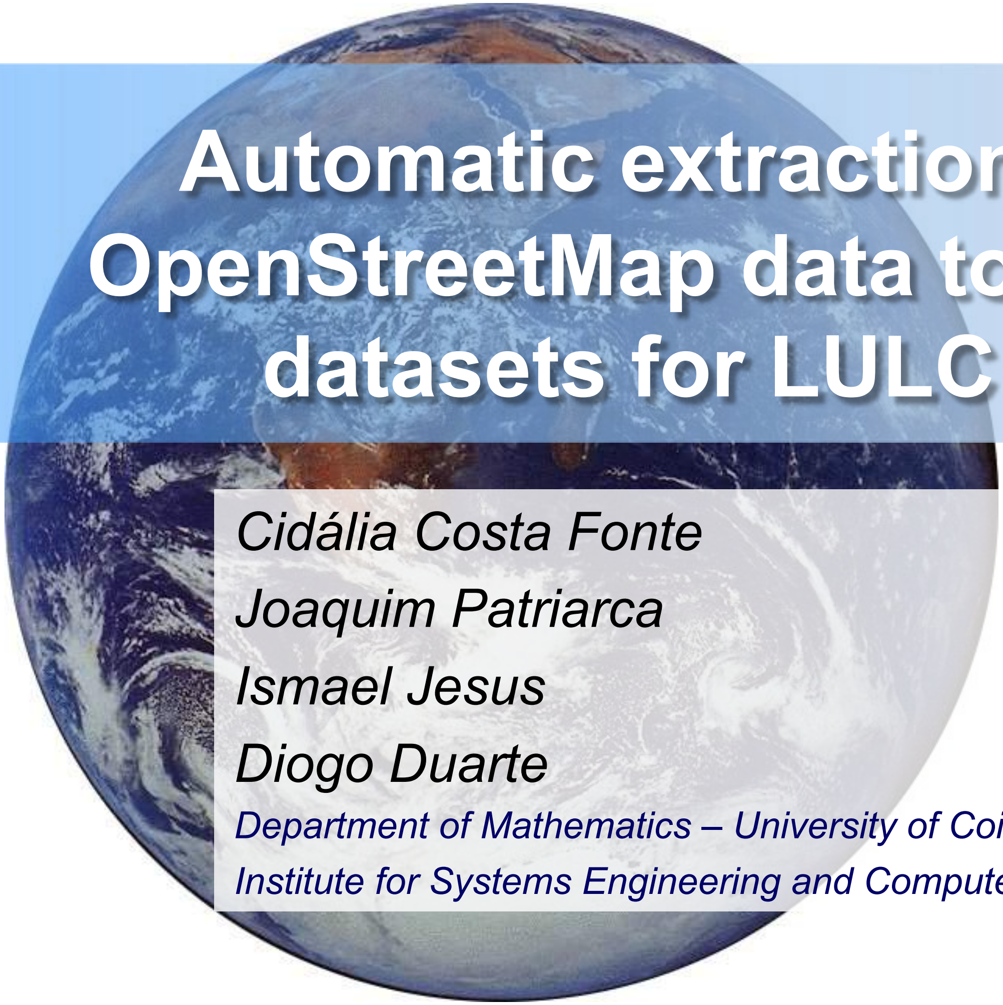
THE USE OF VOLUNTEER GEOGRAPHIC INFORMATION FOR PRODUCING AND MAINTAINING AUTHORITATIVE LAND USE AND LAND COVER DATA



Automatic extraction and filtering of OpenStreetMap data to generate training datasets for LULC classification

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Summary

- Objective
- The OpenStreetMap (OSM) project and data
- Conversion of OSM data into LULC data
- Study areas
- Methodology to extract and filter OSM to train classifiers
- Results
- Conclusions

Objective

- Test an automated methodology for generating training data from OpenStreetMap (OSM) to classify Sentinel-2 imagery into Land Use/Land Cover (LULC) classes

- The methodology filters data extracted from OSM to generate high quality training data

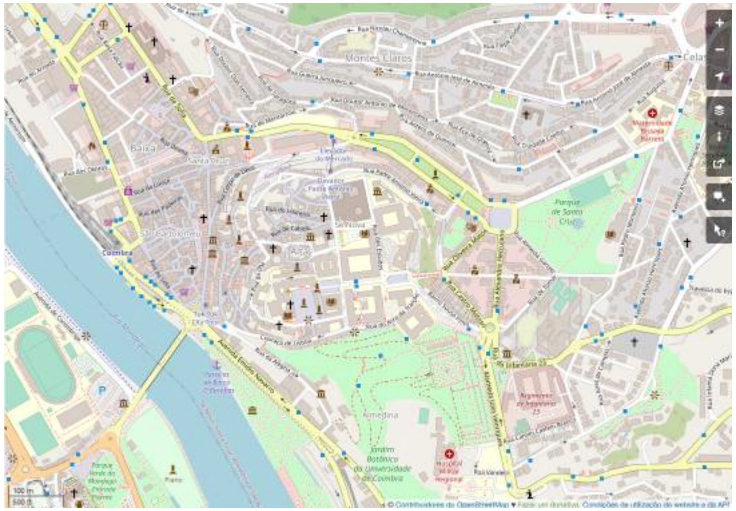
OSM project and OSM data

- OpenStreetMap (OSM) (http://www.openstreetmap.org/)
  - Project created in 2004 in the United Kingdom
  - Objective
    - Create geospatial data with open access

Pavilhão Carlos Lopes
Carlos Lopes
Miraparque
Avenida Sidónio Pais
Sidónio Pais
Avenida António Augusto Aguiar
Turim Europa Hotel
Rua de São Sebastião da Pedreira
HF Fénix Urban
Ordem dos Engenheiros Região Sul
Eduardo VII
O Cardo
Restaurante Sapore
Banco Finantia Centro de Investimento
Instanta
Rua Martens Ferrão
Ciclovia da Avenida
Avenida Fontes Pereira de Melo
Virgin Active Palácio SottoMayor
Palácio Sotto Mayor
Largo do Andaluz
Rua do Andaluz
Arroios
Cofiquina
Rua Luciano Cordeiro
Rua Sousa Martins
Maria Picoas
Pastelaria Restaurante Tentações
Futura clínica
Residência Erasmus UTL
Vasco Lx
Avenida Duque de
Dom Carlos Park

- Geospatial entities available in OSM
  - http://wiki.openstreetmap.org/wiki/Map_Features

OSM data



OSM – Coimbra (Portugal)

Kaisermühlen
Donauinsel
Stadlau
Praterbrücke
Prater Hauptallee

OSM – Vienna (Austria)

Porte de Vincennes
Saint-Mandé
Avenue de Paris

OSM – Paris (France)

Porta Nuova
Moscova
Parco Sempione
Giardini pubblici Indro Montanelli
Porta Venezia
Brera
Porta Monforte
San Babila
Duomo

OSM – Milan (Italy)

OSM data

- Why use OSM for training?
  - Detailed data is available
  - Includes local knowledge
  - Can be automatically downloaded

May increase speed + lower costs

Automate

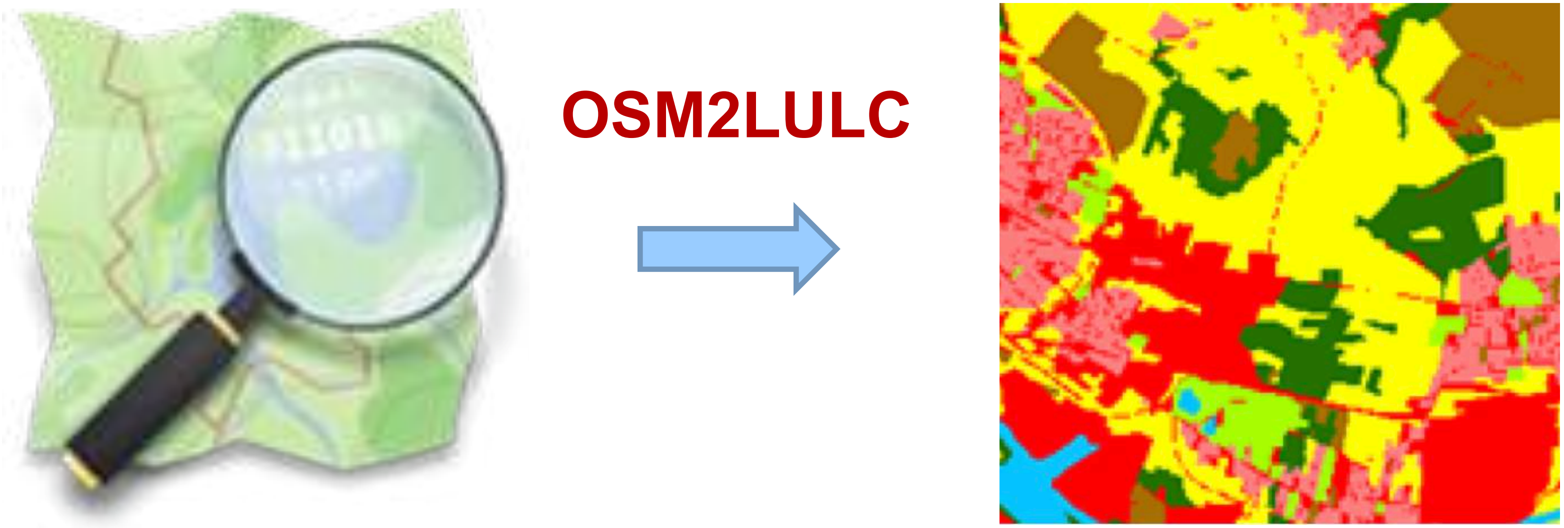
OSM data for training

Main challenge

Obtain high quality training data

OSM conversion to LULC maps

- Tool to **convert automatically** the data available in OSM into a LULC map



OSM2LULC

Patriarca, J., Fonte, C.C., Estima, J., Almeida, J.P., Cardoso, A. (2019) Automatic conversion of OSM data into LULC maps: comparing FOSS4G based approaches towards an enhanced performance. Open Geospatial Data, Software and Standards., 4: 11. DOI: 10.1186/s40965-019-0070-2

Fonte, C.C., Patriarca, J., Minghini, M., Antoniou, V., See, L., Brovelli, M.A. (2017). Using OpenStreetMap to create land use and land cover maps: development of an application. In: Campelo, C.E.C., Bertolotto, M., Corcoran, P. (Eds.), *Volunteered Geographic Information and the Future of Geospatial Data*. IGI Global, Hershey, pp. 113 - 137. ISBN: 9781522524465. DOI: 10.4018/978-1-5225-2446-5.ch007

OSM conversion to LULC maps

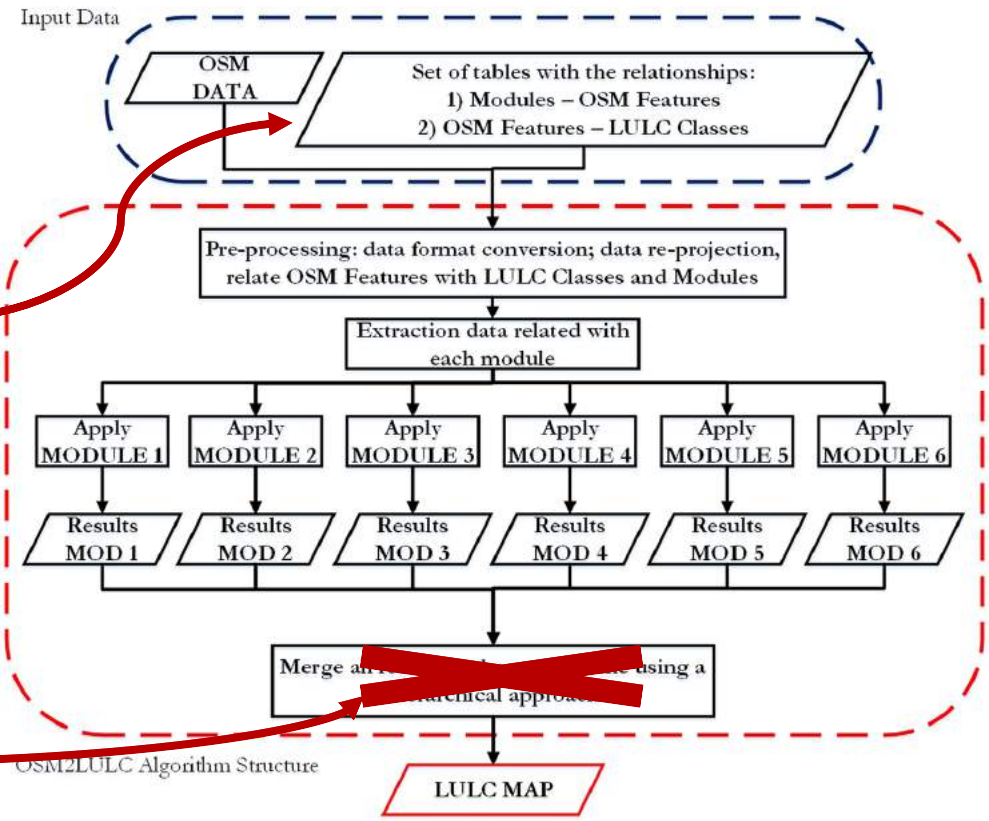
- OSM2LULC
  - Structured into 6 modules
  - Four versions available (1.2 – 1.4)
    - Using different technologies
      - GRASS GIS
      - PostGIS
      - GDAL
      - Numpy
    - With vector and raster outputs
  - Three output nomenclatures
    - Urban Atlas (UA)
    - Corine Land Cover (CLC)
    - GlobeLand 30 (GL30)
- A modified version of OSM2LULC was used
  - OSM2LULC-4T
    - CLC output nomenclature

