

# Spatial modelling of viral loads in wastewater: an evaluation of sampling strategies for comprehensive surveillance programs

James D Munday, Julien Riou,  
Moritz Wagner, Tim Julien, Christoph Ort, Tanja Stadler

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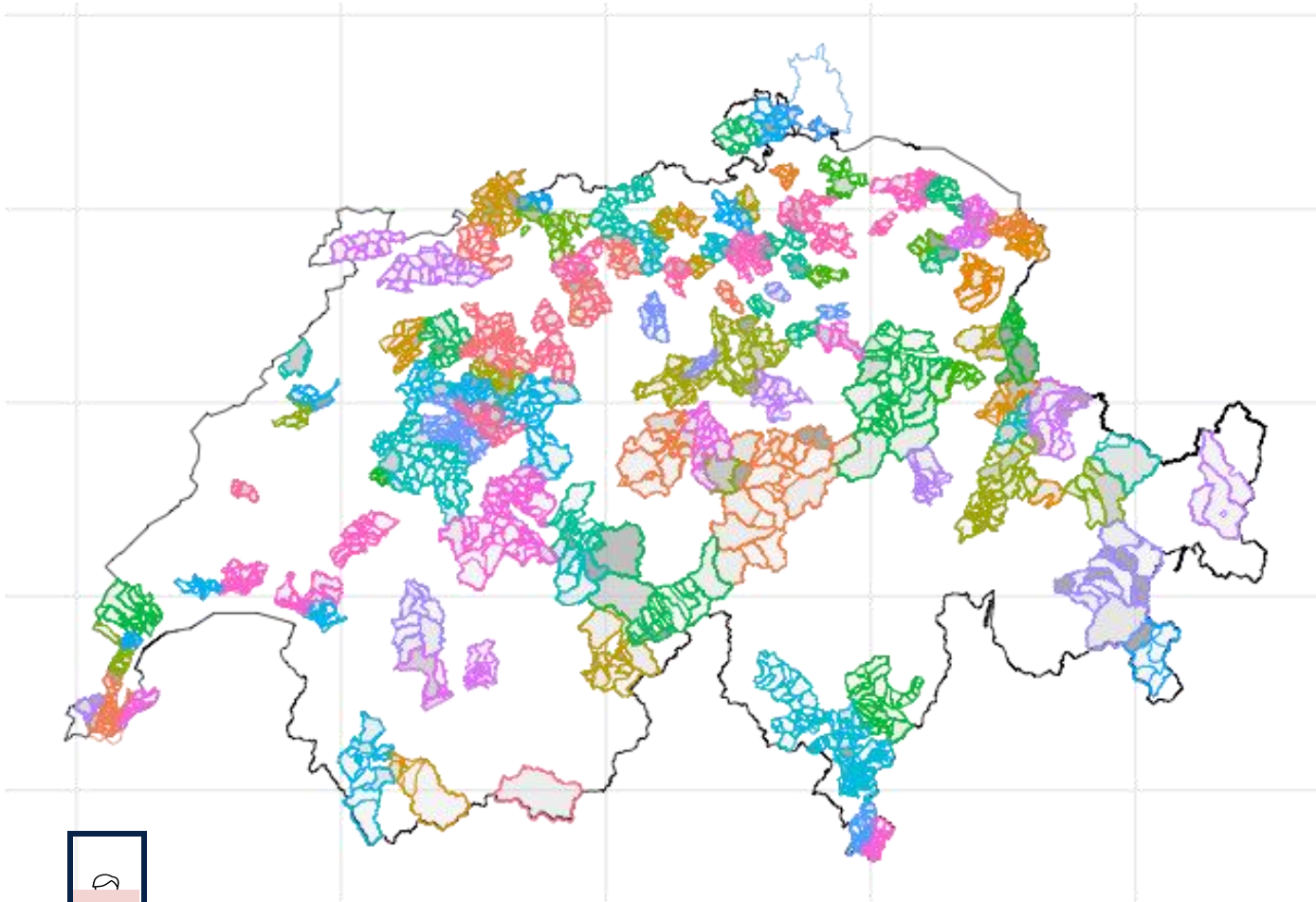
# Overview

1. Wastewater (WW) based pathogen monitoring in Switzerland
2. How might we choose a more sustainable sampling strategy?
  - a) Administrative regions
  - b) Geographical proximity
  - c) Mobility data
3. Evaluation of selection strategies with spatio-temporal model
  - a) Back validation
  - b) Spatial projections to administrative regions (Cantons)
4. Summary



# A comprehensive WW monitoring programme

# A history of pathogen monitoring in municipal wastewater in Switzerland



**120 Wastewater Treatment Plants (WWTP)**

monitored for **SARS-CoV-2** at various times

since **March 2020** (most since **February 2022 – January 2023**) .

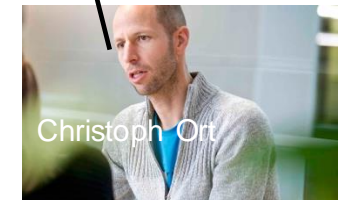
Quantification of viral concentrations via **qPCR or ddPCR** across **8 Laboratories**.



February 2020

Shall we track  
nCoV19 in  
Wastewater?

Yes



# A history of pathogen monitoring in municipal wastewater in Switzerland

Sampling consistency varied

between Feb 2022 – Jan 2023

between WWTPs – here between

**104 and 118 WWTP** were sampled

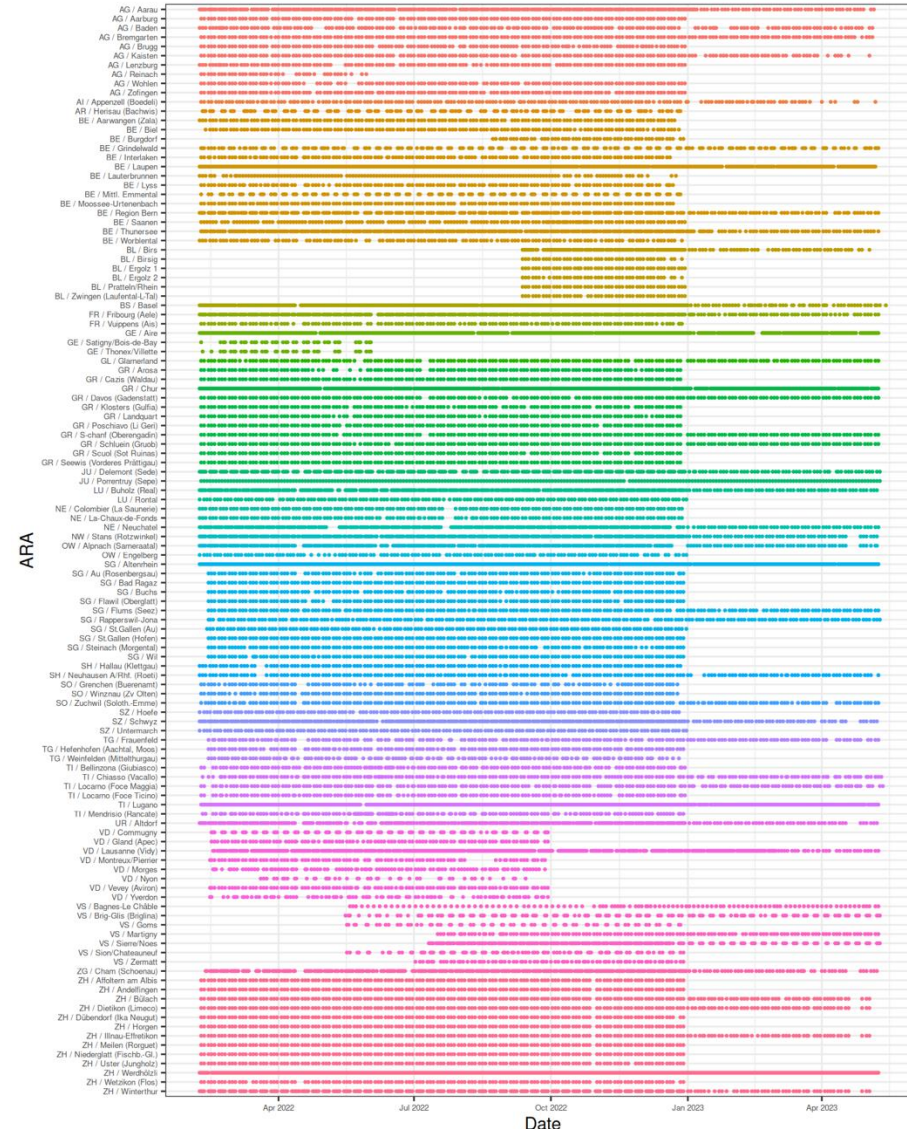
at any given time. After **Jan 2023** the

number was roughly halved to **50**.

After **July 2023** this was **reduced**

again to **15** and all processing

moved to **one lab (Eawag)**.





# Geographical based selection

## **Administrative regions + population size**

**Rational:** easily accessible + understood

Likely to hold some geographical information which may relate to transmission

**Approach:** Highest population catchment in each “NUTS2” region (n=7) plus 3 highest population remaining catchments (10 total)

## **Spatial cluster based + population size**

**Rational:** captures groups of WWTPs that are highly proximal so likely to share information

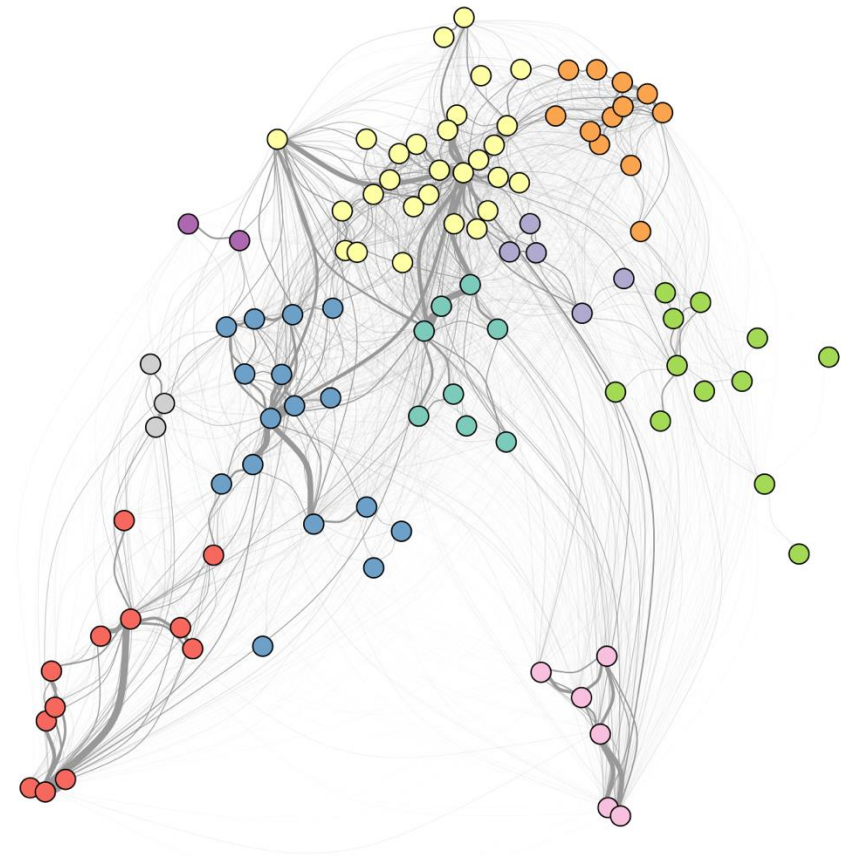
Locations of WWTPs are usually known and even better – their catchments

**Approach:** Partition catchments based on distance matrix – stipulate 10 ‘communities’ – choose the highest population in each.

