



# Multi-Temporal multi-scalar modelling of the dynamics of urban landscape changes by remote sensing

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# Multi-Temporal multi-scalar modelling of the dynamics of urban landscape changes by remote sensing.

## Examples of Yakutsk and Tiksi

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# Yakutsk



Yakutsk: eastern Siberia



Yakutsk center



Yakutsk center (RGB SPOT 6 -2016- )

- The circumpolar regions are characterised by significant changes in both social, territorial, climatic, and economic policies.
- Cross dynamics of globalisation, territorial integration, and climate changes impacts.
- Urban area up to 330 000 inhabitants in extreme climatic environment.

## Emergence of endogenic processes of globalisation

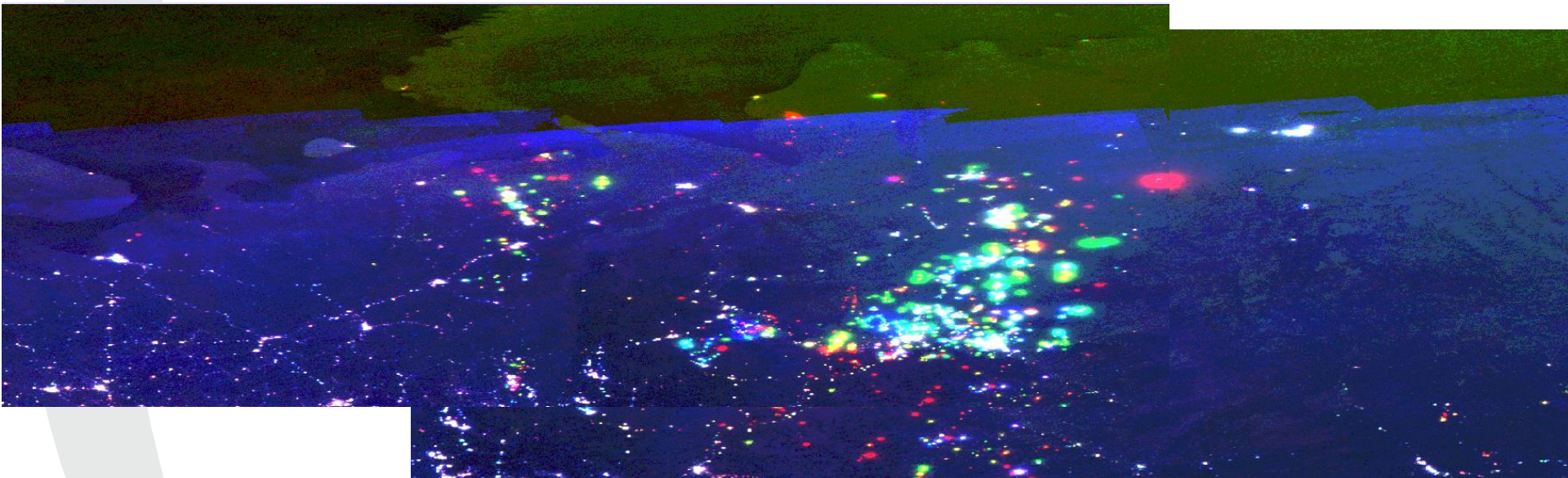
- Since the middle/end of the 2000's, the emergence of processes of endogenic dynamics of globalisations in some territories as Yakutsk driving the transformations of the North society and territories in the European parts and Asiatic Russia (Siberia).
- Metropolisation, globalisation, cultural codes and lifestyles, sectorial economic integrations are the main drivers.
- Economic crisis lowering the territorial and societal change dynamics. In any case stopping the dynamics of transformations.
- Territories in development as Yakutsk, with some serious technical and technological delays and distances; little urbanism have impacts to the processes ingoing.
- Extreme climate and high natural hazard exposure too.

