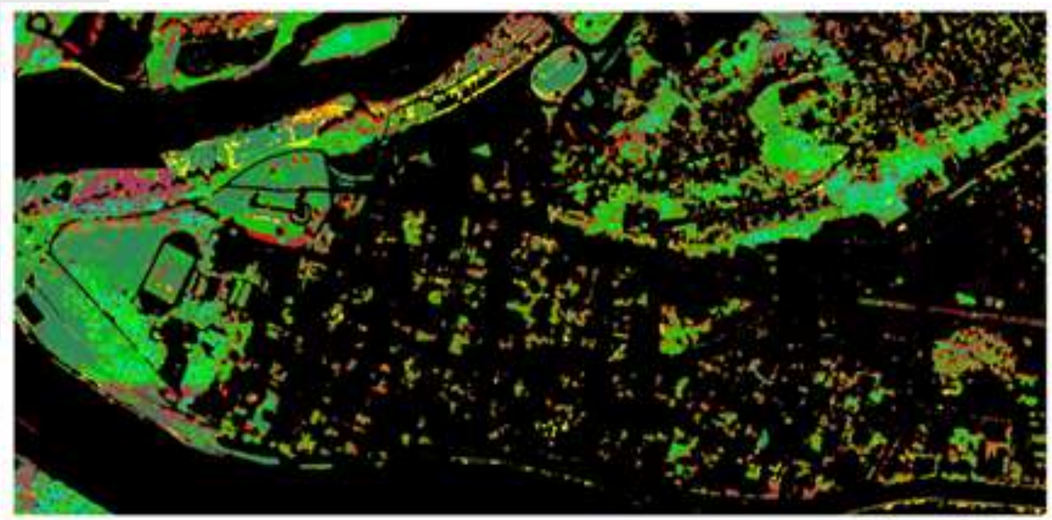
The key-issues of the Geographic Knowledge in Remote Sensing Image Processing Artificial Intelligence

Sébastien GADAL
sebastien.gadal@univ-amu.fr
https://cv.archives-ouvertes.fr/sebastien-gadal

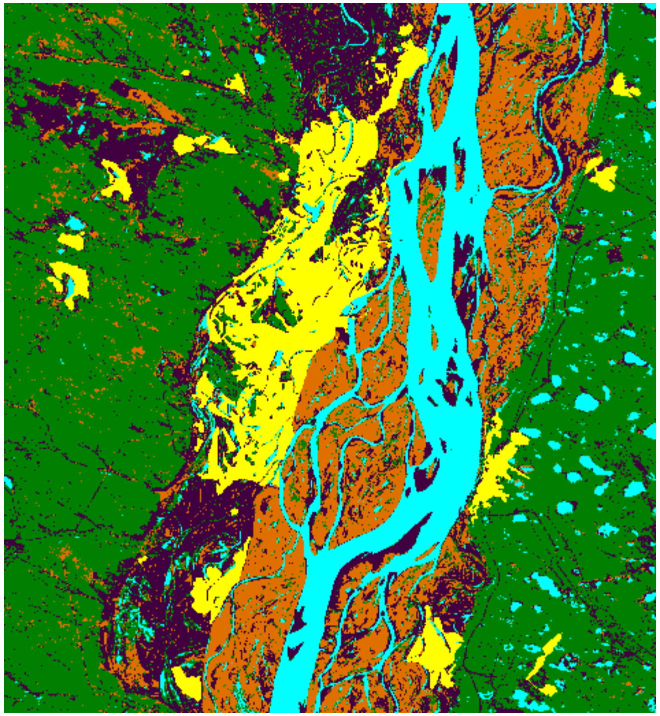
Artificial Intelligence in Remote Sensing Applied to the Geography

Geographic modelling, cartography and algorithms

- Spatial modelling methods
- Image Processing (Random Forest, SVM, Neural Networks, etc.)
- Modelling and simulation (SMA, Markov chains, cellular automata, etc.)



Kaunas urban vegetation mapping by machine-learning and spectral knowledge databases - S. Gadal, W.Ouerghemmi, 2018



Simulation of urban expansion by Markov chains Cellular automats
S. Gadal, 2014

Artificial Intelligence in Remote Sensing Applied to the Geography

Geographic knowledge models and spatial ontologies

- **Geographical knowledge of environments and environments**
  * Expert knowledge (field missions, perception / representation)
  * Existing databases (maps, geographic comics, statistical databases)
  * GIS / DBMS (Structuring and adaptation of data, information and knowledge)

- **Spatial ontologies (Definition, characterization and description of geographical objects)**
  * Shapes (morphologies, structures, textures, metrics, topologies)
  * Biophysical characterization (spectral signatures, spectral databases)
  * Semantics (geo-linguistics: identification, description of landscapes, uses, territorial knowledge lived, perceived, conceptualized)

General context and problems in remote sensing

- **Multiplication of Earth Observation Systems and Geographic and Geospatial Databases**

  *Fusion and multi-source processing, multi-sensors, crowdsourcing, data enrichment, etc.

  *Increase of measurements, data, information, and their size (up to a few thousand spectral bands), high temporal repetitiveness of images (every 15 minutes, continuous, etc.)

- **Issues in remote sensing data processing**

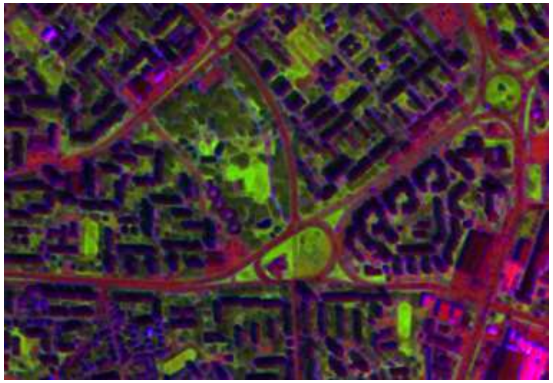
  *Storage and processing of massive and heterogeneous data

  *Methodology and computing power needs: convolutional neural networks, machine learning, deep learning, etc.

