Adaptive Bayesian learning and forecasting of epidemic evolution — Data analysis of the COVID-19 outbreak — COVID-19 Impact on Global Maritime Traffic

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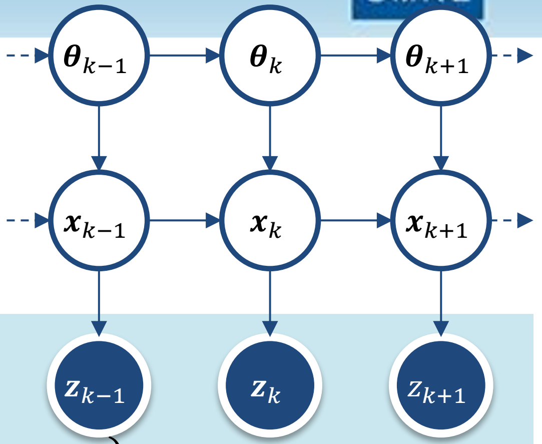
Adaptive Bayesian learning and forecasting



Motivation

- Need for mathematical models to **predict the evolution of the spread of infectious diseases** in support of decision and policy making
- **Deterministic compartmental models**
  - Suffer from **noisy observation**
  - Time-invariant model parameters
    - Need segmentation parameter fitting
- **Stochastic compartmental models**
  - Account for **noisy observations**
  - Time-invariant model parameters
    - Infection rate β; recovery rate γ
  - Metapopulation
- **Idea**: **Bayesian learning and forecasting** technique from epidemic data with **time-varying parameters**

Bayesian sequential estimation

- Dynamic model

$$\boldsymbol{x}_k = \boldsymbol{f}(\boldsymbol{\theta}_k, \boldsymbol{\theta}_{k-1}, \boldsymbol{x}_{k-1}; \boldsymbol{u}_k)$$

- Observation model

$$\boldsymbol{z}_k = \boldsymbol{h}(\boldsymbol{x}_k, \boldsymbol{\theta}_k; \boldsymbol{v}_k)$$

- Assumption: The joint evolution of $\boldsymbol{x}_k$ and $\boldsymbol{\theta}_k$ follows a **first-order Markov model**

$$\mathcal{P}(\boldsymbol{x}_k, \boldsymbol{\theta}_k | \boldsymbol{x}_{k-1}, \boldsymbol{\theta}_{k-1}, \dots, \boldsymbol{x}_1, \boldsymbol{\theta}_1) = \mathcal{P}(\boldsymbol{x}_k, \boldsymbol{\theta}_k | \boldsymbol{x}_{k-1}, \boldsymbol{\theta}_{k-1})$$

- **Objective**: compute the posterior pdf of the state and parameter vectors

$$\mathcal{P}(\boldsymbol{x}_k | \boldsymbol{z}_{1:k}), \qquad \mathcal{P}(\boldsymbol{\theta}_k | \boldsymbol{z}_{1:k})$$