# Mobility driven selection

**Rational:** Captures how individuals move between catchments therefore indicating which are likely to be highly correlated based due to transmission and shedding into the Wastewater.

**Mobile phone data** from the Swiss Sunrise network (35% market share). **'Trips'** defined as a person travelling from **one place to another** and remaining there for **> 30 mins**. We **filtered for regular travellers** and **averaged the number of trips** made between catchments over the analysis period.





# Mobility driven selection

**Rational:** Captures how individuals move between catchments therefore indicating which are likely to be highly correlated based due to transmission and shedding into the Wastewater.

## Approaches:

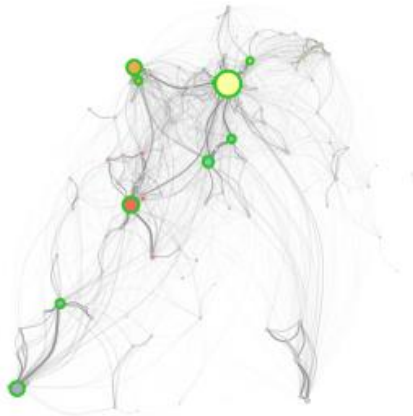
10 highest degree

10 highest betweenness

10 highest page rank

Identify 'commuting hubs' (info map) – choose the highest degree node from each.

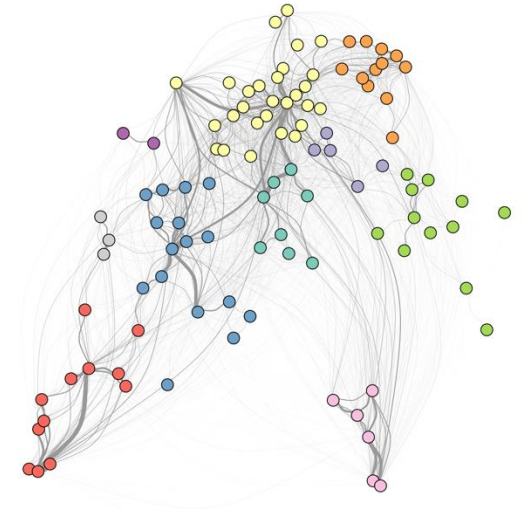
Degree



Betweenness

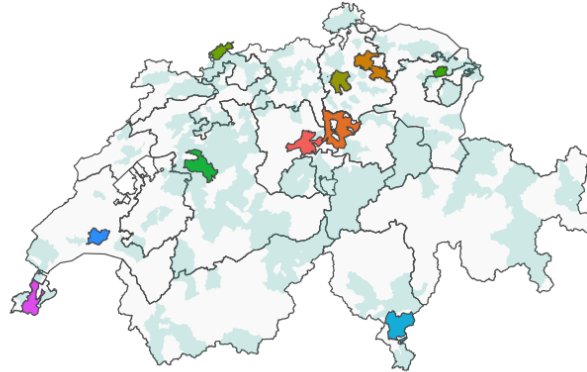


Page rank

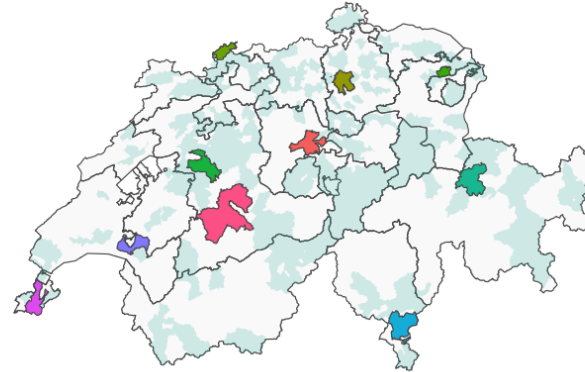


# Selected WWTPs

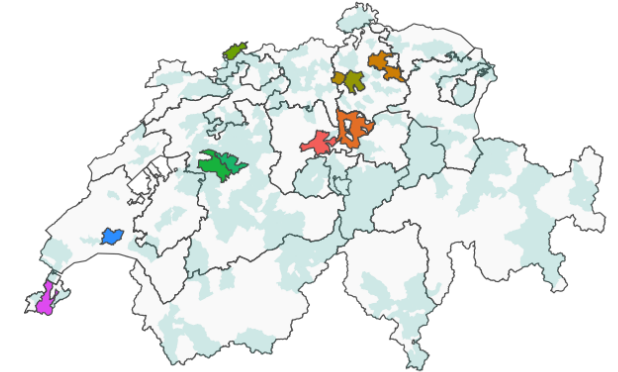
NUTS2



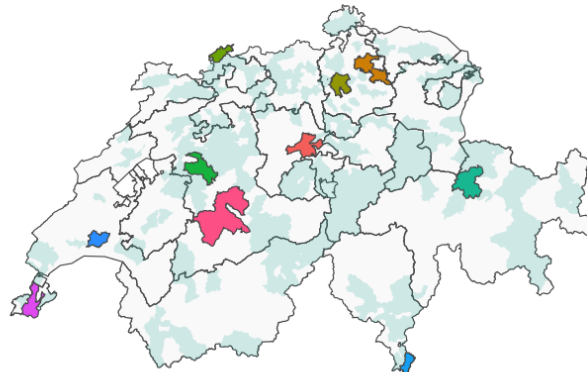
Spatial Cluster



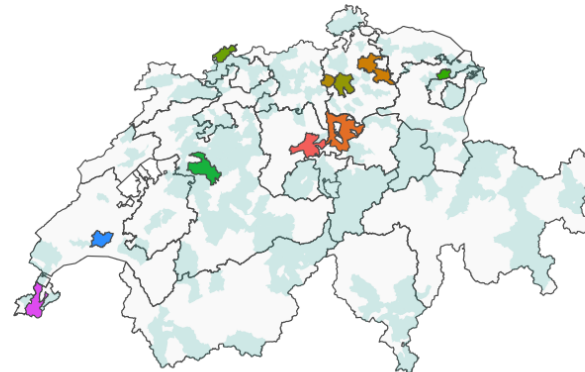
Mobility - Degree



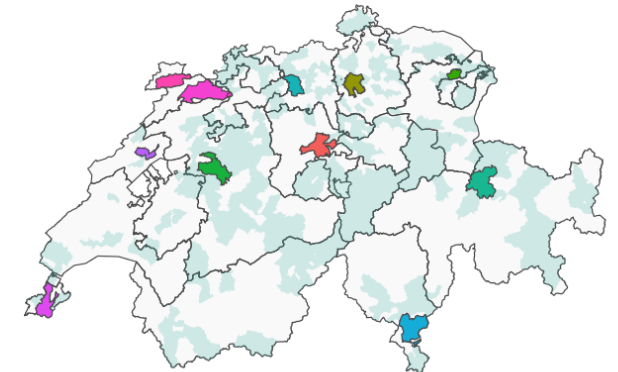
Mobility - Betweenness

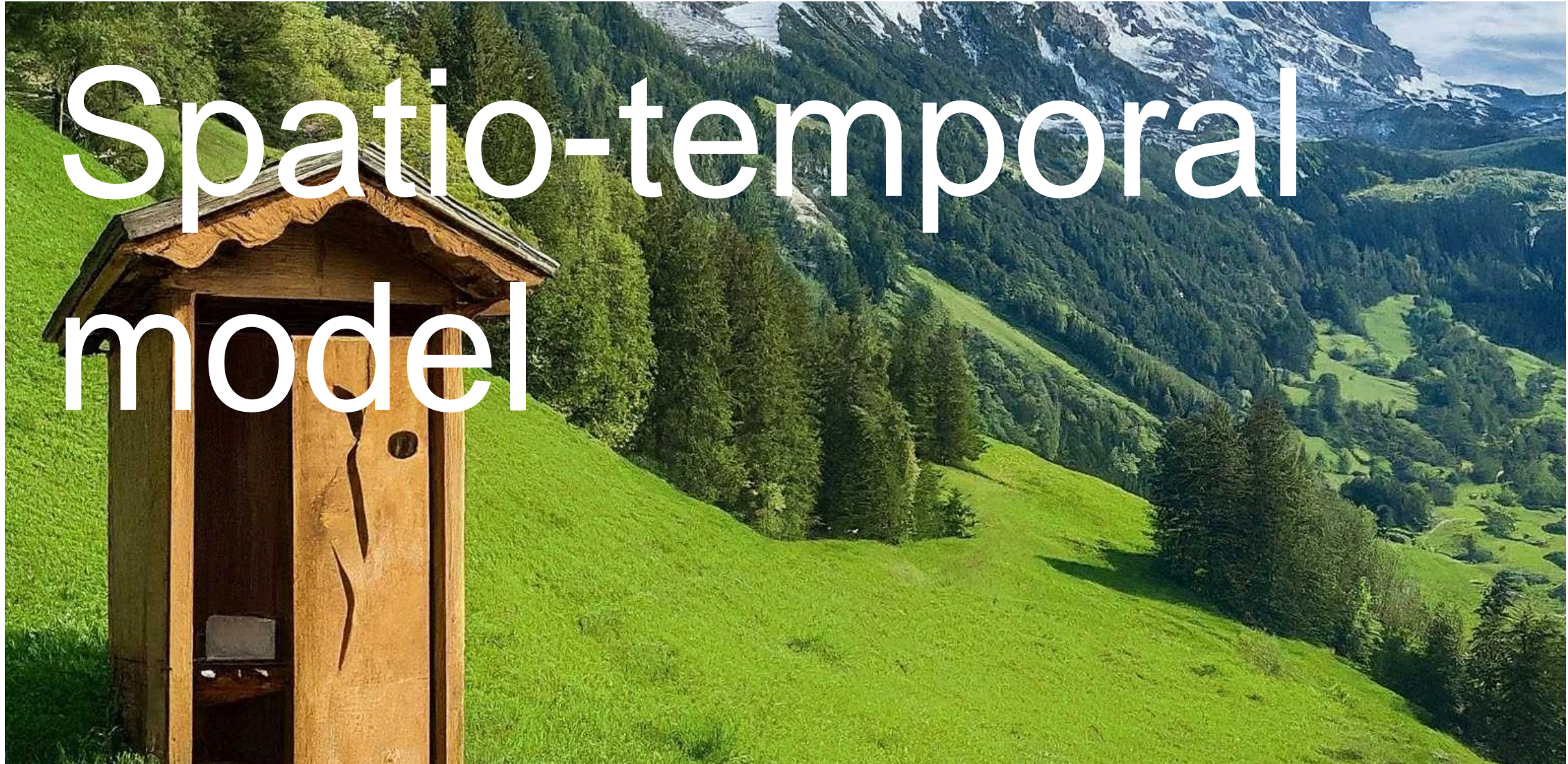


Mobility - Page Rank



Mobility - Commuting Hubs





# Modelling framework

$$\log(vl_{it}) \sim \text{Gamma}(\mu_{it}, \sigma_{vl}^2)$$

Viral loads per person (10bn's of gene copies per person)

$$\mu_{it} \sim \alpha + \mathbf{X}_i\beta + \eta_t + z_{it}$$

Intercept (Baseline VL)

