

Theoretical Background: Radiative Transfer Modelling for Ecosystem Monitoring

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Table of contents

1	Introduction: The Power of Physical Modelling	2
2	Types of Radiative Transfer Models	3
2.1	Leaf-Level RTMs	3
2.2	Canopy-Level RTMs	5
2.3	Levels of Complexity	7
3	Radiative Transfer Model Products	10
3.1	Optical Products	10
3.2	Thermal Products	12
3.3	LiDAR Products	12
3.4	Radiative Budget	13
4	Applications of Radiative Transfer Models	13
4.1	1. BRDF/BRF Correction and Normalization	13
4.2	2. Biophysical and Biochemical Trait Retrieval	14
4.3	3. Sensitivity Analysis	14
4.4	4. Radiative Budget Modeling	17
4.5	5. Sensor Simulation and Mission Design	17
5	The Radiation transfer Model Intercomparison (RAMI) Initiative	17
6	The DART Model: A Comprehensive 3D RTM	19
6.1	Key Features	19
6.2	DART Advantages and Limitations	21
7	Advantages	21

8 Disadvantages	22
9 Vegetation Traits Retrieval	23
9.1 Retrieval Workflow Overview	23
9.2 Choosing the Right Approach	24
9.3 Field Data Collection	25
9.4 Scene Configuration	26
9.5 3D Forest Scene Parameters	26
9.6 Look-Up Table Design	28
9.7 Processing Simulated Images	29
9.8 Applying Retrieval to Real Imagery	31
10 Challenges and Future Directions	32
11 Summary and Key Takeaways	33
12 RTM Fundamentals	33
13 DART Model	34
14 Retrieval Workflow	34
15 Practical Advice	34
16 Future Outlook	34
17 Glossary of Key Terms	35
18 Additional Resources	36
19 References	36

1 Introduction: The Power of Physical Modelling

Remote sensing provides us with unprecedented capabilities to observe Earth’s ecosystems from above. However, the spectral signals captured by satellite and airborne sensors represent complex interactions between electromagnetic radiation and vegetation structures. To unlock the full information content of these signals, we need more than statistical relationships—we need physical understanding of how light interacts with plant canopies.

Radiative Transfer Models (RTMs) are powerful tools that use physical equations to simulate light interaction within virtual scenes, including forests, agricultural fields, and urban environments (Gastellu-Etchegorry et al. 2017). Unlike empirical models that rely on correlations between spectral data and field measurements, RTMs are based on the fundamental laws of

physics governing light propagation, scattering, and absorption (Knyazikhin et al. 1998). This physical foundation makes RTMs invaluable for:

- **Interpreting remote sensing observations** by linking canopy reflectance to biophysical and biochemical properties
- **Understanding ecosystem processes** related to light scattering and energy balance
- **Designing new sensors** and optimizing acquisition strategies
- **Retrieving vegetation traits** that cannot be directly measured from space

The evolution from simple 1D turbid medium approximations to complex 3D ray-tracing models has paralleled advances in computational power and our understanding of canopy architecture (Widlowski et al. 2015). Today's RTMs can simulate scenes with remarkable detail, from individual leaf biochemistry to landscape-scale heterogeneity.

2 Types of Radiative Transfer Models

RTMs operate at different spatial scales and levels of complexity, each designed for specific applications and data types. Understanding this hierarchy is essential for selecting the appropriate model for a given research question.

2.1 Leaf-Level RTMs

Leaf-level RTMs simulate the optical properties of individual leaves based on their internal structure and biochemical composition (Jacquemoud and Baret 1990). Figure 1 illustrates the complex interactions of light within leaf tissues. Key components include:

Internal Leaf Structure:

- **Upper and lower epidermis:** Protective layers with minimal pigment content
- **Palisade mesophyll:** Tightly packed cells containing high concentrations of chloroplasts
- **Spongy mesophyll:** Loosely arranged cells with air spaces creating scattering interfaces
- **Vascular tissues:** Veins transporting water and nutrients

Light Interaction Mechanisms:

The plate model (Figure 1 panels b-d) shows how light propagates through leaf layers. At each interface between materials with different refractive indices (typically air $n=1$ and cell wall material $n \approx 1.4$), light undergoes:

1. **Specular reflection** at the surface (~4% of incident light)
2. **Refraction** into the leaf interior following Snell's law
3. **Absorption** by pigments (chlorophylls, carotenoids, anthocyanins, water)
4. **Scattering** at cell walls and air-cell interfaces

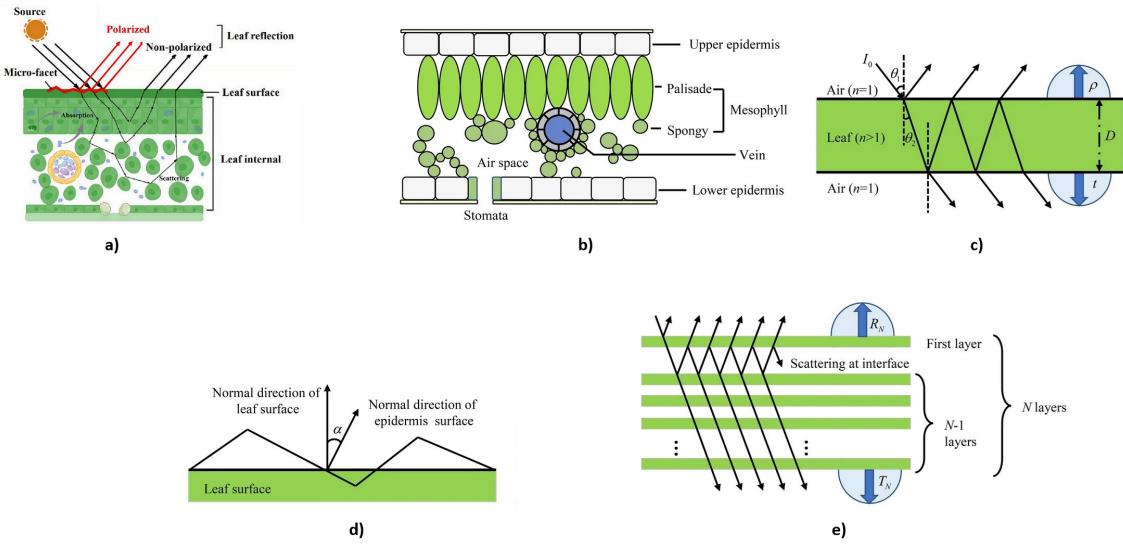


Figure 1: Leaf-level radiative transfer mechanisms. (a) Light interaction with leaf structure: polarized (red) and non-polarized (black) light interact through surface reflection at micro-facets, absorption by chloroplasts, and scattering within mesophyll tissue. (b) Conceptual diagram showing light interaction with leaf surface and internal structures including epidermis, palisade, spongy mesophyll, and air spaces. (c) Simplified plate model showing light transmission and reflection through mesophyll layers with refractive index $n>1$. (c) Detailed representation of light path including surface reflection and internal scattering at multiple interfaces. (d) Multi-layer representation with N layers showing transmittance (T_N) and reflectance (R_N) terms. Sources: (a) Li et al. (2025), (b) Xu and Ye (2023)

5. Multiple internal reflections within the mesophyll structure

PROSPECT Model:

The most widely used leaf-level RTM is PROSPECT (Jacquemoud and Baret 1990; Féret et al. 2017), which treats the leaf as a stack of N identical layers, each characterized by a refractive index and specific absorption coefficients. The model requires as inputs:

- **N**: Leaf structure parameter (related to mesophyll thickness and compactness)
- **C_ab**: Chlorophyll a+b content (g/cm²)
- **C_ar**: Carotenoid content (g/cm²)
- **C_brown**: Brown pigments (arbitrary units)
- **C_w**: Equivalent water thickness (g/cm² or cm)
- **C_m**: Dry matter content (g/cm²)
- **C_anth**: Anthocyanin content (g/cm²) [in PROSPECT-D and later versions]

The model outputs hemispherical reflectance and transmittance spectra (typically 400-2500 nm), which serve as inputs to canopy-level models.

PROSPECT Model Evolution

The PROSPECT model has evolved through several versions:

- **PROSPECT** (1990): Original version with 4 parameters
- **PROSPECT-5** (2008): Added brown pigments
- **PROSPECT-D** (2017): Added anthocyanins (Féret et al. 2017)
- **PROSPECT-PRO** (2021): Improved protein absorption features

Each version improves spectral fidelity and retrieval accuracy for specific compounds.

