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Aizu-Wakamatsu, Japan 2017

POLITECNICO DI MILANO



OSM seen from a GIS researcher: experiences & perspectives

Marco Minghini

Aizu-Wakamatsu, Fukushima, Japan | August 19, 2017

Who I am

- ✓ Postdoctoral Research Fellow at Politecnico di Milano, Italy
 - ➔ research topics: Volunteered Geographic Information (VGI), Citizen Science, (geo)crowdsourcing & OpenStreetMap
- ✓ Secretary of the ISPRS (International Society for Photogrammetry and Remote Sensing) WG IV/4 "Collaborative Crowdsourced Cloud Mapping (C³M)" since 2016
- ✓ Charter Member of the Open Source Geospatial Foundation (OSGeo) since 2015
- ✓ OSM contributor since 2014 [username: mingo23]
- ✓ OSM teacher and mapathon organizer since 2015
- ✓ Voting Member of HOT since 2017
- ✓ Faculty Advisor of PoliMappers – a YouthMappers chapter based at Politecnico di Milano, since 2016
 - ➔ <https://wiki.openstreetmap.org/wiki/User:Mingo23>



Research on OSM

- ✓ Over the last few years, OSM has become a research topic on its own
 - ➔ 5 core research areas (+ 50 research trends) were identified [1]:
 - ✗ quality assessment and analysis
 - ✗ assessment of contributors' behavior
 - ✗ application to navigation and disaster
 - ✗ traffic simulation and mobility
 - ✗ indoor navigation models
- ✓ This presentation will focus on 3 recent research works on OSM:
 - ➔ 1. quality assessment of OSM road networks
 - ➔ 2. analysis of OSM contribution patterns
 - ➔ 3. use of OSM to generate Land Use/Land Cover maps

[1] Sehra S.S., Singh J. & Rai H.S. (2017). Using Latent Semantic Analysis to Identify Research Trends in OpenStreetMap. *ISPRS International Journal of Geo-Information*, 6(7), 195.

1

Quality assessment of OSM road networks

OSM quality

- ✓ Increasing availability of open data from National Mapping Agencies and Commercial Mapping Companies usable as a source of comparison for VGI (and OSM) data, i.e. for extrinsic quality assessment
- ✓ Literature provides plenty of works assessing or comparing OSM quality against that of authoritative datasets:
 - ➔ strongly focused on road network
 - ➔ OSM compared to data from NMA (UK Ordnance Survey, French NMA, USGS TNM/TIGER, etc.) and CSC (Navteq, TeleAtlas, etc.)
 - ➔ semi- or fully-automated
- ✓ Comparison techniques are very strong and fit for purpose, but mostly application and dataset specific:
 - ➔ hard to replicate
 - ➔ difficult to extend to other dataset comparisons

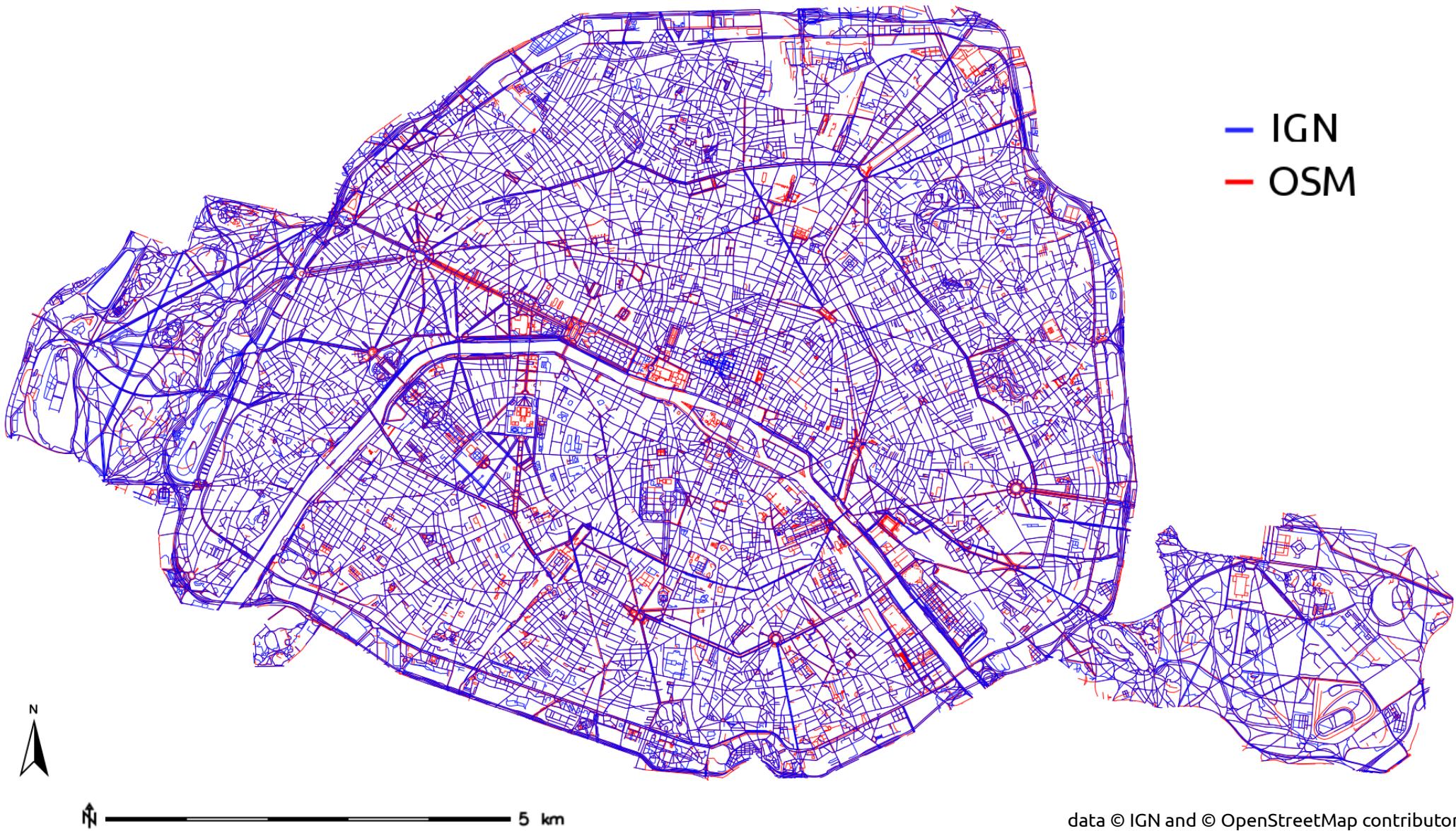
Our methodology

- ✓ Novel methodology to compare OSM and authoritative road datasets:
 - ➔ fully automated
 - ➔ focused on spatial accuracy and completeness
 - ➔ flexible, i.e. not developed for a specific dataset
 - ➔ built with FOSS4G (Free and Open Source Software for Geospatial)
 - ✗ reusable and extensible in case of need

Our methodology – Overview

- ✓ Currently developed as 3 GRASS GIS modules:
 - ➔ written in Python
 - ➔ available with a Graphical User Interface (GUI)
- ✓ Comparison between the OSM & the reference road network datasets composed of 3 consecutive steps:
 - ➔ 1. Preliminary comparison of the datasets and computation of global statistics
 - ➔ 2. Geometric preprocessing of the OSM dataset to extract a subset which is fully comparable with the reference dataset
 - ➔ 3. Evaluation of OSM spatial accuracy using a grid-based approach
- ✓ Source code: <https://github.com/MoniaMolinari/OSM-roads-comparison>

Case study: Paris



Step 1: Preliminary comparison of the datasets

- ✓ Compute the total length of the OSM and IGN datasets and their length difference, both in map units and percentage [required]
 - output values are returned in a text file

