

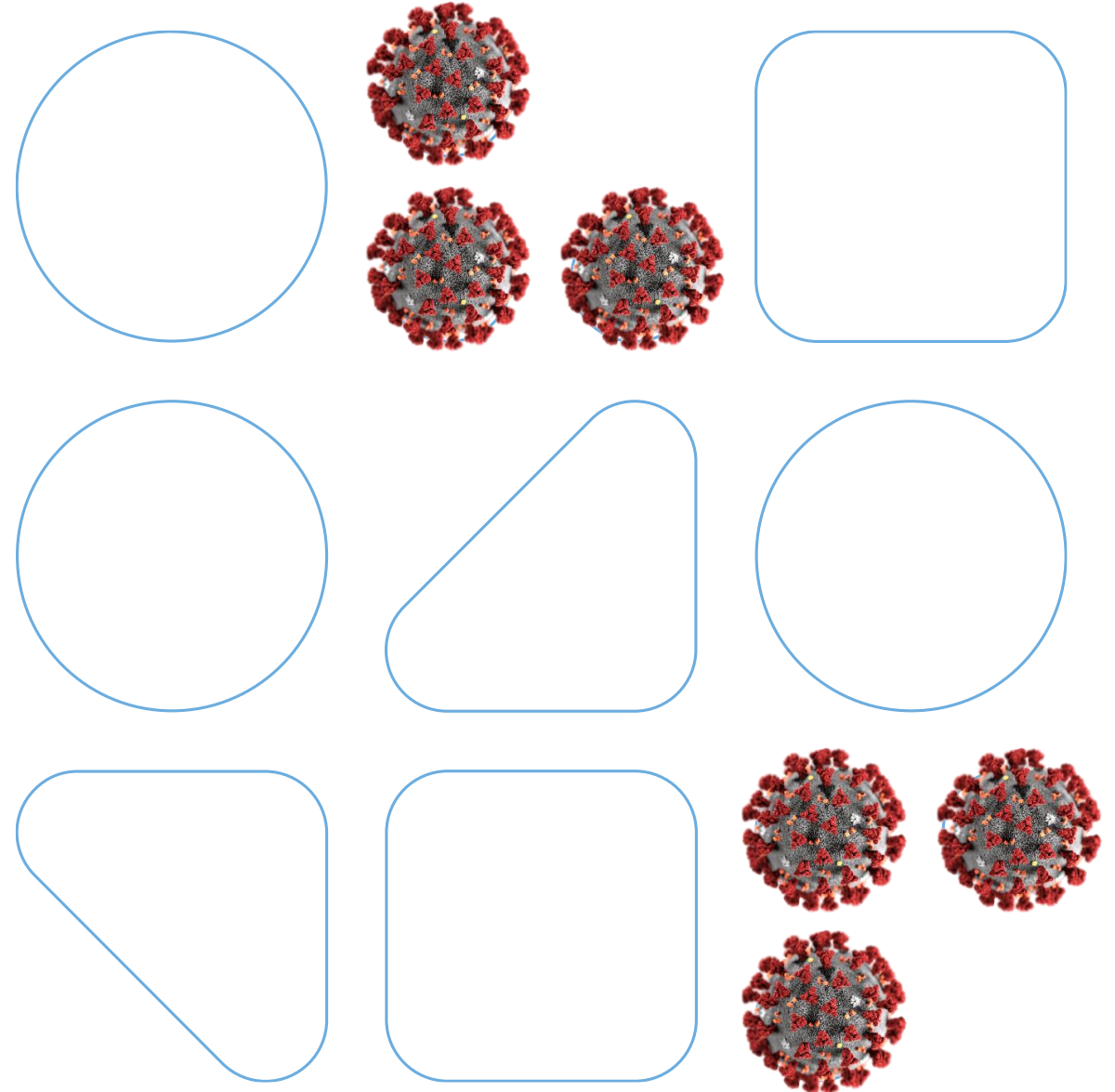
# Short term forecast of new daily pandemic hospitalizations:

A time series model for a single hospital

**Presentation by LF Heupink**

Co-authors: Espen Rostrup Nakstad, Hilde Lurås, Pål Wiik, Kristine Lippestad, Fred Espen Benth, Jūratė Šaltytė Benth

17.06.2026 | Model Invariance and Constancy in  
the Face of Large Shocks



# Few tools published to make local forecast

- Reliable hospital admission can aid contingency planning during pandemics
- Previous studies developed models for predicting new hospitalizations, but often only on regional or national level
- Models tailored to single hospitals are important as they:
  - Can use local/detailed patient data
  - Can consider heterogeneity in catchment area



