Fuel types classification by simulation with radiative transfer model DART and spectral mapping methods SAM and MESMA

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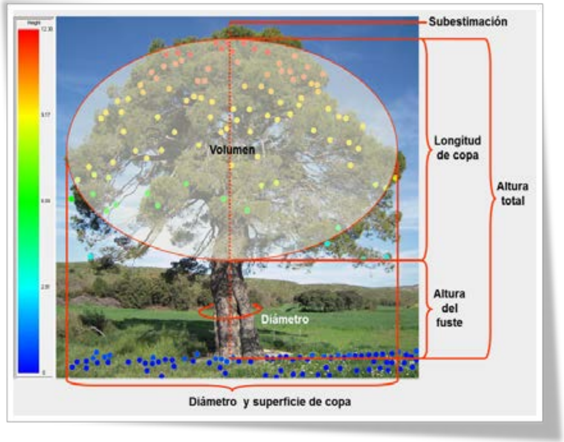
Introduction ¿Why?

Wildfires have become a mayor natural hazard

Fuel types drive fire ignition and propagation



LiDAR provides information on vegetation structure

Need to reduce field work and site and sensor depencency

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Objective

create a "library of LiDAR waveforms" useful to classify using spectral mapping methods different fuel types as described by Scott and Burgan (2005)

Methodology

Three methodological steps:

1. Simulation in Discrete Anisotropic Radiative Transfer (DART) model
2. Selection of endmembers in Visualization and Image Processing for Environmental Research (VIPER) tools
3. Classification using spectral matching algorithms: multiple endmember spectral mixture analysis (MESMA) and spectral angle mapping (SAM)

1. Simulation in DART model

Selection of the fuel models to simulate:

The fuel classification established by **Scott and Burgan (2005)** differentiate several fuel models classified in seven fuel types in relation to the main fire-carrying fuel:

- **NB:** Non burnable (90-99)
- **GR:** Grass (100-119)
- **GS:** Grass-Shrub (120-139). Shrub coverage lower than 50%
- **SH:** Shrub (140-159) Shrub coverage higher than 50%
- **TU:** Timber-understory (160-179)
- **TL:** Timber litter (180-199)
- **SB:** Slash blowdown (200-220)

Main criteria to differentiate fuel types:

- in **GR, GS, SH and TU** first division in models **common in arid areas** and those **in humid and sub-humid**. Second division fine **fuel load and fuelbed depth**
- in **TL** a first division in **broadleaf and conifer** litter, second **liter load and compactness**
- in **SB** a first division considering the **origin in fuel activity or blowdown**

1. Simulation in DART model

Selection of the fuel models to simulate:

Model	Fuel load/ dead 1hr	Fuel load/ live herb	Fuel load/ live woody	Fuel load/ Total	Description
GR2	0.1	1	0	1.1	The primary carrier of fire in GR2 is grass, though small amounts of fine dead fuel may be present. Load is greater than GR1, and fuelbed may be more continuous. Shrubs, if present, do not affect fire behavior.
GR7	1	5.4	0	6.4	The primary carrier of fire in GR7 is continuous dry-climate grass. Load and depth are greater than GR4. Grass is about 3 feet tall.
GS2	0.5	0.6	1	2.1	The primary carrier of fire in GS2 is grass and shrubs combined. Shrubs are 1 to 3 feet high, grass load is moderate. Spread rate is high; flame length moderate. Moisture of extinction is low.
SH2	1.35	0	3.85	5.2	The primary carrier of fire in SH2 is woody shrubs and shrub litter. Moderate fuel load (higher than SH1), depth about 1 foot, no grass fuel present. Spread rate is low; flame length low.
SH7	3.5	0	3.4	6.9	The primary carrier of fire in SH7 is woody shrubs and shrub litter. Very heavy shrub load, depth 4 to 6 feet. Spread rate lower than SH7, but flame length similar. Spread rate is high; flame length very high.
TU1	0.2	0.2	0.9	1.3	The primary carrier of fire in TU1 is low load of grass and/or shrub with litter. Spread rate is low; flame length low.
TU5	4	0	3	7	The primary carrier of fire in TU5 is heavy forest litter with a shrub or small tree understory. Spread rate is moderate; flame length moderate.
TL3	0.5	0	0	0.5	The primary carrier of fire in TL3 is moderate load conifer litter, light load of coarse fuels. Spread rate is very low; flame length low.
SB1	1.5	0	0	1.5	The primary carrier of fire in SB1 is light dead and down activity fuel. Fine fuel load is 10 to 20 t/ac, weighted toward fuels 1 to 3 inches diameter class, depth is less than 1 foot. Spread rate is moderate; flame length low.
SB2	4.5	0	0	4.5	The primary carrier of fire in SB2 is moderate dead and down activity fuel or light blowdown. Fine fuel load is 7 to 12 t/ac, evenly distributed across 0 to 0.25, 0.25 to 1, and 1 to 3 inch diameter classes, depth is about 1 foot. Blowdown is scattered, with many trees still standing. Spread rate is moderate; flame length moderate.

