



Les modèles de connaissance dans le traitement des images satellitaires

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Intelligence artificielle en télédétection spatiale et aéroportée (1)

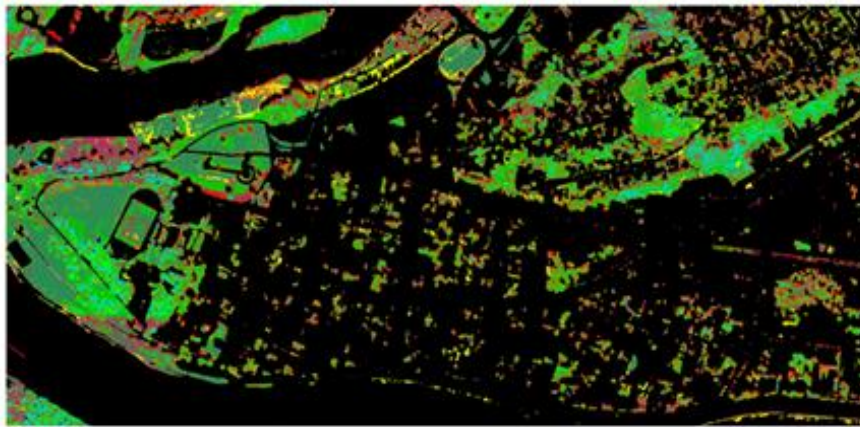
Traitement, modélisation et modèles de connaissances

Deux aspects interdépendants :

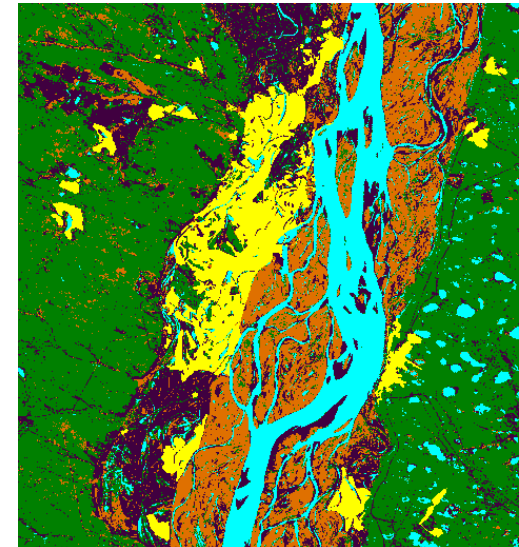
- **Méthodes de traitement d'image et de modélisation spatiale**

Traitement d'image (Random Forest, SVM, Réseaux de neurones, etc.)

Modélisation et simulation (SMA, Chaînes de Markov, Automatiques cellulaires, etc.)



Cartographie de végétation urbaine de Kaunas par machine-learning
S. Gadal, W.Ouerghemmi, 2018



Simulation de l'expansion urbaine par chaînes de Markov
S. Gadal, 2014

Intelligence artificielle en télédétection spatiale et aéroportée (2)

- **Modèles de connaissances géographiques et ontologies spatiales**

1- Connaissance géographique des milieux et environnements

- ***Connaissance experte** (missions de terrain, perception/représentation)
- ***Bases de données existantes** (cartes, BD géographiques, BD statistiques)
- ***SIG/SGBD** (Structuration et adaptation des données, informations et connaissances)

2- Ontologies spatiales (Définition, caractérisation et description des objets géographiques)

- ***Formes** (morphologies, structures, textures, métriques, topologies)
- ***Caractérisation biophysique** (signatures spectrales, bases de données spectrales)
- ***Sémantiques** (géolinguistique : identification, description de paysages, des usages, connaissance territoriales vécus, perçus, conceptualisées)

Contexte général et problématiques en télédétection

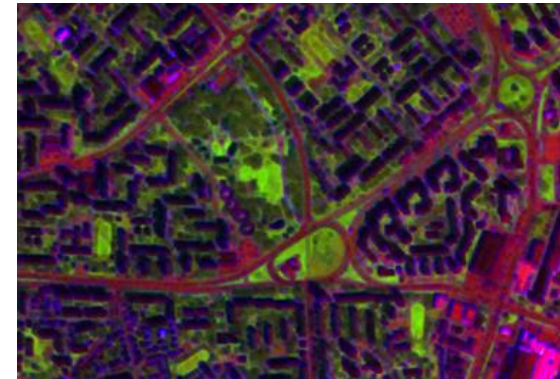
- **Multiplication des systèmes d'observation de la Terre et de bases de données géographiques et géo-spatialisées**

- * **Fusion et traitements multi-sources**, multi-capteurs, enrichissement mutuel, etc.
- * **Explosion des mesures, données, informations, et de leur taille** (jusqu'à quelques milliers de bandes spectrales), haute répétitivité temporelle des prises de vues images (chaque 15 minutes, continue, etc.)
- * **Implémentation de connaissances environnementales**, territoriales, sociales, climatique, économiques, etc.

- **Problématiques en traitement de données de télédétection**

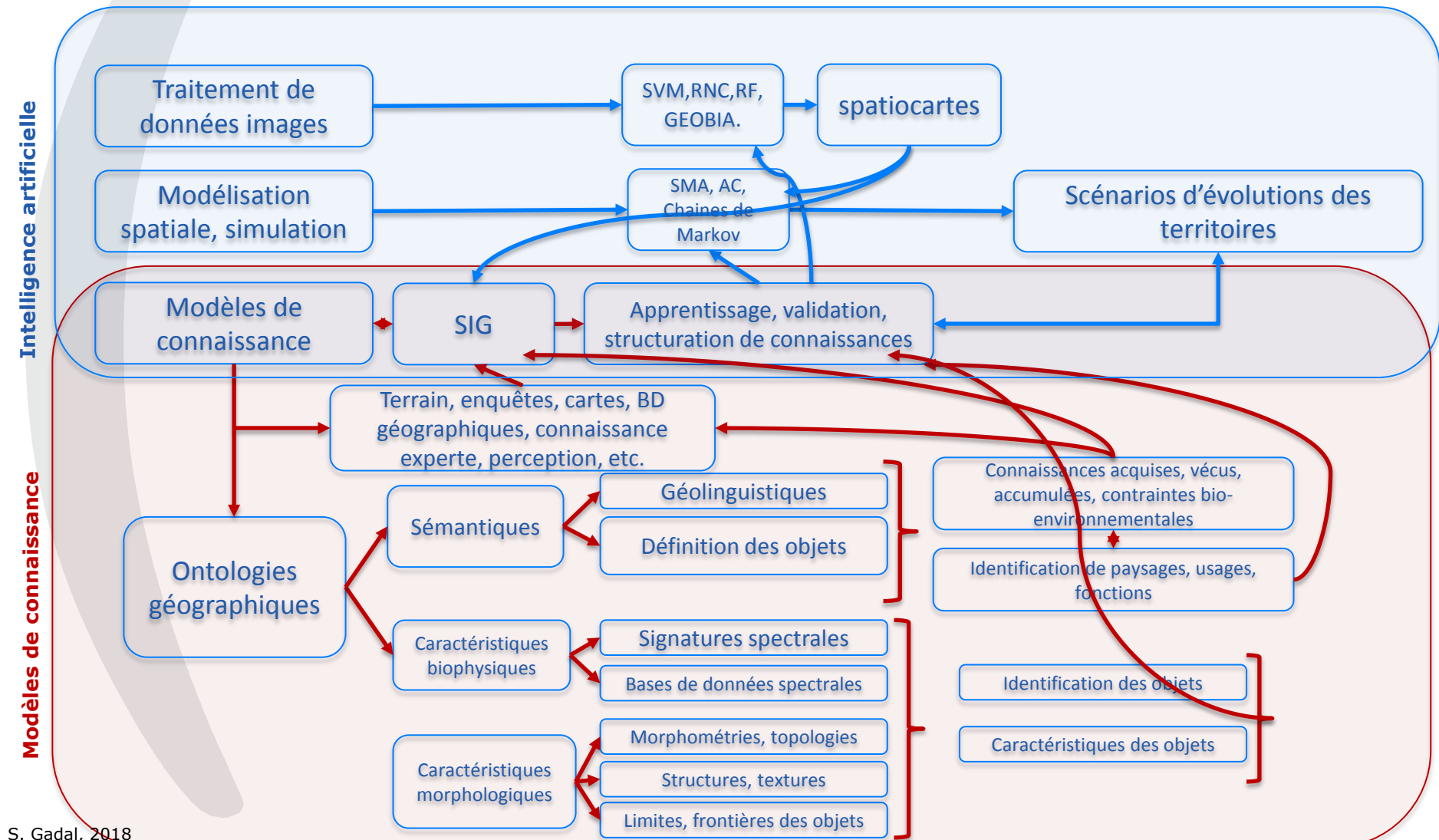
- * **Stockage et traitement de données massives et hétérogènes**
- * **Méthodologie de traitements et besoins en puissance de calcul** : réseaux de neurones convolutifs, *machine learning*, *deep learning*, etc.
- * **Complexification des méthodes de traitement et d'analyse**
Méthodes d'apprentissage et de validation à partir de banques de données hétérogènes : bibliothèques spectrales, bases de données morphologiques, bases de données géographiques, démographiques, économiques, environnementales, etc.

