Incidentalità stradale in Lombardia

Corso di Formazione: Elementi di geo-statistica e microsimulazione spaziale

25 Giugno 2024

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PoliS Lombardia

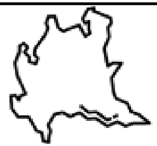
Regione Lombardia

Introduction

Goals:

- Introduce a series of **statistical methods** to describe and analyse road accident data.
- **Explore** the spatio-temporal car crashes **hotspots** in Milan and on Via Olimpica, years 2018 - 2021.
- Pinpoint areas and periods of **high incidence**, examining the **safety patterns’** variations along the years.

Data sources

	Spatial domain	Temporal domain	Sources
Car crashes		2018 - 2021	PoliS Lombardia
Ambulance interventions		2018 - 2020	AREU
Open Street Map		Continuous updates	OpenStreetMap

Spatio-temporal analysis - Milan

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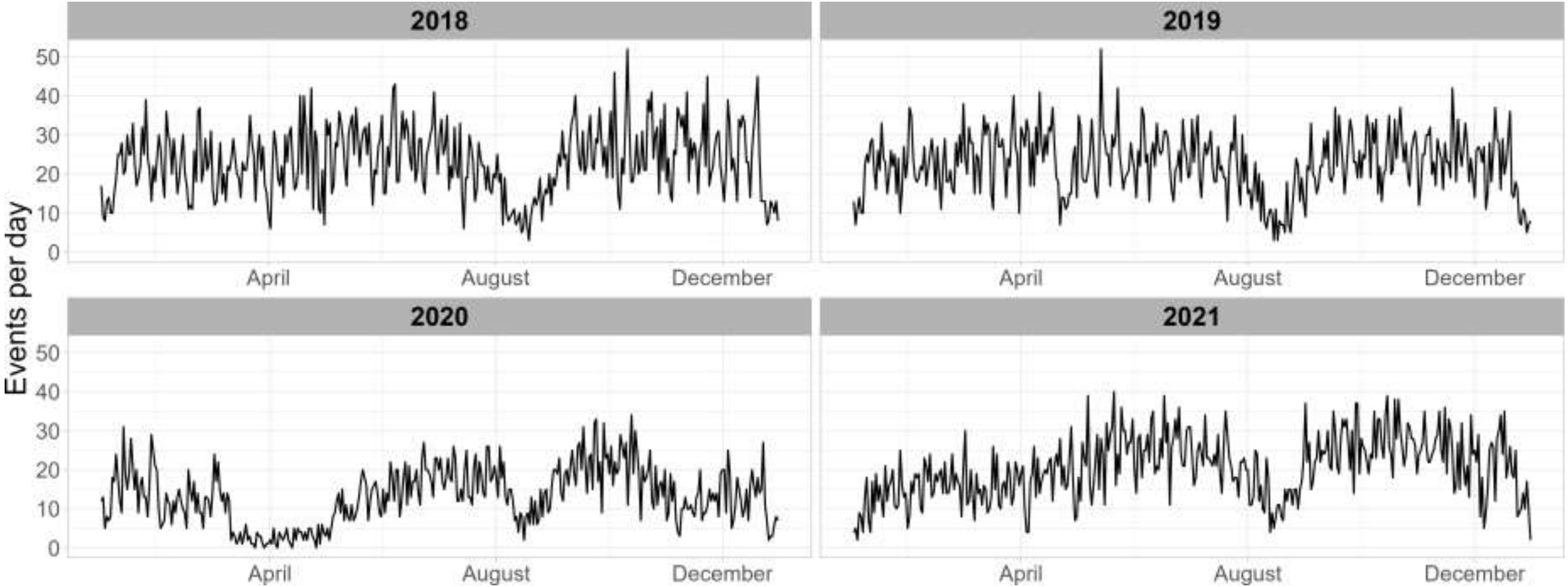
Temporal analysis - Milan



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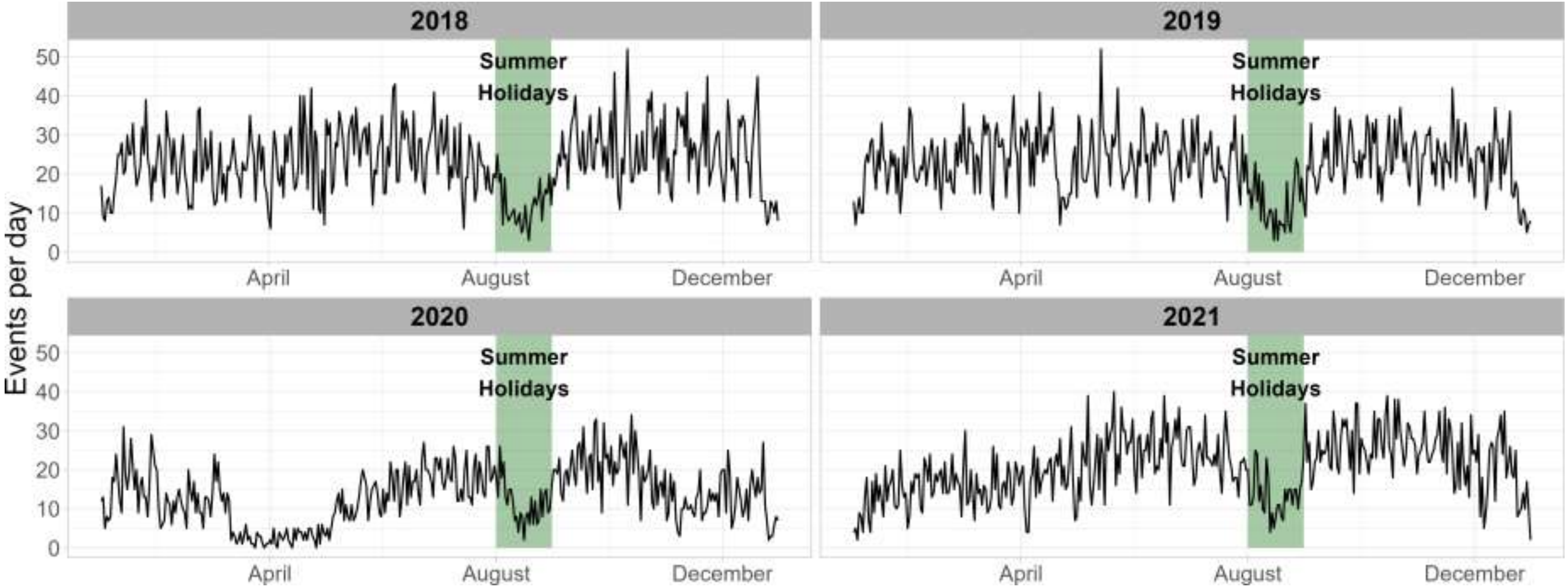
Temporal analysis - Milan



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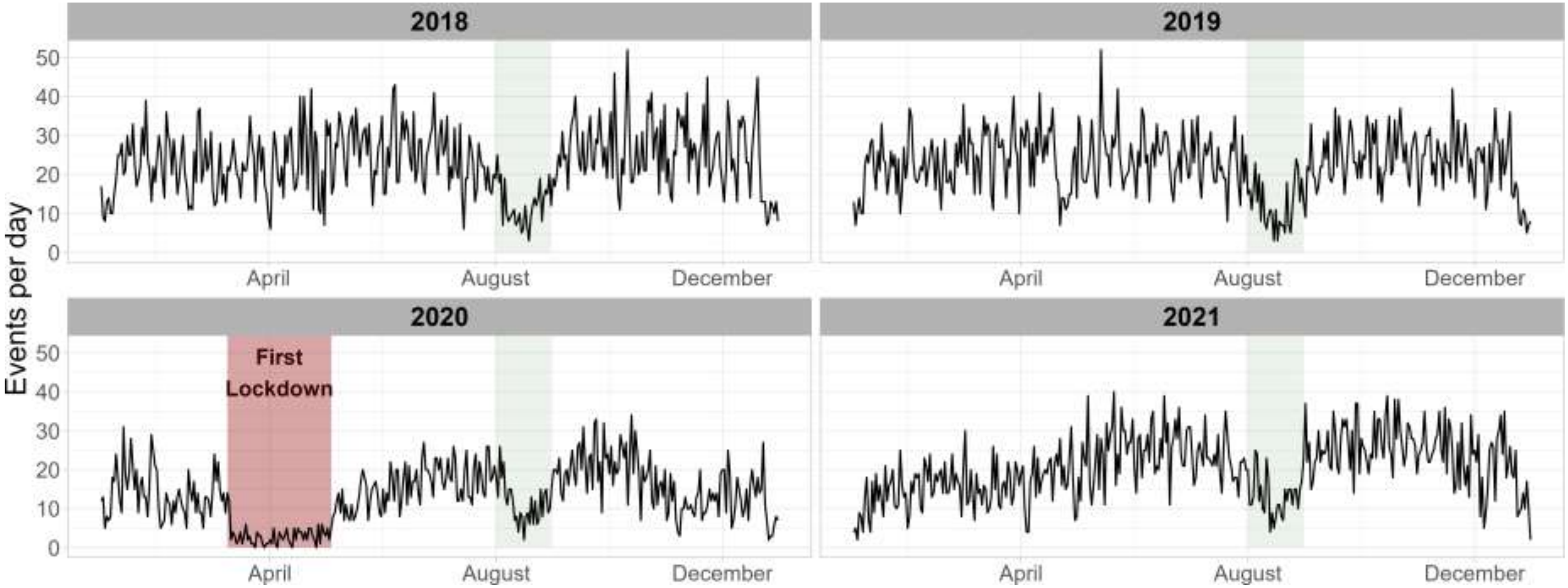
Temporal analysis - Milan



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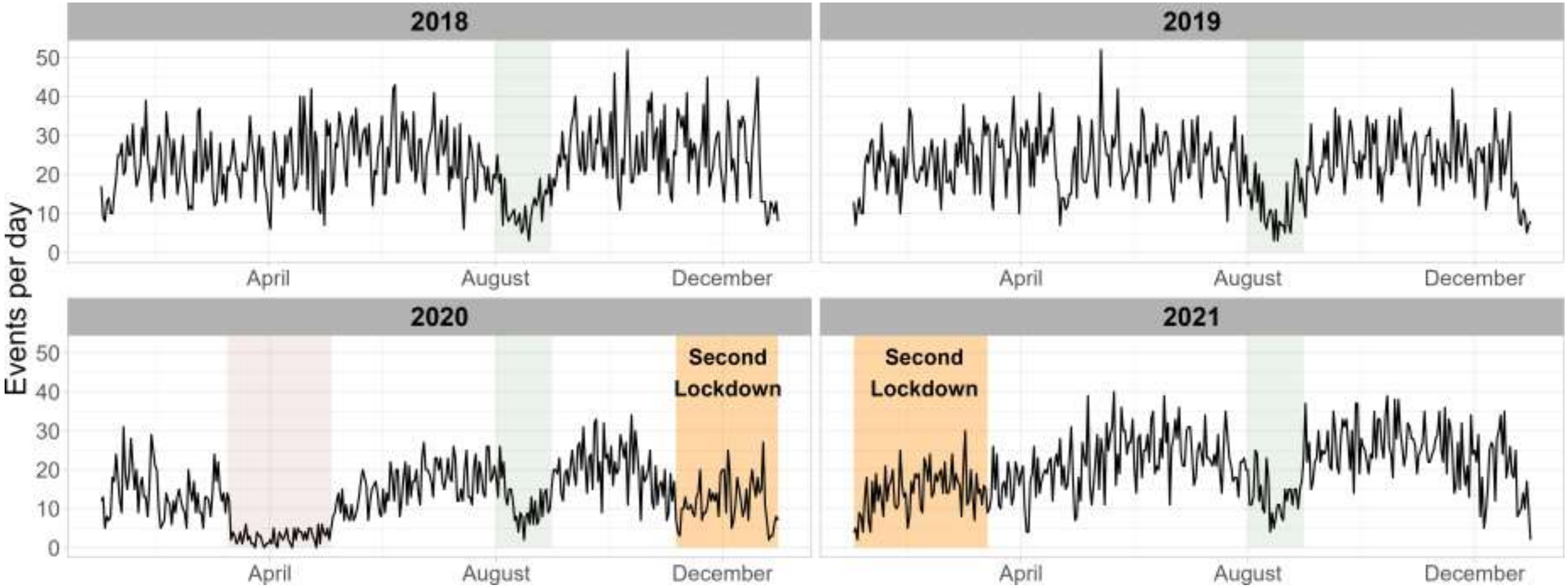
Temporal analysis - Milan



