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Mobile Phone-based Data in Human Spatial Mobility Research

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Context

1. Societal transformations

- Mobile technologies, virtual space, individualization

Increasing mobility, flexible & fragmenting, blending of mobility forms

(Doherty, 2006; Hubers et al., 2008; Schwanen et al., 2008)

2. The ”new mobilities paradigm” in social sciences

- Interdependent and constant mobilities of everything: people, objects, information, wastes… *(Urry, 2000)*
- Moving beyond aggregated and static spatial units and focus on individual mobility to understand social processes *(Kwan, 2013)*

Context

3. Need for better planning and managing society:

- Human spatio-temporal mobility at individual and aggregated level
- From local up to global scale
- From hourly up to annual temporal patterns & monitoring

4. Big Data revolution

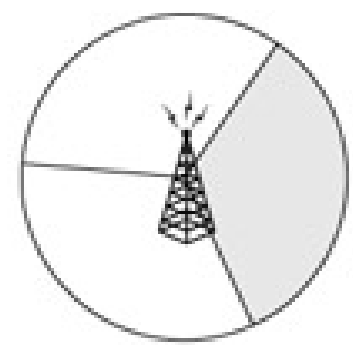
- New ICT tools to complement traditionl methods
- mobile phones (MP) are ubiquitous around the world

MPs as one of promising medium to understand human mobility and provide enhanced information for planners and policy-makers

Mobile phone positioning

- **Handset-based** (individual) & network-based (aggregate)
- Active positioning (initiated by the network provider)
- **Passive positioning** (automatically stored in to a log file)
- **Call Detail Records (CDR)** - Call activities (call, SMS/MMS, data)
  - Random ID for a SIM-card
  - Time & date
  - Location coordinates (antenna/base station)

Base station
(Site ID)



Antenna
(Cell ID)

The implementation of CDR Data: Case studies from Estonia

CDR Dataset:

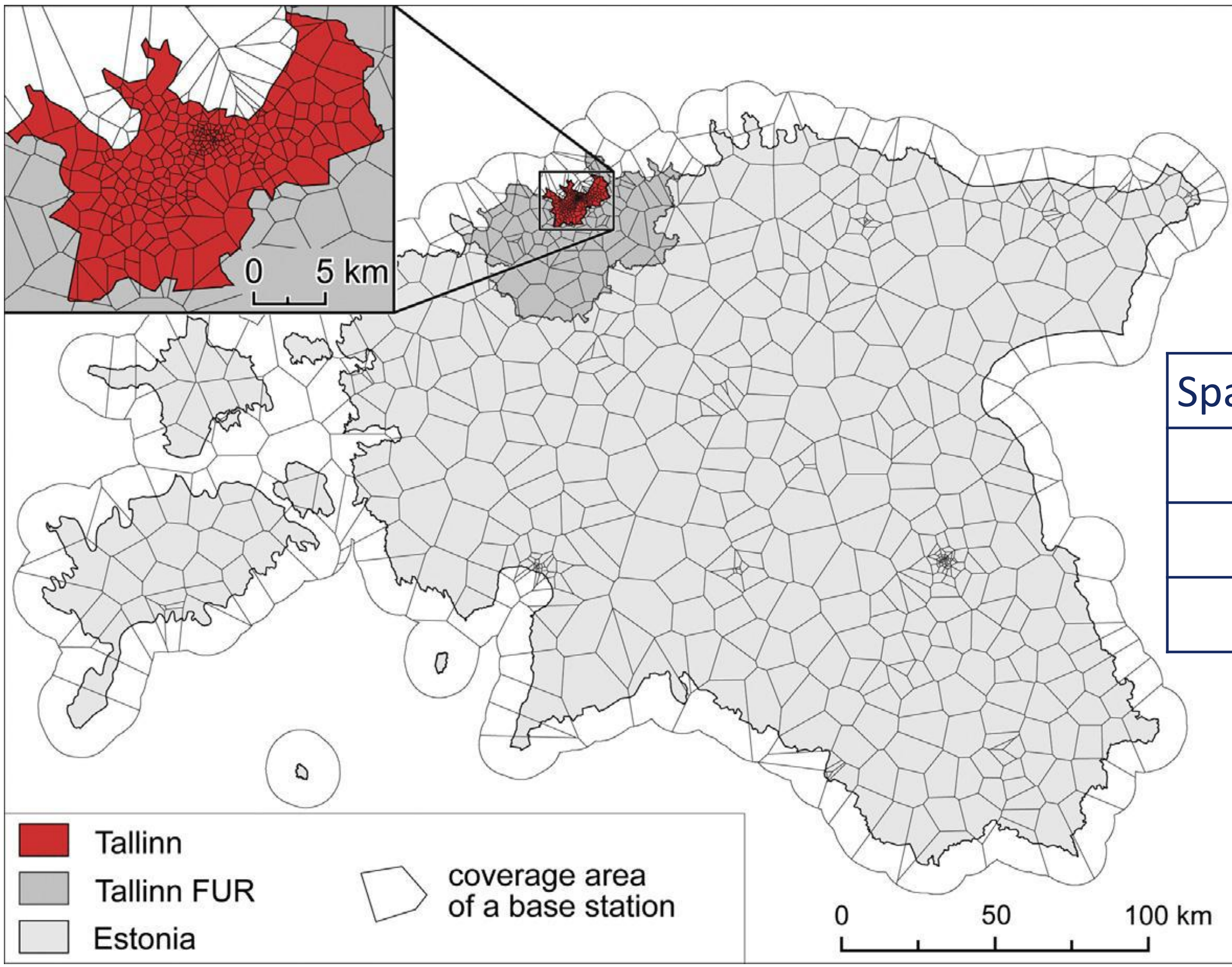
- Largest network operator (40-45% market share)
- Dataset since 2006
- 0.5 million subscribers per month
- 70 million call activities per month (outgoing call activities)

Assumptions:

- A mobile phone (SIM-card) as an individual;
- Call activities (CA) are one's digital footprint in space and time

Spatial resolution

Spatial granularity depends on intensity of human presence (e.g. mobile phone usage)



