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Hyperspectral recognition of the urban vegetation using spectral library. Example of Kaunas (Lithuania)

Sébastien Gadal

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Hyperspectral recognition of the urban vegetation using spectral library. Example of Kaunas (Lithuania)

Sébastien GADAL

Context and goals

Goals

- Characterize, monitor and map urban vegetation over Kaunas city (Lithuania).
- Propose practical solutions for city actors and urban architects in terms of vegetation mapping and inventory gathering.

Geographic context and study zone choice:

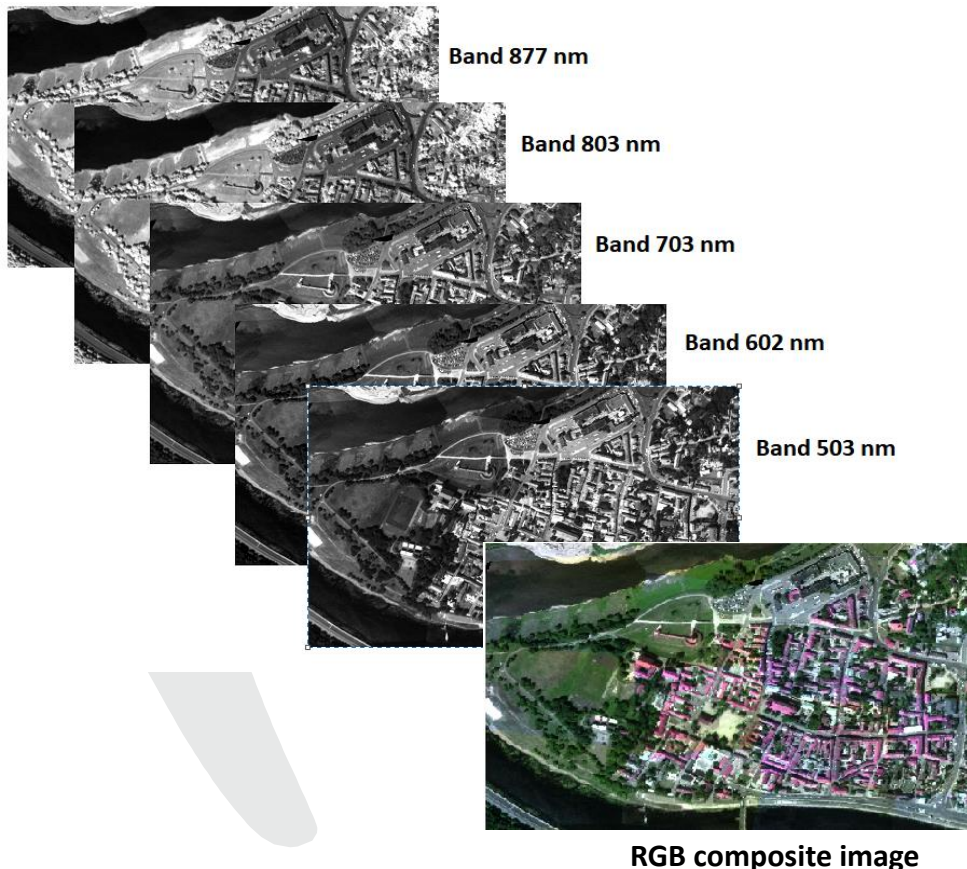
- High Vegetation diversity in urban areas.
- Complex distribution of vegetation species within the city.
- Various Morphologies and urban structures: 15e-17e centuries, 19e century, Art-Nouveau, Soviet, post-soviet, etc.
- Canopy state (green, dry, sick).



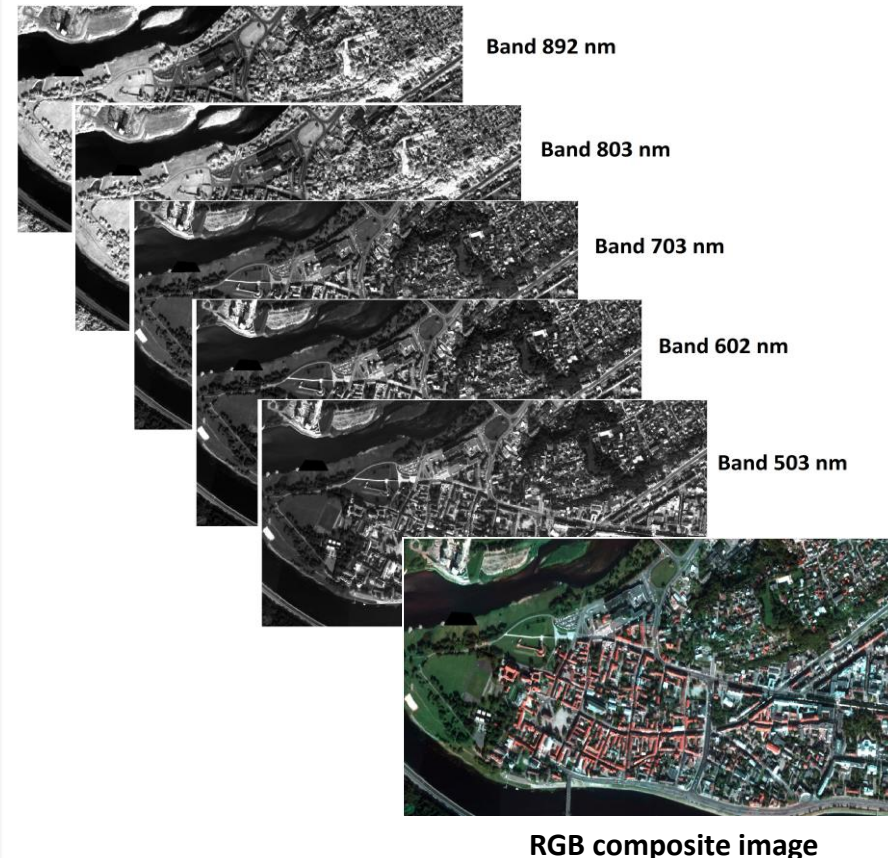
Airborne hyperspectral data (Rikola)

- Two images acquired over Kaunas city, in July 2015 and September 2016.
- 16 and 64 bands 500nm-900nm (Vis-NIR).
- Spatial resolution of 0,7 m and 0,5 m.
- Covered area: 5km².

Kaunas center July 2015 (16 bands)



