

Bayesian estimation of small-area (healthy) life expectancy: Methodology & Applications

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Structure of presentation

1. Introduction
2. Methodology
3. Real-life applications
4. Key points to remember



Introduction (1)

- Many urban policies aim to improve areas and address socioeconomic deprivation
- The resulting investment is often delivered through area-based programmes
 - ▶ targetting complete neighborhoods instead of individuals
- Validating evidence is scarce: ‘population health’ is extremely difficult to quantify and compare at the small-area level
 - ▶ Which neighborhoods should be targetted?
 - ▶ Are area-based programs successful?

Introduction (2)

Theoretically, LE and HLE are ideally suited for this:

- .. combines mortality and morbidity into a single indicator;
- .. can be readily compared between areas (i.e. corrected for important confounders);
- .. can be easily communicated to a broad audience;
- .. can be calculated for a large number of areas;
- .. is comparable over time.

2. Small area problems

- a) Standard life table methodology is developed for large populations and unsuitable for small-area analyses
- b) Health surveys often have sample sizes that are too small (for small-area analyses)



Sparse data problems!

1. Large SE

2. unreliable SE

3. biased estimates

Solution: Bayesian random effects modelling

Statistical methodology that efficiently combines information from similarities between:

- a) adjacent age groups (age-mortality curve, but not relational);
- b) males/females (within the same area);
- c) morbidity/mortality (within the same area);
- d) surrounding area's.

Structure of the model (without priors)

1. Mortality model

$Deaths_{[s,i,x]} \sim \text{Poisson}(pop_{[s,i,x]} * mrate_{[s,i,x]})$

$\log(mrate_{[s,i,x]}) <- b0_{[s]} + b1_{[s,x]} + b2_{[s,i]} * b3_{[s,x]}$

2. Morbidity model

$nrHealthy_{[s,i,x]} \sim \text{Binomial}(prob_{[s,i,x]}, nrSurvey_{[s,i,x]})$

$\text{logit}(prob_{[s,i,x]}) <- b4_{[s]} + b5_{[s,x]} + (b5_{[s,x]})^2 * b6_{[s,i]} + b7_{[s,i]}$

3. (standard) HLE life table calculations

Bayesian random effects approach performs much better than traditional LE estimation approach:

Size of simulated population

		<u>500</u>	<u>1,000</u>	<u>2,000</u>	<u>5,000</u>	<u>10,000</u>	<u>25,000</u>
Traditional:	bias	1.1	0.7	0.6	0.3	0.2	0.1
Bayesian:	bias	0.1	0	0	0	0	0

Source: Jonker et al., American Journal of Epidemiology (2012)

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Traditional:	bias	1.1	0.7	0.6	0.3	0.2	0.1
	rmse	6.3	4.5	3.1	2.2	1.5	0.9
Bayesian:	bias	0.1	0	0	0	0	0
	rmse	3.8	2.8	2.0	1.5	1.1	0.8

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	coverage	86%	90%	91%	92%	93%	94%
Bayesian:	bias	0.1	0	0	0	0	0
	rmse	3.8	2.8	2.0	1.5	1.1	0.8
	coverage	89%	92%	94%	95%	96%	96%

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How is it implemented?

Neither available nor easily implemented in SAS..

**Instead, programmed in the “BUGS” language
(i.e. Bayesian Inference Using Gibbs Sampling)**

and fitted using software called “OpenBUGS”