=> Dynamics of adaptation and resilience



# Urbanisation and development: the main driver of the natural resources (1)

## European Russian arctic changes



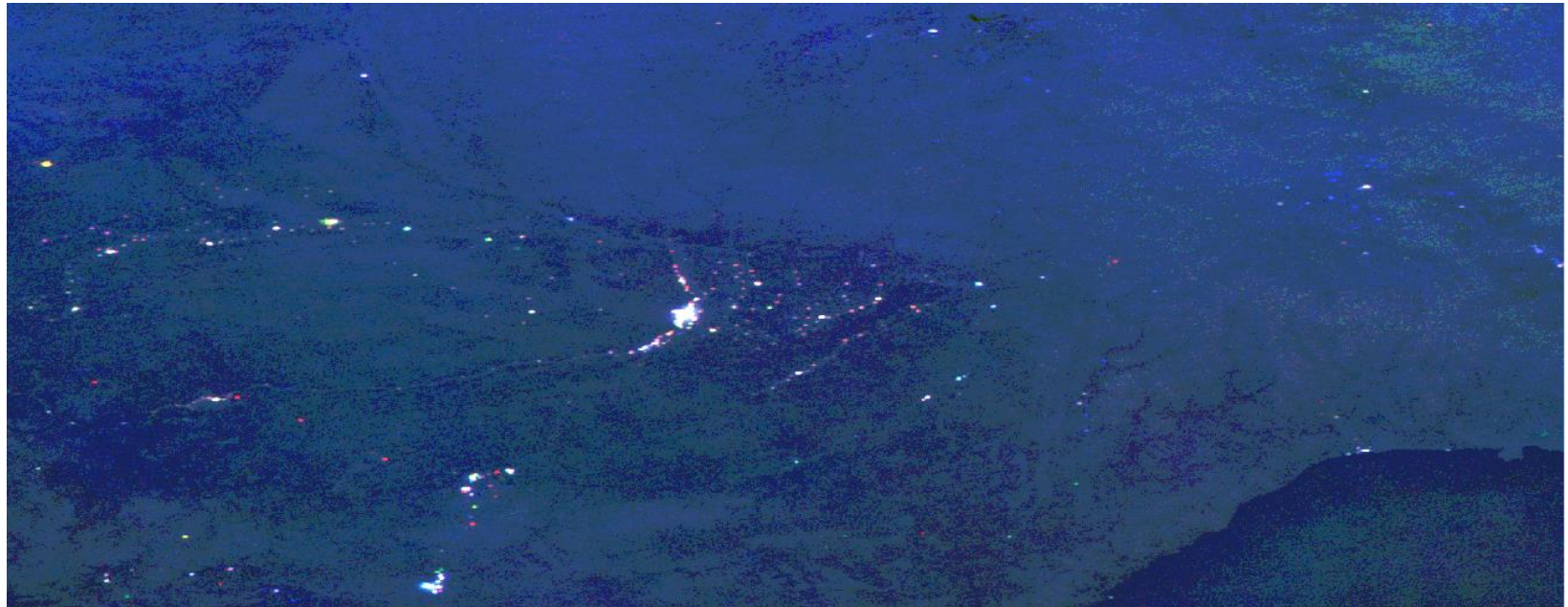
Sébastien Gadal, 2017

Data: NOAA-USAF DMSP F10, F15, F18, Ensembles' modelling Alg. (sensor VNIR OPL-PS – mean annual spectral measurement), S. Gadal, Nov. 2017

Legend: Blue: 1992 (no change); Green: 2005 - Emergence of urban/natural resources spots; Red: 2013 - Emergence of urban/natural resources spots; Yellow: change recognition between 2005 and 2013

## Urbanisation and development: the main driver of the natural resources (2)

### Territorial changes in the Siberian Arctic (1992-2013)



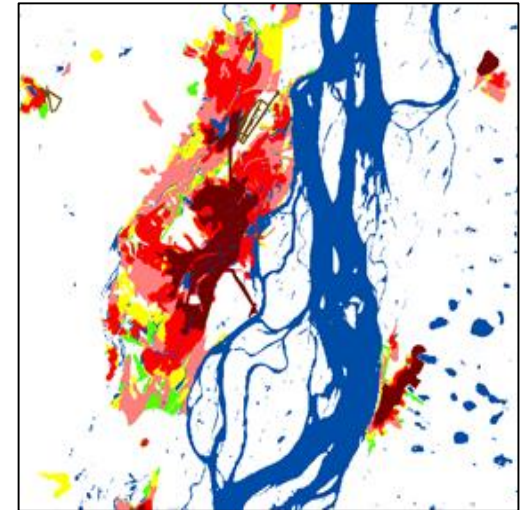
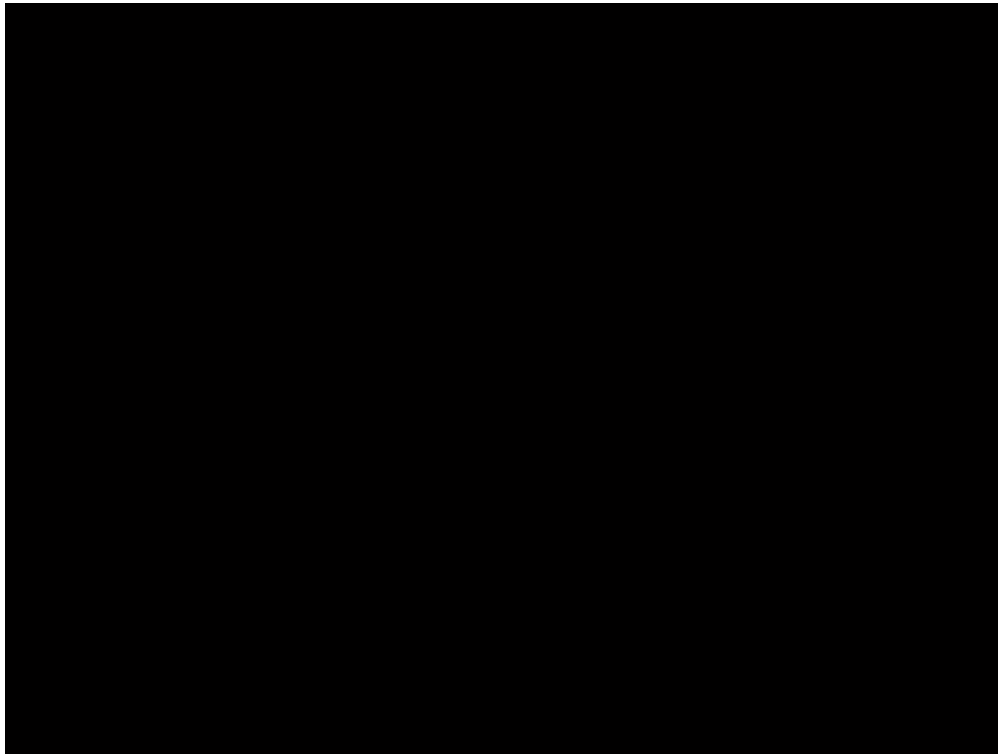
Sébastien Gadal, 2017

Data: NOAA-USAF DMSP F10, F15, F18, Ensembles' modelling Alg. (sensor VNIR OPL-PS – mean annual spectral measurement), S. Gadal, Nov. 2017

Legend: Blue: 1992 (no change); Green: 2005 - Emergence of urban/natural resources spots; Red: 2013 - Emergence of urban/natural resources spots; Yellow: change recognition between 2005 and 2013

## Context and goals

- Massive urban and demographic expansion of Yakutsk (capital of Sakha Republic, Russia)
- Settlements of new inhabitants near risky areas: Permafrost, debacle's flooding.

