DART simulations of remote sensing observations of Toulouse (VIS/NIR, TIR, LiDAR)

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Technical objective: **to illustrate the use of the DART radiative transfer model to simulate remote sensing observations and radiation budget of cities, and in particular Toulouse, with account of 3D urban architecture.**

Examples of applications:

- **Time series of maps of urban albedo, temperature, evapotranspiration,… using satellite and airborne VIS / TIR observations.**
- **Preparation of satellite missions (e.g., détermination of optimal spectral bands for given local atmospheric conditions and 3D architecture).**
- **Creation of database (images, radiative budget) for AI models.**

Outline

- The DART 3D radiative transfer model

- Inversion of VIS and TIR satellite images

- Simulations of Toulouse

DART

- *Objective*: 3D VIS / TIR radiative budget (absorption, SIF,…) & remote sensing observations (imaging spectro-radiometer, LiDAR) of urban and natural landscapes

- *Development*: **CESBIO** since 1992. **Patented** in 2003. Team : 10 persons.

- *Code*: **C++** (> $5\ 10^5$ lines) + **GUI** (Java) + **Python tools**

Free licenses from Toulouse University

https://dart.omp.eu

DART 5.10.11 V1463. **907 licences UT**: **NASA** (Lidar, RB, SIF), **DLR**, **UZH** (fusion Hyper-Lidar, Ecology), **Reading** (TIR, urban), **ISRO**,…

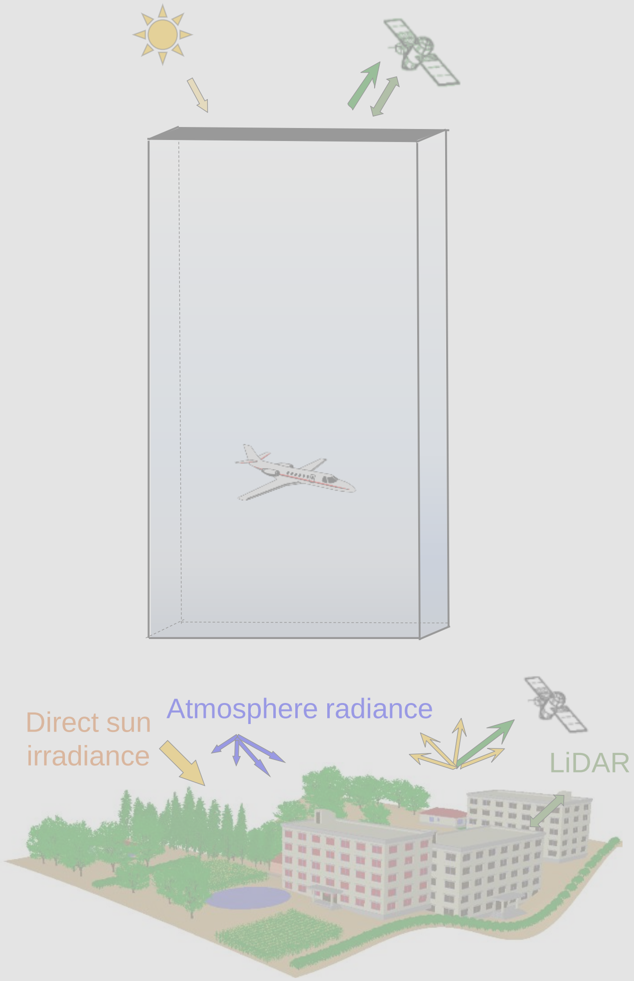
DART

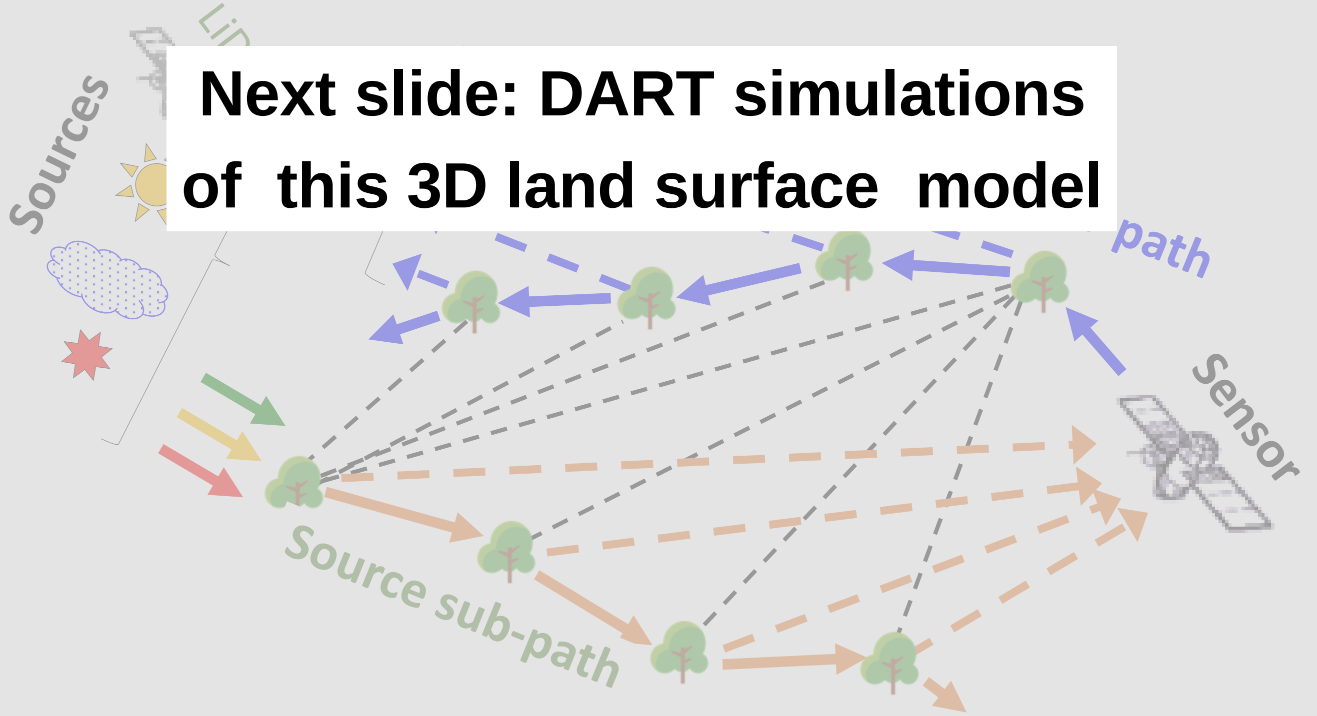
Scene: **turbid / fluid volumes, facets**; voxels not needed

RT modeling: **bi-directional Monte Carlo** (LuxCoreRender)

$\Rightarrow$ Computer time & RAM reduced by 100!

Photons run over **most probable "Source - Sensor" paths**



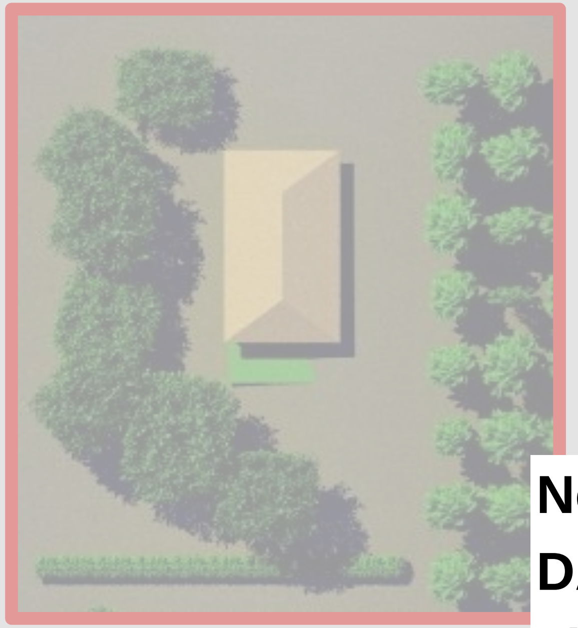


Next slide: DART simulations of this 3D land surface model

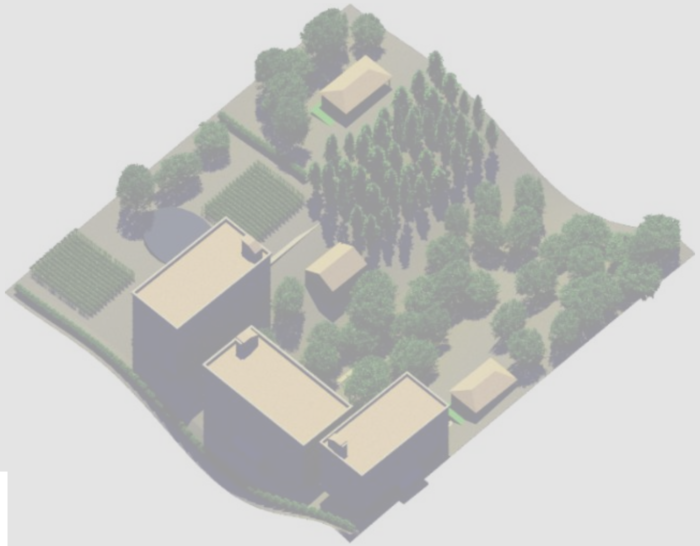
Products: **- VIS TIR hyperspectral images, LiDAR**

- 3D radiation budget (RB)

DART: a few products

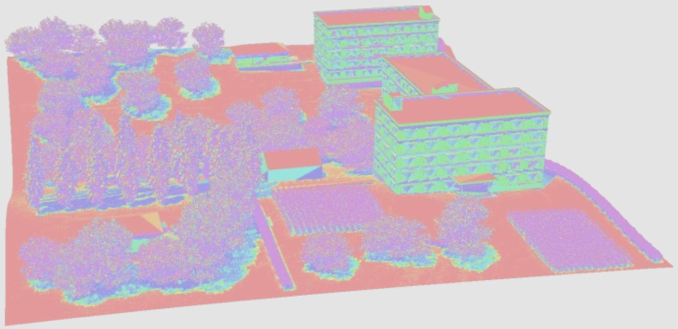


RGB color composite



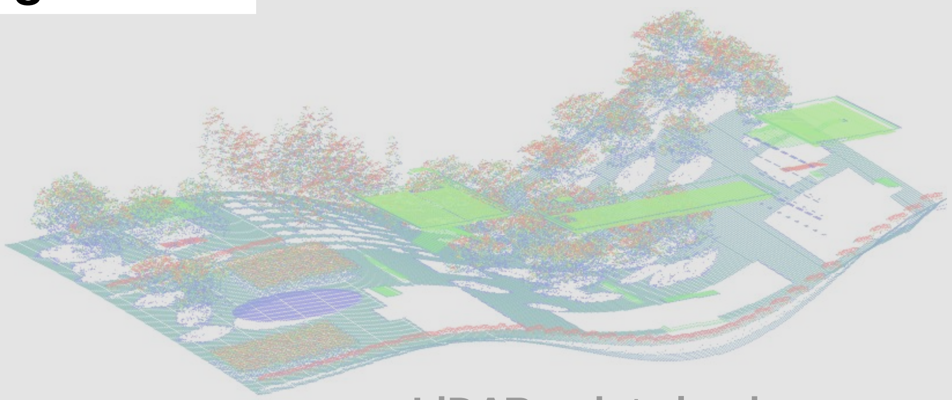
BOA: oblique viewing direction

Next slide: the BRF map, an original DART product, illustrated with a simple scene with specular ground



3D radiation budget: absorption,… per voxel & facet

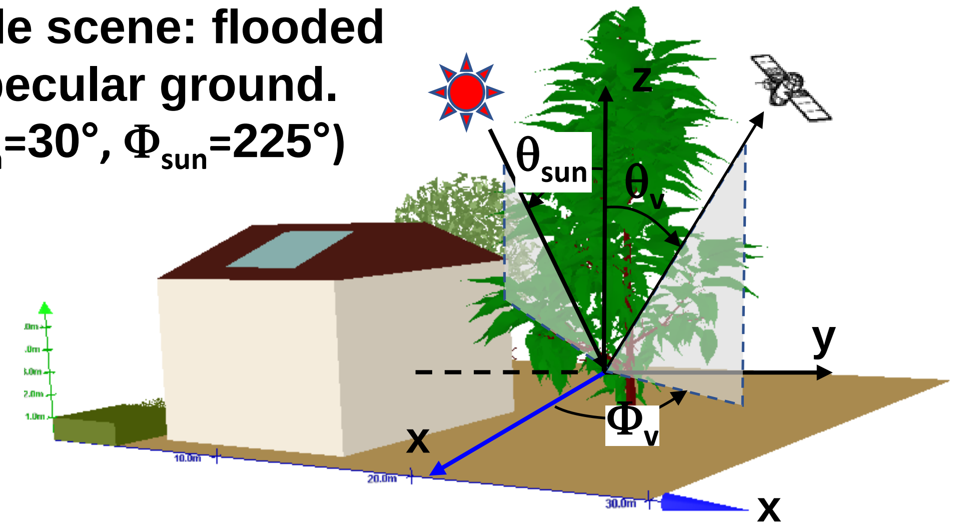
TOA: nadir

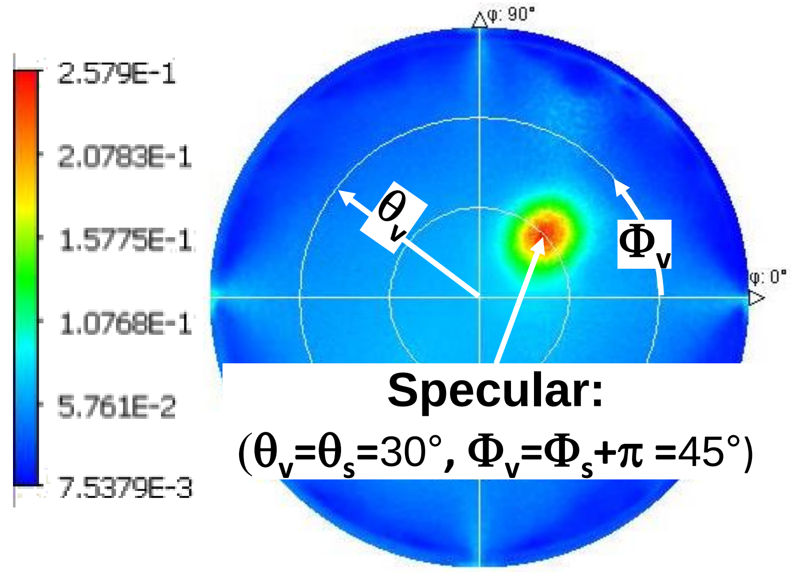


LiDAR point cloud

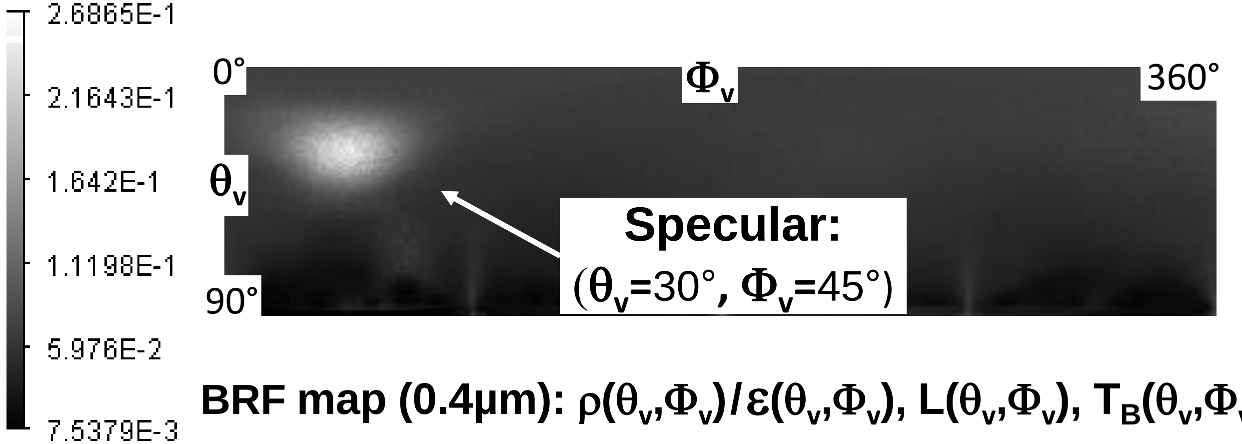
DART: a few products

Simple scene: flooded / specular ground.
(θ_{sun}=30°, Φ_{sun}=225°)





Polar BRF (blue band)



BRF map (0.4µm): $\rho(\theta_v,\Phi_v)/\varepsilon(\theta_v,\Phi_v)$, $L(\theta_v,\Phi_v)$, $T_B(\theta_v,\Phi_v)$

