Spatial Analysis of Road Safety and Traffic Behaviour using High Resolution Multi-parametric Data

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Scope of the dissertation

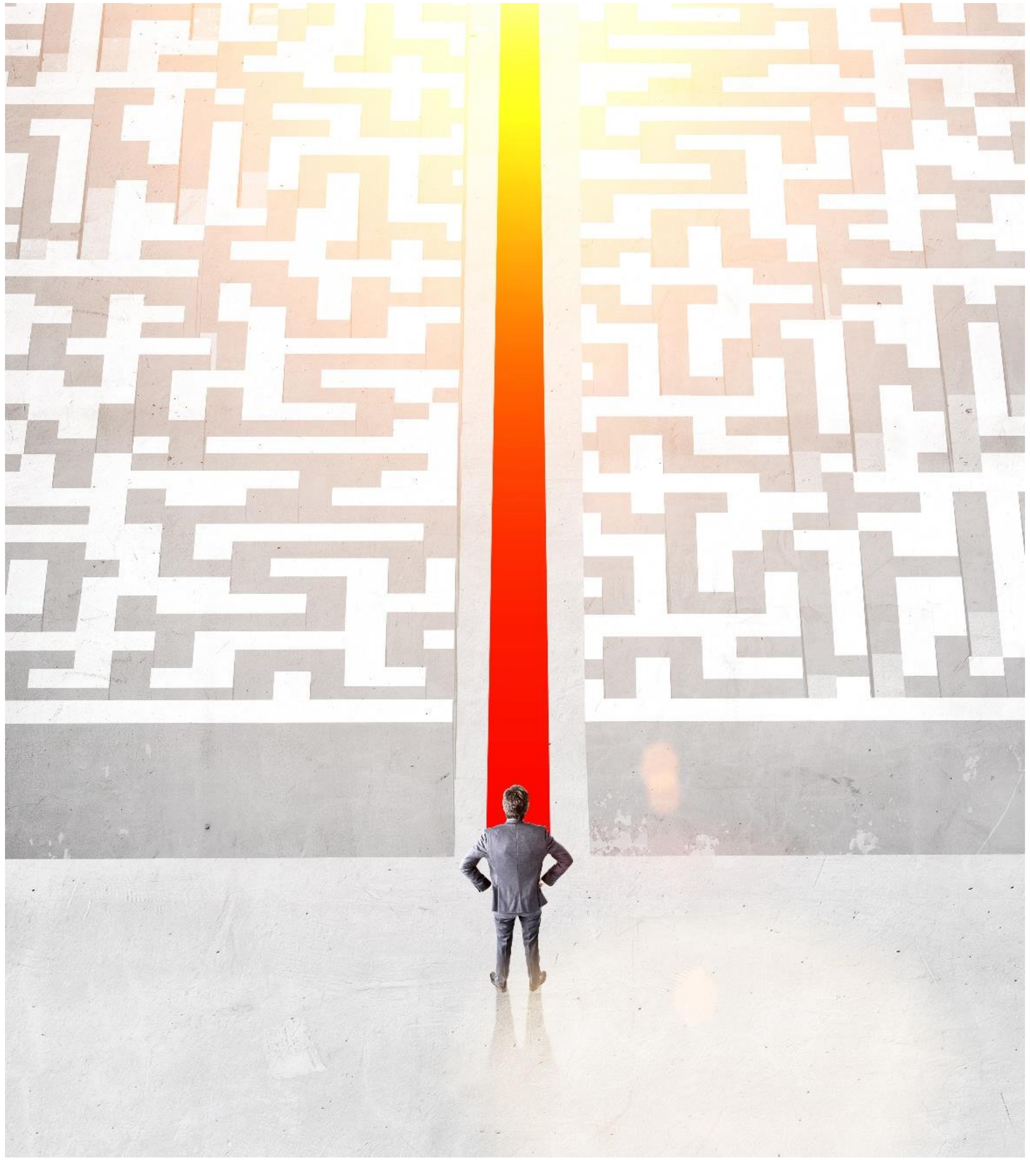
Spatial analysis of harsh event frequencies (harsh brakings/accelerations) in road segments

Exploitation of **multi-parametric** high-resolution data:

1. Road segment **geometric** and **road network** characteristic data from digital maps

2. **Naturalistic driving** data from smartphone sensors

3. High resolution **traffic data**



Literature review: Spatial analyses (1/2)

Thorough review of **132 international scientific studies** of **spatial analysis** applications in road safety

Available methodologies:
1. Geographically Weighted Regression (GWR)
2. Bayesian Conditional Autoregression (CAR)
3. Full/Empirical Bayesian Analyses
4. Machine learning approaches
5. Kernel density approaches etc.

Wide array of **parameters** related to:
1. Road traffic (speed, traffic volume, vehicle-kilometers)
2. Road environment (gradient, curvature, lane number/width, intersection number/density etc.)
3. Demographic characteristics (population, road user age)
4. Socio-economic characteristics (income, employment)
5. Land use (commercial, industrial, residential)

Several available **unit scales** for spatial analysis
(road segment, TAZ, region, grid structures)

Literature review: Spatial analyses (2/2)

The majority of studies analyze crash frequency specially with **count-data models** (GWPR/CAR Poisson)

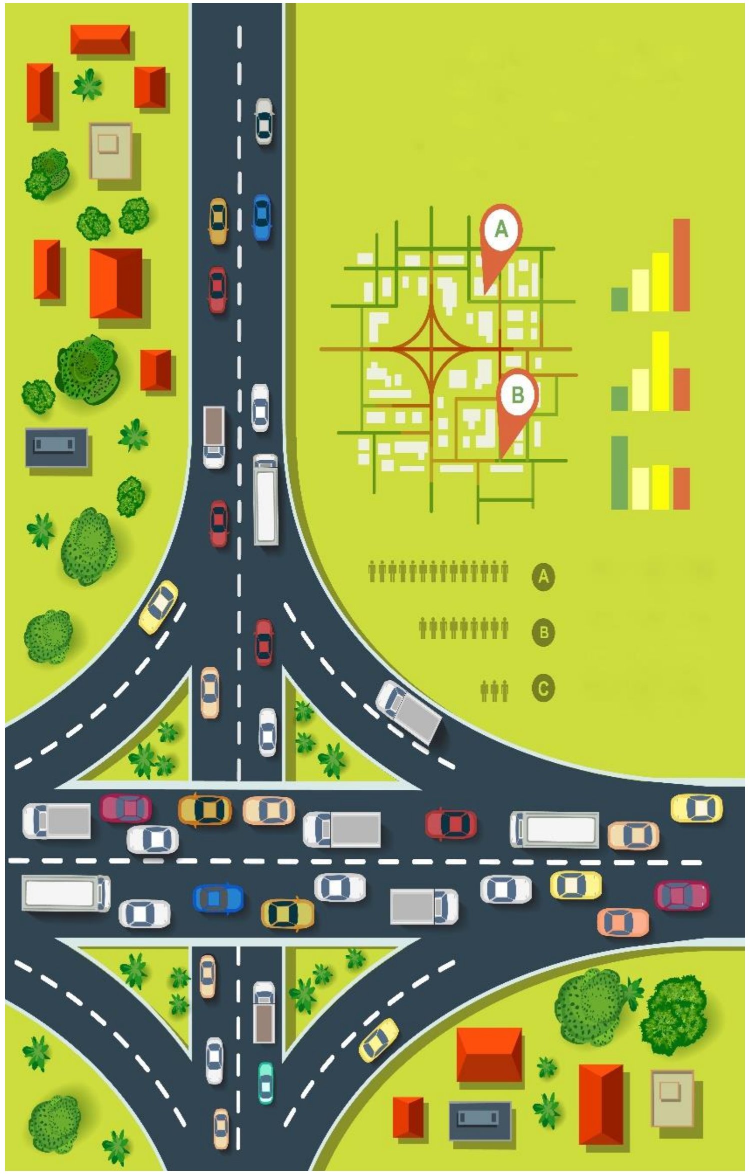
Additional **issues**:

1. **Boundary** problem
2. **Modifiable areal unit** problem
3. Lack of common working **framework**
4. Most research done in **modernized countries**
5. Harder examination of certain **parameters** due to lack of data or means of calculation (e.g. geometric characteristics)

All variables – parameters are examined and analyzed on a **spatial unit basis** (AADT/zone, average speed/road section)

Methodological advantages and disadvantages:

1. **Frequentist models** (e.g. GWPR): Intuitive interpretation, reduced fit capabilities
2. **Bayesian models** (e.g. CAR): Wide applications & adaptation to new data trends, lack of informative priors for initialization
3. **Machine learning** (e.g. SVM/CNN): Flexibility & handling of big data, harder interpretation – occasional ‘black box’ effect



Literature review: Knowledge gaps in road safety spatial analyses

Spatial analysis objectives are dictated by **data availability:**

- No research was found in **urban road networks** due to lack of data

Dependent variables:

- Limited analyses regarding crash injury severity
- **No research** pertinent with spatial analysis of harsh events was found

Despite precise hotspot location capabilities, there is a lack of transferability of spatial analysis results:

- No predictions are conducted for **different study areas**

Large margins for exploitation of **new technological advancements** for spatial analyses:

- **Enhancement** of existing data – **production of new datasets**

Literature review: Meta-regressions

Parameters of exposure to danger

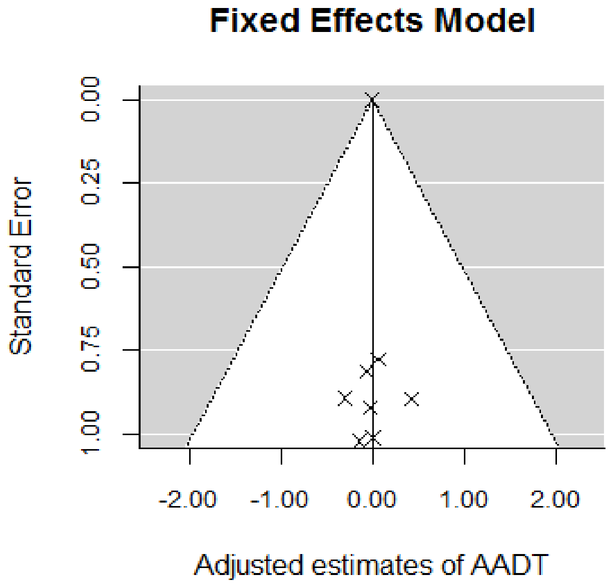
- Serve for the creation of a **common baseline** between models and results
- Most prevalent parameters:
  roadway length, vehicle-miles/kms, AADT

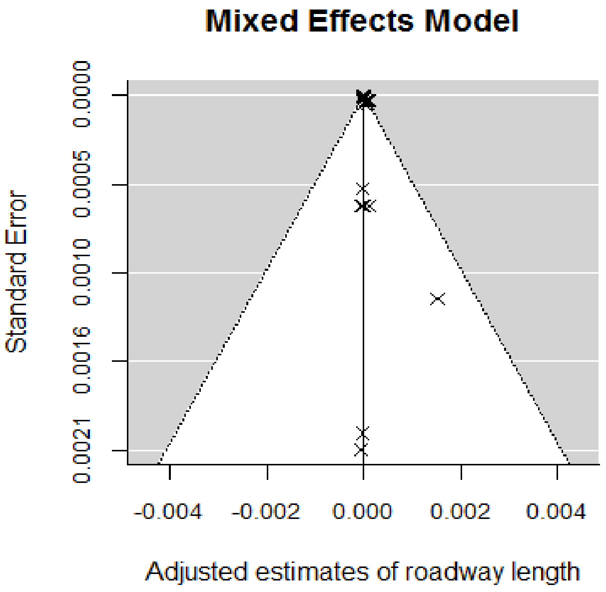
Meta-regressions: Original research

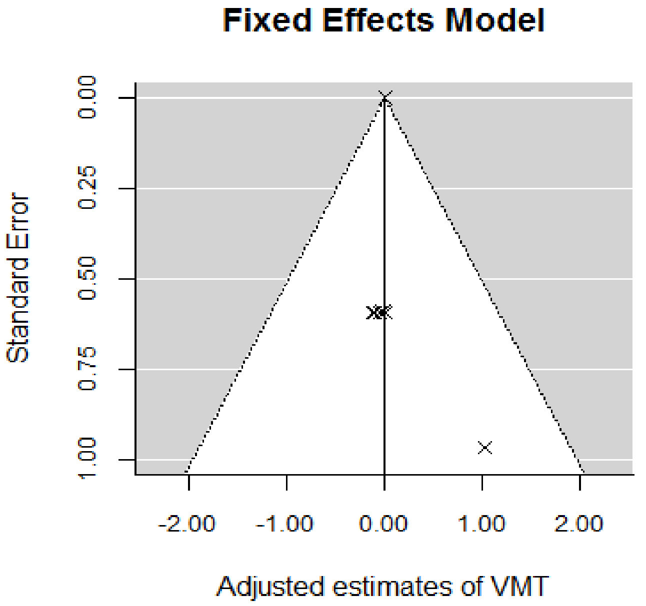
- **Quantitative investigation** of factors which systematically influence exposure parameters
- A means of investigating **heterogeneity** of scientific study results
- Conducted with the **inverse variance technique**

Results for road safety spatial analyses

1. AADT coefficients are positively correlated with taking **speed limit and road user age** into consideration
2. Roadway length coefficients are positively correlated with analyzing **only fatal crashes** compared to total crashes
3. AADT coefficients are positively correlated with analyzing crashes on a **county level** compared to TAZ level







Literature review: Driver recording tools

A significant number of **driver recording tools** was identified

Recording tools	Main advantages	Main disadvantages
Surveys on opinion and stated behaviour	low cost, flexibility	hypothetical questions, lower detail/reliability, biased data
Past **police or hospital record** investigation	low cost, official records	missing data/variables, underreporting, maintenance requirements, time delays
Direct **observer** method	observer specialization, removal of intermediaries	high person-hours, lack of randomization, observer bias
Driving simulator	safe environment, greater experimental control, precise reaction time	learning effects, nausea, high costs, maintenance requirements
Naturalistic driving - Vehicle instrumentation (& On-road driving)	examination of real traffic conditions and events, uses in driver training – evaluation, interdisciplinary extensions	rare traffic incidents, high costs, driver screening requirements, time-consuming process
OBD/IVDRs	Real-time recording, accurate indications of crash involvement probability	unclear sampling frame
In-depth incident investigation	identification and reconstruction of crash factors, research of injury prevention	insufficient reconstruction evidence, long analysis time, demanding data analysis
Smartphone data exploitation	seamless and rapid data recording and storage, programmable means, increased flexibility, phone distraction measurements	demanding in data storage/analysis, upfront costs during development, lower cost during collection

Literature review: Harsh events

Harsh events: **harsh brakings** and **harsh accelerations** occurring during naturalistic driving

- Parameters measuring **road safety levels** (correlations with spatial and temporal headways)
- **Different phenomena**, correlations with different variables
- Correlation with **driver risk**

Considerable **comparative advantages** for investigation:

1. Applications in driver **evaluation** and **classification**

2. **Proactive** road safety indicators – evaluations **before** crashes occur

3. Considerable **research gaps** regarding the investigation of harsh event frequencies

Research questions

1. How can smartphone data and map data be **combined** (map-matched) and **examined** in road safety investigations?

2. How can **harsh event** frequencies be **analyzed spatially** in these environments, and which methods are appropriate for that purpose?

3. Is there **spatial autocorrelation** present in harsh event frequencies for road segments in urban road environments?

4. Which **road geometry** and **road network characteristics** affect harsh event frequencies in urban road network environments? **How transferable** are the previous results in a different study area?