COVID-19  
**ForecastHub**

- University Massachusetts Amhers
- US forecasts



**IHME**

- US and national/regional global forecasts



EuropeanCOVID-19  
**ForecastHub**

- EU National/regional forecasts



Norwegian Institute of Public Health

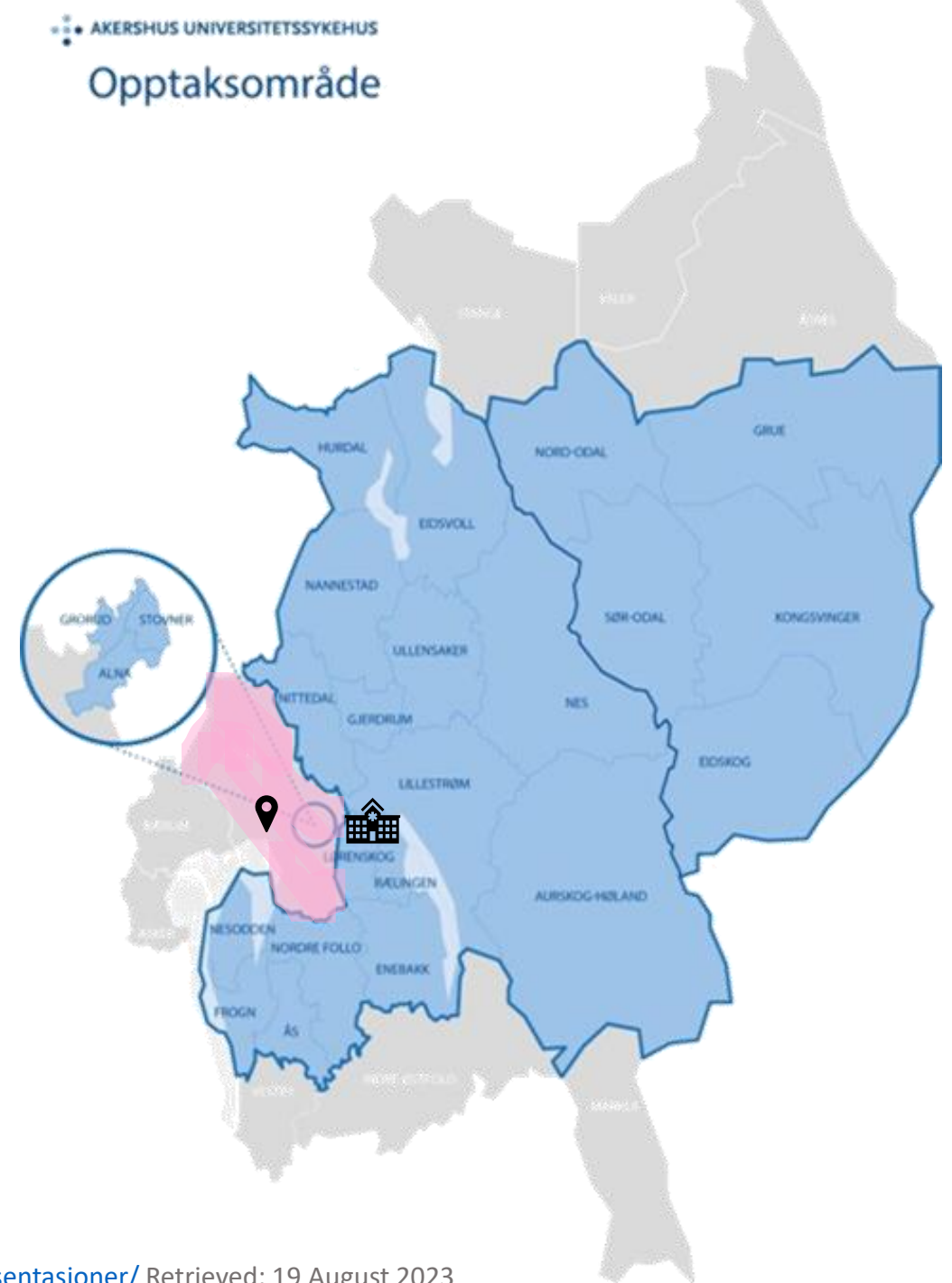
- National/regional forecasts Norway

**Aim develop a forecasting model for new daily pandemic admissions to a single hospital, accounting for heterogeneity (infection rate & demography) in the catchment area**

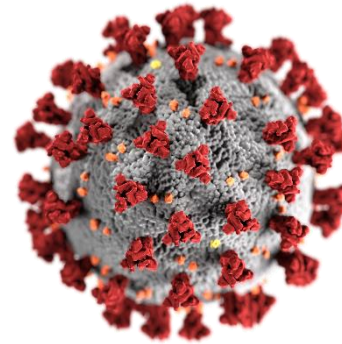
# Setting



- Case example Akershus University Hospital (Ahus)
- Population in catchment area:  $\pm 650,000$   
*approx. 10% of Norwegian population*
- Covid-19 hospitalizations: 4602  
*between 1 March 2020 - 13 November 2022*



# Data sources



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## Inputs

Inpatient hospital  
admissions

COVID-19 infections,  
positive tests

Demographic data  
Health status

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## Source

Ahus data warehouse

Oslo Municipality  
Github repository by  
NIPH

KommuneHelsen  
statisikkbank (by NIPH)