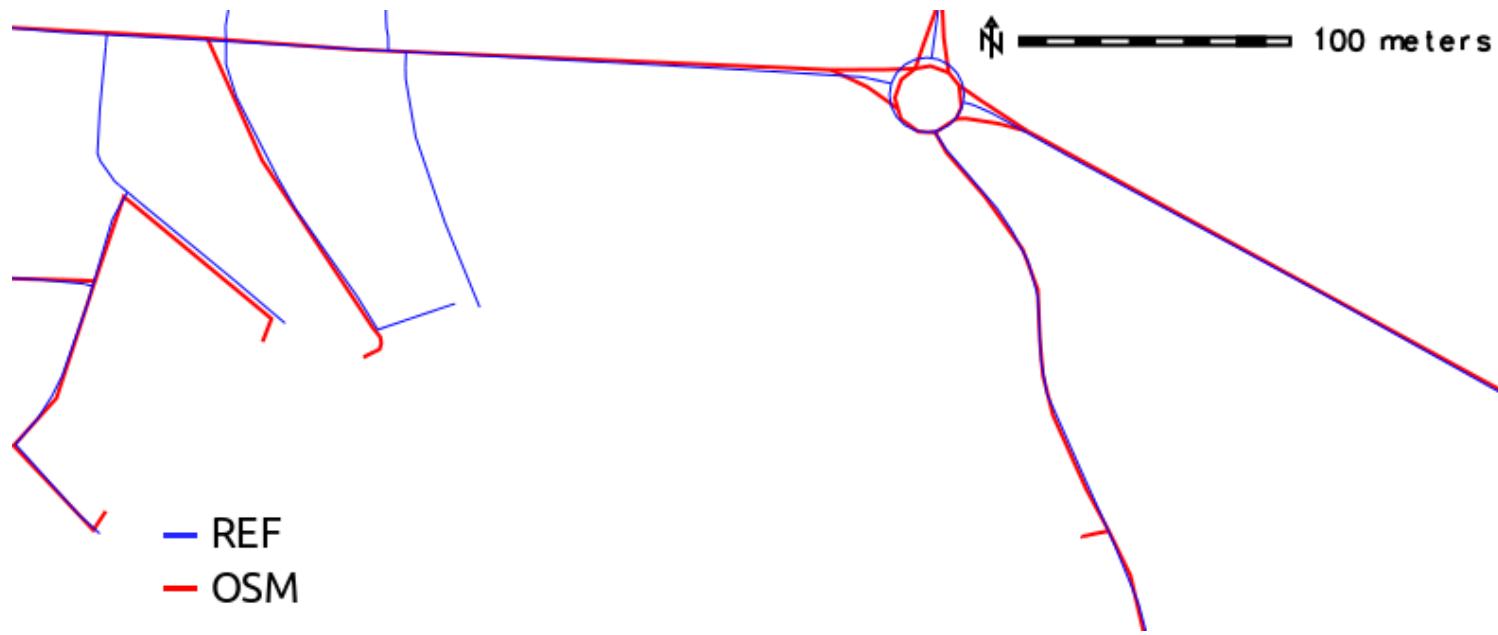
```
REF length: 2686373.1 m
OSM length: 3124627.0 m
REF-OSM difference: -438253.9 m (-16.3%)
```

$\times \approx 450$ km more in OSM than IGN dataset!

BUFFER(m)	OSM_IN(m)	OSM_IN(%)	OSM_OUT(m)	OSM_OUT(%)	REF_IN(m)	REF_IN(%)	REF_OUT(m)	REF_OUT(%)
1.0	1374755.9	44.0	1749871.2	56.0	1366471.0	50.9	1319902.1	49.1
2.0	2014259.9	64.5	1110367.2	35.5	1982713.7	73.8	703659.4	26.2
3.0	2298072.4	73.5	826554.6	26.5	2223153.5	82.8	463219.6	17.2
4.0	2464185.0	78.9	660442.0	21.1	2329270.3	86.7	357102.8	13.3
5.0	2582784.2	82.7	541842.9	17.3	2387687.7	88.9	298685.4	11.1
6.0	2671758.8	85.5	452868.2	14.5	2424463.5	90.3	261909.6	9.7
7.0	2738327.0	87.6	386300.0	12.4	2451476.9	91.3	234896.2	8.7
8.0	2792053.8	89.4	332573.2	10.6	2471557.1	92.0	214816.0	8.0
9.0	2828903.0	90.5	295724.1	9.5	2488514.1	92.6	197859.0	7.4
10.0	2859512.1	91.5	265114.9	8.5	2501974.7	93.1	184398.4	6.9
11.0	2886190.1	92.4	238436.9	7.6	2513592.9	93.6	172780.2	6.4
12.0	2908071.9	93.1	216555.1	6.9	2523138.5	93.9	163234.6	6.1
13.0	2925602.0	93.6	199025.1	6.4	2532070.5	94.3	154302.6	5.7
14.0	2941922.8	94.2	182704.2	5.8	2540322.9	94.6	146050.2	5.4
15.0	2956112.7	94.6	168514.3	5.4	2548274.0	94.9	138099.1	5.1
16.0	2967813.5	95.0	156813.5	5.0	2555431.5	95.1	130941.6	4.9
17.0	2977318.7	95.3	147308.3	4.7	2562238.1	95.4	124135.0	4.6
18.0	2986371.8	95.6	138255.2	4.4	2568276.5	95.6	118096.6	4.4
19.0	2994833.4	95.8	129793.7	4.2	2574052.2	95.8	112320.9	4.2
20.0	3001796.0	96.1	122831.1	3.9	2579434.1	96.0	106939.0	4.0

Step 2: preprocessing of the OSM dataset¹⁰

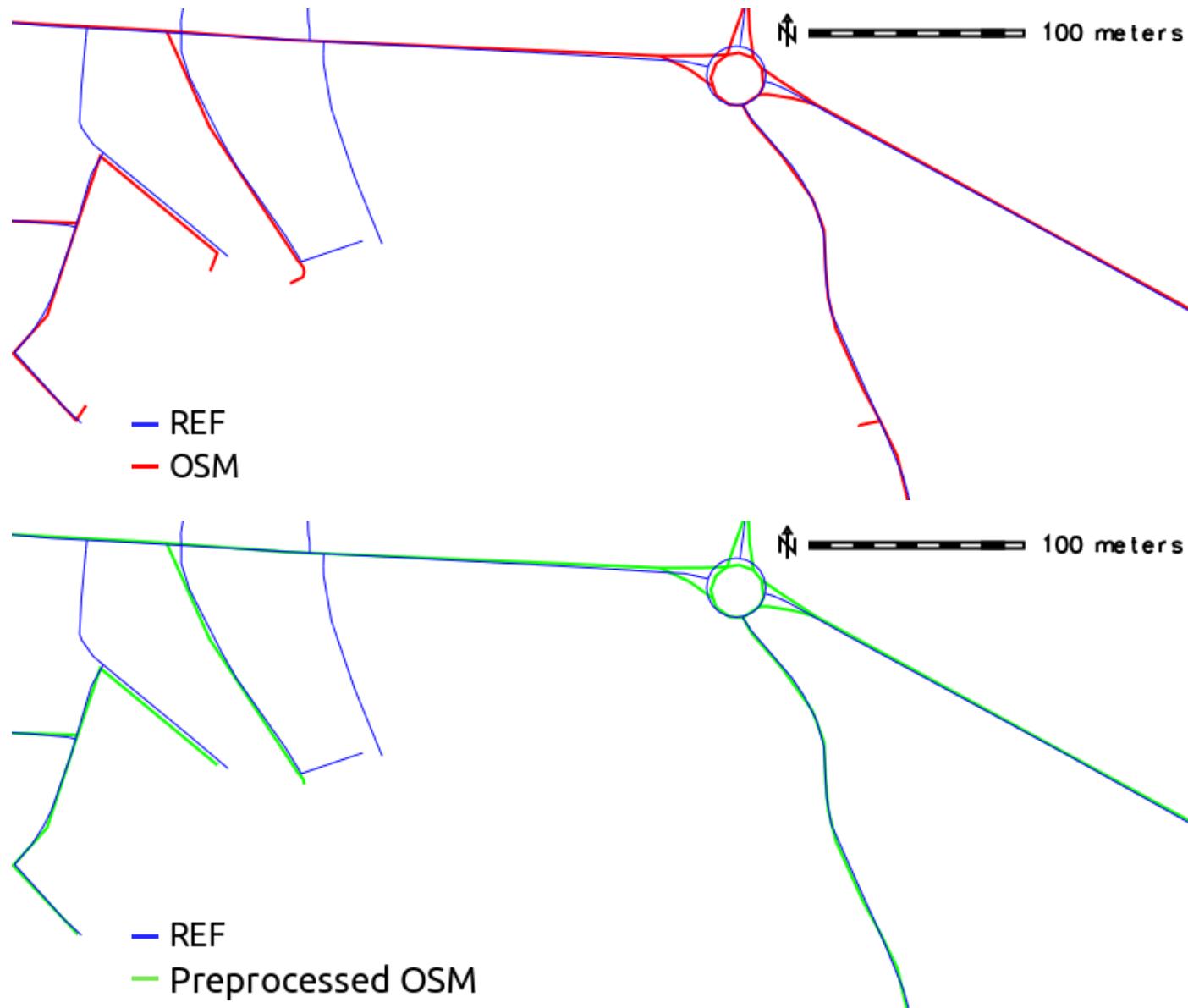
- ✓ Cleaning of OSM dataset to make it comparable with IGN dataset
- ✓ Apply a buffer of user-specified width around the IGN dataset
 - suitable buffer width derived from Step 1
 - delete all the OSM roads falling outside the buffer



