Methods for Subnational Estimation of Child Mortality

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Outline

Motivation

Complex Survey Data

Space-Time Smoothing

Child Survival Modeling

The `SUMMER` Package

Final Thoughts

Motivation

Logistics

The website:

http://faculty.washington.edu/jonno/UNICEF-WORKSHOPS.html

Contains:

- Course notes.
- Datasets and R code.
- Additional materials, including a link to a course on small-area estimation (SAE) taught by JW and ZRL.

Sustainable Development Goal 3.2: "By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce ... under-5 mortality to at least as low as 25 per 1,000 live births".

Additionally:

- Paragraph 74.g, with reference to review processes: "They will be rigorous and based on evidence, informed by country-led evaluations and data which is high-quality, accessible, timely, reliable and disaggregated by income, sex, age, race, ethnicity, migration status, disability and geographic location and other characteristics relevant in national contexts."
- Paragraph 17.18, under data, monitoring and accountability: "By 2020, enhance capacity-building support to developing countries, including for least developed countries and small island developing States, to increase significantly the availability of high-quality, timely and reliable data disaggregated by income, gender, age, race, ethnicity, migratory status, disability, geographic location and other characteristics relevant in national contexts."

Subnational Estimation

Data and Methodology:

- With a civil registration system, one can obtain accurate estimates of child mortality directly.
- Without such a system, one must combine available data, from surveys and censuses, for example, to produce the best possible estimates (with uncertainty).
- To obtain estimates at a useful geographical and temporal scale, smoothing across space and time is beneficial.
- I will focus on U5MR estimation based on full birth history (FBH) data, in which birth and death times are known for each child of interviewed mothers.
- As an example, we will use data from the 2017–2018 Jordan Population and Family Health Survey (JPFHS).

Study Design:

- There are 26 strata (12 governorates by urban/rural + Syrian camps in Zarqa and Mafraq).
- 970 clusters are selected with probability proportional to size. In each cluster, 20 households are ultimately selected. Within each household, all ever-married women of fertile age was selected.
- An example of a stratified cluster design.

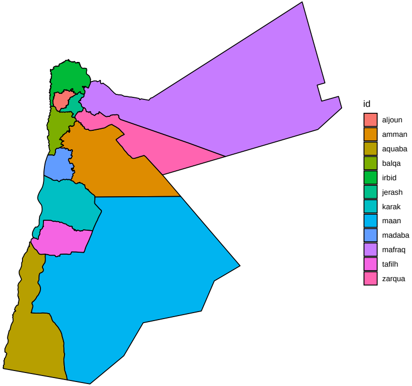


Figure 1: Governorates of Jordan.

Motivation for Smoothing: Temporal Case

- When looking at estimates over space or time, we want to know if the differences we see are “real”, or simply reflecting sampling variability.
- Temporal setting: Even if the underlying prevalence is the same over time, we will see estimates in the empirical estimates.
- Figure 2 demonstrates: We sampled binomial data with $n = 10, 20, 200$ and $p = 0.2$ (constant over time in blue) in all cases.
- In the top plot in particular, we might conclude large temporal variation, but all we are seeing is sampling variation.
- Figure 3 summarizes estimates from a second simulation in which there is a real temporal pattern – here we would not want to oversmooth and remove the trend.
- Later we will apply temporal smoothing models to these two sets of data.
- The same principles apply to spatial data, it’s just more difficult to gain insight, because two dimensions are harder than one!

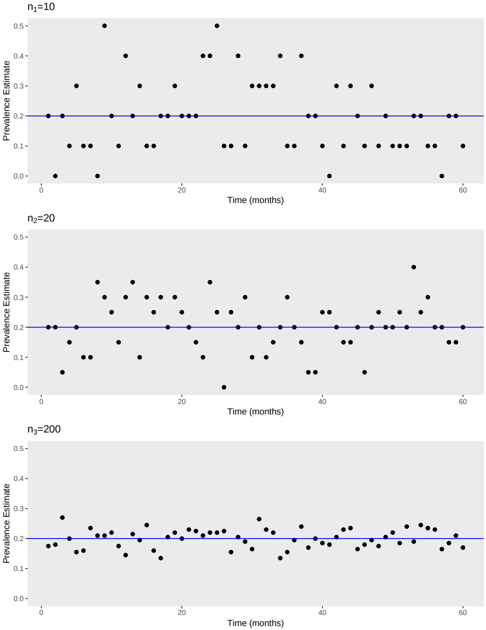


Figure 2: Prevalence estimates over time from simulated data with true prevalence of $p = 0.2$ (blue solid lines).

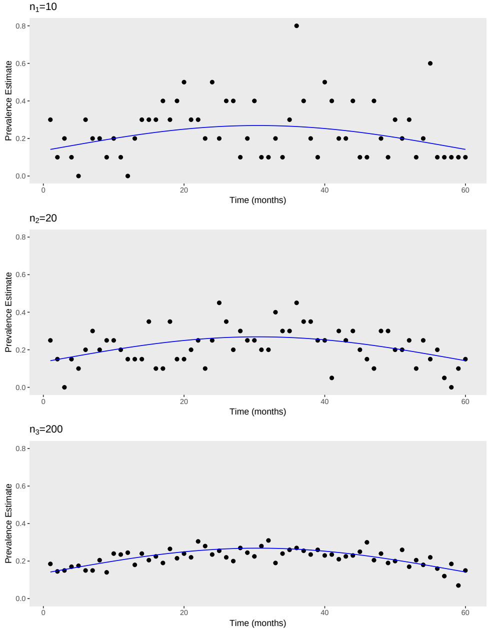


Figure 3: Prevalence estimates over time from simulated data, true prevalence corresponds to curved blue solid line.