1. Simulation in DART model

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Parameters of LIDAR sensor (main decisions):

- Single pulse
- LVIS
- Zenith angle/azimuth (footprint)
- Height below/above

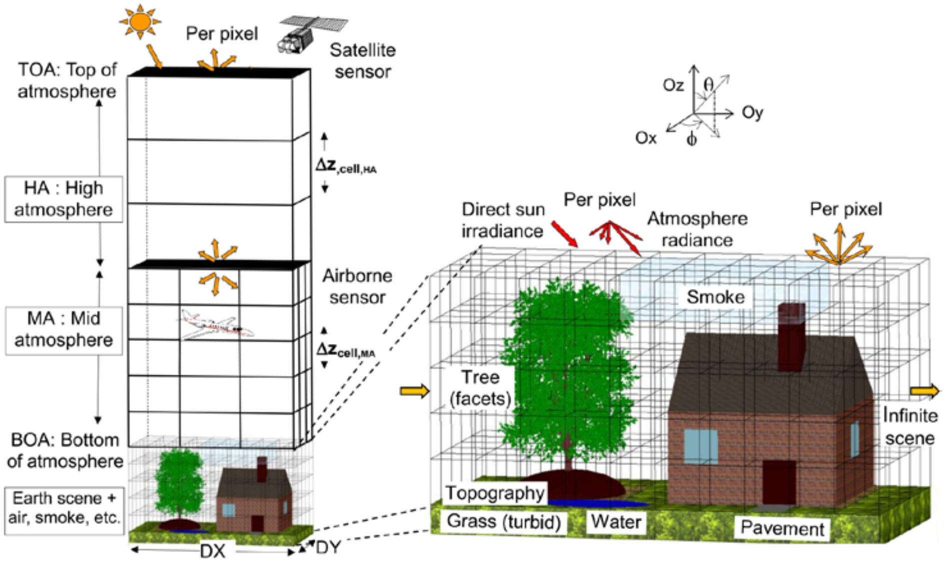
Energy each pulse (mJ)	5
Number of DART simulated photons (SP)	1,000,000
Fraction of photons at LiDAR radius	0.368
Lidar acquisition rate (ns)	2
Maximum order of scattering	200
Maximum RAM (Mo)	1000
Central wavelength (µm)	1.064
Area of LiDAR sensor (m^2)	0.0314
Height above/below minimum altitude (m)	60/10
Zenith angle (°)	0-20
Azimuth angle (°)	90-225
footprint and FOV center cell X/Y	20/20
ALS/altitude (km)	10
Footprint diameter (m)	20
FOV diameter (m)	38

1. Simulation in DART model

Parameters used in the “maket” module to simulate every fuel model:

In DART every simulation consists in an earth scene representing a fuel model (maket)

An Earth scene is an array of 3-D cells (Δx, Δy, Δz) where any scene element is created with a dual approach as a set of cells that contain turbid media or a set of geometric primitives (triangles) called “facets”.



Schneider et al. 2014: voxel grid based reconstruction yields better results

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Parameters used in the “maket” module to simulate every fuel model:

Turbid vegetation medium are defined by:

- their orientation, i.e. Leaf Angle Distribution (LAD)
- volume density or Leaf Area Index (LAI)
- optical properties: transmittance and reflectance

1. Simulation in DART model

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Parameters used in the "maket" module to simulate every fuel model:

Optical properties and LAD:

- DART model includes two databases with optical properties, Lambertian and Vegetation
- no information in any of the DART databases concerning shubs; values extracted from spectral signatures captured in fieldwork in 2014, within the framework of the HyspIRI Planning Mission (NASA Grant # NNX12AP87G)

Component	Optical properties	Database	LAD
grass as soil	grass-rye	Lambertian	N/A
soil	clay_brown; loam_sandy_brown; sand_white	Lambertian	N/A
bark	bark_coniferous	Lambertian	N/A
litter as soil	litter1; litter2	Lambertian	N/A
needle	needle conifer	Vegetation	Spherical
twig spruce	twig_spruce	Vegetation	Spherical
grass as vegetation	grass_rye; grass_dry	Vegetation	Spherical
shrub	reflectance1tranmitance1/ multiplicativefactor 0.4 /0.4/0.4; 0.3/0.3/0.4	Vegetation	Plagiophile
litter as vegetation	reflectande1tranmitance1/ multiplicativefactor 0.45/ 0.45 /0.2; 0.35/0.35/0.3	Vegetation	Plagiophile

1. Simulation in DART model

Parameters used in the “maket” module to simulate every fuel model:

LAI value: Used to simulate the fine fuel load

- Casas et al. (2014) measured LAI and Leaf Mass per Area (LMA) in grass, shrub and forest in Coast Range of California, USA
- The values of fine fuel load (ton/ac) in each fuel model were converted to the units of LMA (g/cm2) and then to LAI applying a lineal function obtained for the minimum and maximum values of LAI and LMA

