

Inspire Policy Making with Territorial Evidence

## Potentials of big data for integrated territorial policy development in the European growth corridors

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### **ESPON** scientific report 2019

 "The <u>speed of change</u> in Europe in economic and social terms is accelerating, accompanied by an increasing <u>fragmentation of</u> <u>society</u> and territories that implies a real <u>threat to integration</u>."

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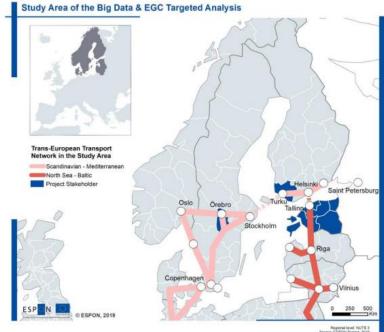
 "In ESPON we develop research to <u>support policymakers</u> to narrow this gap. It is important though to ensure that we are asking the right questions, those that policy-makers raise seeking to receive <u>answers from the researchers</u>."

### • Fresh scientific approaches and tools in territorial research

- iii) New data sources
  - Mobile phone data: these can be used to track the movement patterns of tourists, residents and students and generate new territorial insights on a more granular scale.
  - Estonia mobile positioning data have been used to produce an official nationwide mobility database and investigate mobility patterns

### **Big Data & European Growth Corridors**

 one-year-long project that addressed the challenge of data utilization in corridor development by analysing the potentials of big data for integrated territorial policy development in the European growth corridors



### Scientific partners

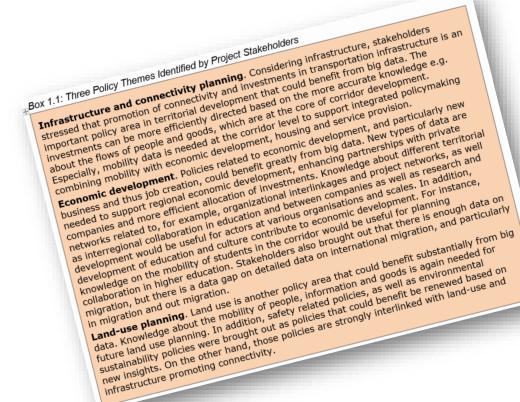
- University of Turku, Finland
- University of Tartu, Mobility Lab, Tartu, Estonia

### Practical needs of stakeholders

- The Regional Council of Southwest Finland (lead stakeholder),
- the Region of Örebro in Sweden,
- the Ministry of Economic Affairs and Communications in Estonia

## **Project themes**

- During the first project workshop, the stakeholders identified three themes as the most important policy dimensions related to corridor development that would benefit from big data:
  - 1. infrastructure and connectivity planning;
  - 2. regional economic development, and;
  - 3. land-use planning



### Corridor development

Figure 2.1: Conceptual framework describing the three overlapping spatial dimensions of corridor development that should be taken into account in comprehensive corridor governance

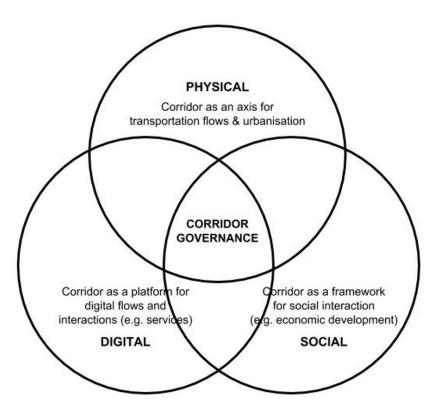


Figure 3.1: Categories and subcategories of big data tools from FirstMarks Capital's Big Data and Artificial Intelligence Landscape.

Industry-Specific

Applications

Gov't

Transport

Finance -

Lending

Real

Estate

Life

Science

Other

Security

Research

Advertising

Education

Finance -

Investing

Insurance

Industrial

Commerce

Agriculture

Health Cares

Mapping of Enterprise Infrastructure Analytics Applications Graph Hadoop Hadoop in Data Data Speech the Cloud DBs Sales on-Premise Analyst Science and NLP Platforms Platforms Marketing B2B MPP GPU NoSQL Streaming / Computer DBs<sup>1</sup> DBs In-Memory DBs Vision Marketing B2C **BI Platforms** Machine Learning Data Data Data Social Back Office Governance Transformatio Integration Analytics Automation Visualization Horizontal landscape AI Mgmt / Cluster App Log Legal Security Dev Monitoring Svcs Analytics Web / Mobile / Commerce Analytics Productivity Search Crowd Sourcing Hardware Storage Customer Service Finance **Cross-Infrastructure Analytics** Human Capital **Open Source** Search Visualization Collaboration Stat Coordination Framework Query & Data Logging & Data Flow Tools Access Monitoring AI - Machine Learning - Deep Learning Data Sources & APIs Data Resources Health Other Financial Air, People / Location IoT Data Incubators Space, & Economic Data Entities Intelligence Services & Schools Sea

Source: Turck & Obayomi (2018).