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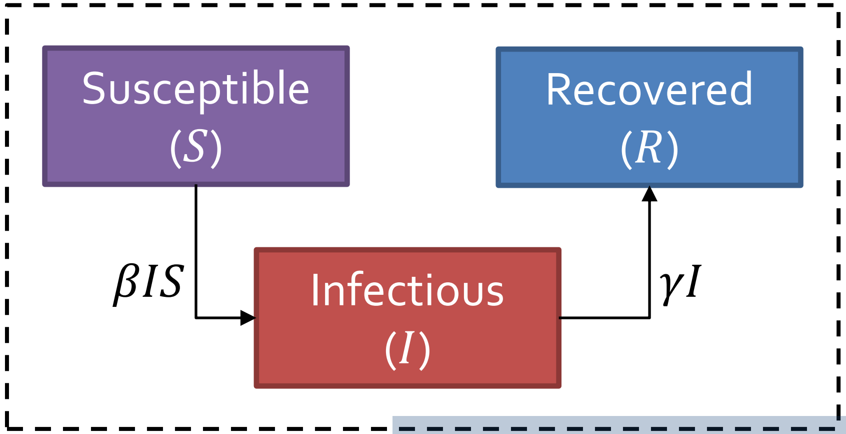
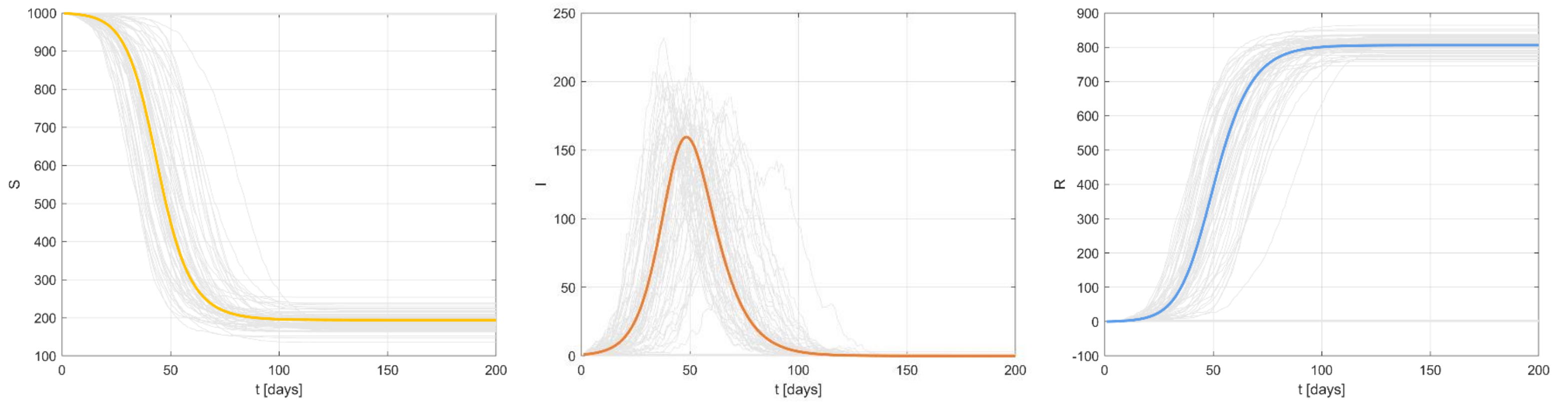
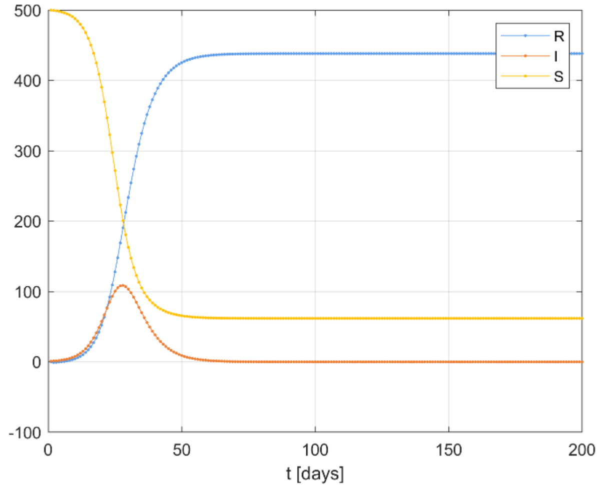
Deterministic and stochastic SIR model





$$\frac{ds}{dt} = -\beta i s$$
$$\frac{di}{dt} = \beta i s - \gamma i$$
$$r = 1 - s - i$$

$$P = S + I + R$$
$$s = {}^{S}/_{P},\ i = {}^{I}/_{P},\ r = {}^{R}/_{P}$$



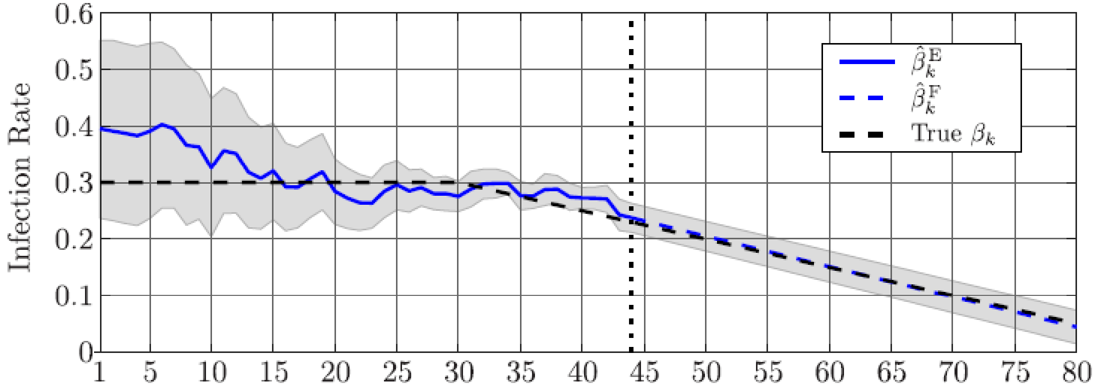
$$\frac{ds}{dt} = -\beta i s + \sigma_q \xi$$
$$\frac{dI}{dt} = \beta i s - \sigma_q \xi - \gamma i + \sigma_\beta \zeta$$
$$r = 1 - s - i$$