Intégration de méthodologies d'intelligence artificielle, construction de connaissances, intégration d'ontologies géographiques et spatiales.

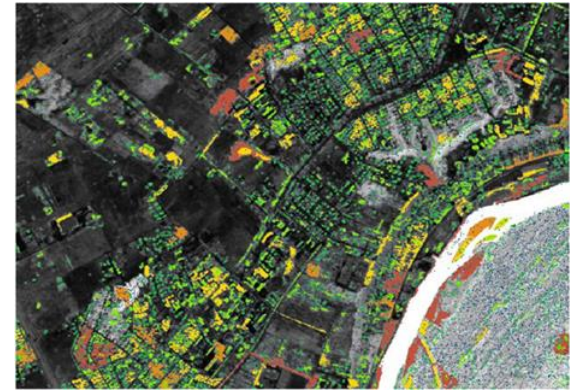


S. Gadal, HDR vol. 2. 2011

Intelligence artificielle, Modèles de connaissances et traitement des données de télédétection

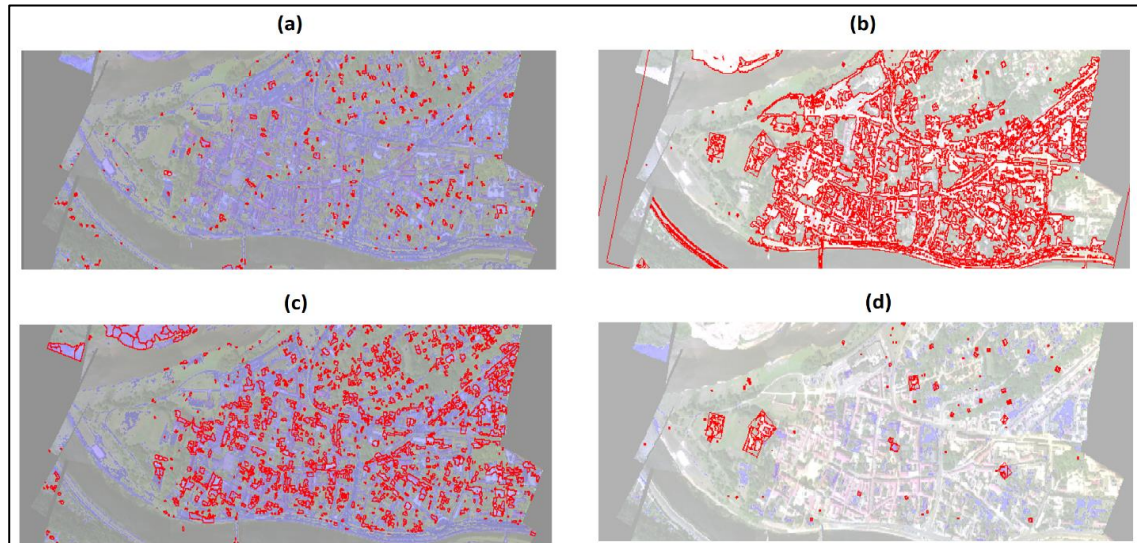


Exemples de segments (blocs) (modèles de connaissance)



	A	B	C	D	E	F	G	H
1	INDEX	AREA	BOUNDING_BOX_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	3555.30	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	3583.50	61.50	1.00	1.00
15	14	28.00	0.58	1.31	3599.14	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	3388.50	81.50	1.00	1.00

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



détection de différentes structures urbaines sur la ville de Kaunas, en utilisant différents attributs morphologiques, CNRS ESPACE UMR7300, S. Gadal, M. Khelfa (2017).

Exemples de segments (blocs) (modèles de connaissance)

dynamic and rather sharp	unstable and very sharp	stable and rather smooth
the border belongs to the entity (left) eg.: closed interval [a,b] and exterior U-[a,b]	the edge or bound belongs to no-one, eg.: b belongs to neither [a,b] nor [b,c]	the limit belongs to both, eg.: b belongs to both [a,b] and [b,c]
the border for a move, the end or the frontier for a conquest	the bound marks a conflictual balance "flat"	the limit is an agreement balance "bona fide"
transitional progressive (smooth then sharp), dynamic progression	transitional and re-inforced (smooth between sharp edges)	Transitional "defensive" (sharp then smooth)
the front belongs to the entity (left) eg.: closed interval [a,b] against [b,c]	the limit belongs to both, eg.: b belongs to both [a,b] and [b,c]	the outer edge belongs to [a,b] and partially to exterior U-[a,b]
"Marche", "Glacis"	the limit is a "No Man's Land", of type "flat", but physically land-marked	the limit between the world and "terra incognita", one-side land-marked (Fr-once du bois, inter-axial land)

- the original contact relation (reflexive and symmetrical)

$$C(x,y)$$

- the external contact (or strong contact) relation

$$EO(x,y) = C(x,y) \leftrightarrow \neg C(x,y)$$

which means: contact but not overlap

$$overlap: O(x,y) = \exists z (P(x,z) \leftrightarrow P(y,z))$$

$$part of: P(x,y) = \forall z (C(x,z) \rightarrow C(y,z))$$

- the weak contact relation

$$WC(x,y) = \neg C(x,y) \leftrightarrow \forall z ((P(x,z) \leftrightarrow OP(z)) \rightarrow C(z,y))$$

which means: not contact but wherever an open part contains one object (say x), then its close counterpart is in contact with the other object (ie. can't be disconnected with y)

In this mereo theory, the open part of x, o(x), is such that any object in contact with o(x) must also be in contact with some strictly internal part of x. Then c(x) = $\neg o(\neg x)$, is the complement of the open part of the complement of x.