Motivation for Smoothing: Spatial Case

- We repeat the previous simulation example, but now for spatial data.
- Counts Y_i are simulated for each area i from a binomial distribution with prevalence p_i and sample size n_i:

$$Y_i \mid p_i \sim \text{Binomial}(n_i, p_i).$$

- We look varying sample sizes $n_i = 10, 50, 500, 1000$, so that the influence of sampling variability can be examined.
- To differentiate from real data, for all simulations in this talk, we use the Afghanistan map instead.

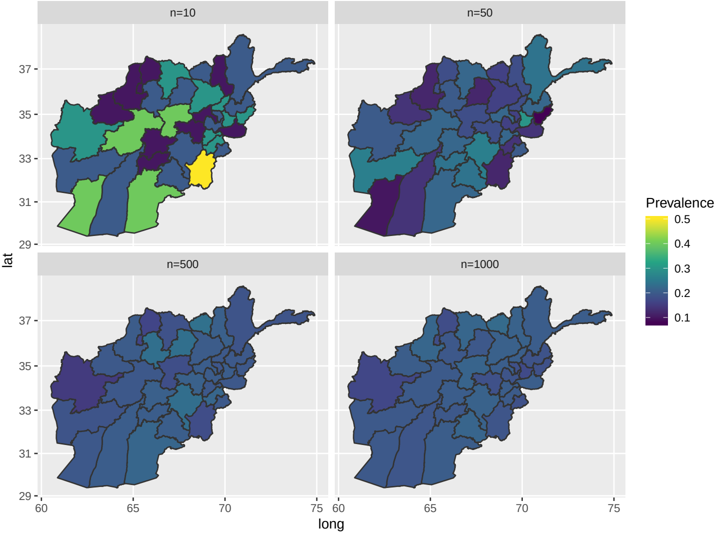


Figure 4: Prevalence estimates over space for simulated data with sample sizes of $n = 10, 50, 500, 1000$. True prevalence is 0.2 in all areas.

Complex Survey Data

Stratified Cluster Sampling

Most national surveys have a **stratified cluster sampling design** in which:

- The country is partitioned into a set of strata (e.g., province by urban/rural).
- Within each strata, clusters are sampled.
- Within each strata, households are sampled.
- Within each household, individuals are selected for interview.

The responses of the individuals provide the sample data with which we try to infer population characteristics.

When inference on the sample is performed, the design must be acknowledged:

- Ignoring the stratified sampling gives an estimate susceptible to **bias**, and an incorrect **variance** estimate.
- Ignoring the cluster sampling gives an incorrect **variance** estimate.

Motivation for Weighted Estimation

- We repeat the previous simulation example, but now add strata within regions.
- Suppose the population within each region contains 80% rural and 20% urban.
- Suppose the prevalence is 0.2 within all rural population, and 0.05 within all urban population.
- Using a stratified SRS, n urban and n rural people are sampled within each region.
- Again we look at varying sample sizes.

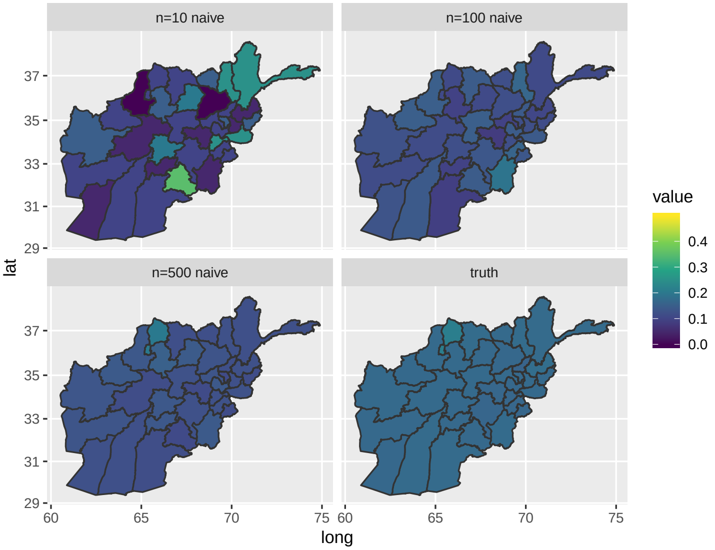


Figure 5: Naive prevalence estimates over space for simulated data with sample sizes of $n = 10, 100, 500$ and the true prevalence.