OSM conversion to LULC maps

- OSM2LULC-4T
  - Version 1.2
    - Vector output

Some modifications

Association OSM features - LULC class


Input Data
OSM DATA
Set of tables with the relationships:
1) Modules – OSM Features
2) OSM Features – LULC Classes
Pre-processing: data format conversion; data re-projection, relate OSM Features with LULC Classes and Modules
Extraction data related with each module
Apply MODULE 1
Apply MODULE 2
Apply MODULE 3
Apply MODULE 4
Apply MODULE 5
Apply MODULE 6
Results MOD 1
Results MOD 2
Results MOD 3
Results MOD 4
Results MOD 5
Results MOD 6
~~Merge all results using a hierarchical approach~~
LULC MAP

OSM2LULC Algorithm Structure

Methodology to extract and filter OSM to train classifiers

- Concept:
  - The data extracted from OSM is filtered
    - To remove regions with higher uncertainty or that changed

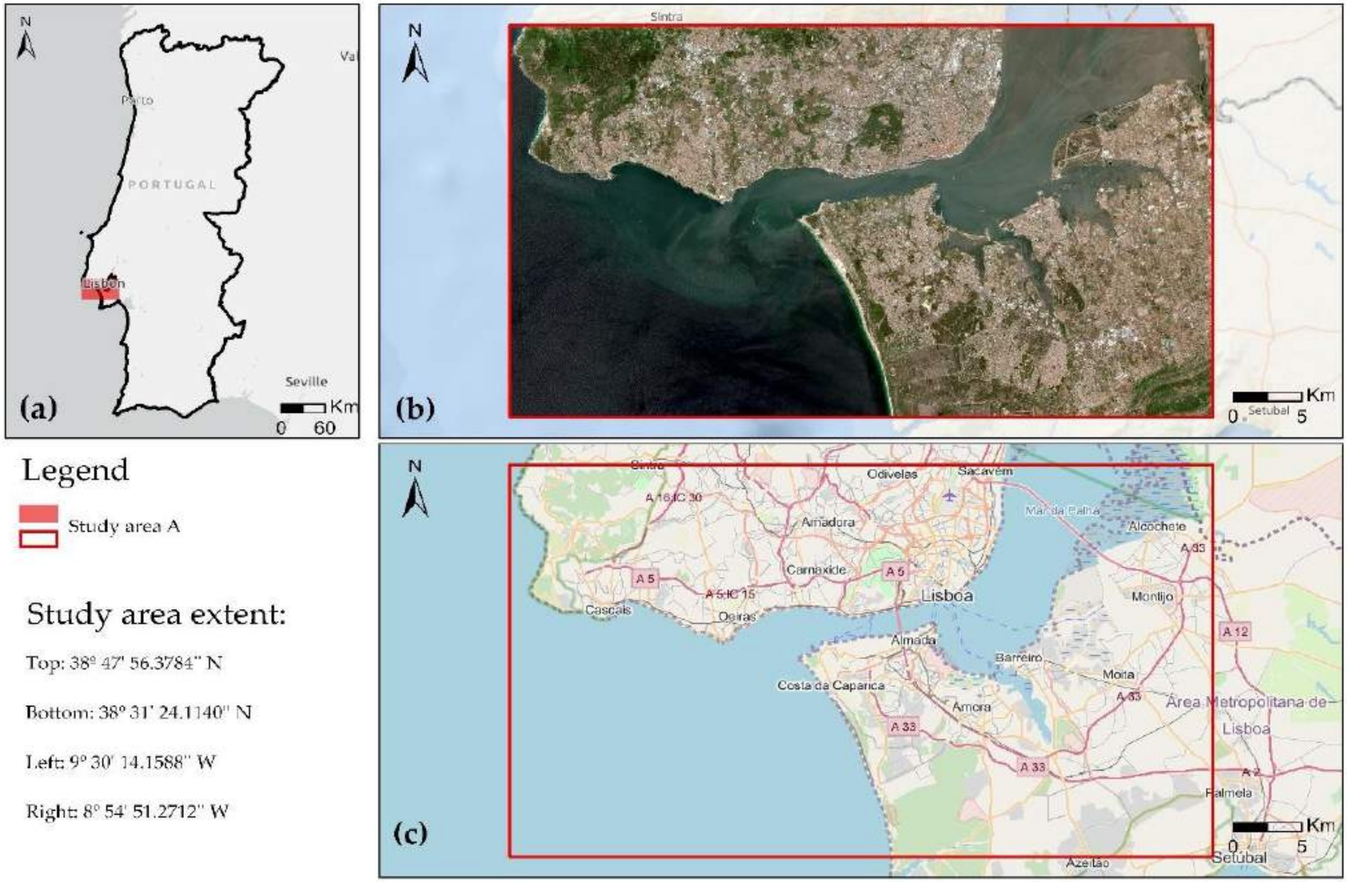
Based on:

Uncertainty due to possible overlaping classes in the pixels

Radiometric indices of the images to classify

Case studies

- Case study A



Study area extent:

Top: 38º 47' 56.3784" N

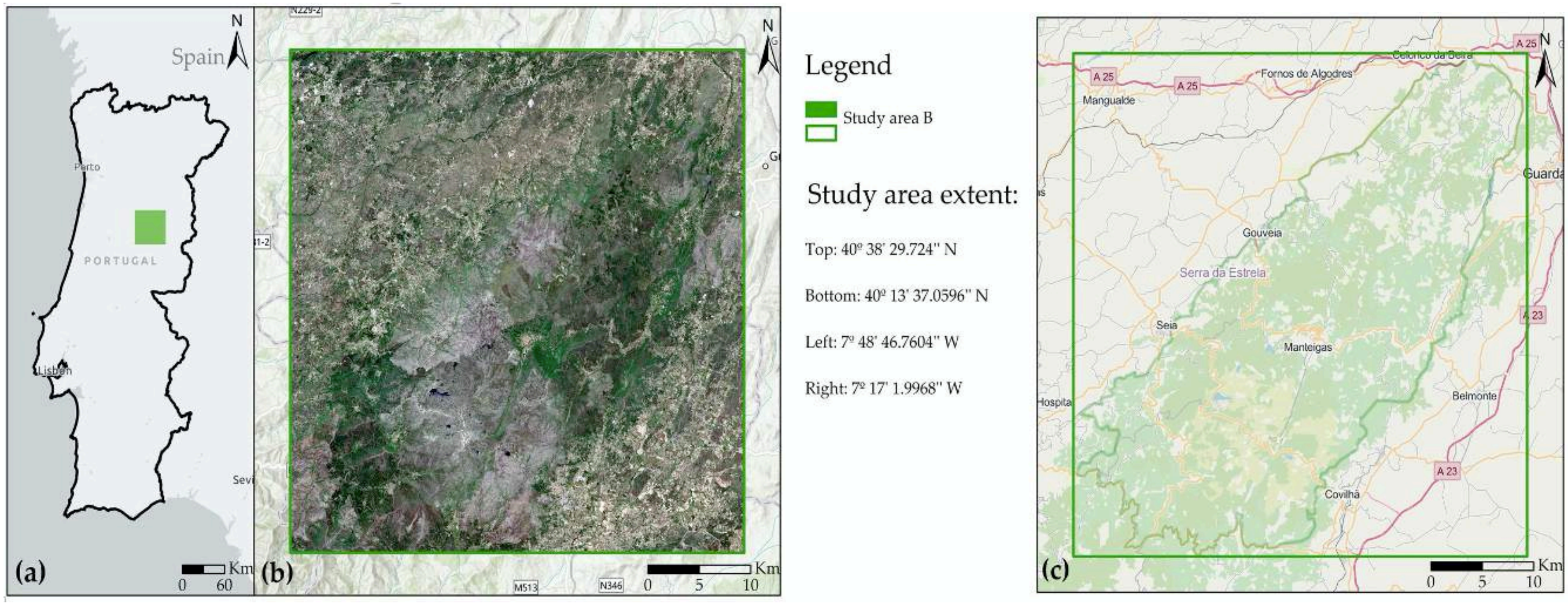
Bottom: 38° 31' 24.1140" N

Left: 9° 30' 14.1588" W

Right: 8° 54' 51.2712" W

Case studies

- Case study B



Methodology to extract and filter OSM to train classifiers

- Used data:
  - OSM for training
  - Sentinel-2 multiespectral images
    - Only bands B2, B3, B4 and B8
    - Three images were used for each study area

	Satellite	Product Type	Collection date	Sentinel GRID
Study area A	Sentinel-2A	Level-2A	2018-03-21	T29SMC
	Sentinel-2A	Level-2A	2018-06-19	T29SMC
	Sentinel-2B	Level-2A	2018-10-22	T29SMC
Study area B	Sentinel-2B	Level-2A	2018-03-26	T29TPE
	Sentinel-2A	Level-2A	2018-06-19	T29TPE
	Sentinel-2B	Level-2A	2018-10-22	T29TPE

  - Portuguese Land Cover Map (COS 2018)
    - With nomenclature harmonization
    - As reference data

Methodology to extract and filter OSM to train classifiers

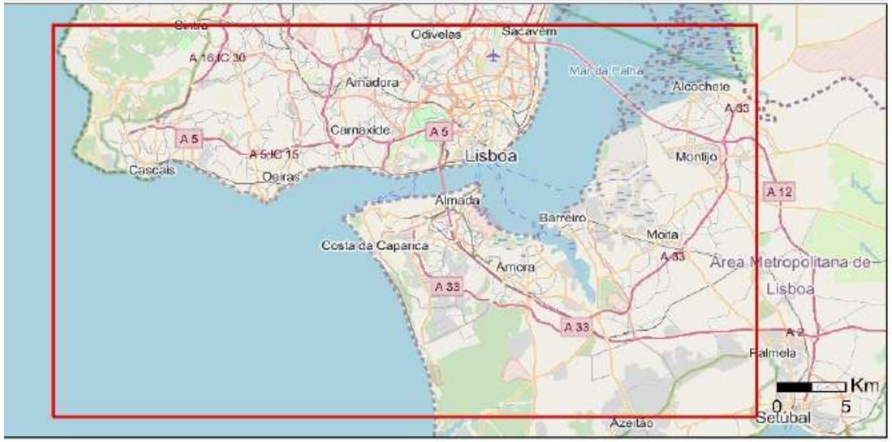
- Nomenclature harmonization

Used classes	OSM2LULC	COS 2018
1. Artificial surfaces	1.1 Urban fabric 1.2 Industrial, commercial and transport units 1.3 Mine, dump and construction sites 1.4.2 Sport and leisure facilities (excluding golf courses)	1 Artificial surfaces, excluding: - Golf courses (1.6.1.1) - Public gardens and playground (1.7.1.1)
2. Agricultural areas	2.1 Arable land 2.2 Permanent crops 2.4 Heterogeneous agricultural areas	2 Agriculture
3. Herbaceous vegetation	1.4.1 Green urban areas 2.3 Pastures 3.2.1 Natural grasslands 1.4.2 Sport and leisure facilities (only golf courses)	3 Herbaceous 1.6.1.1 Golf courses 1.7.1.1 public gardens and playgrounds
4. Forest areas	3.1 Forests	4 Agroforestry 5 Forestry
5. Shrublands	3.2.4 Transitional woodland-shrub	6 Shrublands
6. Open spaces with little or no vegetation	3.3 Open spaces with little or no vegetation	7 Open spaces with little or no vegetation
7. Wetlands	4 Wetlands	8 Wetlands
8. Water bodies	5.1 Inland waters 5.2 Marine waters	9 Water bodies

