



Validation of OpenStreetMap road data for integration into the gROADS v1

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Content

Context

• OSM

- $_{\circ}$ Background
- Quality aspects
- Previous validation methods
- Current validation methods

Assessment methods

- 。 Historic assessment
- Attribute structure
- $_{\circ}~$ Positional accuracy
- Completeness assesment
- $_{\circ}~$ Versioning as trust parameter
- Ingestion decision
- Conclusion

Context

gROADS v1

- Global dataset best available open access road data by country
- Low positional accuracy (RMSE > 900m) + Low completeness

OpenStreetMap

- Successful Volunteered Geographic Information product (> 2 million active users)
- Best source of data to improve gROADS v1

Problematic

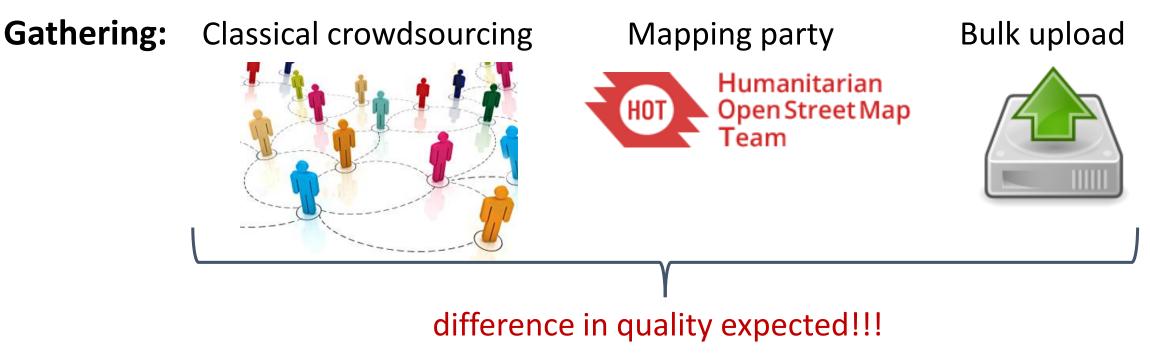
- OSM has no systematic quality control
- OSM's quality is highly variable

Objective

- Develop diagnostics that can give a sense about overall quality of OSM
- Decide if OSM country data should be ingested into gROADS

OSM

OSM Background



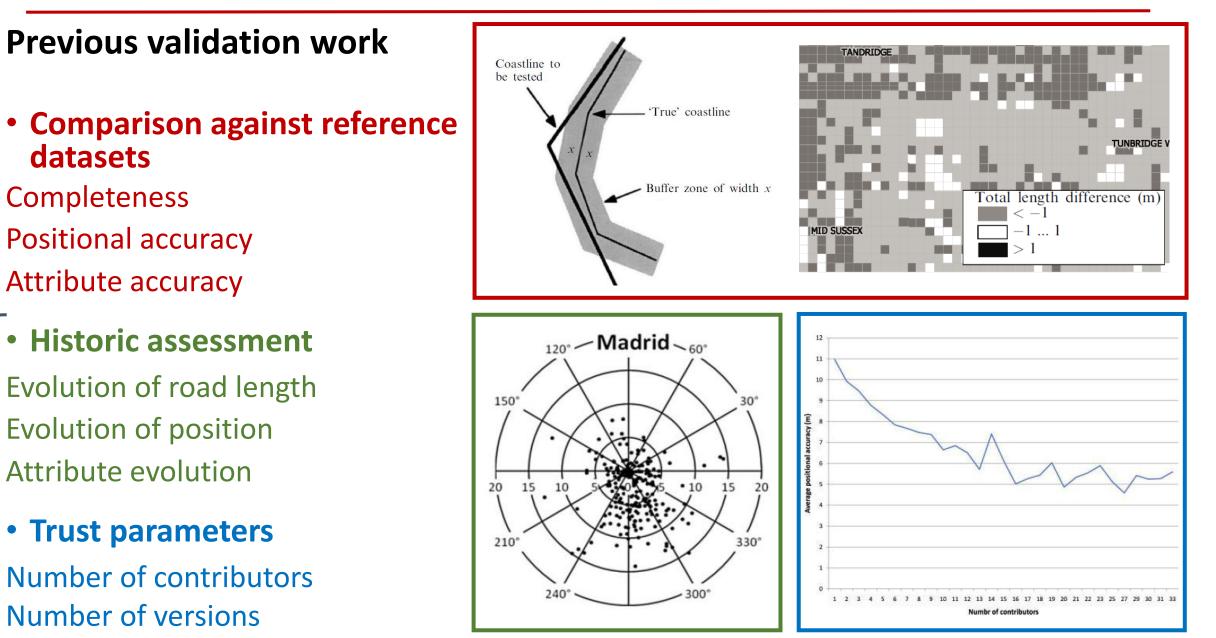
Offline use:

- OSM current data: .osm (XML) -> ArcGIS, Qgis edits necessary → gROADS would
- **OSM historic data:** .osh (XML) -> No tools built for common GIS
- Ingestion into → gROADS would increase ease of use!!!