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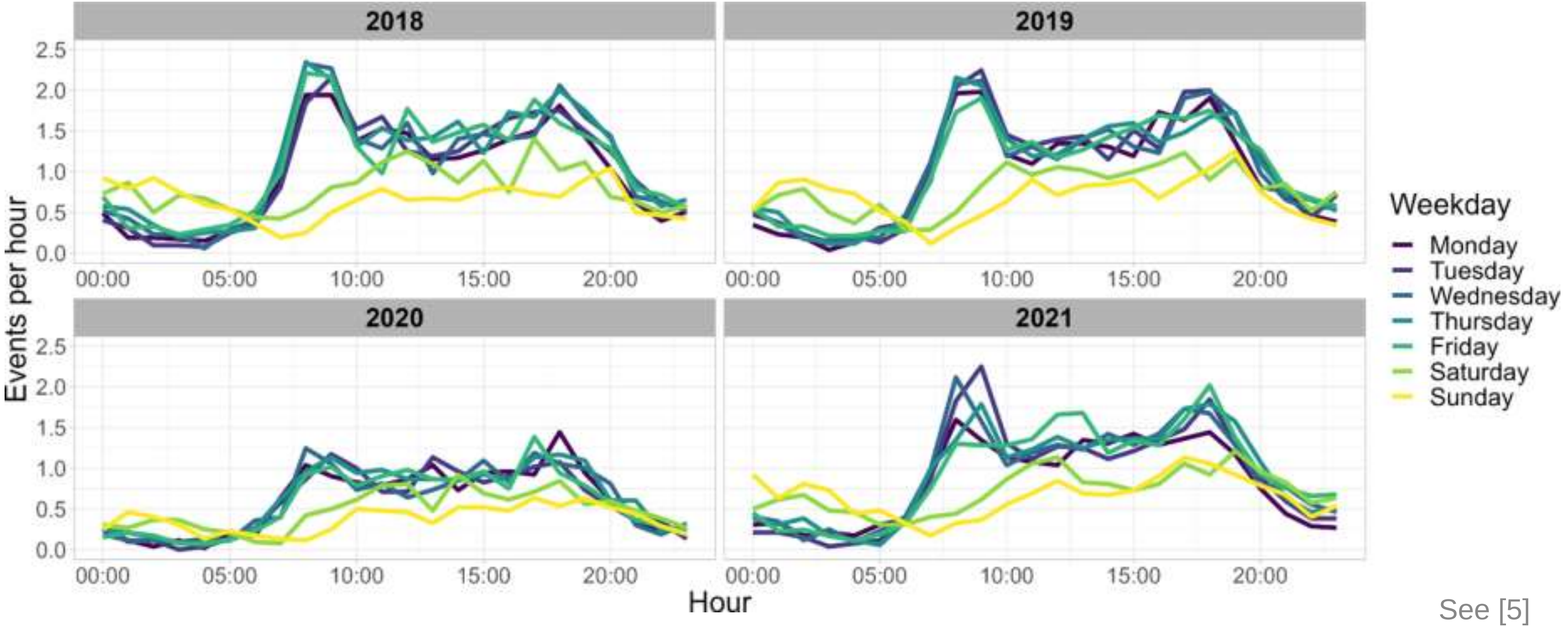
Temporal analysis - Milan



See [5]

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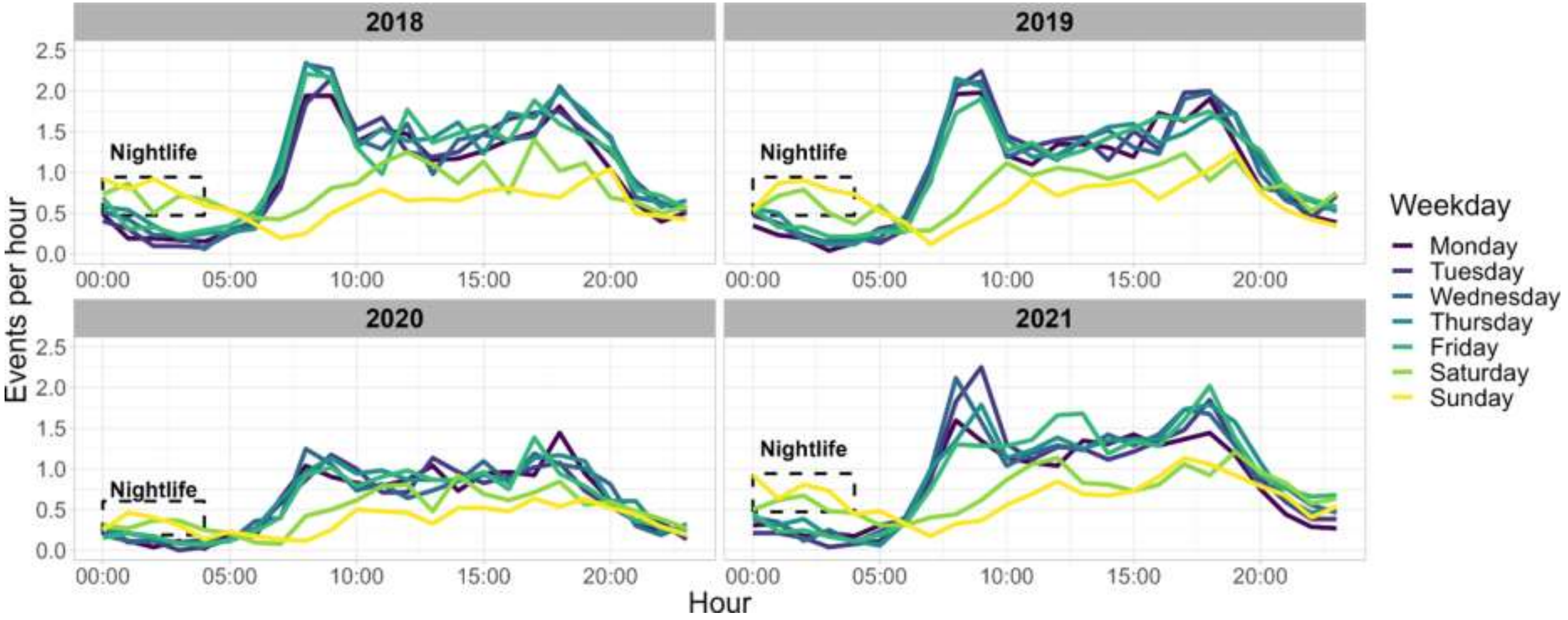
Temporal analysis - Milan



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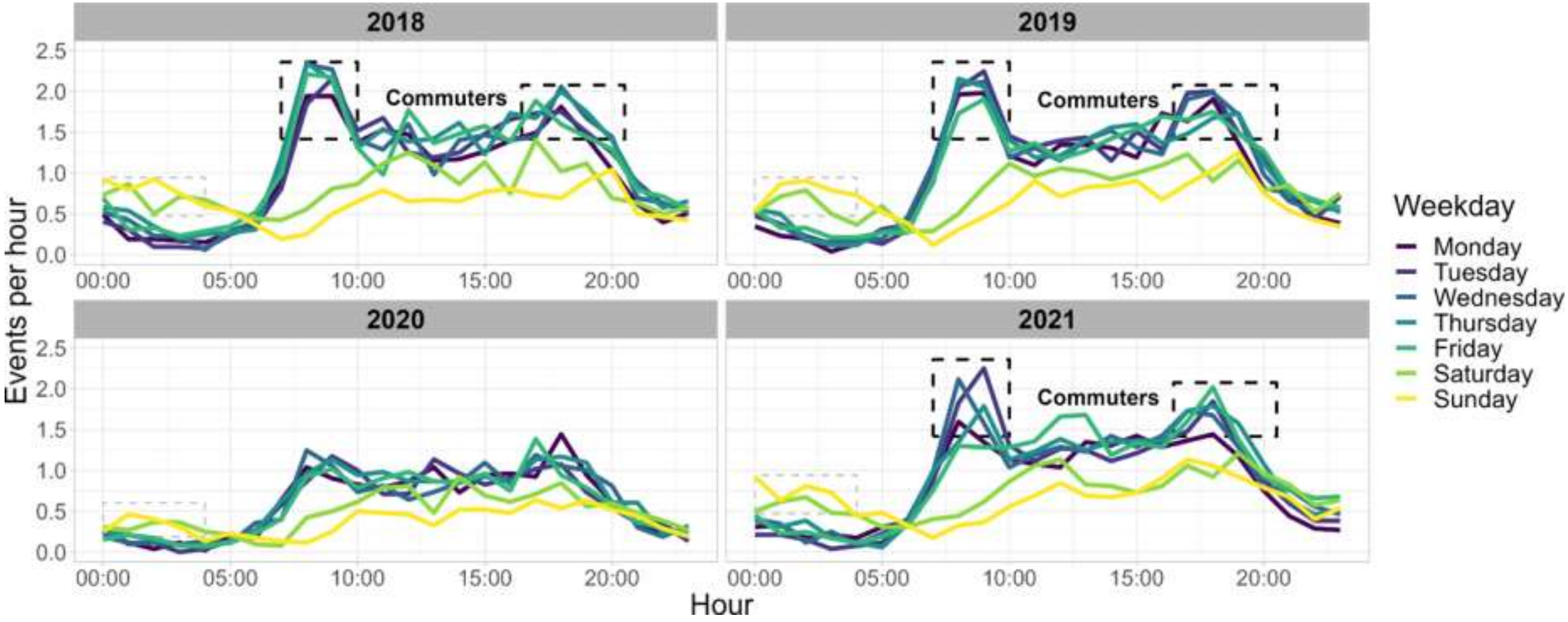
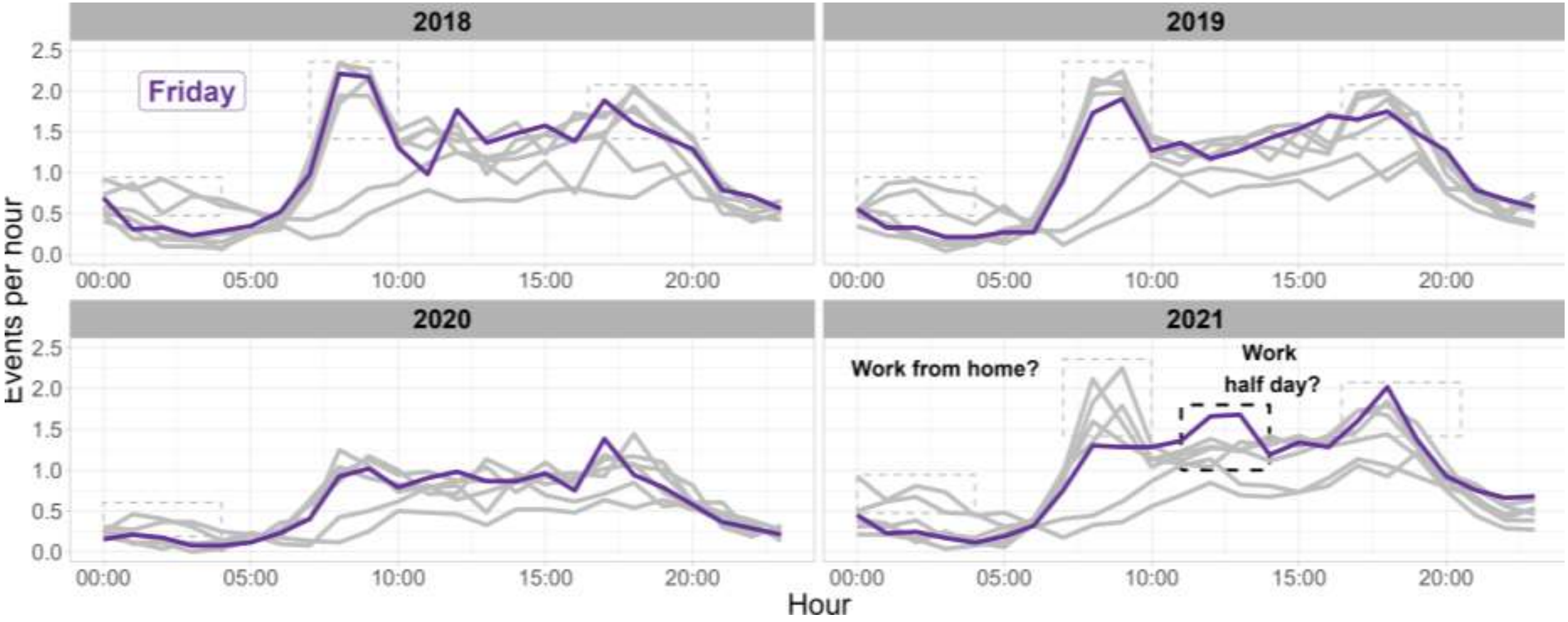
Temporal analysis - Milan



