OBJECT-BASED CLASSIFICATION FOR ESTIMATION OF BUILT-UP DENSITY WITHIN URBAN ENVIRONMENT

Master thesis defence

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Agenda

- Introduction
- Background
- Thesis objective
- Data, study area, pre-processing
- Process (Rule Set) development
- Results, discussion
- Conclusion

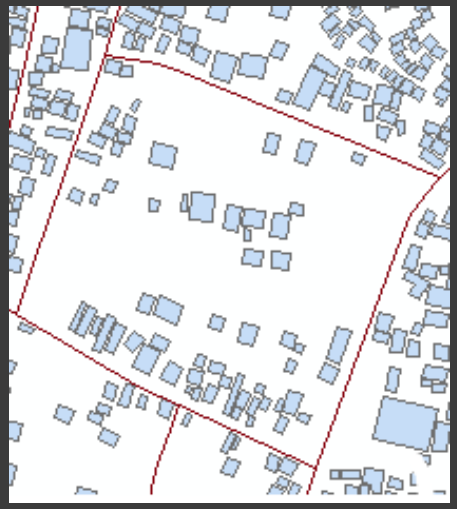
Introduction

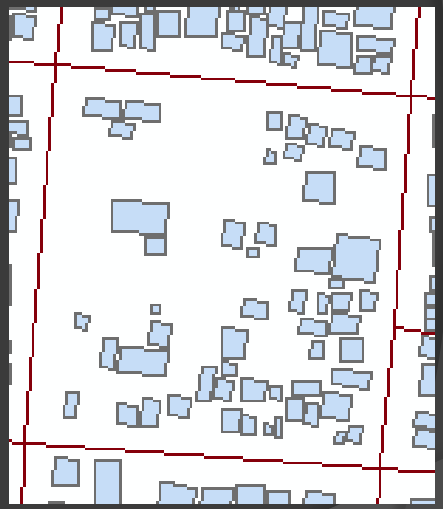
- Remote Sensing data – important source of information for studying urban environments
- Satellite, aerial imagery
- Image analysis
- Classification, land use / land cover (LULC)
- Quantitative (e.g. vegetation) analysis, spectral indices, hyperspectral analysis
- Spatial indicators, land statistics (e.g. greeness, imperviousness, built-up density)
- Spatial data extraction (image classification, OBIA)

Background

- **Built-up density**: proportion of built-up surface on the total surface of an area
  - Indicator of urban growth
  - Often related to population density
  - Can be calculated on a regular grid, administrative units, parcels, other area units
  - 1 value - not representative, if the area is not homogeneus

Various spatial distribution of built-up structures within an area unit (road enclosed segments)





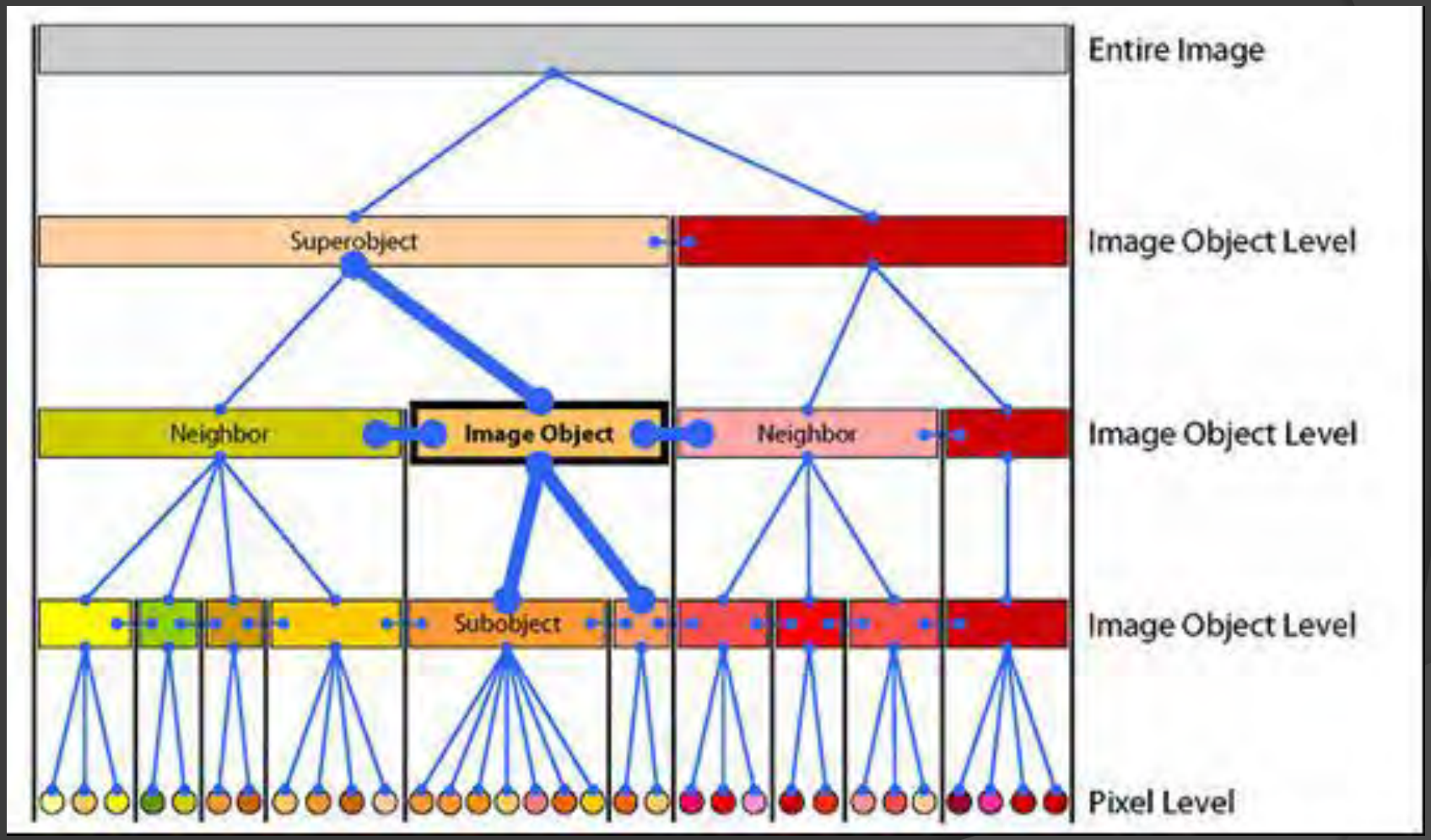
Master Thesis Objective

- **To develop, implement and describe** a semi-automated **object-based image classification approach** for mapping built-up areas from VHR imagery and **classification of built-up density** within blocks of broader built-up areas that are homogeneous in their urban fabric.
- These blocks **are not a priori defined**, but instead should be **created** based on the remote sensing image data itself.

Object-based Image Analysis

- OBIA – object-based image analysis
  - Image segmentation + image analysis + image classification
- Analysis of image objects (vs pixels)
- Image object features (spectral, textural, spatial) and relationships
- Image object level hierarchy (sub-objects, neighboring objects, super-objects)
- OBIA classification – supervised vs. Rule-based
- Rule Set development
  - potentialy transferable to other images

Image Object Level Hierarchy

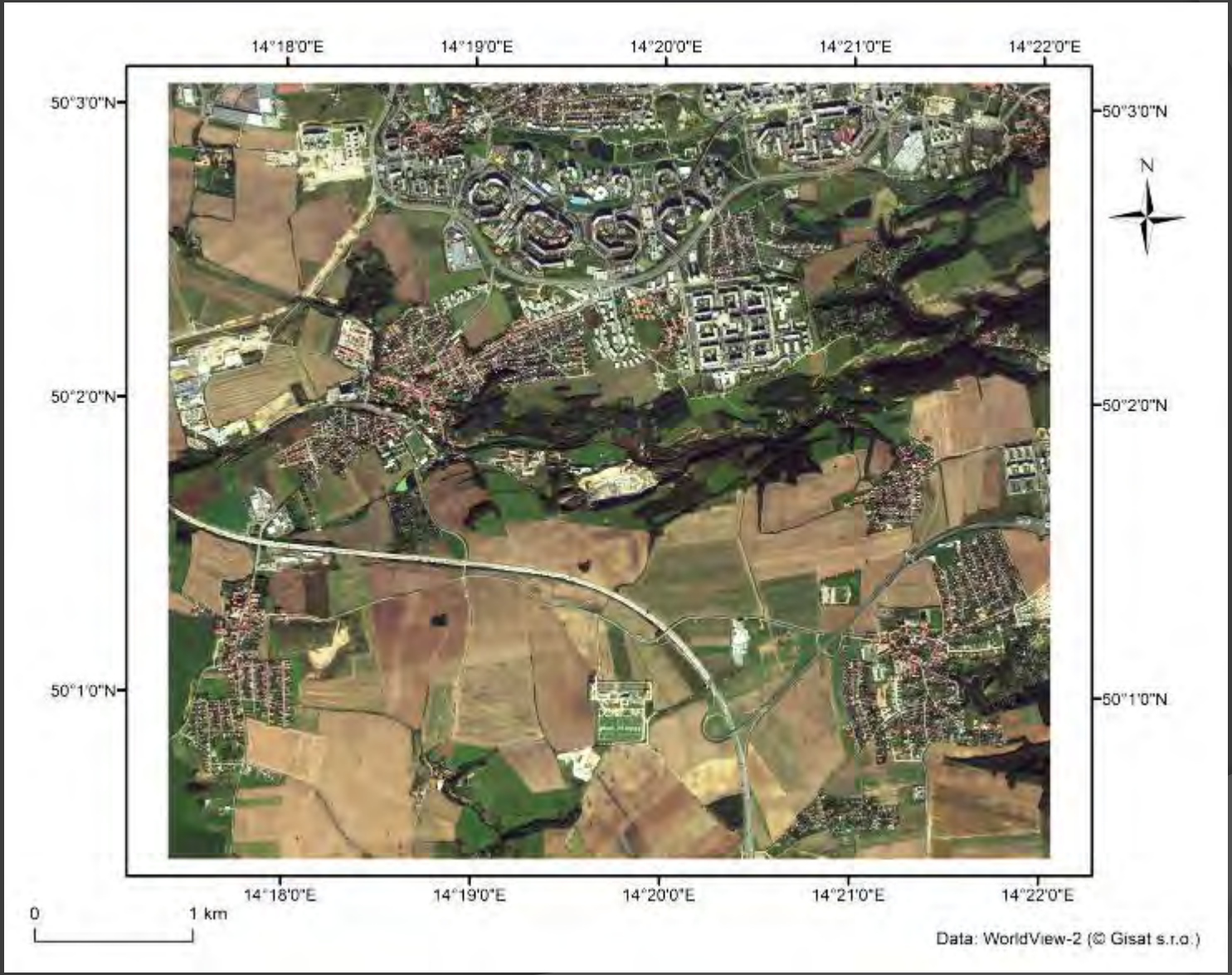


Source: eCognition Reference Book

Study area and DATA

- 2 different urban areas
  - different urban morphology, surfaces, materials
  - testing Rule Set transferability
- Prague, Czech Republic
  - suburban / rural area – built-up, parks, forests, lakes, agricultural land
- Mandalay, Myanmar
  - central urban area –dense, perpendicular roads

Prague, Czech Republic



Mandalay, Myanmar

Input DATA

- VHR Image WorldView-2 - Prague

Info	Band	Wavelengths	Resolution (m)
Sensor: WorldView-2	BLUE	450-510 nm	0.5
Location: Prague	GREEN	510-580 nm	0.5
Acquisition: 10.9.2010	RED	630-690 nm	0.5
Original resolution	NIR	770-895 nm	0.5
Panchromatic: 0.5m			
Multispectral: 2m			

- VHR Image Pléiades - Mandalay

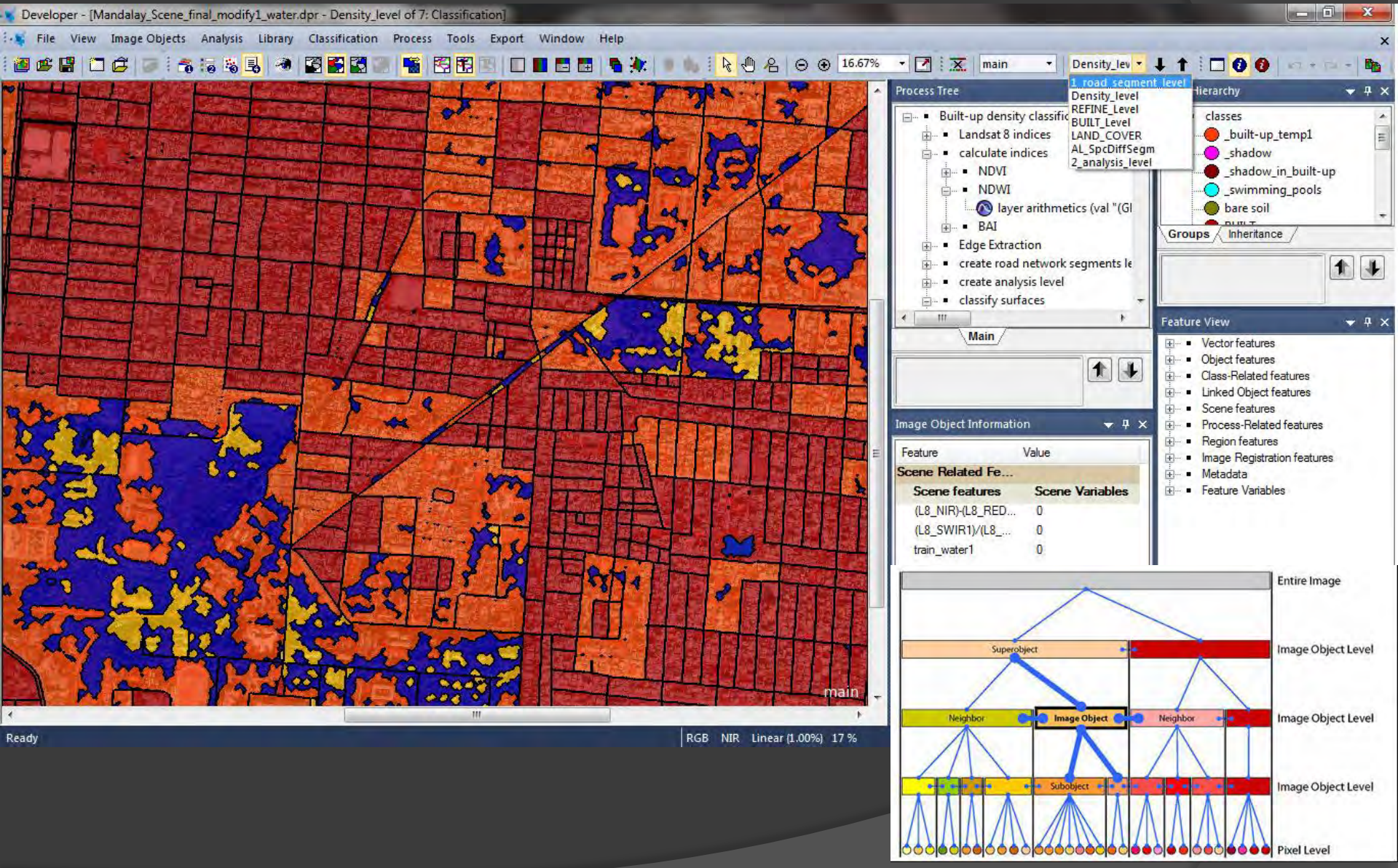
Info	Band	Wavelengths	Resolution (m)
Sensor: Pléiades-2	BLUE	430-550 nm	0.5
Location: Mandalay	GREEN	500-620 nm	0.5
Acquisition: 7.1.2014	RED	590-710 nm	0.5
Original resolution	NIR	740-940 nm	0.5
Panchromatic: 0.5m			
Multispectral: 2m			