2.2 Canopy-Level RTMs

Canopy-level RTMs simulate light interaction within entire plant canopies or landscape scenes (Gastellu-Etchegorry et al. 2017). Figure 2 illustrates the comprehensive approach of 3D canopy models like DART, which can represent:

Vertical Structure:

- **Atmospheric layers**: High and mid atmosphere with gas absorption, aerosol scattering
- **Canopy layers**: Vegetation at multiple heights with varying density
- **Understory**: Ground vegetation, leaf litter, soil
- **Urban elements**: Buildings, roads, other artificial structures when applicable

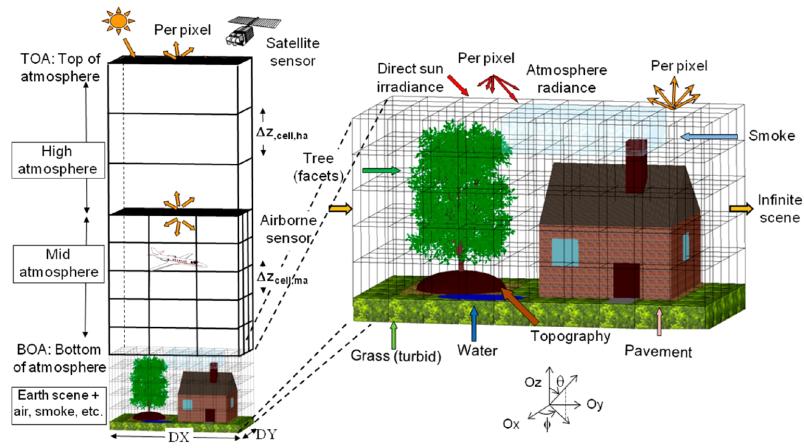


Figure 2: Canopy-level radiative transfer in 3D scene. The diagram shows the DART model structure including atmosphere layers (high and mid atmosphere), Earth scene with detailed 3D vegetation (trees, grass, water, topography), and multiple sensor configurations. Key elements include: TOA (Top of Atmosphere), BOA (Bottom of Atmosphere), direct sun irradiance, atmosphere radiance, per-pixel radiation, and both satellite and airborne sensor geometries. Source: Gastellu-Etchegorry et al. (2017).

Horizontal Heterogeneity:

- **Tree crowns:** Individual trees with species-specific architecture
- **Canopy gaps:** Openings allowing direct sunlight to reach understory
- **Topography:** Terrain elevation affecting local illumination geometry
- **Mixed surfaces:** Combination of vegetation, water, bare soil

Radiation Components:

Canopy-level RTMs must account for multiple radiation pathways:

1. **Direct solar radiation:** Unscattered photons from the sun
2. **Diffuse sky radiance:** Light scattered by atmosphere before reaching canopy
3. **Multiple scattering within canopy:** Photons bouncing between leaves, stems, ground
4. **Atmospheric coupling:** Light exiting canopy, being scattered by atmosphere, and potentially re-entering
5. **Topographic effects:** Shadows, adjacency effects from nearby terrain

Model Inputs:

Canopy-level RTMs require comprehensive parameterization:

- **Optical properties:** Leaf/bark/soil reflectance and transmittance spectra
- **Structural parameters:** LAI (Leaf Area Index), canopy height, crown dimensions
- **3D Architecture:** Tree positions, sizes, shapes; or turbid medium descriptions
- **Environmental conditions:** Sun angles, atmospheric composition
- **Sensor geometry:** View angles, spatial resolution, spectral bands

Model Outputs:

These models generate various products:

- **Bidirectional Reflectance Factor (BRF):** Directional reflectance images
- **Radiative budget:** Absorbed, transmitted, and reflected radiation
- **LiDAR waveforms:** Simulated laser scanning returns
- **Brightness temperature:** Thermal radiation (if thermal module enabled)

2.3 Levels of Complexity

RTMs can be categorized by their representation of canopy architecture (Bailey, Ponce de León, and Krayenhoff 2020):

1D Models (Turbid Medium):

The simplest approach treats vegetation as horizontally infinite, vertically stratified layers with uniformly distributed scatterers (Figure 3, left panel). Examples include SAIL (Verhoef 1984) and GeoSAIL. Advantages:

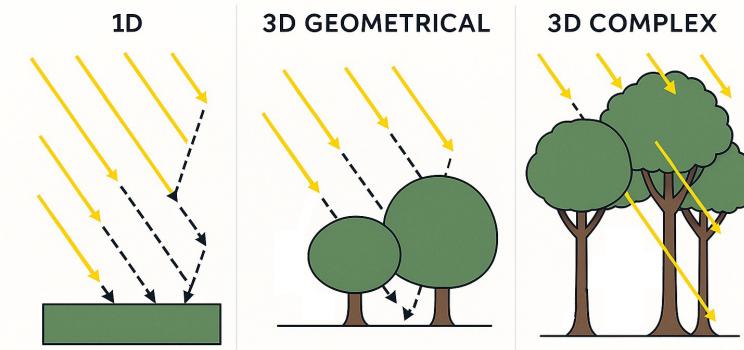


Figure 3: Three levels of canopy representation in radiative transfer models. Left: 1D turbid medium with horizontally homogeneous layers. Center: 3D geometrical objects with simple crown shapes. Right: 3D complex representation with explicit 3D tree structures. Yellow arrows indicate incident direct solar radiation, with scattered radiation paths shown by dashed lines.

- Computationally fast
- Well-suited for homogeneous canopies (crops, grasslands)
- Many analytical solutions available

Limitations:

- Cannot represent gaps, tree crowns, or horizontal heterogeneity
- Poor performance for forests and sparse vegetation
- Neglects directional structure effects

3D Geometrical Models:

An intermediate approach represents trees as geometric primitives (cones, ellipsoids, cylinders) filled with turbid medium (Figure 3, center panel). Examples include FLIGHT (North 1996) and discrete models. Advantages:

- Captures crown-scale structure and gaps
- More realistic than 1D for forests
- Moderate computational demands

Limitations:

- Still simplified crown architecture
- Cannot represent branch-level structure
- Less accurate for detailed structural studies

3D Complex Models:

The most sophisticated approach explicitly represents 3D tree architecture using detailed geometric meshes or voxelized structures (Figure 3, right panel). Examples include DART-Lux (Gastellu-Etchegorry et al. 2017), LESS (Qi et al. 2019), and Helios++ (Bailey 2019). Advantages:

- Highest realism and accuracy
- Can incorporate terrestrial laser scanning (TLS) data
- Suitable for LiDAR simulation and fine-scale studies

Limitations:

- Computationally intensive
- Requires detailed 3D vegetation data
- Complex parameterization

! Choosing the Right Model

Model selection depends on:

- **Application scale:** Leaf, plot, landscape
- **Available data:** Biochemical measurements, structural data, TLS point clouds
- **Research questions:** What traits need to be retrieved?
- **Computational resources:** Runtime and memory constraints
- **Ecosystem type:** Homogeneous crops vs. heterogeneous forests

For high-resolution hyperspectral imagery of forests, 3D complex models offer the best performance.

3 Radiative Transfer Model Products

RTMs generate a variety of outputs useful for different remote sensing applications (Gastellu-Etchegorry et al. 2017):

3.1 Optical Products

Bidirectional Reflectance Factor (BRF):

The most common output, BRF quantifies how reflectance varies with illumination and viewing geometry. It is defined as the ratio of reflected radiance in a given direction to the radiance that would be reflected by an ideal Lambertian surface under identical illumination (Schaepman et al. 2009):

$$\text{BRF}(\theta_s, \phi_s, \theta_v, \phi_v, \lambda) = \frac{\pi \cdot L(\theta_v, \phi_v, \lambda)}{E(\theta_s, \phi_s, \lambda)}$$

where:

- θ_s, ϕ_s : Solar zenith and azimuth angles
- θ_v, ϕ_v : View zenith and azimuth angles
- λ : Wavelength
- L : Reflected radiance
- E : Incoming irradiance

Figure 4 illustrates how BRF varies with viewing geometry at different wavelengths. Key features include:

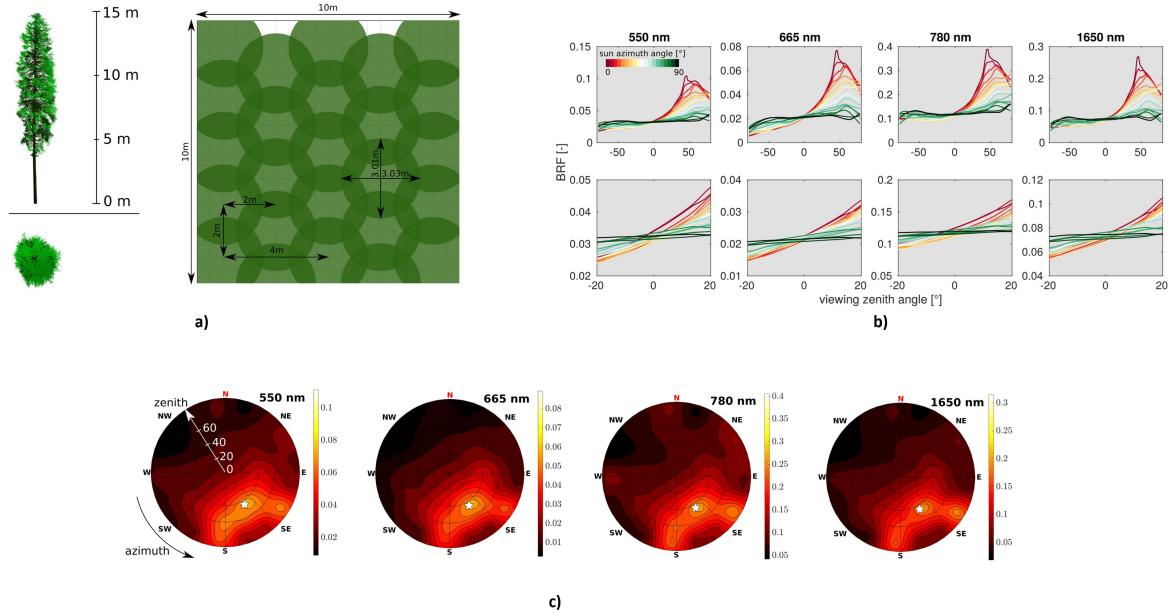


Figure 4: Multi-angle BRF patterns for a forest canopy. Polar plots showing BRF at four wavelengths (550 nm, 665 nm, 780 nm, 1650 nm) across viewing hemisphere. (a) Canopy simulation design. (b) BRF vs. viewing zenith angle for different solar positions (shown as colored lines). (c) Polar projections with solar position marked by star symbol. Patterns reveal strong forward scattering (hotspot) and angular anisotropy varying with wavelength. Source: Hanuš et al. (2023)

