Urban mapping through object–based image analysis

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UNIVERSIDAD POLITECNICA DE VALENCIA

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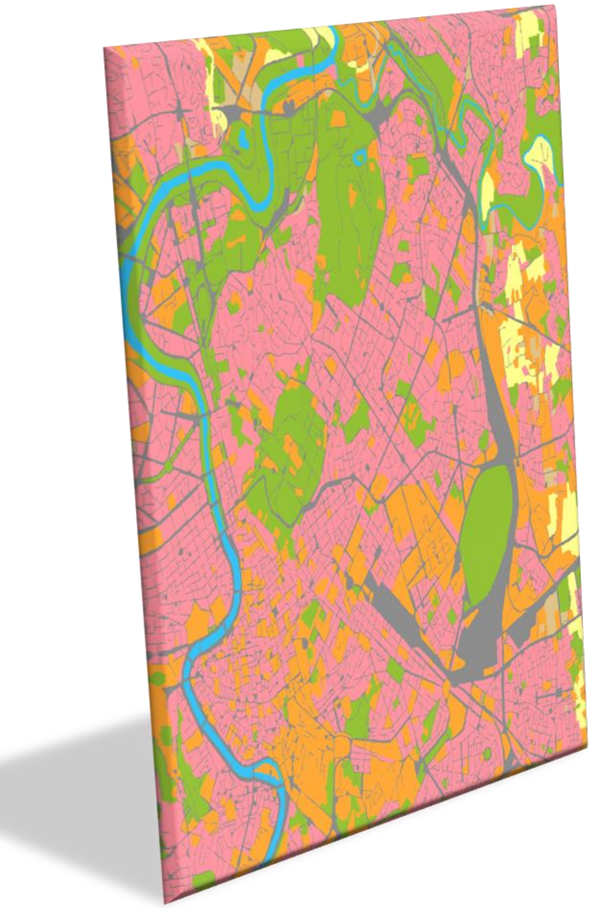


Introduction

Land Use vs. Land Cover

Land cover data documents how much of a region is covered by forests, wetlands, impervious surfaces, agriculture, and other land and water types.

Land use shows how people use the landscape – whether for development, conservation, or mixed uses. The different types of land cover can be managed or used quite differently.

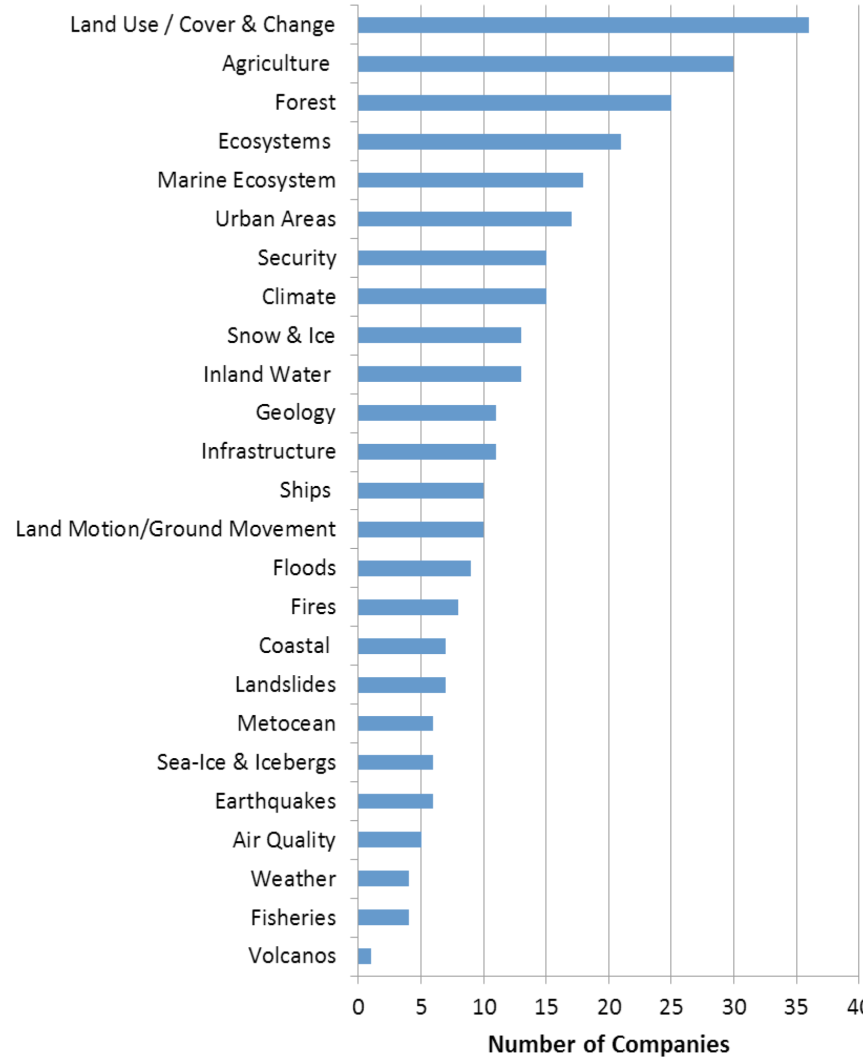
Identification of **land cover** establishes the baseline from which monitoring activities (change detection) can be performed, and provides the ground cover information for baseline thematic maps.

Land use knowledge helps to develop strategies to balance conservation, conflicting uses, and developmental pressures. This is used for studies including the removal or disturbance of productive land, urban sprawl, and forests evolution.

Introduction

Earth Observation Industry in the European Union

Number of companies by thematic area of the final product

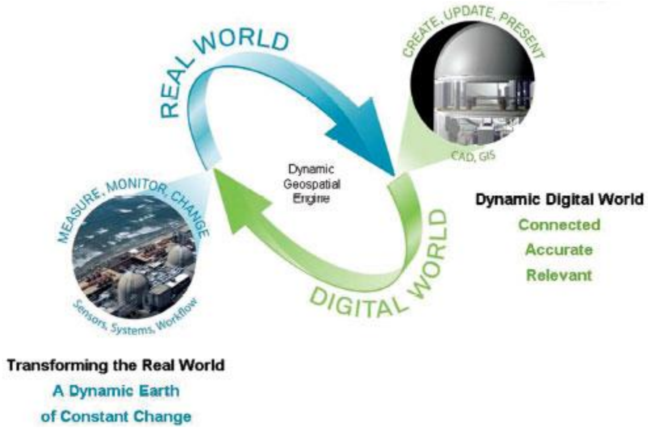


<u>Source</u>: *European Association of Remote Sensing Companies* (EARSC)

Introduction

- Accurate **LU/LC cartography of cities** can be used for physical (viewshed, analysis, environmental impact assessment), economic (accessibility, transport), or social (socio-demographic distributions) **planning**, and forecast **models** (urban growth) (*Donnay et al., 2001*)

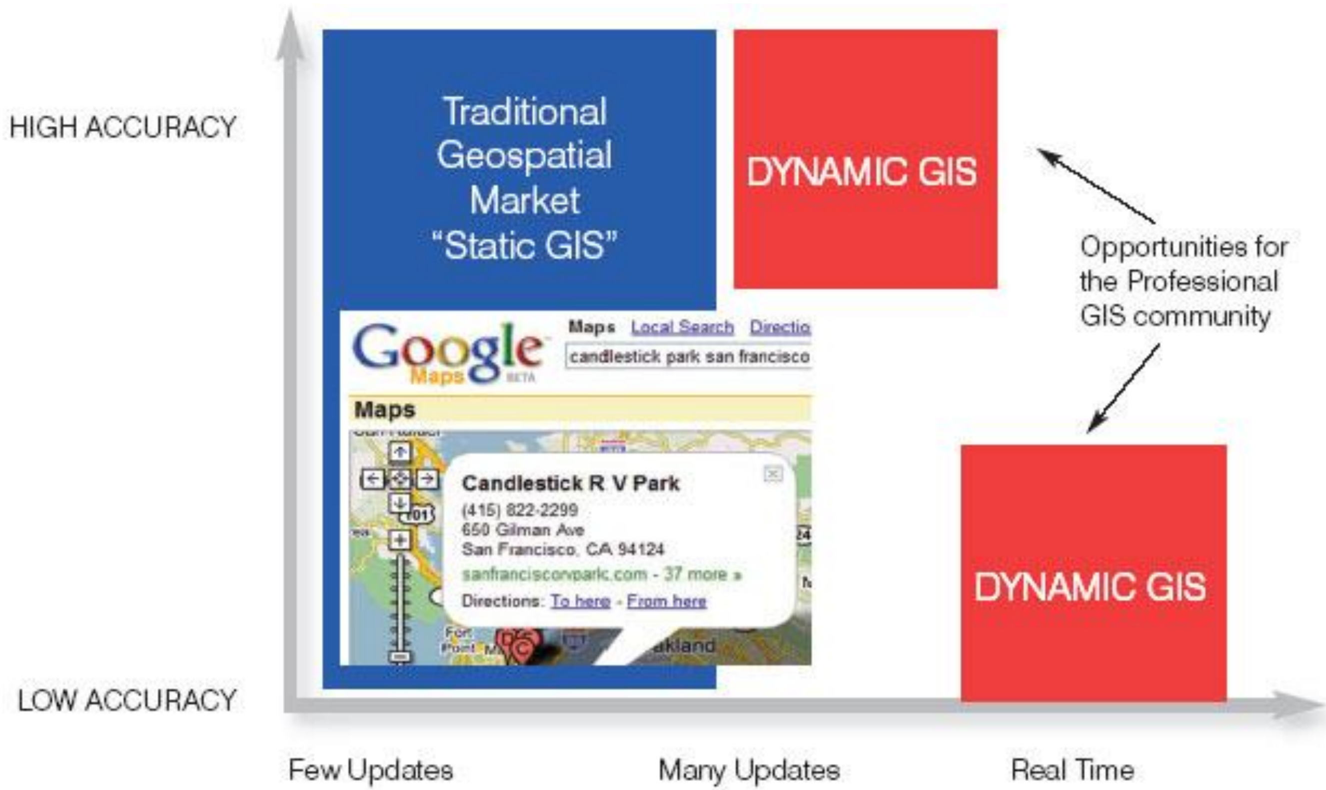
- Today, applications require **updated information**. LULC geodatabases need to be updated with high frequency, but this is difficult using traditional methods (field, photointerpretation) because of high cost and delay.



- Nowadays, there is a large amount of data acquired from the territory (images, LiDAR,…) as a regular basis and from different sensors, but new and more efficient methods to process and integrate them are needed (**Object-based image analysis/classification**)

Introduction

Precision vs. Updating frequency



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Introduction

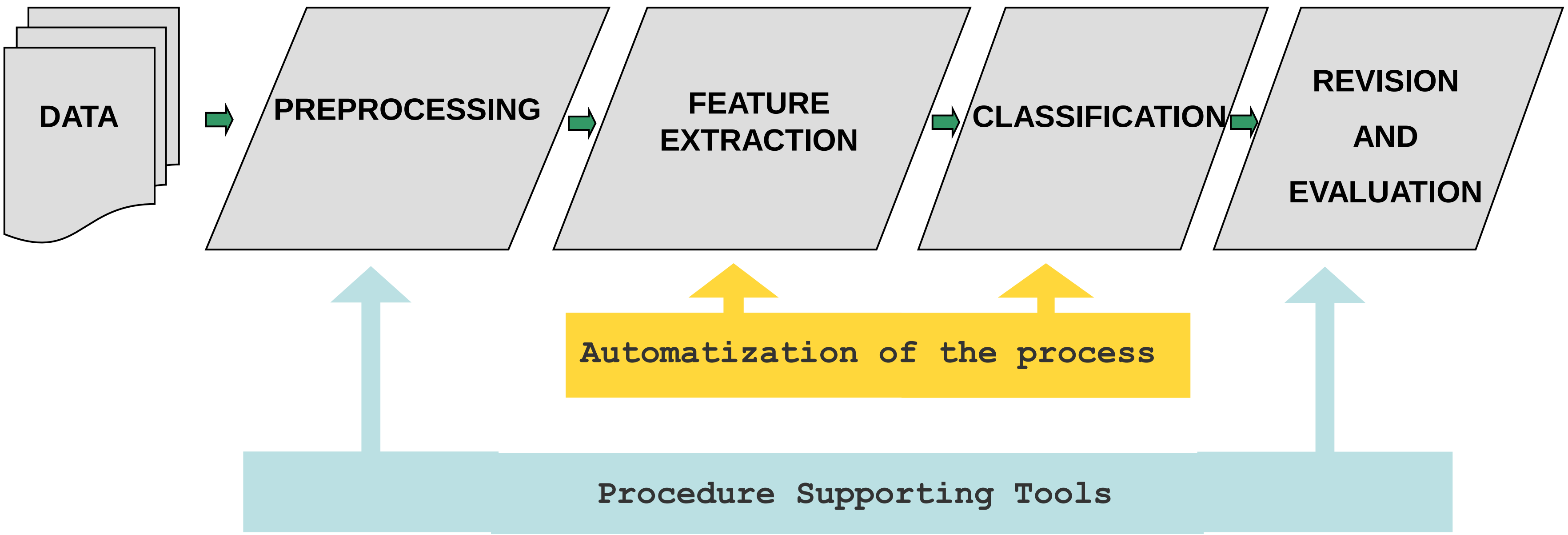
- Nowadays, there is a large amount of data acquired from the territory (images, LiDAR,…) as a regular basis and from different sensors, but new and more efficient methods to process and integrate them are needed (**Object-based image analysis/classification**).

- In GEOBIA (*Geographic Object-Based Image Analysis*) approaches, the unit of analysis and classification is not the pixel, but an aggregation of pixels that constitute a **semantic unit**.

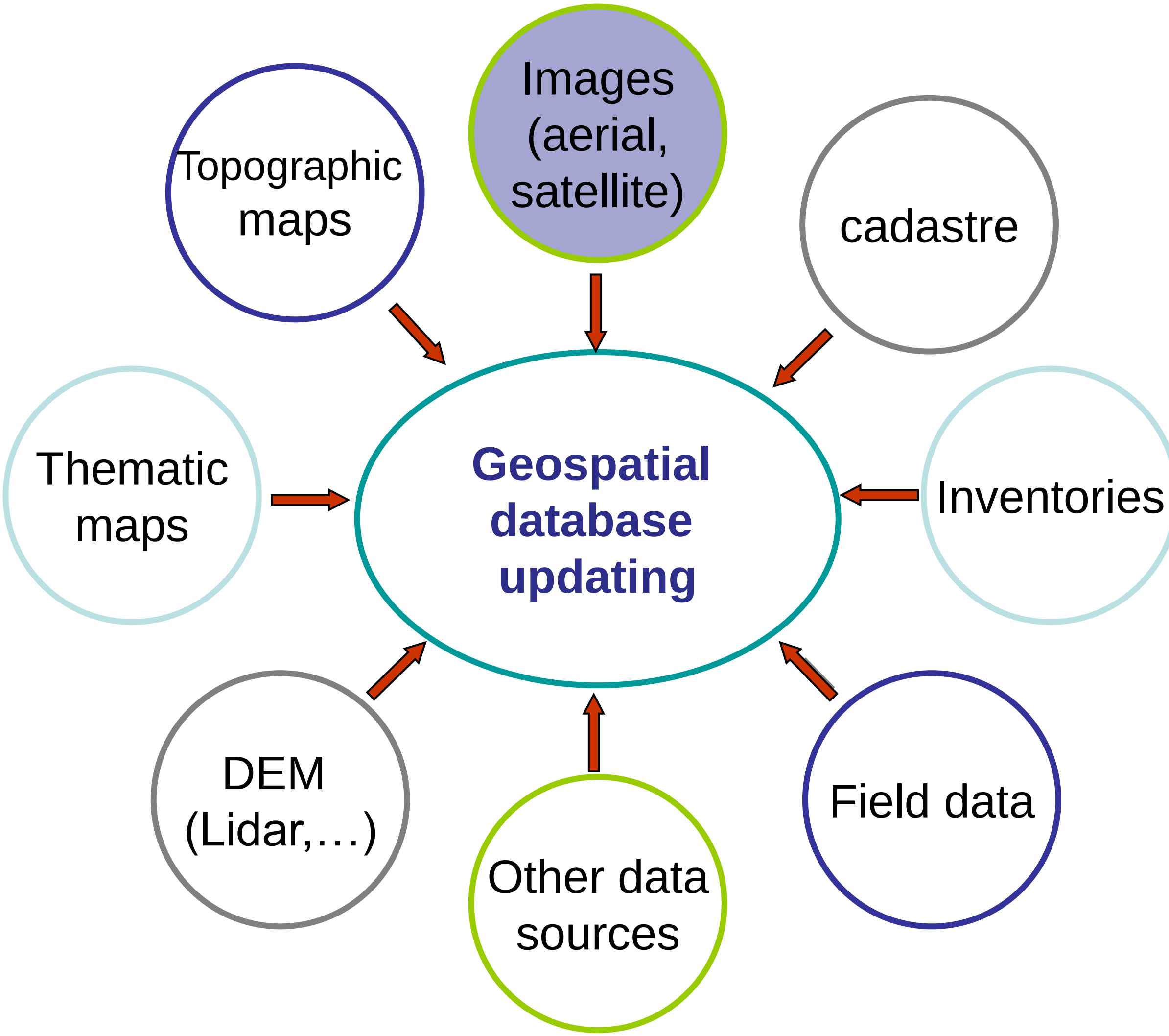
- As compared to pixel classification, object-oriented techniques have some **advantages**, such as the reduction of **processing time**, higher **spatial coherence** of the results, and the potential for **combination** with other geospatial databases.