- OpenStreetMap road network
  - for the respective areas (Prague, Mandalay subsets)
  - Used in segmentation
- Landsat 8 scene
  - for the respective areas (Prague, Mandalay subsets)

Software

- eCognition Developer – OBIA - Rule Set development
- ArcMap – Data management, visualisation
- ENVI - Atmospheric correction (QUAC), Accuracy assessment

eCognition Developer

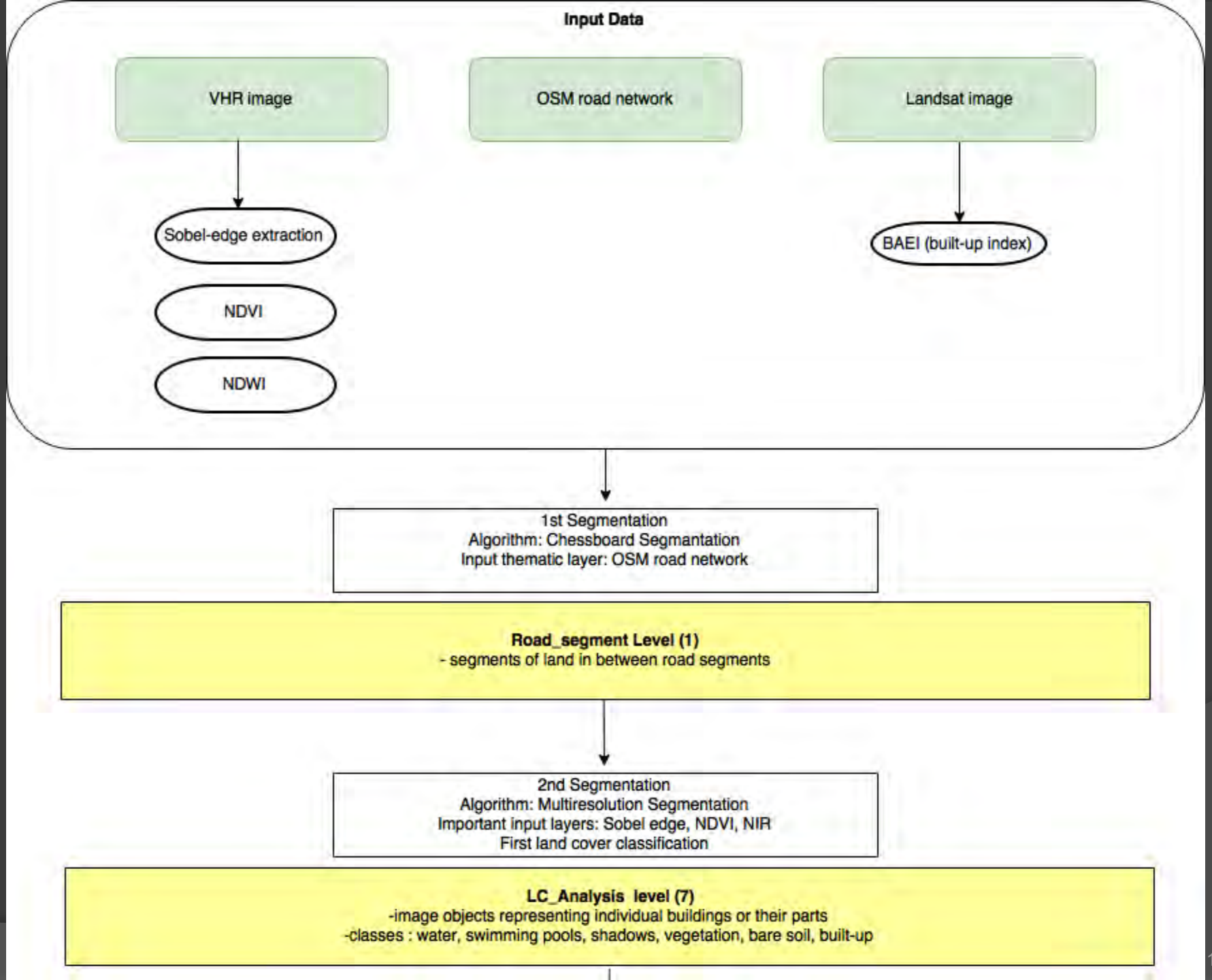


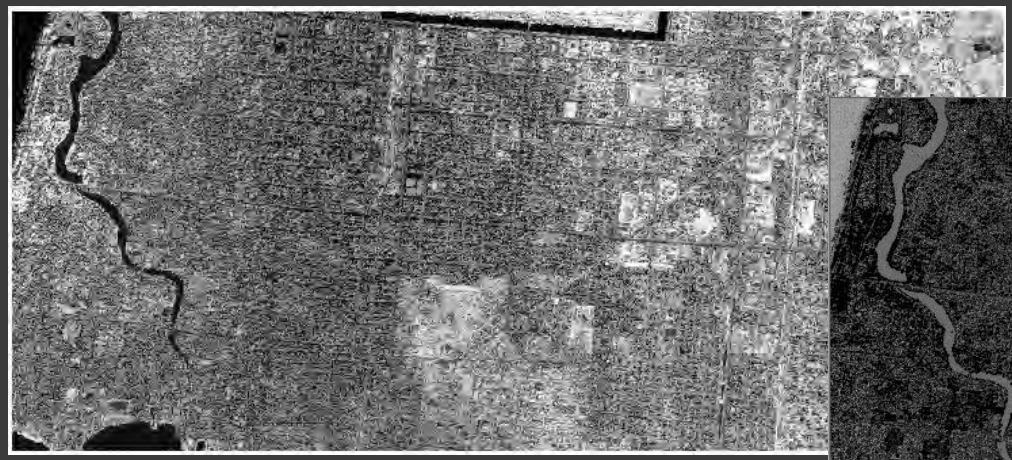
Pre-processing

- Atmospheric correction of the VHR images
  - QUick Atmospheric Correction – QUAC (ENVI)
- Bit-depth conversion
  - from 16bit to 8bit
- Geometric corrections
  - georeferencing, co-registration, spatial adjustment
- Clipping
  - to area of interest extent

Rule Set development

- Developing image processing workflow for built-up density analysis
- Using algorithms, segmentation, image analysis, classicication, refinement, post-processing, export
- Implemented in Cognition Network Language within eCognition Developer software


Input Data
VHR image
OSM road network
Landsat image
Sobel-edge extraction
NDVI
NDWI
BAEI (built-up index)
1st Segmentation
Algorithm: Chessboard Segmantation
Input thematic layer: OSM road network
Road_segment Level (1)
- segments of land in between road segments
2nd Segmentation
Algorithm: Multiresolution Segmentation
Important input layers: Sobel edge, NDVI, NIR
First land cover classification
LC_Analysis level (7)
-image objects representing individual buildings or their parts
-classes : water, swimming pools, shadows, vegetation, bare soil, built-up



NDVI

NDWI

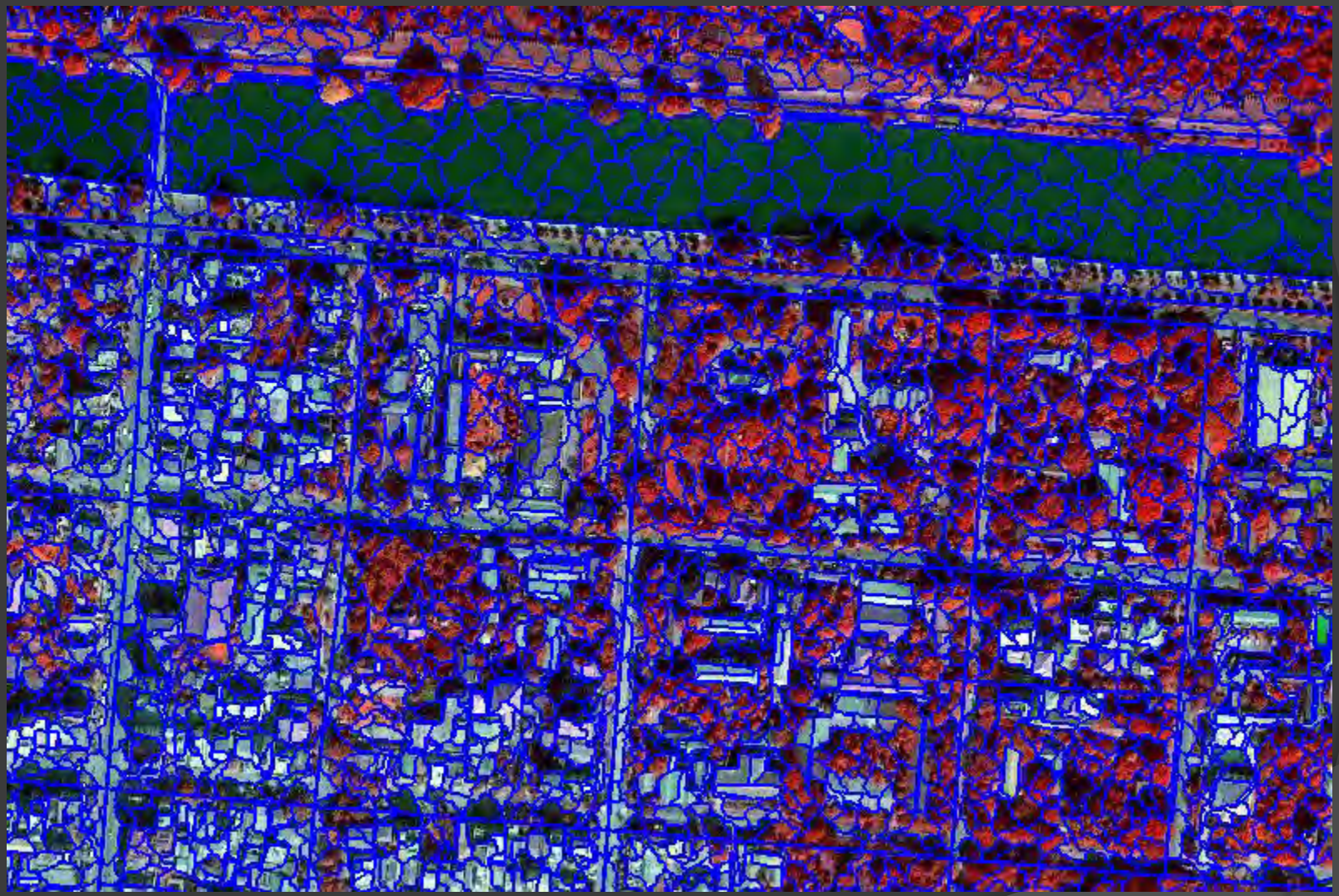
Sobel

L8_BAEI

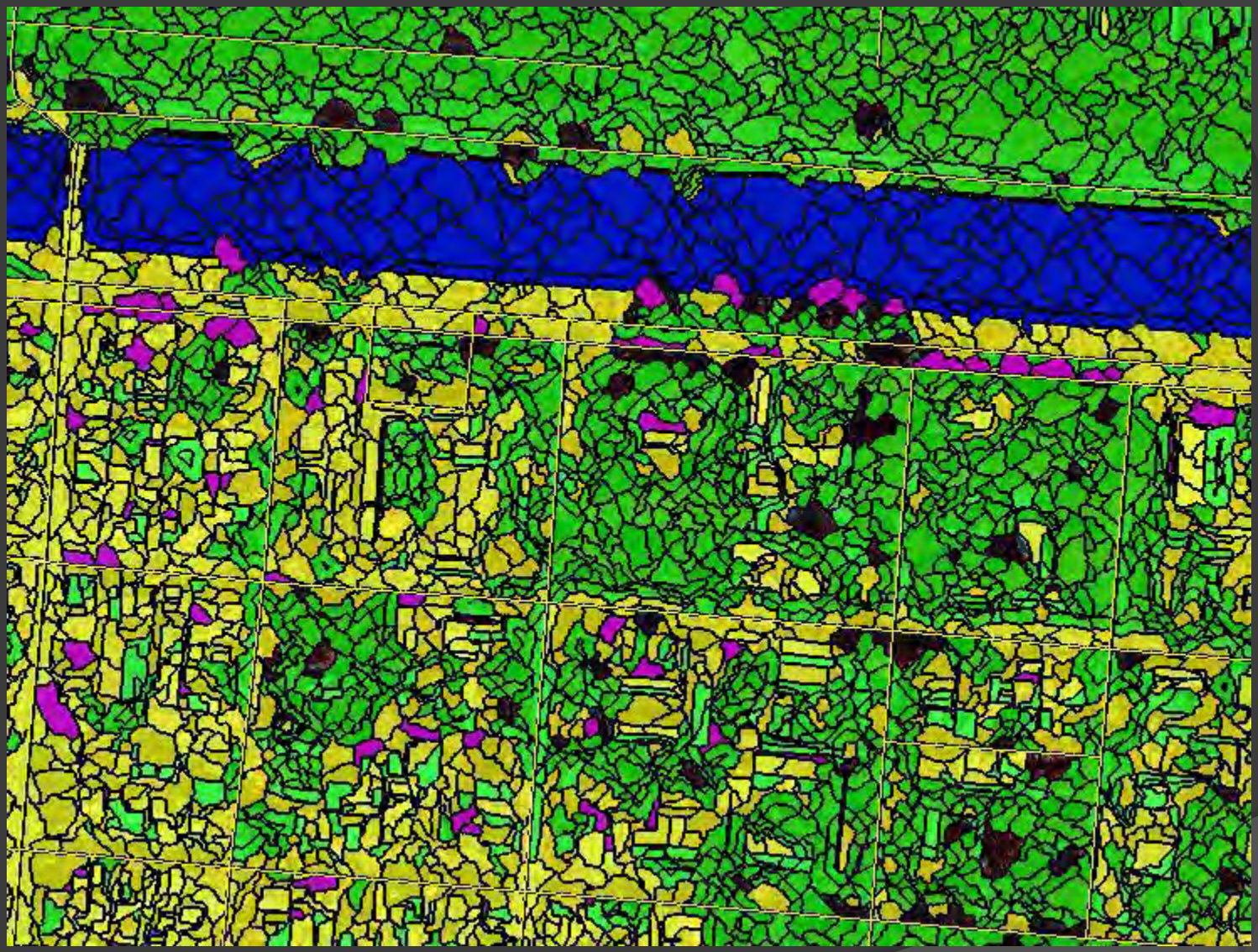
Segmentation by road network (Chessboard segmentation)

Result of first segmentation – Chessboard Segmentation on pixel level using OSM road network – creation of ROAD_SEGMENT level

Multiresolution segmentation – Parameters:
Scale : 20, Shape 0.8, Compacstness: 0.2