$$\xi, \zeta \sim \mathcal{N}(0,1)$$

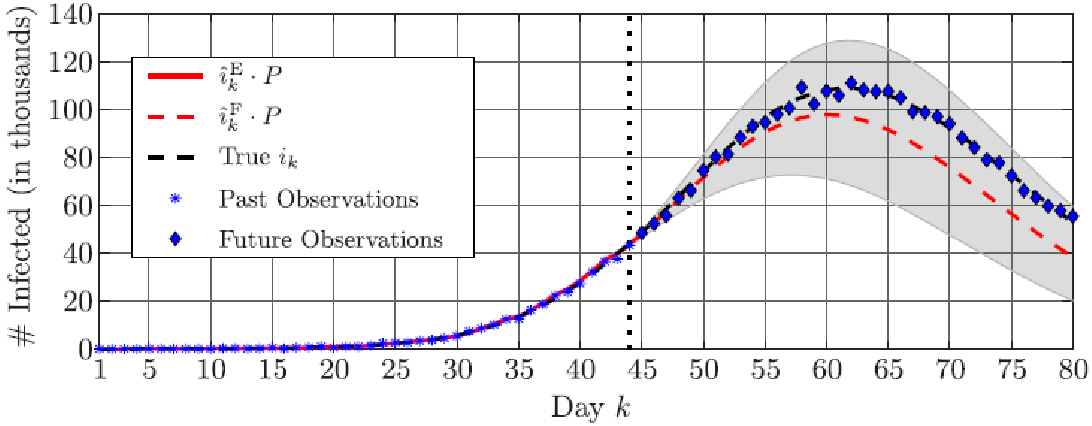
$$\sigma_q \equiv \sigma_q(s,i) \approx \sqrt{\frac{\beta i s}{P}}\,, \qquad \sigma_\beta \equiv \sigma_\beta(s,i) \approx \sqrt{\frac{\beta i}{P}}$$

Results with synthetic data – Scenario 1

Learning and forecasting of the infection rate



Learning and forecasting of the number of infected individuals



- **Dashed black line: Infection rate β_k**
- **Blue (dashed) line: estimate (forecast) of β_k**
- **Blue stars: actual number of infected persons**
- **Red line: Estimated number of infected persons**
- **Blue diamonds: actual number of infected persons used for comparison**
- **Predicted number of infected persons in red with 90% confidence area**

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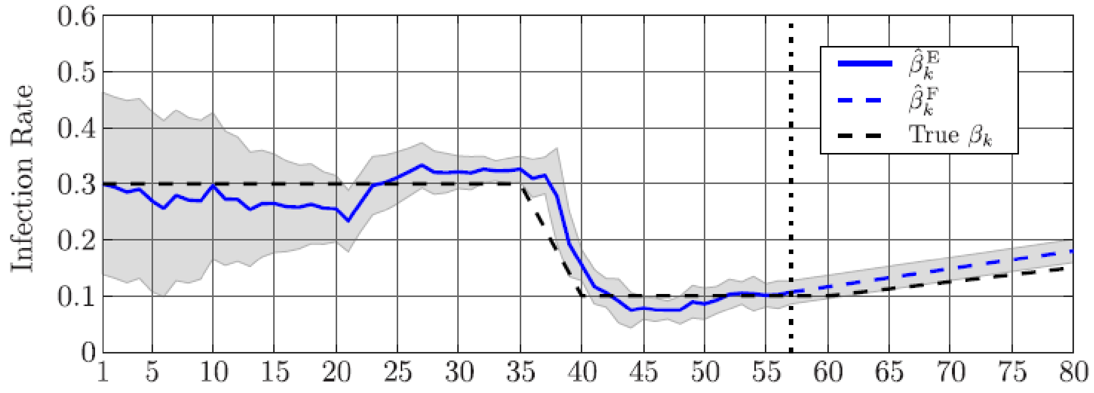
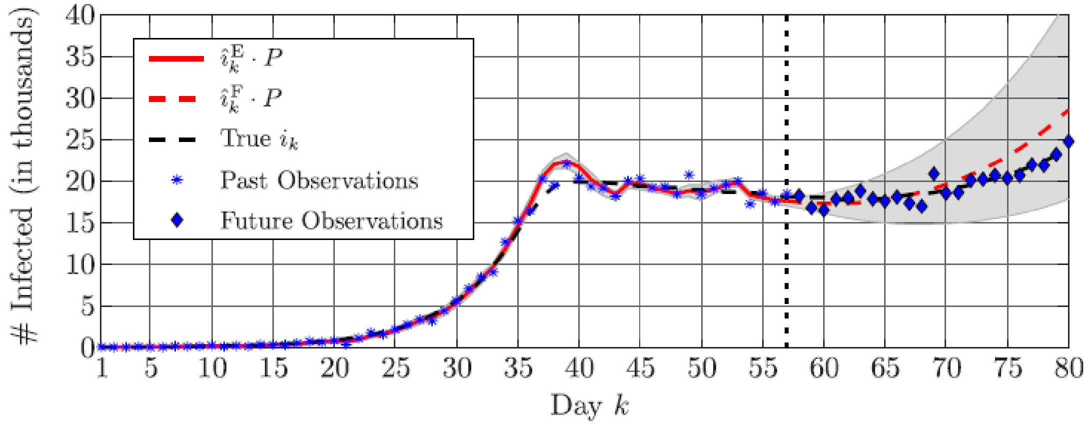
Results with synthetic data – Scenario 2