Introduction

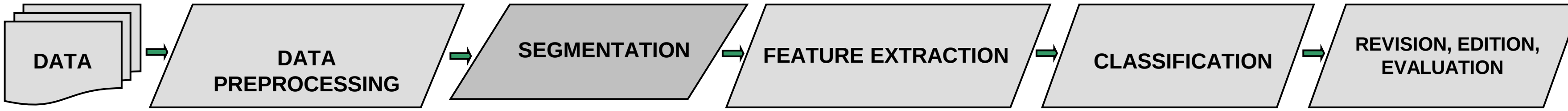
Geodatabase updating steps



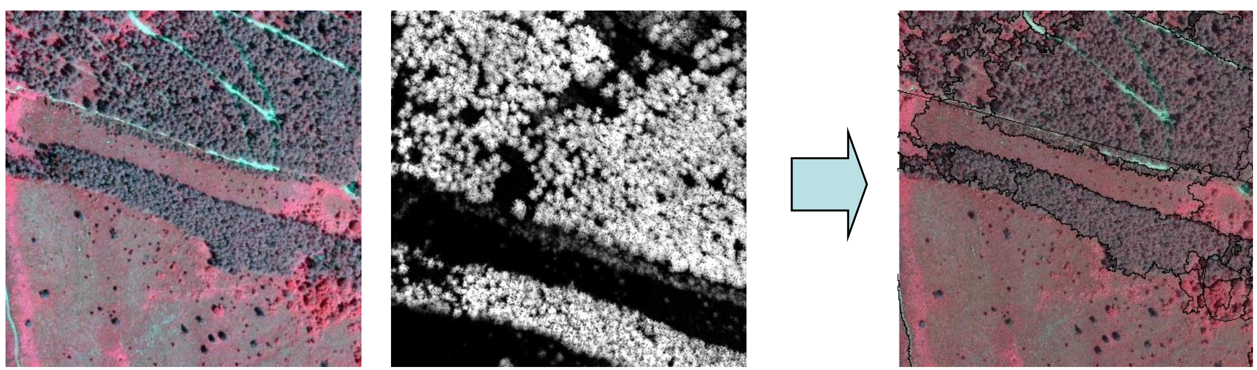
Introduction



Object-based LULC classification



<u>Segmentation</u> is the process of identifying and extracting distinct, homogeneous regions from an image.



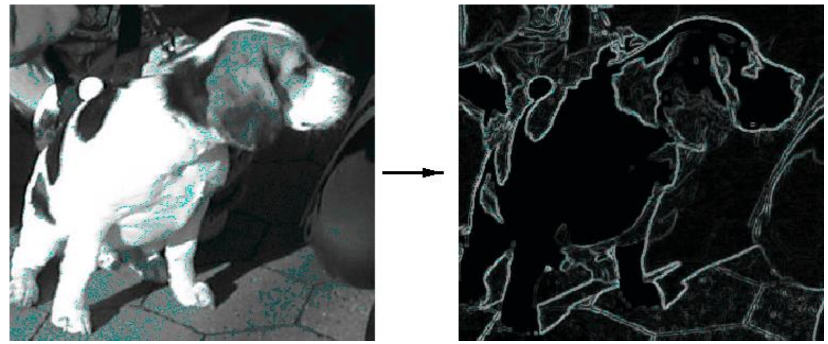
Object-based LULC classification

Edge based segmentation

With this technique, detected edges in an image are assumed to represent object boundaries, and used to identify these objects.

Gradient operator

$$\nabla f = \left[\frac{\partial f}{\partial x}, \quad \frac{\partial f}{\partial y} \right] = \left[G_x, G_y \right]$$

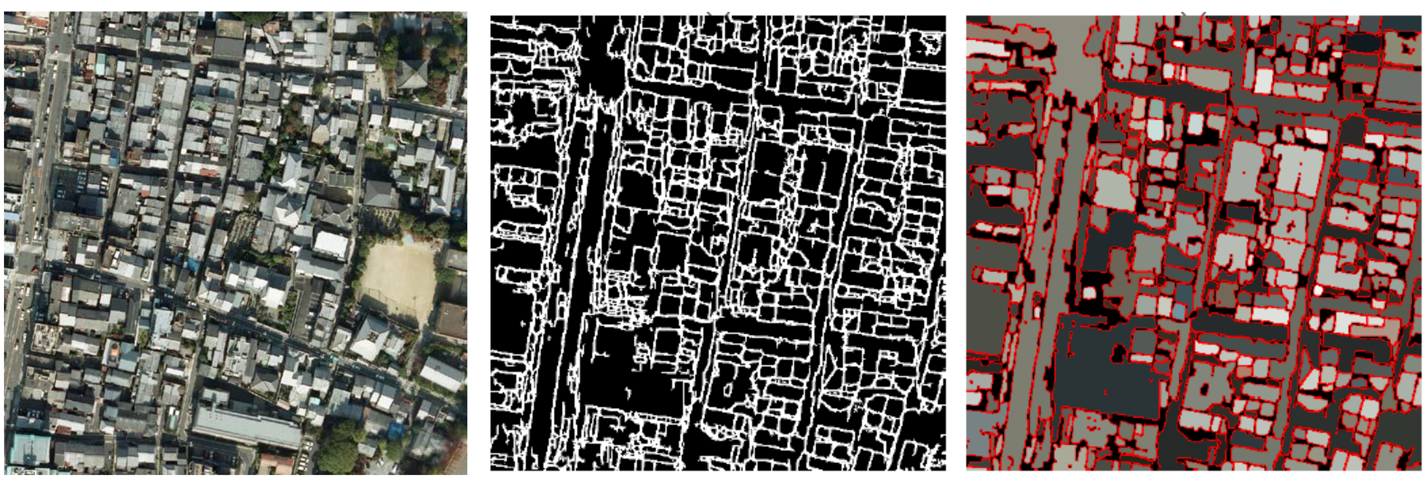


Module

$$| \nabla f | \approx |G_x| + |G_y|$$

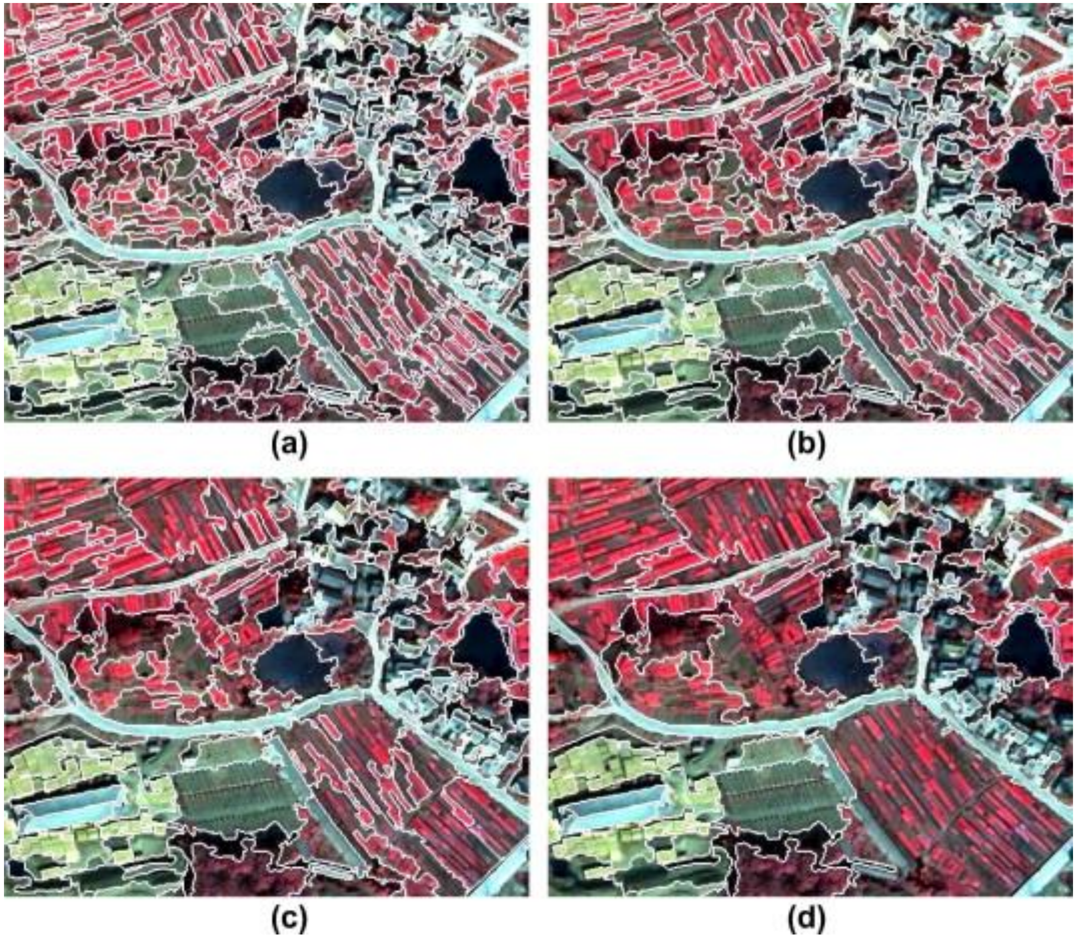
Direction

$$\alpha(x,y) = tan^{-1}\left(\frac{G_y}{G_x} \right)$$



Object-based LULC classification

Region Merging



Multi-scale segmentation results of T-1: (a) scale 10, 614 regions; (b) scale 14, 320 regions; (c) scale 20, 158 regions and (d) scale 30, 57 regions.

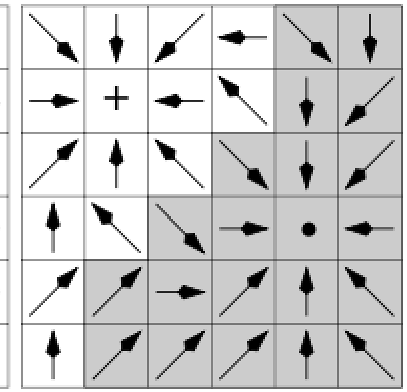
Object-based LULC classification

Watershed algorithm

The Watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minima (LMI). Pixels draining to a common minimum form a catchment basin, which represent the regions.
The figure depicts how the regions are found. (a) is a matrix showing typical GMI values with the LMIs circled. (b) shows the morphological gradient directions for the matrix in (a).

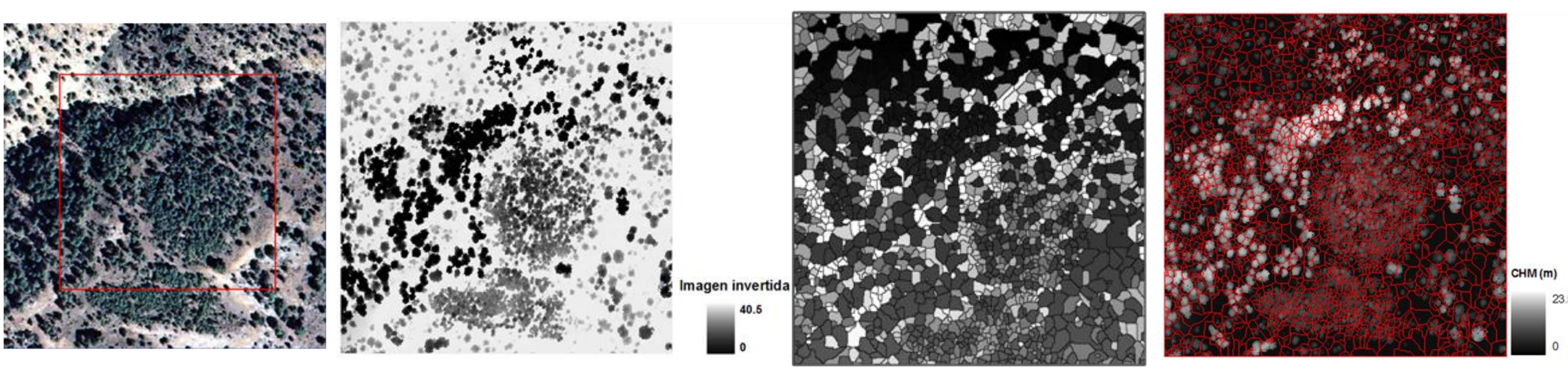
16.8	19.2	13.5	20.5	31.2	30.1
18.7	11.9	15.4	18.5	22.1	18.4
20.1	21.9	26.6	20.8	17.3	18.1
25.3	22.8	20.9	19.8	15.1	15.9
30.7	35.5	29.9	18.7	17.6	39.9
34.8	38.6	33.4	32.7	33.5	36.7

(a)



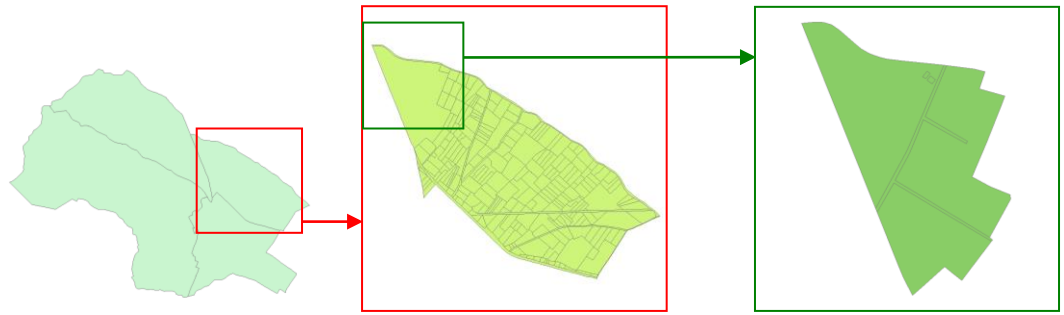
(b)

Example: *Watershed* algorithm



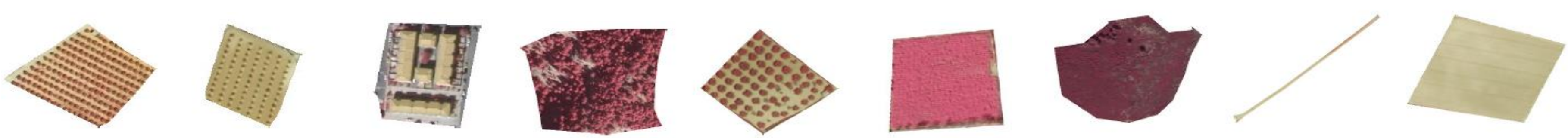
Object definition

• Pre-defined objects:



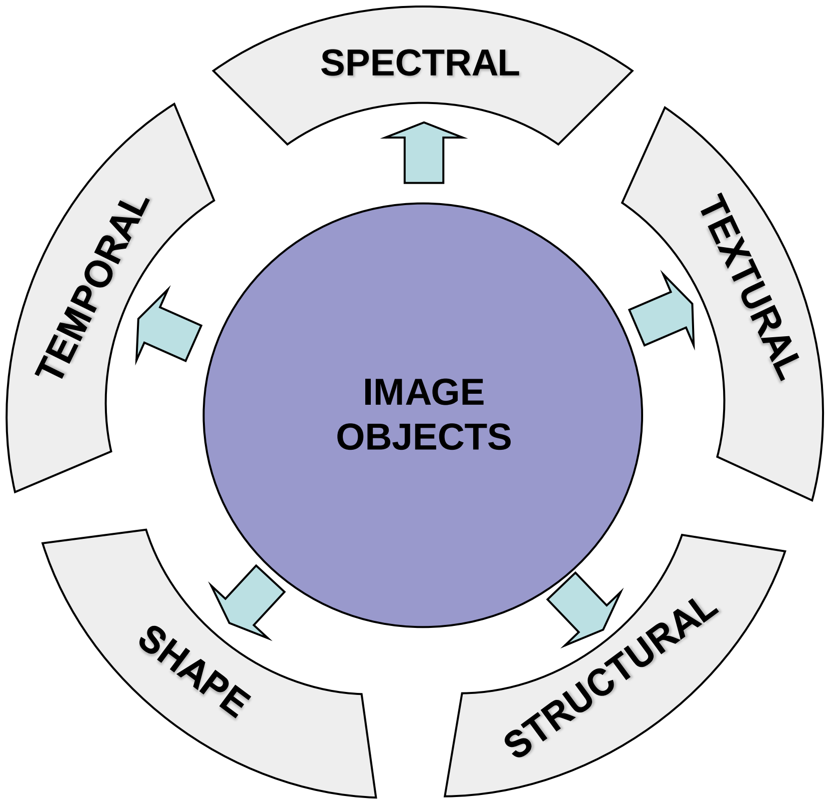
POLYGONS PARCELS SUB-PARCELS

⇨ Definition of image objects



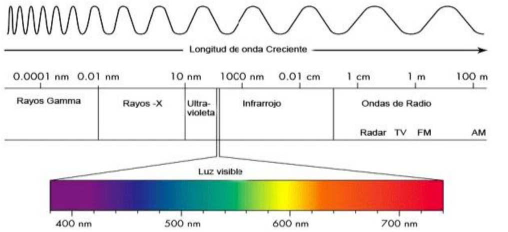
Object-based LULC classification

Feature Extraction

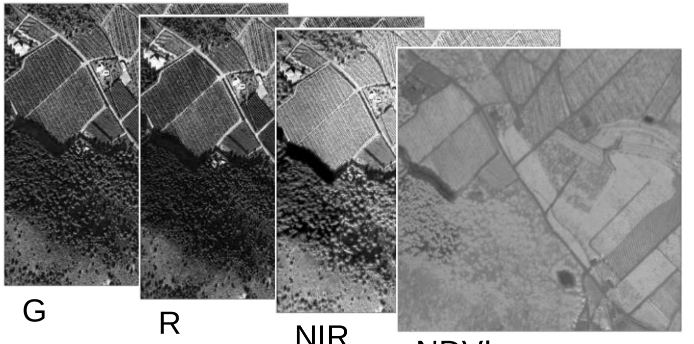


Object-based LULC classification

Feature Extraction

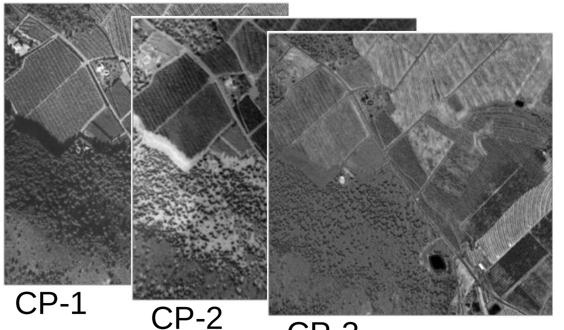


Spectral Information: Based on the spectral response differences of the land cover types



G R NIR NDVI

- Spectral bands
- Indices or ratios (NDVI, …)
- Transforms based on combination of bands: principal components, etc.

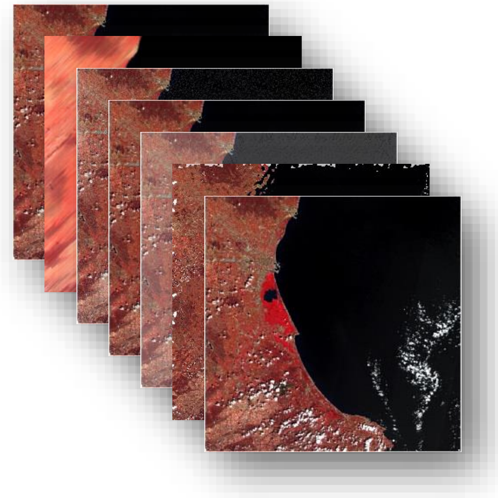


CP-1 CP-2 CP-3

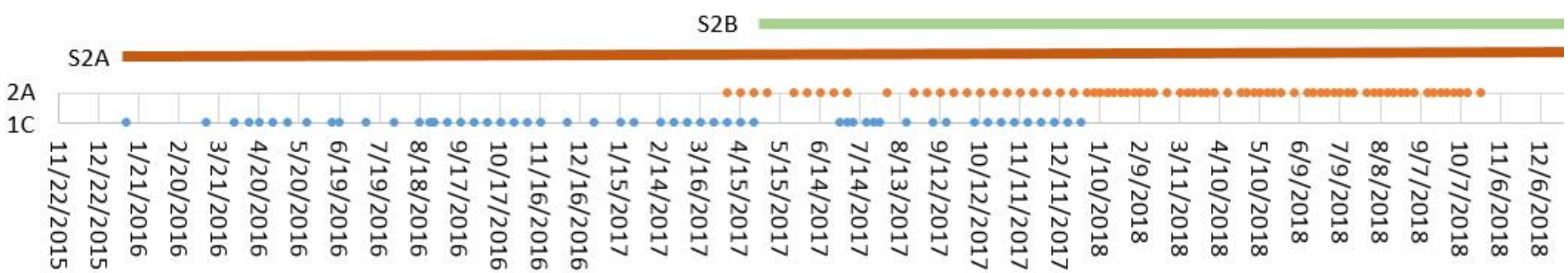
Object-based LULC classification

Feature Extraction

Temporal Information: Based on the intensity values of the objects obtained at different dates



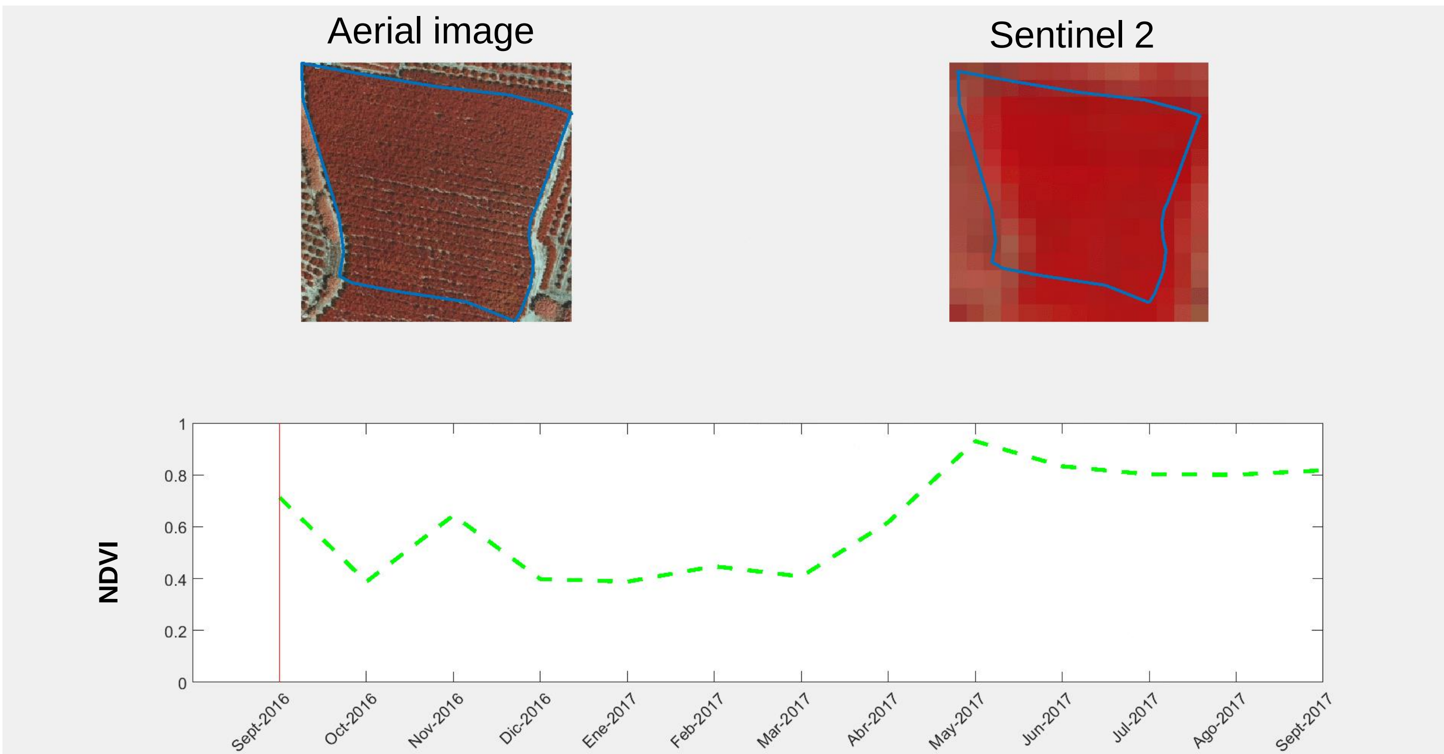
Time distribution of Sentinel 2 scenes



Object-based LULC classification

Feature Extraction

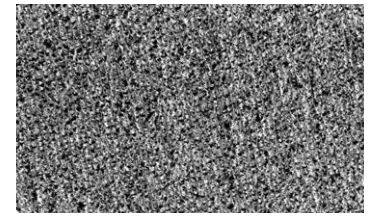
<u>**Temporal Information**</u>: intensity values or indices of an object along the time

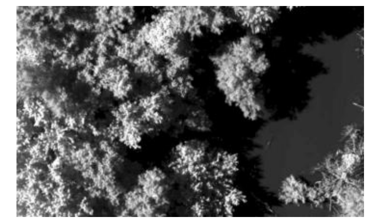


Object-based LULC classification

Texture features

Texture attributes: Provide information about the **spatial distribution** of the values of a **variable** (intensity) within the **object**. They quantify properties such as heterogeneity, contrast, roughness, directionality, or uniformity in the different areas of an image, which vary as a function of the land use or land cover in the object.



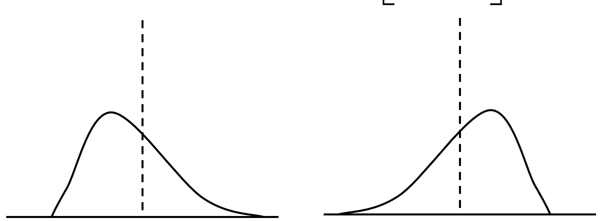


- **First order texture features:** representing the distribution of values of the histogram of an object: *kurtosis* and *skewness*

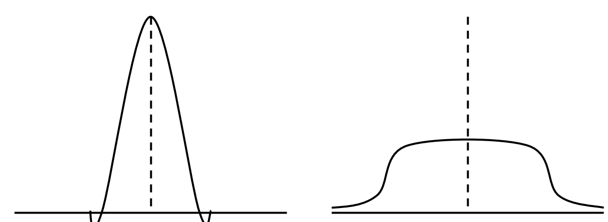
$$Variance = \frac{1}{N}\sum_{j=1}^{N}\left[x_j - \bar{x}\right]^2$$

$$Skewness = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \bar{x}}{\sigma}\right]^3$$

$$Kurtosis = \left\{\frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \bar{x}}{\sigma}\right]^4\right\} - 3$$



Positive skewness *Negative skewness*



Leptokurtic *Platikurtic*

Object-based LULC classification

Feature Extraction

Structural information: Distribution and spatial relations of the elements that compose an object (regularity patterns, directionality, distances between elements, etc.)

Some **approaches**:

- Semivariogram-based features
- Hough transform
- Fourier spectrum
- Etc.

Object-based LULC classification

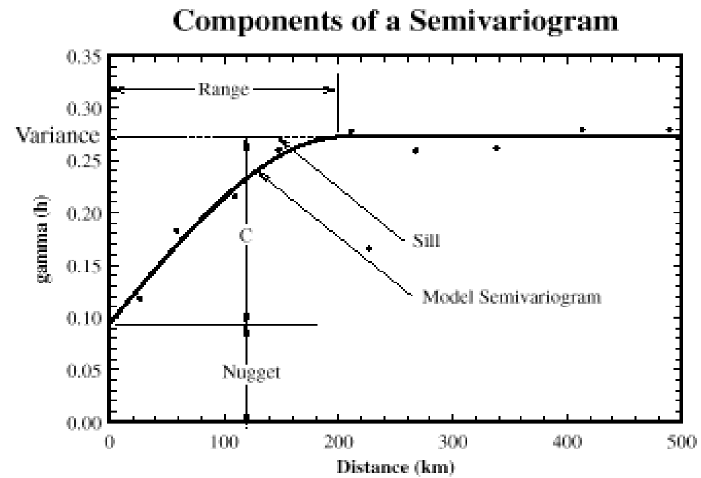
Feature Extraction – Structural features

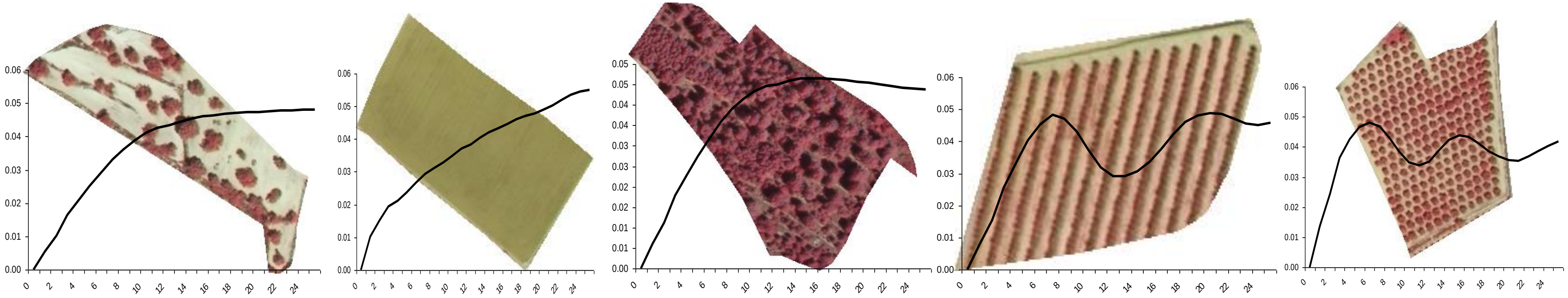
Spatial arrangement and relations of the elements inside each object (regularity paterns, distances, directionality, etc.)