Temporal analysis - Milan



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Take-home messages

1. Weekly seasonal effects due to **summer holidays** in August, which are also present in 2020 and 2021

2. **Drastic reductions** due to COVID-19 lockdowns

3. Hourly seasonal components linked to **nightlife** and **commuters** are clearly evident in 2018, 2019, and 2021.

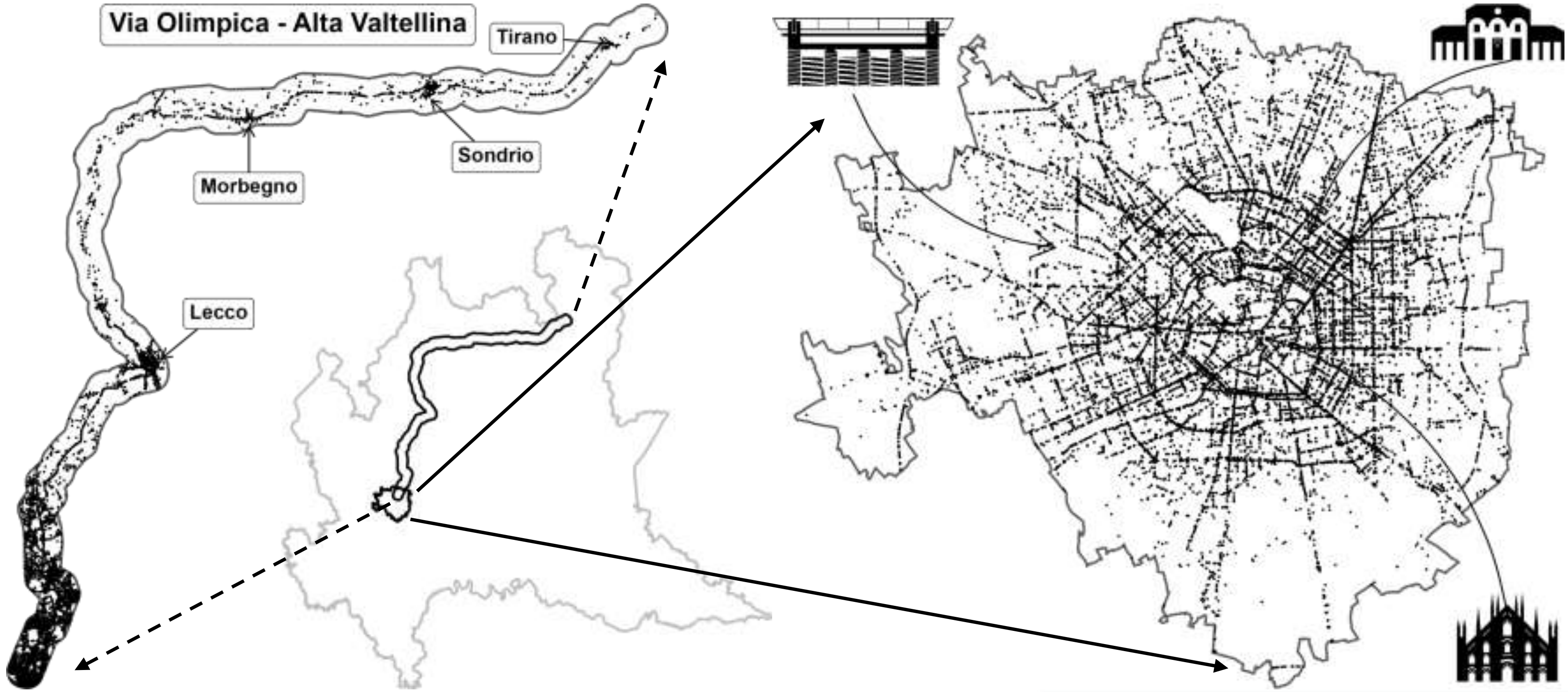
Take-home messages

4. These hourly patterns are **almost absent** in 2020

5. Nevertheless, the behaviour on **friday** during 2021 is substantially different from 2018 and 2019.

Work-from-home policies adopted by large firms near Milan?

Spatial representation



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Spatial Statistics - Theory

Road accidents represent a classic example of **spatial point patterns**: sets of **points** place inside an **observation window (W)**

Typical statistical analyses involve:

1. Detection of spatial trends/**hotspots**;
2. Identification of **clustering behaviours**
3. Exploring the relationship with **external covariates** (e.g. the road type)

Spatial Statistics - Theory

- Given a spatial point pattern $X = \{x_1, \ldots, x_n\}$, we can define its **intensity** function $\lambda(s), s \in W$ as

Intensity function at location $s \in W$

Expected number of events in proximity of s

$$\lambda(s) = \lim_{|d(s)| \to 0} \frac{\mathbb{E}[N(d(s))]}{|d(s)|}$$

Area of a region surrounding s

Spatial Statistics - Theory

- $\boldsymbol{\lambda}(\boldsymbol{s})$ represents the **expected number of events** per unit area that we may observe in **proximity** of $\boldsymbol{s}$

- When $\lambda(s)$ is **constant** for all $s \in W$, we say that the pattern is **homogeneous,** otherwise it's **inhomogeneous**

- We can define the **density** of $\boldsymbol{X}$ as a **normalised** intensity:

$$f(s) = \frac{\lambda(s)}{n}$$

- The usual (non-parametric) **estimator** of the intensity function for a (planar) point pattern is:

The estimate of $\lambda(s)$

$$\hat{\lambda}(s) = \frac{1}{e(s)} \sum_{i=1}^{n} K(s, x_i, h)$$

Spatial Statistics - Theory

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$K(\cdot)$ is a kernel function (i.e. an arbitrary density function)

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$$\hat{\lambda}(\boldsymbol{s}) = \frac{1}{\boldsymbol{e}(\boldsymbol{s})} \sum_{i=1}^{n} \boldsymbol{K}(s, x_i, \boldsymbol{h})$$

$\boldsymbol{h}$ **is a smoothing parameter known as *bandwidth***

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An edge-correction term

h is a smoothing parameter known as *bandwidth*

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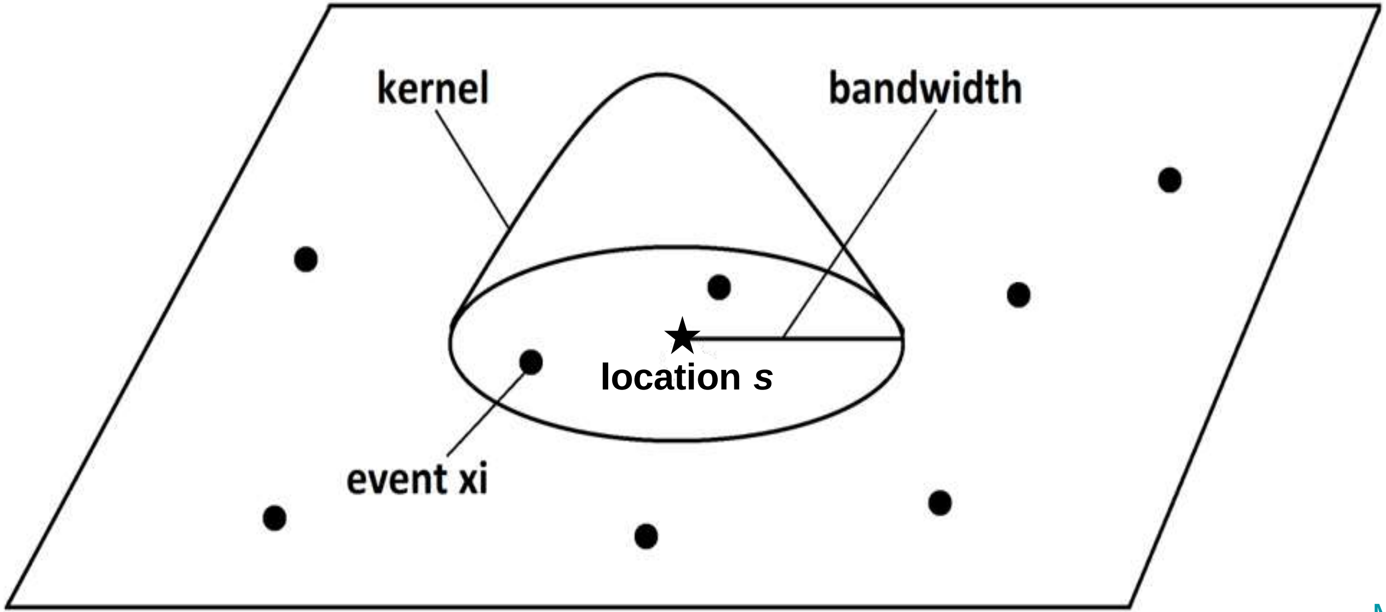
Graphical representation of the estimation process



Courtesy of Moraga (2023)

Spatial Statistics - Theory

- Nevertheless, car crashes represent a classic example of **point patterns on a linear network (L)**

- A proper spatial analysis must always consider the **spatial domain** of the data…

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- Therefore, we need to **correct** the usual estimator:

The network-corrected estimate of $\lambda(s)$

The Kernel function (same as before)

$$\widehat{\lambda_L}(s) = \frac{1}{e(s)} \sum_{i=1}^{n} \frac{K(s, x_i, h)}{c_L(s)}$$

A linear-network correction term

Spatial Statistics - Theory

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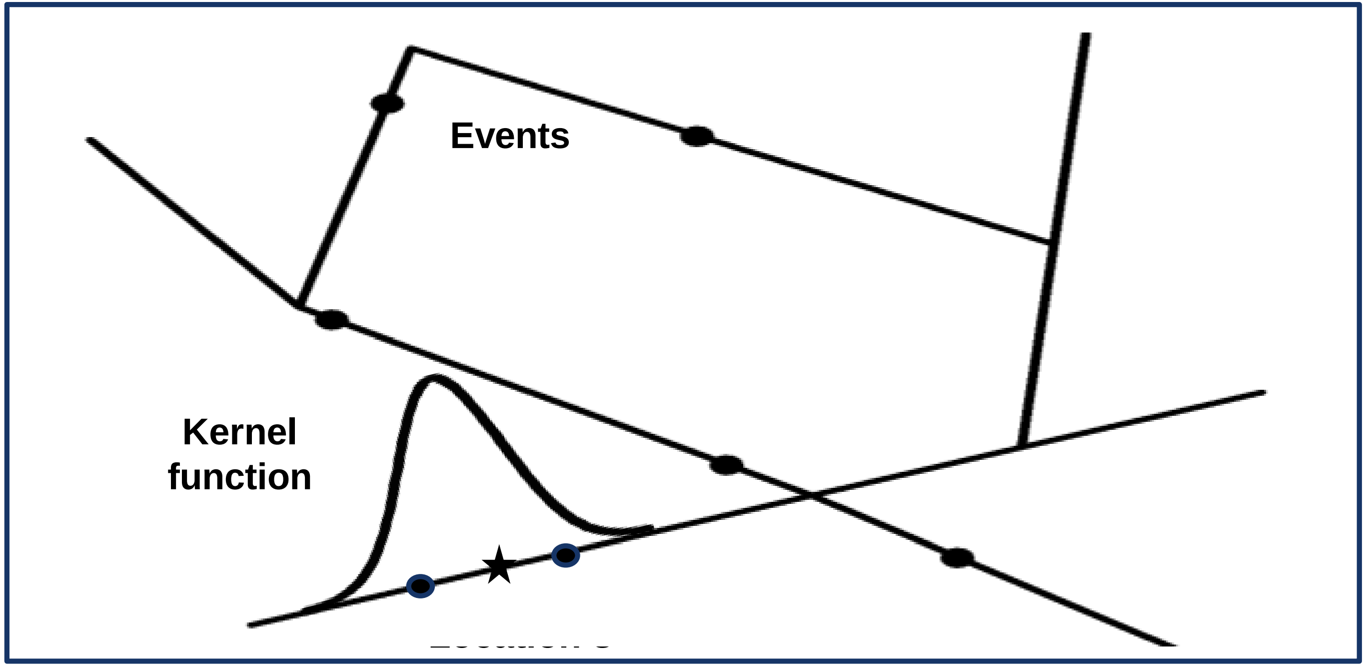
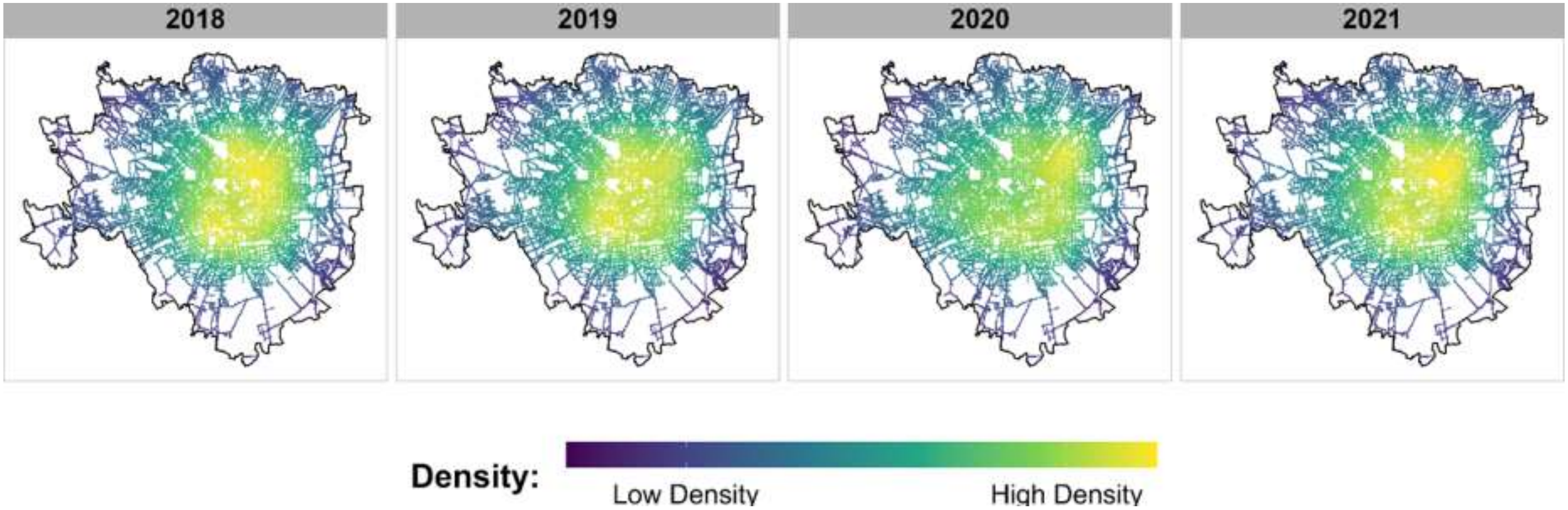
Graphical representation of the estimation process