Learning and forecasting of the infection rate



Learning and forecasting of the number of infected individuals



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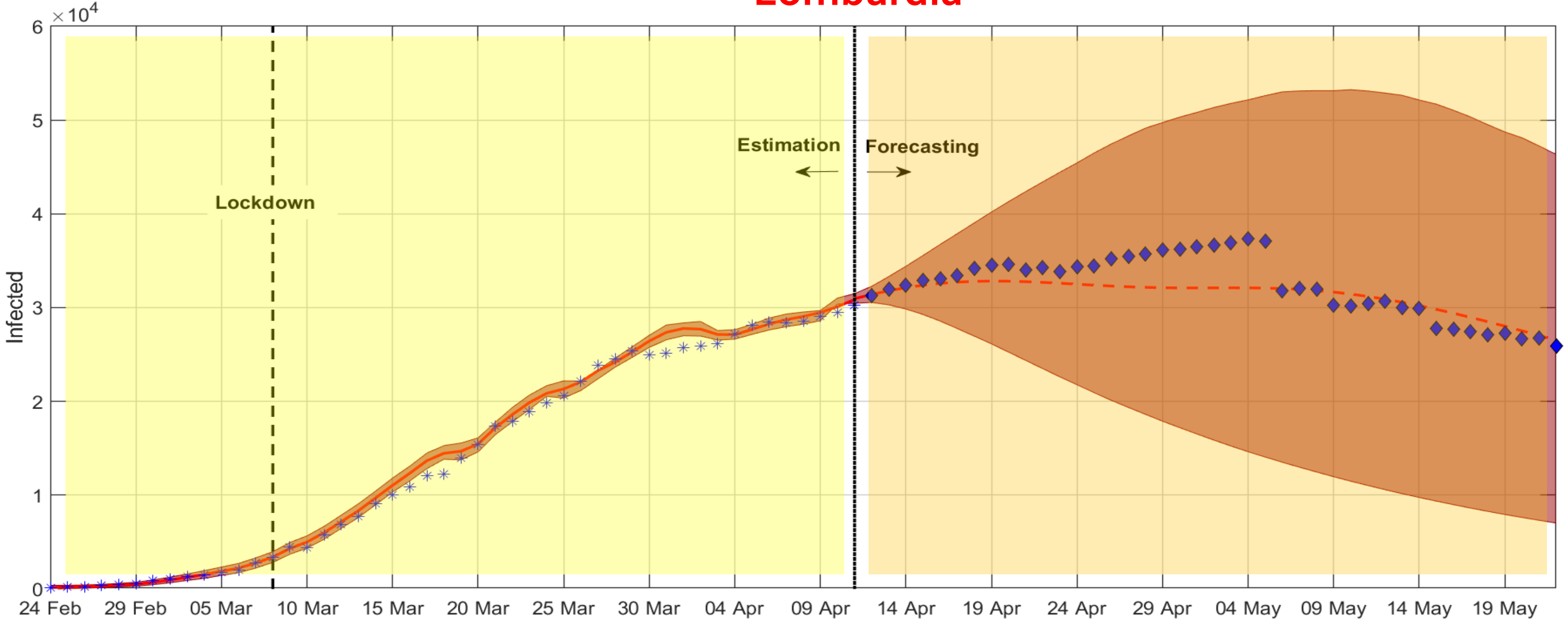
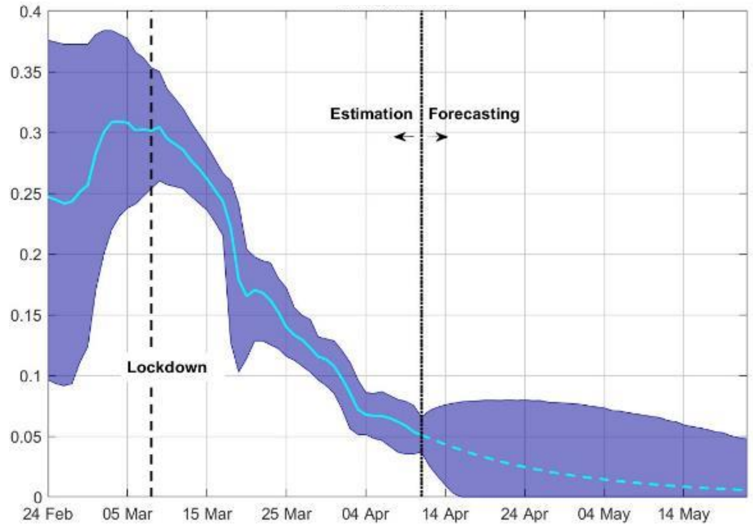
Results with official COVID-19 data (1)

Lombardia



Learning and forecasting of the infection rate



- Blue stars: actual number of infected persons, data from the Italian CPD, used for learning
- Red line: Estimated number of infected persons

- Blue diamonds: actual number of infected persons; data from the Italian CPD, used for comparison
- Predicted number of infected persons in red with 90% confidence area (last observation: April 10)

