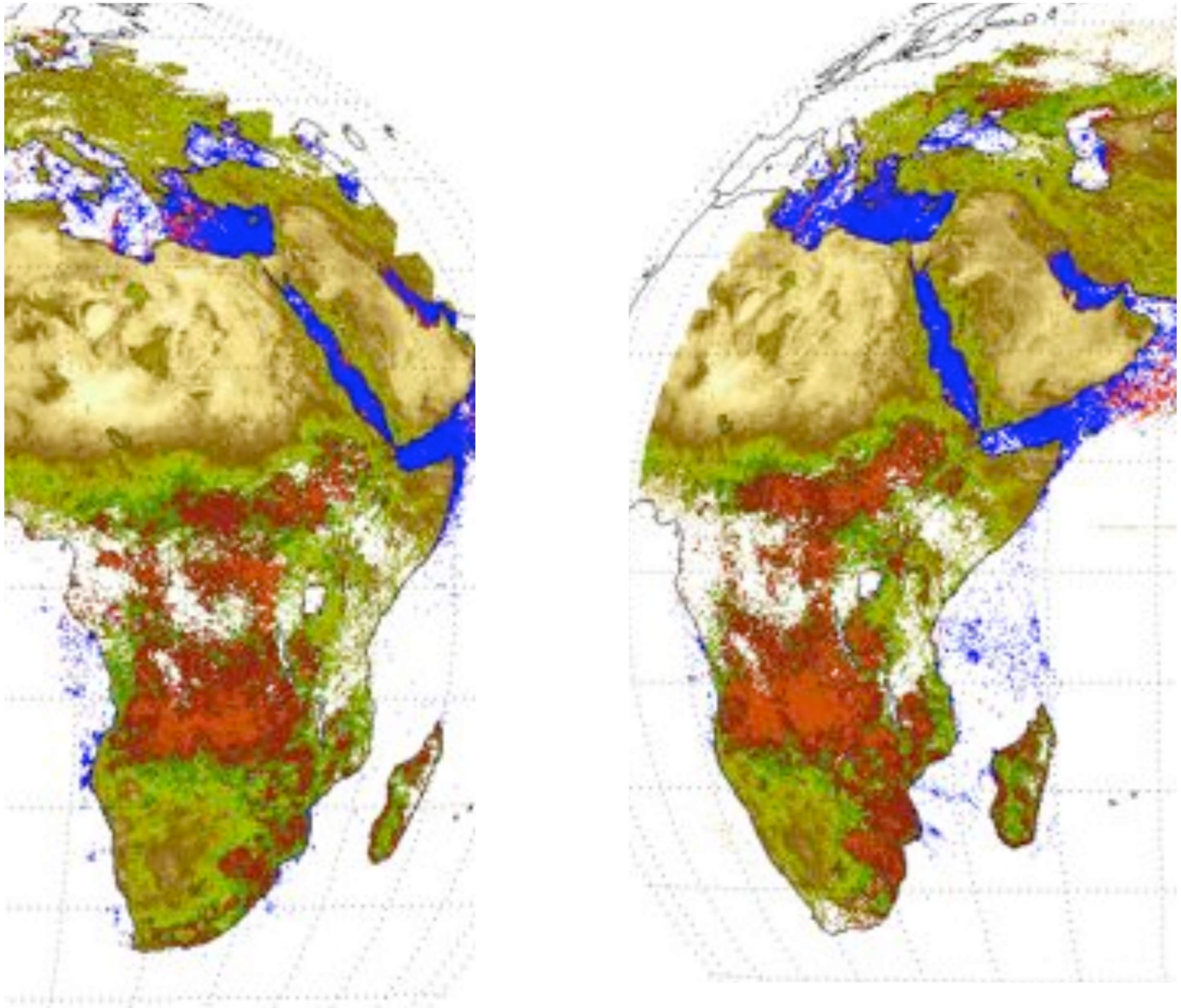
Example 1: Ensuring consistency

May 1999

EUMETSAT

Ref: Govaerts et al (2004) *Geophysical Research Letters*, **31**, L15201 10.1029/2004GL020418.

Example 1: Ensuring consistency



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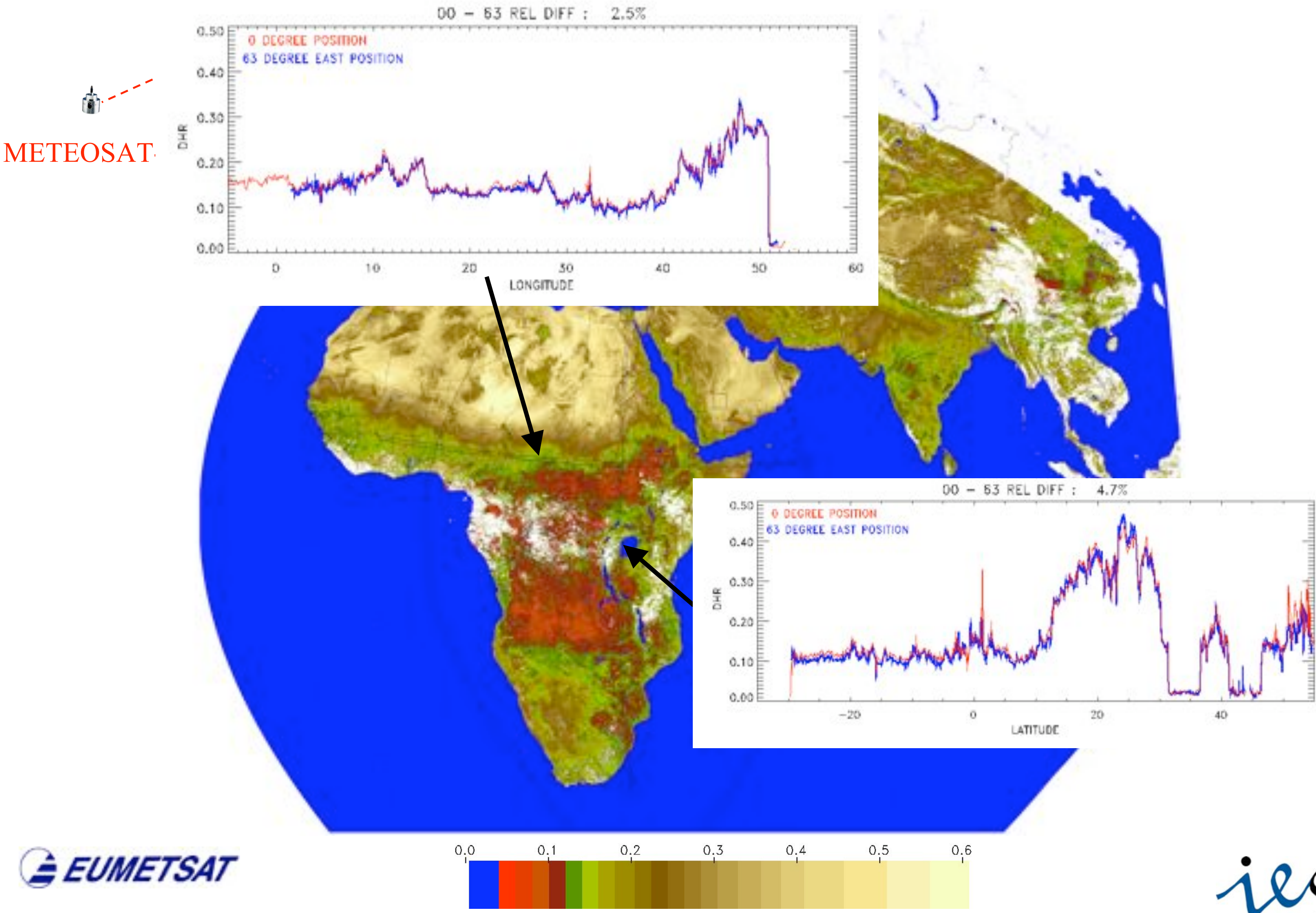

EUMETSAT

Ref: Govaerts et al (2004) *Geophysical Research Letters*, **31**, L15201 10.1029/2004GL020418.