The **semivariogram** quantifies spatial associations of the values of a variable, being a measure of the correlation between the pixels inside an object

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}\left[Z(x_i) - Z(x_i + h)\right]^2$$

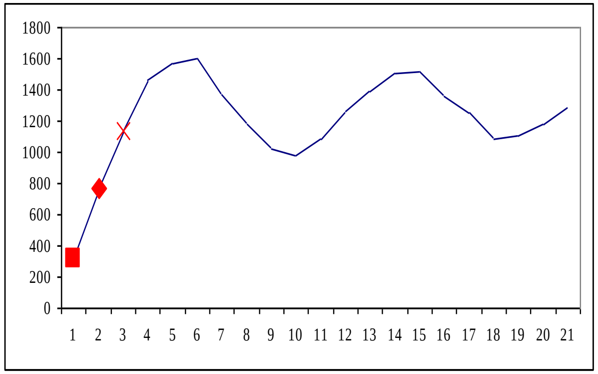
- $Z(x_i)$: intensity of a pixel x_i ;
- N : number of pixels
- h : distance between pixels in a direction

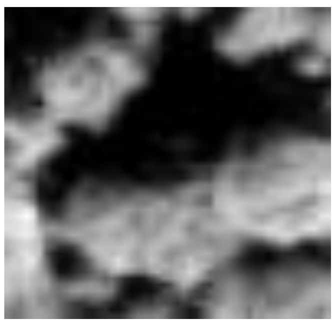


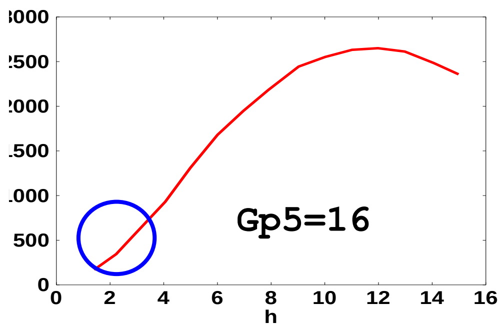


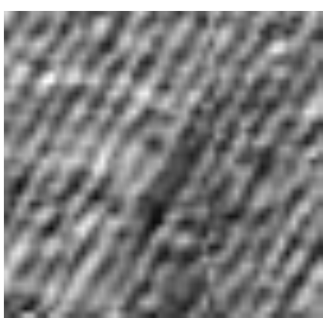
Object-based LULC classification

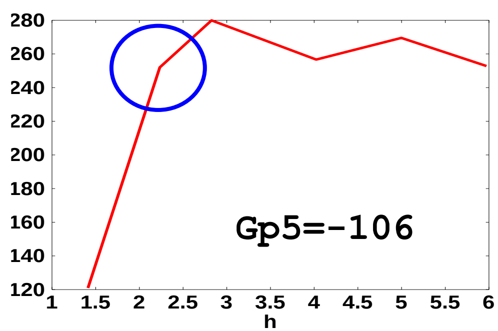
Semivariogram











First derivative in h_1

$$Gp4 = \frac{\gamma(h_2) - \gamma(h_1)}{h}$$

Slope in the first 2 values of *h*

Second derivative in h_2

$$Gp5 = \frac{\gamma(h_3) - 2\gamma(h_2) + \gamma(h_1)}{2h^2}$$

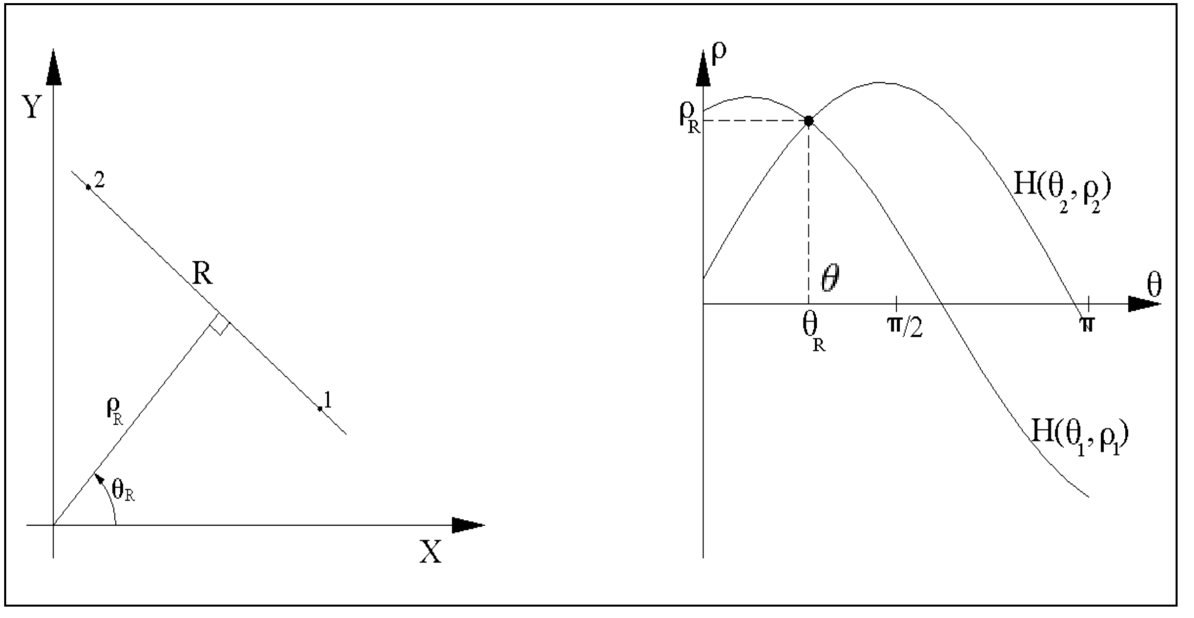
Concavity/convexity:

Variability in short distances

Object-based LULC classification

The Hough transform

A straight line can be described as *y = ax + b* and can be graphically plotted for each pair of image points *(x1, y1), (x2, y2)*.

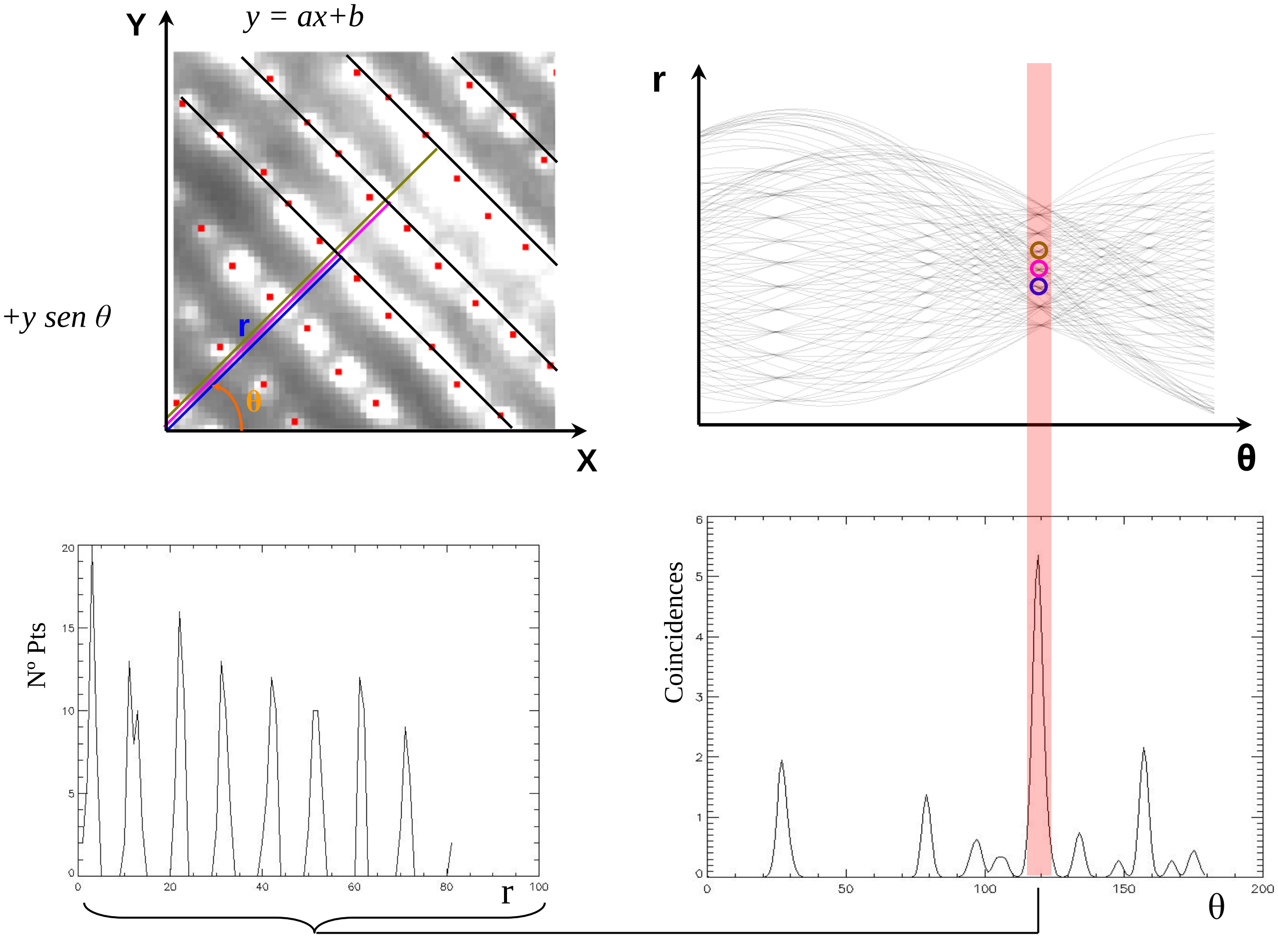


But also in a parameter space where *ρ* represents the distance between the line and the origin, while *θ* is the angle of the vector from the origin to its closest point

Object-based LULC classification

Hough Transform

$r = x \cos\theta + y \,\mathrm{sen}\, \theta$



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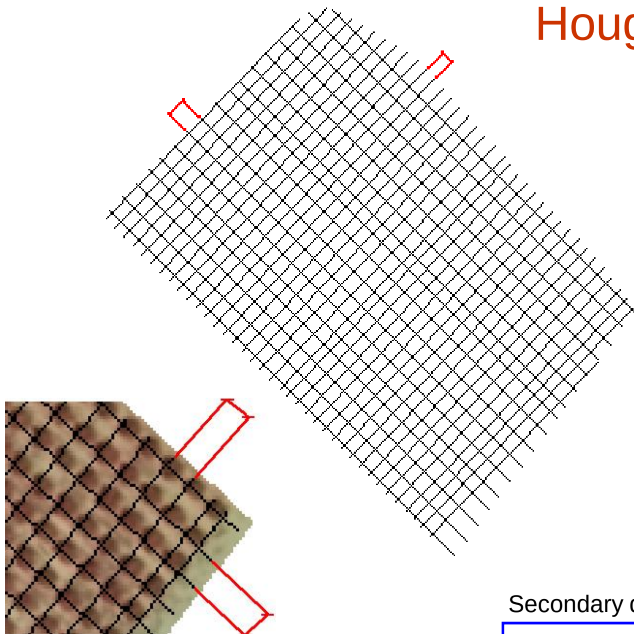
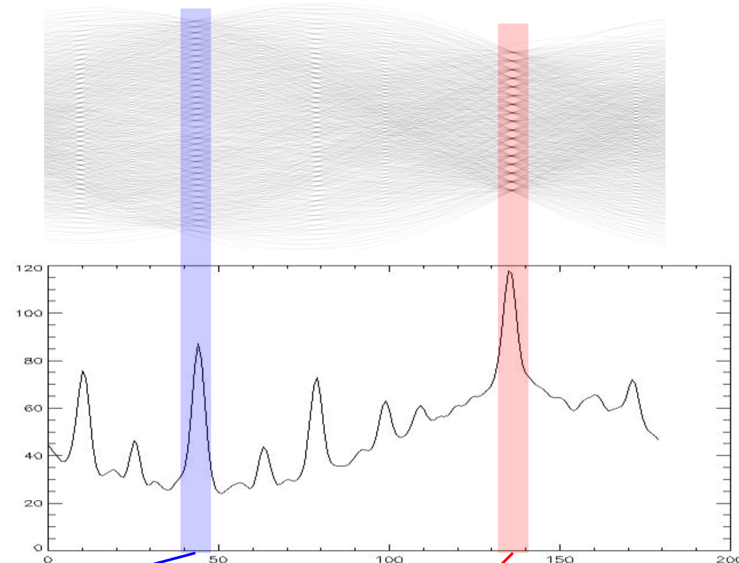
Object-based LULC classification

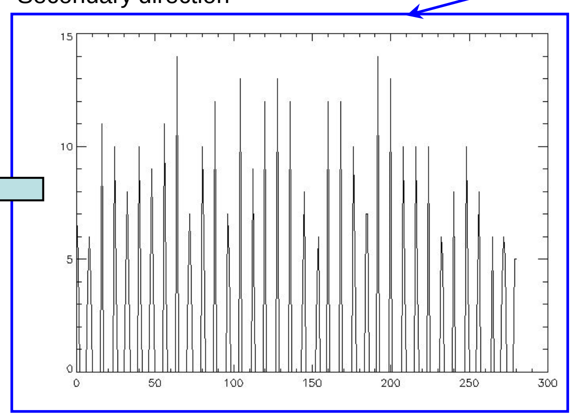
Hough Transform



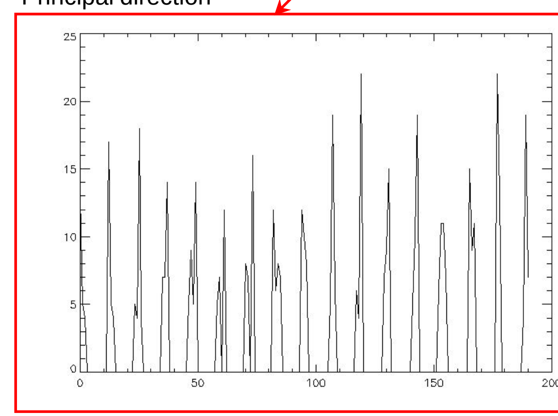
Plantation patterns



Secondary direction



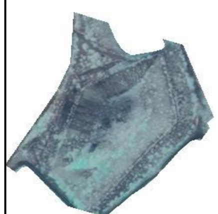
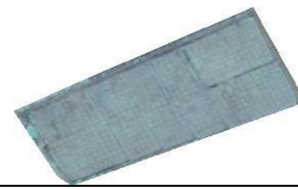
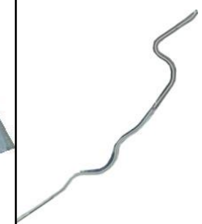
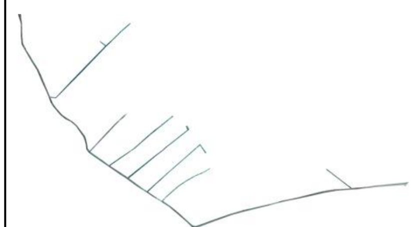
Principal direction



- Difference between directions
- Proportion of points in both directions
- Std. Deviation of distances between points

Feature Extraction

Shape: Information about the shape of the objects

				
$C = \frac{4 \cdot \pi \cdot Area}{Perimetro^2}$	0,64226	0,66491	0,04289	0,00418
$SI = \frac{Perimetro}{4 \cdot \sqrt{Area}}$	1,10583	1,08684	4,27991	13,70696
$FI = 2 \cdot \frac{\log\left(\frac{Perimetro}{4}\right)}{\log(Area)}$	1,02067	1,01752	1,27993	1,54265

Object-based LULC classification

Feature Extraction

Finally, A **vector of features** is created for each object, describing it from different perspectives

FEATURES

OBJECTS (PARCELS)