5. Do **traffic** and **driver behavioural parameters** have a statistical impact on harsh event frequencies?

Methodological approach

Spatial analysis of harsh event frequencies along two pillars:

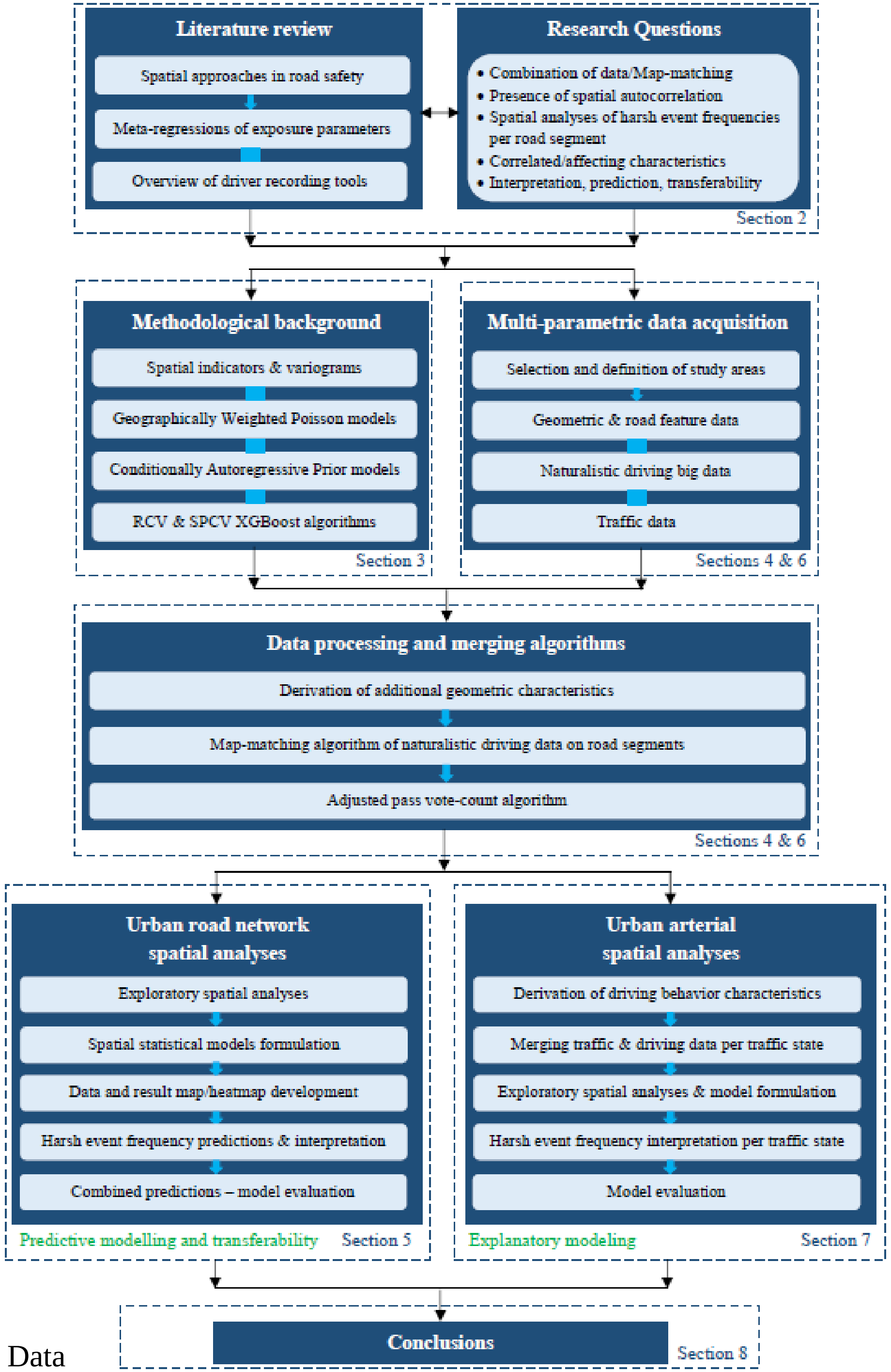
1. Urban road networks
Predictive modelling – Measurement of result transferability

2. Urban arterials
Explanatory modelling – Examination of additional traffic and driver behaviour characteristics (without result transferability)

Exploratory spatial analyses (Moran's I coefficients and variograms)

Selection of **four spatial analysis** methods
1. Geographically Weighted Poisson Regression (**GWPR**)
2. Conditional Autoregressive Prior Regression (**CAR**)
3. Extreme Gradient Boosting (**XGBoost**) with Random Cross-Validation (**RCV**)
4. Extreme Gradient Boosting (**XGBoost**) with Spatial Cross-Validation (**SPCV**)

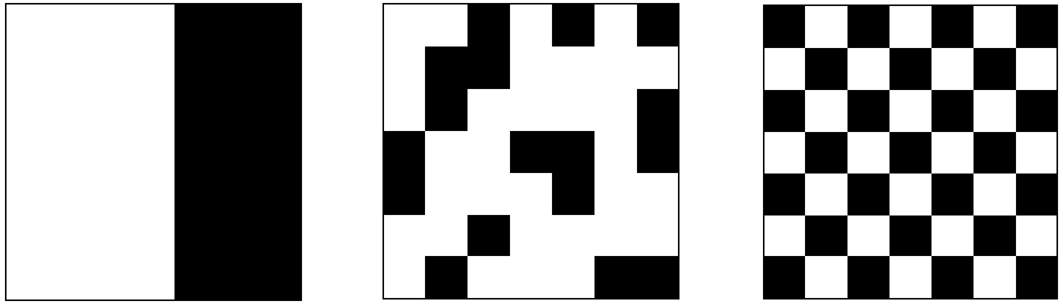
Model averaging for harsh event predictions in urban road networks



Theory of exploratory spatial analyses

*"Everything is related to everything else, but **near** things are more related than **distant** things."*

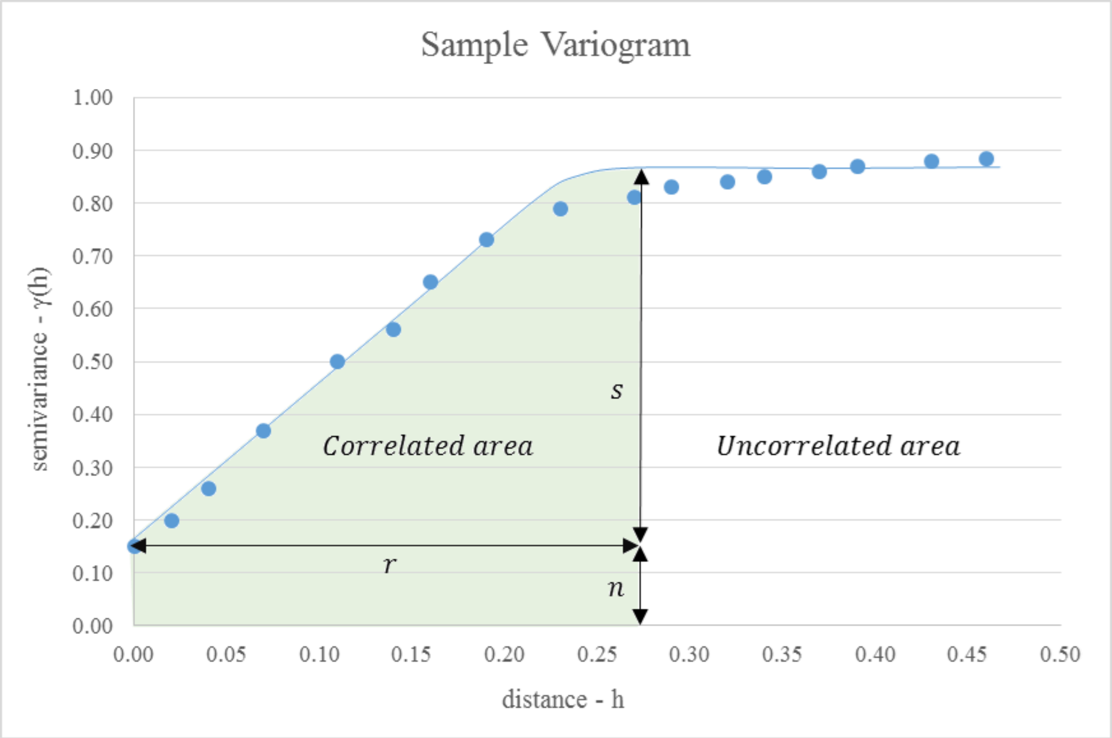
– Tobler, 1970



Positive (areas) **Zero** (groups) **Negative** (uniformity)

1. **Moran's I**
   - Measurement of **spatial autocorrelation**
   - Can be calculated **globally** [-1, 1] and **locally** ($\in$ R)
   - Several available geographical weighting options

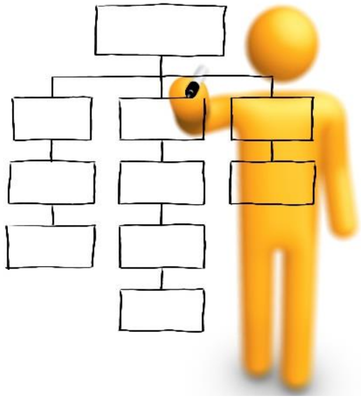
2. **Variograms**
   - Measurement of **distance** of spatial autocorrelation
   - Graphs of **(semi)variance** of the measured quantity by distance
   - **Theoretical** (mathematical curves) and **Empirical** (real observation cluster points)
   - Additional information: geographical anisotropy and cyclicity



Theory of spatial statistical models

Integration of **spatial heterogeneity**

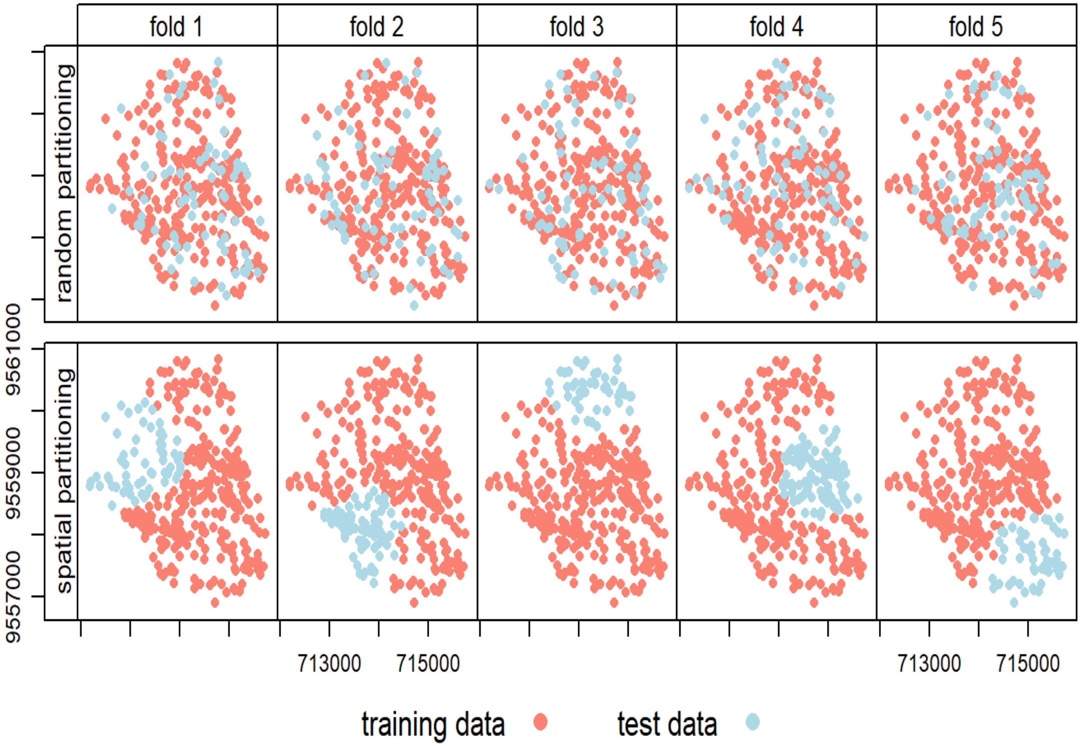
Event **frequencies: Log-normal Poisson** framework



1. Geographically Weighted Poisson Regression **(GWPR)**
- Frequentist functional models: local micro-regressions are conducted, b coefficients can vary locally

2. Conditional Autoregressive Prior Regression **(CAR)**
- Bayesian functional models: Bayesian regressions are conducted with spatially structured and unstructured terms, b coefficient distributions are obtained

3. Extreme Gradient Boosting **(XGBoost)**
- Machine learning: Multiple additive regression trees (ensemble), obtained information regarding variable contribution (gain)
- Random Cross-Validation – **RCV**
- Spatial Cross-Validation – **SPCV**



Source: Lovelace et al. (2019)

Evaluation of model performance

Model performance metrics:
Difference between true and predicted values

1. Root Mean Squared Error (**RMSE**)

2. Mean Absolute Error (**MAE**)

3. Root Mean Squared Log Error (**RMSLE**)

Additional indicator:

4. Custom accuracy (**CA** – percentage):
   Percentage of accurate predictions within a ± 1 margin over total number of predictions

Performance metric selection is also affected by **input** and **output data**

Frequencies: **Natural numbers** (positive integer or zero values)

Data collection (1/3): Digital map road geometry data

Data of **road segment geometry** and **road network** characteristics on a **microscopic level** from digital maps

OpenStreetMap: Open source digital map platform

Hierarchical elements:

1. **Nodes**
2. **Ways** from node groups
3. **Relations** from node and way groups

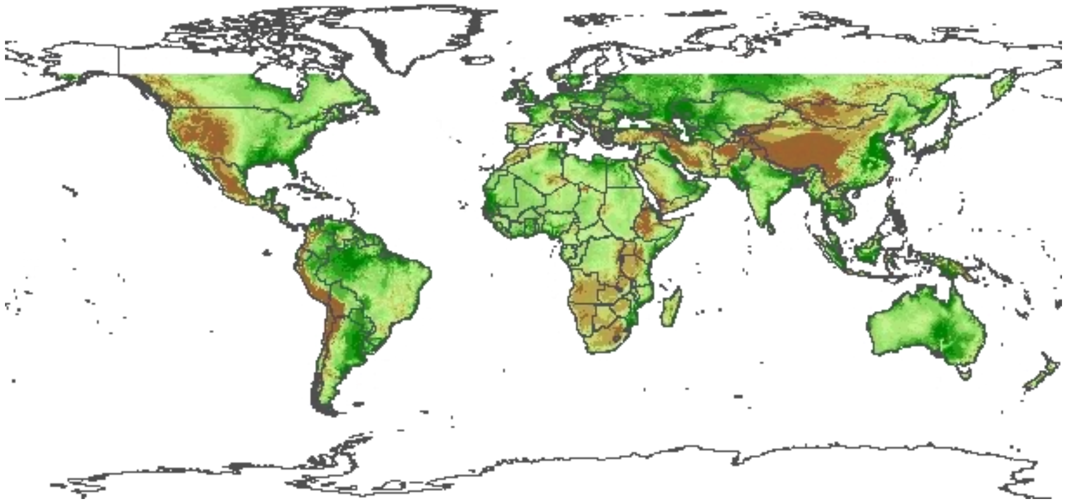
Obtaining a wealth of data in WGS84 through API queries (Overpass Turbo API through Overpass Query Language)

NASA SRTM topography

Altitude data provided by NASA:

- **Freely** available
- Altitude resolution per **10 cm**
- Majority of **populated areas** available

Hierarchy level	Core Element	Schematic representation	OSM symbol	
1	Node	Tags	Node	
			Tag	k=v
2	Way	Tags	Open polyline	
			Closed polyline	
			Area	
3	Relation	Tags	Relation	



Source: SRTM website, (2020)

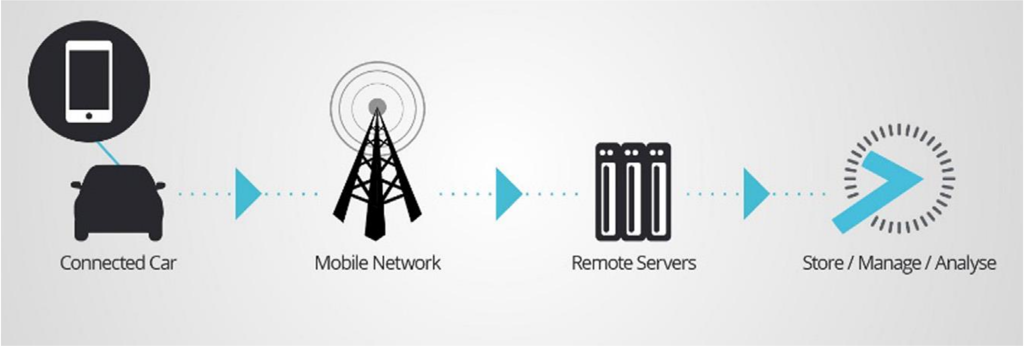
Data collection (2/3): Naturalistic driving data from smartphones

Naturalistic driving data from real-world conditions obtained from smartphones (per trip-second)

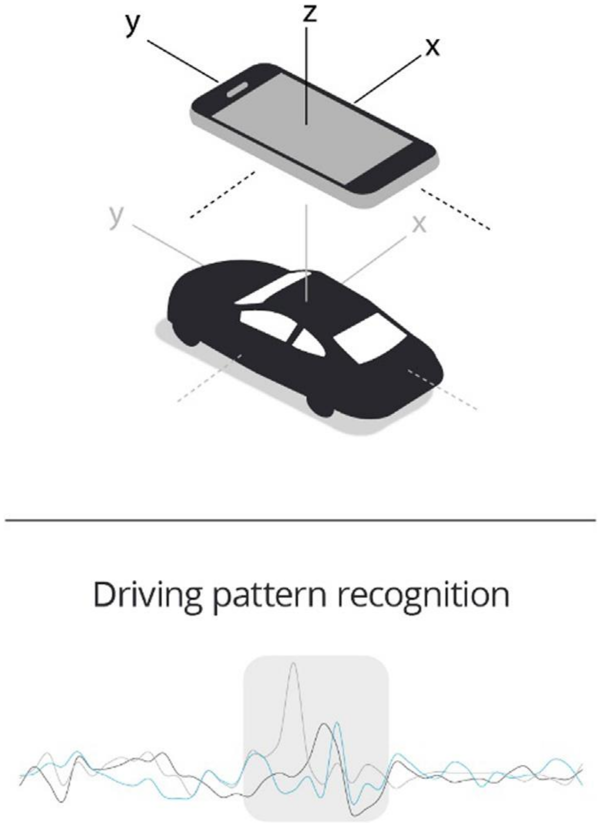
Utilization of the application/platform of **OSeven Telematics**