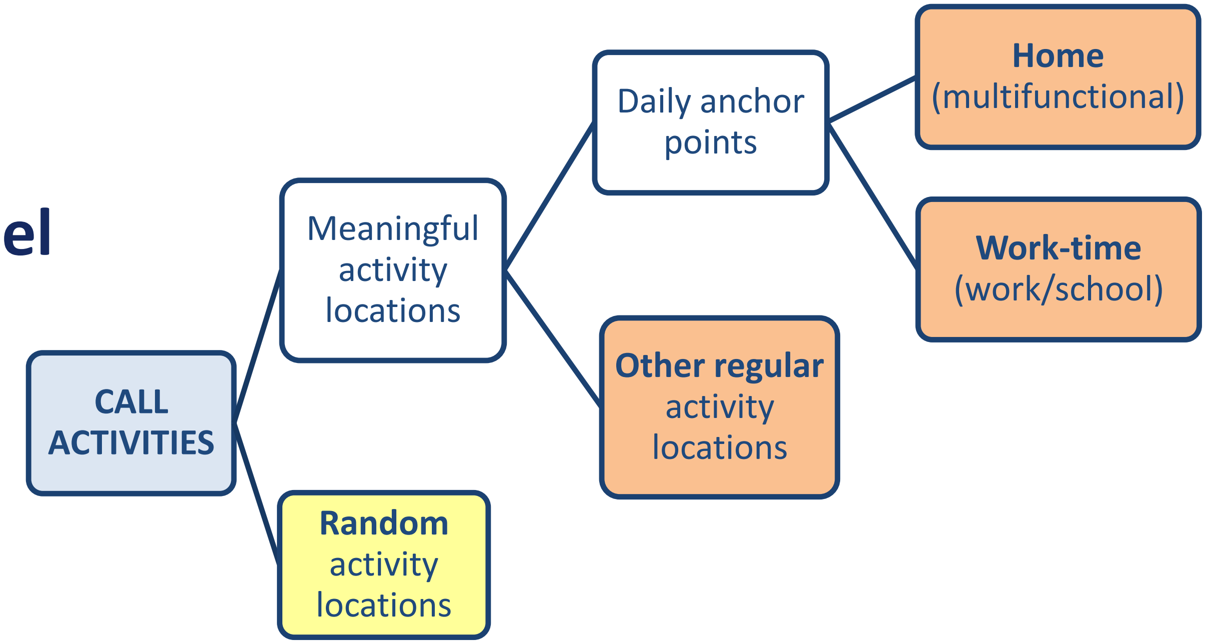
Spatial resolution at BS level, avg	
Tallinn	1 km^2
Tallinn FUR	15 km^2
Estonia	120 km^2

Implementing mobile phone-based data: Examples from Estonia

1. Identifying and extracting activity locations

Ahas, R., Silm, S., **Järv, O.**, Saluveer E. and Tiru, M. (2010) **Using mobile positioning data to model locations meaningful to users of mobile phones**. *Journal of Urban Technology*, 17(1), 3–27.

The anchor point model

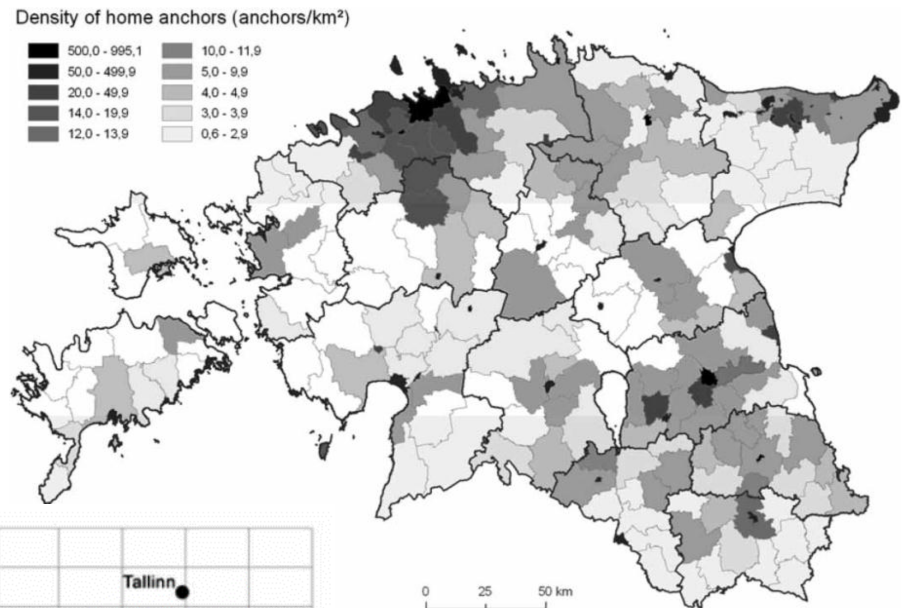


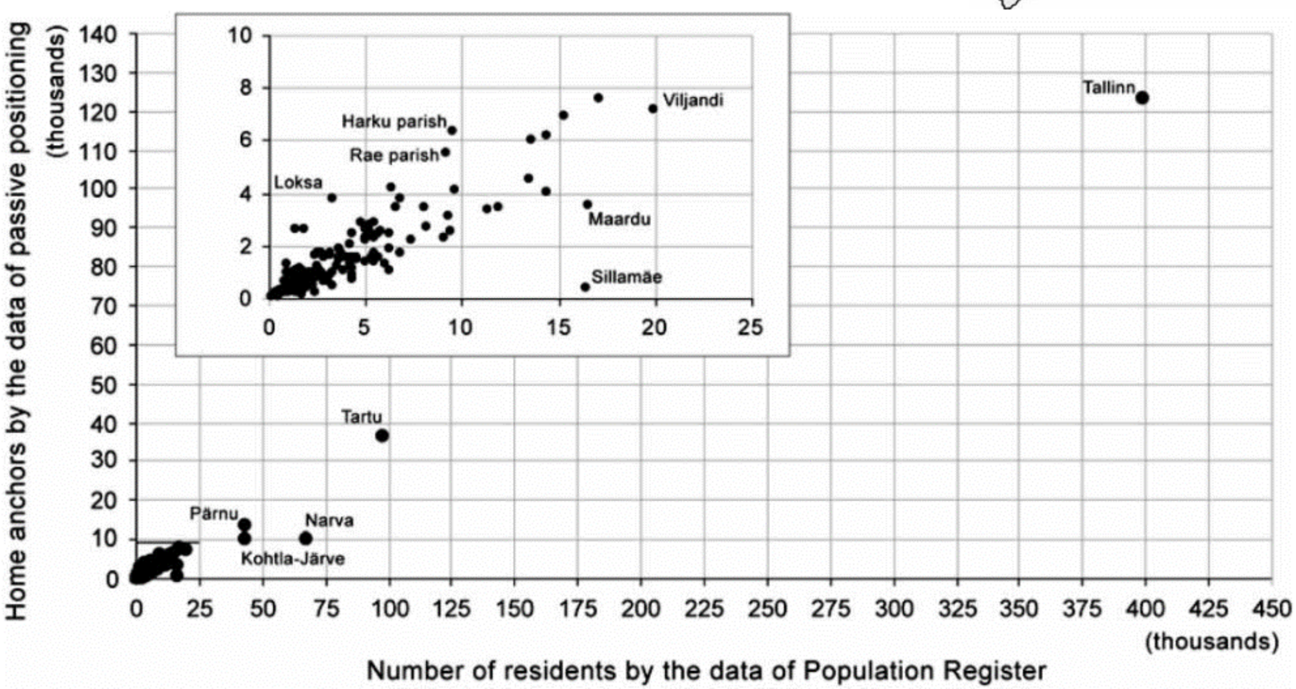
- Validation survey (n=205) for individual anchor points
  - >80% correct at base station level
  - >90% correct at municipality level