VISIBLE AND NEAR-INFRARED HYPERSPECTRAL IMAGING TO DESCRIBE SOME PROPERTIES OF CONVENTIONALLY AND ECOLOGICALLY GROWN VEGETABLES

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Background: In recent years, the demand for organically grown agricultural products has significantly increased. Simultaneously, this increased the need for new approaches for quick evaluation and control of the quality of such type of agricultural production. There are numerous solutions used to monitor the food products aiming to ensure their quality – analytical methodologies such as potentiometry, conductivity, mass spectra, screen-printed biosensors, etc. However, most of these methods are based on complex processing of samples, require expensive chemical reagents and highly qualified personnel, are time consuming and hard to implement operationally at mass production level. Along with the growing investments and research in the area of organic production, the importance for objective technique to evaluate the quality of organic products is also increasing. The potential of hyperspectral imaging as such technique is discussed in this study.

Objective: The aim of the study was to determine the opportunities to predict hydrogen ion concentration (pH), electrical conductivity (EC), reduction potential (ORP), and nitrates (NO₃) of tubers of potatoes (*Solanum tuberosum*) and carrots (*Daucus carota* var. *sativa*) using hyperspectral imaging approach. The potential of visible and near-infrared hyperspectral imaging as one of possible solutions for fast and free from subjectum separation of organically and conventionally grown carrots was also investigated.

Materials and methods: Totally, 140 carrots and 160 potatoes samples were used for investigation. Four different carrot varieties were represented in the study. Carrot samples for all varieties represented vegetables originating from organic and conventional farms. The samples of the tubers were prepared by cutting the tubers along into half using non-cooking knives. Thus one tuber sample was represented by one slice.

Hyperspectral scanning was conducted and hyperspectral images were acquired for each sample using Themis Vision Systems LLC portable scanning hyperspectral imaging camera VNIR4000 which records object's spectral properties in the 400–1000 nm range with the sampling interval of 0.6 nm, producing 955 spectral bands.

Scanned samples were immediately submitted for laboratory measurements of NO₃, EC, pH, and ORP, using standardized chemical tests.

In total, 140 reflectance curves for carrots and 160 reflectance curves for potatoes were constructed. In a spreadsheet, each reflectance curve was treated as a series of numbers (reflectance coefficients) in 955 wavebands in 400 nm – 1000 nm. These series of numbers were used for statistical analyses.

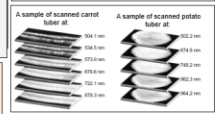
Principal component analysis (PCA) was employed to reduce the dimensionality and redundancy inherent in hyperspectral data and to compute the contribution of the reflectance coming from each wavelength to the principal components. The linear discriminant analysis (LDA) was applied for classification of conventionally and ecologically grown carrots by evaluating the possibilities to determine the method of growing. The following classification cases were tested:

- 1) Discrimination of organic and conventional samples at the species level, i.e. not taking into account the variety.
- 2) Discrimination of organic and conventional samples at the variety level.

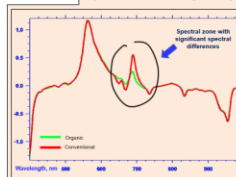
The partial least squares regression (PLSR) was used to predict the pH, ORP, EC, and NO₃ in potatoes and carrots samples. The leave-one-out cross-validated R² were calculated for each model. All models were also validated using external data sets. The root mean square errors of prediction (RMSEP) and the mean absolute percentage error (MAPE) for prediction of each attribute were estimated as well. The classification accuracy was judged using the overall classification accuracy, "producer's and user's" accuracies and the κ statistics, i.e. the metrics conventionally applied in remote sensing.

Tuber samples used for analysis

variety	Number of samples
Carrots	140
Organic	70
Conventional	70
Shanay	16
Shanay	16
Shanay	16
Shanay	16
Shanay	16
Shanay	16
Potatoes	160
Potatoes	160
Potatoes	160
Potatoes	160
Potatoes	160
Potatoes	160



Results: Separation between organically and conventionally grown carrots



Derivative hyperspectral curves of organically and conventionally grown carrots (1st order derivative, variety 'Shanay')

Optimal wavelengths for carrot variety and farming method separation (PCA)

Wavelength, nm	Red (the red edge)
722.1	Red
678.6	Red
573.9	Yellow
504.1	Green
878.3	Near infrared

Classification accuracy of different varieties of carrots and farming methods

Variety	Farming method	Classified as conventional	Classified as ecological	Producer's accuracy
Gardolite	conventional	18	2	90.0 %
	ecological	0	16	100 %
User's accuracy		100 %	88.9 %	
Overall classification accuracy				94.4 %
Shanay	conventional	20	0	100 %
	ecological	0	16	100 %
User's accuracy		100 %	100 %	
Overall classification accuracy				100 %
Santal	conventional	16	0	100 %
	ecological	0	16	100 %
User's accuracy		100 %	100 %	
Overall classification accuracy				100 %
Shanay	conventional	20	0	100 %
	ecological	0	16	100 %
User's accuracy		100 %	100 %	
Overall classification accuracy				100 %

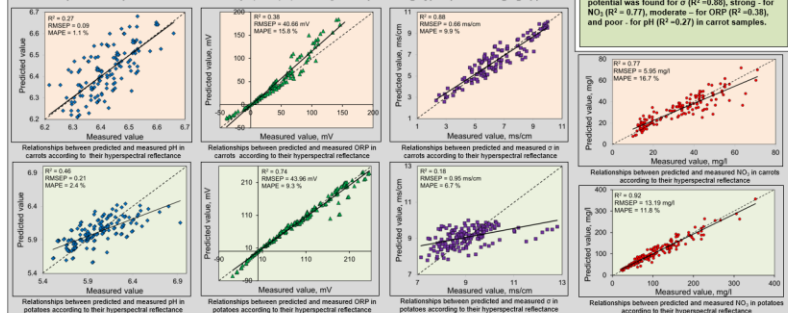
Classification accuracy of farming methods when the variety is not assumed

Farming method	Classified as conventional	Classified as ecological	Producer's accuracy
Conventional	54	22	71 %
Ecological	20	44	68.8 %
User's accuracy	73.0 %	66.7 %	
Overall classification accuracy			70.8 %
κ			0.4

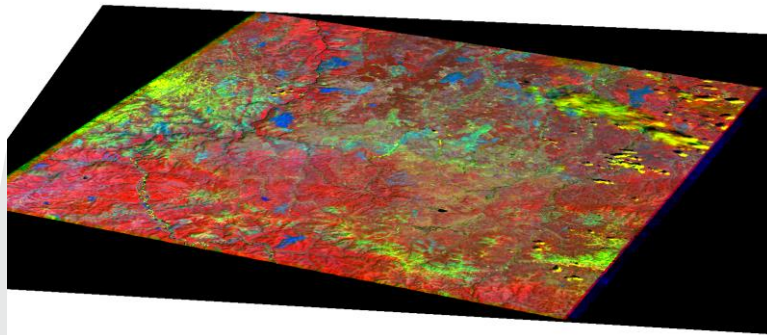
Conclusions:

1. The classification of conventionally and ecologically grown carrots, according to their hyperspectral reflectance, was very precise (overall classification accuracy 94.4 % to 100 %, κ 0.39 to 1.00) when carrot variety was taken into account.
2. Hyperspectral reflectance data was found to moderately discriminate (overall classification accuracy 70 % to 0.40) the conventionally and ecologically grown carrot samples when carrot variety was not taken into account.
3. Very strong prediction potential was found for NO₃ (R² = 0.52), strong – for ORP (R² = 0.74), moderate – for pH (R² = 0.46), and poor for EC (R² = 0.18) in potato samples. Very strong prediction potential was found for EC (R² = 0.88), strong – for NO₃ (R² = 0.77), moderate – for ORP (R² = 0.36), and poor – for pH (R² = 0.27) in carrot samples.