- APIs utilization for data reading from **smartphone sensors**
- **Exploited sensors**: GPS, accelerometer, gyroscope, device orientation
- **Transmission** from smartphone to central storage database
- **Data cleaning** and **processing** via a series of filtering, signal processing, Machine Learning (ML) and scoring algorithms
- Several data are provided, **indicatively**: trip position, speed, acceleration, harsh brakings/accelerations, event intensity, speeding, mobile phone use
- **Total anonymity** during all data handling phases (GDPR)

Obtained **high resolution big data** from driver trips including behaviour indicators



Source: OSeven Telematics, (2020)



Data collection (3/3): Traffic data

Traffic data in **urban arterials** provided by the Traffic Management Centre of Attica Region

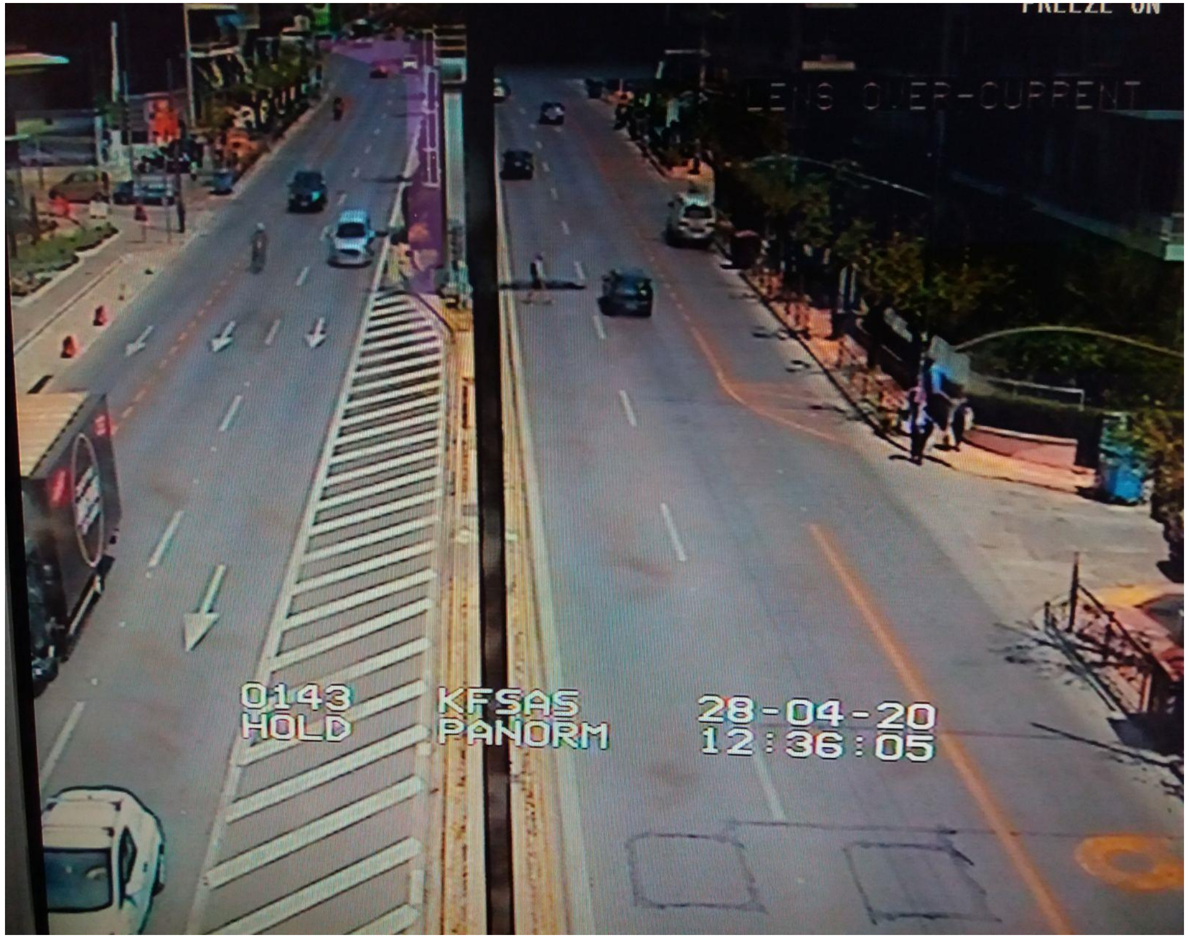
Instrumentation in urban arterial corridors in Attica
- 550 inductive loop detectors
- 217 computer vision traffic cameras
- 24 variable message signs (VMS)

Regulation of ~ 1500 traffic lights in 850 intersections

Through vehicle time occupancy as a percentage, the TMC collects:
- **Occupancy** [% of time]
- **Traffic volume** [vehicle number / temporal unit]

Secondarily, **traffic speed** [km/h] is calculated as well

Several temporal resolutions for data: 1 h, 5 min or **90 s** (high resolution)



Source: TMC, (2020)

Study areas

1. Urban road networks (URNs)

(i) Chalandri (spatial model calibration for URNs)

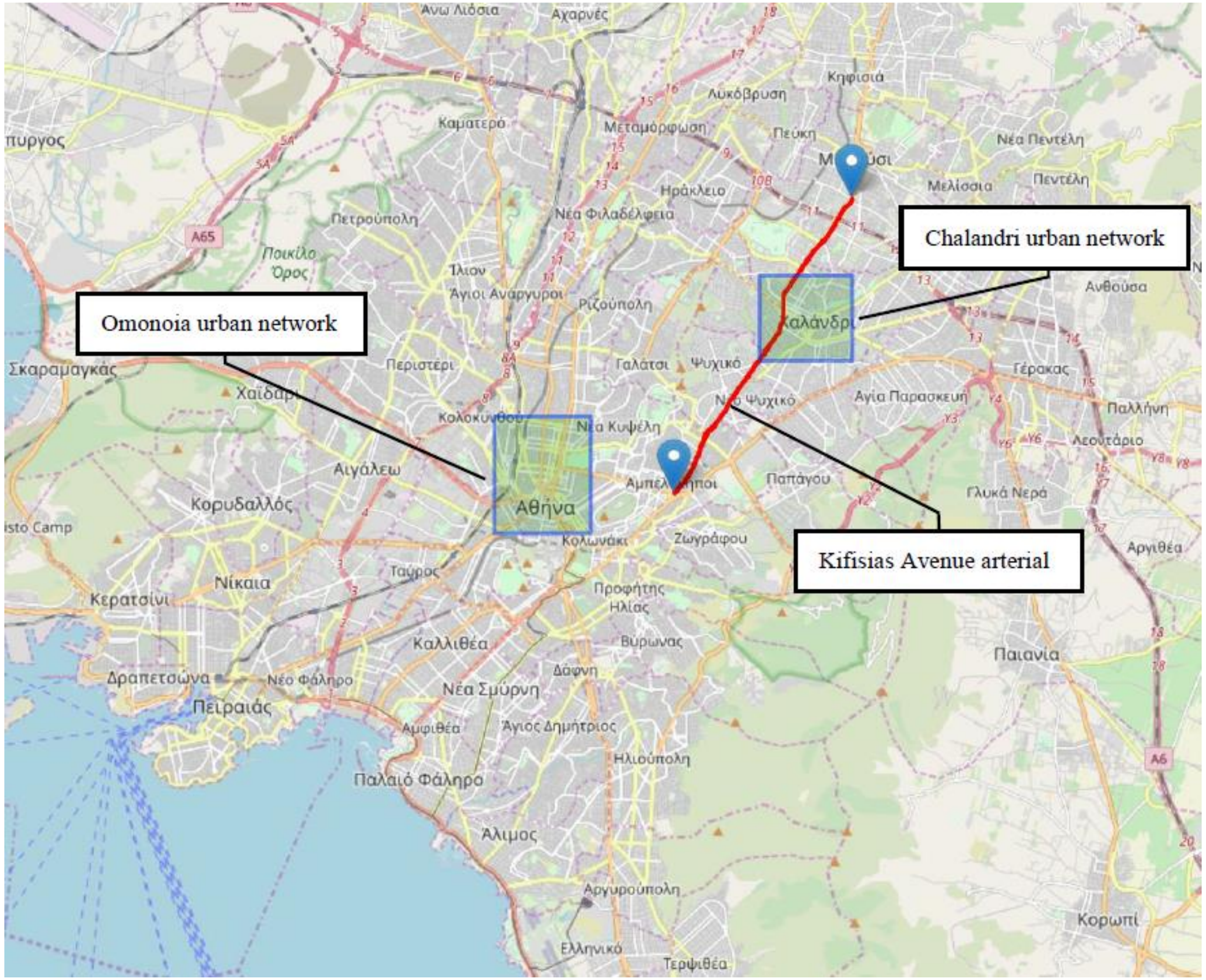
(ii) Omonoia (accuracy evaluation – transferability assessment for URNs)

Road geometry and naturalistic driving high resolution data collection

2. Urban arterials (UA)

Kifisias Avenue (increased modelling depth with added characteristics in UA)

Road geometry, naturalistic driving and traffic high resolution data collection



Data processing: Geometric characteristics (1/2)

Calculation of geometric characteristics based on **OSM node coordinates**

Roadway segment length

- Calculation based on modern geoids/ellipsoid models through available libraries
- Sum of elementary lengths (2 nodes each)

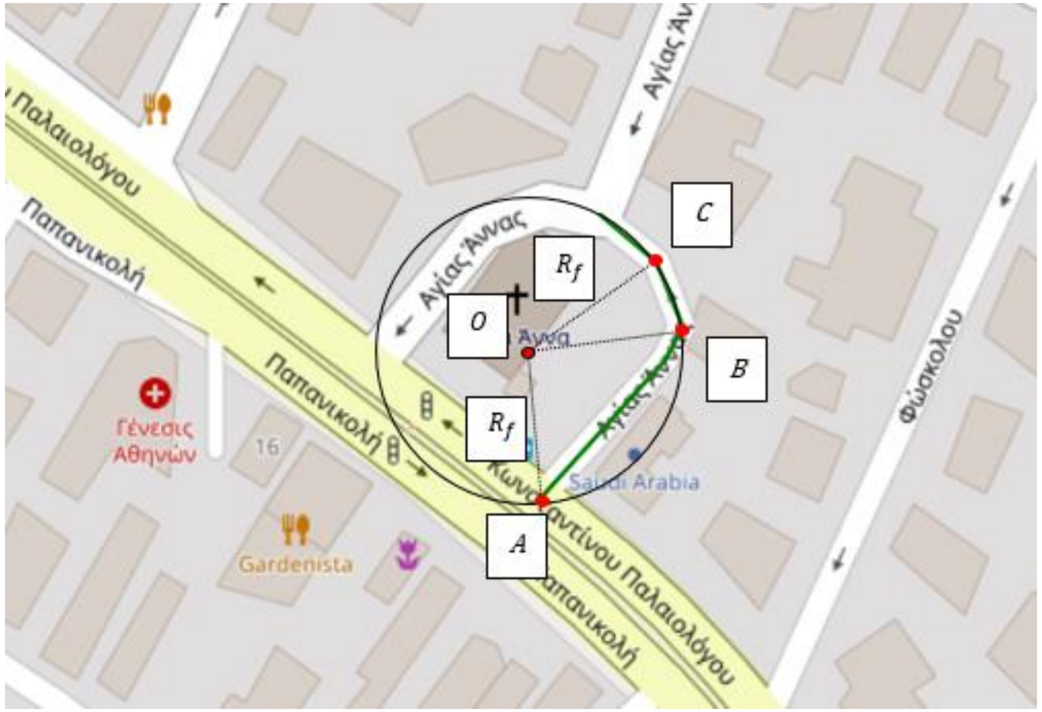
Determination of road segment centroids

Gradient

- Sum of elementary gradients (2 nodes each)
- Road segment average, weighted by elementary lengths

Curvature

- Menger's formula per elementary triangle (3 nodes each)
- Road segment average, weighted by elementary lengths



Data processing: Geometric characteristics (2/2)

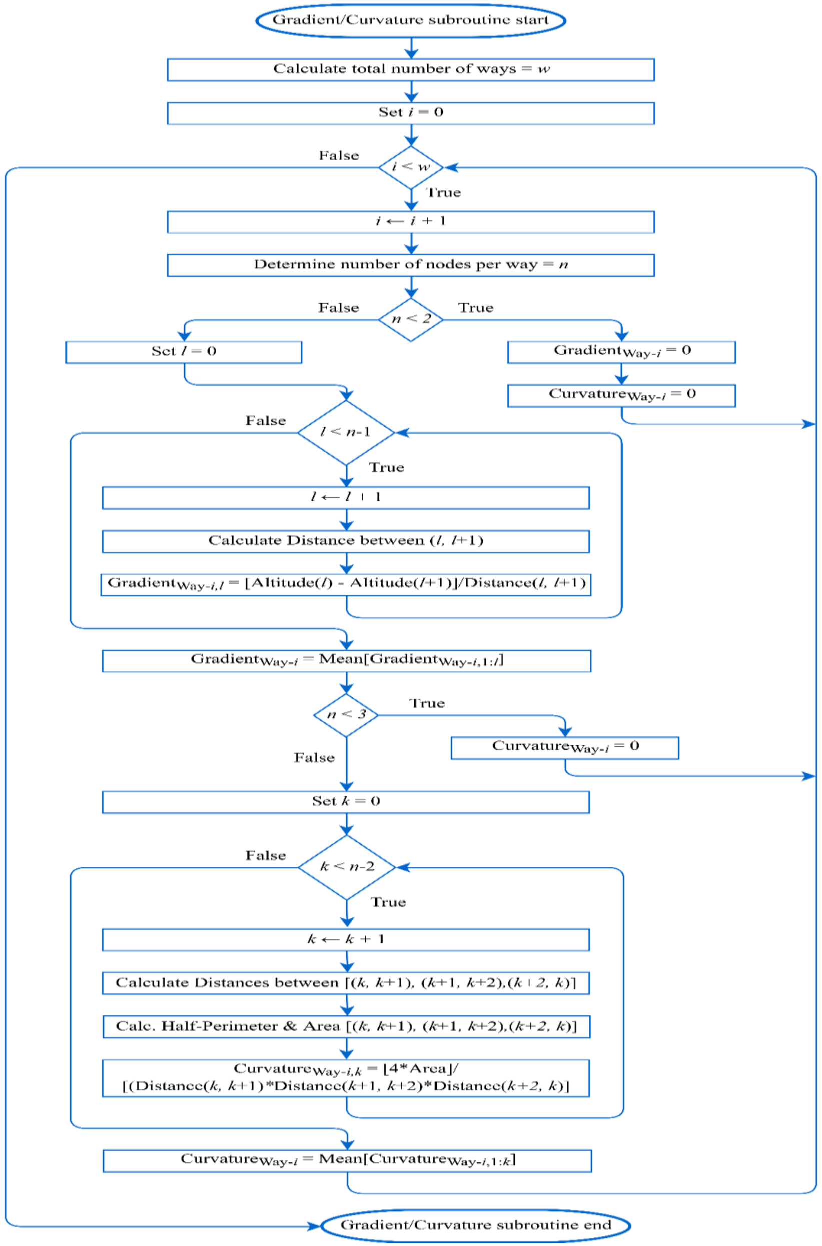
Neighborhood complexity calculation

- Measurement of density and complexity of immediate road segment environment: (i) in reality (ii) on the digital maps
- Logarithm of nodes within a window of 470m * 470m from each road segment centroid

Obtaining of additional **road segment characteristics** from OSM:

1. Presence of **pedestrian crossing**
2. Presence of **traffic lights**
3. **Lane number**
4. Road type
   (exclusion of walkways/footpaths/surfaces without vehicles)
5. Direction **number** (one-way or two-way)

Calculation with original purpose-made algorithms and sub-routines created in R-studio, iteratively for each road segment



Data processing: Map-matching (1/2)

Map-matching: Plotting of naturalistic driving data on maps after determination of the corresponding segment