# Methods

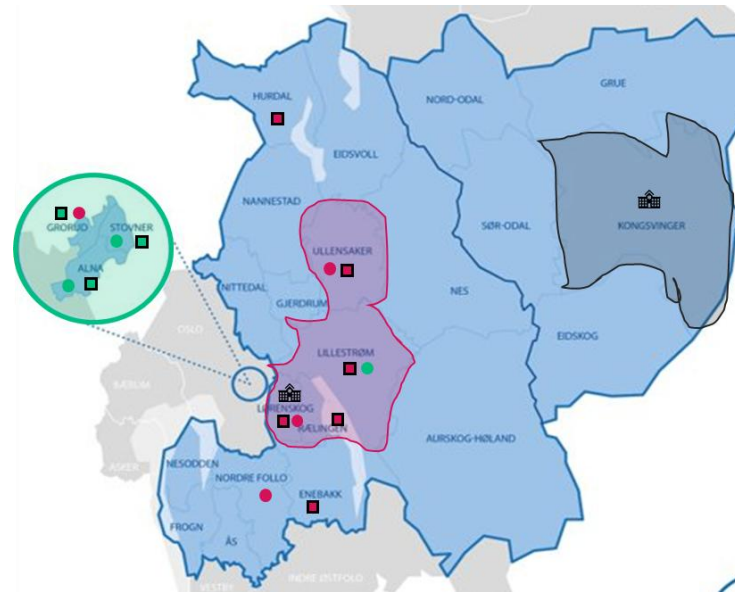
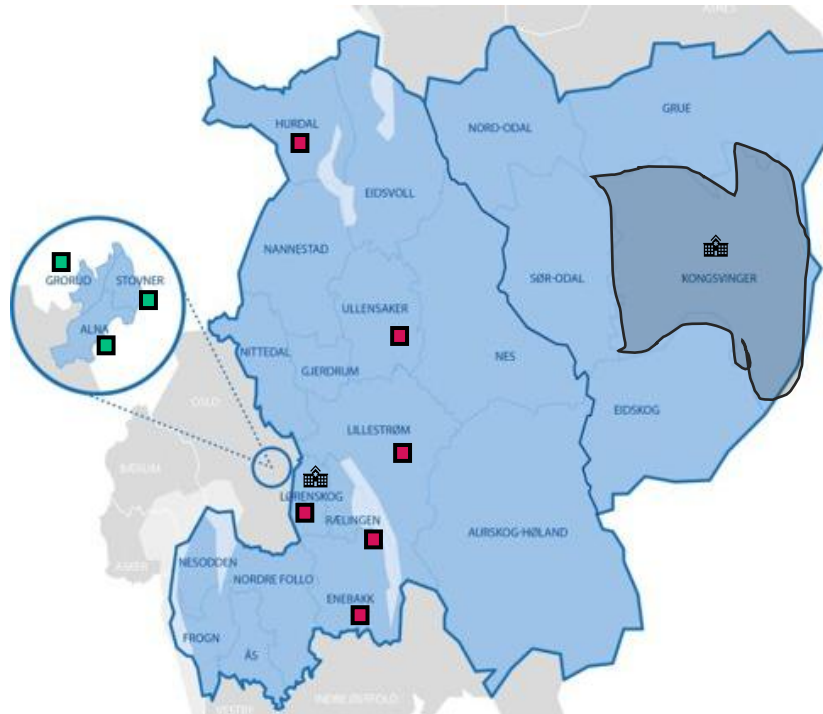
- Time series analysis
- Seven-step process to fit and build applications
- Build model using data from **Alpha wave** 22 Feb till 31 May 2021
- **Challenges**
- R-numbers > infected, as R-numbers are more sensitive to flag an increase or decrease compared to infected
- Many areas & small numbers – ethics concern
- **Solve:**
- Step 1: Estimate local R-numbers ([Šaltytė Benth et al., 2024](#))
- Step 2: Group catchment area

## Two approaches to grouping the catchment area

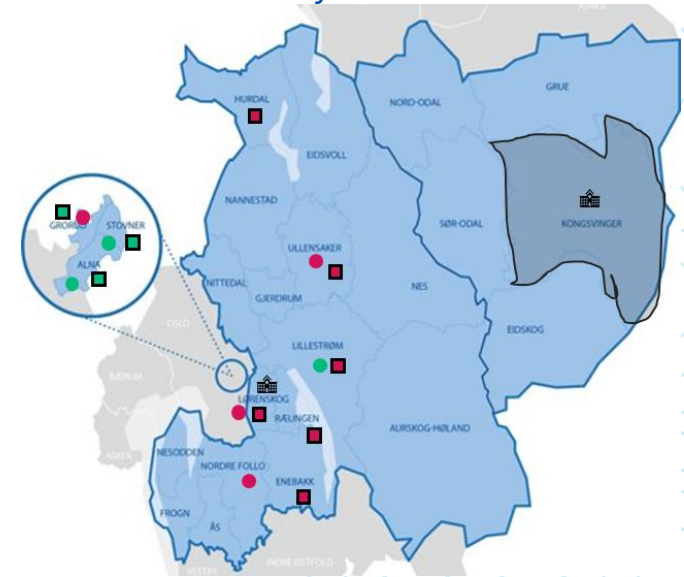
- Group based trajectory modelling of infected data
- Cluster analysis demographic data
  1. Prop. of children, 0-17 years
  2. Prop. of 80+ years
  3. Prop. Immigrant or norwegian born with immigrant parents
  4. Prop. Lives in crowded dwelling, 0-17 år
  5. Population density
  6. Prop. Overweight/obesity pregnant women
  7. Rate premature deaths (45-74 years)
  8. Cardiovascular diagnosis per 1000 (0-74 years)
  9. *Number of admitted per 1000*
  10. *Number of admitted women and men per 1000*
  11. *Number of admitted in different age groups per 1000*

# Catchment area grouped in three

- Found slight variation between grouping methods...



