Simulation based studies for the assessment of mechanisms

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7. Juni 2016

Challenges in identifying mechanistic pathways to assess neighbourhood effects

- Social epidemiology is the study of the influence of
  - individual social attribute
  - individual behaviour
  - interaction between individuals
  - contextual effects
  - Spatial distribution of individual attributes
  - ....

  on the distribution of health outcome of the population

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- We use linear regression models
  - Provide a measure of association between outcome and factors mentioned earlier
  - Assume simple relation (linear)
  - Fail to take into account the reason why people moved to where they are living
  - Fail to take the population dynamics into account

Challenges in identifying mechanistic pathways to assess neighbourhood effects

To identify mechanistic pathways in the study of contextual effects on health we need models which can take into account

- Population dynamics: People are moving - neighbourhood characteristics change over time
- Feed backs: pathway which goes from co-variate to outcome and vice-versa

We would like to

- model social contagion
- mechanisms for individual spatial mobility (why are people moving)
- Estimation of the effect of interventions

Agent based models for spatial data

Agent based models (ABM) are computer based methods with

- simulated individuals
- simulated space
- simulated time

- micro-level programmed “health-behaviour”

$\rightarrow$ “observe” the effects at macro-level

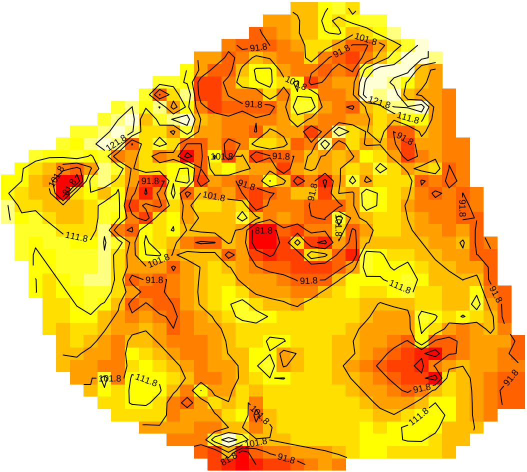
Example

- 5000 simulated observations
- live in a town which looks like Hamburg
- observed over a period of 12 years

- Outcome: hypothetical continuous health indicator
- Attribute of the observations (which cannot be changed): date of birth, gender
- Variables: income, place of residence, health status
- Attribute of places of residence: green yes/no and income indicator (5 levels)

Example: spatial distribution of health at baseline

Darker means poorer health



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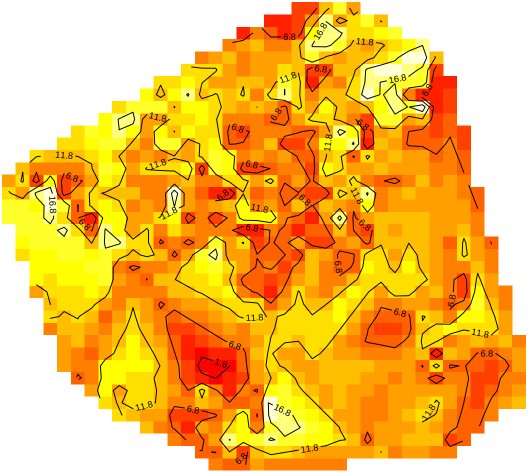
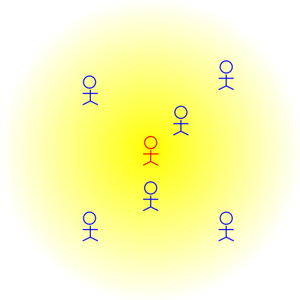


Example: Spatial correlation of health outcomes

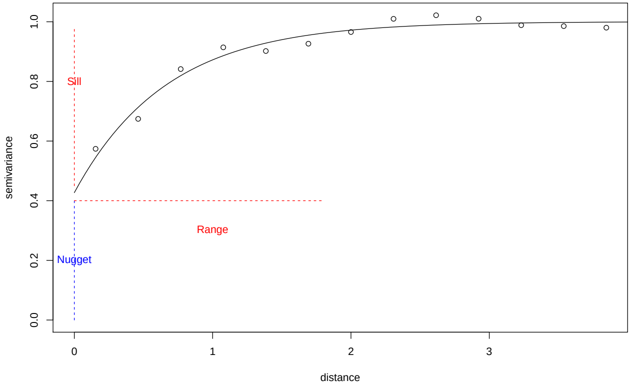
- Macro level: Spatial correlation of health outcomes
- Do health outcomes have a spatial correlation structure?
- Because similar people tend to live close together, we need to control for individual attributes and variables



Evaluate the effects of predefined dynamic models on the characteristics of the spatial correlation of health outcomes

Example: Spatial correlation of health outcomes

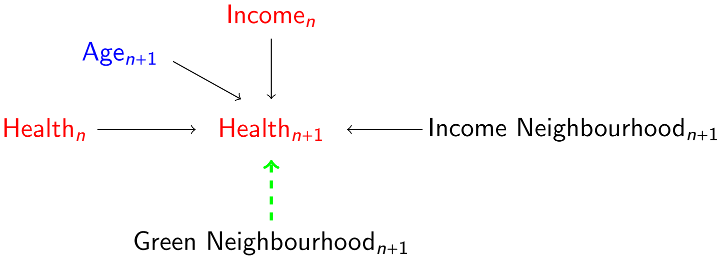
Semivariogram: a model for the spatial correlation structure of the city