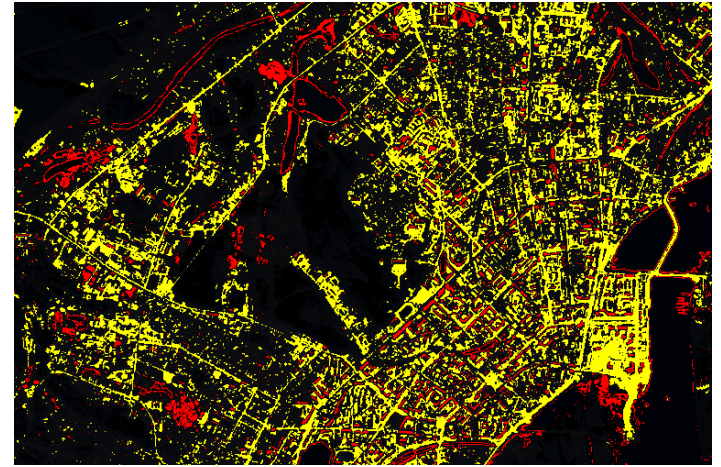


Extraction of the GIS territorial change  
S. Gadal, 2011-2016

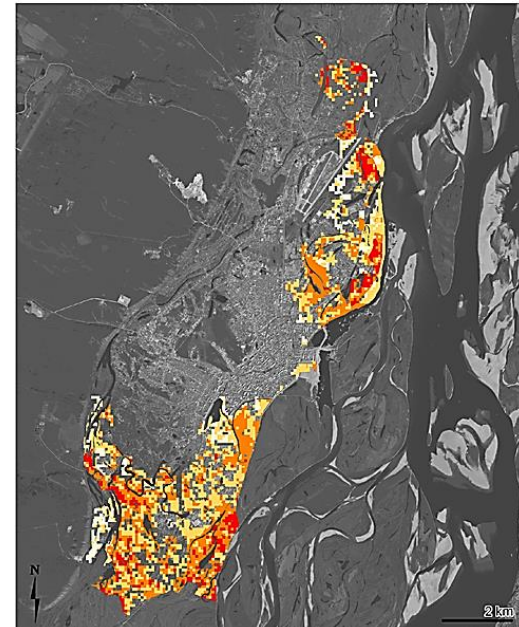


## Objects and issues

- **Multi-sensors, Multi-level urban characterisation (SPOT 6/7, Sentinel 2)**
- Urban fabric extraction and change detection using spectral indices (Sentinel 2)
- Built-up functions extraction using morphological methods (SPOT 6/7): industrial, individual, cultural/religious, etc.
- Simulation of the urban expansion to the next 10-15 years (Markov chain, Neural Network)
- **Modelling the vulnerable urban areas of the debacle's flooding**