- **Hotspot:** Peak reflectance when sun and sensor are aligned (zero phase angle)
- **Darkspot:** Minimum reflectance in backscattering direction (opposite sun)
- **Bowl shape:** General decrease in reflectance with increasing view zenith angle
- **Spectral dependence:** Angular patterns differ between visible and NIR wavelengths

RTMs can simulate BRF for any combination of sun-sensor geometries, enabling:

- **BRDF normalization** of multi-temporal imagery (Hanuš et al. 2023)
- **Atmosphere-corrected reflectance estimation**
- **Optimal view angle selection** for trait retrieval

3.2 Thermal Products

Some RTMs (e.g., DART) simulate brightness temperature by coupling radiative transfer with energy balance equations (Gastellu-Etchegorry et al. 2015). This enables:

- **Canopy temperature** mapping from thermal imagery
- **Evapotranspiration** estimation via surface energy balance
- **Water stress detection** using thermal-optical indices

3.3 LiDAR Products

Advanced 3D RTMs can simulate laser scanning returns (Gastellu-Etchegorry et al. 2017), providing:

- **Airborne LiDAR waveforms:** Full-waveform returns at nadir or off-nadir angles
- **Terrestrial Laser Scanning (TLS) point clouds:** Ground-based returns from tree structure
- **Mobile LiDAR:** Vehicle-mounted or handheld scanner simulations

These synthetic LiDAR data support:

- **Sensor design:** Testing new LiDAR configurations before deployment
- **Algorithm development:** Validating extraction methods for canopy height, LAI, biomass
- **Point cloud interpretation:** Understanding how 3D structure affects returns

3.4 Radiative Budget

RTMs compute the absorption, transmission, and reflection of radiation throughout the canopy (Widlowski et al. 2015):

- **Absorbed PAR (Photosynthetically Active Radiation):** Critical for photosynthesis models
- **Transmitted radiation:** Light reaching understory
- **Vertical profiles:** Radiation availability at different canopy heights
- **Per-triangle/voxel budget:** Spatially explicit energy balance

These outputs link remote sensing to ecosystem functioning and carbon cycle models (Malenovský et al. 2013).

4 Applications of Radiative Transfer Models

RTMs serve multiple roles in ecosystem science and remote sensing (Malenovský et al. 2021):

4.1 1. BRDF/BRF Correction and Normalization

Multi-temporal remote sensing imagery suffers from varying sun-sensor geometries that create artificial reflectance changes unrelated to vegetation state. RTMs enable physics-based corrections (Hanus et al. 2023):

Problem: Reflectance of the same surface can vary by 20-50% depending on viewing angle (Schaepman et al. 2009).

Solution:

1. Simulate BRF patterns for the actual scene using RTM
2. Normalize observed reflectance to a standard geometry (e.g., nadir view, 45° solar zenith)
3. Apply corrections accounting for topography, adjacency effects

Benefits:

- Improved phenology tracking
- Better change detection
- Enhanced time-series analysis

4.2 2. Biophysical and Biochemical Trait Retrieval

The primary application of RTMs is estimating vegetation properties from remote sensing spectra. This is typically accomplished through Look-Up Table (LUT) inversion (Dorigo et al. 2007):

Workflow:

1. **Generate LUT:** Run RTM thousands of times varying input traits (LAI, chlorophyll, etc.)
2. **Create spectral database:** Store simulated spectra with corresponding trait values
3. **Match observations:** Find LUT entry with spectrum closest to observed pixel
4. **Retrieve traits:** Extract corresponding trait values

Retrieved Traits Include:

- **Biochemical:** Chlorophyll (C_{ab}), carotenoids (C_{ar}), water content (C_w), dry matter (C_m), anthocyanins (C_{anth})
- **Structural:** LAI, canopy height, canopy cover, clumping index
- **Photosynthetic:** Absorbed PAR, light use efficiency

Figure 5 demonstrates trait retrieval results from airborne hyperspectral imagery, showing detailed spatial patterns of biochemical content and canopy structure.

4.3 3. Sensitivity Analysis

Before collecting expensive remote sensing data or designing retrieval algorithms, RTMs can reveal which spectral bands contain information about specific traits (Malenovský et al. 2021):

Approach:

1. Vary one trait while holding others constant
2. Simulate spectra for each trait value
3. Quantify spectral sensitivity: $\partial BRF(\lambda)/\partial \text{Trait}$
4. Identify optimal wavebands for trait estimation

Figure 6 illustrates how different levels of structural representation (3D detailed vs. turbid medium vs. simple geometry) affect simulated imagery. This type of analysis reveals:

- Which traits are retrievable given sensor specifications
- How structural simplifications affect spectral accuracy
- Trade-offs between model complexity and simulation quality

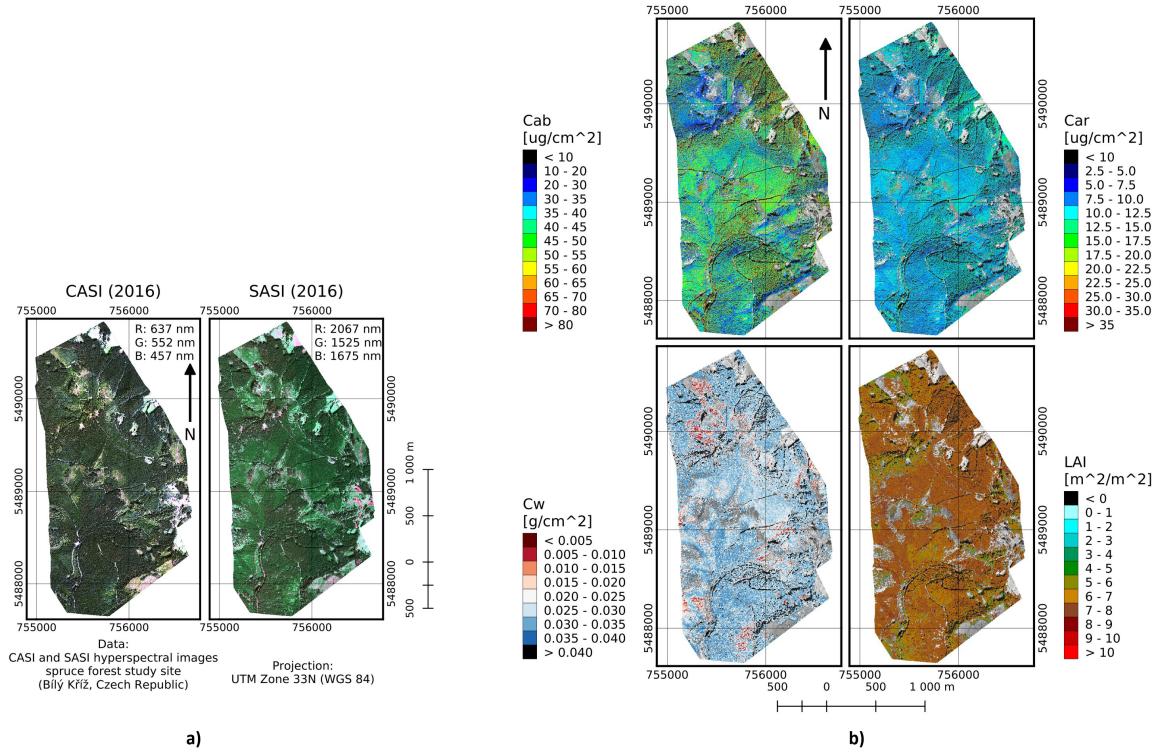


Figure 5: Vegetation trait retrieval workflow. Left: True-color (CASI 2016) and false-color (SASI 2016) hyperspectral images of a forest study site. Right: Retrieved trait maps showing spatial distribution of leaf chlorophyll content (Cab), leaf carotenoids content (Car), leaf water content (Cw), and leave area index (LAI). Color scales indicate concentration gradients across the heterogeneous canopy. Source: Janoutová et al. (2021)