**Big Data** 

and Al

### Mapping the potential data sources

Data Categorization Variables	Range of Attributes				
Availability	Open Data $\leftarrow \rightarrow$ Exists but not easily Available $\leftarrow \rightarrow$ Purchasable Proprietary Data $\leftarrow \rightarrow$ Unavailable Proprietary Data				
Level of Processing	Raw (e.g. direct from sensors) $\leftrightarrow$ Pre-Processed Data $\leftarrow \rightarrow$ Processed Data $\leftarrow \rightarrow$ Highly Processed Data				
Intended Audience	Humans $\leftarrow$ Programmers of Machines $\rightarrow$ Machines				
Observational Qualities	Direct Observation $\leftarrow \rightarrow$ Synthetic				
Level-of Detail	Fine-Grained (e.g. vehicle journeys) $\leftarrow \rightarrow$ Rolled-up (e.g. average household income by zip code)				
Level of Structure	Highly Structured $\leftarrow \rightarrow$ Semi-Structured $\leftarrow \rightarrow$ Unstructured				
Refresh Frequency	Instant $\leftarrow \rightarrow$ Milliseconds $\leftarrow \rightarrow$ Daily $\leftarrow \rightarrow$ Weekly $\leftarrow \rightarrow$ Monthly $\leftarrow \rightarrow$ Quarterly $\leftarrow \rightarrow$ Annually $\leftarrow \rightarrow$ Every few years				
Confidence in Updates	Low Confidence (updates are uncertain) $\leftarrow \rightarrow$ High Confidence (updates are highly likely to occur)				
Extraction Effort	Requires much effort and resources to extract data $\leftarrow \to$ Requires little effort to extract data				
Clarity of Ownership	Ownership is clear and singular $\leftarrow \rightarrow$ Ownership is clear but shared $\leftarrow \rightarrow$ Ownership is clear on paper and unclear in practice (e.g. "Do I or Facebook or 3rd party app makers own my Facebook data?") $\leftarrow \rightarrow$ Ownership is unclear or no longer traceable				
Spatial Resolution	Individual, Local, Neighbourhood, Municipal National, Multi-national, Global				
Temporal Resolution	$Milliseconds \leftarrow \rightarrow Decades$				

Table 3.1: Typology of new data sources by variables and ranges of attributes

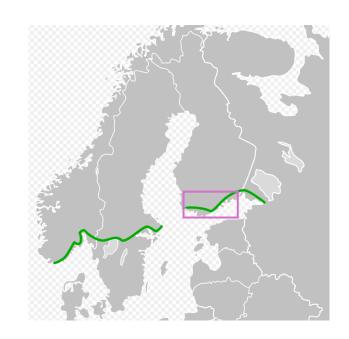
### **Case studies**

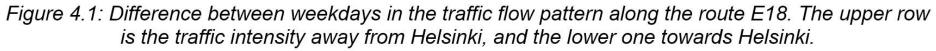
- 1. Traffic Flows on Highway E18 in Finland
- 2. Project Partnerships in the EU
- 3. Mobile Positioning Data for an Estonian Everyday Mobility Database

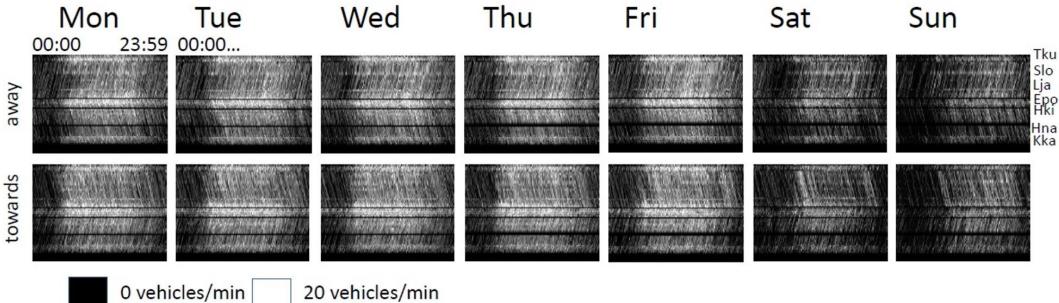
# Case 1: Traffic Flows on Highway E18 in Finland

- Traffic Flows on Highway E18 in Finland
  - Data: Traffic intensity data detected by 79 induction loop sensors

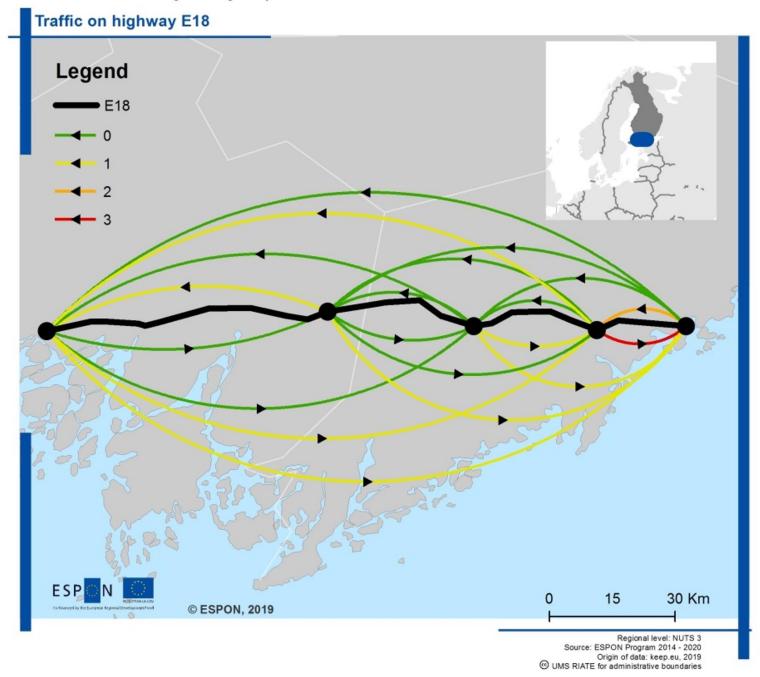








Map 4.1: Summary of the traffic flows from 7:30 to 9:30 Monday-Thursday, 23-26 January 2017 between Turku and Helsinki along the highway E18.