data © IGN and © OpenStreetMap contributors

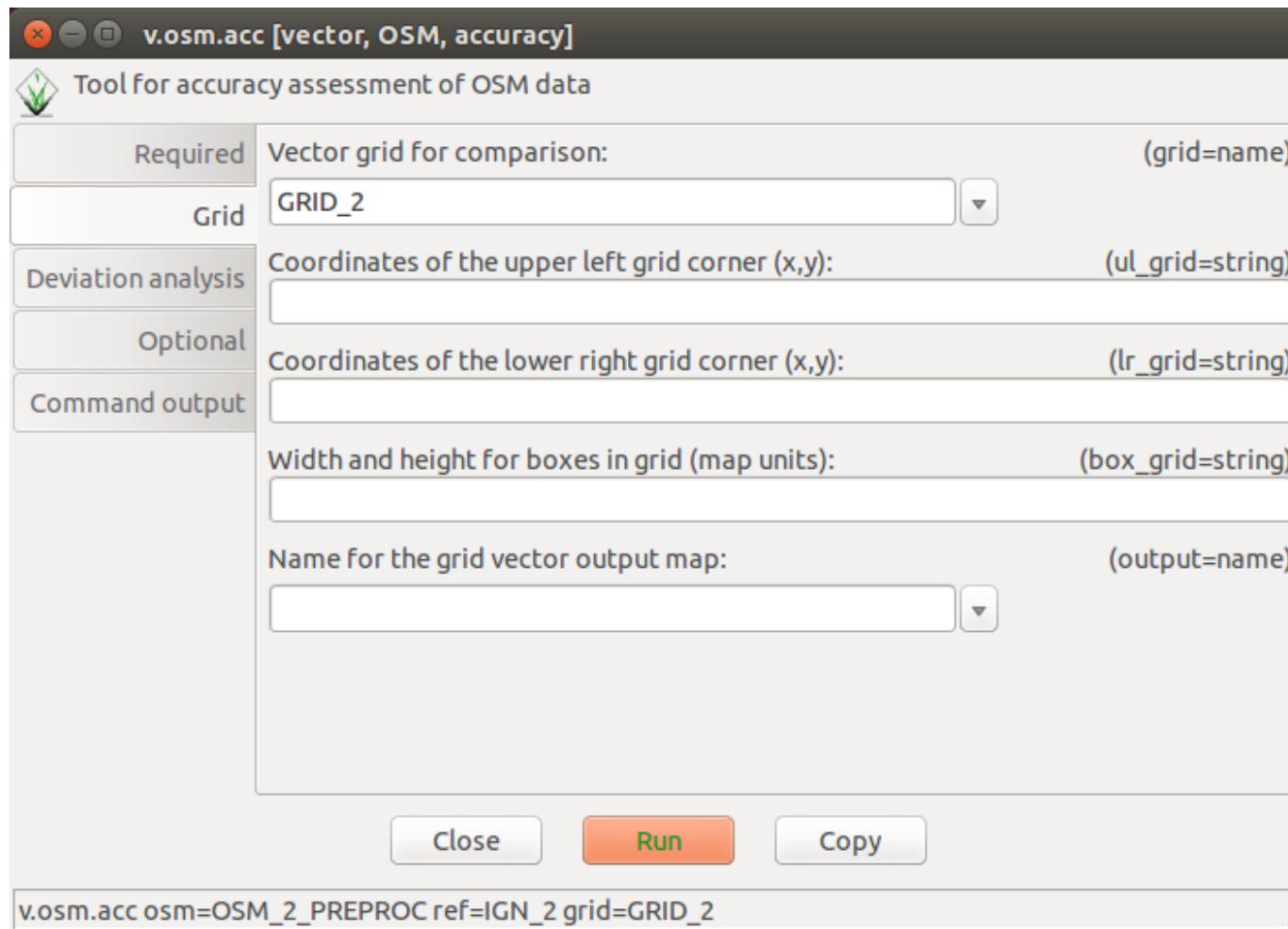
Step 2: preprocessing of the OSM dataset

- ✓ Further clean the OSM dataset:



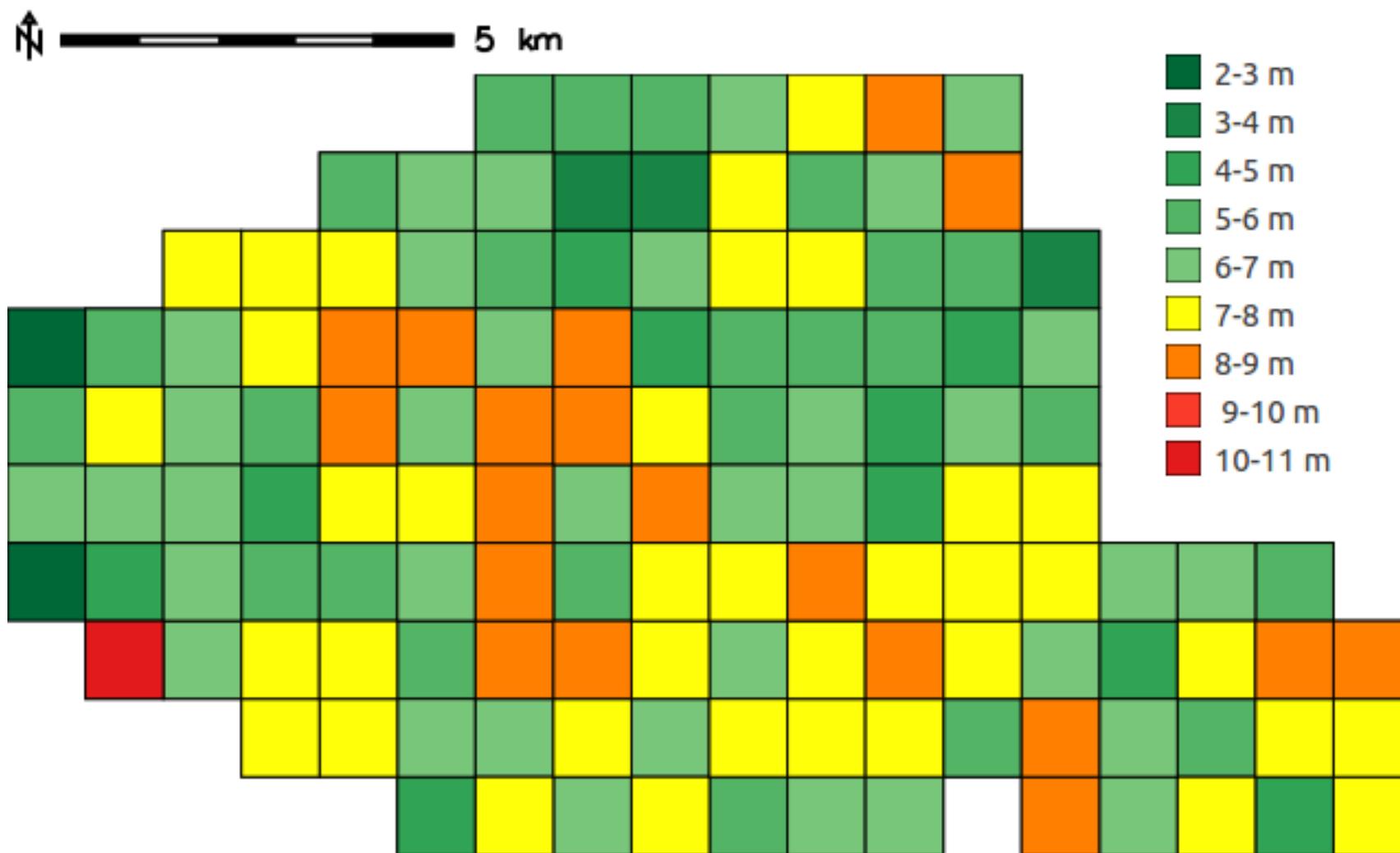
Step 3: grid-based evaluation of OSM accuracy