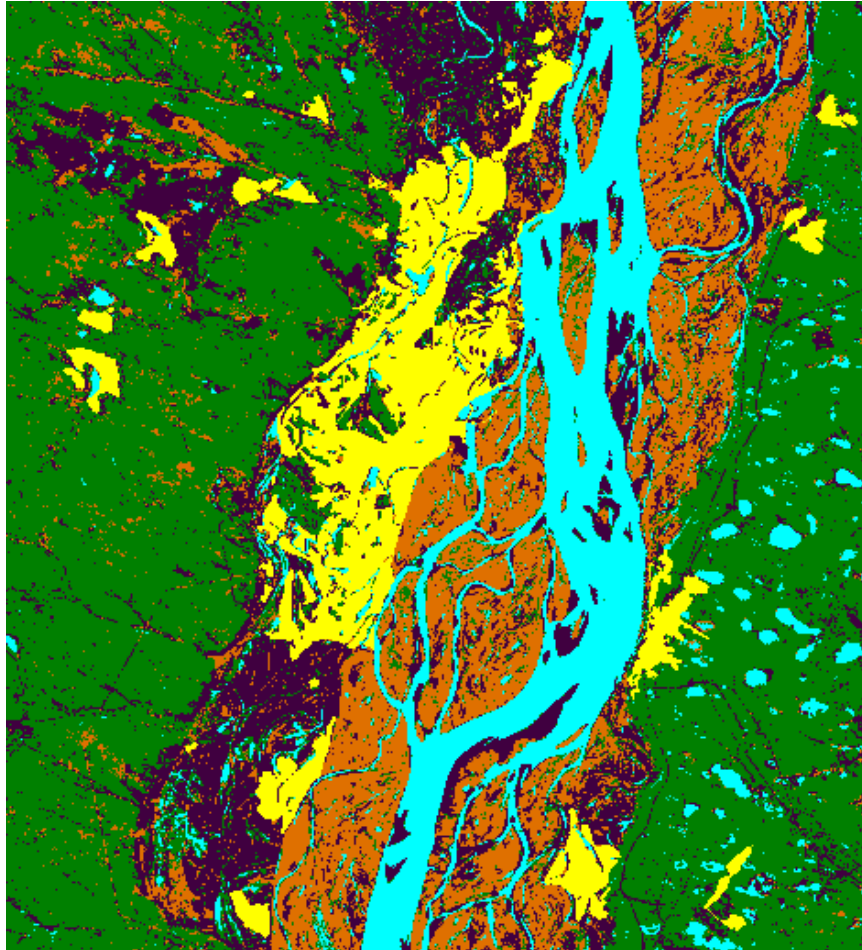
S. Gadal, W. Ouerghemmi, 2018



R. Rollot, S. Gadal,  
Y. Danilov, 2015-2016



# Example of the simulation of the future changes of Yakutsk (Markov chain modeling)



Sébastien Gadal, Alireza Iranmanesh, 2014

## • Urban fabric extraction and change detection using spectral indices (Sentinel 2)

- **Inter-annual** study; 2 images acquired at **different dates** and **different years** (e.g. 2015 and 2017)
- **Intra-annual** study: 2 images acquired at **different dates** and **same year** (e.g. 2017)



September 2015

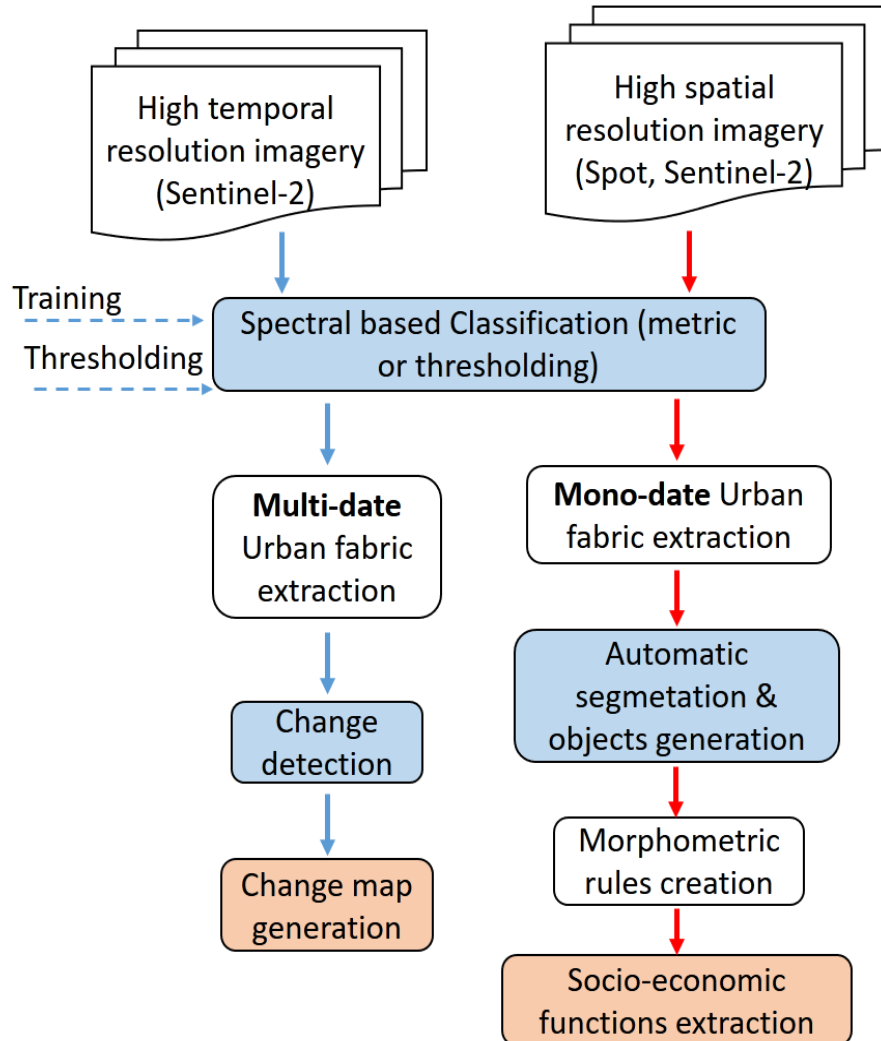
June 2017

September 2017

Walid Ouerghemmi, Sébastien Gadal, 2018

Sentinel-2 RGB (10x10m) -2016-

# Methodology



**Change detection and socio-economic fabric extraction, using simultaneously high temporal Sentinel-2 data, and mono-date Spot-6 data.**

- High temporal repetitiveness **Sentinel-2 imagery**: changes detection and urban fabric expansion estimation.
- High spatial resolution **Spot Imagery**: characterisation of socio-economic functions of built-ups.

## Objectives:

- 1- Use conventional spectral classifier (e.g. SAM) to detect land use classes and extract built-ups areas.
- 2- Experiment spectral indices to extract built-ups areas.
- 3- Use morphological indices to characterize built-ups areas.



# Intra-annual recognition

- **Building settlements, blocs, dachas, commercial centers, etc. are made between mi-April to mi-October.**
- Urban fabric recognitions use developed 3 spectral indices to characterise built-ups.
- The methodology is based on the fusion of the 3 spectral indices:
  - Water index:** second normalised water index (NDWI),
  - Vegetation index:** normalised difference vegetation index (NDVI),
  - Soil index:** second brightness index (BI) with two thresholds for dark and clear buildings recognition.