Structure of presentation

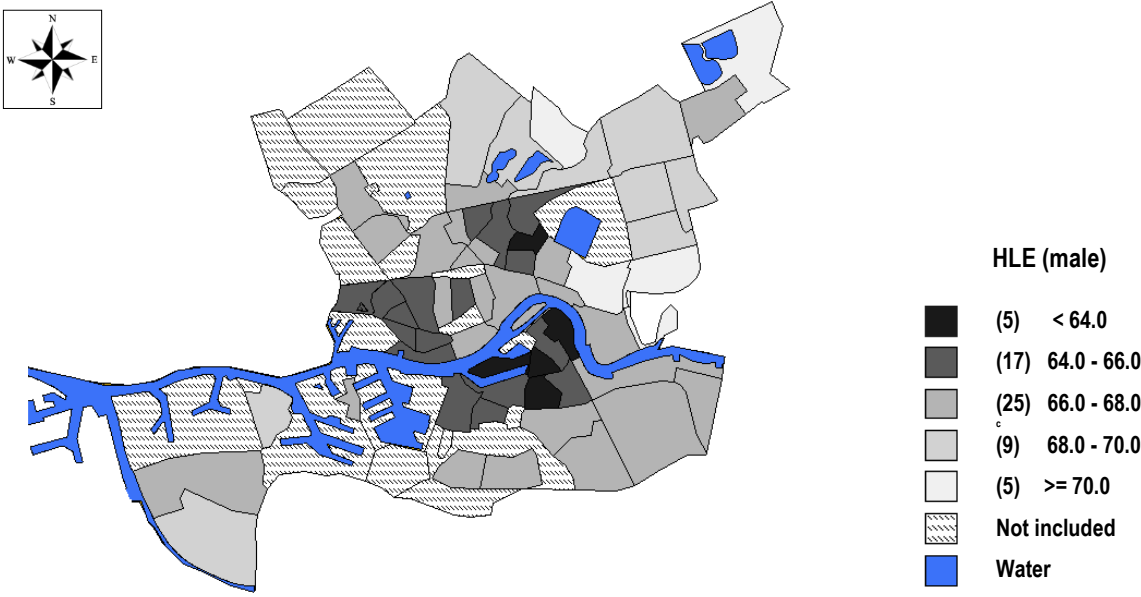
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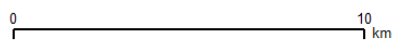
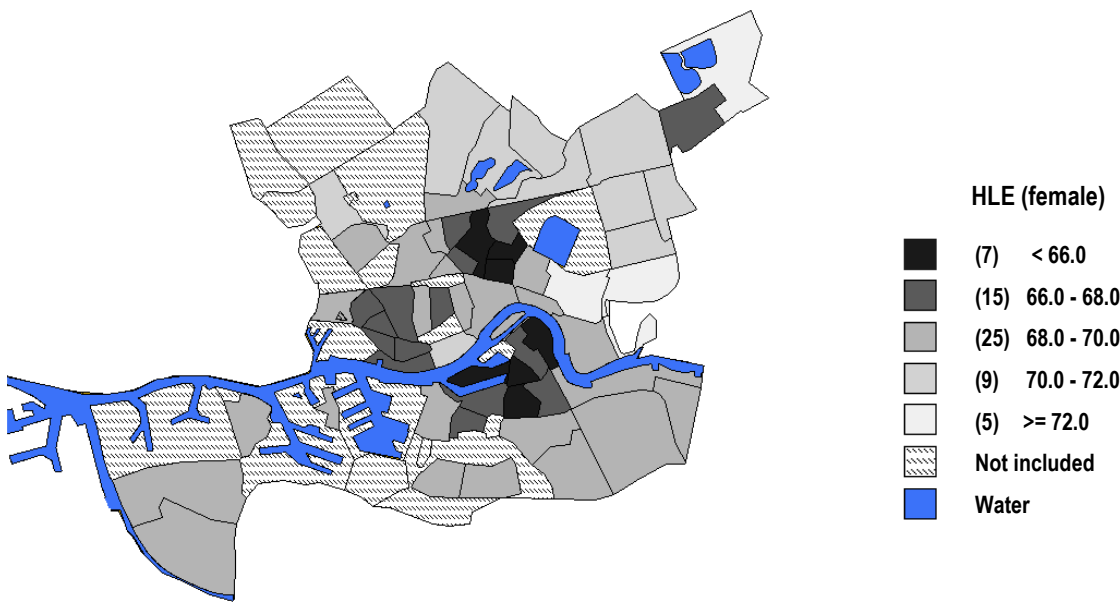
Example 1. Targetting of neighborhoods