- ✓ Use a **grid** to take into account OSM heterogeneous nature:



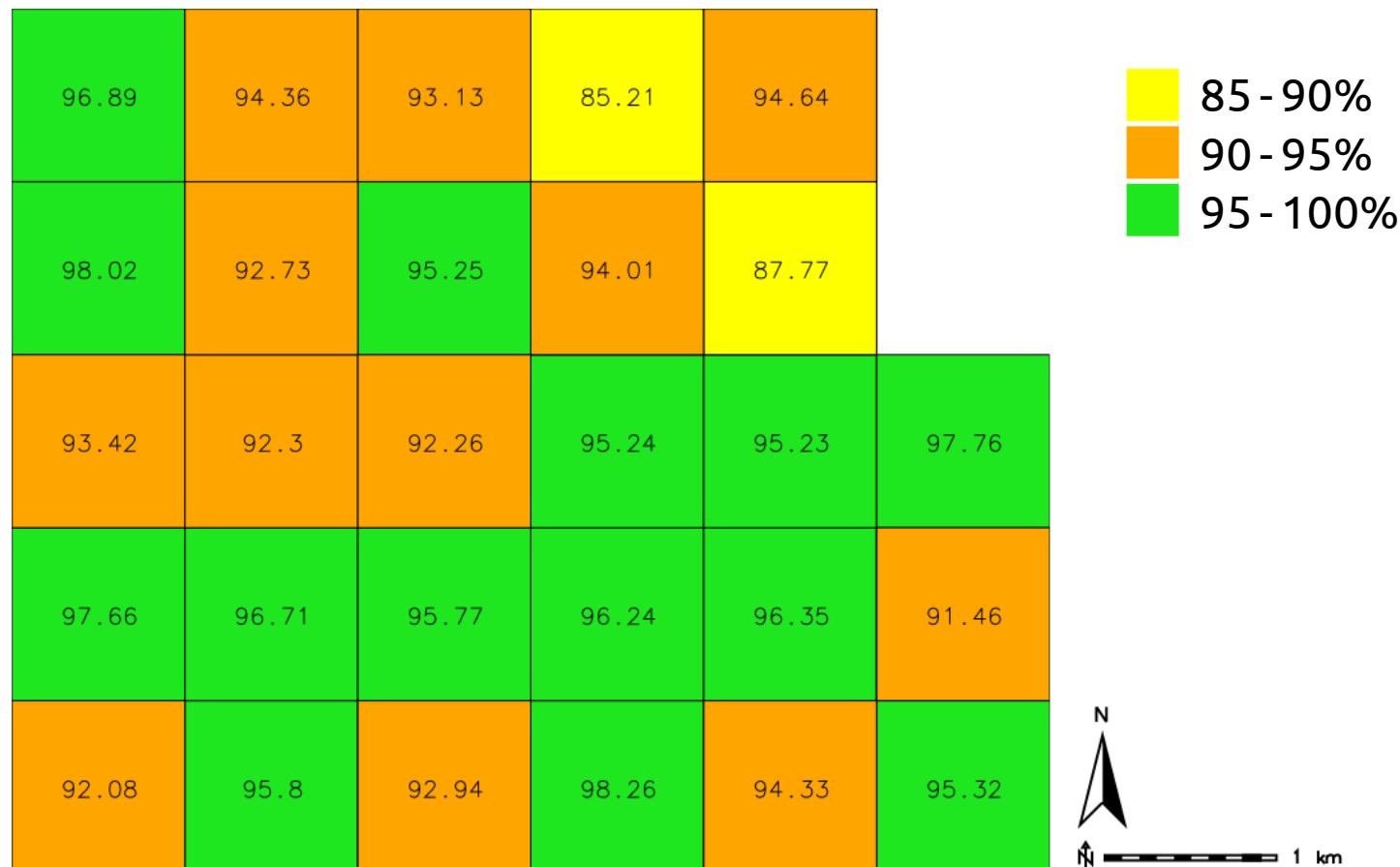
Step 3: grid-based evaluation of OSM accuracy

- ✓ For each grid cell, find the OSM maximum deviation from IGN:
 - generalization threshold = 0.5 m, buffer = 11 m, OSM length % = 95



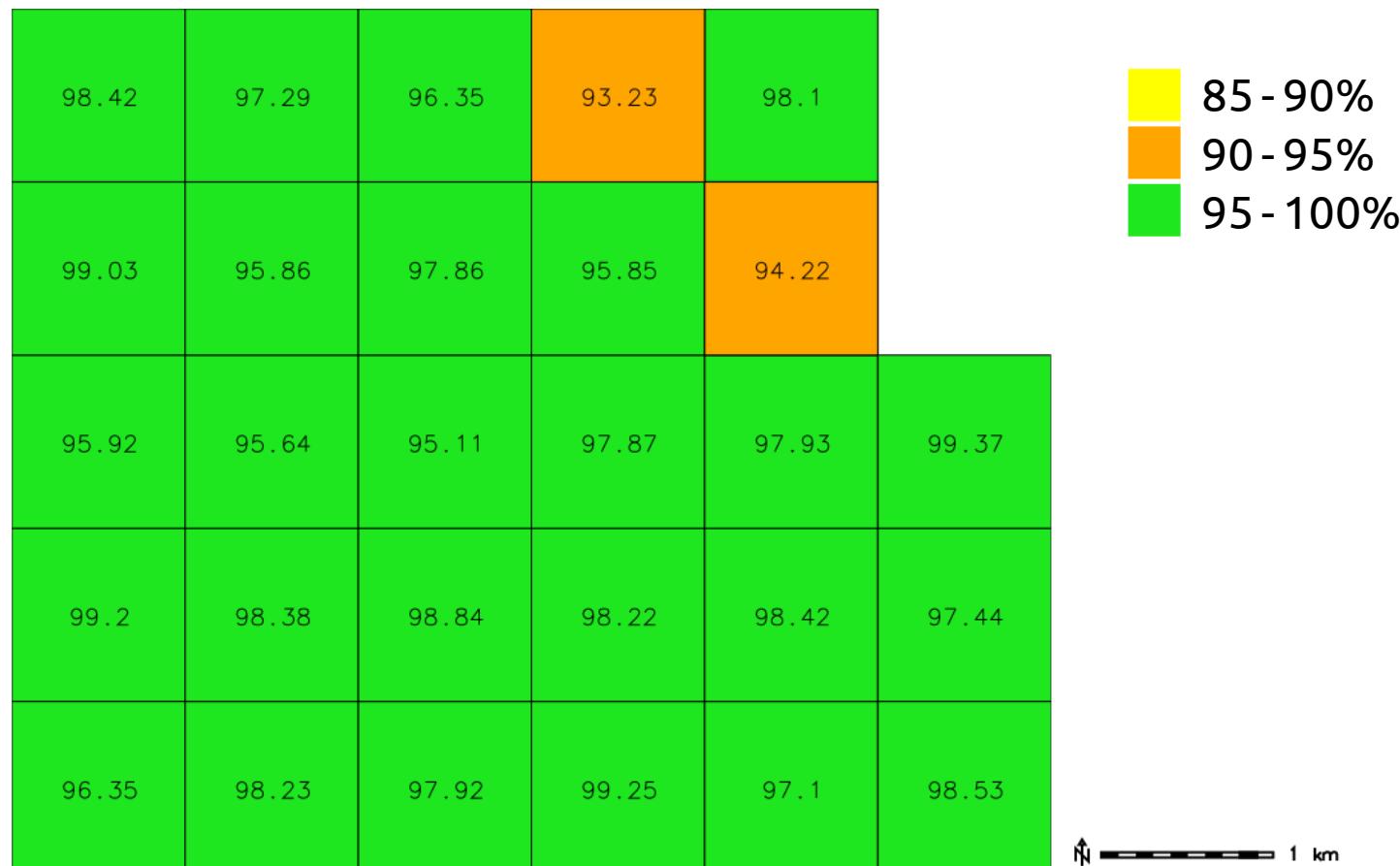
Step 3: grid-based evaluation of OSM accuracy

- ✓ For each grid cell, evaluate OSM accuracy against one or more target values of OSM deviation from IGN:
 - length percentage of OSM roads included in the target buffer
 - Area 2: target buffer = 6 m