  *Complexification of methods of treatment and analysis

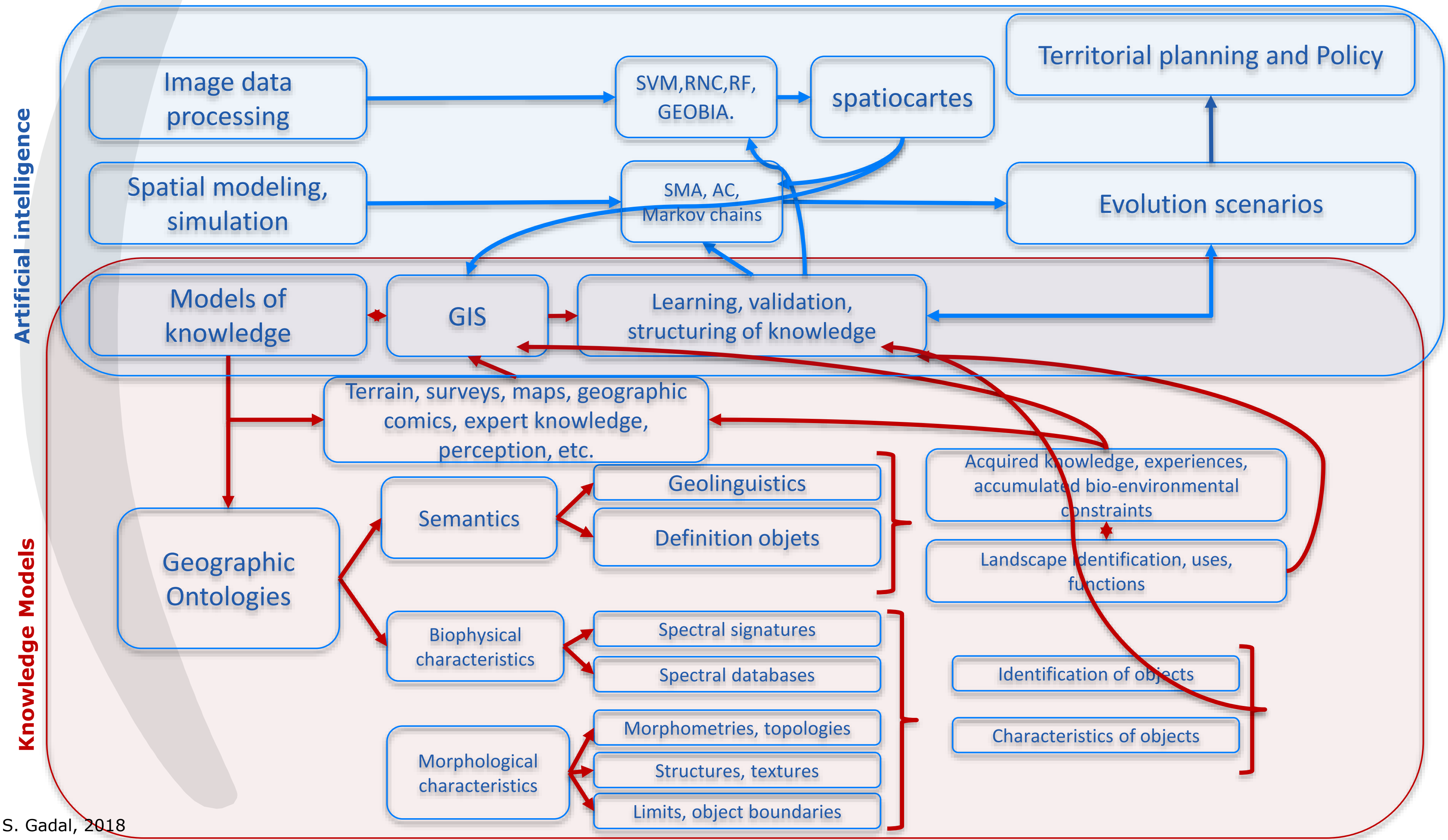
Methods of learning and validation from heterogeneous databases: spectral libraries, morphological databases, geographic, demographic, economic, environmental databases, etc.

Integration of **artificial intelligence** methodologies, **knowledge** building, integration of **geographical and spatial ontologies**.



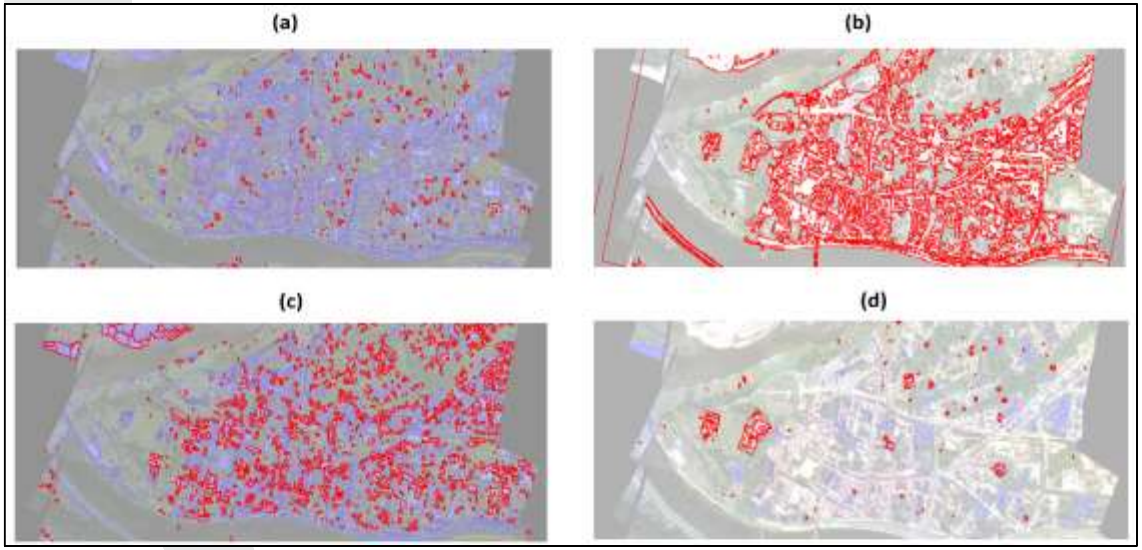
Sébastien Gadal, HDR vol. 2. 2011

Knowledge Models and Remote Sensing Data Processing



S. Gadal, 2018

Examples of knowledge models based on object morphologies

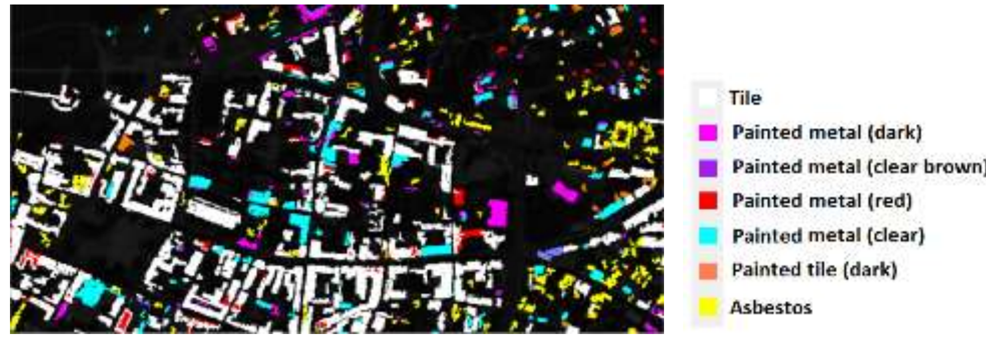


	A	B	C	D	E	F	G	H
1	INDEX	AREA	BOUNDING_	BR_TO_PERI	CENTROID.X	CENTROID.Y	CIRCULARITY	COMPACTNE
2	1	4.00	1.00	1.00	3588.00	13.00	1.00	1.00
3	2	1.00	1.00	1.00	3547.50	41.50	1.00	1.00
4	3	11.00	0.44	1.00	3536.77	47.14	0.61	0.44
5	4	5.00	0.42	1.00	3595.30	49.10	0.71	0.41
6	5	2.00	1.00	1.00	3565.50	49.00	1.00	0.89
7	6	5.00	0.63	1.00	3525.10	52.90	0.75	0.56
8	7	10.00	0.56	1.11	3590.90	55.20	0.55	0.40
9	8	12.00	0.48	1.00	3539.33	57.25	0.72	0.48
10	9	3.00	1.00	1.00	3557.50	56.50	0.90	0.75
11	10	3.00	0.75	1.00	3577.83	56.83	1.00	0.75
12	11	5.00	0.83	1.00	3575.30	59.90	1.00	0.80
13	12	2.00	1.00	1.00	3572.00	60.50	1.00	0.89
14	13	1.00	1.00	1.00	3563.50	61.50	1.00	1.00
15	14	25.00	0.58	1.31	3599.24	63.11	0.35	0.25
16	15	2.00	1.00	1.00	3510.00	62.50	1.00	0.89
17	16	4.00	1.00	1.00	3521.00	64.00	1.00	1.00
18	17	22.00	0.69	1.08	3518.23	69.05	0.64	0.52
19	18	3.00	0.75	1.00	3594.17	69.17	1.00	0.75
20	19	7.00	0.58	1.00	3507.79	70.21	0.80	0.57
21	20	4.00	0.44	1.00	3600.25	70.50	0.78	0.44
22	21	1.00	1.00	1.00	3603.50	73.50	1.00	1.00
23	22	11.00	0.39	1.00	3559.41	75.86	0.51	0.36
24	23	1.00	1.00	1.00	3448.50	79.50	1.00	1.00
25	24	1.00	1.00	1.00	3383.50	81.50	1.00	1.00