Key aspect:
Infection rate is time-varying

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Results with official COVID-19 data (2)

Mean absolute percentage errors (MAPEs)

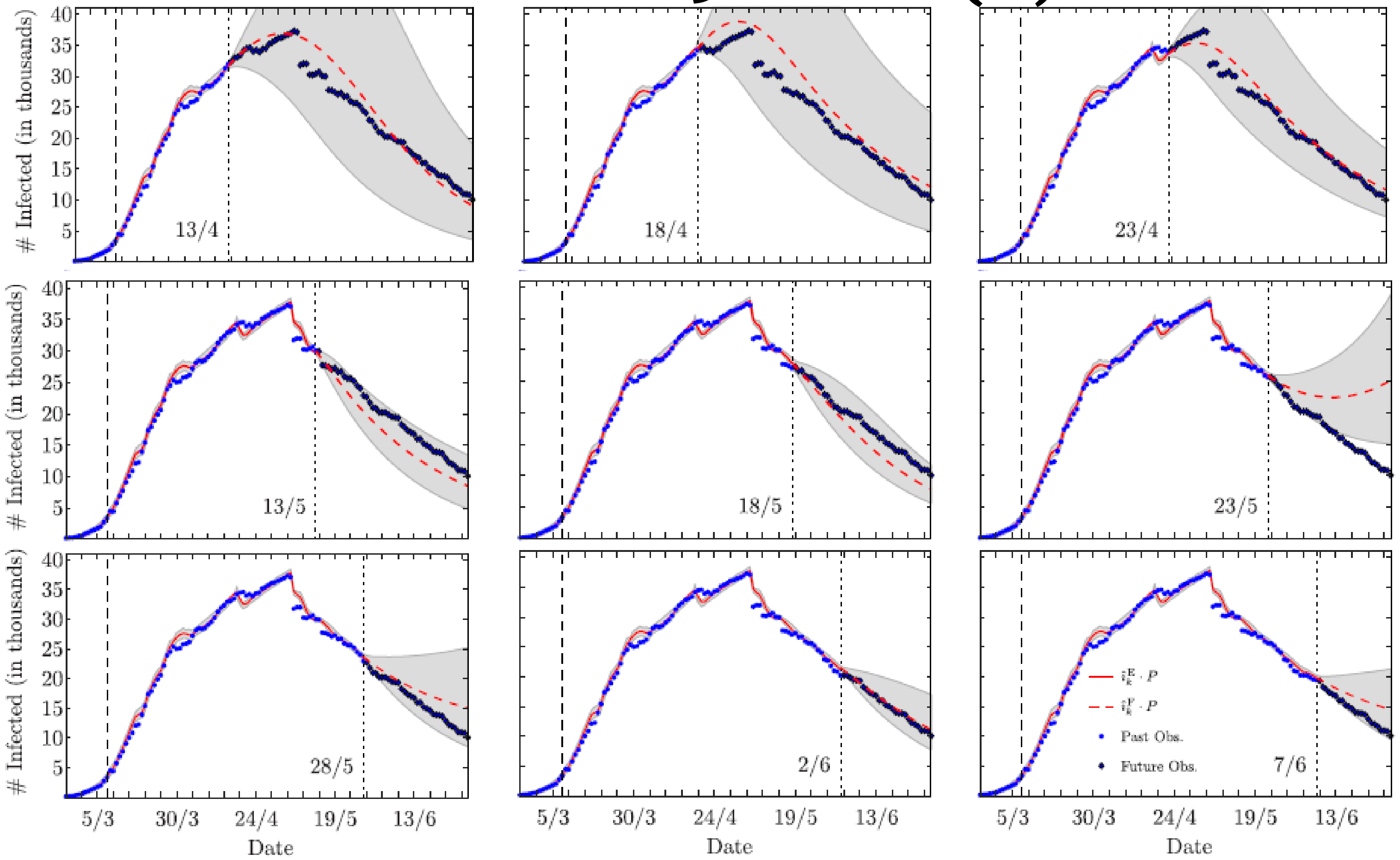
Algorithm	3 Days (%)	7 Days (%)	14 Days (%)
Proposed	6.2	10.4	23.5
SIR-fit	77.5	115.3	225.8
GSEIR-fit	10.3	13.0	18.5

Average over the interval from March 4 to June 16

Algorithm	3 Days (%)	7 Days (%)	14 Days (%)
Proposed	3.3	4.9	9.4
SIR-fit	88.2	123.0	213.2
GSEIR-fit	11.6	13.6	16.8

Average over the interval from April 1 to June 16

Forecast Date	3 Days (%)	7 Days (%)	14 Days (%)
April 13	0.54	0.50	2.49
April 18	3.47	6.48	6.84
April 23	1.25	1.91	3.88*
April 28	0.42	1.07	14.91*
May 3	8.02*	18.44*	30.07*
May 8	9.14	7.47	6.31
May 13	2.30	2.59	6.48
May 18	0.92	2.24	3.29
May 23	0.69	3.78	9.02
May 28	4.67	5.10	4.99
June 2	2.70	1.87	1.93
June 7	4.02	6.61	10.76
Average	2.74	3.60	5.79