- Or on the use of Spectral Angle Mapper (**SAM**) classifier

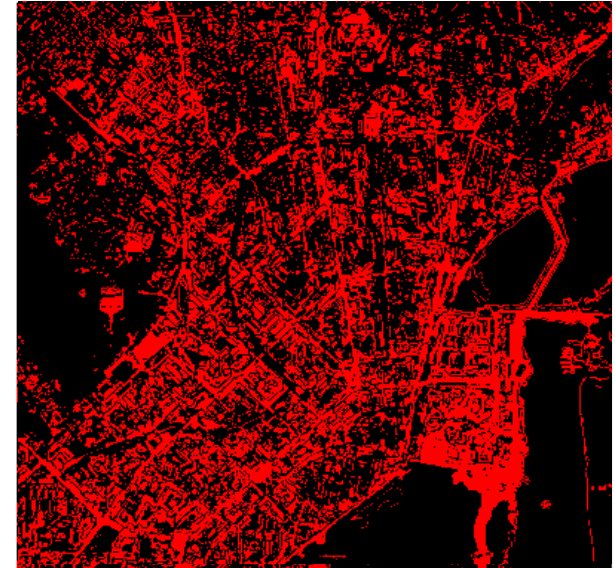
June 2017

- **High intra-annual environmental change inside the city**

Impact the indices recognition method within the year of interest.

Metric method impacted.

September 2017



Urban fabric June 2017 (spectral indices)

Urban fabric September 2017 (spectral indices)





# Intra-annual accuracy recognition of the built-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).

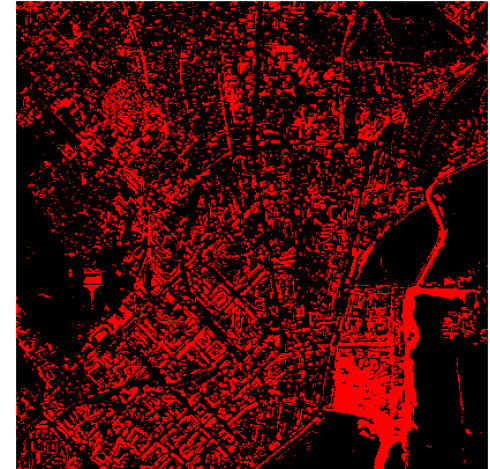
## Inter-annual recognition (2015-2017)

- **Building settlements, blocs, dachas, commercial centres, etc. are made between mi-April to mi-October (2015-2017)**
- Urban fabric recognition and built-ups characterisation done using two methods:
  - (1) The fusion of the 3 spectral indices:  
**Water index:** second normalized water index (NDWI),  
**Vegetation index:** normalized difference vegetation index (NDVI),  
**Soil index:** second brightness index (BI).
  - (2) The use of metric based classifier **Spectral Angle Mapper (SAM)**
- **Notes:**

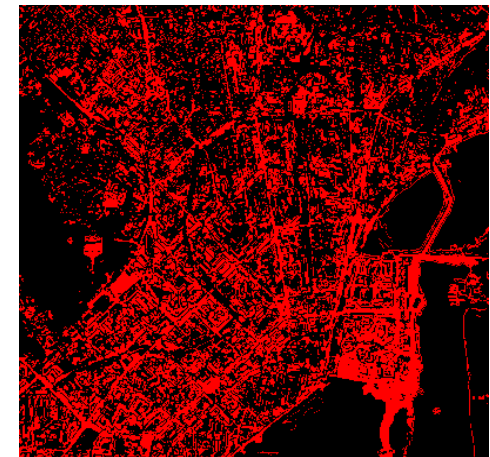
**Inter-annual** change detection is more **suitable** to change detection at condition to take **same season** images.

The risk of **bias** is **lower** than for intra-annual detection case.

Problem of **sandbanks** which have random moves depending on **debacle** and **water flow**.



Urban fabric September 2015 (spectral indices)



Urban fabric September 2017 (spectral indices)