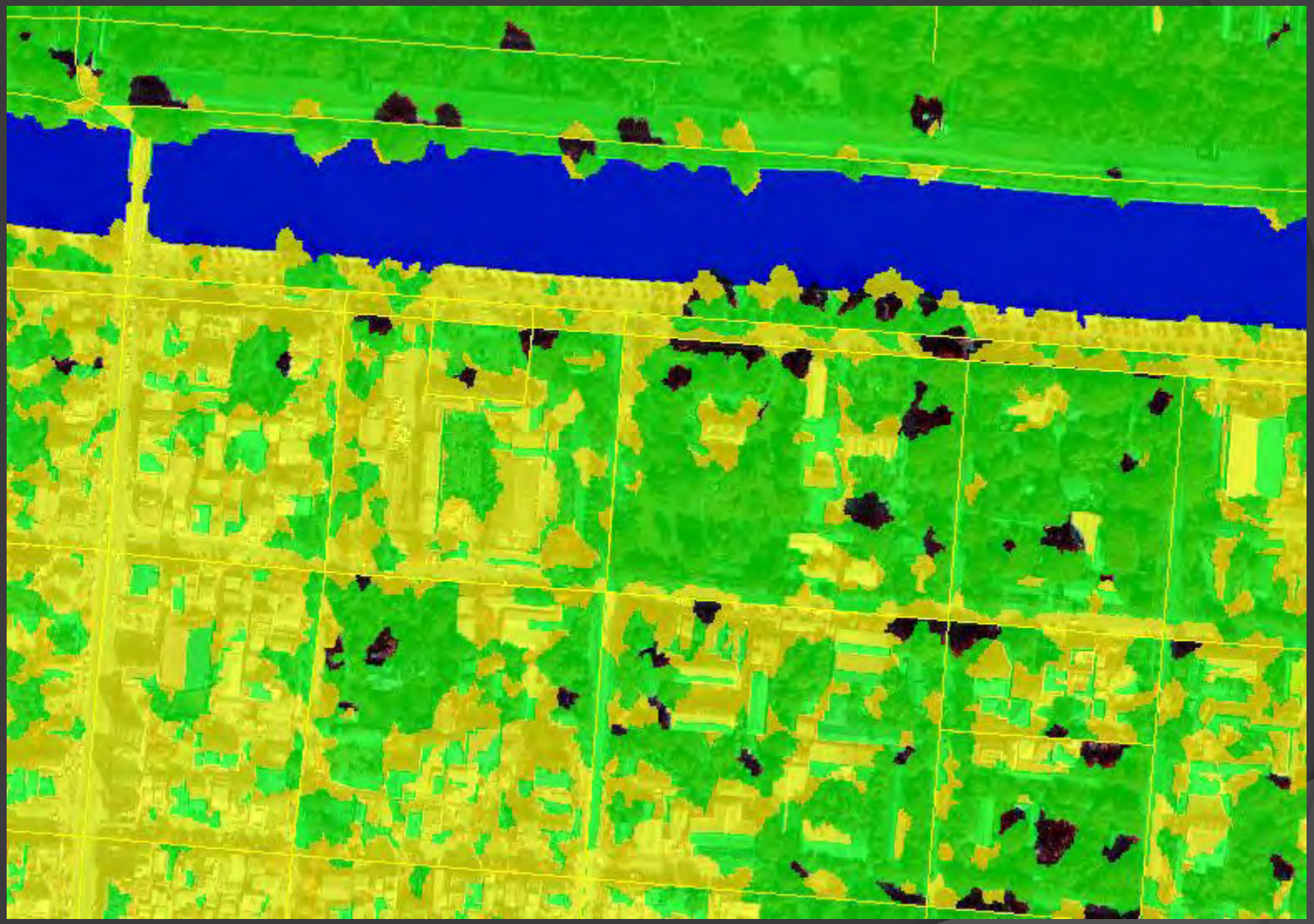
Result of Multiresolution Segmentation and creation of LC_ANALYSIS level



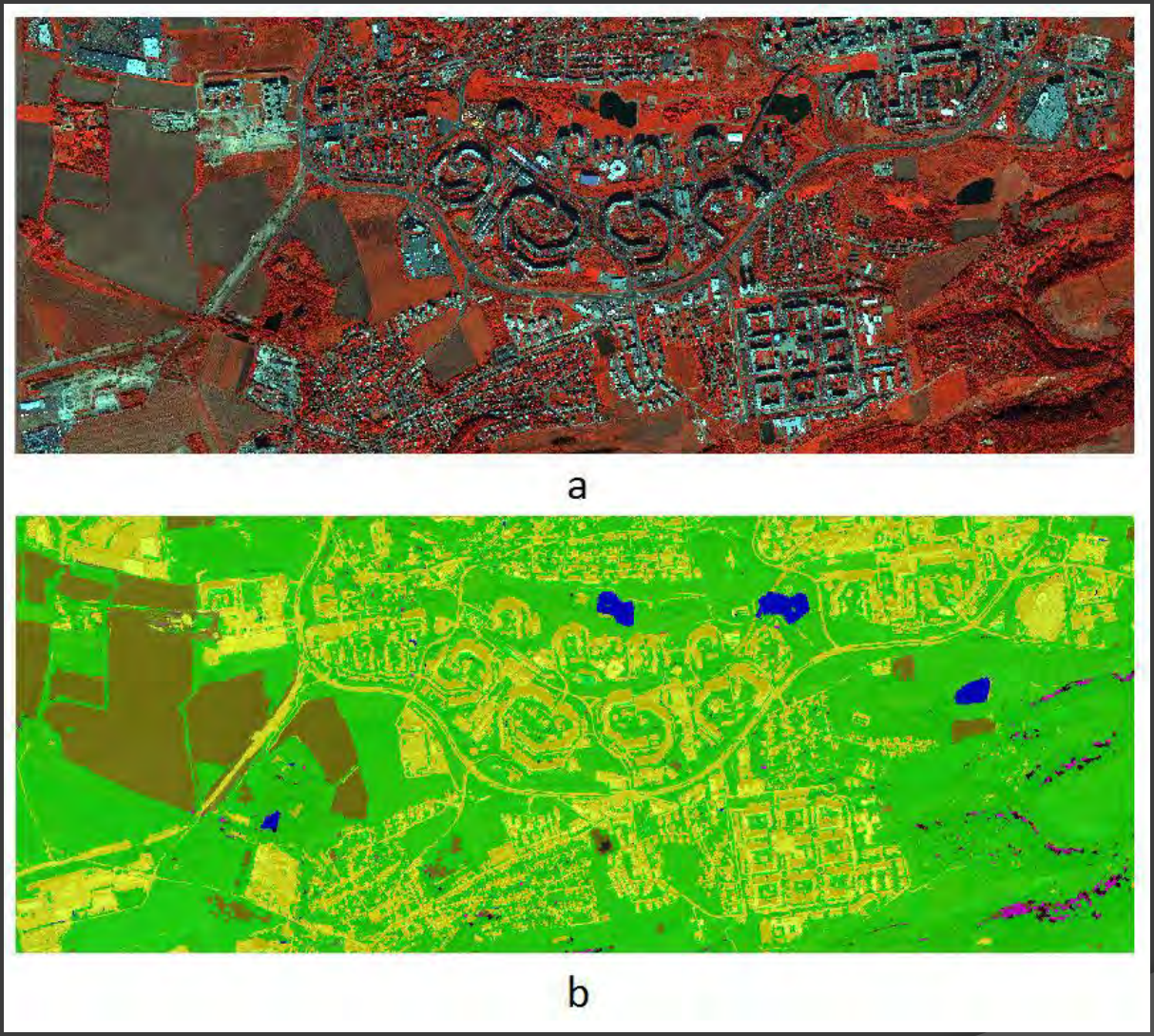
Classified image objects at the LC_ANALYSIS level
(yellow=built-up, green=vegetation, blue=water, purple=shadow, no color=unclassified)

Class	Image object features used	
	Prague	Mandalay
Built-Up	• NDVI < 0 • RED > 70	• NDVI < 0.15 • RED > 100 • mean Sobel edge > 4
Vegetation	• NDVI > -0.25 • NIR > 40	• NDVI > -0.15 • RED < 110
Water	• NIR < 35.5 • NDVI < -0.37 • NDWI > 0.4 • mean Sobel edge < 4	• NIR < 60 • NDVI < -0.2 • NDWI > 0.3 • mean Sobel edge < 8 • Std. NIR < 8
_Swimming pools	• Area < 3000px • -0.65 < NDVI < -0.55 • 0.55 < NDWI < 0.6	• Area < 3000 px • -0.65 < NDVI < -0.55 • 0.55 < NDWI < 0.62
Bare soil	• -0.28 < NDVI < -0.2 • Area > 10000 px • Std. NIR < 12	• N/A
_Shadows	• NIR < 35 • Std. NIR > 4	• NIR < 35 • Std. NIR > 4 • Brightness < 100

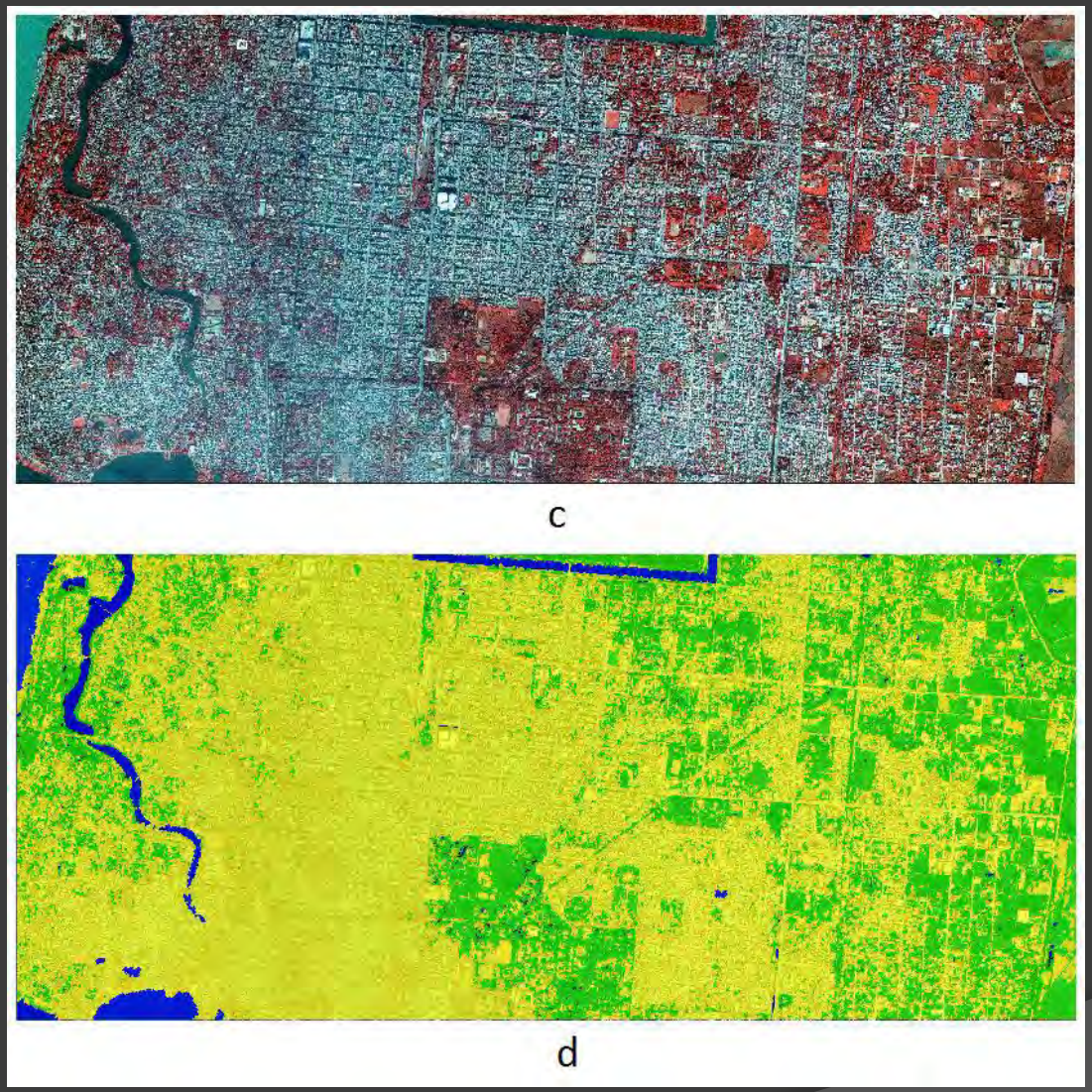
Image object features used to classify different surfaces ("_" prefix indicates temporary class)



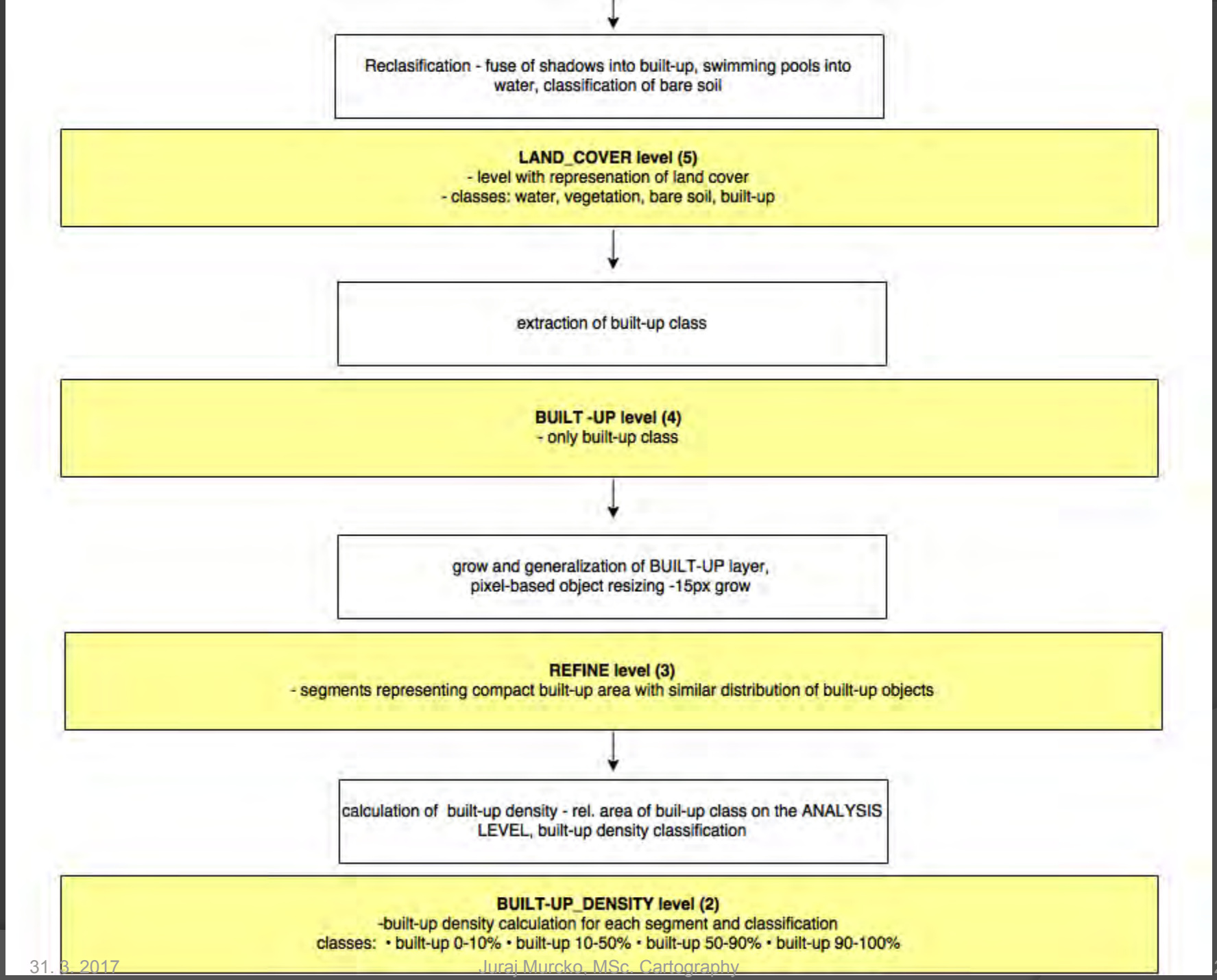
land cover classification on LAND_COVER image object level



a) Prague – false color composite b) Prague - LC classification



c) Mandalay - false color composite d) Mandalay - LC classification


Reclasification - fuse of shadows into built-up, swimming pools into water, classification of bare soil
LAND_COVER level (5)
- level with represenation of land cover
- classes: water, vegetation, bare soil, built-up
extraction of built-up class
BUILT -UP level (4)
- only built-up class
grow and generalization of BUILT-UP layer, pixel-based object resizing -15px grow
REFINE level (3)
- segments representing compact built-up area with similar distribution of built-up objects
calculation of built-up density - rel. area of buil-up class on the ANALYSIS LEVEL, built-up density classification
BUILT-UP_DENSITY level (2)
-built-up density calculation for each segment and classification
classes: • built-up 0-10% • built-up 10-50% • built-up 50-90% • built-up 90-100%