FEATURE SELECTION

ID	MED_IR	DES_IR	MED_R	DES_R	MED_G	DES_G	MED_NDVI	DES_NDVI	MED_IB1	DES_IB1	MED_IB2	DES_IB2	MED_IB3	DES_IB3	UNIFOR	ENTROP
1	184.216	28.462	167.254	47.532	150.697	44.870	0.066	0.098	367.295	211.387	368.961	232.811	363.978	[illegible]	0.011	2.307
2	167.530	18.053	152.134	19.962	132.685	18.669	0.050	0.050	397.950	194.250	421.780	231.764	[illegible]	[illegible]	0.019	1.959
3	146.683	48.668	126.317	51.333	116.446	46.944	0.087	0.096	404.171	187.665	416.407	207.623	[illegible]	[illegible]	0.004	2.728
4	196.411	13.331	186.054	14.246	138.102	14.139	0.027	0.008	371.484	206.118	400.900	[illegible]	[illegible]	[illegible]	0.058	1.649
5	160.156	6.104	157.368	6.177	125.184	5.829	0.009	0.016	354.965	230.084	377.803	[illegible]	[illegible]	275.215	0.097	1.203
6	123.684	12.414	102.261	13.441	86.761	10.147	0.097	0.057	383.161	212.666	[illegible]	[illegible]	[illegible]	248.677	0.020	1.886
7	160.719	16.380	119.665	29.322	102.669	16.841	0.158	0.149	360.676	213.757	[illegible]	[illegible]	384.470	243.568	0.019	2.061
8	172.601	10.652	170.048	11.588	136.140	11.071	0.008	0.007	365.508	[illegible]	[illegible]	[illegible]	385.164	265.748	0.047	1.628
9	129.537	20.478	106.750	26.098	93.056	21.073	0.104	0.070	390.201	[illegible]	[illegible]	237.819	405.843	246.679	0.007	2.327
10	155.564	34.532	136.947	46.070	116.622	38.672	0.084	0.084	[illegible]	[illegible]	[illegible]	227.323	384.612	227.329	0.011	2.440
11	164.131	32.324	117.785	36.685	105.174	31.623	0.176	0.101	[illegible]	[illegible]	415.397	208.974	420.746	214.685	0.003	2.662
12	196.942	8.413	189.034	11.318	156.010	16.955	0.021	[illegible]	[illegible]	[illegible]	353.188	241.308	361.147	247.977	0.087	1.414
13	164.336	23.492	155.433	24.720	123.438	21.497	0.028	[illegible]	[illegible]	211.511	366.436	239.872	379.969	249.823	0.048	1.938
14	165.044	20.689	116.260	38.913	103.198	24.820	[illegible]	[illegible]	[illegible]	204.904	391.088	229.880	395.584	239.047	0.010	2.348
15	140.528	20.188	123.038	26.582	102.920	25.755	[illegible]	[illegible]	362.055	204.266	386.162	245.885	385.149	253.506	0.030	1.859
16	166.877	7.851	144.462	15.513	127.923	[illegible]	[illegible]	[illegible]	380.362	219.459	383.054	237.196	342.719	219.783	0.021	1.785
17	152.990	21.347	144.010	25.507	120.670	[illegible]	[illegible]	0.023	350.545	197.860	367.673	211.871	372.032	208.904	0.014	2.063
18	138.276	9.769	121.750	11.097	[illegible]	[illegible]	[illegible]	0.013	374.753	215.245	388.534	246.592	390.322	261.280	0.023	1.755
19	163.306	18.494	147.189	29.757	[illegible]	[illegible]	0.060	0.094	358.911	213.227	382.206	236.806	394.645	248.625	0.049	2.041
20	195.170	26.937	194.598	[illegible]	[illegible]	[illegible]	0.003	0.018	353.846	209.766	373.302	238.146	382.134	242.520	0.026	2.141
21	161.807	32.527	[illegible]	[illegible]	[illegible]	[illegible]	0.018	0.090	394.964	191.488	408.802	217.096	413.374	227.129	0.012	2.432
22	180.689	28.736	[illegible]	[illegible]	[illegible]	31.390	0.217	0.100	384.730	172.789	393.111	210.943	399.037	176.621	0.009	2.184
23	195.434	[illegible]	[illegible]	[illegible]	165.928	22.273	0.010	0.006	359.188	191.390	371.729	220.800	369.988	219.700	0.015	2.161
24	[illegible]	[illegible]	[illegible]	[illegible]	116.215	10.528	0.059	0.027	371.664	199.874	376.909	211.736	350.177	196.303	0.036	1.680
25	[illegible]	[illegible]	[illegible]	28.817	92.622	24.439	0.106	0.051	399.755	185.864	408.611	208.653	408.706	216.094	0.004	2.497
26	[illegible]	[illegible]	[illegible]	27.851	112.153	17.113	0.100	0.105	346.084	216.235	368.428	244.124	372.823	246.077	0.038	1.987
27	[illegible]	[illegible]	186.127	23.348	148.726	18.185	0.025	0.013	342.902	191.720	347.653	207.044	350.236	212.733	0.025	1.913
28	165.518	21.956	126.223	32.492	107.488	22.367	0.147	0.113	380.673	218.582	393.122	248.648	395.825	244.610	0.012	2.309
29	174.231	23.058	111.167	32.828	102.537	23.935	0.232	0.129	397.267	192.658	408.344	216.531	408.719	231.451	0.007	2.441

.....

Object-based LULC classification

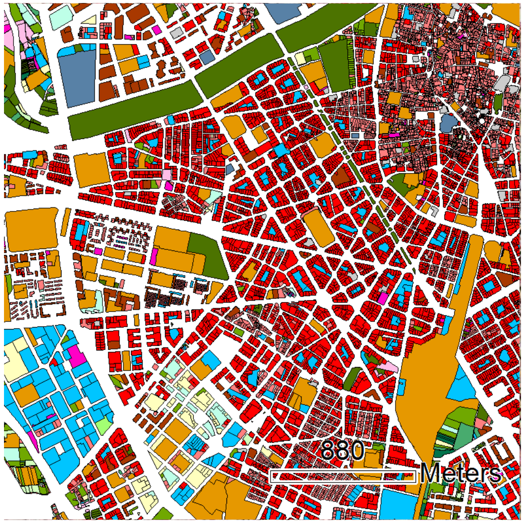
Classification

CLASSIFICATION OF PARCELS / POLYGONS

- Application of a classification algorithm , eg. **decision trees**: Set of rules organised in a hierarchical manner

```
ASIMETRIA > 0.832587: citricos alineados (8)
ASIMETRIA <= 0.832587:
:...PERIMET <= 28.87988:
    :...PERIMET <= 10.2806: plantones (5)
    :   PERIMET > 10.2806:
    :   :...LARGOAN_STD <= 1.240833: citricos independientes (9)
    :       LARGOAN_STD > 1.240833: plantones (5/2)
    PERIMET > 28.87988:
    :...NDVIARB > 0.302364: citricos independientes (3/1)
        NDVIARB <= 0.302364:
        :...ASIMETR_STD <= 0.170912: algarrobos (7)
            ASIMETR_STD > 0.170912:
            :...NDVIARB <= 0.188967: olivos (6)
                NDVIARB > 0.188967: algarrobos (2)
```

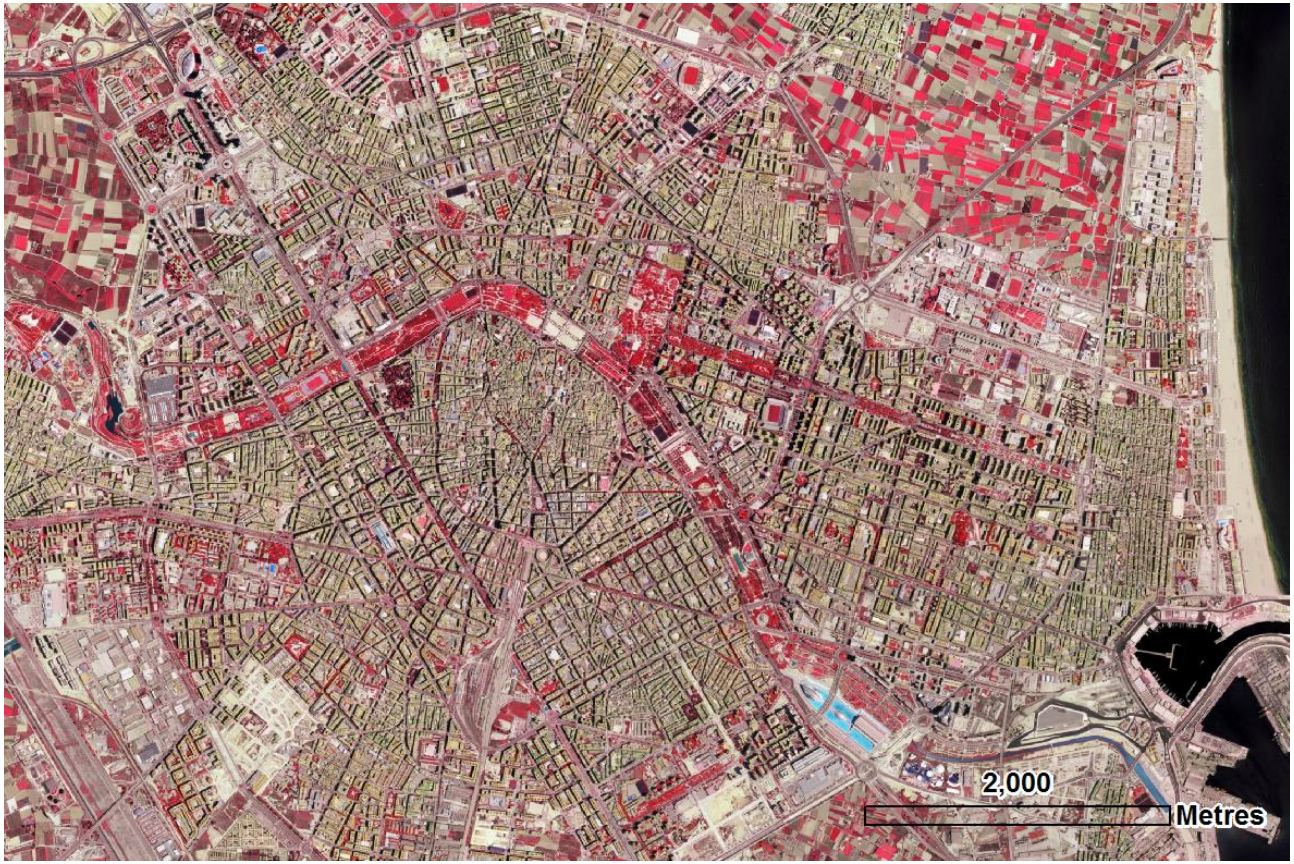
- Boosting: iterative learning
- Probability/confidence index
- Evaluation: error matrix,…
- Editing and Mapping



Study case

Data *(images)*

- Spanish *National Program of Aerial Ortophotography* (PNOA)

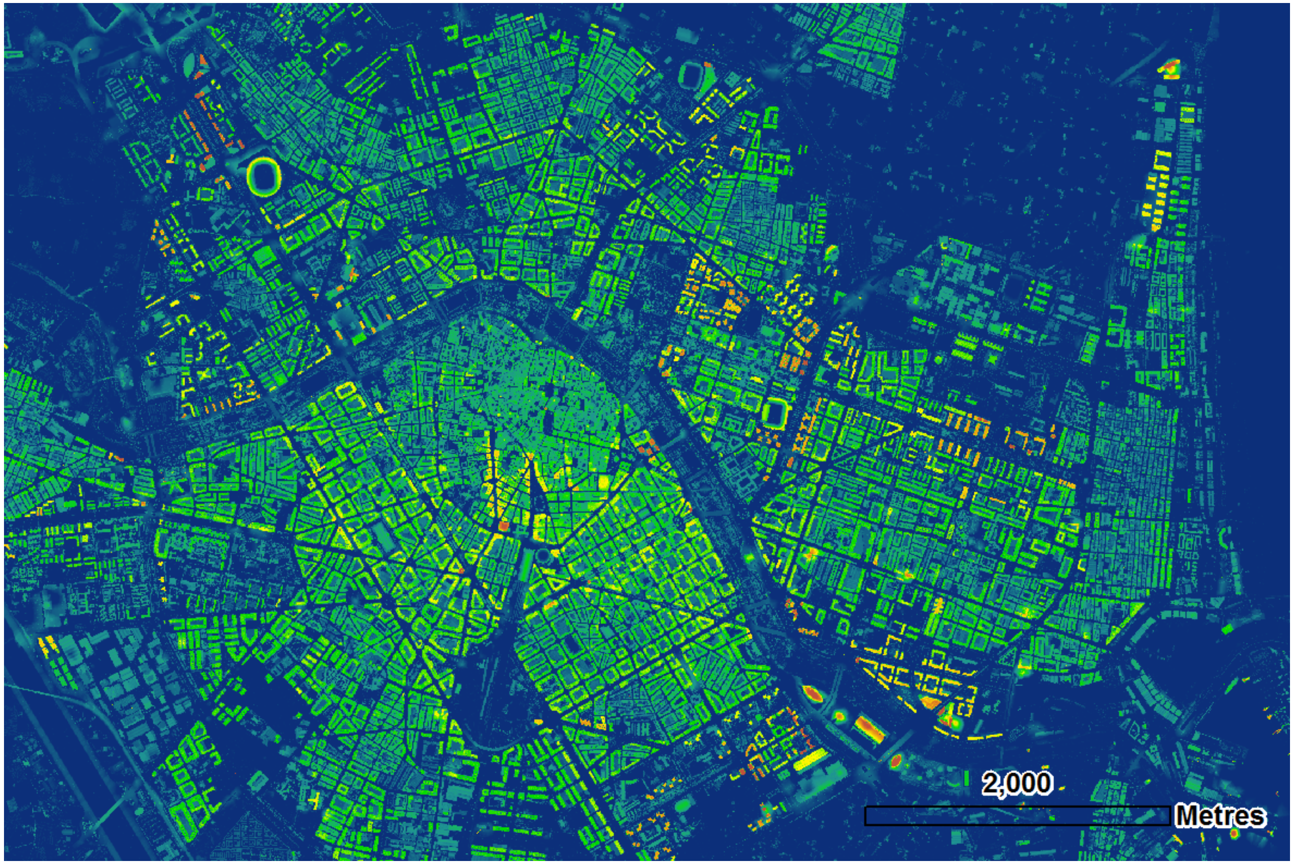


•Spatial Res.:
0.5 m/pixel
• Radiometric Res.:
8 bits
• Spectral bands:
Green, red and NIR

Study case

Data *(LiDAR)*

- Spanish *National Program of Aerial Ortophotography* (PNOA)



- Instrument:
  RIEGL LMS-Q680 ALS
- Mean flying height:
  1,300 m
- Nominal density:
  0.5 points/m^2
- Scan frequency:
  46 Hz
- Pulse repetition:
  70 kHz
- Scanning angle:
  60º

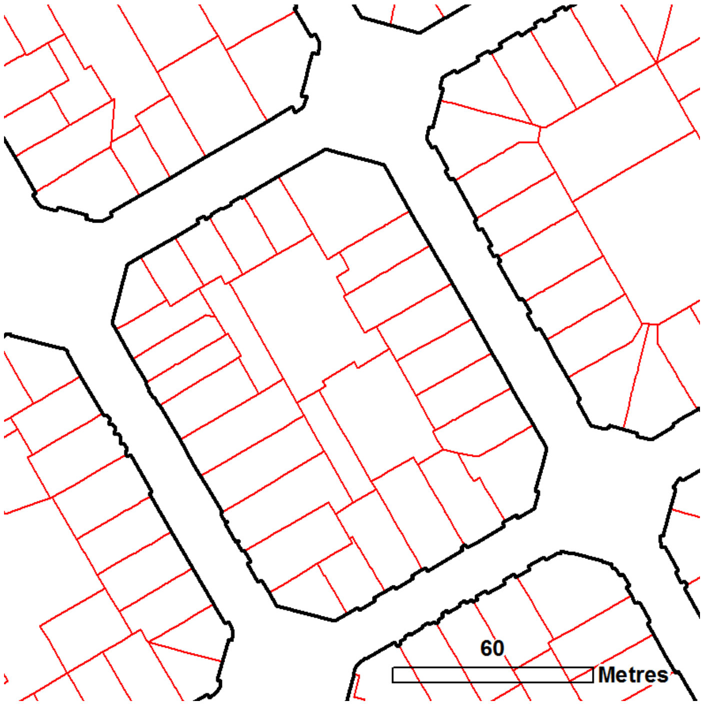
➡ DTM algorithm *(Estornell et al., 2011)*

➡ Normalised DSM

Study case

Data *(GIS data)*

- Cadastral plots; Urban blocks (*Spanish General Directorate for Cadastre);* Neighbourhoods; population data.



Cadastral plot

Urban block

- Cadastral **plots** and urban **blocks** were used to generate the **objects** for attribute extraction and classification.

Study case

Feature extraction

(previous processing)

Automatic building detection from images and Lidar data

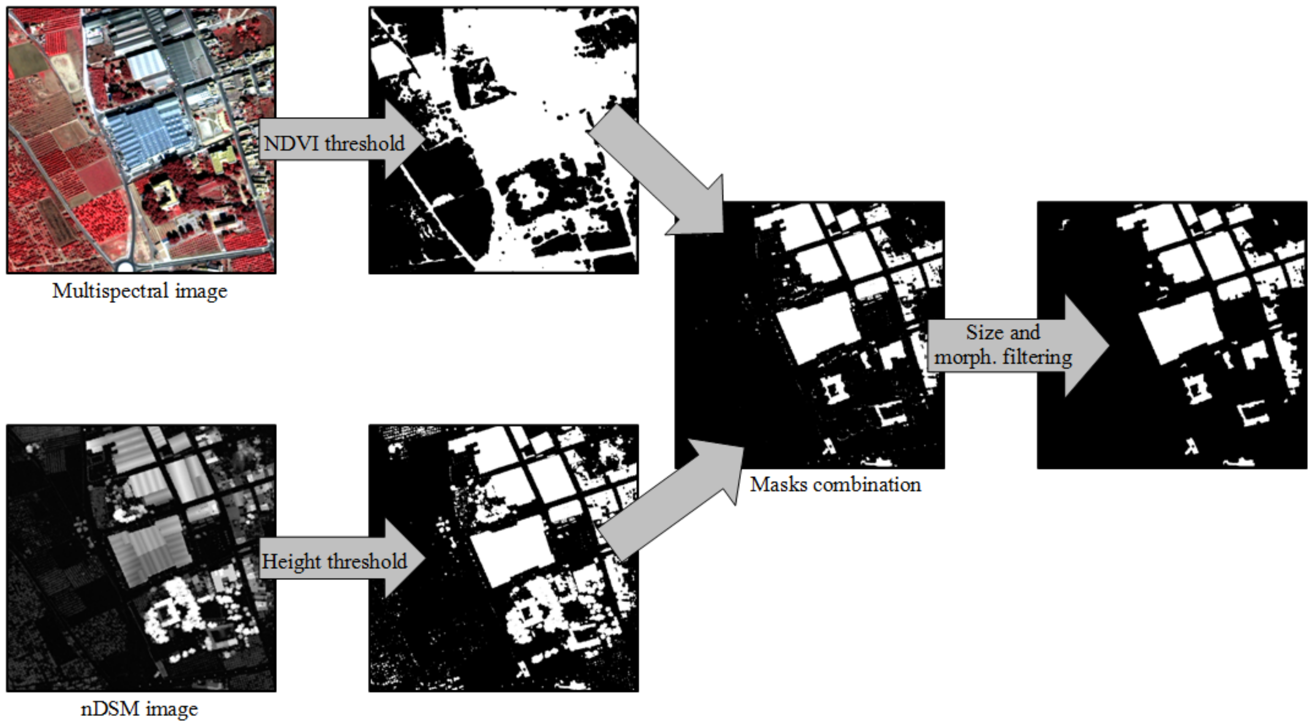
Methodology based on images and lidar data for **automatic detection of buildings** in urban and periurban landscapes

Integration of this information **in parcel-based classification** processes for updating geodatabases

Study case

Building detection

Building detection approach based on vegetation masking and height thresholding *(Hermosilla et al., 2011)*.



