SPATIALLY RESOLVED INFECTIOUS DISEASE MODELS FOR LOCALIZED OUTBREAK MITIGATION (AND EFFICIENT MATH. SOFTWARE)

Martin J. Kühn

joint work with many others (see slides)

Exchange at Charité

Berlin, 2025/10/10







GEFÖRDERT VOM



With funding from the:















Outline / Info



- Who are we?
- Motivation for spatial resolution
- Software aspects: Efficiency and performance
- Metapopulation models with epidemic control application
- Spatially resolved Al-surrogate models for on-the-fly computation
- Agent-based models with some applications
- "Off-Topic": Basic model properties and influence on outcomes
- Concluding

[→] In many places, I will only present a very brief insight into the model or the application and I am happy to discuss more details at any time.

The team



Institute of Software Technology

Department High-Performance Computing

Predictive Simulation Software







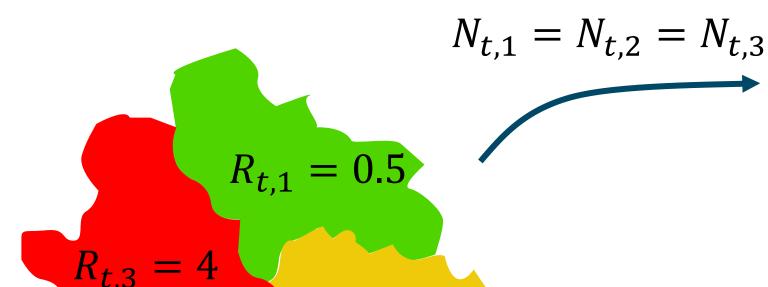
Life and Medical Sciences Institute and
Bonn Center for Mathematical Life Sciences

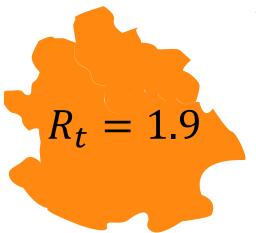
Mathematical-Epidemiological Modeling



We care not enough about spatial resolution

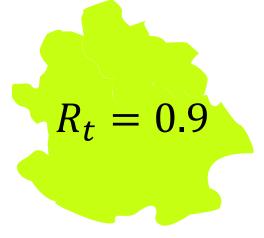


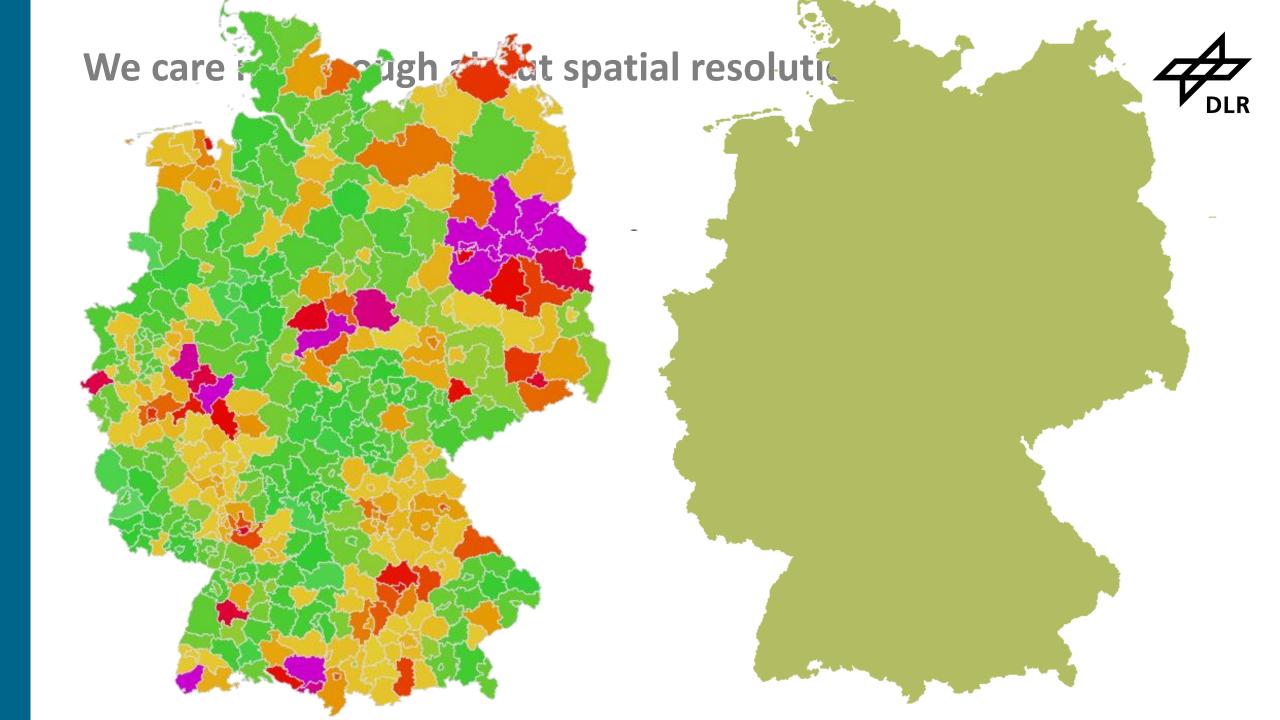




With which strictness to act?

$$R_{t,2} = 1.1$$
 $N_{t,1} > N_{t,2} > N_{t,3}$





We care graph graph at spatial resolution



Aggregated metrics...

- ...only give blurred information and intervention strictness is unclear
- ...do not allow for **local action** and **targeted** deployment of **limited resources**

Post-COVID-era: For many diseases, not enough data for this spatial resolution...

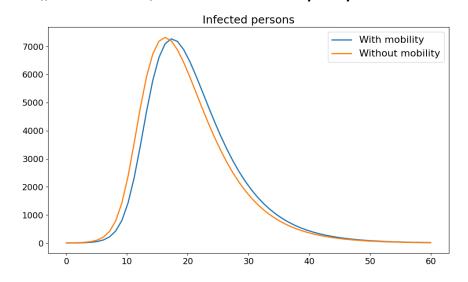
- Data will increase substantially with digitisation and digital tools in the next decades
- Develop advanced models such that they are ready to use when data is
- Pandemic preparedness

Missing out spatial resolution: some reasons



Aside from data availability, ODE*-SIR-type models are too easy to implement...

• "in the end, it will arrive anyway…"



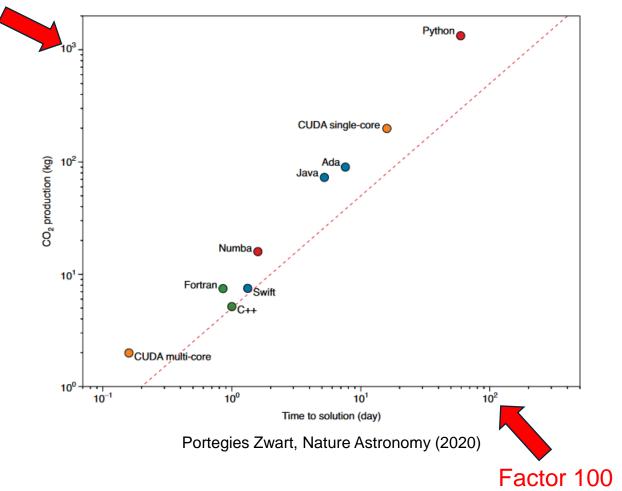
→ If it looks like that, you do not use the degrees of freedom and power in spatially resolved models

- "you cannot do metapopulation models in a small time frame"
 - → well, you can...