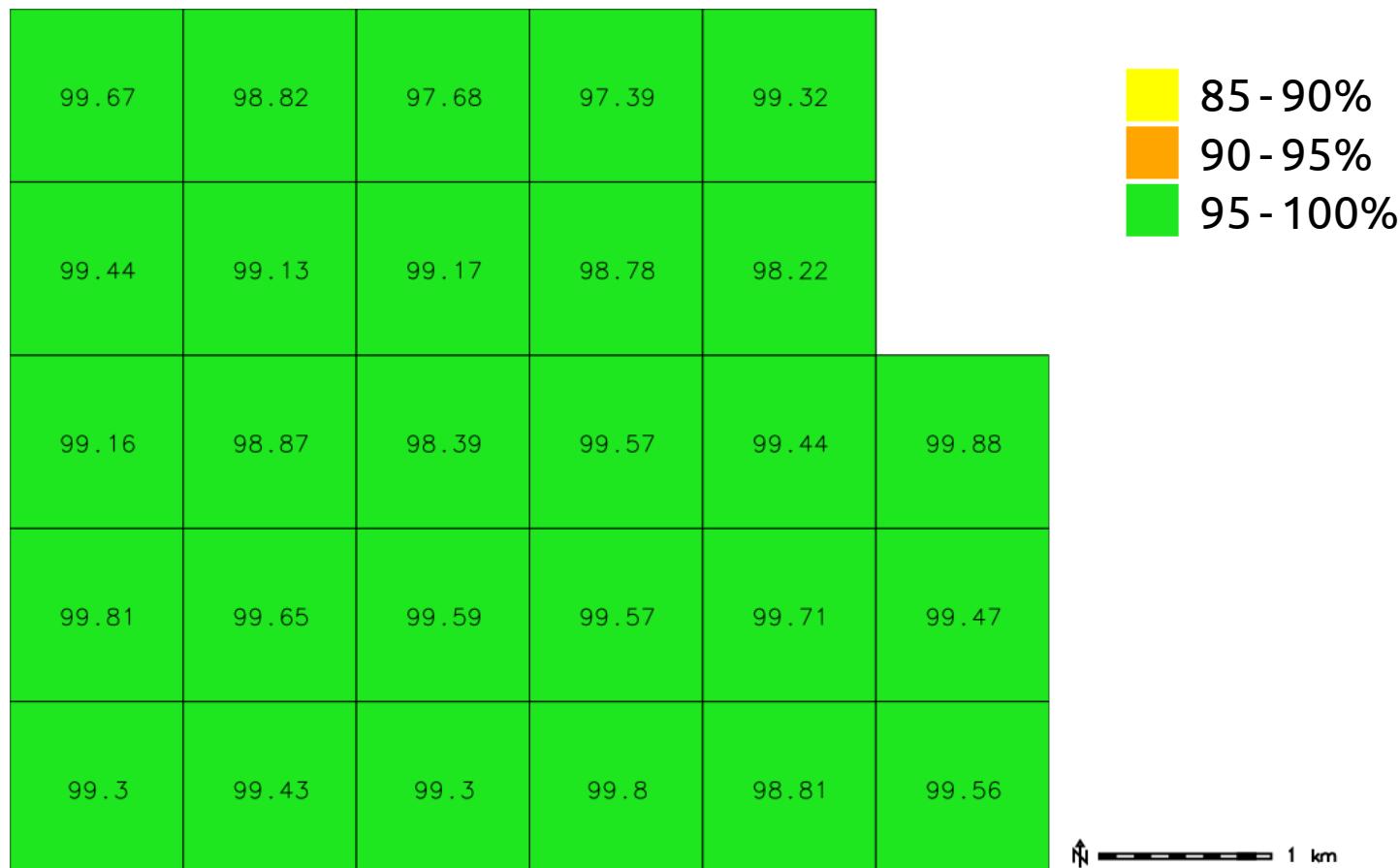
Step 3: grid-based evaluation of OSM accuracy

- ✓ For each grid cell, evaluate OSM accuracy against one or more target values of OSM deviation from IGN:
 - length percentage of OSM roads included in the target buffer
 - Area 2: target buffer = 8 m



Step 3: grid-based evaluation of OSM accuracy

- ✓ For each grid cell, evaluate OSM accuracy against one or more target values of OSM deviation from IGN:
 - length percentage of OSM roads included in the target buffer
 - Area 2: target buffer = 10 m



2

Analysis of OSM contribution patterns

Tagging in OSM

- ✓ OSM applies a [folksonomy](#) approach to tagging with no formal rules or ontologies forced
 - ➔ tagging rule-book is the [OSM Map Features](#) wiki page
 - ✗ guidance on which tags and [combinations of tags](#) to use

Used on these elements



Useful combination

- [name=*](#)
- [Address](#)
- [operator=*](#)
- [cuisine=*](#)
- [opening_hours=*](#)
- [website=*](#)
- [phone=*](#)

Tagging in OSM

- ✓ OSM applies a [folksonomy](#) approach to tagging with no formal rules or ontologies forced
 - tagging rule-book is the [OSM Map Features](#) wiki page
 - ✗ guidance on which tags and combinations of tags to use
 - taginfo shows that this guidance may not be universally adopted!

Used on these elements



Useful combination

- [name=*](#)
- [Address](#)
- [operator=*](#)
- [cuisine=*](#)
- [opening_hours=*](#)
- [website=*](#)
- [phone=*](#)

amenity=restaurant

Overview Combinations Map Wiki Projects

Combinations

This table shows only the most common combinations of the most common tags.

Count →	Other tags
687 829 91.36%	name=*
329 005 43.70%	cuisine=*
246 939 32.80%	addr:street=*
204 893 27.22%	addr:housenumber=*
180 841 24.02%	addr:city=*
168 643 22.40%	addr:postcode=*
140 042 18.60%	building=*
127 409 16.92%	building=yes
113 375 15.06%	phone=*
111 769 14.85%	website=*
93 607 12.43%	source=*

Analysis of OSM tagging practices

- ✓ Research questions:
 - do OSM contributors comply to the suggested combinations of tags?
 - does this compliance vary spatially?
- ✓ Selection of 10 among the most frequently occurring tags in OSM

Target Tag	TagInfo Ranking	Number of Objects
<i>highway=residential</i>	2	34,688,039
<i>natural=tree</i>	17	7,019,552
<i>highway=footway</i>	18	6,126,861
<i>highway=path</i>	24	4,506,593
<i>highway=tertiary</i>	25	4,328,513
<i>amenity=parking</i>	52	2,061,012
<i>highway=primary</i>	59	1,869,021
<i>highway=bus_stop</i>	66	1,677,724
<i>railway=rail</i>	69	1,584,142
<i>leisure=pitch</i>	93	977,983

Analysis of OSM tagging practices

- ✓ Research questions:
 - do OSM contributors comply to the suggested combinations of tags?
 - does this compliance vary spatially?
- ✓ Selection of 10 among the most frequently occurring tags in OSM
- ✓ Selection of 40 world cities



Methodology

- ✓ For each **city**, for each **target tag** and for each of the **suggested tags** to be used in combination:
 - ➔ computation of the fraction of objects containing both the target tag and the suggested tag
 - ➔ mapping of the fraction to a **5 part Likert Scale**
 - ✗ 0-20% – POOR
 - ✗ 20-40% – FAIR
 - ✗ 40-60% – AVERAGE
 - ✗ 60-80% – GOOD
 - ✗ 80-100% – EXCELLENT
- ✓ Example: Christchurch (New Zealand), tag *leisure=pitch*

Report for Tag: *leisure=pitch*

Total number of objects: 470

<i>sport</i>	364	77.5%	GOOD
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<i>surface</i>	42	9.0%	POOR
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Total number of different tags used: 26

Results

- ✓ *highway=residential*

KEY	Poor	Fair	Average	Good	Excellent
<i>name</i>	8	1	7	5	19
<i>oneway</i>	34	5	1	0	0

- ✓ *natural=tree*

KEY	Poor	Fair	Average	Good	Excellent
<i>circumference</i>	38	0	1	0	1
<i>taxon</i>	38	0	0	0	2
<i>leaf_type</i>	34	2	2	1	1
<i>start_date</i>	39	0	0	1	0
<i>height</i>	37	0	1	0	2
<i>denotation</i>	36	1	2	0	1
<i>genus</i>	38	1	1	0	0
<i>species</i>	35	1	2	0	2