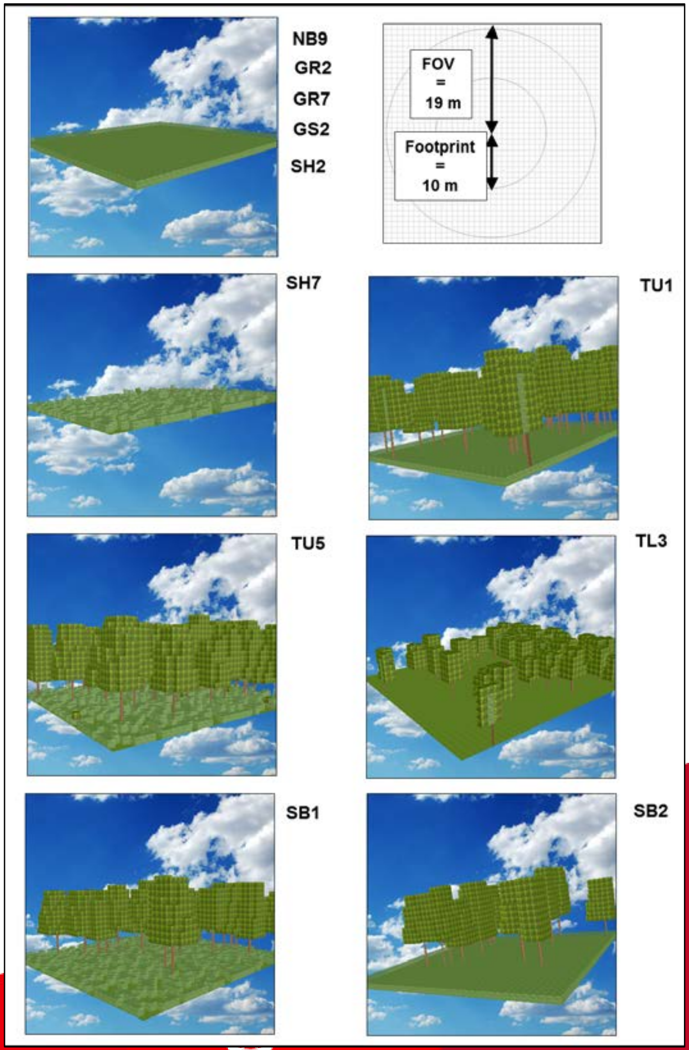
	Grasses (min-max)	**Shrubs (min-max)**	**Forest (min-max)**
LMA (g/cm^2)	0.006–0.03	0.005–0.04	0.01–0.02
LAI (m^2/m^2)	0.1–2	0.1–2.5	1–2.5

Model	**LAI/ dead 1hr**	**LAI/ live herb**	**LAI/ live woody**
GR2	0.030	1.581	0.000
GR7	1.494	10.189	0.000
GS2	0.610	0.799	1.452
SH2	2.114	0.000	6.281
SH7	5.917	0.000	5.518
TU1	0.079	0.016	1.282
TU5	6.802	0.000	4.840
TL3	0.610	0.000	0.000
SB1	2.379	0.000	0.000
SB2	7.687	0.000	0.000

1. Simulation in DART model

Parameters used in the “maket” module to simulate every fuel model:

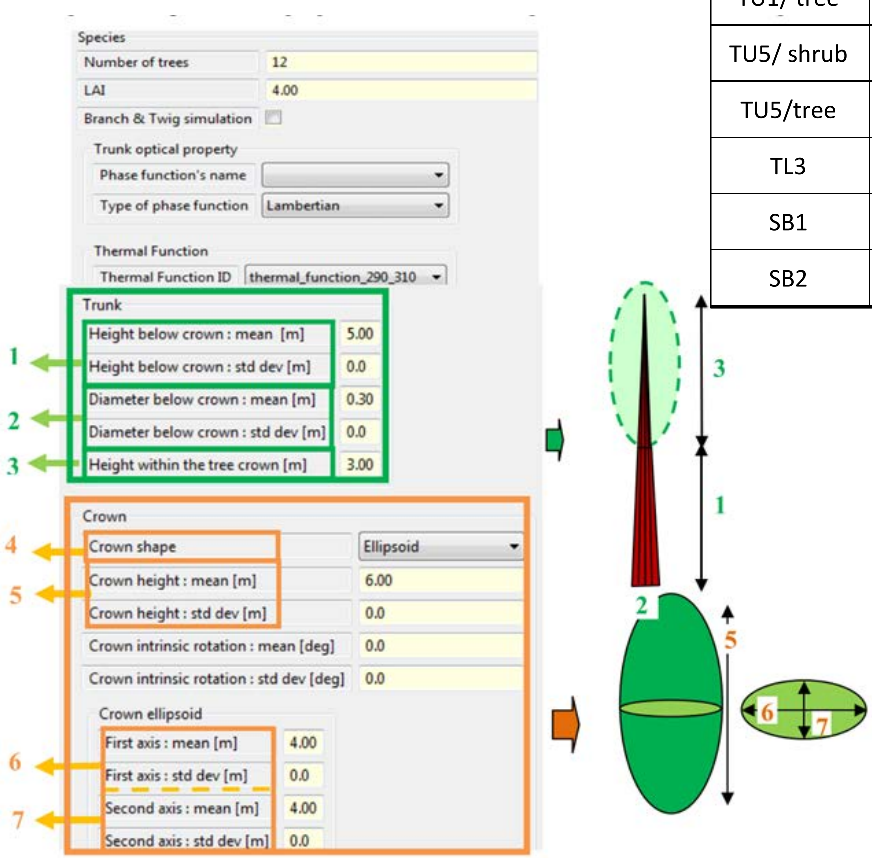
Fuel model	Scene plot			Scene tree		
	Mean height (m)	Std deviation height (m)	LAI	LAI	Number	Inter tree distance (m)
GR2	0.2/0.3	0.1	1.5/1.7	NA	NA	NA
GR7	0.8/0.9/1	0.1	6/7/8	NA	NA	NA
GS2	0.6/0.8	0.1	1.5/1.7	NA	NA	NA
SH2	0.2/0.3	0.1	5/6	NA	NA	NA
SH7	0.1	0.05	5.5/5.9	5/5.5	300/400	0.2
TU1	0.2/0.3	0.1	1/1.2	2	30/50	1
TU5	0.1	0.05	6/6.5	4.5/4.8	200/400	0.2
				2	30/50	1
TL3	NA	NA	NA	2/2.5	30/50/70	1
SB1	0.1	0.05	2/2.5	2/2.5	15/25	2
SB2	0.3	0.1	6.5/7.5	2/2.5	20	2