^{*} ODE: Ordinary differential equations

Chances of efficiency and performance

Factor 100-1000



- 1		Time	
	(c) C	1.00	
	(c) Rust	1.04	
	(c) C++	1.56	
	(c) Ada	1.85	Г
	(v) Java	1.89	
	(c) Chapel	2.14	
	(c) Go	2.83	
	(c) Pascal	3.02	
	(c) Ocaml	3.09	
	(v) C#	3.14	
	(v) Lisp	3.40	
	(c) Haskell	3.55	
	(c) Swift	4.20	
	(c) Fortran	4.20	
	(v) F#	6.30	
	(i) JavaScript	6.52	
	(i) Dart	6.67	
	(v) Racket	11.27	
	(i) Hack	26.99	
	(i) PHP	27.64	
	(v) Erlang	36.71	
	(i) Jruby	43.44	
	(i) TypeScript	46.20	
	(i) Ruby	59.34	
	(i) Perl	65.79	
	(i) Python	71.90	
	(i) Lua	82.91	

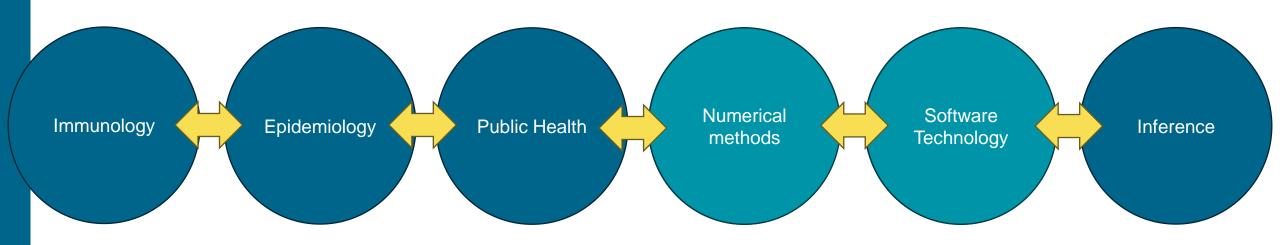


Pereira et al., SLE'17 (2017)

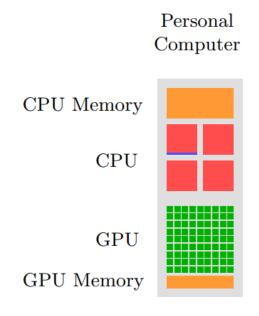
- → In hardware or other contexts: Would we build solutions for (time) critical tasks that are more than 50 times slower or use that more energy for the same task?
- → Do large-scale models in an efficient and scalable language (at least for the backend: R, python... have other use cases)

