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Bayesian Modeling of Family Planning Indicators: The Family Planning Estimation Model (FPEM)

Herb Susmann

October 2021

Outline

- Introductions
- Family Planning Indicators
- Family Planning Estimation Model (FPEM)
- Demo

Links to all resources: http://herbsusmann.com/fp_map5

About me

- PhD student, University of Massachusetts Amherst
- Research interests
  - Hierarchical spatio-temporal Bayesian modeling
  - Causal inference, targeted learning
- Website: http://herbsusmann.com, Twitter: @herbps10

Alkema Lab

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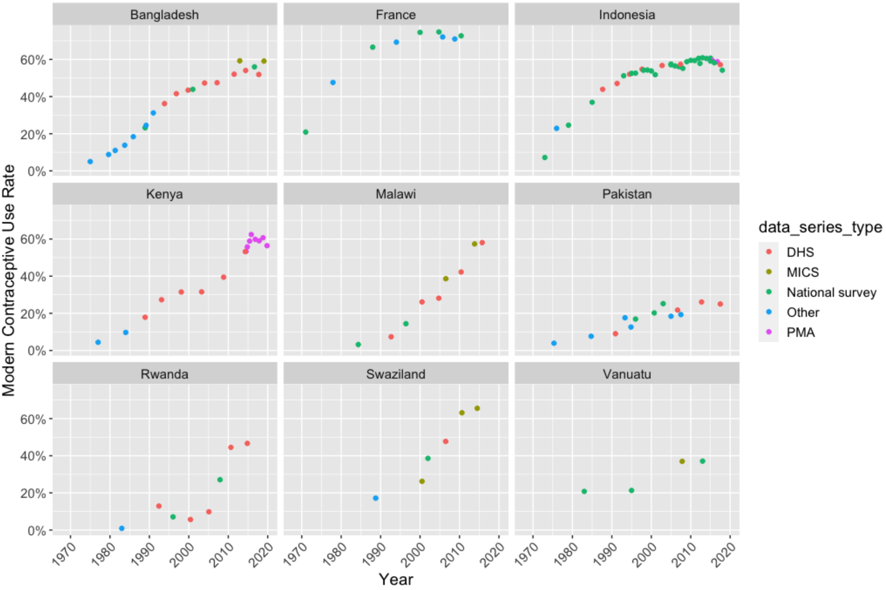
- Leontine Alkema, University of Massachusetts Amherst
- Lab website: https://leontinealkema.github.io/alkema_lab/
- Bayesian modeling of demographic and health indicators
  - Family planning
  - Fertility
  - Sex ratio at birth
  - Maternal mortality
  - ...

Family Planning Indicators

- Study population: women of childbearing age (15-49 years) currently married or in-union
- Modern contraceptive prevalence
  - Percentage of women who report themselves (or their partner) using a modern contraceptive method
- Traditional contraceptive prevalence
- Unmet need
  - Proportion of women who want to stop or delay childbearing but are not using any contraceptive method
- Demand satisfied with modern methods
  - Proportion of women who want to stop or delay childbearing and who use a modern contraceptive method

Data Sources

- International surveys (DHS, MICS, PMA)
- National Surveys
- Data are of varying quality and availability
- There may be multiple observations for the same country and year
- Data may exhibit systematic biases
  - Example: survey conducted for women of different age group than 15-49

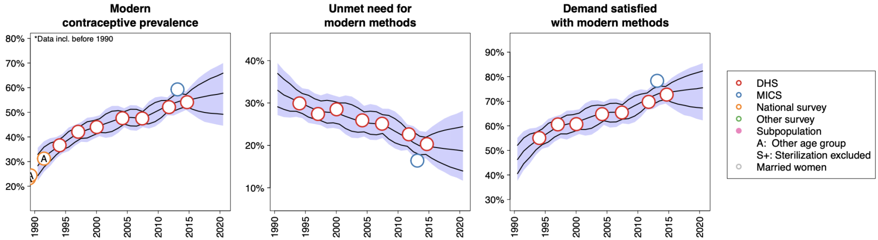


Bangladesh
France
Indonesia
Kenya
Malawi
Pakistan
Rwanda
Swaziland
Vanuatu
0%
20%
40%
60%
1970
1980
1990
2000
2010
2020
Modern Contraceptive Use Rate
Year
data_series_type
DHS
MICS
National survey
Other
PMA