Quality components

- **Positional accuracy** Accuracy of coordinate values (horizontal and vertical)
- Attribute accuracy Accuracy of quantitative attributes, the correctness of nonqualitative ones and the correctness of classification.
- Completeness A measure of the absence of data and the presence of excess data
- Lineage Traceability of geographic data capacity to describe the origin and evolution

OSM



OSM

Objective

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- Decide if OSM country data should be ingested into gROADS

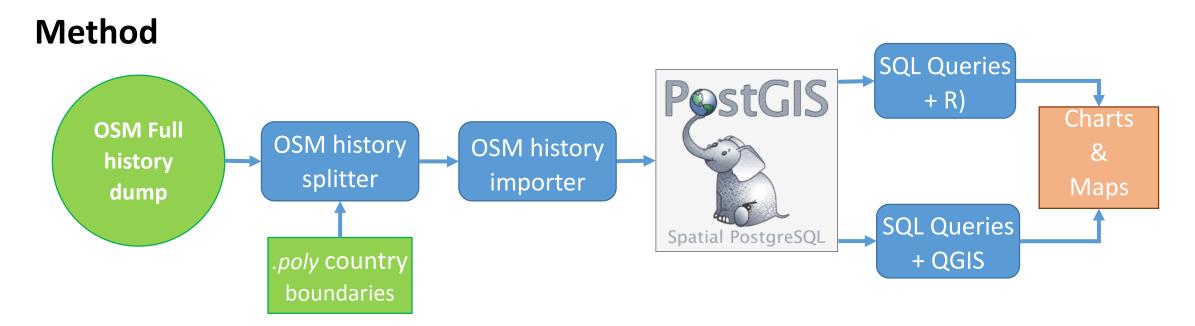
Assessments:

- Length evolution (Historic assessment)
- Attribute structure (Intrinsic quality)
- Completeness (Use of complementary datasets) New approach!
- Positional accuracy (Comparison against reference dataset)
- Versioning (Trust parameter)

Case study: Liberia, Guinea, Ghana, Senegal

Analysis Platform : R, ArcGIS, PostGIS

Historic assessment



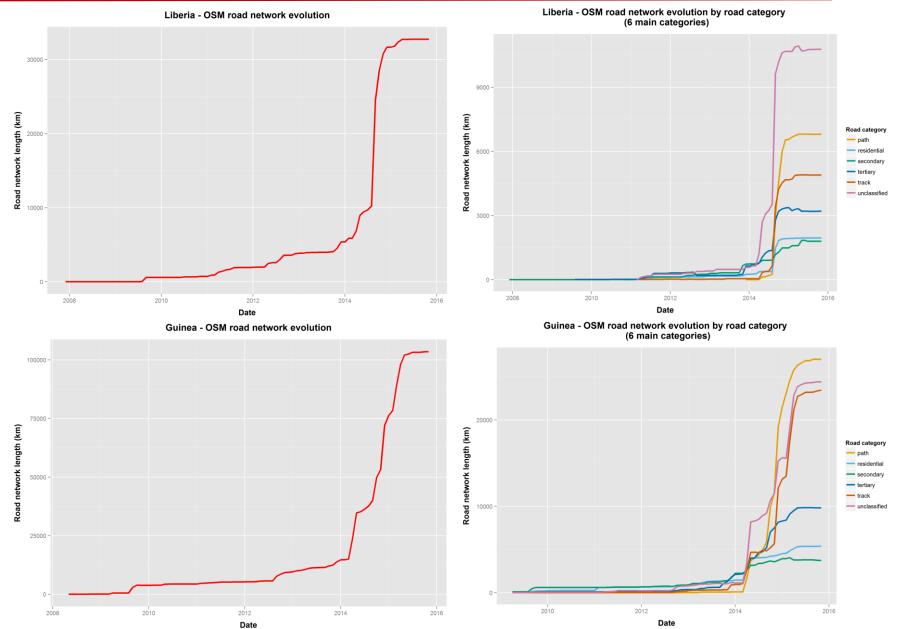
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4634293	5	2	TRUE	34124	Sunny	2009-01-22 16:48:47	2009-01-22 16:48:55	"ref"=>"W4	9	010200002031BF00
4634293	5	3	TRUE	34124	Sunny	2009-01-22 16:48:55	2009-01-22 16:49:14	"ref"=>"W/	9	010200002031BF00
4634293	5	4	TRUE	34124	Sunny	2009-01-22 16:49:14	2009-03-05 20:13:32	"ref"=>"W4	9	010200002031BF00
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4634293	5	6	TRUE	34124	Sunny	2009-03-05 20:13:43	2009-03-05 20:14:09	"ref"=>"W/	9	010200002031BF0[

Historic assessment

Results

Liberia & Guinea

- Mapping intensified during Ebola crisis
- Contribution stagnates in the present