S. Gadal, 2011, Kompast-2, Kaunas, Lithuania

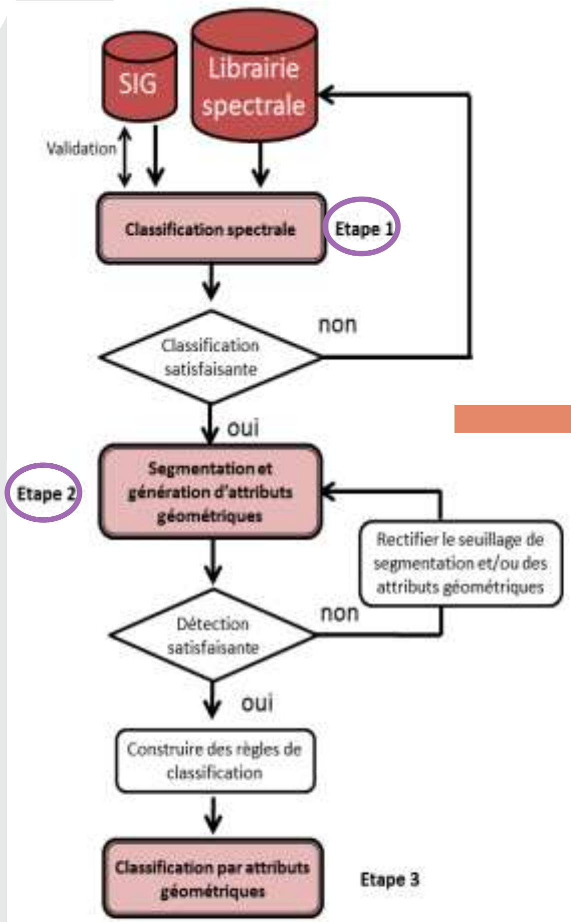
Recognition f urban structures f Kaunas city centre using morphometric rules S. Gadal M. Khelfa 2016-2017

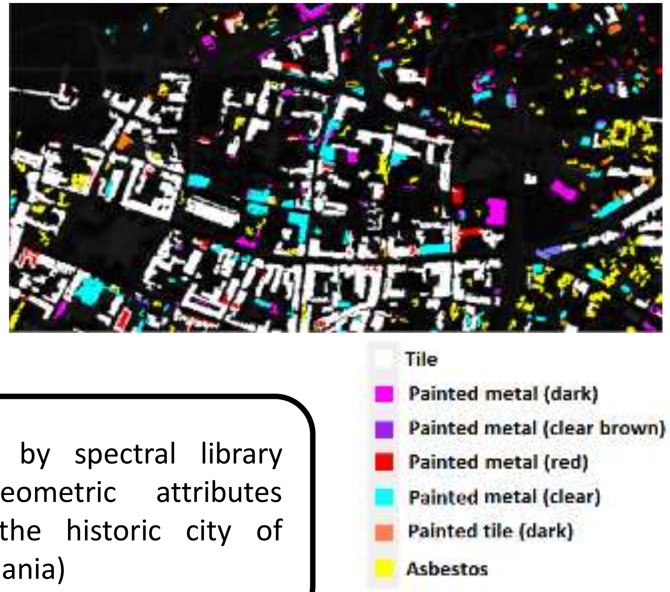
Detection and characterisation of buildings (1)



Example of classification by geometric attributes; [elongation + area], [circularity + convexity], [convexity + area]

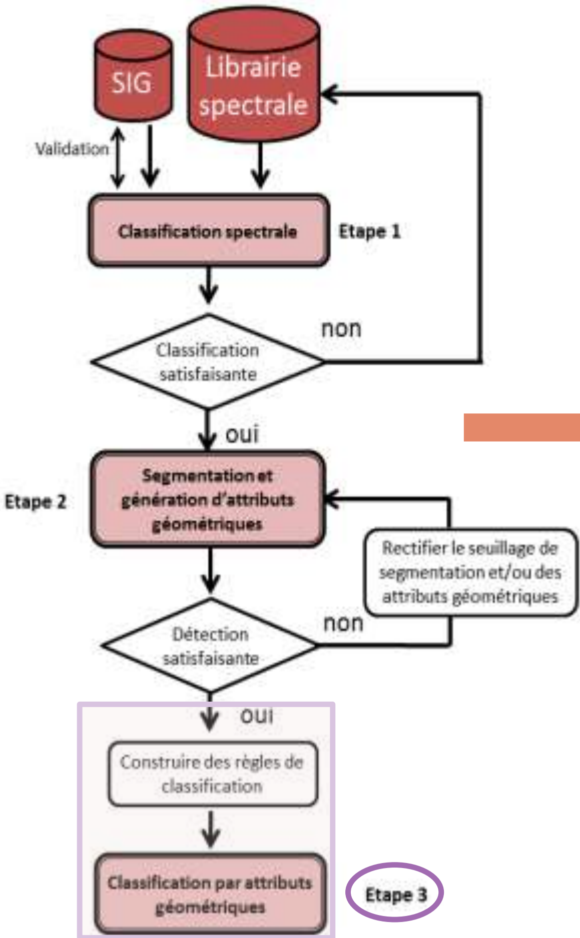
Detection and characterisation of buildings (2)