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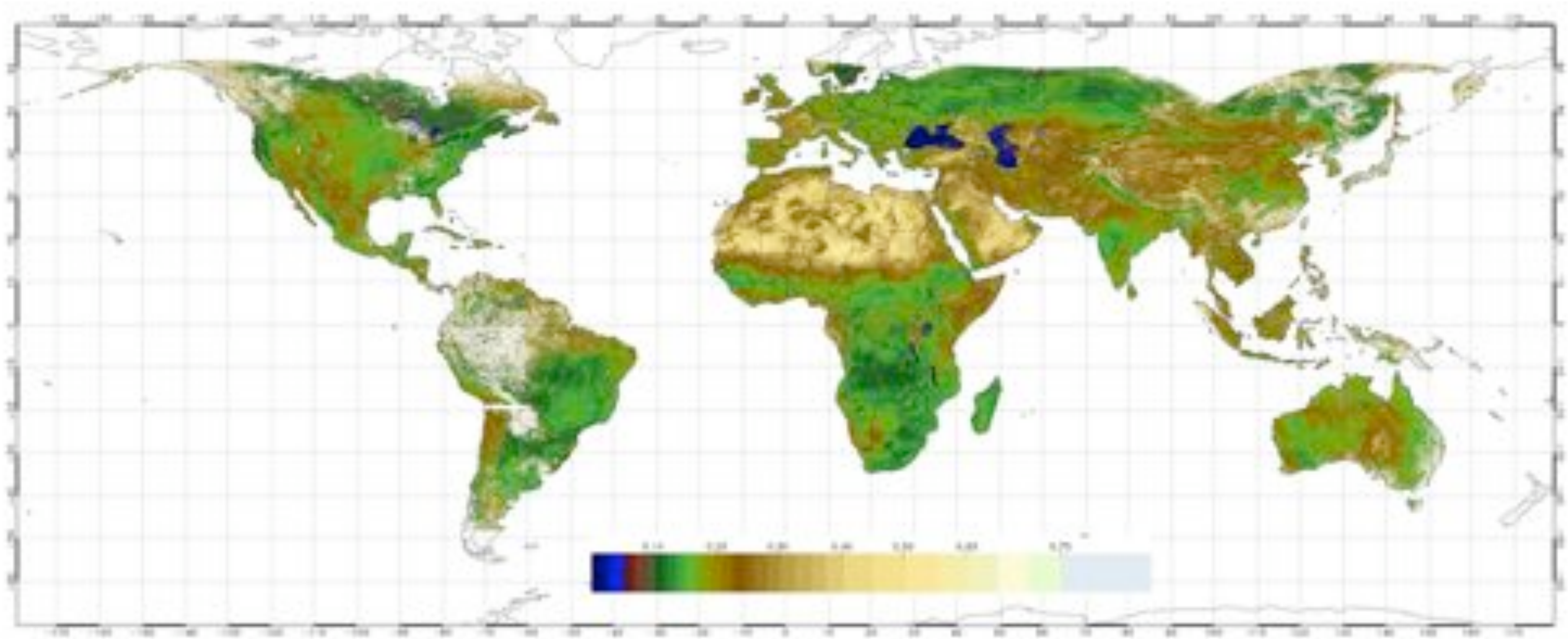
Example 1: Global albedo product



Broadband surface albedo derived at EUMETSAT (in collaboration with JRC) from two European (Meteosat-5 and -7), two American (GOES-8 and -10) and one Japanese (GMS-5) geostationary satellites, 1-10 May 2001.

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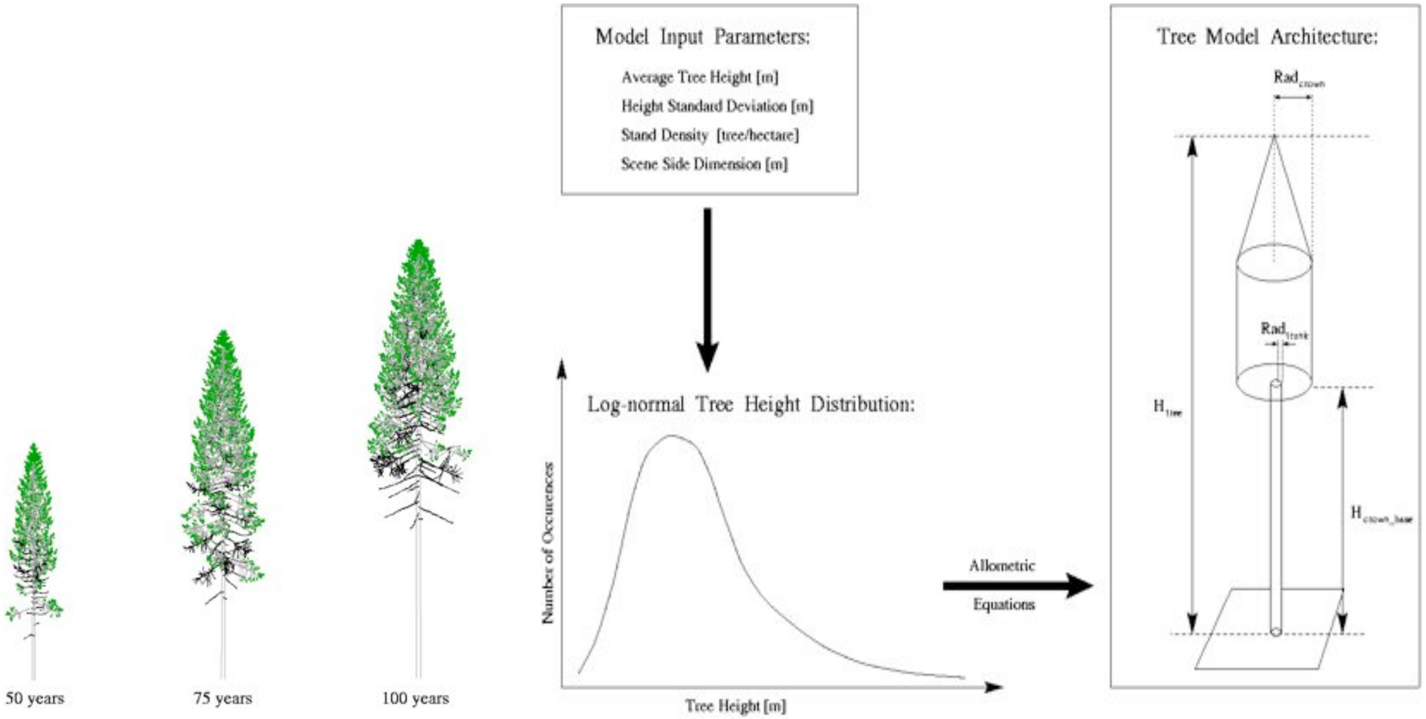
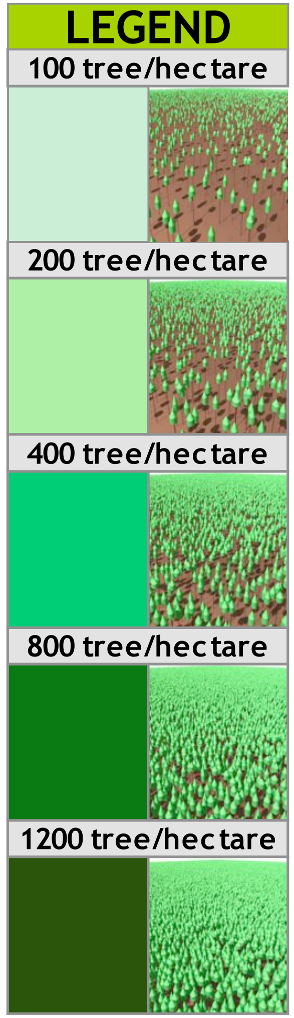
Example 2: Simulating forest stands