Coefficients

Local spatio-temporal component

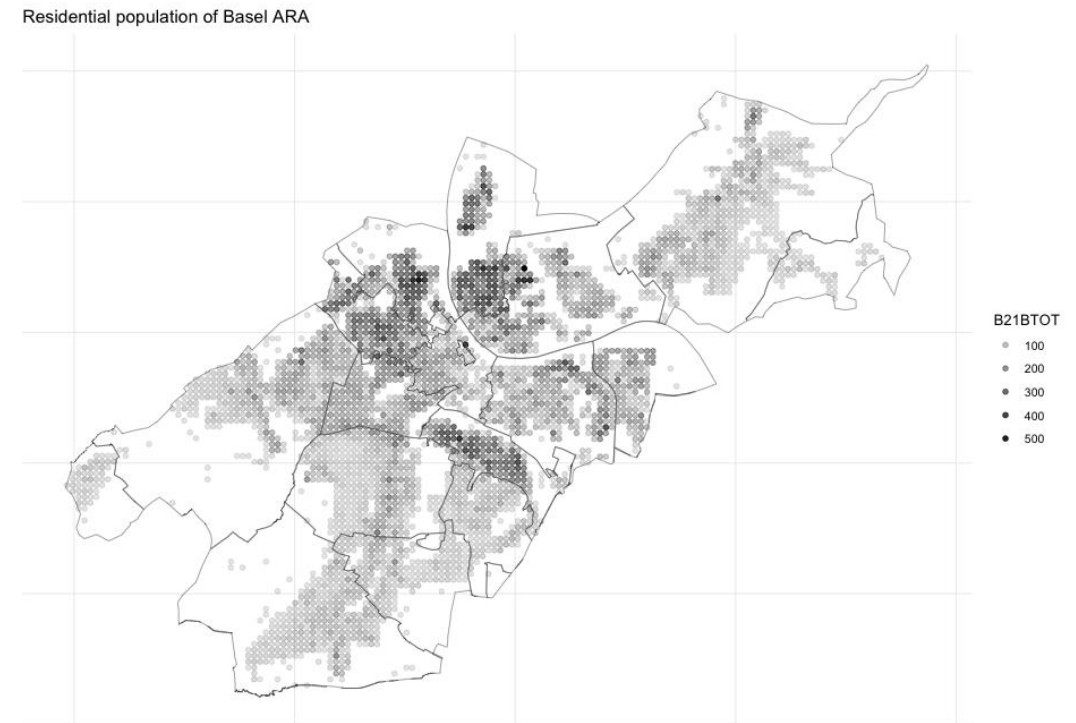
Popn. covariates

Global temporal component (1st order random walk)

# Model covariates

1. Population density
2. Proportion under 20yo
3. Proportion over 65yo
4. Proportion born non CH/EU
5. WW processing Lab

$$\mu_{it} \sim \alpha + \mathbf{X}_i \beta + \eta_t + z_{it}$$



# Spatiotemporal component

$$\mu_{it} \sim \alpha + \mathbf{X}_i \beta + \eta_t + \mathbf{z}_{it}$$

$$t = 0 \quad \mathbf{z}_t \sim \text{Normal}(0, \Sigma_z)$$

$$t > 1 \quad \mathbf{z}_t \sim \text{Normal}(\rho \mathbf{z}_{t-1}, \Sigma_z)$$

## Matern covariance function:

(Covariance between the i-th and j-th site)

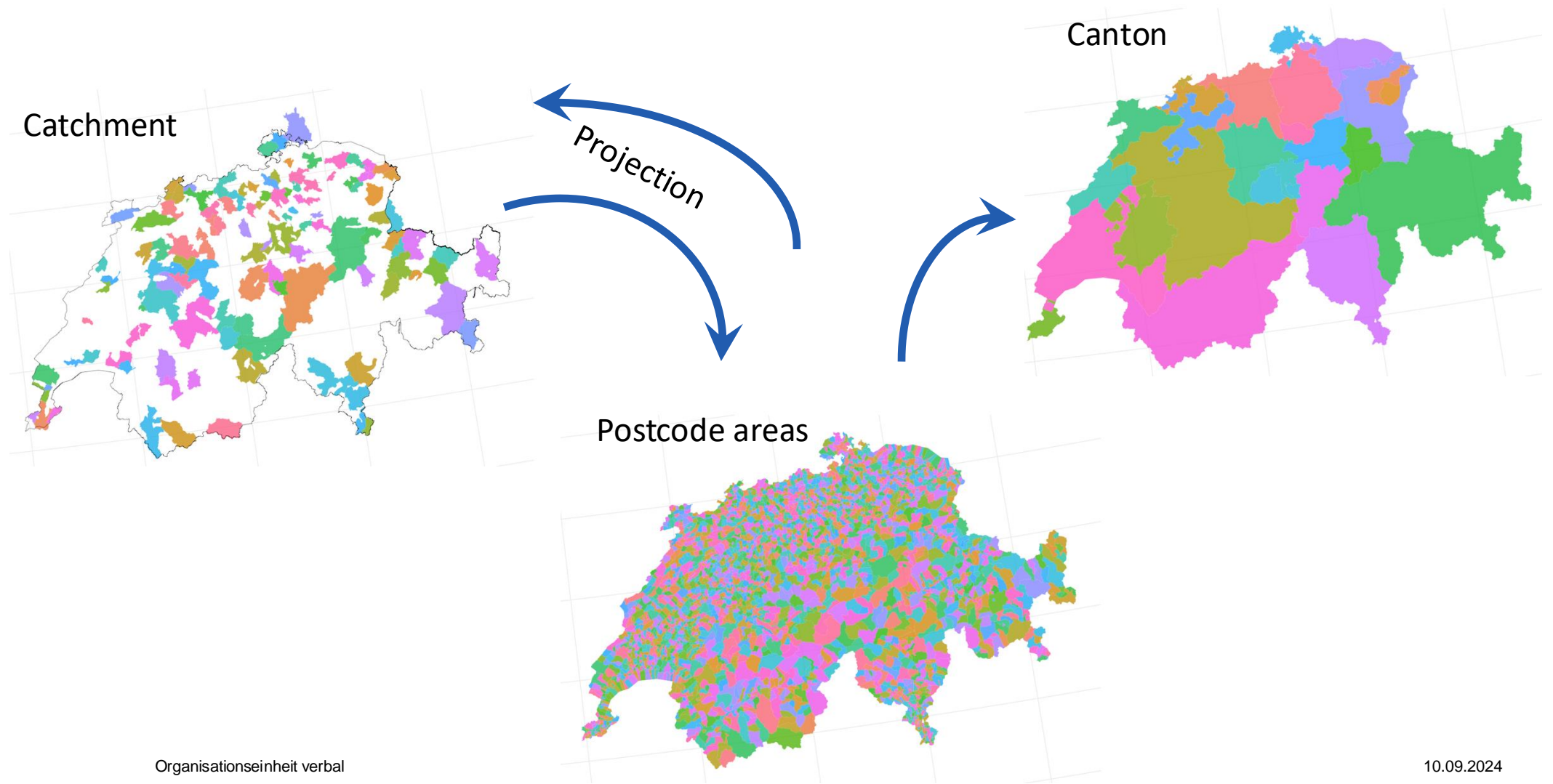
$$\Sigma(z_i, z_j) = \frac{\sigma_z^2}{\Gamma(\lambda) 2^{2\lambda-1}} (kd_{ij})^\lambda K_\lambda(kd_{ij})$$

Annotations:

- $\sigma_z^2$ : Scales the overall variance
- $\Gamma(\lambda)$ : Gamma function
- $K_\lambda(kd_{ij})$ : Type 2 Bessel function (order  $\lambda$ )

d – Distance  
 $\lambda$  – Smoothness  
k – Range parameter

# Estimating viral loads at different geographic aggregations



Organisationseinheit verbal

10.09.2024

15

# Wastewater data

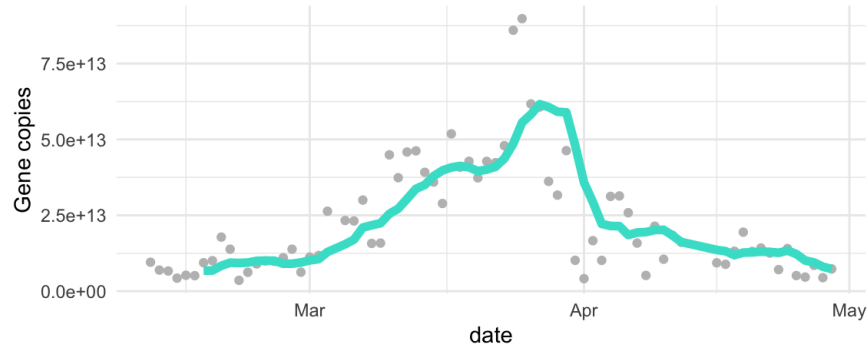
In this work we use concentrations from the very **early**