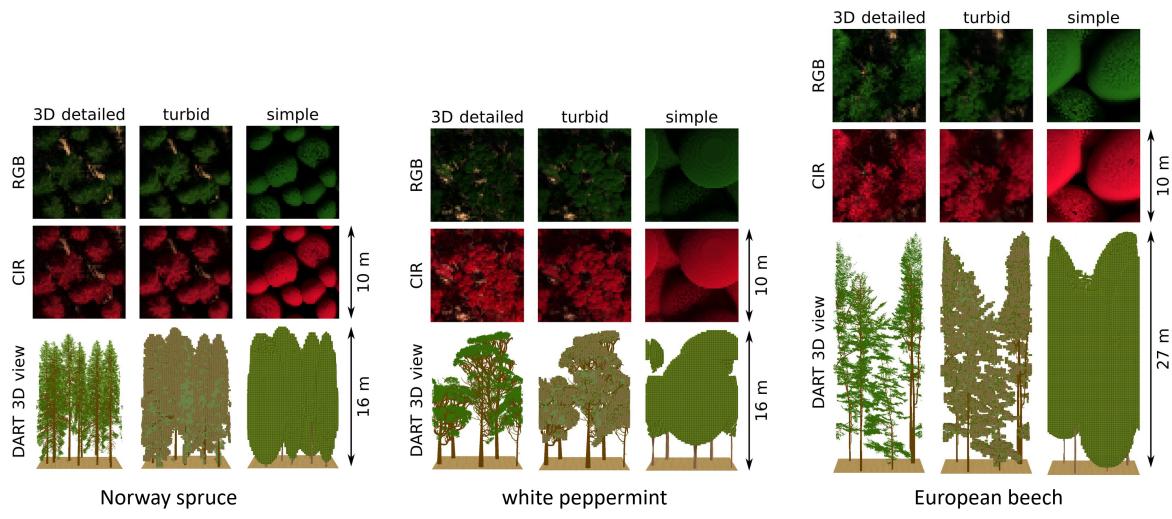


Figure 6: Sensitivity analysis for different tree types and canopy representations. Simulated RGB, CIR (Color Infrared), and 3D canopy views for three species (Norway spruce, white peppermint, European beech) using three modeling approaches: 3D detailed, turbid medium, and simple geometric representation. Each representation creates different spatial patterns and spectral responses, revealing the importance of architectural fidelity for accurate simulations. Source: Janoutová et al. (2021)

4.4 4. Radiative Budget Modeling

Understanding how much light is absorbed, transmitted, or reflected by vegetation is fundamental to ecosystem energy balance and photosynthesis (Malenovský et al. 2013):

Applications:

- **Carbon cycle modeling:** Linking absorbed PAR to gross primary productivity
- **Energy balance studies:** Partitioning radiation into sensible and latent heat fluxes
- **Vertical profile analysis:** Light availability for understory species
- **Climate model parameterization:** Albedo and roughness for land surface schemes

4.5 5. Sensor Simulation and Mission Design

Before launching new satellites or airborne campaigns, RTMs can test sensor configurations and optimize acquisition strategies:

Questions Addressed:

- What spatial resolution is needed to resolve canopy gaps?
- Are 10 nm bands better than 20 nm bands for chlorophyll retrieval?
- What view angles maximize sensitivity to LAI?
- How does along-track vs. across-track scanning affect shadowing?

Case Study: The FLEX (Fluorescence Explorer) satellite mission used RTM simulations extensively to define optimal spectral bands, view angles, and overpass times for measuring solar-induced chlorophyll fluorescence (Malenovský et al. 2021).

5 The Radiation transfer Model Intercomparison (RAMI) Initiative

Given the diversity of RTMs with different underlying assumptions and implementations, the community recognized the need for systematic model benchmarking. The RAMI initiative provides standardized test scenes and reference solutions (Widlowski et al. 2015).

RAMI Objectives:

1. **Identify model errors** through systematic comparison
2. **Provide reference datasets** for model validation
3. **Establish best practices** for model use
4. **Benchmark computational performance**

Test Scenarios:

- **Abstract scenes:** Homogeneous canopies, geometric primitives with known solutions

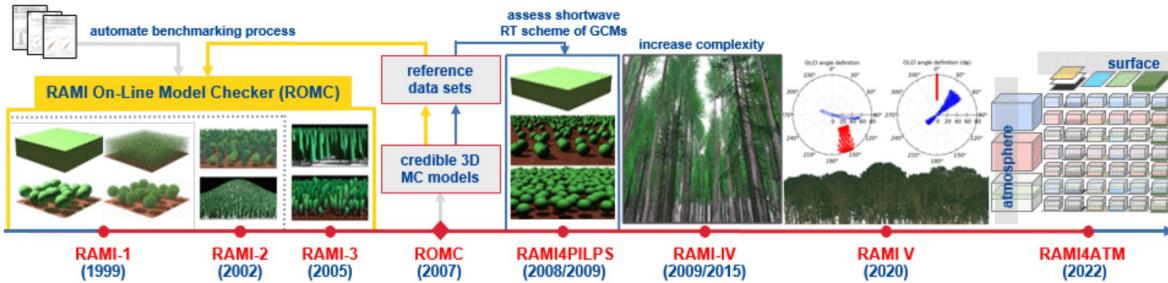


Fig 1: the figure shows all RAMI phases from the beginning (evolution from 1999 until 2022).
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Figure 7: Evolution of the RAMI initiative from 1999 to 2022. Timeline showing progression through RAMI phases: RAMI-1 (1999) for basic benchmarking, RAMI-2 (2002) for expanded scenarios, RAMI-3 (2005) for 3D heterogeneous scenes, ROMC (2007) for online model checker, RAMI4PILPS (2008/2009) coupling with land surface models, RAMI-IV (2009/2015) for realistic forest scenes, RAMI-V (2020) for comprehensive validation, and RAMI4ATM (2022) for atmospheric coupling. Source: https://rami-benchmark.jrc.ec.europa.eu/_www/index.php

- **Realistic scenes:** Laser-scanned forests, heterogeneous landscapes
- **Multi-scale challenges:** Leaf-to-landscape scaling tests

Participating Models:

Over 30 RTMs have participated in RAMI exercises, including DART, FLIGHT, FRT, RAYTRAN, Sprint, SCOPE, and librat. Results have driven substantial improvements in model accuracy and efficiency.

RAMI Best Practices

RAMI exercises revealed common issues:

- **Interpolation errors** in tabulated optical properties
- **Insufficient angular sampling** for anisotropic scattering
- **Numerical precision** problems in multi-scattering calculations
- **Boundary condition** artifacts at scene edges

Modern models incorporate fixes for these issues, but users should remain aware of potential limitations.

6 The DART Model: A Comprehensive 3D RTM

Among canopy-level RTMs, DART (Discrete Anisotropic Radiative Transfer) stands out for its comprehensiveness, computational efficiency, and active development (Gastellu-Etchegorry et al. 2017).

6.1 Key Features

1. Multiple Computational Modes:

DART offers three ray-tracing engines optimized for different applications (Figure 8):

- **DART-FT (Flux Tracking)**: Discrete ordinates method, fast for large scenes, good for satellite simulations
- **DART-RC (Ray Carlo)**: Forward Monte Carlo, accurate for complex geometry, suitable for airborne sensing
- **DART-Lux**: Bi-directional path tracing, highest accuracy for detailed 3D scenes, optimal for UAV/TLS simulation

2. Comprehensive Product Suite:

- **Optical**: BRF at any wavelength, any view angle
- **Thermal**: Brightness temperature accounting for 3D structure
- **LiDAR**: Full-waveform airborne, TLS, and mobile laser scanning
- **Radiative budget**: 3D voxel grid of absorbed/transmitted radiation
- **Fluorescence**: Solar-induced chlorophyll fluorescence (SIF)

3. Integrated Leaf Model:

PROSPECT is built into DART, enabling seamless simulation from biochemical traits to canopy reflectance. Users can specify C_{ab} , C_{ar} , C_w , etc., and DART automatically computes leaf optical properties.