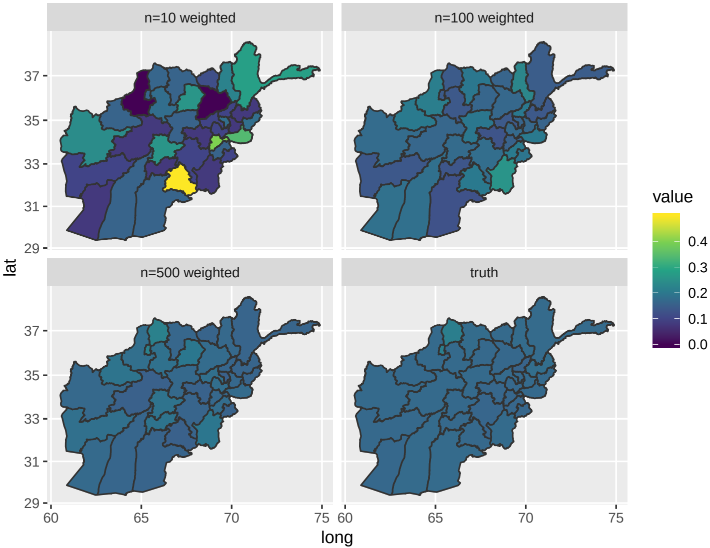


Figure 6: Prevalence estimates accounting for survey design over space for simulated data with sample sizes of $n = 10, 100, 500$ and the true prevalence.

Weighted Estimation

Suppose we wish to estimate the prevalence P of some condition in an area, e.g., smoking, attaining an educational level, dying within the first month of life.

Let $y_1, \dots, y_n$ be 0/1 variables which indicate absence/presence of the condition of interest, with w_k the accompanying **design weight**.

The design weight is the reciprocal of the probability of being sampled, i.e.,

$$w_k = \frac{1}{\pi_k},$$

where π_k is the sampling probability and depends on the strata of the person.

Weighted Estimation

The weight w_k can be thought of as the number of people in the population represented by sampled person k.

Example 1: Suppose an area contains 1000 people:

- Using simple random sampling (SRS), 100 people are sampled.
- Sampled individuals have weight $w_k = 1/\pi_k = 1000/100 = 10$.

Example 2: Suppose an area contains 1000 people, 200 urban and 800 rural.

- Using stratified SRS, 50 urban and 50 rural people are sampled.
- Urban sampled individuals have weight $w_k = 1/\pi_k = 200/50 = 4$.
- Rural sampled individuals have weight $w_k = 1/\pi_k = 800/50 = 16$.

Weighted Estimation

To account for the design we use a **weighted estimate** of the prevalence:

$$\widehat{P} = \frac{\sum_k w_k y_k}{\sum_k w_k} = \frac{\text{Estimate of Total with Condition}}{\text{Population Size}}$$

A variance estimate V can be obtained, which takes into account the design.

A 95% confidence interval for the prevalence is:

$$\widehat{P} \pm 1.96 \times \sqrt{V}$$

For small samples sizes, this interval will be wide.

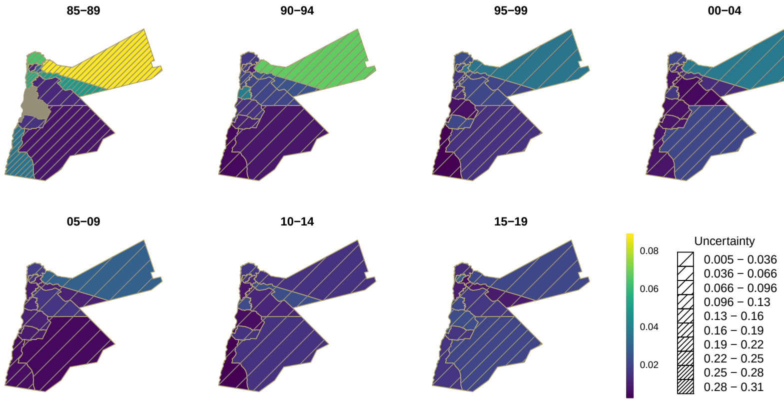


Figure 7: Weighted estimates (from a discrete survival model) of under-5 mortality in Jordan, with uncertainty indicated by density of hatching; more hatching → more uncertainty, with the latter measured though width of uncertainty interval.

Space-Time Smoothing

Smoothing over Time

Rationale and overview of models for temporal smoothing:

- We often expect that the true underlying mortality in an area will exhibit some degree of smoothness over time.
- A linear trend in time is unlikely to be suitable for more than a small number of years, and higher degree polynomials can produce erratic fits.
- Hence, local smoothing is preferred.
- Spline and random walk models have proved successful as local smoothers.
- In either approach, the choice of smoothing parameter is crucial.

Random Walk Models

We use random walk models which encourage the mean responses (e.g., prevalences) across time to not deviate too greatly from their neighbors.

The true underlying mean of the mortality at time t is modeled as a function of its neighbors:

$$\mu_t \mid \mu_{\text{NE}(t)} \sim \text{Normal}(m_t, v_t),$$

where

- μ_t is the mean mortality (or some function of it such as the logit) at time t.
- $\mu_{\text{NE}(t)}$ is the set of neighboring means – with the number of neighbors chosen depending on the model used – typically 2 or 4.
- m_t is the mean of some set of neighbors – for a **first order random walk** or **RW1** it is simply $\frac{1}{2}(\mu_{t-1} + \mu_{t+1})$.
- v_t is the variance, and depends on the number of neighbors – for the RW1 model it is $\sigma^2/2$, where σ^2 is a smoothing parameter – small values give large smoothing.

The smoothing parameter σ^2 is estimated from the data, and determines the extent deviations from the mean are penalized.