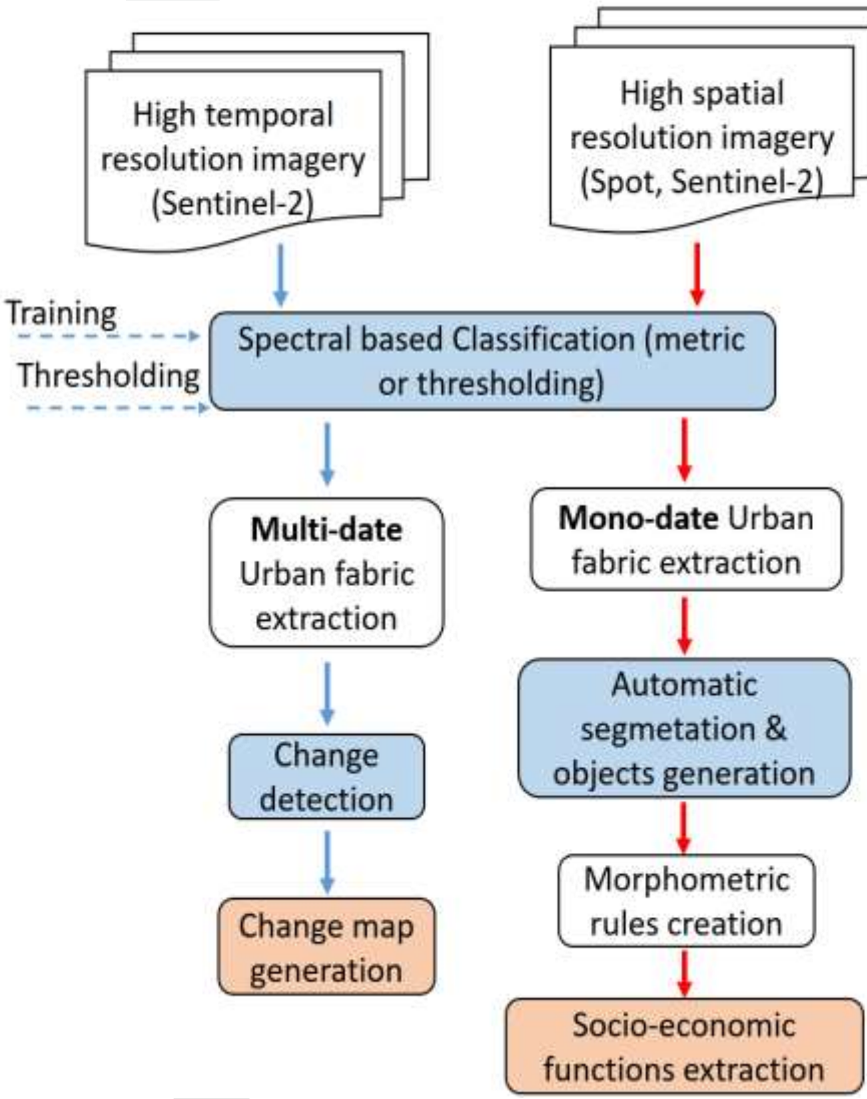
Classification by spectral library and by geometric attributes applied to the historic city of Kaunas (Lithuania)

Detection and characterisation of buildings (3)



Recognition by geometric attributes (morphometric database) [elongation + area], [circularity + convexity], [convexity + area]

Example of built-ups change detection (Sentinel 2)



ber 2017

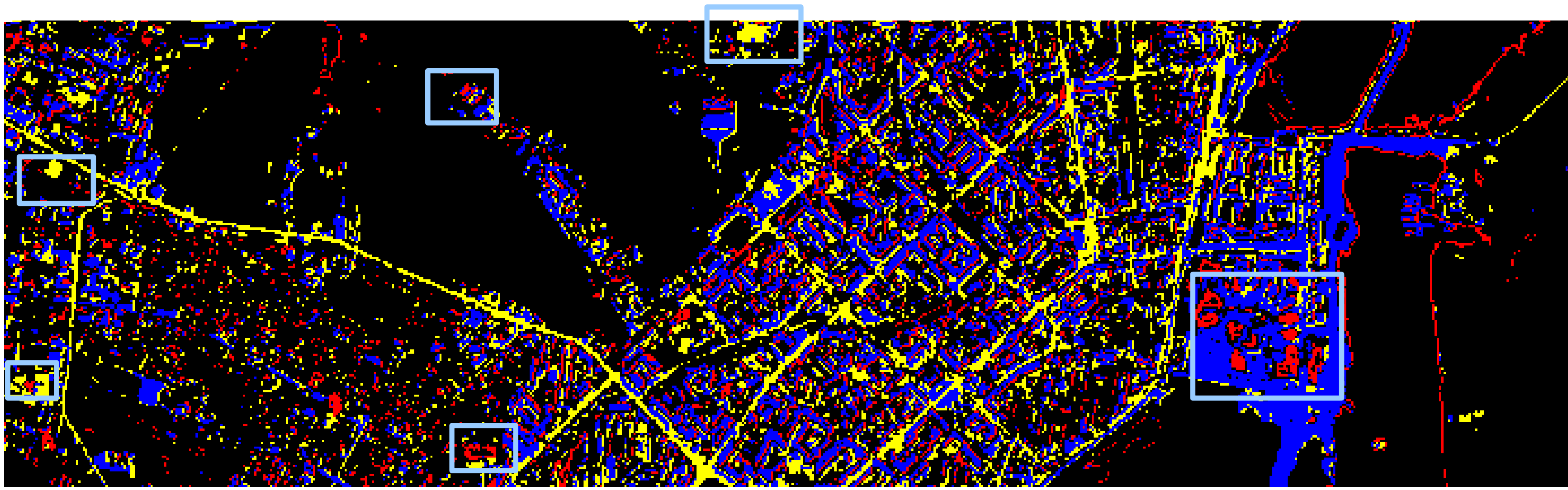
Clear built-ups
Dark built-ups

September 2015

September 2017

Walid Ouerghemmi, Sébastien Gadal, 2018

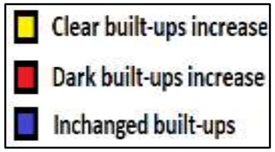
Example of built-ups change detection (Sentinel 2)



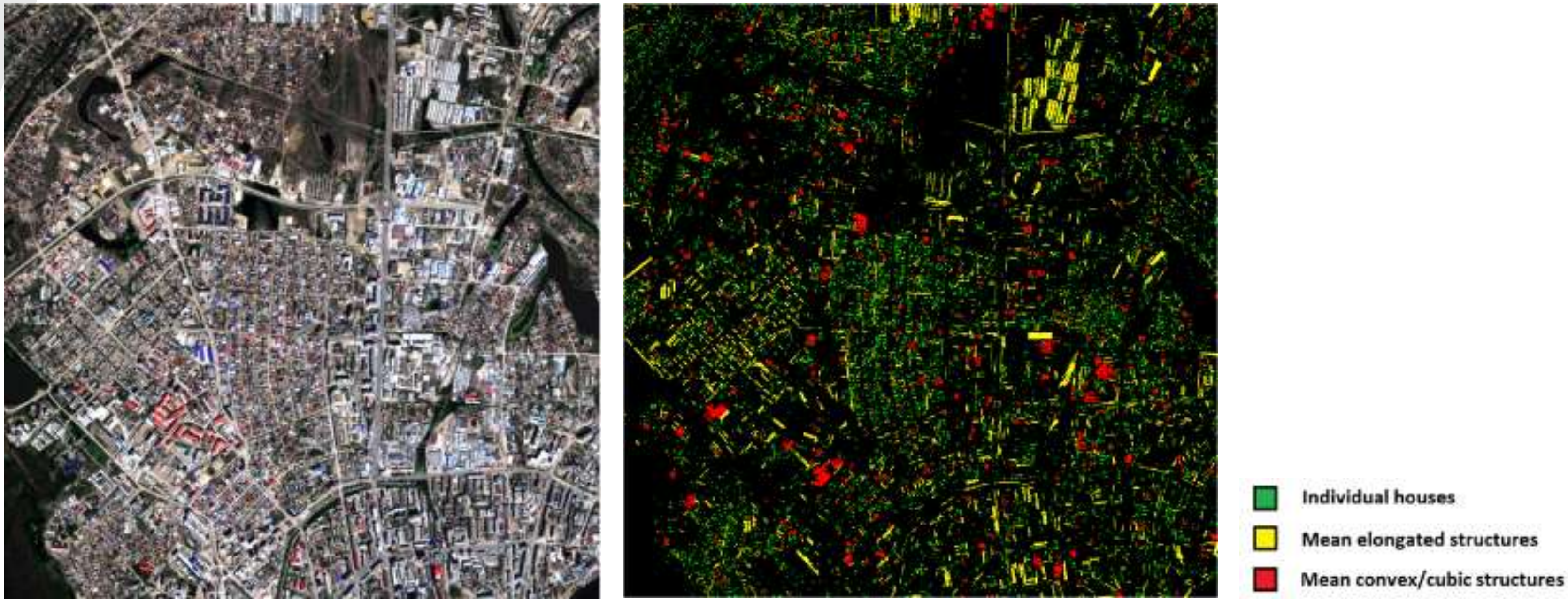
Walid Ouerghemmi, Sébastien Gadal, 2018

September 2015

September 2017



Morphological characterisation of built-ups (Spot 6)

