Assessing the Completeness of Urban Green Spaces in OpenStreetMap

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State of the Map 2019, Heidelberg, Germany





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Definition: Publicly accessible, vegetated land within a city.

Urban green spaces are important factors for the quality of life, because they provide recreational and cultural services to citizens.





Developing a recommendation system for nearby green spaces based on personal needs and activities.

Information sources:

- Municipal data
- Satellite Imagery
- Social Media
- OpenStreetMap
 - \rightarrow Quality Assessment



Study area: Dresden, Germany











Step 1:

Extracting public green spaces from OSM

1.1 Which OSM tags indicate public green spaces?

OSM Tags for Public Green Spaces





OSM Tags for Public Green Spaces





Association between OSM tags and greenness





Ranking of OSM gags for greenness in Dresden







If available, use "access" key.

Otherwise, assume:

- 1. Everything that is mapped in OSM is publicly accessible.
- 2. Features with *landuse=residential* are private.



Step 1.2:

Generating a mesh of polygons with homogenous land use



Orthophoto of Dresden





Generation of City blocks using linear topographic elements from OSM

- Road network (motorized)
- Railway network
- Water network





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Exclusion of areas for transport by buffering of the roads and railway tracks according to type (primary, secondary, trains, trams, etc.)



Generation of polygon mesh



Further segmentation of the city blocks using OSM objects describing land use

Hierarchy of objects defined by area size (e.g. *leisure=park* polygon above larger *landuse=residential* polygon)

 $MMU = 10 m^2$



Generation of polygon mesh



Final segmentation using foot paths and buildings



Extracted public green spaces from OSM







Step 2: Extrinsic Data Quality Assessment

Comparison to municipal data

Extrinsic comparison to municipal data





Municipal data:

- public green spaces
- parks
- cemeteries
- forests
- playgrounds
- allotments



Extrinsic comparison to municipal data





Extrinsic comparison to municipal data







- Public Green Spaces are fuzzy geographic concepts.
- Quantitative comparison to external data difficult due to ...
 - different definitions of "green space"
 - timeliness of external data set
 - different scale at which data sets have been created.



Step 3:

(Intrinsic) Identification of Missing Public Green Spaces from OSM itself

Identifying missing public green spaces in OSM





Evidence for public green spaces from geographic context:

- dense foot path network (OSM)
- presence of a playground (OSM)
- high vegetation index (satellite data)

Evidence contains uncertainties

→ Combine evidence using Dempster-Shafer Theory



- \rightarrow Public
- \rightarrow Public
- \rightarrow Green



- Framework for reasoning under uncertainty using evidence from different sources
- Evidence is converted to beliefs (or masses) using belief functions
- Beliefs can be about a set of events, not just single events
- \rightarrow Uncertainty can be expressed explicitly

	Probability Theory	Dempster-Shafer
Fair coin	p({heads}) = 0.5 p({tails}) = 0.5	mass({heads}) = 0.5 mass({tails}) = 0.5
Total ignorance	p({heads}) = 0.5 p({tails}) = 0.5	mass({heads}) = 0 mass({tails}) = 0 mass({heads, tails}) = 1

Belief functions





amenity=parking

Path Density

Identified green spaces from geographic context

30

Uncertainty of identified green spaces

31

- There are **several OSM tags that indicate public green spaces** with varying degrees of certainty.
- Quantitative comparison is not feasible due to fuzzy definition of green spaces.
- Missing public green spaces can be inferred from geographic context such as path network and playgrounds.

Outlook

- Consider additional aspects of geographic context as evidence (e.g. benches, building geometries)
- **Combine DST with machine learning** to define belief functions automatically and evaluate other ML methods that consider uncertainty

Thank you for your attention. Any questions?

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Images:

https://upload.wikimedia.org/wikipedia/commons/2/29/Green_Gables_House_backyard.jpg https://upload.wikimedia.org/wikipedia/commons/0/05/Gillette_New_Jersey_residential_road_in_autumn.jpg https://commons.wikimedia.org/wiki/File:Brussels_Cinquantenaire_R04.jpg