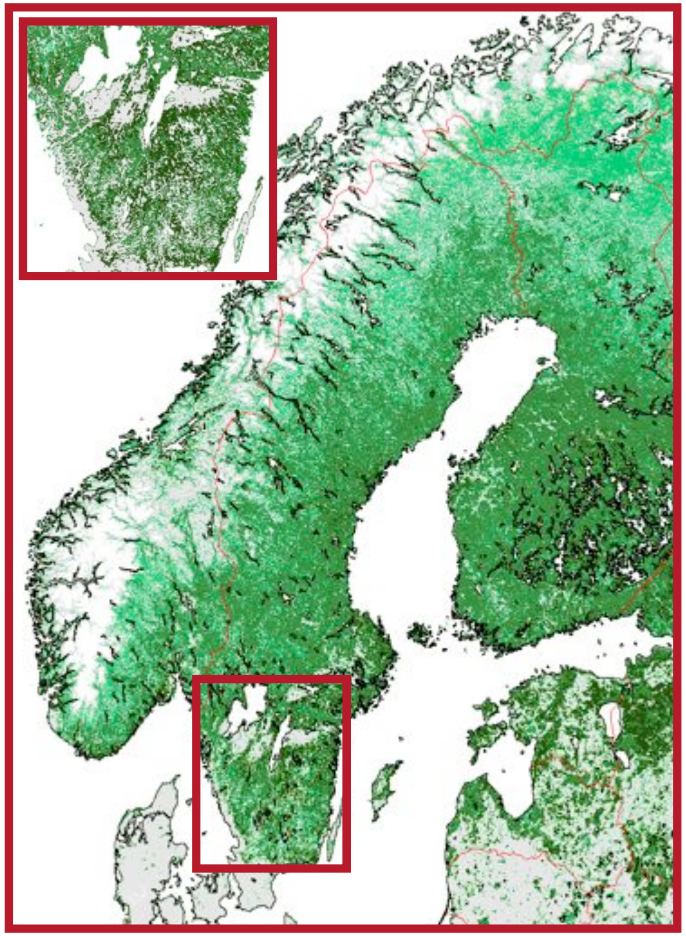
- Application to SPOT-Vegetation sensor:
  - § simulate the ToA BRF that should be measured
  - § search the LUT (database) for the closest match
  - § save the geophysical properties of that match

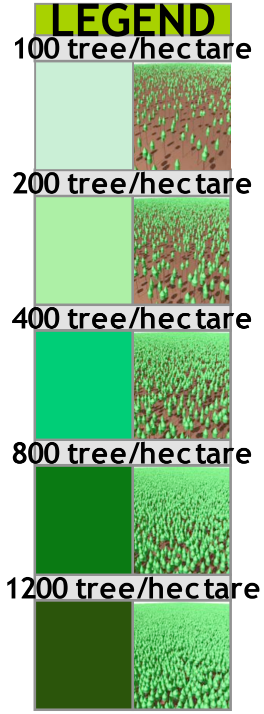


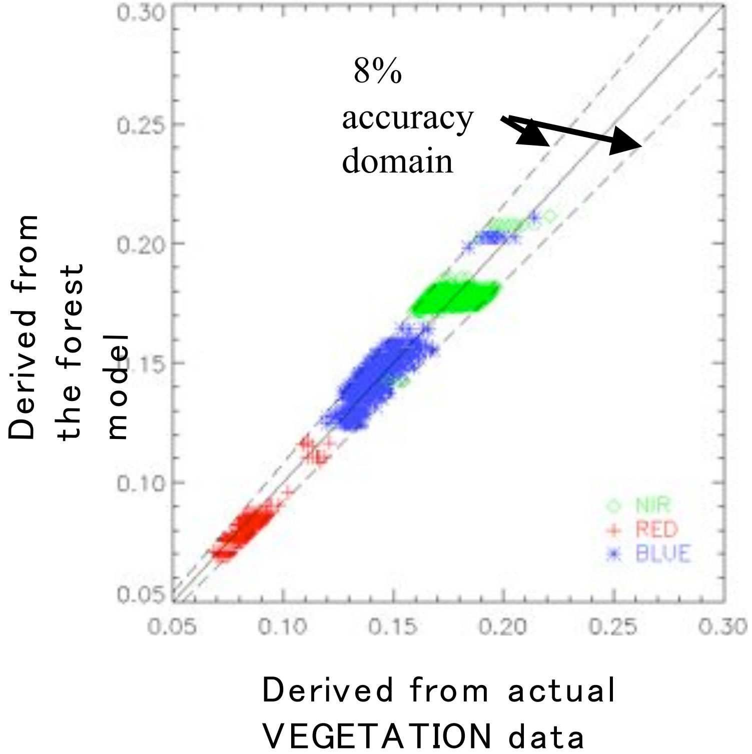


Ref: Widlowski, J-L., B. Pinty, N. Gobron and M. M. Verstraete (2001) 'Detection and Characterization of Boreal Coniferous Forests from Remote Sensing Data', *Journal of Geophysical Research*, **106**, 33,405-33,419.

Example 2: Estimating forest density







- Values compare favourably with independent, field-based estimates (PELCOM and FMERS)
- Accuracy is user-specified; more stringent requirements result in more limited spatial coverage

Ref: Widlowski, J-L., B. Pinty, N. Gobron and M. M. Verstraete (2001) 'Detection and Characterization of Boreal Coniferous Forests from Remote Sensing Data', *Journal of Geophysical Research*, **106**, 33,405-33,419.