5. HLE Results for Rotterdam (2004-06)

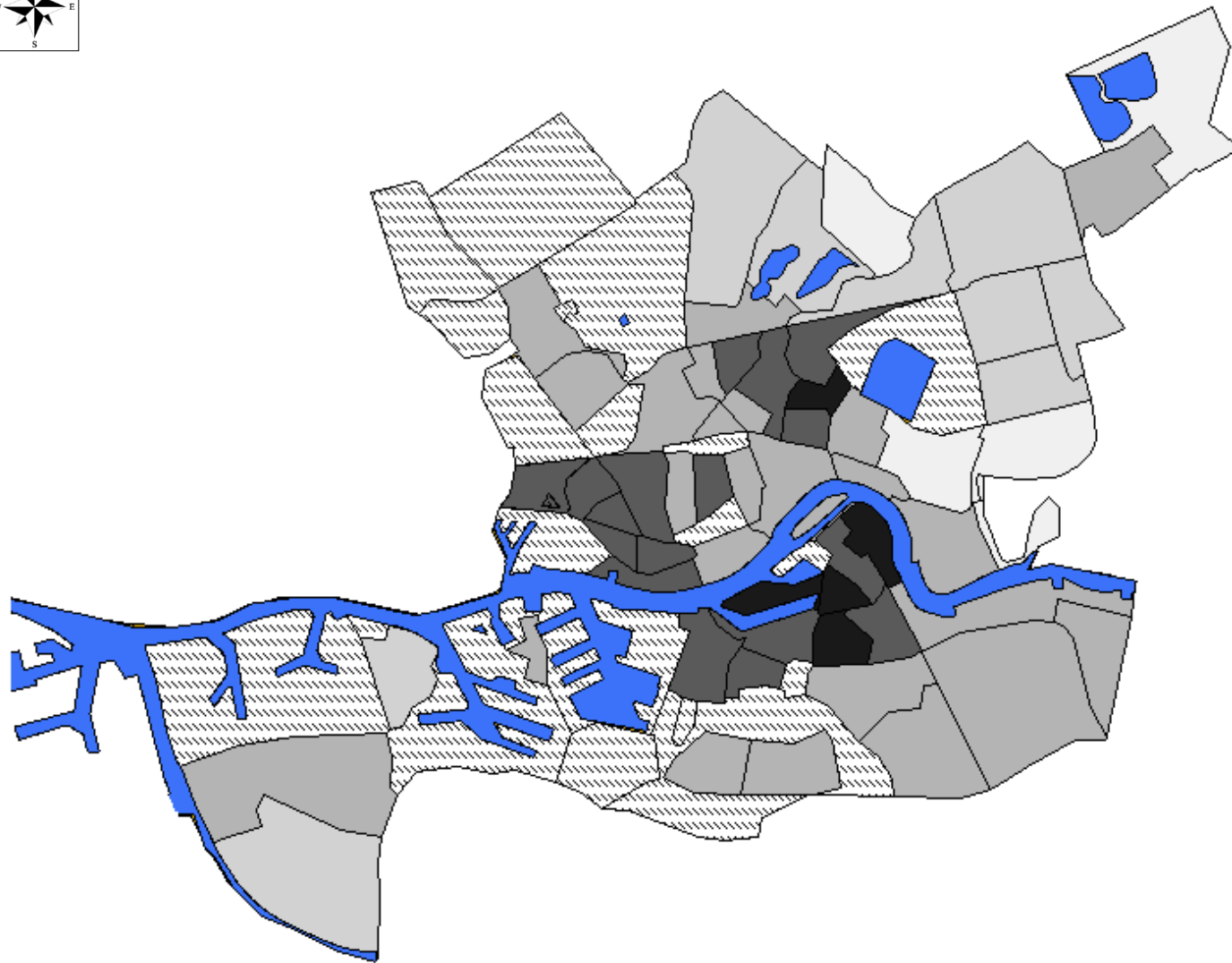
Males










Females



5. HLE Results for Rotterdam (2004-06)



HLE (male)

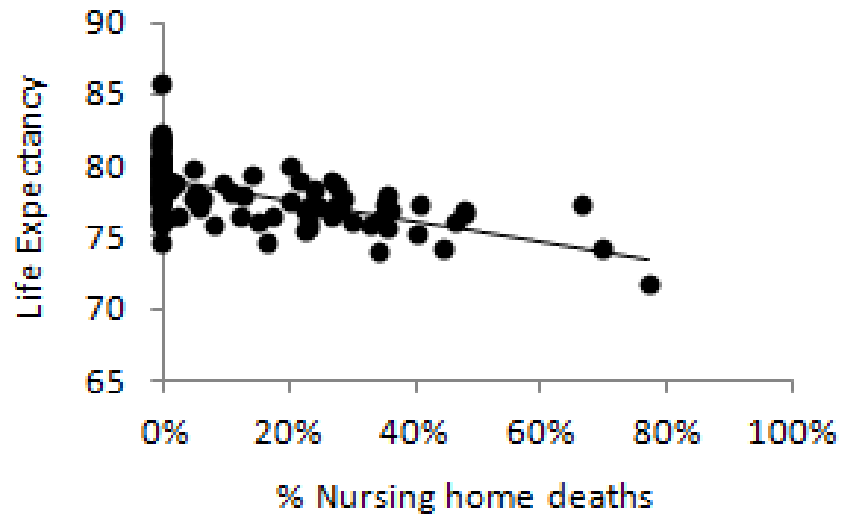
-  (5) < 64.0
-  (17) 64.0 - 66.0
-  (25) 66.0 - 68.0
-  (9) 68.0 - 70.0
-  (5) >= 70.0
-  Not included
-  Water