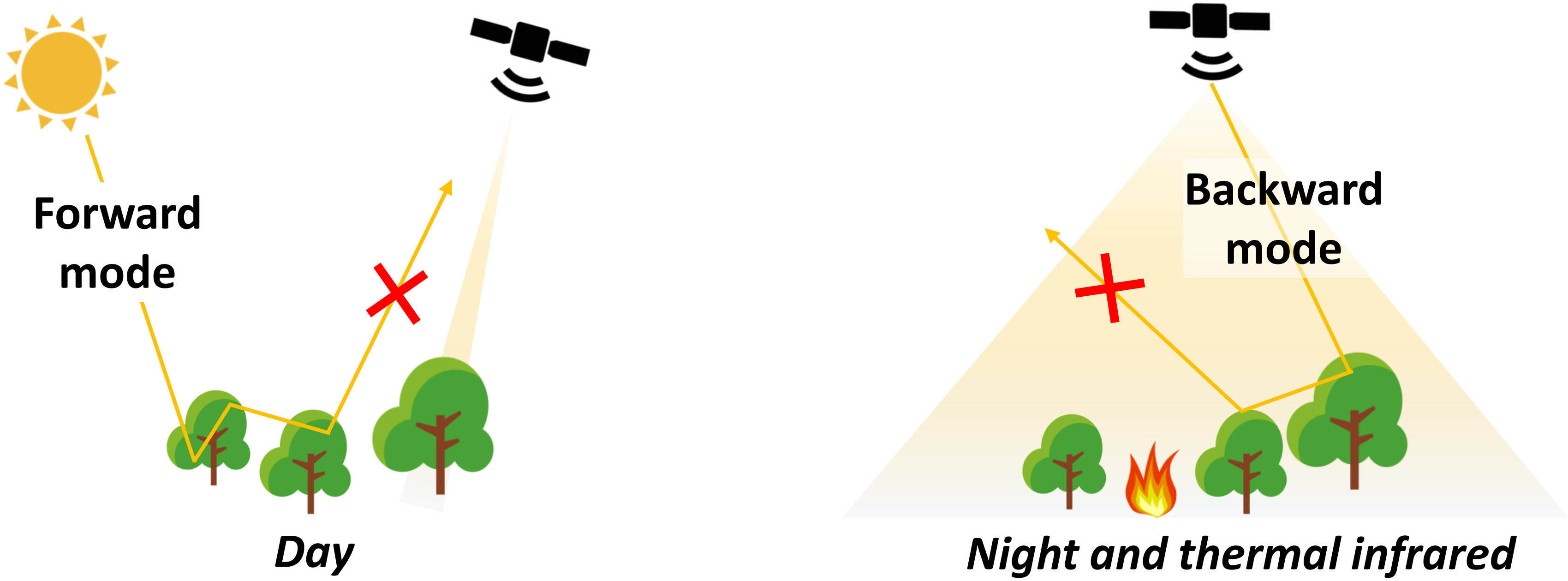
Total, polarized, per light source, per scene element

Integral of BRF map ⇨ **Exitance, Albedo (short waves)**

TIR: LST (Land Surface Temperature) and LSE

Why bi-directional path tracing?

Bidirectional more efficient than forward or backward tracing alone

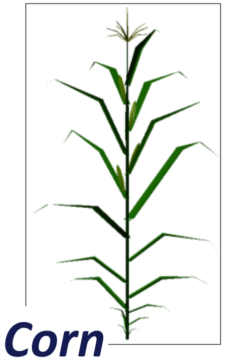


❌ Useless path ⇒ increase of computation time

- Depth-first strategy: ray 100% tracked before next one
- Efficiency "independent" of landscape complexity

⇒ Accuracy + Robustness + Efficiency

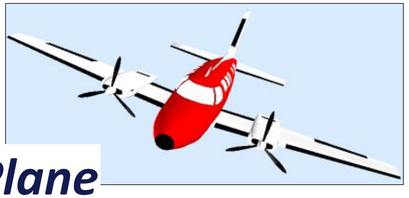
DART: examples of 3D landscape elements that DART imports


Corn


Rice

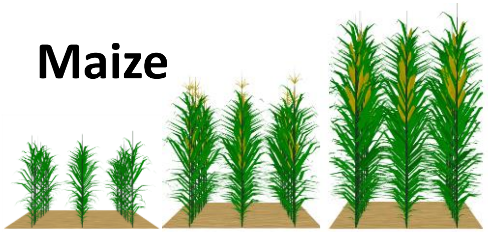

Sunflower

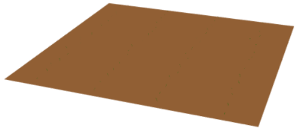

Forest


Plane

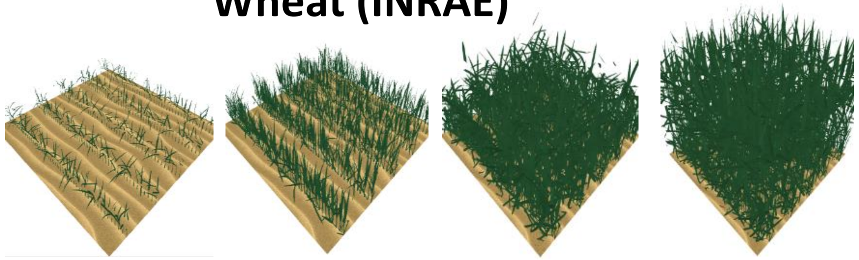

Building

Maize




Time series
R. Demoulin

Wheat (INRAE)

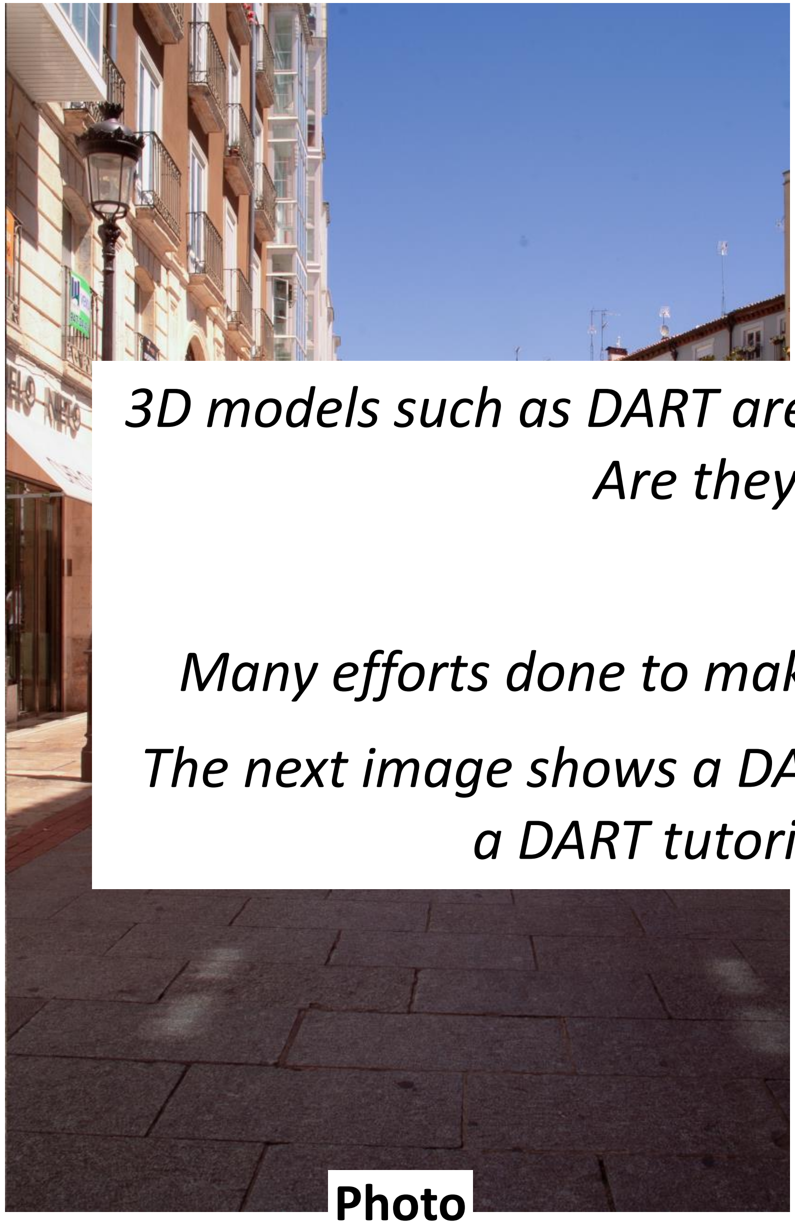



Artificial lights

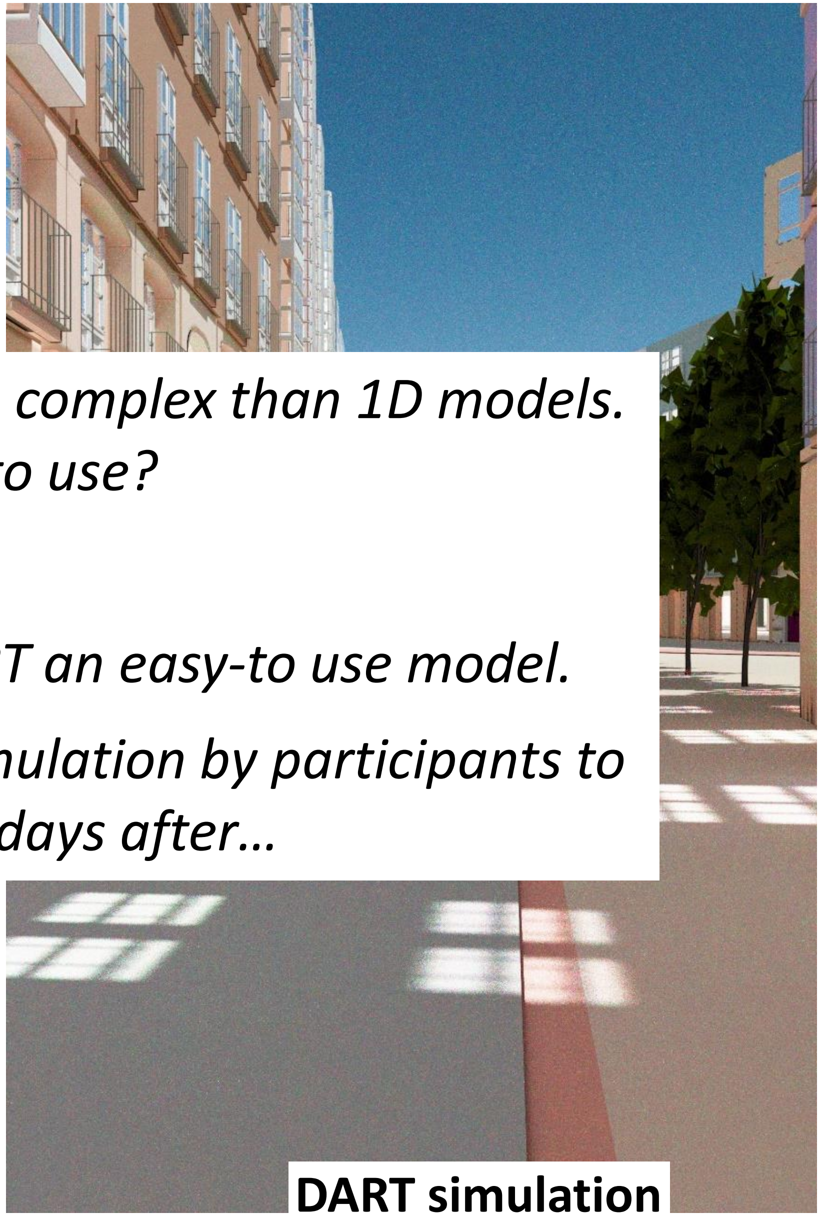
Urban geometric database

DART: urban specular effects

dgranados@ubu.es



Photo



DART simulation

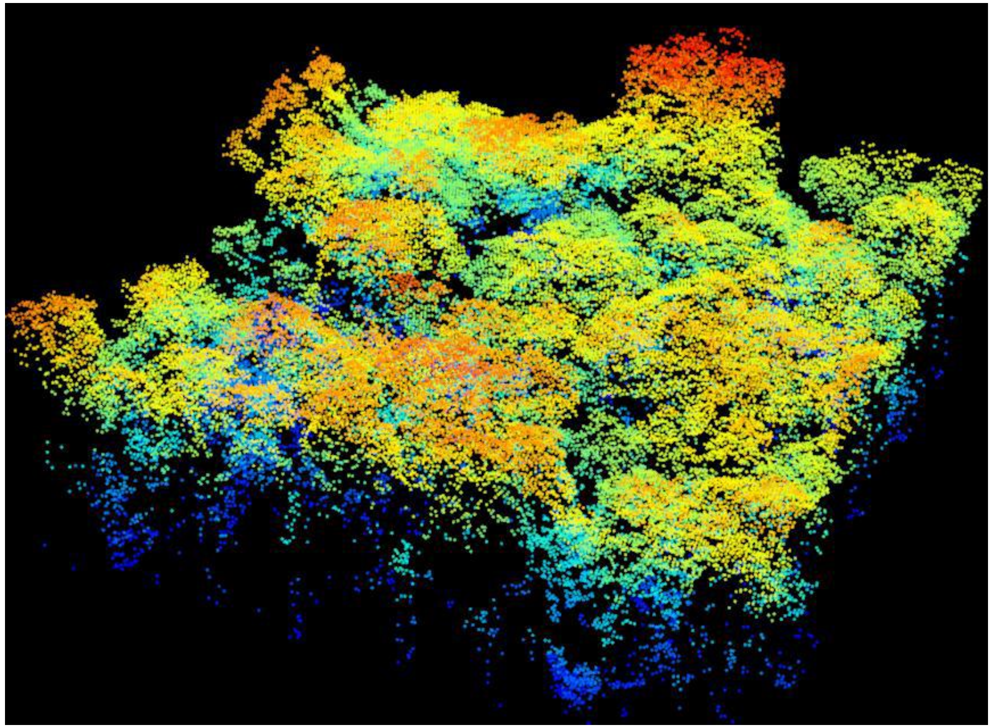
3D models such as DART are more complex than 1D models. Are they easy to use?

Many efforts done to make DART an easy-to use model.

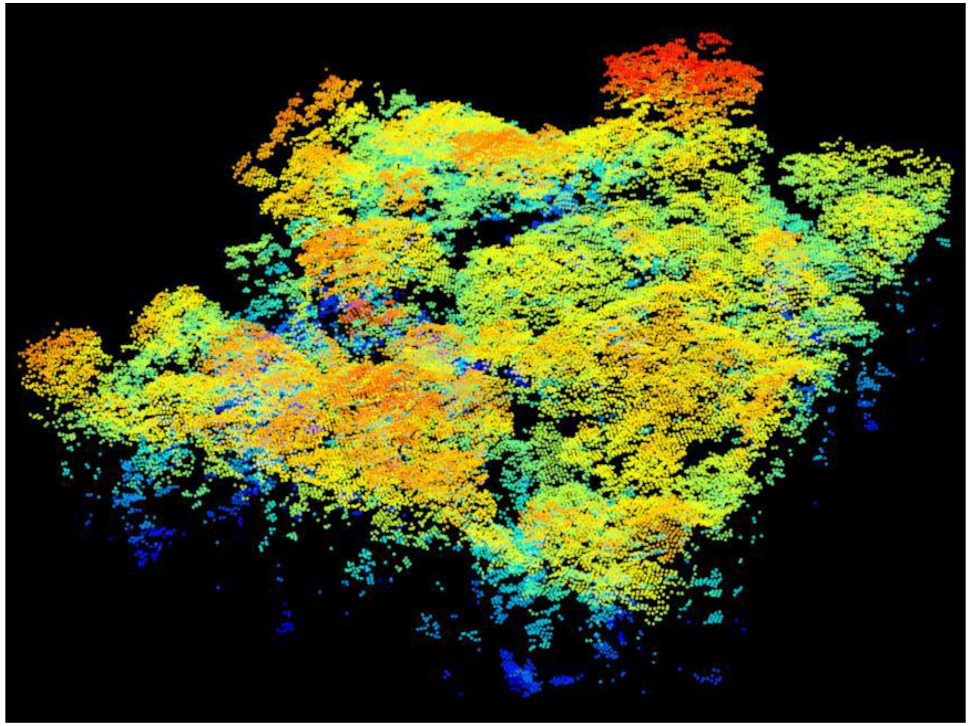
The next image shows a DART simulation by participants to a DART tutorial, 15 days after…

Preparation of satellite LiDAR mission LEAF

Simulation of airborne and satellite LiDAR signals of tropical forest (Paracou, Guyana)



Airborne **Riegl LMS-Q780**



DART: Measurements ⇒ optical properties
TLS ⇒ 3D architecture

(Durrieu et al., 2019; De Boissieu et al., 2023)

DART: original products (in RS models) for better interpretatation of RS observations,...