Let's create more interdisciplinary synergies

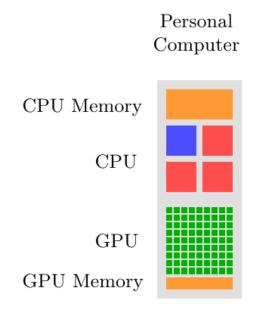




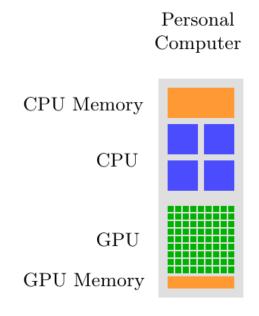






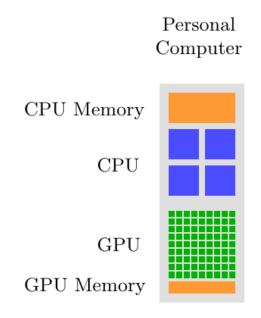


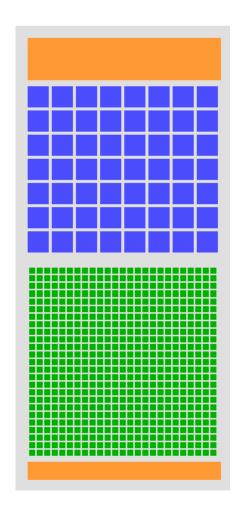




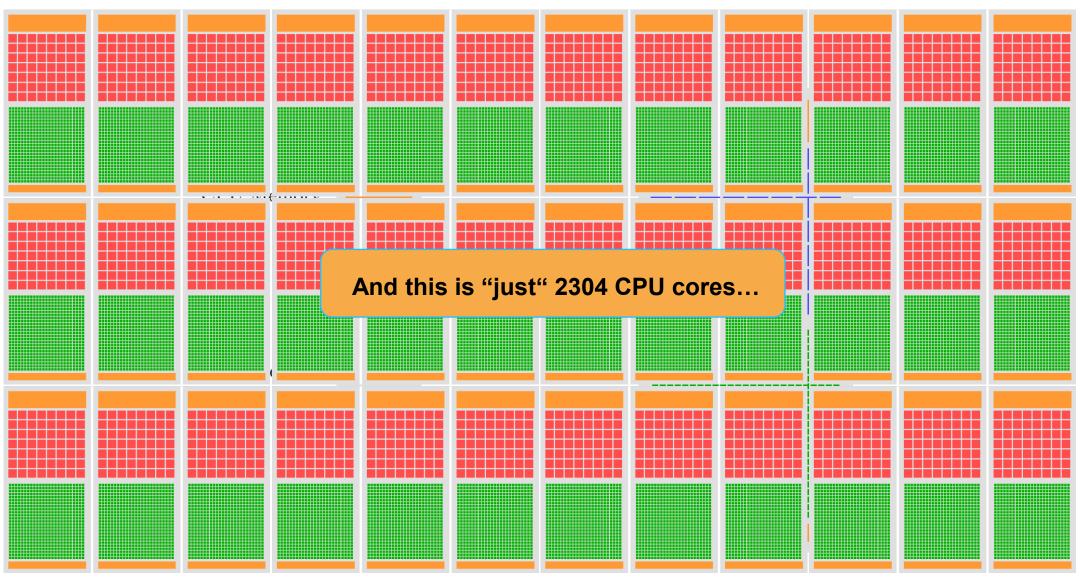


HPC Node

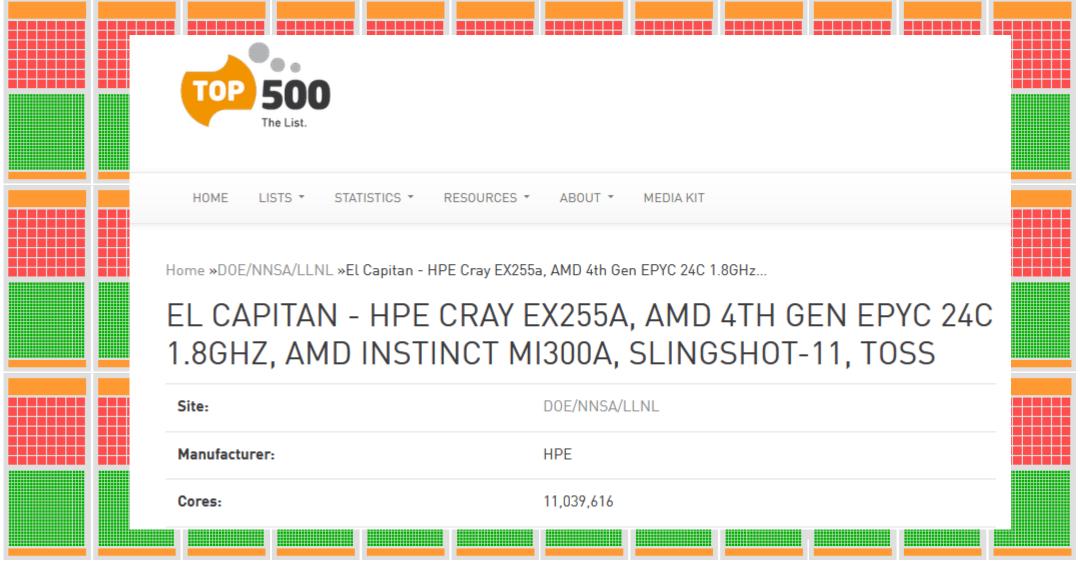




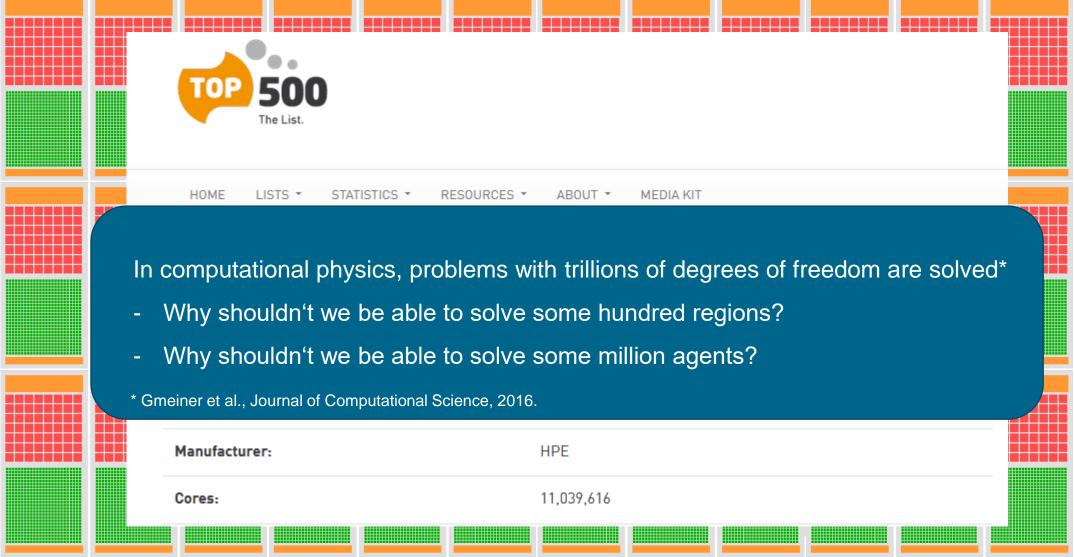




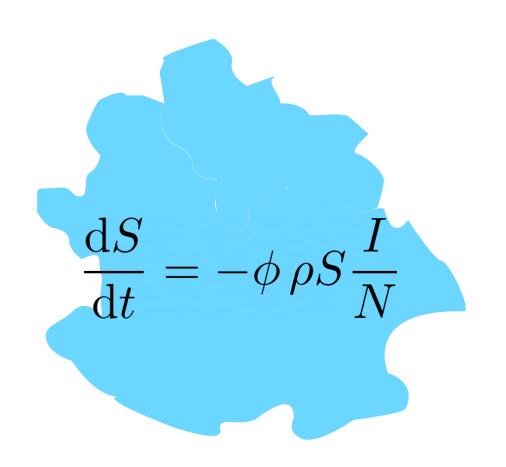












S: Susceptible population

I: Infected/Infectious population

N: Total population

b: Contact rate

 ρ : Transmission probability



$$\frac{\mathrm{d}S_1}{\mathrm{d}t} = -\phi_1 \, \rho \frac{I_1}{P_1} S_1$$

$$\frac{\mathrm{d}S_3}{\mathrm{d}t} = -\phi_3 \, \rho \frac{I_3}{P_3} S_3$$

$$\frac{\mathrm{d}S_2}{\mathrm{d}t} = -\phi_2 \, \rho \frac{I_2}{P_2} S_2$$



$$\frac{\mathrm{d}S_1}{\mathrm{d}t} = - \underbrace{A}_{\text{No commuting}} - \underbrace{B}_{\text{Commuting}}$$



$$\frac{\mathrm{d}S_2}{\mathrm{d}t} = -\underbrace{A}_{\text{No commuting }} - \underbrace{B}_{\text{Commuting}}$$



$$\frac{\mathrm{d}S_1}{\mathrm{d}t} = -\underbrace{\frac{1}{2}\phi_1 \,\rho \frac{I_1}{P_1} S_1}_{\text{No commuting phase}} - \underbrace{B}_{\text{Commuting phase}}$$

$$\frac{\mathrm{d}S_3}{\mathrm{d}t} = -\underbrace{\frac{1}{2}\phi_3\,\rho\frac{I_3}{P_3}S_3}_{\text{No commuting phase}} - \underbrace{B}_{\text{Commuting phase}}$$

 h_{ij} : Commuter from region i to j

 I^c : commuting infectious

 I^r : remaining infectious

$$P_i = \sum_{j=1}^n h_{ij}$$

$$N_i = P_i - \sum_{j \neq i} h_{ij} + \sum_{j \neq i} h_{ji}$$

$$\frac{\mathrm{d}S_2}{\mathrm{d}t} = -\underbrace{\frac{1}{2}\phi_2 \,\rho \frac{I_2}{P_2} S_2}_{\text{Commuting phase}} - \underbrace{B}_{\text{Commuting phase}}$$

No commuting phase



$$\frac{dS_{1}}{dt} = -\underbrace{\frac{1}{2}\phi_{1}\rho\frac{I_{1}}{P_{1}}S_{1}}_{\text{No commuting phase}} - \underbrace{\frac{1}{2}\left(\phi_{1}\rho\frac{I_{1}^{r}}{N_{1}}S_{1}^{r} + \phi_{1}\rho\frac{I_{1}^{c}}{N_{1}}S_{1}^{r} + \rho S_{1}\sum_{j\neq 1}\phi_{j}\frac{h_{1j}}{P_{1}}\frac{I_{j}^{r} + I_{j}^{c}}{N_{j}}\right)}_{\text{No commuting phase}}$$

Commuting phase

$$\frac{\mathrm{d}S_3}{\mathrm{d}t} = -\underbrace{\frac{1}{2}\phi_3 \,\rho \frac{I_3}{P_3}S_3}_{\text{No commuting phase}} - \underbrace{\frac{B}{\mathrm{Commuting phase}}}_{\text{No commuting phase}}$$

 h_{ij} : Commuter from region i to j

 I^c : commuting infectious

 I^r : remaining infectious

$$P_i = \sum_{j=1}^n h_{ij}$$

$$N_i = P_i - \sum_{j \neq i} h_{ij} + \sum_{j \neq i} h_{ji}$$

$$\frac{\mathrm{d}S_2}{\mathrm{d}t} = -\underbrace{\frac{1}{2}\phi_2 \,\rho \frac{I_2}{P_2} S_2}_{\text{Commuting phase}} - \underbrace{B}_{\text{Commuting phase}}$$

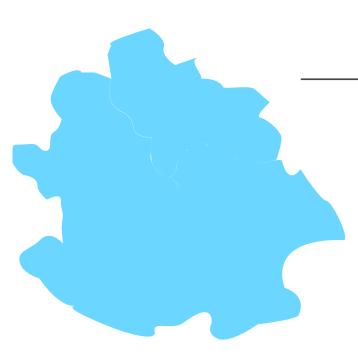
No commuting phase

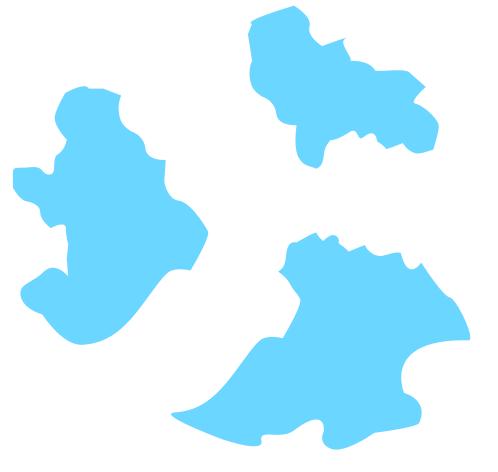


→ For uniformly distributed cases, the models should return the same output

Basic reproduction numbers for different numbers of regions.