Smoothed density of car crashes



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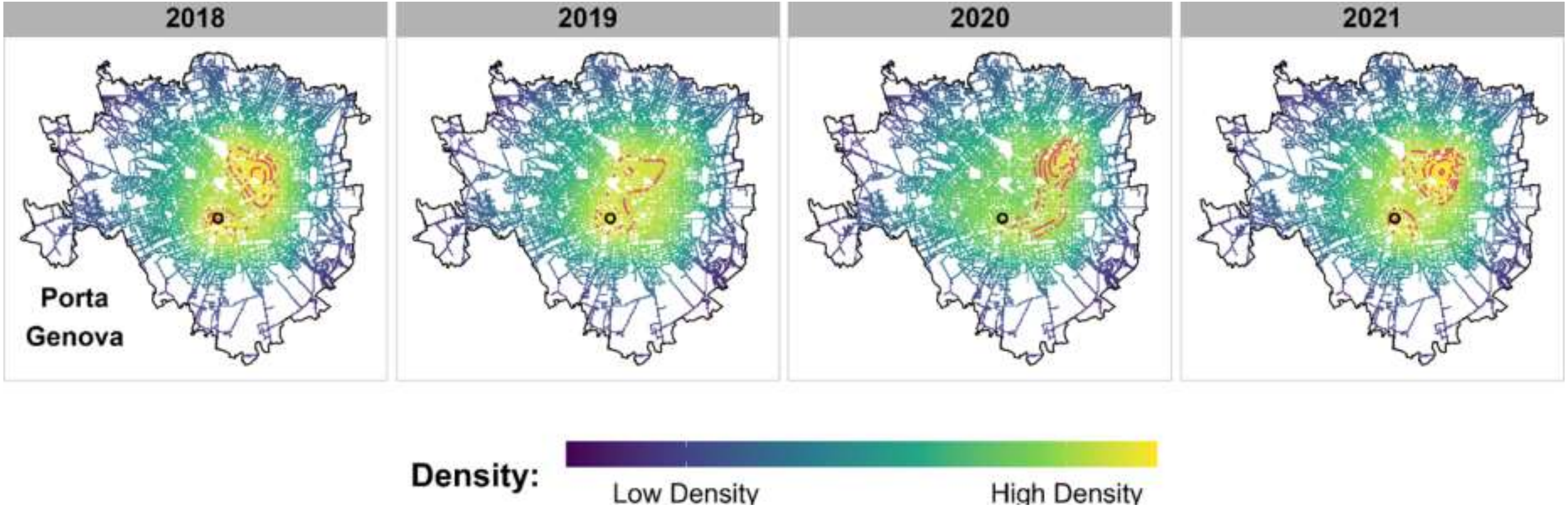

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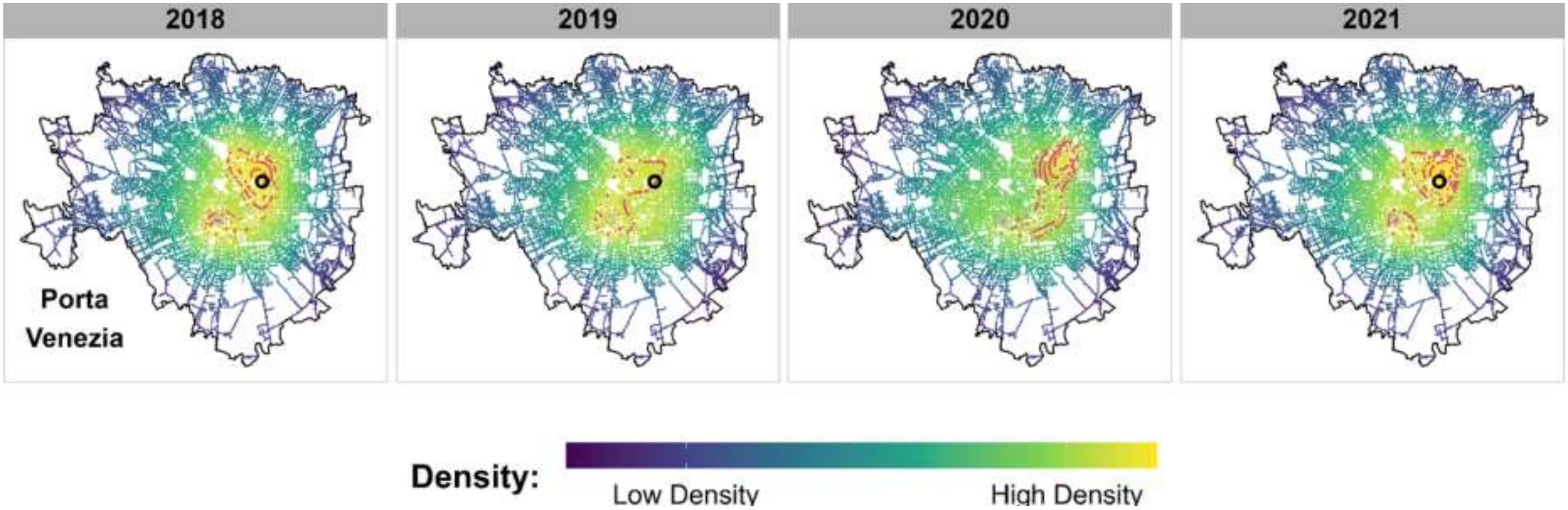

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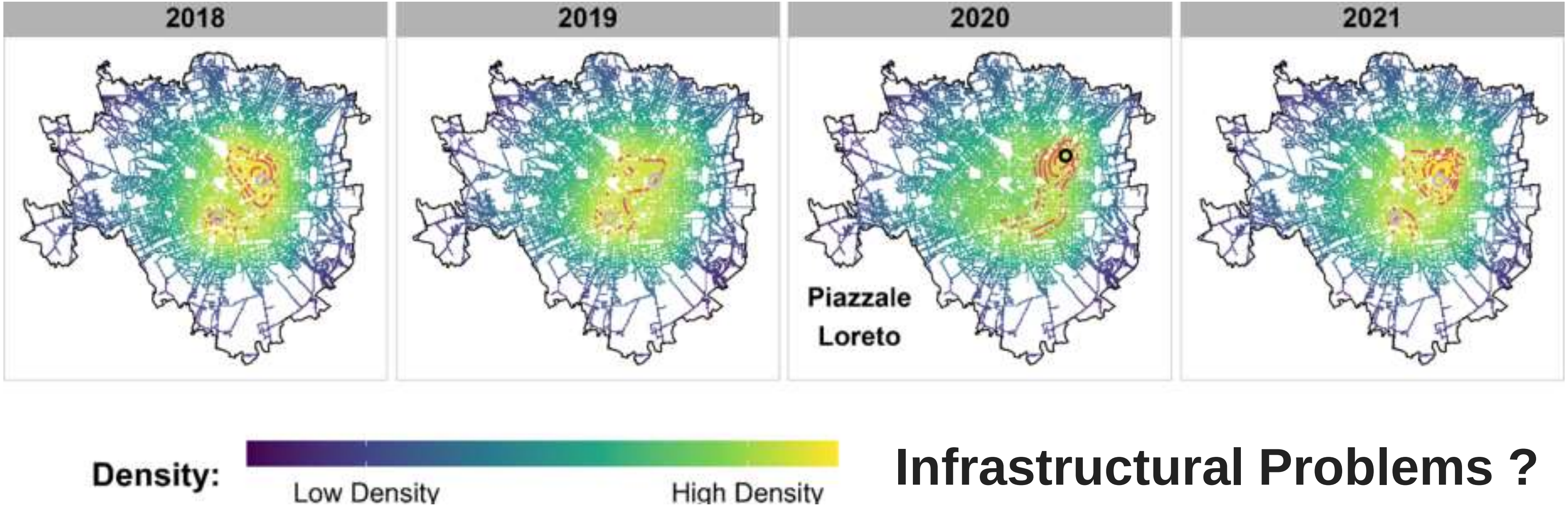

Infrastructural Problems ?

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Spatial Statistics - Theory

- The **spatial relative risk,** $\rho(s)$, is a statistical technique to compare two point-patterns observed at **different times**.

- It can be mathematically defined as:

$$\widehat{\rho_t}(s) = \frac{\hat{f}_t(s)}{\hat{f}_t(s) + \hat{f}_{2018}(s)}$$

Spatial density during year t

Estimate of the spatial relative risk

Spatial density during a reference year (2018)

$$\widehat{\rho_t}(\boldsymbol{s}) = \frac{\hat{f}_t(\boldsymbol{s})}{\hat{f}_t(\boldsymbol{s}) + \hat{f}_{2018}(\boldsymbol{s})}$$

Interpretation:

$$\hat{\rho}_t(\boldsymbol{s}) \simeq 0 \Rightarrow \hat{f}_t(\boldsymbol{s}) \ll \hat{f}_{2018}(\boldsymbol{s})$$

The car crashes' density during year ***t*** at location **s** is **much smaller** than during 2018

$$\widehat{\rho_t}(\boldsymbol{s}) = \frac{\hat{f}_t(\boldsymbol{s})}{\hat{f}_t(\boldsymbol{s}) + \hat{f}_{2018}(\boldsymbol{s})}$$

Interpretation:

$$\hat{\rho}_t(\boldsymbol{s}) \simeq 0.5 \Rightarrow \hat{f}_t(\boldsymbol{s}) \simeq \hat{f}_{\mathbf{2018}}(\boldsymbol{s})$$

The car crashes' density during year ***t*** at location **s** is **almost the same as** during 2018

Spatial Statistics - Theory

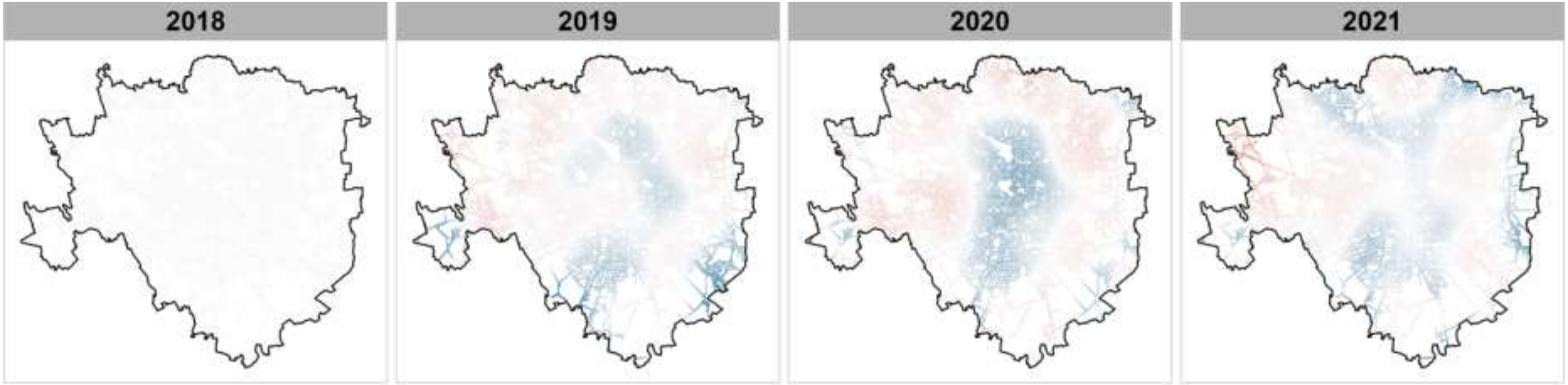
$$\widehat{\rho_t}(s) = \frac{\hat{f}_t(s)}{\hat{f}_t(s) + \hat{f}_{2018}(s)}$$

Interpretation:

$$\hat{\rho}_t(s) \simeq 1 \Rightarrow \hat{f}_t(s) \gg \hat{f}_{2018}(s)$$

The car crashes' density during year ***t*** at location **s** is **much larger** than during 2018

Ratio of spatial densities



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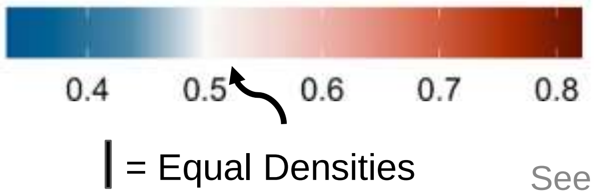

See [1, 2, 4]

Take-home messages

1. During 2018, 2019, and 2021, the hotspots are located in proximity of **Porta Genova** and **Porta Venezia**.

2. We notice a **peak** of events near **Piazzale Loreto** during 2020.

3. The density-ratio maps showcase a reduction of car crashes density near the city centre in 2020, possibly due to the **lower traffic volumes**.