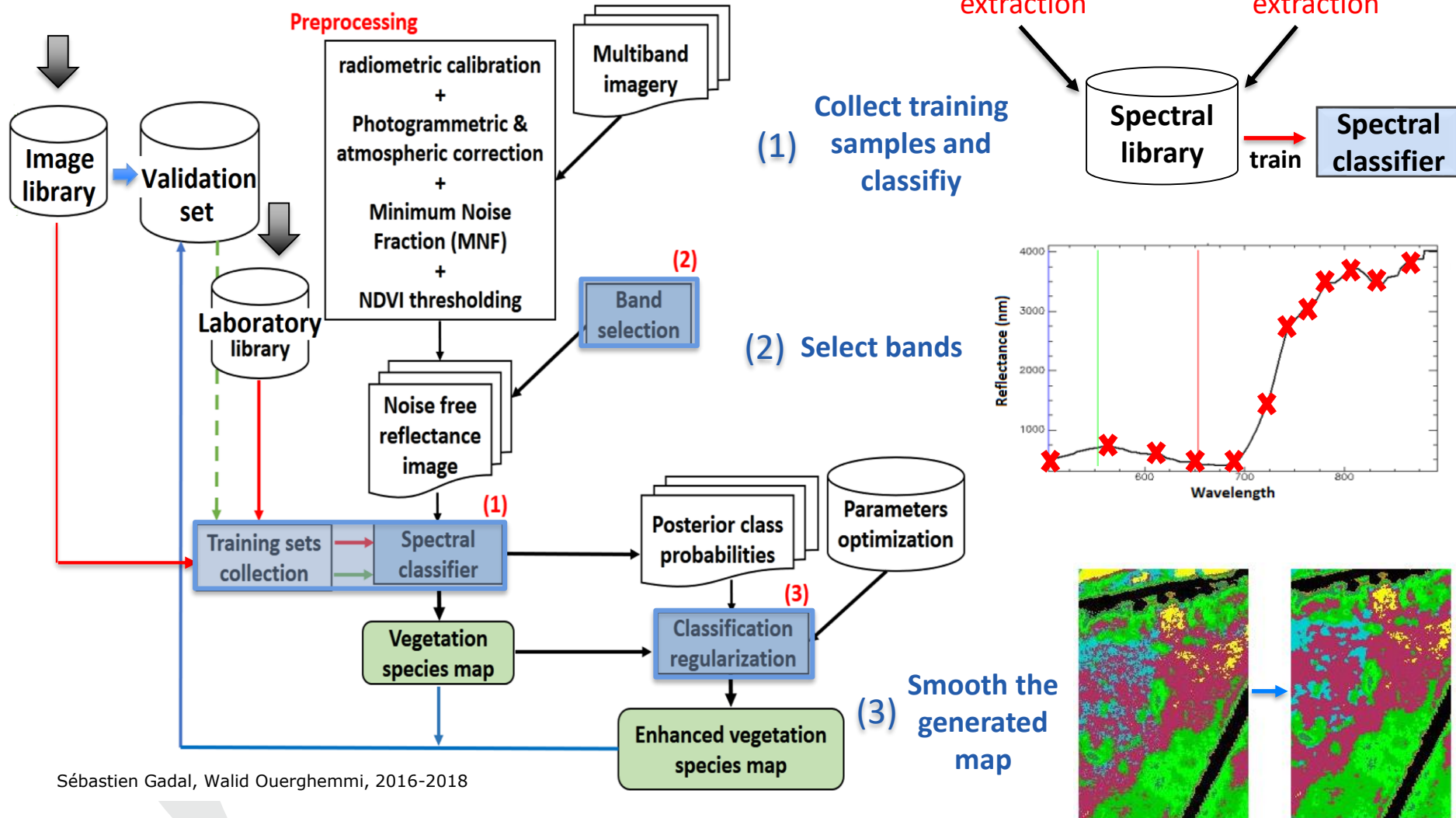
Kaunas center September 2016 (64 bands)



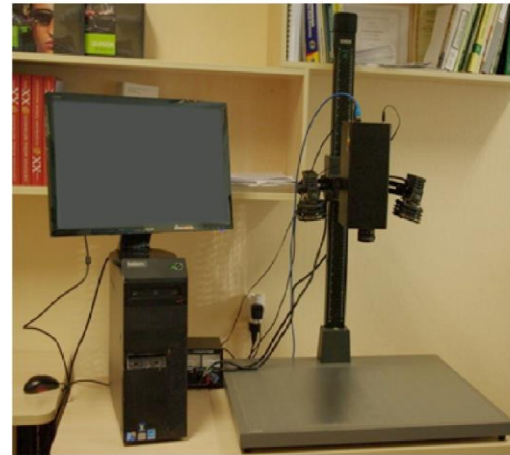
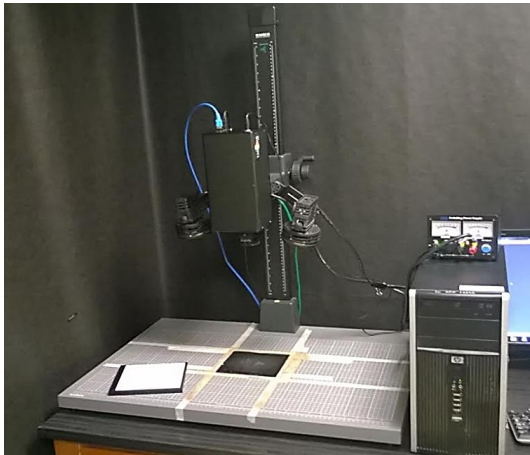
Methodological framework

- **Based on the spectral libraries**
- **Automatic (based on the machine learning)**
- **Based on the vegetation database (Kaunas tree database and field survey)**

Methodology: spectral libraries (1)



Spectral library: laboratory based training samples



Hyperspectral laboratory imager features:

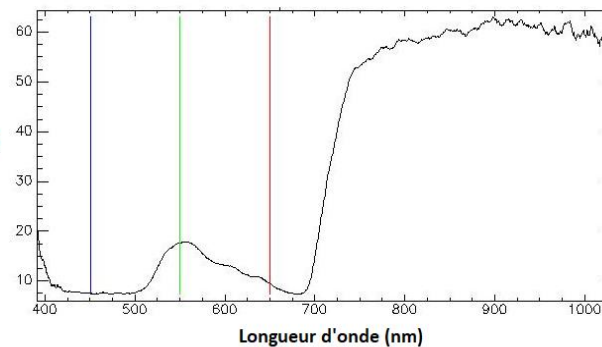
- Brand: Themis Vision VNIR400H (Themis Vision systems LLC).
- Spectral Range: Vis-NIR, 400nm to 1000 nm.
- Spectral resolution: 0,6nm
- Sensor type: CCD.
- Bands number: 955.
- Light: 2 halogen lamps of 100W
- Image Scan: line by line
- Measurements conditions: black room

Oak sample

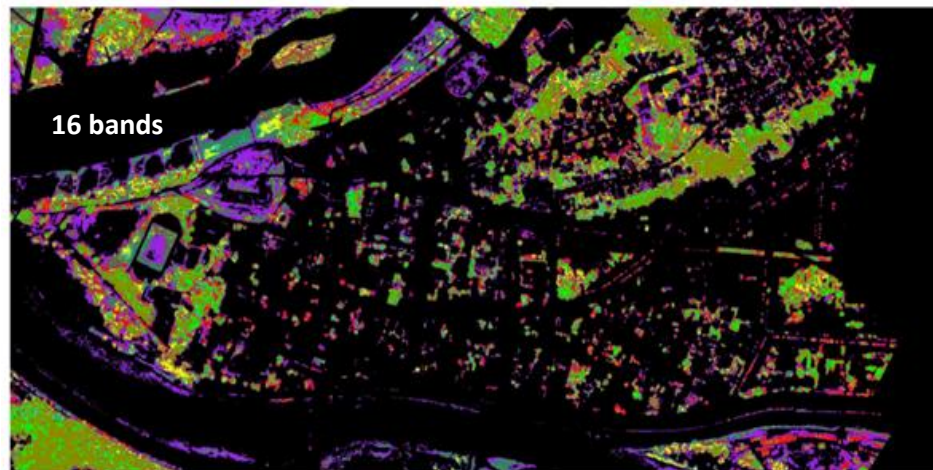
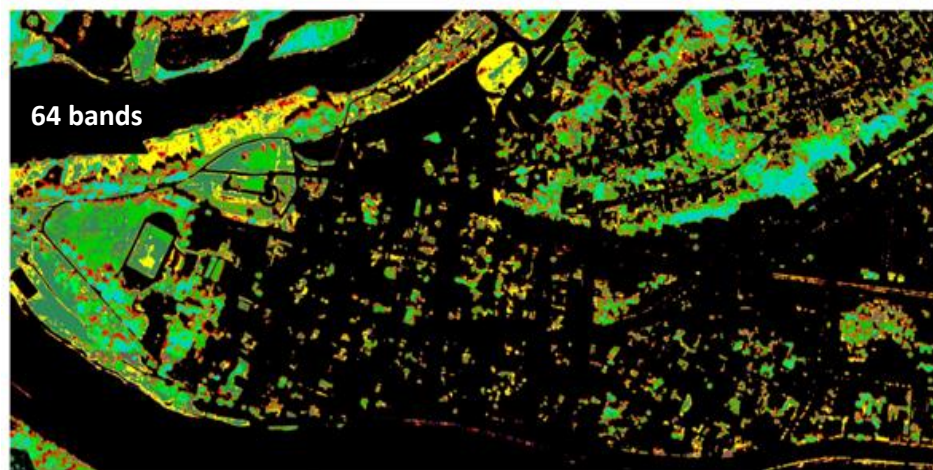