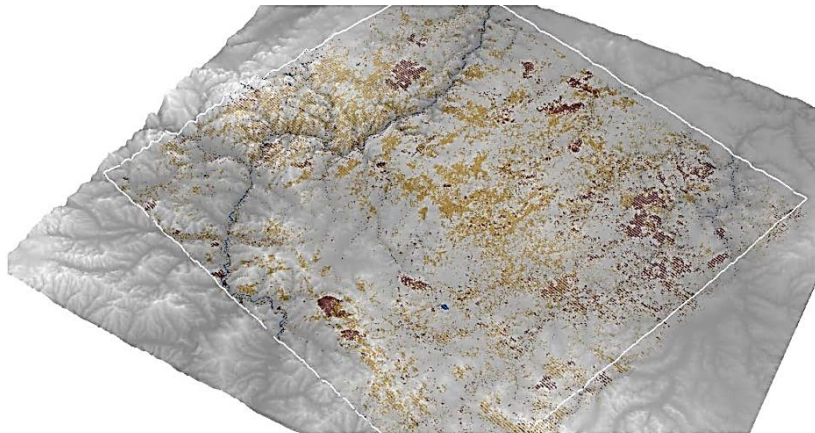
Relationships between predicted and measured pH, ORP, EC, and NO₃ in samples using hyperspectral imaging approach



Exemples de segments (blocs) (modèles de connaissance)



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.

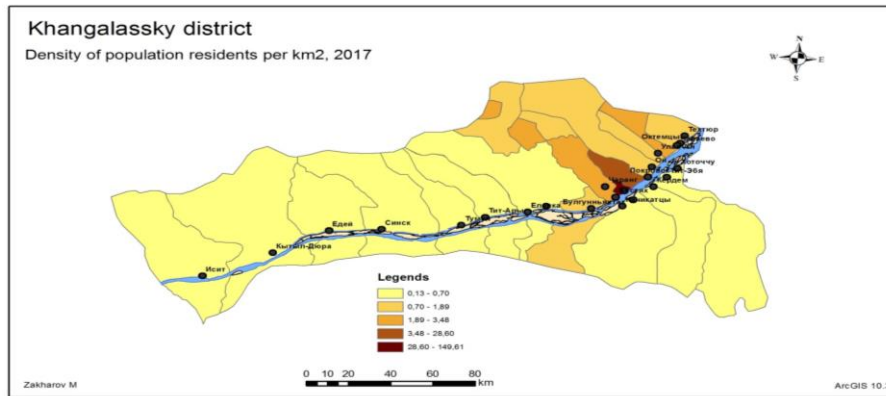
2. Biogéographie

2.1. Couvert forestier

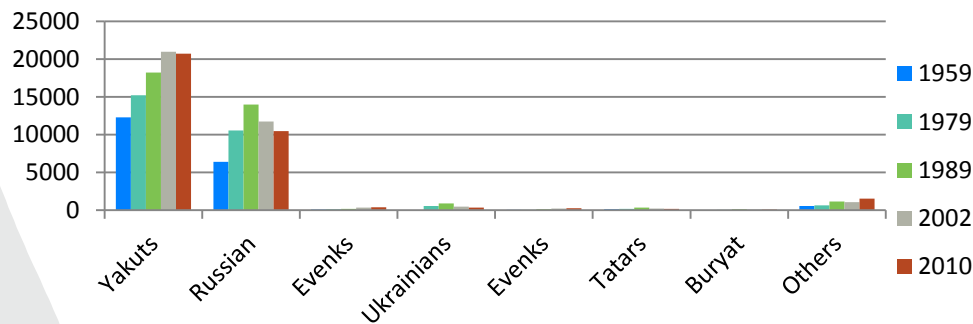
- 2.1.1. Zones de pinèdes (pins) : terres sèches et planes, commode pour les déplacements. Ce n'est pas occupé par les ruisseaux qui peuvent gêner les déplacements. Les chiens se déplacent facilement car il n'y a pas de buissons et chasser les zibelines.
- 2.1.2. Zones de sapins : partie avec les aiguilles 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 pins 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.

Exemples de segments (blocs) (modèles de connaissance)

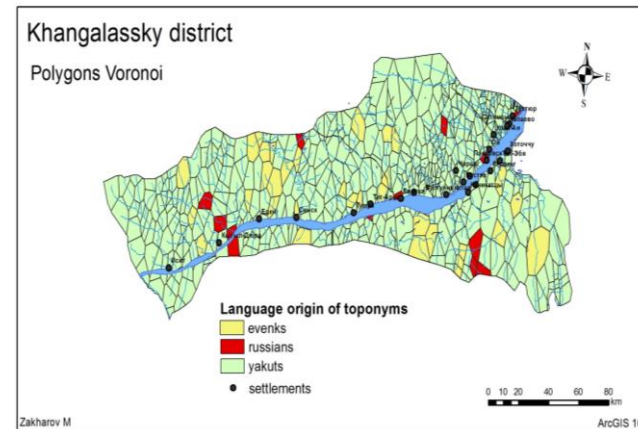
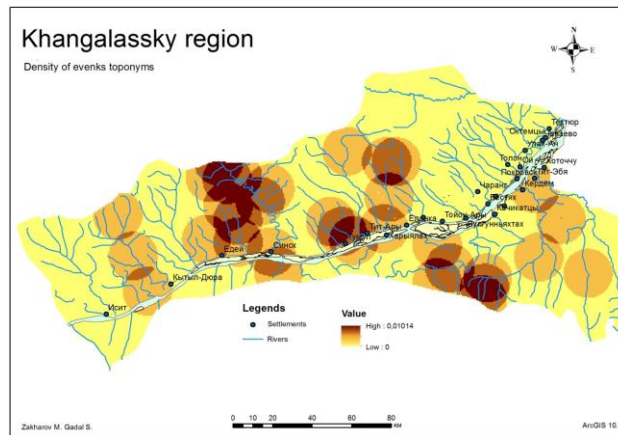
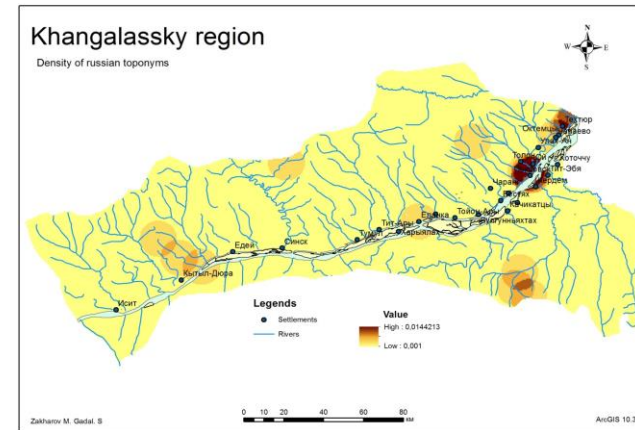
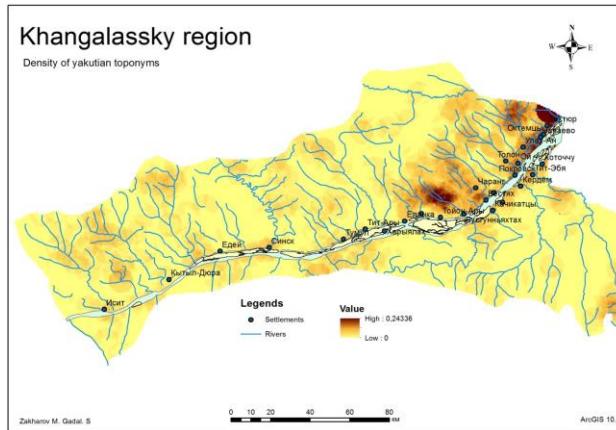
Ethnic composition of the population