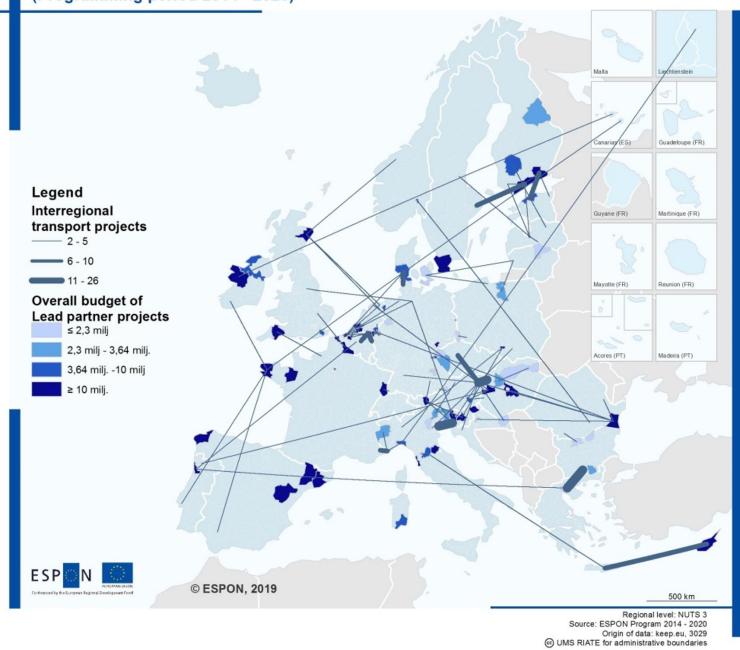


### Case 2: Project Partnerships in the EU

- goal is to analyse the open data about the EU funded regional development projects to create understanding about collaborative relationships and their characteristics across regional and national boundaries
- EU funded regional development programmes have a joint and openly available depository for the data about the projects and their partners, funding, themes and location. The project data acquired from programming period 2014-2020 contained 2353 projects. A new dataset was generated comparing projects and the NUTS areas, forming a pairing for all the projects and their respective NUTS3 areas.

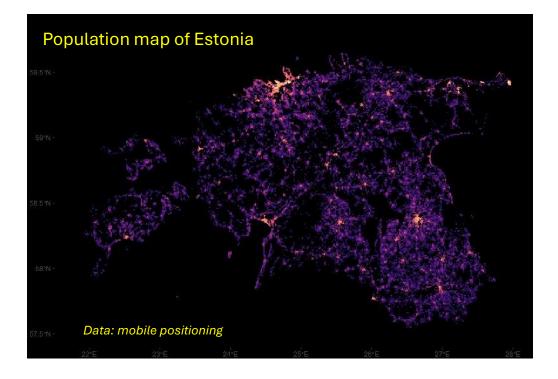
Map 4.2: Transport and mobility partnership network in the EU for the programming period 2014-2020.





# Case 3: Mobile Positioning Data for an Estonian Everyday Mobility Database

• <u>**Objective:</u>** To develop methodology for everyday mobility database which contains the OD-matrices of movements between territorial communities.</u>



### Data used:

• OD-matrices are based on mobile positioning data and applied to road network based on Dijkstra routing algorithm and Open Street Map roads data. Mobile positioning data contains locations of call activities (Call Detail Records (CDR)) in network cells (location, time and random unique ID).

### Novelty of the approach:

• The mobile positioning data has high accuracy in time, the data allows to short-term differences (find the OD-matrices by months), include in addition to movements between the place of residence and the workplace, also other regular places and differentiate the movements of different social groups (gender, age, nationality) and the types of movers.

### Challenges:

• The main limitation of passive mobile positioning data is access to data, because mobile network operators are hesitant to provide their data and relatively long value chain of implementing mobile positioning data, which requires expertise from several research fields.

### Policy implications:

• The resulting database would support mobility-related policymaking.

### Background and objectives

- Mobility Lab of University of Tartu
- Ministry of Economic Affairs and Communications of the Republic of Estonia
- objective of the Ministry is to develop high quality database of mobility and traffic data covering whole Estonia.
- Developed database would be an important data input for the Ministry in the spatial planning decision-making process to answer questions related to transport and mobility

## • Mobile positioning provides more accurate spatio-temporal information than the conventional methods, and data can be collected almost in real-time.

- Passive mobile positioning has two main strengths longitudinality and extensive sample.
- the Mobility Lab of the University of Tartu has already a continuous CDR data from Estonia since 2006

### Data

- Call Detail Record
- Sample > 420000
- Period: 2016 2018
- Monthly OD-matrix

Figure 4.3: Structure of the mobile positioning dataset.

data tahla

uala labie	7					
parameter	value		antonnas	tahla		
ID	246513389	antennas table				
event	call		parameter	value		
timestamp	12:15:11 07/04/2014		cell ID	6547		
cell ID	6547	$\checkmark$	longitude	25.80527		
			latitude	58.34998		

### Anchor point model

Routledge Taylor & Francis Group

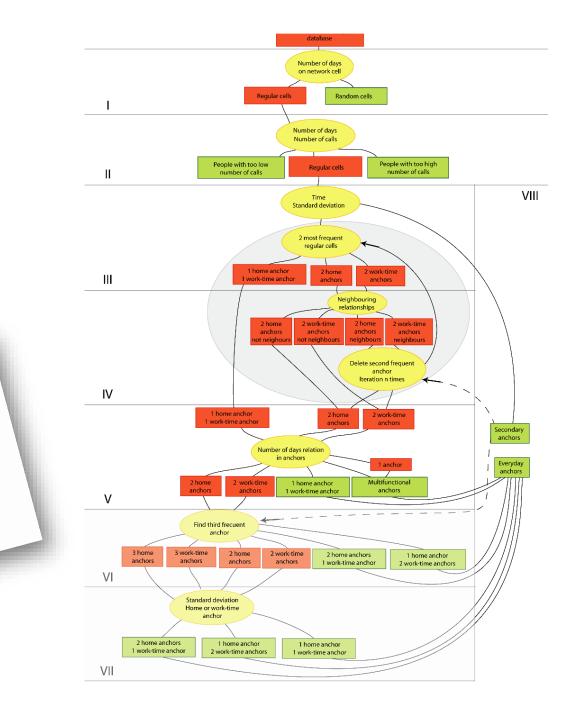
- Regularly visited places
  - Home
  - Work-time
  - Secondary