1. Simulation in DART model

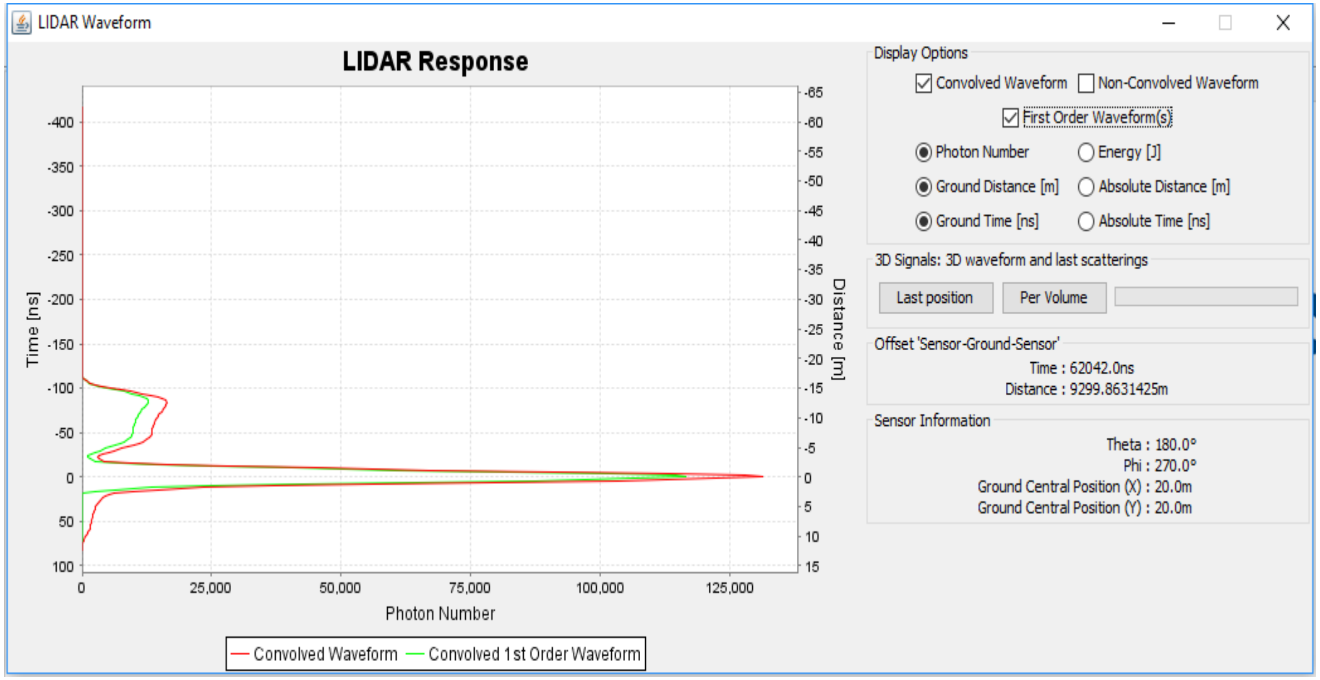
Parameters used in the "maket" module to simulate every fuel model:

Fuel model/layer	Trunk				Crown		
	Diameter below crown (m)	Height below crown (m)	Diameter within crown (m)	Height within crown (m)	Mean height (m)	First axis (m)	Second axis (m)
SH7/ shrub	0.05	0.3	0.04	1.5/1.8	1.6/2	1.2	1.2/2
TU1/ tree	0.4/0.5	5/10	0.3/0.4	7/14	10/20	3/4	2/3
TU5/ shrub	0.05/0.1	0.3	0.04/0.08	1.9/3.9	2/4	1.2/2	1.2/2
TU5/tree	0.4/0.5	5/10	0.3/0.4	7/14	10/20	3/4	2/3
TL3	0.3/0.4/0.5	5/10/20	0.2/0.3/0.4	4/7/14	5/10/20	2/3/4	1.5/2/3
SB1	0.4	5	0.3	7	10	3	2
SB2	0.4	5	0.3	7	10	3	2



2. Selection reference spectre

Transformation of fullwaveforme to "spectra":