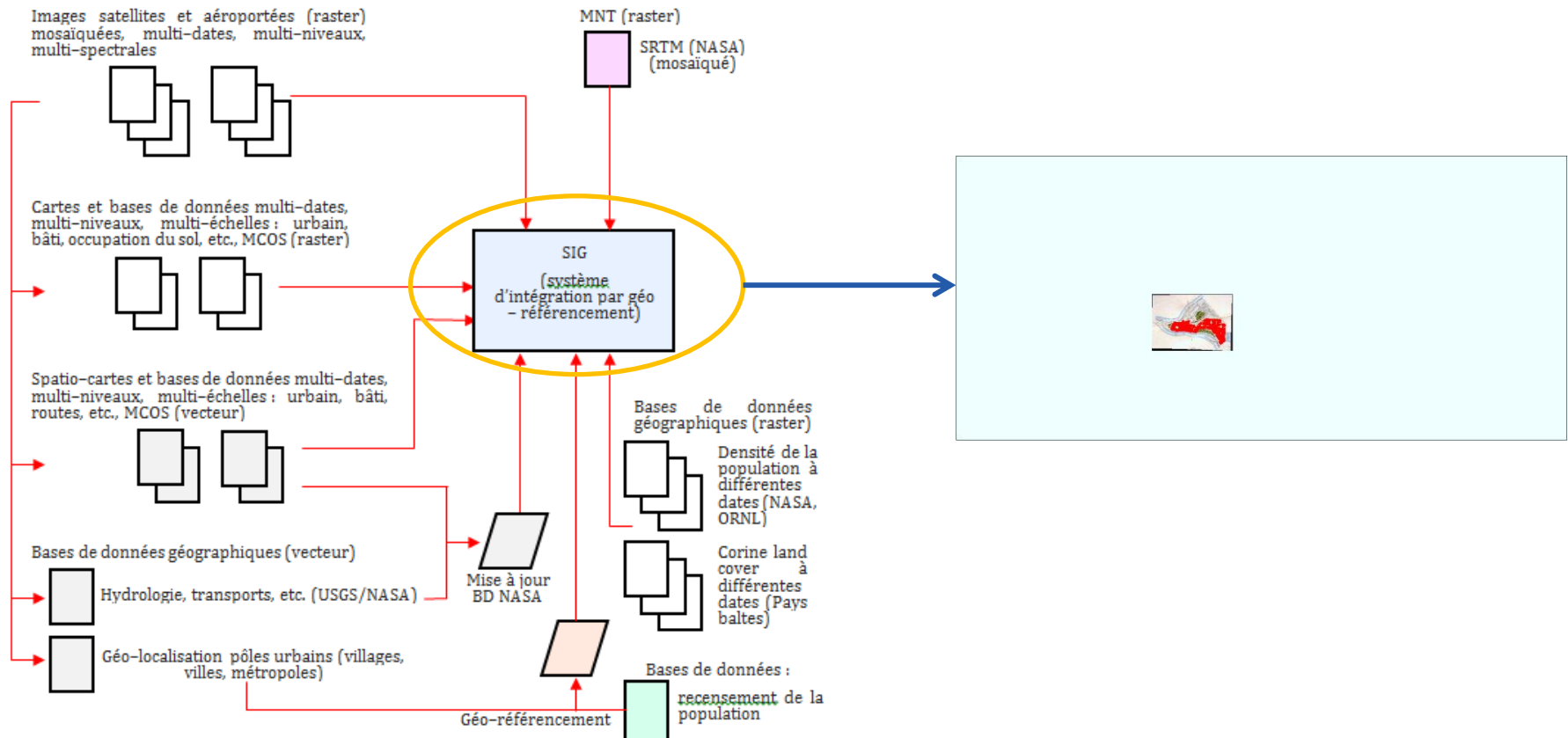
The national composition of the Khangalassky district for population censuses from 1959-2010 (Source: The Federal Statistics Service)



