# Estimating Population and Health Quantities and their Uncertainty from Data of Limited Quality

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Joint work with Leontine Alkema, Samuel Clark, Patrick Gerland and Mark Wheldon
In collaboration with the UN Population Division

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    - Multiple data sources, each with their own issues

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  - Raftery (2014, arXiv): experiences and types of user

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  - Complex models can be estimated by Monte Carlo methods

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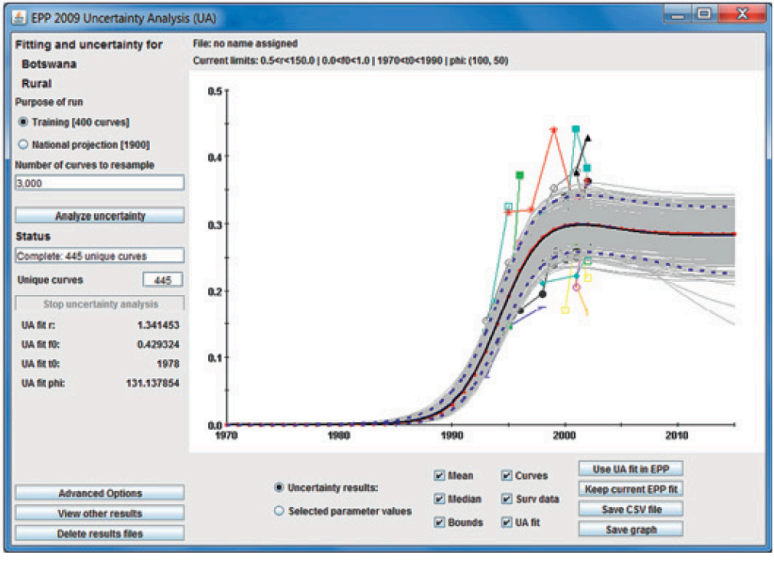
  - Now used for UNAIDS estimation and projection (EPP/Spectrum software)


EPP 2009 Uncertainty Analysis (UA)
Fitting and uncertainty for
Botswana
Rural
File: no name assigned
Current limits: 0.5<r<150.0 | 0.0<f0<1.0 | 1970<t0<1990 | phi: (100, 50)
Purpose of run
Training [400 curves]
National projection [1900]
Number of curves to resample
3,000
Analyze uncertainty
Status
Complete: 445 unique curves
Unique curves 445
Stop uncertainty analysis
UA fit r: 1.341453
UA fit f0: 0.429324
UA fit t0: 1978
UA fit phi: 131.137854
0.5
0.4
0.3
0.2
0.1
0.0
1970
1980
1990
2000
2010
Uncertainty results:
Selected parameter values
Mean
Median
Bounds
Curves
Surv data
UA fit
Use UA fit in EPP
Keep current EPP fit
Save CSV file
Save graph
Advanced Options
View other results
Delete results files

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  - Software: `popReconstruct` R package

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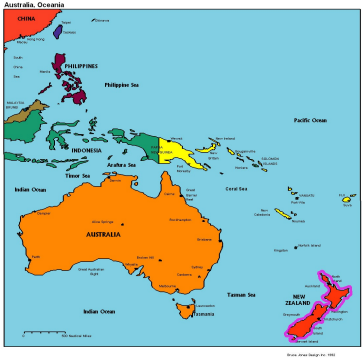

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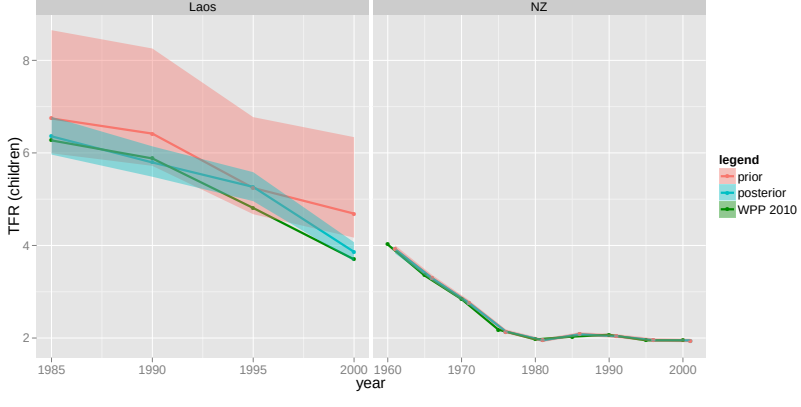