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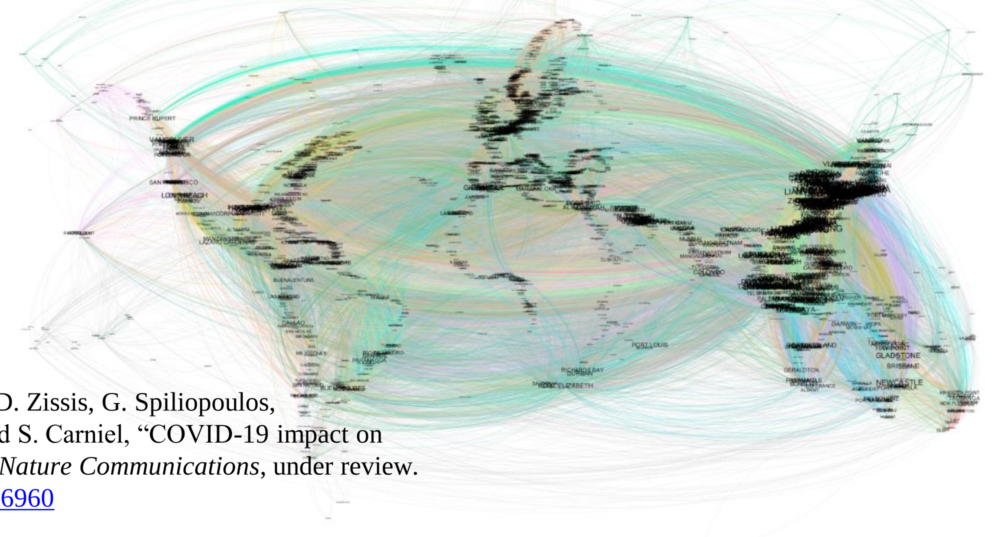
COVID-19 impact on global maritime traffic (1)



L. M. Millefiori, P. Braca, D. Zissis, G. Spiliopoulos, S. Marano, P. K. Willett and S. Carniel, "COVID-19 impact on global maritime mobility," *Nature Communications*, under review. https://arxiv.org/pdf/2009.06960

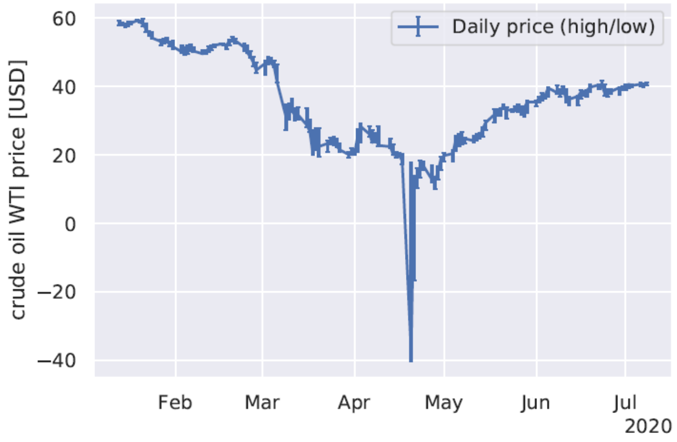
Motivation

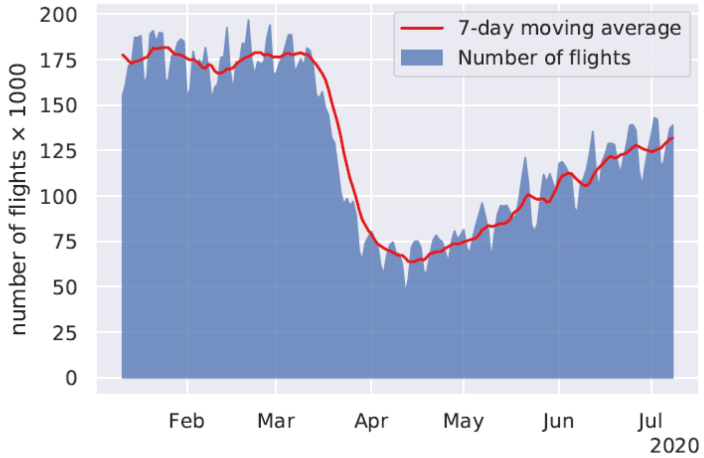
- To prevent the outbreak of COVID-19, many countries all around the world went into **full lockdown** in the first half of 2020
- **Unprecedented containment measures**
  - Produced changes to all aspect of social life
  - Dramatically **changed mobility patterns**
- **Shipping industry** accounts alone for more than **80% of world trade**
  - **Reduced ship mobility** could imply **reduced goods mobility** on the global scale
- Need to **assess qualitatively and quantitatively** the **impact of lockdowns** on global shipping mobility