Pixel-based image object grow (dilation)

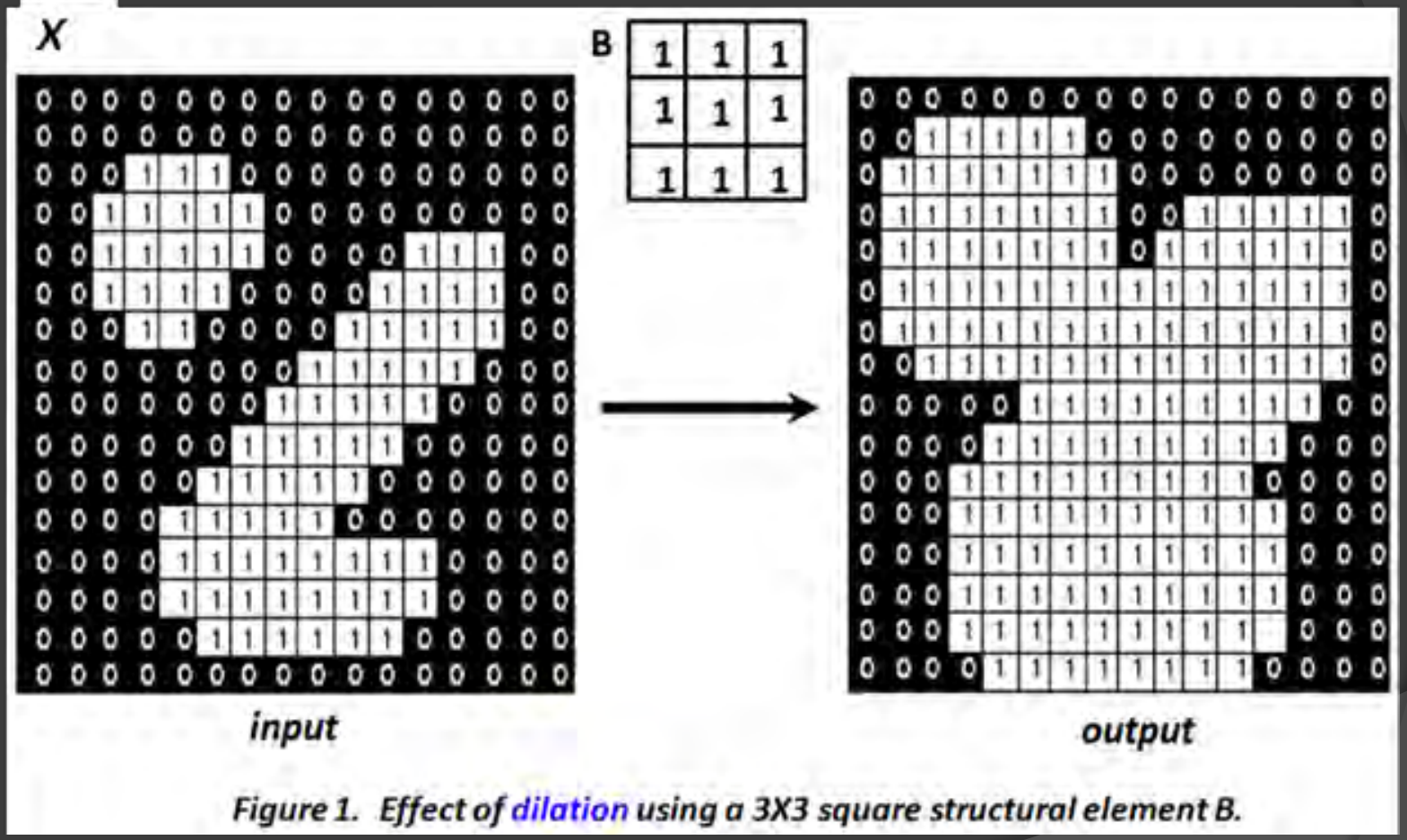
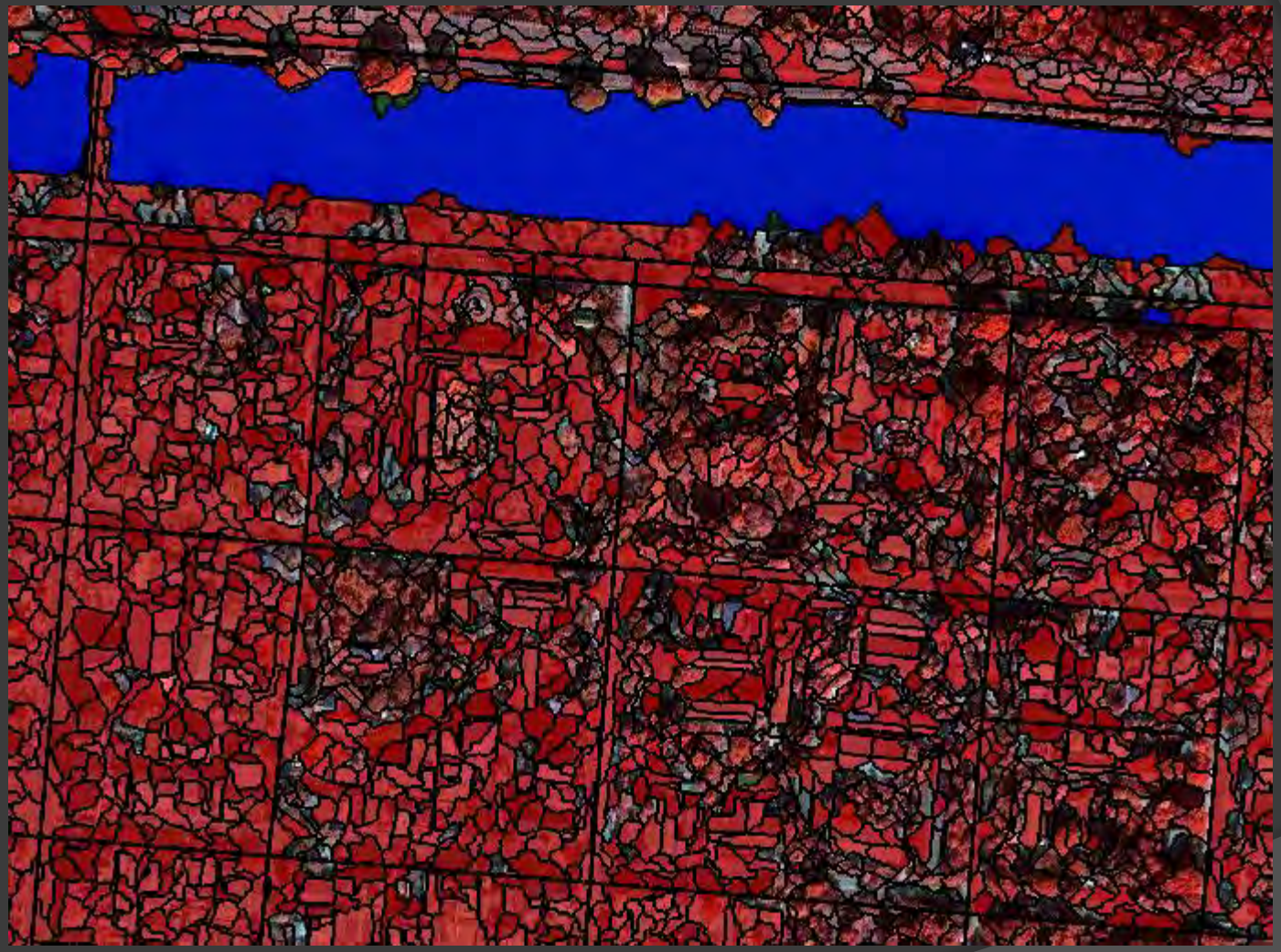


Figure 1. Effect of dilation using a 3X3 square structural element B.

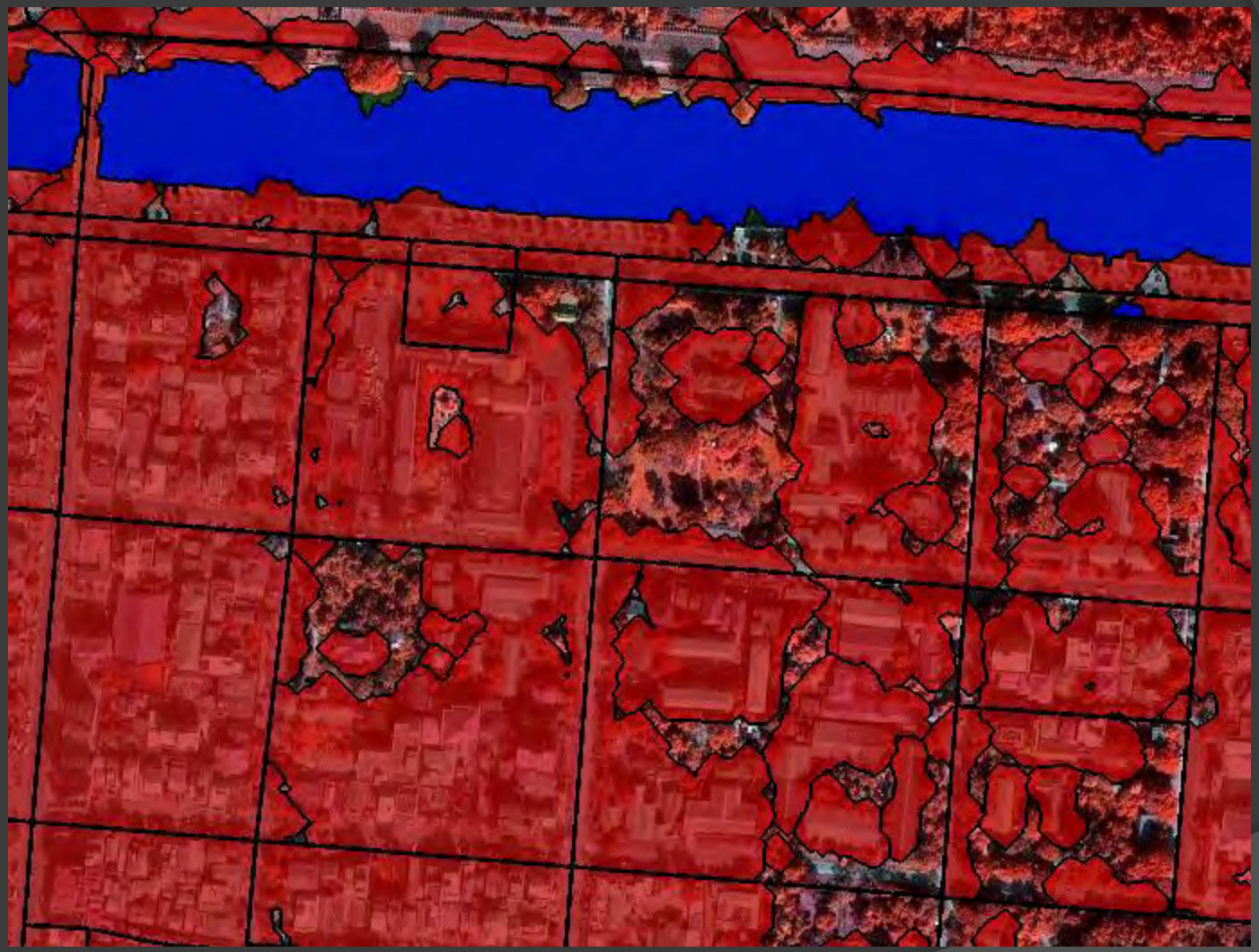
Source: http://homepages.inf.ed.ac.uk/rbf/HIPR2/dilate.htm