The penalty term for the RW1 model is:

$$p(\mu_t \mid \mu_{t-1}, \mu_{t+1}, \sigma^2) \propto \exp\left\{-\frac{1}{2\sigma^2}\left[\mu_t - \tfrac{1}{2}\left(\mu_{t-1} + \mu_{t+1}\right)\right]^2\right\}.$$

Hence:

- Values of μ_t that are close to $\frac{1}{2}(\mu_{t-1} + \mu_{t+1})$ are favored (higher density).
- The relative favorability is governed by σ^2 – if this variance is small, then μ_t can't stray too far from its neigbors.

Figure 8: Illustration of the RW1 model for smoothing at time 3. The mean of the smoother is the average of the two adjacent points (and is highlighted as ●), and deviations from this mean are penalized via the normal distribution shown in **red**.

Bayesian Inference

Bayesian inference:

- a Data Model (Likelihood) is probabilistically combined with
- a Penalization (Prior) that expresses beliefs about the parameters θ encoding the model.
- Combination occurs via Bayes Theorem:

$$\underbrace{p(\theta|y)}_{\text{Posterior}} \propto \underbrace{L(\theta)}_{\text{Likelihood}} \times \underbrace{\pi(\theta)}_{\text{Prior}}.$$

- On the log scale:

$$\underbrace{\log p(\theta|y)}_{\text{Updated Beliefs}} = \underbrace{\log L(\theta)}_{\text{Data Model}} + \underbrace{\log \pi(\theta)}_{\text{Penalization}}.$$

Bayesian Inference

- In a Bayesian analysis the complete set of unknowns (parameters) is summarized via the multivariate posterior distribution.
- The marginal distribution for each parameter may be summarized via its mean, standard deviation, or quantiles.
- It is common to report the posterior median and a 90% or 95% range for parameters of interest.
- The range that is reported is known as a credible interval.
- The computations required for Bayesian inference (integrals) is often not trivial and many be carried out using a variety...
- We use the integrated nested Laplace approximation (INLA)

Bayes Example

Imagine the data model is normal with an unknown mean μ:

$$\bar{y} \mid \mu \sim \text{Normal}(\mu, \sigma^2/n),$$

where σ^2/n is assumed known ($\sigma/\sqrt{n}$ is the standard error).

We also imagine the prior is normal:

$$\mu \sim \text{Normal}(m, v),$$

so that values of the mean μ that are (relatively) far from m are penalized.

The log posterior is:

$$\underbrace{\log p(\mu \mid y)}_{\text{Updated Beliefs}} = -\underbrace{\frac{n}{2\sigma^2}(\bar{y} - \mu)^2}_{\text{Data Model}} - \underbrace{\frac{1}{2v}(\mu - m)^2}_{\text{Penalization}}.$$

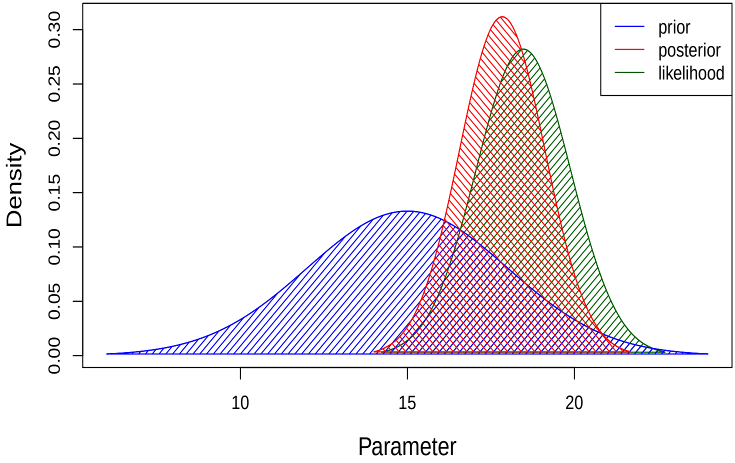


Figure 9: Normal data model with $n = 10$, $\overline{y} = 19.3$ and standard error 1.41. The prior for μ has mean $m = 15$ and $v = 3^2$. The posterior for the parameter μ is a compromise between the two sources of information: the posterior mean is 18.5 and the posterior standard deviation is 1.28.

RW Fitting to Simulated Data

- The second order RW (RW2) model produces smoother trajectories than the RW1, and has more reasonable short term predictions, which is desirable for modeling child mortality.
- We illustrate fitting with the RW2 model, using the simulated data seen earlier.
- The model is:

$$
\begin{aligned}
Y_t | p_t &\sim \text{Binomial}(n_t, p_t) \\
\frac{p_t}{1 - p_t} &= \exp(\alpha + \phi_t) \\
(\phi_1, \ldots, \phi_T) &\sim \text{RW2}(\sigma^2) \\
\sigma^2 &\sim \text{Prior on Smoothing Parameter} \\
\alpha &\sim \text{Prior on Intercept}
\end{aligned}
$$

- On Figures 10 and 10 the fitted values are shown in red – in both the no signal and curved signal cases, the reconstruction is reasonable.