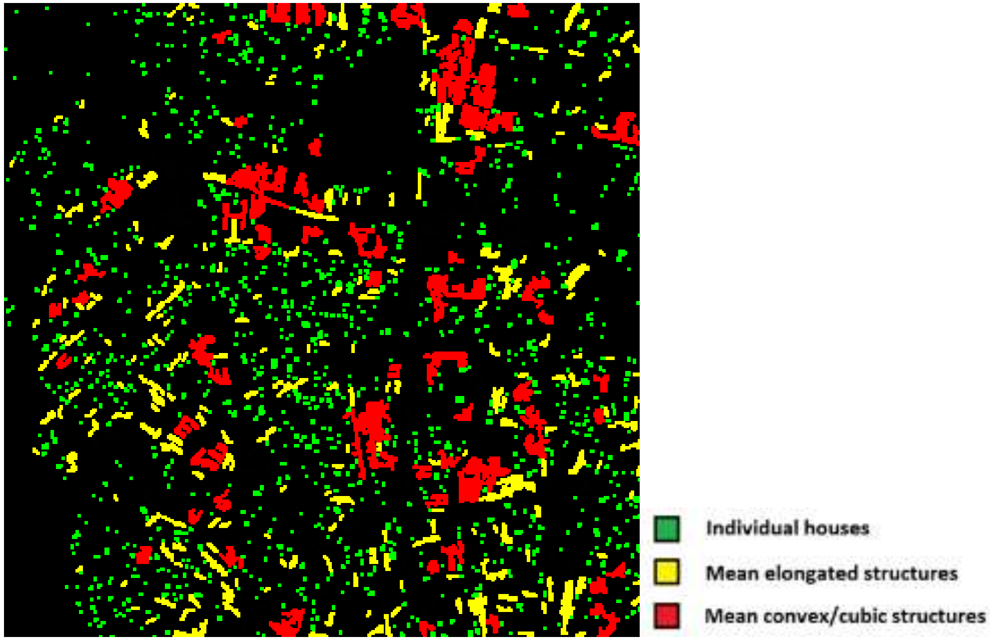


Walid Ouerghemmi, Sébastien Gadal, 2018

- Morphological characterisation over Yakutsk city using **3 socio-economic** categories:
  - -Individual houses (including dachas): area and bounding rectangle fill ratio
  - -Residential buildings, state administrations structures, garages/storage containers etc.: convexity and elongation
  - -industrial buildings, cultural structures, stores: area, elongation and bounding rectangle fill ratio

- Efficient **characterisation** and recognition of the **object morphologies**

Morphological characterisation of built-ups (Sentinel-2)



Walid Ouerghemmi, Sébastien Gadal, 2018

- Morphological characterisation over Yakutsk city using **3 socio-economic** classes :
  - -Individual houses (including dachas): area and compactness
  - -Residential buildings, state administrations structures, garages/storage containers etc.: convexity and elongation
  - -industrial buildings, cultural structures, stores: area, elongation and bounding rectangle fill ratio
- Difficulty to distinguish between **elongated** and **convex** structures, **less** individual houses detected
- Decreasing resolution**, affected the detection accuracy.**

Intra-annual accuracy recognition of the buit-up changes

	O.A. (Spectral indexes -SI-)	O.A. (Spectral classification -SAM-)	Change estimation compared to reference date (pixels)(Spectral Indices)	Change estimation compared to reference date (pixels) (SAM)
Sentinel-2 (2017-06-04)	64.1 %	94.7%	--	--
Sentinel-2 (2017-09-12)	74.1%	93.0%	(↓7%)	(↓33%)

Table 1. Classification overall accuracy (O.A.) estimation, and **urban fabric change quantification** (i.e. in percent, respectively, **relative change**, **absolute change**).

index/Pixels count	Water	Vegetation	Dark built-ups	Clear built-ups
Sentinel-2 (2017-06-04)	270.474	935.381	135.646	48.879
Sentinel-2 (2017-09-12)	245.043 (↓9%)	1.039.889 (↑12%)	119.602 (↓11%)	55.174 (↑12%)

Table 2. **Land use change quantification using Spectral Indices** (i.e. pixels count) between June 2017 and September 2017.

- Intra-annual change detection by **SAM** and **Spectral Indices** did not give an increase in terms of built-ups **within 2017** year (final results biased with changes occurring to non-built-ups) (Table 1).
- Built-ups detection by **Spectral Indices** offered **finer estimation of change**, the **SAM** classifier **over-estimated** the built-ups at date 1 (Table 1).
- An increase of about **12%** was noticeable for **clear built-ups** using spectral indices (Table 2).

Inter-annual recognition of the built-ups changes (2015-2017)

	O.A. (Spectral indexes -SI-)	O.A. (Spectral classification -SAM-)	Change estimation compared to reference date (pixels)(Spectral indices)	Change estimation compared to reference date (pixels) (SAM)
Sentinel-2 (2015-09-03)	60.0 %	92.7%	--	--
Sentinel-2 (2017-09-12)	74.1%	93.0%	(↑13%)	(↑27%)