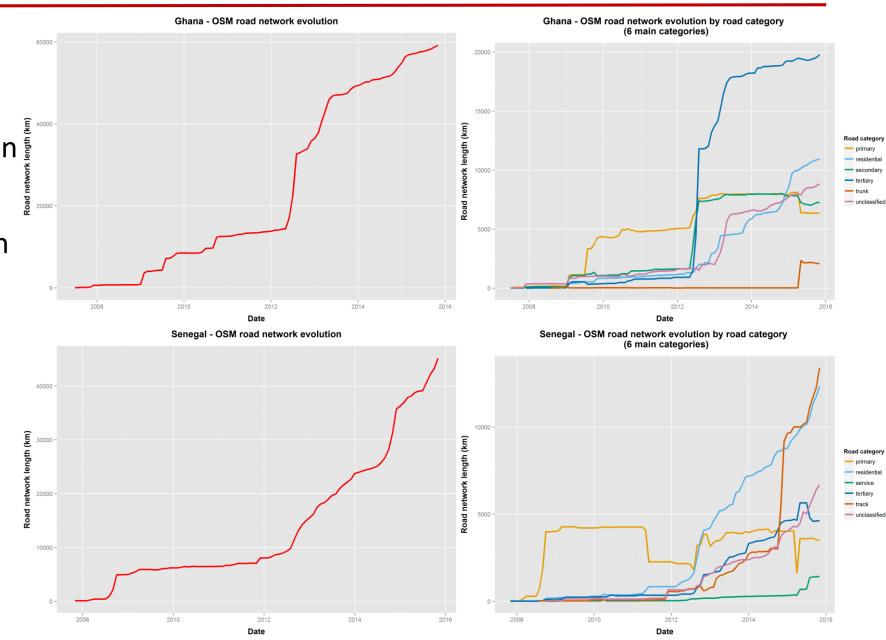


Historic assessment

Results

Ghana & Senegal

- More steady evolution
- Reclassifications
- Strong contribution in the present
- No pattern for road types



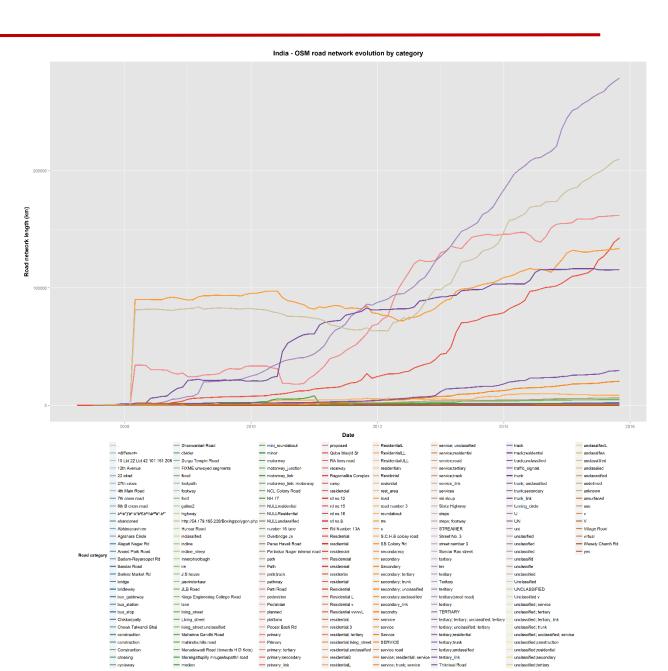
Attribute structure

Assessments:

- Proportion of 'misclassified' features
- Proportion of unclassified features

Metrics

- Number of unclassified / 'misclassified' features out of total number of features (%)
- Length of unclassified / 'misclassified' features out of total length of the road network (%)



Attribute structure(2/2)

Countrios	Unclassif	sified roads Misclassified road		
Countries	Count (%)	Length (%)	Count (%)	Length (%)
Liberia	13.39	32.89	0.01	> 0.01
Guinea	10.72	23.57	> 0.01	0.01
Ghana	7.57	14.94	0	0
Senegal	3.44	14.80	> 0.01	> 0.01

- 'Misclassified' roads not a problem
- Length (%) a better metric \rightarrow Longer segments are unclassified

Assumption

Presence/absence of roads is influenced by 3 quantifiable variables: **Population**, Wealth, Terrain Variability

IF TRUE \rightarrow The 3 variables can be used to predict regions with missing roads in OSM