BUILT–UP surface



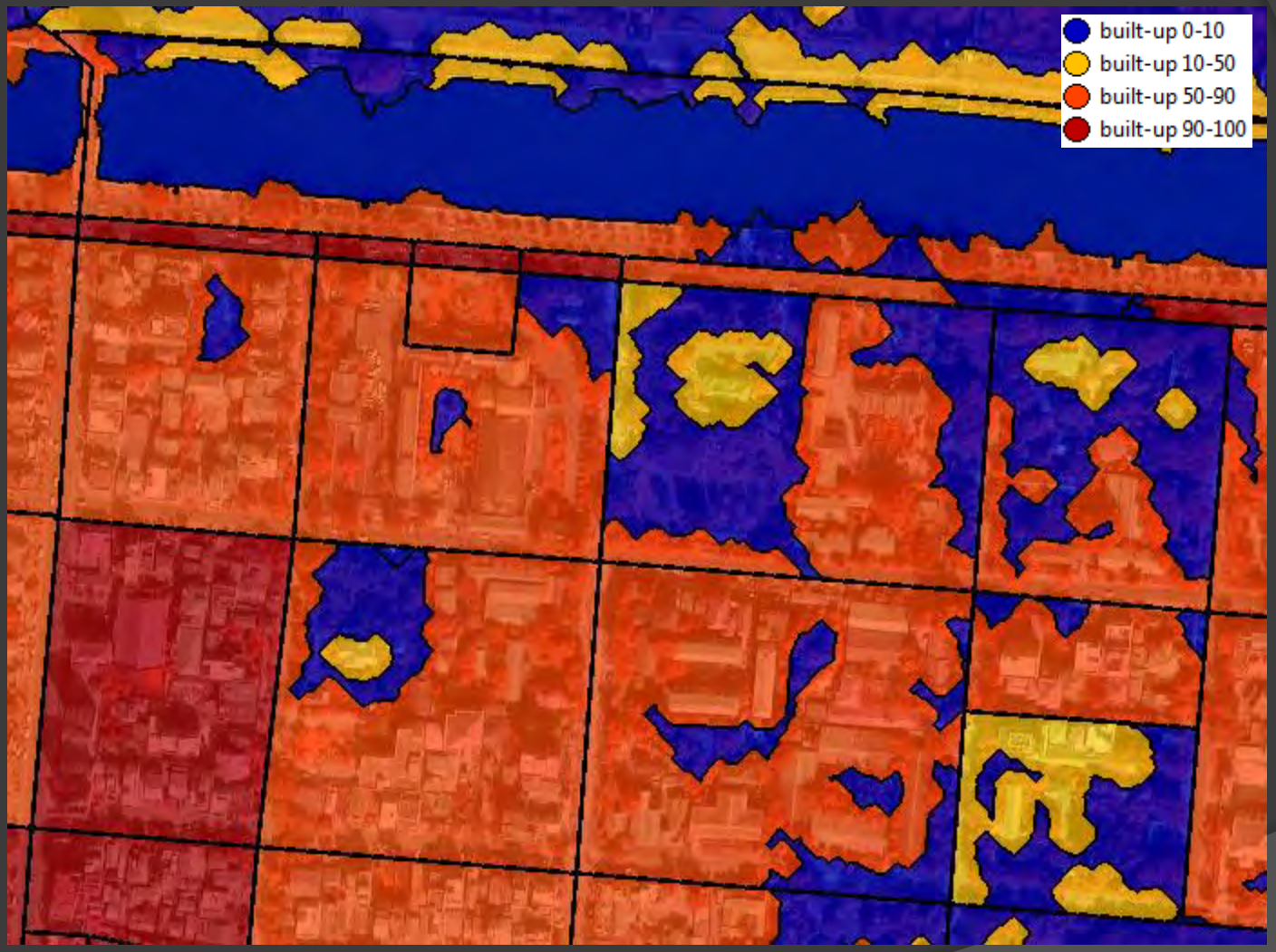
BUILT–UP level – only built-up surfaces

15 px grow



REFINE level – result of pixel-based object grow

Built-up density classification



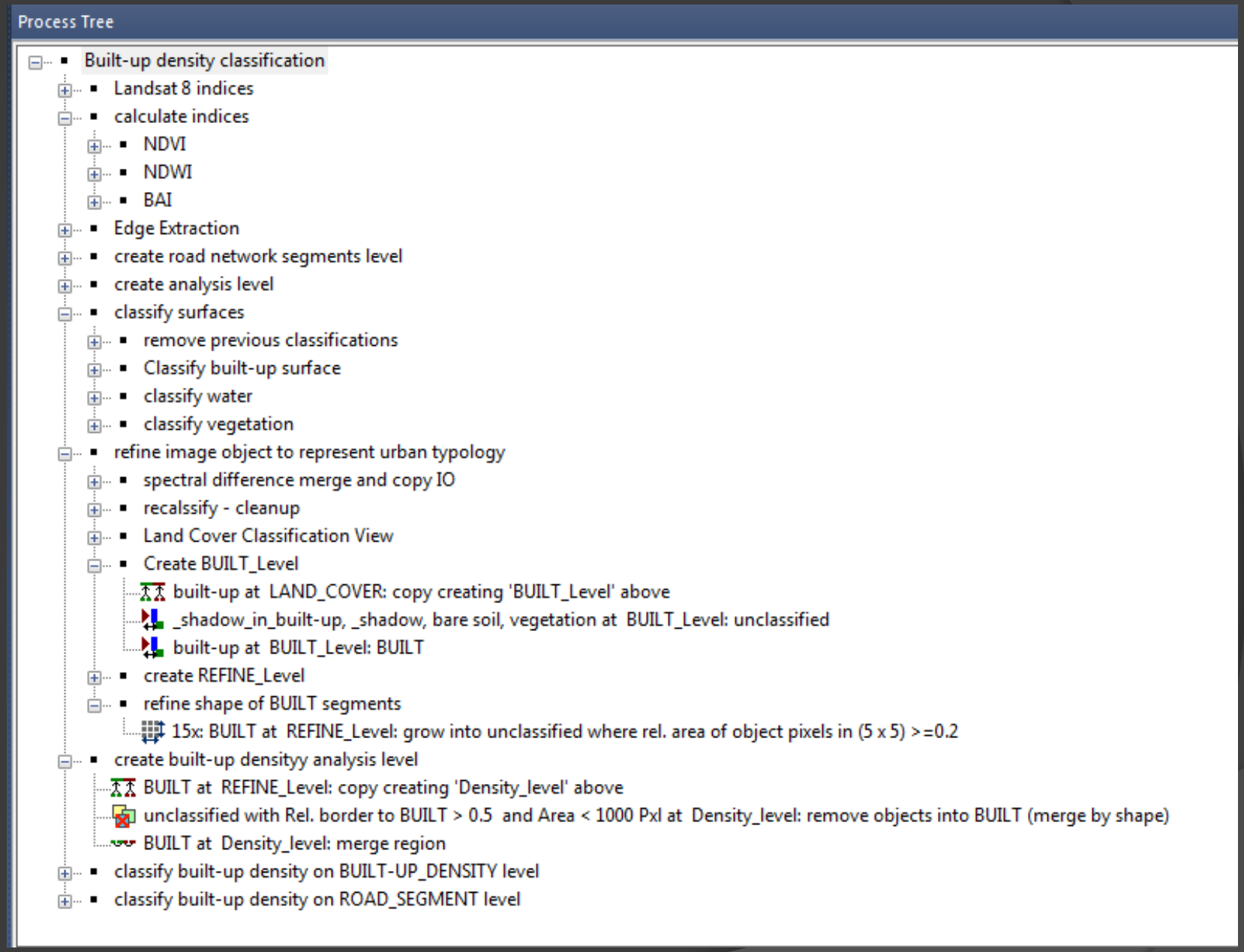
Built-up density classification on the refined extended built-up area- BUILT-UP_DENSITY level

Image Object Level	Description
1. ROAD_SEGMENT level	Image segmented into blocks created by road network
2. BUILT-UP_DENSITY level	Level closely representing the overall shape of compact built-up area used for built-up density classification
3. REFINE level	15px buffer on built-up level – grow, generalisation, smoothing
4. BUILT-UP level	Only built- up layer
5. LAND_COVER level	Abstracted land cover – built-up, vegetation, water, bare soil
6. SPECTRAL_DIFFERENCE level	Segments representing objects with high spectral homogeneity
7. LC_ANALYSIS level	Segments closely representing individual buildings and distinct features, scale level 20

Description of the created image object level hierarchy

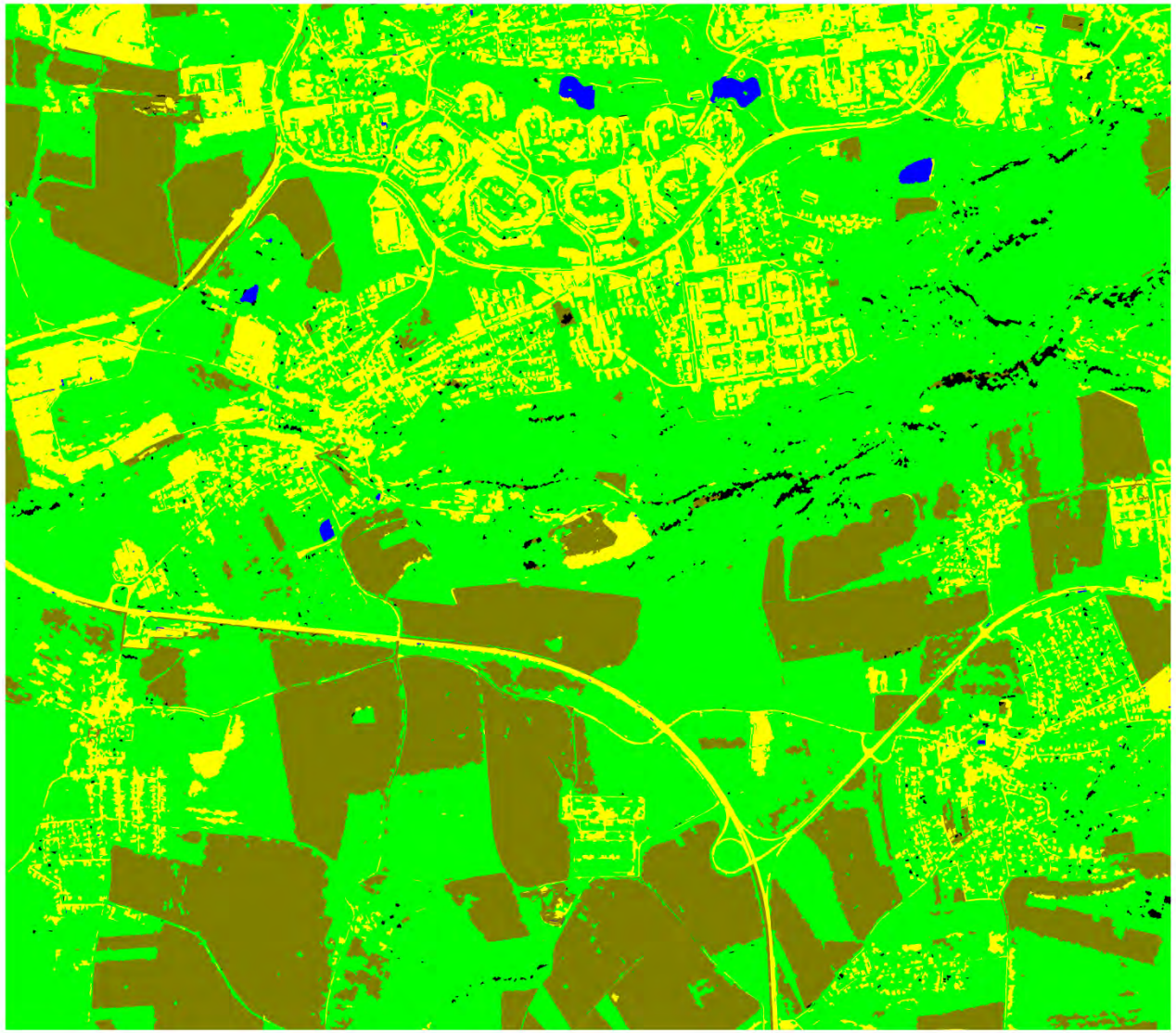
Results

- Rule Set
- Land Cover map
  - 4 classes: built-up, vegetation, water, bare soil
- Built-up density blocks – broader built-up area
- Built-up density classification on 2 levels:
  - 1. ROAD_SEGMENT level (road enclosed segments)
  - 2. BUILT-UP_DENSITY level (refined extended built-up area)


Process Tree
Built-up density classification
Landsat 8 indices
calculate indices
NDVI
NDWI
BAI
Edge Extraction
create road network segments level
create analysis level
classify surfaces
remove previous classifications
Classify built-up surface
classify water
classify vegetation
refine image object to represent urban typology
spectral difference merge and copy IO
recalssify - cleanup
Land Cover Classification View
Create BUILT_Level
built-up at LAND_COVER: copy creating 'BUILT_Level' above
_shadow_in_built-up, _shadow, bare soil, vegetation at BUILT_Level: unclassified
built-up at BUILT_Level: BUILT
create REFINE_Level
refine shape of BUILT segments
15x: BUILT at REFINE_Level: grow into unclassified where rel. area of object pixels in (5 x 5) >=0.2
create built-up densityy analysis level
BUILT at REFINE_Level: copy creating 'Density_level' above
unclassified with Rel. border to BUILT > 0.5 and Area < 1000 Pxl at Density_level: remove objects into BUILT (merge by shape)
BUILT at Density_level: merge region
classify built-up density on BUILT-UP_DENSITY level
classify built-up density on ROAD_SEGMENT level

Rule Set

Prague - land cover



Mandalay - land cover

Land cover accuracy assessment

- Reference points from visual interpretation
- Confusion matrix

Prague – land cover reference points

Mandalay– land cover reference points

Prague – land cover statistics		
Class	**Area (ha)**	**Area (%)**
Built-up	439.358725	16.12
Vegetation	1669.98735	61.28
Water	7.278375	0.27
Bare soil	588.877525	21.61
unclassified	19.611625	0.72
Total	2725.1136	100.00

Mandalay – land cover statistics		
Class	**Area (ha)**	**Area (%)**
Built-up	1920.438175	70.02
Vegetation	741.952975	27.05
Water	72.7274	2.65
Bare soil	0	0.00
unclassified	7.7713	0.28
Total	2742.88985	100.00

Prague land cover classification - confusion matrix

	Reference (px)				
Classification	built-up	vegetation	water	bare soil	Total
built-up	89	0	4	3	96
vegetation	7	99	0	15	121
water	0	0	46	0	46
bare soil	4	1	0	82	87
Total	100	100	50	100	350

Overall Accuracy = (316/350) 90.2857%

Kappa Coefficient = 0.8675

Mandalay land cover classification

	Reference (px)			
Classification	built-up	vegetation	water	Total
built-up	99	9	12	120
vegetation	1	91	1	93
water	0	0	32	32
Total	100	100	50	250