- ✓ *highway=primary*

KEY	Poor	Fair	Average	Good	Excellent
<i>lanes</i>	10	10	6	6	8
<i>ref</i>	8	10	6	2	14
<i>name</i>	0	2	4	10	24

Results

- ✓ *highway=bus_stop*

KEY	Poor	Fair	Average	Good	Excellent
<i>operator</i>	28	4	2	3	3
<i>public_transport</i>	21	7	5	3	4
<i>name</i>	3	4	3	9	21

- ✓ *leisure=pitch*

KEY	Poor	Fair	Average	Good	Excellent
<i>sport</i>	0	2	7	16	15
<i>surface</i>	40	0	0	0	0

- ✓ Summary:

Tag	Keys	Poor	Fair	Average	Good	Excellent
<i>highway=primary</i>	3	15.00	18.33	13.33	15.00	38.33
<i>highway=tertiary</i>	4	40.00	20.00	13.75	14.38	11.88
<i>highway=bus-stop</i>	3	43.33	12.50	8.33	12.50	23.33
<i>railway=rail</i>	9	46.39	18.61	12.78	11.67	10.56
<i>leisure=pitch</i>	2	50.00	2.50	8.75	20.00	18.75
<i>highway=residential</i>	2	52.50	7.50	10.00	6.25	23.75
<i>amenity=parking</i>	6	90.83	6.67	2.50	0.00	0.00
<i>highway=path</i>	7	91.78	5.71	2.50	0.00	0.00
<i>natural=tree</i>	8	92.19	1.56	2.81	0.62	2.81
<i>highway=footway</i>	6	94.58	4.58	0.83	0.00	0.00

3

Use of OSM to generate Land Use/ Land Cover maps

Land Use/Land Cover (LULC) maps

- ✓ LULC maps are crucial products for multiple areas of application:
 - ➔ modeling climate and biochemistry of the Earth
 - ➔ biodiversity monitoring
 - ➔ natural resources management
 - ➔ planning/urban studies
 - ➔ many others
- ✓ LULC maps are created through the classification of satellite imagery and validated using reference data:
 - ➔ the creation and updating process is long, costly & time-consuming
 - insufficient to describe rapidly-changing environments
 - ➔ the level of detail and spatial coverage are inadequate for many applications

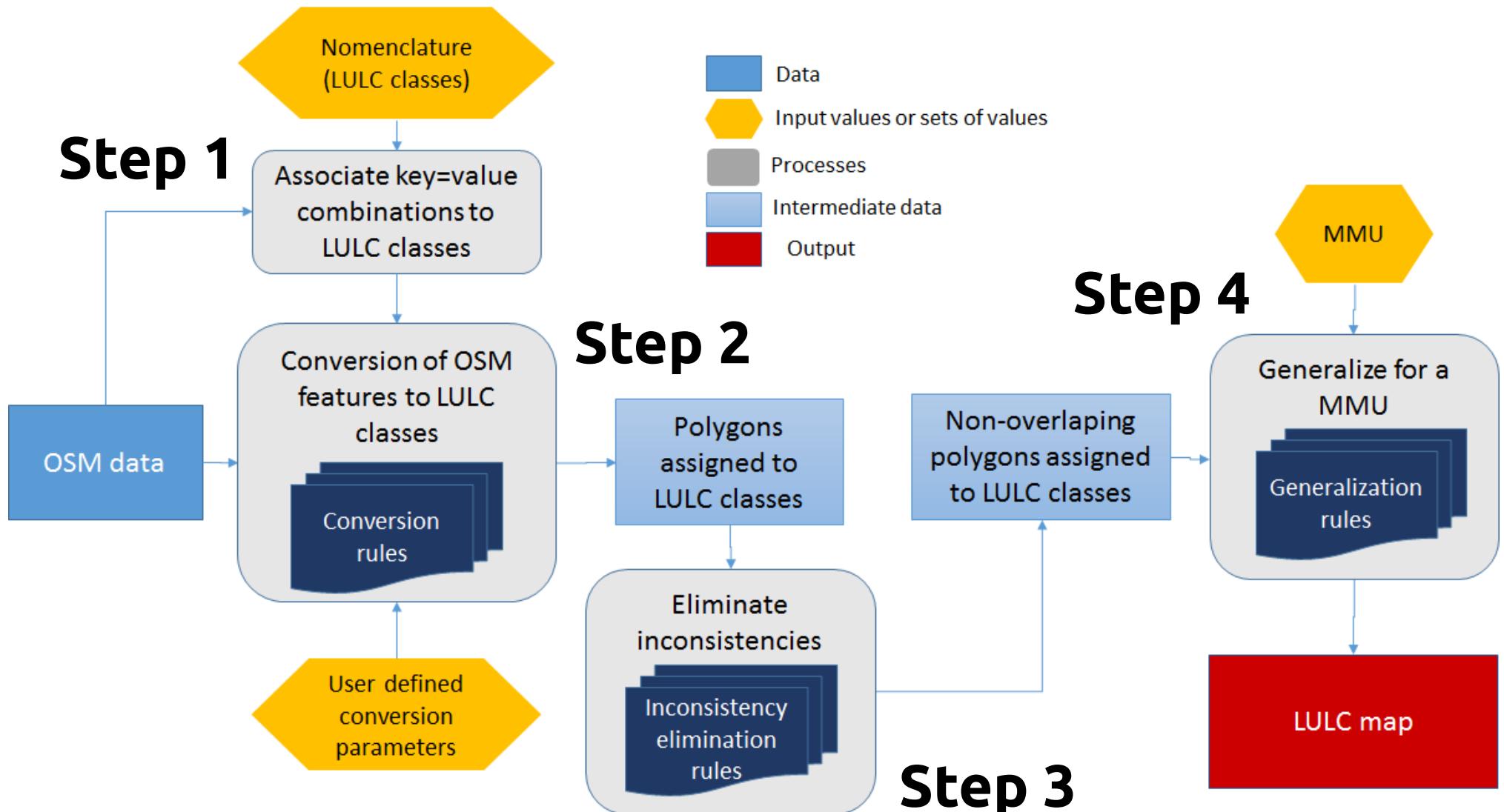
OSM as a source of LULC maps

- ✓ Exploiting OSM as a source for LULC maps has a number of advantages:
 - ➔ OSM full spatial coverage in the world
 - ➔ OSM richness
 - ➔ OSM non-stop updating
 - ➔ OSM open license
- ✓ Exploiting OSM as a source for LULC maps has some disadvantages:
 - ➔ OSM uneven spatial coverage
 - ➔ OSM positional accuracy & geometrical inconsistencies
 - ➔ OSM semantic inconsistencies
- ✓ Purpose: creating an automated procedure which converts OSM data in a specific area into a LULC map
 - ➔ reference nomenclatures of current EU and global LULC maps (e.g. Urban Atlas, Corine Land Cover, GL30)

Example of nomenclature: Urban Atlas

Level 1	Level 2	Level 3
1 Artificial Surfaces	1.1 Urban Fabric	1.1.1 Continuous urban fabric 1.1.2 Discontinuous urban fabric 1.1.3 Isolated Structures
	1.2 Industrial, commercial, public, military, private and transport units	1.2.1 Industrial, commercial, public, military and private units 1.2.2 Road and rail network and associated land 1.2.3 Port areas 1.2.4 Airports
	1.3 Mine, dump and construction sites	1.3.1 Mineral extraction and dump sites 1.3.3 Construction sites 1.3.4 Land without current use
	1.4 Artificial non-agricultural vegetated areas	1.4.1 Green urban areas 1.4.2 Sports and leisure facilities
2 Agricultural, semi-natural areas, wetlands		
3 Forests		
5 Water		