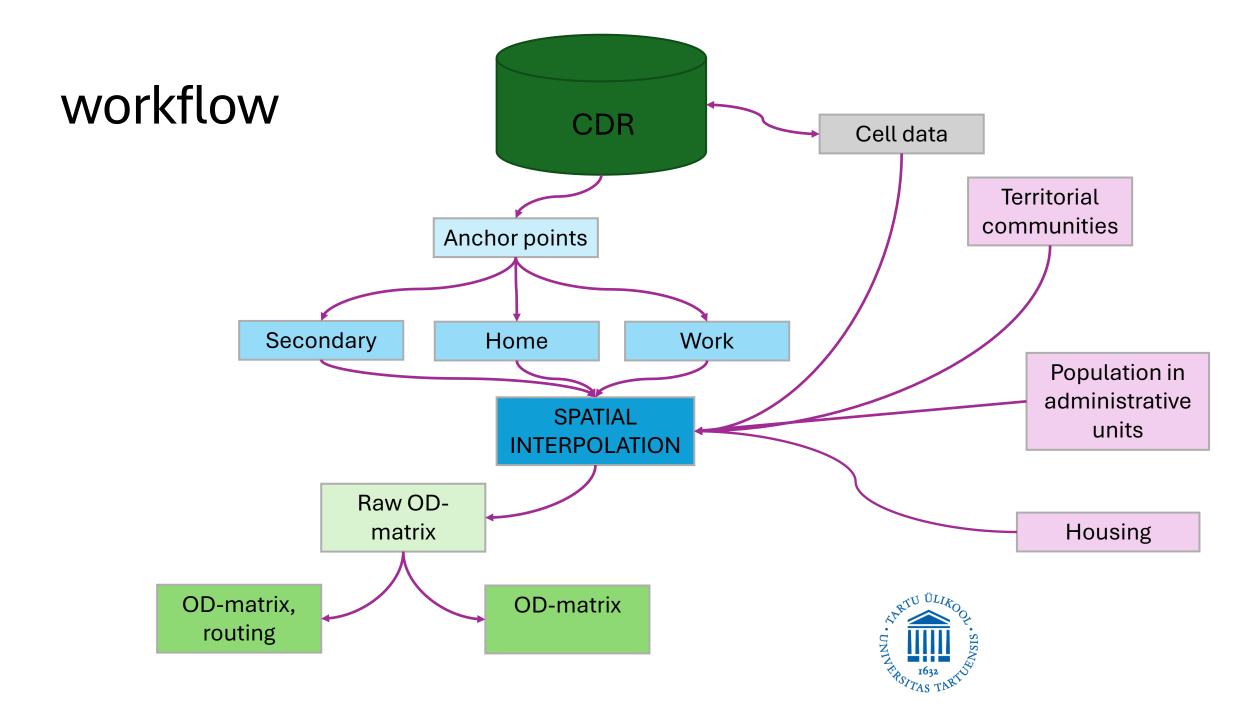
Journal of Urban Technology, Vol. 17, No. 1, April 2010, 3–27

Meaningful to Users of Mobile Phones

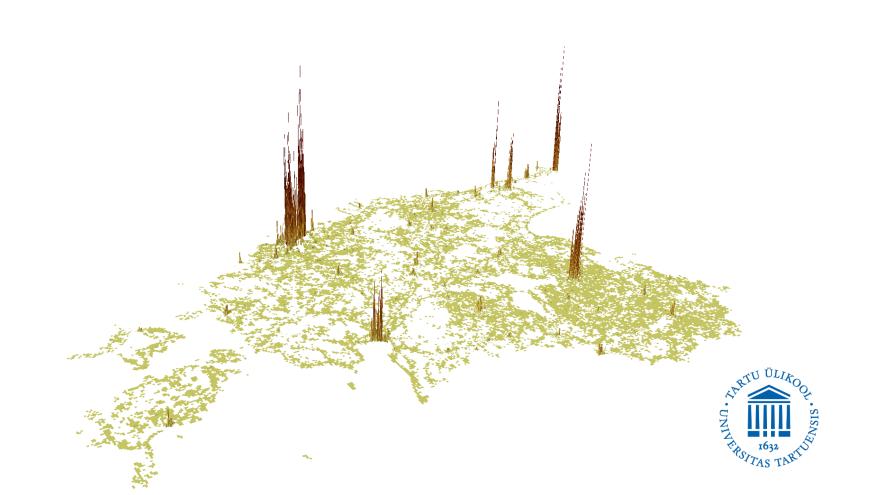
Using Mobile Positioning Data to Model Locations