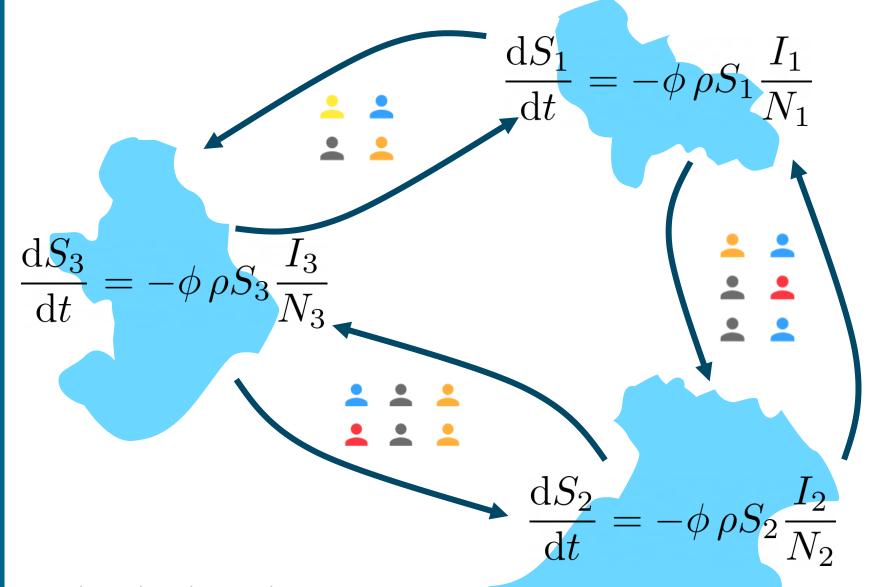
Number of Regions	Model A	Model B	Model C
1	4.48161	4.48161	4.48161
2	4.48161	6027	4.48161
5	4.48161	6.2 43	4.48161
10	4.48161	6 3 54	4.48161
20	4.48161	.6105	4.48161
50	4.48161	6.67782	4.48161





From simple ODE to metapopulation: A Graph-ODE alternative





- Use a graph with regions as nodes
- One edge per, e.g., pair (infection state, age group)
- Advance nodes in parallel from t to t+0.5 and from t+0.5 to t+1

Advantage:

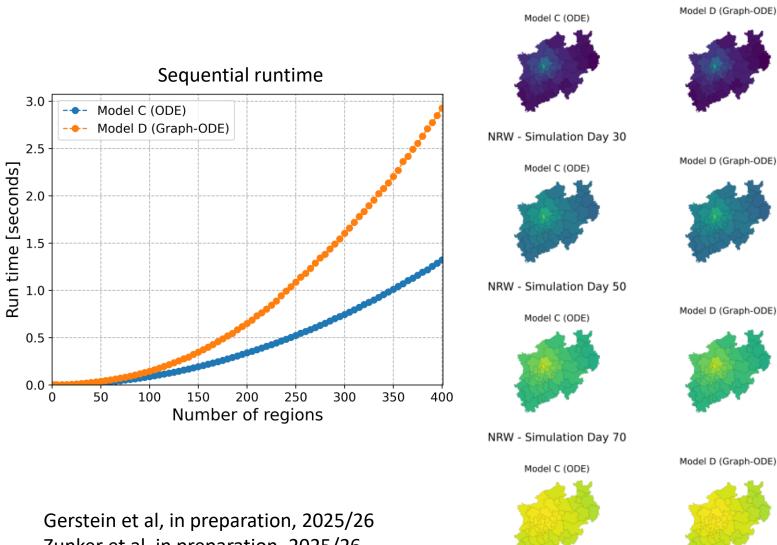
Parallelism

Disadvantage:

- Returning commuters need to be approximated
- Theory more complex

ODE vs. Graph-ODE metapopulation

NRW - Simulation Day 10

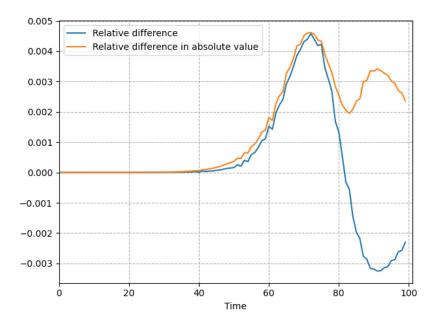






Carlotta Gerstein

Henrik Zunker

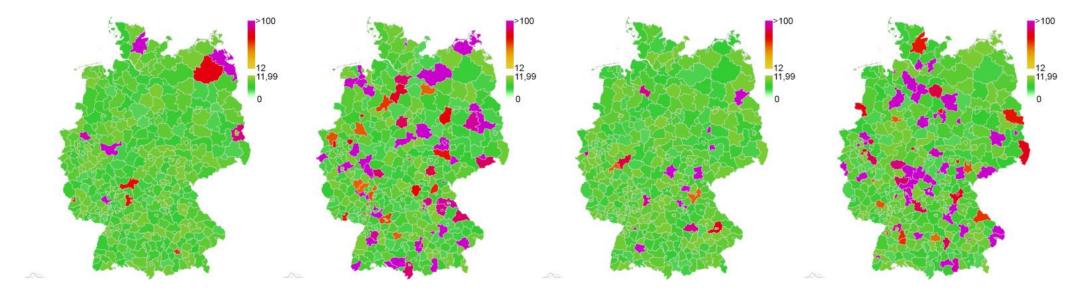


Zunker et al, in preparation, 2025/26

Application: Numerical assessment of the "NoCovid" control strategy



- "NoCovid" is not "ZeroCovid"
- NoCovid: "Controlling the Covid-19 pandemic through Green Zones"



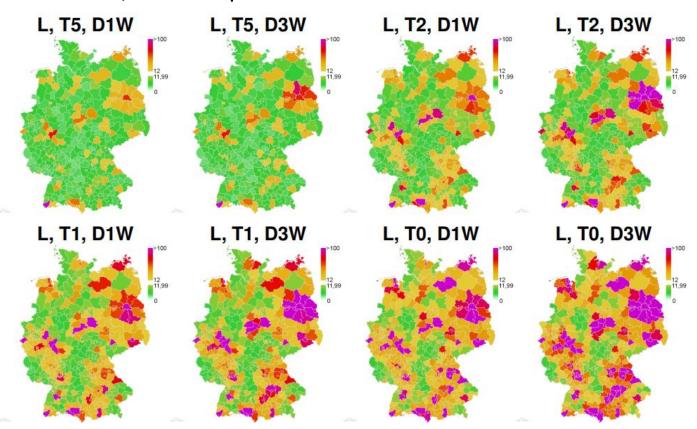
Four different initial scenarios. Random initial incidence (weekly cases per 100 000 individuals) of 75-150 for 2-20% of the counties and incidence below 10 otherwise

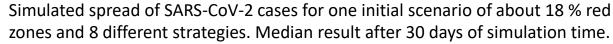
- Test of commuters coming from red zones
- 75 % detection ratio (averaged value for mix of massive deployment of antigen tests plus PCR, RTD-PCR and pool tests)
- Considering different frequencies (daily, twice per week, ...)