Spatial Statistics - Theory

- Let $\boldsymbol{X} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n\}$ be a point pattern and let $\boldsymbol{\lambda(s)}$ denote its intensity function

- We can also relate $\boldsymbol{\lambda(s)}$ to one or more fixed variables (e.g the road type). For example:

$$\boldsymbol{\lambda(s)} = \boldsymbol{\lambda(s;\theta)} = \mathbf{exp}(\boldsymbol{\theta_0 Z_0} + \boldsymbol{\theta_1 Z_1} + \cdots + \boldsymbol{\theta_p Z_p})$$

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Unknown coefficients (to be estimated)

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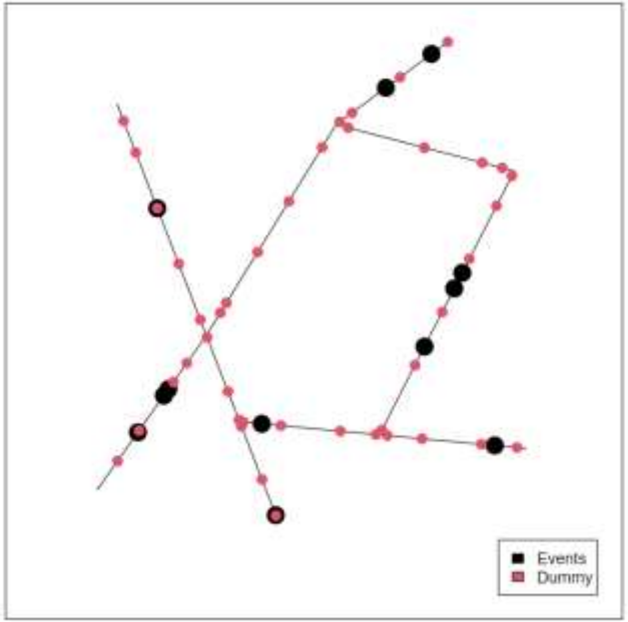
Unknown coefficients (to be estimated)

Known spatial functions

Spatial Statistics - Theory

- The coefficients are estimated employing a techniques known as Berman Turner device:
  - Simulate a set of **dummy points** and *superimpose* them to the events
  - Compute a **weight** for each point after **splitting** the network into smaller parts
  - Calculate the Z_p value in **each segment** and sum the weights
  - Estimate $\theta_1, \ldots, \theta_p$ using standard **GLM** techniques



Deep dive on car crashes and road types

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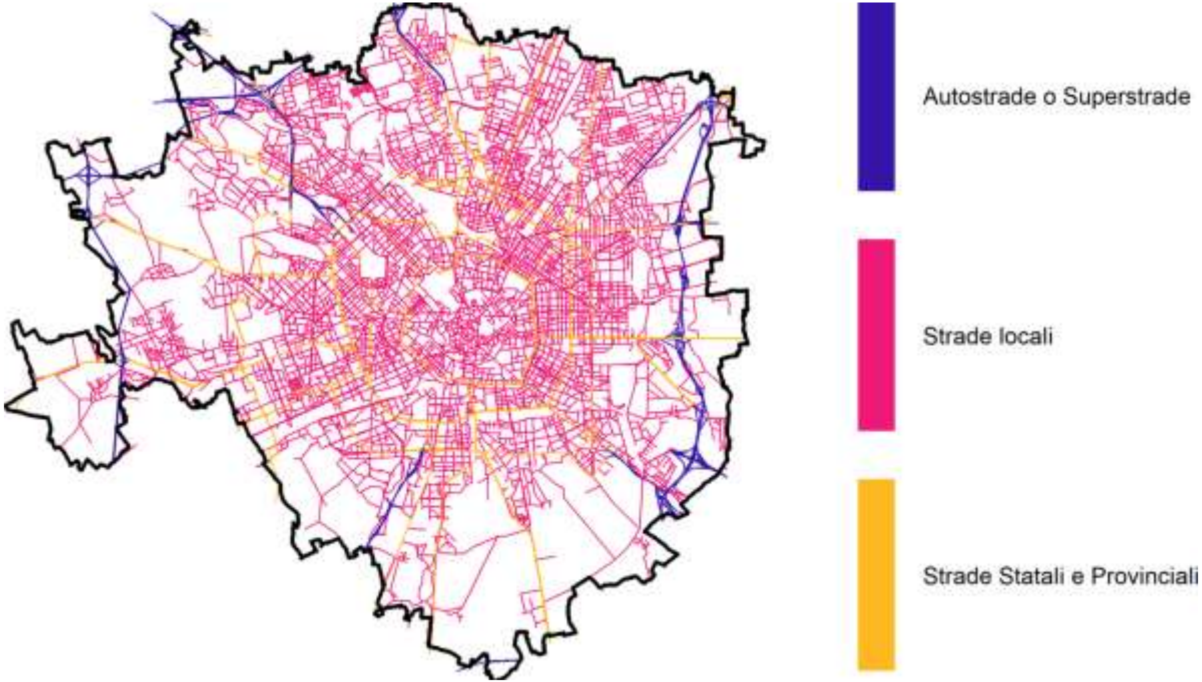
- According to a recent report shared by PoliS: *"La categoria di strada più a rischio incidentalità, lesività, e mortalità è quella delle* ***strade urbane*** *(di Regione Lombardia) dove si concentra il 76,9% di incidenti, il 49,9% di morti e il 73,7% di feriti."*

CATEGORIA STRADA	Incidenti	Morti	Feriti	Indice mortalità	Var.% incidenti 2020-2021	Var.% morti 2020-2021	Var.% feriti 2020-2021
Strade urbane [a]	19.860	178	24.807	0,9	29,3%	20,3%	29,2%
Autostrade	1.474	32	2.275	2,2	51,0%	6,7%	53,4%
Altre strade [b]	4.504	147	6.590	3,3	24,0%	5,8%	25,3%
TOTALE	**25.838**	**357**	**33.672**	**1,4**	**29,4%**	**12,6%**	**29,8%**

(a) Sono incluse nella categoria "Strade urbane" anche le Provinciali, Statali e Regionali entro l'abitato.
(b) Sono incluse nella categoria "Altre strade", le strade Statali, Regionali e Provinciali fuori dall'abitato e Comunali extraurbane.

Deep dive on car crashes and road types

We used two types of **parametric Poisson regression model** to further explore these findings.



Deep dive on car crashes and road types

Ratio of car accident rates **(Reference year: 2018)**

2019	2020	2021
0.97 (0.95; 1.00)	**0.57 (0.55; 0.60)**	0.88 (0.86; 0.91)

Interpretation: On average, the number of car crashes per metre observed in 2020 is **57%** of that observed in 2018. The 95% confidence interval is (0.55; 0.60).

Deep dive on car crashes and road types

***Ratio of car accident rates* (Reference category: Autostrade)**

	2018	2019	2020	2021
Strade Locali	1.32 (1.19; 1.46)	1.32 (1.18; 1.46)	**1.58 (1.37; 1.83)**	1.44 (1.28; 1.62)
Strade Statali e Provinciali	3.83 (3.44; 4.26)	3.70 (3.32; 4.12)	**4.26 (3.66; 4.96)**	4.08 (3.62; 4.59)

Interpretation: On average, the number of car crashes per metre observed in 2020 on *Strade Statali e Provinciali* is **426%** of that observed in *Autostrade e Superstrade* during the same year. The 95% confidence interval is (3.66; 4.96).

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Take-home messages

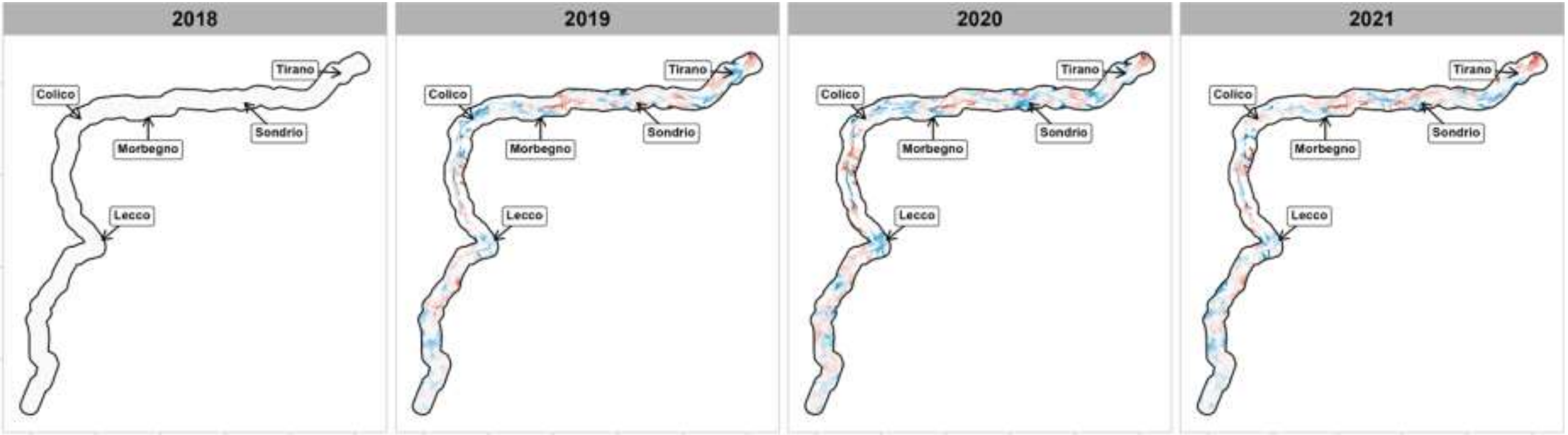
1. The statistical models let us **reproduce** and **replicate** the findings detailed in the report shared by **PoliS**.

2. We can notice that, on average, *Strade Statali* is much **more dangerous** than *Autostrade or Superstrade*.

3. These effects do not seem to be stationary along the years.

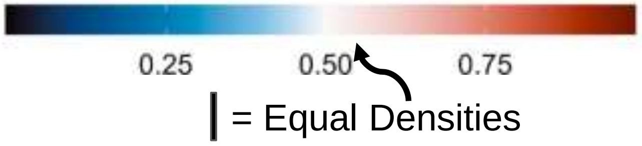
Spatio temporal analysis - Via Olimpica

Ratio of spatial densities



$$\widehat{\rho_t}(s) = \frac{\hat{f}_t(s)}{\hat{f}_t(s) + \hat{f}_{2018}(s)}$$

$\widehat{\rho_t}(s)$:



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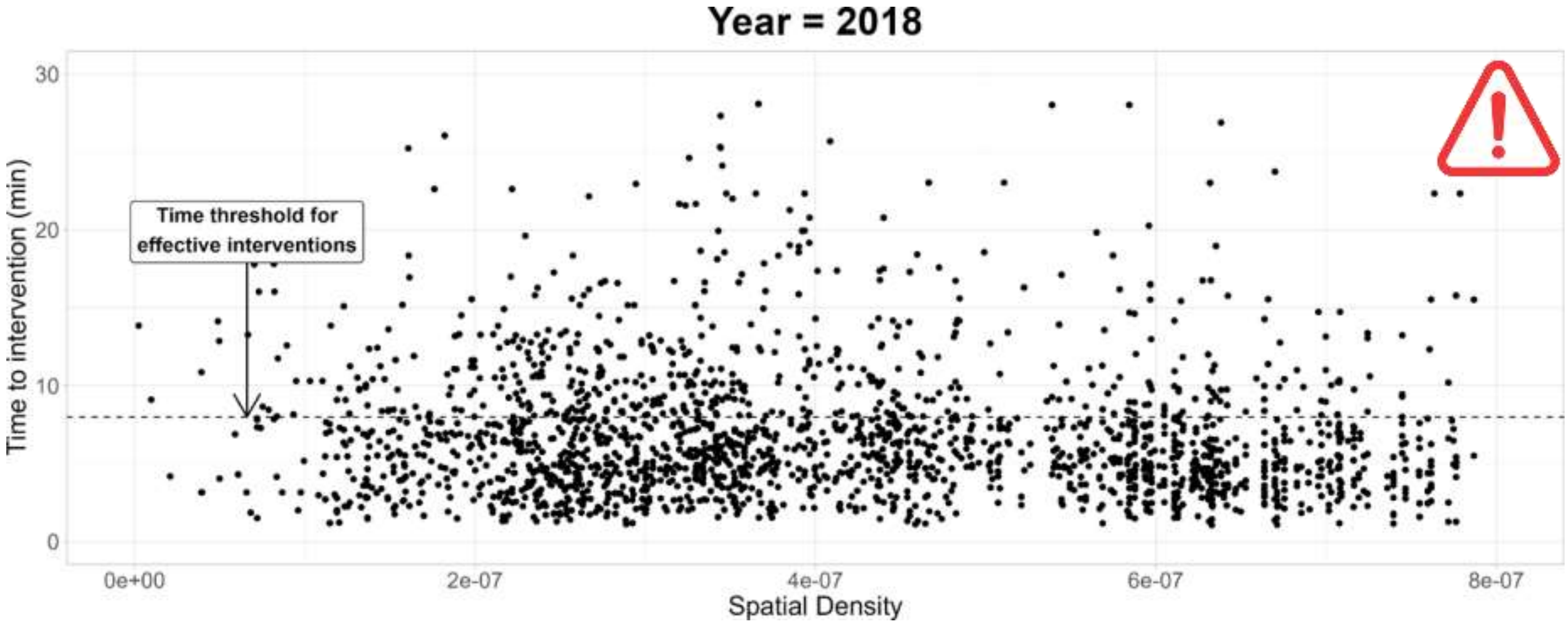
Data fusion