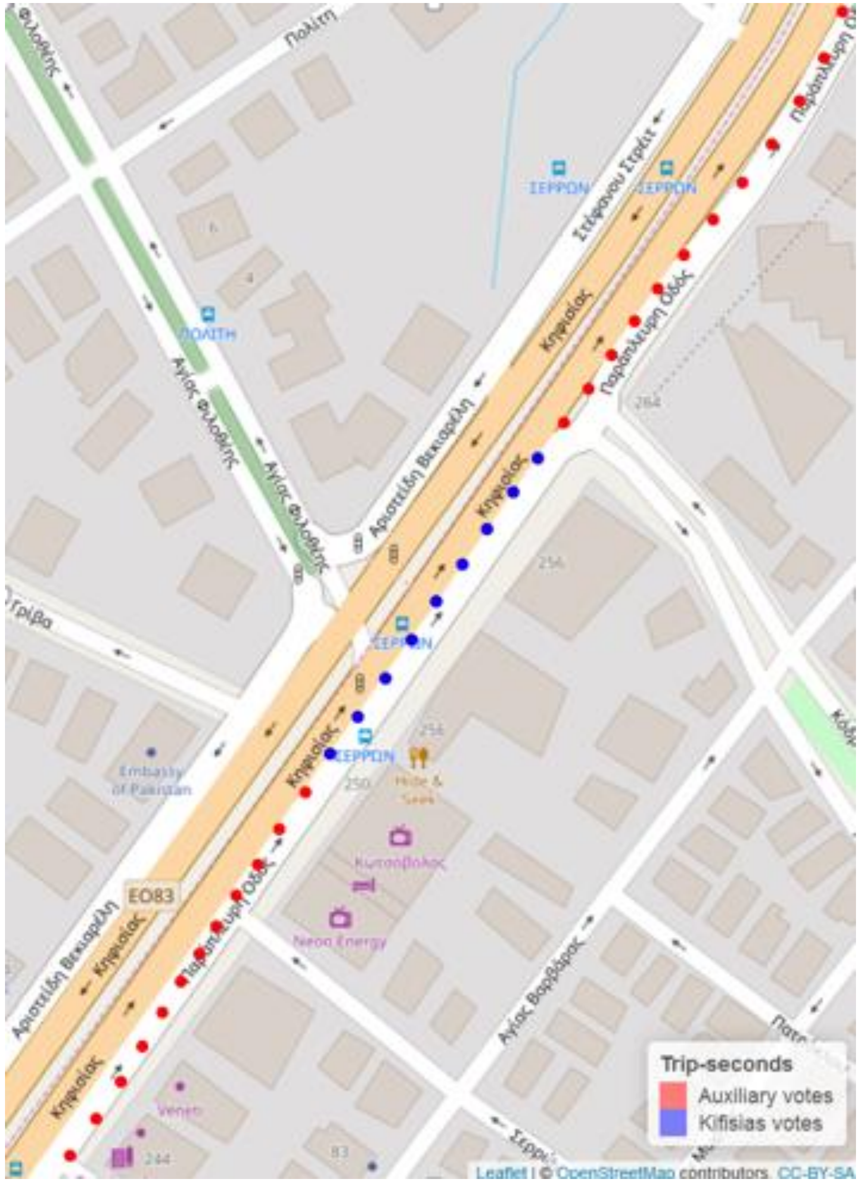
Matching of GPS trace to each road segment **per second**

Identification of:

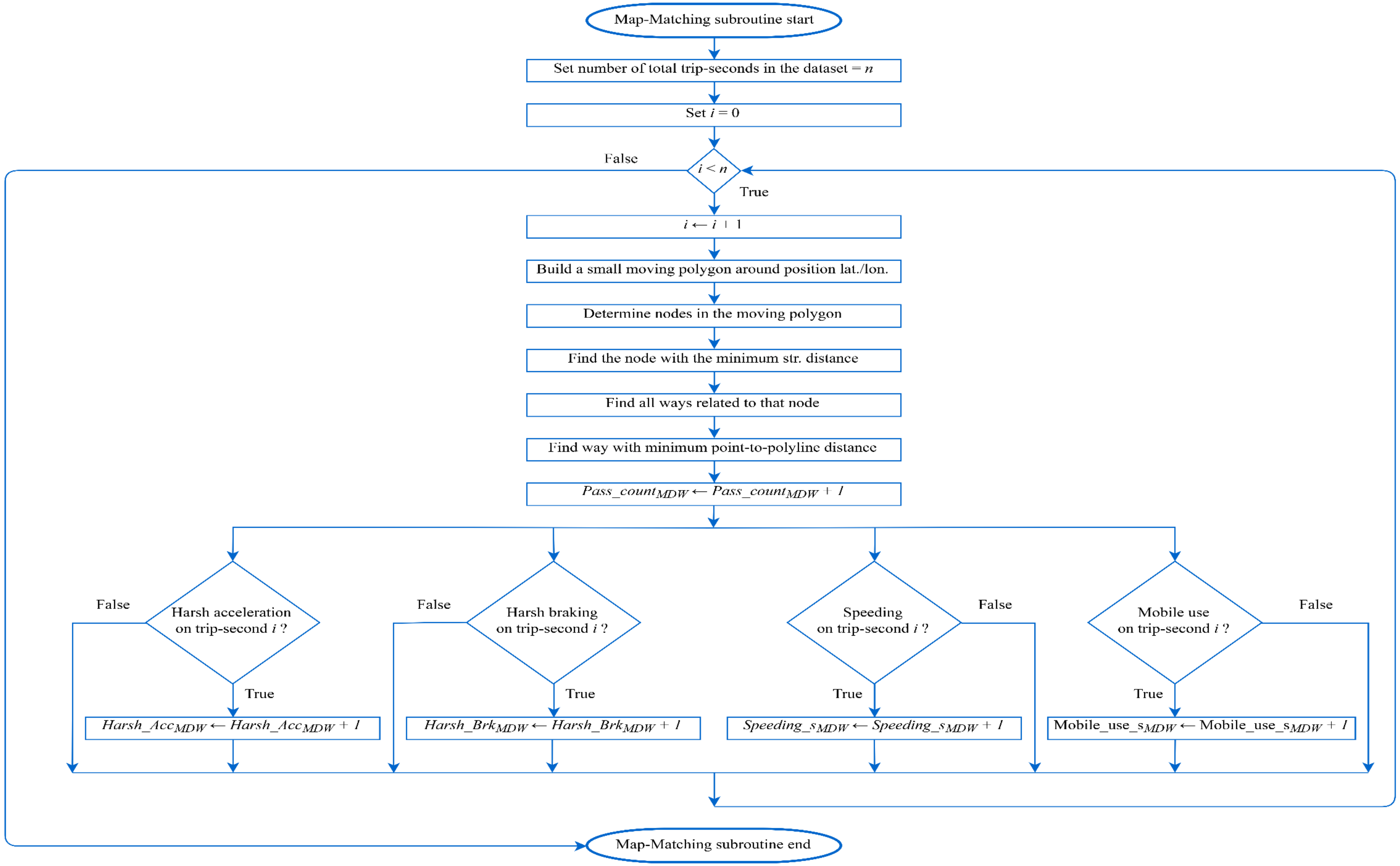
1. Nearest node (point-to-point distance)
2. Minimum distance way – MDW (point-to-polyline distance)
   - **Moving polygon** serving to reduce candidate ways
   - **Time-consuming** and **computationally demanding** process
   - **Corrections** are essential in dense road segments with parallel axes through a specialized vote-count algorithm

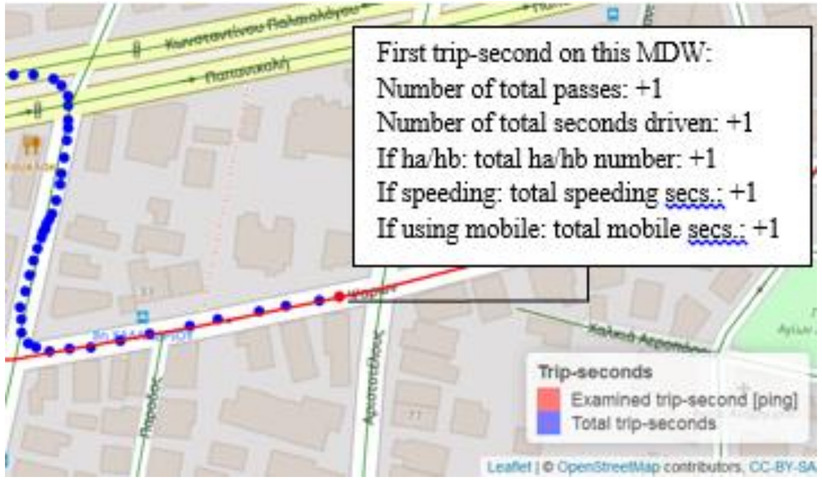
Recording and assignment per road segment**:**

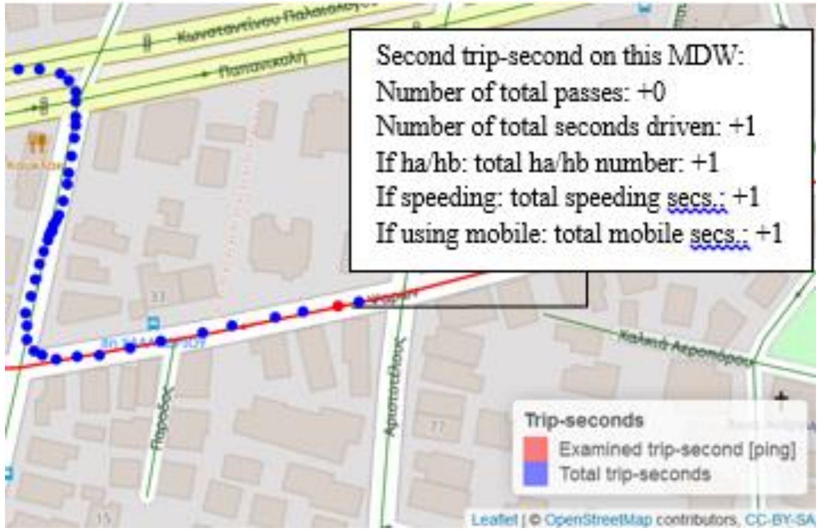
1. Pass count
2. Harsh brakings/accelerations
3. Speeding seconds
4. Mobile use seconds



Data processing: Map-matching (2/2)







Data processing: Traffic parameter integration

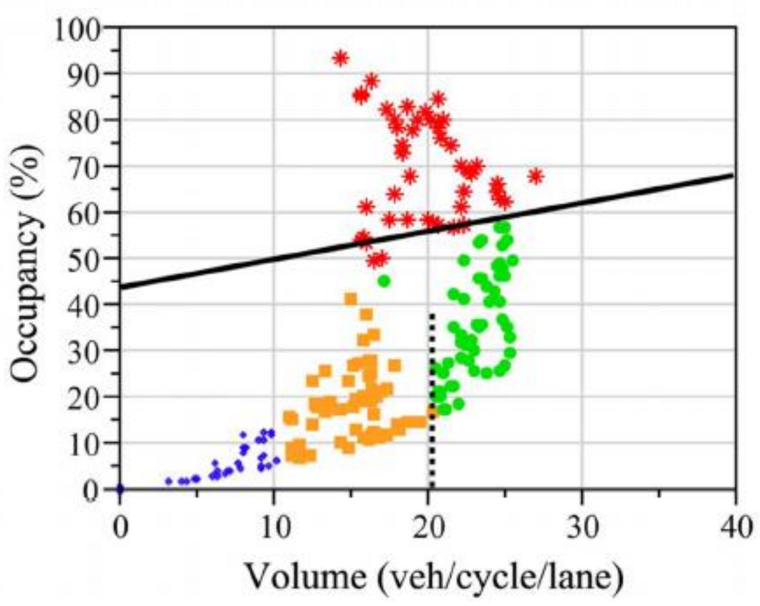
Theory of **three traffic states** (indicatively Kerner, 2012)

1. Free flow
2. Synchronized flow
3. Congested flow

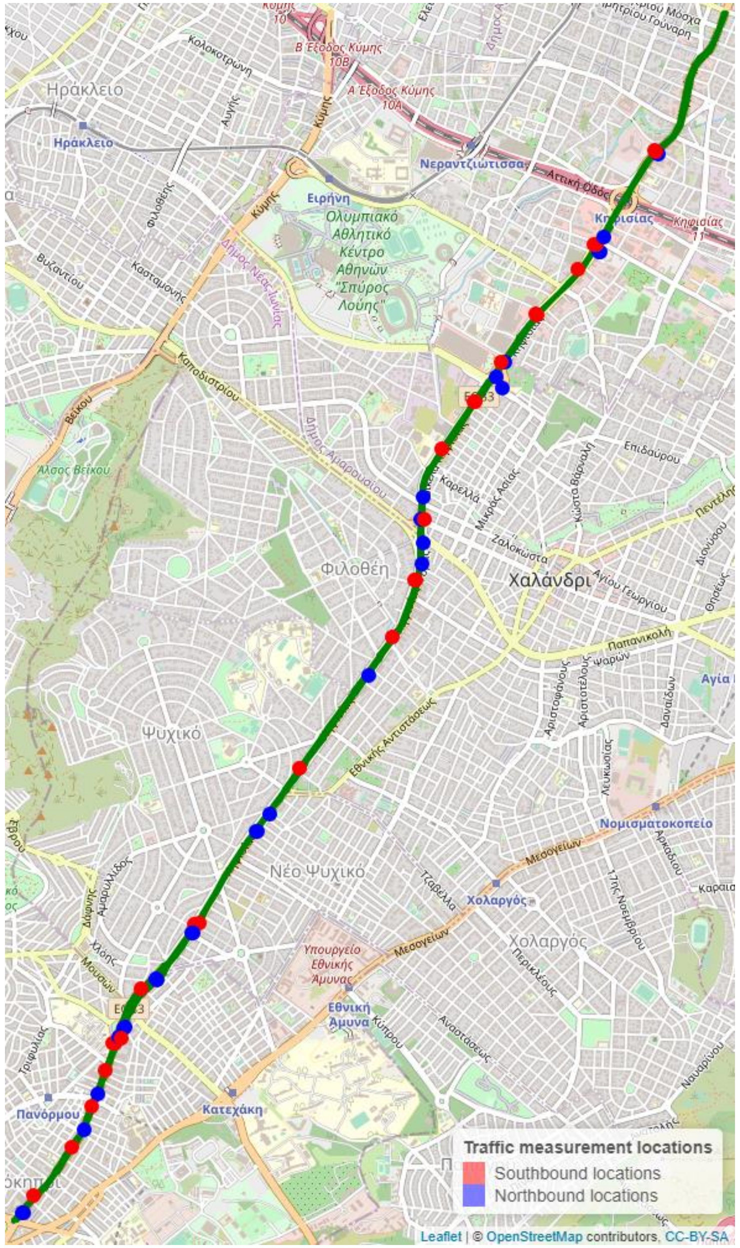
Matching of **naturalistic driving** data with **traffic** data spatio-temporally (closest measurement)

Classification of each trip-second per traffic state based on traffic data and on determined limits (Vlahogianni et al., 2008)

Map-matching of trips and maps: Creation of spatial data per **traffic flow state** for each **road segment**



Source: Vlahogianni et al. (2008)



Urban road networks: Sample description (1/2) – Chalandri

869 road segments (removal of 14 footways) with **4293** nodes

- **49** road segments with traffic lights
- **80** road segments with pedestrian crossings

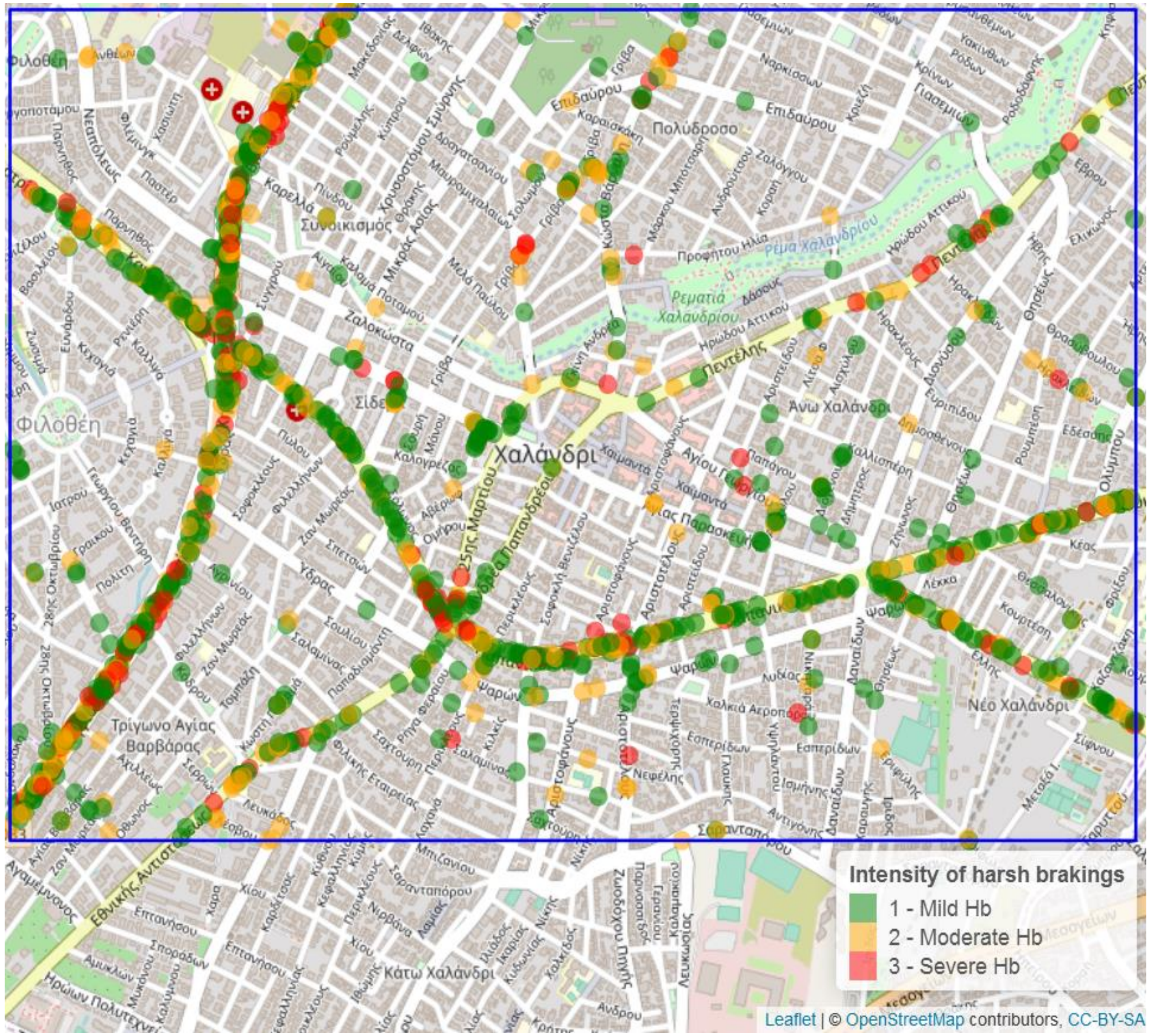
Naturalistic driving data:

- Trips between 01-10-2019 & 29-11-2019 – **2 months**
- **A total of** 3294 trips from 230 drivers
- 1,000,273 **driving seconds**: average trip duration 304 s
- 1348 harsh **brakings**
- 921 harsh **accelerations**

90% of road segments feature **at least 1** trip

Variable distributions

- **Positive** skewness (larger right tails)
- **High** kurtosis (non-normal distributions)



Urban road networks: Sample description (2/2) – Omonoia

1237 road segments (removal of 78 footways) with **6115** nodes

- **319** road segments with traffic lights
- **317** road segments with pedestrian crossings

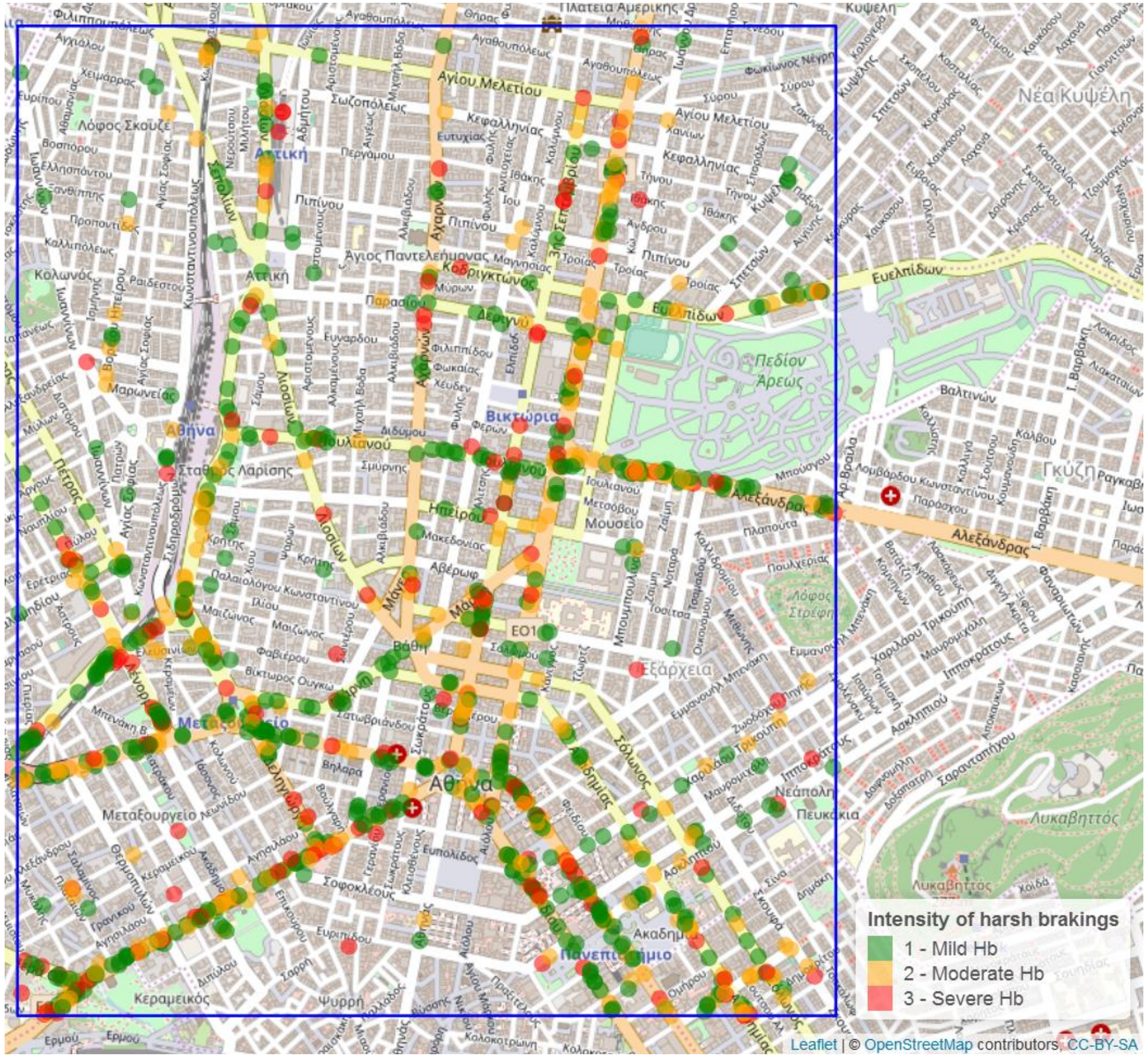
Naturalistic driving data:

- Trips between 01-10-2019 & 29-11-2019 – **2 months**
- **A total of** 2615 trips from 257 drivers
- 964,693 **driving seconds**: average trip duration 369 s
- 1036 harsh **brakings**
- 938 harsh **accelerations**

86% of road segments feature **at least 1** trip

Variable distributions

- **Positive** skewness (larger right tails)
- **High** kurtosis (non-normal distributions)



Urban road networks: Exploratory spatial analyses (1/2)

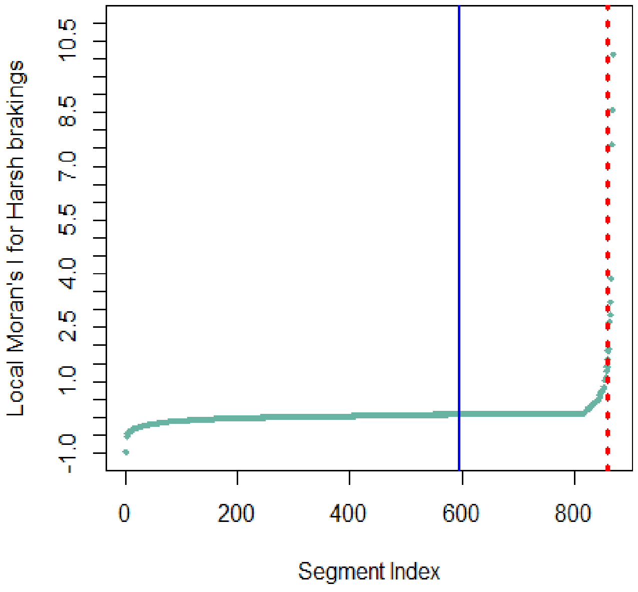
Global and local Moran's I coefficients (Chalandri area)
1. Distance-based weighting (DB)
2. k nearest-neighbor weighting (kNN)

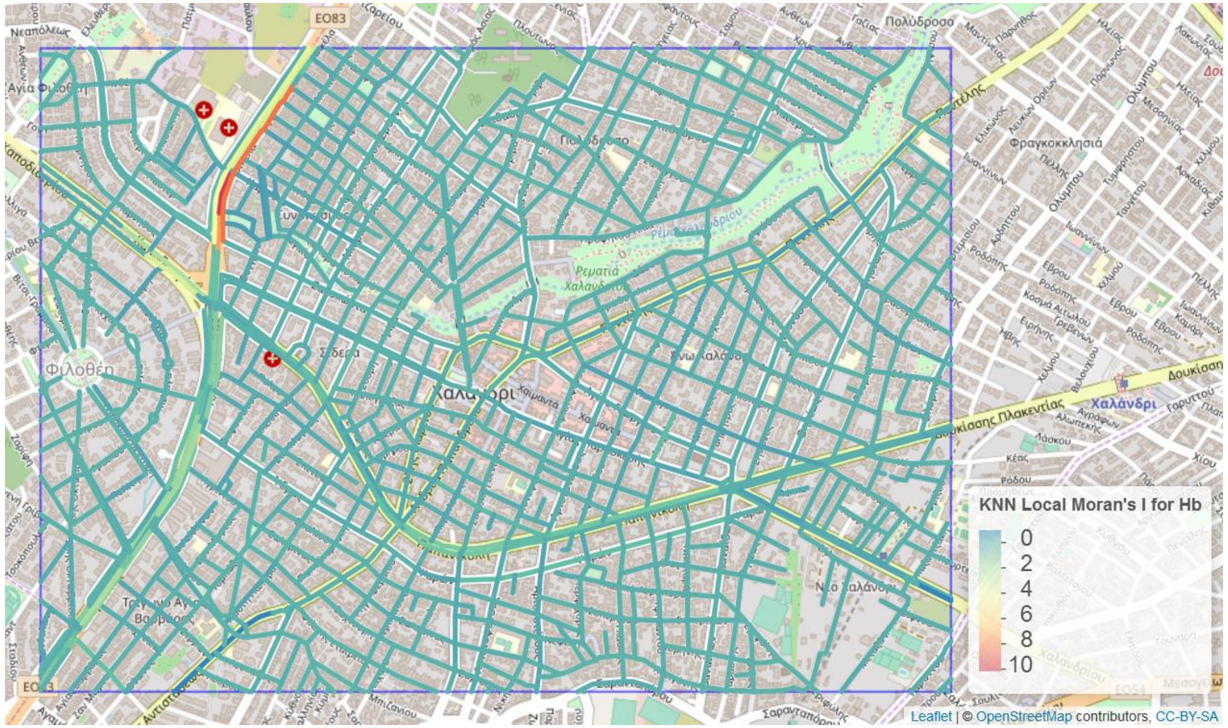
Interpretation of k nearest-neighbors is more **reasonable:**
- Harsh event frequencies are influenced from the **more proximal** road environment
- **Positive spatial autocorrelation** manifests in harsh event frequencies

Very few outlier values appear for local Moran's I (within 2σ per Anselin, 1995)

Volatility of the coefficient: appropriate for preliminary – exploratory analysis

kNN Global Moran's I	Correlation threshold	k	Coefficient value	Expectation	p-value
Harsh brakings	0.0	15	0.0806	-0.0012	0.000
Harsh accelerations		39	0.0945	-0.0012	0.000
Harsh brakings	0.1	5	0.1421	-0.0012	0.000
Harsh accelerations		5	0.2206	-0.0012	0.000





Urban road networks: Exploratory spatial analyses (2/2)

Variograms of semivariance per directional axis [N-S, W-E]

Spherical theoretical variograms describe harsh event frequencies per road segment with a better fit

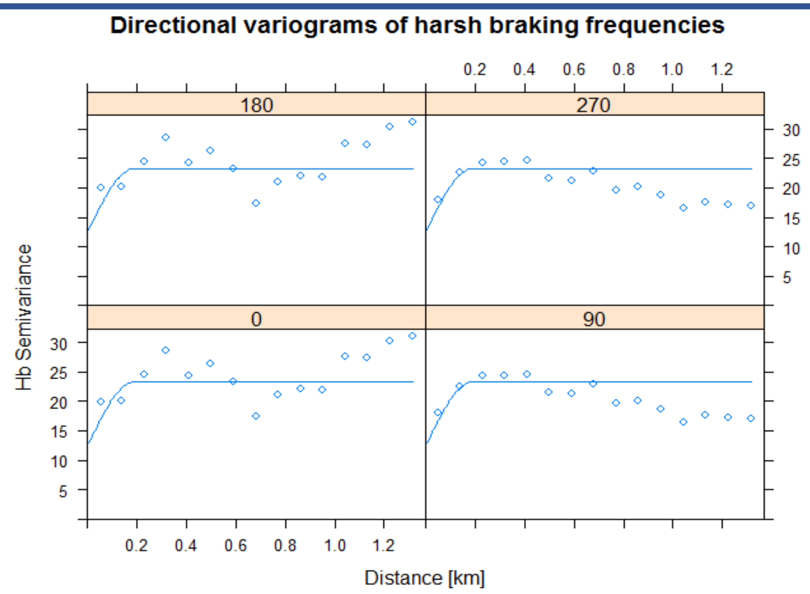
Spatial autocorrelation manifests mainly:

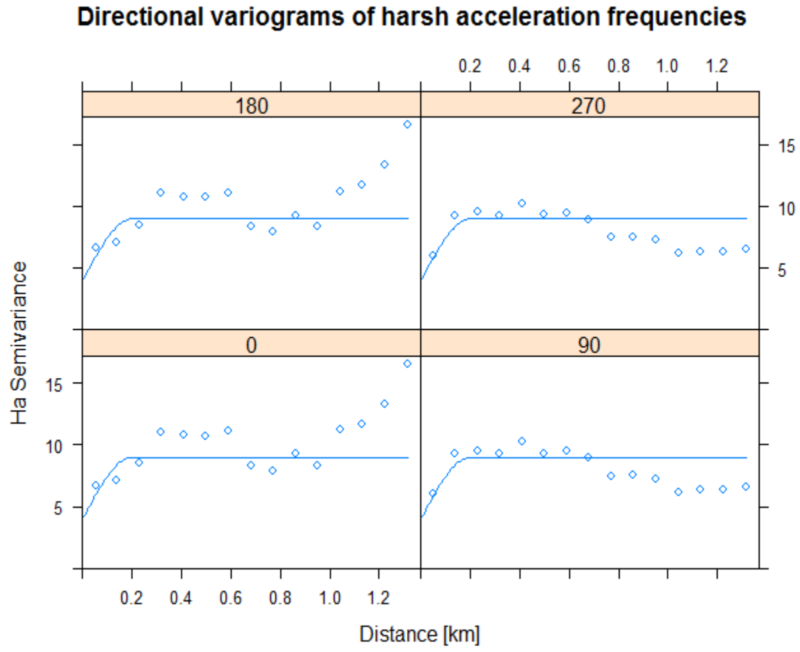
- Within **190** m from road segment centroids for harsh brakings
- Within **200** m from road segment centroids for harsh accelerations

In large theoretical road segment samples, harsh events are expected to have:

- Mean values of **4.83** and majority within [0.00, 9.65] for harsh brakings
- Mean values of **3.00** and majority within [0.00, 6.00] for harsh accelerations

- Geographical **anisotropy** along the N-S axis as opposed to the W-E axis
- Partial geographical **cyclicity** (wave patterns) along the N-S axis





Urban road networks: Harsh braking spatial analyses

Positive correlation:
Segment length
Pass count

Negative correlation:
Gradient
Neighborhood complexity
Road type [Residential]

Marginally positive correlation:
Road type [Secondary]
Traffic lights
Pedestrian crossing

Marginally negative correlation:
Road type [Tertiary]

Independent variables	GWPR Coefficients	CAR Mean posterior values	RCV XGBoost Gain values	SPCV XGBoost Gain values
Intercept	0.4636	**-1.4134**	N/A	N/A
Gradient	**-2.4864**	**-9.7538**	**0.0806**	**0.0860**
Curvature	—	—	**0.0444**	**0.0626**
Neighborhood complexity	**-0.2919**	**-0.1787**	**0.0344**	**0.0684**
Segment length	**0.0039**	**0.0075**	**0.1436**	**0.1400**
Pass count	**0.0040**	**0.0086**	**0.6788**	**0.6271**
Traffic lights: Yes [Ref.: Traffic lights: No]	**0.2563**	-0.0902	**0.0037**	**0.0010**
Pedestrian crossing: Yes [Ref.: Pedestrian crossing: No]	-0.1463	**0.3820**	**0.0024**	**0.0024**
Lanes: 2 [Ref.: Lanes: 1]	**-0.2435**	**-0.1713**	**0.0072**	**0.0048**
Lanes: 3 [Ref.: Lanes: 1]	**0.3669**	**-0.5719**		
Lanes: 4 [Ref.: Lanes: 1]	0.3578	**1.9169**		
Road type: secondary [Ref.: Road type: primary]	**1.0520**	-0.1094	**0.0049**	**0.0078**
Road type: tertiary [Ref.: Road type: primary]	-0.0070	**-1.6389**		
Road type: residential [Ref.: Road type: primary]	**-1.0084**	**-2.5578**		
Sigma-phi^2 [Spatially structured effects]	N/A	**700.3172**	N/A	N/A
Sigma-theta^2 [Spatially unstructured effects]	N/A	**2.3455**	N/A	N/A
Performance metrics				
RMSE	3.2954	1.2830	1.4215	1.8293
MAE	1.3048	0.4115	0.4971	0.4994
RMSLE	0.5569	0.1727	0.3140	0.2390
CA	80.90%	96.32%	90.56%	91.71%

Urban road networks: Harsh braking prediction & transferability

Predictions using Omonoia spatial data

1. Geographically Weighted Poisson Regression **(GWPR)**
   - Local b-coefficient fluctuations are not transferable
   - Predictions using global Poisson regression