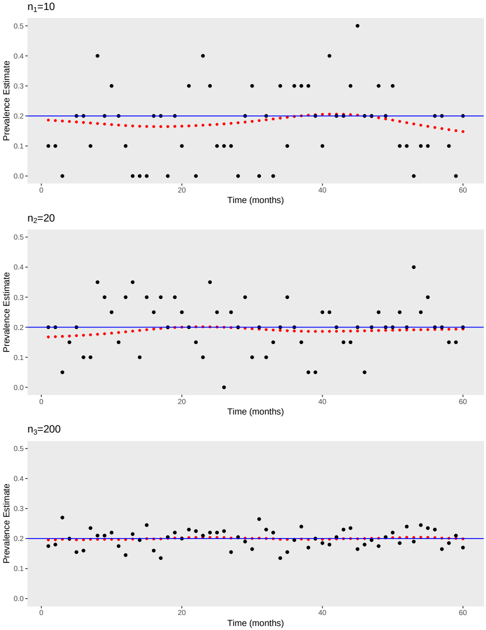


Figure 10: Prevalence estimates over time from simulated data, true prevalence $p = 0.2$ (blue solid lines). Smoothed random walk estimates in **red**.

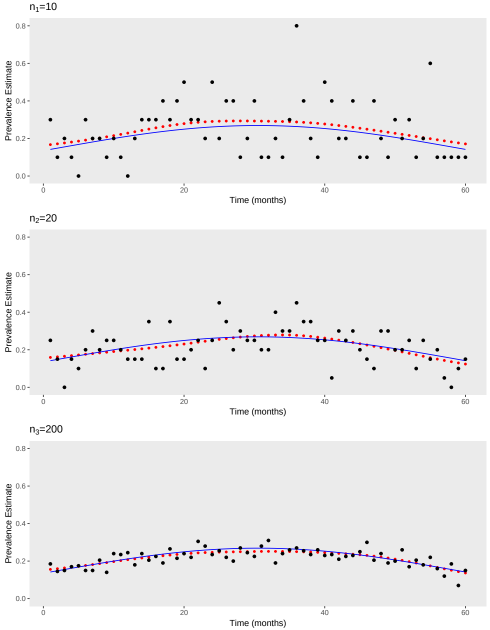


Figure 11: Prevalence estimates over time from simulated data, true prevalence corresponds to curved blue solid line. Smoothed random walk estimates in **red**.

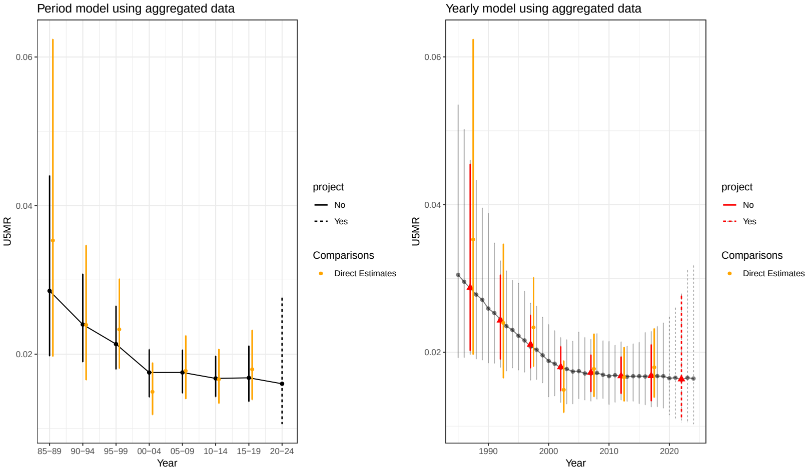


Figure 12: Yearly and Period RW2 smoothing of weighted estimates of under-5 mortality in Jordan, with 95% uncertainty intervals. We apply different models to data aggregated over 5 years. The dashed lines on the right of each plot are projections. Details on smoothing discrete survival model later.

Spatial Smoothing of Simulated Data

Data Model: For area i:

$$\underbrace{Y_i}_{\text{Count}} \mid \underbrace{p_i}_{\text{Prevalance}} \sim \underbrace{\text{Binomial}(n_i, p_i)}_{\text{Data Model}}.$$

Smoothing Model: For the odds in area i:

$$\frac{p_i}{1-p_i} = \exp(\alpha + \phi_i).$$

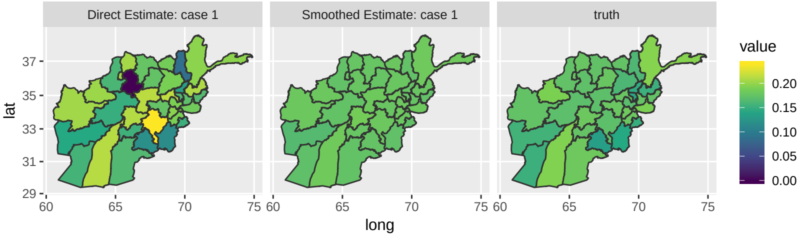
We consider two choices for the smoothing model:

- IID model: Smooth to the overall mean with no spatial s$\pi_i \sim \text{Normal}(0, \sigma^2)$ where σ^2 controls the amount of smoothing — small/large corresponds to strong/weak smoothing.
- BYM2[1] model: Add a spatial component that encourages local similarity analogously to the random walk model with a suitable choice of neighbors, sharing a common boundary being the commonest choice.