Application: Numerical assessment of the "NoCovid" control strategy

DLR

- T0, T1, T2, T5: No testing, testing once, twice or five times per week
- L: Lockdown
- D1W, D3W: Implementations of interventions with one or three weeks delay





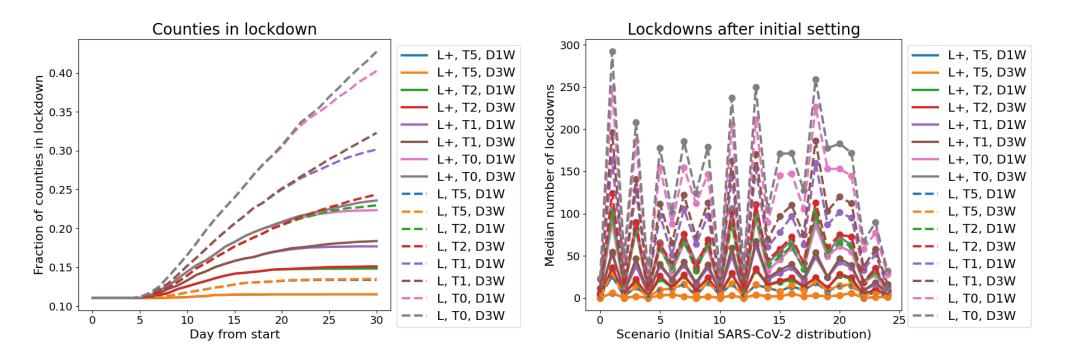


https://doi.org/10.1186/s12879-022-07302-9



Application: Numerical assessment of the "NoCovid" control strategy





- T0, T1, T2, T5: No testing, testing once, twice or five times per week
- L, L+: Lockdown or strict lockdown
- D1W, D3W: Implementations of interventions with one or three weeks delay



ODE-based metapopulation with feedback mechanism





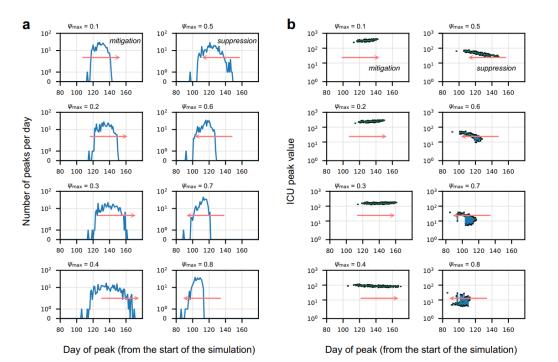
Dead

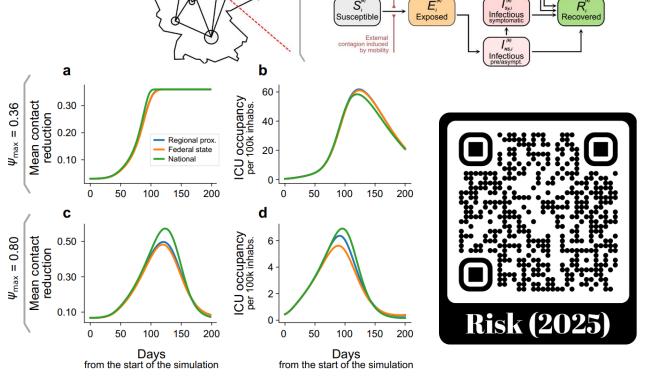
Henrik Zunker

Within-node dynamics

Measured

- Integration of spatially resolved human behavior
- Feedback loop based on perceived risk with memory kernel
- Nominal ICU capacity as threshold for regulation measures
- Regulation updates the effective contact rate





Meta-population model for

https://doi.org/10.1016/j.chaos.2025.116782

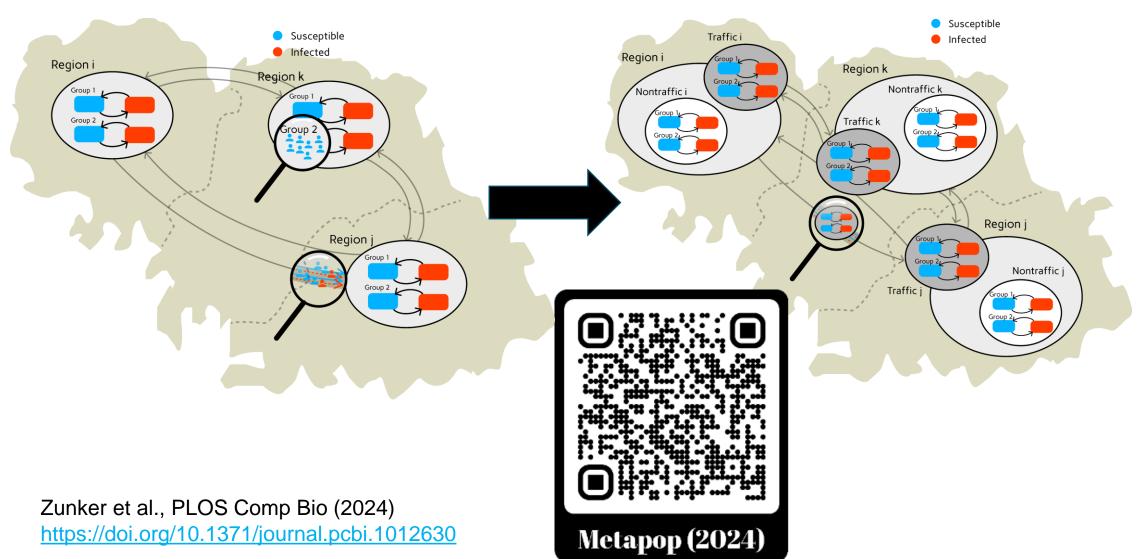
Zunker et al., Chaos, Solitons & Fractals (2025)

Extension to travel-time aware Graph-ODE metapopulation





Henrik Zunker



Al-based on-the-fly computation for web applications







Output

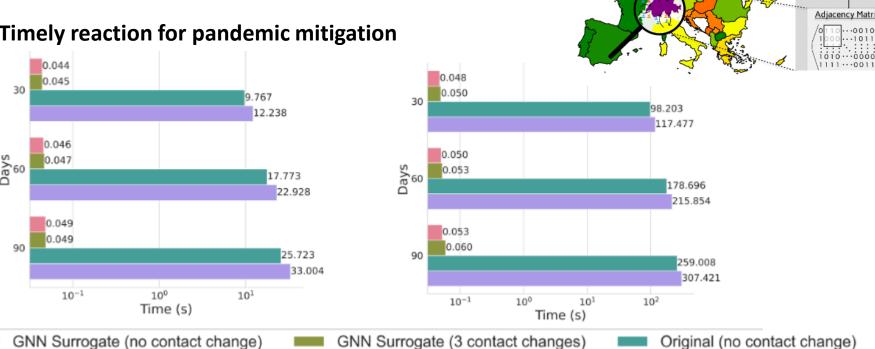
Agatha Schmidt

Henrik Zunker

Graph neural network

- Simulate spatially resolved expert models
- Train spatially resolved AI surrogates (Graph Neural Networks) on expert model' outcomes
- → Enables low-barrier web access for decision makers

→ Timely reaction for pandemic mitigation





Original (3 contact changes)

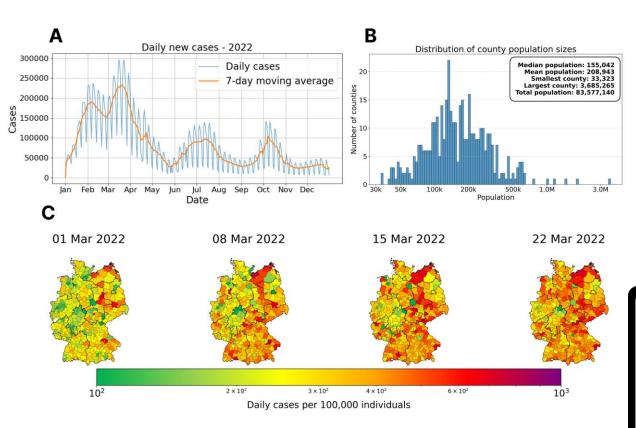
Federated learning with differential privacy

- Centralizing data challenging due to high sensitivity and privacy constraints
- Federated learning train a shared model without centralizing raw data
- Differential privacy ensures protection of private and sensitive data