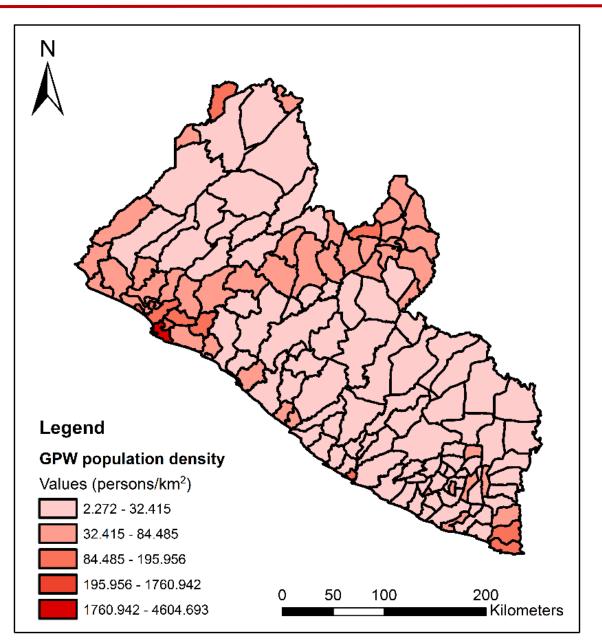
Workflow

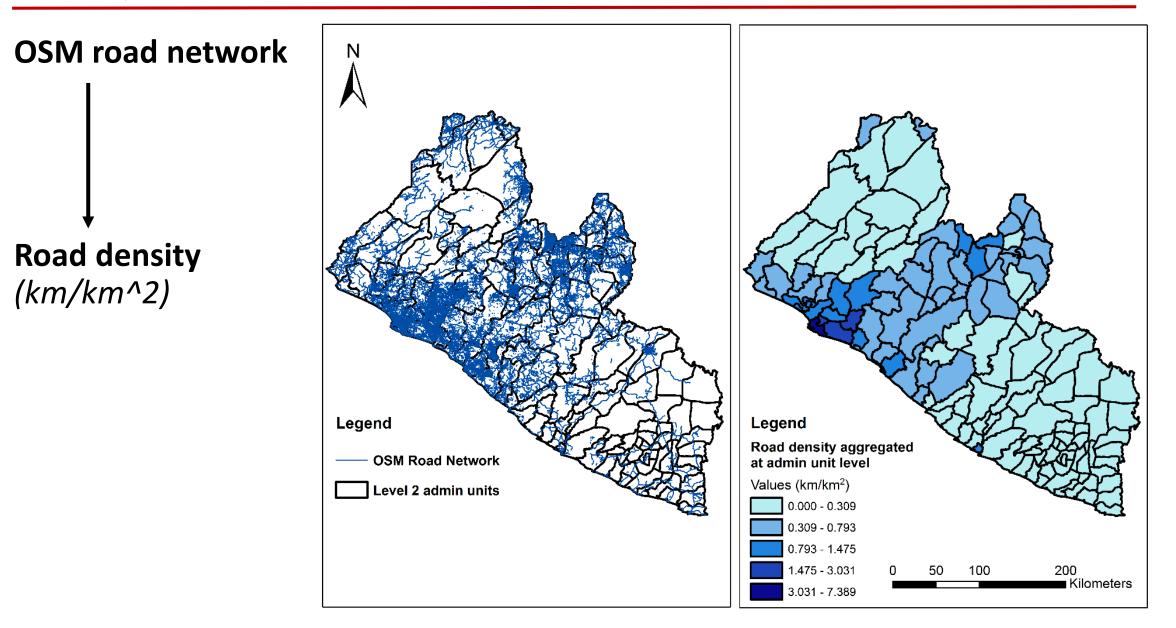
- Identify suitable datasets: GPW, DSH survey, STRM-1 Arc Second Global
- Aggregate datasets: Subnational admin units 2
- Asses data correlation
- **Develop prediction methods:** Discrete classification & Regression model
- Verify prediction accuracy

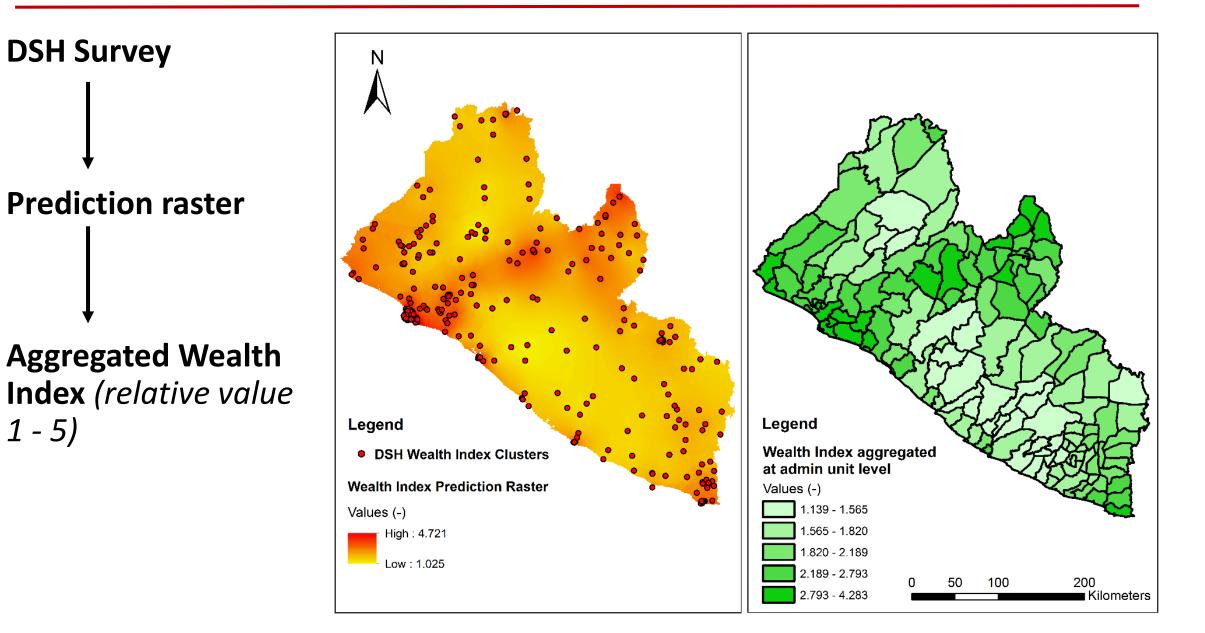
GPW 4

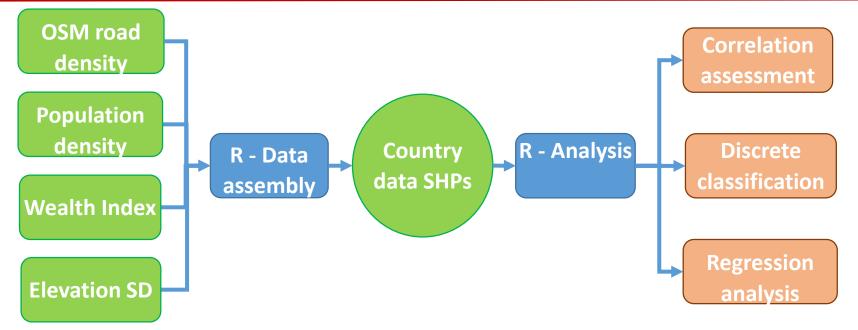
No transformation needed

Population density (pers./km2)