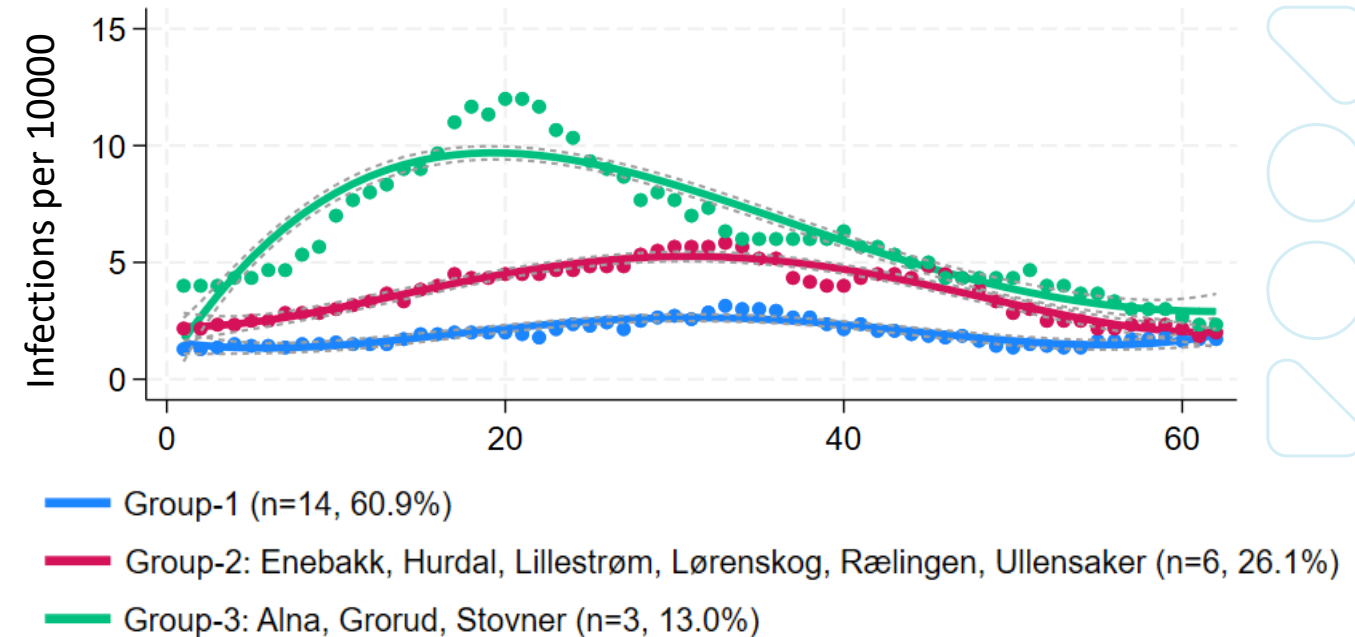
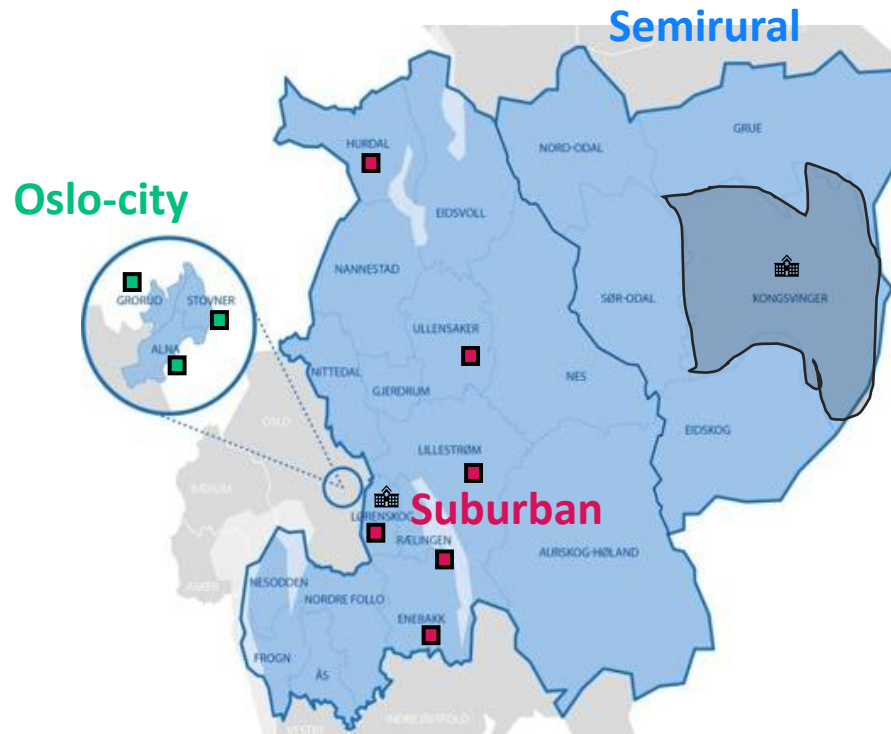
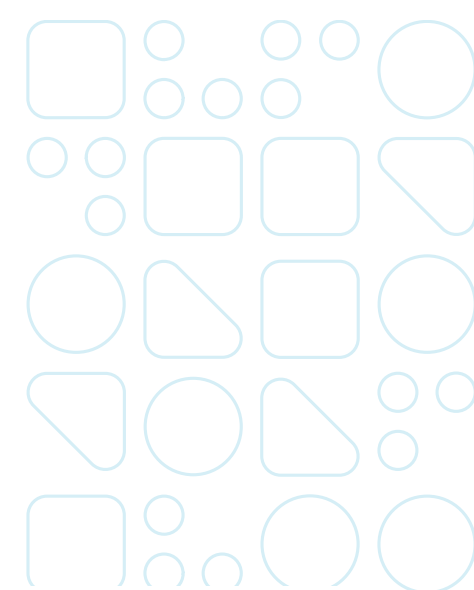
*Result cluster analysis*