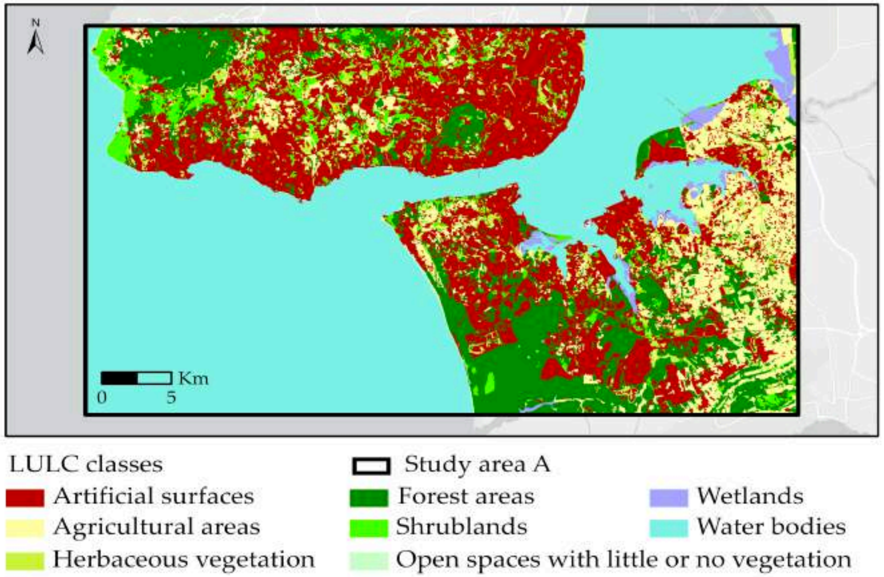
Case studies

- Case study A

Sintra
Km
0
Setubal
5

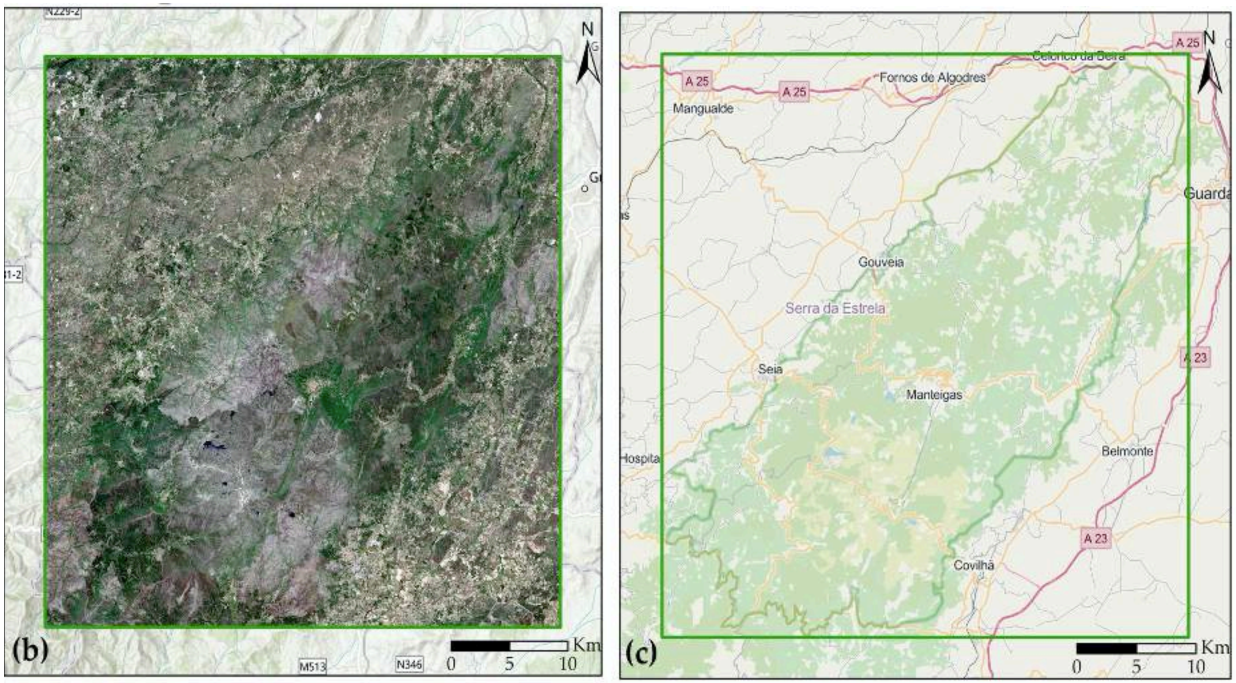


COS derived reference data

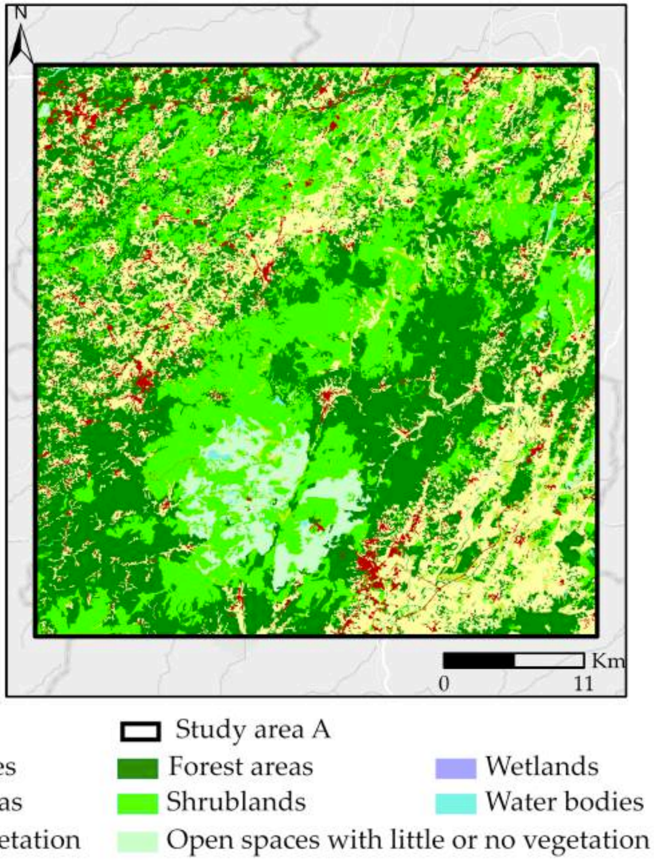


Case studies

- Case study B

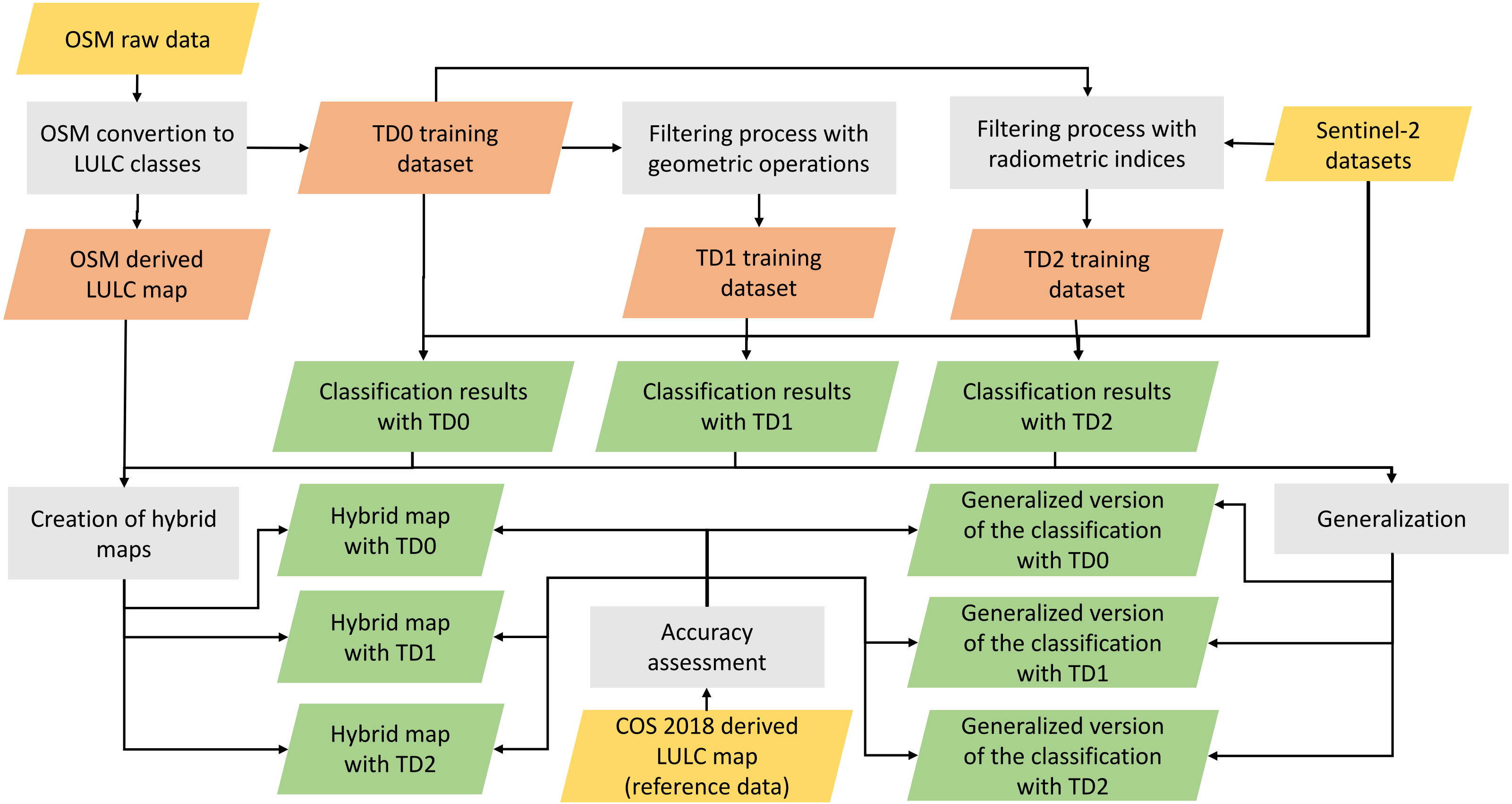


COS derived reference data



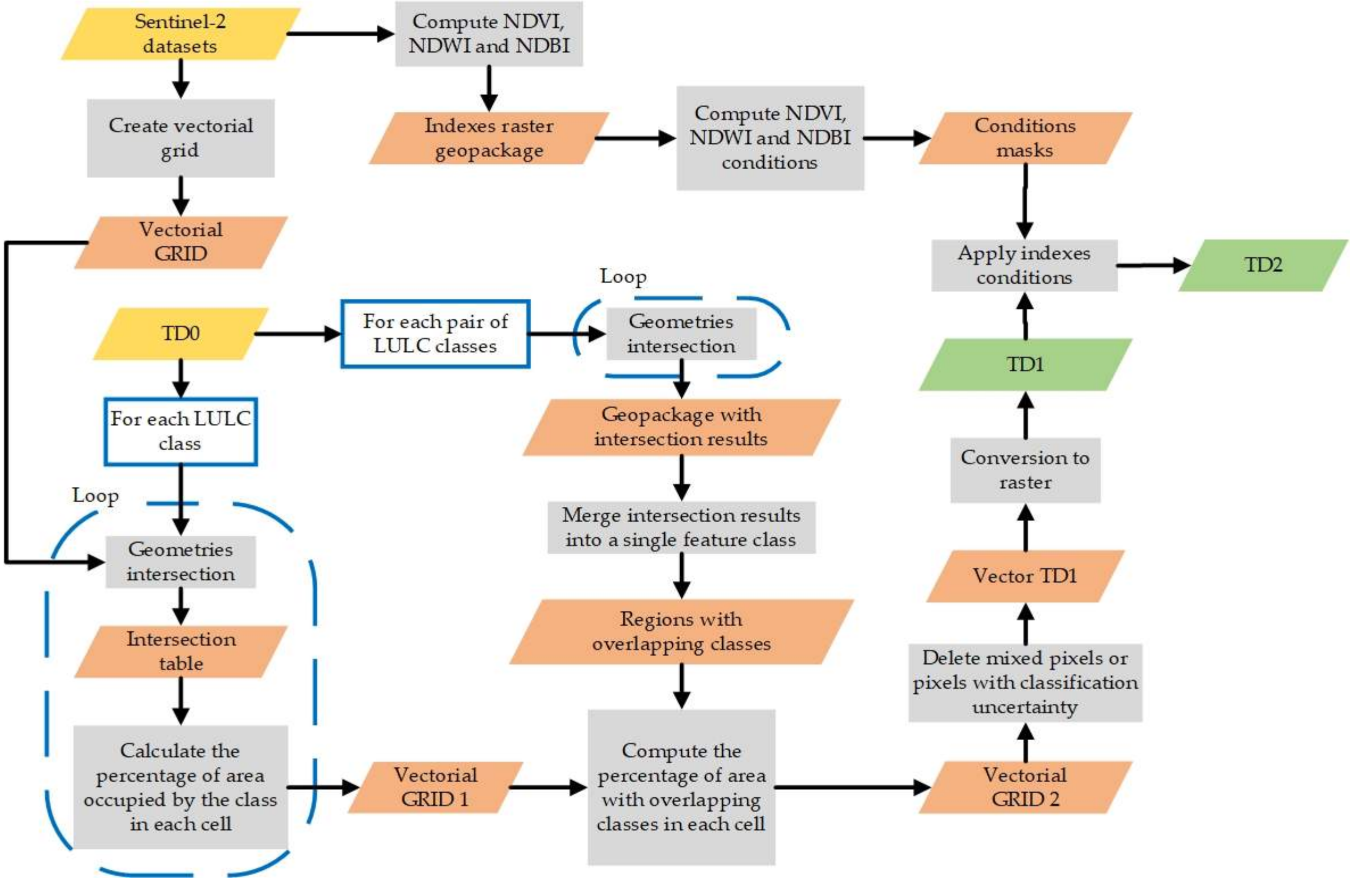
Methodology to extract and filter OSM to train classifiers