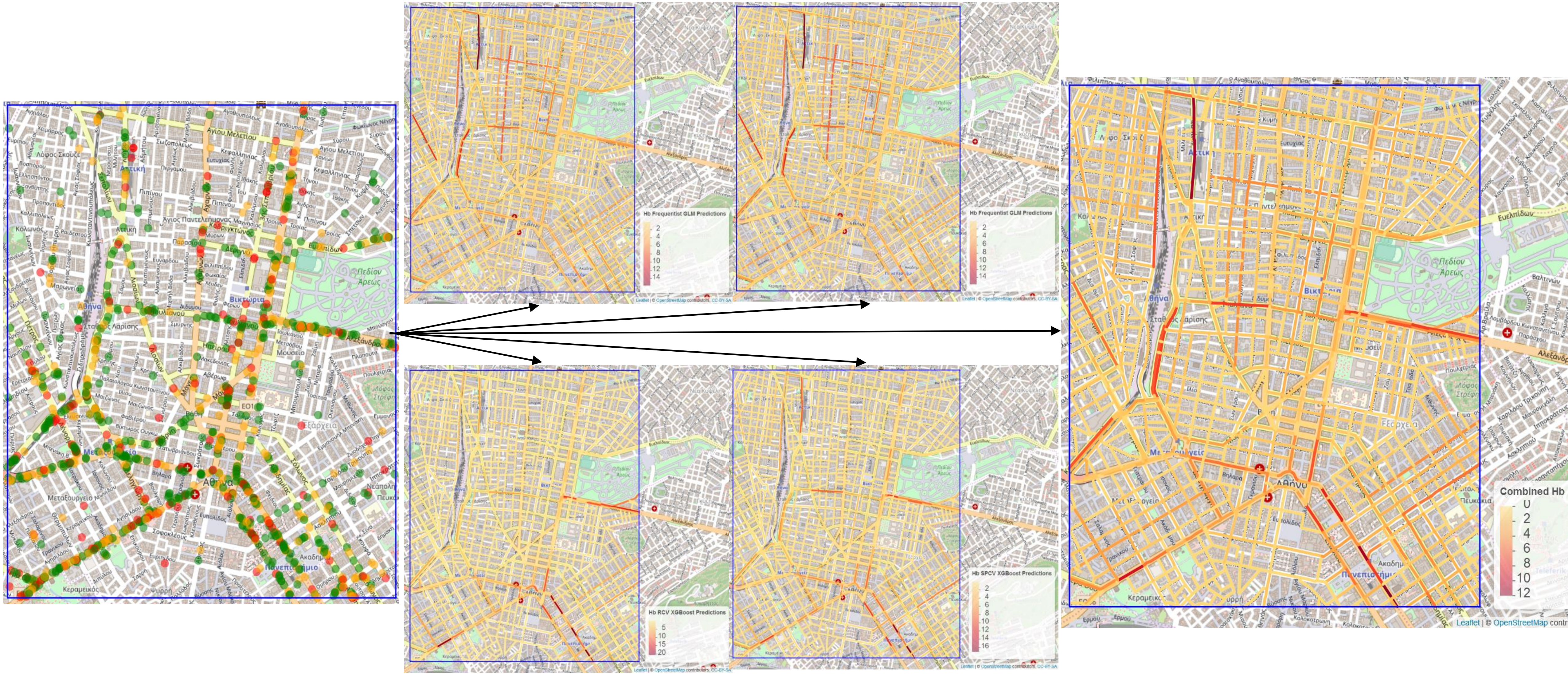
2. Bayesian Conditional Autoregressive Prior Regression **(CAR)**
   - Spatially structured and unstructured effects are not transferable
   - Predictions using new Bayesian Poisson regression

3. Extreme Gradient Boosting **(XGBoost)**
   - **Seamless transferability** of machine learning ensemble trees/rules using both RCV and SPCV

SPCV XGBoost has the **best individual performance** from all implemented methods

Performance metrics	GWPR global Poisson	Bayesian Poisson	RCV XGBoost	SPCV XGBoost	Combined Average
RMSE	1.9792	1.9804	1.9834	1.8418	1.6114
MAE	1.0265	1.0290	0.8415	0.7542	0.6645
RMSLE	0.5508	0.5520	0.5484	0.5189	0.4514
CA	82.64%	82.74%	83.40%	85.27%	87.55%

Urban road networks: Combined harsh braking predictions



Using **combined average**, spatial models **mitigate** their weaknesses and lead to a **balanced** predictive outcome for harsh brakings

Urban road networks: Harsh acceleration spatial analyses

Positive correlation:
Segment length
Pass count
Curvature
Road type [Secondary]
Road type [Tertiary]
Traffic lights

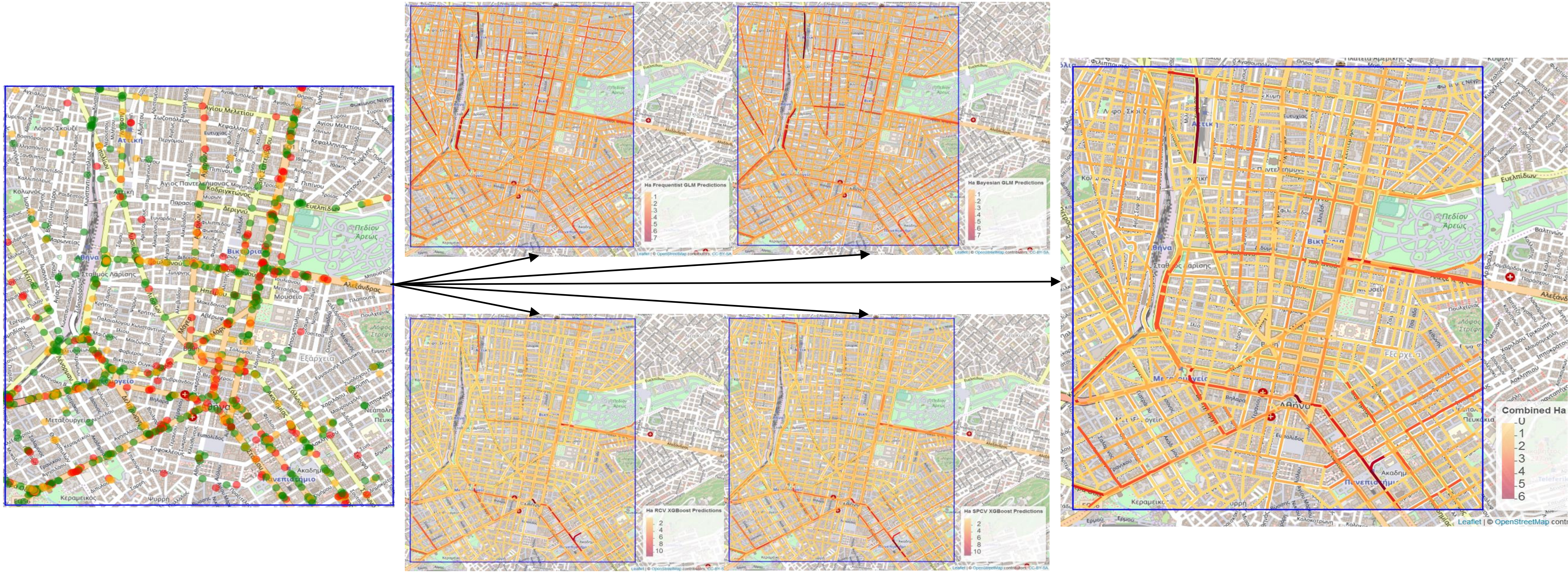
Negative correlation:
Road type [Residential]

Marginally positive correlation:
Pedestrian crossing

Marginally negative correlation:
Neighborhood complexity

Independent variables	GWPR	CAR	RCV XGBoost	SPCV XGBoost
	Coefficients	Mean posterior values	Gain values	Gain values
Intercept	**-1.4230**	**-1.2399**	N/A	N/A
Gradient	—	—	**0.0588**	**0.0189**
Curvature	**9.0471**	**6.3926**	**0.0323**	**0.0309**
Neighborhood complexity	—	**-0.2308**	**0.0532**	**0.0355**
Segment length	**0.0030**	**0.0038**	**0.1058**	**0.0766**
Pass count	**0.0042**	**0.0071**	**0.7184**	**0.8253**
Traffic lights: Yes [Ref.: Traffic lights: No]	**0.3791**	**0.1147**	**0.0069**	**0.0026**
Pedestrian crossing: Yes [Ref.: Pedestrian crossing: No]	—	**0.4554**	**0.0045**	**0.0011**
Lanes: 2 [Ref.: Lanes: 1]	0.0794	-0.0134	**0.0033**	**0.0027**
Lanes: 3 [Ref.: Lanes: 1]	**0.4741**	**-0.1702**		
Lanes: 4 [Ref.: Lanes: 1]	0.3828	**0.4380**		
Road type: secondary [Ref.: Road type: primary]	**0.7323**	**0.7202**	**0.0109**	**0.0065**
Road type: tertiary [Ref.: Road type: primary]	**0.3720**	**0.3610**		
Road type: residential [Ref.: Road type: primary]	**-0.6642**	**-0.6715**		
Sigma-phi^2 [Spatially structured effects]	N/A	**255.3276**	N/A	N/A
Sigma-theta^2 [Spatially unstructured effects]	N/A	**0.2827**	N/A	N/A
Performance metrics				
RMSE	2.0861	0.7961	0.9128	1.1327
MAE	0.9125	0.4111	0.3728	0.4891
RMSLE	0.4704	0.2512	0.3000	0.3504
CA	84.69%	95.74%	93.32%	89.87%

Urban road networks: Combined harsh acceleration predictions



Performance metrics	GWPR global Poisson	Bayesian Poisson	RCV XGBoost	SPCV XGBoost	Combined Average
RMSE	1.6836	1.6841	1.9834	1.6250	1.5010
MAE	0.8721	0.8700	0.8415	0.7064	0.6903
RMSLE	0.5082	0.5071	0.5484	0.4791	0.4316
CA	87.71%	87.62%	83.40%	87.42%	89.09%

Urban road networks: Main findings

- **Spatial analyses** of harsh braking and harsh acceleration frequencies are feasible using GWPR, CAR, RCV XGBoost and SPCV XGBoost methodologies

- **Very good model fit** on training spatial data (Chalandri) and precise predictions in the test spatial data (Omonoia)

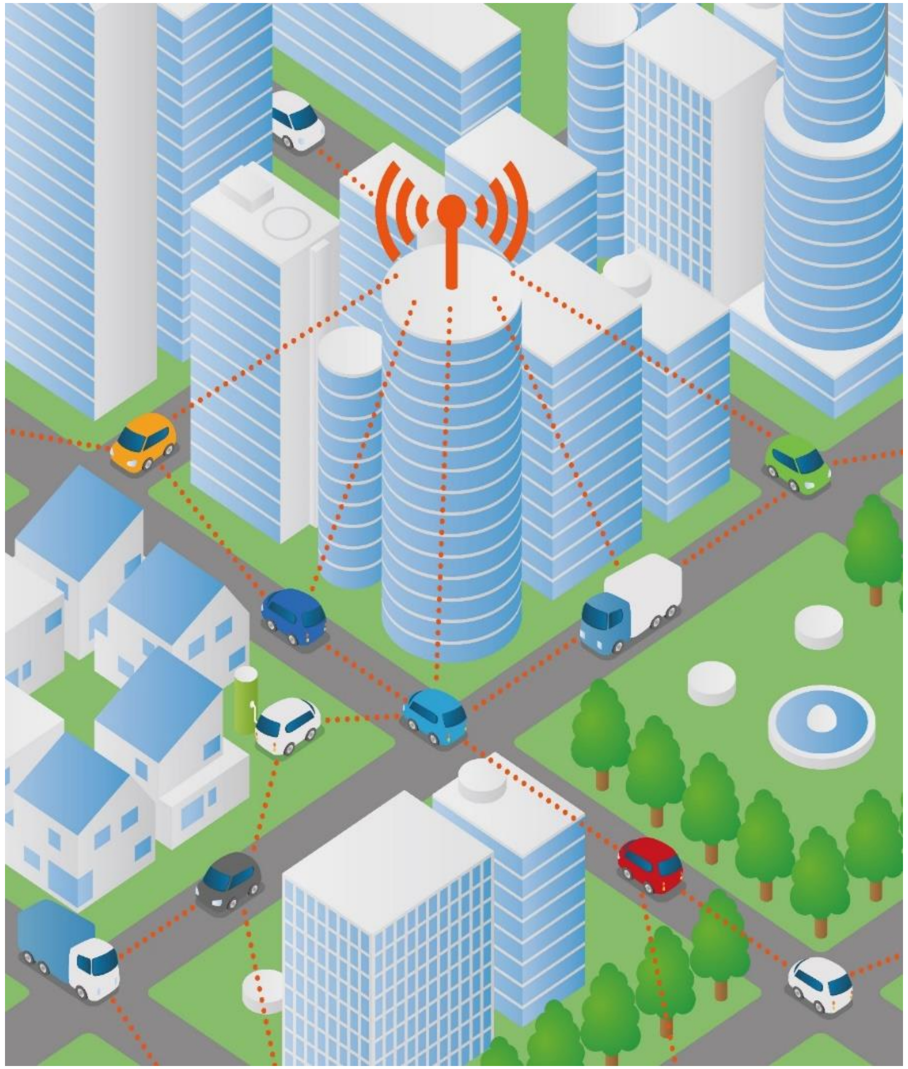
- The investigated **exposure parameters** (segment length and pass count) are consistently **positively correlated** with harsh braking and harsh acceleration frequencies

- The presence of pedestrian crossings and traffic lights is **mostly positively correlated** with harsh braking and harsh acceleration frequencies

- Conversely, **gradient** and **neighborhood complexity** are negatively correlated with harsh acceleration frequency

- **Curvature** is positively correlated with harsh acceleration frequency

- **Road type** and **number of lanes** are parameters with unclear influence: However, they offer useful information for the calibration of spatial terms/ tree separation limits

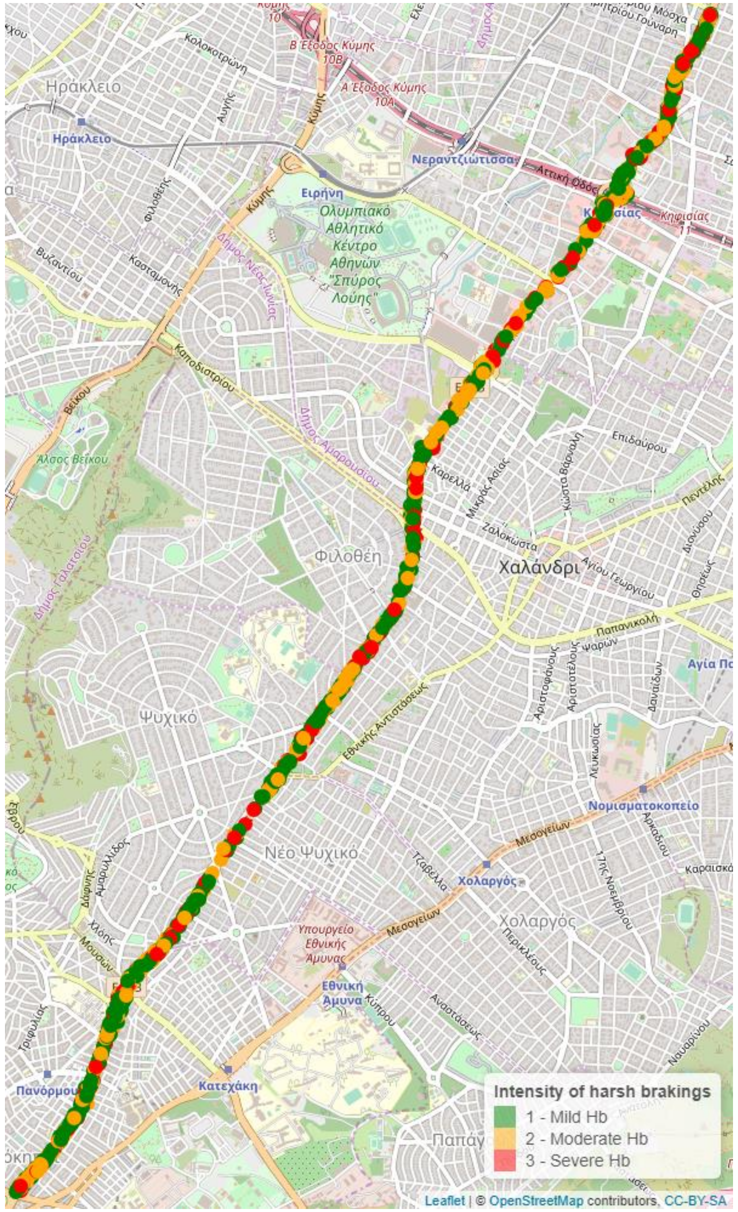


Urban arterial: Sample description – Kifisias Avenue (1/2)

152 road segments with **658** nodes
- **15** road segments with traffic lights
- **21** road segments with pedestrian crossings

Naturalistic driving data:
- Trips between 01-09-2019 & 29-11-2019 – **3 months**
- **A total of** 8756 trips from 314 drivers
- 930,346 **driving seconds**: average trip duration 221 s
- 1543 harsh **brakings**
- 1033 harsh **accelerations**

Variable distributions
- **Positive** skewness (larger right tails)
- **High** kurtosis (segment length/neighborhood complexity) and **low** kurtosis (gradient/curvature) – **non-normal** distributions



Urban arterial: Sample description – Kifisias Avenue (2/2)