**comprehensive phase (11<sup>th</sup> February – 29<sup>th</sup> April) - where**

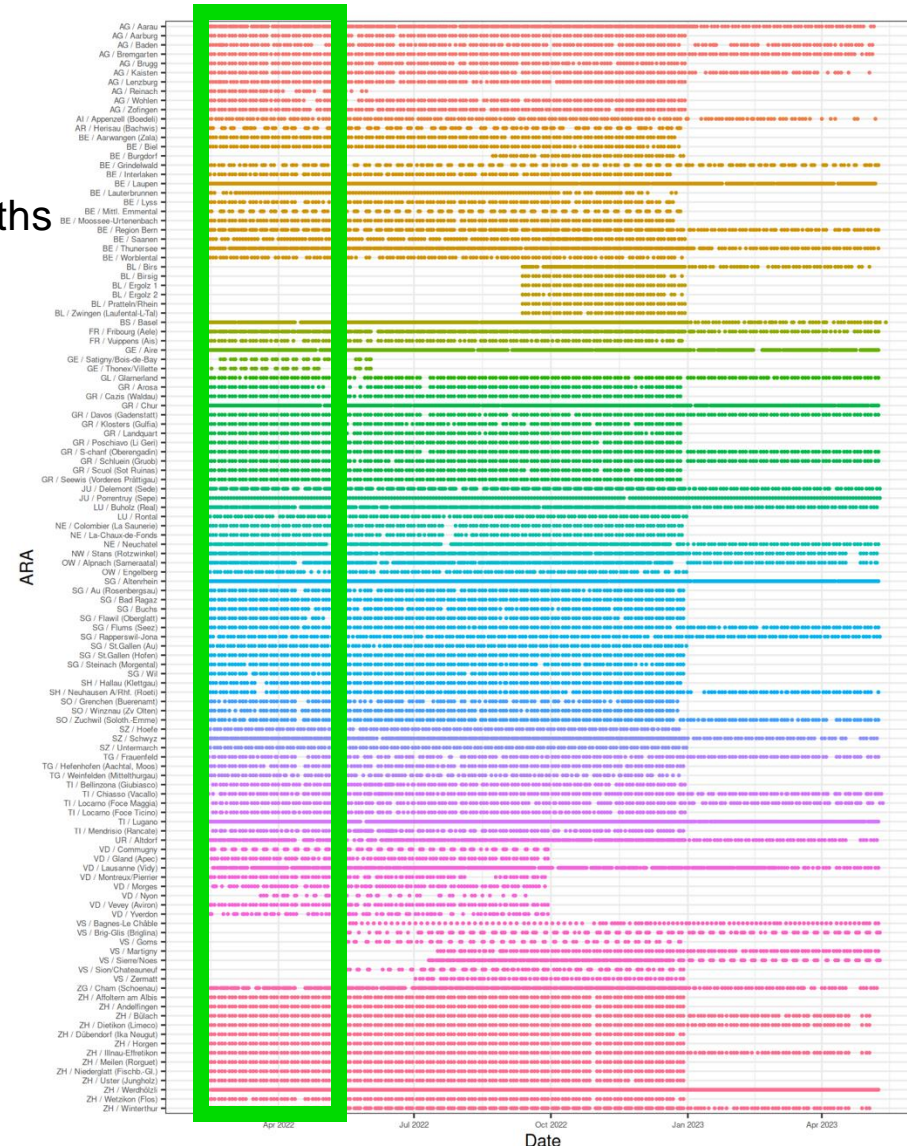
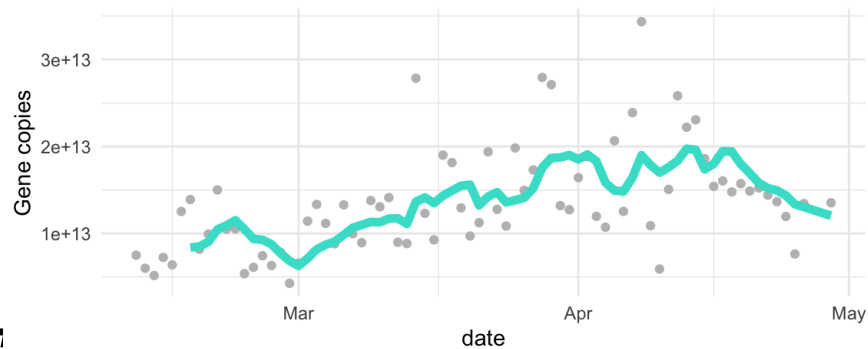
there were **104 WWTPs** consistently sampled for several months

– with no changes in lab protocol.

Daily viral load per 100k population in Basel

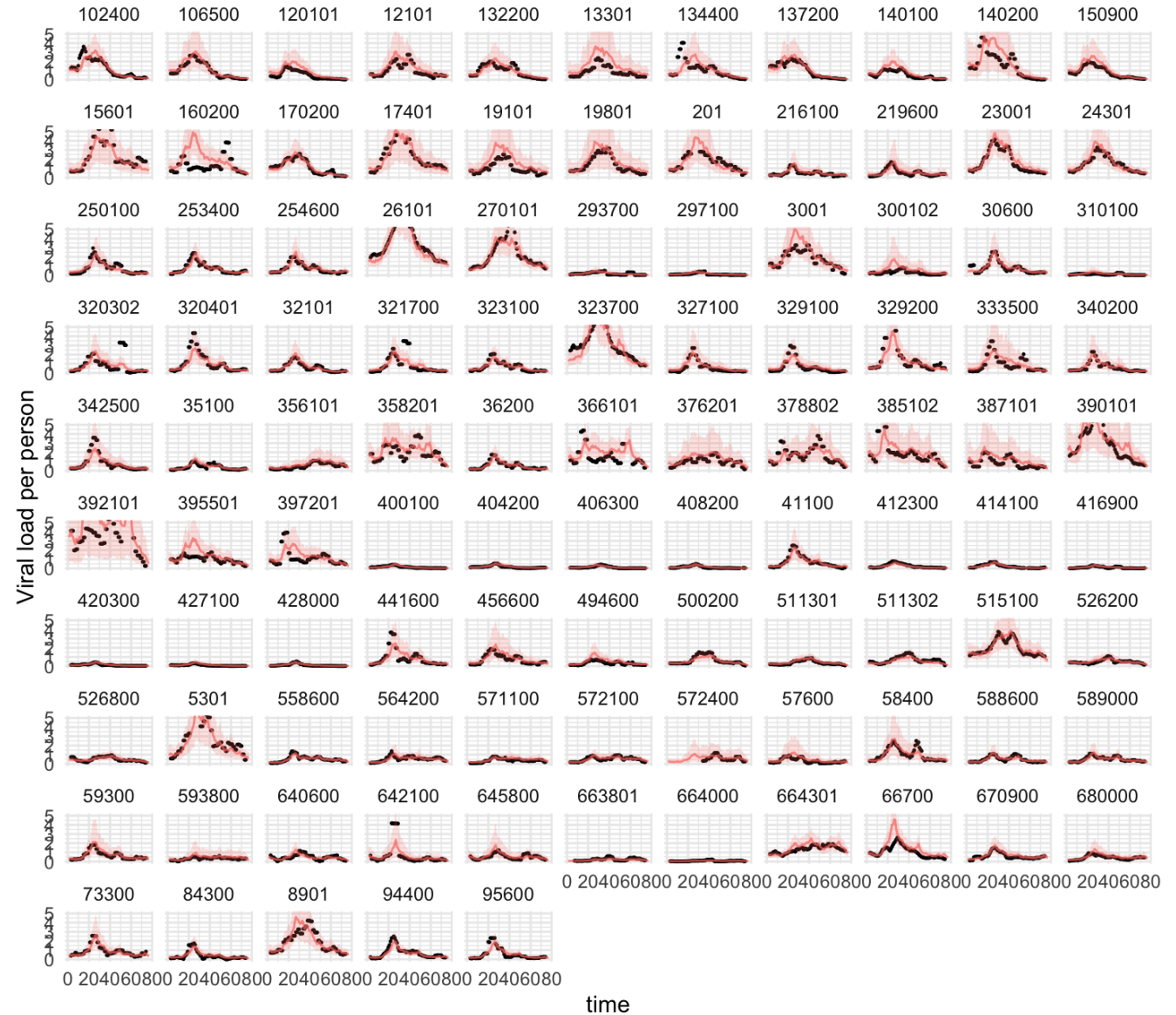
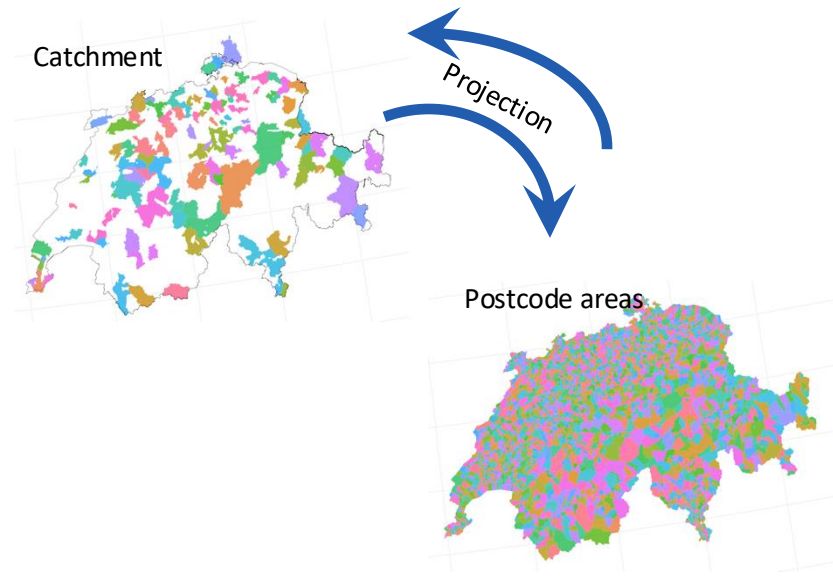


Daily viral load per 100k population in Geneva (Aire)