Rein Ahas, Siiri Silm, Olle Järv, Erki Saluveer, and Margus Tiru





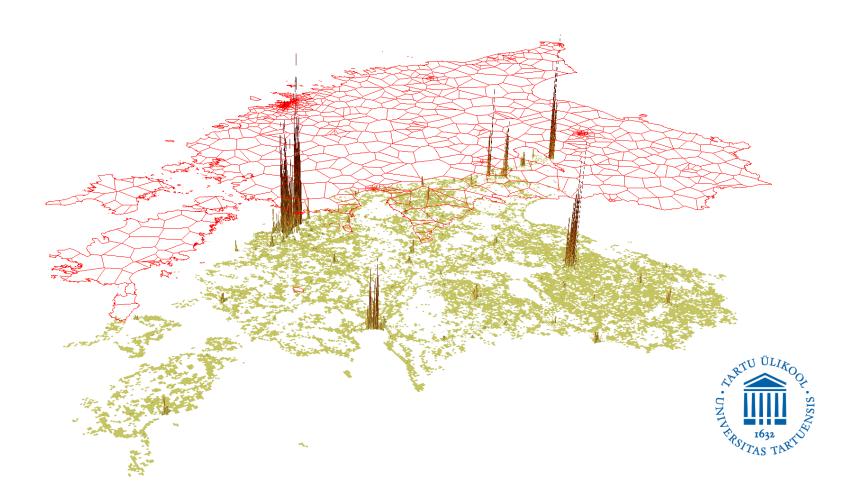
### Population in 1km regular grid



Population in 1km grid

### Theorethical coverage of mobile antennas

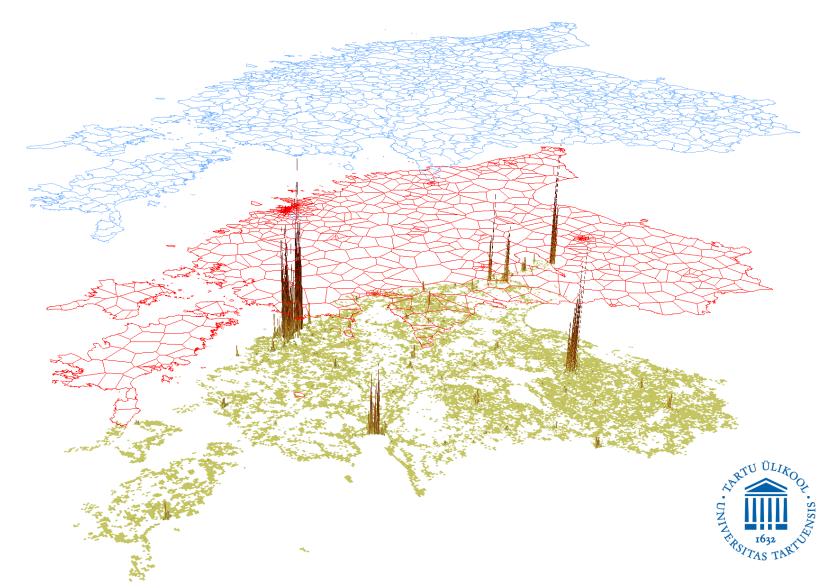
Population in 1km grid

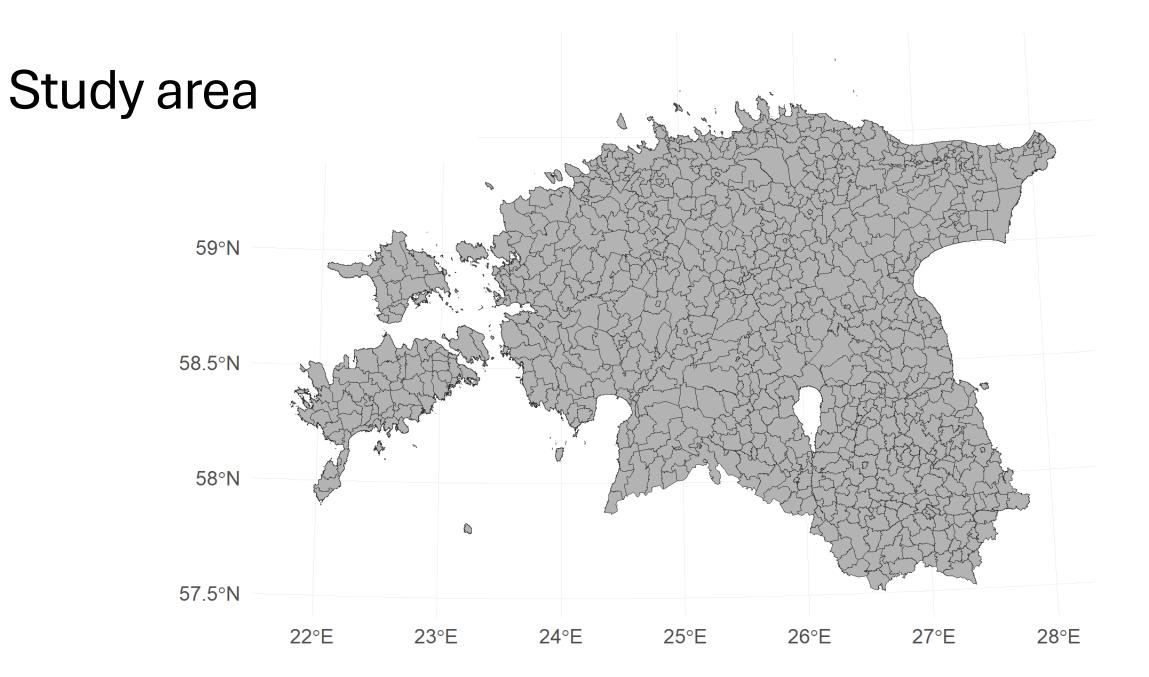




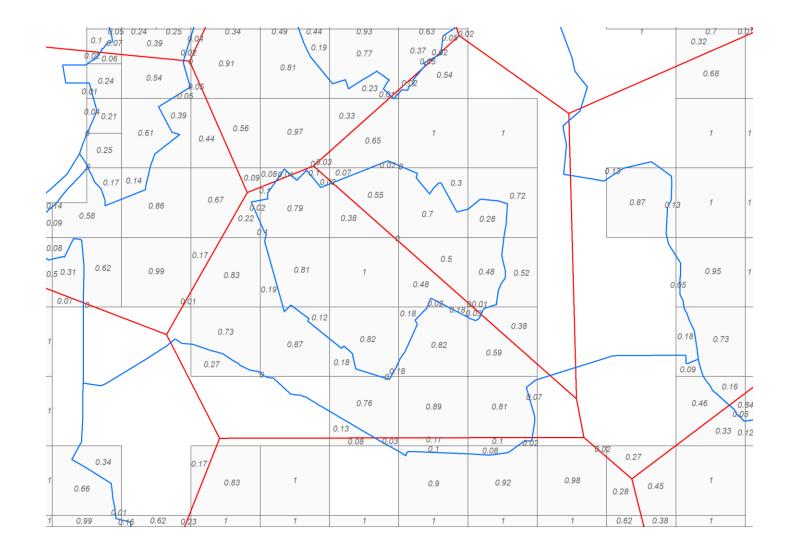
Theorethical coverage of mobile antennas