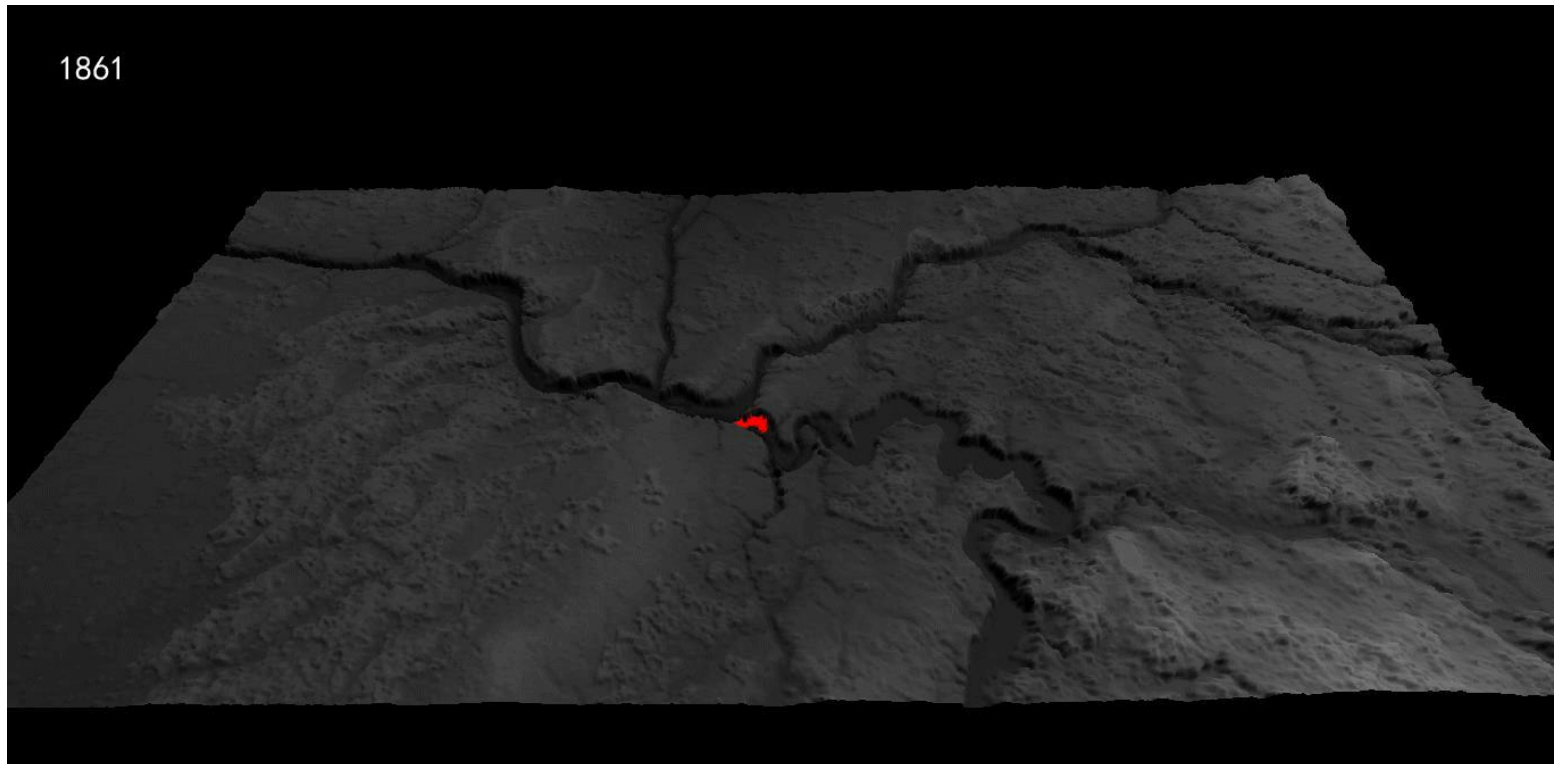
Exemples de segments (blocs) (modèles de connaissance)



Modélisation (simulation) de la croissance urbaine (1)



Modélisation (simulation) de la croissance urbaine (2)



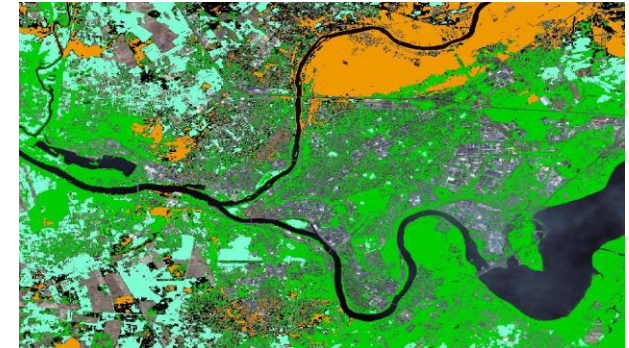


Occupation du sol: végétation urbaine

Espèce végétale	S2A Printemps	S2A Été	S2A Automne	S2A Hiver	Landsat 8 OLI
Feuillus (%)	100	98,3 8	66,41	0	69,42
Conifères (%)	96,67	99,3	97,57	100	98,43
Pelouse (%)	94,74	90,5 3	94,74	0	100
OA(%)	98,04	97,5 3	89,1	96,32	93,32
Coeff de kappa	0,97	0,96	0,8	0	0,84

Classification saisonnière SVM par groupe
d'espèces sur images Sentinel-2 et Landsat 8
OLI (Kaunas, Lituanie)

S2A : ClassificationSVM–Kaunas-12/05/2017–**Printemps**



Conifères Feuillus Pelouse

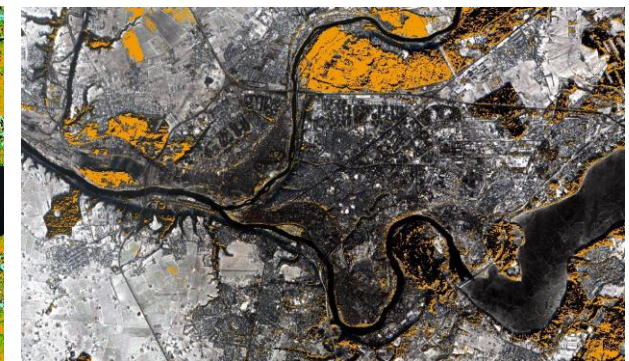
S2A/L8 OLI : ClassificationSVM–Kaunas-28/08/2016– **Été**



S2A : ClassificationSVM–Kaunas-17/10/2016–**Automne**

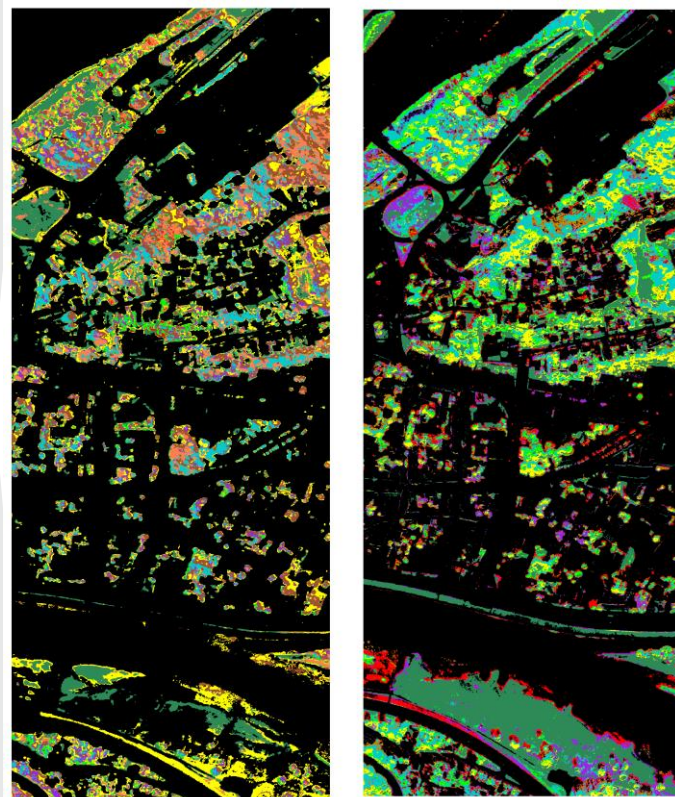


S2A : ClassificationSVM–Kaunas-25/01/2017–**Hiver**



Occupation du sol: végétation urbaine

Cartographie de la végétation urbaine par SVM (16 and 64 bandes)