Correlation results

	Road	Pop.	Wealth	Elevation	Slope
	density	density		SD	AVG
Road density	1.00	0.86	0.68	-0.18	-0.35
Pop. density	0.86	1.00	0.45	-0.16	-0.25
Wealth	0.69	0.45	1.00	-0.07	-0.29
Elevation SD	-0.18	-0.17	-0.07	1.00	0.67
Slope Avg	-0.35	-0.25	-0.29	0.67	1.00

Conclusions

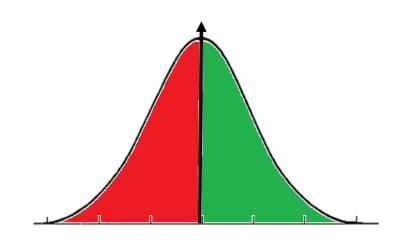
- Road Dens. correlates with Pop. Dens. & Wealth
- No correlation with terrain variables
- Interrelation between Pop.
 Dens. & Wealth

Method 1: Discrete classification prediction

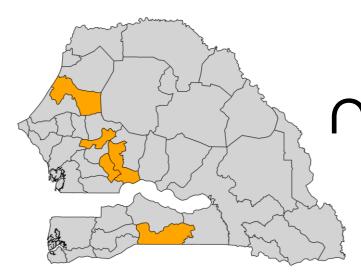
Determine: Low-High Road density, **Low-High** Population density, **Low-High** Wealth

Use: Median

Tag: Regions with **Low** Road Density but **High** Pop. Denisty & **High** Wealth



Low Road density - High Population density



Low Road density - High Wealth Index

Discrete classification prediction (Intersect)

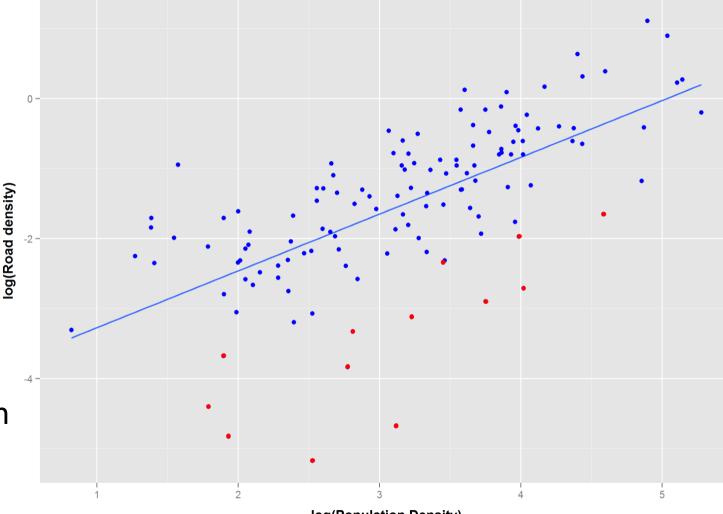


Method 2: Spatial regression prediction

- Predict Road density with Population density & Wealth
- Tag regions with extreme negative residuals
- Extreme residuals: lower quartile of negative residuals (<25%)