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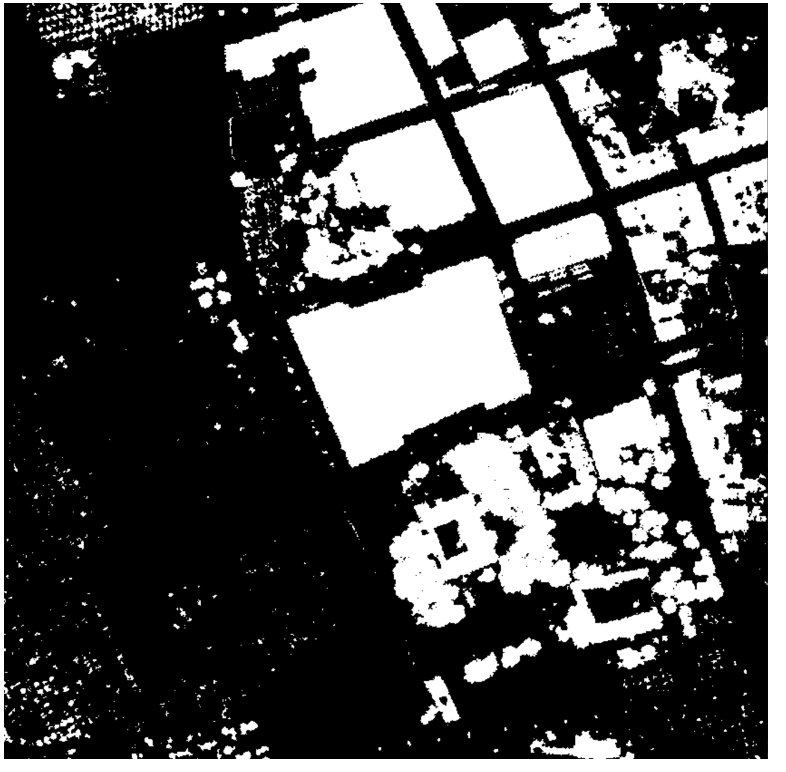
Building detection

Thresholding approach

nDSM= DSM-DTM → nDSM > height thresh. → Height mask

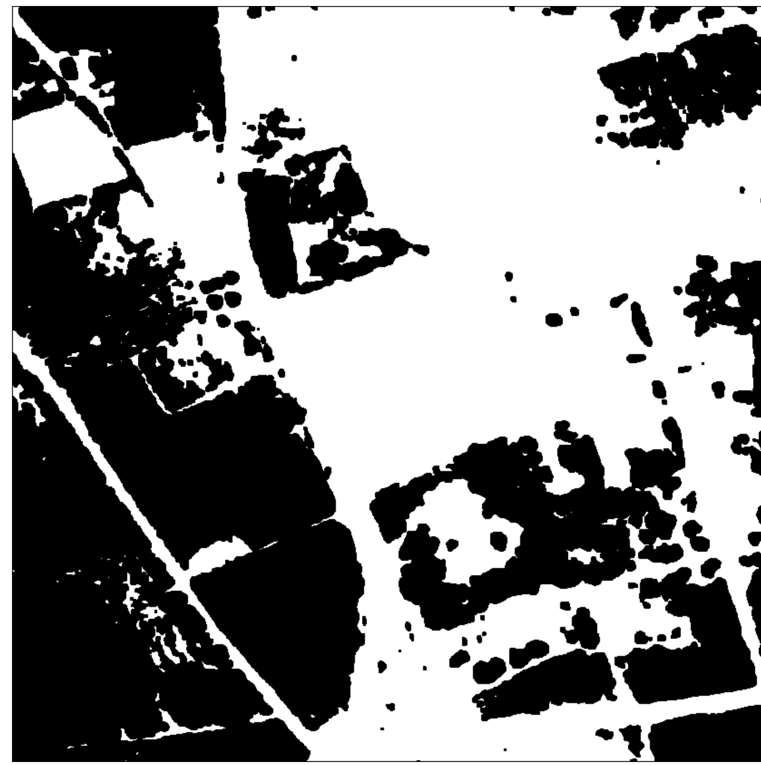


Building detection

Thresholding approach

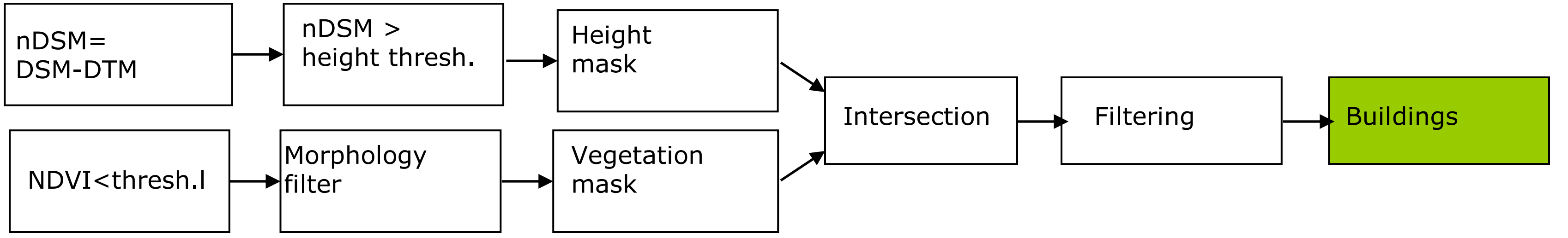
nDSM= DSM-DTM → nDSM > height thresh. → Height mask

NDVI<thresh. → Morphology filter → Vegetation mask



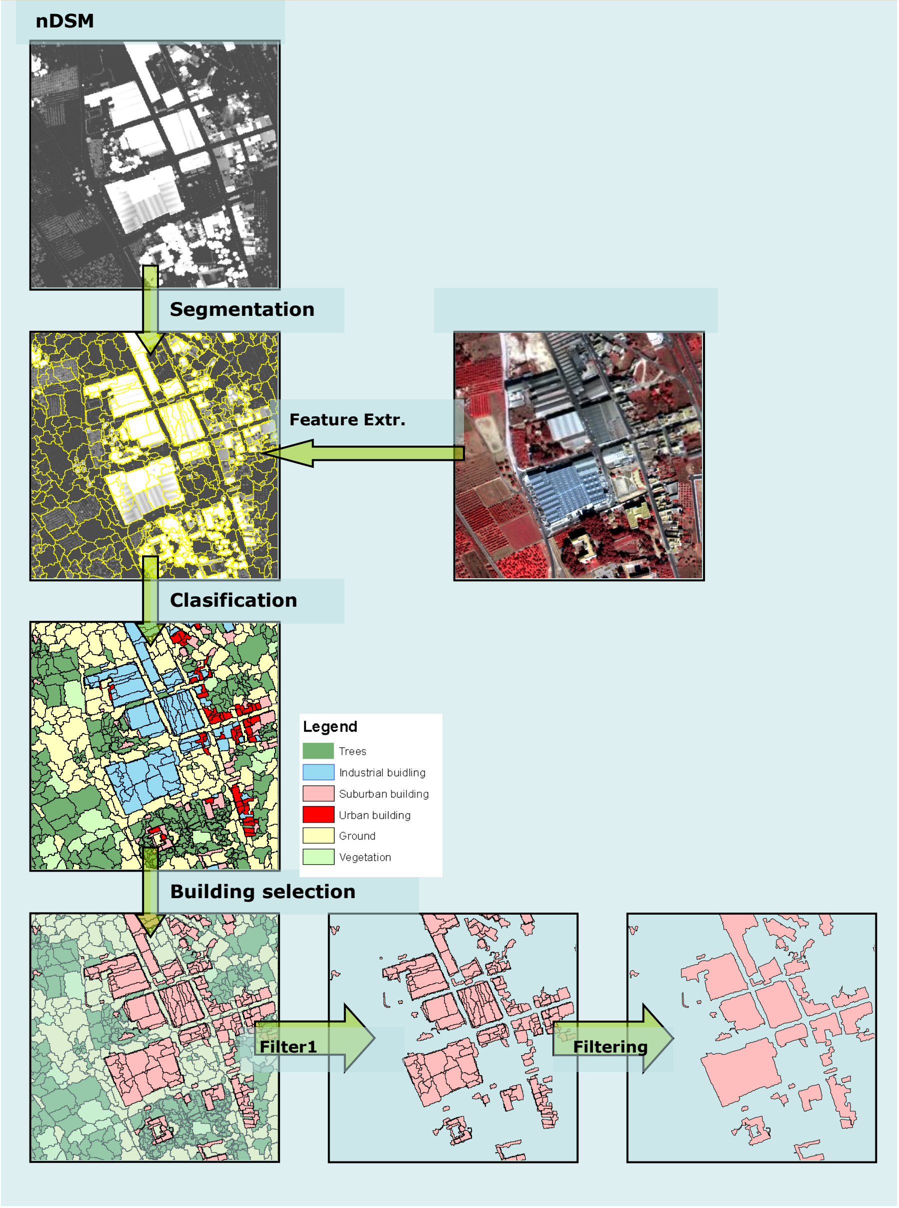
Building detection

Thresholding approach



Building detection

Classification approach

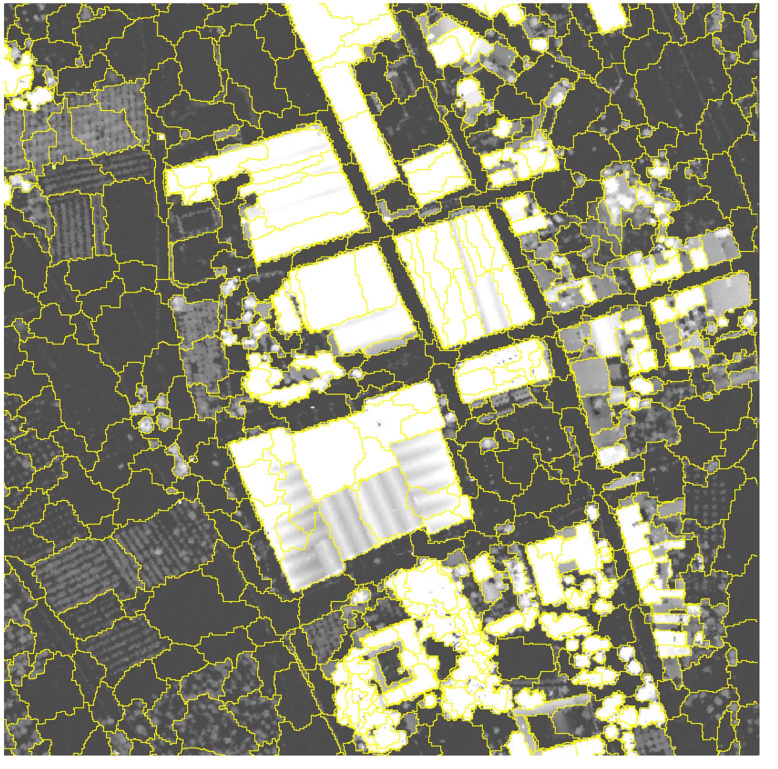


Building detection

Classification approach

Segmentation
- nDSM

- Edge detection
- Region growing



Building detection

Classification approach

Segmentation
- *nDSM*

→

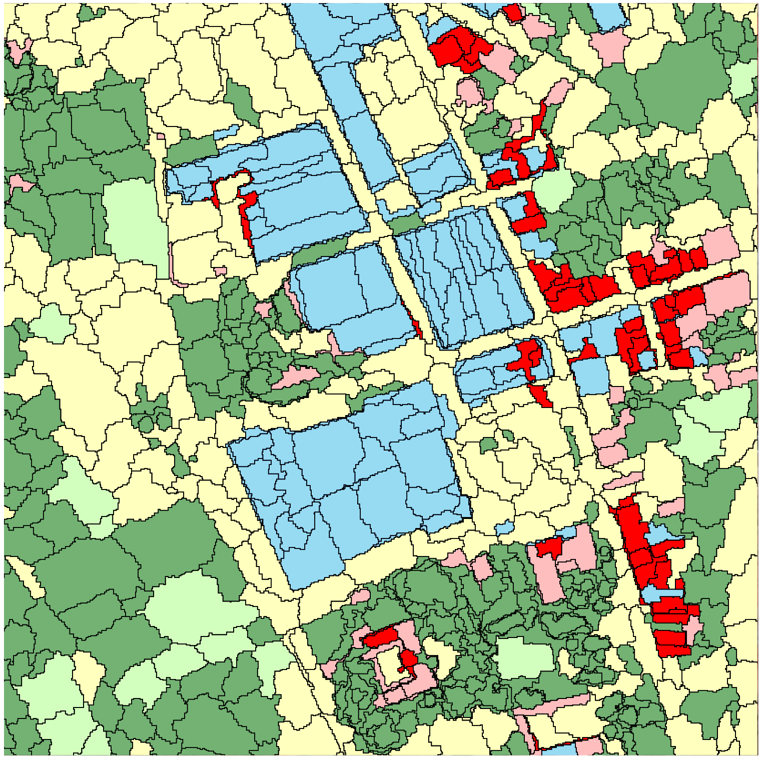
Feature extraction
- Spectral
- Texture
- Shape
- Height

→

Feature selection

→

Clasification



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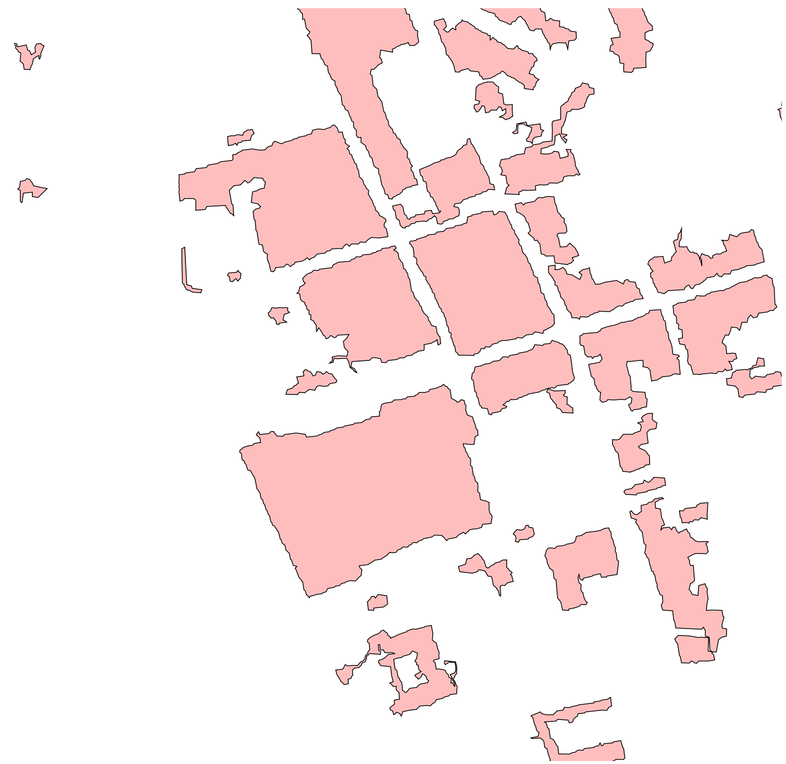
Building detection

Classification approach

Segmentation
- *nDSM*

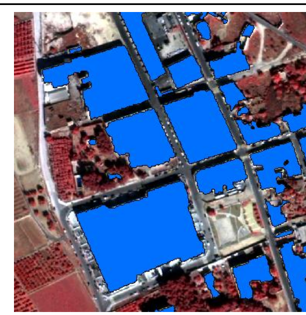
→ **Feature extraction**
- Spectral
- Texture
- Shape
- Height

→ **Feature selection** → **Clasification** → **Selection** → **Buildings**



Study case

Results (Moncada)

Image *QuickBird*			
Clasification approach			
Threshold-based approach			

Detalles de los resultados de detección de edificios en zonas urbana, industrial y periurbana de Moncada empleando los métodos de umbralización y de clasificación orientada a objetos.