0 10 km

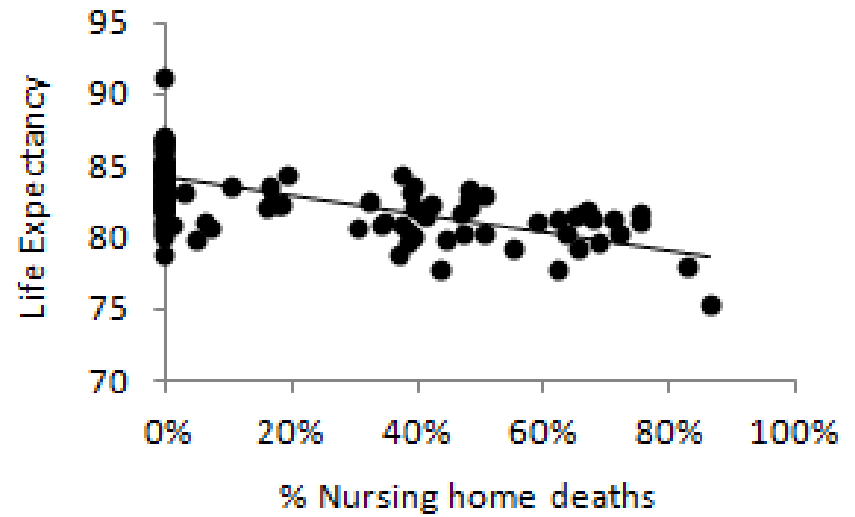
Example 2. The impact of nursing homes

Impact of location of nursing homes

Males



Females

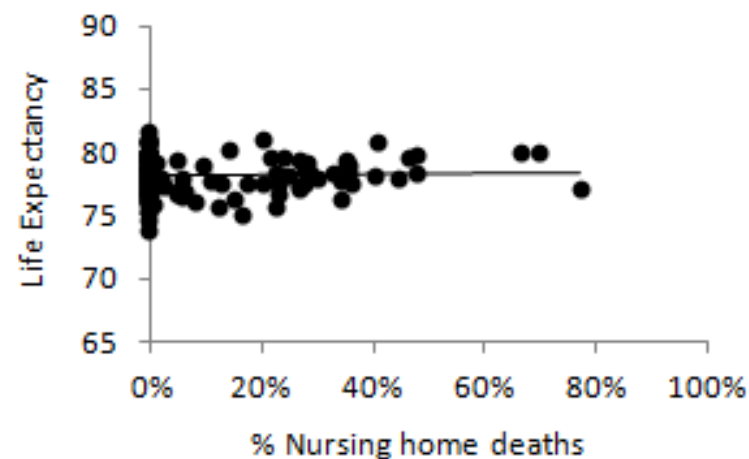
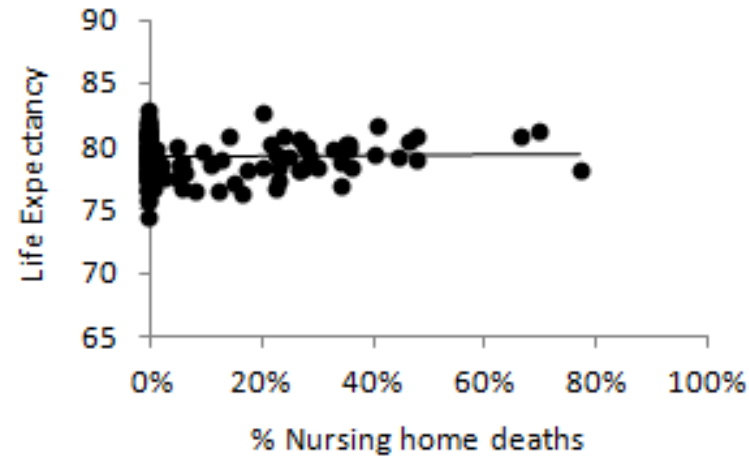


The Bayesian approach corrected for the location of nursing homes (!)