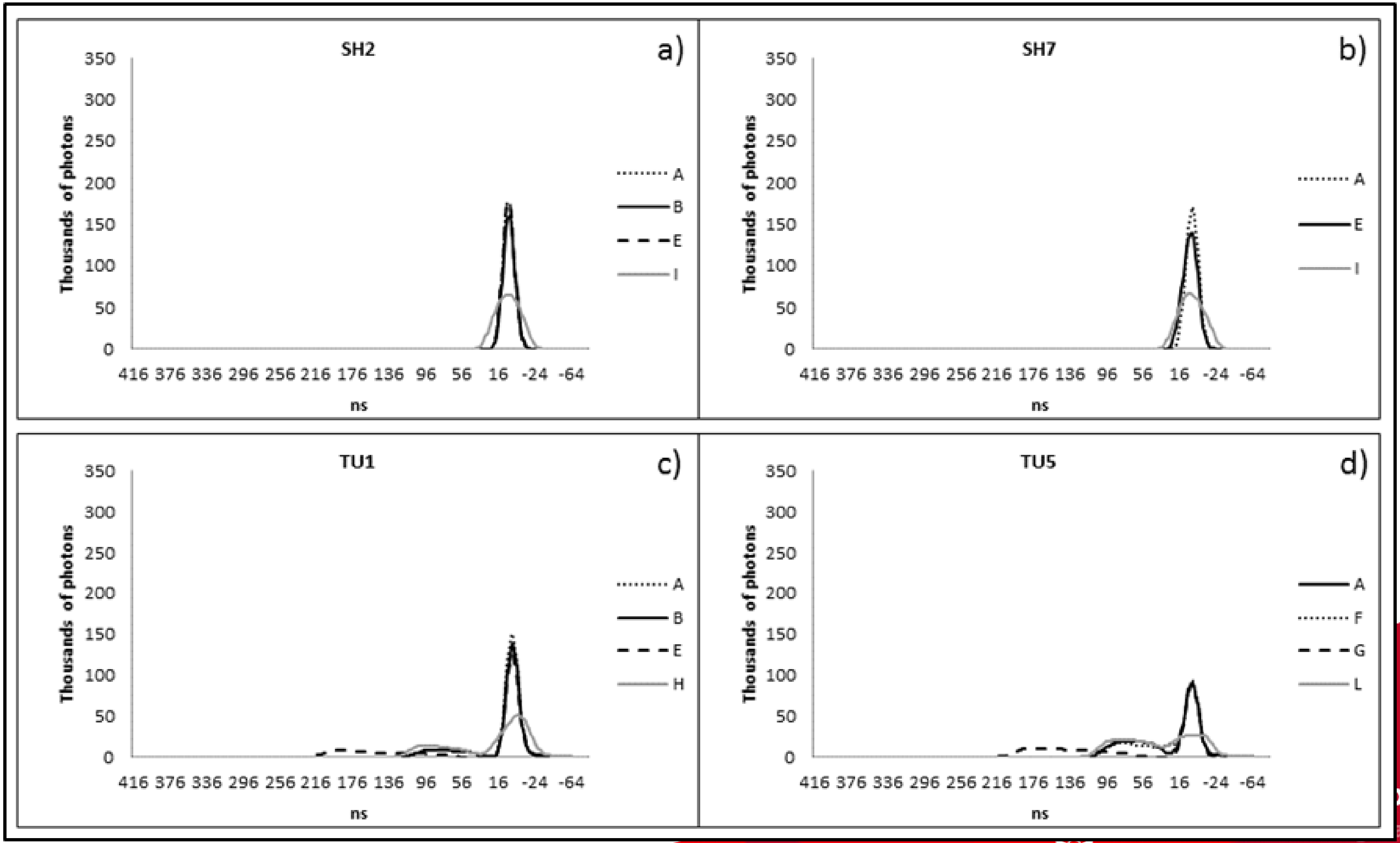


two assumptions were maid:

1) each bins stored in the waveform is similar to a spectral band and
2) the number of photos in similar to the reflectivity