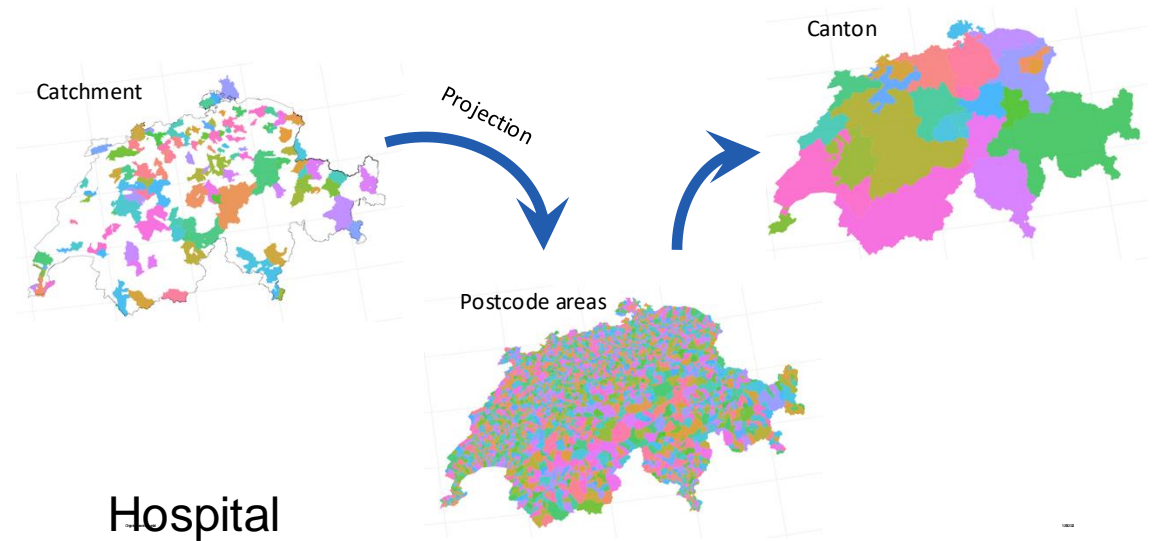


# Full model test... Back-validation

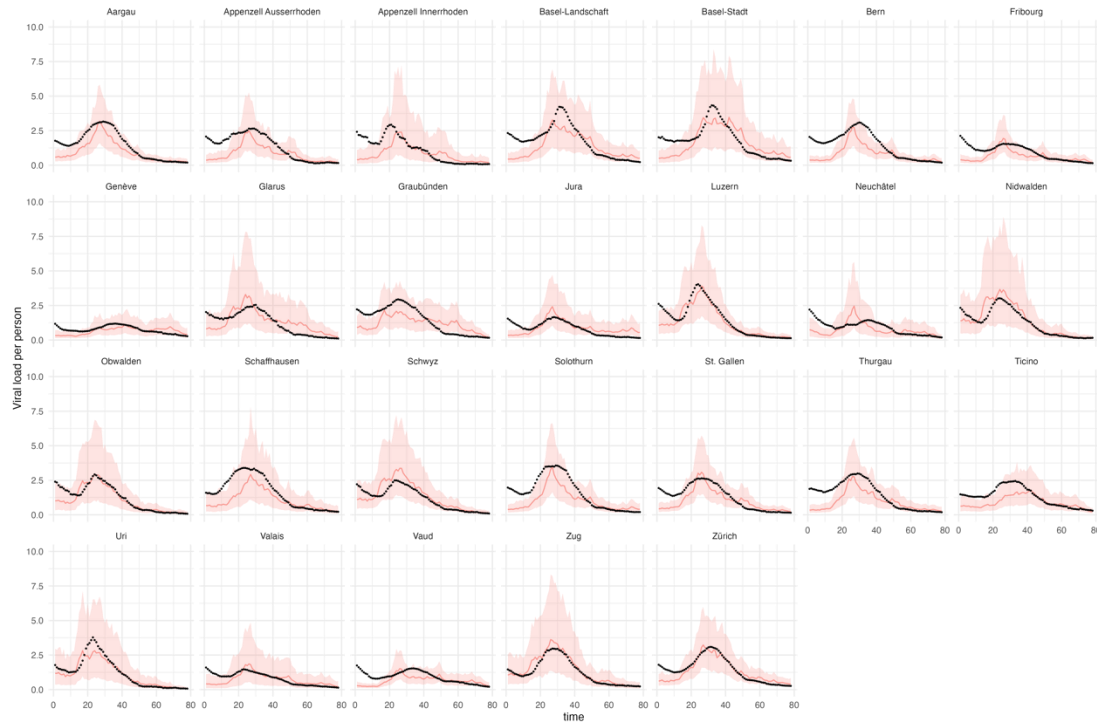


# Projections to cantons...

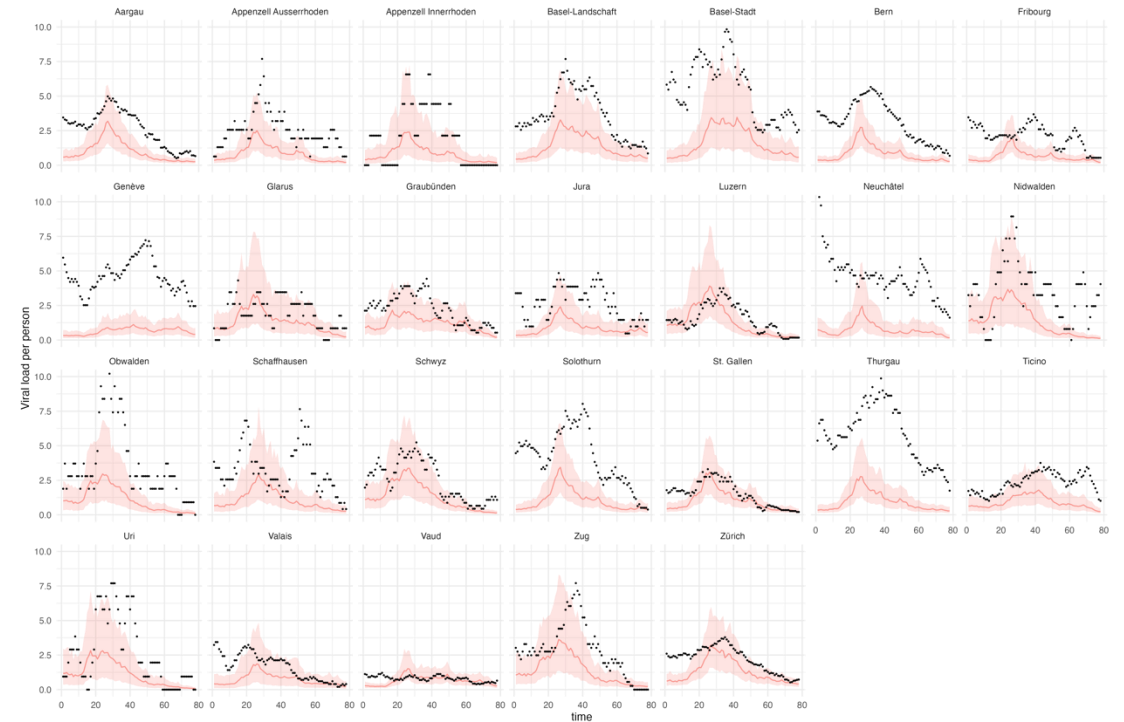
Allows us to compare directly to clinical data- which is not available at catchment level



## Cases



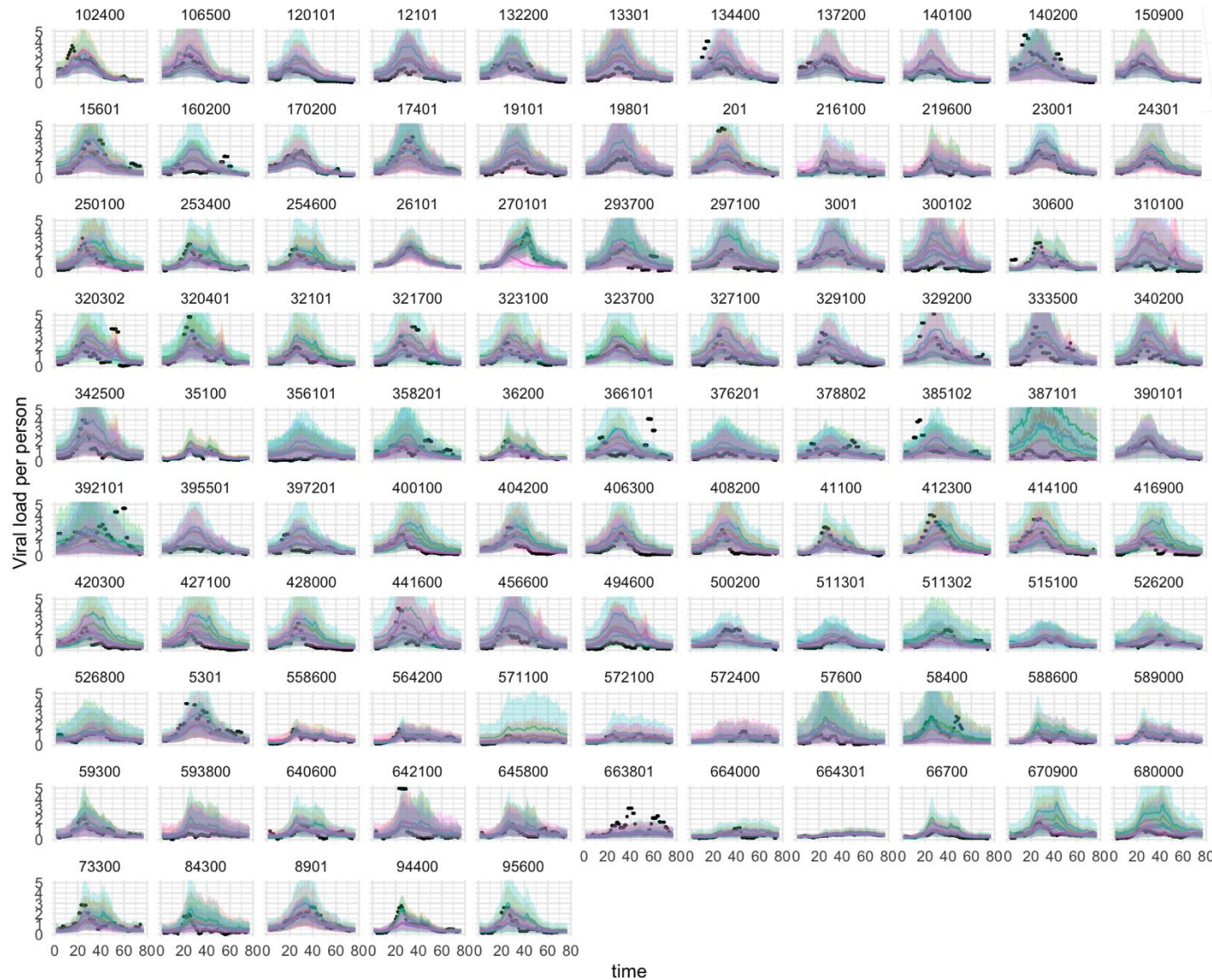
## Hospital admissions



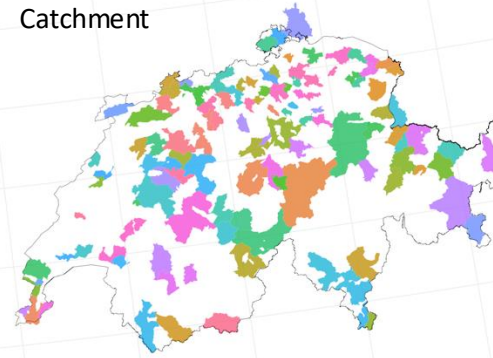


# Evaluation of site selection

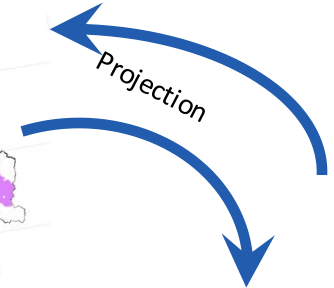
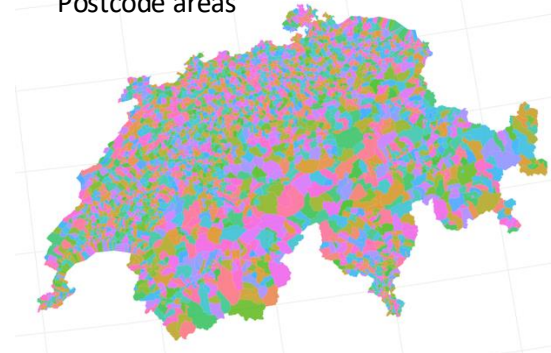
# Re-prediction of WWTP measurements



Catchment



Postcode areas



- Model
- NUTS2
  - Spatial Cluster
  - Mobility - Degree
  - Mobility - Betweenness
  - Mobility - Page Rank
  - Mobility - Commuting Hubs

- Continuous ranked probability score (**CRPS**)
- Absolute error of the median prediction (**AE\_median**)
- **Bias** (average proportion over/under predicted)
- Median absolute dispersion of the prediction (**mad**)