- Workflow


OSM raw data
OSM convertion to LULC classes
TD0 training dataset
Filtering process with geometric operations
Filtering process with radiometric indices
Sentinel-2 datasets
OSM derived LULC map
TD1 training dataset
TD2 training dataset
Classification results with TD0
Classification results with TD1
Classification results with TD2
Creation of hybrid maps
Hybrid map with TD0
Generalized version of the classification with TD0
Generalization
Hybrid map with TD1
Accuracy assessment
Generalized version of the classification with TD1
Hybrid map with TD2
COS 2018 derived LULC map (reference data)
Generalized version of the classification with TD2

Methodology to extract and filter OSM to train classifiers

- Filtering procedures


Sentinel-2 datasets
Compute NDVI, NDWI and NDBI
Create vectorial grid
Indexes raster geopackage
Compute NDVI, NDWI and NDBI conditions
Conditions masks
Vectorial GRID
Apply indexes conditions
TD2
Loop
TD0
For each pair of LULC classes
Geometries intersection
TD1
For each LULC class
Geopackage with intersection results
Conversion to raster
Loop
Merge intersection results into a single feature class
Geometries intersection
Vector TD1
Intersection table
Regions with overlapping classes
Delete mixed pixels or pixels with classification uncertainty
Calculate the percentage of area occupied by the class in each cell
Vectorial GRID 1
Compute the percentage of area with overlapping classes in each cell
Vectorial GRID 2

Methodology to extract and filter OSM to train classifiers

- Training data
  - Classes‘ separability was computed with the Bhattacharyya distance
- Classification
  - Samples of the training sets were used
    - Due to computational constraints
    - Sample size proportional to class area
  - Random forest classified
- Generalization
  - A majority filter - circular moving window with 5 cells - was applied to remove isolated small regions
- Hybrid maps
  - Data from OSM2LULC + classification results
- Accuracy assessment

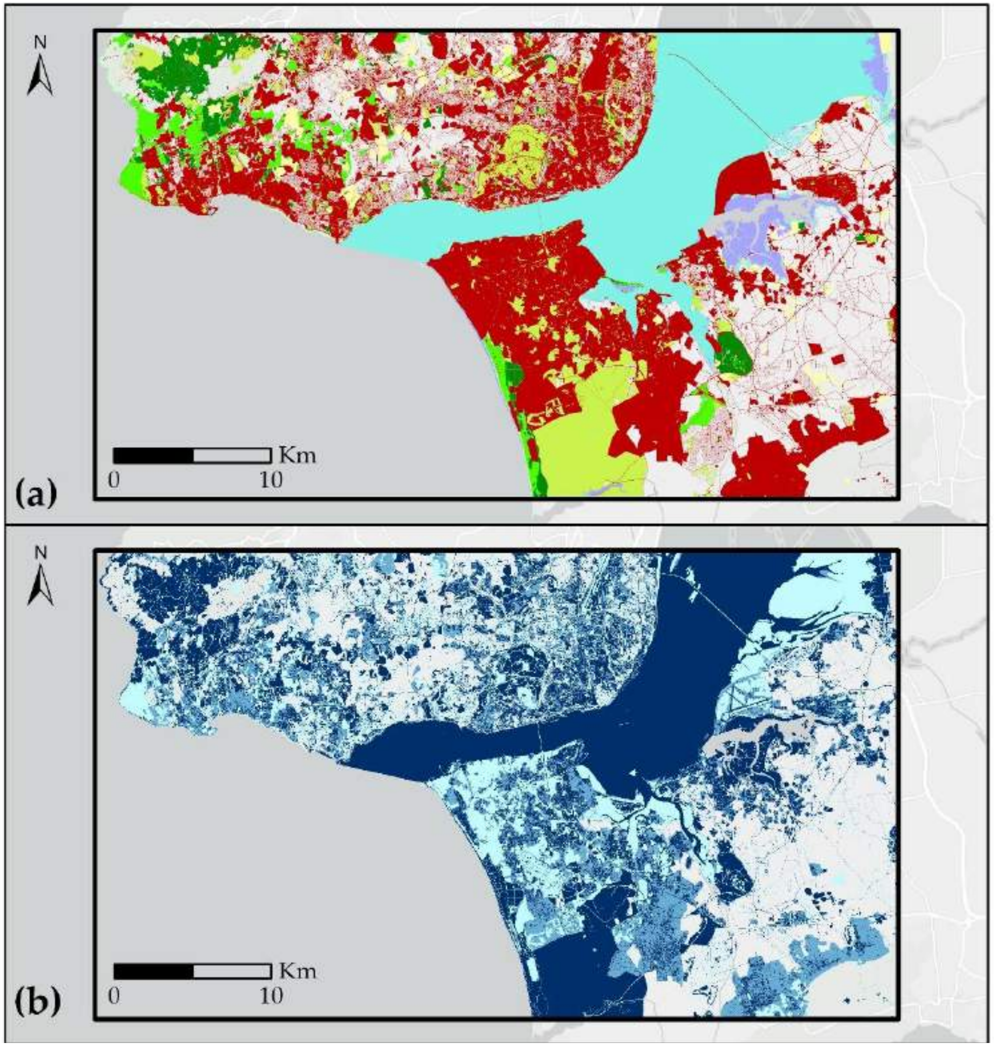
Methodology to extract and filter OSM to train classifiers

- Radiometric indices
  - Conditions used for all the images

Classes	NDVI / images	NDWI / images	NDBI / images
1. Artificial surfaces	< 0.3 / all	< 0.0 / all	> 0.0/at least one
2. Agricultural areas	> 0.3 / all	< 0.0 / all	---
3. Herbaceous vegetation	> 0.3 / all	< 0.0 / all	---
4. Forest areas	> 0.3 / all	< 0.0 / all	---
5. Shrublands	> 0.3 / all	< 0.0 / all	---
6. Open spaces with little or no vegetation	> 0.0/at least one	< 0.0/at least one	---
7. Wetlands	> 0.0/at least one	< 0.0/at least one	---
8. Water bodies	< 0.3/at least one	> 0.0 / all	---

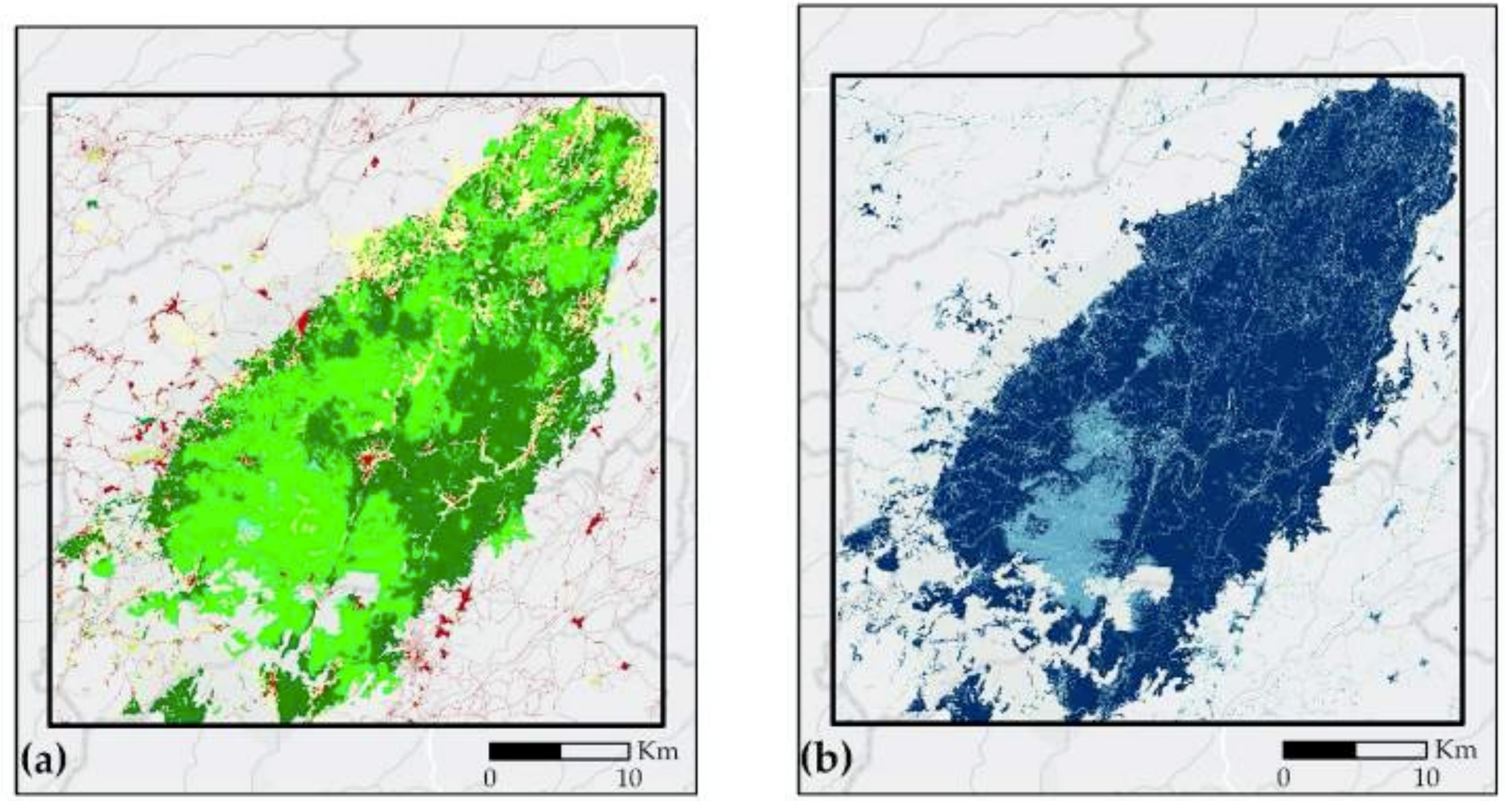
Results

- Training data obtained
  - Study area A



Results

- Training data obtained
  - Study area B



Results

- Percentage of the TD0, TD1 and TD2 datasets belonging to each class for study areas A and B

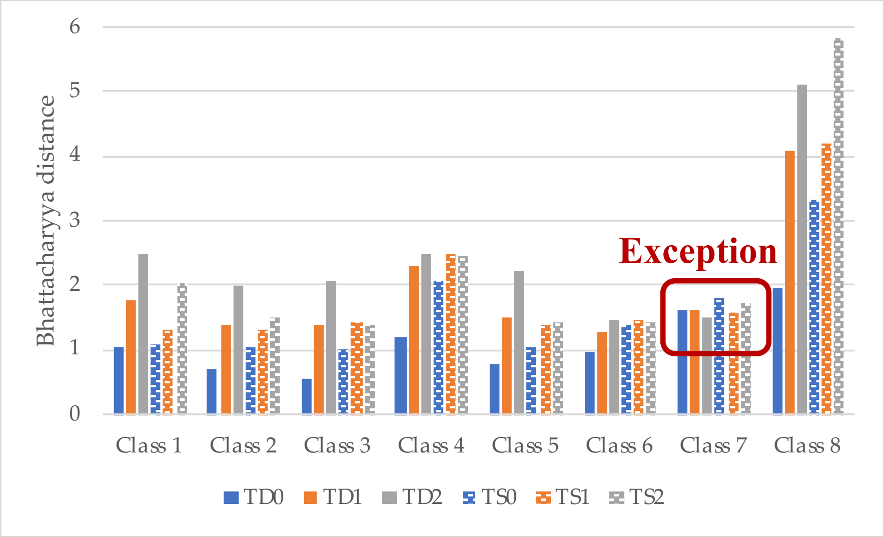
Most regions excluded from TD0 belong to class 1