1) Image per type u of scene element (*e.g.*, roof, street,...) ⇨ intra pixel information

Pixel (i,j) of image of scene element of type u stores only radiation scattered or emitted by elements of the component u of this pixel (i,j). $\sum_u \text{Component u} = \text{Pixel}$

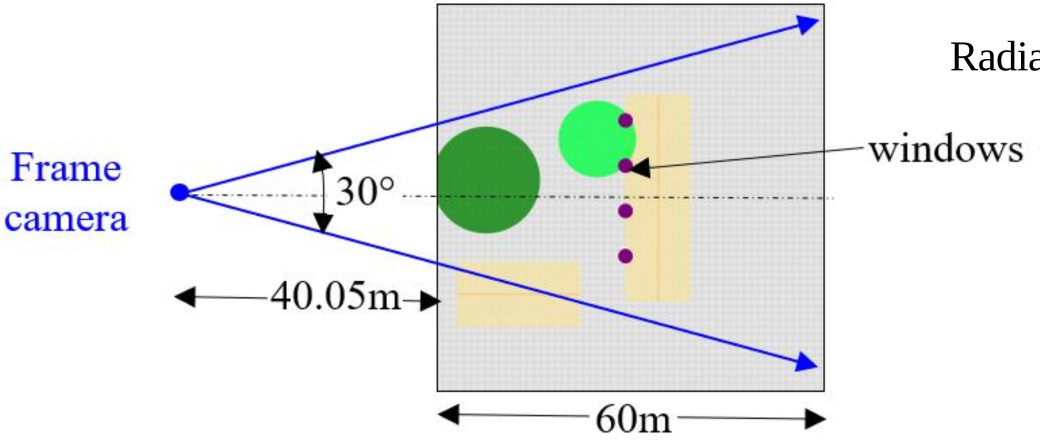
2) Image per light source u (*e.g.*, wall, atmosphere, vegetation,...)

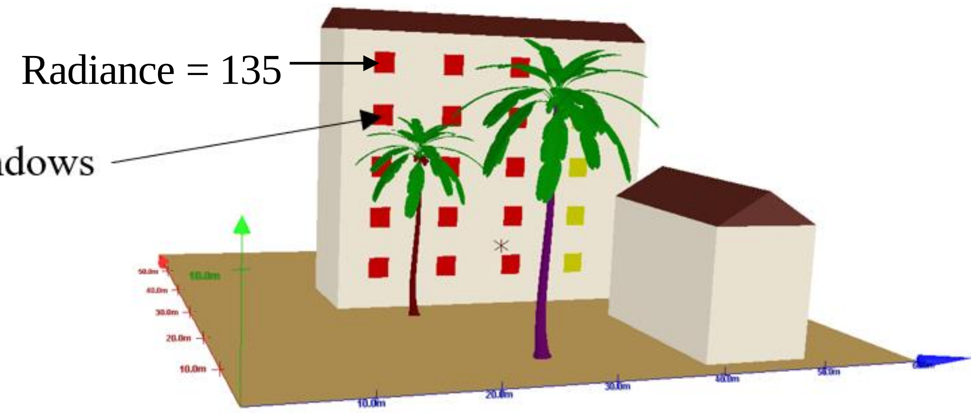
Pixel (i,j) of image of light source of type u stores only radiation caused by the thermal emission of light sources of type u anywhere in the 3D scene.

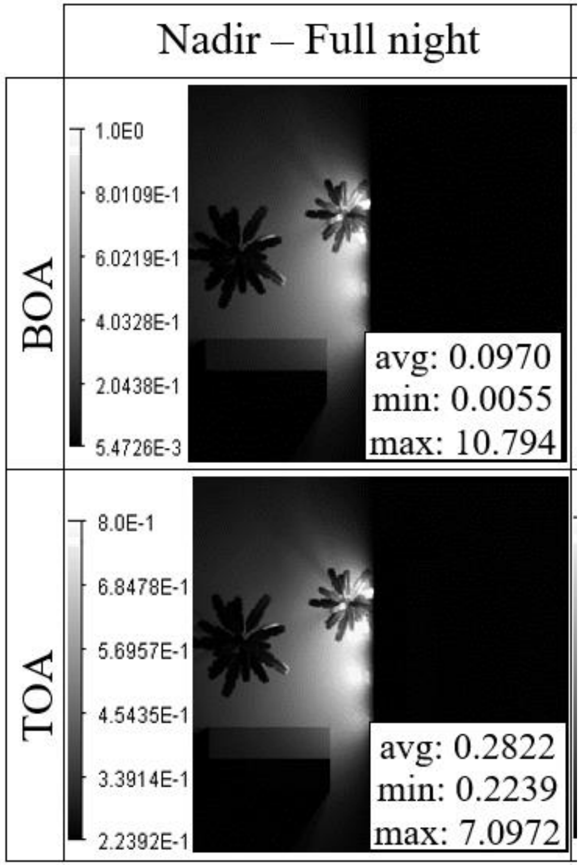
3) Jacobian $J_u(i,j)=\frac{\partial Q(i,j)}{\partial X_u}$ ⇨ Sensitivity study, Error propagation, satellite image inversion,...

Derivative of reflectance, radiance or brightness temperature Q(i,j) at image pixel (i,j) for reflectance, emissivity or thermodynamic temperature X of scene element of type u

Recent: modeling of artificial lights







Two examples of DART-based satellite image inversion

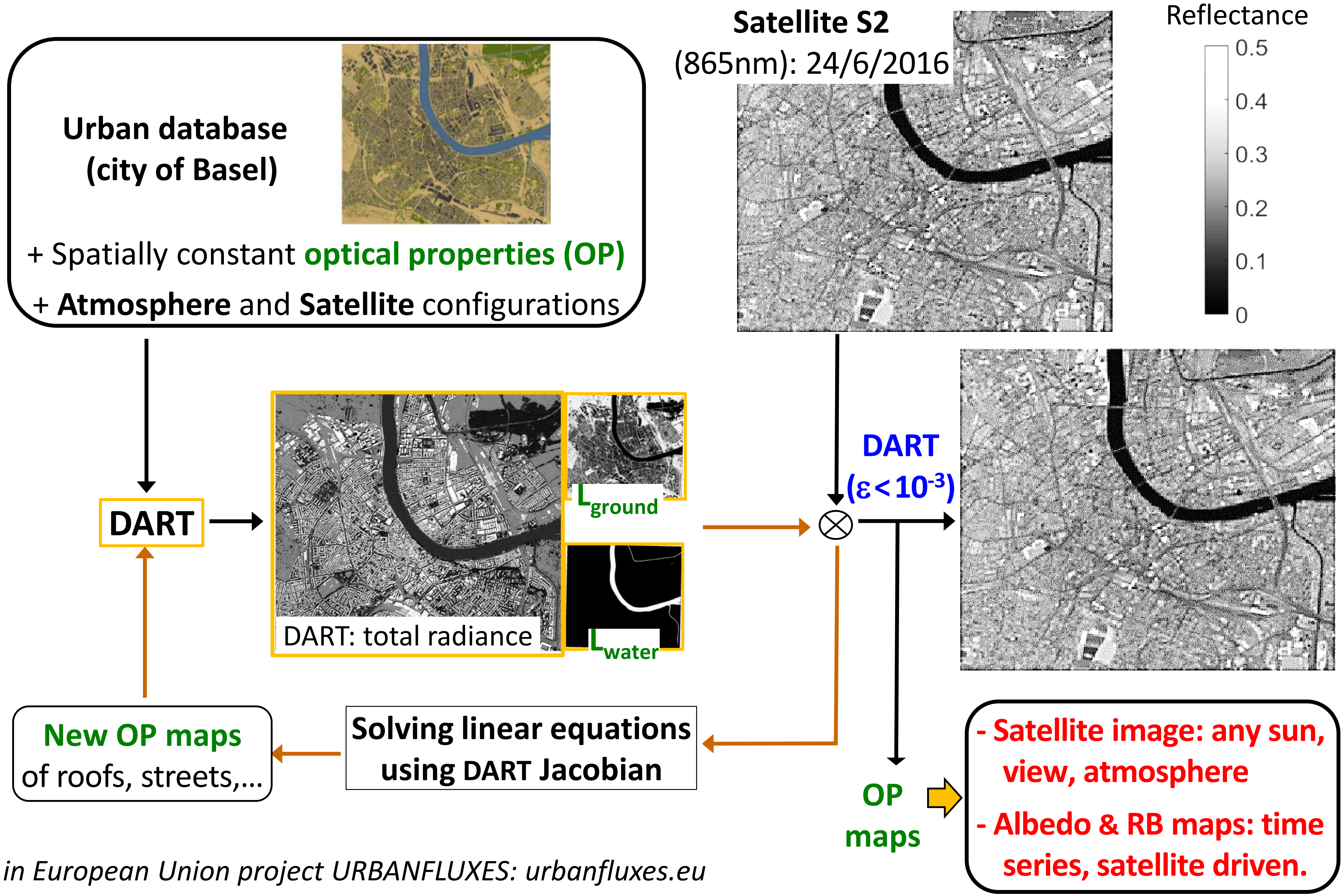
Inversion of satellite images: Basel, Switzerland

Basel geometric database

- **Elements:** buildings, water, vegetation, ground
- **Number of trees** ≈ 78,000
- **Number of facets:** - Urban ≈ 570,000
  - Trees ≈ 11,333,244,000
- **Foliar area volume density** = 0.5 m^{-1} (hypothesis)
- **Size** = 4970 m × 5170 m

Basel high spatial resolution image from Google Earth Engine

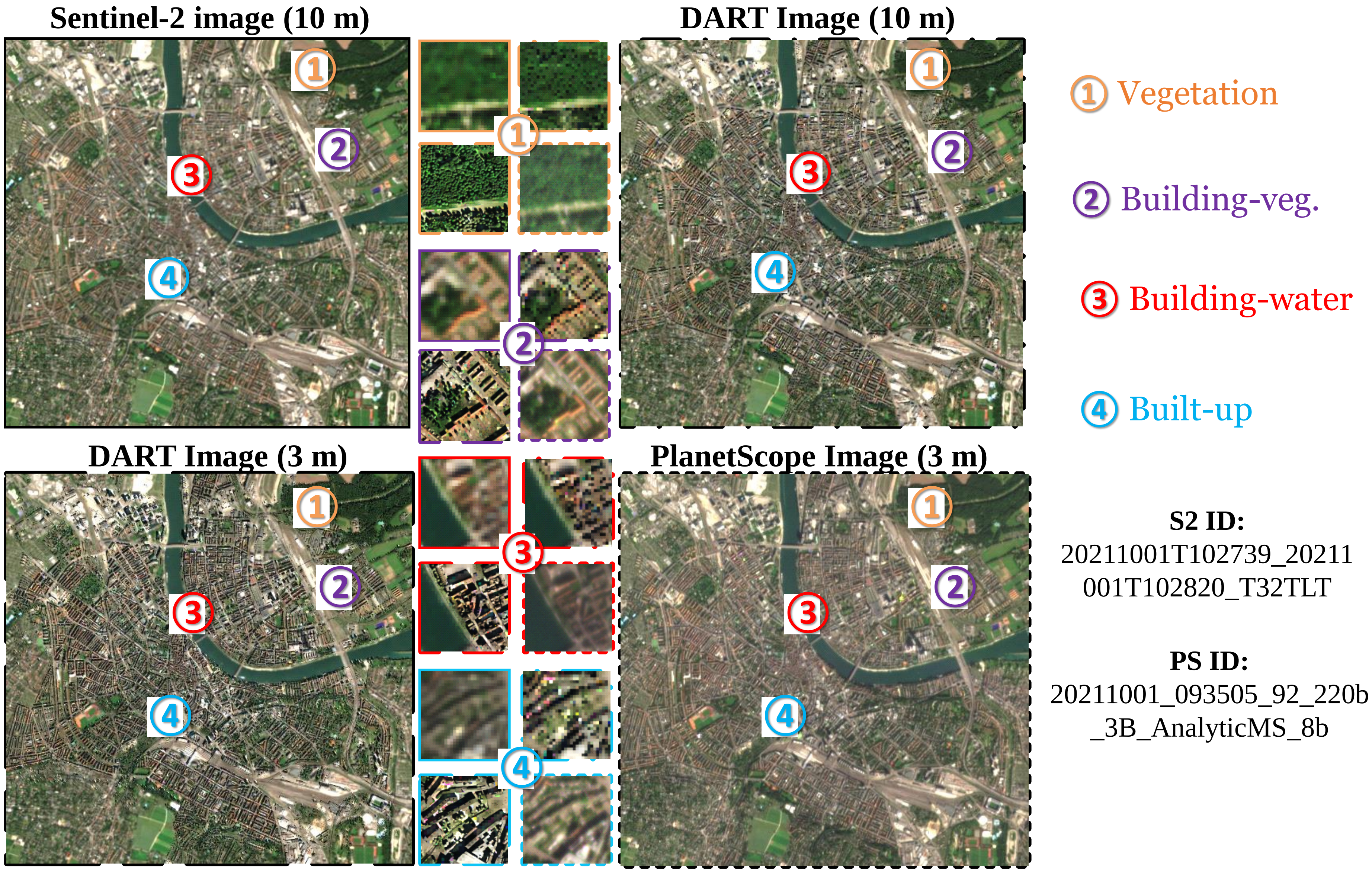
Inversion of short wave satellite images: the approach



European Commission

Initially in European Union project URBANFLUXES: urbanfluxes.eu
for quantifying urban energy budget (N. Chrysoulakis, Z. Mitraka)

Inversion of short wave satellite images: Basel

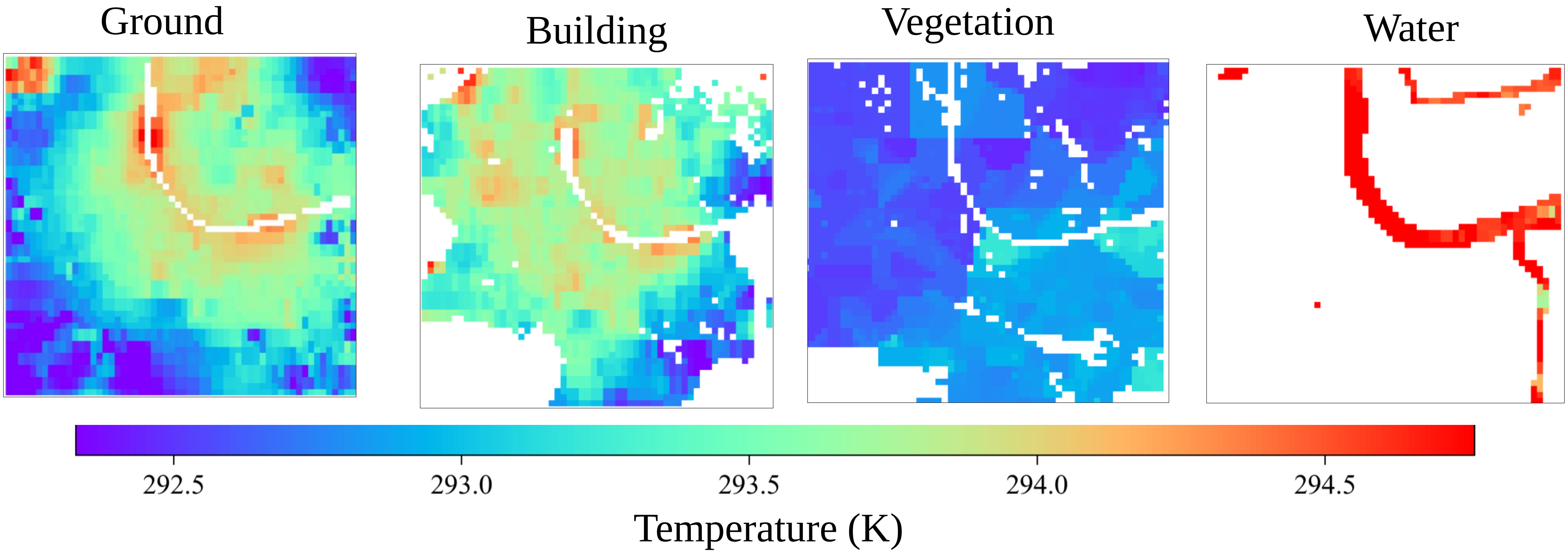


S2 ID:
20211001T102739_20211001T102820_T32TLT

PS ID:
20211001_093505_92_220b_3B_AnalyticMS_8b

Inversion ⇒ possibility of time series of radiative budget at any spatial resolution