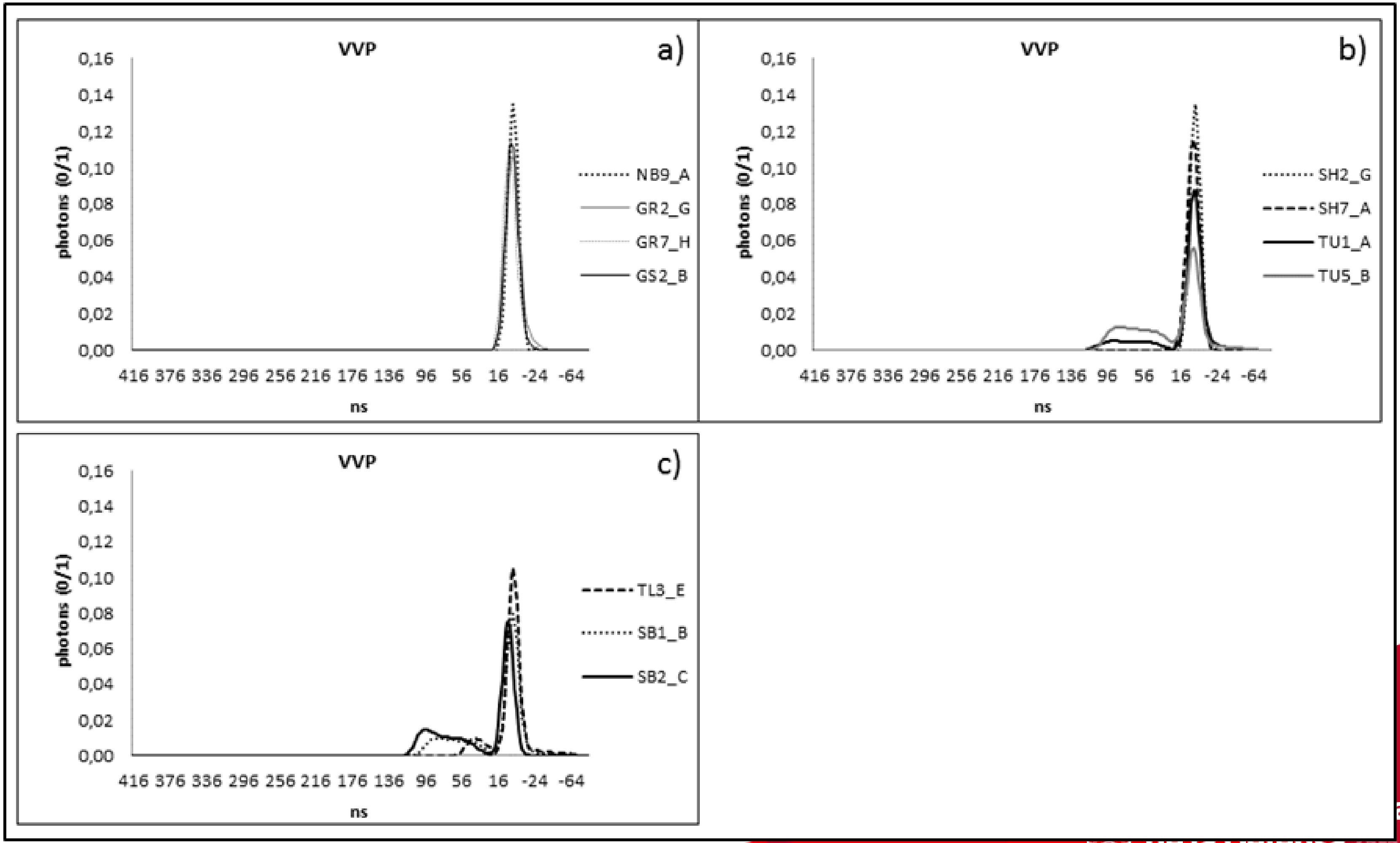
2. Selection reference spectre

Transformation of fullwaveforme to “spectra”:



2. Selection reference spectre

Transformation of "spectra" to simulate the Vegetation Vertical Profile:



2. Selection reference spectre

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Three techniques to select the most appropriate endmembers:

1) Count based Endmember Selection (CoB): endmembers are selected that model the greatest number of endmembers within their class (Roberts et al., 2003).

2) Endmember Average RMSE (root mean squared error) (EAR): endmembers are selected that produce the lowest RMSE within a class (Dennison & Roberts, 2003);

3) Minimum Average Spectral Angle (MASA): endmembers are selected that have the lowest average spectral angle (Dennison et al., 2004)

In addition the VVP analysis determined the selection of a second **endmember** covering the different **scan angle** and a **third** one in the models simulated with **different tree heights.**

3. Classification using SMA

Two classification methods:

1) Spectral Angle Mapper (SAM; Kruse et al., 1993) with 0.1 radians angle constraint

2) Multiple Endmember Spectral Mixture Analysis (MESMA; Roberts et al., 1998). A standard 2.5 % VVP error and -50 and 150 % minimum and maximum fraction partially constrain this endmember

Two approaches:

1) Classification with only **one endmember** per fuel model (11 endmembers). Validation with the rest of simulations (90 simulations) using the percentage of agreement and kappa index