Classes	Study area A			Study area B		
	TD0	TD1	TD2	TD0	TD1	TD2
1. Artificial surfaces	50.3	44.6	27.0	6.9	4.4	1.5
2. Agricultural areas	2.7	2.7	3.6	12.8	11.9	13.4
3. Herbaceous vegetation	9.6	11.5	15.4	2.3	2.0	2.0
4. Forest areas	4.8	5.3	7.1	36.6	37.8	42.1
5. Shrublands	3.7	4.4	5.9	40.4	43.1	40.5
6. Open spaces with little or no vegetation	0.5	0.4	0.5	0.4	0.4	0.4
7. Wetlands	7.4	3.1	4.0	0.001	---	---
8. Water bodies	20.9	28.0	36.4	0.8	0.4	0.2

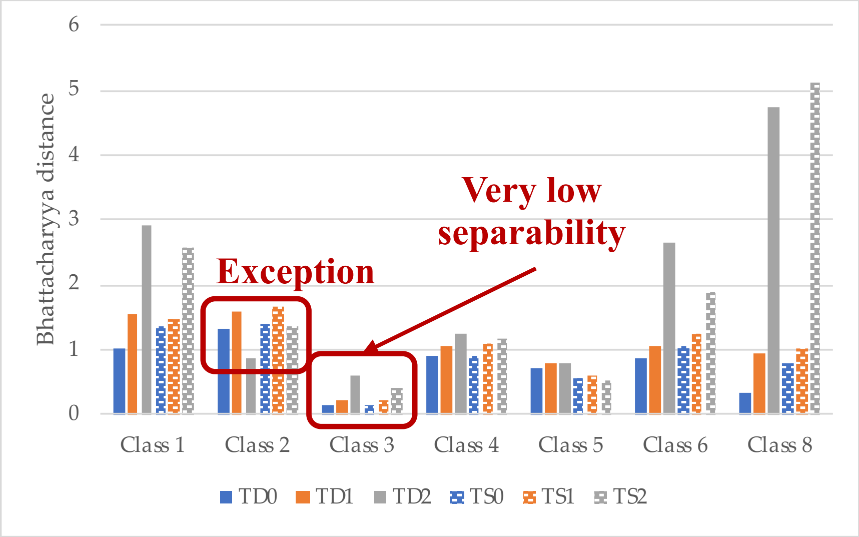
Results

- Class separability (the great the better)
  - Classes' separability improves with the filtering for most classes

Study area A



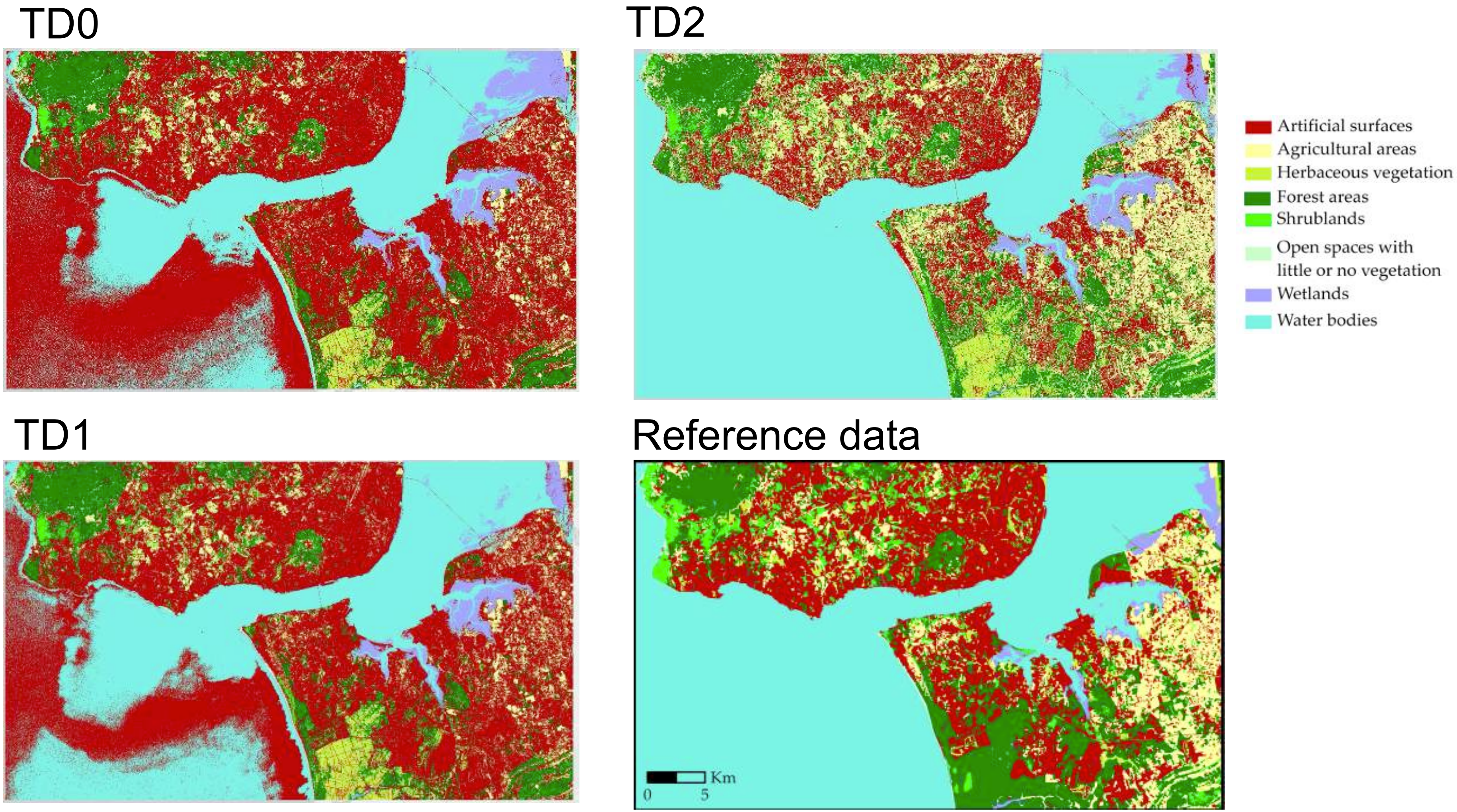
Study area B



Results

Classification results

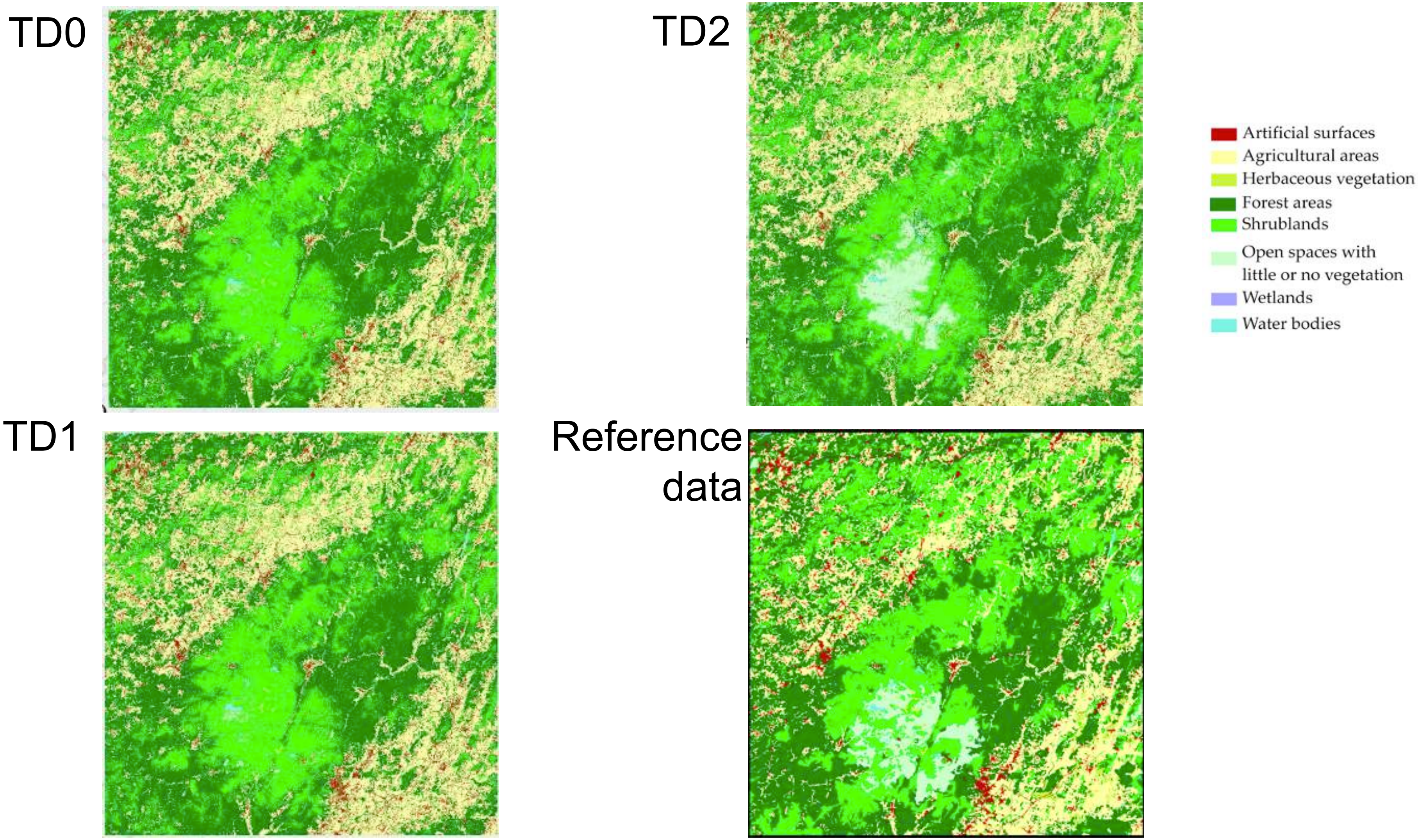
Study area A



Results

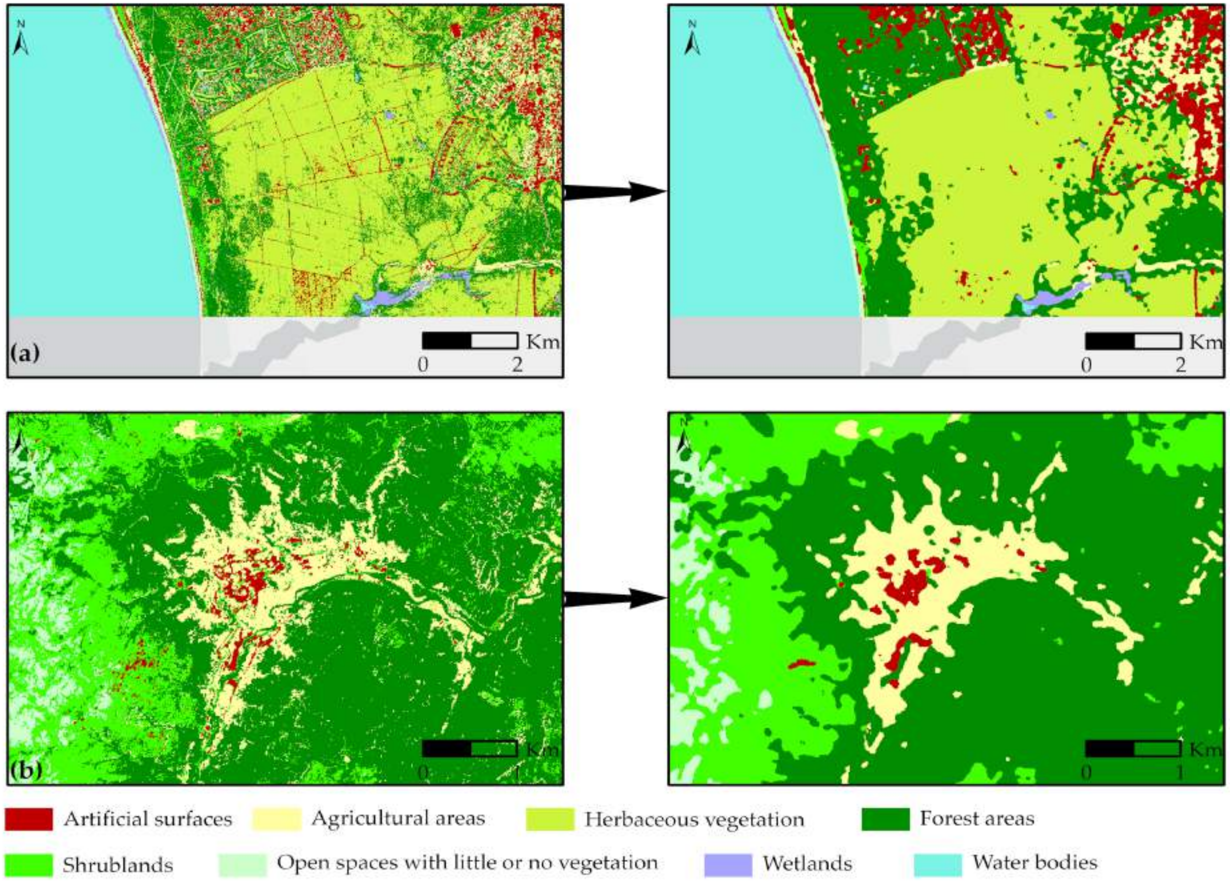
Classification results

Study area B



Results

- Effect of the generalization step



Results

- Overall Accuracy
  - Increases with the filtering for
    - the training datasets
    - Classification for study area A