a) Bayesian modelling approach

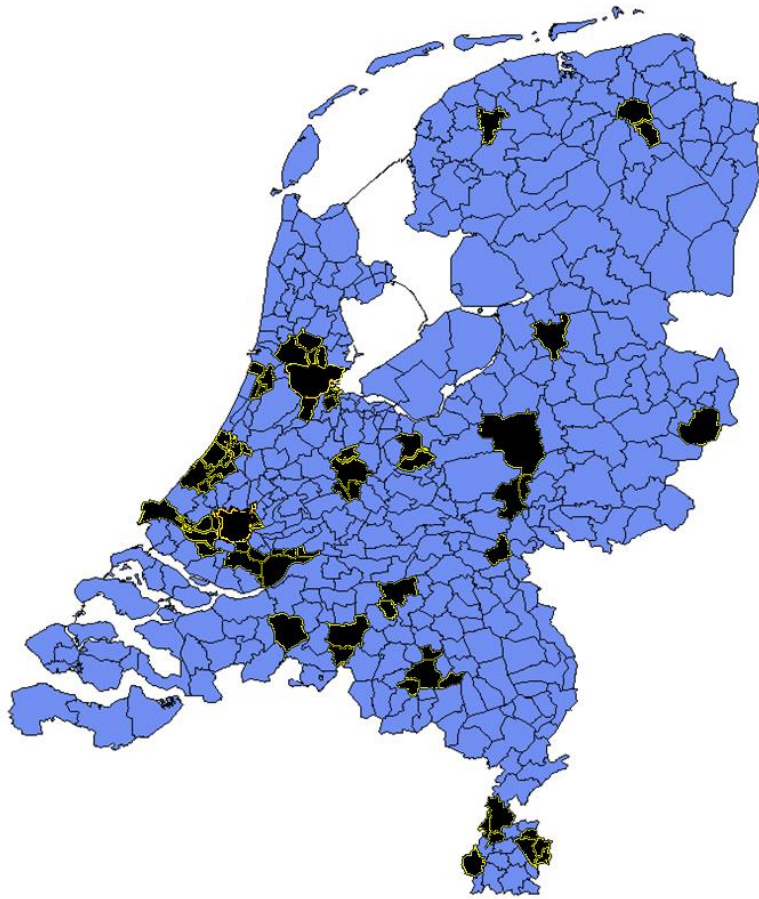
b) True values
▶ based on registry data

Males

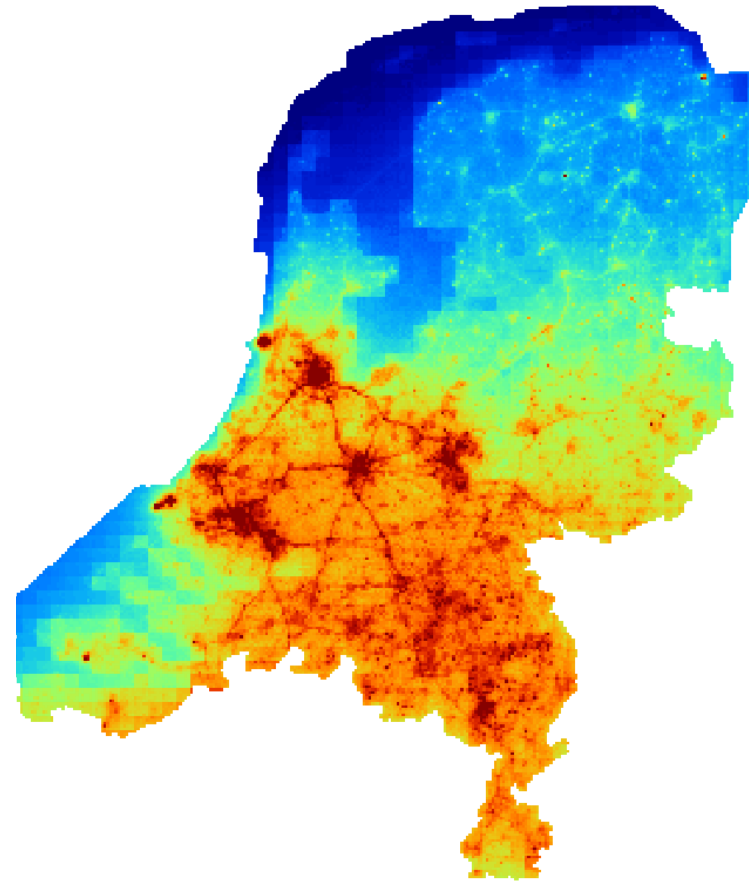


Example 3. The effect of air pollution on (H)LE

Big-25 cities (1500 neighborhoods)



Air pollution (PM₁₀)



.. also temperature (during heatwaves), urban green, etc.

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Summary

Key-points:

- 1) small-area health: sparse data & location of nursing homes.
- 2) Bayesian modelling approach: unbiased, efficient, and reliable method to improve small-area estimates
- 3) Availability of LE and HLE opens up new possibilities to:
 - a) target and evaluate health policies,
 - b) investigate the impact of determinants (e.g. air pollution).

Thank you.