Reflectance (%)

Spectral measurement



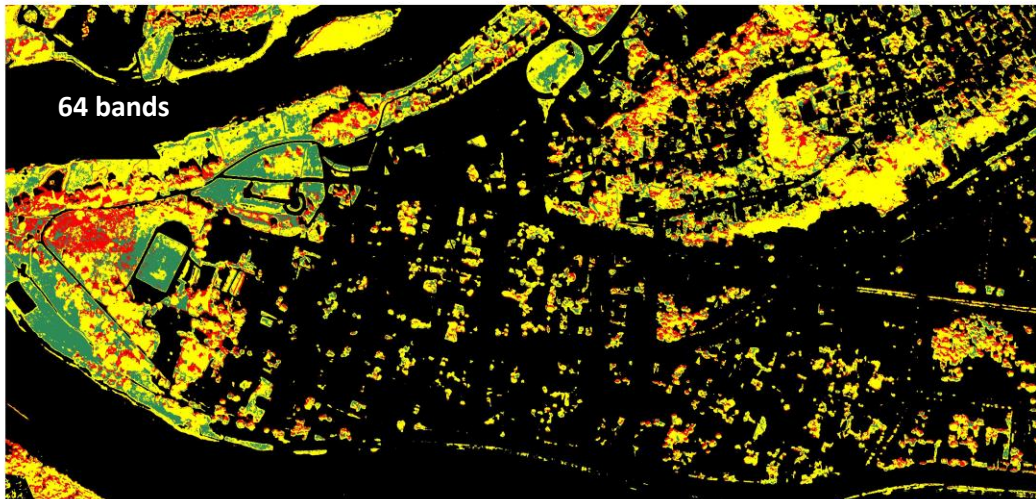
Vegetation Mapping and recognition of species using image library training samples and SAM classifier (results)



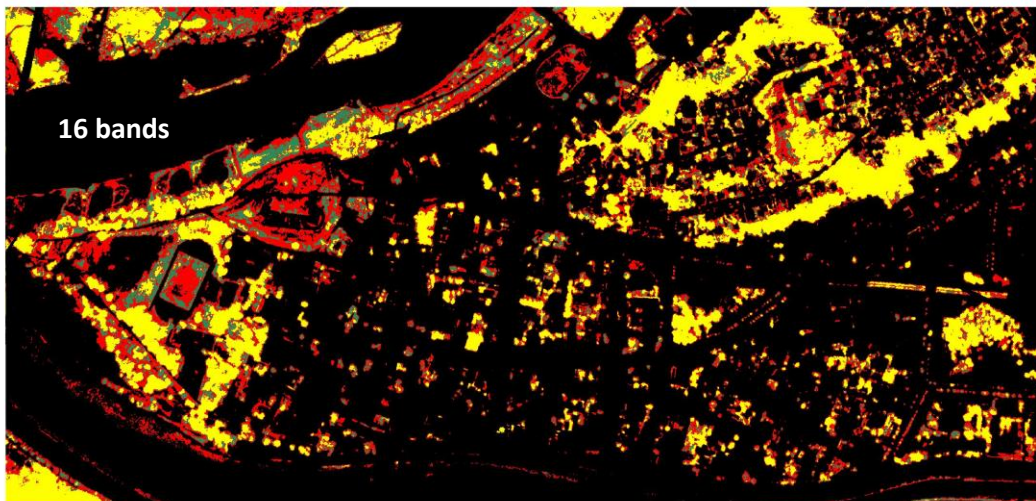
Species	SAM (16 bands)	SAM (64 bands)
H. Chestnut	6.6	8.7
E. Beech	7.9	33.1
Linden	10.5	11.6
Maple	12.0	11.0
M.Ash	30.0	15.7
Oak	11.5	10.2
N. Spruce	15.0	16.6
Juniperus horizontalis	0.3	0.0
S. Pine	27.7	30.1
Arborvitae	50.0	0.7
Grass	59.4	36.0
O.A. (%)	16.2	21.1

- «slight» to «fair» accuracy ($0\% < \text{O.A.} < 40\%$)
- Better **identification rate** given by **64 bands** image (40% more pixels identified)
- High variability per species

Vegetation Mapping and recognition of group of species using image library training samples and SVM classifier (results)

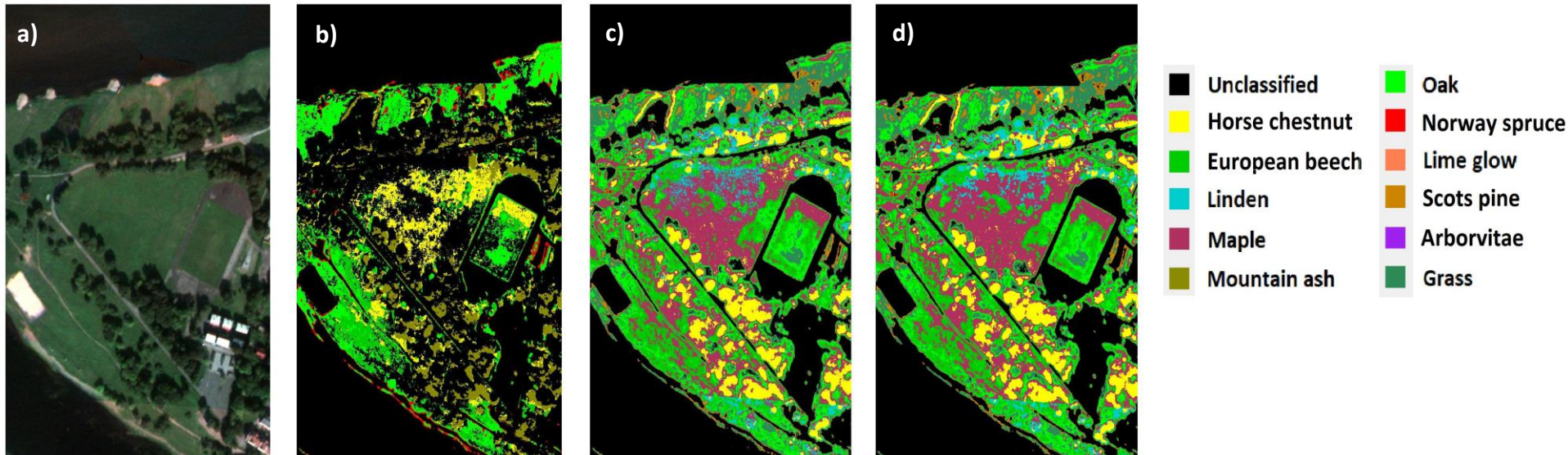


Species\Classifier	SVM (16 bands)	SVM (64 bands)
Deciduous	57.9	63.2
Coniferous	45.6	35.0
Grass	56.8	31.3
O.A. (%)	57.0	49.8



- «Moderate» accuracy for both case (40%<O.A.<60%)
- **64 bands** image: better estimation of deciduous, under-estimation of coniferous
- **16 bands** image: over-estimation of coniferous over grass

Vegetation Mapping and recognition of species using image library training samples and regularization process (results)