Inversion of TIR satellite images: retrieved thermodynamic temperature



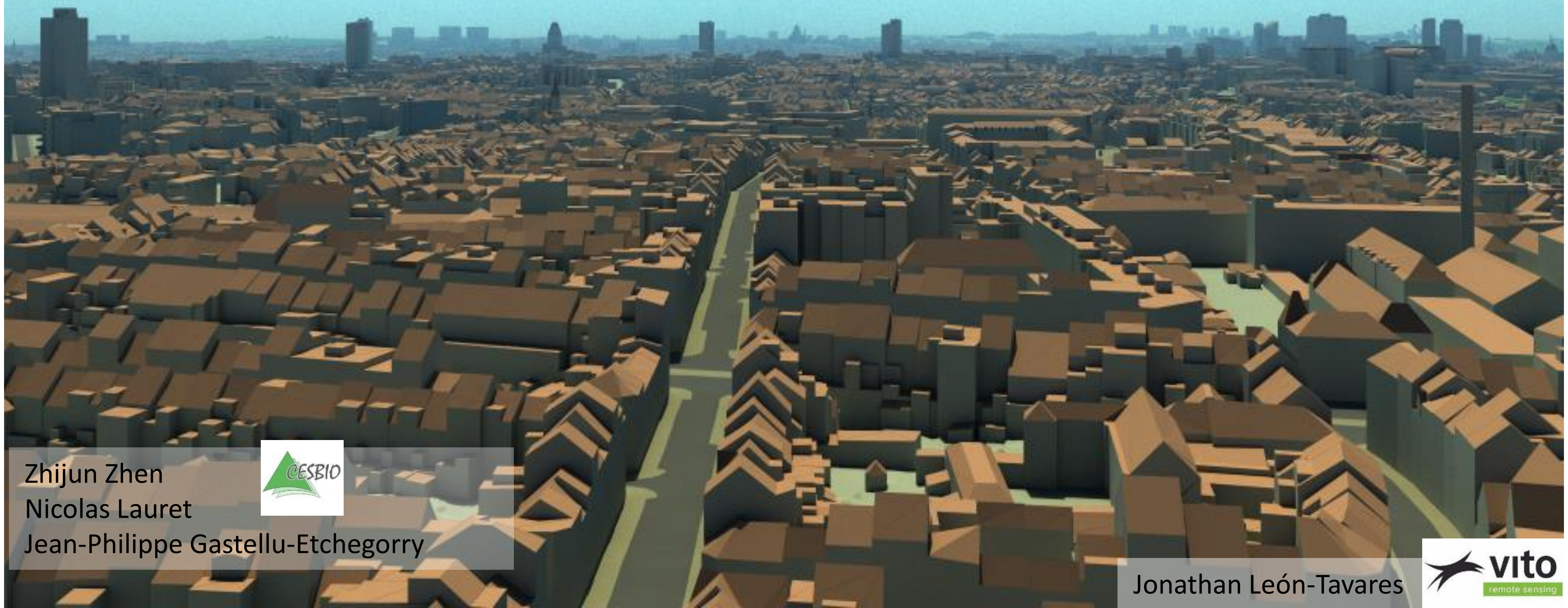
Ground Temperature: mean±std: 293.292±0.571

Building Temperature: mean±std: 293.489±0.419

Vegetation Temperature: means±std: 292.723±0.175

Water Temperature: mean±std: 294.794±0.333

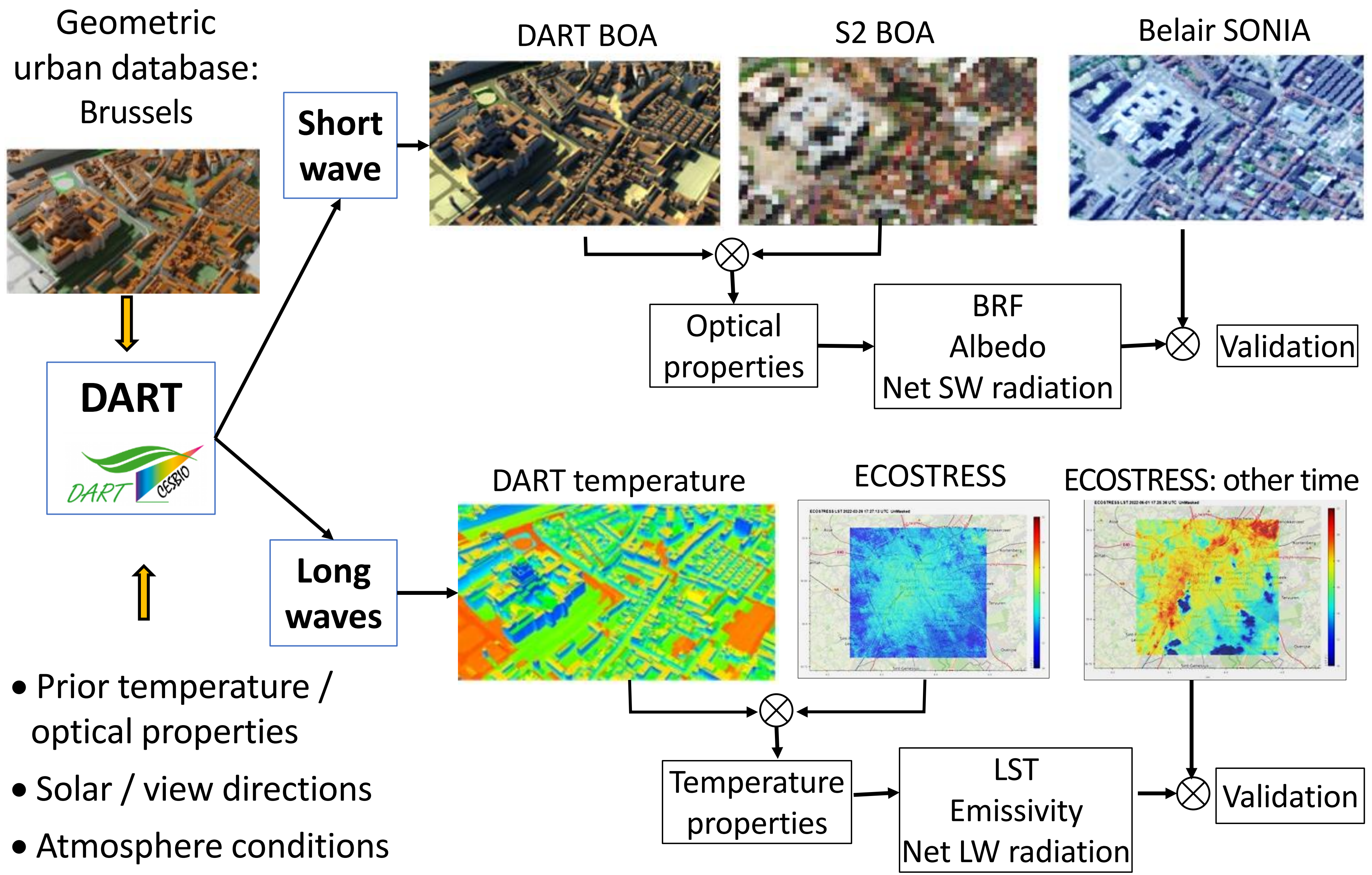
Surface albedo and emissivity for Belgian cities (SuaBe)



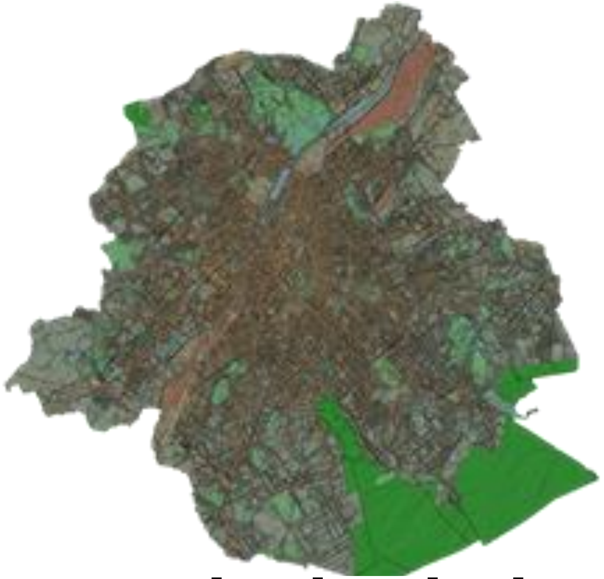
Zhijun Zhen
Nicolas Lauret
Jean-Philippe Gastellu-Etchegorry

Jonathan León-Tavares

SUABE project: Surface albedo & emissivity of Belgian cities



Inversion of satellite images: Brussels, Belgium



Brussels urban database

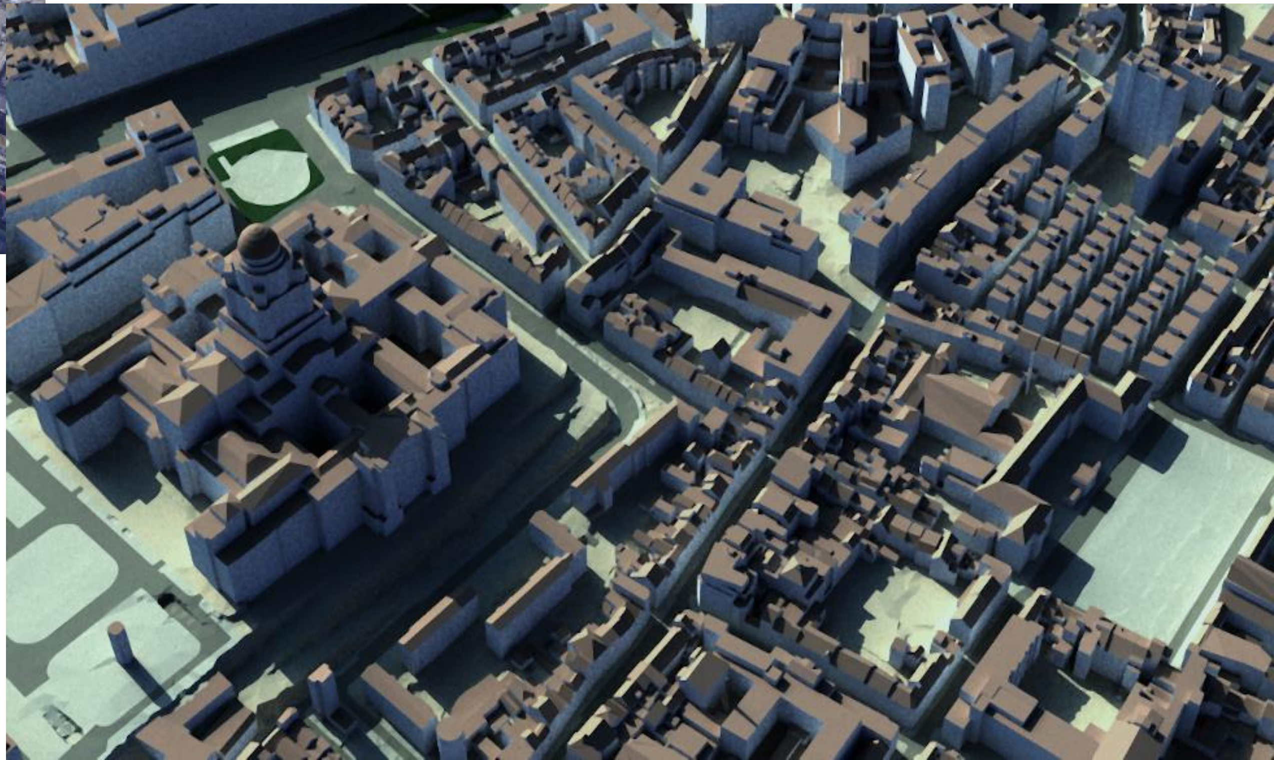
- **Elements:** buildings, water, vegetation, ground
- **Number of trees** ≈ 1,248,000
- **Number of facets: -** Urban ≈ 92,170,000
  - Tree ≈ 13,940,615,000
- **Foliar area volume density** = 1 m^{-1} (hypothesis)
- **Size** = 17 km × 17 km

