Predicting the Impact of COVID-19 on the Emergency Medical Service in Lombardy, Italy

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Introduction - TSUNAMI project

The Lombardy region in Italy relies on the emergency medical service called **AREU**.

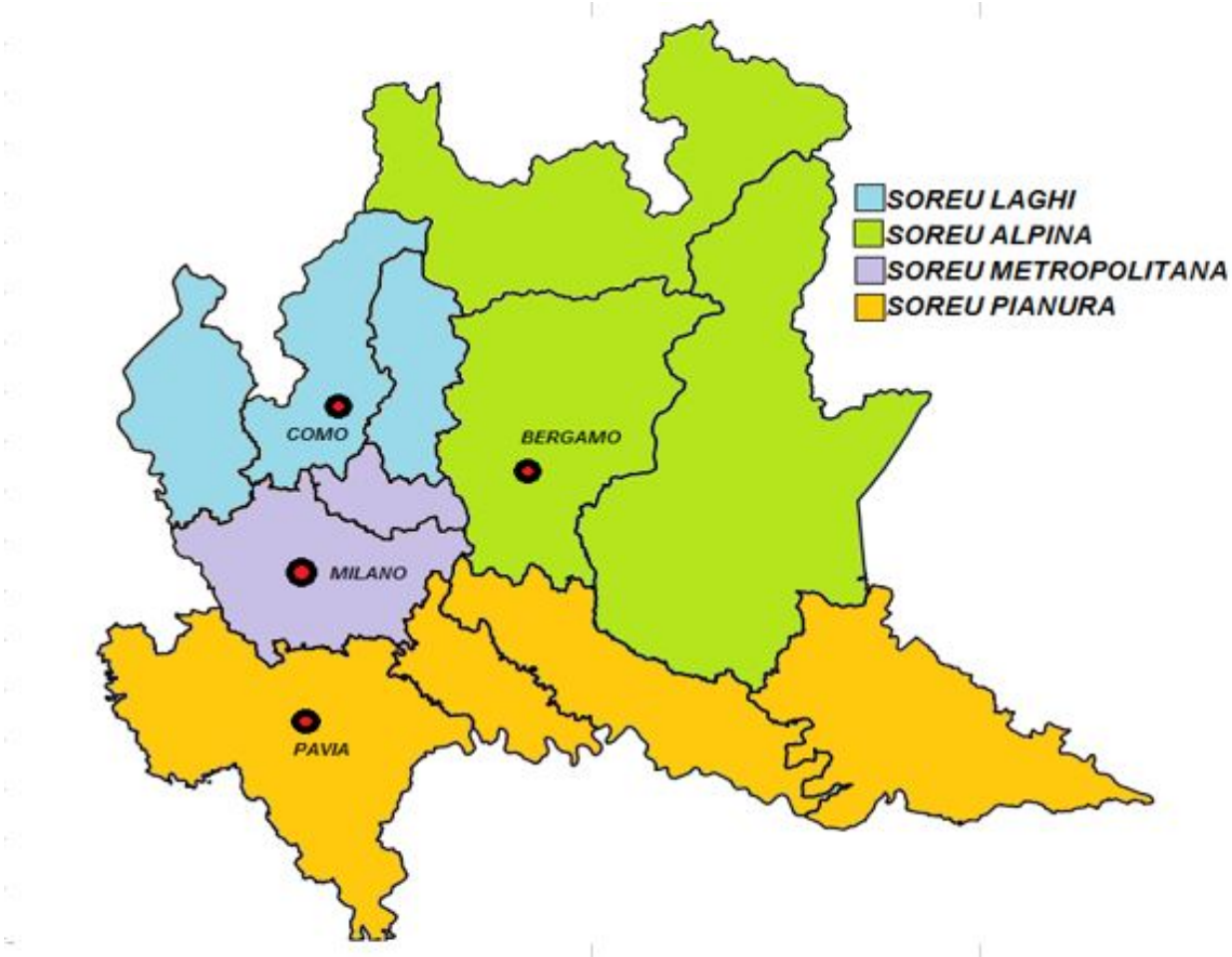
PROBLEM: The number and type of **calls** to the emergency call center changed dramatically due to **COVID-19** pandemic.

AIM: Predictive model of the upcoming ambulance trips is crucial to **organize** the available emergency response resources.

TSUNAMI PROJECT

Supported by Lombardy region - Italy

AREU is organized in four regions: Lakes, Alps, **Metropolitan**, Plane.



Data

AREU can use: daily-seasonal variations, social and demographic factors, weather circumstances, and epidemiological factors.