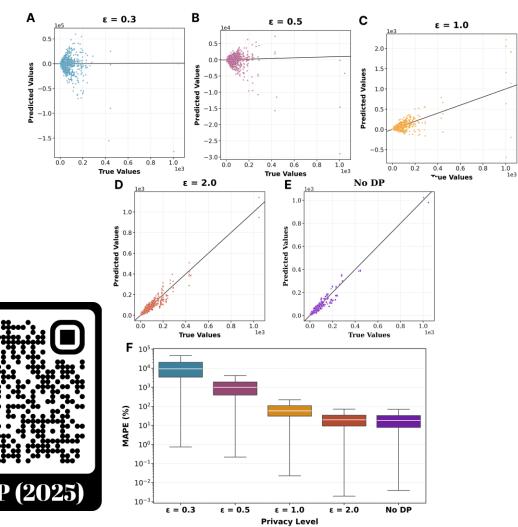




Henrik Zunker



Kerkouche, Zunker et al., Submitted (2025) https://arxiv.org/abs/2509.14024



Agent-based modeling











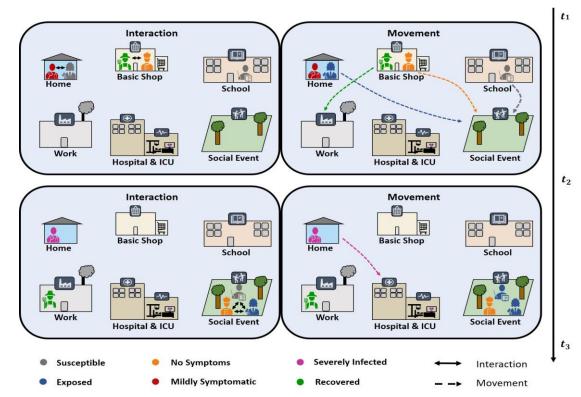
- Model individuals (or households) as individual agents
- Computational cost scales (super)linearly with number of agents







• Study and answer research questions on a "microscopic" level (e.g. individual decisions, test strategies, viral load...)



Algorithm 1: Trip-based agent-based simulation

1 $t \leftarrow t_0 \in \mathbb{R}$

2 while $t \leq t_{\text{max}}$ do

for each location do

Execute agents' interactions

for each agent do

Perform individual movement

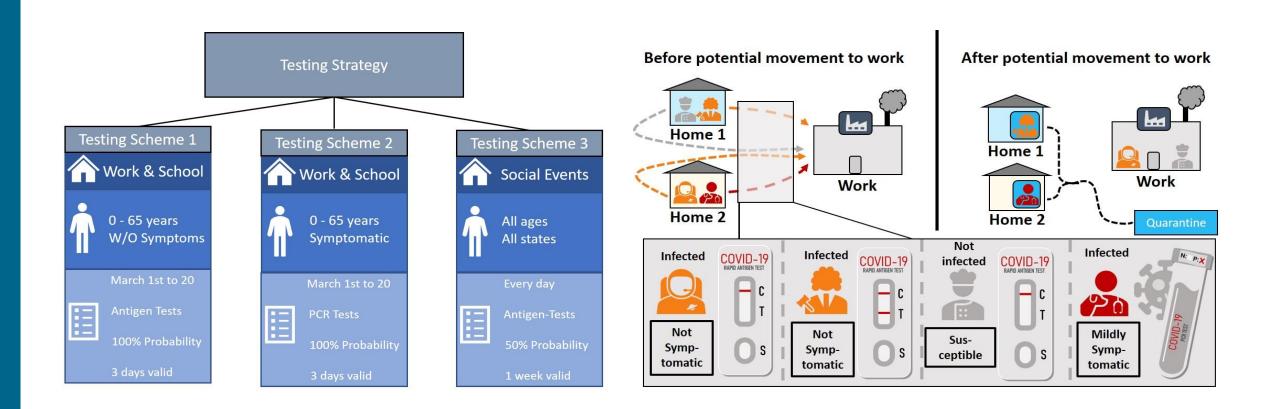
7 $t \leftarrow t + \Delta t$

Agent-based modeling: Testing strategies





Sascha Korf



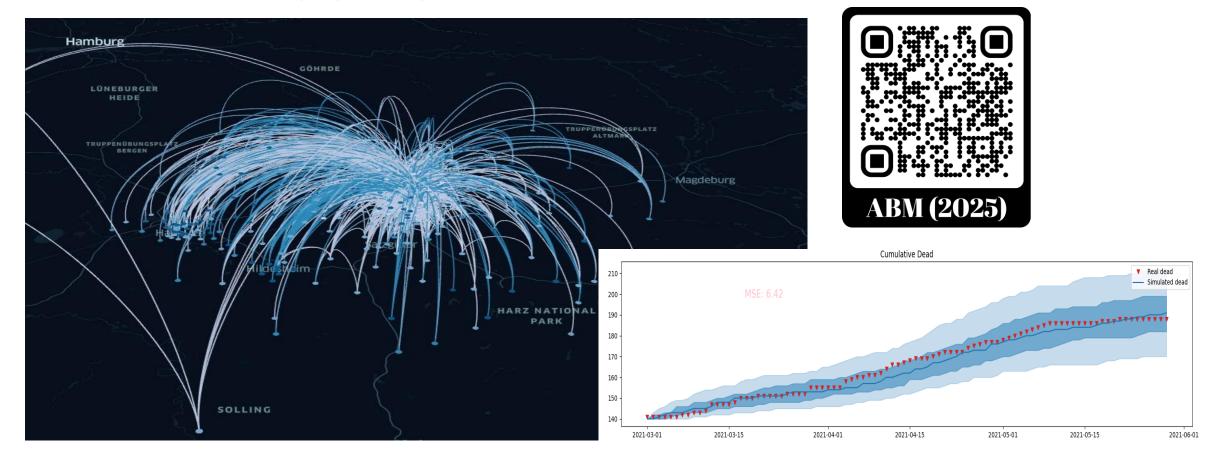
ABM: Application to city-scale





Sascha Korf

- Approximately 370.000 persons from Brunswick and the surrounding area
- Over 1.3 million trips per day



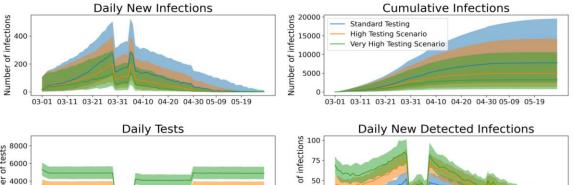
ABM: Advanced testing strategies

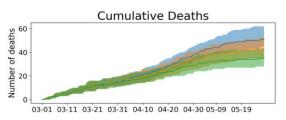
Scenario analysis



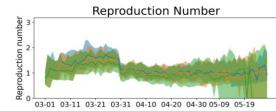


Sascha Korf

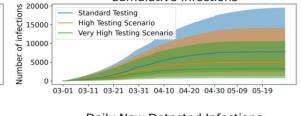


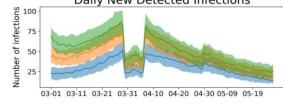


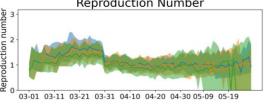
03-01 03-11 03-21 03-31 04-10 04-20 04-30 05-09 05-19

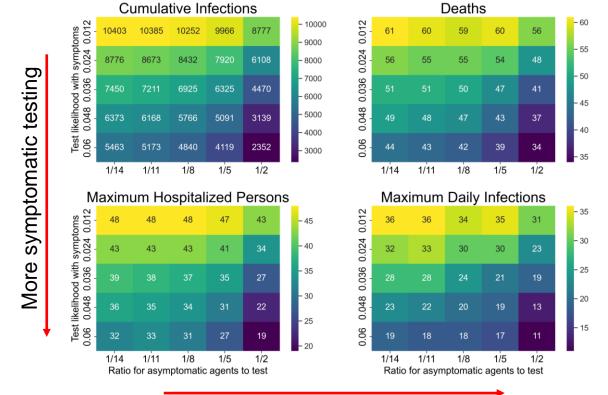












Symptomatic vs. general testing

More symptom-independent testing

Kerkmann, Korf et al., Computers in Biology and Medicine (2025) https://doi.org/10.1016/j.compbiomed.2025.110269