[1] named after the paper that introdced the model, Besag, York and Mollié (1991)

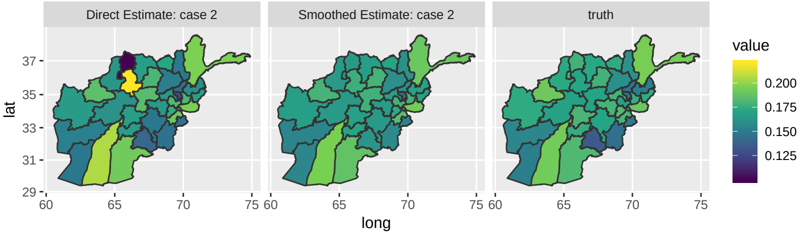
Spatial Smoothing of Simulated Data

If we sample 1% of people within each stratum.



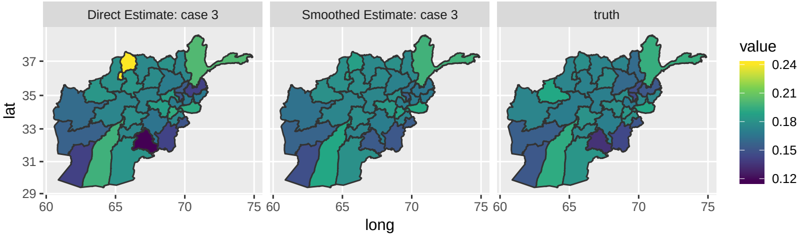
Spatial Smoothing of Simulated Data

If we sample 5% of people within each stratum.



Spatial Smoothing of Simulated Data

If we sample 10% of people within each stratum.



Child Survival Modeling

Discrete Survival Model

We know that infant mortality varies greatly over the first 5 years of life and two possible approaches to modeling how mortality varies with age:

- A continuous function of age, via a parametric model (e.g., weibull, gamma,...).
- A discrete function of age, which involves splitting age into intervals.

For flexibility, we follow the latter route and assume a **discrete survival model**, with six **discrete hazards** (probabilities of dying in a particular interval, given survival to the start of the interval) for each of the age bands:

1. $[0, 1)$,
2. $[1, 12)$,
3. $[12, 24)$,
4. $[24, 36)$,
5. $[36, 48)$,
6. $[48, 60]$.

The first category corresponds to neonatal, the first two, infant mortality, and all six, under-5 mortality.

Discrete Survival Model

Each child contributes up to 60 months of observation time, and can contribute less if censoring.

For a generic calendar period:

$$\begin{aligned}\text{Survival to 60 months} &= \text{Survival in month 1}\\ &\times \text{Survival in month 2} \mid \text{survived to end of month 1}\\ &\cdots\\ &\times \text{Survival in month 60} \mid \text{survived to end of month 59}\end{aligned}$$

Hence, we are following a **synthetic cohort** approach.

The hazards are estimated using a logistic regression model, with weighting to account for the survey design.

At the end of this process we have an estimate $\widehat{\text{U5MR}}$ in each area and to period, along with its variance.

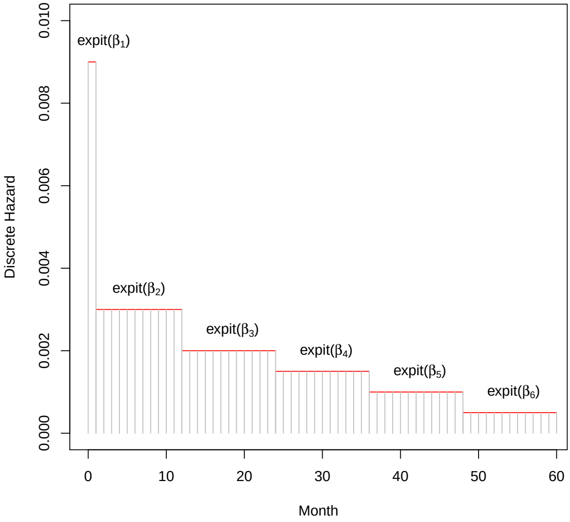


Figure 13: Representation of the conditional probabilities (hazards) of death by month.

The SUMMER Package

Spatial Smoothing Model

Key Idea: Take as data the weighted estimator – in large samples this follows a normal distribution.

Data Model: Specifically, we take as data in area **area** i, the logit of the weighted estimates: $y_i = \text{logit}(\widehat{P}_i)$

$$\underbrace{y_i \mid \mu_i \sim \text{Normal}(\mu_i, V_i)}_{\text{Survey design acknowledged here}}$$

where V_i is the design variance.

Smoothing Model:

$$\mu_i = \underbrace{\alpha}_{\text{Intercept}} + \underbrace{S_i}_{\text{Spatial}} + \underbrace{\epsilon_i}_{\text{Independent}}$$

The model is implemented in the `R` package `SUMMER`:

- A design object being created in the `survey` package.
- The `INLA` package is used for Bayesian computation.
- It is computationally inexpensive – country-specific estimates in seconds.

Space-Time Smoothing Model

Hierarchical Model:

1. The Data Model:

$$\underbrace{y_{it} \mid \lambda_{it} \sim \mathrm{N}\left(\lambda_{it}, \widehat{V}_{it}\right)}_{\text{Survey design acknowledged here}} .$$

2. The Space-Time (Random Effects) Prior:

$$\underbrace{\lambda_{it} = f(\text{ space } i, \text{ time } t)}_{\text{Smoothing here}} .$$

Different space (e.g., area-based or pixel-based) and time (e.g. random walks, splines) smoothing models can be slotted into this framework.