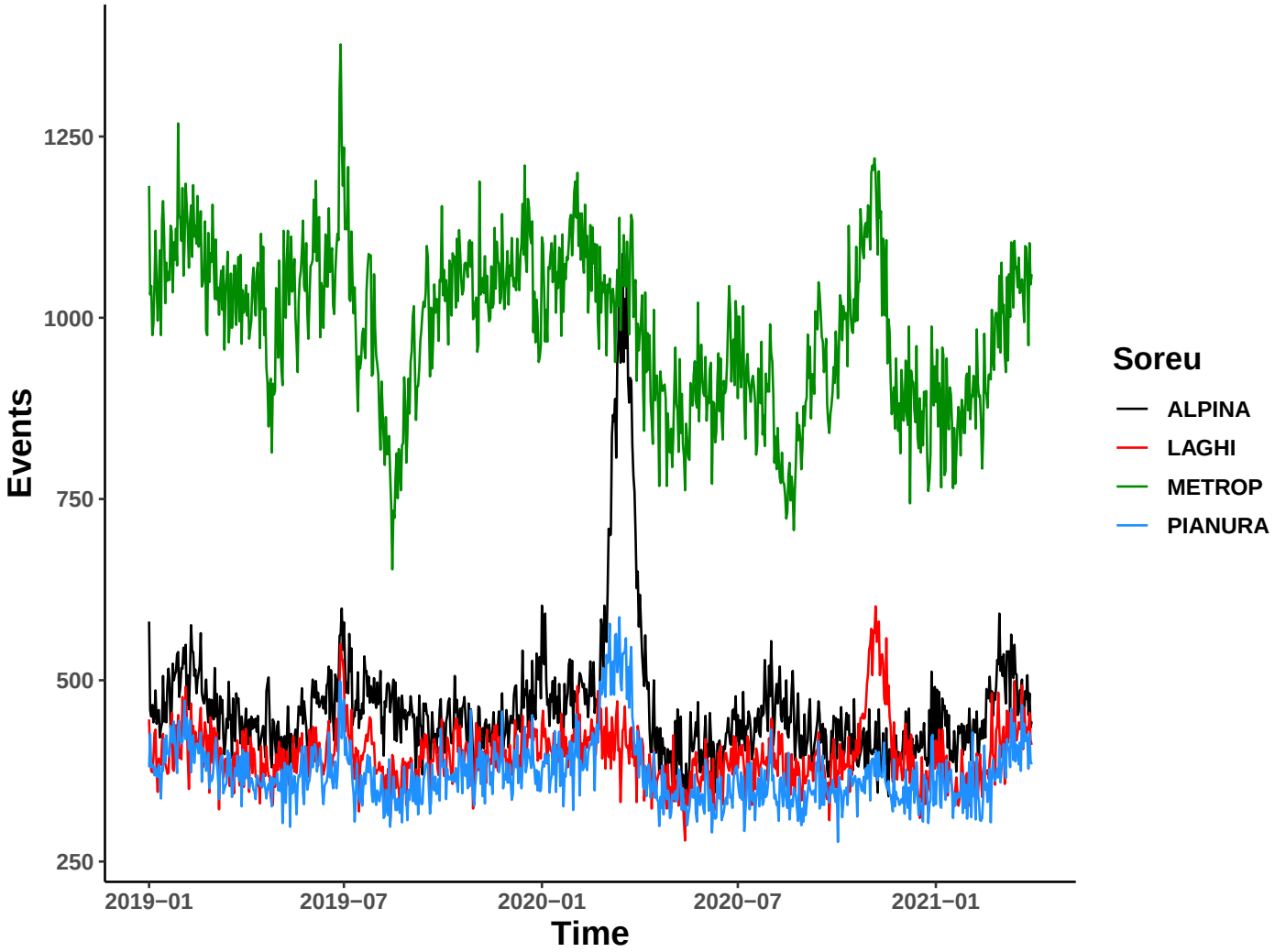
- **AREU data**: information about all the calls received → Region, Time, if the calls activated an aid, i.e., it becomes an event, etc;
- **ARPA data**: weather data collected from sensors located across the Lombardy → Temperature, rainfall, snowfall;

- **ISTAT and ISS data**: demographic and epidemiological data
  → Flu incidence, number of car accidents, etc.

BUT also COVID-19 related factors.

- **Department of Civil Protection**: number of hospitalized patients with symptoms, swabs, etc;
- **ISS**: reproduction number R_t.

Events: Dispatch of transport and/or equipment.



GOAL: Predict number of **events** for each of 4 regions.

- We focus here on **Metropolitan** area (Milan and Monza).

METHOD:

- **Generalized Additive Model** with **negative-binomial** family;
- The data were aggregated at **hour** and **region** levels;
- Final predictions were aggregated at the **day** level.

We select model with best **mean absolute prediction error**.

- **Prediction error**:

$$\boxed{\frac{\hat{y}_i - y_i}{y_i}},$$

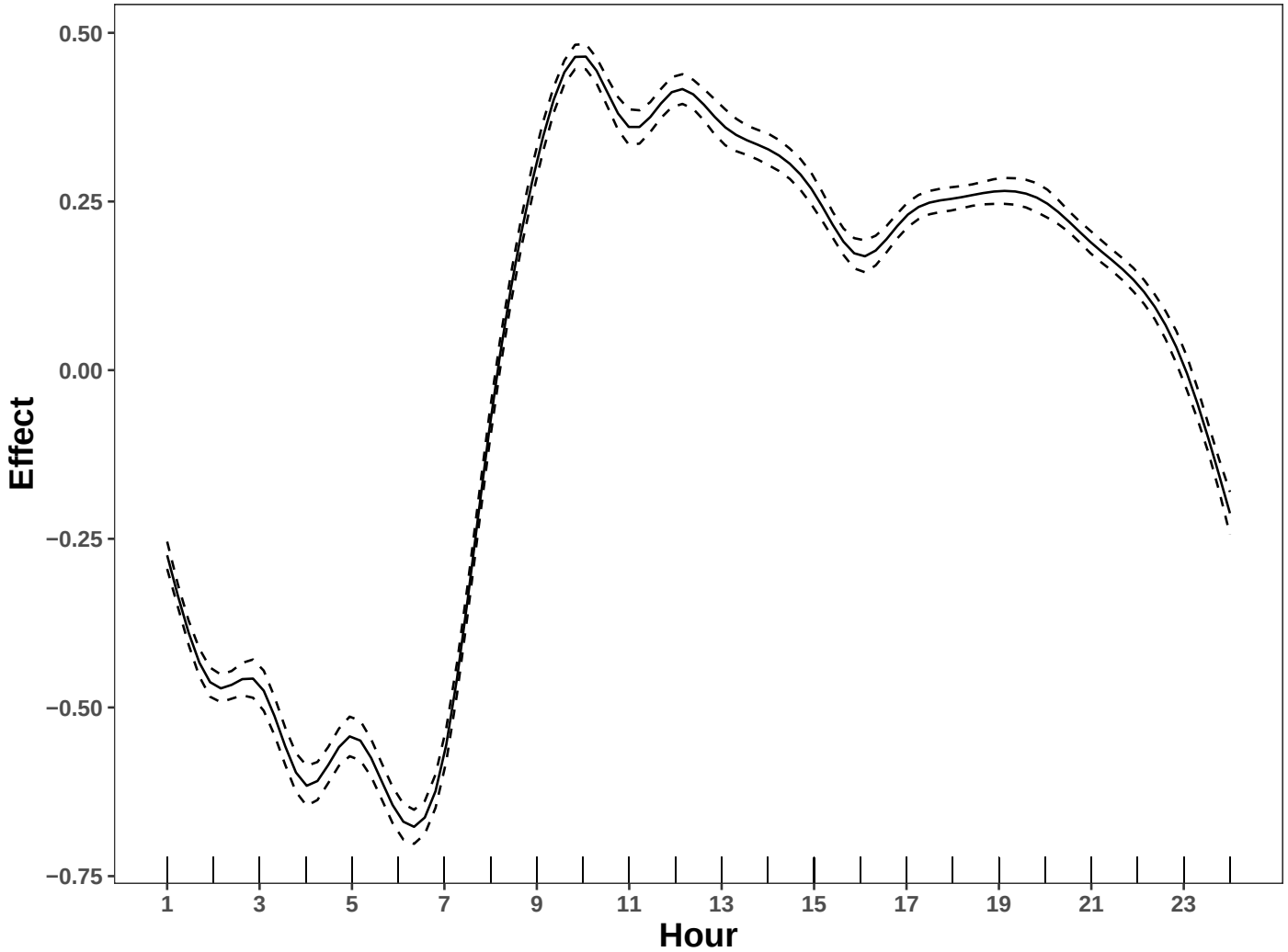
  where y_i is the observed value and $\hat{y}_i$ the predicted one at day i level.

- Using 4 fold **Cross-validation** across 2020 and 2021.

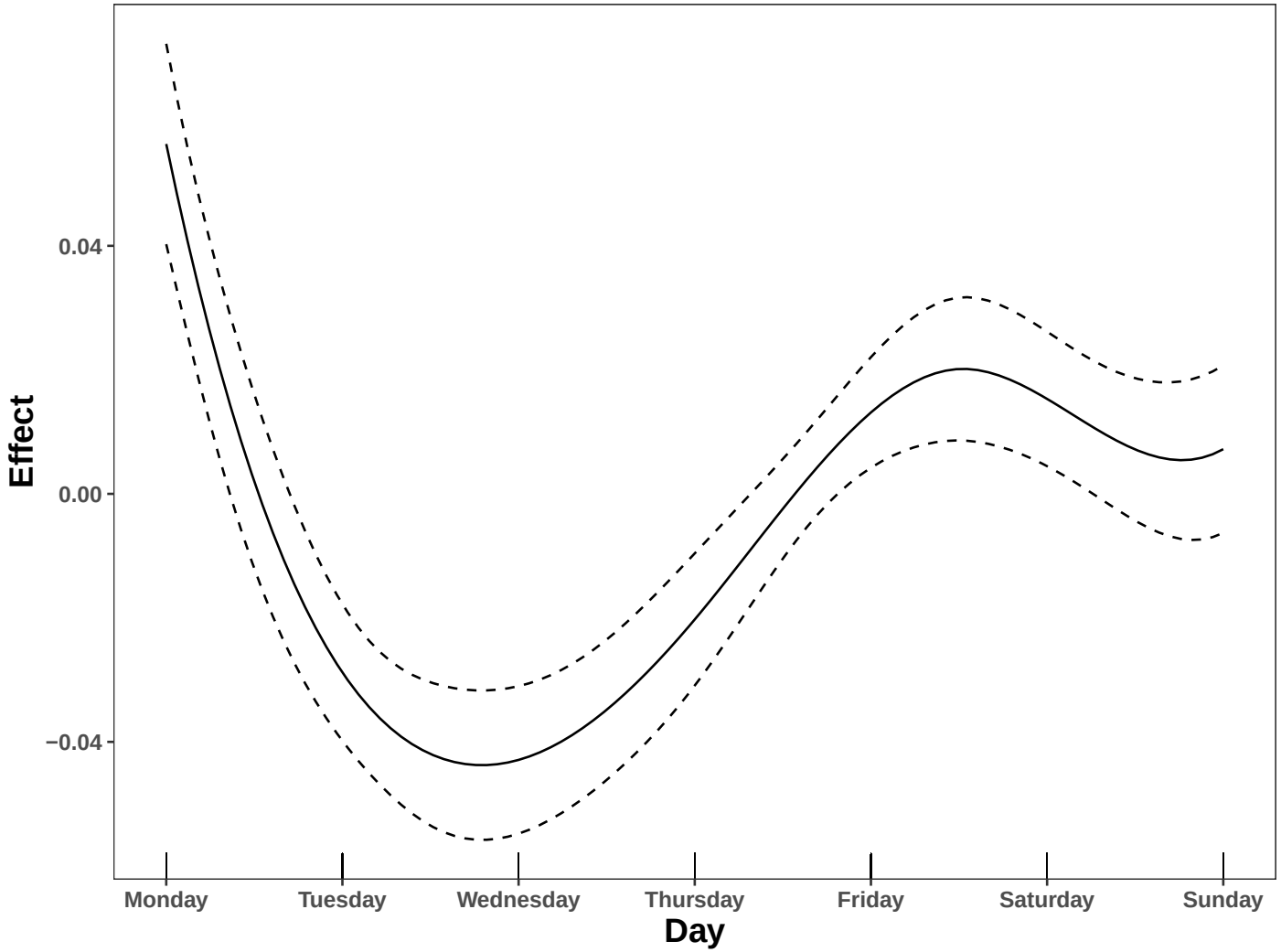
The following covariates were then selected:

- cubic regression spline for **Hours** with 24 basis;
- cubic regression spline for **Quarter** with 4 basis;
- P-spline for **Day** with 7 basis;
- Tensor product smooths between **Day** and **Hour**;
- **Temperature** lagged one day;
- **Events** of the day before lagged 1-2-3 by hour;
- **Events** aggregated by day and lagged 1, 2 and 7 days;
- R_t lagged one day;
- **Flu** incidence lagged one day.

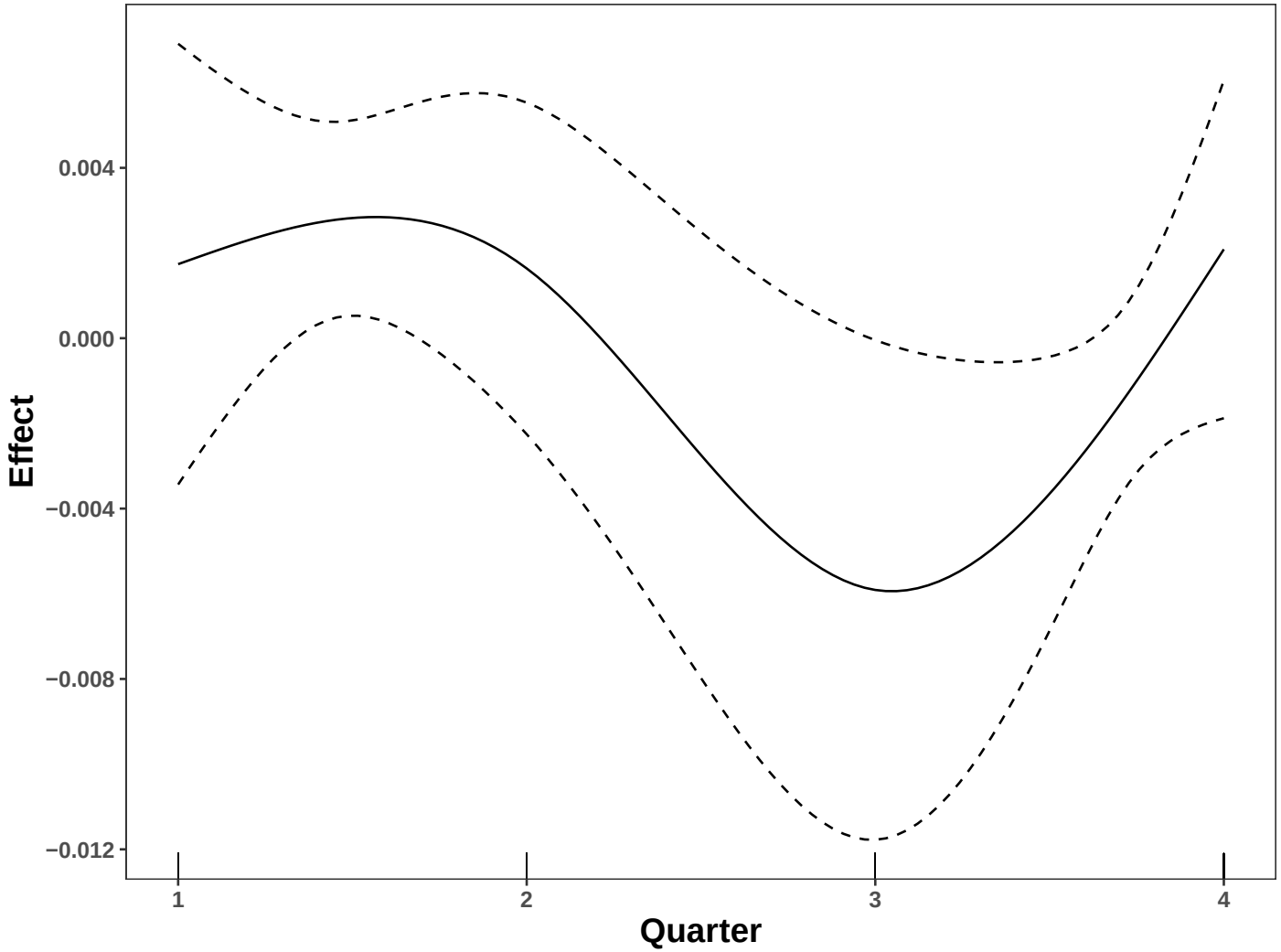
Results

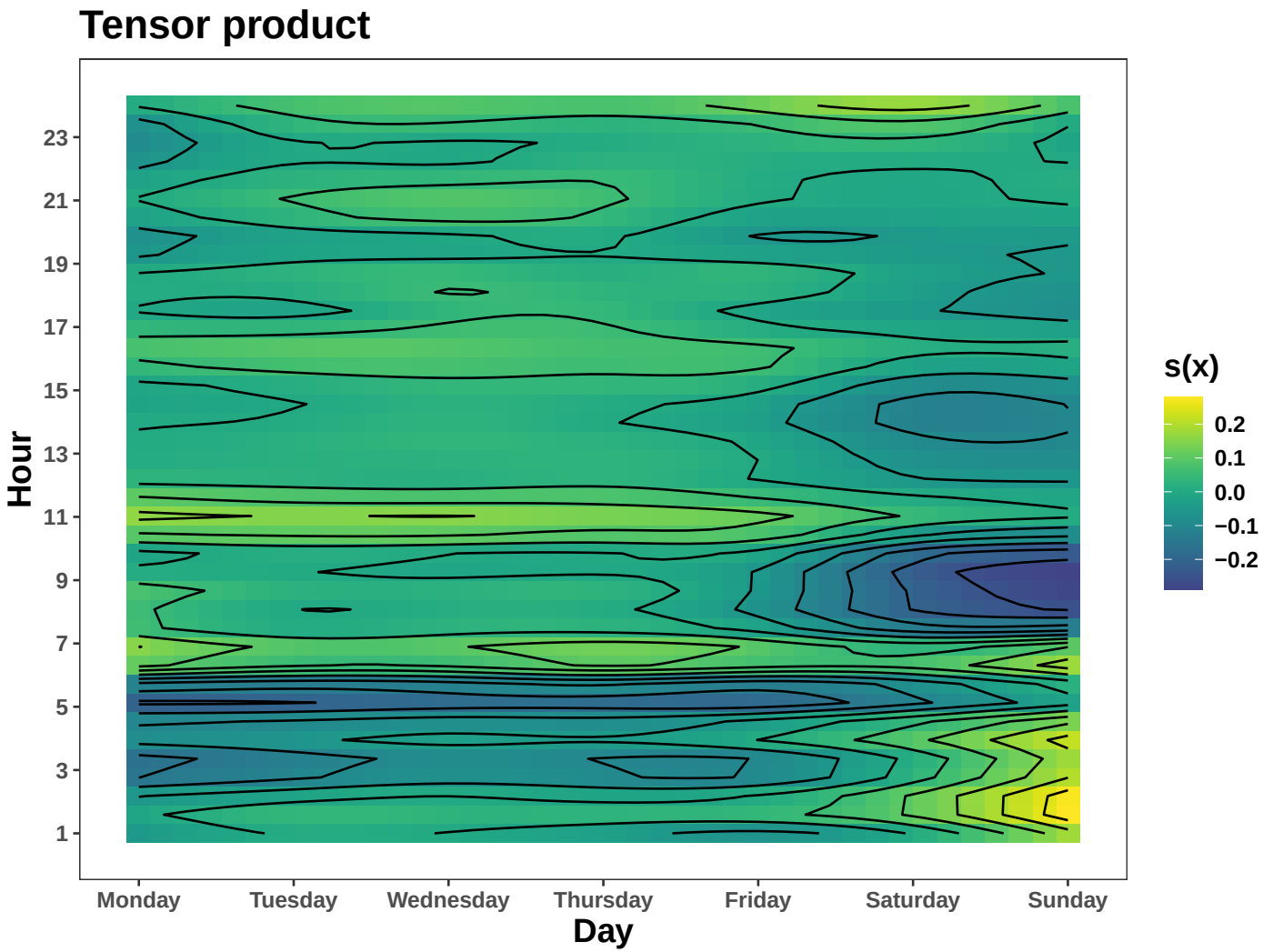


Results

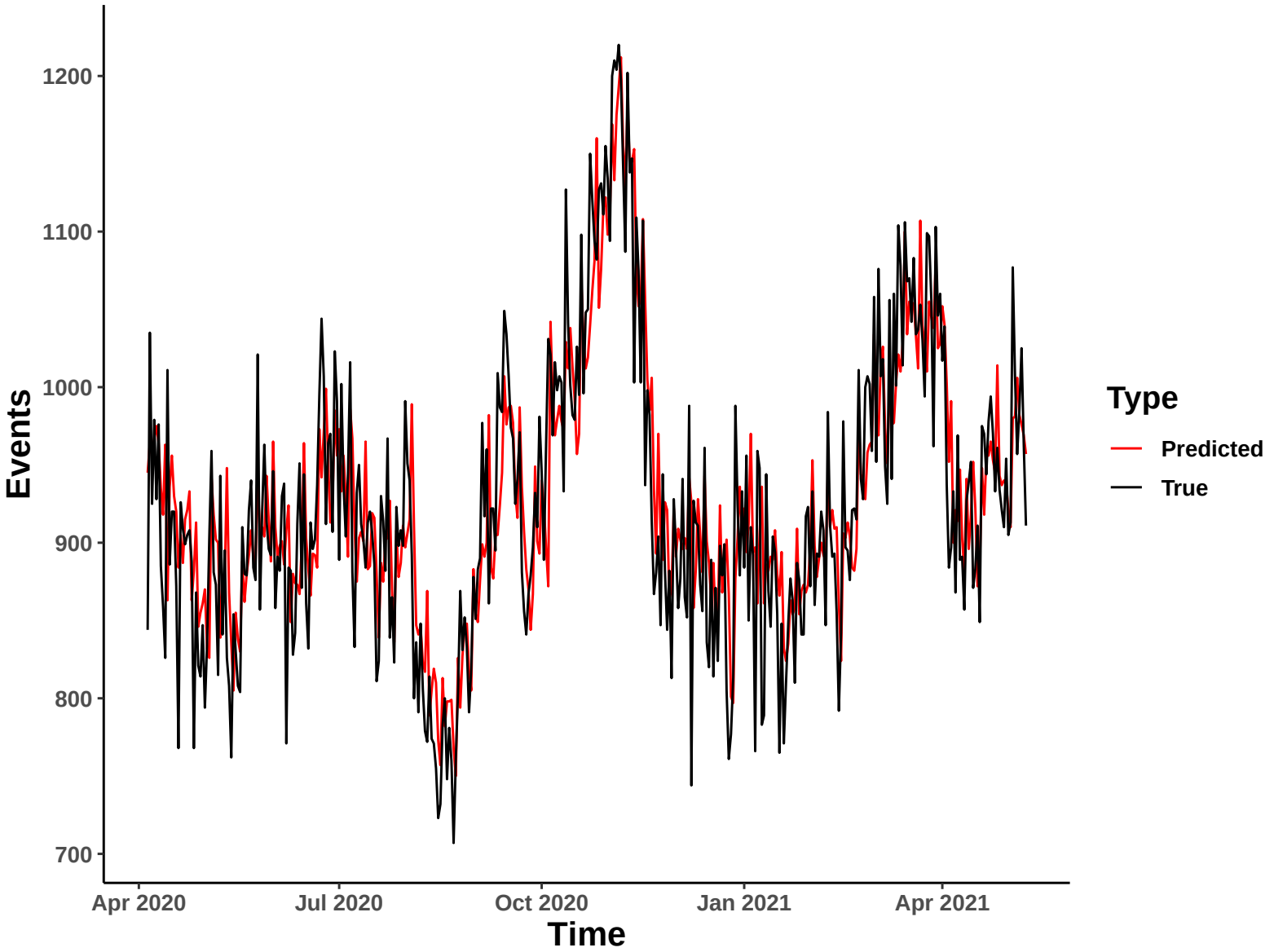