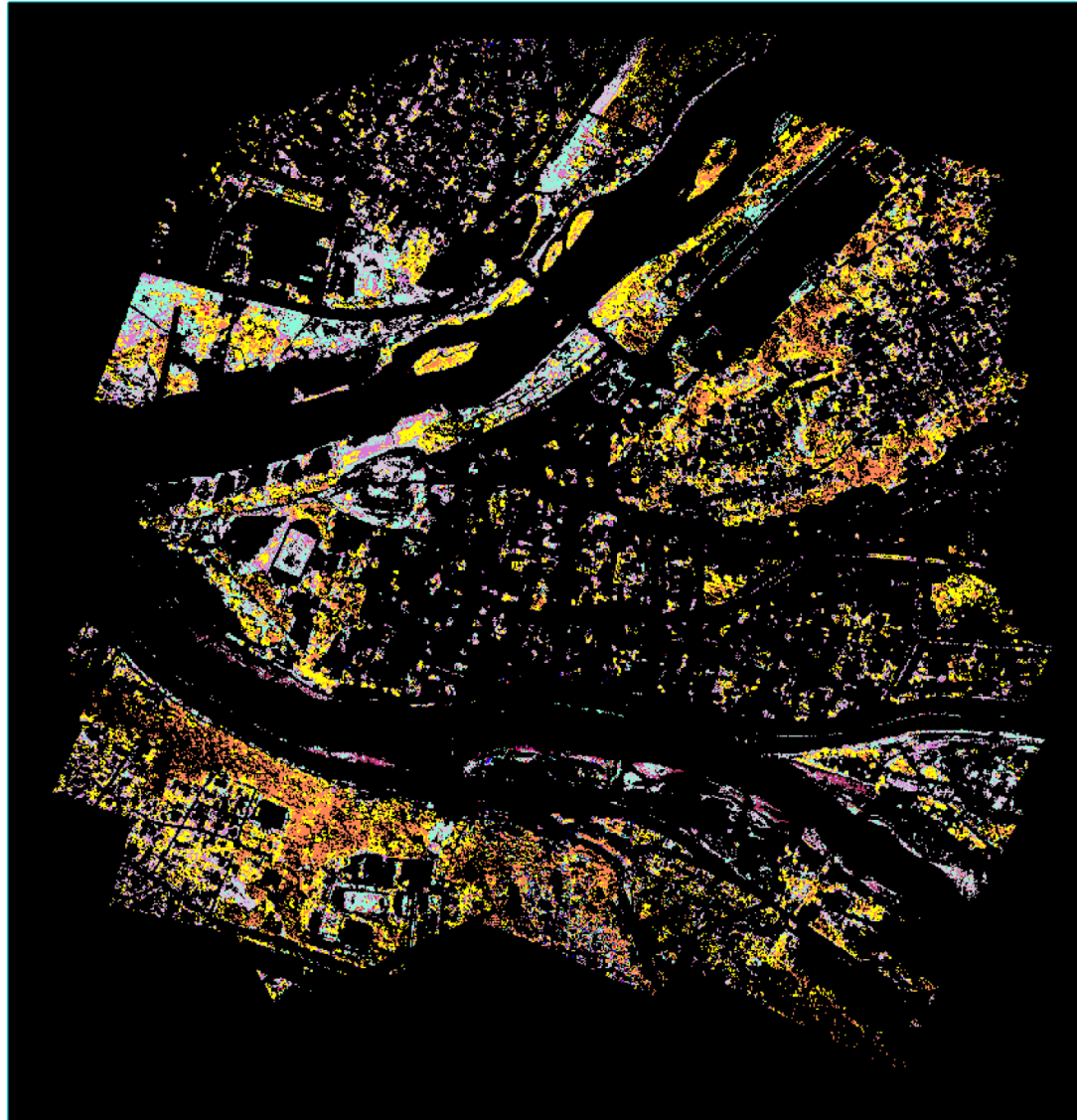


Walid Ouergemmi, Sébastien Gadal, 2016-2018

a) RGB composite test portion over Kaunas city, **b)** classification by laboratory spectral library, **c)** classification by image spectral library, and **d)** regularization of the generated map

- **Poor** identification rate and statistical accuracy using **laboratory spectral library** for classification training (**b**)
- **Good** identification rate and **significant enhancement** of statistical accuracy using **image spectral library** for classification training (**c**)
- **Enhancement** and smoothing of the classification map using **regularization** graph-cut algorithm (**d**)

Recognition of the species based on the spectral library and SAM classifier



LEGENDE

- Unclassified
- Mean-aspen
- mean-chesnut
- Mean-corylus
- mean-fir
- Mean-green-grass
- mean-green-grass-90
- Mean-lime-glow
- Mean-linden
- Mean-maple
- Mean-mountain-ash
- Mean-oak
- Mean-pine
- Mean-flower-red-clover
- Mean-red-clover
- Mean-silver
- Mean-thuja

Accuracy Results (compilation)

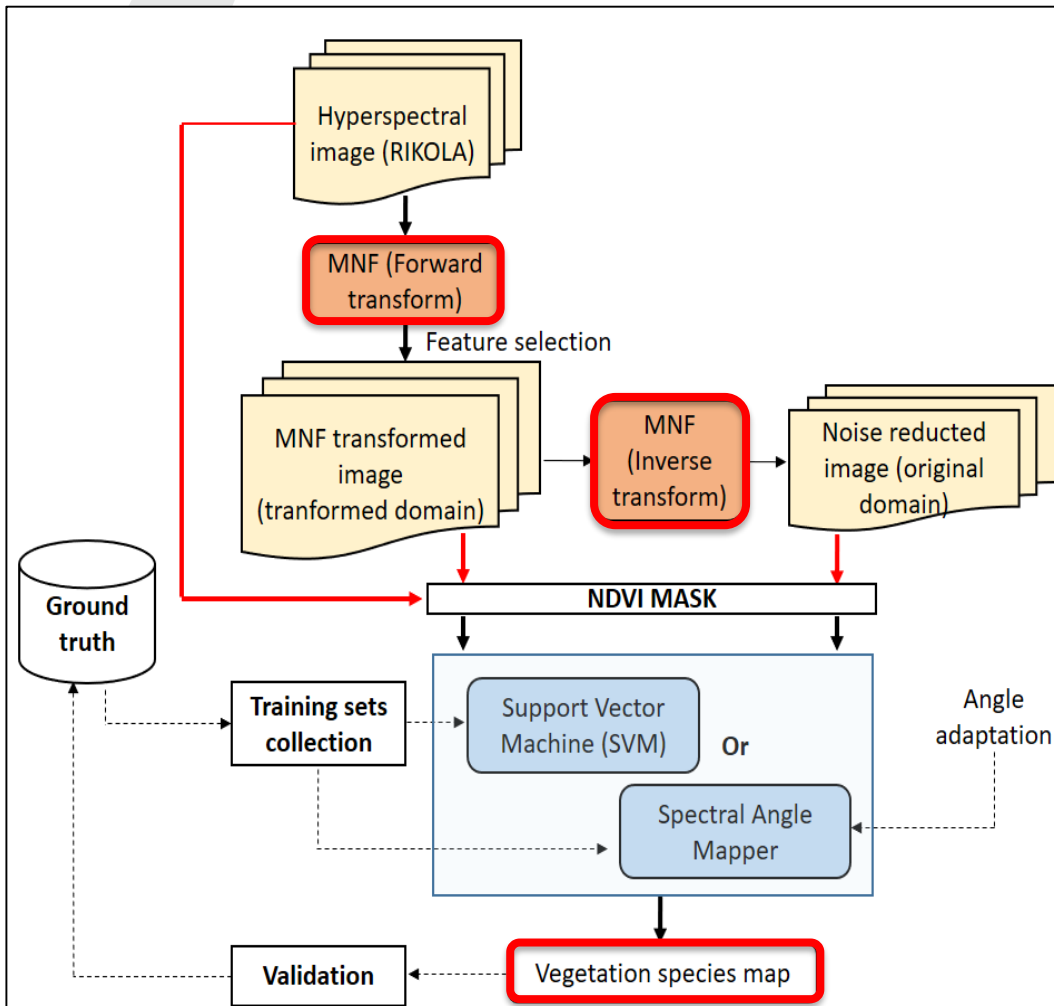
Veg. species	Classif. accuracy (16 bands image)						Classif. accuracy (64 bands image)							
	Image acquired spectra			laboratory spectra			Image acquired spectra			laboratory spectra				
										All bands			Band selection	
Classifier Training										No reg.	Reg.			
Samples	10	50	100	10	50	100	10	50	100	10	50	100	50	50
H. Chestnut	0.0	3.7	5.4	20.1	6.4	4.3	2.3	8.3	8.7	20.0	3.2	1.1	3.3	3.2
E. Beech	21.0	7.9	7.9	2.6	10.0	11.1	20.2	38.7	33.1	0.2	4.0	5.2	20.0	19.9
Linden	4.3	17.5	9.2	0.7	0.0	0.0	3.7	2.4	11.6	0.0	0.0	0.0	8.5	8.8
Maple	30.4	14.8	12.4	0.3	0.0	0.1	13.3	12.9	11.0	0.0	0.0	0.0	29.5	28.9
M.Ash	10.2	11.8	22.5	0.0	59.8	59.6	15.2	21.0	15.7	0.0	26.2	20.7	0.0	0.0
Oak	33.8	34.3	17.1	2.1	6.8	8.7	8.8	11.7	10.2	1.6	1.7	3.97	21.9	21.9
N. Spruce	11.3	43.3	21.7	4.9	3.2	4.6	5.8	11.6	16.6	0.4	1.2	2.7	0.0	0.0
Lime glow	0.0	0.3	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
S. Pine	21.5	24.0	22.8	0.0	0.0	0.1	63.8	51.5	30.1	0.0	0.0	0.0	0.4	0.4
Arborvitae	11.8	25.9	46.1	0.0	0.0	4.9	0.7	0.5	0.7	0.0	0.0	0.0	0.0	0.0
Grass	30.4	56.9	60.8	0.0	0.0	0.4	34.1	31.3	36.0	0.0	0.0	0.0	16.6	16.5
O.A. (%)	19.4	18.2	15.6	2.7	3.0	2.9	19.7	19.1	21.1	1.5	1.1	0.9	16.8	16.7
Kappa × 10 ⁻³	70	70	70	-4	-0.9	-0.4	50	100	110	-3	-0.6	-0.1	14	11
Deciduous	--	57.9	--	--	78.0	--	--	63.2	--	--	36.2	--	71.2	71.2
Coniferous	--	45.6	--	--	5.4	--	--	35.0	--	--	1.0	--	3.7	3.7
Grass	--	56.8	--	--	0.0	--	--	31.3	--	--	0.0	--	16.6	16.5
O.A. (%)	--	57.0	--	--	67.2	--	--	49.8	--	--	20.7	--	47.0	46.0
Kappa × 10 ⁻³	--	170	--	--	-20	--	--	190	--	--	-7	--	-3	-7