	Study area A			Study area B		
Dataset	**TD0**	**TD1**	**TD2**	**TD0**	**TD1**	**TD2**
Training datasets	64	74	76	87	89	93
Classification results	55	64	73	65	65	65
Generalized maps	55	64	78	69	69	69
Classification only for regions with OSM data	69	73	66	66	66	66
Data obtained with OSM2LULC	70			87		

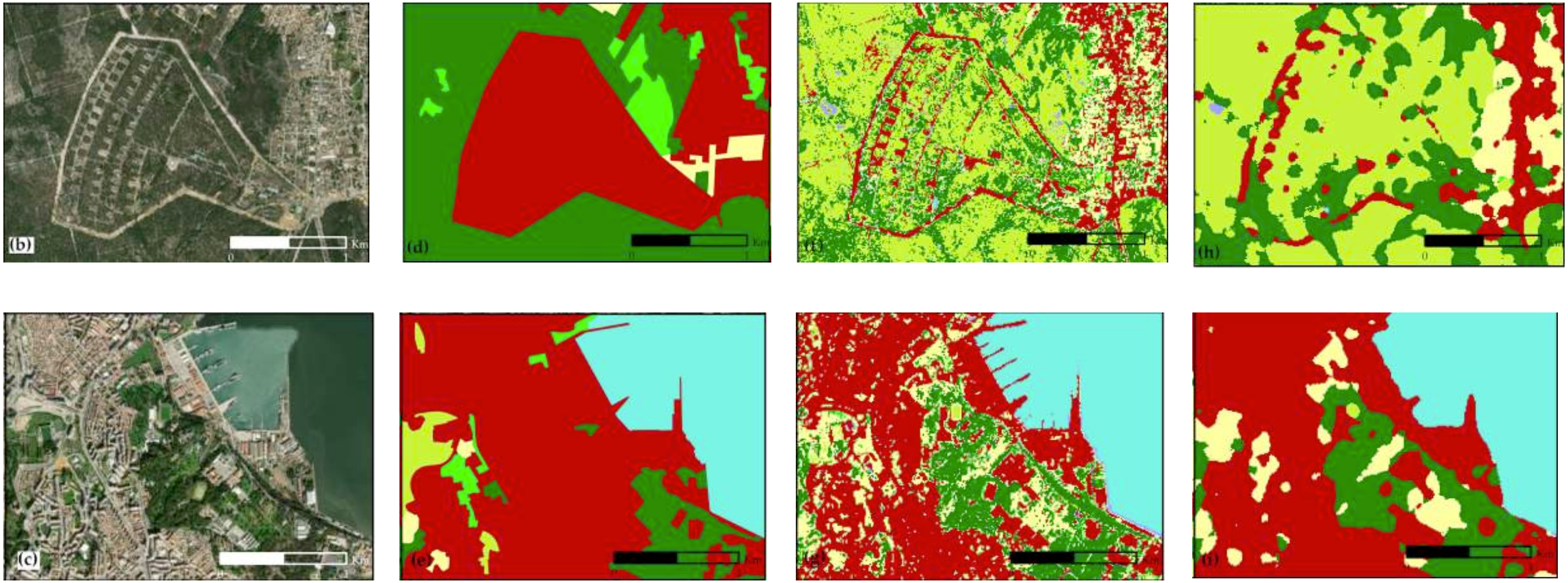
Results –Study area A

Classes	USER'S ACCURACY					PRODUCER'S ACCURACY				
	Training datasets									
	TD0	TD1	TD2	TD1-TD0	TD2-TD1	TD0	TD1	TD2	TD1-TD0	TD2-TD1
1. Artificial surfaces	71	81	97	10	16	66	97	95	31	-2
2. Agricultural areas	62	72	72	10	0	73	33	63	-40	30
3. Herbaceous vegetation	12	10	10	-3	0	11	42	59	31	17
4. Forest areas	75	84	84	9	0	56	24	30	-32	6
5. Shrublands	38	40	40	3	0	21	41	52	20	11
6. Open spaces with little or no vegetation	42	47	48	5	0	49	45	48	-4	3
7. Wetlands	16	34	34	18	0	67	61	78	-6	17
8. Water bodies	94	97	99	3	1	85	93	93	8	0
	Classification									
	TS0	TS1	TS2	TS1-TS0	TS2-TS1	TS0	TS1	TS2	TS1-TS0	TS2-TS1
1. Artificial surfaces	41	48	88	7	40	93	92	62	-1	-30
2. Agricultural areas	53	53	42	0	-11	40	40	74	0	34
3. Herbaceous vegetation	4	5	6	1	1	3	5	7	2	2
4. Forest areas	72	73	63	1	-10	44	47	58	3	11
5. Shrublands	41	38	26	-3	-12	9	14	18	5	4
6. Open spaces with little or no vegetation	22	25	6	3	-19	46	44	46	-2	2
7. Wetlands	15	28	25	13	-3	42	51	60	9	9
8. Water bodies	97	99	99	2	0	50	68	95	18	27
	Generalization									
	TS0	TS1	TS2	TS1-TS0	TS2-TS1	TS0	TS1	TS2	TS1-TS0	TS2-TS1
1. Artificial surfaces	41	47	89	6	42	97	97	75	0	-22
2. Agricultural areas	61	60	45	-1	-15	36	36	85	0	49
3. Herbaceous vegetation	2	4	6	2	2	2	4	6	2	2
4. Forest areas	75	77	69	2	-8	44	48	64	4	16
5. Shrublands	55	53	42	-2	-11	6	9	12	3	3
6. Open spaces with little or no vegetation	36	45	32	9	-13	47	44	47	-3	3
7. Wetlands	16	30	29	14	-1	45	53	66	8	13
8. Water bodies	97	99	99	2	0	48	67	95	19	28

Results –Study area A

- Examples

Reference Classification Generatization



Results –Study area B

Classes	User's accuracy					Producer's accuracy				
	Training datasets									
	TD0	TD1	TD2	TD1-TD0	TD2-TD1	TD0	TD1	TD2	TD1-TD0	TD2-TD1
1. Artificial surfaces	48	68	90	20	22	96	98	96	2	-2
2. Agricultural areas	99	99	99	0	0	86	93	99	8	6
3. Herbaceous vegetation	71	72	69	2	-4	89	96	99	7	3
4. Forest areas	100	100	100	0	0	94	97	98	4	1
5. Shrublands	80	80	86	0	6	98	99	100	2	0
6. Open spaces with little or no vegetation	97	98	98	1	0	4	4	7	0	3
7. Wetlands	---	---	---	---	---	---	---	---	---	---
8. Water bodies	51	93	99	42	6	93	97	97	4	0
	Classification									
	TS0	TS1	TS2	TS1-TS0	TS2-TS1	TS0	TS1	TS2	TS1-TS0	TS2-TS1
1. Artificial surfaces	52	48	58	-4	9	47	53	39	6	-14
2. Agricultural areas	63	63	63	1	0	85	84	85	-1	1
3. Herbaceous vegetation	46	47	42	1	-6	5	6	4	1	-2
4. Forest areas	71	72	74	0	2	73	73	70	0	-3
5. Shrublands	60	60	59	0	-1	54	55	54	1	0
6. Open spaces with little or no vegetation	54	53	41	-1	-12	8	8	38	0	30
7. Wetlands	---	---	---	---	---	---	---	---	---	---
8. Water bodies	93	63	88	-29	24	38	64	47	26	-17
	Generalization									
	TS0	TS1	TS2	TS1-TS0	TS2-TS1	TS0	TS1	TS2	TS1-TS0	TS2-TS1
1. Artificial surfaces	77	72	77	-5	5	47	55	37	8	-18
2. Agricultural areas	63	64	63	1	-1	91	90	91	-1	1
3. Herbaceous vegetation	74	75	56	1	-19	2	3	1	1	-2
4. Forest areas	75	75	78	0	3	78	77	74	-1	-3
5. Shrublands	65	65	65	0	0	56	57	56	1	-1
6. Open spaces with little or no vegetation	78	82	42	4	-40	4	4	38	0	34
7. Wetlands	---	---	---	---	---	---	---	---	---	---
8. Water bodies	94	78	90	-16	12	40	58	47	18	-11

Results

- Hybrid maps
  - Overall accuracy (%)

	Class / Gen			Hybrid map (HM)			HM – Class / HM - Gen		
	TS0	**TS1**	**TS2**	**TS0**	**TS1**	**TS2**	**TS0**	**TS1**	**TS2**
Study area A	55 / 55	64 / 64	73 / 78	56	62	76	1 / 1	-2 / -2	3 / -2
Study area B	65 / 69	65 / 69	65 / 69	75	75	74	10 / 10	10 / 10	9 / 9

  - The quality of these hybrid products is very much dependent on the characteristics of the region and the data available in OSM

Conclusions

- In general the filtering processes improved the class separability
  - Problematic regions were successfully removed from the training datasets
- The accuracy of the classification results and their generalized versions may improve with the filtering
  - increased for the study area with urban characteristics
  - remained unchanged for the rural study area

Conclusions

- Some classes were very hard to classify
  - Worse classes:
    - Agricultural areas
    - Herbaceous vegetation
    - Shrublands
    - Open spaces with little or no vegetation
  - The nomenclature also included land use classes

Conclusions

- An accuracy of up to 78% was achieved with an automated procedure
  - Study area A and training data TD2
- The use of reference data with 1 ha MMU raises problems

Additional tests are under development

Using all Sentinel-2 bands

Without using samples for training

Different approach for accuracy assessment

THE USE OF VOLUNTEER GEOGRAPHIC INFORMATION FOR PRODUCING AND MAINTAINING AUTHORITATIVE LAND USE AND LAND COVER DATA

Quality assessment of Land Use and Land Cover information with VGI

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Department of Mathematics – University of Coimbra, Coimbra, Portugal
Institute for Systems Engineering and Computers at Coimbra (INESC Coimbra), Portugal

24-25 November 2020

Quality assessment

Requires the use of reference data

“ground truth”

Difficult to collect

Expensive

Time consuming

Requires human intervention

Hardly automated

Quality assessment

- The reference data should be formed by a sample
  - Probability sample
    - All spatial units have the same probability of being selected

Will VGI be available to provide the reference condition at all locations?

If volunteers can be directed to the required locations

Maybe yes!

If existing VGI will be used

Probably not!

Types of VGI that may be used for LULC map validation

- Photographs and descriptions
  - Degree Confluence project
  - Geograph
  - Panoramio
  - Flickr
- Volunteer initiatives to map the world
  - Such as OpenStreetMap (OSM)
- Land cover data collected by projects
  - such as Geo-Wiki and VIEW-IT

Quality assessment

What about the quality of that VGI?

Strategies need to be used so that

ONLY HIGHLY RELIABLE VGI

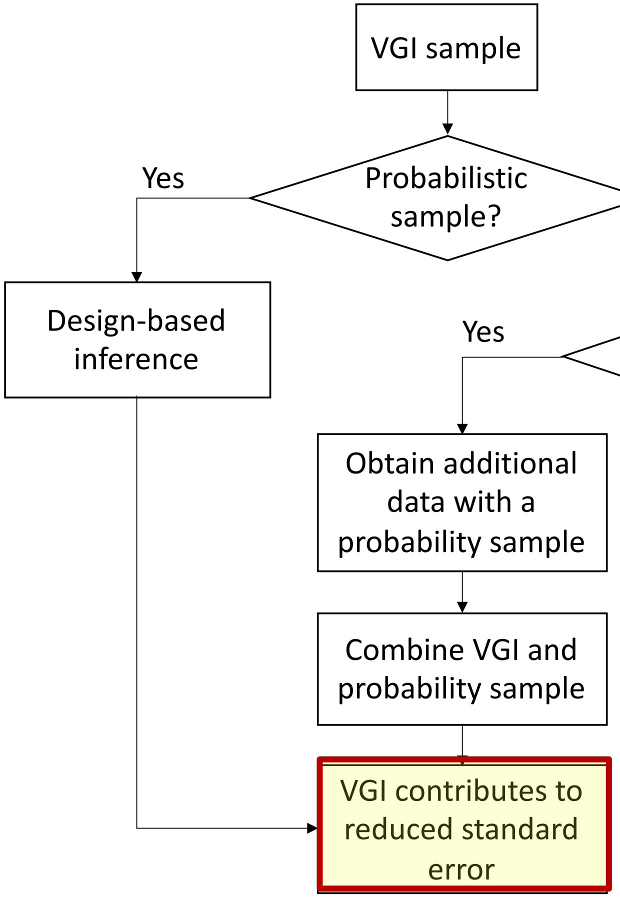
is used for LULC map validation!