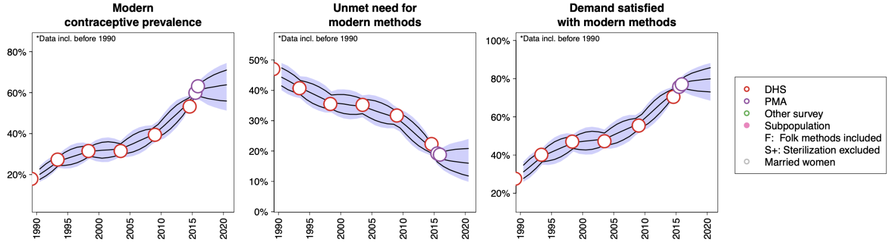
Family Planning Estimation Model

- Family Planning Estimation Model (FPEM): hierarchical Bayesian model of modern contraceptive use, traditional contraceptive use, and unmet need.
- Originally published as Alkema et al. (2013), updated by Cahill et al. (2018).
- Used by the United Nations Population Division and the Family Planning 2020 initiative.
- R packages: `FPEMglobal`, `FPEMlocal`.

Bangladesh



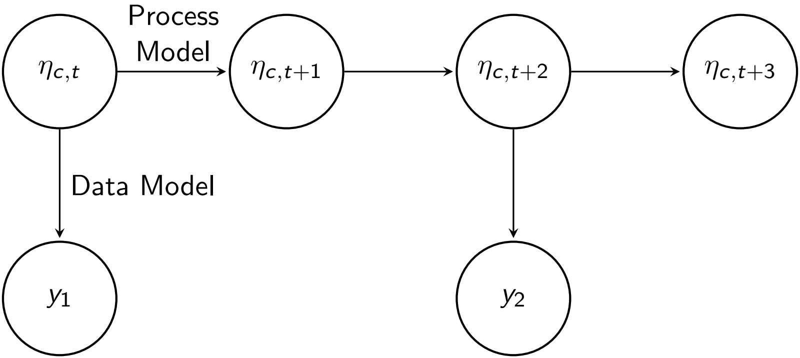
Kenya



Modeling Framework

- This presentation will focus on how FPEM models the modern contraceptive use rate indicator.
- $\eta_{c,t}$: true modern contraceptive use rate in country c and year t, for $c = 1, \ldots, C$, $t = 1, \ldots T$.
- Observed data y_i for $i = 1, \ldots, N$, with associated properties $c[i]$, $t[i]$, $s[i]$, ...
    - country $c[i]$, year $t[i]$, data source $s[i]$
- *Process model* describes evolution of $\eta_{c,t}$.
- *Data model* describes relationship between y_i and $\eta_{c[i],t[i]}$.

Modeling Framework



(Temporal Models for Multiple Populations)

Preprint: https://arxiv.org/abs/2102.10020

Statistics > Methodology

[Submitted on 19 Feb 2021]

Temporal models for demographic and global health outcomes in multiple populations: Introducing a new framework to review and standardize documentation of model assumptions and facilitate model comparison

Herbert Susmann, Monica Alexander, Leontine Alkema

There is growing interest in producing estimates of demographic and global health indicators in populations with limited data. Statistical models are needed to combine data from multiple data sources into estimates and projections with uncertainty. Diverse modeling approaches have been applied to this problem, making comparisons between models difficult. We propose a model class, Temporal Models for Multiple Populations (TMMPs), to facilitate documentation of model assumptions in a standardized way and comparison across models. The class distinguishes between latent trends and the observed data, which may be noisy or exhibit systematic biases. We provide general formulations of the process model, which describes the latent trend of the indicator of interest. We show how existing models for a variety of indicators can be written as TMMPs and how the TMMP-based description can be used to compare and contrast model assumptions. We end with a discussion of outstanding questions and future directions.