Brussels high spatial resolution image from Google Earth Engine

SUABE project: Brussels CourtHouse

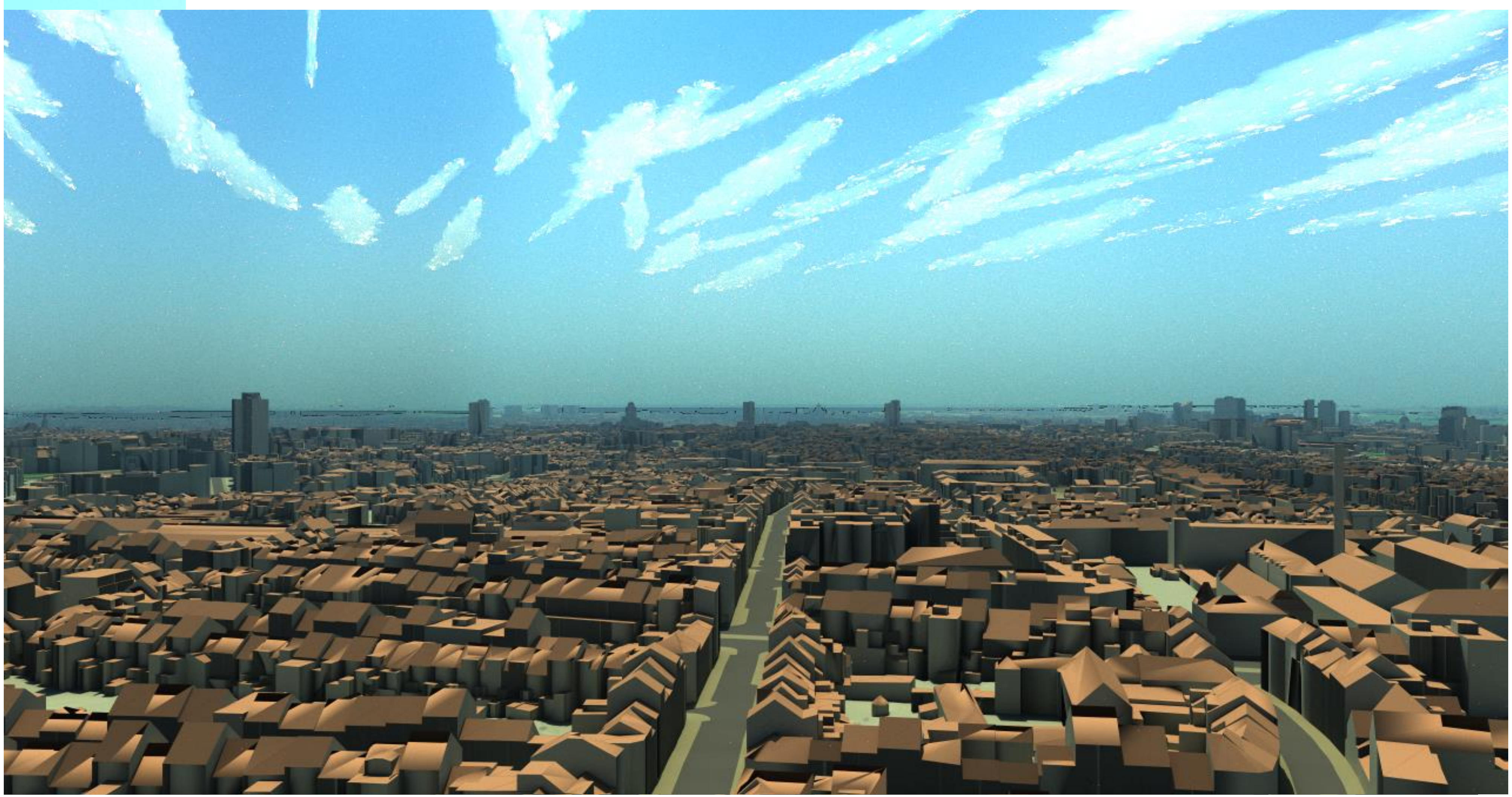
Google map

DART image

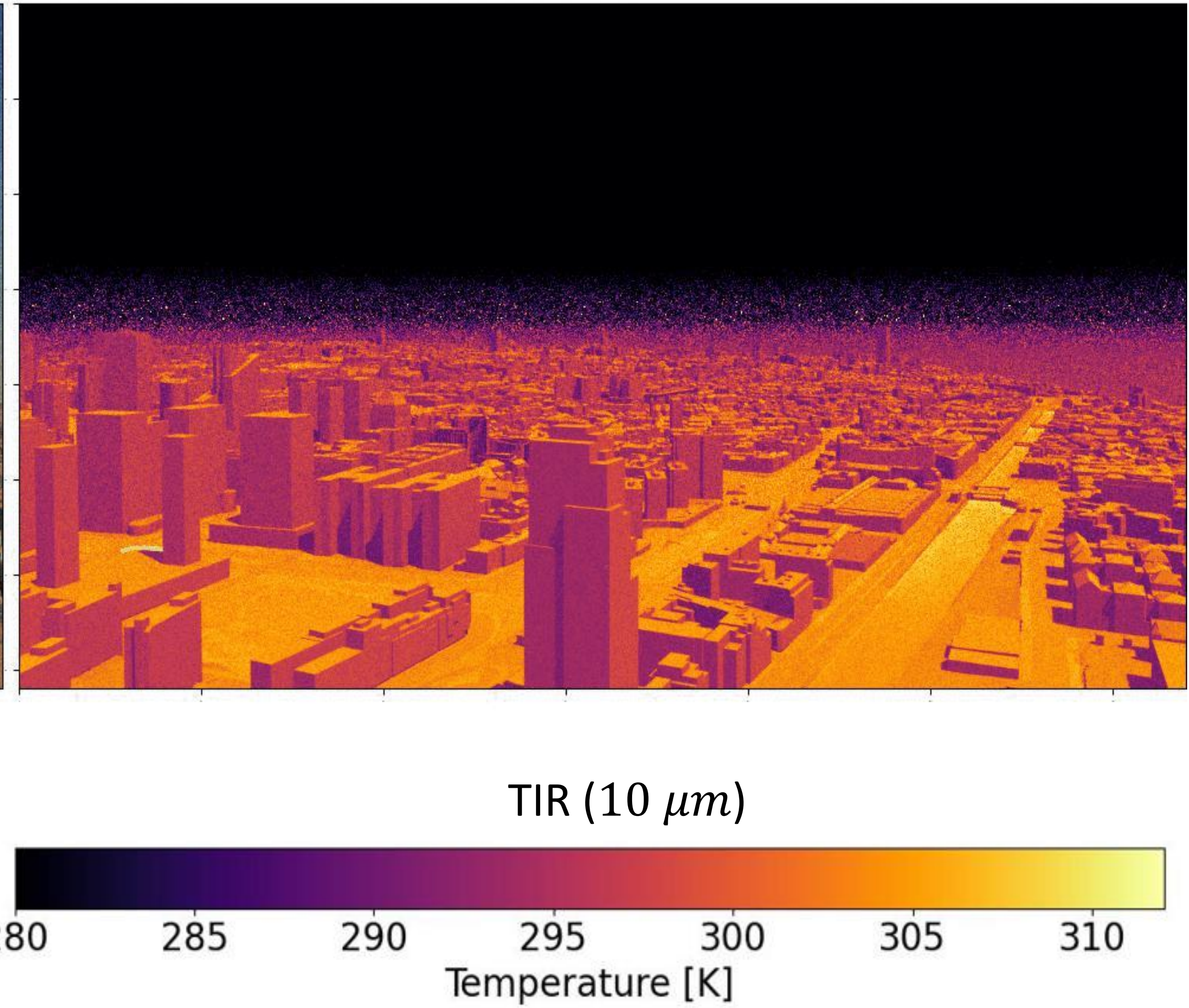


DART: Bruxelles with 3 atmosphere conditions (SUABE project)

Clear atmosphere (aerosol model: Urban V23) + Clouds



RGB $(0.66\ \mu m, 0.55 \mu m, 0.49 \mu m)$



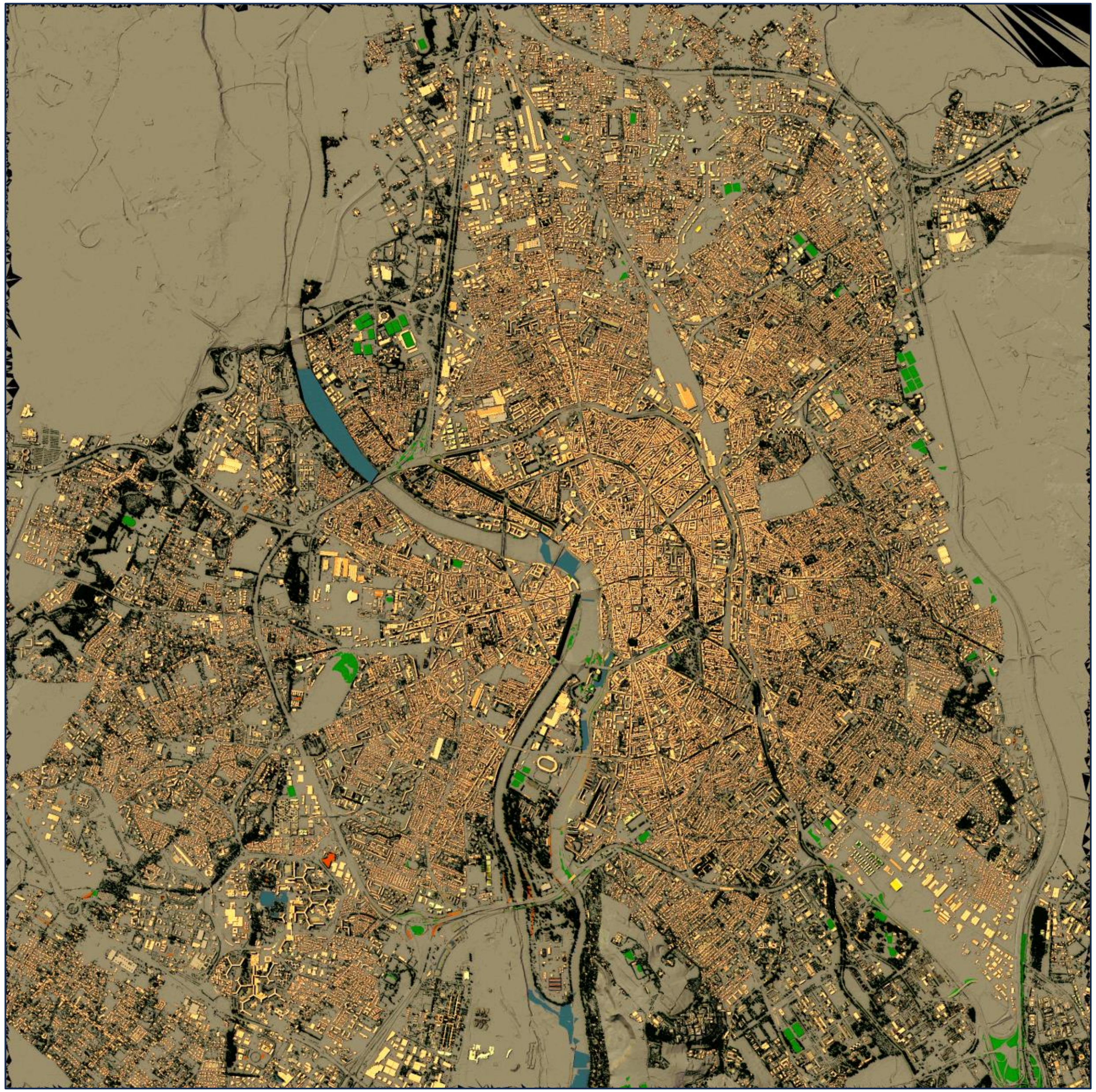
TIR $(10\ \mu m)$

DART: Toulouse, France

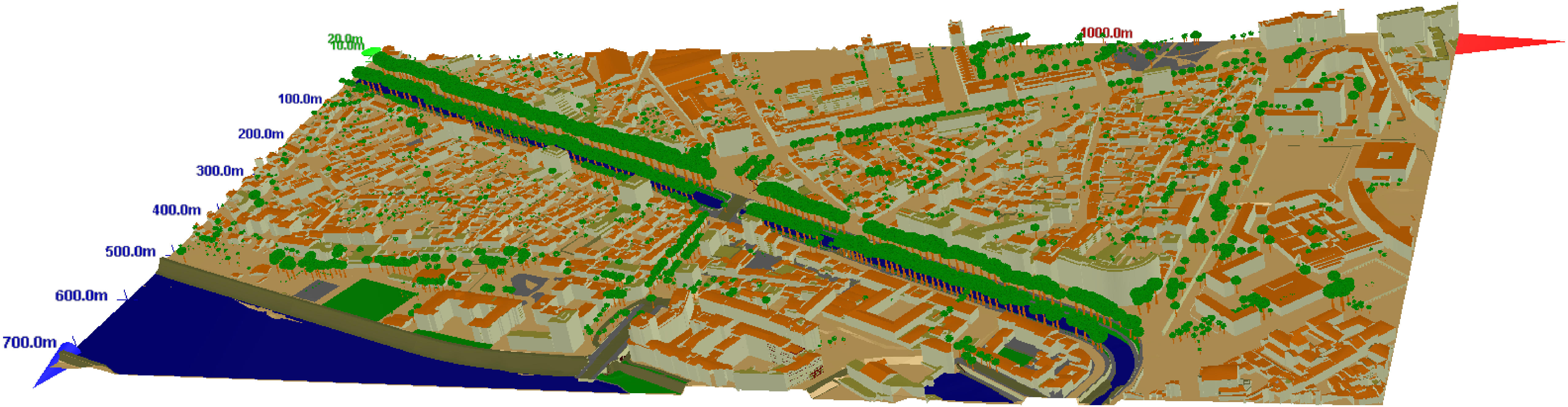
Toulouse 3D model

(Toulouse city council, 2014)

DART



DART: district of Brienne, Toulouse, France



3D model of the district of Brienne

(Toulouse City Council's urban database, 2014)

DART: RGB of Brienne district (Toulouse, France)

DART simulation using the Toulouse City Council's urban database

DART: TIR image of Brienne district (Toulouse, France)

DART simulation using the Toulouse City Council's urban database

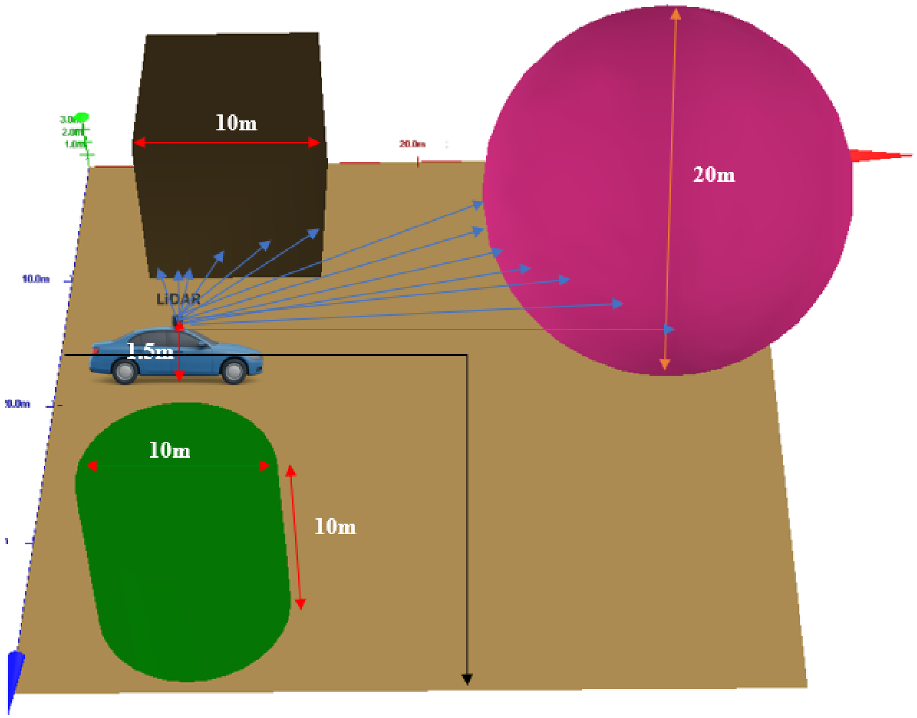
DART: Mobile / UAV LiDAR

Objective: to develop a model of Mobile / UAV LiDAR (CNES project 3D-Earth)

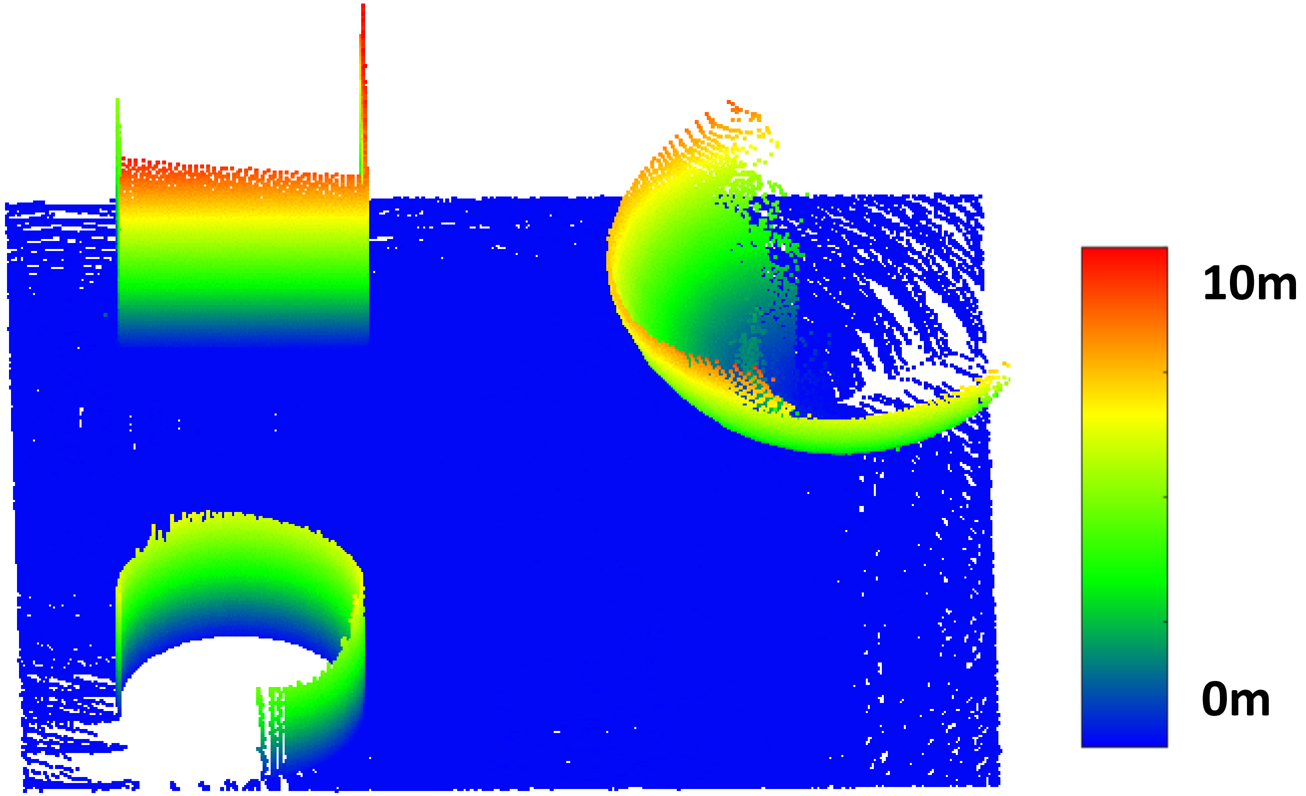
Approach: new model in DART of Lidar with any flight path and scanning orientation.

2 examples of LiDAR point clouds are shown:
- Schematic environment.
- District "Brienne", Toulouse.