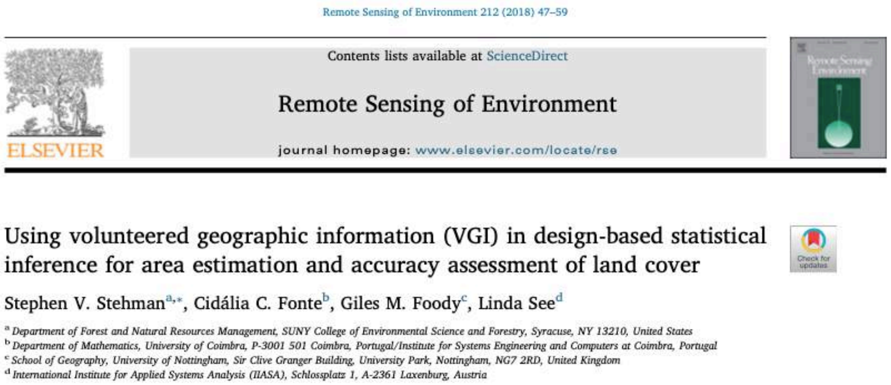
VGI quality assessment

Let us assume only highly reliable VGI is used

Can VGI be useful for quality assessment?

- Possible strategies:


VGI sample
Probabilistic sample?
Yes
No
Design-based inference
Yes
Use VGI in design-based inference?
No
Obtain additional data with a probability sample
Model-based inference
Combine VGI and probability sample
VGI contributes to reduced standard error



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Using volunteered geographic information (VGI) in design-based statistical inference for area estimation and accuracy assessment of land cover

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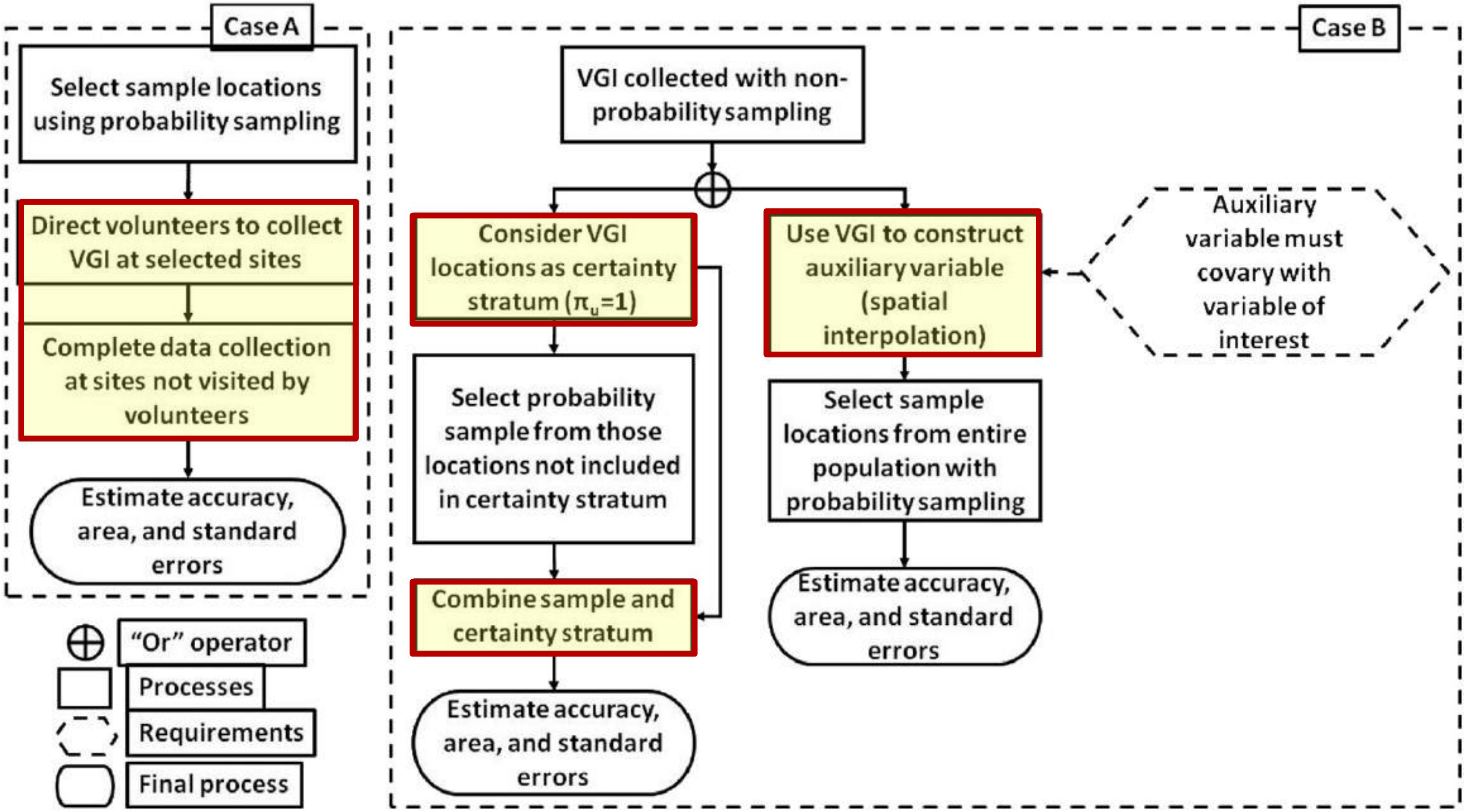
Can VGI be useful for quality assessment?

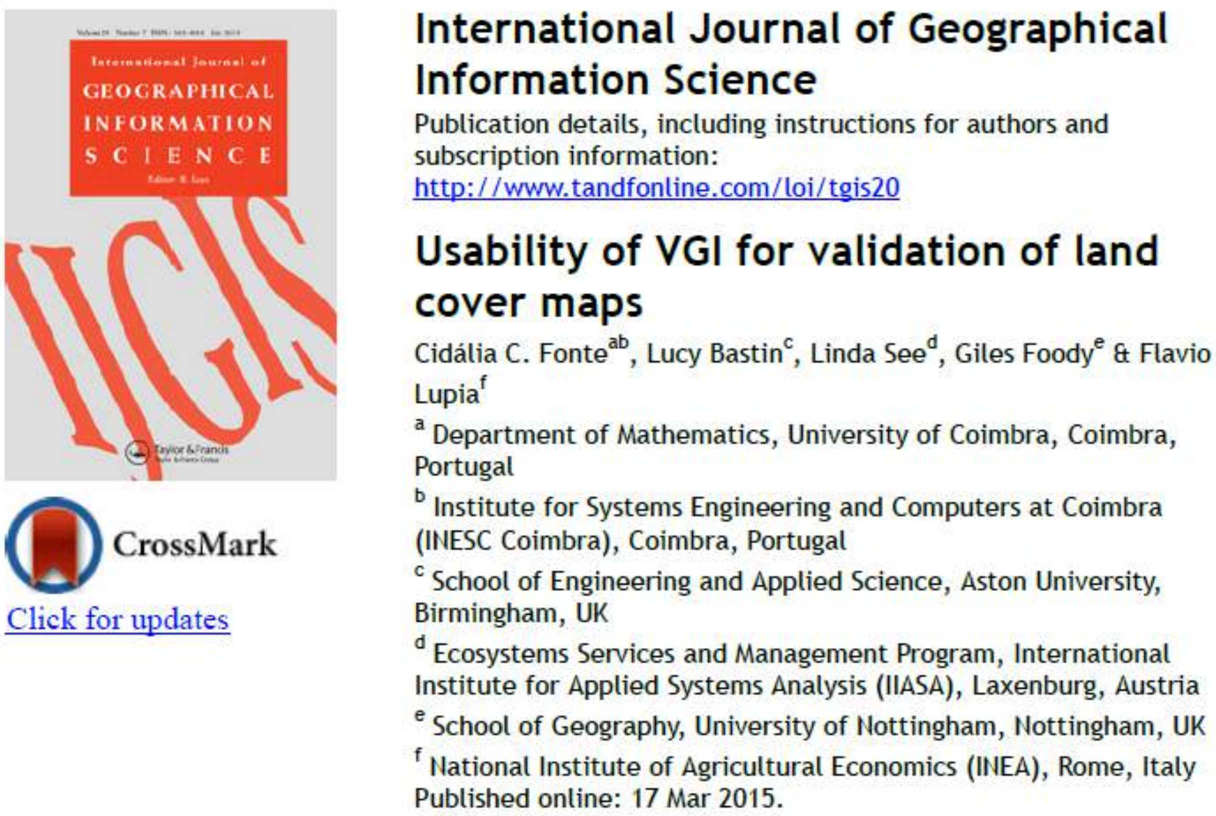
- Possible strategies:



Case A
Select sample locations using probability sampling
Direct volunteers to collect VGI at selected sites
Complete data collection at sites not visited by volunteers
Estimate accuracy, area, and standard errors
Case B
VGI collected with non-probability sampling
Consider VGI locations as certainty stratum (π_u=1)
Select probability sample from those locations not included in certainty stratum
Combine sample and certainty stratum
Estimate accuracy, area, and standard errors
Use VGI to construct auxiliary variable (spatial interpolation)
Auxiliary variable must covary with variable of interest
Select sample locations from entire population with probability sampling
Estimate accuracy, area, and standard errors
⊕ "Or" operator
Processes
Requirements
Final process

Use of VGI for the validation of LULC maps

- Review article



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Usability of VGI for validation of land cover maps

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Published online: 17 Mar 2015.

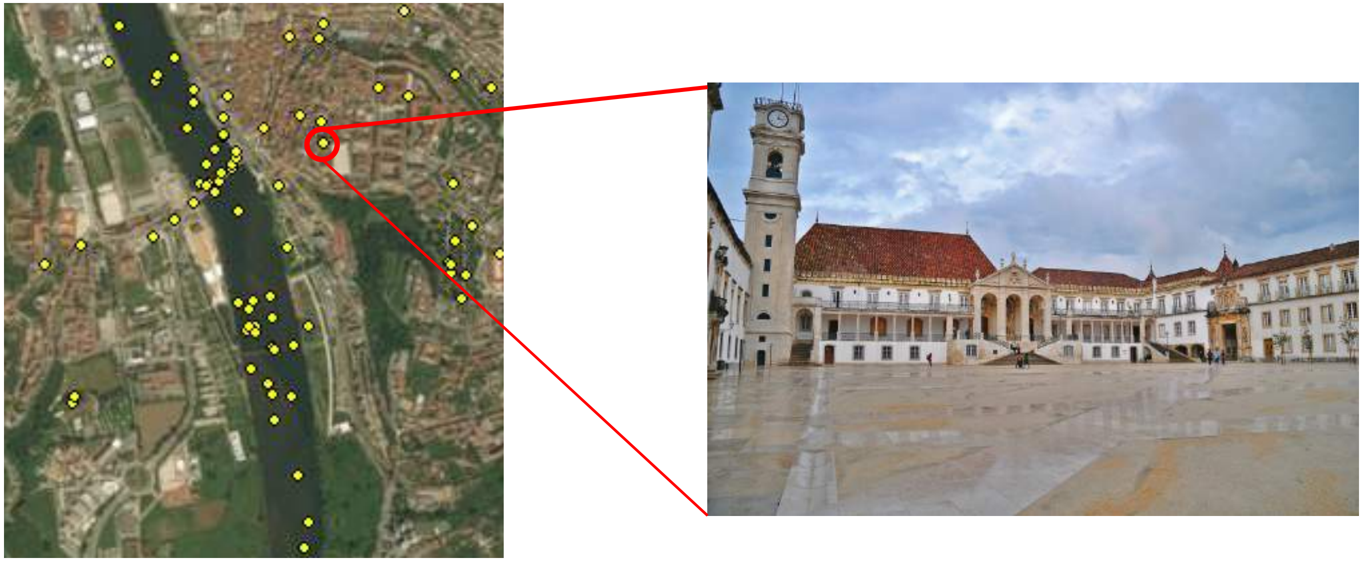
Use of VGI for the creation and/or validation of LULCM

- Review article

Types of VGI	Example projects
Photographs and descriptions	Degree Confluence Project Flickr Instagram Panoramio Geograph
Classification of images	Geo-Wiki VIEW-IT
Vector maps	OpenStreetMap

Examples

- Use of georreferenced photographs
- Raises problems:
  - May have positioning errors