Study case

Results

(*Alcalá de Henares*)

Imagen PNOA			
Con relaciones contextuales			

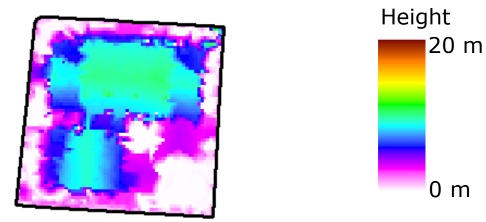
Study case

Context feature extraction

In addition, context was described by analyizing higher and lower aggregation levels of the plots. Thus, **internal context** attributes describe an object attending to the distribution of the elements within the object (buildings, vegetation). **External context** characterizes each object by considering the properties of the urban block containing the plot (*Hermosilla et al., 2012*).

Methods *(Plot-level characterization)*

- Plot-level attribute extraction
  - From aerial orthoimages
    - Spectral
    - Texture
  - Three-dimensional

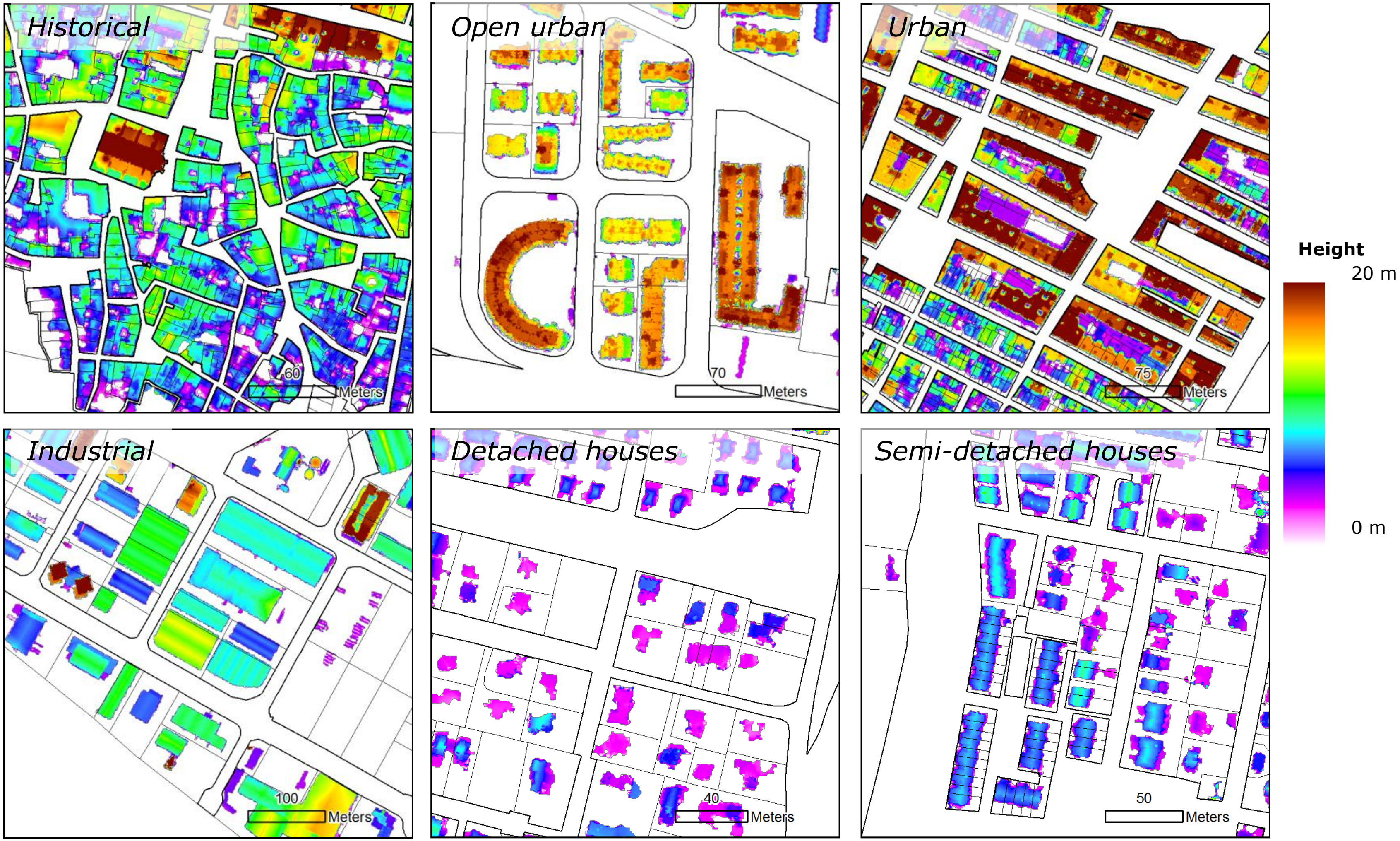


nDSM

- H mean
- H std.dev.
- H max.

Study case

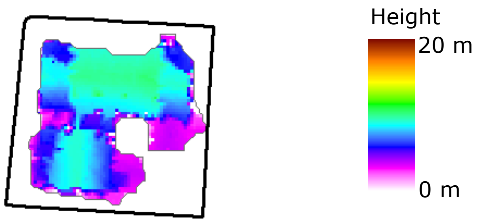
Building heights



Study case

Methods *(Plot-level characterization)*

- Plot-level attribute extraction
  - From aerial orthoimages
    - Spectral
    - Texture
  - Three-dimensional
  - Geometric
- Internal context attributes
  - Building related
  - Vegetation related

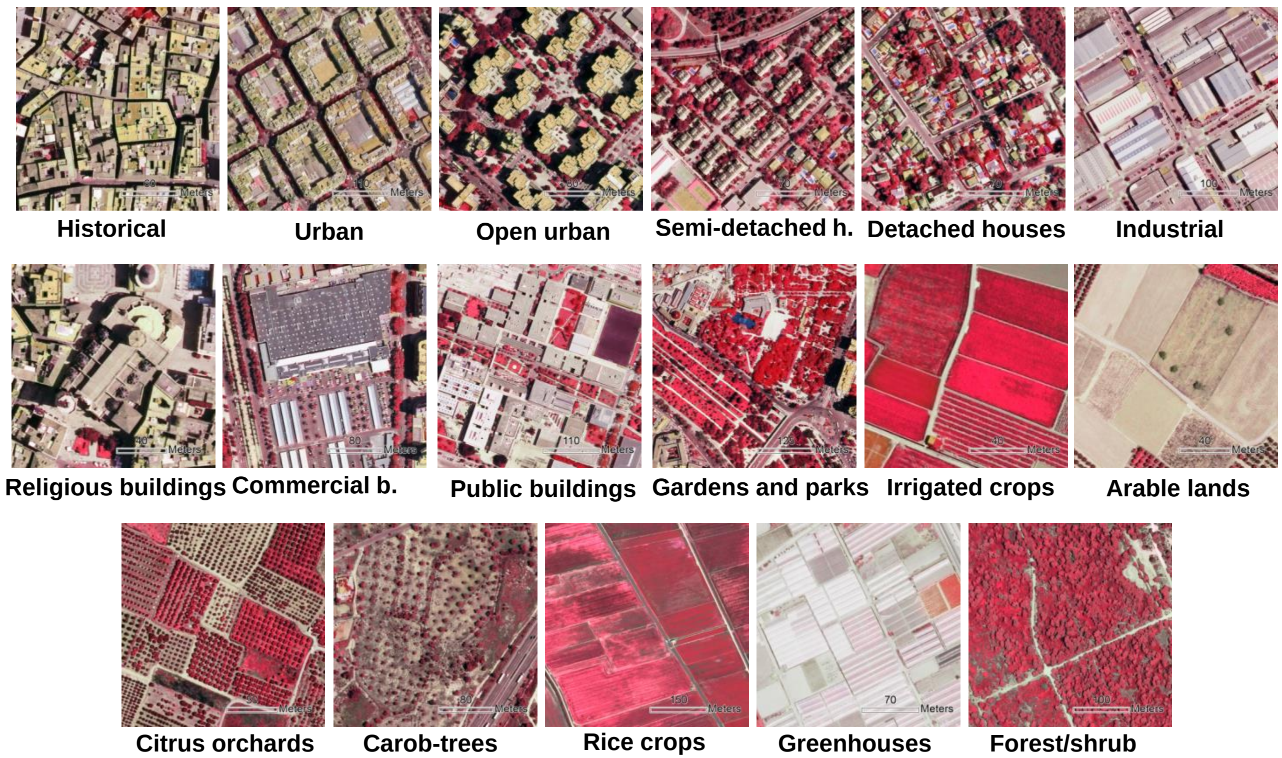


Buildings
- Bldg. covered area
- Bldg. covered %
- Height mean
- Height std. dev.
- Height max.

Vegetation
- Height mean
- Height std. dev.
- NDVI mean
- NDVI std. Dev.
- Veget. Covered %