Process Model

- Process Model: how does the true modern contraceptive use rate evolve over time?
- Demo: https://observablehq.com/@herbps10/fpem
- The process model decomposes the indicator into two components:

$$\text{logit}(\eta_{c,t}) = \underbrace{g(t, \eta_c, \alpha_c)}_{\text{systematic}} + \underbrace{\epsilon_{c,t}}_{\text{smoothing}}$$

Systematic Component

$$\mathrm{logit}(\eta_{c,t}) = \underbrace{g(t, \boldsymbol{\eta}_c, \boldsymbol{\alpha}_c)}_{\text{systematic}} + \underbrace{\epsilon_{c,t}}_{\text{smoothing}}$$

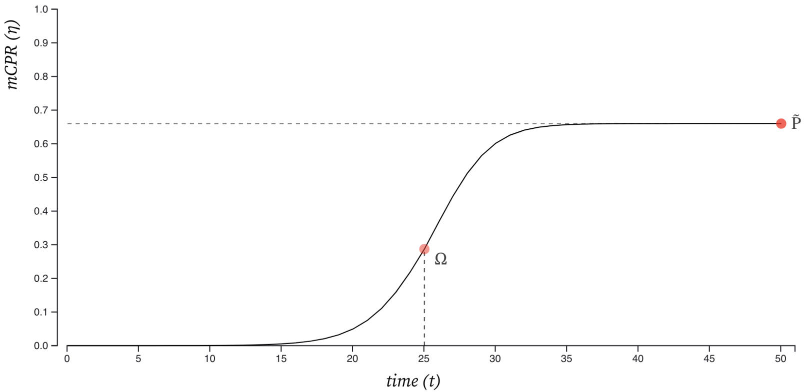
- The systematic component models logistic growth
- First, we choose a "reference year" t^*
- Then we define g as:

$$g(t, \boldsymbol{\eta}_c, \boldsymbol{\alpha}_c) = \begin{cases} \Omega_c, & t = t^*, \\ \mathrm{logit}(\eta_{t-1}) + f(\eta_{t-1}) & t > t^* \\ \mathrm{logit}(\eta_{t+1}) - f(\eta_{t+1}) & t < t^* \end{cases} \tag{1}$$

where

$$f(\eta_{c,t}, \tilde{P}_c, \omega_c) = \frac{(\tilde{P}_c - \eta_{c,t}) \cdot \omega_c}{\tilde{P}_c \cdot (\eta_{c,t} - 1)} \tag{2}$$

Systematic Component



Systematic Component

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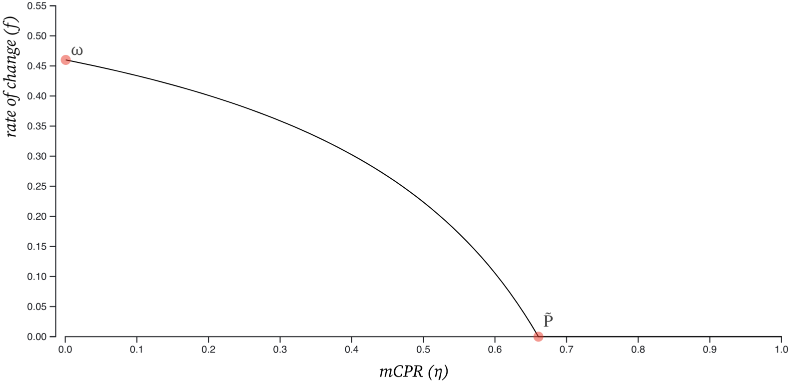

Smoothing Component

$$\text{logit}(\eta_{c,t}) = \underbrace{g(t, \eta_c, \alpha_c)}_{\text{systematic}} + \underbrace{\epsilon_{c,t}}_{\text{smoothing}}$$

- The smoothing component models trends not captured by logistic growth
- Affects the *rate of change* of the indicator
- FPEM assigns an AR(1) process to $\epsilon_{c,t}$, starting at $t = t^*$ and propagating forwards and backwards:

$$\epsilon_{c,t} \sim \begin{cases} N(0, \frac{t^2}{1-\rho^2}), & t = t^* \\ N(\rho \cdot \epsilon_{c,t-1}, \tau^2), & t > t^* \\ N(\rho \cdot \epsilon_{c,t+1}, \tau^2), & t < t^* \end{cases} \tag{3}$$