4. Atmosphere Modeling:

DART couples canopy and atmosphere radiative transfer, simulating:

- Gas absorption (H_2O , O_2 , O_3 , CO_2)
- Aerosol scattering (multiple aerosol models)
- Top-of-atmosphere (TOA) and bottom-of-atmosphere (BOA) products
- Atmospheric correction via inversion

5. Flexible Scene Construction:

Users can build scenes using:

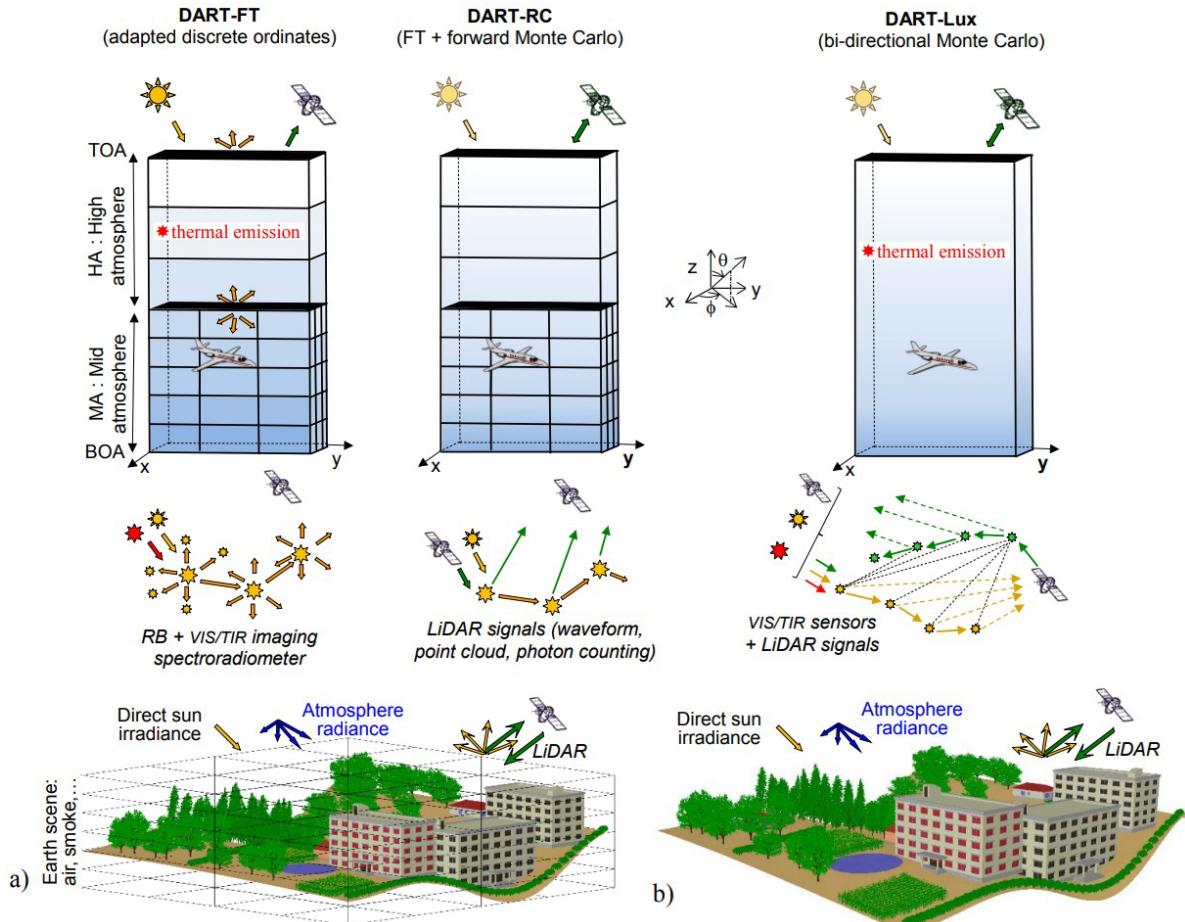


Figure 8: DART model architecture showing three computational modes. Left: DART-FT using adapted discrete ordinates with voxelized atmosphere and scene. Center: DART-RC using forward Monte Carlo ray tracing with photon tracking. Right: DART-Lux using bi-directional path tracing with explicit triangle meshes. All modes simulate optical, thermal, and LiDAR products for natural and urban landscapes. Source: DART User Manual - https://dart.omp.eu/Public/documentation/contenu/documentation/DART_User_Manual.pdf

- **3D geometric objects:** Import OBJ/PLY meshes from TLS, photogrammetry, or modeling software
- **Voxel grids:** Define LAI and optical properties per voxel
- **Turbid medium:** Quick parametric description for homogeneous stands
- **Mixed representations:** Combine approaches (e.g., explicit crowns + turbid understory)

6.2 DART Advantages and Limitations

7 Advantages

Comprehensive Capabilities:

- Simulate almost any remote sensing scenario
- Optical, thermal, LiDAR in one framework
- Natural and urban landscapes

Computational Efficiency:

- Highly optimized code (C++/CUDA)
- Parallelized (multi-core CPU, GPU acceleration)
- Large, detailed scenes feasible on desktop computers

Active Development:

- Regular updates with new features
- Optimization ongoing
- Responsive development team

Validated Accuracy:

- Consistently performs well in RAMI exercises
- Peer-reviewed and widely used in literature

Strong Community Support:

- Active user forum
- Comprehensive manual (600+ pages)
- Regular training workshops (2-3 per year)
- Prepared tutorials and example scenes

8 Disadvantages

Steep Learning Curve:

- Complex graphical interface with hundreds of parameters
- Overwhelming for new users
- Requires understanding of radiative transfer theory

Parameterization Challenges:

- Requires detailed input data (optical properties, structure)
- Many parameters create opportunity for errors
- Sensitivity to some parameters not always intuitive

Computational Demands:

- Despite optimization, complex 3D scenes still take hours
- Large LUTs require significant storage and computation time
- GPU acceleration helps but not always available

Product Interpretation:

- Rich output requires expertise to interpret correctly
- Multiple products can be confusing
- Units, coordinate systems need attention

Software Maturity:

- Some features still experimental
- Occasional bugs (though rapidly fixed)
- Documentation sometimes lags new features

💡 Getting Started with DART

For newcomers to DART:

1. **Start Simple:** Begin with abstract scenes (homogeneous canopy) before attempting complex forests
2. **Use Tutorials:** Work through provided examples in the DART manual
3. **Attend Training:** DART summer schools offer hands-on guidance
4. **Engage Community:** Post questions on the forum—developers and experienced users respond quickly
5. **Validate Incrementally:** Compare simulations with field measurements at each step
6. **Leverage Tools:** Use DART's built-in tools (database manager, 3D viewer, sequence

launcher) to streamline workflows

9 Vegetation Traits Retrieval

The primary application of RTMs in ecosystem monitoring is retrieving biophysical and biochemical traits from remote sensing imagery. Unlike empirical methods that rely on statistical correlations, RTM-based retrieval has a physical foundation, making it more robust across different ecosystems, sensors, and viewing conditions (Dorigo et al. 2007).

9.1 Retrieval Workflow Overview

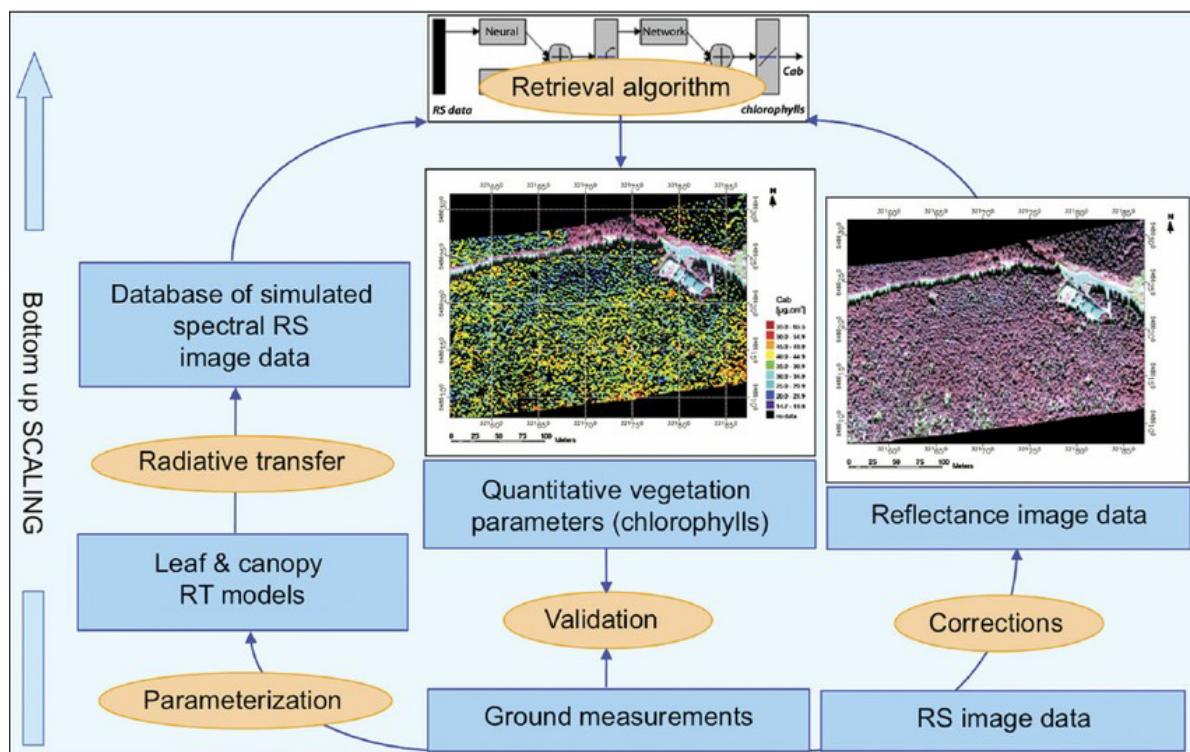


Figure 9: Vegetation traits retrieval workflow. The process flows from bottom to top: (1) Leaf & canopy RT models are parameterized with ground measurements, (2) Radiative transfer simulations generate a database of spectral signatures for quantitative vegetation parameters (chlorophylls shown as example), (3) Retrieval algorithm compares this database with reflectance image data (after corrections), (4) Validation using ground measurements confirms accuracy. The workflow represents bottom-up scaling from leaf to canopy level. Source: Malenovský et al. (2009)

Figure 9 illustrates the complete RTM-based retrieval workflow (Malenovský et al. 2013). The process involves:

1. **Parameterization:** Field measurements provide inputs for leaf and canopy RT models
2. **Database generation:** RTM simulations create a Look-Up Table (LUT) of spectra for different trait combinations
3. **Image matching:** Retrieval algorithms compare observed spectra with the LUT database
4. **Validation:** Retrieved traits are compared with independent field measurements

This approach enables quantitative trait estimation from spectral data, bridging the gap between remote sensing observations and ecosystem properties.

