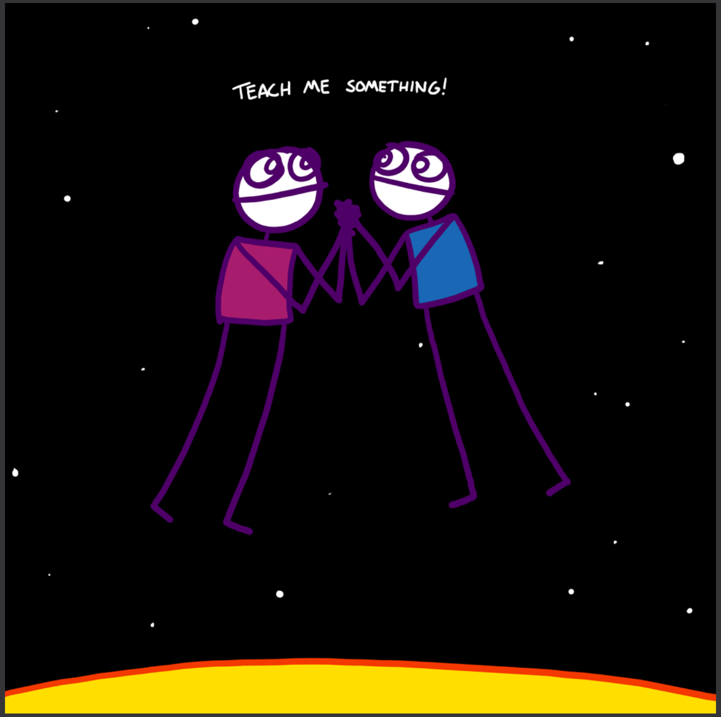
An introduction to:

Spatial Microsimulation

(and the wonderful things it can do)



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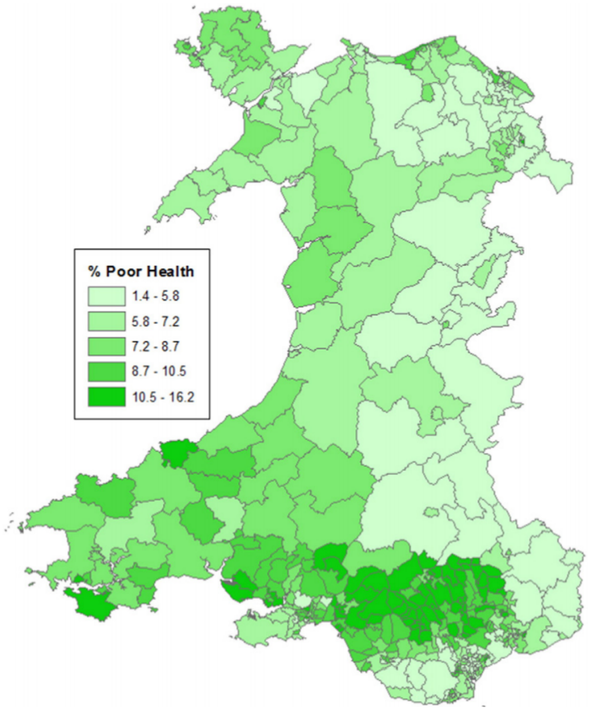
CSAP Research Group Meeting – 21st February 2018

What is spatial microsimulation?

- A technique for estimating the **characteristics of a population** by combining individual level data (e.g. from a representative survey) with aggregate data (e.g. from a national census)
- Generates a **synthetic population** based on the data you have at the individual level which matches the aggregate statistics for a given area e.g. national, regional or local authority scale
- This population can be mapped to visualise the **area statistics** e.g. health, crime
- Basic premise: you can achieve a **more realistic picture** of aggregate behaviour by analysing individual behaviour and then scaling this up



Small area estimates of poor health across Welsh MSOAs (Whitworth et al, 2017)

Why is it useful?