Systematic Component

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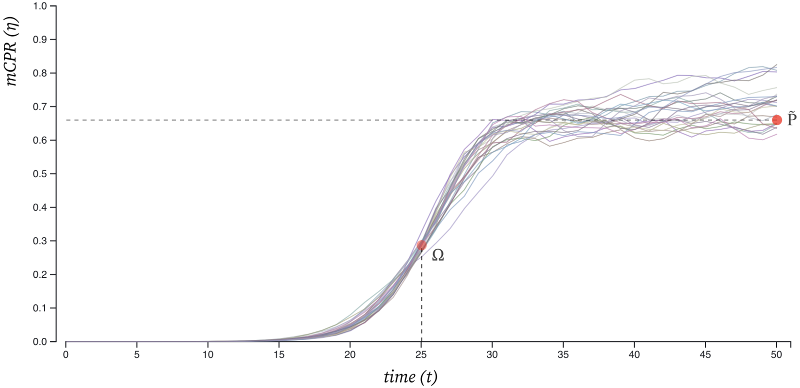

Hierarchical Modeling

- Information is shared between countries through *hierarchical modeling*
- Example: pace parameter ω_c is given three-level hierarchical distribution (sub-regions, regions, and world).

$$\omega_c^* = \log\left(\frac{\omega_c - 0.01}{0.5 - \omega_c}\right) \tag{4}$$

$$\omega_c^* \sim N(\omega_{s[c]}^*, \kappa_\omega^{(c)}) \tag{5}$$

$$\omega_s^* \sim N(\omega_{r[s]}^*, \kappa_\omega^{(s)}) \tag{6}$$

$$\omega_r^* \sim N(\omega_w^*, \kappa_\omega^{(r)}) \tag{7}$$

where $s[c]$ is the sub-region of country c and $r[s]$ is the region of sub-region s.

Data Model

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- Goal of the data model: describe the relationship between the truth and the observed data
  - The data model is "generative": given the true unobserved (latent) values of mCPR, it describes how the data is generated
  - For example: sampling error from surveys
- Toy data model for illustration:

$$\operatorname{logit}(y_i) \sim N(\operatorname{logit}(\eta_{c[i],t[i]}), \sigma^2_{s[i]}) \quad (8)$$

  where $\sigma^2_{s[i]}$ is the estimated sampling variance of data source $s[i]$.
- FPEM data model (in very brief): logistic normal for compositional data
- Incorporates sampling and non-sampling errors for each data source, as well as systematic biases
- See appendix of Alkema (2013) for detailed description

One country model overview

- Fitting FPEM to data from all countries is computationally intensive
- Individual countries may be interested in producing estimates for just their country using additional/different data
- General strategy
    - Fit FPEM to all global data
    - Extract point estimates of all non country-specific parameters
    - Rerun the model on only one country, but fix all non-country specific parameters to the point estimates

Demo: `Fpemlocal`

- `Fpemlocal` R package provides routines for fitting FPEM to data from one country
- Demo code: https://github.com/herbps10/fpemdemo

herst

Check for updates

SOFTWARE TOOL ARTICLE

Fpemlocal: Estimating family planning indicators in R for a single population of interest [version 1; peer review: 2 approved]

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Abstract

The global Family Planning Estimation model (FPEM) combines a Bayesian hierarchical model with country-specific time trends to yield estimates of contraceptive prevalence and unmet need for family planning for countries worldwide. In this paper, we introduce the R package *fpemlocal* that carries out the estimation of family planning indicators for a single population, for example, for a single country or smaller area. In this implementation of FPEM, all non-population-specific parameters are fixed at outcomes obtained in a prior global FPEM run. The development of this model was motivated by the demand for computational efficiency, without loss of model accuracy, when estimates and projections from FPEM were needed only for a single country. We present use cases to produce estimates for a single

Open Peer Review

Reviewer Status ✓ ✓

	Invited Reviewers	
	1	**2**
version 1 24 Feb 2021	✓ report	✓ report

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2. **Qingfeng Li**, Johns Hopkins Bloomberg School of Public Health, Baltimore, USA

Any reports and responses or comments on the