2. Population distribution in Estonia

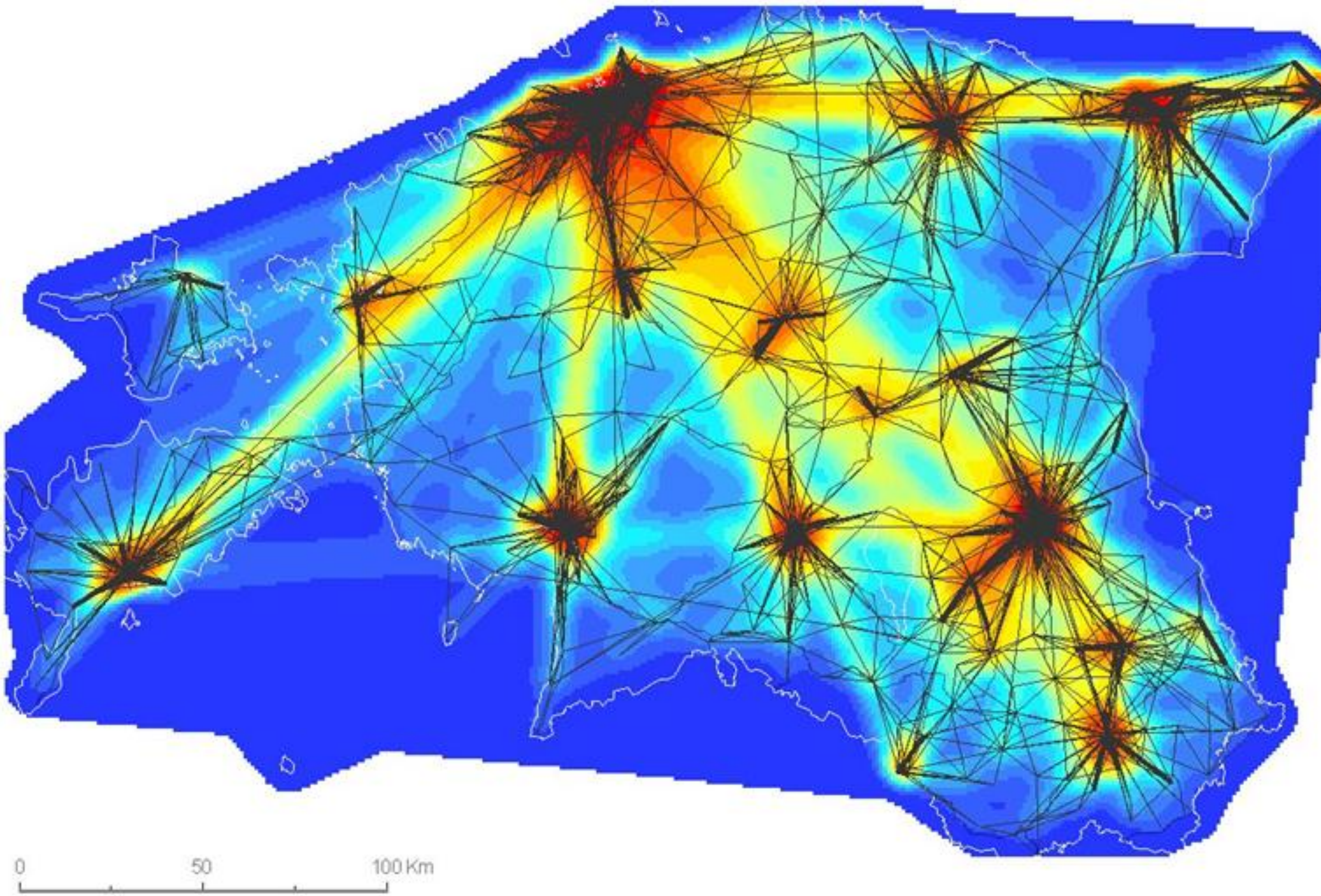
(Ahas et al.,2010)

- Strong correlation at municipality level (r=0.99)