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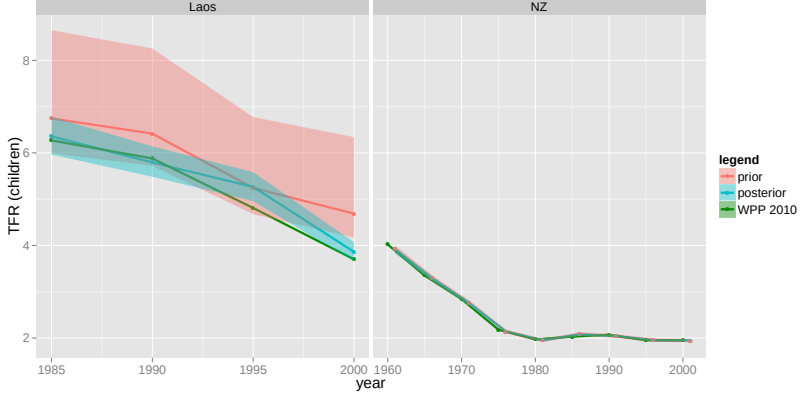


## Average 95% Posterior Interval Half-widths

| | |
|---|---|
| Laos | 0.30 |
| NZ | 0.03 |

# Life Expectancy at Birth

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| NZ | 0.04 |

# Age Specific Mortality Rate

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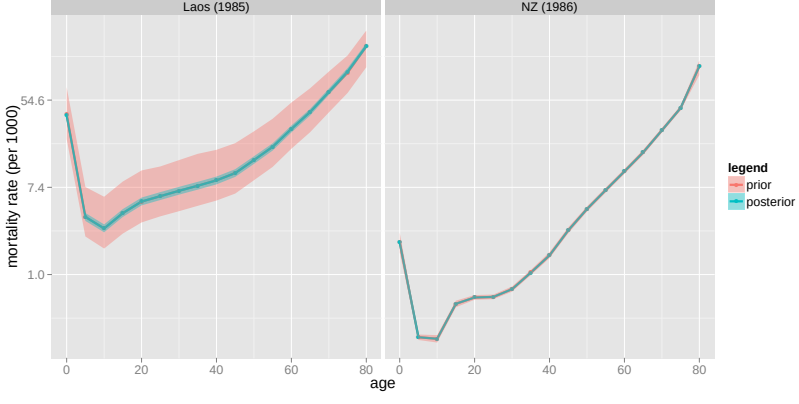


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| NZ | 0.1 |

# Total Net Migration

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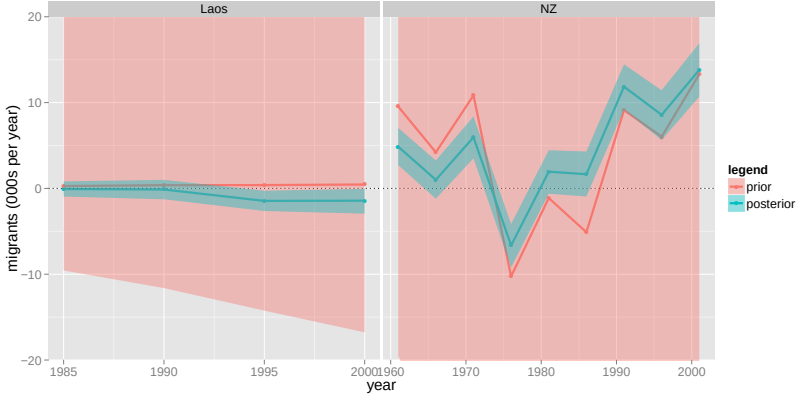

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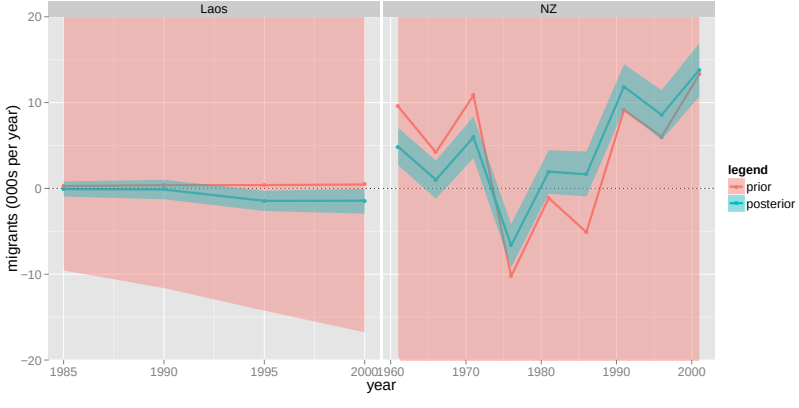


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| | % of Median |
|---|---|
| Laos | 570 |
| NZ | 80 |

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