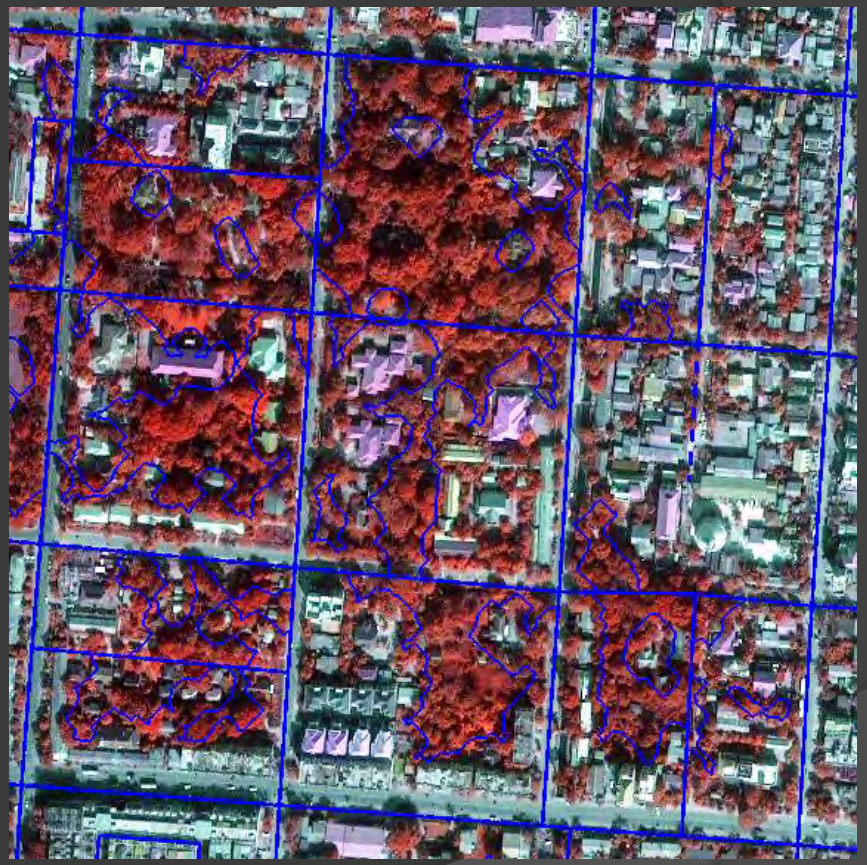
Overall Accuracy = (222/250) 88.8000%

Kappa Coefficient = 0.8232

Built-up density classification

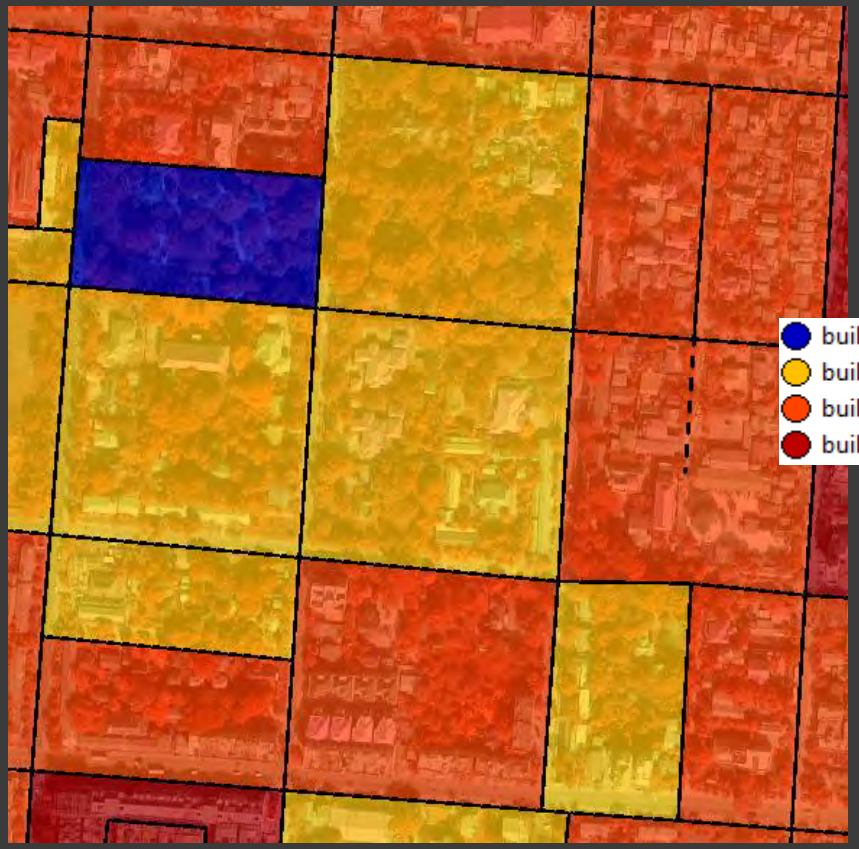
ROAD_SEGMENT level

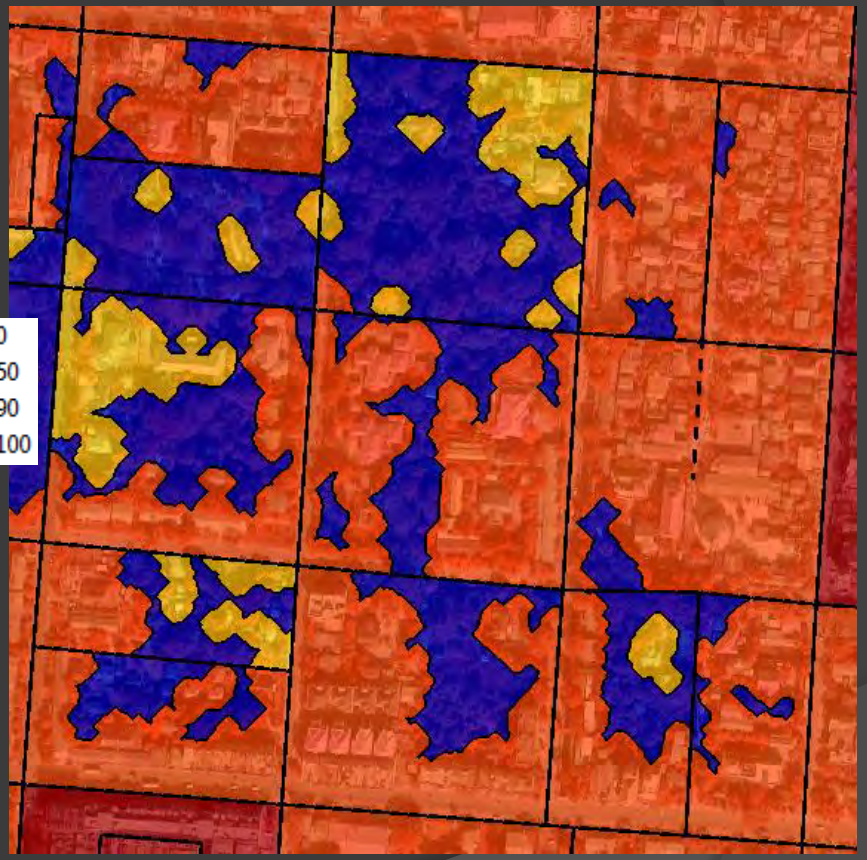
VS



BUILT-UP_DENSITY level

Built-up density classification

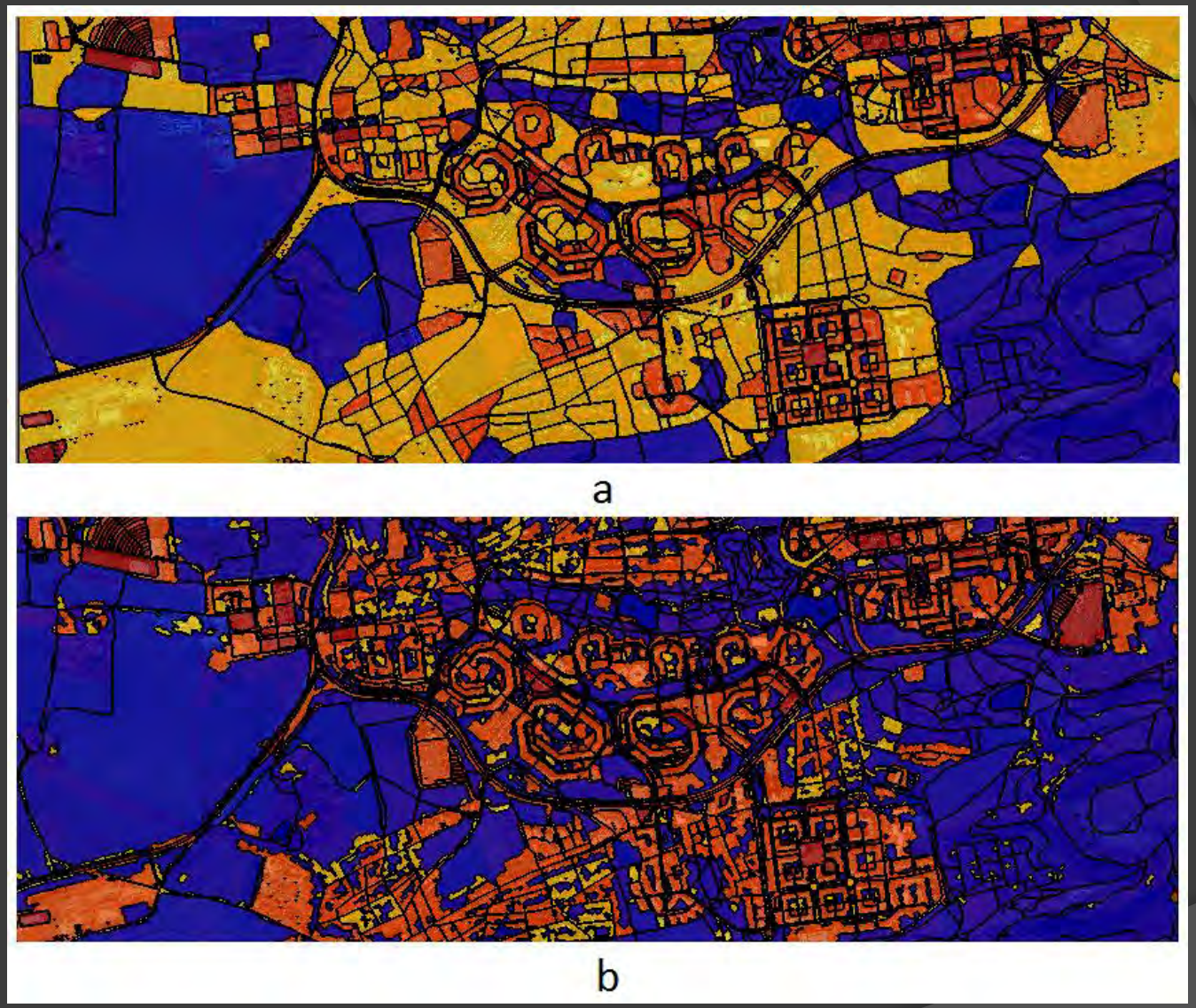




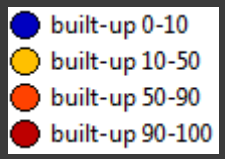
ROAD_SEGMENT level

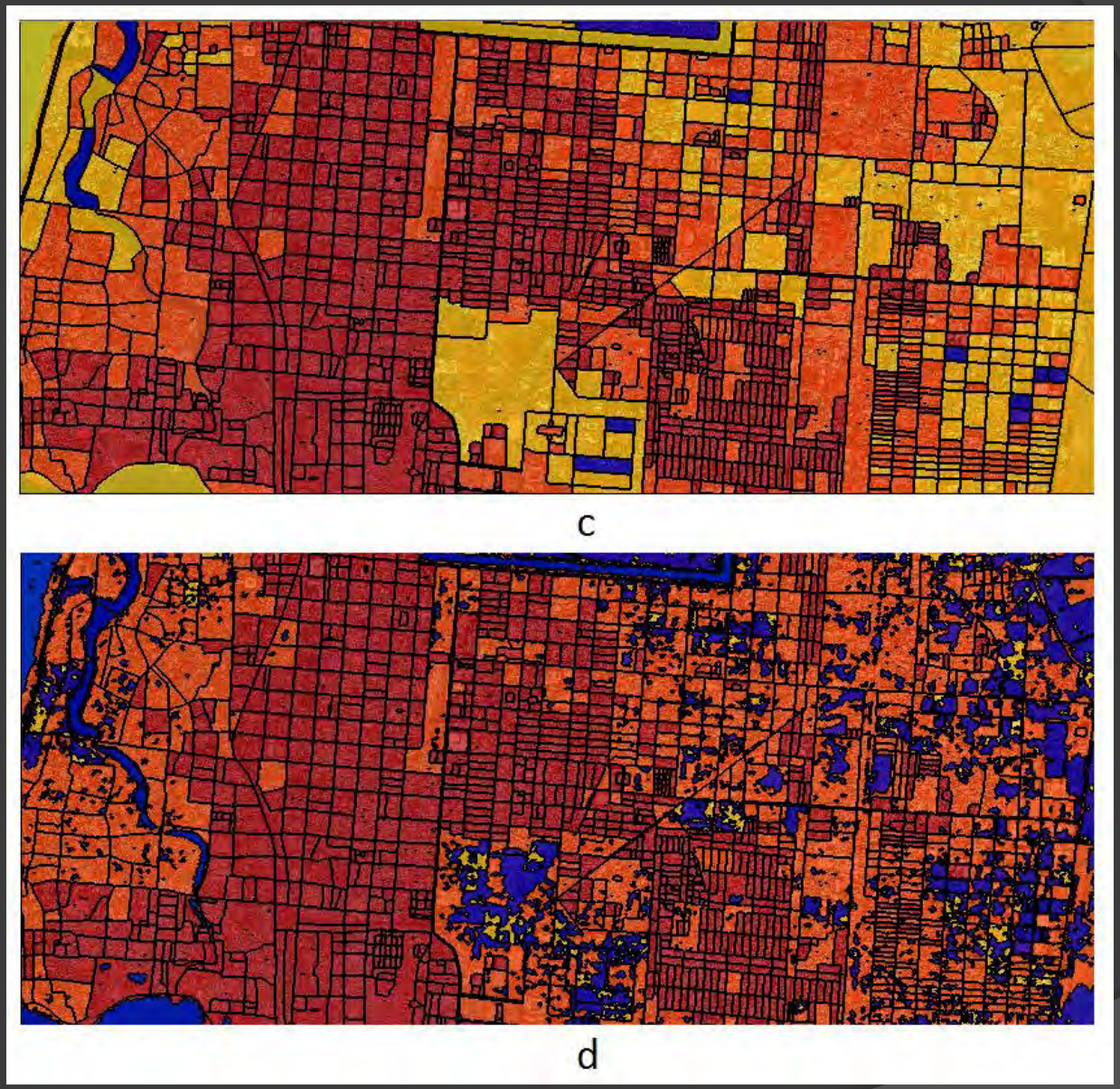
VS

BUILT-UP_DENSITY level



a)Prague subset - built-up density at ROAD_SEGMENT LEVEL
b) built-up density at BUILT-UP DENSITY level



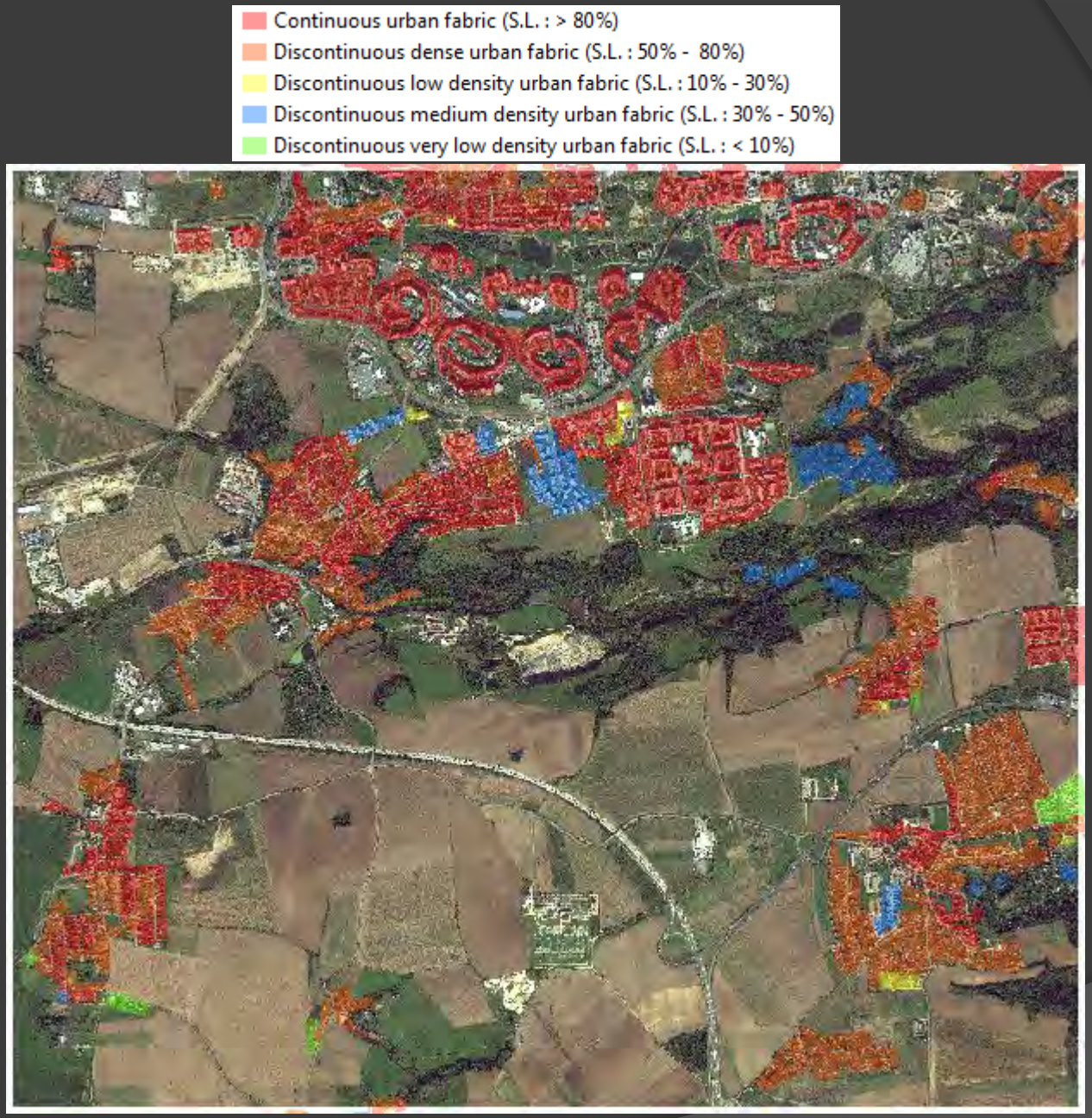


c) Mandalay - built-up density at ROAD_SEGMENT LEVEL
d) built-up density at BUILT-UP DENSITY level

