

Estimating death rates in complex humanitarian emergencies using the network method

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Motivation for study

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- ▶ How do you best estimate death rates in **humanitarian emergencies**?
- ▶ We can't use conventional methods
 - ▶ Civil war, earthquake, etc.

We still need new methods....

[Emerg Themes Epidemiol.](#) 2007; 4: 9.

Published online 2007 Jun 1. doi: [10.1186/1742-7622-4-9](https://doi.org/10.1186/1742-7622-4-9)

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Wanted: studies on mortality estimation methods for humanitarian emergencies, suggestions for future research

Working Group for Mortality Estimation in Emergencies ^{✉1}

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Overview of Network Survival Method

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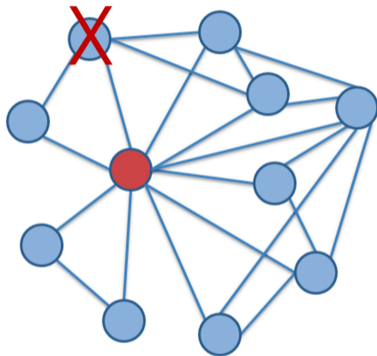
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Insights from social networks



People can report valuable information about mortality among their social network

Network survival method

$$\widehat{M}_\alpha = \frac{D_\alpha}{N_\alpha} \quad (2)$$

$$= \frac{\sum_{i \in s} w_i y_{i,D}}{\sum_{i \in s} w_i d_i E_i} \quad (3)$$

where

- ▶ $\sum_{i \in s} w_i y_{i,D}$ is the (weighted) total number of people in respondents' personal network who have died in time window

Network survival method

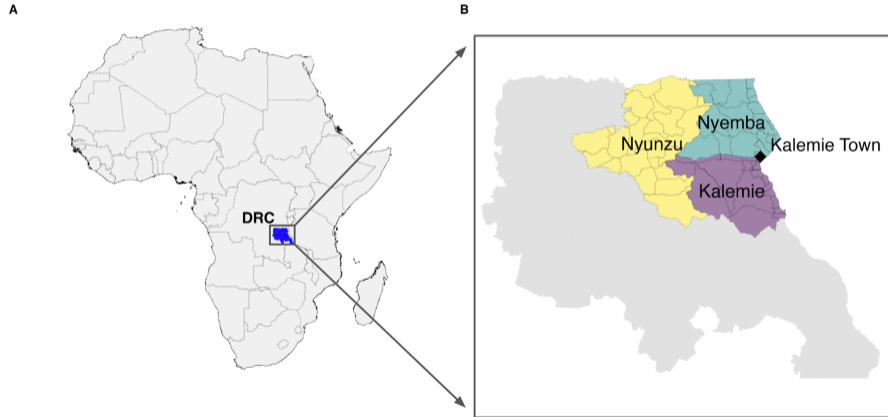
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- ▶ $\sum_{i \in S} w_i d_i E_i$ is the (weighted) total amount of exposure reported on in respondents' personal network

Case Study: Democratic Republic of the Congo



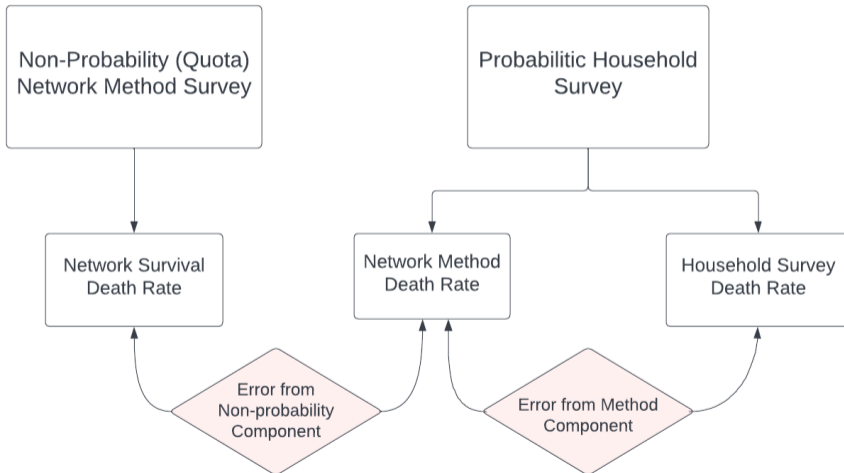
Case Study: Democratic Republic of the Congo

Tanganyika Province, Three Zone De Santes



Intercept respondents
in Kalemie Town

Study design



Key design question – how do we pick a network tie?