Space-Time Smoothing Model

The data model is

$$y_{it} | \lambda_{it} \sim \text{Normal}(\lambda_{it}, \widehat{V}_{it}),$$

where

- y_{it} is the logit of the direct estimator in area i and period t,
- λ_{it} is the logit of the true U5MR in county i and period t, and we emphasize that $\widehat{V}_{\text{DES},it}$ is known.

We decompose λ_{it} into temporal, spatial and space-time components:

$$\lambda_{it} = \underbrace{\mu}_{\text{Intercept}}$$

$$+ \underbrace{\alpha_t}_{\text{Independent}} + \underbrace{\gamma_t}_{\text{Random Walk}} \qquad \text{Temporal Model}$$

$$+ \underbrace{\theta_i}_{\text{Independent}} + \underbrace{\phi_i}_{\text{Spatial}} \qquad \text{Spatial Model}$$

$$+ \underbrace{\delta_{it}}_{\text{Interaction}} \qquad \text{Space-Time Model}$$

Smoothing of ENSANUT Data

- We calculate 5-year weighted estimates of U5MR using a discrete survival model for the periods 85–89, 90–94, 95–99, 00–04, 05–09, 10–14, and 15–19.
- We smooth these estimates using the model in the `SUMMER` package.
- Figure 14 gives the weighted estimates with hatching representing uncertainty.
- Figure 15 gives the smoothed estimates with hatching representing uncertainty – these estimates show less spatial variability and reduced uncertainty.
- Figure 16 shows clearly the drop in U5MR over time, and reduced between-province variability. The uncertainty in estimates is also apparent.

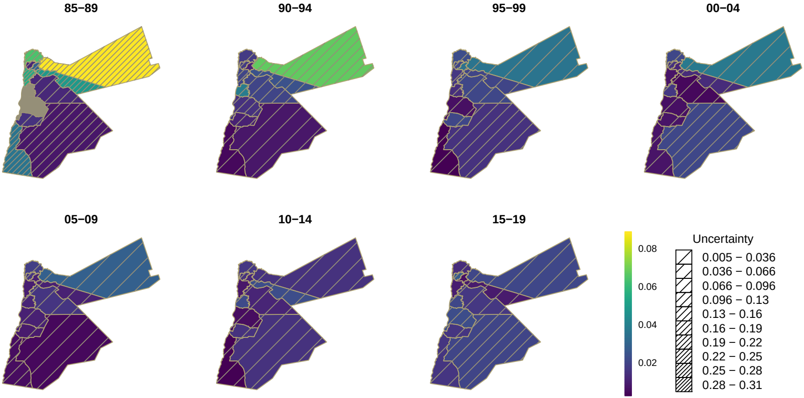


Figure 14: Weighted estimates (from a discrete survival model) of under-5 mortality in Jordan, with uncertainty indicated by density of hatching; more hatching → more uncertainty, with the latter measured though width of uncertainty interval.

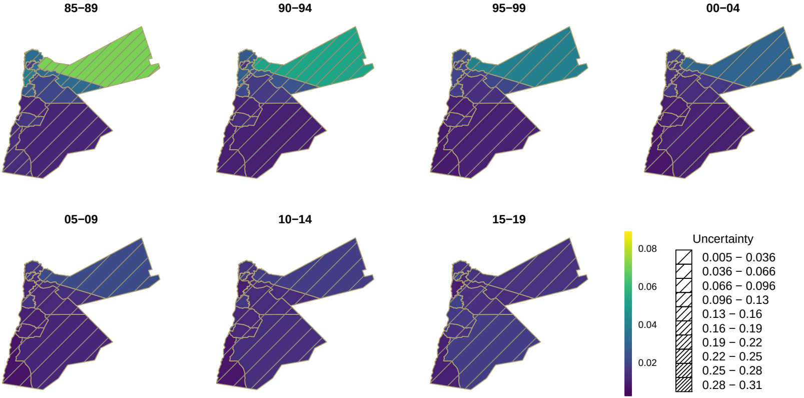


Figure 15: Smoothed estimates (from a discrete survival model) of under-5 mortality in Jordan, with uncertainty indicated by density of hatching; more hatching $\rightarrow$ more uncertainty, with the latter measured though width of uncertainty interval.

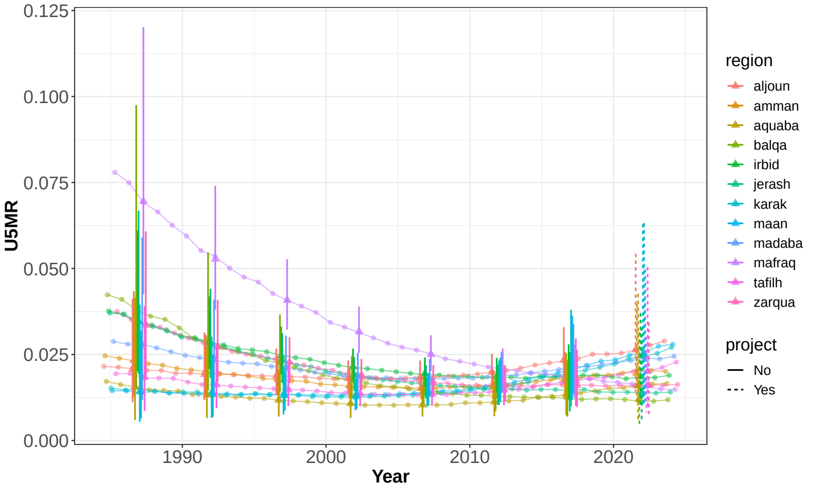


Figure 16: Smoothed estimates (from a discrete survival model) of under-5 mortality in Jordan, with uncertainty intervals