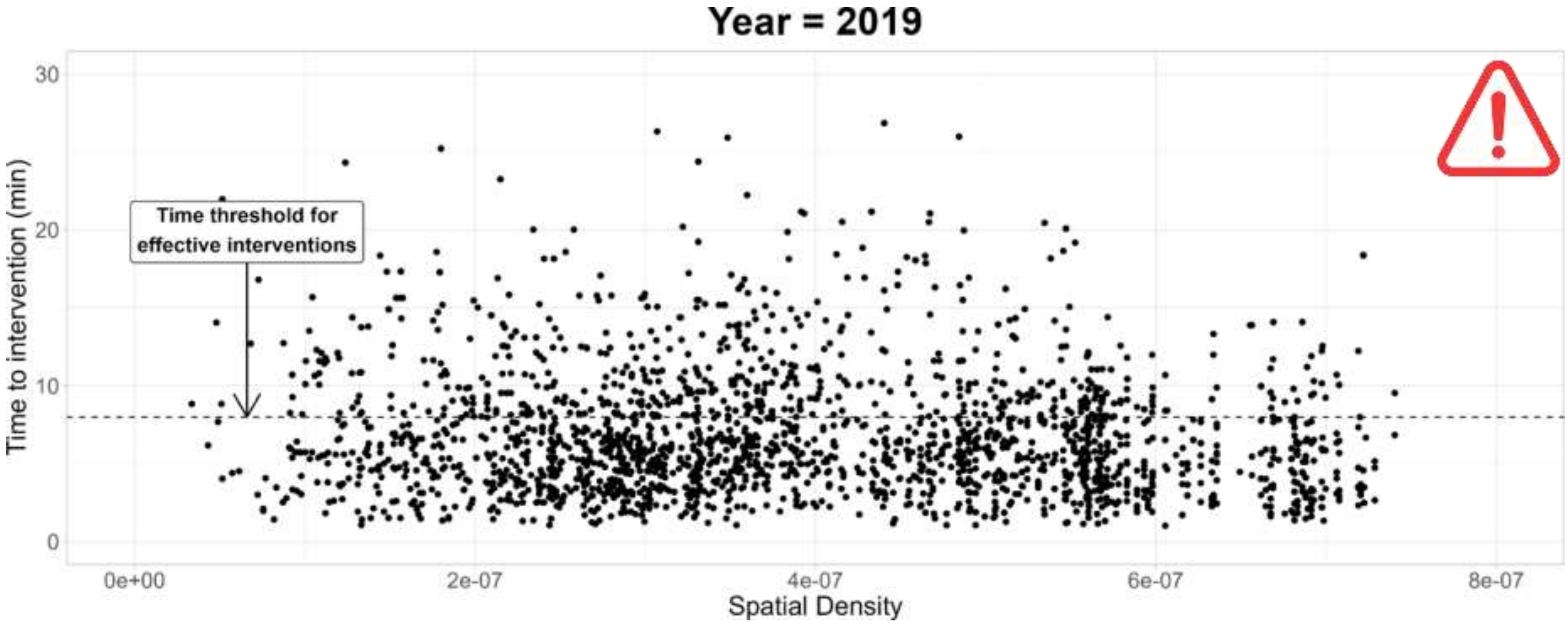
- First, we **merged** the car crashes data with the database of ambulance interventions using a **spatial matching operation**.

- Then, we derived an index that represents the **time** required for the first ambulance to **arrive at the location of the car crash**.

Spatial densities and time to intervention



Spatial densities and time to intervention



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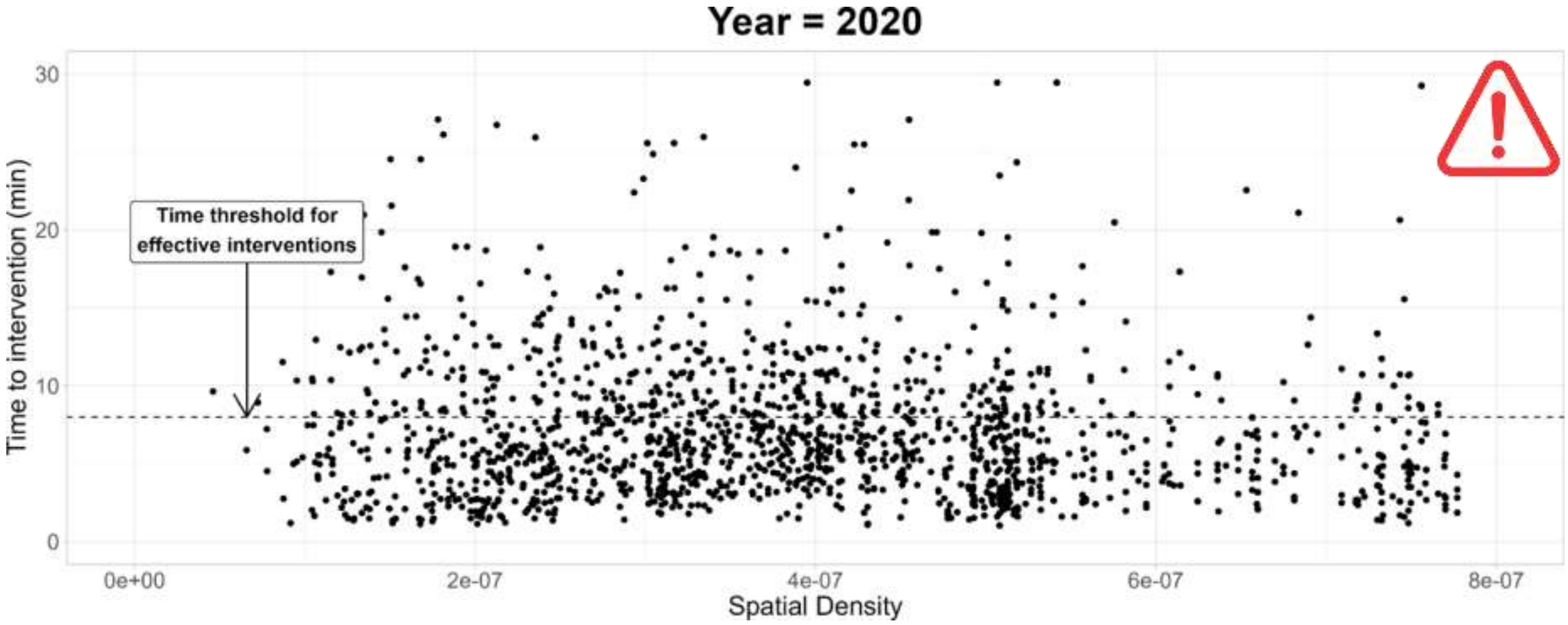
Spatial densities and time to intervention



Take-home messages

1. The spatial ratios appear quite **stable** in the **first half of Via Olimpica**, from Milan to Colico.

2. There are slightly **more pronounced** differences in **Alta Valtellina**, especially near Morbegno or Sondrio.

3. During 2018, several crashes occurred in **proximity of an hotspot** and required **more than 8 minutes** to get an ambulance intervention.

Take-home messages

4. The situation is **remarkably better** in 2019!

5. Unfortunately, the **performances** of the ambulance intervention system **get worse** during 2020.

6. Integrating **PoliS** and **AREU** data let us identify risky areas where we could **optimise** the ambulance response times through **reallocation** algorithms.

Further developments

• Estimation of **road traffic** to measure the exposure [7].	
• Development of marked point process models for **multivariate estimation** of safety indices.	

Acknowledgments

This study was carried out within the GRINS: Growing Resilient, INclusive and Sustainable project, which is part of the Next Generation EU program (National Recovery and Resilience Plan).

References

Seminal and review papers:

[1] Kelsall, J. E., & Diggle, P. J. (1995). Non-parametric estimation of spatial variation in relative risk. *Statistics in medicine*, *14*(21-22), 2335-2342.

[2] McSwiggan, G., Baddeley, A., & Nair, G. (2020). Estimation of relative risk for events on a linear network. *Statistics and Computing*, *30*, 469-484.

[3] Rakshit, S., Davies, T., Moradi, M. M., McSwiggan, G., Nair, G., Mateu, J., & Baddeley, A. (2019). Fast kernel smoothing of point patterns on a large network using two-dimensional convolution. *International Statistical Review*, *87*(3), 531-556.

State of the art:

[4] Baddeley, Adrian, Gopalan Nair, Suman Rakshit, Greg McSwiggan, and Tilman M. Davies. "Analysing point patterns on networks—A review." *Spatial Statistics* 42 (2021): 100435.

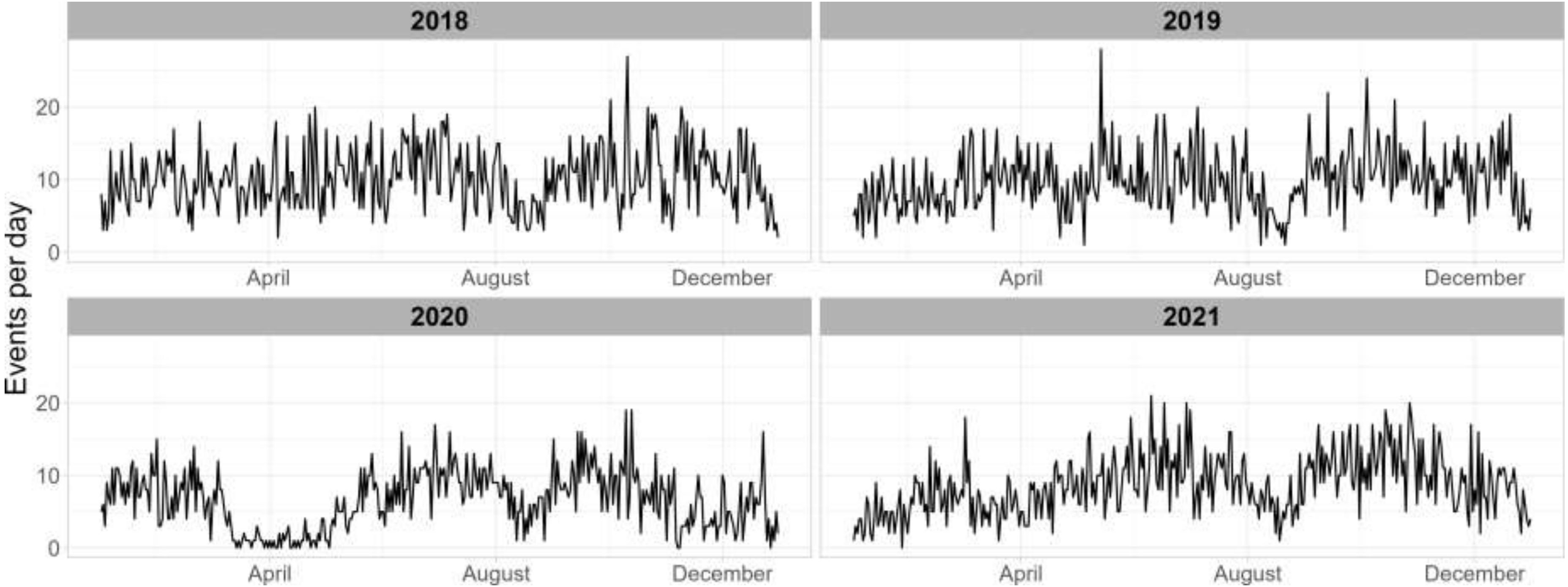
[5] Gilardi, A., Borgoni, R., Mateu, J. (2023+) A non-separable first-order spatio-temporal intensity for events on linear networks: an application to ambulance interventions. Accepted for publication in *Annals of Applied Statistics*.

[6] Ferraccioli, F., Arnone, E., Finos, L., Ramsay, J. O., & Sangalli, L. M. (2021). Nonparametric density estimation over complicated domains. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *83*(2), 346-368.

[7] Gilardi, A., Borgoni, R., Presicce, L., & Mateu, J. (2023). Measurement error models for spatial network lattice data: Analysis of car crashes in Leeds. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *186*(3), 313-334.