We scaled VL by

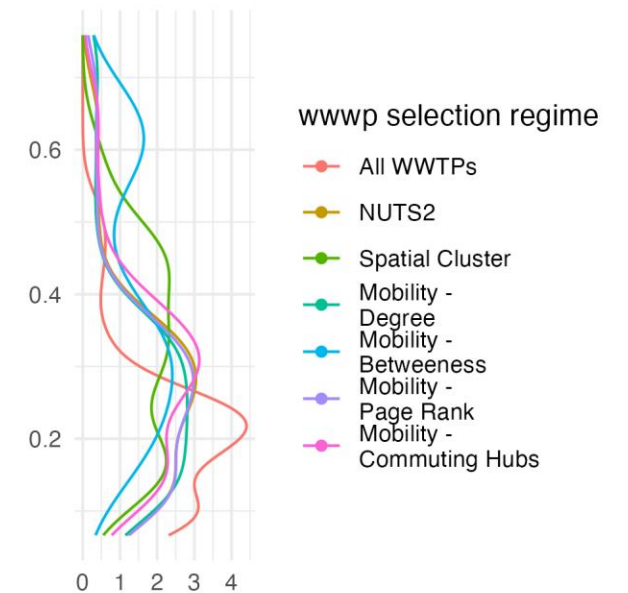
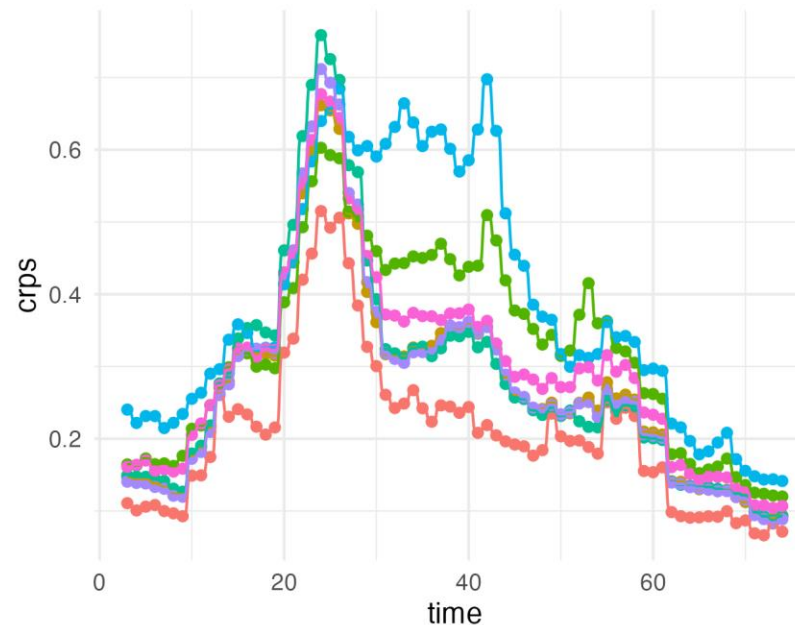
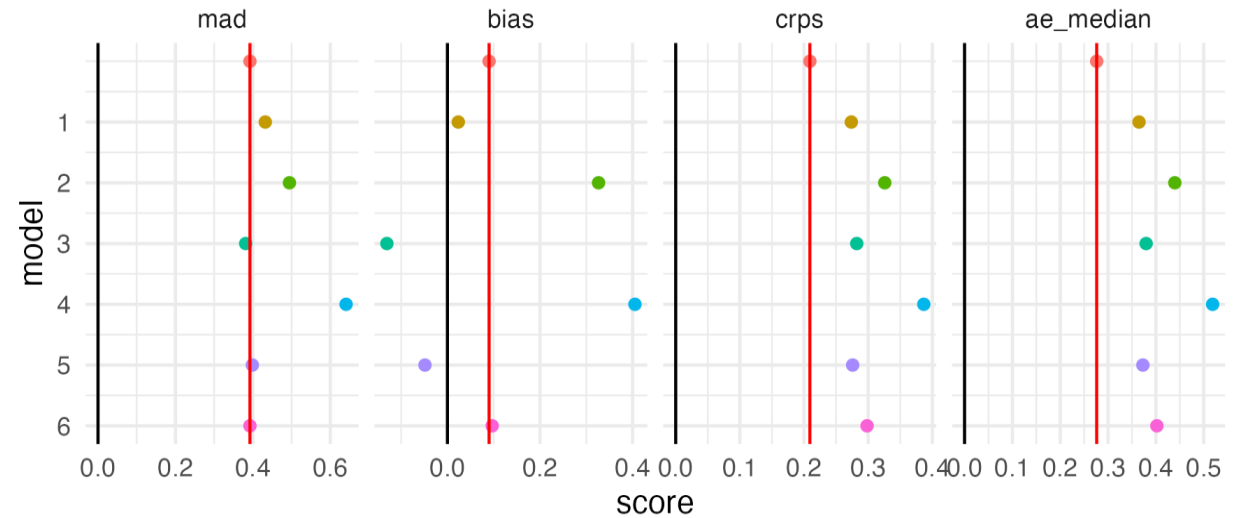
# Overall scores

The **betweenness** based selection **performs comparatively poorly** in all measures

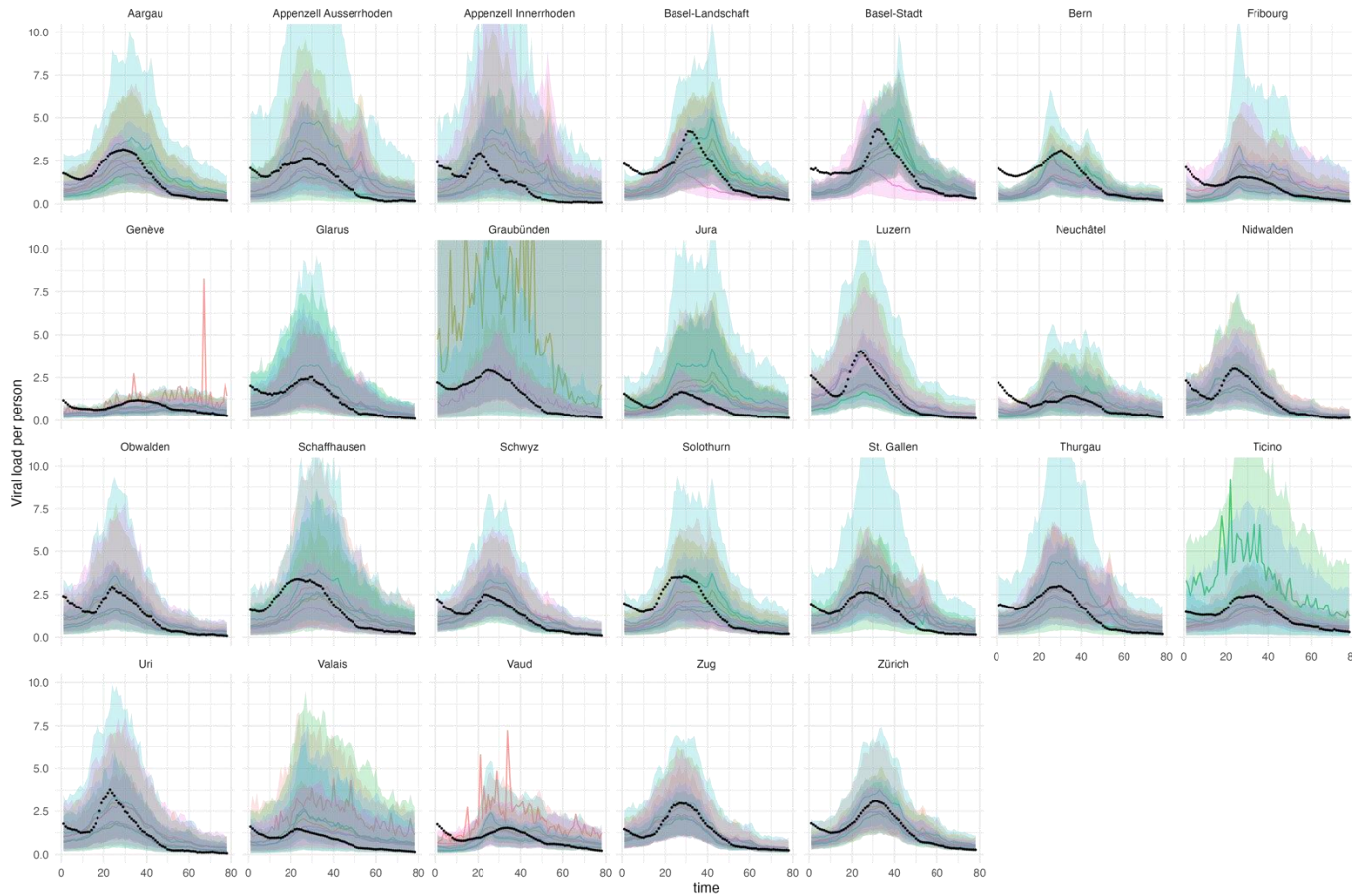
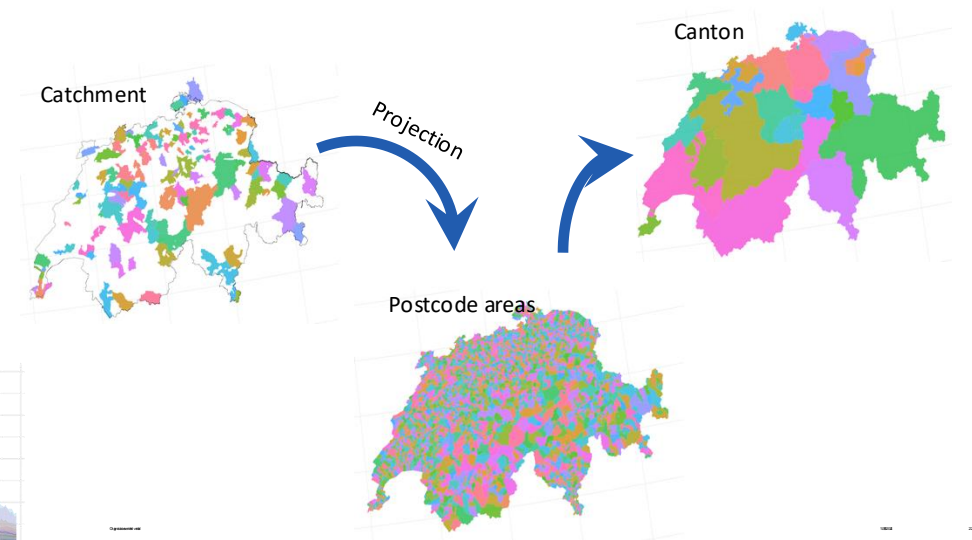
**Region based selection (NUTS2), Degree and Page Rank** appear to perform better than the clustering based approaches

These are both **less biased overall and more accurate** (lower CRPS and absolute error)