Regression model: Spatial Durbin

Weighting scheme: Queen 1 contiguity

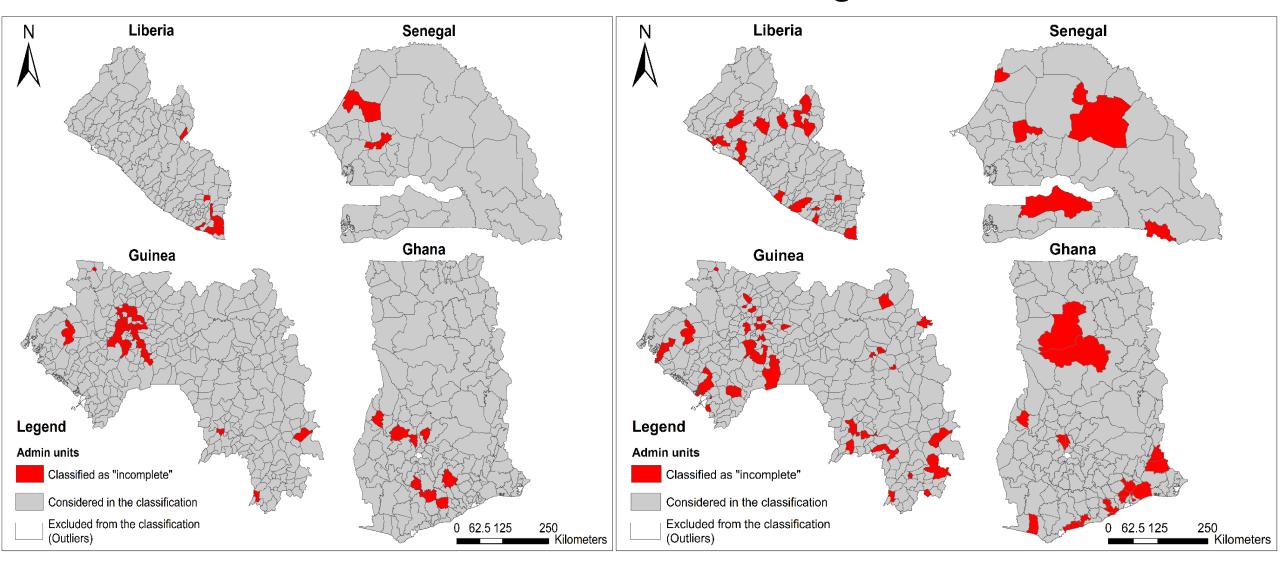


log(Population Density)

Simplification !

Discrete classification

Regression model



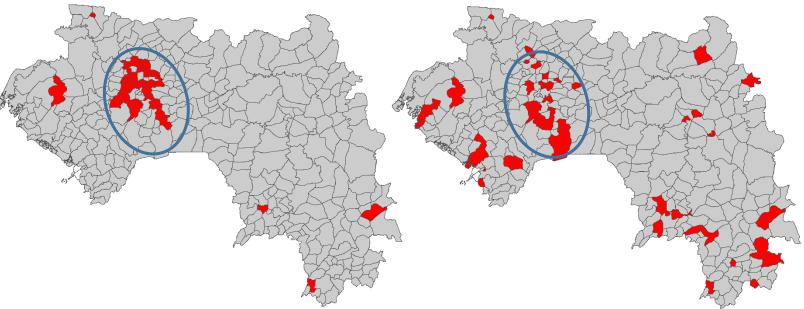
Conclusions

- Some patterns can be spotted
- Generally different predictions!
- Big number of erroneous predictions!
- Methods suitable for exploration (complementarily)

Limitations

- Modifiable area unit
- Quality of input datasets
- Cut-off values
- + Others

	Incorrect clas	Incorrect classifications				
Country	Discrete classification (%)	Regression models (%)				
Liberia	21%	31%	1			
Guinea	0%	11%	 ?			
Ghana	22%	23%				
Senegal	0%	0%				



Method

Compare position of OSM road intersections with the position of road intersections digitized on imagery (ground truth). Provide one RMSE value for each country.

Issue

Which source of imagery? How to sample? How big of a sample?

Preliminary tests

- 2 imagery sources: Google Earth, Esri
- 3 sampling schemes
- 2 countries: Liberia, Guinea

Conclusions

- Imagery: Google Earth
- Sample size: 100
- Sampling scheme: 10 random admin units (urban + rural) & 10 random intersections in each

Positional accuracy

Results

- RMSE < 50m
- Urban RMSE < Rural RMSE
- Classical gathering < Mapping party

Limitation

- Relative value of accuracy
- Digitization process and imagery induce systematic errors
- Digitization is time consuming

Country	Total RMSE (m)	Urban RMSE (m)	Rural RMSE (m)	Regional RMSE SD (m)
Liberia	31.57	7.97	43.93	26.68
Guinea	11.50	8.06	13.30	5.17
Senegal	7.46	4.10	8.99	3.66
Ghana	9.47	9.90	9.03	3.46

Assumption

Positional accuracy & Segment complexity increases as Number of versions increases

IF TRUE \rightarrow 'version' attribute – trust parameter

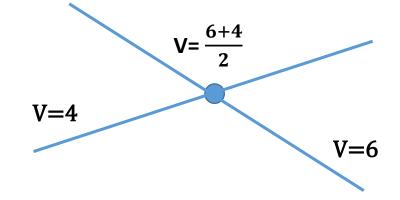
Methods

Positional accuracy

- Use the road intersection of known RMSE already samples
- Transfer them a the version of the parent segments

Segment complexity

- Segment complexity = number of nodes / segment length
- Use directly 'version' attribute