3D Earth: mobile / UAV LiDAR in schematic environment



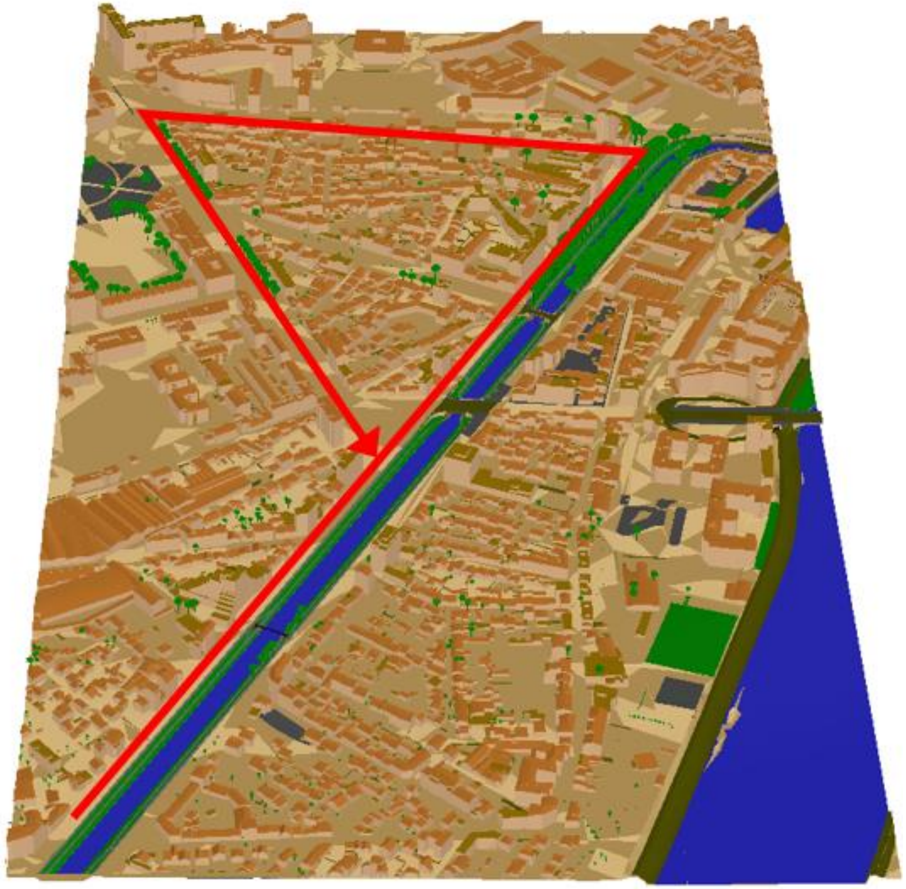
40m x 40m schematic scene



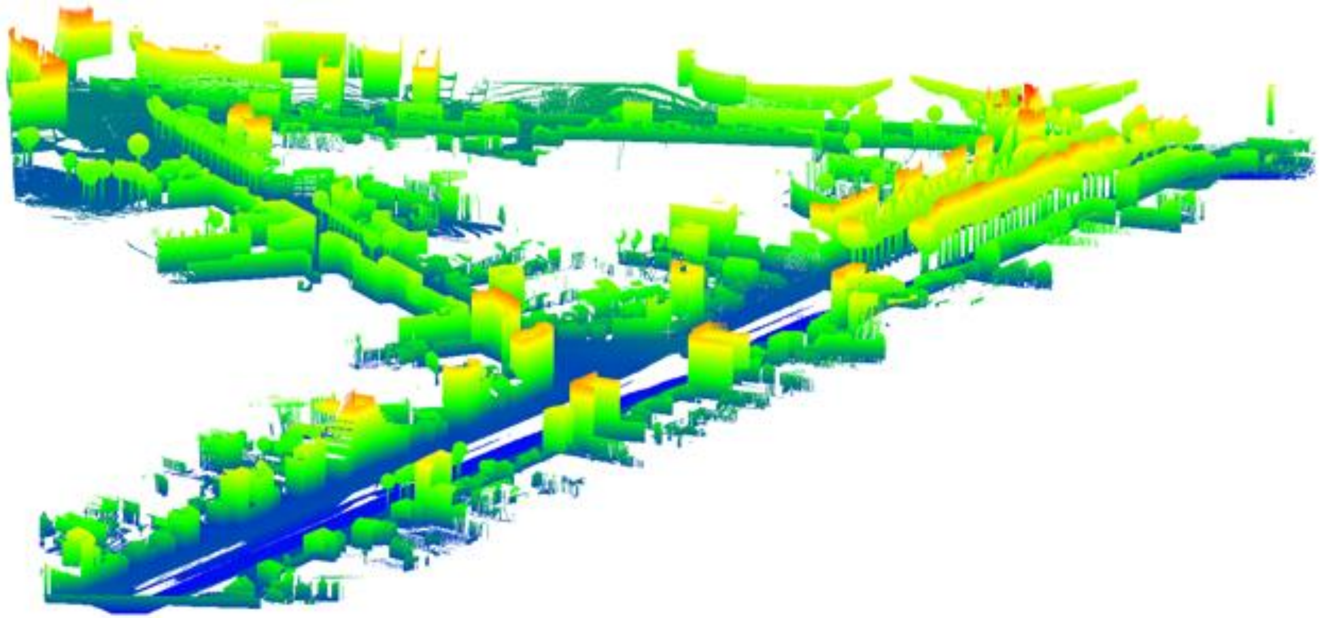
DART simulation of mobile LiDAR

Colors indicate the altitude of LiDAR points

3D Earth: mobile / UAV LiDAR in district "Brienne", Toulouse



District of Brienne (Toulouse) with path of the mobile LiDAR.



DART simulation of mobile LiDAR

On-going work

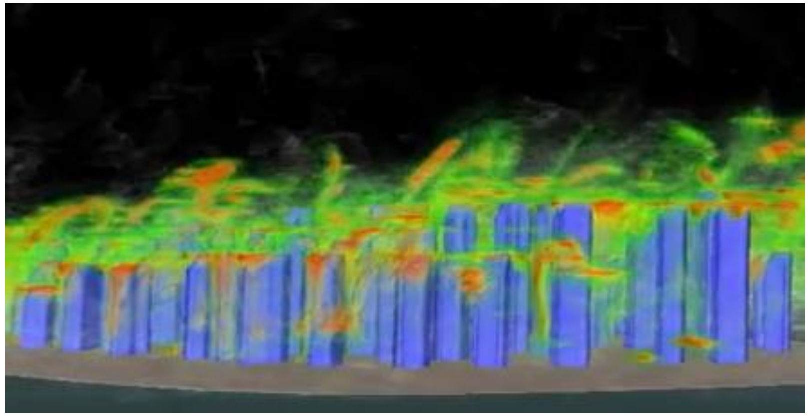
⇨ **Improvement of urban observation by remote sensing sensors (LiDAR, UAV, etc.).**

⇨ **Coupling DART and urban meteorological model PALM-4U**

(palm.muk.uni-hannover.de/trac/wiki/palm4u)

Context: preparation of LSTM & TRISHNA satellite missions

Collaboration: Twente University (Netherlands), ONERA

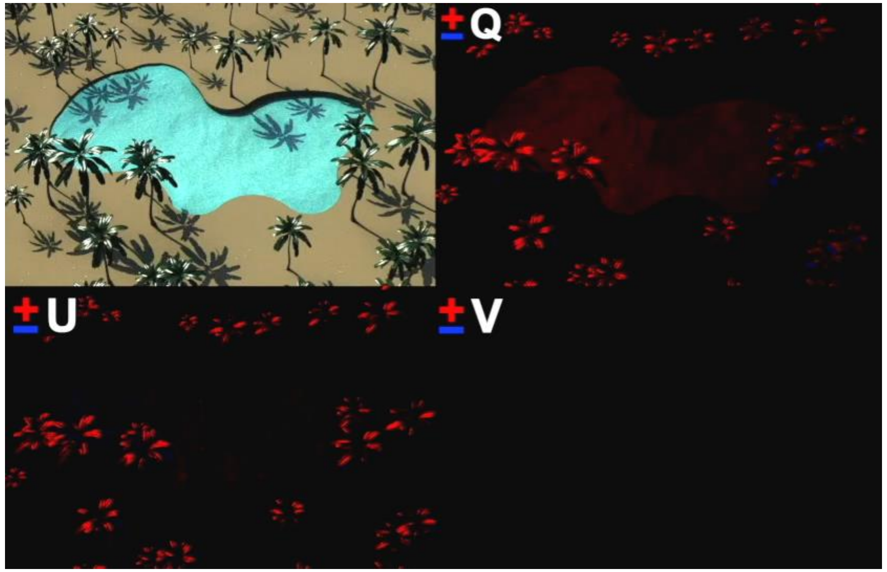


Turbulence in Macao
(from Institute of meteorology and Climatology, Hanover, Germany)

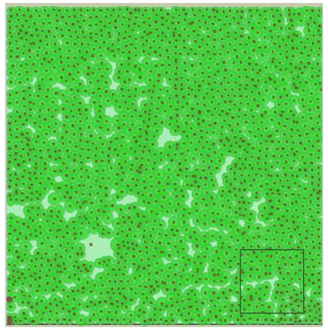
⇨ **Emulating thermal comfort and air temperature in Brussels.**

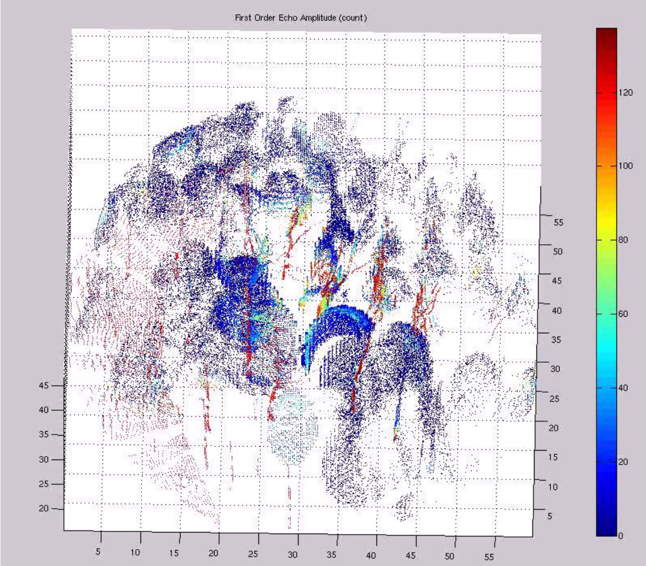
Collaboration: VITO (Belgium).

Specular reflectance & Polarisation



Terrestrial LiDAR





Lageren forest
(RSL, Switzerland)

شكرًا

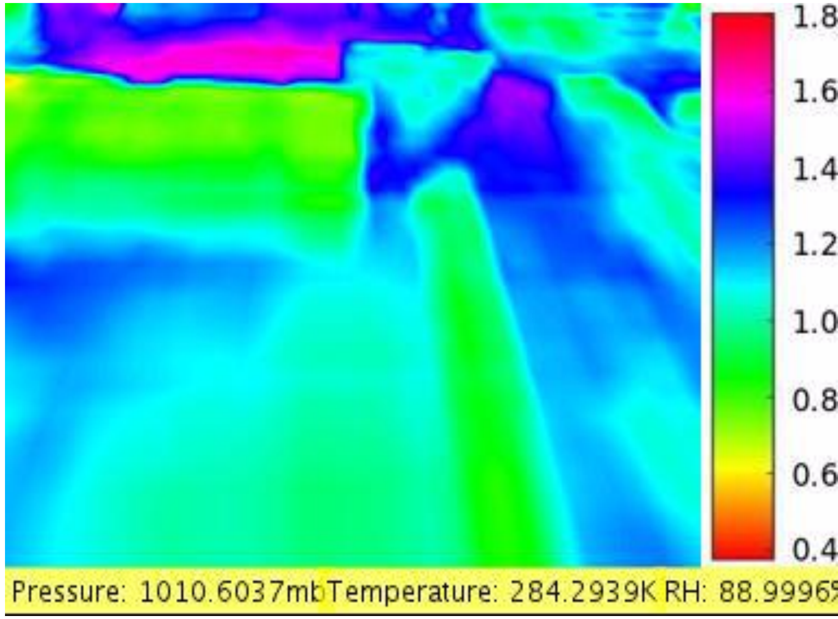
UAV: forest

Obrigado, 谢谢,

Merci, Thank you,...

TIR camera - London

Thermal radiance = f(P_{atm}, RH, T_{atm})

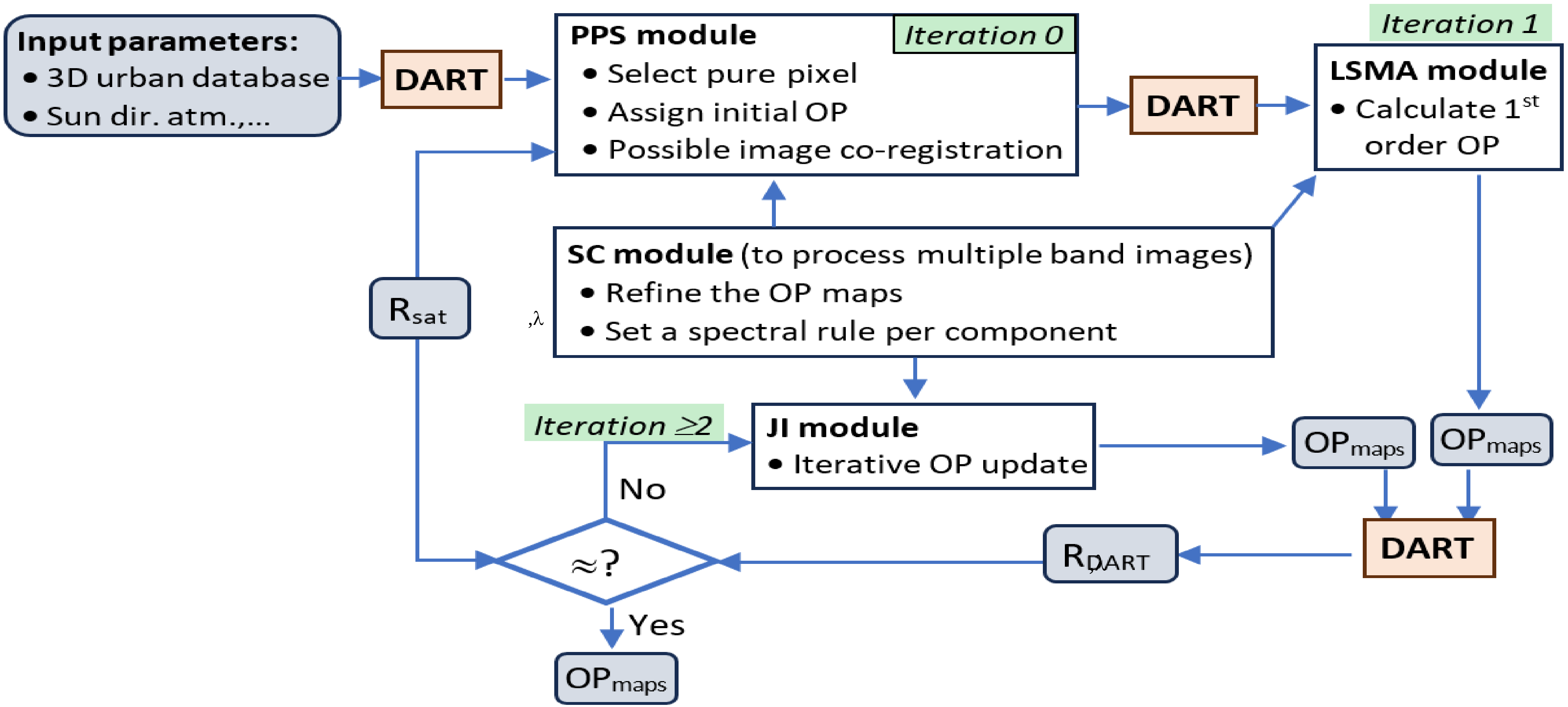


شكرًا

Obrigado, 谢谢,

Merci, Thank you,...

Technical Route in VIS band



$R_{sat,\lambda}$: satellite reflectance image
$R_{DART,\lambda}$: DART reflectance image
OP$_{map}$: optical properties maps
PPS: pure pixel selection module

LSMA: linear spectral mixing analysis module
JI: Jacobian module (*i.e.*, $\frac{\partial R_{\mathrm{DART},\lambda}(x,y)}{\partial \rho_{\mathrm{element},\lambda}}$)
SC: spectral correlation module

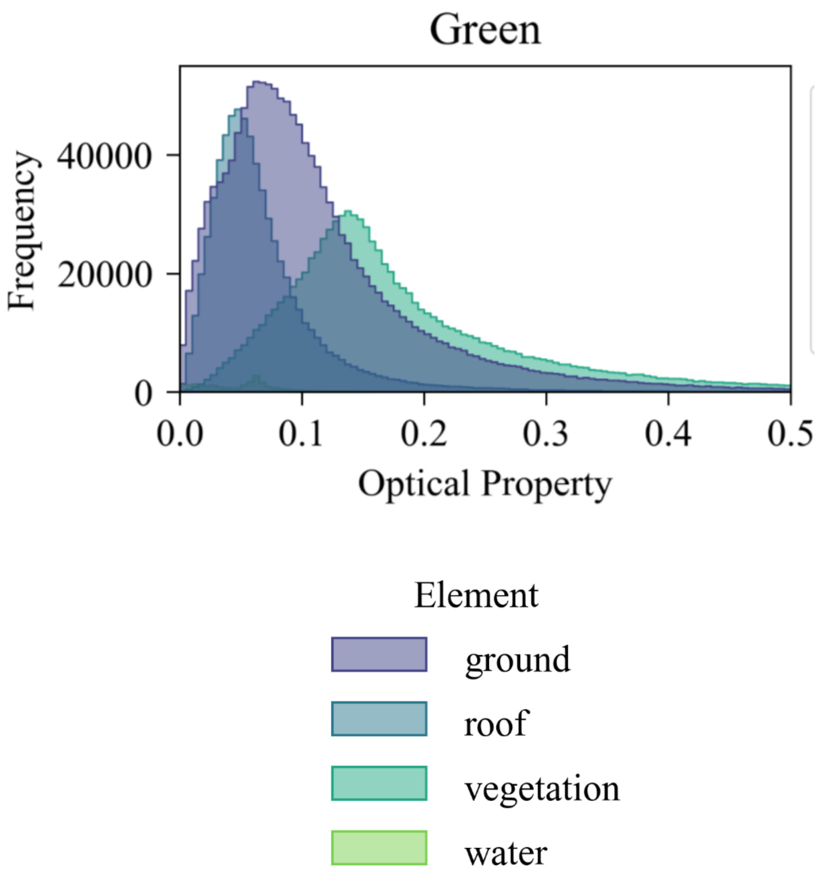
Inversion of short wave satellite images: Histogram of the 4 elements