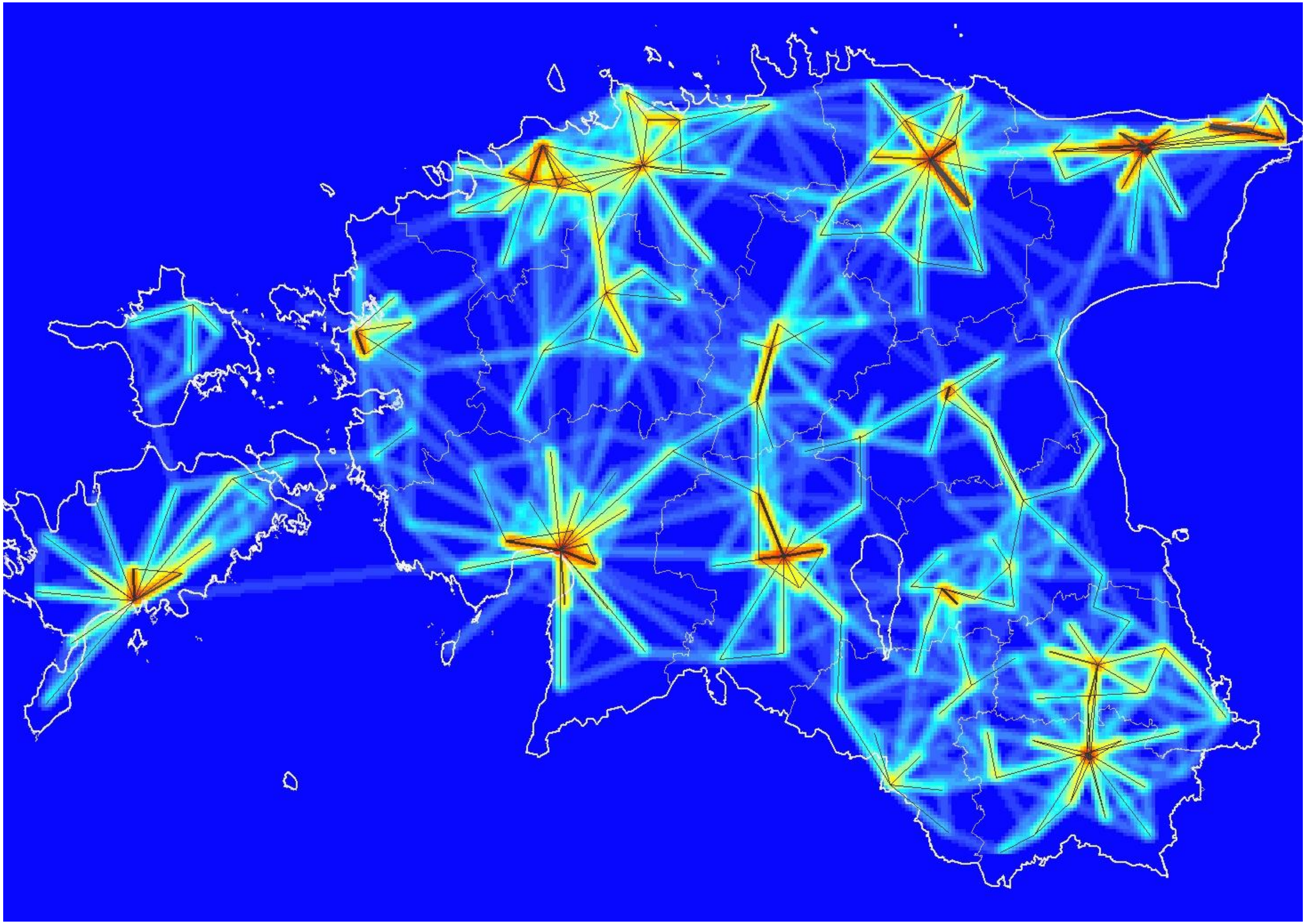


3. Uncovering spatial mobility within Estonia …

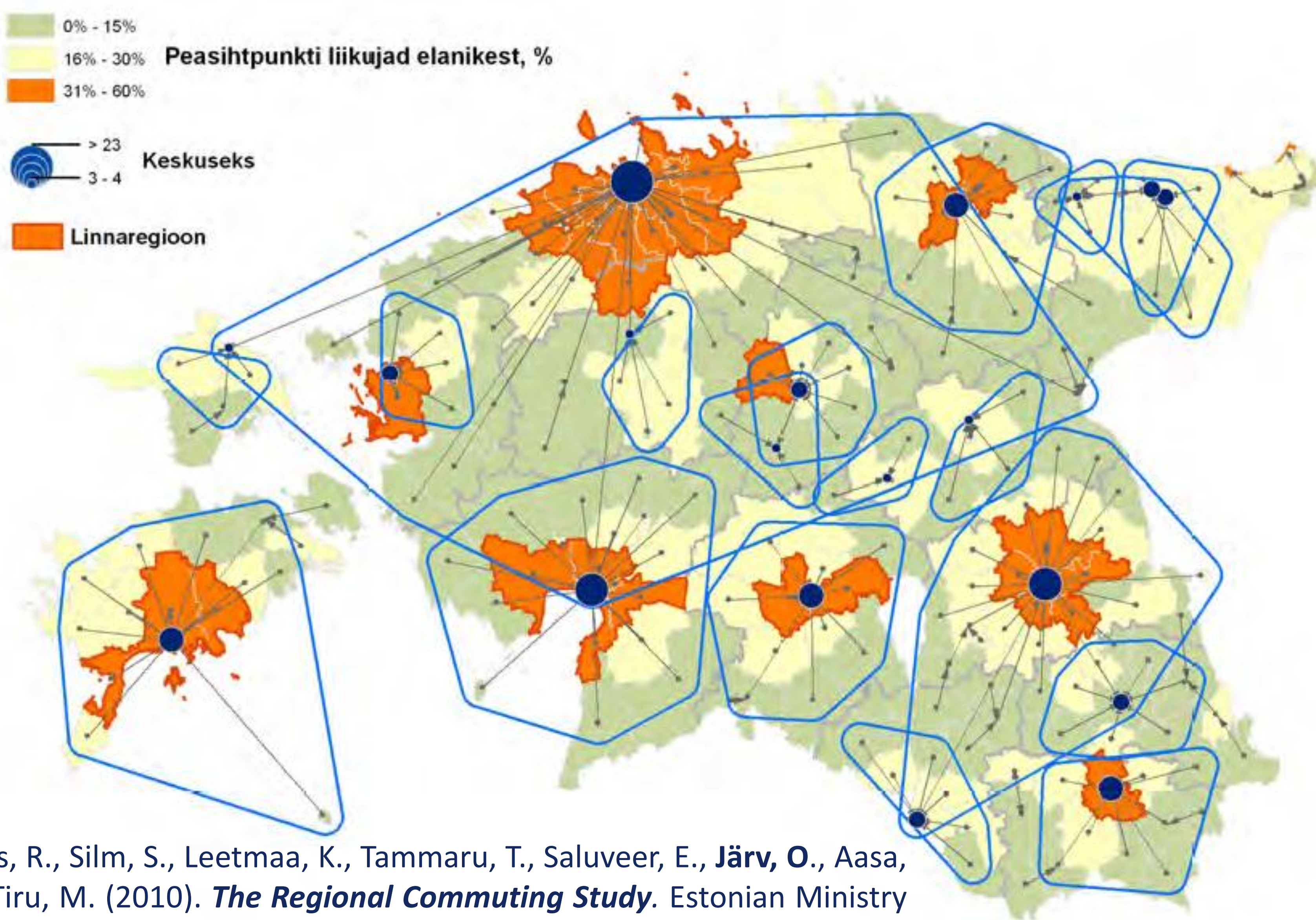


3. … and daily home-work commuting

(excluding Tallinn and Tartu)