*Result group based trajectory modelling infections*

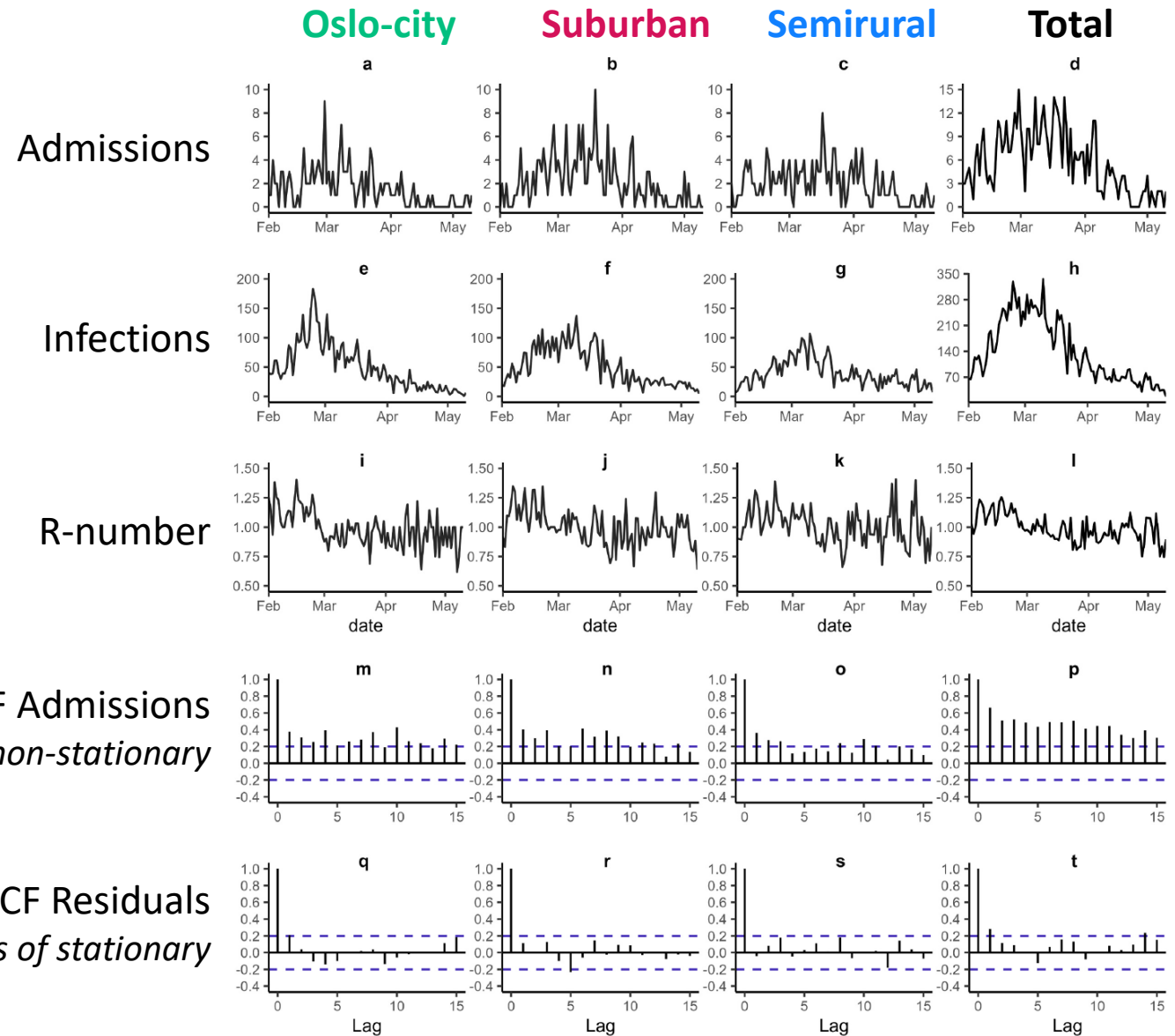
# Catchment area grouped in three

- Found slight variation between grouping methods...
- Most weight to the per 1000 grouping based on infection trends



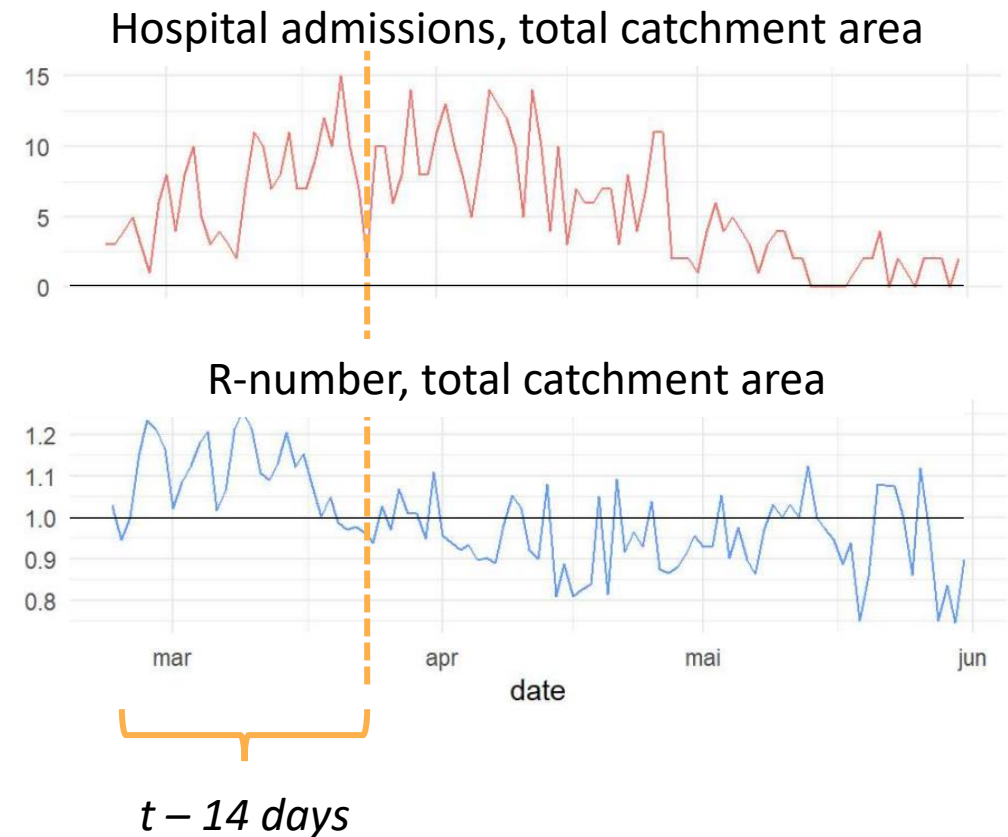
# Time serie properties

- Steps 3: **assess** non-stationarity & co-integration
- ACF of outcome: admissions
- Hospitalizations and R-number are cointegrated
- We relied more on graphical evidence than ADF-test alone