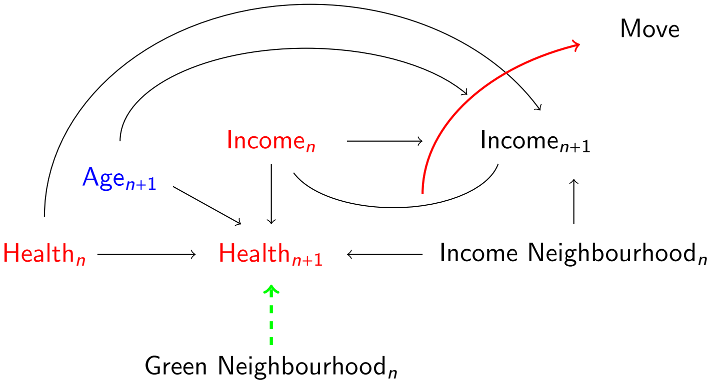
Range: the maximal distance where at least 5% of the total variance is due to spatial factors

Relative structured variability (RSV): Sill/Total variance is a measure of the degree of spatial structure

Example: Simulations

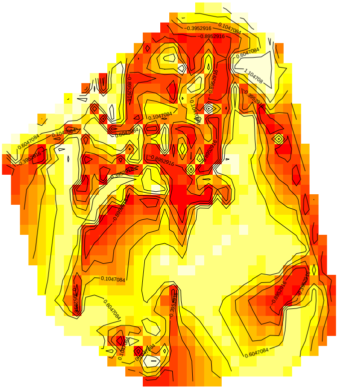


Example: Simulations



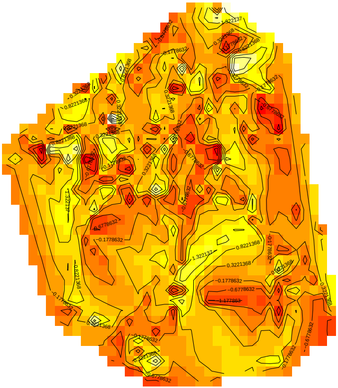
Example: one simulated population - before and after

Range: 1.980 km ; RSV: 0.57



Baseline

Range: 2.400 km ; RSV: 0.28

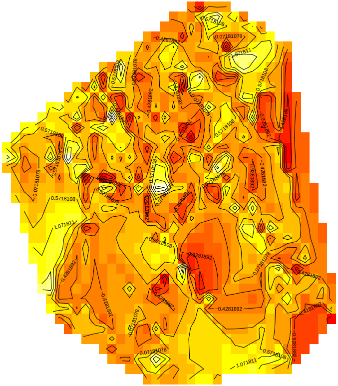


Without green model − After 12 years

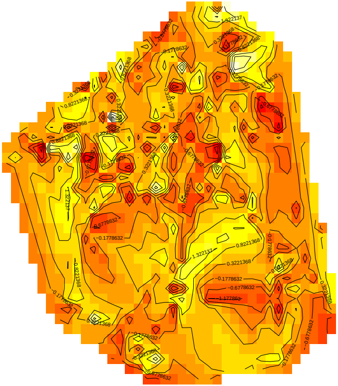
Example: one simulated population - correlation of residuals - comparison of models

Range: 1.600 km ; RSV: 0.29
Green Effect

Range: 2.400 km ; RSV: 0.28
No green effect



Green model



Without green model

Example: results

Avarage values over simulated population for which a correlation structure could be evaluated

	Green model	W/o green model
Baseline RSV (SD)	0.59 (0.03)	0.59 (0.03)
Baseline range (SD) (km)	2.03(0.15)	2.03 (0.15)
After 12 years		
No spatial correlation	516/1000	598/1000
RSV (SD)	0.25 (0.09)	0.30 (0.13)
Range (SD) (km)	2.08 (1.15)	2.49 (1.32)

RSV: Relative structured variability

ABM and empirical data

Can we do social epidemiology without data collection?

☺

ABM and empirical data

- NO
- And we still need regression models!

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  - to specify the models
  - to validate the models

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- Data is needed twice:
  - to specify the models
  - to validate the models
- Two sets of data are needed

ABM and empirical data

Specification of models

- The stochastic models need quantitative values to be specified
- These values need to be estimated from empirical data using
  - Regression models with interaction
  - Directed acyclic graph with mediation analysis

ABM and empirical data

Validation of models

- A difficult exercise

ABM and empirical data

Validation of models

- A difficult exercise
- A model to be valid need to be well specified!
- There are no real method how to do that.
  - Verify the robustness of the results obtained when the parameters values of the models are sightly modified
  - Take the uncertainty of the simulation paramters in the results
- Results of various competing models need to be compared to real data

Literature

- El-Sayed, A M; Scarborough, P; Seemann, L; Galea, S Social network analysis and agent-based modeling in social epidemiology. *Epidemiologic perspectives & innovations* 2012, 9 (1)
- Galea S, Riddle M, Kaplan GA, Causal thinking and complex system approaches in epidemiology. *Int J Epidemiol.* 2010 Feb;39(1):97-106. doi: 10.1093/ije/dyp296.
- Yang Y, Diez Roux AV, Auchincloss AH, Rodriguez DA, Brown DG. A spatial agent-based model for the simulation of adults' daily walking within a city. *Am J Prev Med.* 2011 Mar;40(3):353-61. doi: 10.1016/j.amepre.2010.11.017.