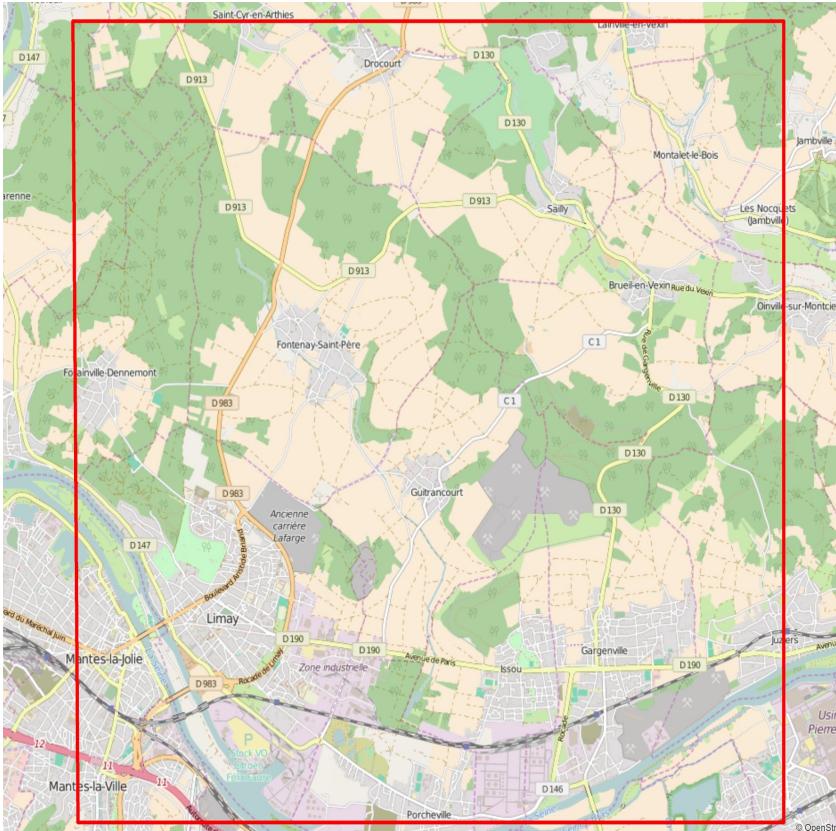
Methodology to convert OSM into LULC maps



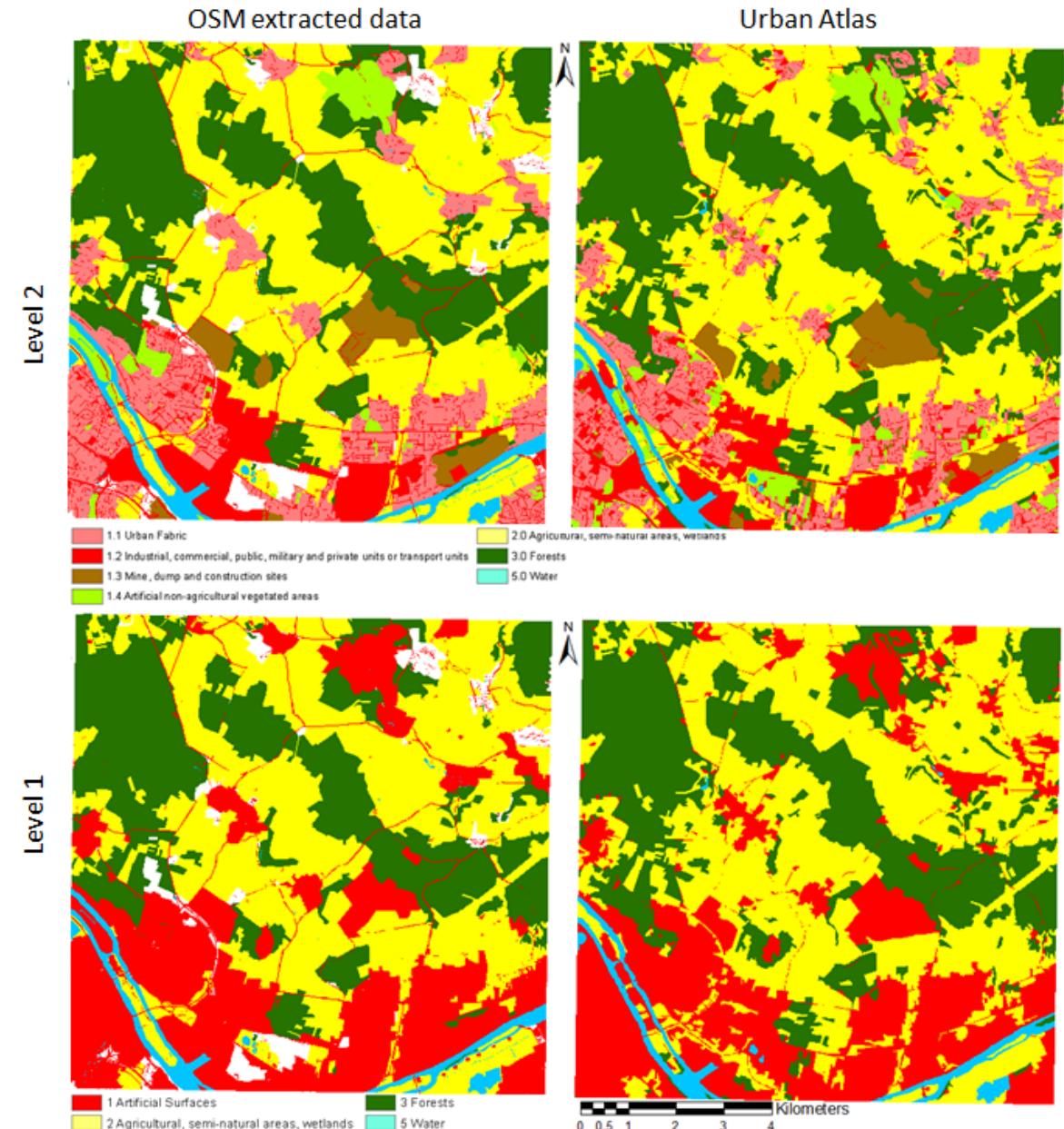
- ✓ Source code: <https://github.com/JoaquimPatriarca/senpy-for-gis>
- ✓ Web service: <http://vgi.mat.uc.pt/vgi/osm/osm2lulc> – work in progress!