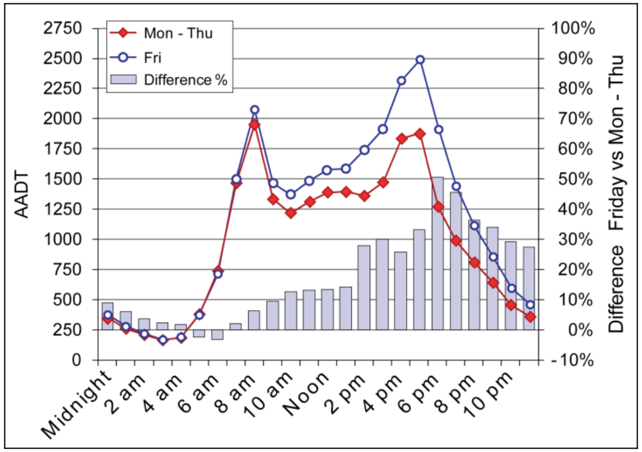
4. Delineating urban regions for regional planning

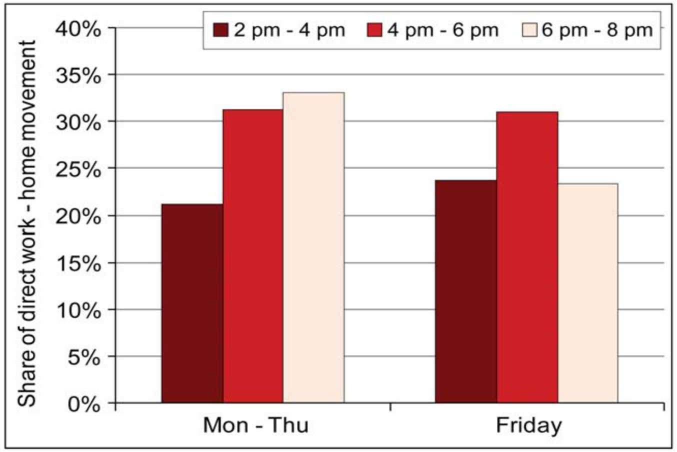


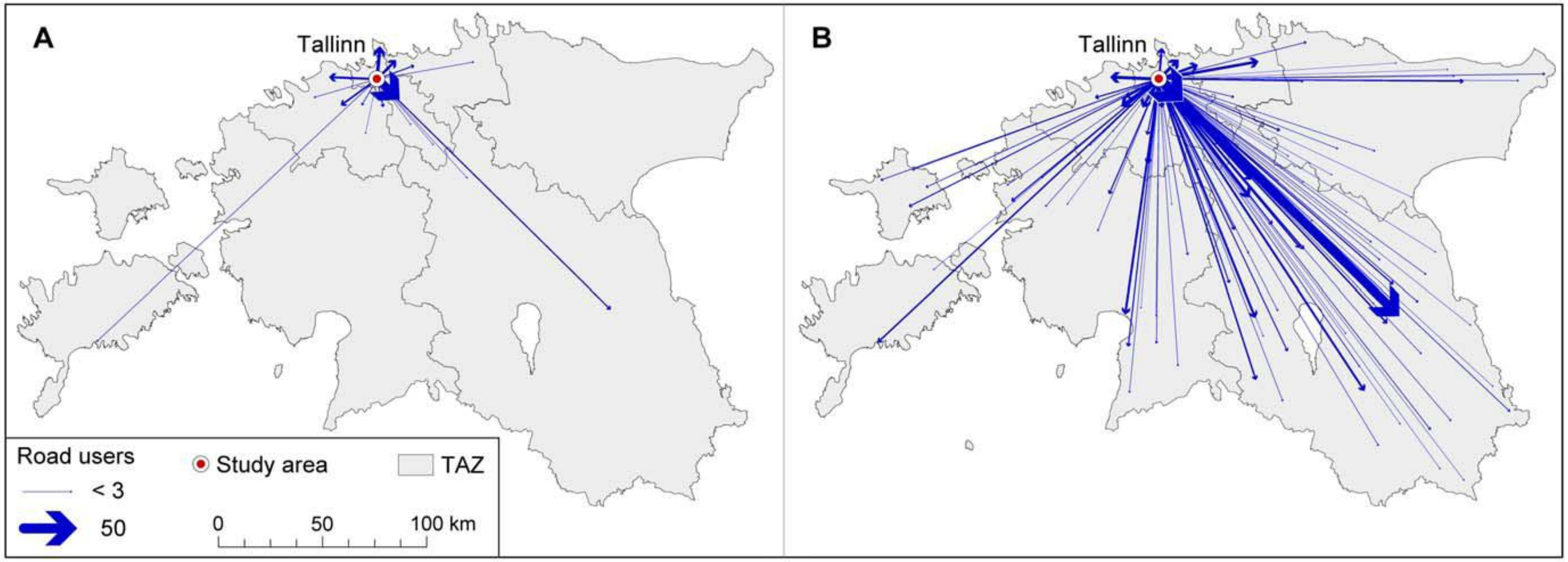
Ahas, R., Silm, S., Leetmaa, K., Tammaru, T., Saluveer, E., **Järv, O.**, Aasa, A., Tiru, M. (2010). ***The Regional Commuting Study.*** Estonian Ministry of the Interior.

5. Revealing the composition of road users

Järv, O., Ahas, R., Saluveer, E., Derudder, B. and Witlox, F. (2012) **Mobile phones in a traffic flow: a geographical perspective to evening rush hour traffic analysis using call detail records**. *PLoS ONE,* 7(11), e49171.