Effect
0.04
0.00
−0.04
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day

Results

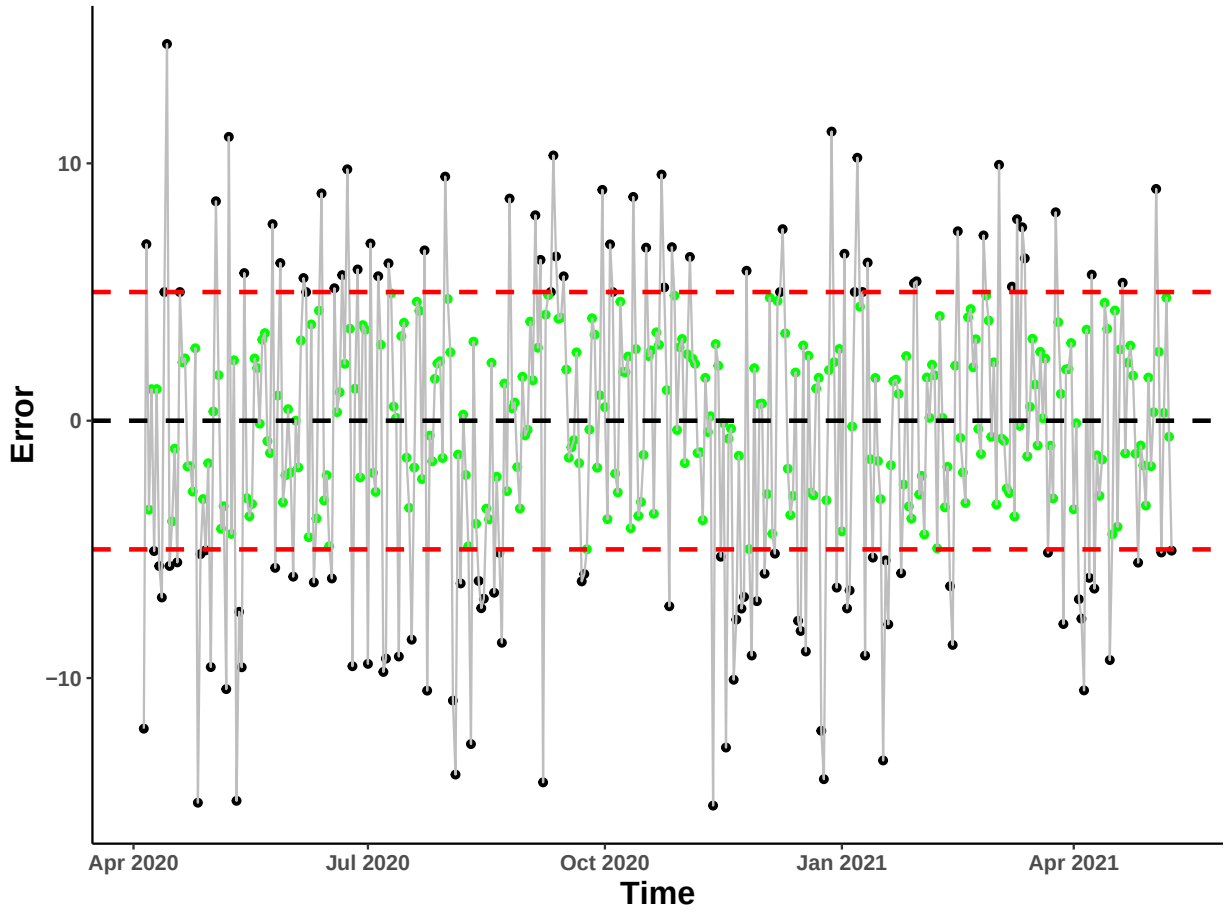



Tensor product
Hour
23
21
19
17
15
13
11
9
7
5
3
1
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day
s(x)
0.2
0.1
0.0
−0.1
−0.2