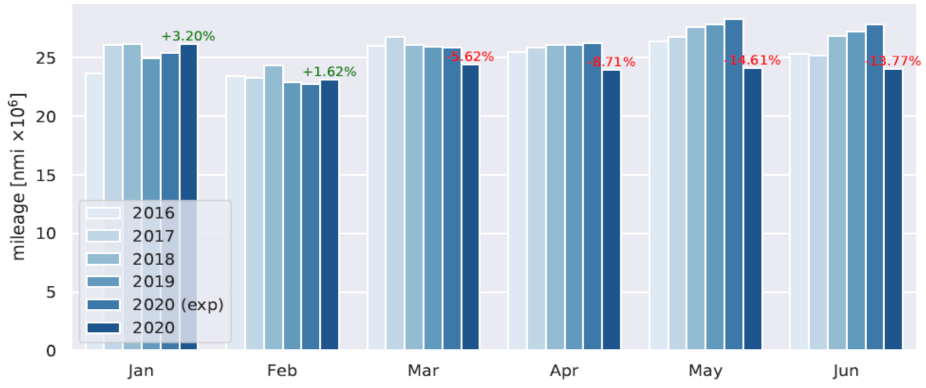
Proposed approach

- Data-driven computation of a **ship mobility index** from AIS
  - **Cumulative navigated miles (CNM)**
    - Captures changes in average speed and activity
- Analysis based on a very large dataset of AIS messages (data from ~50000 ships, approx. the size of world's merchant fleet)

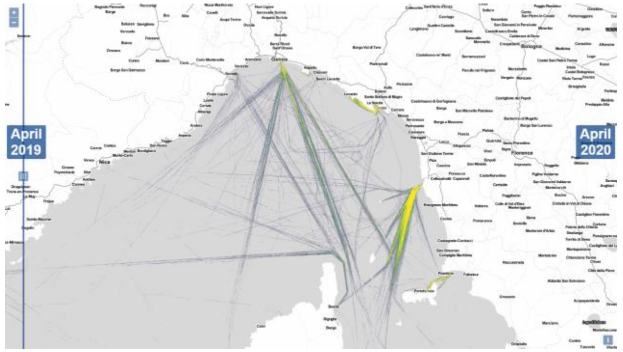
COVID-19 impact on global maritime traffic (2)