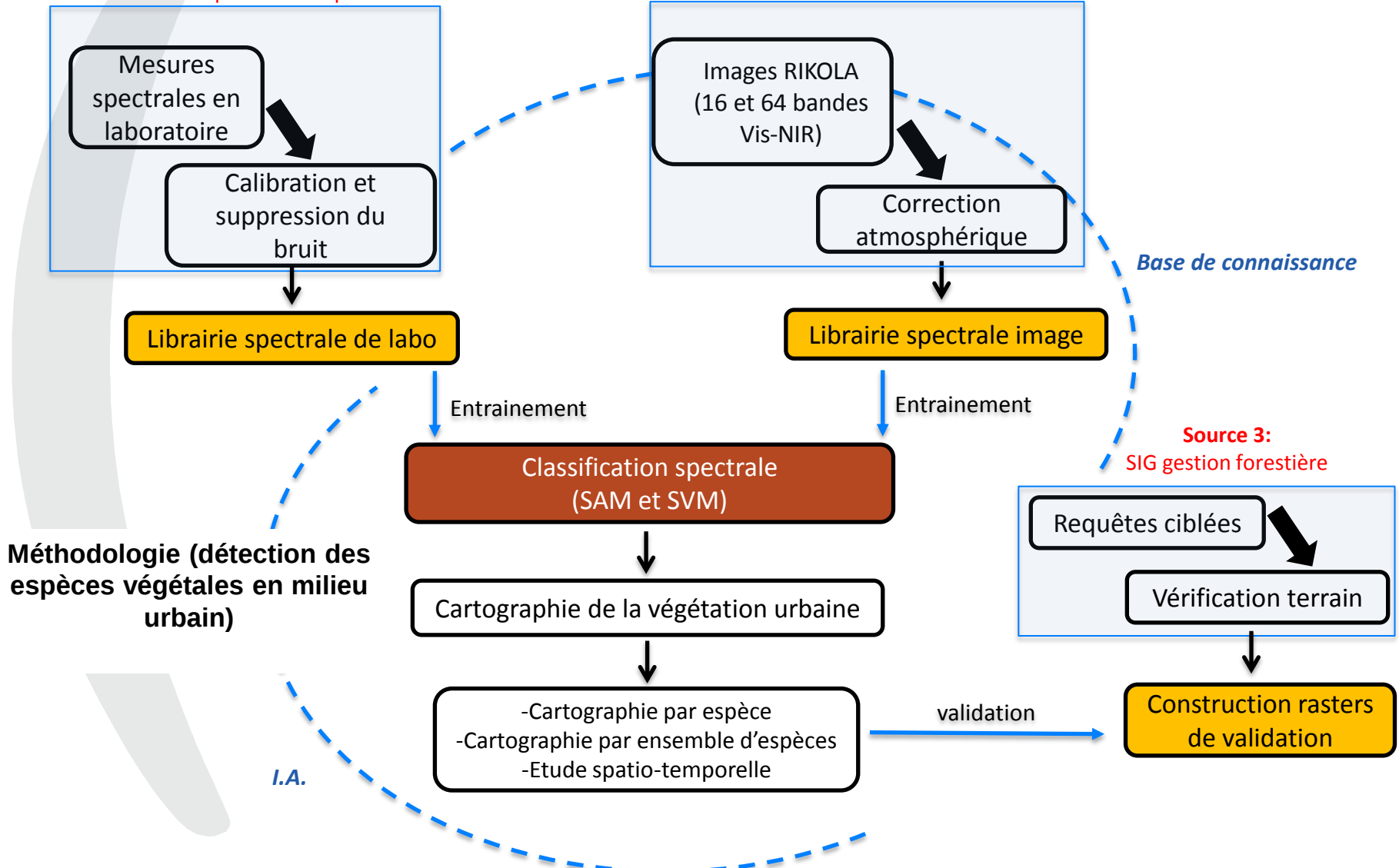
Species	SVM (16 bands)	SVM (64 bands)
H. Chestnut	19.1	28.0
Linden	36.0	19.2
M. Ash	38.4	38.8
Oak	36.5	72.5
N. Spruce	15.0	51.6
S. Pine	47.3	18.1
Thuja	50.1	27.6
Grass	91.2	85.5
O.A. (%)	41.2	45.7

- «moderate» ($40\% < \text{O.A.} < 60\%$) accuracy
- Better **mapping accuracy** given by **64 bands** image
- Coniferous better identified using **16 bands** image

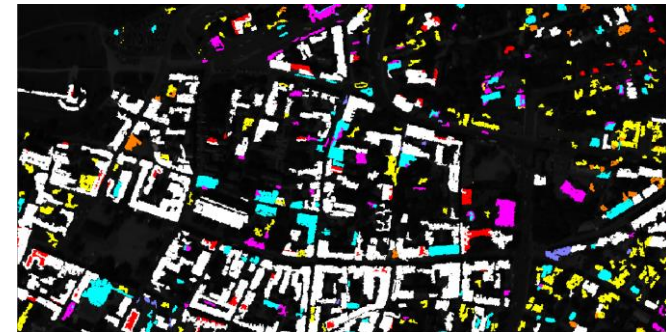
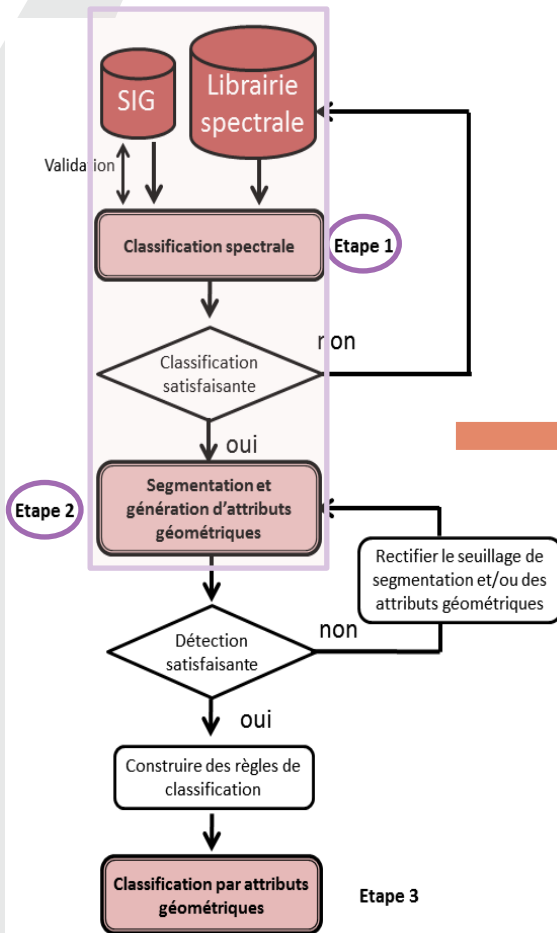
Occupation du sol: végétation urbaine

Source 1:
Données spectrométriques

Source 2:
Données images



Occupation du sol (détection et caractérisation du bâti)