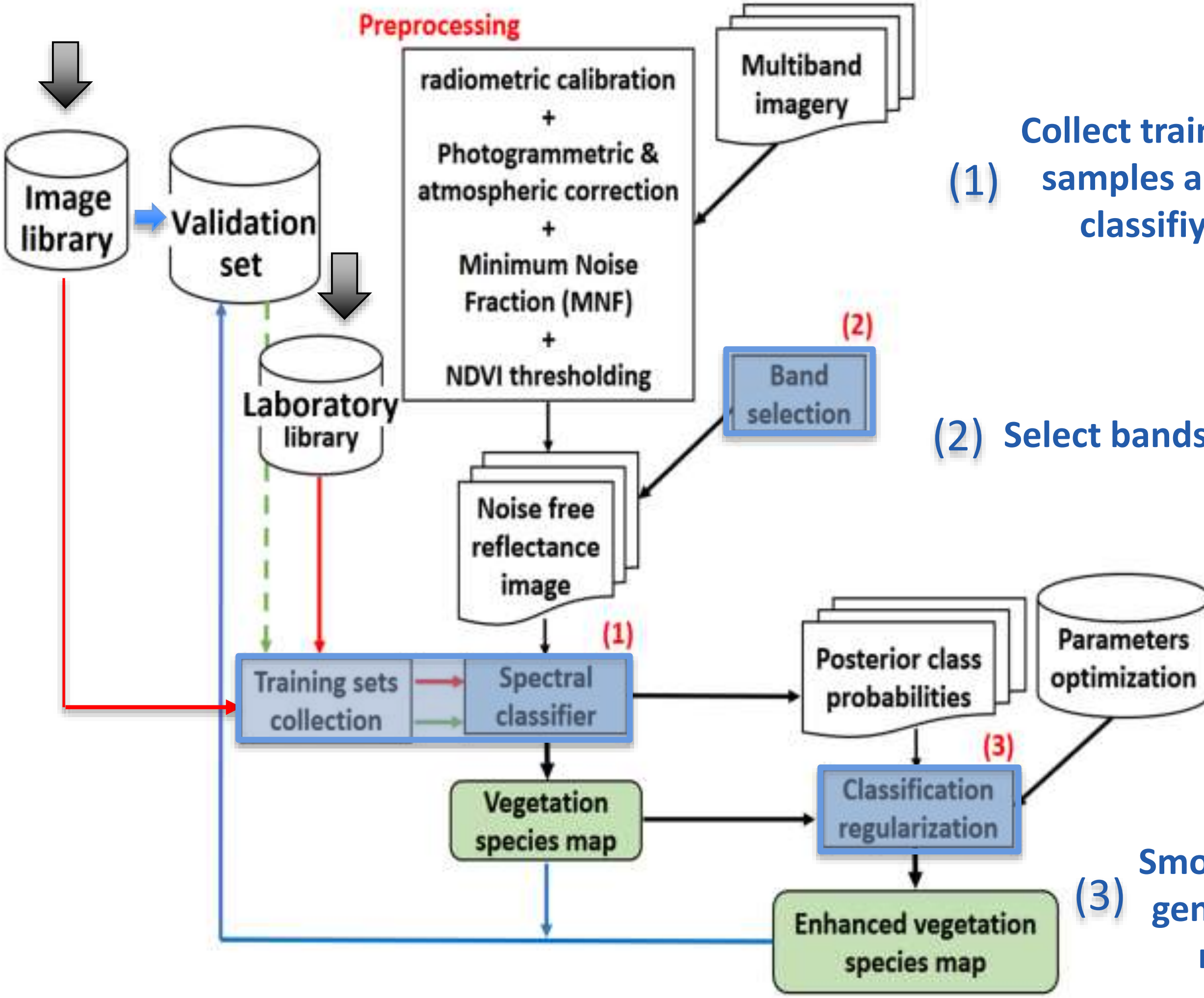
Table 3. Classification overall accuracy (O.A.) estimation, and **urban fabric change quantification** (i.e. in percent, respectively, **relative change, absolute change**).

Index/ Pixels count	Water	Vegetation	Dark built-ups	Clear built-ups
Sentinel-2 (2015-09-03)	179.660	1.204.745	108.421	48.794
Sentinel-2 (2017-09-12)	245.043 (↑36%)	1.166.595 (↓3%)	119.602 (↑10%)	55.174 (↑13%)

Table 4. **Land use change quantification using Spectral Indices** (i.e. pixels count) between June 2017 and September 2017.

- Change detection: **increase** of built-ups of about **13% to 27%** between 2015 and 2017 (Table 3).
- Built-ups detection by **Spectral Indices** offered **finer estimation of change**, the **SAM** classifier **over-estimated** the built-ups at date 2 (Table 3).
- If combining these results and after subtracting a **bias** of **false detections** (**5% to 10% depending on the used method**), we can reasonably estimate an increase of **12%** between **2015** and **2017**.
- An increase was noticeable for both **dark and clear built-ups** using spectral indices (Table 4).

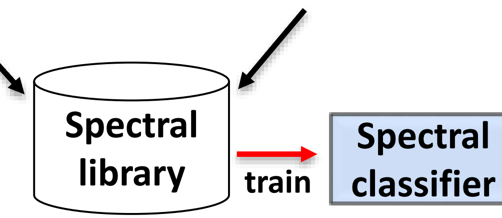
Spectral libraries



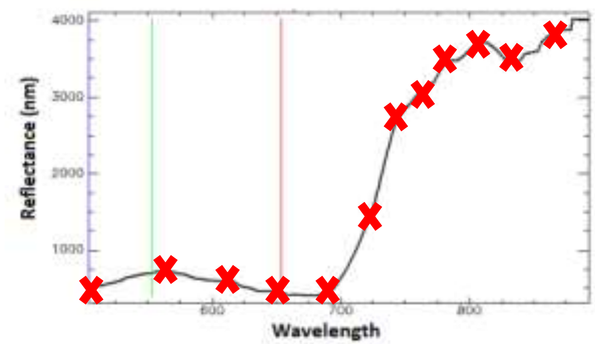
Source 1: Laboratory spectra extraction

Source 2: Image spectra extraction

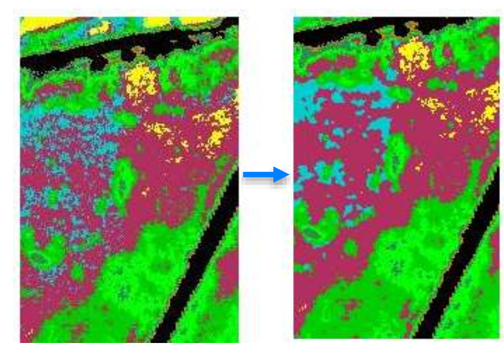
(1) Collect training samples and classifiy



(2) Select bands



(3) Smooth the generated map

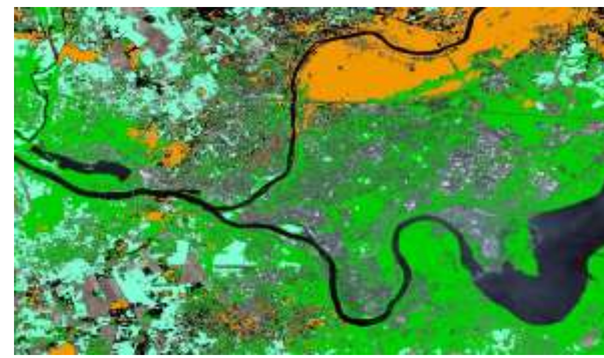


Land cover of urban vegetation

Species	S2A Spring	S2A Summer	S2A Autumns	S2A Winter	Landsat 8 OLI Summer
Hardwood (%)	100	98,38	66,41	0	69,42
Conifers (%)	96,67	99,3	97,57	100	98,43
Grass (%)	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

Seasonal SVM classification by species on Sentinel-2 and Landsat 8 images OLI (Kaunas, Lithuania)