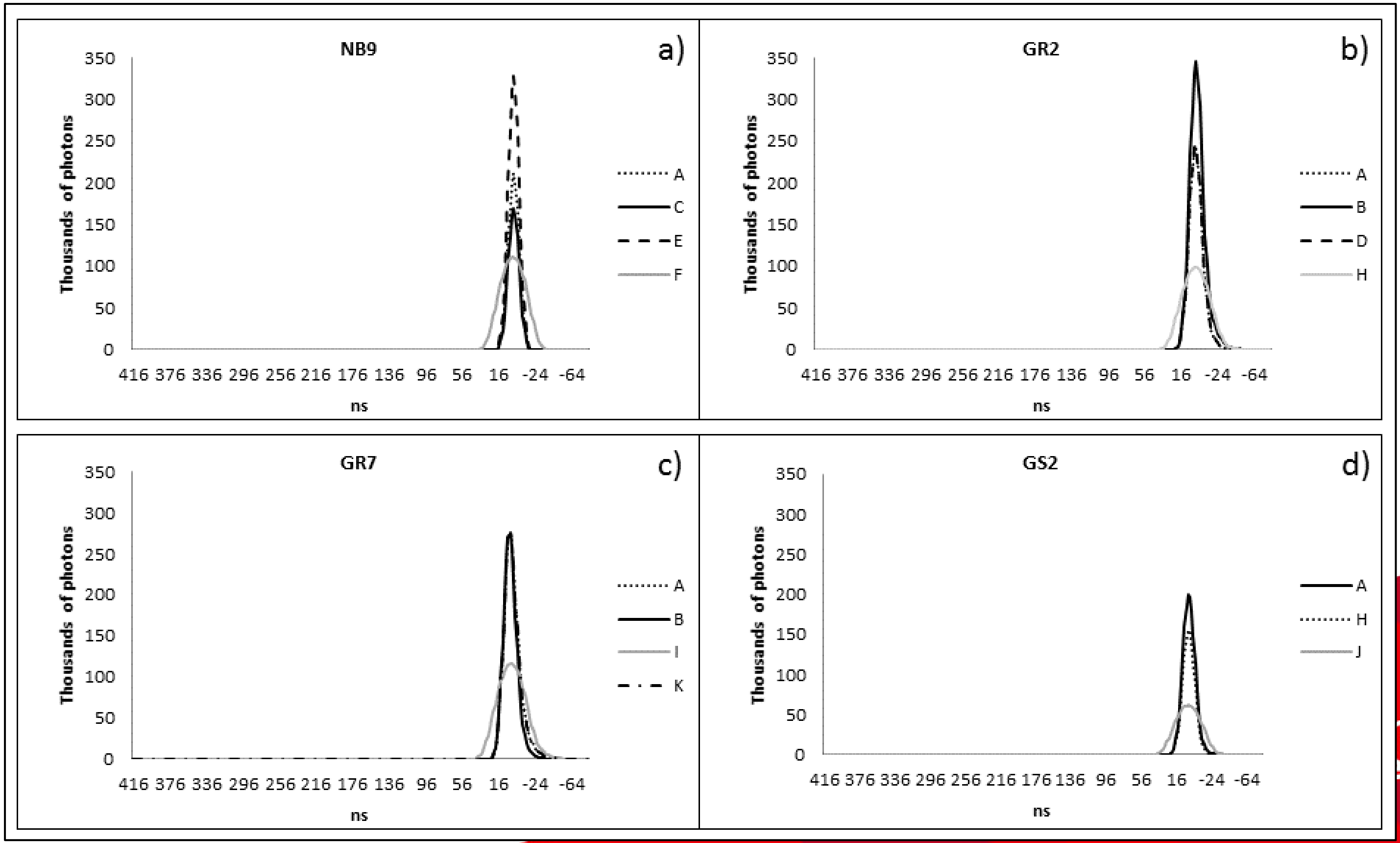
2) Classification with **two or three** endmembers per fuel model (27 endmembers). Validation with the rest of simulations (75 simulations) using the percentage of agreement and kappa index