Ground

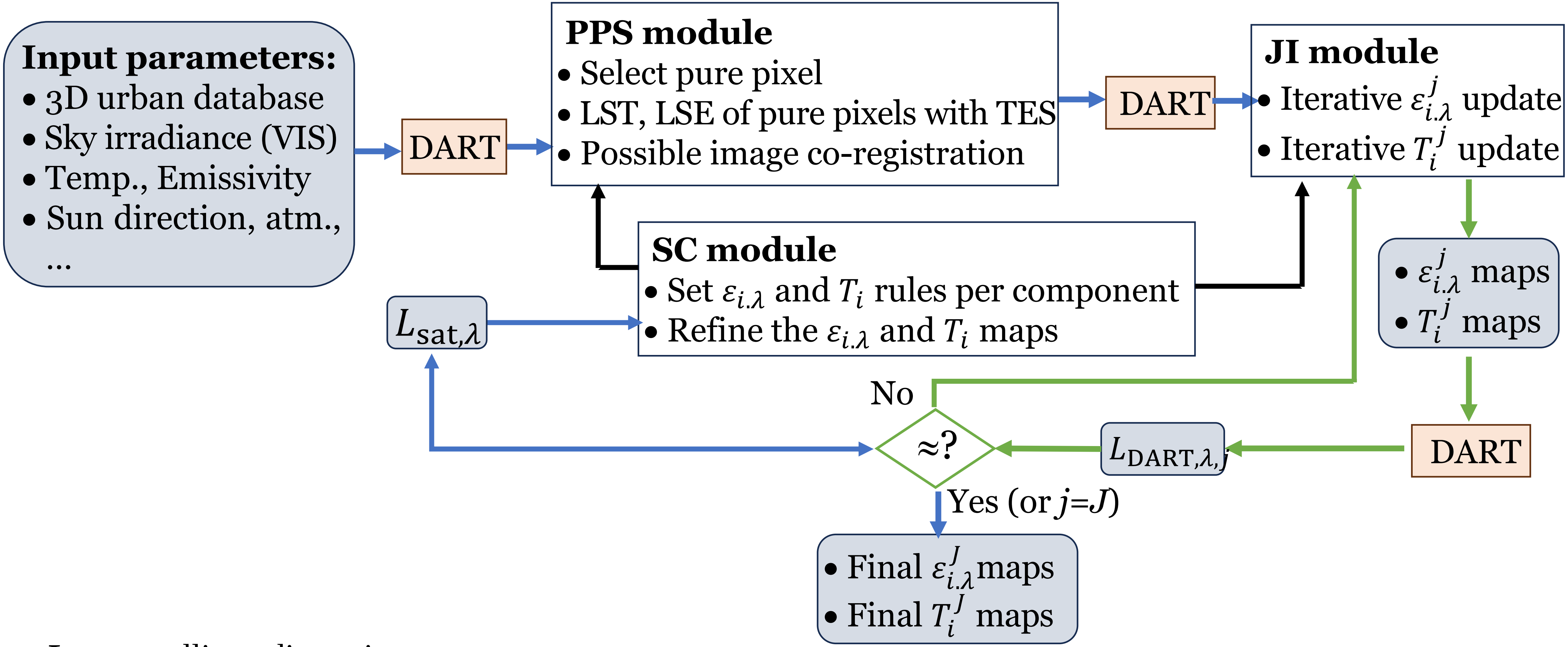
Roof

Vegetation

Water



Inversion of TIR satellite images: the approach



$L_{sat,\lambda}$: satellite radiance image

$L_{DART,\lambda,j}$: DART radiance image at iteration j

PPS: pure pixel selection module

JI: Jacobian module (*i.e.*, $\frac{\partial L_{DART,\lambda}(x,y)}{\partial \varepsilon_{element,\lambda} \text{ or } \partial T_{element}}$)

SC: spectral correlation module

Inversion of TIR satellite images: Brussels

ASTER

DART simulation after inversion

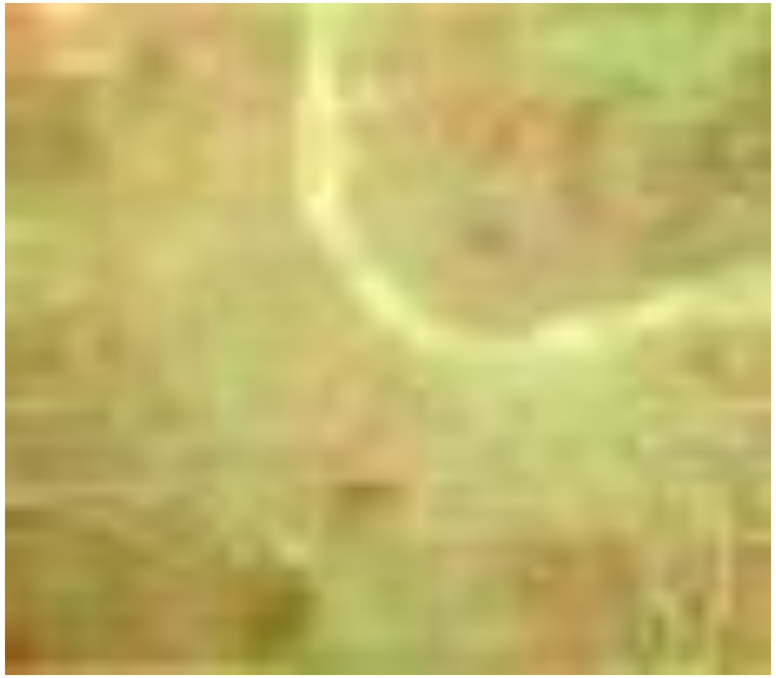
ASTER ID: 00309262018212643 **Date:** 2018.09.26 21:26:43

RGB false composition: 11.3, 9.1, 8.3 μm

ASTER λ ($\Delta\lambda$): 8.3 (0.35), 8.65 (0.35), 9.1 (0.35), 10.6 (0.7) , 11.3 (0.7) μm

Inversion of TIR satellite images: Basel

ASTER



DART simulation after inversion

ASTER ID: 00309192018211943 **Date:** 2018.09.19 21:19:43

RGB false composition: 11.3, 9.1, 8.3 µm

ASTER λ ($\Delta\lambda$): 8.3 (0.35), 8.65 (0.35), 9.1 (0.35), 10.6 (0.7) , 11.3 (0.7) µm

Two approaches for assessing the accuracy of satellite image inversion:

1) Comparison of time series of exitance (W/m^2) measured in urban ground stations and simulated by DART.

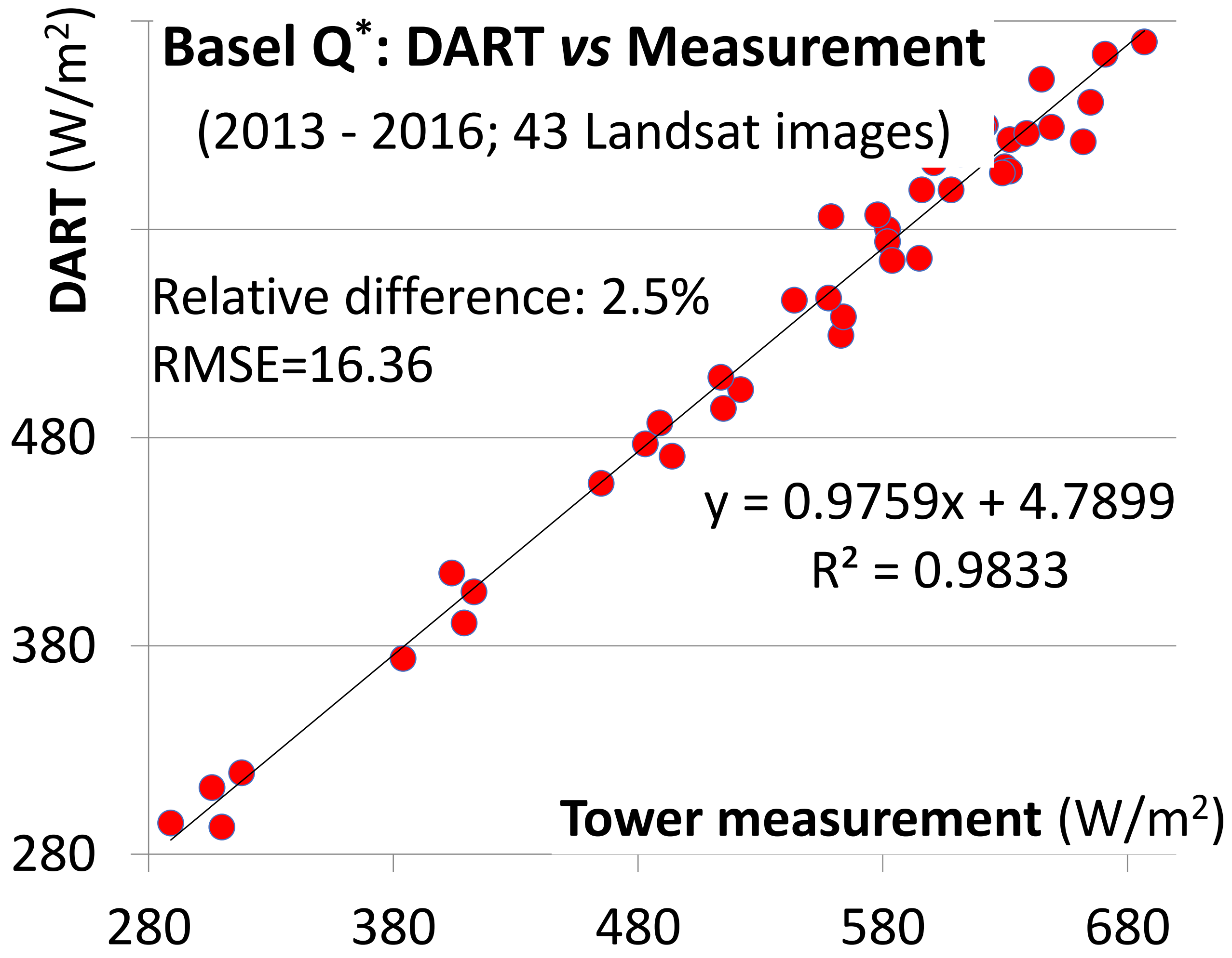
2) We simulate a pseudo satellite image using the 3D urban database and maps of reflectance and temperature that we compare with the maps obtained by inversion of the pseudo-satellite image.

Accuracy:

Median relative VIS and TIR radiance error usually $\leq$ 1%.

TIR: emissivity median relative error $\leq$ 5% and temperature median relative error $\leq$ 2K.

☞ These results are for ideal configurations without co-registration error and sensor noise.



$LUT_{black\ sky}$ & $LUT_{white\ sky}$ for date with no satellite image $\Rightarrow$ Q*(t) with Δt=1h,...

An example of DART use for urban studies

Maps of optical properties and temperature of urban elements (roofs, trees,...) from remote sensing images, with consideration of urban 3D architecture

Scientific objective: time series maps of urban albedo, temperature / UHI / confort,... through modeling urban energy budget (*i.e.*, sensible / latent fluxes, etc.)

Approach: DART-based inversion of satellite images as a map of reflectance (short waves) and temperature / emissivity (long waves) per type of urban element (roof,..)

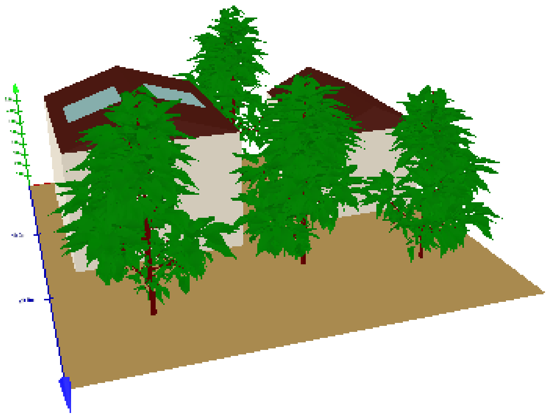
Major difficulties: - 3D architecture ⇨ Multiple scattering, directional effects (hot spot)

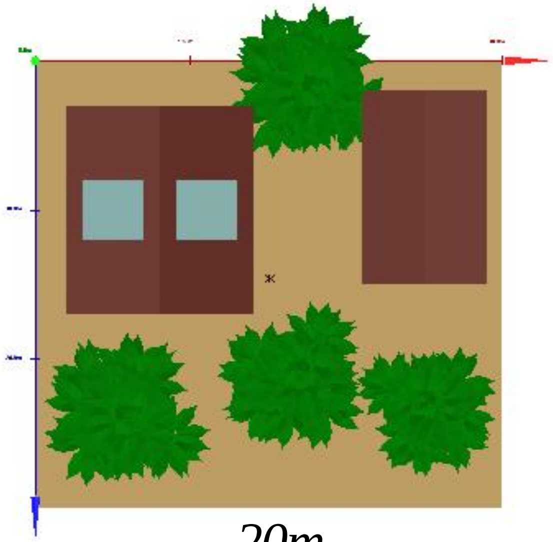
⇨ Standard un-mixing is unsuccess ⇨ Need of non-linear un-mixing.

- No unique solution for the OP / Temperature maps obtained by inversion

Illustration of the issue: 2 sets of $OP_{\text{scene elements}}$ give a same 20 m RS image pixel value

20m x 20m 3D scene





20m

Solution 1

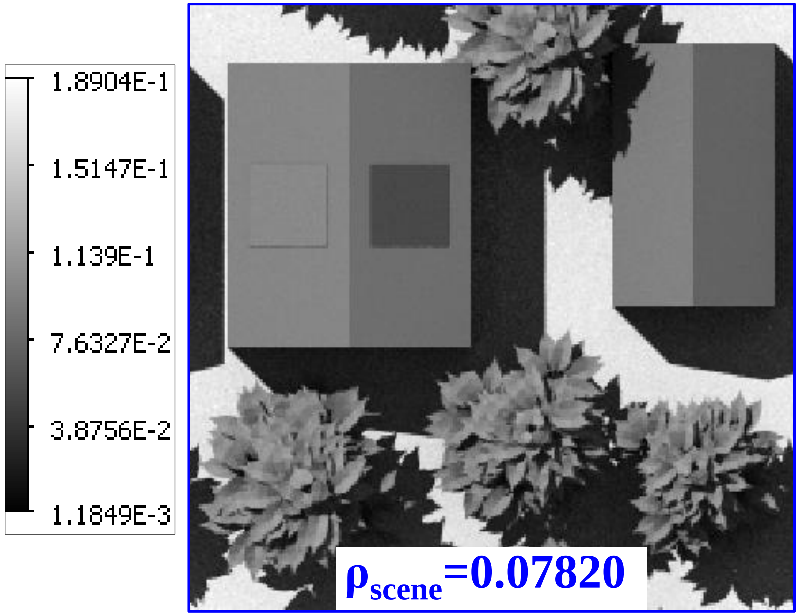
ρ_{roof}

ρ_{wall}

ρ_{leaf}

…

ρ_{ground}



Solution 2

$\frac{\rho_{roof}}{2}$

$\frac{\rho_{wall}}{2}$

$\frac{\rho_{leaf}}{2}$

…

$1.85275\rho_{ground}$

☠ Solutions 1 & 2 give same ρ_{pixel}

Is it an issue?