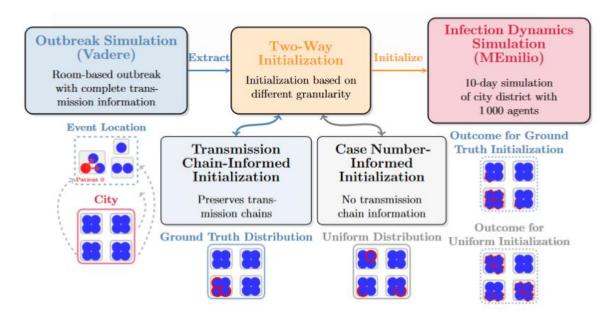
E 2000

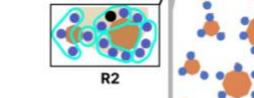
ABM: Effects of missing transmission chains



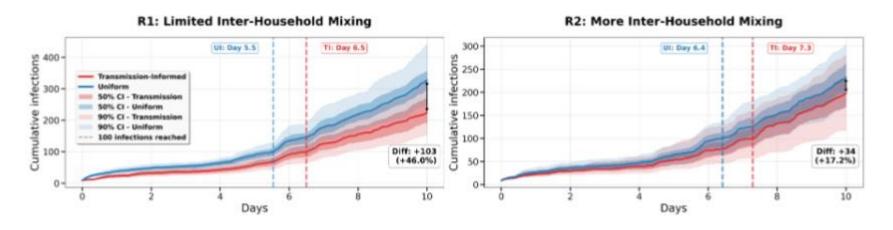


Sascha Korf





Infection Curves: Transmission-Informed vs Uniform Initialization



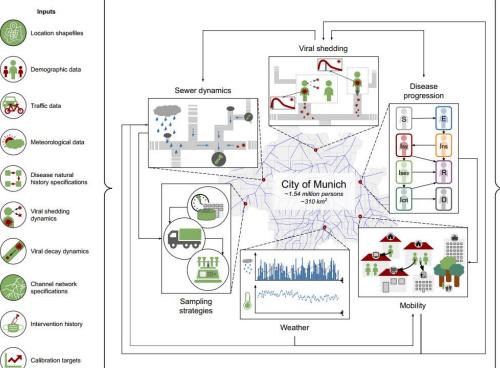
-- Link to come --Korf et al., Submitted (2025)

37

ABM: Joint ABM-Wastewater model



"How does can testing-based detection be improved by combination with wastewater?"



Studying the effect of different Detailed insights into wastewater dynamics

Munich (2025)

normalization strategies ~

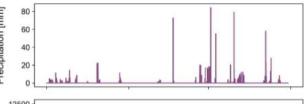
for rain events

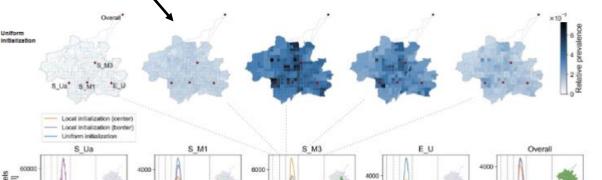
population and





Julia Bicker





Bicker, Tomza, Wallrafen et al., Submitted (2025)

https://doi.org/10.1101/2025.09.25.25336633

Hybrid agent-metapopulation: Spatial hybrid







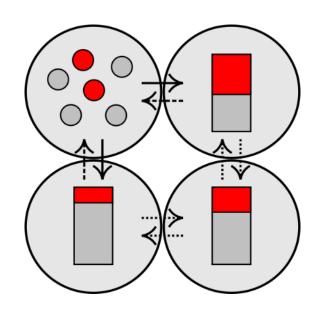
Julia Bicker René Schmieding

• Idea:

- Interest in infection spread in particular region
- Exclusive availability of data in specific region (or computational resources limited)

Concept:

- Agent-based model in region of interest (focus region)
- ODE-based models for connected regions
- → Detailed results in focus region while considering influence of connected regions in runtime efficient manner



Hybrid agent-metapopulation: Temporal hybrid



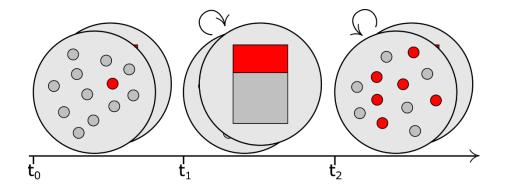




Julia Bicker René Schmieding

• Idea:

- Low case numbers:
 High stochasticity and individual behavior is important
- High case numbers:
 Individual behavior is less influential and single simulation outcomes are close to averaged results



Concept:

- Switch between agent-based and ODE-based model during the simulation according to a threshold value
- → Capture stochasticity and individual behavior when necessary for accurate outcomes while using runtime advantage when possible

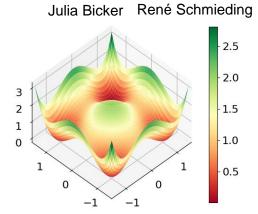
Proof-of-concept spatial hybrid model

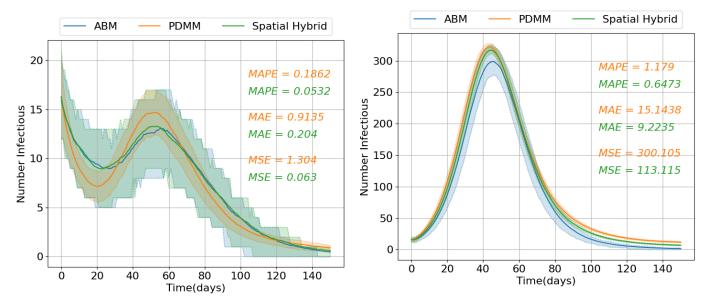


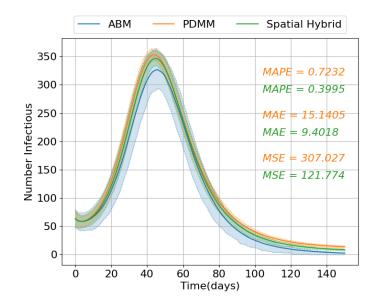




- Setup: 8000 agents, 1% of population initially infected
- Focus region: $\Omega_1 = (-\infty, 0) \times (0, \infty)$
- Transmission rate in $\Omega_2=(0,\infty)\times(0,\infty)$ corresponding to $R_0=2.4$
- Transmission rate in other regions corresponding to $R_0=0.8$







Bicker, Schmieding et al., Infectious Disease Modelling (2025)

https://doi.org/10.1016/j.idm.2024.12.015

Proof-of-concept spatial hybrid model



PDMM



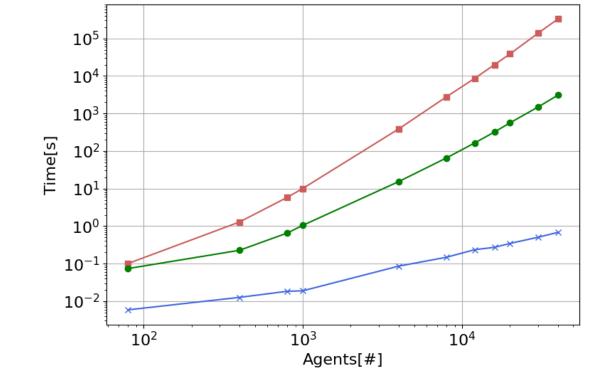
Spatial Hybrid



Julia Bicker René Schmieding

- Spatial-hybrid has same scaling behavior like ABM
- For 400 agents: Runtime of spatial-hybrid 1 order of magnitude lower than for ABM
- For 40,000 agents: Spatial-hybrid reduces runtime by 98%