- ▶ Too big a network: respondents can't report accurately (everyone you have ever talked to)

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- ▶ Too big a network: respondents can't report accurately (everyone you have ever talked to)
- ▶ Too small a network: we need a much bigger sample size (e.g, parents, siblings)

Formative research (qualitative)

- ▶ **Goal:**
 - ▶ What deaths can respondents report on accurately?
 - ▶ What reference date and reporting window should we chose?
- ▶ 8 focus groups + 20 individual interviews

Group	Age	Gender	Location
1	<45	Male	Urban
2	<45	Female	Urban
3	<45	Male	Rural
4	<45	Female	Rural
5	45+	Male	Urban
6	45+	Female	Urban
7	45+	Male	Rural
8	45+	Female	Rural

Best option — kin and neighbor networks

Module	Group	Notes
Neighbor	Respondent's Household	
Neighbor	1st Closest Neighbor Household	
Neighbor	2nd Closest Neighbor Household	
Neighbor	3rd Closest Neighbor Household	
Neighbor	4th Closest Neighbor Household	
Neighbor	5th Closest Neighbor Household	
Kin	Respondent's Grandchildren	
Kin	Respondent's Children	
Kin	Respondent's Siblings	
Kin	Respondent's Cousins	
Kin	Respondent's Aunts/Uncles	
Kin	Respondent's Parents	
Kin	Respondent's Grandparents	

Data Collection, Quota (Partnership with REACH Initiative)

- ▶ Interview respondents at major transit hubs in Kalemie Town
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- ▶ Quota sample by geographic region + gender (non-probability)

Data Collection



Interviews conducted at transit hubs such as markets, ports, taxi stations, health clinics, etc.

Informed consent on paper form, survey administered on smartphone



Quota sample: Interviews by month (N = 2,650)

Month	Kalemie	Nyemba	Nyunzu
March	203	198	200
April	201	203	202
May	216	221	232
June	228	237	204

Note: All respondents report on deaths since January 1st, 2023

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 - ▶ Primary sampling units at the village level
- ▶ The household survey asked detailed information about deaths occurring within their household after January 1st, 2023

Quota sample re-weighting strategies - 3 different scenarios

1. No weights (rely on quota design)

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1. No weights (rely on quota design)
2. Poststratification weights (age, gender, geography only)
3. Inverse probability weights (requires high-quality reference sample)

Inverse probability weights

Fit a model to estimate inclusion probability:

$$w_i = \frac{1}{\hat{P}(S_i = 1)} \quad (4)$$

where w_i is a weight define as the the inverse probability of being included in the sample ($S_i = 1$).

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$$\begin{aligned} \text{logit}(\text{Pr}(\text{inclusion} = 1|\mathbf{X})) = & \beta_0 + \beta_{(\text{gender})} + \beta_{(\text{age class})} + \beta_{(\text{gender} \times \text{age_class})} + \beta_{(\text{hh size})} \\ & \beta_{(\text{radio})} + \beta_{(\text{bed})} + \beta_{(\text{wall material})} + \beta_{(\text{modern fuel type})} + \\ & \beta_{(\text{hh count age 0-4})} + \beta_{(\text{hh count age 5-17})} + \beta_{(\text{hh count age 18+})} \end{aligned} \quad (5)$$

Blended estimates - combined neighbor and kin estimates

$$\underbrace{\widehat{M}}_{\text{Blended Estimate}} = \underbrace{\theta \widehat{M}^A}_{\text{Weighted Estimator A}} + \underbrace{(1 - \theta) \widehat{M}^B}_{\text{Weighted Estimator B}} \quad (6)$$

where θ is a weight $\in [0, 1]$.