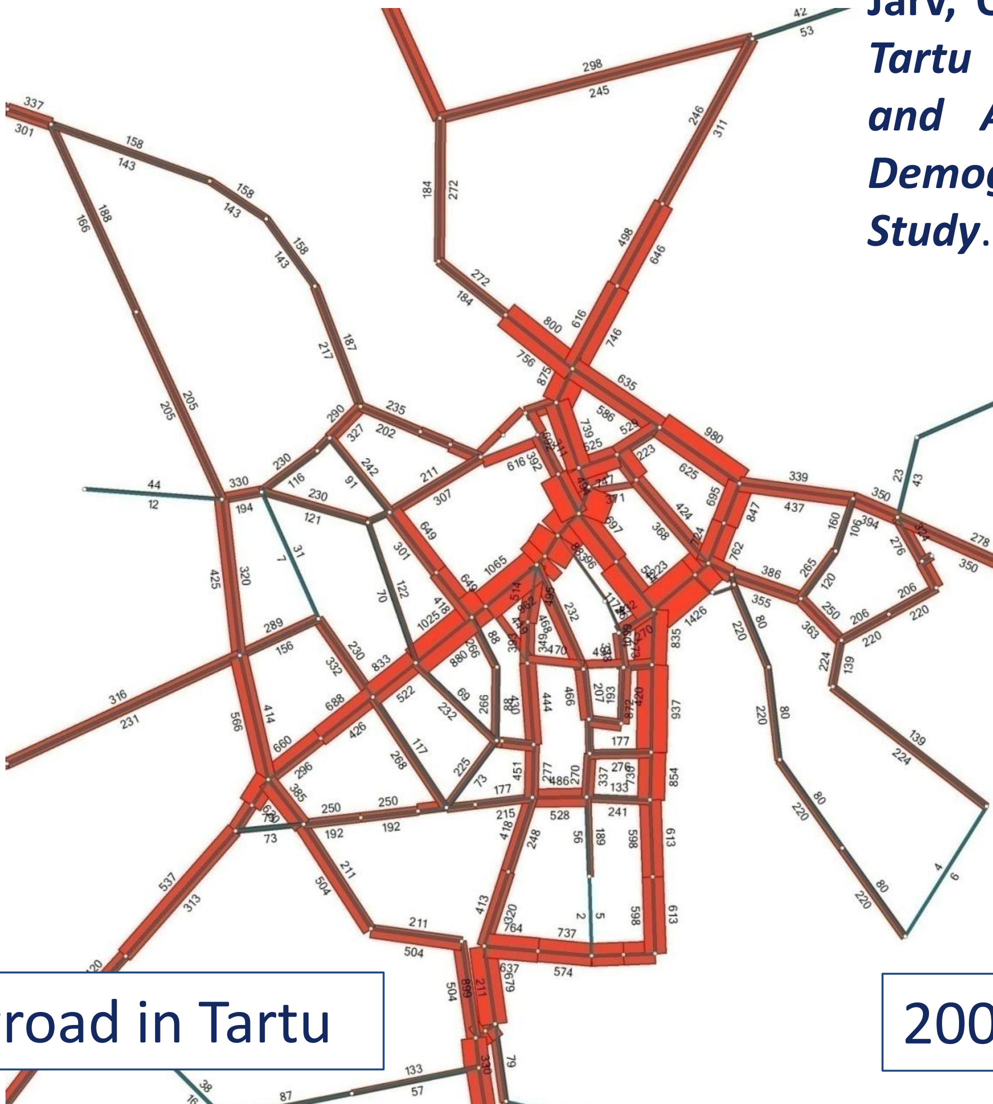






6. O-D matrices to transportation planners for modelling road network

Järv, O., Saluveer, E., Ahas, R. (2009). ***The Tartu City Eastern Ring Road – Collecting and Analysing Mobile Positioning and Demographic Data for the Transportation Study***. Ramboll Estonia Ltd.



Ringroad in Tartu

2008

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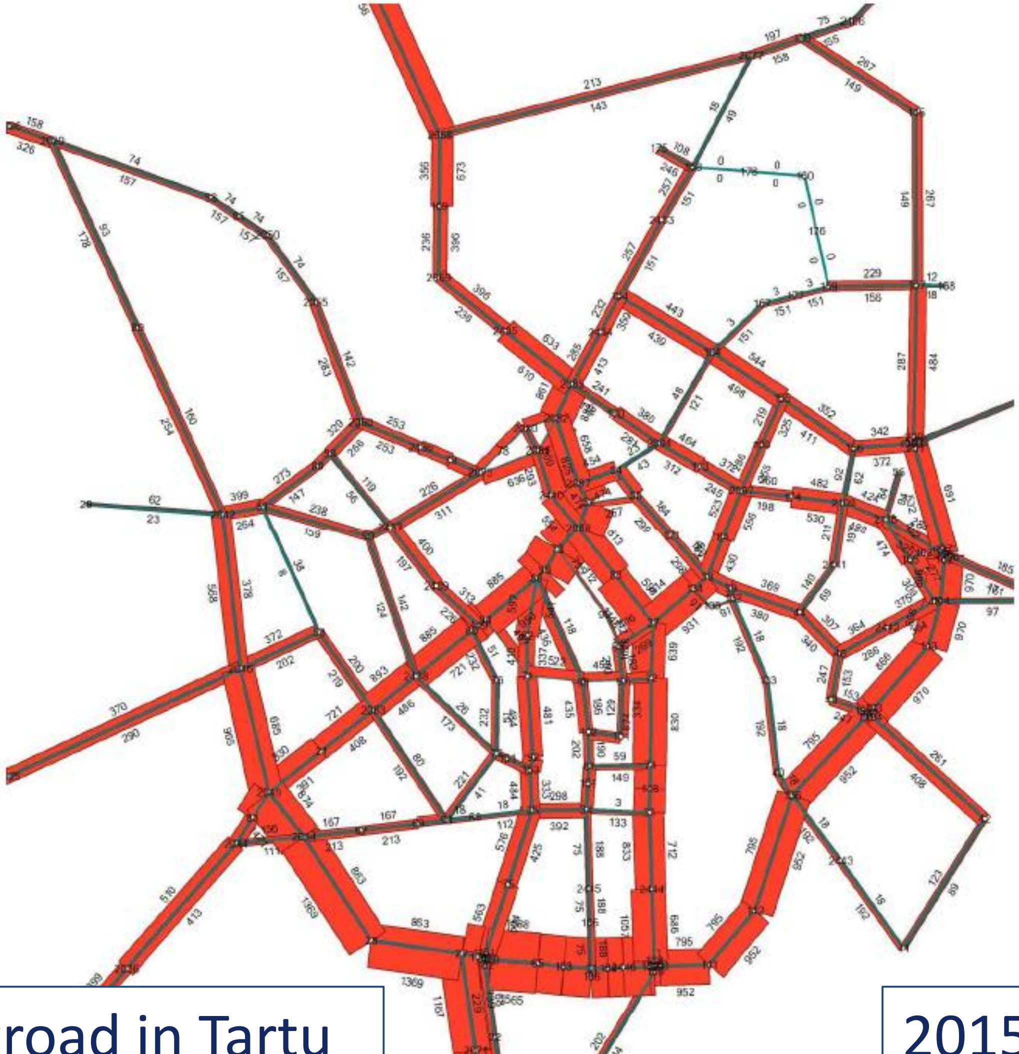
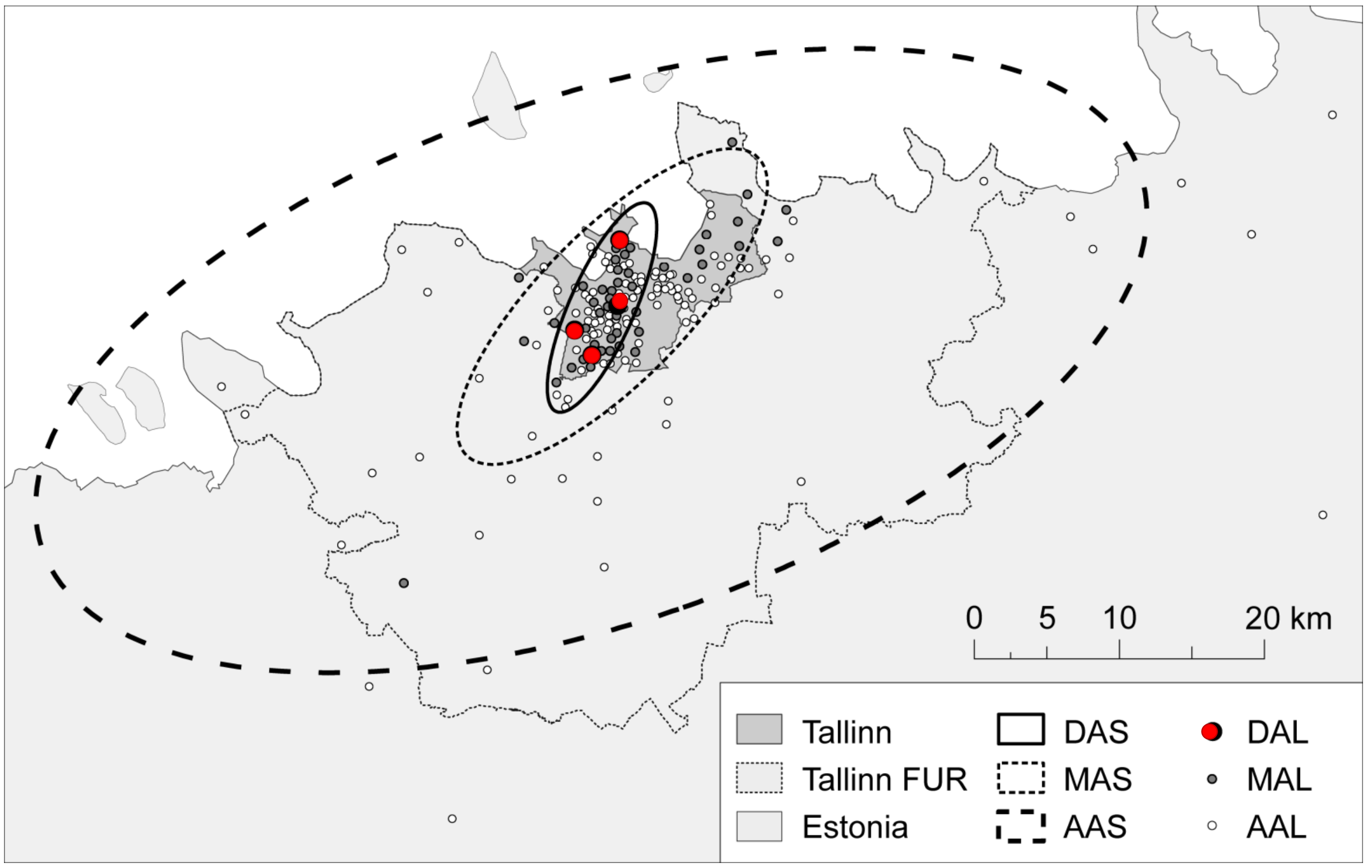