Case studies

✓ Paris area

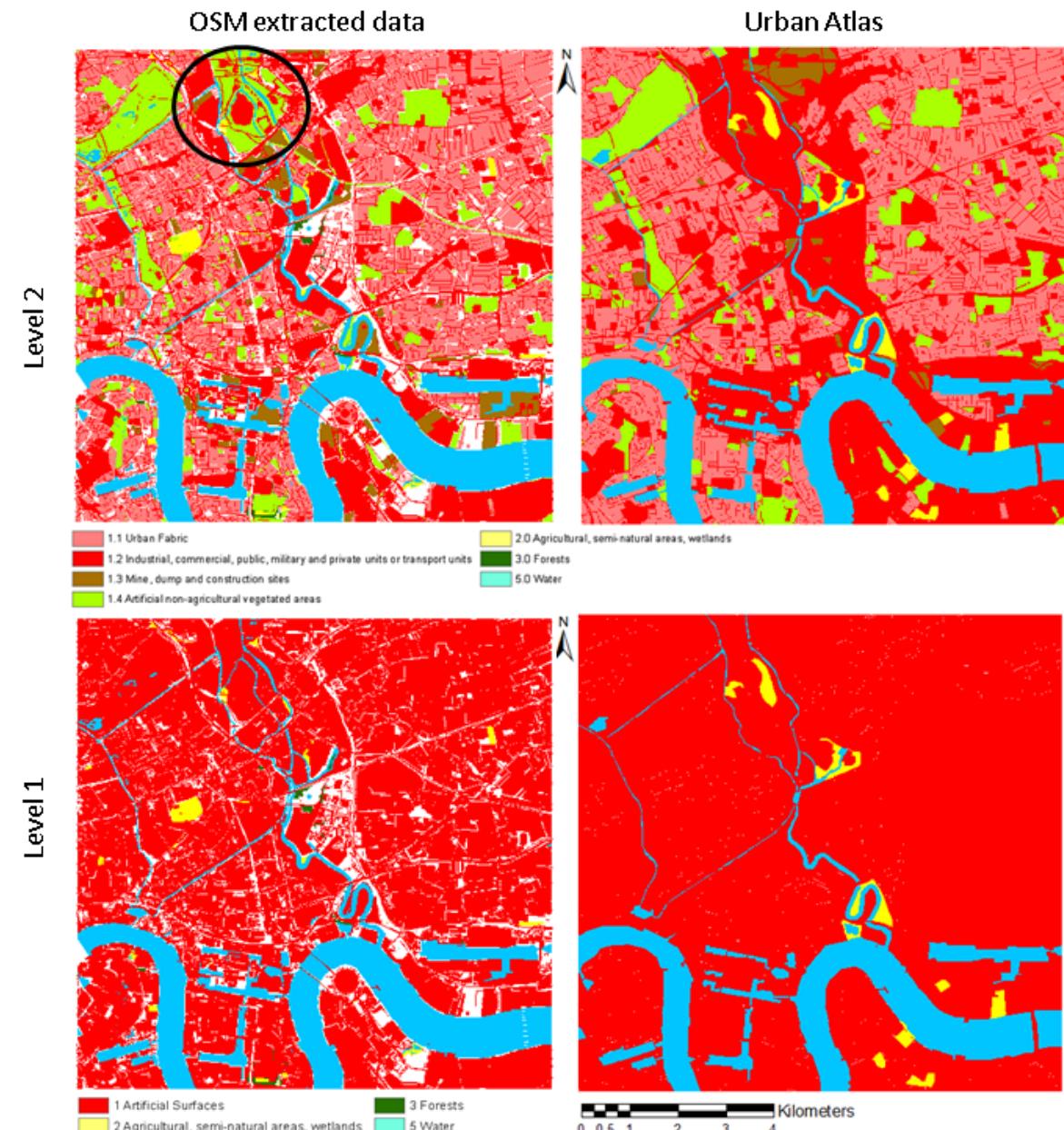
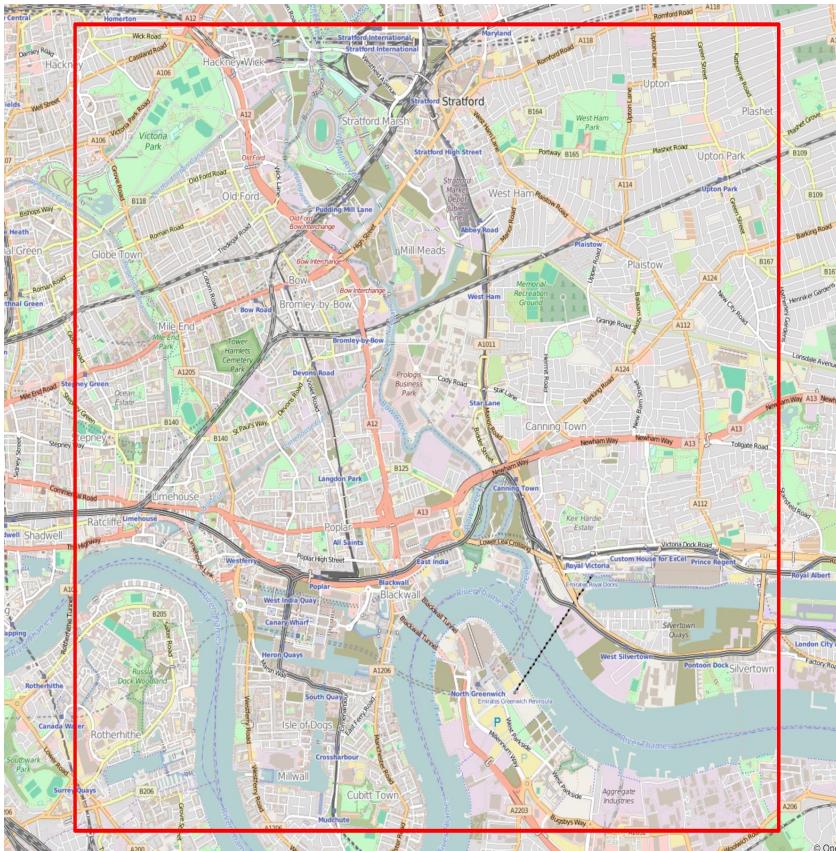


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Case studies

✓ London area



Case studies

- ✓ Areas [ha] occupied by Level 2 classes associated to the overlapping regions in the Urban Atlas & the OSM-derived maps – Paris study area

PARIS		Classes assigned to the overlapping regions in the OSM-derived map							Match/ Row Sum (%)
		1.1	1.2	1.3	1.4	2	3	5	
Classes assigned to the overlapping regions in UA	1.1	967	106	1	11	50	24	1	83
	1.2	186	640	37	20	50	13	3	67
	1.3	19	24	227	0	45	7	0	71
	1.4	56	26	0	161	57	6	5	52
	2	108	148	33	43	3545	124	10	88
	3	21	28	11	44	138	2425	5	91
	5	3	4	1	1	6	5	221	92
Match/Column Sum (%)		71	66	73	57	91	93	90	85

Case studies

- ✓ Areas [ha] occupied by Level 2 classes associated to the overlapping regions in the Urban Atlas & the OSM-derived maps – London study area

LONDON		Classes assigned to the overlapping regions in the OSM-derived map							Match/ Row Sum (%)
		1.1	1.2	1.3	1.4	2	3	5	
Classes assigned to the overlapping regions in UA	1.1	2346	796	16	86	8	2	21	72
	1.2	525	2323	214	174	32	8	86	69
	1.3	25	51	18	26	5	3	7	14
	1.4	19	111	5	644	17	5	18	79
	2	5	18	41	23	3	3	9	3
	3	0	0	0	0	0	0	0	0
	5	12	22	8	5	0	0	1107	96
Match/Column Sum (%)		80	70	6	67	4	0	89	73

References

- ✓ Antunes F., Fonte C.C., Brovelli M.A., Minghini M., Molinari M.E. & Mooney P. (2015) Assessing OSM Road Positional Quality with Authoritative Data. *Proceedings of the VIII Conferência Nacional de Cartografia e Geodesia*, Lisbon (Portugal), October 29-30, 2015.
- ✓ Brovelli M.A., Minghini M., Molinari M.E. & Mooney P. (2017) Towards an automated comparison of OpenStreetMap with authoritative road datasets. *Transactions in GIS* 21(2), 191-206.
- ✓ Brovelli M.A., Minghini M. & Molinari M.E. (2016) An automated GRASS-based procedure to assess the geometrical accuracy of the OpenStreetMap Paris road network. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XLI-B7, 919-925.
- ✓ Brovelli M.A., Minghini M., Molinari M.E. & Mooney P. (2015) A FOSS4G-based procedure to compare OpenStreetMap and authoritative road network datasets. *Geomatics Workbooks* 12, 235-238.
- ✓ Davidovic N., Mooney P., Stoimenov L. & Minghini M. (2016) Tagging in Volunteered Geographic Information: An Analysis of Tagging Practices for Cities and Urban Regions in OpenStreetMap. *ISPRS International Journal of Geo-Information* 5(12), 232.
- ✓ Fonte C.C., Minghini M., Patriarca J., Antoniou V., See L. & Skopeliti A. (2017) Generating Up-to-Date and Detailed Land Use and Land Cover Maps Using OpenStreetMap and GlobeLand30. *ISPRS International Journal of Geo-Information* 6(4), 125.
- ✓ 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: *Volunteered Geographic Information and the Future of Geospatial Data*. IGI Global, 113-137.
- ✓ Fonte C.C., Minghini M., Antoniou V., See L., Patriarca J., Brovelli M.A. & Milcinski G. (2016) An automated methodology for converting OSM data into a land use/cover map. *Proceedings of the 6th International Conference on Cartography & GIS* 1, 462-473, Albena (Bulgaria), June 13-17, 2016.

Acknowledgements

- ✓ Thanks to all the amazing people I have worked with on these exciting topics!
 - ➔ Vyon Antoniou
 - ➔ Francisco Antunes
 - ➔ Maria Antonia Brovelli
 - ➔ Cidália Costa Fonte
 - ➔ Nikola Davidovic
 - ➔ Monia Elisa Molinari
 - ➔ Peter Mooney
 - ➔ Joaquim Patriarca
 - ➔ Linda See
 - ➔ Andriani Skopeliti
 - ➔ Leonid Stoimenov
- ✓ Thanks to all OSM contributors for making this possible :)

Thank you!

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Special Issue on JGS on VGI

- ✓ The Journal of Geographical Systems (JGS) is an interdisciplinary journal aiming to encourage and promote high quality scholarship on important theoretical, methodological & empirical issues with a central spatial or regional dimension
 - ➔ Impact Factor: 1.314 (2016), Journal Citation Reports®
- ✓ Special Issue “Volunteered Geographic Information: Looking Towards the Next 10 Years”:
 - ➔ the first 10 years of VGI have seen an explosion of activity, particularly in the form of projects such as OpenStreetMap – but what will the next 10 years hold?
 - ➔ Guest Editors:
 - ✗ Linda See, IIASA, Austria
 - ✗ Cidália Costa Fonte, University of Coimbra, Portugal
 - ✗ Vyrion Antoniou, Hellenic Military Geographical Service, Greece
 - ✗ Marco Minghini, Politecnico di Milano, Italy