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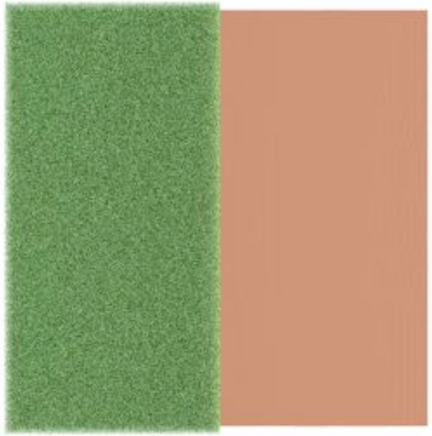
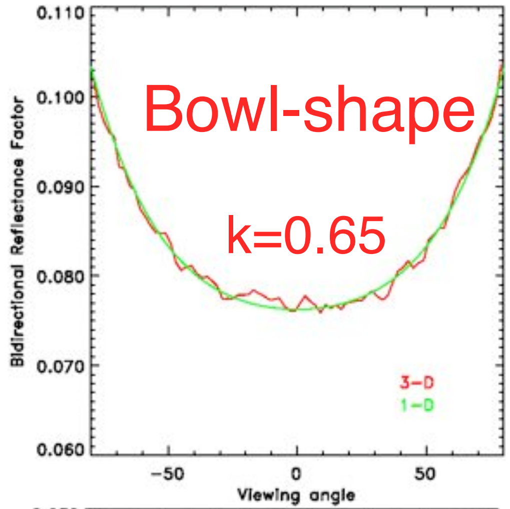
Outline

1. How good are BRF models?
2. Principles of model inversion in a remote sensing context
3. Look-Up Tables (LUT) approach
4. Applications
5. Exploiting RPV

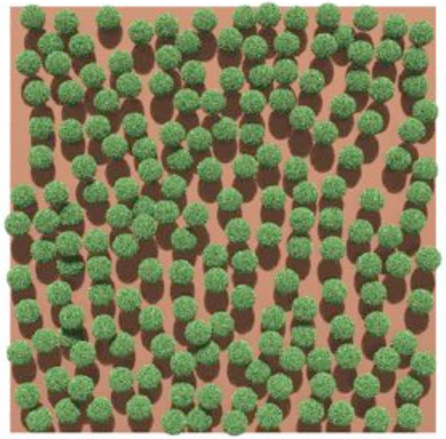
Characterizing heterogeneity

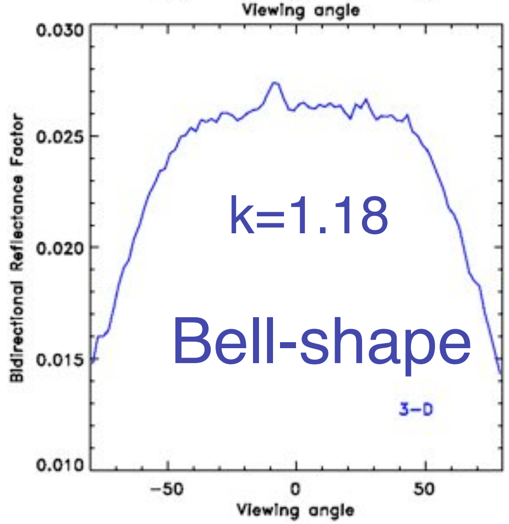
IPA





3-D





Ref: Pinty, B. et al. (2002) 'Uniqueness of Multiangular Measurements, Part 1: An Indicator of Subpixel Surface Heterogeneity from MISR', *IEEE Transactions on Geoscience and Remote Sensing*, MISR Special Issue, **40**, 1560-1573.

Overview of AirMISR

- 1 camera pointable at ±70.5, ±60, ±45.6, ±26.1, 0°
- Spectral bands at 446, 558, 672, and 866 nm
- Spatial resolution: L1B2 data re-sampled at 27.5 m
- Image length: 9 – 26 km (0 –70°)
- Swath: 11 – 32 km (0 – 70°)
- Coverage: on request
- Data: LaRC DAAC

Ref: http://www-misr.jpl.nasa.gov/mission/minst.html.

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Atmospheric correction of AirMISR

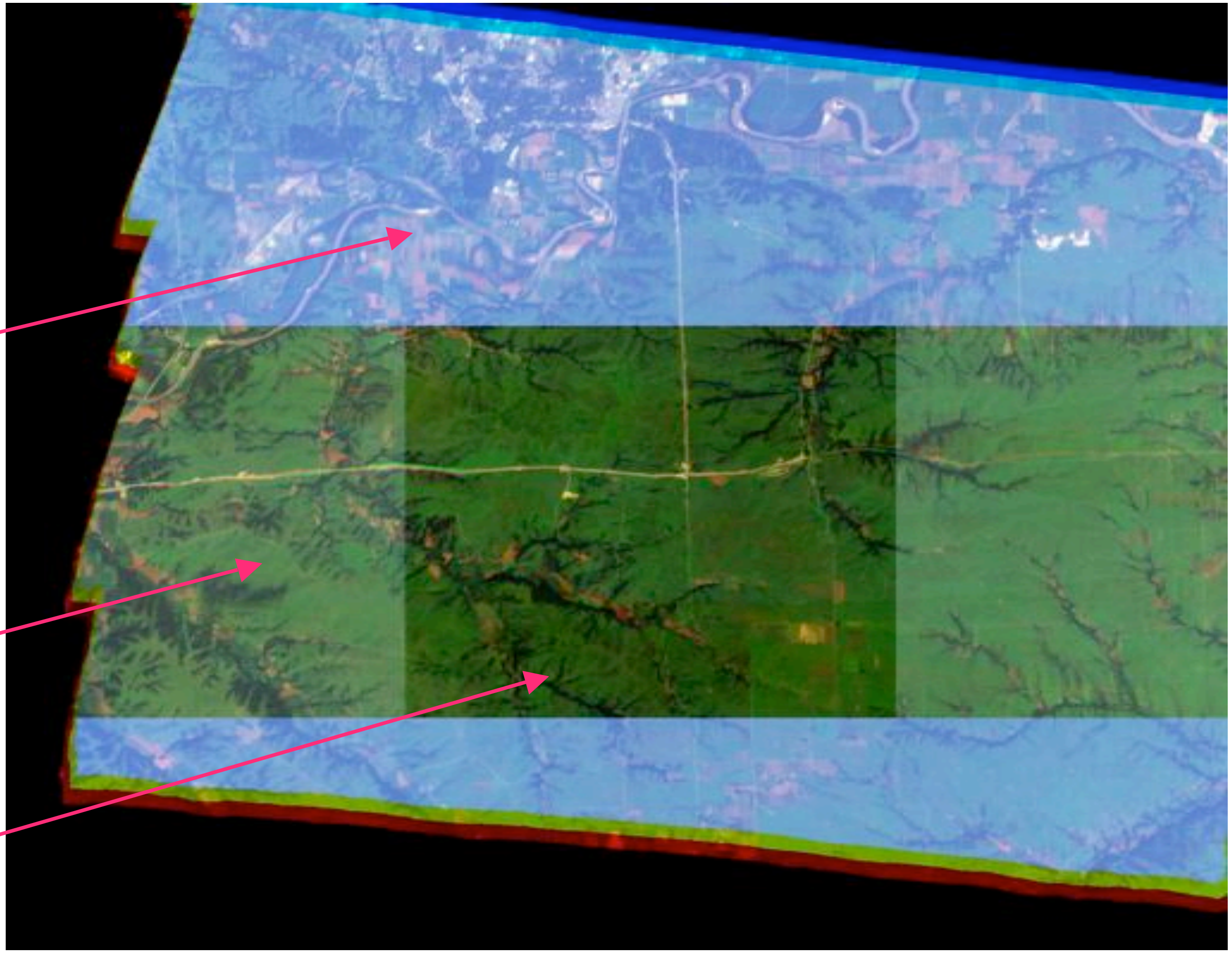
AirMISR

SALINA, KS
July 1999

Top-of-atmosphere Image (70°)

Rayleigh-corrected

Rayleigh + aerosol corrected



Ref: http://www-misr.jpl.nasa.gov/mission/minst.html.