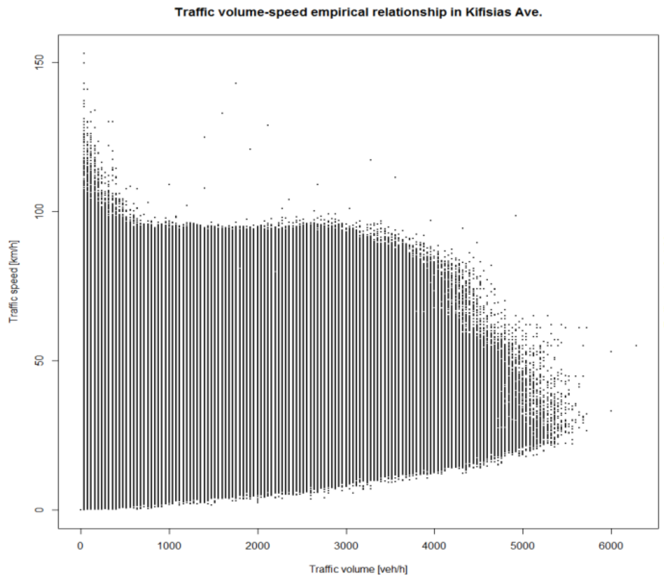
Classification of trip-seconds and traffic data per **traffic state**

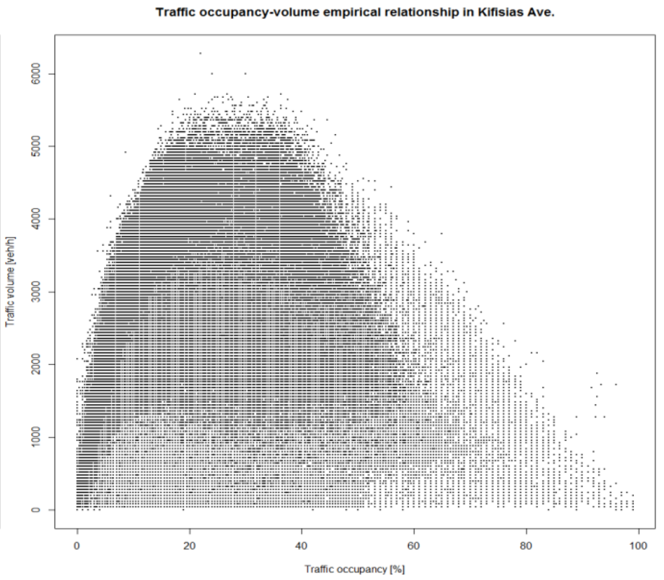
At least 1 trip:
- 100% of road segments under free flow conditions
- 94.74% of road segments under synchronized flow conditions
- 95.39% of road segments under congested flow conditions

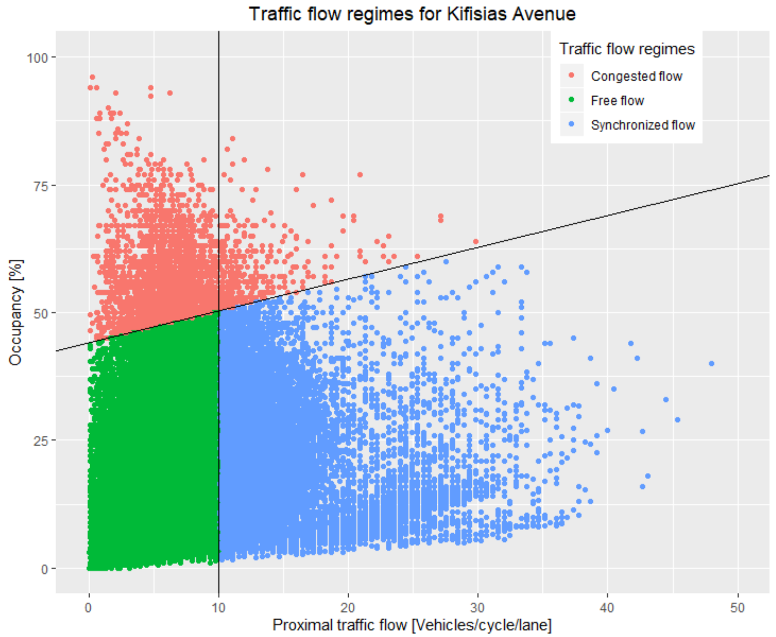
Free flow conditions
- 563 harsh brakings & 363 harsh accelerations

Synchronized flow conditions
- 215 harsh brakings & 142 harsh accelerations

Congested flow conditions
- 10 harsh brakings & 4 harsh accelerations
- No sufficient harsh event frequencies to conduct spatial analysis







Urban arterial: Exploratory spatial analyses (1/2)

Global and local Moran's I coefficients (Chalandri area)

1. Distance-based weighting (DB)
2. k nearest-neighbor weighting (kNN)

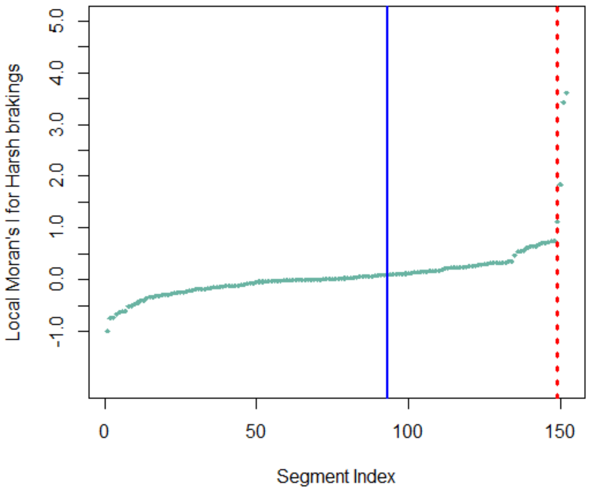
Interpretation of k nearest-neighbors is more **reasonable:**

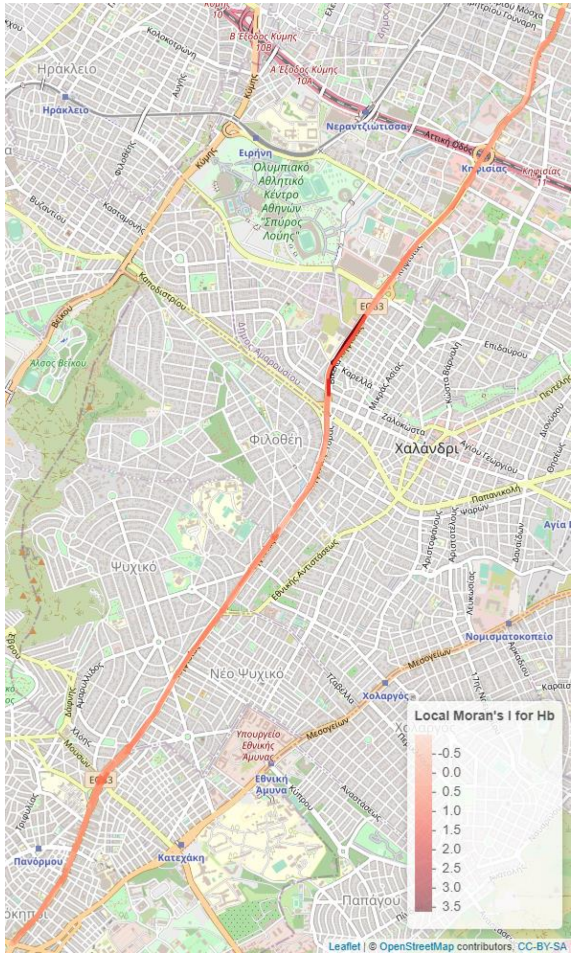
- **Rapid reduction** of spatial autocorrelation between segments (fewer neighboring segments)
- **Positive spatial autocorrelation** manifests in harsh event frequencies

Very few outlier values appear for local Moran's I (within 2σ per Anselin, 1995)

Volatility of the coefficient:
appropriate for preliminary – exploratory analysis

kNN Global Moran's I	Correlation threshold	k	Coefficient value	Expectation	p-value
Harsh brakings	0.0	5	0.0913	-0.0066	0.0389
Harsh accelerations		9	0.1261	-0.0066	0.0002





Urban arterial: Exploratory spatial analyses (2/2)

Merged variograms of semivariance

Exponential theoretical variograms describe harsh event frequencies per road segment with a better fit

Spatial autocorrelation manifests mainly:

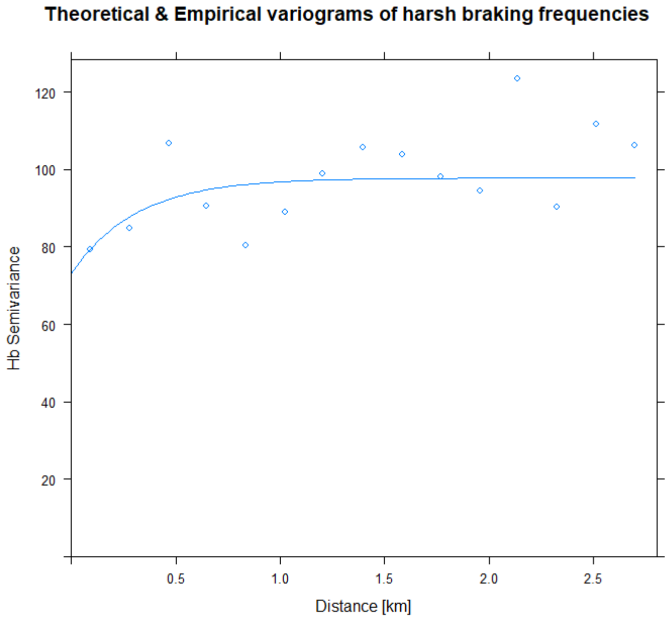
- Within **310** m from road segment centroids for harsh brakings
- Within 3**20** m from road segment centroids for harsh accelerations

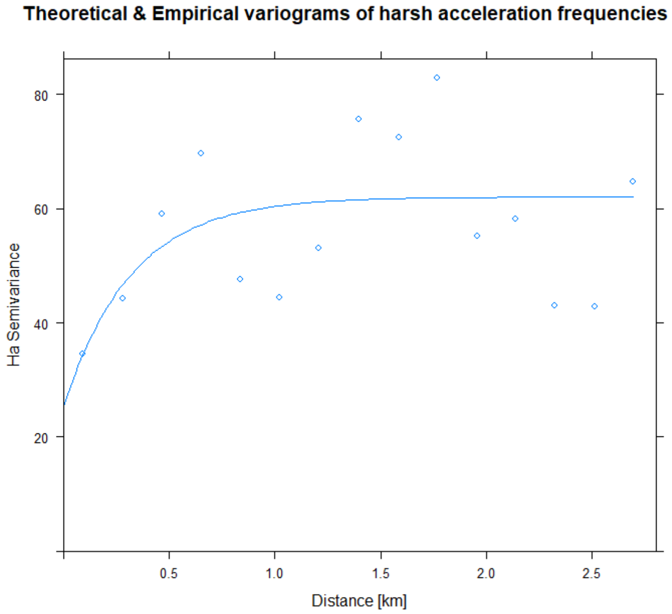
In large theoretical road segment samples, harsh events are expected to have:

- Mean values of **9.89** and majority within [0.00, 19.78] for harsh brakings
- Mean values of **7.88** and majority within [0.00, 15.75] for harsh accelerations

Additional observations:

- Greater empirical variogram **volatility** compared to urban road networks
- Partial geographical **cyclicity** (wave patterns), denoting **patterns of repetition** in the data





Urban arterial: Harsh braking analyses under free flow

Positive correlation:
Segment length
Pass count
Mobile phone use seconds
Speed difference (driver – traffic)

Marginally positive correlation:
Average occupancy

Marginally negative correlation:
Bearing [Southbound]
Standardized traffic flow

Independent variables	GWPR	CAR	RCV XGBoost	SPCV XGBoost
	Coefficients	Mean posterior values	Gain values	Gain values
Intercept	-0.2544	-0.4664	N/A	N/A
Gradient	-1.1013	—	**0.0642**	**0.0408**
Curvature	—	—	**0.0208**	**0.0183**
Segment length	**0.0033**	**0.0031**	**0.0454**	**0.0572**
Pass count	**0.0023**	**0.0027**	**0.0577**	**0.0364**
Speeding seconds	—	—	**0.1374**	**0.0330**
Mobile use seconds	**0.0022**	**0.0042**	**0.4583**	**0.5496**
Speed difference	**0.0385**	**0.0318**	**0.0755**	**0.0548**
Average std. current traffic volume	**-0.1640**	-0.0417	**0.0328**	**0.0469**
Average occupancy	**0.0595**	—	**0.0370**	**0.0310**
Average driver speed	—	—	**0.0387**	**0.0687**
Average traffic speed	—	—	**0.0115**	**0.0493**
Lane number	—	—	**0.0013**	**0.0027**
Bearing: Southbound [Ref.: Northbound]	**-0.2611**	-0.2746	**0.0195**	**0.0067**
Pedestrian crossing: Yes [Ref.: Pedestrian crossing: No]	—	—	—	**0.0025**
Traffic lights: Yes [Ref.: Traffic lights: No]	—	—	—	**0.0021**
Sigma-phi^2 [Spatially structured effects]	N/A	**0.0662**	N/A	N/A
Sigma-theta^2 [Spatially unstructured effects]	N/A	**0.3796**	N/A	N/A
Performance metrics				
RMSE	2.8905	1.1052	0.4730	0.4730
MAE	2.0705	0.9002	0.1579	0.1316
RMSLE	0.6046	0.3565	0.0579	0.2105
CA	56.58%	84.22%	98.03%	99.34%

Urban arterial: Harsh braking analyses under synchronized flow

Positive correlation:

Segment length

Pass count

Mobile phone use seconds

Average occupancy

Independent variables	GWPR	CAR	RCV XGBoost	SPCV XGBoost
	Coefficients	Mean posterior values	Gain values	Gain values
Intercept	**-2.1012**	**-2.4520**	N/A	N/A
Gradient	—	1.0782	**0.0491**	**0.0638**
Curvature	71.643	6.6068	**0.0084**	**0.0269**
Segment length	**0.0024**	**0.0019**	**0.0282**	**0.0533**
Pass count	**0.0059**	**0.0057**	**0.0833**	**0.4146**
Speeding seconds	—	0.0020	**0.0810**	**0.0781**
Mobile use seconds	**0.0113**	**0.0134**	**0.6446**	**0.2250**
Speed difference	—	—	**0.0167**	**0.0231**
Average std. current traffic volume	—	-0.0195	**0.0298**	**0.0266**
Average hourly traffic volume	**-0.0002**	—	—	—
Average occupancy	**0.0495**	**0.0371**	**0.0216**	**0.0172**
Average driver speed	—	—	**0.0219**	**0.0610**
Average traffic speed	—	—	**0.0092**	—
Lanes: 2 [Ref.: Lanes: 1]	—	0.2878		
Lanes: 3 [Ref.: Lanes: 1]	—	-0.0207	—	—
Lanes: 4 [Ref.: Lanes: 1]	—	**-1.9839**		
Bearing: Southbound [Ref.: Northbound]	—	0.0119	**0.0060**	**0.0095**
Pedestrian crossing: Yes [Ref.: Pedestrian crossing: No]	—	—	—	**0.0006**
Traffic lights: Yes [Ref.: Traffic lights: No]	—	—	**0.0000**	**0.0002**
Sigma-phi^2 [Spatially structured effects]	N/A	**0.0309**	N/A	N/A
Sigma-theta^2 [Spatially unstructured effects]	N/A	**0.3916**	N/A	N/A
Performance metrics				
RMSE	1.6733	0.7472	0.2433	0.3441
MAE	0.9404	0.5206	0.0461	0.0472
RMSLE	0.4306	0.2971	0.0268	0.0921
CA	83.55%	90.79%	99.34%	98.68%

Urban arterial: Harsh acceleration analyses under free flow

Positive correlation:
Pass count
Mobile phone use seconds
Speed difference (driver – traffic)
Average occupancy

Negative correlation:
Speeding seconds

Marginally positive correlation:
Segment length

Marginally negative correlation:
Bearing [Southbound]

Independent variables	GWPR	CAR	RCV XGBoost	SPCV XGBoost
	Coefficients	Mean posterior values	Gain values	Gain values
Intercept	-0.2237	**-1.0912**	N/A	N/A
Gradient	–	1.2874	**0.0573**	**0.0756**
Curvature	–	–	**0.0337**	**0.0413**
Segment length	**0.0017**	0.0011	**0.0831**	**0.0759**
Pass count	**0.0032**	**0.0022**	**0.1097**	**0.1183**
Speeding seconds	**-0.0011**	**-0.0012**	**0.0711**	**0.0631**
Mobile use seconds	**0.0027**	**0.0047**	**0.2865**	**0.2212**
Speed difference	**0.0528**	**0.0323**	–	**0.0749**
Average std. current traffic volume	–	–	**0.0795**	**0.1281**
Average occupancy	**0.0258**	**0.0328**	**0.0500**	**0.0656**
Average driver speed	–	–	**0.1457**	**0.1136**
Average traffic speed	**-0.0240**	–	**0.0585**	–
Lane number	–	–	**0.0148**	**0.0092**
Bearing: Southbound [Ref.: Northbound]	**-0.2434**	-0.2327	**0.0001**	**0.0021**
Pedestrian crossing: Yes [Ref.: Pedestrian crossing: No]	–	–	–	**0.0056**
Traffic lights: Yes [Ref.: Traffic lights: No]	–	–	**0.0100**	**0.0058**
Sigma-phi^2 [Spatially structured effects]	N/A	**0.5614**	N/A	N/A
Sigma-theta^2 [Spatially unstructured effects]	N/A	**0.3253**	N/A	N/A
Performance metrics				
RMSE	2.2817	1.0912	0.3974	0.3536
MAE	1.5816	0.8612	0.1316	0.1118
RMSLE	0.6305	0.4286	0.0776	0.0507
CA	63.16%	86.18%	98.68%	99.34%