# Selection of lagged predictors

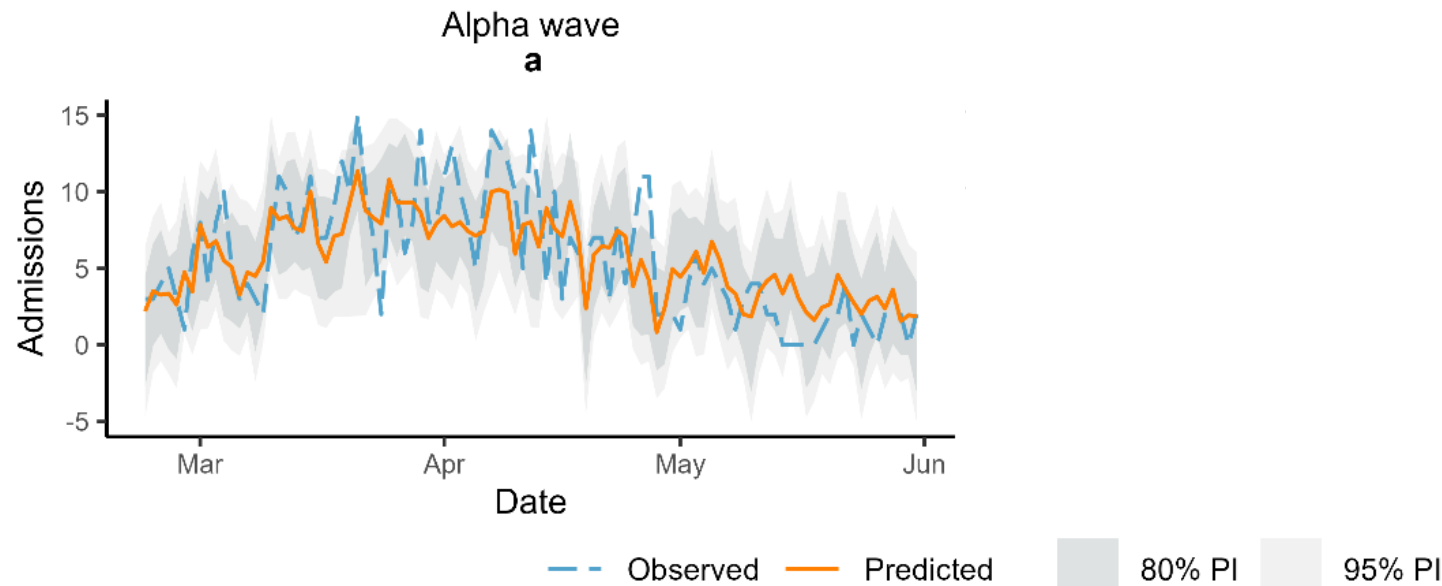
- Step 4: Use step wise process to select combination of best predictors
- First univariate linear regressions for each lag up to 14 days (AIC) for:
  - Hospitalizations
  - R-numbers
    - per sub-areas and total catchment area
- Select lowest three lags for each sub-area and total and estimate and select best multi-variate model (AIC)
  - *Reduce overfitting risk by setting a max on number of predictors*



# Selection of lagged predictors - result

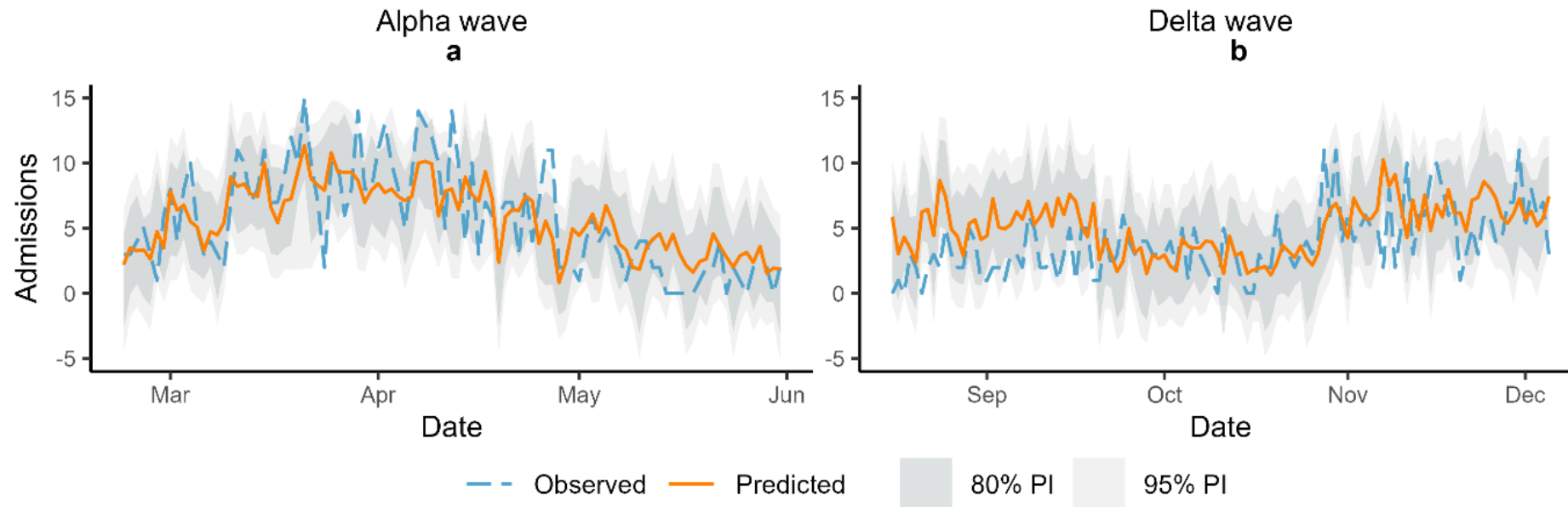
- Result for alpha wave
- Best performing model (in-sample), included:
  - Hospitalizations
  - R-numbers
  - **Hospitalizations and R-numbers**
    - **sub-areas** vs. whole catchment area