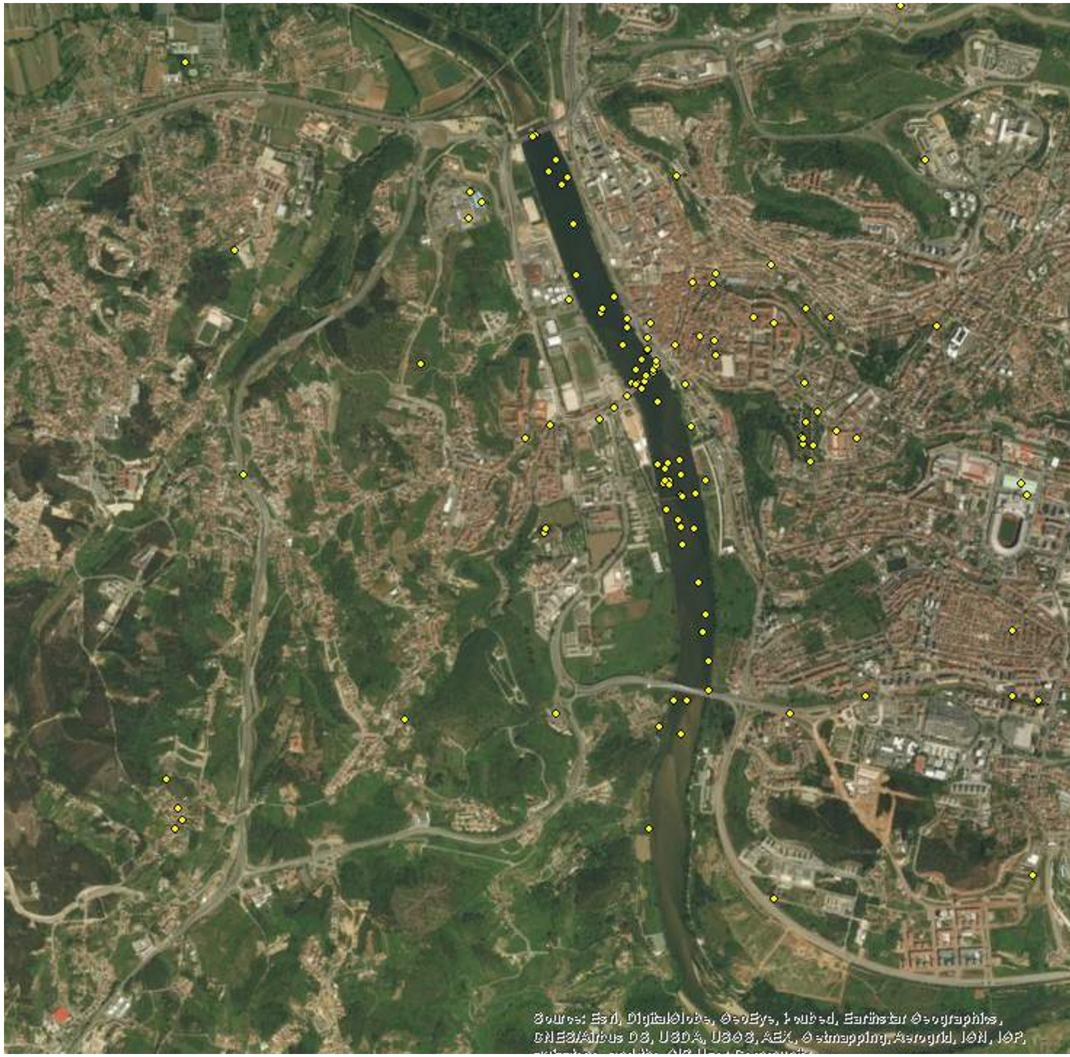
Examples

- Use of georreferenced photographs
- Raises problems:
  - Classify what is visible in the photo

Examples

- Use of georreferenced photographs

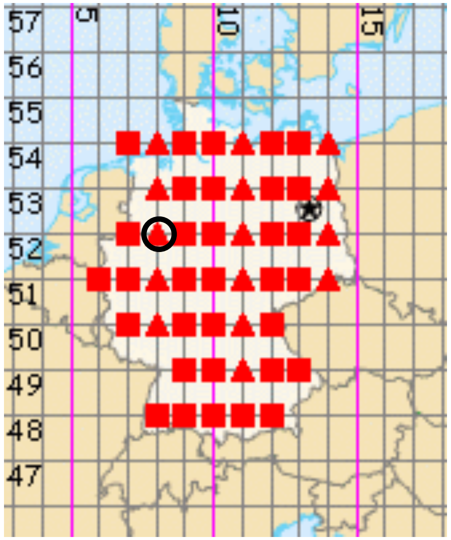
- Raises problems:
  - Representativeness /geospatial distribution

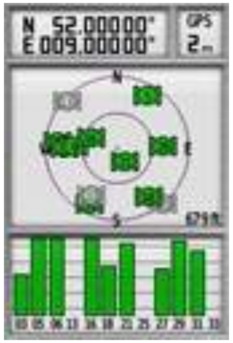


Source: Esri, DigitalGlobe, GeoEye, i-cubed, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Examples

- Use of georreferenced photographs
  - Degree Confluence Project (http://confluence.org/)
    - ➢ Project created in1996
    - ➢ Collects photos and descriptions at each point with an integer value of latitude and longitude
      - Four photos are collected at each point oriented for the four cardinal directions N, S, E, W



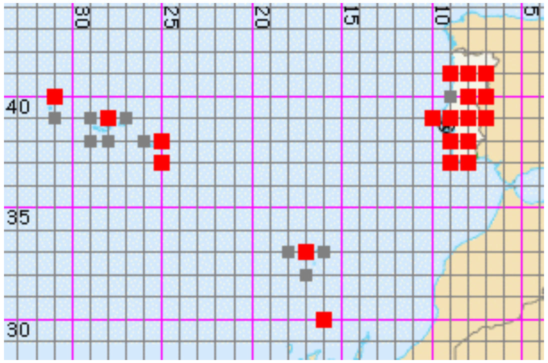


Foody and Boyd, 2013; Iwao et al., 2006, 2011

Examples

- Use of georreferenced photographs
  - Degree Confluence Project (http://confluence.org/)
    - ➢ Points regularly spaced
      - Systematic sample of points!
    - ➢ Total points: 16 345

  - It is of little use for small regions
    - ➢ In Portugal - only 29 points
    - ➢ In Portugal main land - 14!



Examples

- Use OSM as reference data
  - Comparison of reference data obtained from OSM and photointerpretation
    - High correspondence for level 1 classes
    - Problematic for some classes of level 2
      - Photointerpretation may also be problematic
        - Land use classes

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Assessing the applicability of OpenStreetMap data to assist the validation of land use/land cover maps

Cidália C. Fonte & Nuno Martinho

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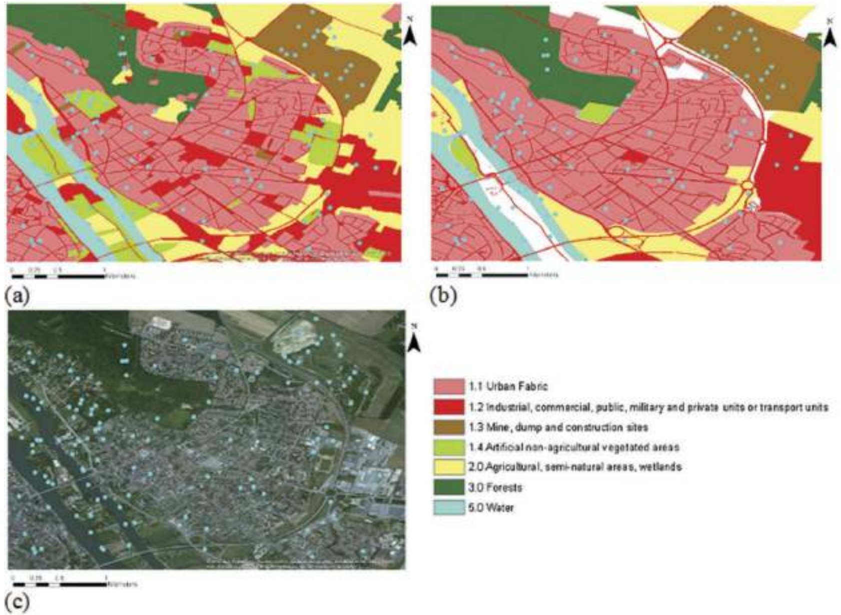
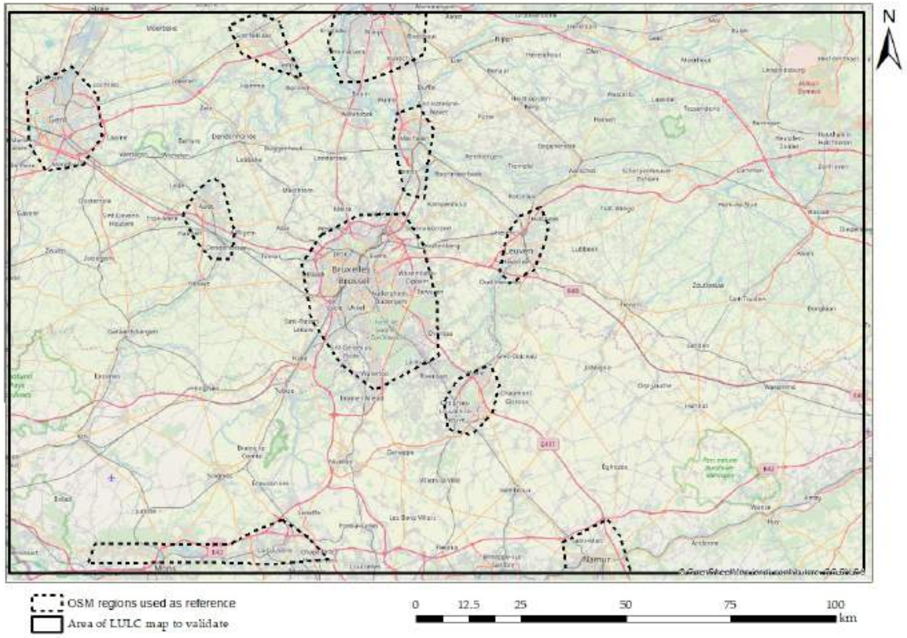
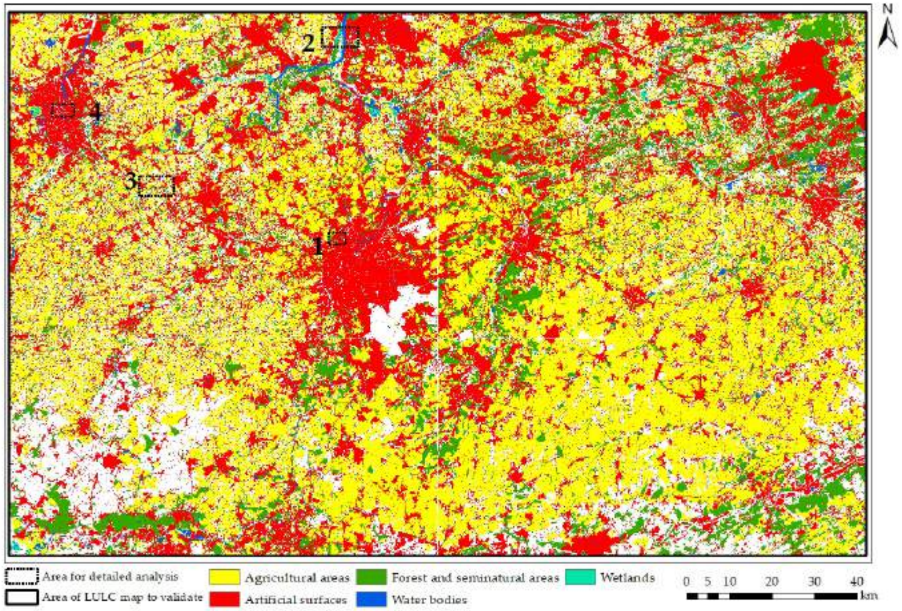

(a)
(b)
(c)
1.1 Urban Fabric
1.2 Industrial, commercial, public, military and private units or transport units
1.3 Mine, dump and construction sites
1.4 Artificial non-agricultural vegetated areas
2.0 Agricultural, semi-natural areas, wetlands
3.0 Forests
5.0 Water

Examples

- Use OSM as reference data
  - Stratification




N
1
2
3
4
Area for detailed analysis
Area of LULC map to validate
Agricultural areas
Artificial surfaces
Forest and seminatural areas
Water bodies
Wetlands
0
5
10
20
30
40
km

How can we:

- Reduce the validation effort
- Obtain more reliable accuracy results with less effort

THE USE OF VOLUNTEER GEOGRAPHIC INFORMATION FOR PRODUCING AND MAINTAINING AUTHORITATIVE LAND USE AND LAND COVER DATA

IGN
INSTITUT NATIONAL
DE L'INFORMATION
GÉOGRAPHIQUE
ET FORESTIÈRE

LandSense
A Citizen Observatory and Innovation Marketplace for Land Use and Land Cover Monitoring

EuroSDR

Thank you !

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24-25 November 2020