Built-up density accuracy assessment

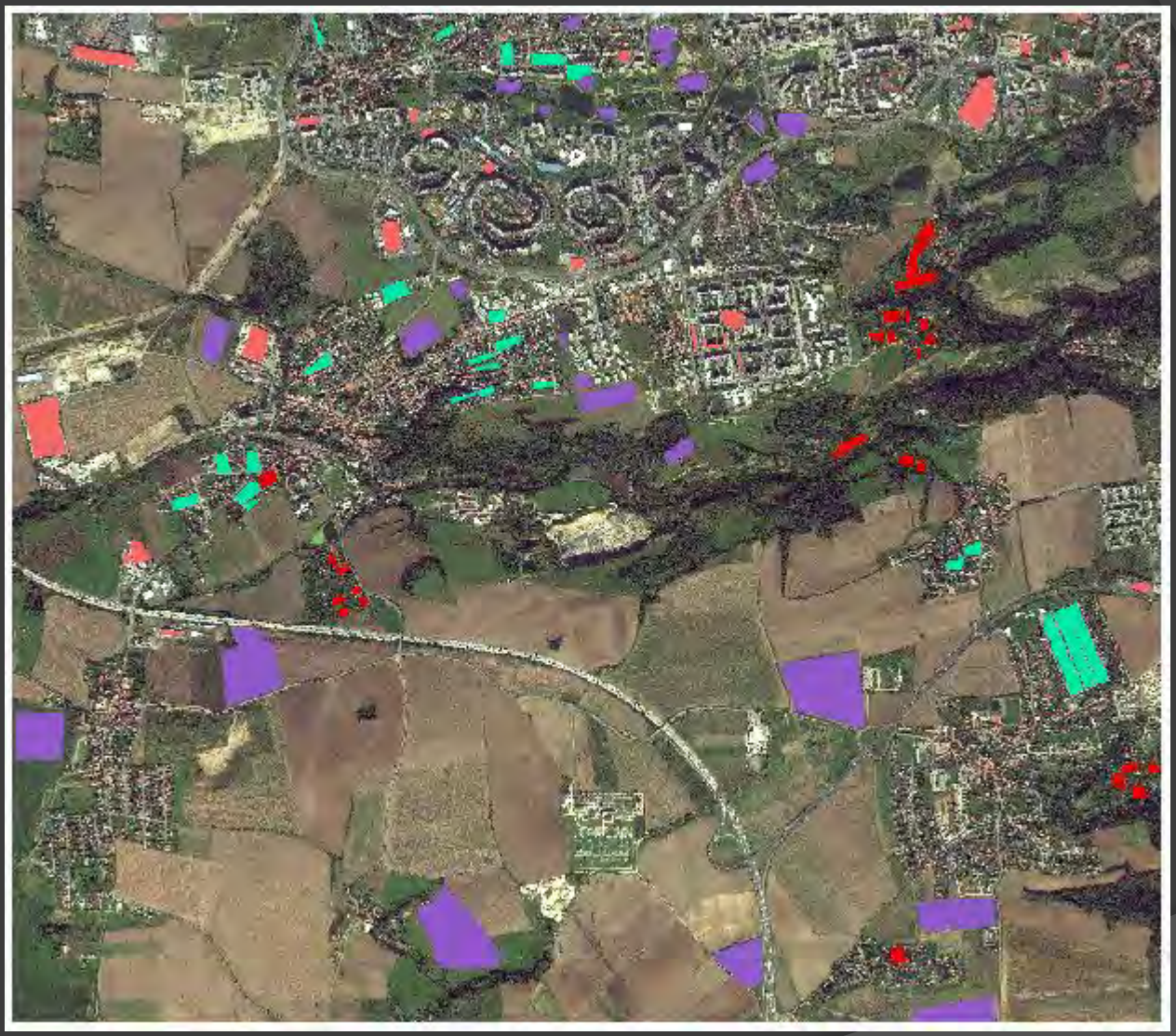
- Digitizing reference polygons by visual interpretation from VHR image
- Comparing to the result of classification
- Built-up density accuracy assessment – reference polygons

  guiding reference (only Prague):
  - Urban Atlas – urban fabric (European Environment Agency)
  - HRL Imperviousness (Copernicus land monitoring service)

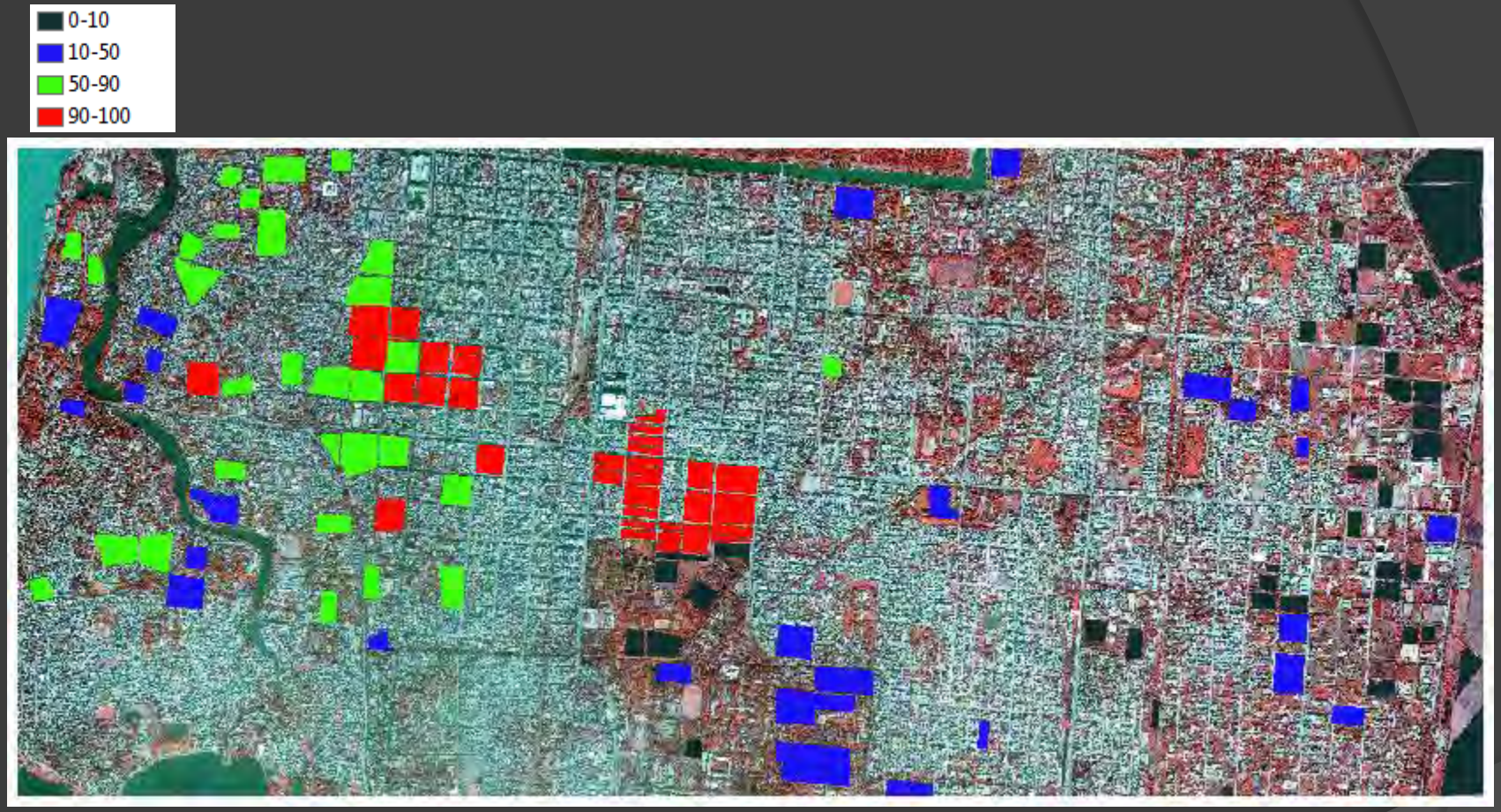


Urban Atlas – urban fabric (European Environment Agency)

HRL Imperviousness (Copernicus land monitoring service)



Prague – Built-up density reference polygons



Mandalay– Built-up density reference polygons

Prague – BUILT-UP_DENSITY level- built-up density classification - confusion matrix										
Reference polygon built-up density class										
	0-10		10-50		50-90		90-100		Total	
Classification	px	%	px	%	px	%	px	%	px	%
built-up 0-10	2416965	99.3	292281	81.62	162039	23.31	13844	1.99	2885129	69
built-up 10-50	12919	0.53	51187	14.29	278772	40.11	1183	0.17	344061	8.23
built-up 50-90	3804	0.16	14311	4	248586	35.76	380925	54.87	647626	15.49
built-up 90-100	282	0.01	316	0.09	5671	0.82	298246	42.96	304515	7.28
Total	2433970	100	358095	100	695068	100	694198	100	4181331	100

Overall Accuracy = (3014984/4181331) 72.1058%

Kappa Coefficient = 0.4960

confusion matrix for built-up density classification on the BUILT-UP_DENSITY level - Prague

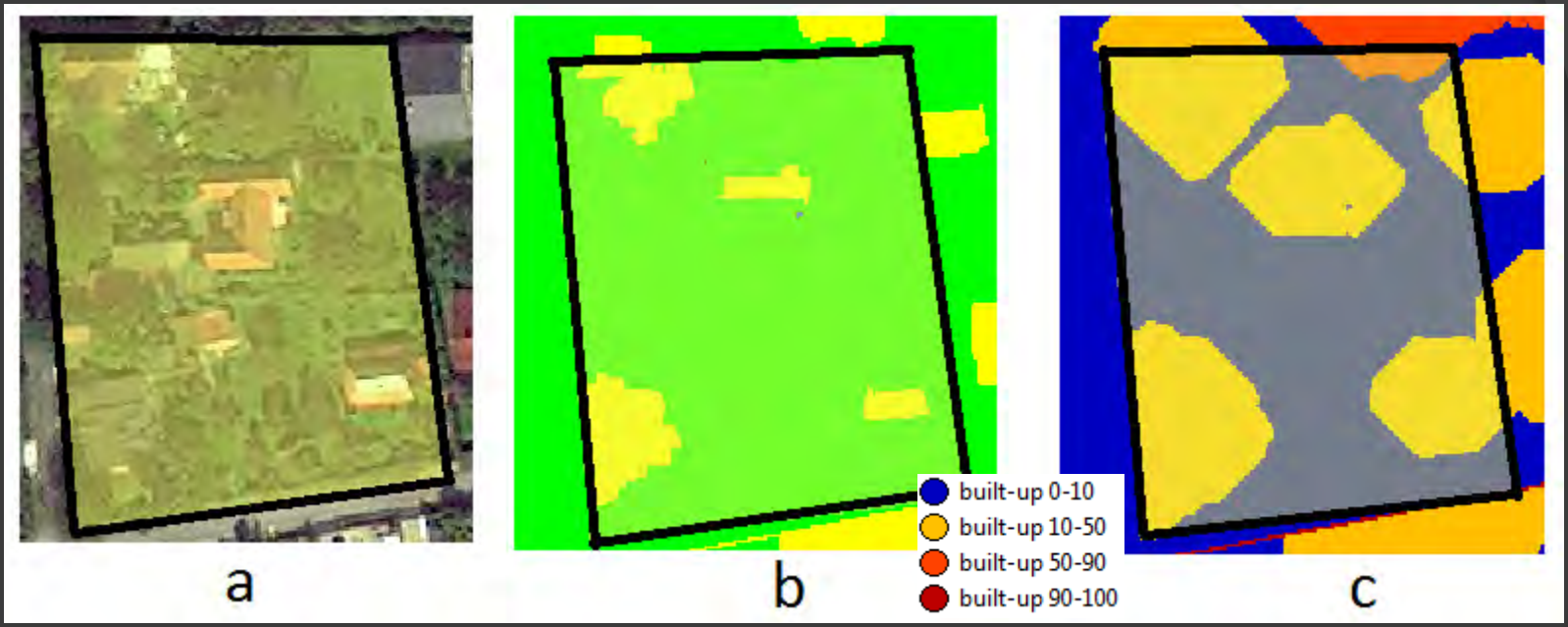
Mandalay – BUILT-UP_DENSITY level - built-up density classification - confusion matrix										
Reference polygon built-up density class										
	0-10		10-50		50-90		90-100		Total	
Classification	px	%	px	%	px	%	px	%	px	%
built-up 0-10	2210533	77.47	1160026	43.59	95894	3.77	1356	0.06	3467809	33.53
built-up 10-50	119011	4.17	459305	17.26	35671	1.4	0	0	613987	5.94
built-up 50-90	522978	18.33	996602	37.45	1467921	57.76	124645	5.45	3112146	30.09
built-up 90-100	921	0.03	45259	1.7	941980	37.06	2160821	94.49	3148981	30.45
Total	2853443	100	2661192	100	2541466	100	2286822	100	10342923	100

Overall Accuracy = (6298580/10342923) 60.8975%

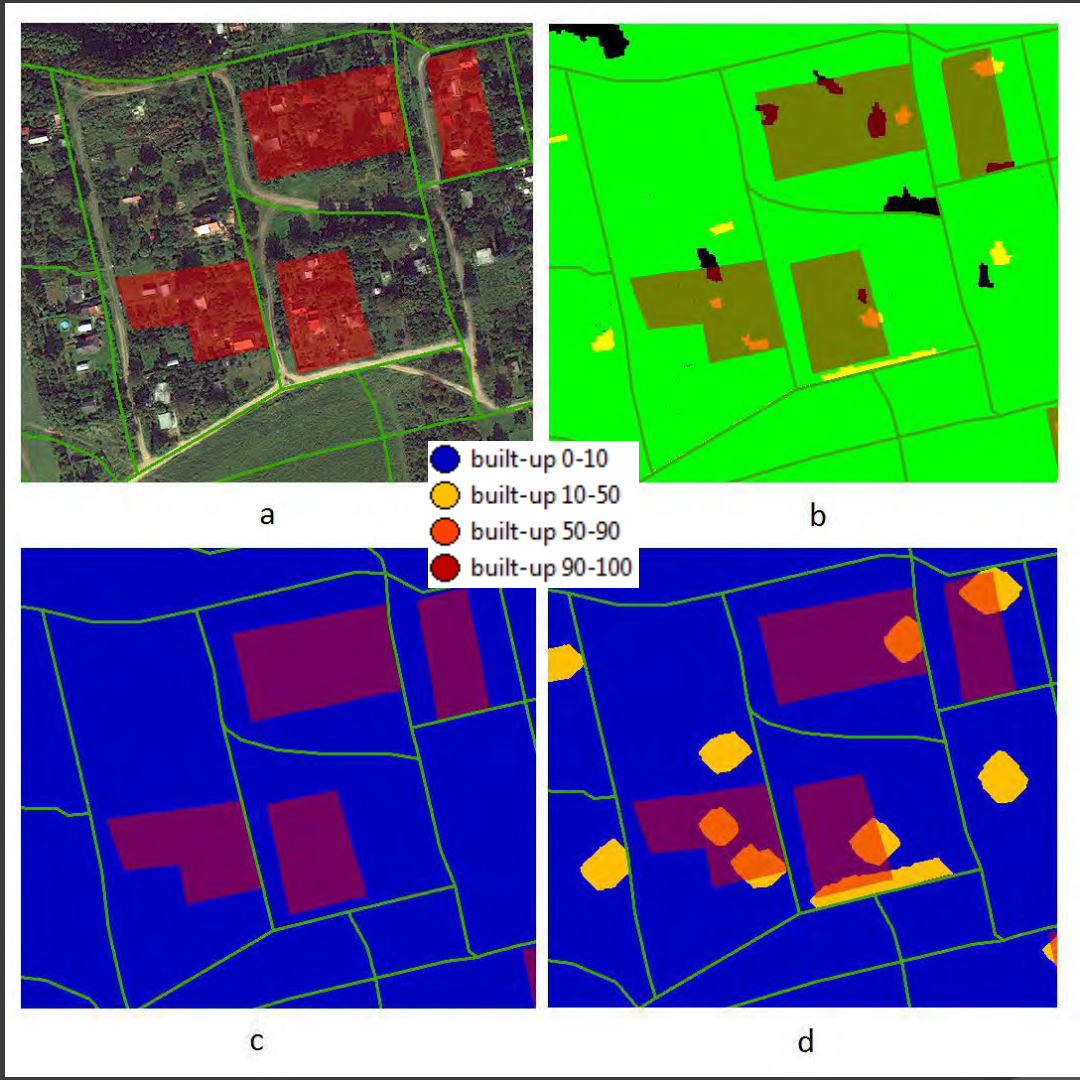
Kappa Coefficient = 0.4793

confusion matrix for built-up density classification on the BUILT-UP_DENSITY level - Mandalay