# 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).

## Example of built-ups change detection (Sentinel 2)

Built-ups extraction for September 2015 and September 2017

- Clear built-ups
- Dark built-ups



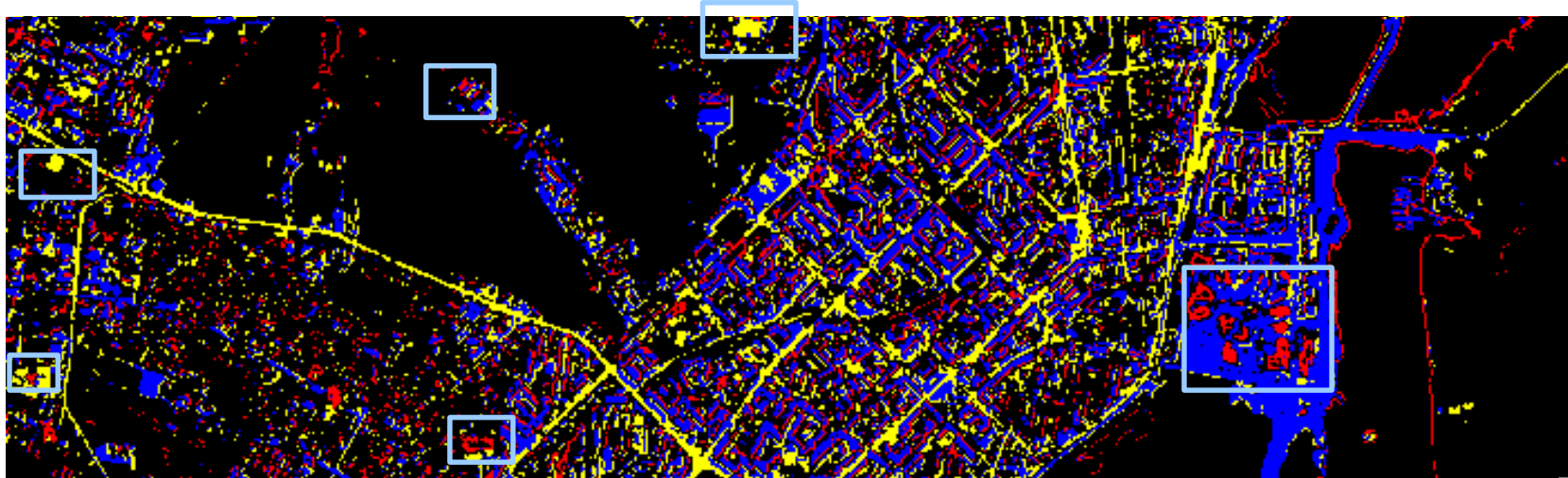
September 2015



September 2017



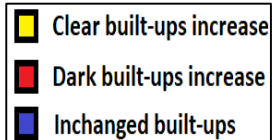
# Example of built-ups change detection (Sentinel 2)



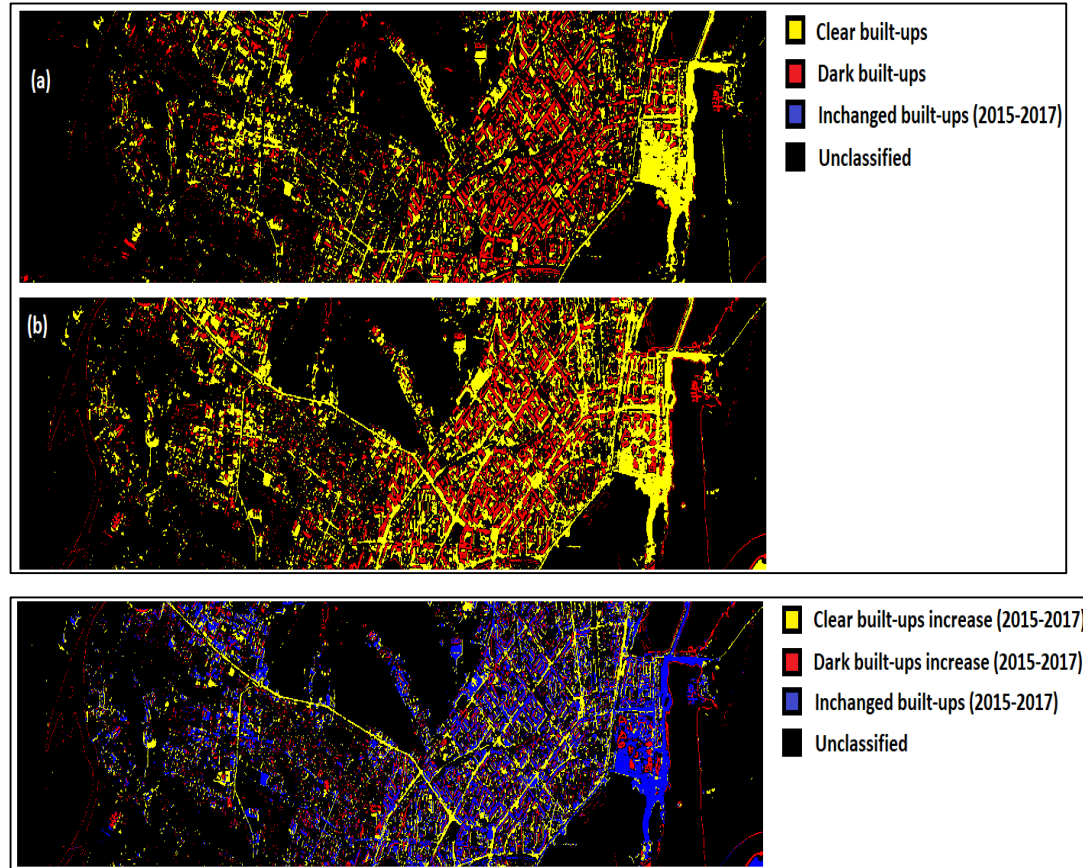
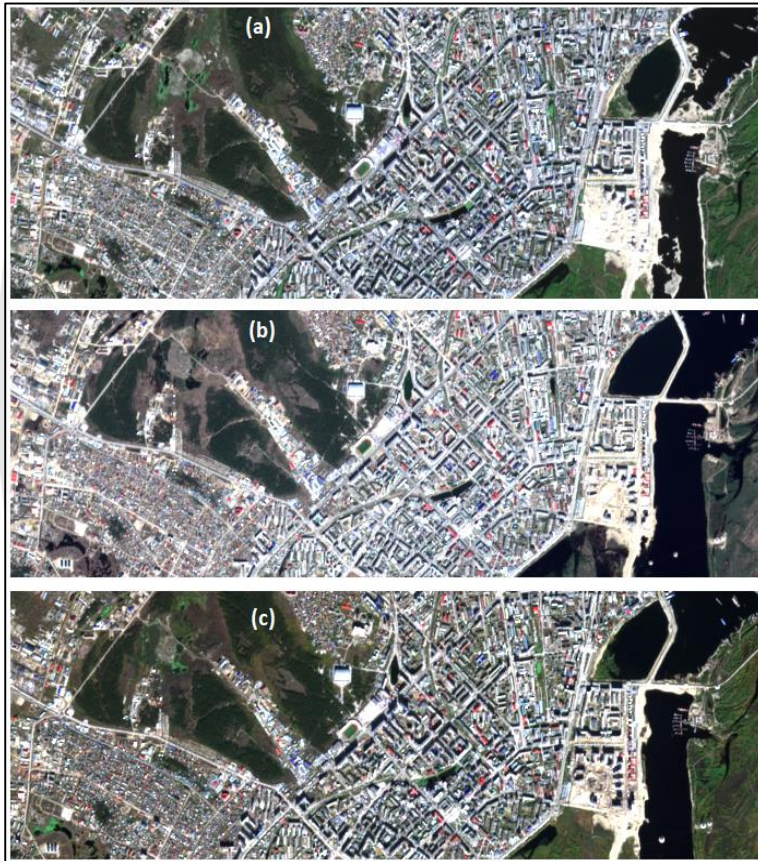
Walid Ouerghemmi, Sébastien Gadal, 2018