Individual species recognition

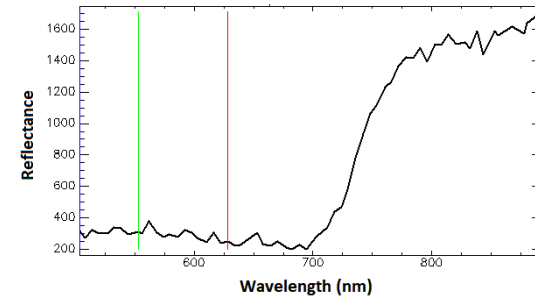
Group of species recognition

- «Slight» accuracy of individual species recognition (overall accuracy of 21% at best)
- «Moderate» to «Substantial» accuracy of group of species recognition (overall accuracy of 67% at best)
- Image spectral library based mapping more accurate than laboratory spectral library based mapping.
- Enhancement of mapping accuracy when increasing band number for individual species
- No enhancement of mapping accuracy when increasing band number for group of species
- Band selection enhanced accuracy of individual and group of species recognition

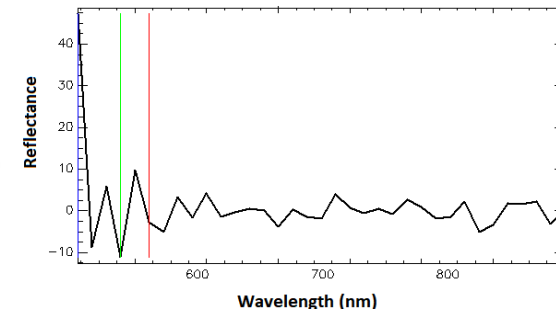
Methodology: machine learning (2)



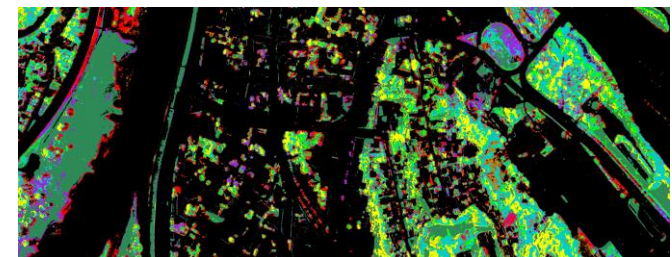
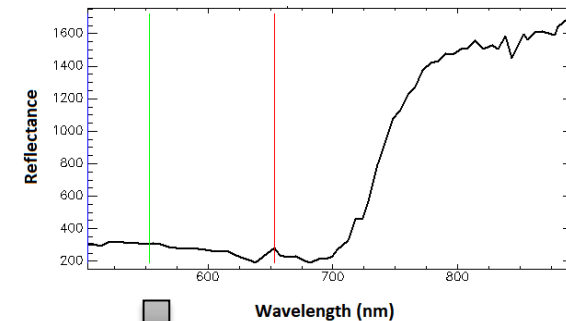
Original
spectrum



NMF
transformed
spectrum
(transformation
domain)

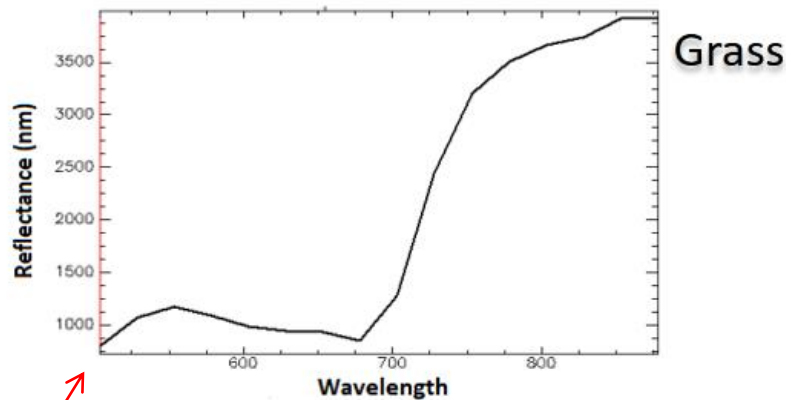


Noise free
reconstructed
spectrum
(original
domain)