# Predictions follows observed data well...



- 1-day ahead predictions
- Sub-area model 8% increase  $R^2$  compared to whole catchment area
- *Did not see clear weekdays effects in raw time series, but fitting model showed*

# Predictions follows observed data well...

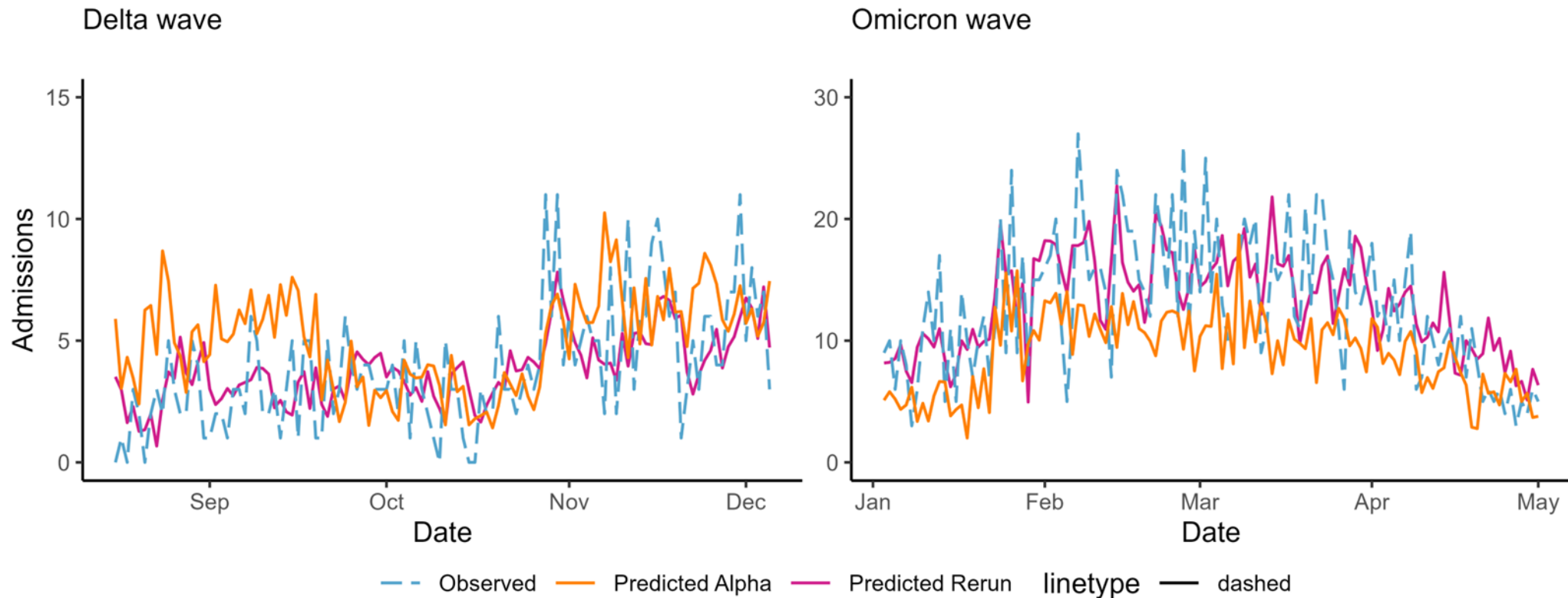


- 1-day ahead predictions
- Predictions from Alpha wave (no-respecification)