Appendix: Temporal analysis along Via Olimpica

Temporal analysis - Via Olimpica



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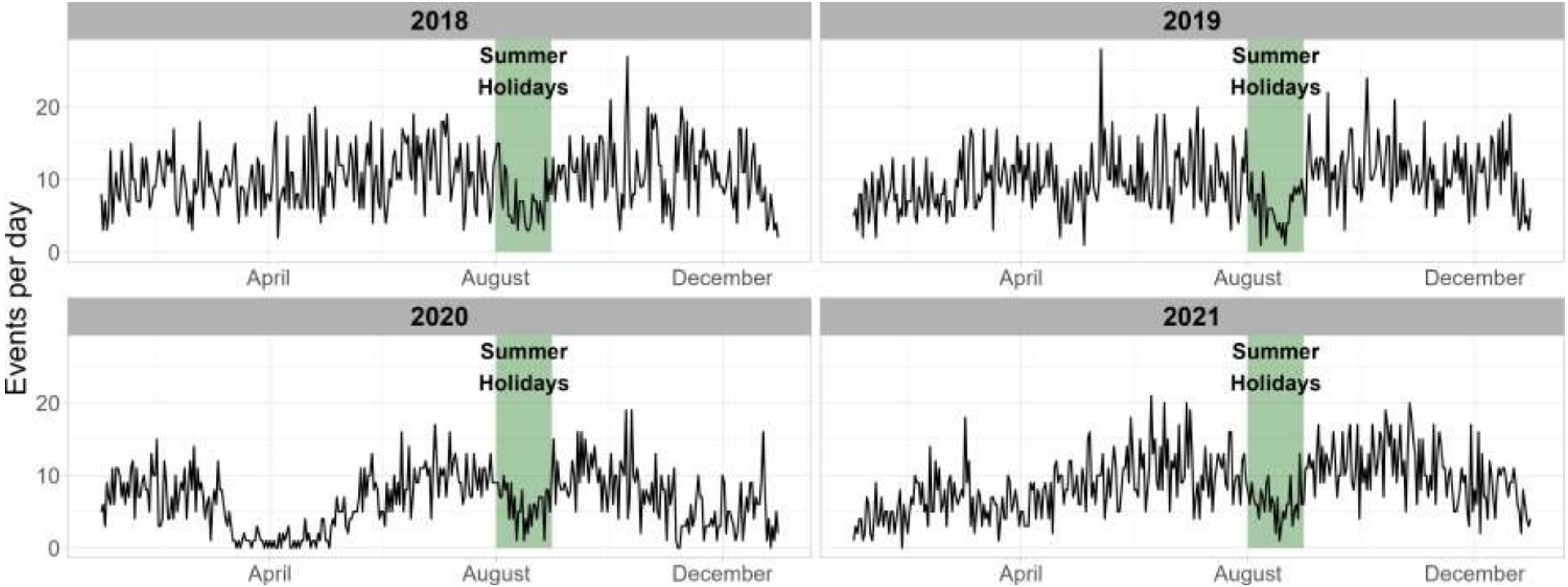
Temporal analysis - Via Olimpica



Temporal analysis - Via Olimpica

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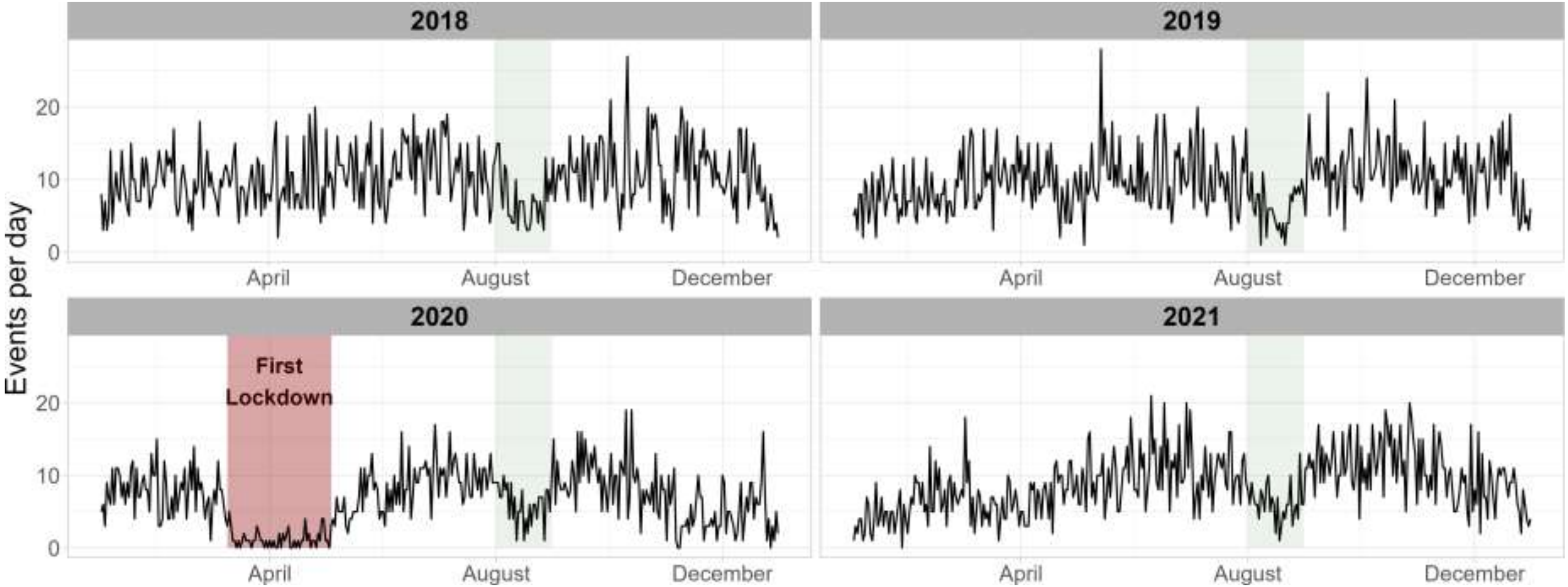

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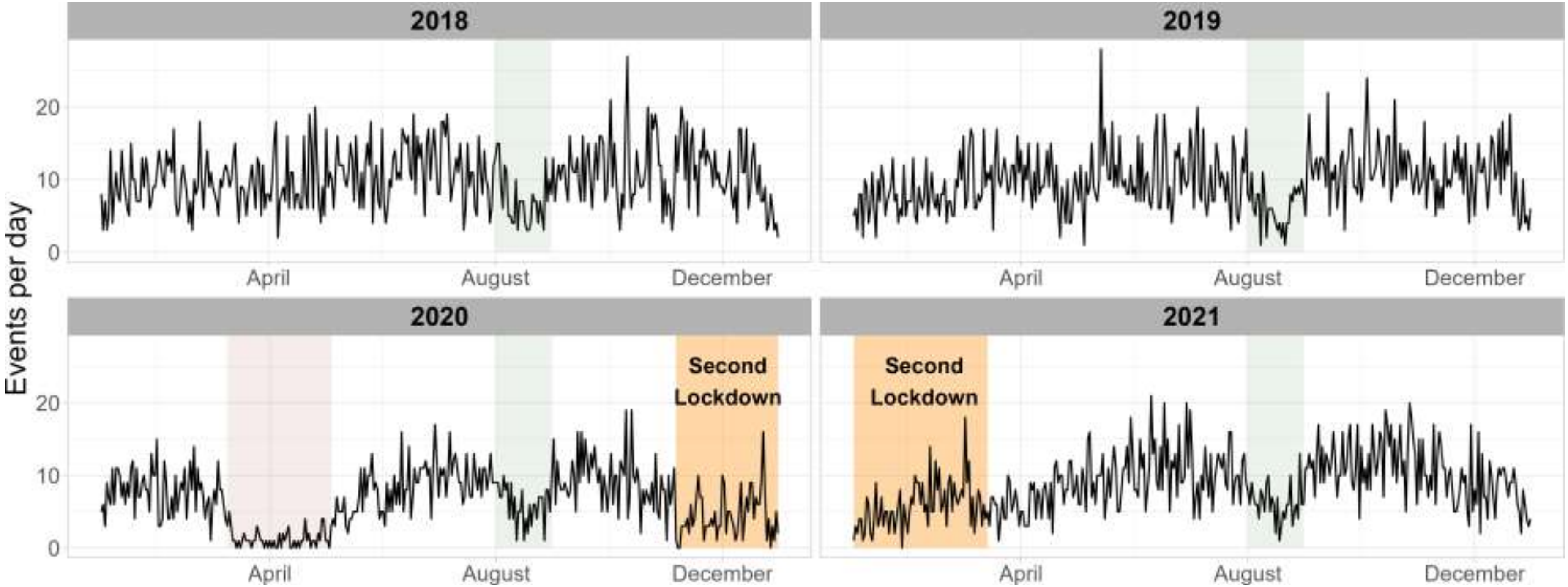
Temporal analysis - Via Olimpica



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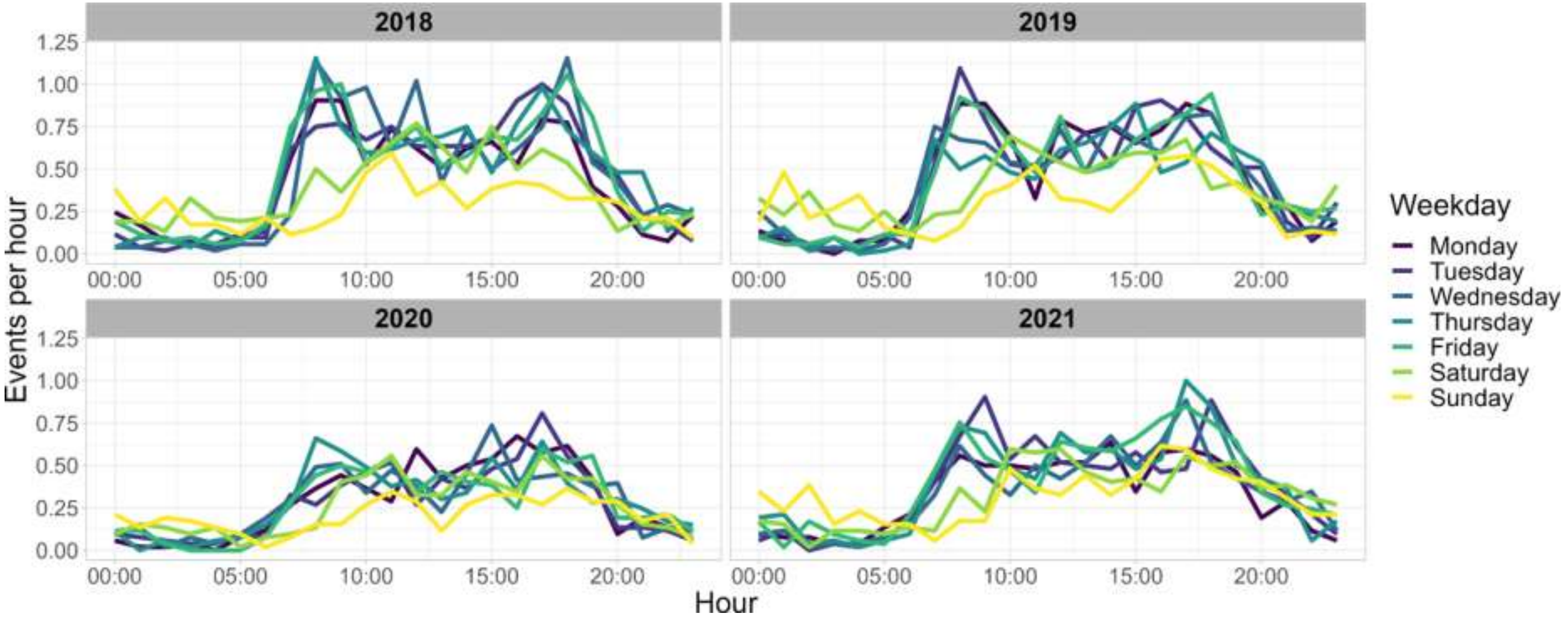
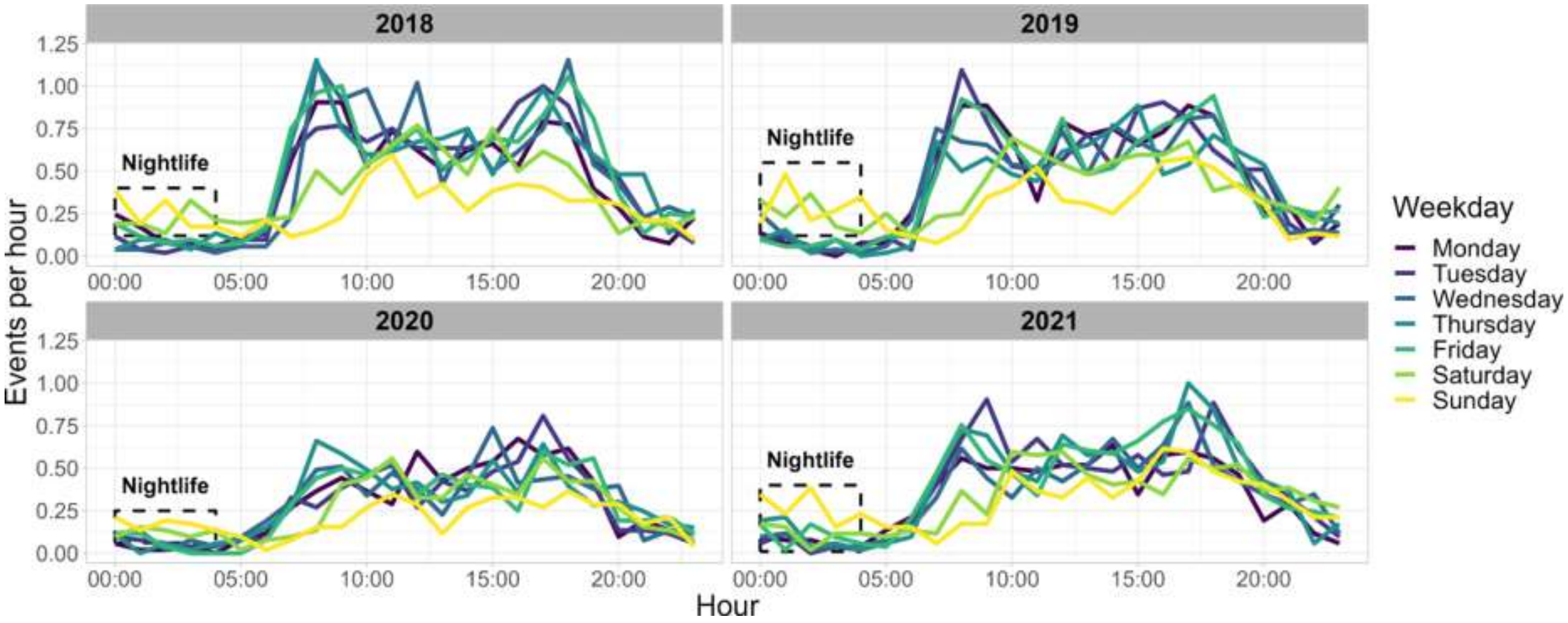
Temporal analysis - Via Olimpica