Final Thoughts

Concluding Comments

- SUMMER allows **different age groups (e.g., NMR, infant,...)** to be examined and also by **gender**.
- **Summary Birth History (SBH)** data from census may be added using the same approach – soon to appear in SUMMER.
- Beyond that: Estimate mortality for ages 5–14.
- Work in progress on **cause of death**.
- Would like to include **geographical variables** in the model, to understand spatial inequality.
- Possible to make **HIV adjustments**, where needed.

We are also pursuing the use of **continuous spatial models**:

- These are routinely used by both WorldPop and IHME, but continuous modeling is a more hazardous approach to estimation.
- However, it is the way forward to allow multiple data sources at different spatial resolutions to be combined.
- And reporting can be on a relevant discrete scale.

Feel free contact Richard (zehang.li@yale.edu) or Jon (jonno@uw.edu) with follow up questions on methods or the SUMMER package.

Additional Resources

- This workshop:
  http://faculty.washington.edu/jonno/UNICEF-WORKSHOPS.html
- More about SUMMER:
  https://cran.r-project.org/web/packages/SUMMER/vignettes/summer-vignette.pdf

Background Literature:

- Smoothing of direct estimates (Fay and Herriot, 1979; Chen *et al.*, 2014; Mercer *et al.*, 2015).
- Comparison of discrete and continuous models (Wakefield *et al.*, 2018).
- Application of space-time smoothing model to 40 African countries (Li *et al.*, 2019).
- Modeling of SBH data (Brass, 1964; Sullivan, 1972; Brass, 1975; Trussell, 1975; Feeney, 1976; Coale and Trussell, 1977; Hill *et al.*, 1983; Rajaratnam *et al.*, 2010; Wilson and Wakefield, 2018a).
- Combining point and area data (Wilson and Wakefield, 2018b).
- INLA (Rue *et al.*, 2009; Lindgren *et al.*, 2011; Blangiardo and Cameletti, 2015; Wang *et al.*, 2018; Krainski *et al.*, 2018).

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Scaling Up the Smoothed Direct Model

The smoothed direct model has been used for 35 African countries to estimate U5MR in Admin-1 regions by year.

Includes space-time interactions that cross random walk models in time with ICAR models in space.

Data:

- 121 DHS in 35 countries
- 1.2 million children
- 192 million child-months

UN have supported this research and these estimates.

Takes around 2.5 hours to obtain estimates for all countries – separate models for each country.

Spatial and space-time smoothed direct estimates models are available in `R`, via the `SUMMER` package.

Smoothed Direct Estimates

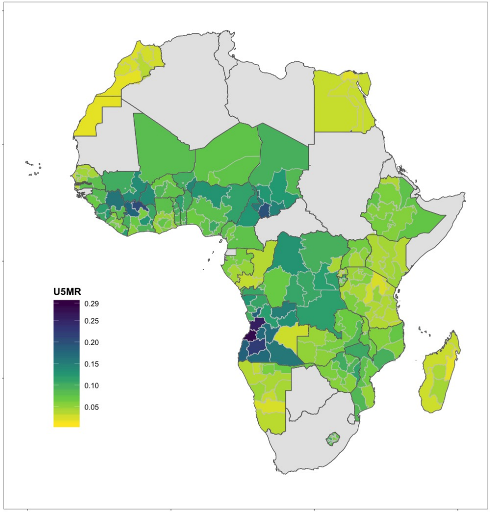

Figure 17: Predictions of U5MR for 2015, in 35 countries of Africa.

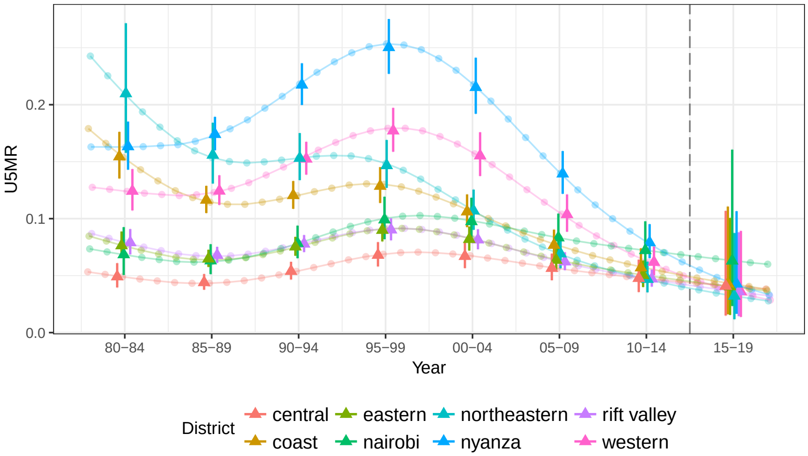

Figure 18: Posterior median estimates for Kenya districts.