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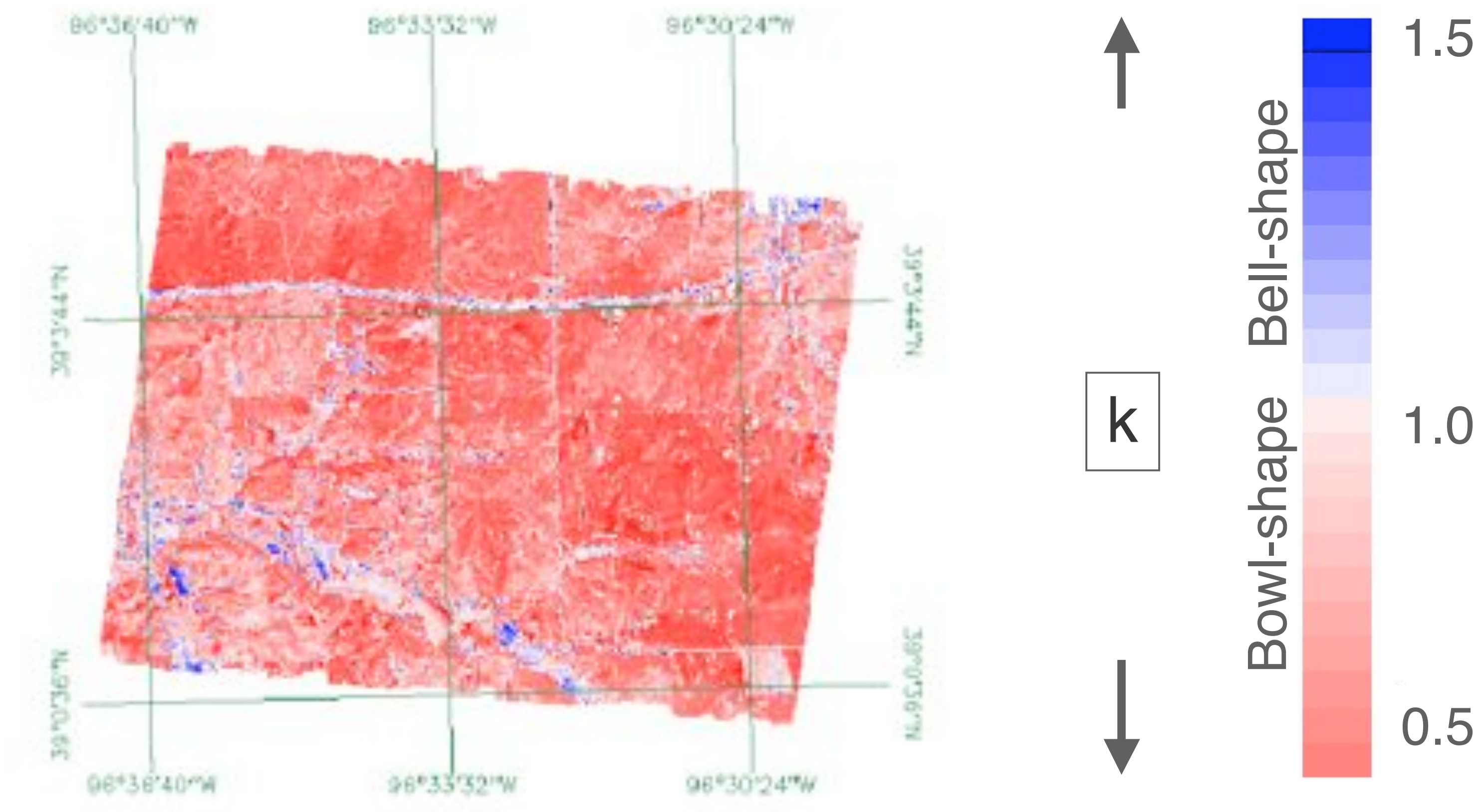
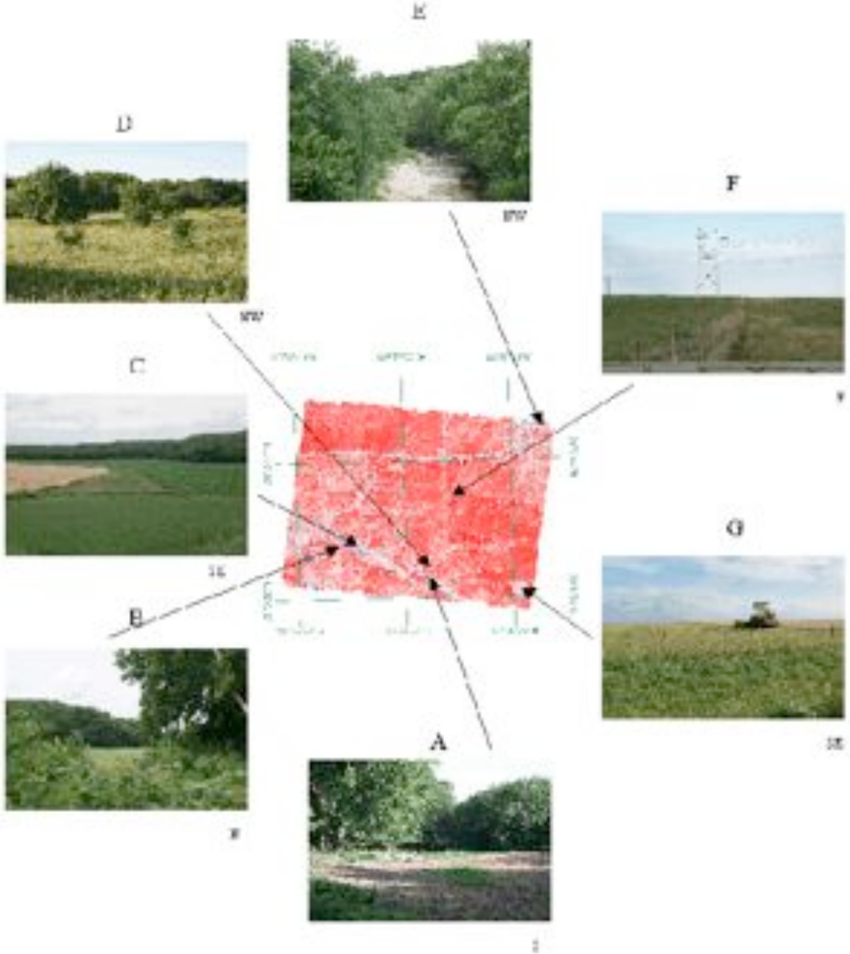
Target structure and anisotropy (1)



AirMISR campaign, Konza Prairie, June 1999

Ref: Gobron, N. et al. (2002) 'Uniqueness of Multiangular Measurements, Part 2: Joint Retrieval of Vegetation Structure and Photosynthetic Activity From MISR', *IEEE Transactions on Geoscience and Remote Sensing*, MISR Special Issue, **40**, 1574-1592.