Ringroad in Tartu

2015

7. Personal spatial mobility: activity spaces

Järv, O., Ahas, R. and Witlox, F. (2014) **Understanding monthly variability in human activity spaces: a twelve-month study using mobile phone call detail records**. *Transportation Research Part C: Emerging Technologies*, 38, 122-135.

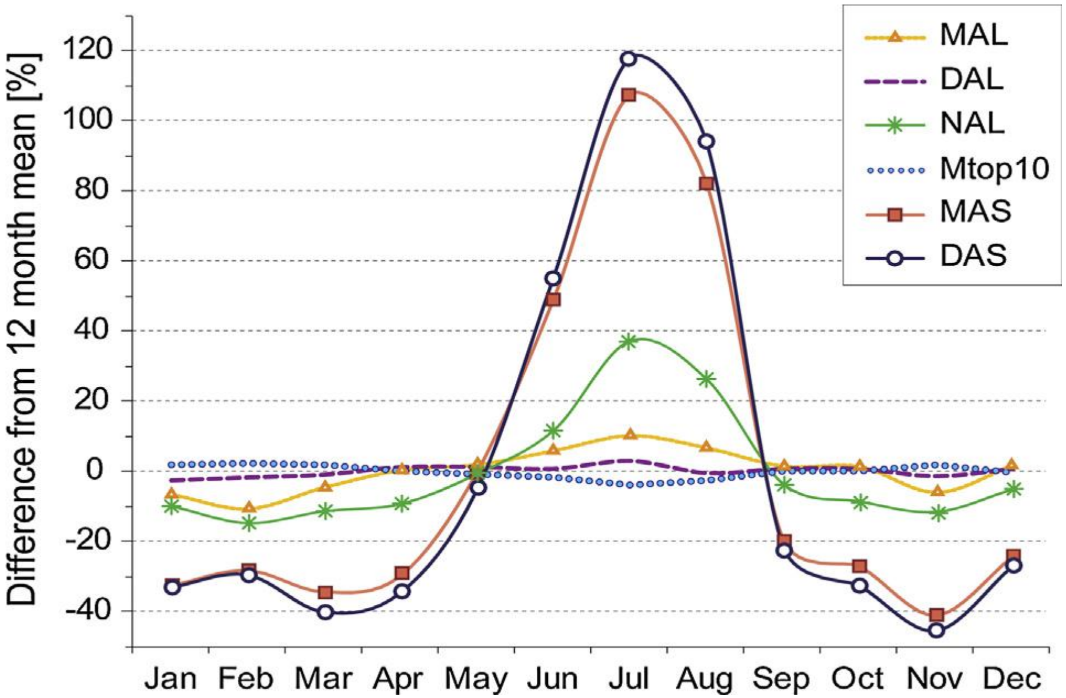


A person's annual activity space (AAS) based on visited activity locations (AAL) in 2009. The monthly (MAS) and daily (DAS) spatial behaviour denotes the actual use of space in April 2009

7. Personal spatial mobility: stability and variability

(Järv et al., 2014)

- 78% of CA's in 10 most visited activity locations (ex. home)
- 17% of locations are "new" (or once a year visited)
- Strong seasonality effect at aggregated level
- Marginal seasonaility effect at individual level, strong intrapersonal impact



Monthly interpersonal variations compared to the 12-month mean

8. Activity spaces and socio-spatial inequality

Järv, O., Müürisepp, K., Ahas, R., Derudder, B., Witlox, F. (2014) **Ethnic differences in activity spaces as a characteristics of segregation: a study based on mobile phone usage in Tallinn, Estonia**. *Urban Studies,* doi:10.1177/0042098014550459.