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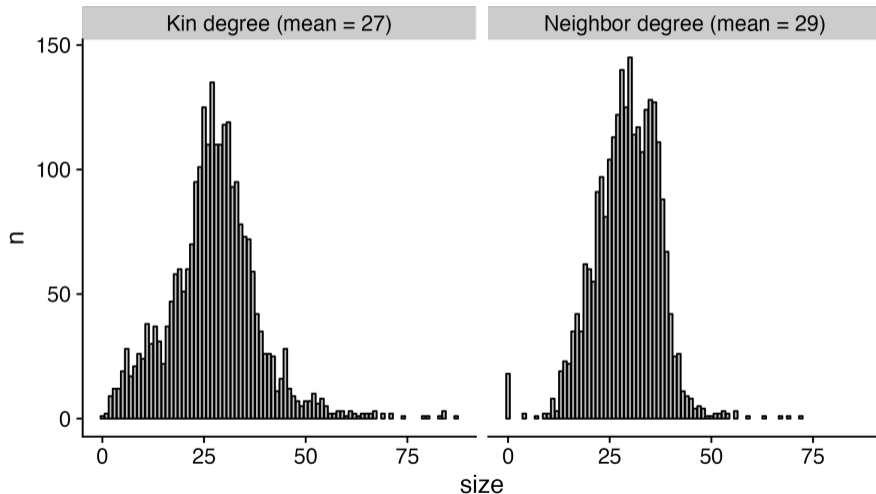
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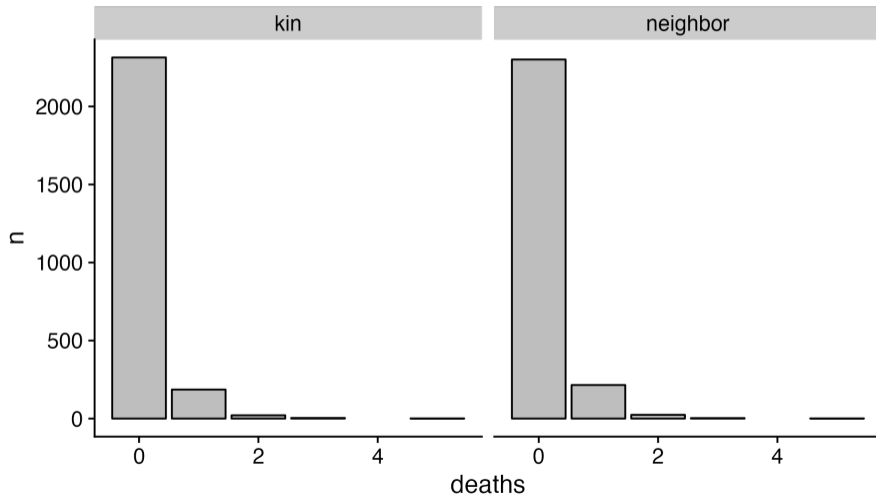
We can pick the optimal θ^* to minimize mean squared error:

$$\theta^* = \frac{\sigma_B^2 - \frac{\sigma_{AB}}{2}}{\sigma_A^2 + \sigma_B^2 - \sigma_{AB}}, \quad (7)$$