Results - One Day Ahead

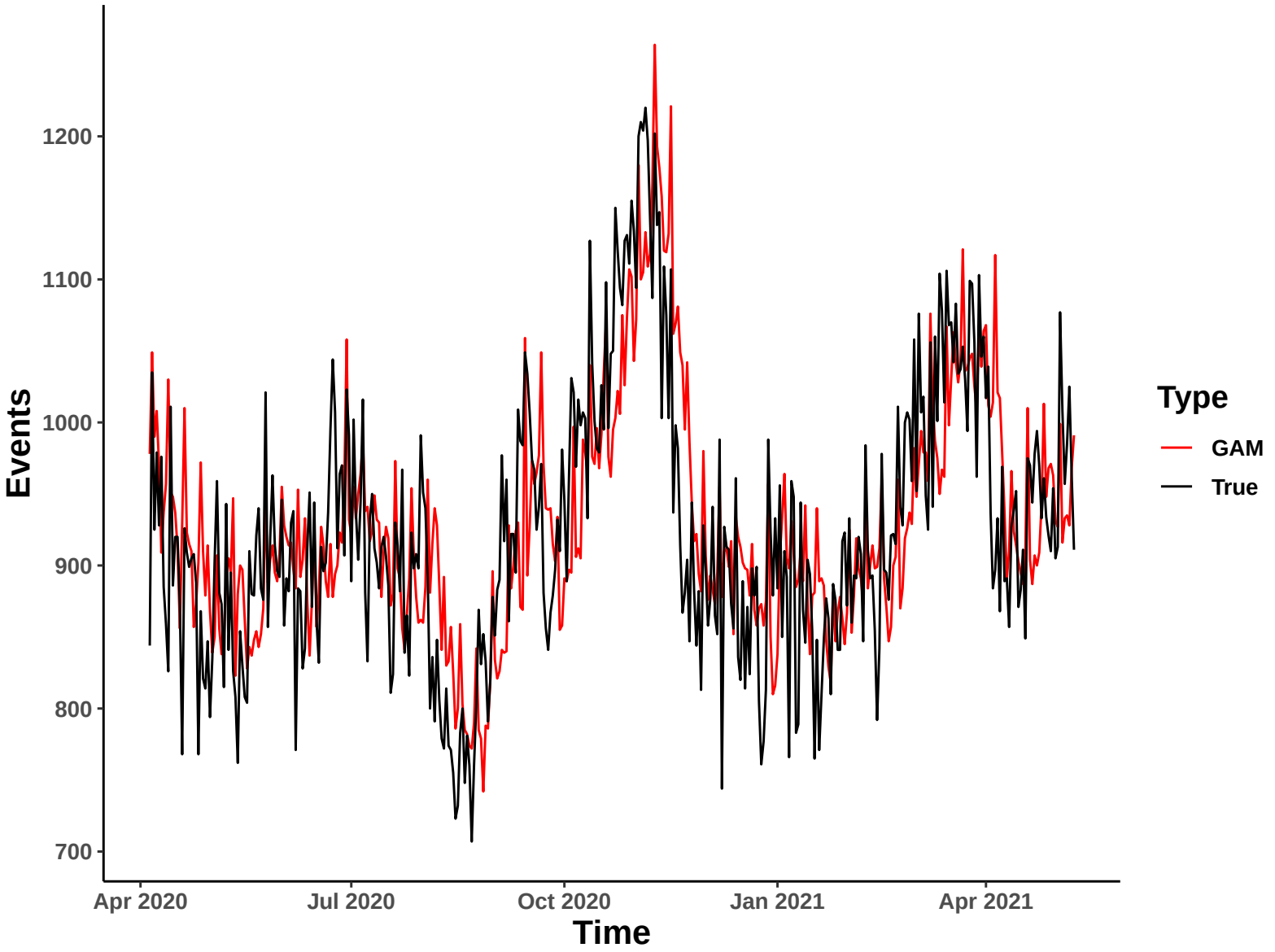


Results - One Day Ahead

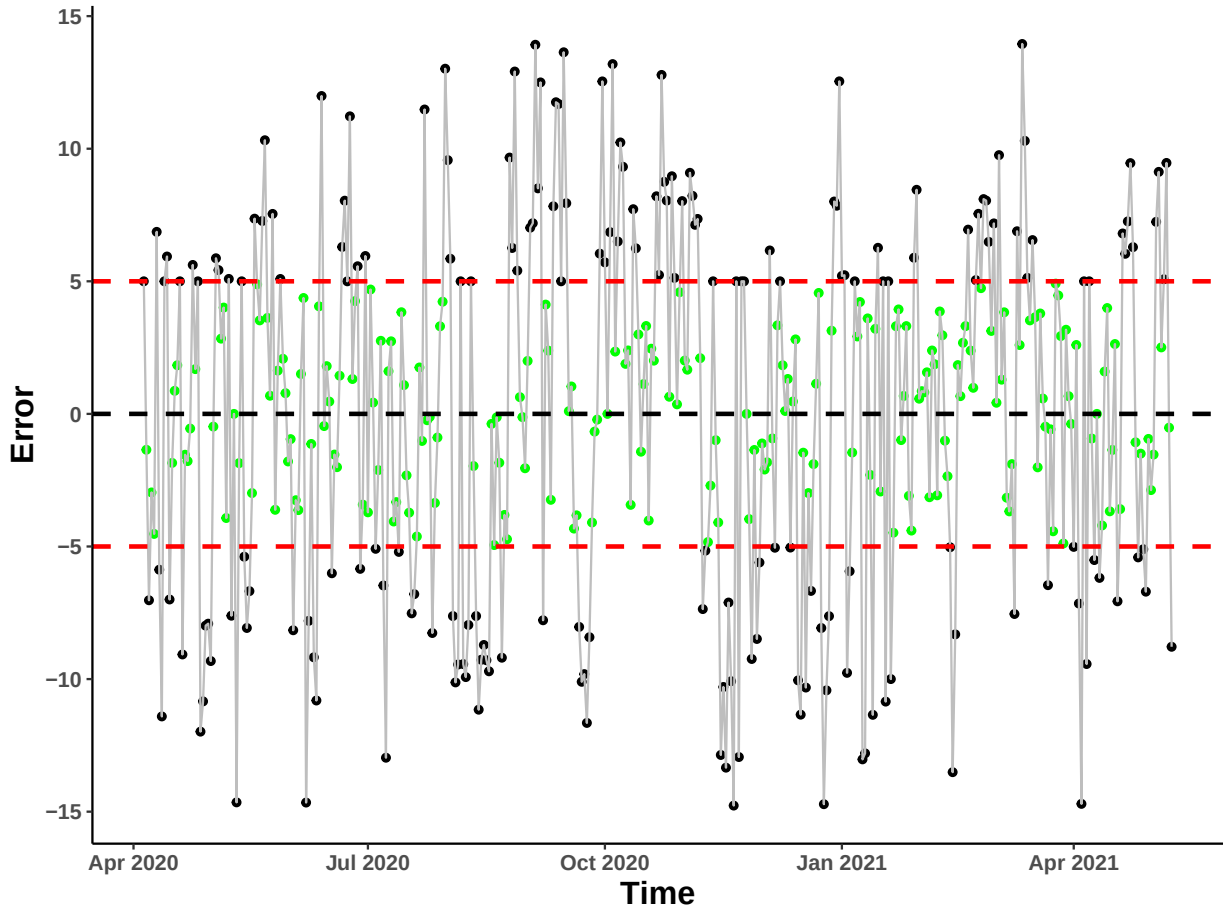


- 87% of predictions has absolute error below 5%;
- Mean absolute error equals 4.41.

Results - Five Days Ahead



Results - Five Days Ahead



- 55% of predictions has absolute error below 5%;
- Mean absolute error equals 5.24.

- We proposed a valuable model to predict number of events occured in **Metropolitan**;
- capturing the **daily** and **seasonal** variation and incorporating **epidemiological** aspects as well as **weather** information.

Also, the model works well also for predicting the number of events for the other regions:

- **Plan** → mean absolute errors equals 4.13;
- **Lakes** → mean absolute errors equals 5.9;
- **Alps** → mean absolute errors equals 6.47.