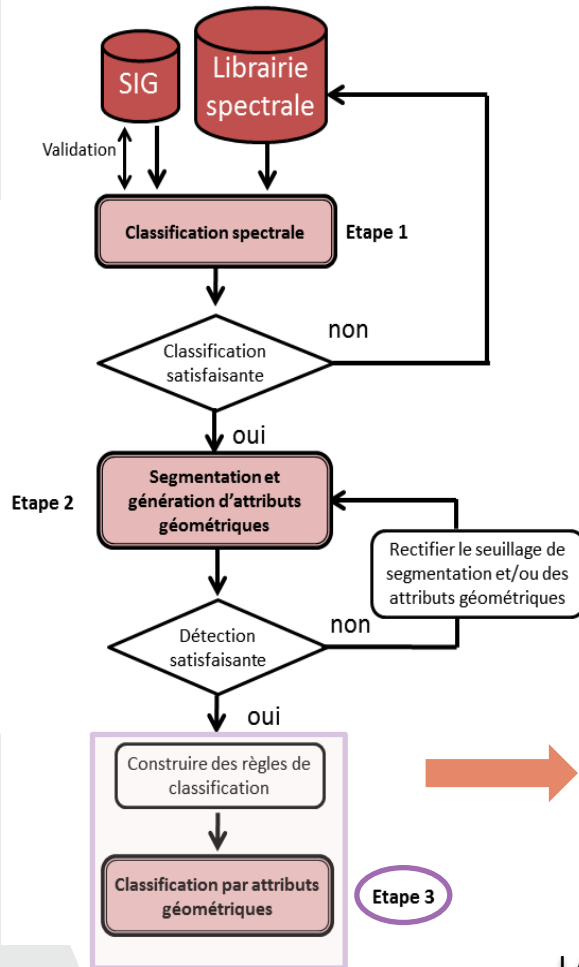


Classification par librairie spectrale et rectification par attributs géométriques appliqués sur le centre ville historique de Kaunas (Lituanie)

- Tile
- Painted metal (dark)
- Painted metal (clear brown)
- Painted metal (red)
- Painted metal (clear)
- Painted tile (dark)
- Asbestos

I.A: génération d'un masque d'objets bâtis +
rectification morphologique (élimination des routes)

Occupation du sol (détection et caractérisation du bâti):

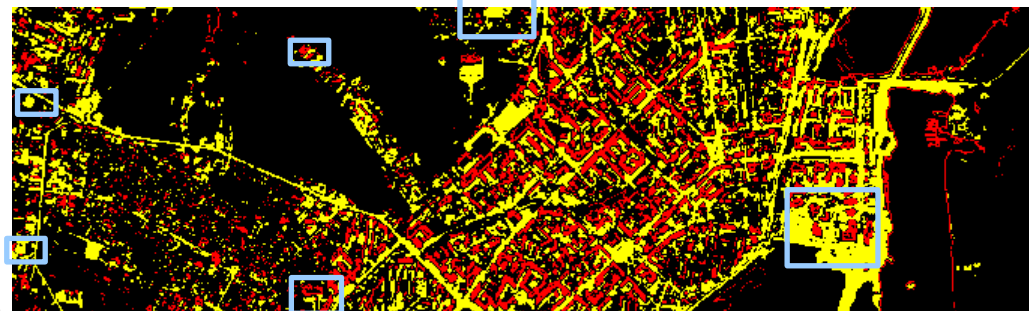
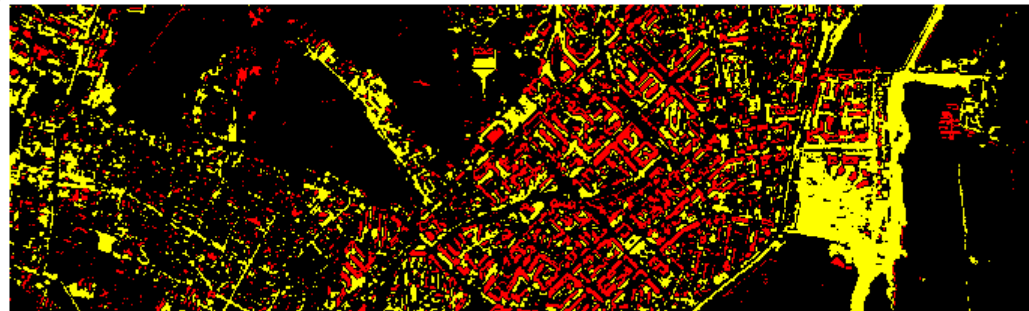


Exemple de classification par attributs géométriques:
[elongation + area], [circularity + convexity], [convexity + area]

I.A: construction de règles morphométriques pour
caractériser des classes socio-économique de bâti

Occupation du sol (détection et caractérisation du bâti)

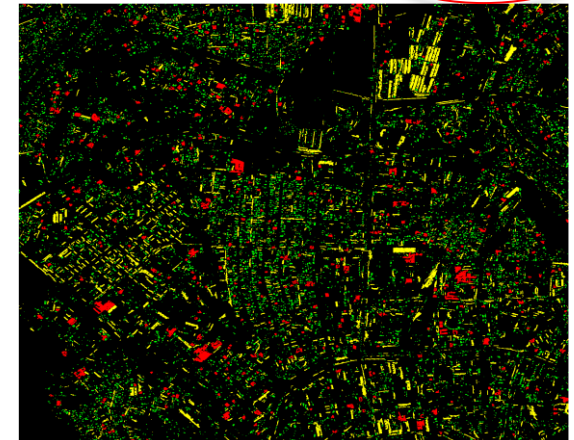
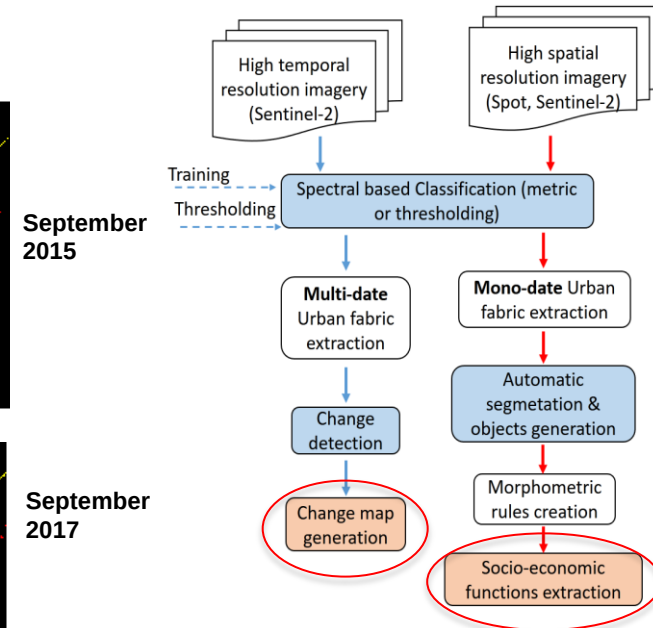
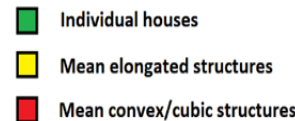
- Détection des changements en milieu urbain et caractérisation du bâti (imagerie Sentinel-2)



S. Gadal et W. Ouerghemmi (2018)

- Caractérisation morphologique des classes socio-économique
Sur la ville de Iakoutsck (Sibérie orientale),

I.A utilisée à deux niveaux: génération de la carte
urbaine et création de règles morphométriques



Enjeux

Enjeux à relever en termes de données massives, machine learning, et deep learning

- **Formalisation des modèles de connaissances et établissement de règles.**
- Utilisation de techniques **d'apprentissages complexes** (par exemple les réseaux de neurones convolutifs)
- **Puissance de calcul importante** (Cluster de calcul, GPU dédié, etc.)
- **Puissance de stockage importante** (apprentissage à partir de grosses bases de données, libraires spectrales, bases de données attributaires, bases de connaissances, etc.)

Quelques éléments de bibliographie

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