9.2 Choosing the Right Approach

Before starting a retrieval study, several key questions determine the appropriate RTM complexity (Gastellu-Etchegorry et al. 2017):

What type of remote sensing data will be analyzed?

- **Sensor platform:** Satellite, airborne, or UAV
- **Data type:** Reflectance (BRF), point cloud, thermal imagery
- **Resolution:** Spatial (pixel size) and spectral (number/width of bands)
- **Ecosystem type:** Forest, agricultural field, or urban area

What traits need to be retrieved?

- **Biochemical traits:** Chlorophyll content, carotenoids, water content, dry matter
- **Structural traits:** LAI, canopy cover, tree height, crown dimensions
- **Other properties:** Absorbed PAR, biomass, species composition

Example decision:

For high-resolution UAV hyperspectral imagery (5 cm pixels, 32-52 nm bands) over a forest site, with the goal of retrieving biochemical traits like chlorophyll and carotenoids:

→ **3D complex RTM** (like DART) is required

The fine spatial resolution captures individual tree crowns and intra-crown variation, requiring explicit 3D representation. The hyperspectral data contains detailed biochemical information that can be extracted through physics-based modeling.

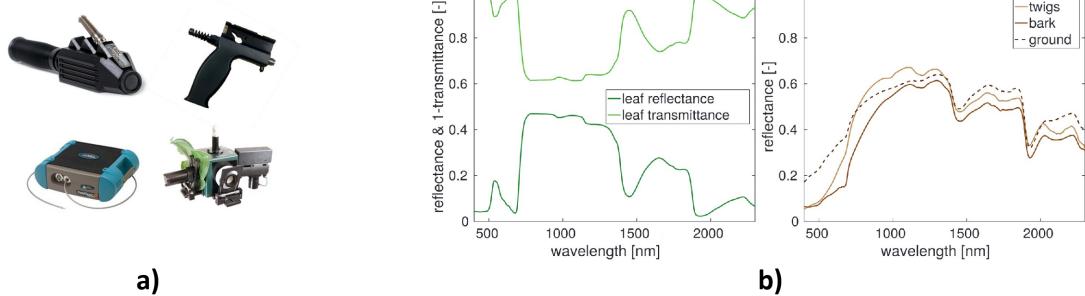


Figure 10: Field measurement equipment and spectral data. (a) Spectroradiometers with contact probe (bark), pistol grip (ground), and integrating sphere (leaves). (b) Example spectral reflectance and transmittance curves for leaves (green wavelengths show characteristic chlorophyll absorption), and reflectance spectra for twigs/bark (brown) and ground (dashed black). These field measurements provide the optical properties needed to parameterize RTMs.

9.3 Field Data Collection

Accurate RTM parameterization requires comprehensive field measurements (Janoutová et al. 2021):

Optical Properties:

Measure reflectance and transmittance of all scene elements using spectroradiometers:

- **Leaves:** Integrating sphere for both reflectance and transmittance
- **Bark/trunks:** Contact probe for reflectance
- **Ground:** Pistol grip for soil/litter reflectance

Biochemical Analysis:

Laboratory measurements complement spectral data:

- Chlorophyll content (a and b)
- Carotenoid content
- Water and dry matter content
- These can be used directly in PROSPECT model or to validate leaf spectra

Structural Parameters:

Document canopy architecture:

- LAI (Leaf Area Index) and canopy cover
- Tree positions, heights, crown dimensions

- For detailed studies: Terrestrial laser scanning (TLS) for 3D structure

Alternative Data Sources:

When field measurements are limited, use databases:

- TRY database for plant traits
- ICP Forest, ICOS networks for forest plots
- Published spectral libraries for common species

9.4 Scene Configuration

RTM simulations require careful scene parameterization. General parameters apply to all RTM studies (Gastellu-Etchegorry et al. 2017):

Site Location and Sun Geometry:

- **Coordinates:** Latitude and longitude of study site
- **Date and time:** Determine solar zenith and azimuth angles
 - Can be calculated using solar position algorithms (available in Python/R libraries or online tools)
- **Sensor geometry:** View zenith and azimuth angles for BRF simulation

Spectral and Spatial Configuration:

- **Spectral bands:** Match your actual sensor (e.g., hyperspectral: 400-2500 nm, $\Delta = 5-10$ nm)
- **Pixel resolution:** Match image resolution (e.g., 5 cm for UAV, 10 m for Sentinel-2)

9.5 3D Forest Scene Parameters

For forest ecosystems, additional structural detail is required (Hanousek et al. 2024):

Two Approaches:

1. **General scene** (for LUT generation):
 - Smaller scene extent (e.g., 30m \times 30m)
 - Multiple structural combinations (varying LAI and canopy cover)
 - Captures full variability of the forest type
 - Requires more simulations but creates comprehensive LUT
2. **Exact scene** (for site-specific simulation):
 - Larger scene matching study site

- Fewer combinations (only realistic structural parameters for that site)
- Includes all factors affecting spectra at specific location
- Used when you have detailed field data for one location

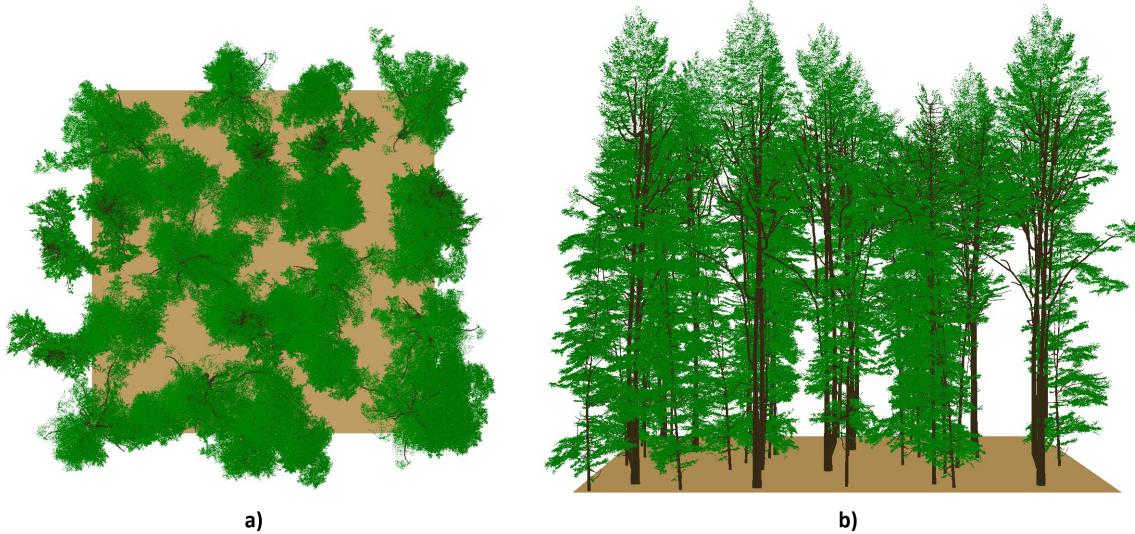


Figure 11: 3D forest scene representation in DART. (a) Top-down view showing tree positions in systematic grid pattern with brown ground visible between crowns. (b) Oblique 3D view showing detailed tree architecture with individual crowns, trunks, and branches. Scene dimensions are 30m × 30m with trees positioned to achieve target canopy cover and LAI. Source: Hanousek et al. (2024)

Scene Components (Figure 11):

- **Tree positions:** Define x, y coordinates for each tree
- **3D tree models:** Import detailed geometry (from DART database, TLS, or modeling software)
- **Optical properties:** Assign leaf, bark, and ground spectra to scene elements
- **Structural parameters:** Set LAI, canopy cover through tree density and size

LUT vs. Site-Specific Simulation

The DART tutorial you've completed shows how to create and run a single simulation with specific parameters. For trait retrieval, researchers typically create Look-Up Tables (LUTs) by running hundreds or thousands of simulations with systematically varied parameters. However, as a tutorial user, you'll likely work with **pre-generated LUTs** created by research groups. Your role is understanding:

- How LUTs are structured (traits → spectra relationships)

- How to apply retrieval algorithms to your imagery
- How scene parameters affect simulated spectra

Creating large LUTs requires computational resources and expertise typically available in research labs.