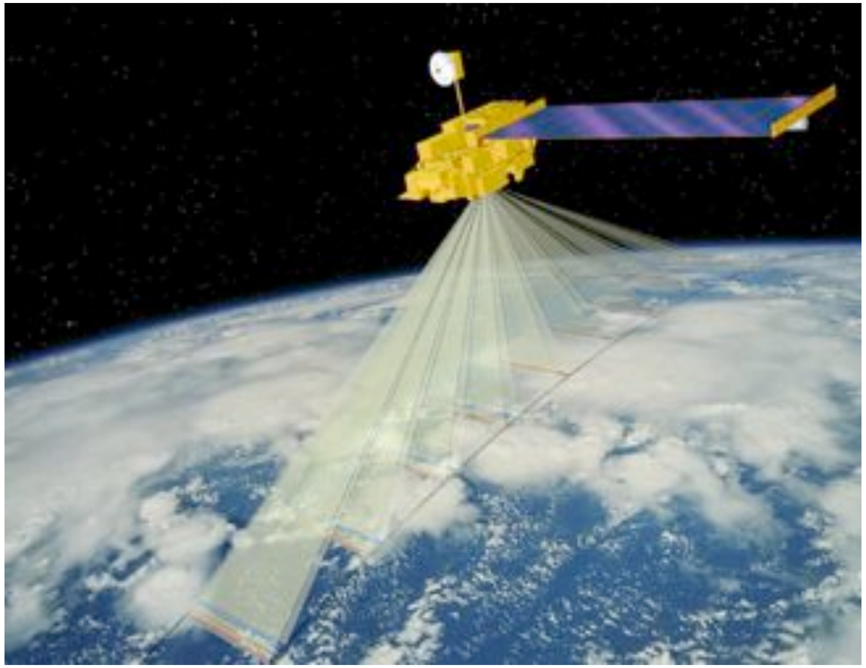
Target structure and anisotropy (2)



- Konza Prairie, June 2000
- A: Bare soil between trees
- B: Clearing between canopies
- C: Young corn field
- D: mixed vegetation
- E: Dry river bed
- F: Fence between two open fields
- G: Agriculture

Ref: Gobron, N. et al. (2002) 'Uniqueness of Multiangular Measurements, Part 2: Joint Retrieval of Vegetation Structure and Photosynthetic Activity From MISR', *IEEE Transactions on Geoscience and Remote Sensing*, MISR Special Issue, **40**, 1574-1592.

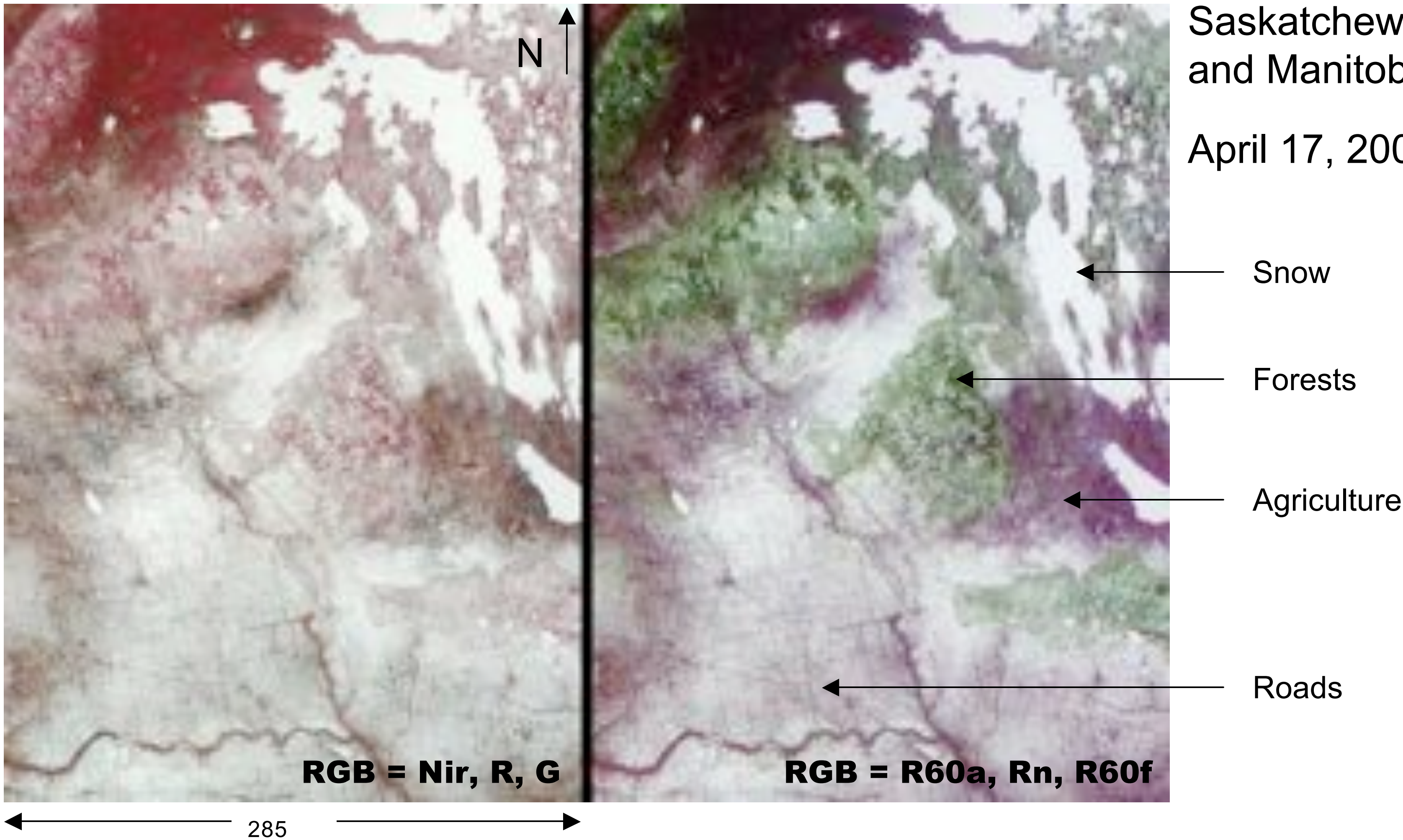
Overview of MISR



- 9 cameras at ±70.5, ±60, ±45.6, ±26.1, 0°
- Each camera at 446, 558, 672, and 866 nm
- Spatial resolution: 275 m (250 m nadir)
- Global mode: Full res. nadir and red, 1.1 km otherwise
- Local mode: Full resolution all cameras and all bands
- Swath: 360 km
- Coverage: global (9 days)

Ref: http://www-misr.jpl.nasa.gov/mission/minst.html.

Target structure and anisotropy (3)



Saskatchewan and Manitoba

April 17, 2001

Ref: http://www-misr.jpl.nasa.gov/gallery/galhistory/2001_may_30.html.

