Using Alternative Spatial Data Sources for Small Area Estimation

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Small area estimation problem

- Interest on estimation of social and demographic indicators at sub-national levels
- Estimates are often built using survey data. Insufficient sample sizes impede obtaining reliable estimates for small areas under the typical survey inference framework
- Use of auxiliary data sources and statistical models to *borrow strength* across areas
- Very active area of research. See Pfeffermann (2013)

Alternative data sources

$$\text{Survey} \sim \text{Census} + \text{Administrative records} + \ldots$$

- Remotely Sensed (RS) data
- Mobile phone (CDR) data
- Web-scrapped data, Social media data, ...

Possible uses as covariates or response

See Marchetti et al. (2015); MAKSWELL Project, Work Package 2: For a discussion of some methodological issues of the use of alternative data sources in the context of SDG monitoring, van den Brakel, Buelens, et al. (2019) and van den Brakel, Smith, et al. (2019).

Use of RS data for SAE

Advantages

- Broadly available and frequently updated (*no one is left behind*). Low cost. Particularly useful in low-income countries where high quality survey, census and administrative data may be scarce. See:
  - US geological survey `https://earthexplorer.usgs.gov/`
  - European Space Agency `www.geoportal.org`
  - `http://trends.earth/docs/en/` (land coverage)
  - Open Street Map `http://extract.bbbike.org/`
  - WorldPop Research Project `http://www.worldpop.org.uk/`
- Flexible definition of target geography

Use of RS data for SAE

Limitations

- Explanatory power? Unclear link between auxiliary information and outcome
- Potential for irregular coverage
- Substantial pre-processing. Measurement error?
- Adequate use requires some degree of specialized knowledge

Modelling approaches

Statistical vs Algorithmic/Mapping approaches [†]

Statistical modelling (SAE)

- Real observations of the phenomenon are required (survey)
- Sampling design is taken into account
- Model assessment (GOF) and area-specific uncertainty of estimates (MSE)
- Area-level models: Fay-Herriot: Frequentist/HB; can include spatial/temporal effects
- Relatively coarse geography. Administrative boundaries + survey design

[†] For a detailed discussion from a geospatial perspective see the report from the Task Team on Satellite Imagery and Geospatial data, UN (2017)

Modelling approaches (2)

Algorithmic/Mapping approaches

- Generally, no consideration of sampling design
- GLMM's, classification trees, support vector machines,...
  Often inclusion of spatial effects as default
- Aim to produce estimates at very granular geographies
- If Bayesian inference, uncertainty measured using posterior variances
- Examples:
  - Poverty measurement in Bangladesh Steele et al. (2017)
  - Slum mapping in Casablanca Rhinane et al. (2011)

Presentation aims

Illustration of both approaches in a realistic set-up.
Poverty measurement in Bangladesh in the spirit of Steele et al. (2017). Wealth index $\sim$ RS covariates.

Aims:

- Identify common points and differences between both approaches
- Illustrate the use of standard packages for each approach (`sae`, `BRugs`, `R-INLA`) for fitting of small area models
- Identify potential methodological issues

Poverty measurement in Bangladesh

Target: Average WI by Upazila (Level 3).