S2A : ClassificationSVM–Kaunas-12/05/2017–spring



S2A/L8 OLI : ClassificationSVM–Kaunas-28/08/2016– summer

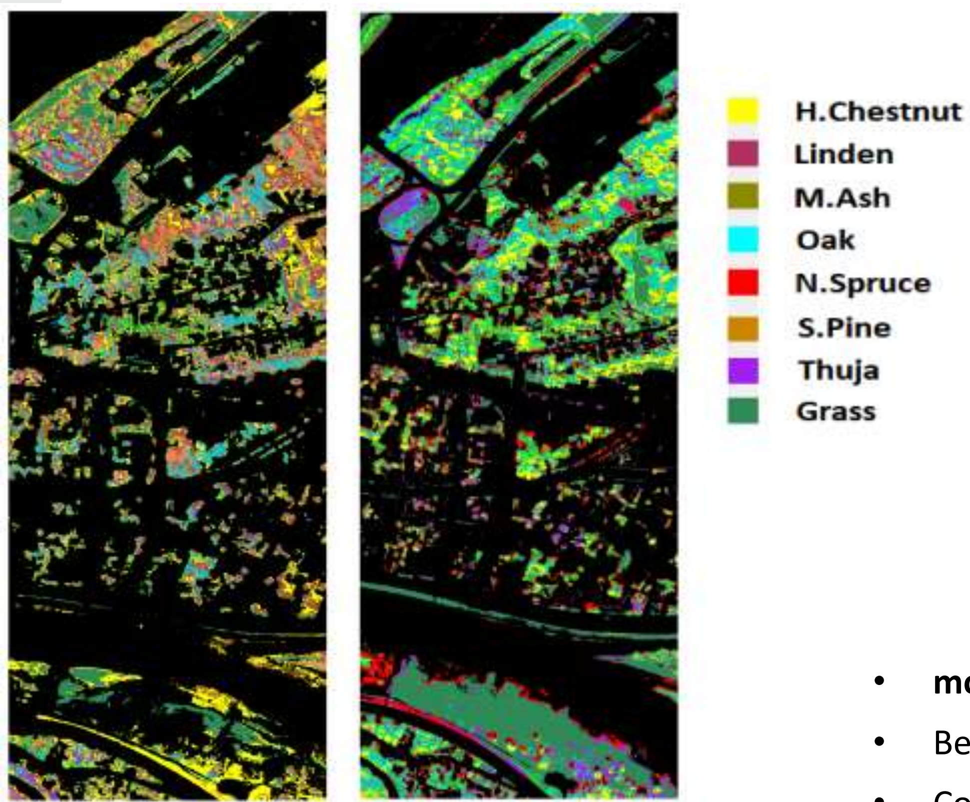
S2A : ClassificationSVM–Kaunas-17/10/2016–Autumns

S2A : ClassificationSVM–Kaunas-25/01/2017–winter

Romain Barlatier, Sébastien Gadal, Walid Ouerghemmi, CNRS ESPACE UMR 7300 – 2018

Land cover of urban vegetation

Mapping of urban vegetation by SVM (16 and 64 bands)



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

Accuracy Results (compilation)

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

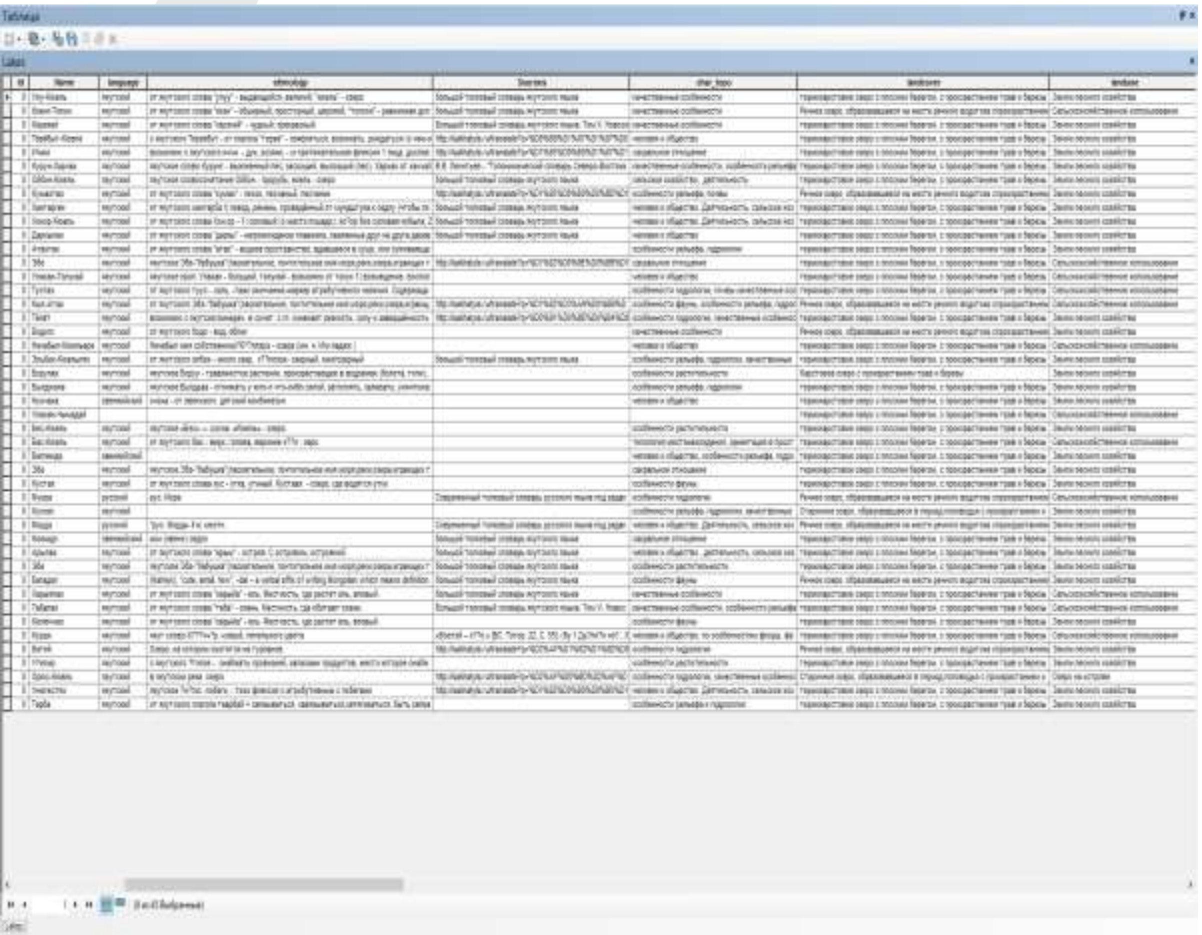
Veg. species	Classif. accuracy (16 bands image)						Classif. accuracy (64 bands image)					
Classifier Training	SAM			SVM			SAM			SVM		
Samples	No NMF	MNF (1)	MNF (2)	No MNF	MNF (1)	MNF (2)	No NMF	MNF (1)	MNF (2)	No MNF	MNF (1)	MNF (2)
H. Chestnut	16.4	16.5	**21.5**	19.2	19.1	**23.3**	11.5	12.1	**27.0**	**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**

deciduous

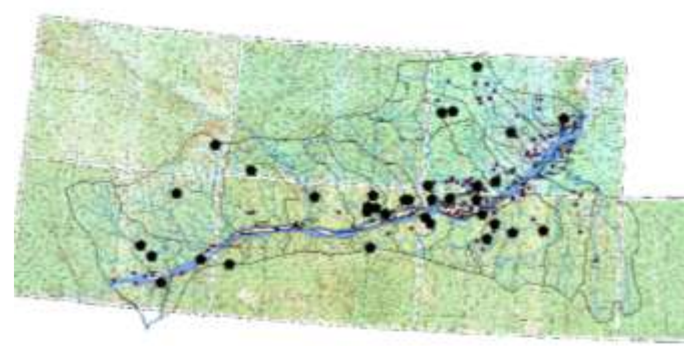
coniferous

- **"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)

Geolinguistic approach (1)