9.6 Look-Up Table Design

LUTs form the core of RTM-based retrieval, systematically exploring the relationship between traits and spectra (Hanousek et al. 2024):

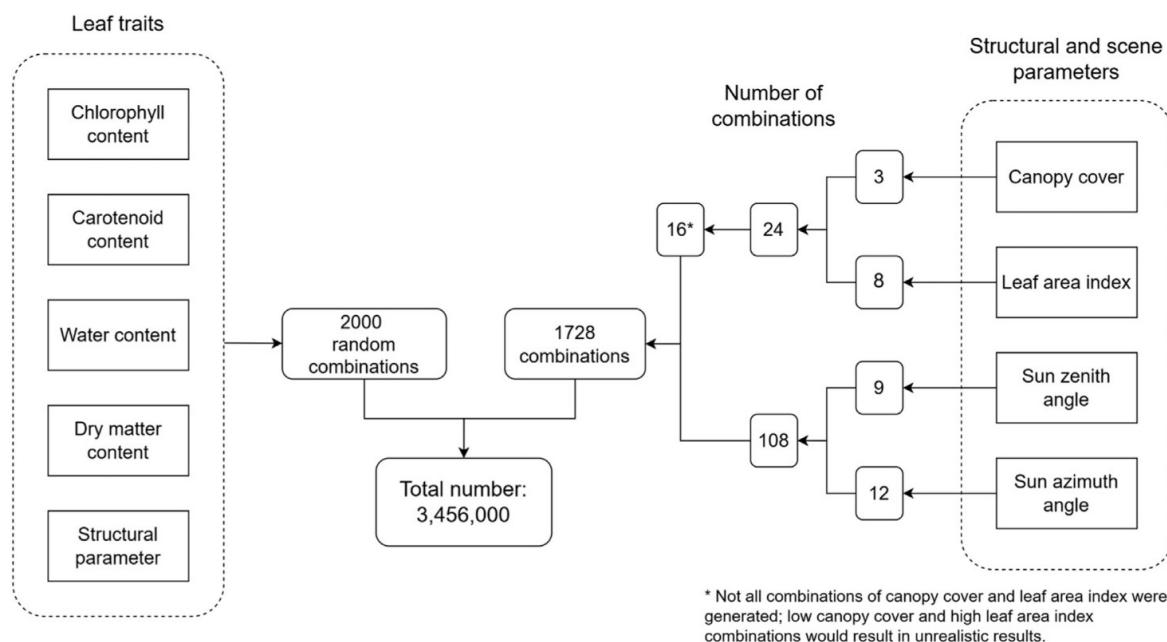


Figure 12: Look-Up Table generation strategy. Flow diagram shows how leaf traits (chlorophyll, carotenoids, water, dry matter, structural parameter) combine with structural and scene parameters (canopy cover, LAI, sun zenith angle, sun azimuth angle). Total possible combinations: 3.5 million. Through random sampling (2000 combinations) and filtering for realism (1728 combinations remain after excluding unrealistic scenarios like low canopy cover with high LAI), these are organized into trait groups, then expanded across structural-geometric combinations, yielding a final database of 3,456,000 spectra. Source: Hanousek et al. (2024)

Figure 12 shows a sophisticated LUT design for broadleaf forests. Key principles:

Parameter Space Definition:

- **Leaf biochemistry:** Chlorophyll, carotenoids, water, dry matter ranges based on literature and field data
- **Canopy structure:** LAI, canopy cover ranges representing forest variability
- **Geometric conditions:** Solar angles covering different times of day and seasons

Sampling Strategy:

- Start with all possible combinations (millions)
- Apply realistic constraints (e.g., high LAI requires sufficient canopy cover)
- Use random or Latin Hypercube Sampling for efficient space coverage
- Result: Computationally feasible database (thousands to millions of spectra)

Practical Considerations:

For the tutorial user, the key insight is that trait retrieval requires this systematic parameter exploration. Pre-generated LUTs available from research groups save you from running thousands of DART simulations yourself.

9.7 Processing Simulated Images

Before using LUT spectra for retrieval, simulated images must be processed consistently with real imagery (Hanousek et al. 2024):

Critical Step: Masking (Figure 13)

Apply identical masking to simulated and observed imagery:

- **Include:** Sunlit leaf pixels (target for trait retrieval)
- **Exclude:**
 - Deep shadows (too dark, unreliable spectra)
 - Trunks and branches (woody parts have different optical properties)
 - Ground/soil (background contamination)
 - Mixed pixels (boundaries, reduce ambiguity)

Spectral Processing:

- Convolve high-resolution RTM spectra to sensor bands
- Apply atmospheric correction (if needed)
- Extract mean/median spectra from masked regions

Consistency is Key:

Whatever processing you apply to simulated images (masking, smoothing, aggregation) must be applied identically to real images. Inconsistency is a major source of retrieval errors.

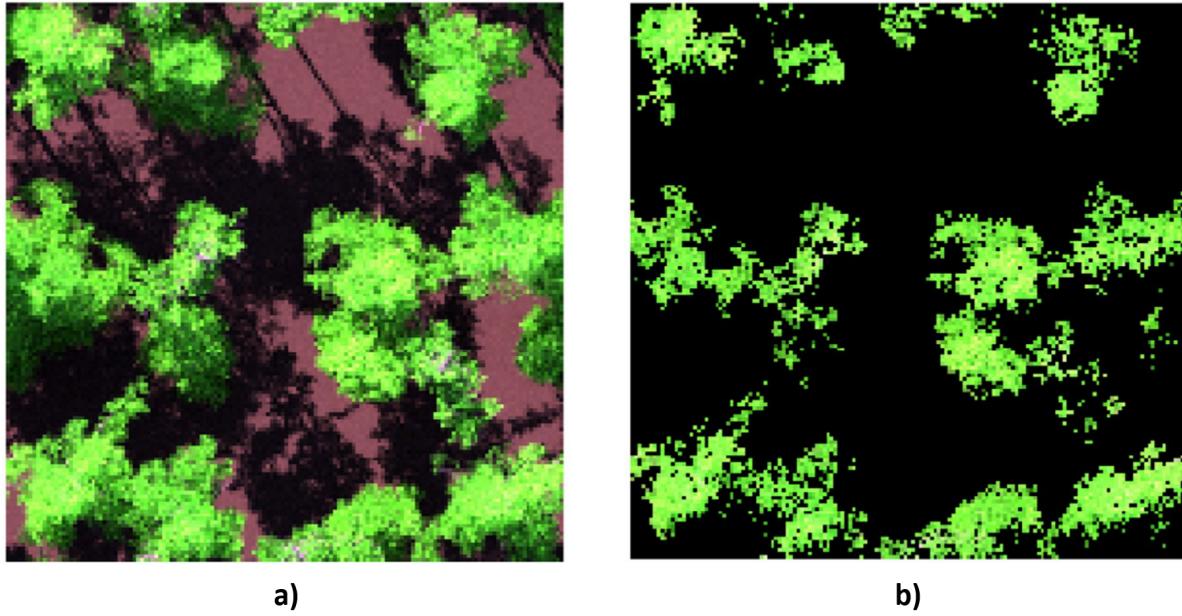


Figure 13: Processing of simulated DART imagery. (a) RGB composite showing forest canopy with green sunlit leaves, dark shadows between crowns, and brown/purple mixed pixels at crown edges. (b) Binary mask isolating only sunlit leaf pixels (bright green) while excluding shadows, woody parts, and ground. This masking ensures that LUT spectra represent the same surface types as pixels used in retrieval from real imagery.
Source: Hanousek et al. (2024)

9.8 Applying Retrieval to Real Imagery

With a prepared LUT and processed imagery, retrieval algorithms estimate traits by matching observed spectra to the database (Slanináková et al. 2025):