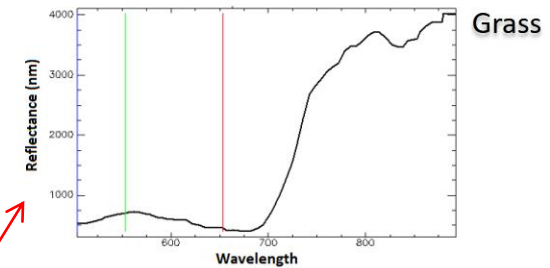


Spectral library : image based training samples

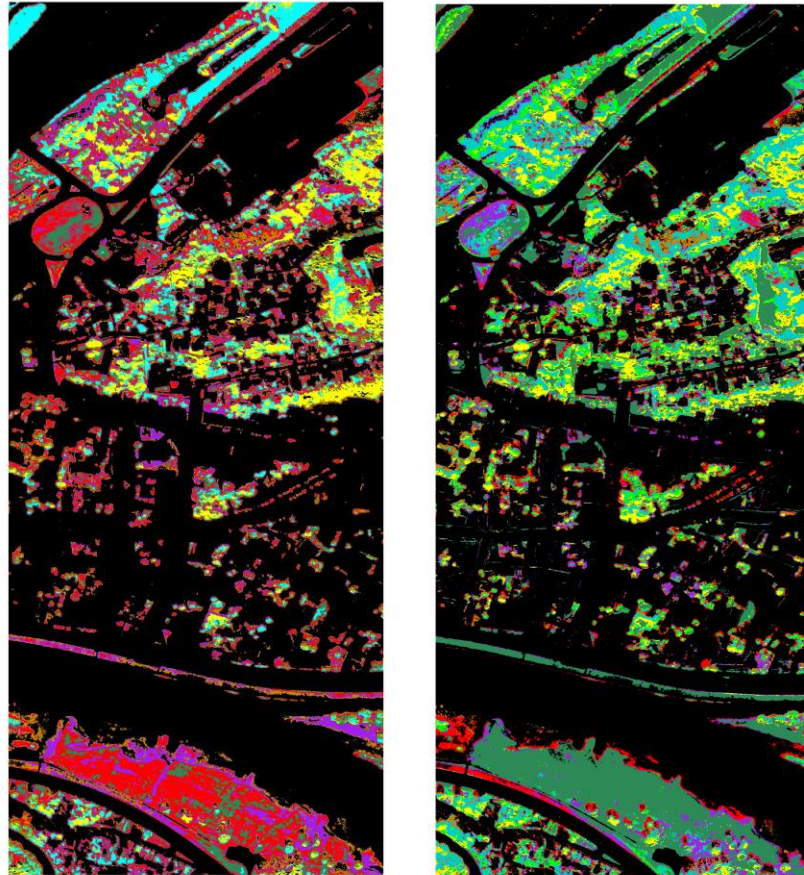
Kaunas Center **16 bands**, RGD
composite image - **July 2015** -



Kaunas Centre **64 bands**, RGB
composite image - **September 2016** -



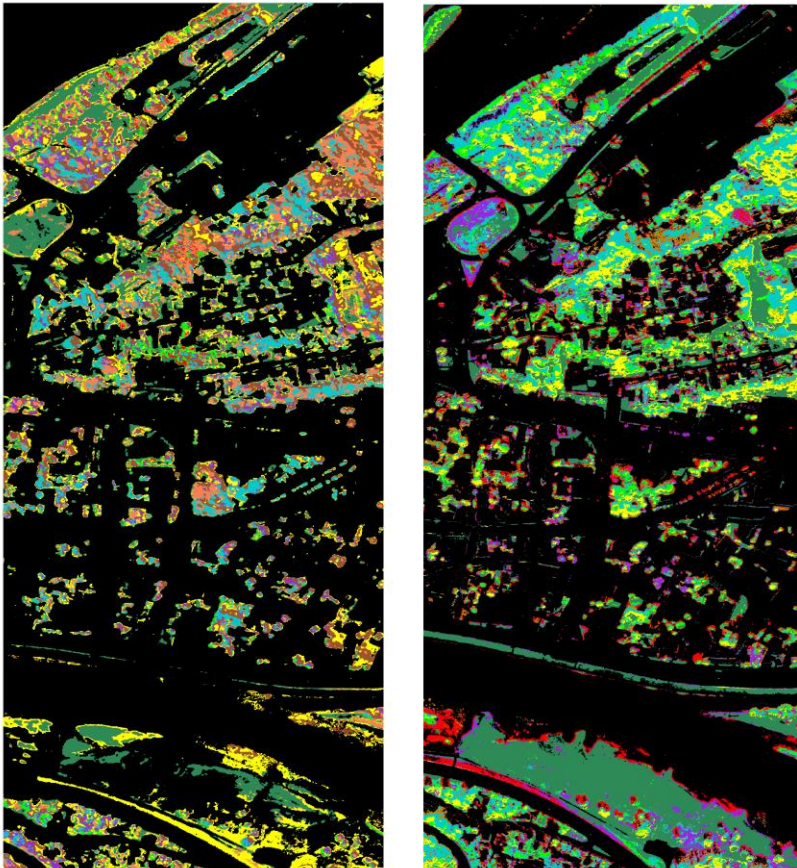
Vegetation Mapping per species using Reflectance MNF images (SAM and SVM comparison over 64 bands image)



Species	SAM (64 bands)	SVM (64 bands)
H. Chestnut	12.1	28.0
Linden	21.1	19.2
M.Ash	49.0	38.8
Oak	61.1	72.5
N. Spruce	26.9	51.6
S. Pine	10.5	18.1
Thuja	10.9	27.6
Grass	21.8	85.5
O.A. (%)	22.6	45.7

- “Fair” (20%<O.A.<40%) to “moderate” (40%<O.A.<60%) accuracies
- Better **mapping accuracy** given by **64 bands** image
- **Underestimation of grass, and overestimation of other species (N.Spruce and Oak) (SAM)**

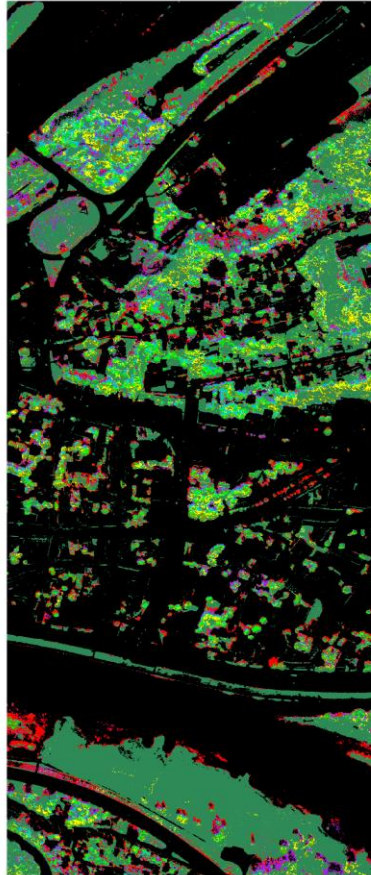
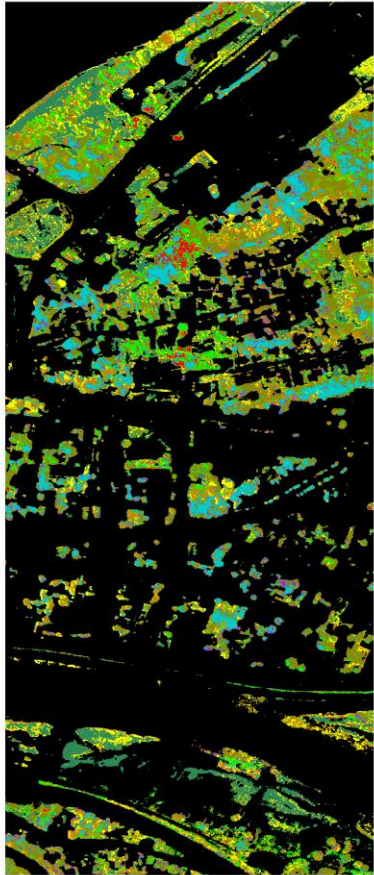
Vegetation Mapping per species using Reflectance MNF images and SVM classifier (16 and 64 bands images comparison)



Species	SVM (16 bands)	SVM (64 bands)
H. Chestnut	19.1	28.0
Linden	36.0	19.2
M.Ash	38.4	38.8
Oak	36.5	72.5
N. Spruce	15.0	51.6
S. Pine	47.3	18.1
Thuja	50.1	27.6
Grass	91.2	85.5
O.A. (%)	41.2	45.7