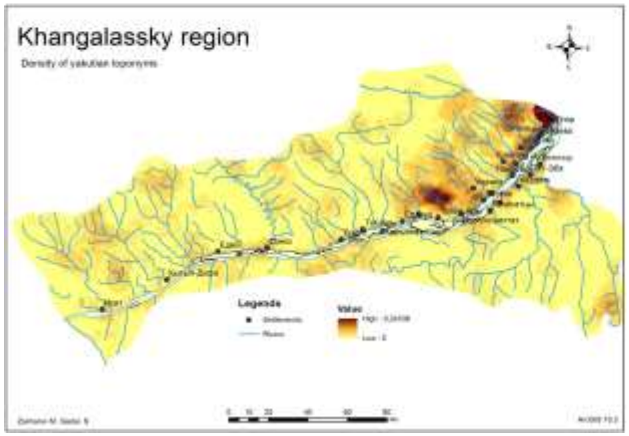


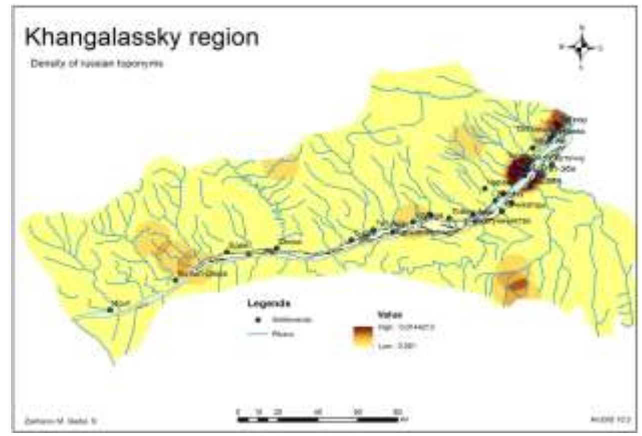
RSF Land Ontology: Semantics, Semiotics, and Geographic Modelling, 2015-2017

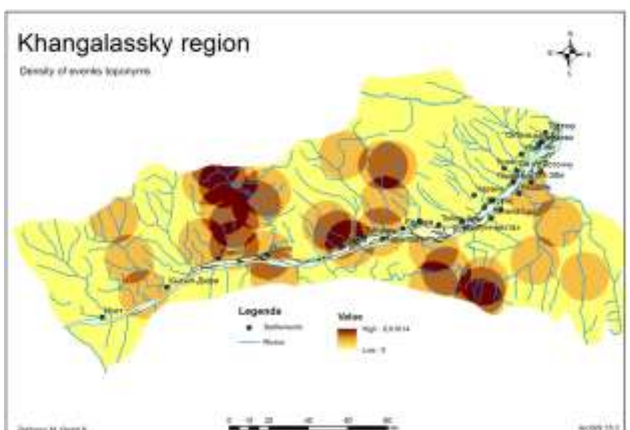


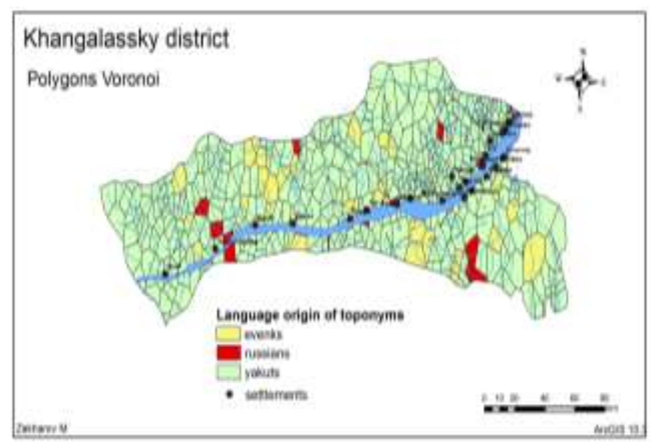
Toponymic features of the territory are inseparably linked with ethnoses and ethnographic groups that lived and live in the given territory.

Geolinguistic approach (2)

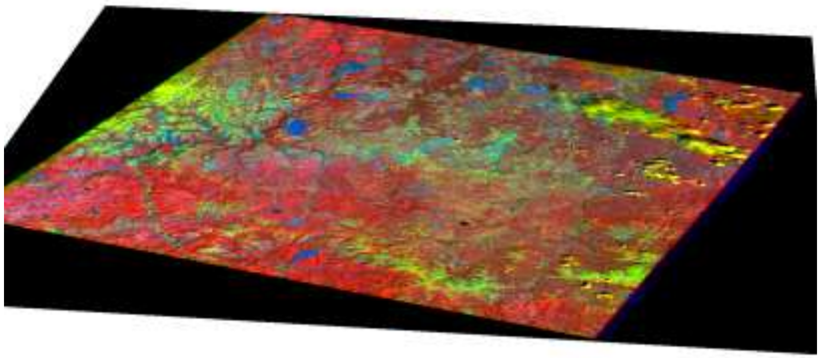








Geolinguistic approach (application to the Evenks)



Occupations des terres nues (marron) et terres végétalisées (orange) le 03.07.09

Dates	05.07.04	16.07.08	03.07.09	Evolution1	Evolution2
Surface des terres nues (ha)	39 923,64	112 990,06	177 843,04	+73 066,42	+64 852,98
Surface des terres végétalisées (ha)	1 079 236,08	328 730,4	556 733,07	-750 505,68	+228 002,67
Total des terres	1 119 159,72	441 720,46	734 576,11	-677 439,26	+292 855,65

1. **Géographie physique**

   1.1. Sommets : avant un passage de col, il est long ou pas, passage entre deux vallées. Couverture végétale qui est dessus. On peut ou non le passer.
   1.2. Plateaux : passage pour passer d'une vallée à une autre, idem. La forme n'est pas importante, c'est le passage ou non.
   1.3. Descentes : Angle raisonnable, pas trop aigue pour une descente confortable. Angle réduit, on peut voir le gibier à viande et les prédateurs.
   1.4. Altitude : si cela est haut ou pas pour passer d'une vallée à une autre. Problème pour descendre. Monter c'est encore OK. Limites d'altitudes : Hautes montagnes (angles abruptes). Les animaux ne peuvent pas passer.

2. **Biogéographie**

   2.1. Couvert forestier

      2.1.1. Zones de pinèdes (pins) : terres sèches et planes, commode pour les déplacements. Ce n'est pas occupé par les ruisseaux qui peuvent gêner les déplacements. Les chiens se déplacent facilement car il n'y a pas de buissons et chasser les zibelines.
      2.1.2. Zones de sapins : partie avec les aiguilles épaisses et il fait froid (important l'été). L'été les bêtes féroces se réfugient comme les gibiers à sang noir. Pas de chasse. Difficile pour se déplacer. On entend bien le gibier.
      2.1.3. Mélèze : espace pour les chasseurs, pas de buissons, on peut trouver des baies, de temps en temps des pines de pins (hommes les récoltent). Du bon bois (chauffage). On peut organiser des feux de fumé pour les rennes l'été. Bois de base pour les constructions (tentes).
      2.1.4. Punius Pumila : Pignon de pins (pour manger) et des animaux (ours et zibelines), beaucoup d'ours. Hiver zibelines et tétra (coq de bruyère).
      2.1.5. Salix xxx : construction, bois souple qu'il faut chauffer, se trouve le long des rivières.

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Thank you for your attention