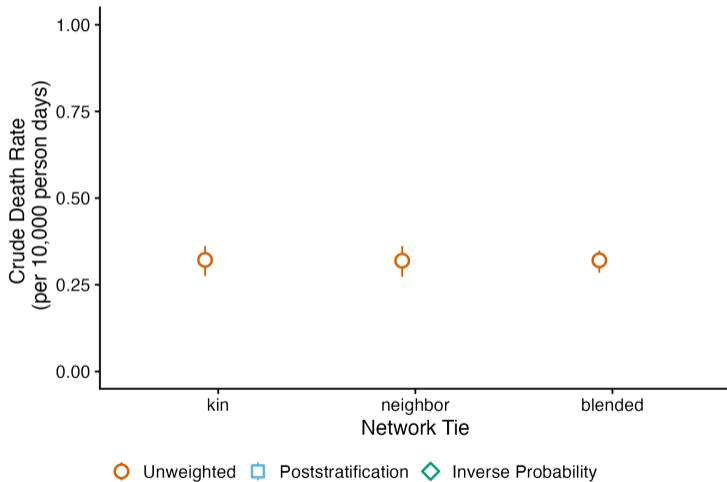
Network size – distribution



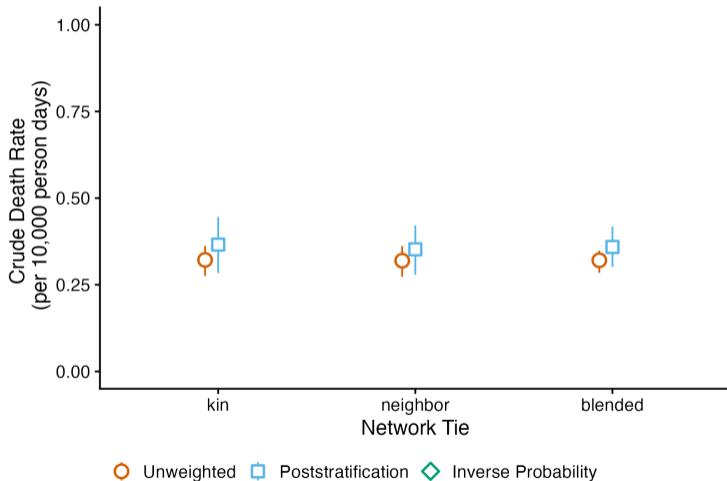
Deaths reported per interview – distribution



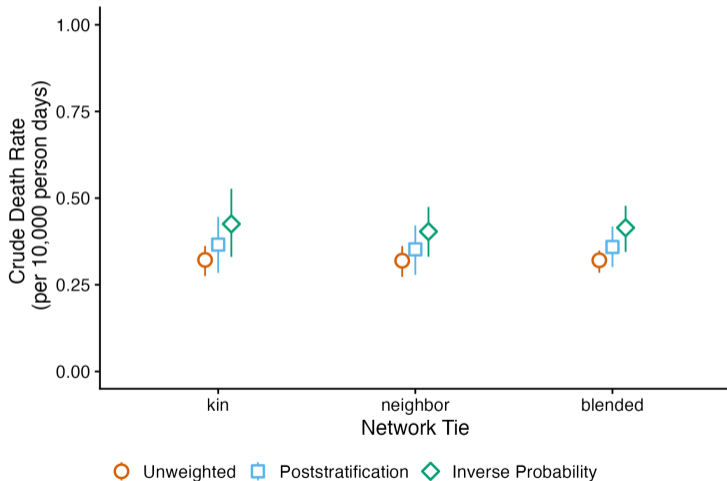
Non-probability network survival results