Population in 1km grid

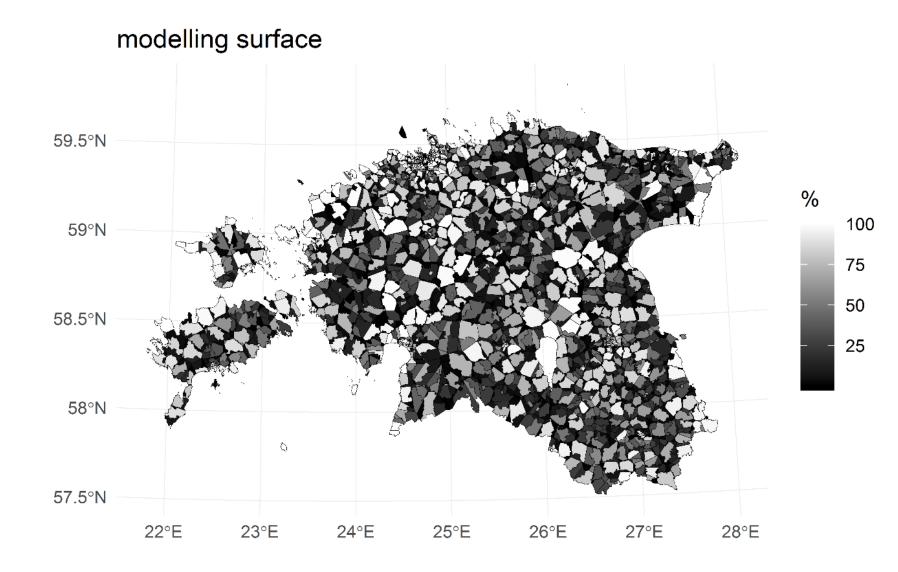




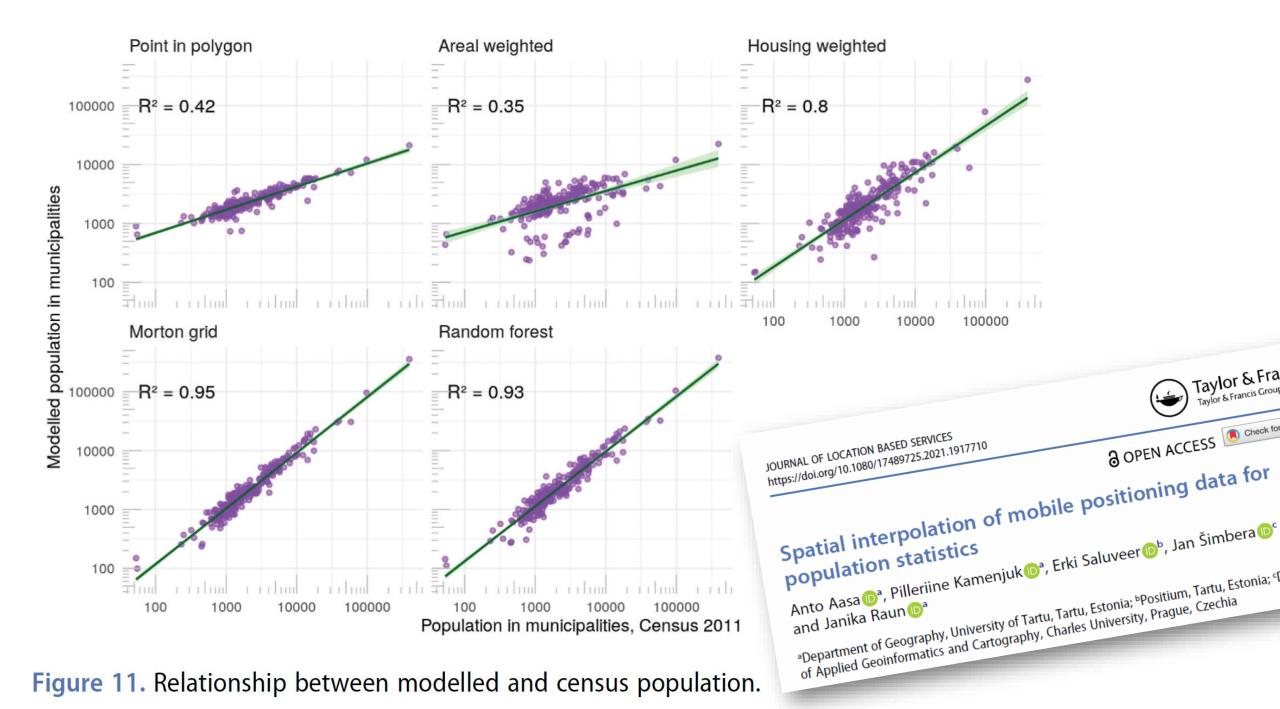
### Spatial interpolation



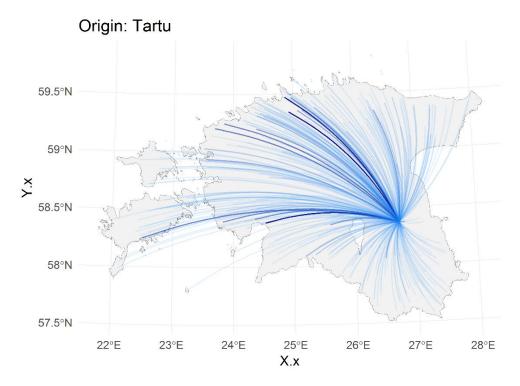


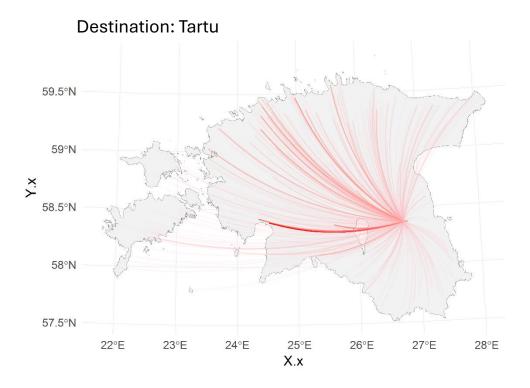






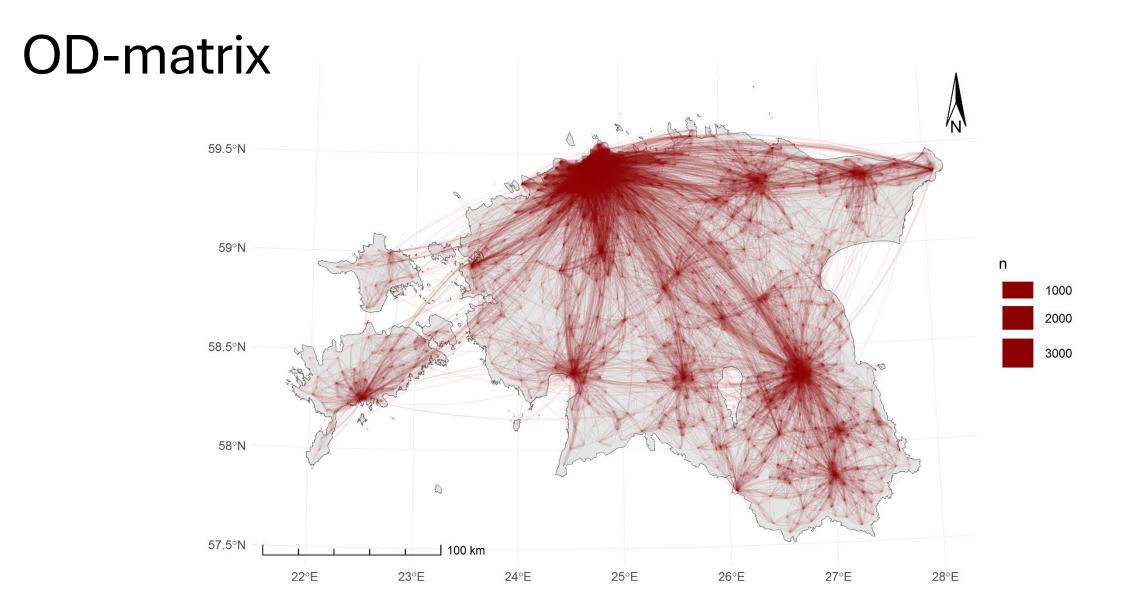
### OD-matrix, Tartu

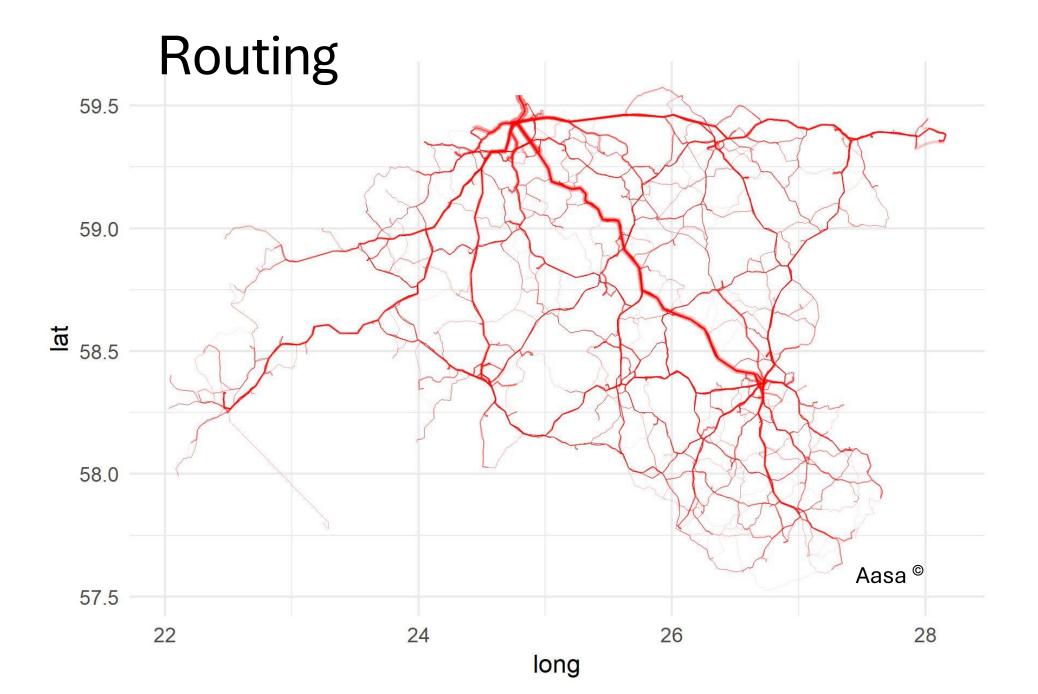




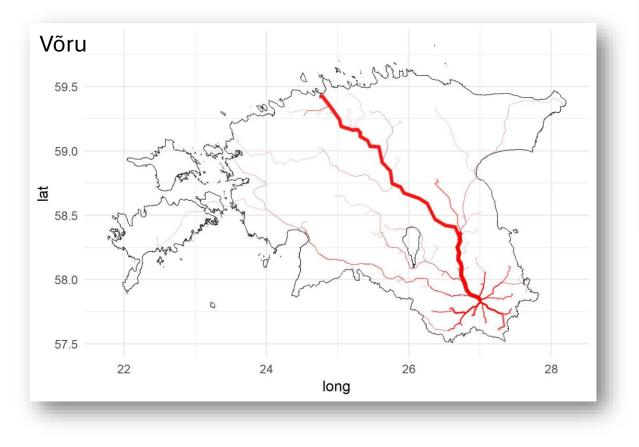
KANT_nk_or	KANT_nk_de	1	N	X.x	Y.x	X.y	Y.y
:	·   <b>:</b>	-	·:   ·	<b>:</b>  -	<b>:</b>  ·	<b>:</b>  -	:
Aakre Valga	Aakre Valga		117	627213	6440209	627213.0	6440209
Aakre Valga	Albu Järva		1	627213	6440209	589941.9	6555843
Aakre Valga	Aruküla Harju		2	627213	6440209	561079.1	6580363
Aakre Valga	Emmaste Hiiu		1	627213	6440209	418365.2	6509690
Aakre Valga	Haabersti linnaosa		5	627213	6440209	535384.5	6587643
Aakre Valga	Haapsalu linn		4	627213	6440209	473490.5	6532856