September 2015

September 2017



# Fast urban and territorial changes

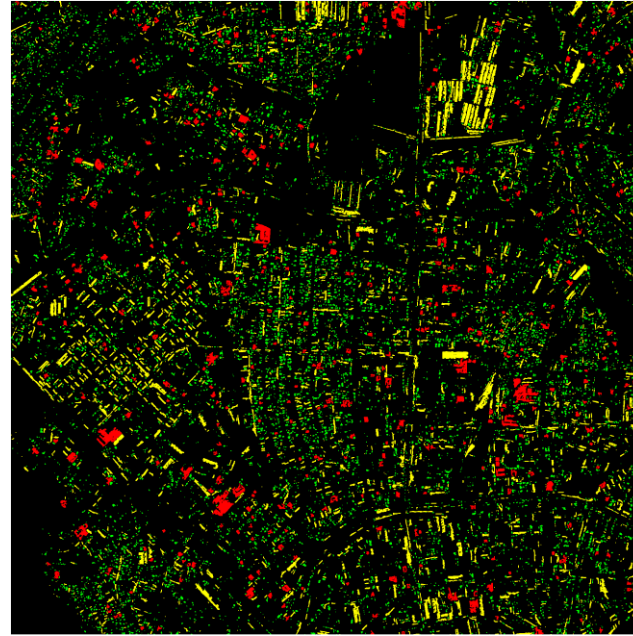




## Morphological characterisation of built-ups (Spot 6)



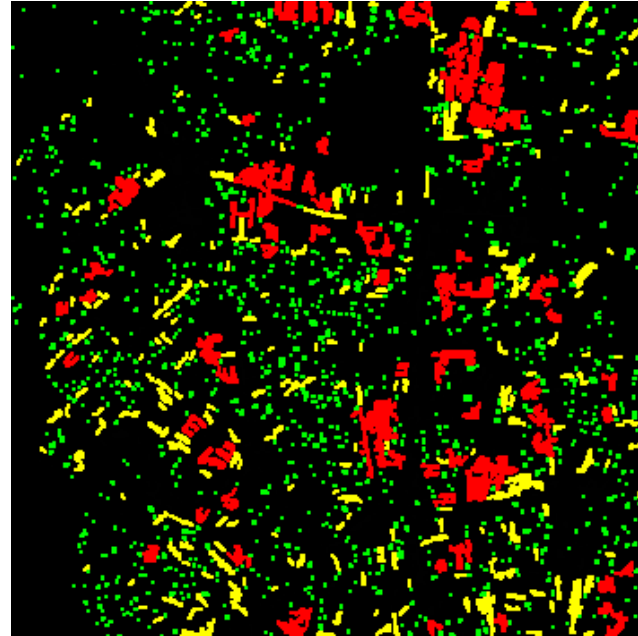
Walid Ouerghemmi, Sébastien Gadal, 2018



- Individual houses
- Mean elongated structures
- Mean convex/cubic structures

- 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)



- Individual houses
- Mean elongated structures
- Mean convex/cubic structures

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.**



## Conclusion

- **High temporal resolution Sentinel 2** imagery allows accurate **change detection quantification** :

**Inter-annual** study between 2015 and 2017 **showed an increase** of approximatively **12%** in terms of built-ups.

**Intra-annual** study within year 2017 **was not reliable enough** to give a global increase of built-ups due to **environmental changes** within the period of interest.

- High spatial resolution **Spot 6** imagery allows an accurate **detection of urban objects**.
- **Sentinel 2** and **Spot 6** were complementary, the first permit to **approximate urban expansion** and the second permit to determine **socio-economic functions** of buildings.

- **Issues** limiting the built-ups recognition:

Presence of **sand banks** which degrade detection efficiency (high correlation with built-ups).