It is an issue because solutions 1 & 2 lead to very different results

ρ_{pixel} for view zenith angle = 30°

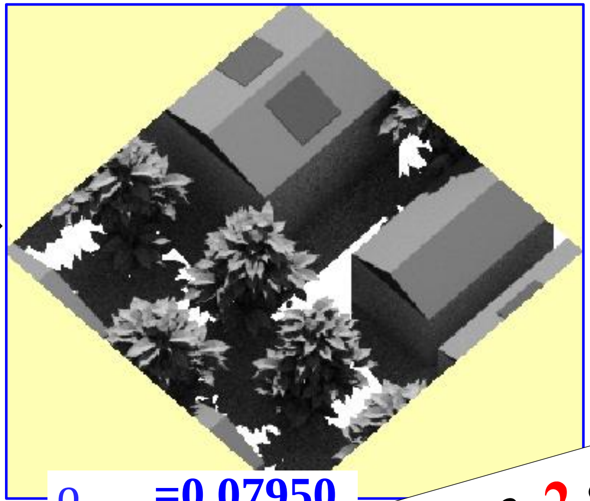
Solution 1

ρ_{roof}

ρ_{leaf}

…

ρ_{ground}



ρ_{scene}**=0.07950**

Solution 2

$\frac{\rho_{roof}}{2}$

$\frac{\rho_{leaf}}{2}$

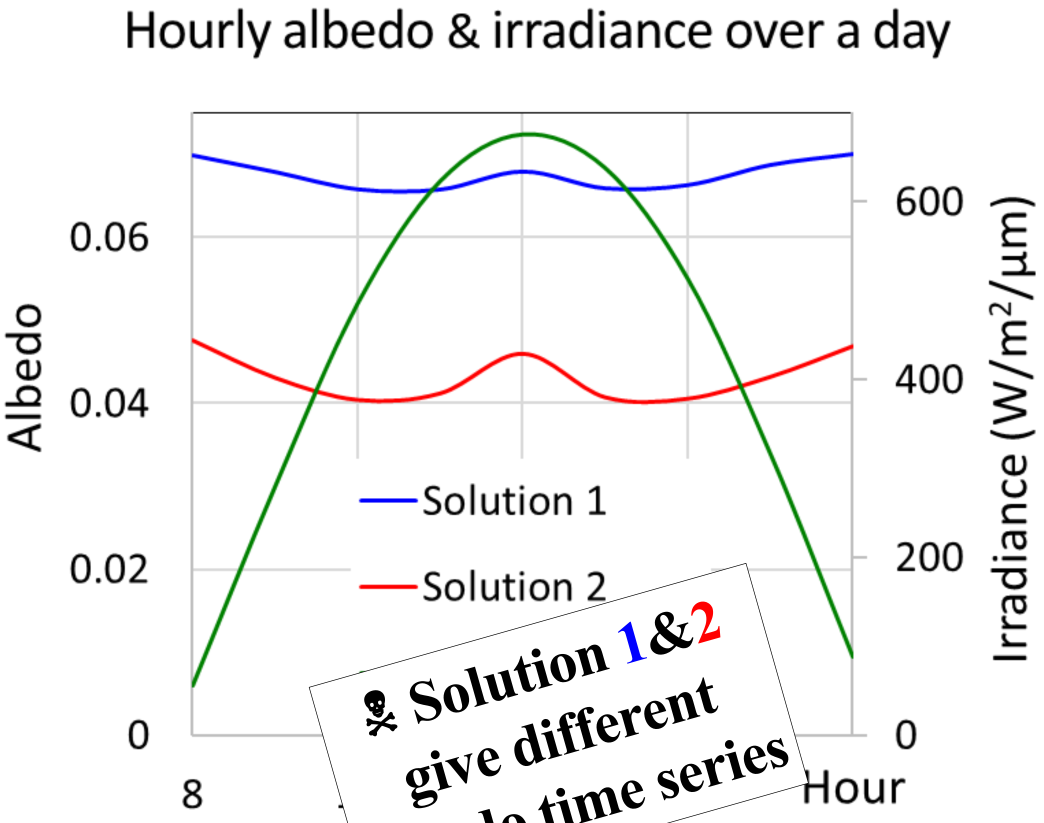
…

$1.85275\ \rho_{ground}$

ρ_{scene}**=0.06569**

☠ **Solution 1 & 2 give different ρ_{pixel} for different VZAs**

Time series of scene albedo



☠ **Solution 1&2 give different albedo time series**

⇨ Need of accurate solutions,
and not only accurate simulation of RS images

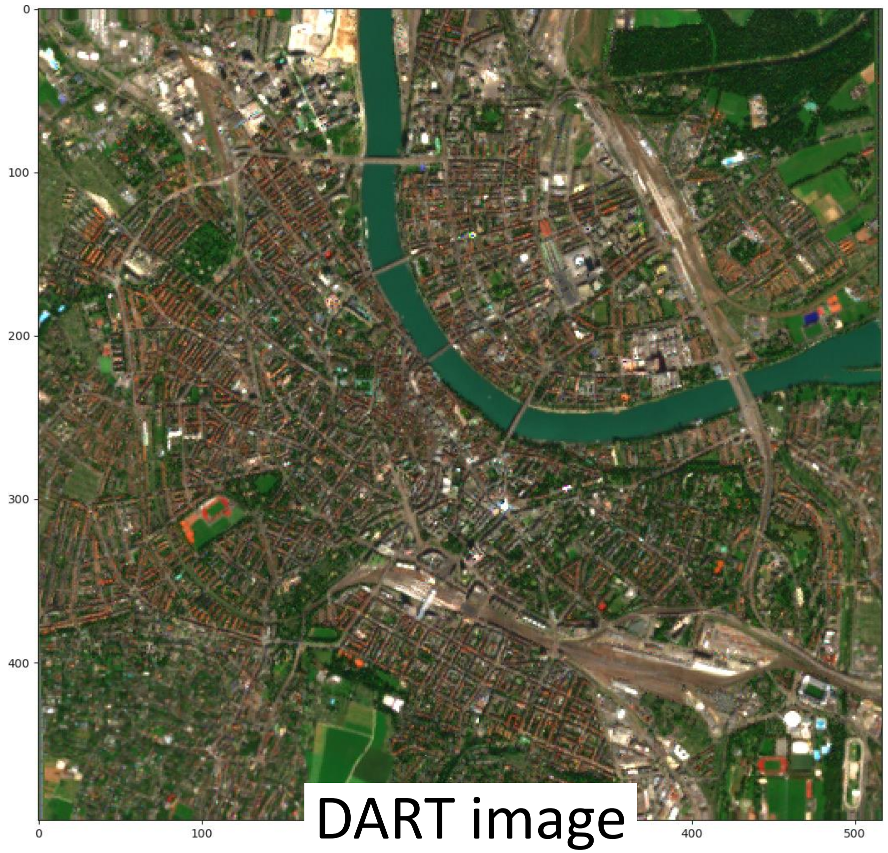
European Commission

Project (https://urbanfluxes.eu): Urban warming

DART-based inversion + {S2 image + 3D urban database}

⇒ Map of optical property / type of urban element (e.g., roof)

S2 image



DART image

Basel, Switzerland

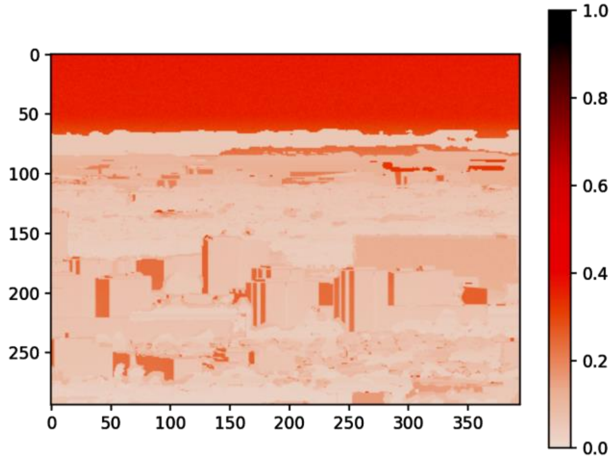
DART: determination of urban aerosol optical depth (AOD)

Objective: real-time automatic determination of urban aerosol concentration

Approach: real time images of a multispectral camera are compared to time series of DART images simulated using a 3D model of the city

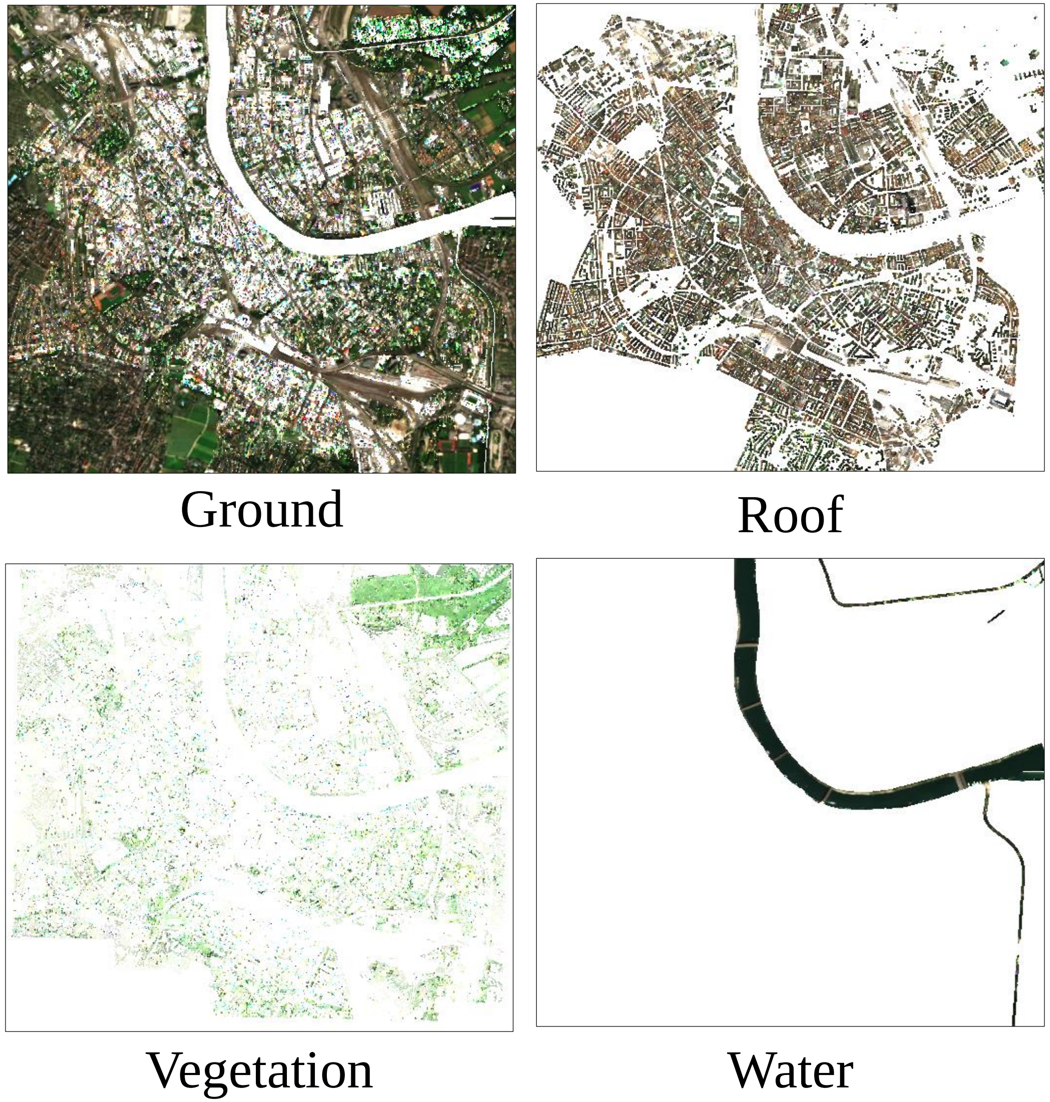
3D urban scene: district Bagatelle, Toulouse

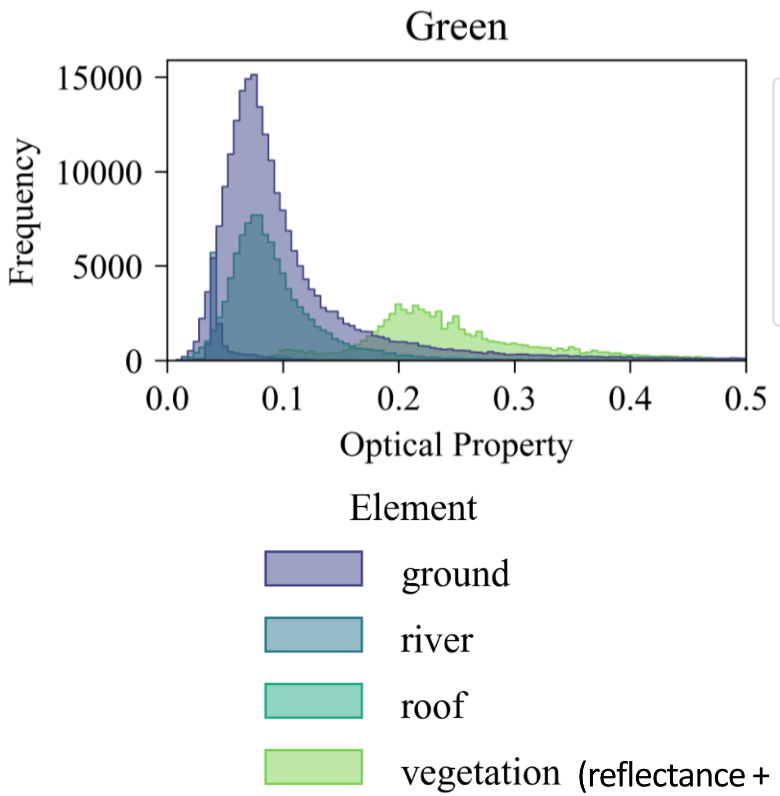
DART image



AOD for any image pixel

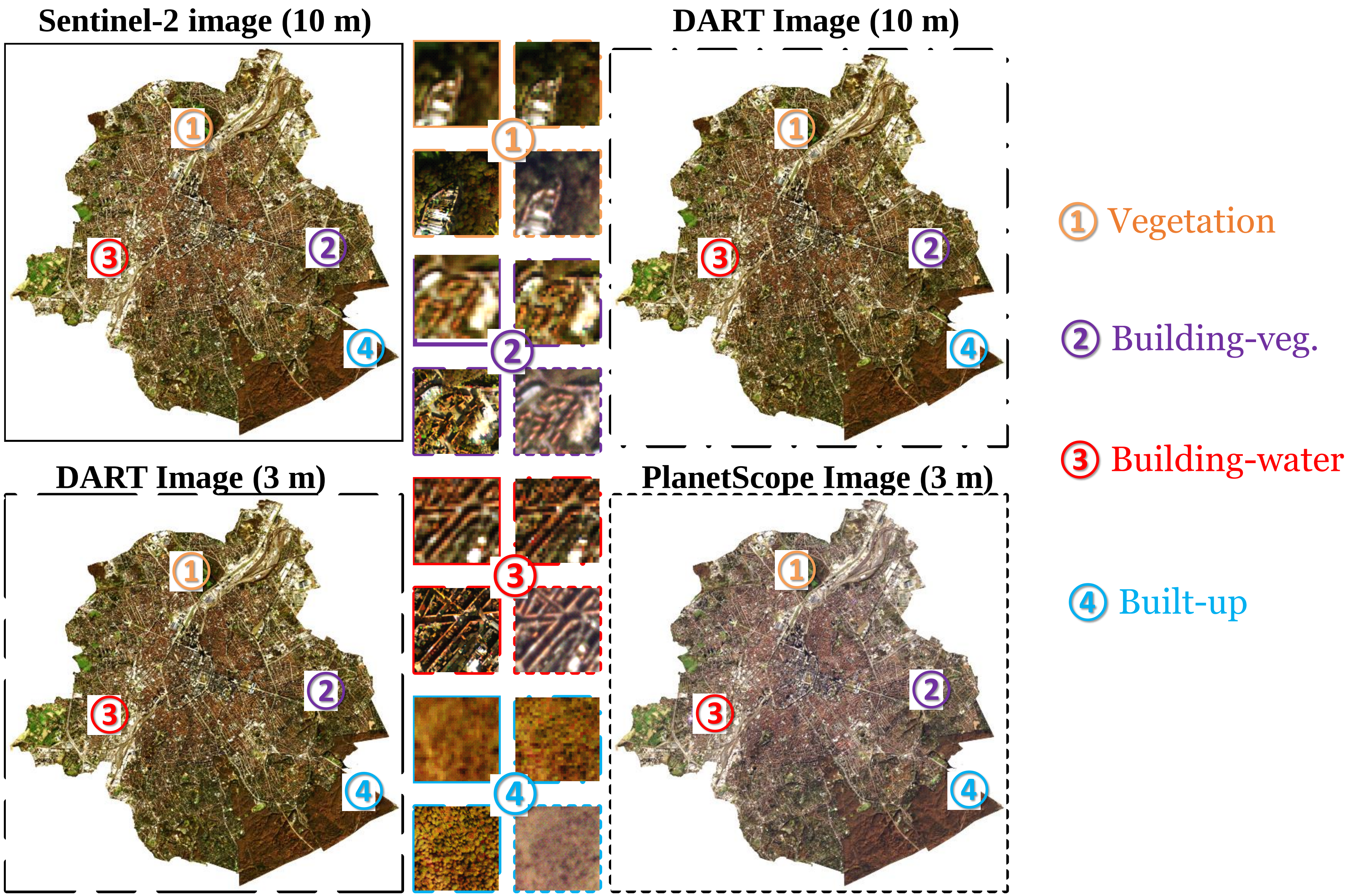
Inversion of short wave satellite images: Histogram of the 4 elements





(reflectance + transmittance)

Inversion of short wave satellite images: Brussels



· **S2 ID:** 20210224T105031_20210224T105442_T31UES

· **PS ID:** 20210224_100339_42_2276_3B_AnalyticMS_8b
20210224_100341_88_2276_3B_AnalyticMS_8b