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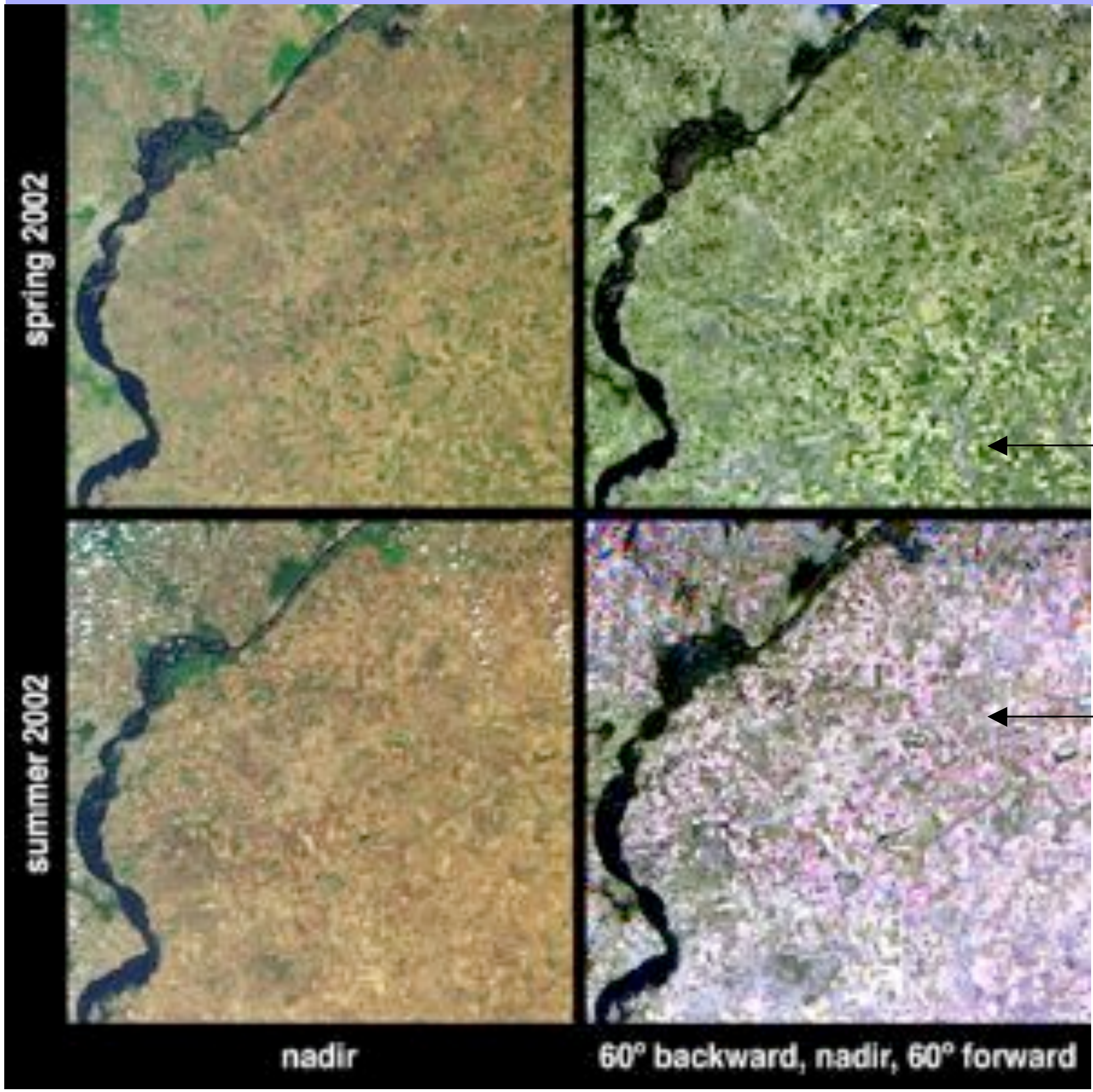
Target structure and anisotropy (4)



Saratov, Russia
31 May 2002 (top)
18 July 2002 (bottom)
'True color' MISR An (left)
Red anisotropy (right):
RGB = MISR Ca, An, Cf

Green: bell-shaped anisotropy controlled by soils and vertical plants

Purple: bowl-shaped anisotropy controlled by bare soils

Ref: http://www-misr.jpl.nasa.gov/gallery/galhistory.html

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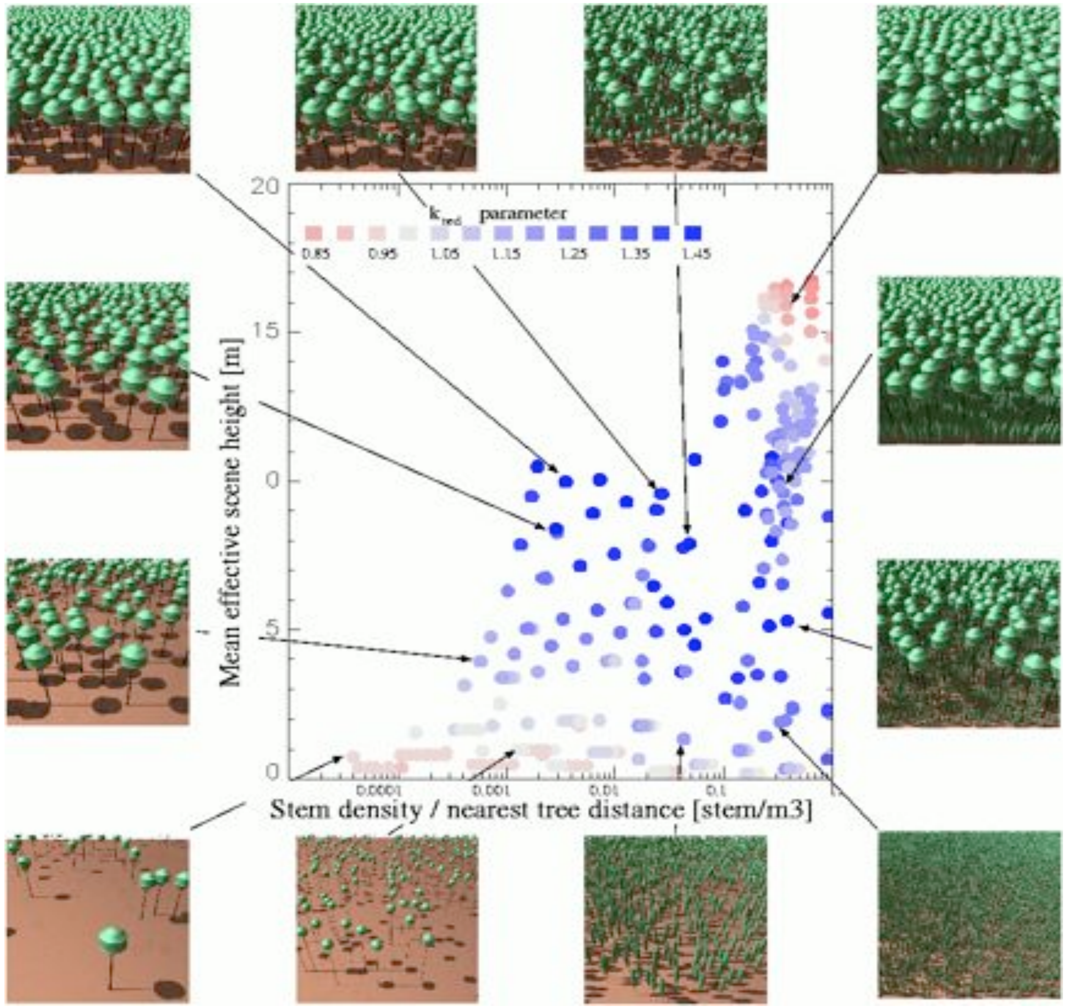
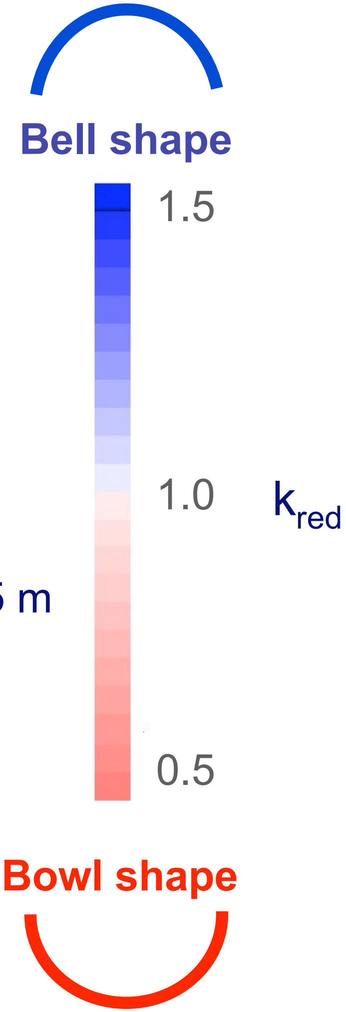
Impact of Canopy Structure on surface BRF (1)