**Environmental changes** between two dates.

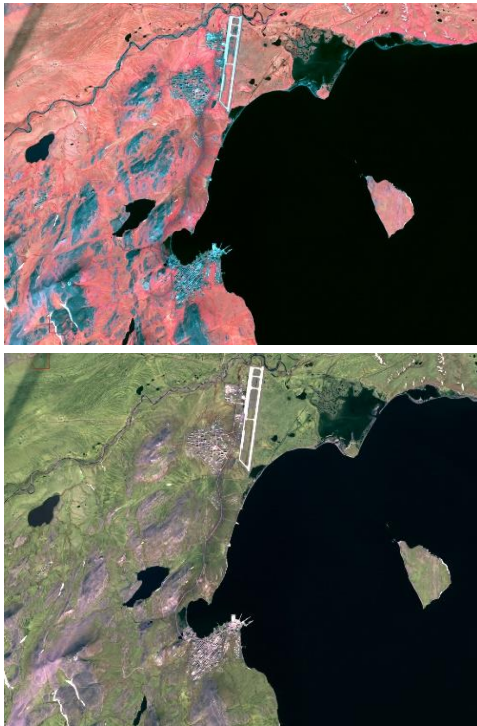
- **Perspectives:**

Automation of built-ups detection process by **Spectral Indices**.

Develop **morphological rules** for **socio-economic functions** extraction.

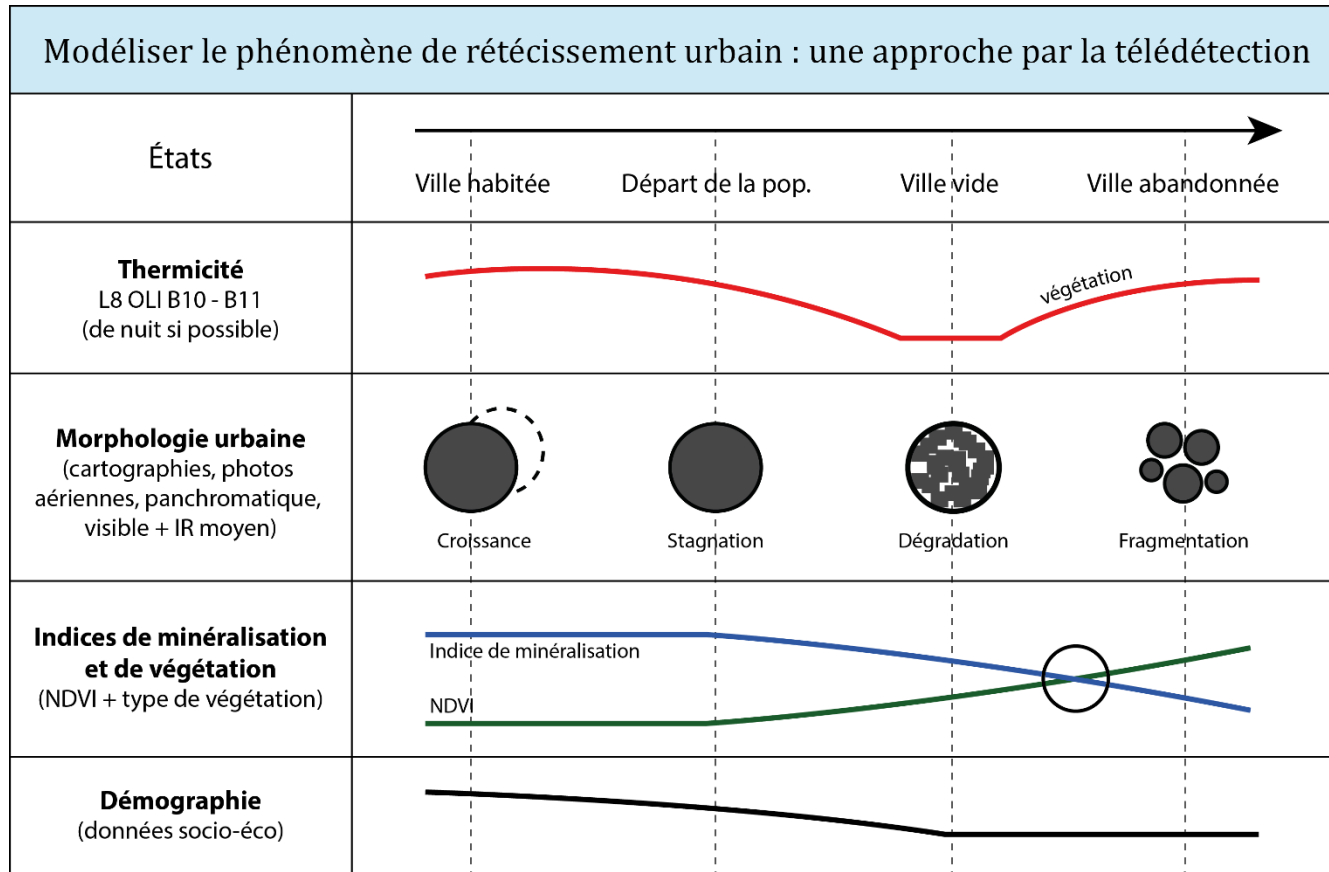
# How to calculus spatially the de-urbanisation? (1)

## Tiksi



Sébastien Gadal, color composite, 2017

# How to calculus spatially the de-urbanisation? (2)



# Publication

Sébastien Gadal, Walid Ouerghemmi. **Multi-Level Morphometric Characterization of Built-up Areas and Change Detection in Siberian Sub-Arctic Urban Area: Yakutsk.** *ISPRS International Journal of Geo-Information*, MDPI, 2019, 8 (3), pp.129. [10.3390/ijgi8030129](https://doi.org/10.3390/ijgi8030129)





**THANK YOU FOR YOUR  
ATTENTION**