- “Moderate” (40%<O.A.<60%) accuracy
- Better **mapping accuracy** given by **64 bands** image
- Coniferous better identified using **16 bands** image

Vegetation Mapping per species using Non Reflectance MNF images and SVM classifier (16 and 64 bands images comparison)



	H.Chestnut
	Linden
	M.Ash
	Oak
	N.Spruce
	S.Pine
	Thuja
	Grass

Species	SVM (16 bands)	SVM (64 bands)
H. Chestnut	23.3	22.0
Linden	35.8	17.3
M.Ash	46.2	34.0
Oak	45.8	62.2
N. Spruce	19.2	40.3
S. Pine	59.3	17.7
Thuja	48.3	26.8
Grass	92.6	95.8
O.A. (%)	43.6	46.1

- “Moderate” (40%<O.A.<60%) accuracy
- Better **statistical accuracy** given by **64 bands** image
- Better **expert accuracy** given by **16 bands** image
- **Overestimation** of grass specie using 64 bands **non reflectance** image
- **Feature selection** over 64 bands MNF image affected badly the mapping accuracy (**information loss**)

Accuracy Results (compilation)

- **MNF (1):** feature selection in the original domain (reflectance)
- **MNF (2):** feature selection in the transformed domain (non reflectance)

deciduous

coniferous

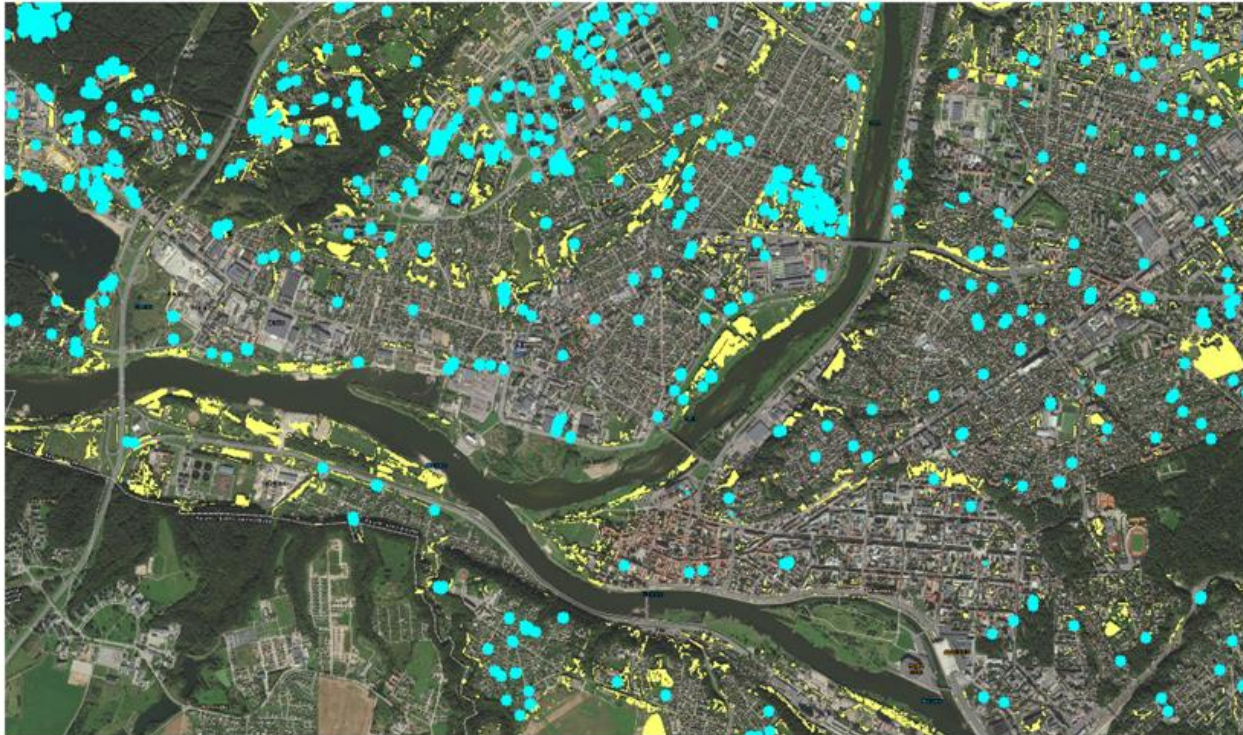
Veg. species	Classif. accuracy (16 bands image)						Classif. accuracy (64 bands image)					
	SAM			SVM			SAM			SVM		
Classifier Training	No NMF	MNF (1)	MNF (2)	No NMF	MNF (1)	MNF (2)	No NMF	MNF (1)	MNF (2)	No NMF	MNF (1)	MNF (2)
Samples												
H. Chestnut	16.4	16.5	21.5	19.2	19.1	23.3	11.5	12.1	27.0	28.1	28.0	22.0
Linden	15.4	16.0	24.5	33.6	36.0	35.8	20.5	21.1	13.1	19.3	19.2	17.3
M.Ash	16.7	11.9	25.8	37.5	38.4	46.2	46.3	49.0	50.1	38.5	38.8	34.0
Oak	41.0	40.2	49.7	36.2	36.5	45.8	62.3	61.1	72.9	69.9	72.5	62.2
N. Spruce	10.0	9.8	21.1	16.4	15.0	19.2	26.8	26.9	16.0	50.7	51.6	40.3
S. Pine	49.8	47.7	55.4	49.1	47.3	59.3	10.7	10.5	18.7	17.9	18.1	17.7
Thuja	35.7	31.9	33.7	52.7	50.1	48.3	10.4	10.9	6.7	28.5	27.6	26.8
Grass	45.2	45.4	93.9	92.5	91.2	92.6	22.3	21.8	65.0	85.1	85.5	95.8
O.A. (%)	22.6	22.4	37.6	40.7	41.2	43.6	21.9	22.6	34.5	45.5	45.7	46.1
Kappa	0.10	0.10	0.28	0.29	0.30	0.33	0.11	0.11	0.24	0.34	0.34	0.34

- “Fair” (20%<O.A.<40%) to “moderate” (40%<O.A.<60%) accuracies for all studied cases
- **Enhancement** of mapping accuracy when **increasing** band number from **16** to **64 bands**.
- **MNF feature selection** enhanced the mapping accuracy (original and transformed domains)
- Mapping over the **transformed domain** (non reflectance images, MNF 2) gives better statistical accuracies than **original domain** (reflectance images, MNF 1)

Conclusions

- The use for **VIS-Nir hyperspectral airborne** imagery, could be considered as a reliable and practical solution for **vegetation mapping** over **urban** areas
- **Limited** spectral samples were used for **classifiers training** (100 samples) due to limited **ground truth** data
- (**SVM**) classifier offer **more accurate** mapping than (**SAM**) classifier (**6%** to **23%** better in term of overall accuracy)
- vegetation **species detection** was enhanced when **increasing the bands number** (from **16** to **64 bands**) (**1%** to **5%** better in term of overall accuracy)
- The use of **MNF feature selection** enhanced the mapping accuracy
- **MNF feature selection** over the **transformed domain** (non reflectance images) offer **better** statistical accuracy than over the **original domain** (reflectance images), but **reliability** is not ensured in case of **under-selection** of features
- **Issues and improvements:** improve ground truth data, use other feature selection strategies, use other classifier training strategies

Methodology: vegetation database (3)



■ Individual trees
(example: Oak)

■ Group of trees

Land field GIS database

- Individual trees (371 species)
- Heterogeneous groups (up to 10 species within group)
- Homogeneous groups (1 or 2 major species)

) Recognition of sets en vegetation using SVM (100% and 50% sample objects database) (16 spectral bands)



Romain Barlatier, Sébastien Gadal, Walid Ouerghemmi, 2017-2018

100%



50%

Recognition of sets en vegetation using SVM (100% and 50% of the sample object database) (64 spectral bands)