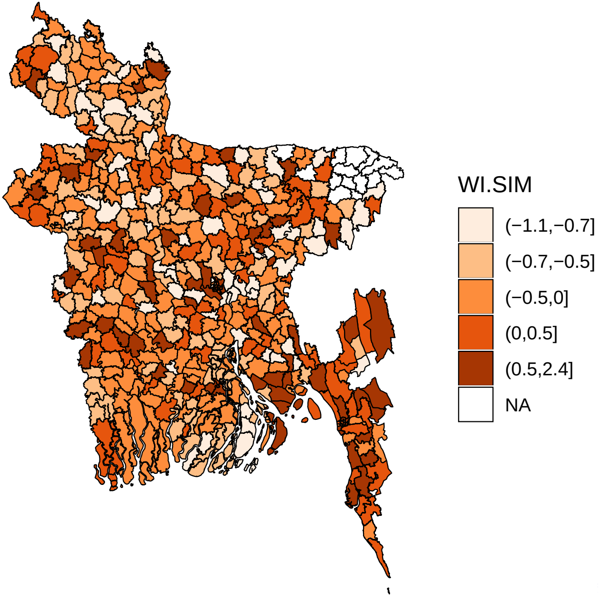
Survey data - DHS 2014

- Stratified 2-stage cluster design. At least one cluster selected in 365/508 (72%) Upazilas
- Response: WI computed via PCA
- $n = 17K$ households. $\bar{n}_i = 34$ households

RS data:

- 18 variables as starting point in Steele et al. (2017).
  - Night time lights (NOAA-US)
  - Elevation (CGIAR-CSI)
  - Accessibility to areas with more than 50K people (A global map of accessibility - European Commission Joint Research Centre)

Direct estimation



Methods

Fay-Herriot model

$$\boxed{\hat{\theta}_i^d = \boldsymbol{x}_i^T \boldsymbol{\beta} + u_i + e_i}$$

$\hat{\theta}_i^d$ a direct estimator of θ_i; $u_i \overset{iid}{\sim} N(0, \sigma_u^2)$; $e_i \overset{ind}{\sim} N(0, \sigma_i^2)$.

From a frequentist perspective, σ_i^2 is assumed known. An EBLUP for θ is given by

$$\hat{\theta}_i^{FH} = \boldsymbol{x}_i^T \hat{\boldsymbol{\beta}} + \hat{u}_i = \hat{\gamma}_i \hat{\theta}_i^d + (1 - \hat{\gamma}_i) \boldsymbol{x}_i^T \hat{\boldsymbol{\beta}}$$

with $\hat{\gamma}_i = \hat{\sigma}_u^2 / (\sigma_i^2 + \hat{\sigma}_u^2)$. Analytic MSE estimator by Prasad and Rao, 1990. Parametric bootstrap can also be used. Available in R package `sae`.

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From a Bayesian (HB) perspective:

$$\hat{\theta}_i^d | \theta_i \overset{ind}{\sim} N(\theta_i, \sigma_i^2)$$
$$\theta_i | \beta, \sigma_u^2 \overset{ind}{\sim} N(\boldsymbol{x}_i^T \boldsymbol{\beta}, \sigma_u^2)$$

Information on σ_i^2 can included via another level or an informative prior. See You and Chapman (2006).
The posterior mean and variance of θ_i are used for inference.
Available in R packages `BayesSAE`, `hbsae`. Can also use BUGS, JAGS, Stan, ...

Small area models

Point estimates and variances obtained using the sampling design. Smoothing of variance estimates using GVF.

$$\widehat{WI}_i = \beta_0 + \beta_1 \times ELEV + \beta_2 \times NL + \beta_3 \times ACC + u_i + e_i$$

$u_i \overset{iid}{\sim} N(0, \sigma_u^2)$; $e_i \overset{ind}{\sim} N(0, \sigma_i^2)$. R-INLA latent specification `iid`.

- M1 Standard FH model using `sae`. $\sigma_i^2 = \hat{\sigma}_i^2$ fixed
- M2 Standard Gaussian model in R-INLA. $\sigma_i^2 = \sigma_e^2$ unknown
- M3 R-INLA with $\sigma_{e_i}^2 = g_i \sigma_e^2$; $g_i = v_i / \bar{v}_i$ fixed.
  $\tau = 1/\sigma_e^2$; $\pi(\tau) \sim \text{Gamma}\left(\frac{\bar{n}_i - 1}{2} - 1\,,\ \frac{(\bar{n}_i - 1)\bar{v}_i}{2}\right)$.
- M4 HB using `BRugs` with $\pi(\tau_i)$ as in M3.