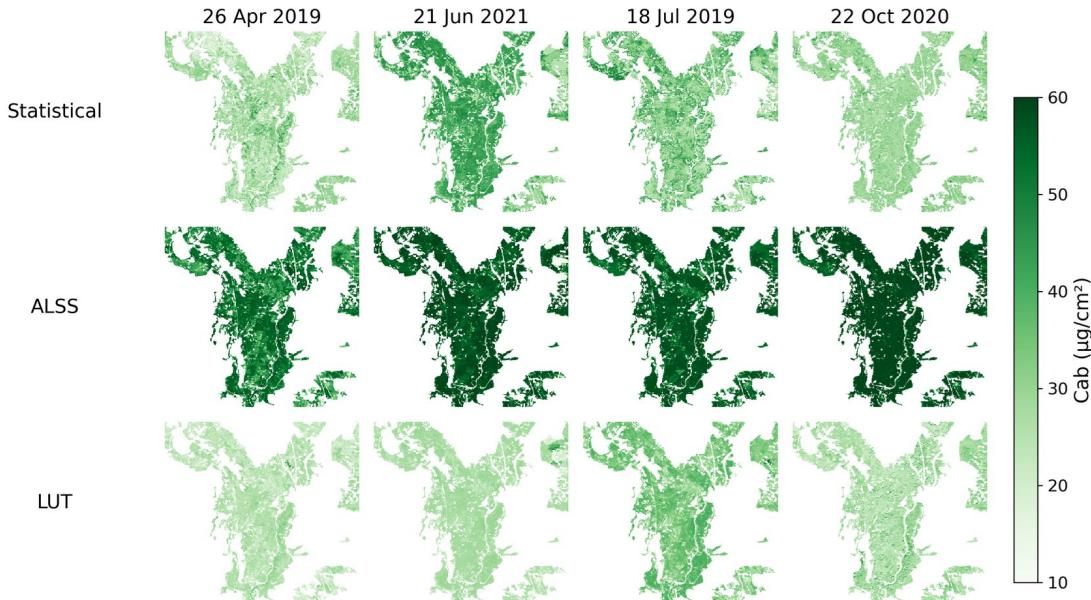


Figure 14: Comparison of retrieval methods on seasonal hyperspectral imagery. Three rows show results from Statistical (empirical regression), ALSS (Adaptive LUT Subset Selection), and LUT (full Look-Up Table matching) methods. Four columns represent different dates: 26 Apr 2019, 21 Jun 2021, 18 Jul 2019, and 22 Oct 2020. Color scale shows chlorophyll content (Cab) from 10-60 $\mu\text{g}/\text{cm}^2$. All methods capture seasonal variation (low chlorophyll in spring/autumn, high in summer) and spatial patterns (individual tree crowns), but differ in smoothness and detail. ALSS balances accuracy and robustness. Source: Slanináková et al. (2025)

Common Retrieval Approaches:

1. **Statistical methods:** Empirical regression calibrated on field samples
 - Fast, simple, but site and sensor-specific
 - Shown in left column of Figure 14
2. **Full LUT matching:** Find closest spectrum in entire database
 - Most detail, but sensitive to model errors
 - Shown in right column of Figure 14

3. Adaptive LUT Subset Selection (ALSS): Iteratively narrow search space

- Balances detail and robustness (Slanináková et al. 2025)
- Shown in middle column of Figure 14
- Recommended for operational use

Key Observations from Figure 14:

- All methods capture seasonal dynamics (spring → summer → autumn)
- Spatial patterns reveal individual tree differences
- ALSS provides intermediate detail level, reducing noise while preserving important variation
- Choice of method depends on priorities: speed vs. detail vs. robustness

Validation:

Always compare retrieved traits against independent field measurements:

- Calculate RMSE, R^2 , and bias
- Check for systematic errors across trait range
- Validate on multiple dates to assess temporal consistency

! Practical Retrieval Workflow

As a DART tutorial user, your practical retrieval workflow will likely be:

1. **Obtain imagery:** Acquire hyperspectral/multispectral data of your study site
2. **Pre-process:** Atmospheric correction, geometric correction, masking
3. **Access LUT:** Use pre-generated LUT from collaborators or published studies
4. **Apply retrieval:** Use provided algorithms (Python/R scripts) to match imagery to LUT
5. **Validate:** Compare with field measurements

You typically won't generate your own LUT unless working on a long-term research project with computational resources. The DART tutorial teaches you the principles behind LUT generation so you understand the retrieval process.

10 Challenges and Future Directions

While RTM-based retrieval is powerful, several challenges remain (Malenovský et al. 2021):

Current Limitations:

- **Computational cost:** Generating large LUTs requires significant time (days to weeks)

- **Parameterization burden:** Accurate simulations need extensive field data
- **Model assumptions:** Even 3D RTMs simplify reality (leaf clumping, bark texture, soil variability)
- **Scale mismatches:** Bridging leaf-level measurements to landscape imagery
- **Validation scarcity:** Limited sites with comprehensive trait measurements

Emerging Solutions:

- **Machine learning emulators:** Neural networks approximate RTM behavior, reducing computation by orders of magnitude (Verrelst et al. 2015)
- **TLS integration:** Laser scanning provides unprecedented structural detail (Janoutová et al. 2021)
- **Multi-sensor fusion:** Combine optical, LiDAR, and thermal for comprehensive characterization
- **Uncertainty quantification:** Bayesian approaches provide confidence intervals, not just point estimates
- **Operational pipelines:** Automated systems for routine trait mapping from satellites

Vision for the Future:

The next decade will see RTM-based trait products become operational:

- Real-time mapping from satellite imagery
- Global coverage at moderate resolution (10-30 m)
- Integration with ecosystem models for carbon cycle and climate studies
- Biodiversity monitoring through spectral diversity proxies

Achieving this requires continued collaboration among remote sensing scientists, ecologists, and operational agencies.

11 Summary and Key Takeaways

12 RTM Fundamentals

- **Physical basis:** RTMs simulate light-vegetation interactions using physics, not correlations
- **Scales:** From leaf (micrometers) to landscape (kilometers)
- **Models:** 1D (homogeneous), 3D geometrical (tree shapes), 3D complex (explicit structure)
- **Products:** BRF, thermal, LiDAR, radiative budget

13 DART Model

- **Comprehensive:** Optical, thermal, and LiDAR in one framework
- **Validated:** Strong performance in RAMI benchmarks
- **Flexible:** Multiple scene representations, 3D object import
- **Practical:** Tutorial teaches basic workflow for forest scenes

Best for high-resolution studies requiring detailed 3D representation.

14 Retrieval Workflow

1. **Field measurements:** Optical properties, traits, structure
2. **Scene setup:** Configure RTM with realistic parameters
3. **LUT generation:** Systematic parameter exploration (typically done by research labs)
4. **Image processing:** Consistent masking and spectral processing
5. **Retrieval:** Match observed spectra to LUT database
6. **Validation:** Compare with independent field data

Critical: Consistency between simulated and observed data processing.

15 Practical Advice

- **Tutorial users:** Focus on understanding principles, use pre-generated LUTs
- **Researchers:** Generate custom LUTs for specific ecosystems/sensors
- **Validation essential:** Always compare retrievals with field measurements
- **Method selection:** ALSS balances accuracy and robustness
- **Start simple:** Master basic simulations before complex scenes

16 Future Outlook

- **Emulation:** ML-accelerated RTMs for operational speed
- **TLS integration:** Explicit 3D structure from laser scanning
- **Multi-sensor fusion:** Optical + LiDAR + thermal
- **Uncertainty:** Probabilistic retrievals with confidence
- **Global products:** Routine trait mapping from satellites

RTMs enable quantitative ecosystem monitoring from space.

17 Glossary of Key Terms

 Expand Glossary

Absorption coefficient: Wavelength-specific rate at which a material absorbs photons, typically per unit path length.

BRDF (Bidirectional Reflectance Distribution Function): Mathematical function describing how reflectance varies with all possible illumination and viewing geometries.

BRF (Bidirectional Reflectance Factor): Ratio of reflected radiance to that from an ideal Lambertian reflector under the same illumination, for specific sun-sensor geometry.

Canopy: Collective foliage and structure of vegetation over an area.

DART: Discrete Anisotropic Radiative Transfer model, a comprehensive 3D RTM.

Flux: Radiant energy passing through a surface per unit time and area (W/m^2).

Hotspot: Peak in reflectance when sun and sensor are aligned (zero phase angle), due to absence of shadows.

Irradiance: Radiant power incident on a surface per unit area (W/m^2).

LAI (Leaf Area Index): One-sided leaf area per unit ground area (m^2/m^2).

LUT (Look-Up Table): Database of simulated spectra and corresponding trait values for inversion.

Monte Carlo: Ray-tracing method using random sampling to simulate photon paths.

Phase angle: Angle between sun, target, and sensor directions.

PROSPECT: Plate model for simulating leaf optical properties from biochemistry.

Radiance: Radiant power per unit solid angle per unit projected area ($\text{W/m}^2/\text{sr}$).

RAMI: RAdiation transfer Model Intercomparison initiative for benchmarking RTMs.

Reflectance: Ratio of reflected to incident radiant flux (dimensionless, 0-1).

RTM (Radiative Transfer Model): Physical model simulating light propagation and interaction in vegetation.

Scattering: Redirection of photons due to interaction with particles or surfaces.

Transmittance: Ratio of transmitted to incident radiant flux (dimensionless, 0-1).

Turbid medium: Approximation of canopy as homogeneous layer with uniformly distributed scatterers.

VZA (View Zenith Angle): Angle between nadir (vertical) and sensor view direction.

18 Additional Resources

💡 Learning Materials

DART Resources:

- [DART Official Website](#): Downloads, manual, forum
- [DART User Manual](#): Comprehensive guide
- DART Summer Schools: Annual training workshops

Key Publications:

- DART model: Gastellu-Etchegorry et al. (2017)
- Retrieval methods: Dorigo et al. (2007), Verrelst et al. (2019)
- LUT design: Hanousek et al. (2024)
- ALSS method: Slanináková et al. (2025)
- TLS integration: Janoutová et al. (2021)

Software and Tools:

- **DART**: <https://dart.omp.eu/>
- **PROSPECT**: Integrated in DART
- **Retrieval algorithms**: Often provided as Python/R scripts by research groups

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This theoretical background document is designed to accompany practical tutorials on RTM application. For hands-on guidance on using DART for forest scenes, see the companion “DART Forest Scene Setup Tutorial”.