SZA=30°

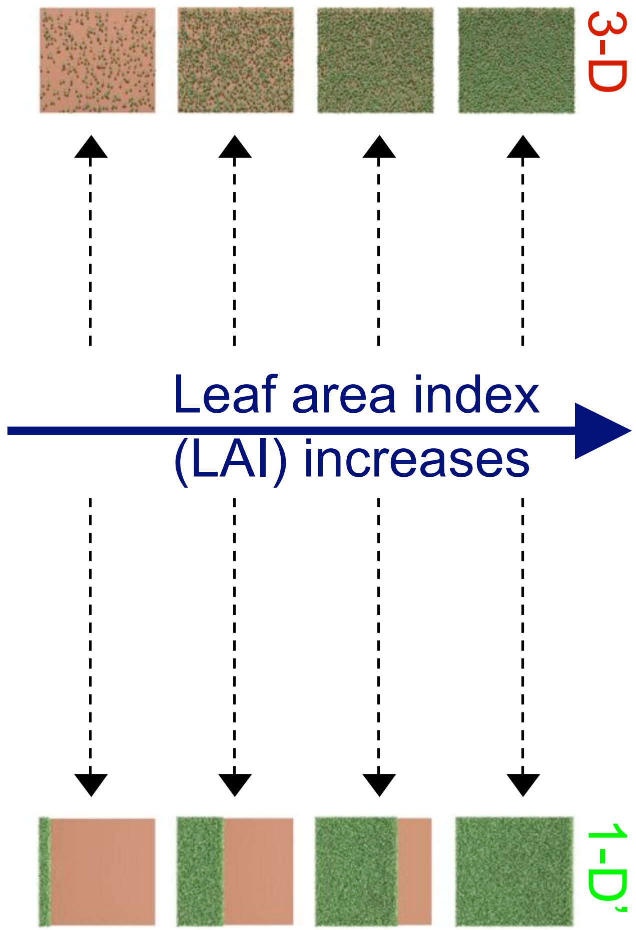
λ=red

IFOV~275 m



Ref: Widlowski, J.-L.et al. (2004) 'Canopy Structure Parameters Derived From Multi-angular Remote Sensing Data for Terrestrial Carbon Studies', *Climatic Change*, **67**, 403-415.

Impact of canopy structure on surface BRF (2)



The **1-D' homologue** of a 3-D surface target features *identical optical* (r_L, t_L, α_{soil})*, directional (Bi-Lambertian) and structural (LAI, LND,* L_{rad}*, LAD) canopy characteristics* as its 3-D original **with the exception of foliage clumping**.

Ref: Pinty, B.et al. (2002) 'Uniqueness of Multiangular Measurements Part 1: An Indicator of Subpixel Surface Heterogeneity from MISR', *IEEE Transactions on Geoscience and Remote Sensing*, MISR Special Issue, **40**, 1560-1573.

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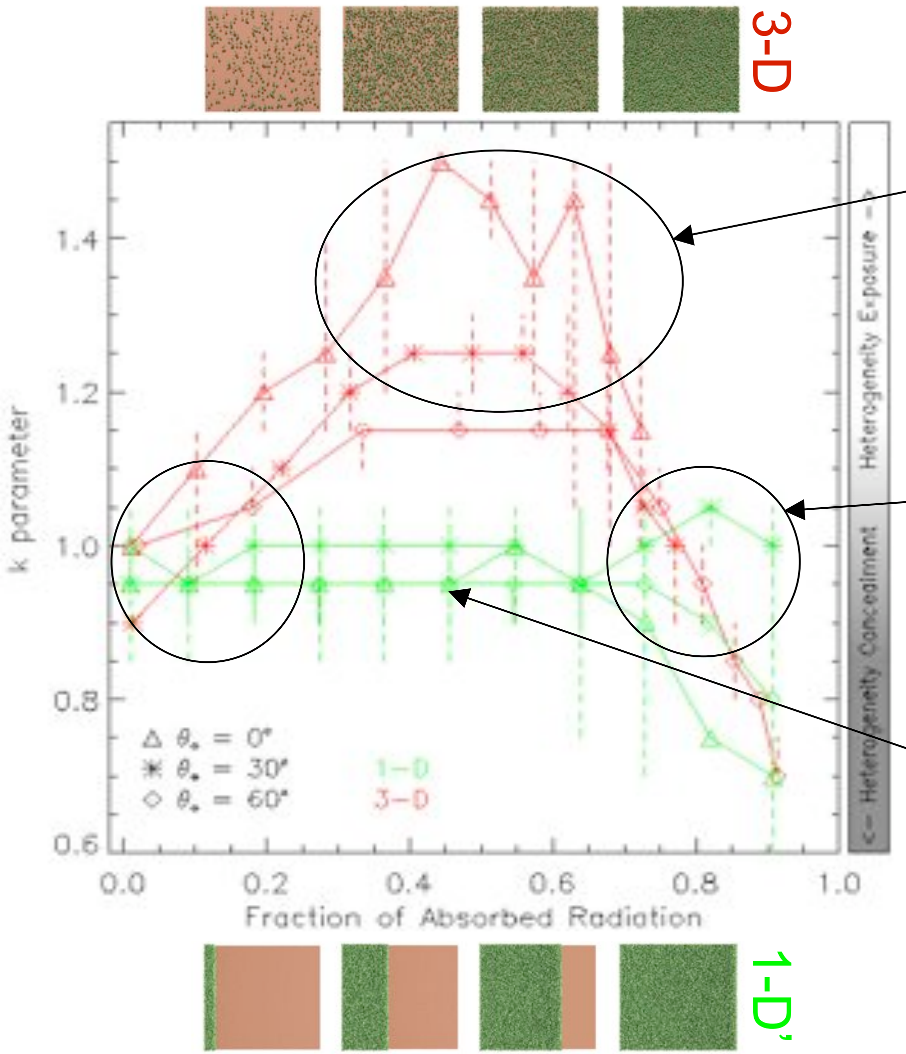
Impact of canopy structure on surface BRF (3)



3-D scene representations of intermediate vegetation coverage tend to exhibit bell-shaped reflectance fields

At low and high vegetation coverage, 3-D scenes also exhibit bowl-shaped BRF fields

1-D' surface representations (IPA) tend to be characterized throughout by bowl-shaped BRF fields

$k_{3-D} \geq k^{*}_{1-D'}$ if $k_{3-D} \geq 1$

Ref: Pinty, B.et al. (2002) 'Uniqueness of Multiangular Measurements Part 1: An Indicator of Subpixel Surface Heterogeneity from MISR', *IEEE Transactions on Geoscience and Remote Sensing*, MISR Special Issue, **40**, 1560-1573.

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Impact of canopy structure on surface BRF (4)

- It is not indifferent to use a 1D' or a 3D model to represent the anisotropy of land surfaces.

- Detailed studies have been carried out to establish when 1D' models provide solutions equivalent to 3D models, and when 3D models are absolutely required: See Widlowski et al. (2005) 'Using 1-D models to interpret the reflectance anisotropy of 3-D canopy targets: Issues and caveats', *IEEE TGRS*, **43**, 2008-2017.

- Using 3D models is particularly necessary to interpret remote sensing data at high spatial resolution; at coarse spatial resolutions (larger than a few hundred m), 1D' models appear generally adequate.


"That's all Folks!"
Cartoon Songs From
MERRIE MELODIES & LOONEY TUNES