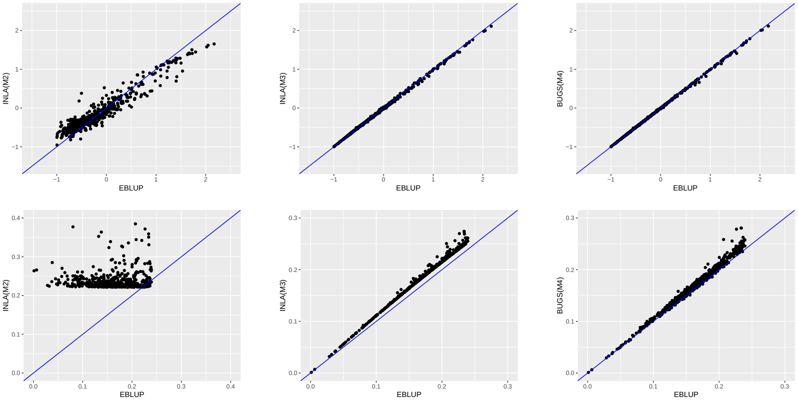
Sensitivity analyses results - Model parameters

- Small differences in the fixed effects
- Large differences in the variance decomposition. Using scaling to allow for heteroscedasticity nearly eliminates all differences

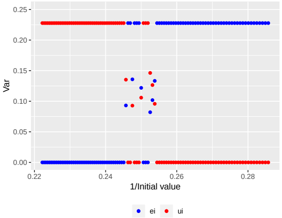
	M1	M2	M3	M4
$\hat{\beta}_0$	0.6662	0.6866	0.6604	0.6469
$\hat{\beta}_{elev}$	-0.0553	-0.0530	-0.0557	-0.0548
$\hat{\beta}_{nl}$	0.3137	0.3112	0.3141	0.3159
$\hat{\beta}_{acc}$	-0.0878	-0.0892	-0.0874	-0.0838
$\hat{\sigma}_e^2$	0.0362	0.1219	0.0423	0.0408
$\hat{\sigma}_u^2$	0.1889	0.1058	0.1800	0.1838

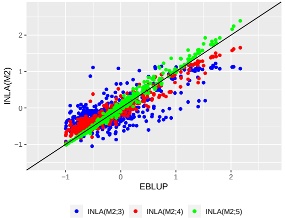
Sensitivity analyses results - Point & Uncertainty estimates

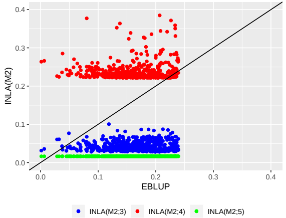
- Some impact on the point estimates
- Large Impact on uncertainty measures



Sensitivity analyses results - Initial values







Concluding remarks

- Ready to use software for approximate Bayesian inference offers interesting possibilities. However, some degree of specialized knowledge and understanding of the model is necessary for its correct use
- Accounting for the sampling design often overlooked
- Current work on a similar assessment with spatial models

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- European Space Agency www.geoportal.org
- http://trends.earth/docs/en/ (land coverage)
- Open Street Map http://extract.bbbike.org/
- WorldPop Research Project http://www.worldpop.org.uk/
- National Oceanic and Atmospheric Administration http://ngdc.noaa.gov/eog/viirs.html
- European Commission Joint Research Centre https://forobs.jrc.ec.europa.eu/products/gam/
- Center for International Earth Science Information Network(CIESIN) http://sedac.ciesin.columbia.edu/data/
- CGIAR Consortium for Spatial Information http://www.cgiar-csi.org/data
- WorldClim Global Climate Data http://www.worldclim.org
- European Commission Global Human Settlement Layer https://ghsl.jrc.ec.europa.eu/
- World Database on Protected Areas http://www.protectedplanet.net/
- Oak Ridge National Laboratory Land Coverage http://webmap.ornl.gov/wcsdown/wcsdown.jsp?dg_id=10024_1
- ETH Zurich International Conflict Research http://www.icr.ethz.ch/data/geoepr