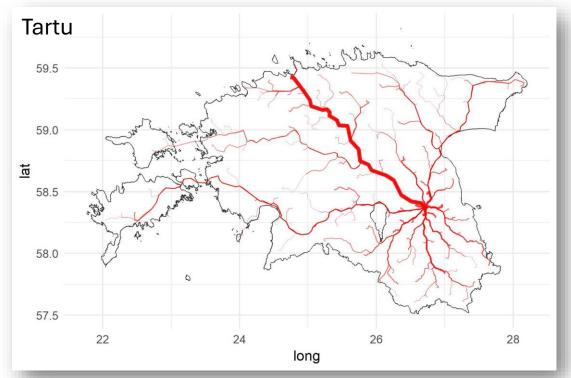






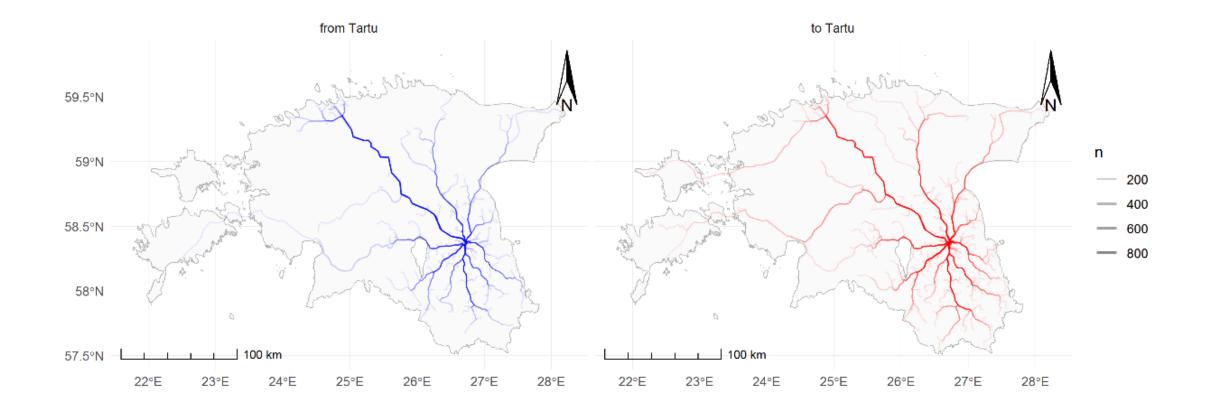
## Next step: Routing!



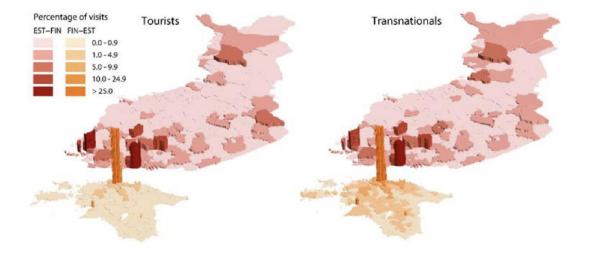




### **OD** matrix & routing



### **Cross-border mobility**

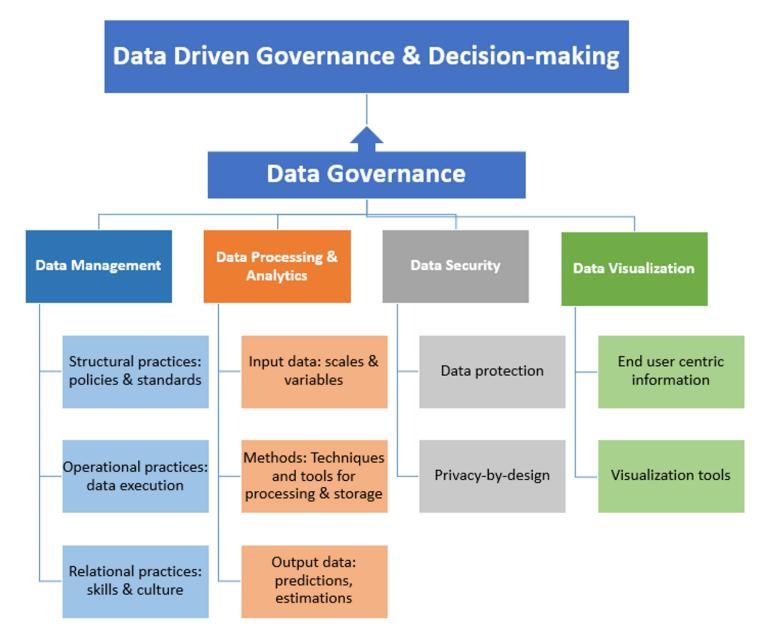






- Novelty
- Limitations
- Policy implications
- Recommendations

Figure 5.1: Aspects of capacity building for big data driven policy-making in growth corridors.



Freely following key aspects identified in the research roadmap for Europe (Cuquent & Fensel 2018).

### https://mobilitylab.ut.ee/OD/

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Summary:

Background & objectives

Data & methods

Results

Data download

#### OD-matricies of regular movements in Estonia

ESPON project:

Potentials of big data for integrated territorial policy development in the European growth corridors





#### Reference:

Aasa, A. (2019). OD-matrices of daily regular movements in Estonia [Data set]. University of Tartu, Mobility Lab. https://doi.org/10.23659/UTMOBLAB-1

#### Regular movements in Estonia in January 2016





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## Thank You!

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