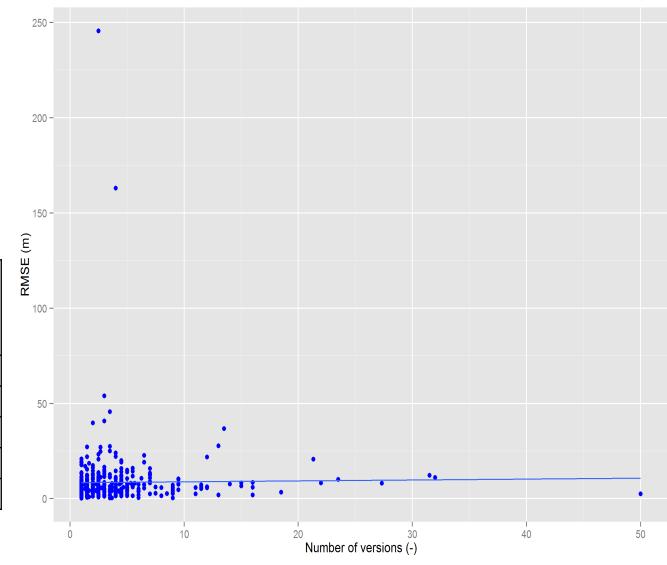
Study

Study

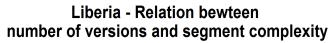
correlation

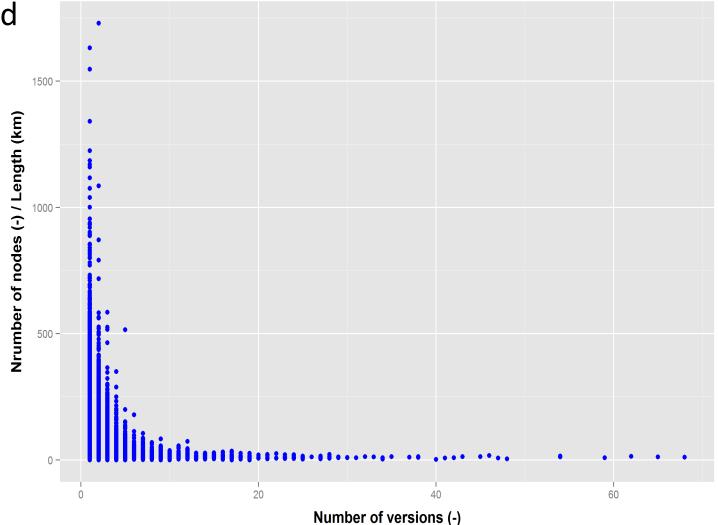
- No significant correlation noticed
- Numbers improve when excluding 1-3 versions
- Small number of points for the assessment

Countries	Correlation coefficient / Nr. of points		Correlation coefficient (subset) / Nr. of points	
Liberia	-0.0357	100	-0.0661	58
Guinea	0.1069	100	-0.0089	40
Ghana	-0.0008 100		-0.0221	54
Senegal	0.0426	99	0.2119	31
All samples	0.0142	399	-0.0189	183

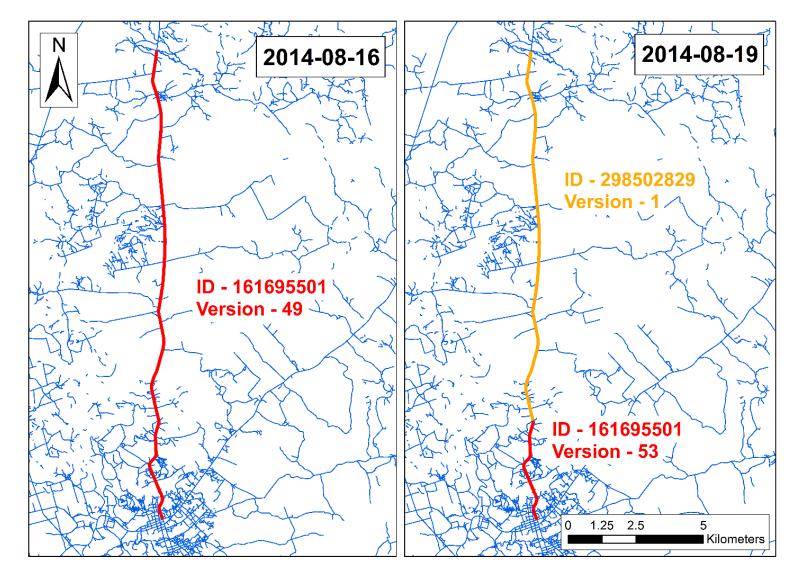


- Opposite results than expected
- Consistent in all cases
- Number of nodes & Segment length individually follow the same trend with increase in version





- Road fragmentation
- Data lineage error
- Magnitude of problem hard to assess
- Use of 'version' as trust parameter not recommended in case of roads !!!



Great! But...

How could we use the methods to make an ingestion decision???

A comparative approach!

- Compare OSM data with gROADS for each criteria
- If OSM is an improvement over gROADS → OK for that criteria
- Weight results for each country and make final decision

		Criteria			
Country	Completeness	Positional	Attribute	Ingestion	
		Accuracy	structure	decision	
Liberia					
Guinea					
Ghana					
Senegal					

Attribute structure

- Results compared based on % of Length
- gROADS generally present a smaller proportion of unclassified roads

		Criteria		
Country	Completeness	Positional	Attribute	Ingestion decision
		Accuracy	structure	uecision
			Improvement	
Liberia			NO	
Guinea			NO	
Ghana			YES	
Senegal			NO	

Countries	Unclassified roads		
	gROADS(%)	OSM(%)	
Liberia	20.98	32.89	
Guinea	9.58	23.57	
Ghana	98.37	14.94	
Senegal	9.18	14.80	

Positional accuracy

- gROADS has a 50m RMSE requirement
- Experience with gROADS indicates RMSE values as superior