Urban arterial: Harsh acceleration analyses in synchronized flow

Positive correlation:
Pass count
Mobile phone use seconds

Marginally positive correlation:
Traffic flow
(hourly or standardized)

Independent variables	GWPR	CAR	RCV XGBoost	SPCV XGBoost
	Coefficients	Mean posterior values	Gain values	Gain values
Intercept	**-1.2573**	**-2.9399**	N/A	N/A
Gradient	–	1.7464	**0.0243**	**0.0258**
Curvature	–	–	**0.0183**	**0.0180**
Segment length	–	-0.0005	**0.0240**	**0.0259**
Pass count	**0.0035**	**0.0065**	**0.2169**	**0.5617**
Speeding seconds	–	-0.0039	**0.0017**	**0.0071**
Mobile use seconds	**0.0148**	**0.0159**	**0.5723**	**0.2209**
Speed difference	–	–	**0.0332**	**0.0144**
Average std. current traffic volume	–	–	**0.0032**	**0.022**
Average traffic volume	**0.0003**	**0.0008**	–	–
Average occupancy	–	0.0237	**0.0457**	**0.0407**
Average driver speed	–	-0.0224	**0.0604**	**0.0568**
Average traffic speed	**-0.0240**	–	–	–
Lanes: 2 [Ref.: Lanes: 1]	–	**-1.0085**	–	–
Lanes: 3 [Ref.: Lanes: 1]	–	**-1.8321**		
Lanes: 4 [Ref.: Lanes: 1]	–	**-2.8837**		
Bearing: Southbound [Ref.: Northbound]	**0.4721**	0.2981	–	**0.0067**
Sigma-phi^2 [Spatially structured effects]	N/A	**0.0699**	N/A	N/A
Sigma-theta^2 [Spatially unstructured effects]	N/A	**1.0935**	N/A	N/A
Performance metrics				
RMSE	1.2978	0.5404	0.5000	0.281
MAE	0.8258	0.3904	0.1711	0.0658
RMSLE	0.4507	0.2475	0.1638	0.0842
CA	86.84%	97.36%	97.37%	98.68%

Urban arterial: Main findings

- **Spatial analyses** of harsh braking and harsh acceleration frequencies are feasible using GWPR, CAR, RCV XGBoost and SPCV XGBoost methodologies **per traffic state as well**
- **Very good model fit** on study area data, with the exception of GWPR under **free flow** conditions
- **GWPR** performance seems to be affected by the pronounced geographical **anisotropy** under free flow conditions – the avenue is practically 1-dimensional
- The other methodologies (**CAR, RCV XGBoost** and **SPCV XGBoost**) are not likewise affected
- Results indicate that **different traffic parameters** are correlated with harsh event frequencies per traffic state
- The **exposure parameters** (segment length and pass count) continue to display a **positive influence** on harsh braking and harsh acceleration frequencies
- The creation – examination of directional variograms does not have physical meaning: merged variograms are appropriate

Conclusions of the dissertation (1/5)

1. It is **possible to combine** high resolution **multi-parametric** naturalistic driving, geometric and traffic data that can be combined and exploited to conduct meaningful spatial analyses on a road segment basis

2. The implementation of both **common** spatial methods (GWPR, CAR, Moran’s I and variograms) and **innovative** methods (RCV & SPCV XGBoost) is feasible for spatial analyses of harsh event frequencies on a road segment basis

3. **Positive autocorrelation** is detected in harsh braking and harsh acceleration frequencies in both urban road networks and urban arterials

4. In urban road networks, spatial autocorrelation manifests mainly within **190 m** from road segment centroids for harsh brakings and within **200 m** from road segment centroids for harsh accelerations. The respective distances for urban arterials are estimated at **310 m** and **320 m**

Conclusions of the dissertation (2/5)

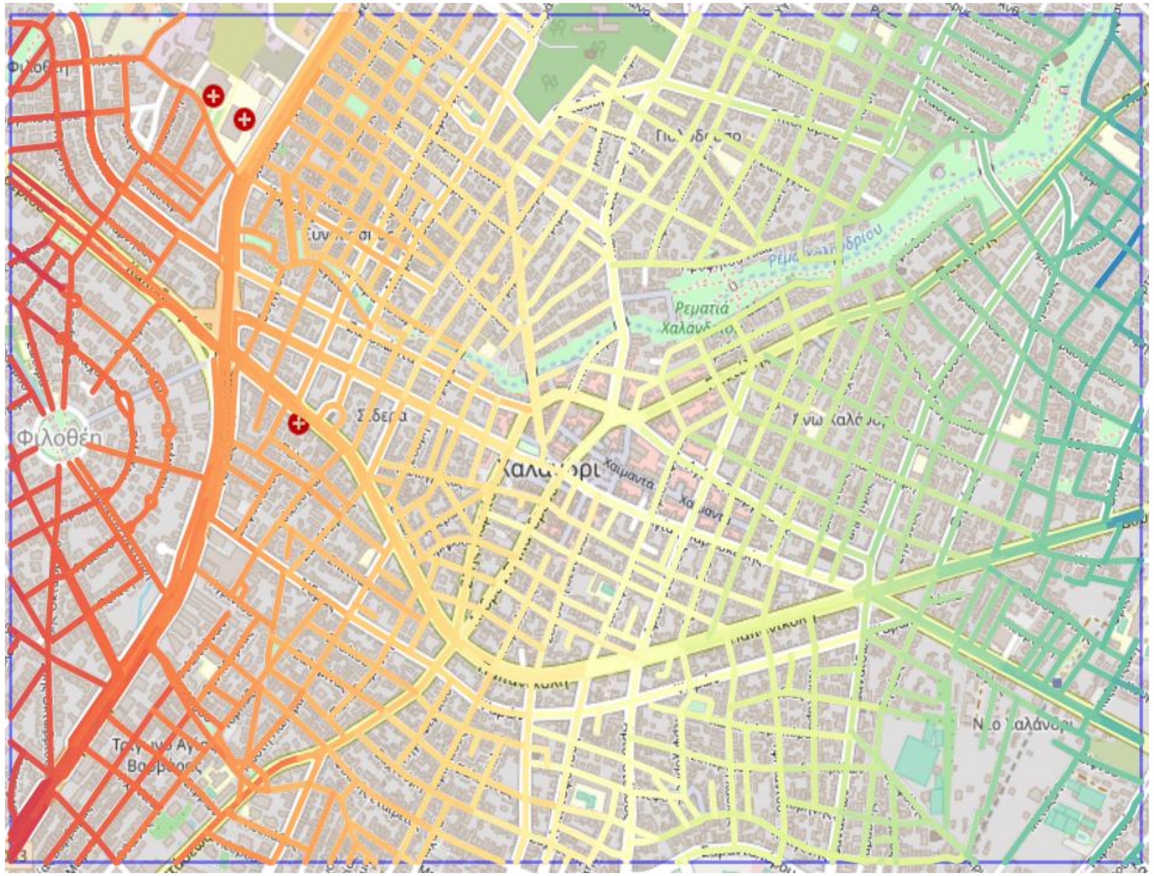
Urban road networks:

1. The exposure parameters **(segment length and pass count)** are positively correlated with harsh braking and harsh acceleration frequencies.

2. Conversely, **gradient, neighborhood complexity and residential road type** are parameters negatively correlated with harsh braking frequencies.

3. **Curvature, traffic lights and secondary and tertiary road types** are parameters positively correlated with harsh acceleration frequencies.

4. **Residential road type** is negatively correlated with harsh acceleration frequencies.



Conclusions of the dissertation (3/5)

Urban road networks:

5. **Precise predictions** of harsh event frequencies can be **successfully conducted** via the exploitation of the examined data and using the implemented methods.
   Custom accuracy achieved:
   87.6% for harsh brakings and
   89.1% for harsh accelerations.

6. Using **combined average**, spatial models **mitigate** their weaknesses and lead to a **balanced** predictive outcome for harsh events. A **more complete** image of hotspots is obtained.

Conclusions of the dissertation (4/5)

Urban arterial:

1. It is meaningful to create and examine spatial data **per traffic state** in order to analyze harsh event frequencies; as a bridge between road safety and traffic flow disciplines.

2. Results indicate that **different variables** are correlated with increased harsh event frequencies under **free flow** conditions compared to **synchronized flow** conditions.

3. The inclusion of **traffic** and **driver behaviour** parameters offers additional capabilities for in-depth examination of causal parameters, without any transferability or prediction capabilities.

Conclusions of the dissertation (5/5)

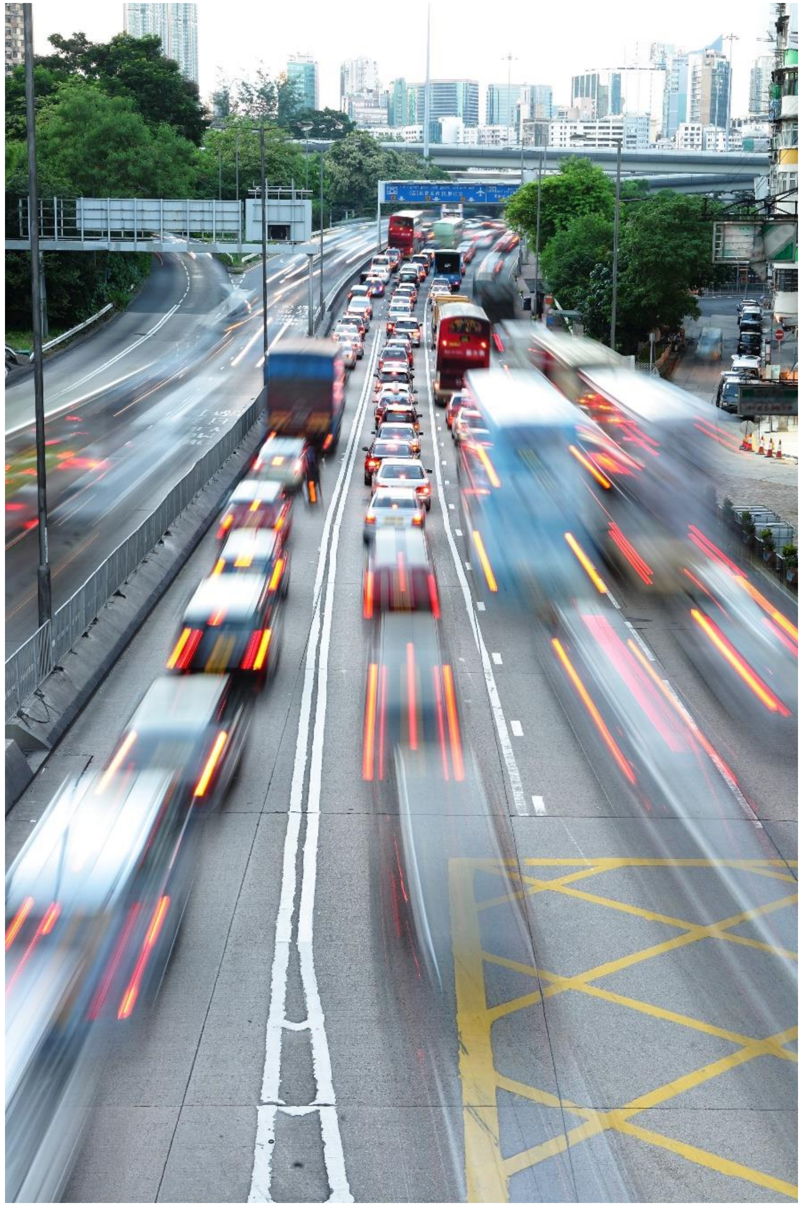
Urban arterial:

4. The exposure parameters **(segment length and pass count)** as well as mobile use seconds are positively correlated with harsh braking and harsh acceleration frequencies.

5. The parameter of **average occupancy** is positively correlated with harsh event frequencies under synchronized flow and marginally positively correlated under free flow.

6. The parameter of **speed difference of driver and vehicle** is positively correlated with harsh braking frequencies under free flow and with harsh acceleration frequencies (under both conditions).

7. Circumstantial correlations are found with **traffic flow parameters** (reduction of brakings under free flow, increase of accelerations under synchronized flow).



Innovative contributions

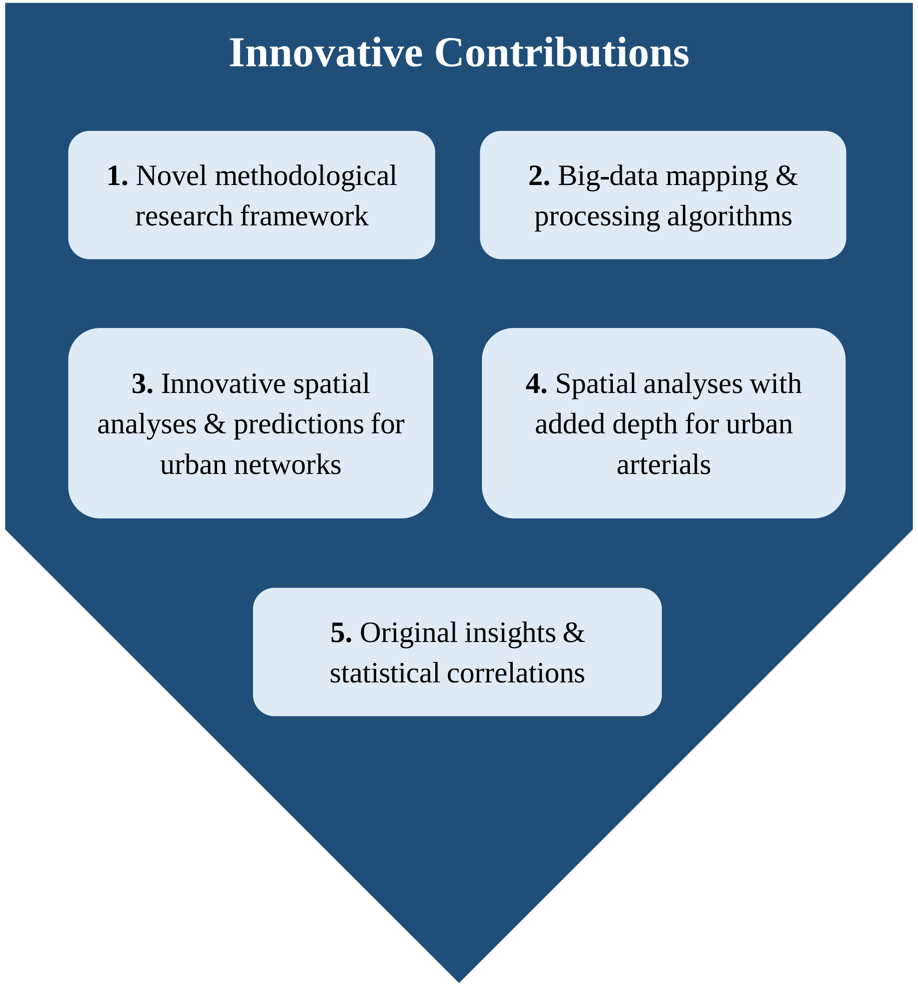
1. Novel methodological **research framework**
   Conducting road safety **spatial analysis** for harsh event frequencies using multi-parametric high-resolution data per road segment

2. Inception of a number of **purpose-made big-data algorithms**
   Implementation of the algorithms for critical functions:
   (i) calculation of additional geometric characteristics
   (ii) data processing and merging
   (iii) map-matching of trip-seconds to road segments

3. **Innovative types of spatial analyses**
   (i) spatial analyses of urban road networks
   (ii) spatial analyses results were used for **successful predictions** of harsh event frequencies

4. Spatial analyses with added depth for urban arterials – Separate examinations for **free flow** and **synchronized flow** traffic states

5. **Original insights** and **statistical correlations** were obtained for the parameters affecting harsh event frequencies



Future research

1. **Correlation with crash data**
   Conducting spatial analyses including crash data per road segment –examination of possible hotspot overlap

2. **Introduction of temporal dimension**
   Conducting spatio-temporal analyses for the identification of seasonal trends and the detection of any hotspot migration effects

3. **Analyses per driver aggressiveness**
   Driver classification based on their aggressiveness and produced harsh events

4. **Implementation of additional spatial or machine learning models**
   Indicatively: Neural networks, additional CAR priors, spatial lag models

5. **Investigation of additional environments or parameters**
   Rural roads, multiple countries, presence of public transport, low speed zones


THANK
YOU

Spatial Analysis of Road Safety and Traffic Behaviour using High Resolution Multi-parametric Data

Apostolos Ziakopoulos

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