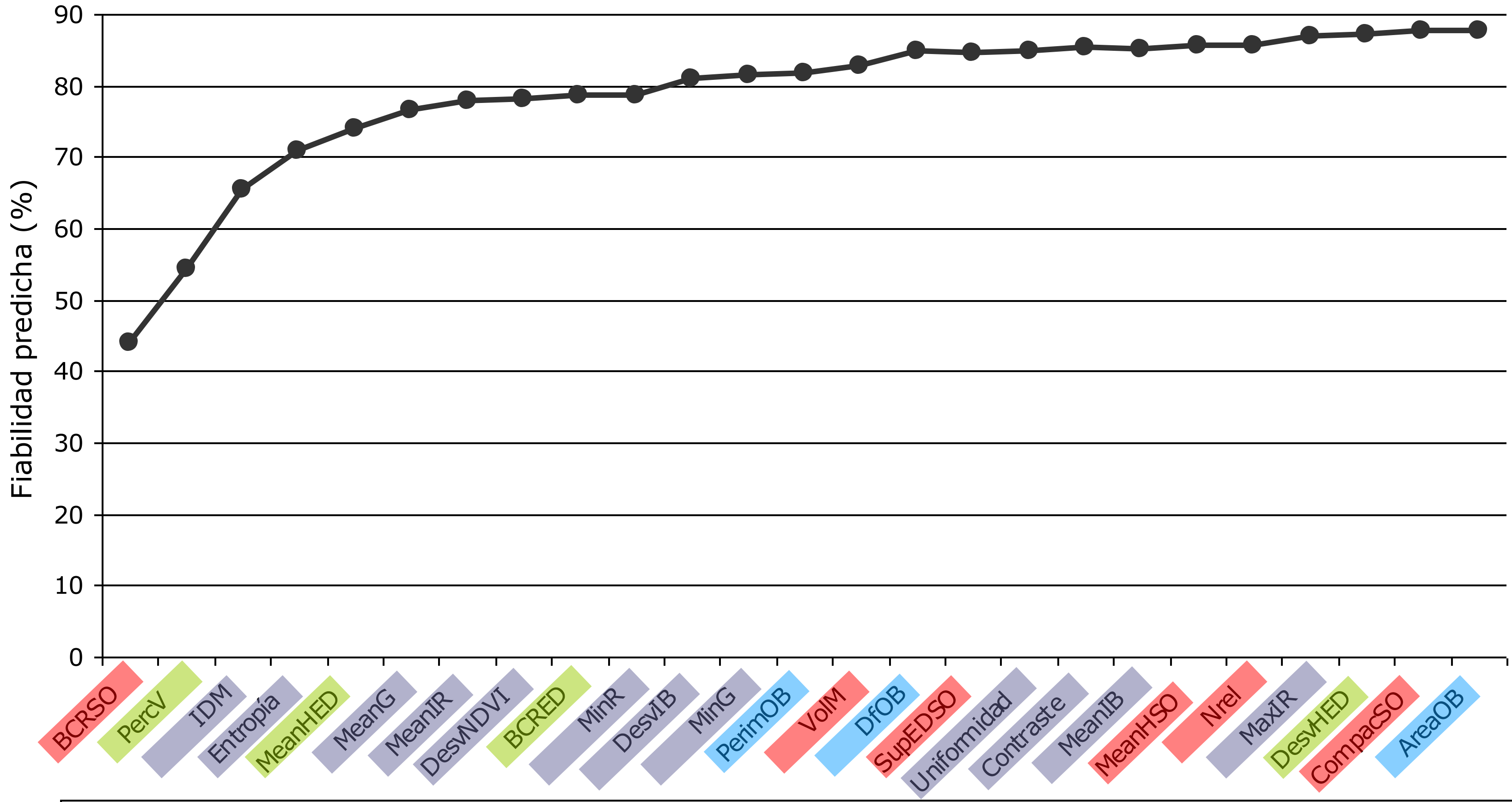
Study case

Land-use classes defined at cadastral plot level



Study case

Feature selection *(stepwise LDA)*



Complementarity of the different types of features

Image derived features

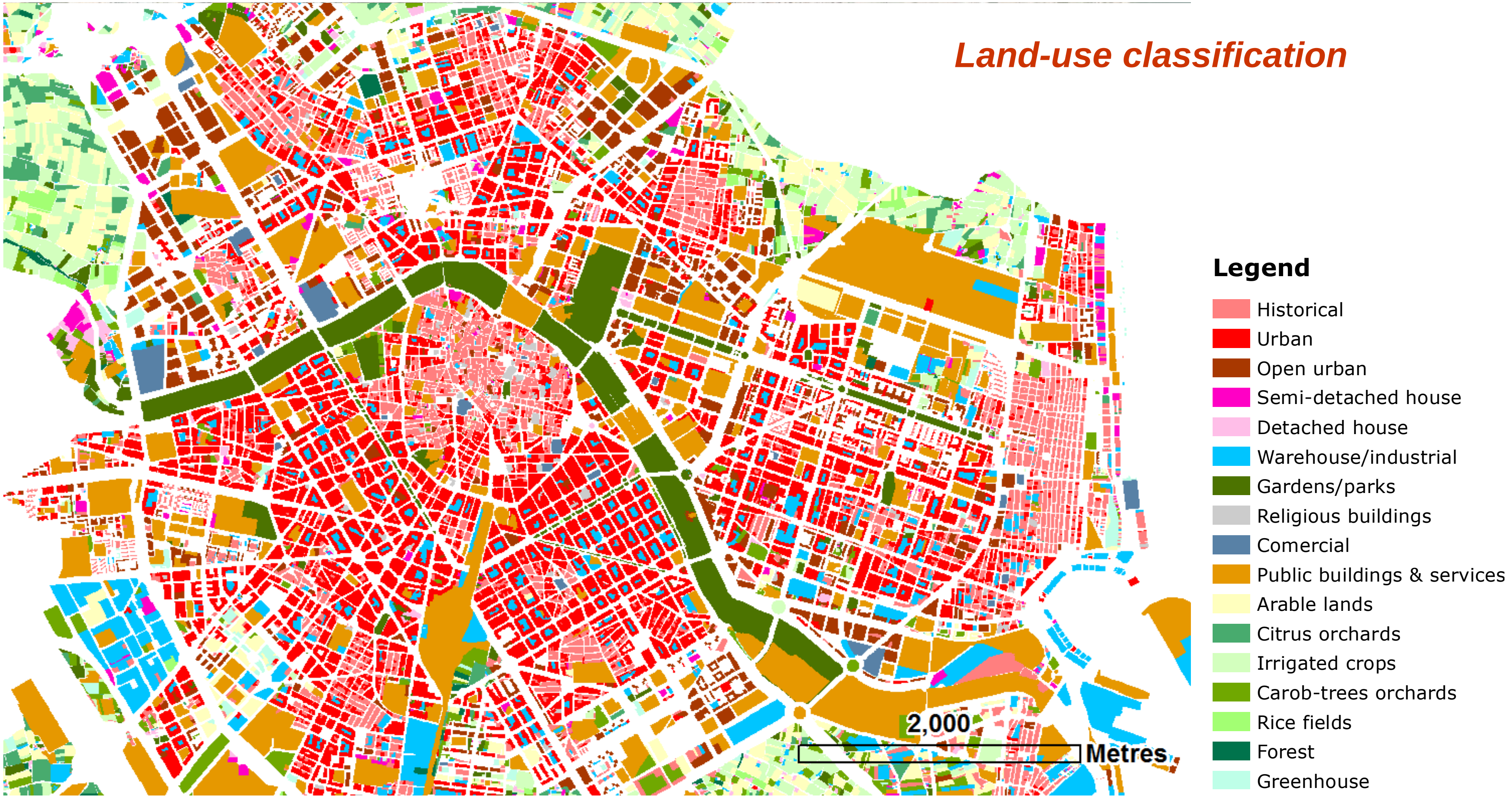
Internal context

3D structure features

External context

Study case

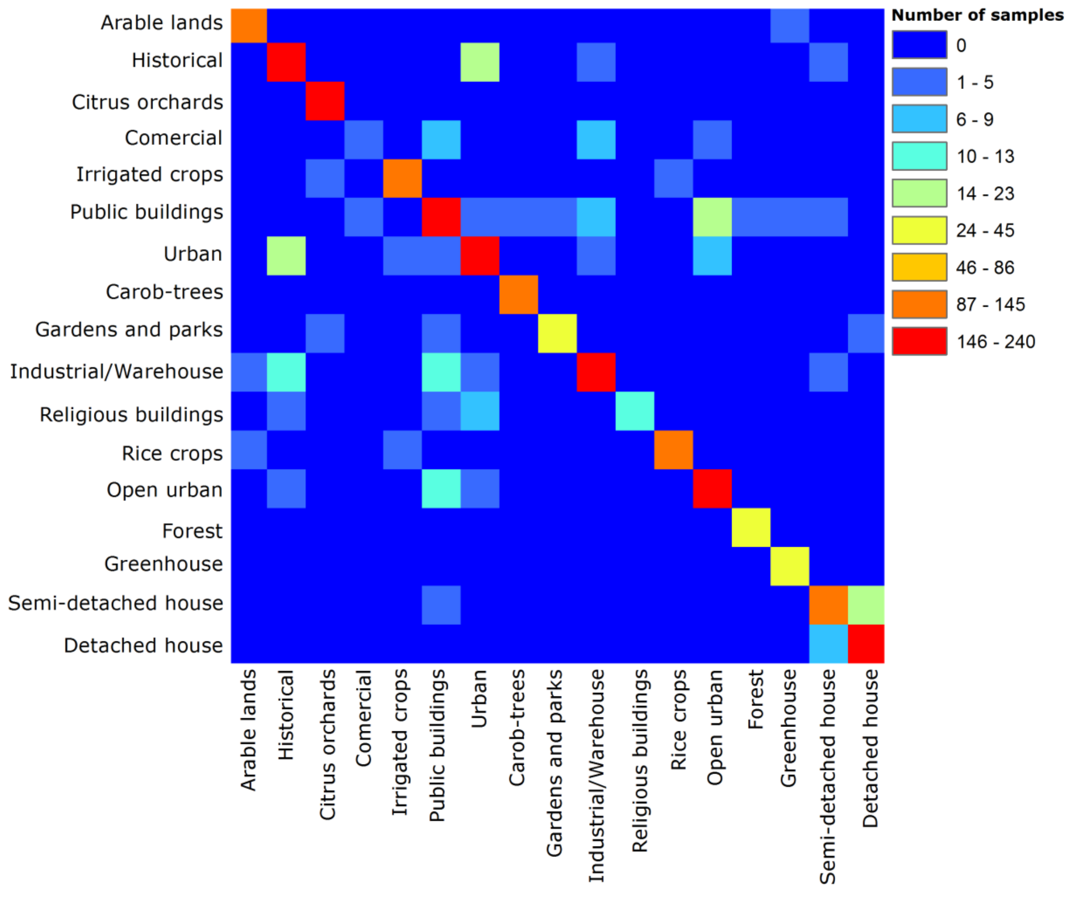
Results



Study case

Results

Land-use classification



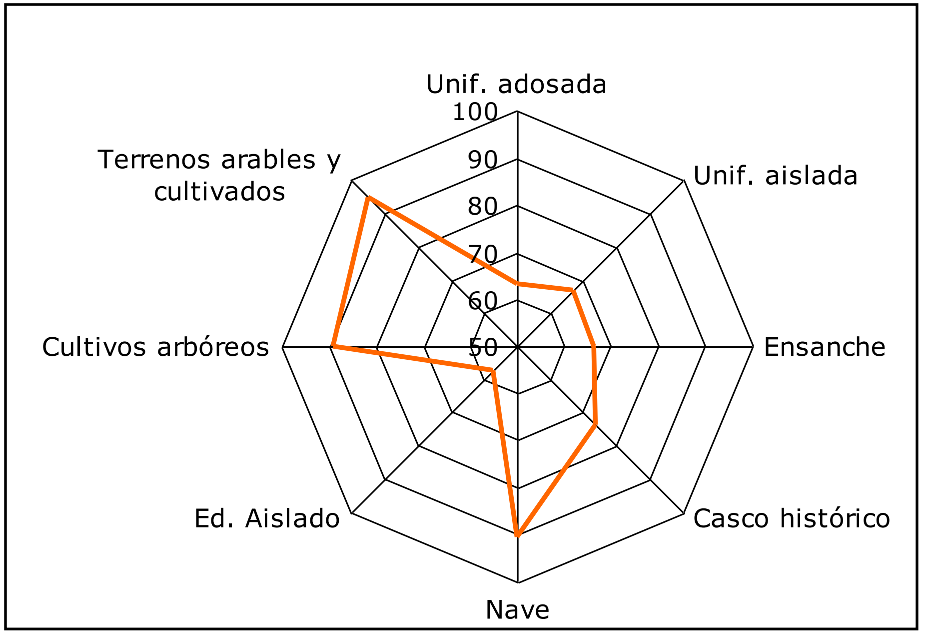
Classification error matrix. Rows represent reference class and columns classified data

Study case

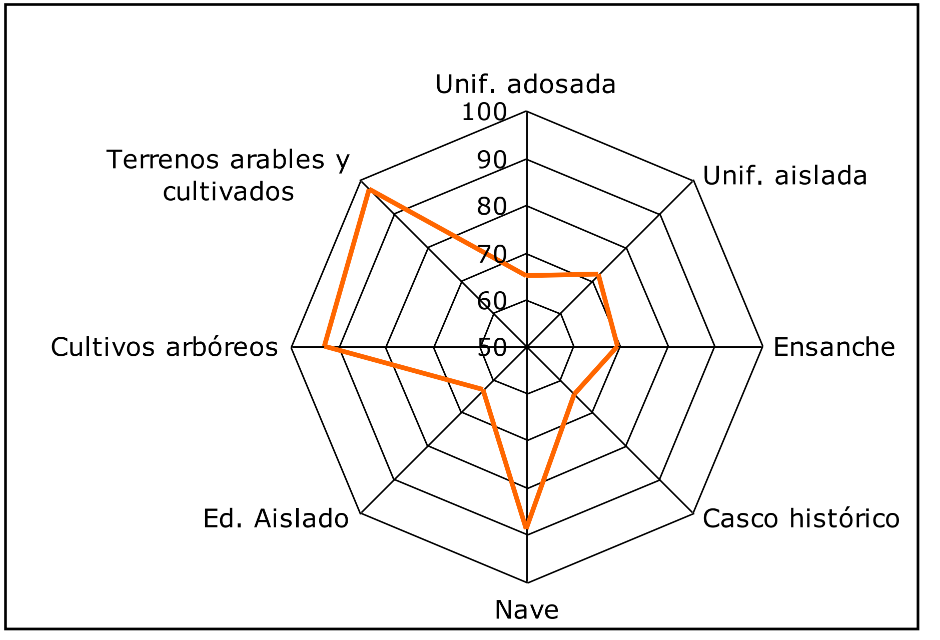
Results *(Land-use classification)*

Overall accuracy: 84.8%

Producer's accuracy



User's accuracy



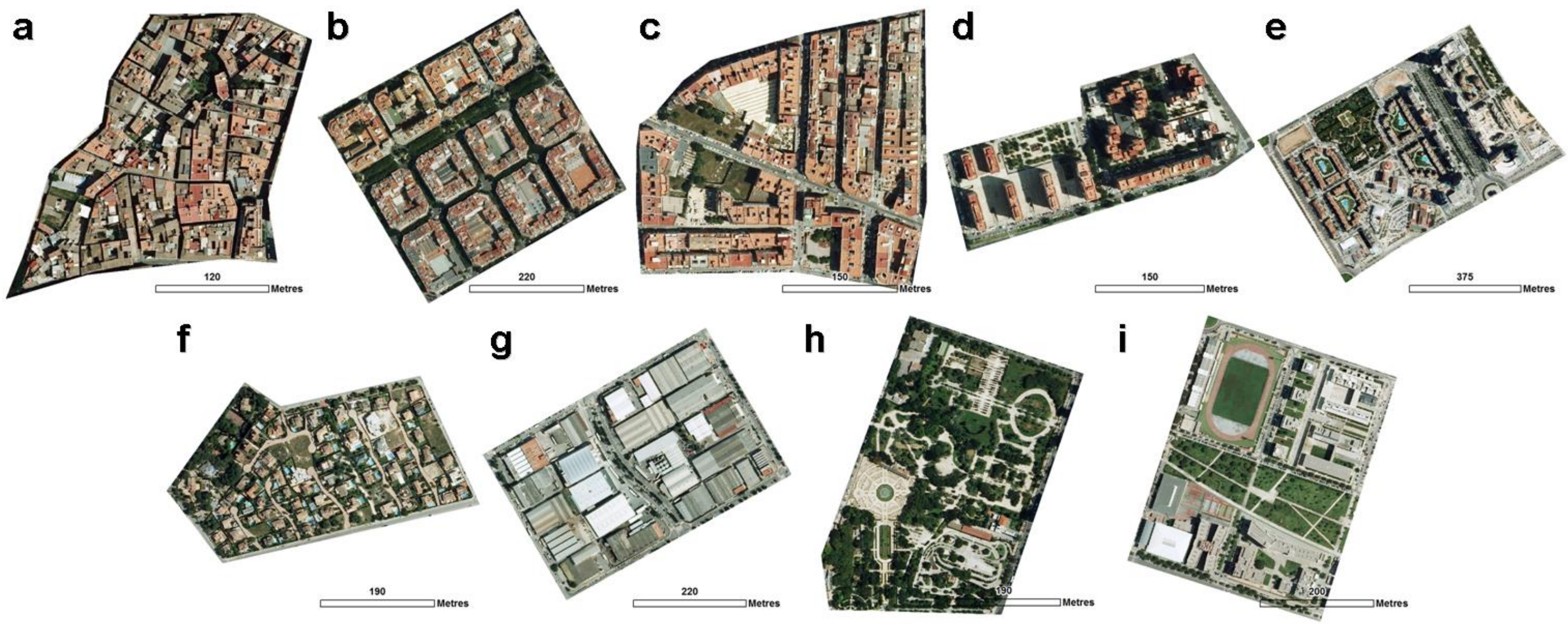
G I

G I: Image features
G II: 3D-structure features
G III: Internal context
G IV: External context

Study case

Classification by structural typologies

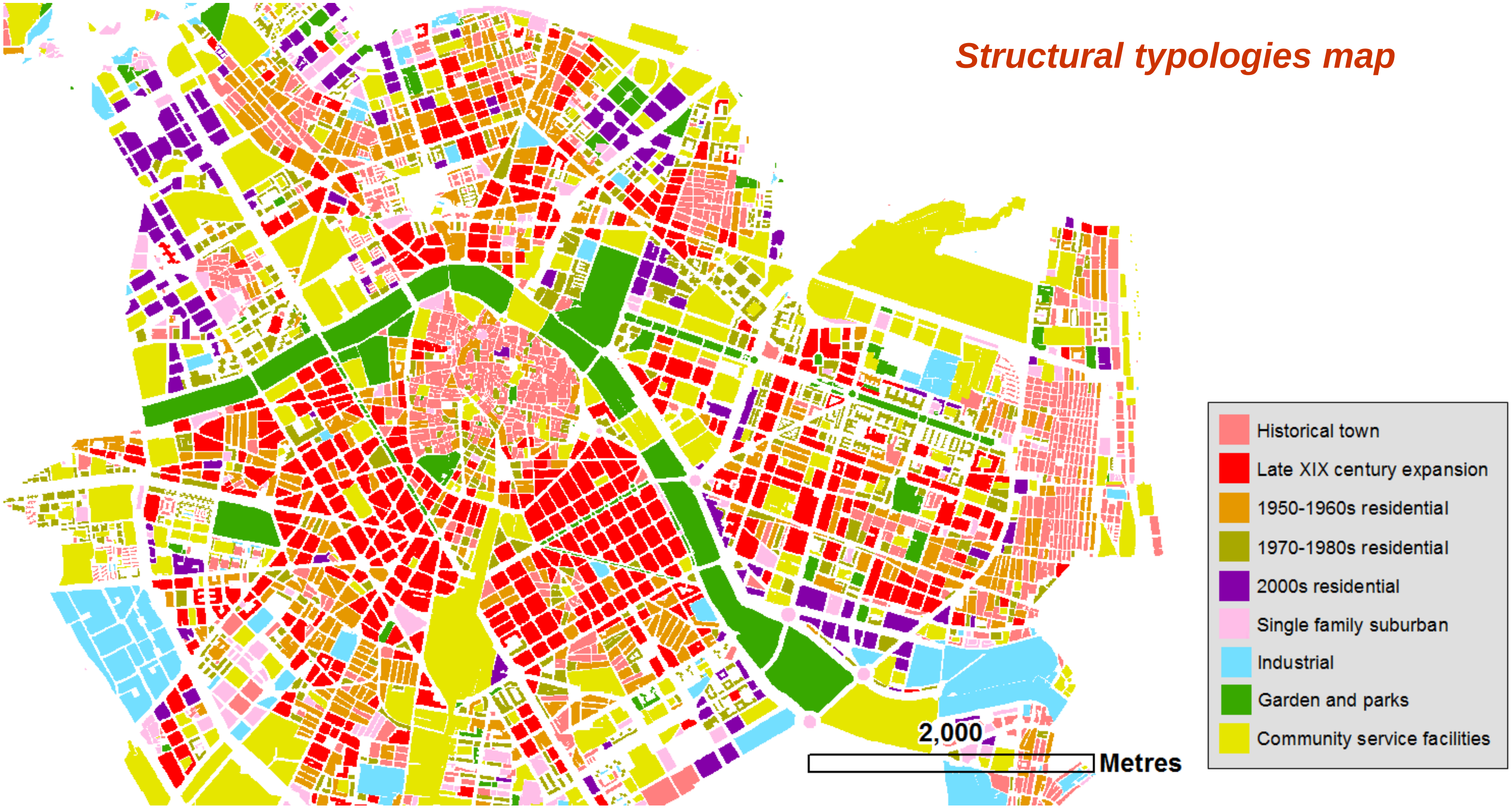
Land-use classes defined at urban block level



Structural typologies defined: a) *Historical town*, b) *late XIX century expansion* (*ensanche*), c) *1950-1960s residential areas*, d) *1970-1980s residential areas*, e) *2000s residential areas*, f) *single-family suburban areas*, g) *industrial areas*, h) *gardens and parks*, i) *community service facilities*

Study case

Results



Final remarks

- The use of **multi-level descriptors** providing specific information about the land use significantly **improves the classification** accuracy of the urban structural typologies
- The proposed methodology enables to derive valuable information for a **massive and non-subjective** characterization of urban areas
- These techniques may be useful to better understand and model the spatial **evolution of urban structures** within a city, to **analyse changes** in population, employment, migration, and other **socio-economical parameters.**

Thank you for your attention!

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