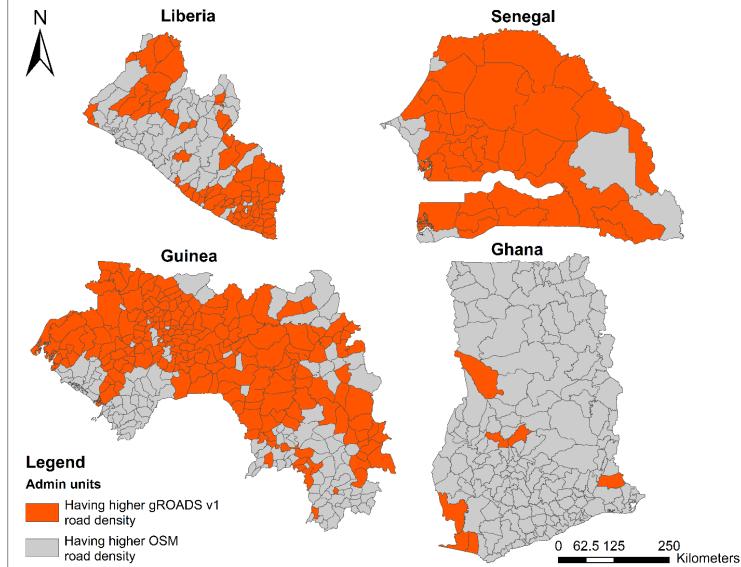
Country	Completeness	Positional	Attribute	Ingestion decision
		Accuracy	structure	aecision
		RMSE < 50m	Improvement	
Liberia		YES	NO	
Guinea		YES	NO	
Ghana		YES	YES	
Senegal		YES	NO	

Country	Total RMSE (m)
Liberia	31.57
Guinea	11.50
Senegal	7.46
Ghana	9.47

Completeness comparison

- OSM mapping is concentrated in urban areas
- Only Ghana seems to be a significant improvement
- Qualitative inspection needed
 → use the prediction models!

Country	OSM road network length (km)	gROADS v1 road network length (km)
Liberia	32'457	25'205
Guinea	101'733	100'401
Ghana	57'613	22'752
Senegal	41'622	71′375



Conclusion

- Decision cannot be taken only base on quantitative aspects
- Data inspections also needed
- Only one country seems to be a clear improvement over gROADS

	Criteria			
Country	VCompletenessPositionalAttributeAccuracystructure		Ingestion decision	
	Improvement	RMSE < 50m	Improvement	
Liberia	NO	YES	NO	NO
Guinea	NO	YES	NO	NO
Ghana	YES	YES	YES	YES
Senegal	NO	YES	NO	NO

Questions

- How should criteria be weighed?
- Can we add other diagnostics?

Conclusion

OSM is not always superior to gROADS v1 for low income countries

- Validation process is necessary
- Implications for datasets derived from OSM: WorldPop...

Ingestion decision based on comparison between datasets

- Easy techniques are very revealing
- Decision is harder to take for countries with similar level of quality for OSM gROADS

Completeness assessment - combination of the 2 methods useful for exploration

- Improvements are necessary
- Other datasets? Different aggregation units? New models?

Conclusion

OSM is not always superior to gROADS v1 for low income countries

- Validation process is necessary
- Implications for datasets derived from OSM: WorldPop...

Ingestion decision based on comparison between datasets

- Easy techniques are very revealing
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Completeness assessment - combination of the 2 methods useful for exploration

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Thank you!

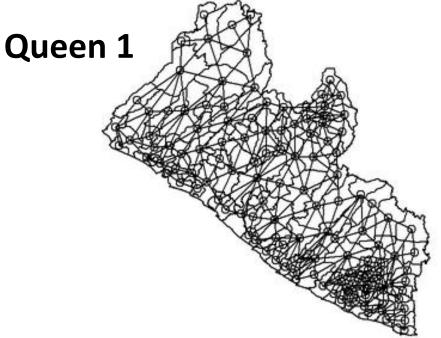
Email: bogdan-mihai.cirlugea@epfl.ch

Spatial Durbin – Backup

Durbin model:
$$y = x\beta + Wx\theta + \varepsilon$$

y - dependent variable
x - set of independent variables
Wx - spatially lagged independent variables
θ - spatial coefficient,

 $\boldsymbol{\varepsilon}$ - vector of error terms.



AIC results

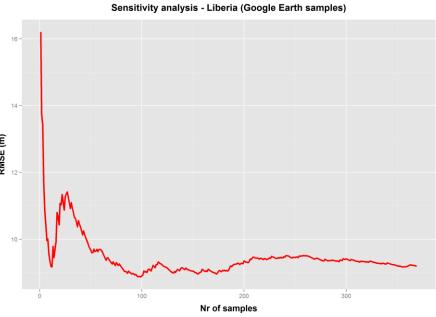
Countries	Lag	Error	Durbin	GWR
Liberia	32.46	32.46	14.91	-97.83
Guinea	503.64	503.64	498.84	416.91
Ghana	167.26	167.26	148.21	156.04
Senegal	-73.48	-73.48	-70.52	-104.74

Moran I

Countries	OLS		Durbin	
	MI	p-value	MI	p-value
Liberia	0.36	3.87e-13	-0.001	0.44
Guinea	0.39	6.67e-35	0.02	0.23
Ghana	-0.05	8.81e-01	0.02	0.27
Senegal	0.12	6.05e-02	0.01	0.34

Positional accuracy - Backup

		Reference Imagery		
		Esri Imagery	Google Earth	
		RMSE (m)	RMSE (m)	
ia	Multi-stage sampling	10.48	14.52	
Liberia	Multi-stage stratified sampling	31.50	31.57	DMSE (m)
	Clustered sampling	17.36	22.98	
Guinea	Multi-stage sampling	10.11	12.08	
	Multi-stage stratified sampling	10.98	11.50	
	Clustered sampling	34.27	4.85	



Sensitivity analysis - Guinea (Google Earth samples)