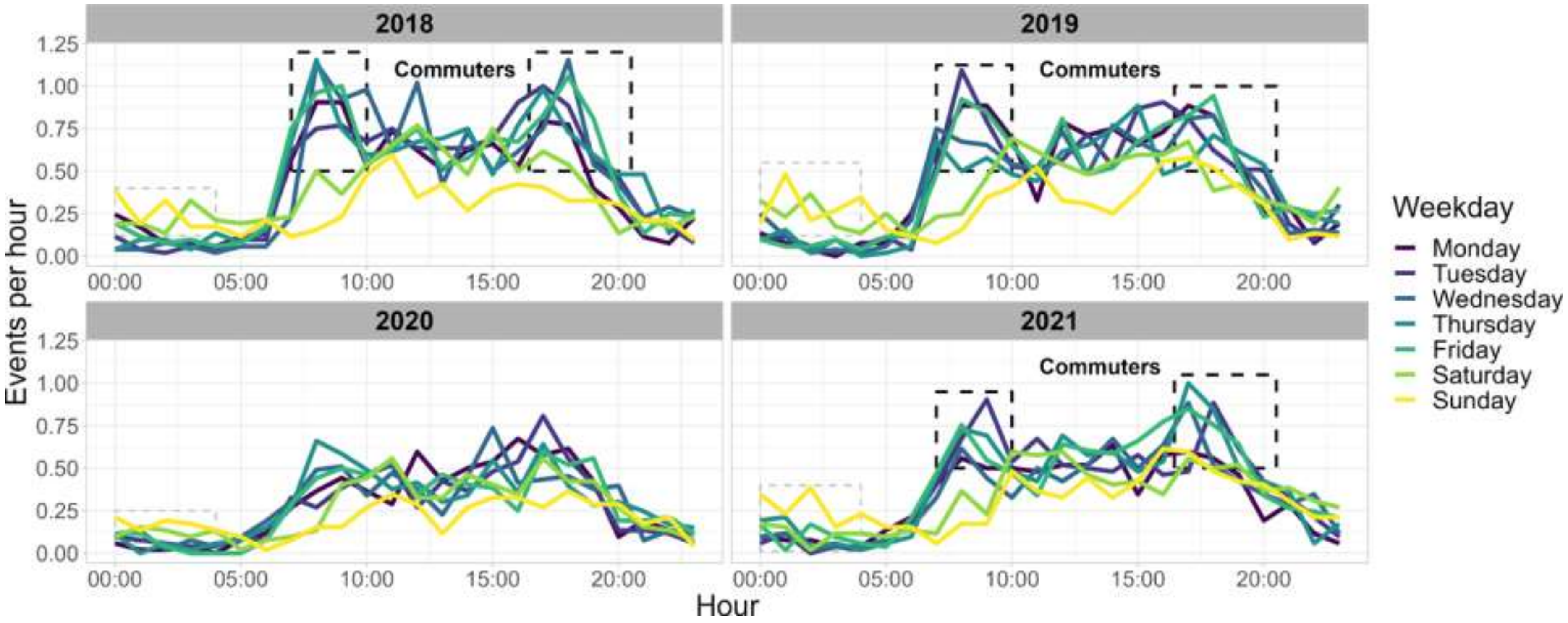
Gilardi, A., Ieva, F., Sangalli, L., Secchi, P.

Temporal analysis - Via Olimpica



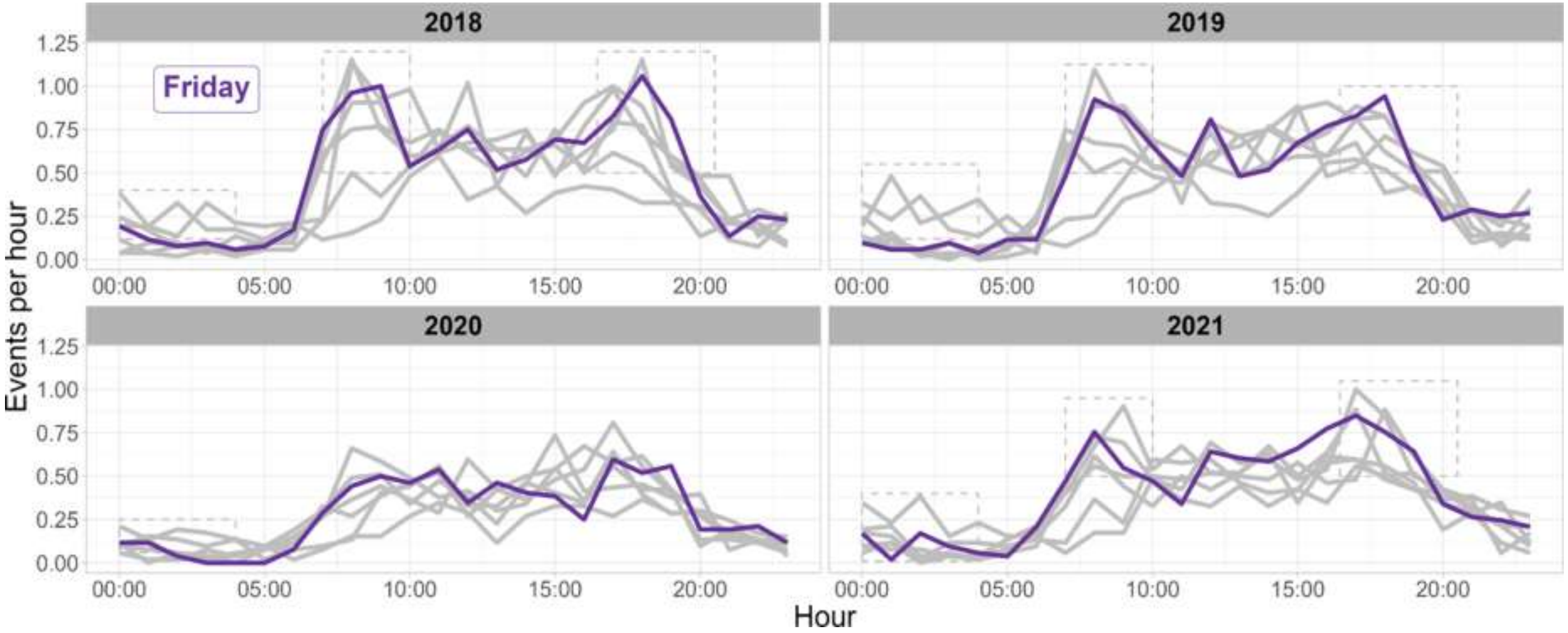
Gilardi, A., Ieva, F., Sangalli, L., Secchi, P.

Temporal analysis - Via Olimpica



Gilardi, A., Ieva, F., Sangalli, L., Secchi, P.

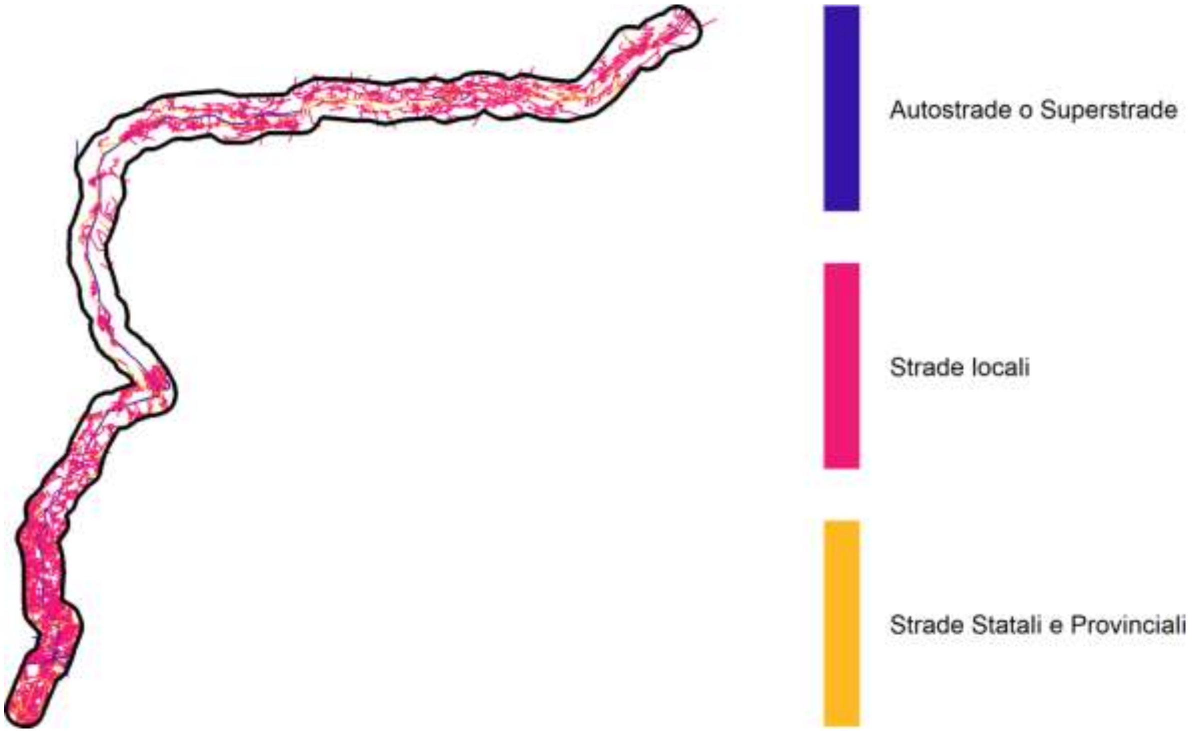
Temporal analysis - Via Olimpica



Gilardi, A., Ieva, F., Sangalli, L., Secchi, P.

Deep dive on car crashes and road types

The main road (**SS 36**) is classified as **Autostrada o Superstrada!**



Deep dive on car crashes and road types

***Ratio of car accident rates* (Reference year: 2018)**

2019	2020	2021
0.97 (0.95; 1.00)	**0.65 (0.62; 0.68)**	0.86 (0.82; 0.90)

Interpretation: On average, the number of car crashes per metre observed in 2020 is **65%** of that observed in 2018.

Deep dive on car crashes and road types

GRINS FOUNDATION

Ratio of car accident rates **(Reference category: Autostrade)**

	2018	2019	2020	2021
Strade Locali	0.55 (0.50; 0.61)	0.51 (0.45; 0.56)	**0.68 (0.59; 0.77)**	0.56 (0.50; 0.62)
Strade Statali e Provinciali	1.40 (1.26; 1.56)	1.16 (1.03; 1.29)	**1.40 (1.21; 1.62)**	1.25 (1.11; 1.42)

Interpretation: On average, the number of car crashes per metre observed in 2020 on *Strade Statali e Provinciali* is **140%** of that observed in *Autostrade e Superstrade* during the same year.