ABM

Bicker, Schmieding et al., Infectious Disease Modelling (2025) https://doi.org/10.1016/j.idm.2024.12.015



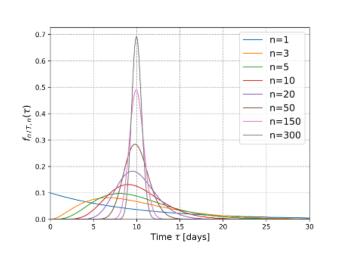
Basic model properties (without spatial resolution for now)

Impact of distributions on epidemic peaks





- Distributions have impact on epidemic peaks and timings
- Literature sometimes mentions over-/ underestimation by exponential distribution
- Situation is highly complex and no general rule





Different Erlang/Gamma distributions

https://doi.org/10.1016/j.matcom.2025.07.045

Plötzke et al., Mathematics and Computers in Simulation (2025)

Lena Plötzke Anna Wendler

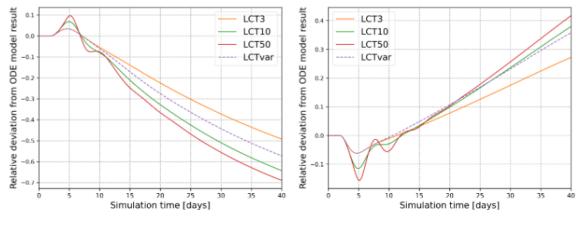


Figure 7: Relative difference in daily new transmissions around change points. Relative comparison of the daily new transmissions of different LCT models compared to a simple ODE model around change points. The contact rate $\phi(t)$ is halved (left) or doubled (right) after the second simulation day. Further notation as in Fig. 3.

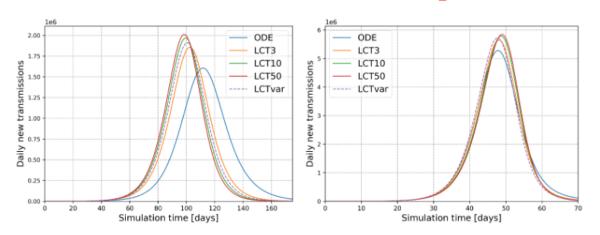


Figure 8: Daily new transmissions to compare the predicted epidemic peaks. Illustration of the predicted peaks of the daily new transmissions of LCT models with different numbers of subcompartments against a simple ODE model. The contact rate is set such that $\mathcal{R}_{\text{eff}}(0) \approx 2$ (left) or $\mathcal{R}_{\text{eff}}(0) \approx 4$ (right). Further notation as in Fig. 3.

Integro-differential equation-based (IDE) model





Anna Wendler

- Simple ODE models are restricted to exponential stay time distributions
 - → not realistic according to literature
- First generalization: Use of Linear Chain Trick allows Erlang distributed stay times
- Full flexibility: Models based on integro-differential equations (IDEs) allow arbitrary stay time
 distribution

Advantages:

- Possibility to capture more realistic
 modeling assumptions than ODE models
- Parameters can be made dependent on time
 since infection, e.g. mean infectivity
- Can include history of disease dynamics when initializing

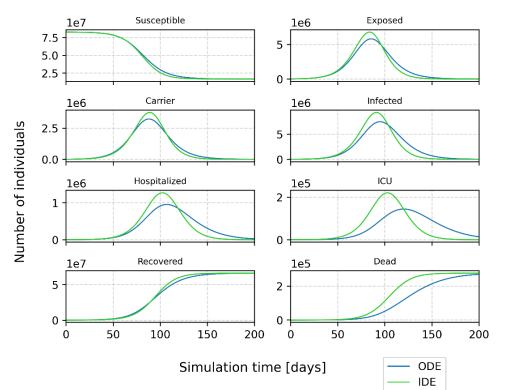
Disadvantages:

- Only few numerical solvers available; not as efficient as ODE solvers
- Data on distributions not widely available
- Assumption of (to some extent)
 homogenous and well-mixed population

IDE application

- Lognormal distributions according to data on COVID-19 in IDE model
- Corresponding exponential distributions in ODE model
- Epidemic peaks differ with respect to size and timing
- → Distribution assumption has impact on simulation results and thus on basis for mitigation action
- Numerical scheme preserves biological properties and converges linearly

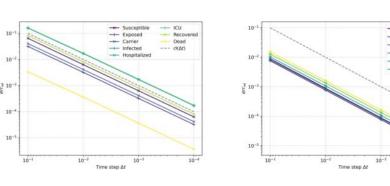
https://doi.org/10.1016/j.amc.2025.129636 Wendler et al., Applied Mathematics and Computation (2025)







Anna Wendler

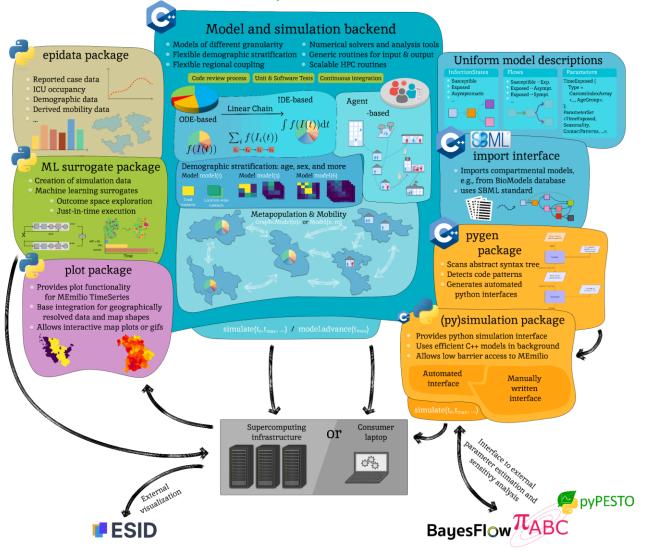




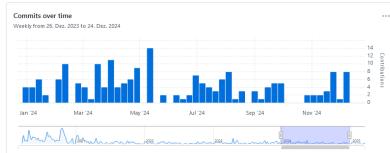


A high performance Modular EpideMIcs simuLatIOn software









Contributors

• 2024: 20

Overall: 41

Activity (on main) August 2025

- 20 active pull requests (12 merged)
- 31 active issues (22 closed)
- 18 active authors

Software & Unit Tests QCI passing Pcodecov 97%

- C++: ca. 650 (2023: ca. 300)
- Python: ca. 230 (2023: ca. 200)

What applications are next (and new)?



- To some extent: RSV, Influenza, highly pathogenic avian influenza (HPAI)
- Post-acute infection syndromes (PAIS), in particular Long Covid/PCC
- Aerosol modeling and transmission chains
- Extension of AI surrogate models
- Model the spread of a foot-and-mouth disease outbreaks
 - affected animals: cattle, sheep, pigs
 - Test out different interventions measures with respect to financial and workforce constraints
 - Use a graph for the transport network and stochastic models for each herd (180.000 nodes)
 - Use spatial information to represent disease spread along other transmission paths





SAVE THE DATE:



Workshop:

Multiscale Infectious

Disease Modeling

March 18-20, 2026







© Volker Lannert / Universität Bonn

Mathematical Biology • Bioinformatics/Omics Analysis

Modelling of the Tumor Microenvironment • Infectious Disease Modelling

Single-Cell Analysis • Modelling of Cellular Pathways • Modelling of Organoids etc.

















Thanks to our funders! / Thank you for your attention!

Questions / Exchange ? → Martin.Kuehn@DLR.de