**All but the betweenness** based selection have **comparable dispersion** to the predictions with **all WWTPs**



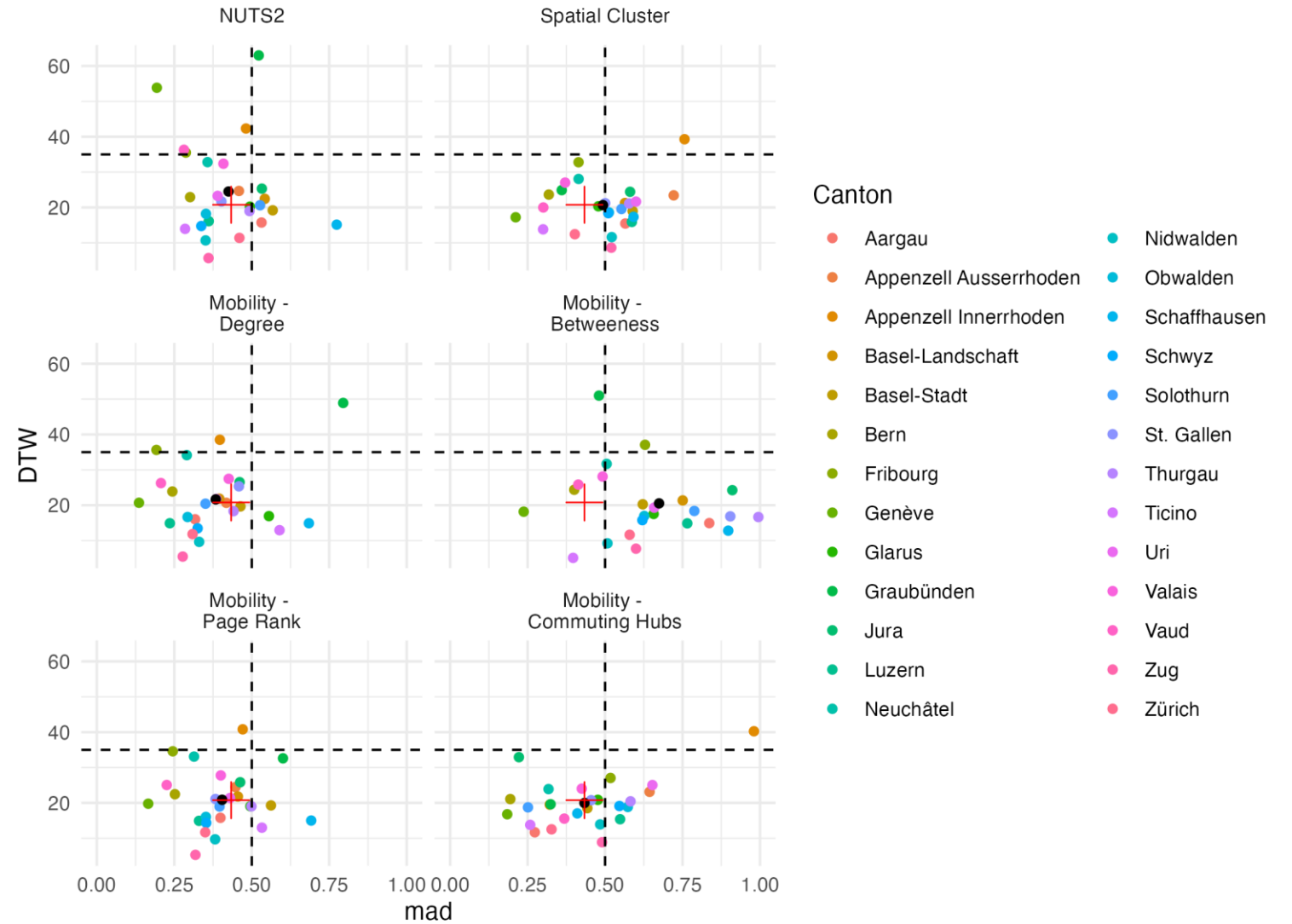
# Correlation with clinical data – Cases



- Dynamic Time Warping (**DTW**) distance between standardised median and case incidence per 100k
- Median absolute dispersion of the prediction (**mad**)

# Correlation with clinical data – Cases

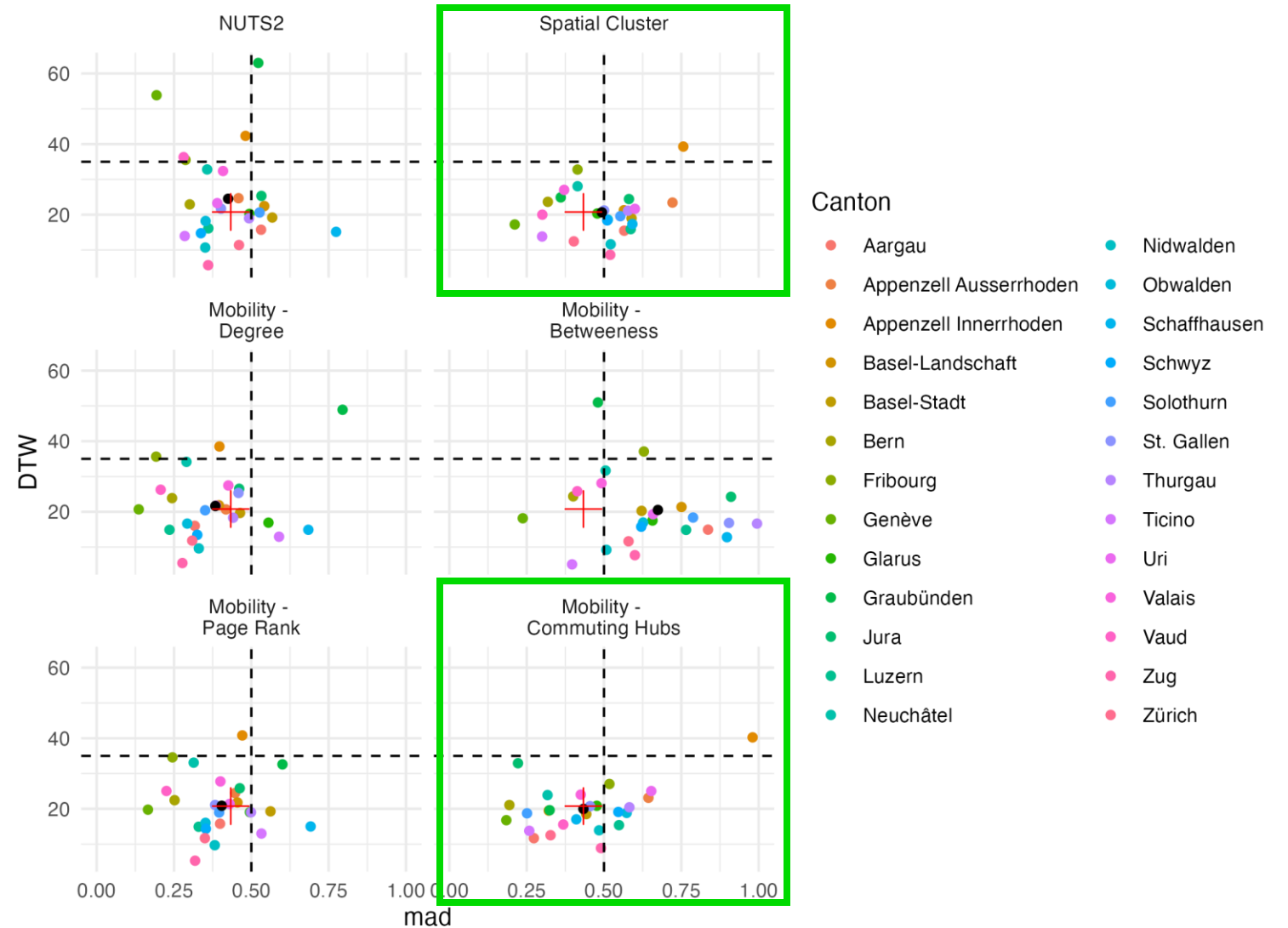
Converse to back-validation – cluster based selection performs marginally better than the others when evaluating correlation with case time-series.



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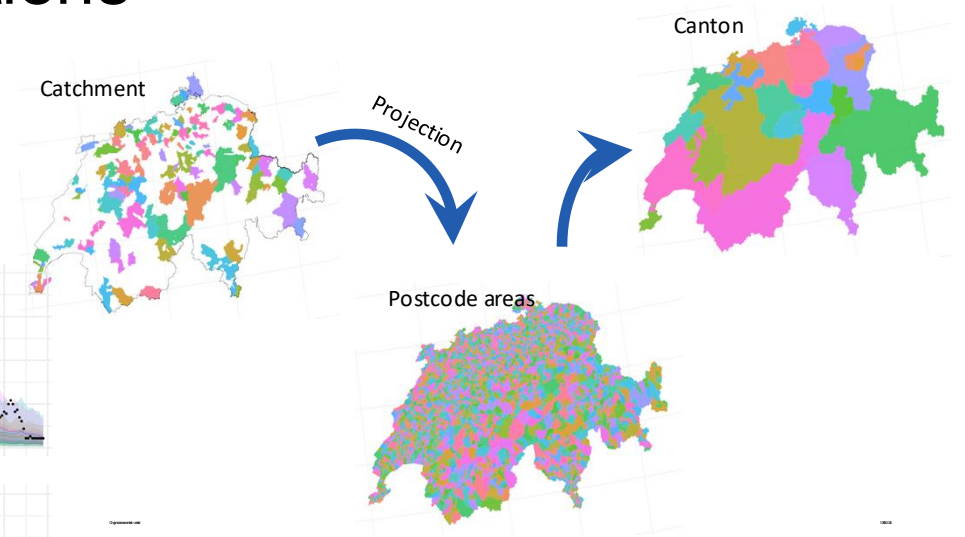
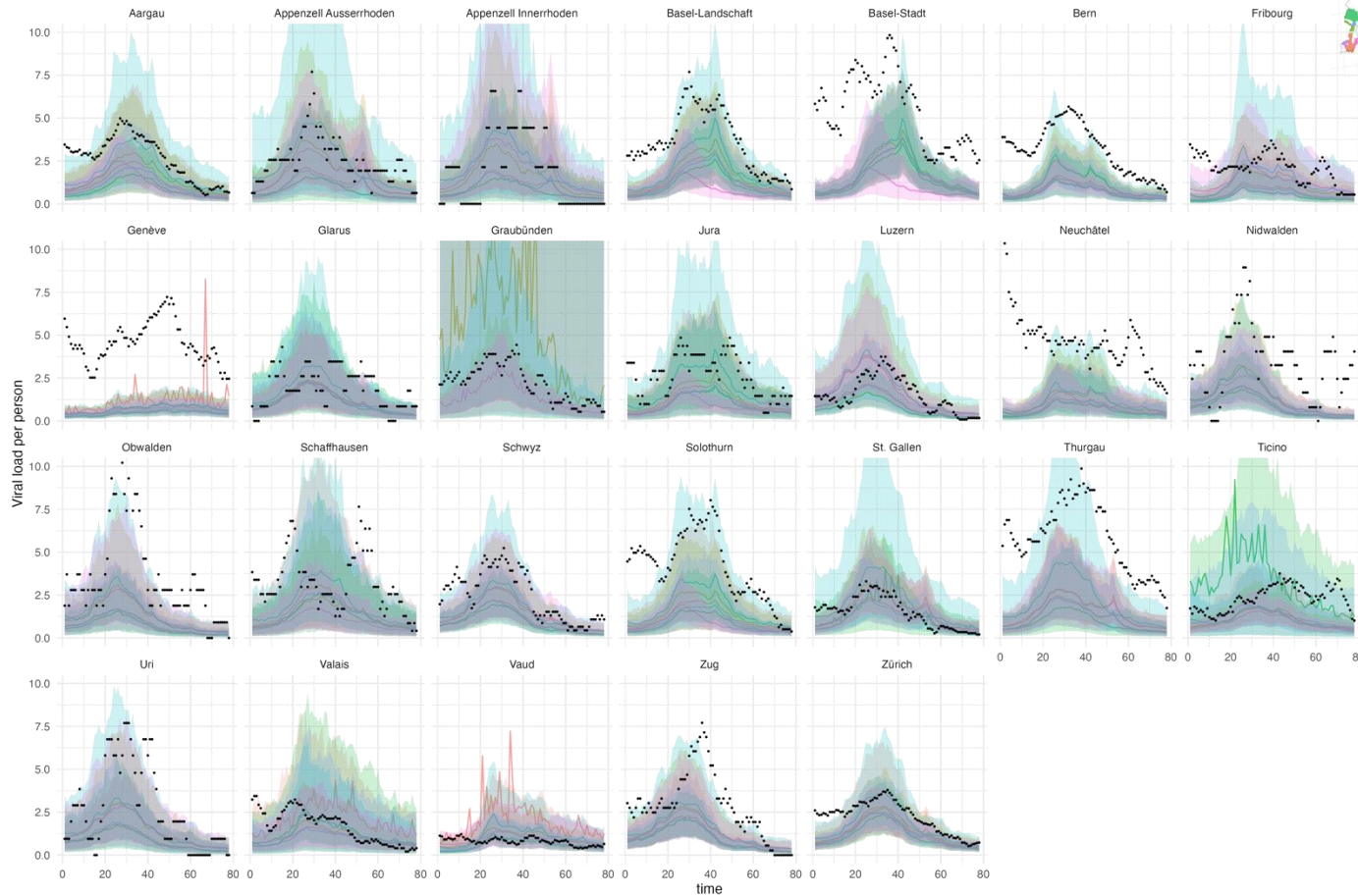
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The distribution of performance across all cantons is also improved