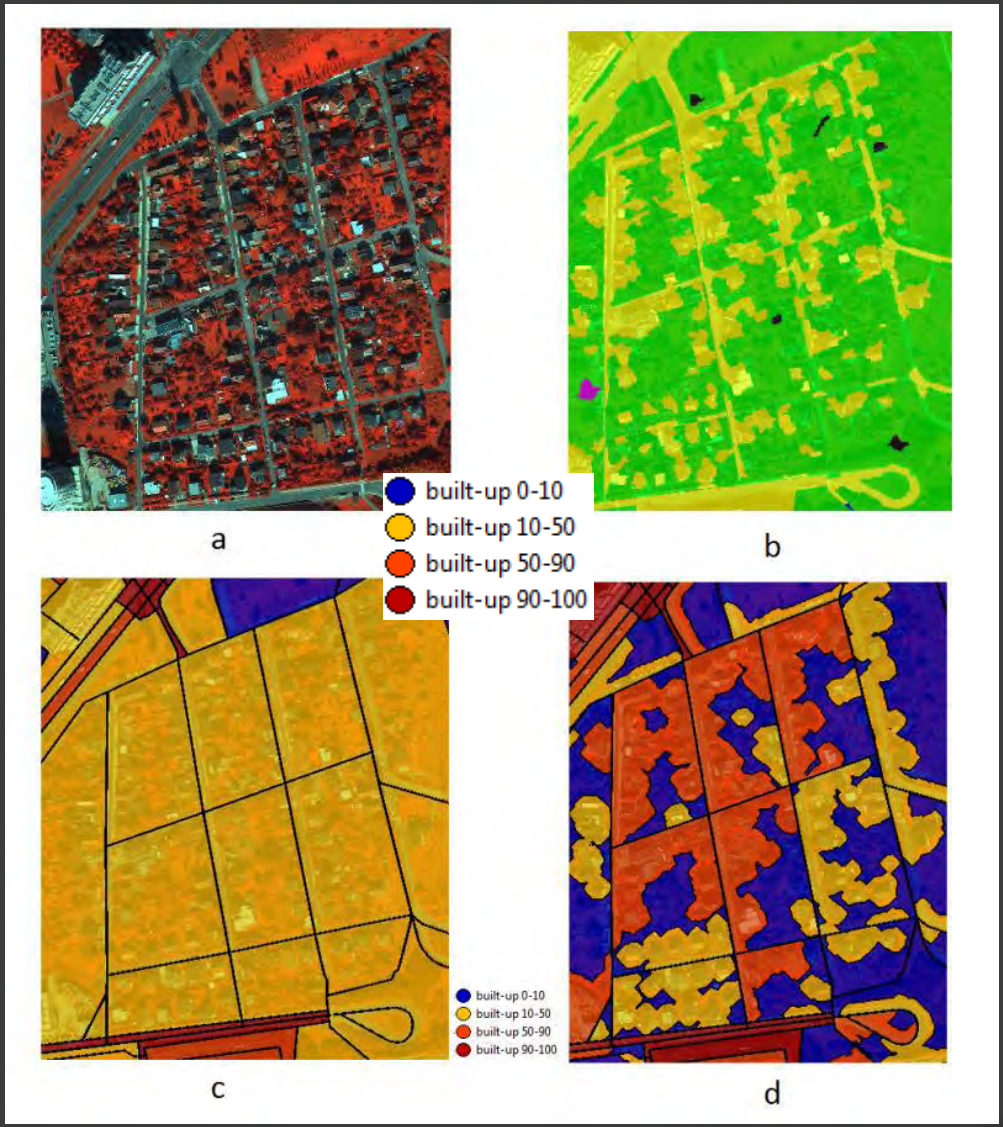
Issue 1 - unsuccessful broader delineation of sparsely built up areas (10-50%)



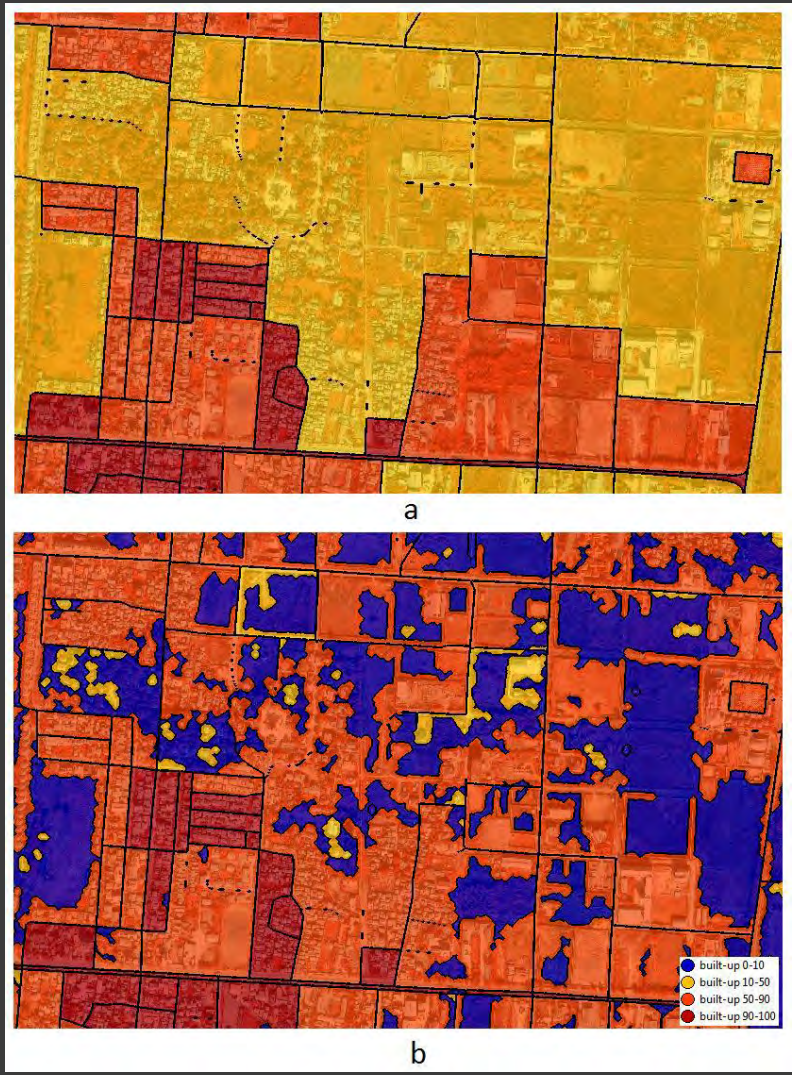
a) original image (*Yellow transparent box with black borders = built-up density* reference polygon **)**
b) land cover classification (yellow = built-up)
c) built-up density classification (yellow = built-up *10-50%) on* BUILT-UP_DENSITY level



a) original VHR image: red polygon = *10-50% reference polygon, green lines=road network*
b) land cover classification: yellow=built-up, green=vegetation, black=unclassified
c) built-up density classification on ROAD_SEGMENT level
d) built-up density classification on BUILT-UP_DENSITY level



a) original image
b) land cover classification
c) built-up density at ROAD_SEGMENT level
d) built-up density at refined BUILT-UP_DENSITY level



a) built-up density classification on the ROAD_SEGMENT level
b) built-up density classification on the BUILT-UP_DENSITY level

Transferability

- Rule Set was developed on a subset of Mandalay image, later tested on Prague image
- The classification part of the Rule Set was optimized for each image
- Image object refinement was uniform for both images
- The results are comparable in both images

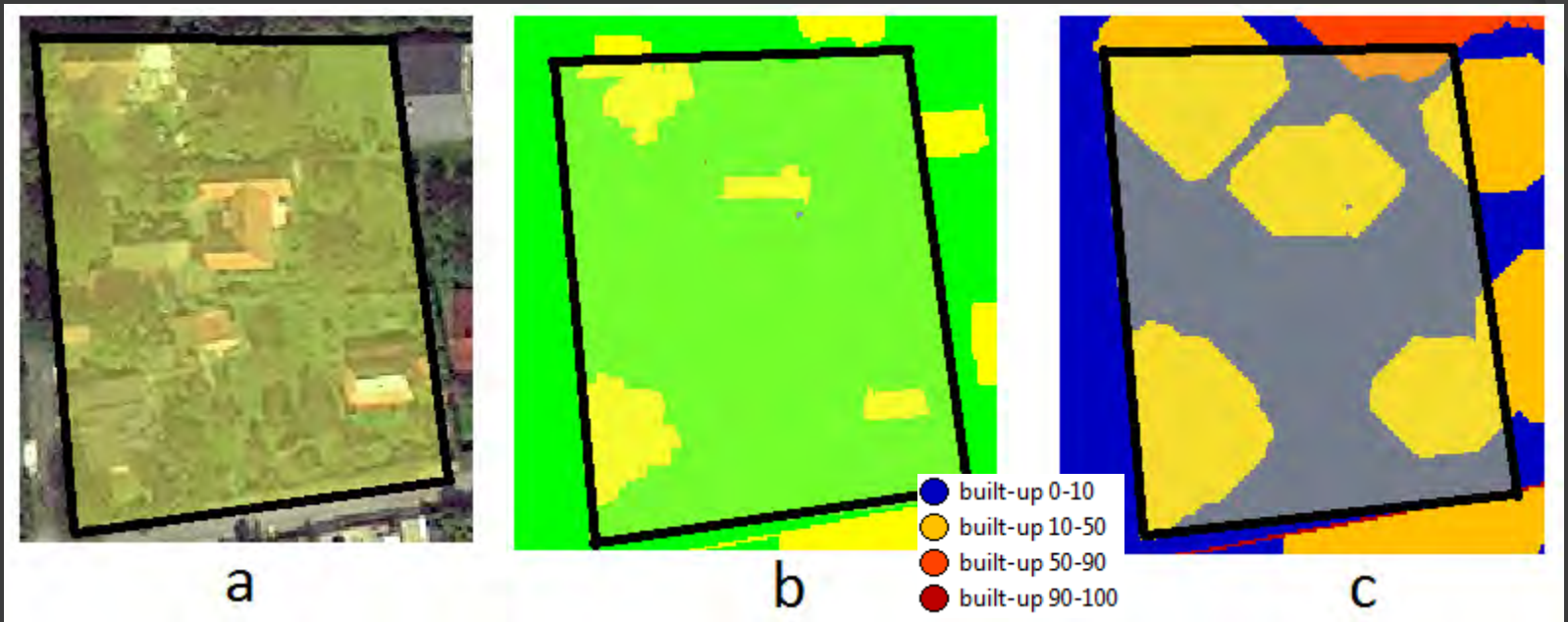
Conclusion

- Image processing workflow was implemented
- Segmentation results were refined to represent broader built-up area – pixel based grow, shape refinement
- Built-up density was calculated
- Segments were classified into 4 built-up density classes
- Transferability was tested - classification optimization needed

Possible improvements and future work

- Using ancillary data (DSM, SAR, vector data) to increase the accuracy of LC classification
- Obtain realiable reference data
- Implement rules for restriction of the grow algorithm only towards densely built-up areas – also deliniation of sparsely built-up areas
- Consider size, shape or color of the buildings to estimate functional use of the built-up area segment
- Classify urban typology

Issue 1 - unsuccessful broader delineation of sparsely built up areas (10-50%)



a) original image (*Yellow transparent box with black borders = built-up density* reference polygon **)**
b) land cover classification (yellow = built-up)
c) built-up density classification (yellow = built-up *10-50%) on* BUILT-UP_DENSITY level

References

- Benz, U., Hofmann, P., Willhauck, G., Lingenfelder, I., and Heynen, M., 2004. “Multiresolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information”. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 58, pp. 239– 258.
- Blaschke, T., Lang, S., Lorup, E., Strobl, J., and Zeil, P., 2000. “Object-oriented image processing in an integrated GIS/remote sensing environment and perspectives for environmental applications”. In: Cremers, A., and Greve, K., eds. Environmental Information for Planning, Politics and the Public, vol. 2, Marburg, Metropolis.
- Divyani Kohli, Pankaj Warwadekar, Norman Kerle, Richard Sliuzas, and Alfred Stein., 2013. "Transferability of Object-Oriented Image Analysis Methods for Slum Identification." MDPI.
- eCognition Reference Book, 2014. Trimble eCognition® Reference Book (Munich, Germany: Trimble Germany GmbH).
- Hamedianfar, Alireza, and Helmi Zulhaidi Mohd Shafri, 2015. “Detailed Intra-Urban Mapping through Transferable OBIA Rule Sets Using WorldView-2 Very-High- Resolution Satellite Images.” International Journal of Remote Sensing, vol. 36, no. 13, pp. 3380–3396.

References

- Herold, M., 2002. “Object-oriented mapping and analysis of urban land use/cover using IKONOS data”. In: Proceedings of 22nd EARSEL Symposium ‘Geoinformation for Europeanwide Integration’, Rotterdam, Millpress.
- Jalan, S., 2011. “Exploring the Potential of Object Based Image Analysis for Mapping Urban Land Cover.” Journal of the Indian Society of Remote Sensing, vol. 40, no., pp. 507–518. doi:10.1007/s12524-011-0182-3.
- Karathanassi, V., Iossifidis, C.H., and Rokos, D., 2000. “A texture-based classification method for classifying built areas according to their density”. International Journal of Remote Sensing, 21, 1807–1823.
- Paul, Obade Vincent De., 2007. "Remote Sensing: New Applications for Urban Areas." Proceedings of the IEEE 2267-268.
- Walker, J. S., and T. Blaschke., 2008. “Object-Based Land-Cover Classification for the Phoenix Metropolitan Area: Optimization vs. Transportability.” International Journal of Remote Sensing, vol. 29, no. 7, pp. 2021–2040.

Thank you

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