# ... but new waves requires recalibration

- **Step 6: out-of-sample validation**

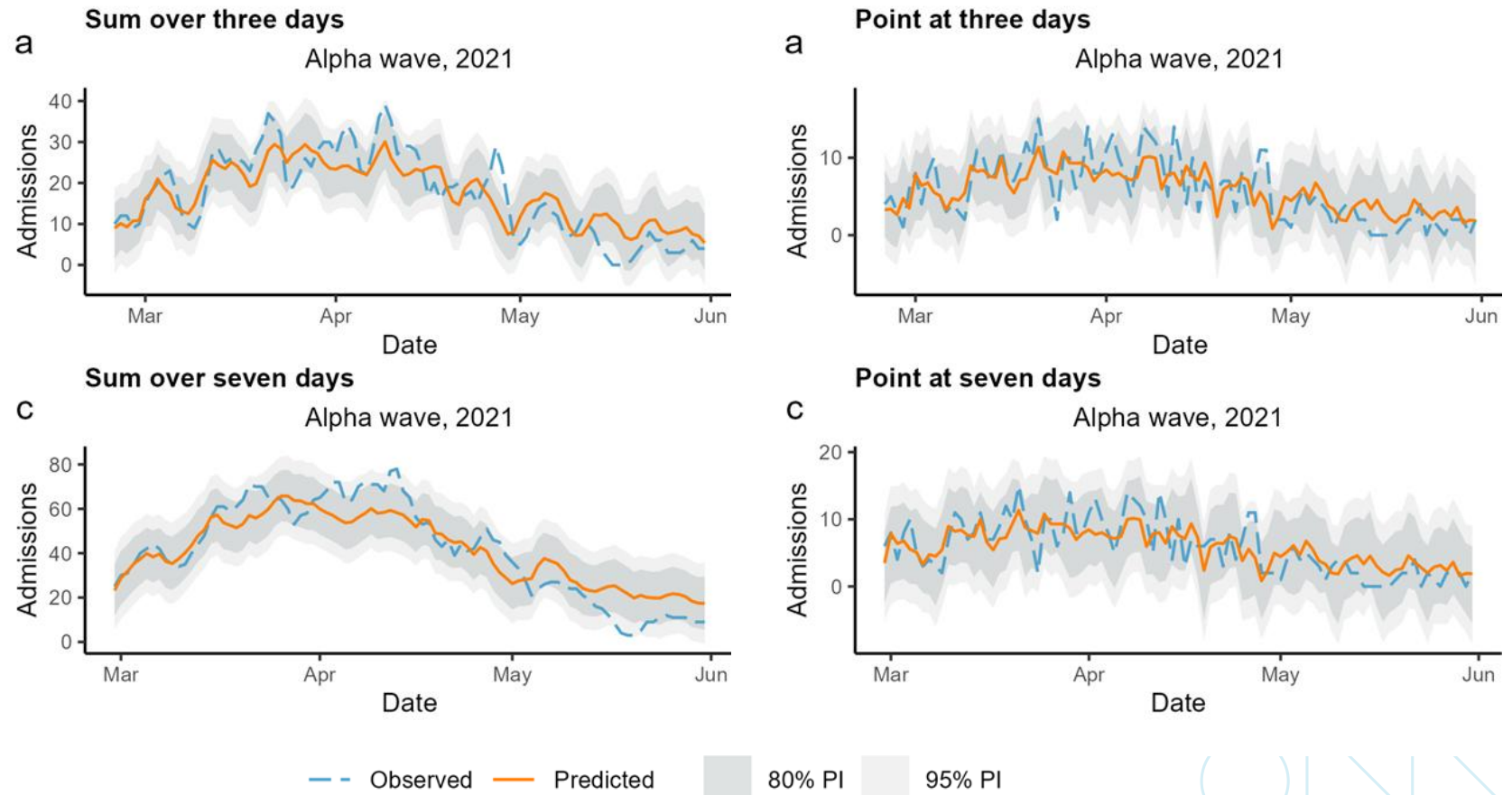
- When pandemic changes, need to update predictors
- Found that the model for total catchment area performed slightly better



# ... Applications of model predict 3- or 7-days ahead

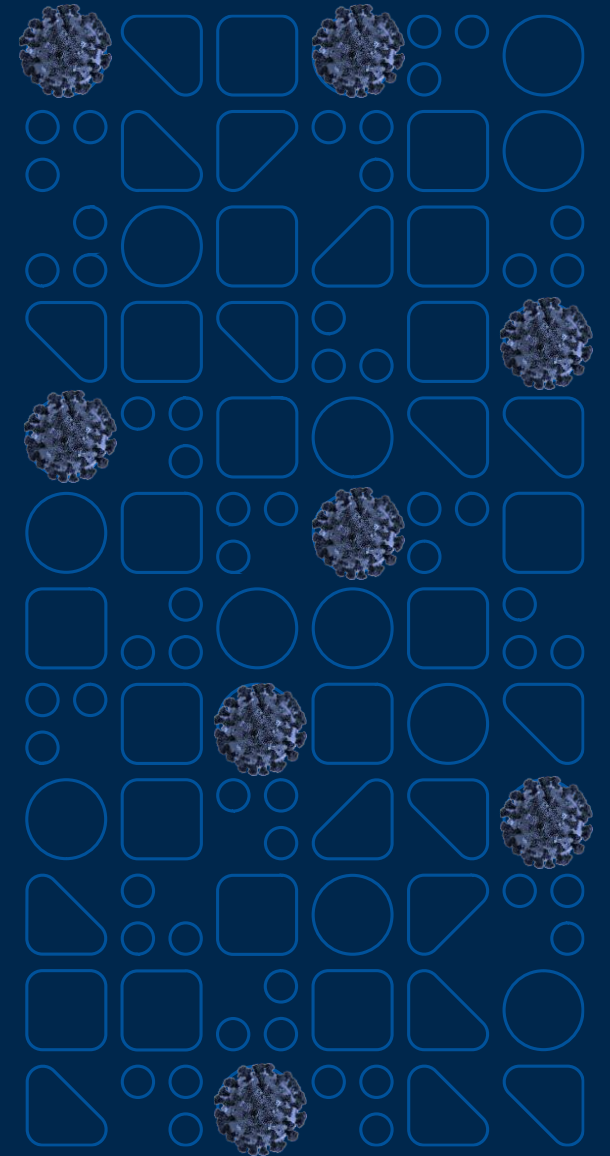
- **Step 7:**  
Hospitals need more information, so 3- and 7-day ahead

*Applications adjust for over and underestimation in prediction intervals.*



# In conclusion...

- Model works but 'small' numbers are hard to predict, 7-day forecast come with wider prediction intervals.
- Longterm nonlinear pandemic effects have limited consequences as we make short term forecast which should capture local dynamics
- Needs good data:
  - Real time data on hospitalizations
  - Infected numbers
- Future research could further develop model by testing in other regions, integrating opportunity cost, etc.



# Thank you for your attention.

# Questions?

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-  Paper: <https://doi.org/10.1016/j.epidem.2026.100894>



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