# Correlation with clinical data - Hospitalisations

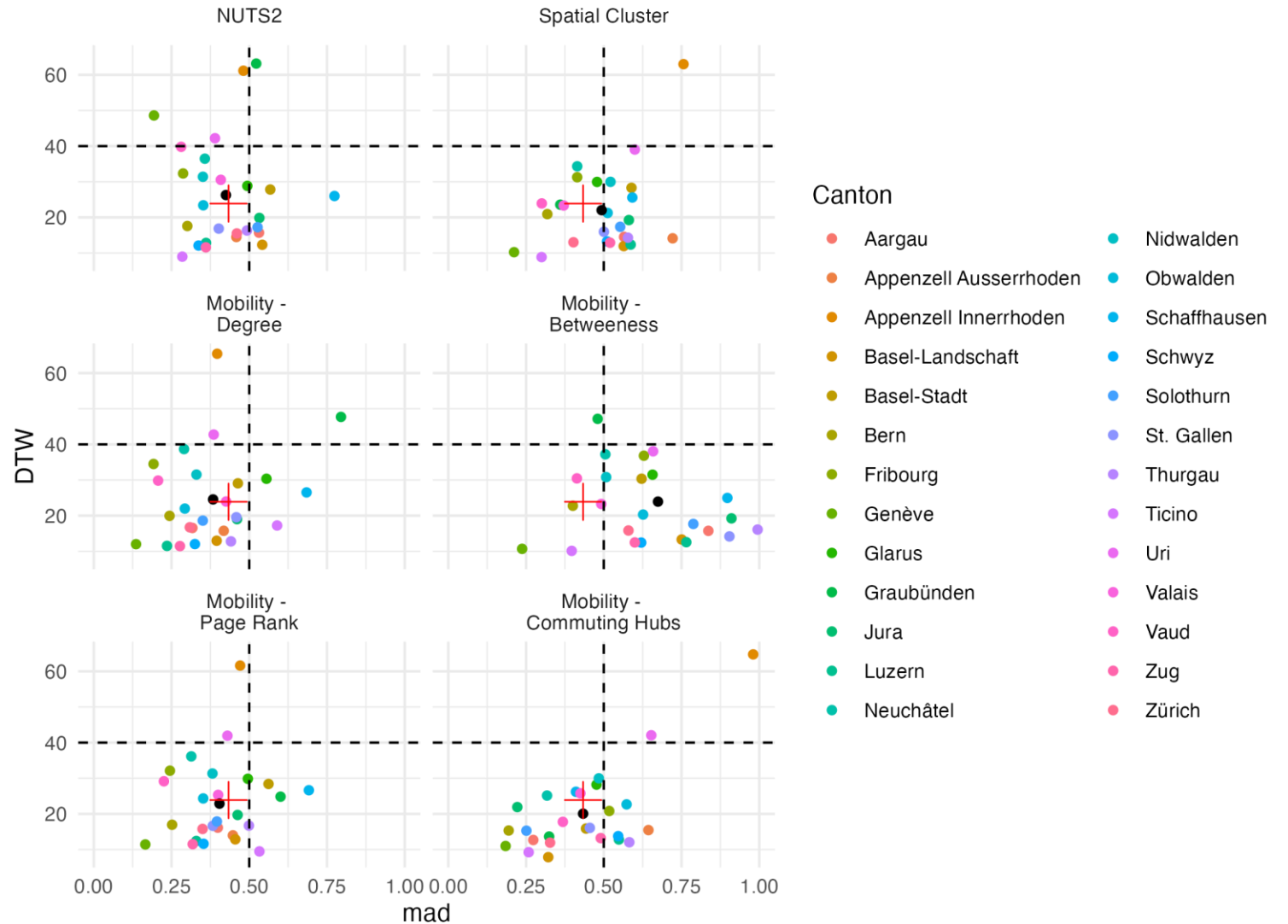


- Dynamic Time Warping (**DTW**) distance between standardised median and hospitalisation incidence per 100k
- Median absolute dispersion of the prediction (**mad**)

# Correlation with clinical data – Hospital admissions

Consistent with case – cluster based selection performs marginally better than the others when evaluating correlation with hospitalisation time-series.

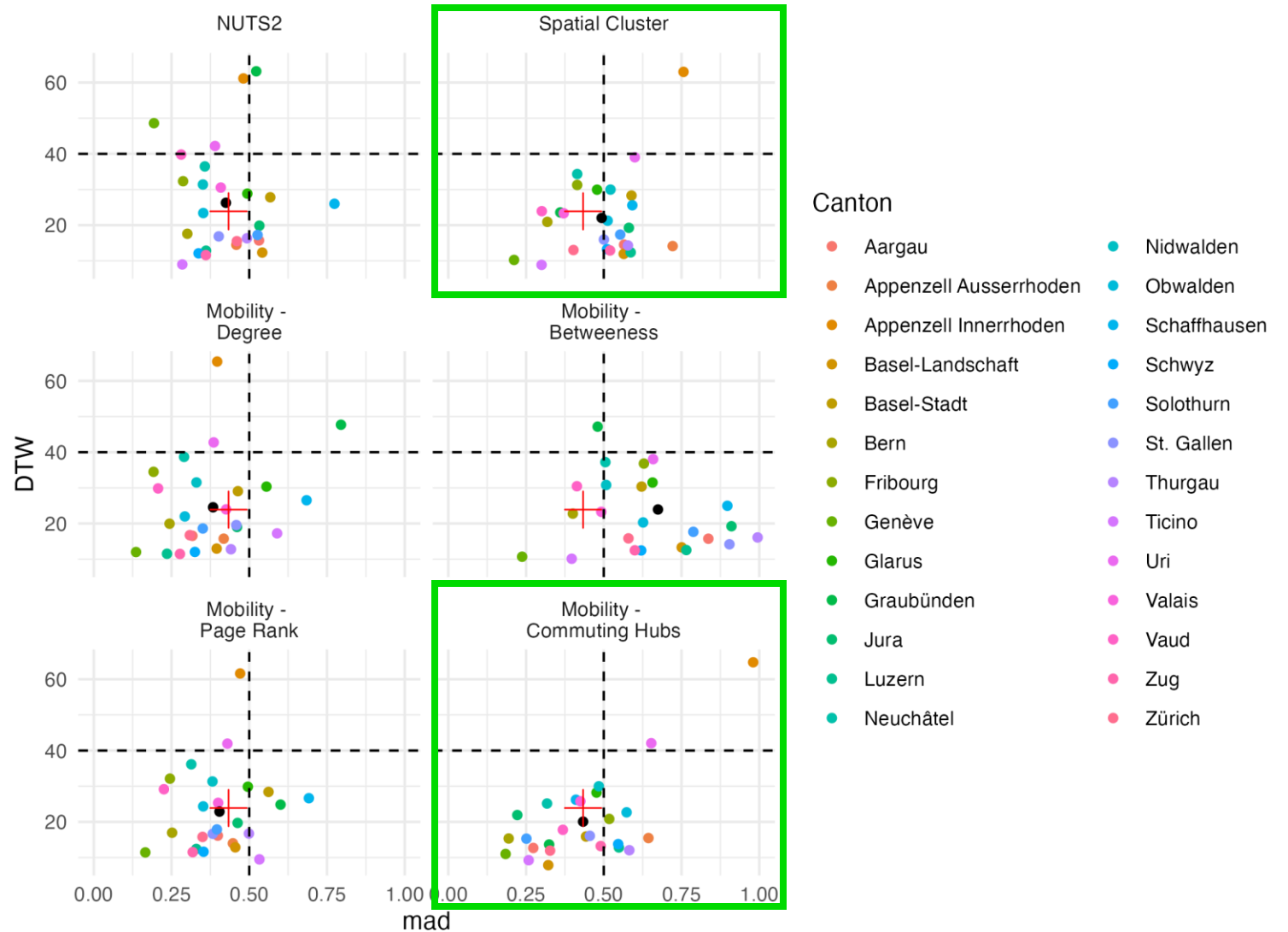
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# Summary

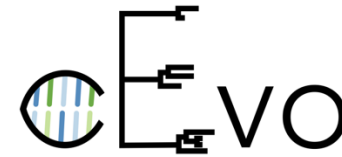
1. We defined six different WWTP site selection criteria
2. We evaluated these selection regimes by using a spatio temporal model to project expected viral loads in unmeasured catchments and also by comparing projections at Canton level with clinical data
3. We found that metrics highly correlated with population size performed better when making predictions at catchment level
4. However when exploring correlations with cases and hospitalisations at canton level, the regimes which clustered the catchments using spatial and mobility data performed better.
5. Overall all models performed comparably and were also relatively close in performance to the original model

# Thanks!

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Moritz Wagner,  
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Tanja Stadler

Members of the WISE project. Especially  
Charlie Gan and team

All the WWTP staff who do the  
sampling for us!



james.munday@bsse.ethz.ch  
@jdmunday  
jdmunday.github.io

<https://wise.ethz.ch/>