100% => 50%

Romain Barlatier, Sébastien Gadal, Walid Ouerghemmi, 2017-2018

Vegetation mapping using SVM with 100% and 50% of the sample object database (16 spectral bands)



Romain Barlatier, Sébastien Gadal, Walid Ouerghemmi, 2017-2018

100%



Classification SVM (50% échantillons) par espèces de végétation - Kaunas - Juillet

2015 (Source : HIS)

50%

LEGENDE	
■	Unclassified
■	azuolas paprastasis
■	berzas karpotasis
■	egle paprastoji
■	gluosnis trapusis
■	kastonas paprastasis
■	klevas paprastasis
■	klevas uosialapis
■	liepa mazalape
■	peulouse
■	pusis kalhiné
■	robinija baltaziede
■	tuja vakariné
■	uosis paprastasis

Vegetation mapping using SVM with 100% and 50% of the sample object database (64 spectral bands)



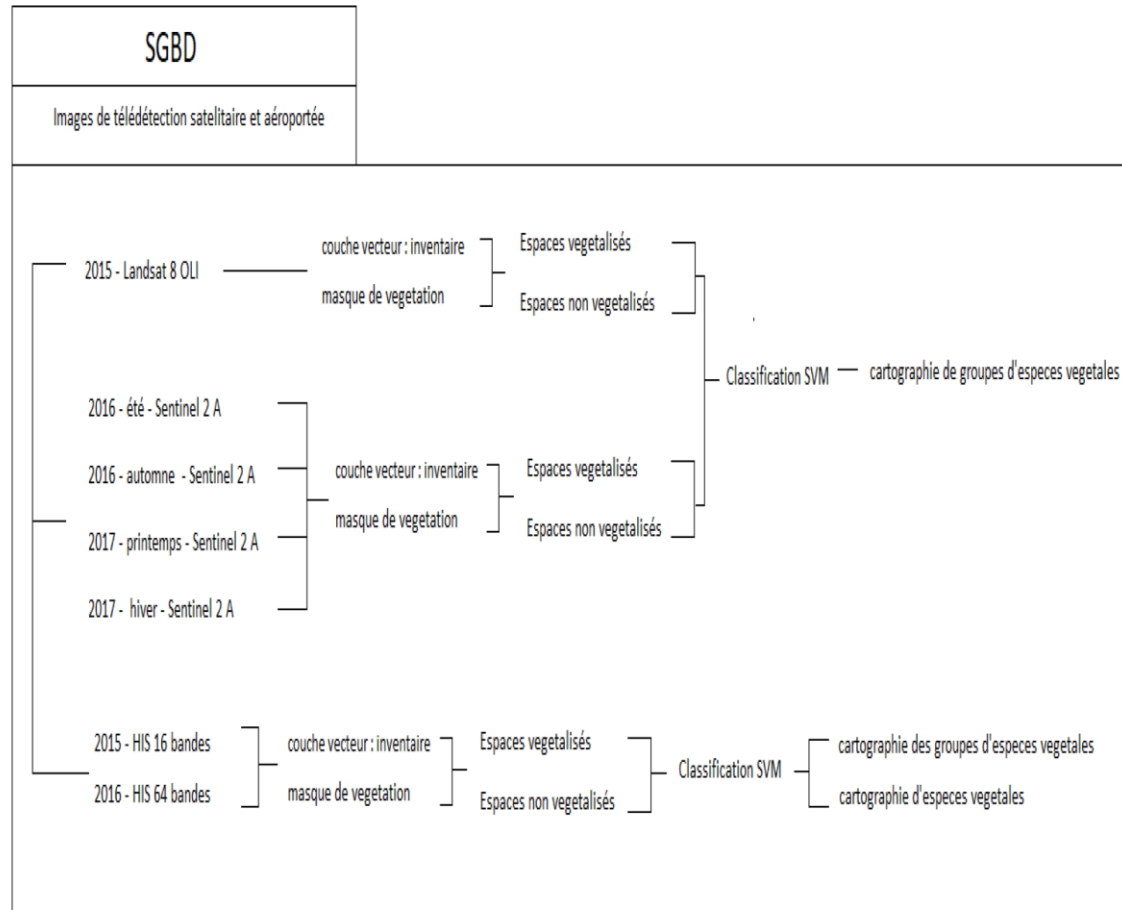
LEGENDE

- Unclassified
- azuolas paprastasis
- berzas karpotasis
- egljé paprastoji
- gluosnis trapusis
- kastonas paprastasis
- klevas paprastasis
- klevas uosialapis
- liepa mazalape
- peulouse
- pusis kalniné
- robinija baltaziede
- tuja vakariné
- uosis paprastasis

Espèces végétales	Image 16 bandes		Image 64 bandes	
	100 échantillons	50,00%	100 échantillons	50,00%
Azuolas paprastasis (%)	0	0,21	0	1,56
Berzas karpotasis (%)	0	0	13,51	44,66
Eglé paprastoji (%)	71,32	43,38	64,41	0
Gluosnis trapusis (%)	0	0	0	0
Kastonas paprastasis (%)	0	2,29	12,8	12,98
Klevas paprastasis (%)	55,18	77,9	12,06	80,39
Klevas uosialapis (%)	28,85	45,45	0,57	16,38
Liepa mazalape (%)	0	23,89	0	75,65
Pelouse (%)	31,98	87,14	22,78	97,9
Pusis kalniné (%)	19,18	0	46,6	0
Robinija baltaziede (%)	42,13	38,07	45,66	40,98
Tuja vakariné (%)	0	14,38	9,09	29,09
Uosis paprastasis (%)	4,29	6,75	16,39	15,57
OA (%)	27,39	63,22	14,72	73,29
Coeff de kappa	0,18	0,47	0,1	0,65
Feuillu (%)	28,42	39,16	15,62	69,48
Conifère (%)	31,27	22,54	36,01	12,44
Pelouse (%)	31,98	87,14	22,78	97,9
OA (%)	30,51	65,75	18,89	79,28
Coeff de kappa	0,12	0,47	0,08	0,65

Classification SVM par espèces et par groupes d'espèces sur les images HIS

Multi-temporal (seasonal) analysis on the Sentinel 2A and Landsat 8 OLI



Performances of recognition of vegetation groups

Espèce végétale	S2A Printemps	S2A Été	S2A Automne	S2A Hiver	Landsat 8
Feuille (%)	100	98,38	66,41	0	69,42
Conifère (%)	96,67	99,3	97,57	100	98,43
Pelouse (%)	94,74	90,53	94,74	0	100
OA (%)	98,04	97,53	89,1	96,32	93,32
Coeff de kappa	0,97	0,96	0,8	0	0,84

Publications

Gintautas Mozgeris, Vytautė Juodkienė, Donatas Jonikavičius, Lina Straigyte, Sébastien Gadal, et al.. **Ultra-Light Aircraft-Based Hyperspectral and Colour-Infrared Imaging to Identify Deciduous Tree Species in an Urban Environment.** *Remote Sensing*, MDPI, 2018, 10 (10), [〈10.3390/rs10101668〉](https://doi.org/10.3390/rs10101668)

Walid Ouerghemmi, Sébastien Gadal, Gintautas Mozgeris, Donatas Jonikavičius. **Urban Vegetation Mapping by Airborne Hyperspectral Imagery: Feasibility and Limitations.** WHISPER 2018 : 9th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing, Sep 2018, Amsterdam, Netherlands. pp.245-249, 2018,

Walid Ouerghemmi, Sébastien Gadal, Gintautas Mozgeris. **Urban Vegetation Mapping using Hyperspectral Imagery and Spectral Library.** *IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2018*, Jul 2018, Valencia, Spain. pp.1632-1635, [〈https://www.igarss2018.org/〉](https://www.igarss2018.org/)



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