- Census microdata are often **protected** for confidentiality reasons, so researchers cannot access (and therefore analyse) the full dataset
- In some cases, data on the variable of interest has **not been collected** in an aggregate form (e.g. social attitudes, demand for goods/services)
- Spatial microsimulation can estimate this characteristic (**the target variable**) in the synthetic individuals and therefore scale up the findings to the population of interest
- For this to work, we need to know there is a strong statistical relationship between the variables we have at the individual *and* the aggregate level (**constraint variables**) and the variable of interest
- AND it can assign **geographical information** to these individuals based on the geographically disaggregated data available, enabling spatial analysis

How can it be applied?

Three main applications for spatial microsimulation models:

1. **Small area estimation** - deriving estimates for small geographical areas, so policies can be more accurately spatially targeted e.g. smoking, obesity
2. **Small area projection** - predicting how populations characteristics of small areas will change into the future e.g. to inform spatial planning to ensure the provision of services to those who need them
3. **Small area policy modelling** - to analyse where a policy will have the greatest effect by modelling its effects across different small areas

*NB. The first example is a **static** microsimulation model, the latter two are **dynamic** models*

Tanton, R. & Edwards, K. I. 'Introduction to Spatial Microsimulation: History, Methods and Applications.'
In: *Spatial Microsimulation: A Reference Guide for Users*. Eds. Robert Tanton & Kimberley Edwards. Springer, 2013.

An applied example of public attitudes to renewable energy technologies in the UK

- Individual-level survey data: UK Government's **Energy and Climate Change Public Attitudes Tracker** (24 waves beginning in 2012, n = ~50,000)
- Asks respondents questions about **support** and **opposition** to onshore wind, offshore wind, biomass, wave and tidal, and solar energy (**the target variable**)
- Also collects **demographic data**: Age; Gender; Social Class; Tenure; Working Status; Urban or Rural Area; Household Income (*plus UK Government Region*)
- Potential **constraint variables** and **aggregate datasets**:
  - Age – UK census (2011)
  - Gender – UK census (2011)
  - Tenure – UK census (2011)
  - Working Status – UK census (2011)
  - Social Class – UK census (2011)
  - Rural Urban Classification – ONS (2011)
  - UK Government Region – BEIS (2012-2018)
  - Household Income – ?

Available at output area level

(Very) early results

- Binary logistic regression for onshore wind
- **Significant variables**: Age; Gender; Working Status; Tenure; Urban or Rural Area
  - Older age groups (45-54, 55-64, 65+) = less likely to support than 16-44 years olds
  - Male = less likely to support than female
  - Unemployed and retired = less likely to support than full-time workers
  - In education = more likely to support than full-time workers
  - Urban = more likely to support than rural

- Most likely to support = female, renter/other, in education, <45
- Least likely to support = male, owner occupier, unemployed/retired, >45

- Variance explained = approximately **10%** (Nagelkerke R Square .104)

Next steps

- Try to improve logistic regression model to **better explain variance** (for other renewable technologies as well as onshore wind) – add in UK region
- **Pilot study**: create synthetic populations for Local Authority Districts (or other geography?) in the Yorkshire and Humber Region
- Create **choropleth maps** showing areas of high/low support for renewable energy technologies (onshore wind, offshore wind, biomass, wave/tidal, solar)
- Analyse **spatial patterns** in the presence/absence of support for these technologies based on existing renewable energy infrastructure
- The idea is test the **NIMBY vs. inverse NIMBY hypothesis** (i.e. are people more or less likely to support renewable energy technologies when they live in close proximity to them?) = contribution to public acceptance literature


BOY, HAVE WE LEARNED SOMETHING TODAY!
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Thank you!

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References

- Tanton, R. & Edwards, K. I. ‘Introduction to Spatial Microsimulation: History, Methods and Applications.’ In: *Spatial Microsimulation: A Reference Guide for Users*. Eds. Robert Tanton & Kimberley Edwards. Springer, 2013.
- Whitworth, A., Carter, E., Ballas, D., & Moon, G. (2017). Estimating uncertainty in spatial microsimulation approaches to small area estimation: A new approach to solving an old problem. *Computers, Environment and Urban Systems*, *63*, 50–57.