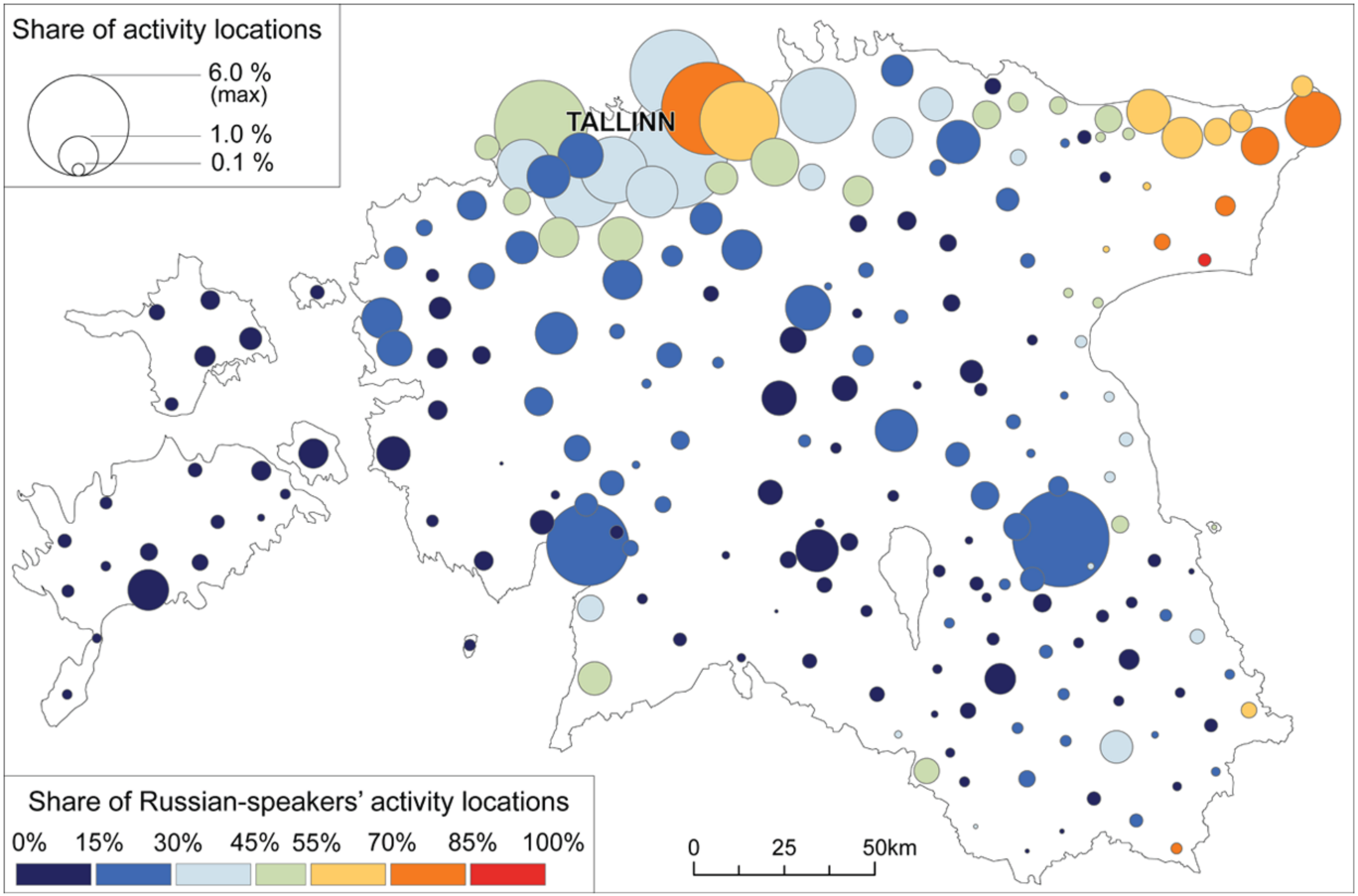
The effect of interpersonal factors on the size of activity spaces.

Independent factors		DAS[a]		MAS[b]		AAS[c]	
		F	Partial eta-squared	F	Partial eta-squared	F	Partial eta-squared
Corrected model		5.796*	0.217	13.890*	0.394	14.937*	0.412
Social	Lang	20.029*	0.037	115.178*	0.177	171.126*	0.243
	Gender	0.706	0.001	0.696	0.001	1.998	0.004
	Age	1.476	0.008	2.846*	0.016	4.967*	0.027
	Gender×Age	1.243	0.007	1.335	0.007	1.371	0.008
	Lang×Age	1.658	0.009	0.634	0.004	0.530	0.003
	Lang×Gender	0.633	0.001	0.673	0.001	0.040	0.000
	Lang×Gender×Age	1.341	0.008	3.085*	0.017	4.271*	0.023
Location	Home	2.278	0.004	2.743	0.005	0.036	0.000
	Work	4.144*	0.008	4.709*	0.009	0.641	0.001
	HW_{dist}	32.312*	0.058	8.793*	0.016	0.003	0.000
Phone usage	Ghour	0.604	0.002	0.032	0.000	0.015	0.000
	Gweek	1.074	0.004	7.899*	0.029	6.198*	0.023
	CDR_{avg}	0.005	0.000	0.194	0.000	0.255	0.000
	CDR_{days}	2.441	0.005	0.254	0.000	1.163	0.002
	notHW	39.333*	0.070	84.778*	0.137	63.120*	0.106

Notes:
*$p < 0.05$.
[a]Size of mean daily activity space (DAS).
[b]Size of mean monthly activity space (MAS).
[c]Size of annual activity space (AAS).

8. Socio-spatial differences in activity locations

(Järv et al., 2014 online)



Distribution of activity locations outside Tallinn visited at the level of local municipalities

Conclusions

- CDR data are a valuable addition to capture and provide new insights on human spatial distribution & mobility to better understand social processes and to solve social phenomena

Huge potential for planners & policy-makers aiming at „smart societies“

- Advantages: sample size (all MP users); study period (unlimited); study area (up to entire world); cost-effective & not disturbing respondents
- Limitations: privacy concerns; access to data?; sampling issues?; limited availability of socio-economic attributes
- Big Data difficulties: conceptual and methodological issues

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