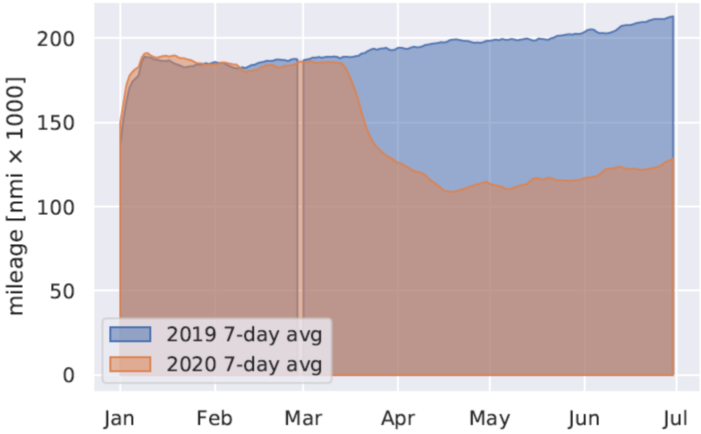


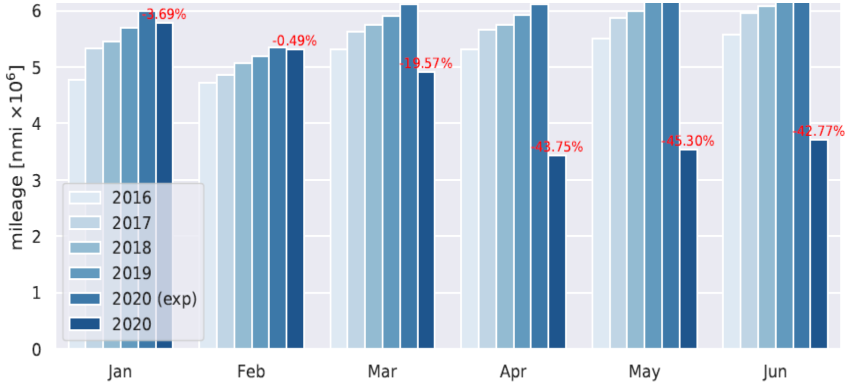




Container: monthly mileage







Passenger: monthly mileage

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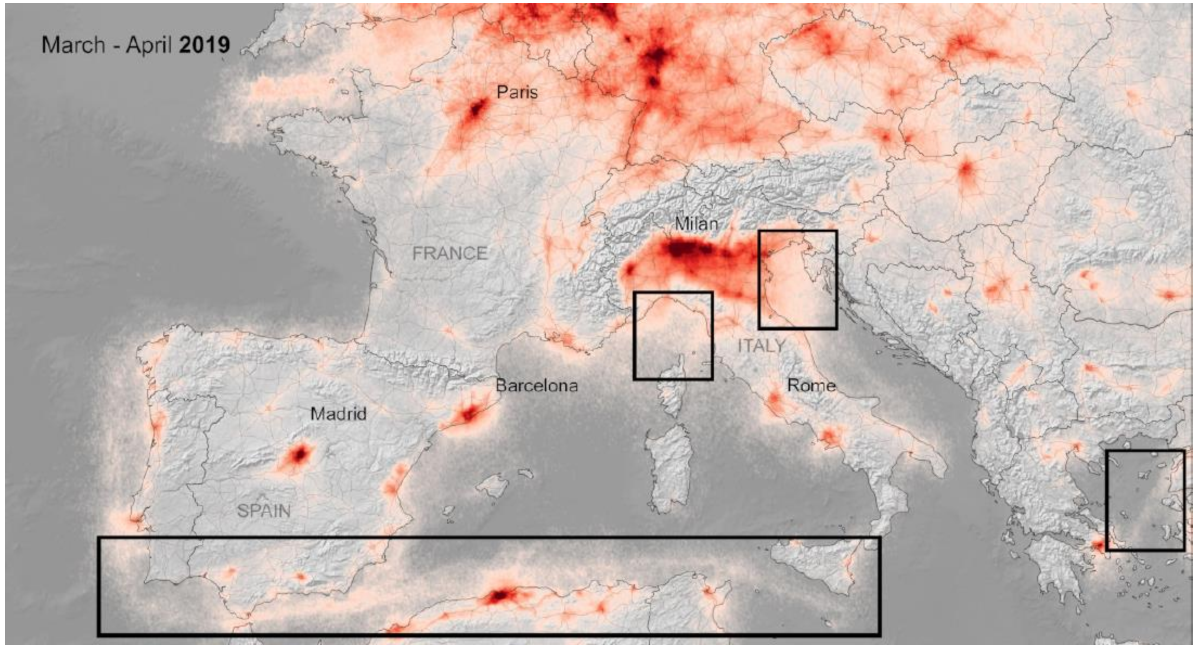
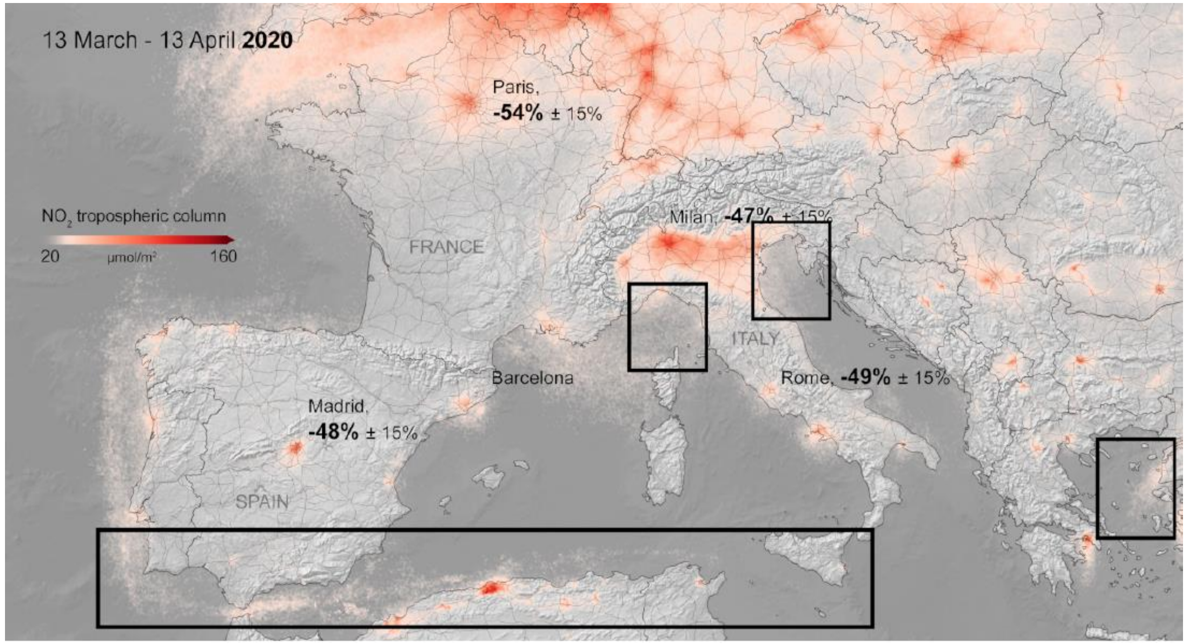
COVID-19 impact on global maritime traffic (3)
NO2 Emissions





Average nitrogen dioxide (NO2) concentrations March-April 2020, compared to the same period in 2019.

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THANK YOU

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