Results

1. Analysis of VVP
2. Classification performance

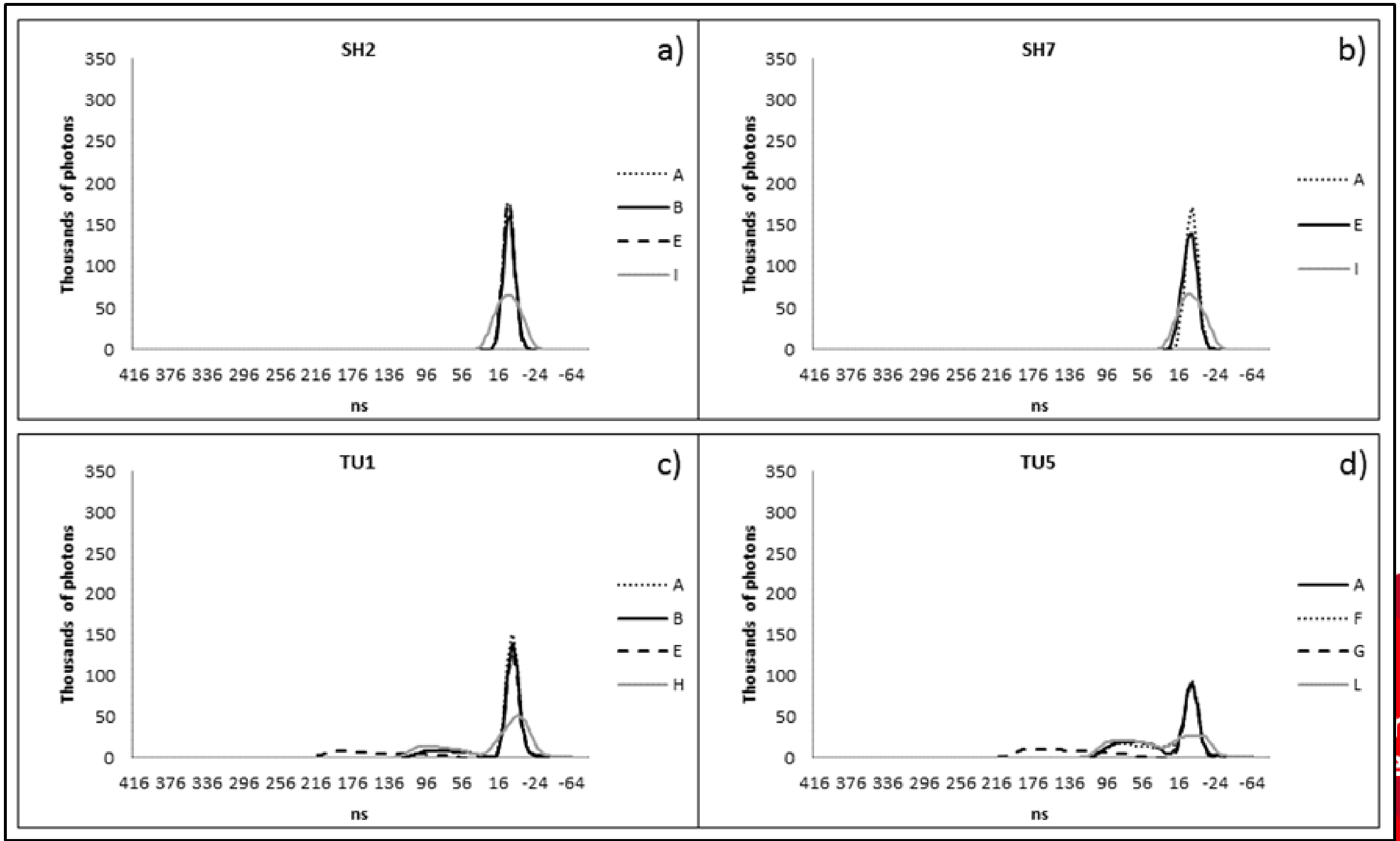
1. Analysis of VVP

- LiDAR waveforms show higher differences for the two simulations in each fuel model performed at off-nadir observation (models in gray in Fig)
- the optical property assigned to the soil in NB9 (bare soil, see Fig. a), implies the highest change in the number of photons
- the soil influence decreases as the vegetation cover increases. For example, the “sand_white” soil in a GR7 simulation (model K in Fig. c) presented a similar amount of stored photons as the ones with the “clay_brown” (models A and B in Fig. c)



1. Analysis of VVP

- the shrub height and LAI do not produce high variation between SH2 models
- the number of trees and LAI causes differences for SH7 (Fig. b). For example, SH7 A and E simulated 400 and 300 shrubs, respectively, and diverse height values assigned to trunk and crown
- the differences due the understory layer are small for TU1 (A and B in Fig. c) compared to the ones due to the number and height of trees (E in Fig. c)
- TU5 has a similar behavior than TU1 (Fig. d), although the understory presents slight variations after modifying the number of trees representing the shrubs



2. Classification

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SAM 1 endmember:

Overall accuracy = **48.9 %**; Kappa index = **0.46**

MESMA 1 endmember:

Overall accuracy = **63.3 %** ; Kappa index = **0.59**

SAM 2-3 endmembers:

Overall accuracy = **85.3 %**; Kappa index = **0.84**

MESMA 2-3 endmembers:

Overall accuracy = **86.5 %**; Kappa index=**0.85**

	Reference fuel type														
Classified	GR2	GR7	GS2	NB9	SB1	SB2	SH2	SH7	TL3	TU1	TU5	NC	Total	User´s accuracy (%)	Error of commission (%)
GR2	**6**	**1**	0	0	0	0	0	0	0	0	0	0	7	85.7	14.3
GR7	0	**6**	**1**	0	0	0	0	0	0	0	0	0	7	85.7	14.3
GS2	**1**	0	**7**	0	0	0	0	0	0	0	0	0	8	87.5	12.5
NB9	0	0	0	4	0	0	0	0	0	0	0	0	4	100.0	0.0
SB1	0	0	0	0	5	0	0	0	0	0	0	0	5	100.0	0.0
SB2	0	0	0	0	0	**4**	0	0	0	0	1	0	5	80.0	20.0
SH2	0	**1**	0	0	0	0	**8**	**1**	0	0	0	0	10	80.0	20.0
SH7	0	0	0	0	0	0	0	6	0	0	0	0	6	100.0	0.0
TL3	0	0	0	0	0	0	0	0	3	0	0	0	3	100.0	0.0
TU1	0	0	0	0	0	0	0	0	**3**	**6**	0	0	9	66.7	33.3
TU5	0	0	0	0	0	0	0	0	**1**	0	**9**	0	10	90.0	10.0
Not classified (NC)	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-
Total	7	8	8	4	5	4	8	7	7	6	10	7	74	88.7	11.3
Producer´s accuracy (%)	85.7	75.0	87.5	100.0	100.0	100.0	100.0	85.7	42.9	100.0	90.0	-	87.9	Overall accuracy=86.5% Kappa index=0.85	
Error of Omission (%)	14.3	25.0	12.5	0.0	0.0	0.0	0.0	14.3	57.1	0.0	10.0	-	12.1		

Conclusions

1. SMA automatically identified fuel types from LiDAR waveforms simulated with DART model.
2. MESMA outperformed SAM when using one endmember and gave similar results when using multiple endmembers.
3. Multiple endmembers that characterize the full signature variation within each fuel type improved the classification results.
4. It is important to consider different scan angles in the simulations and account for the variability in height and number of trees.

Future investigation

1. Development of LiDAR signature library for the complete Scott and Burgan (2005) classification with multiple endmembers that cover the entire range of variability within the fuel models and considering different scan angles and tree heights and number
2. Combine hyperspectral and LiDAR data to create complementary signatures libraries
3. Comparison of the LiDAR library generated by DART with real LiDAR data

Thanks for your attention

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