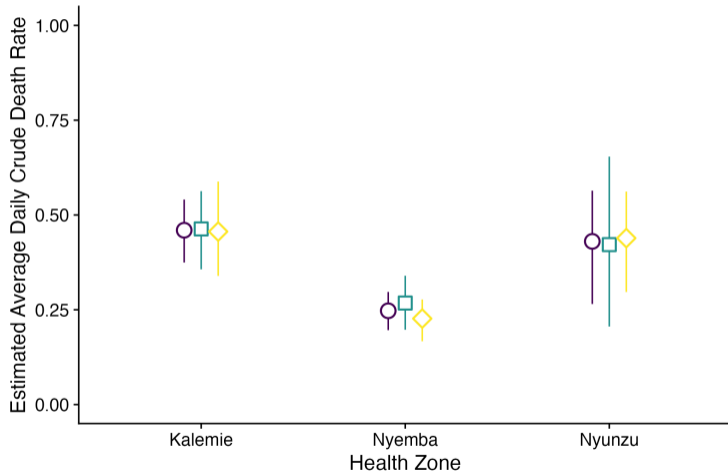
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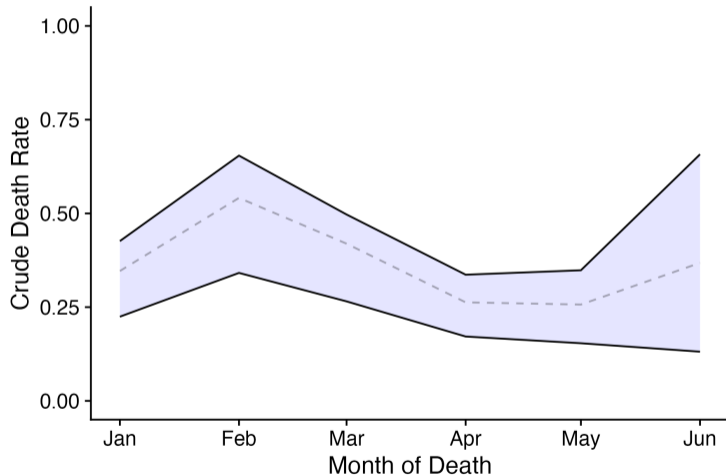
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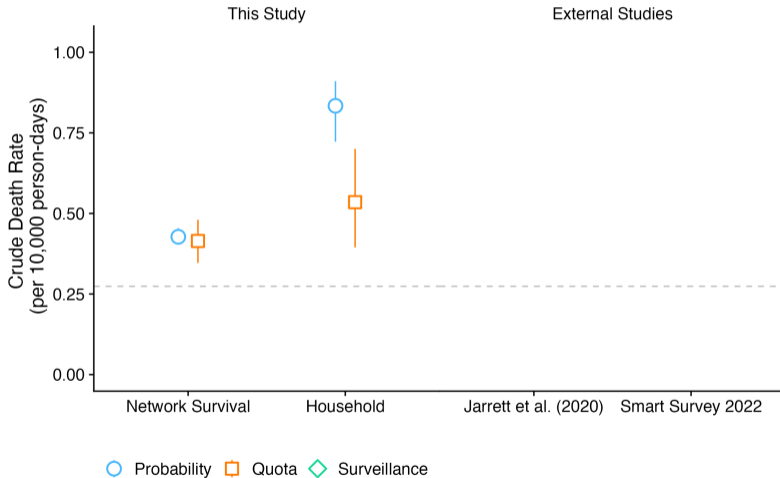
Variation across health zones



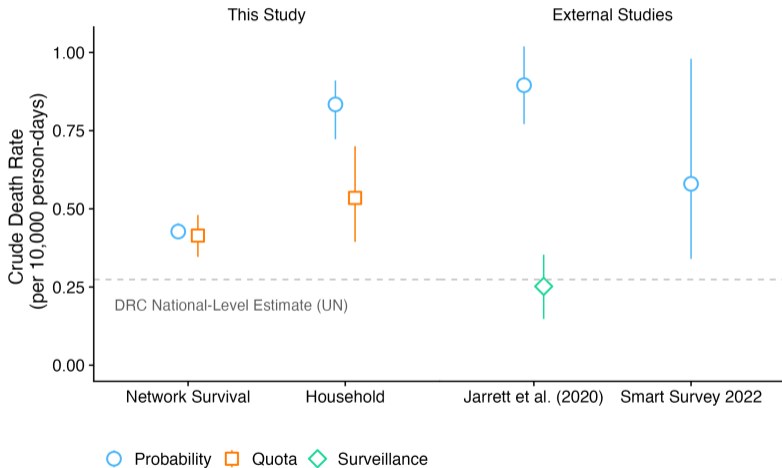
Monitoring trends over time



Full comparisons



Full comparisons + external studies



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- ▶ Developed and tested a promising **new method** for estimating death rates in humanitarian emergencies

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- ▶ Developed and tested a promising **new method** for estimating death rates in humanitarian emergencies
 - ▶ We need more systematic evaluations
- ▶ Highly contextual – **requires** localized knowledge of social networks, diffusion of info about deaths, etc.

Where to next...?

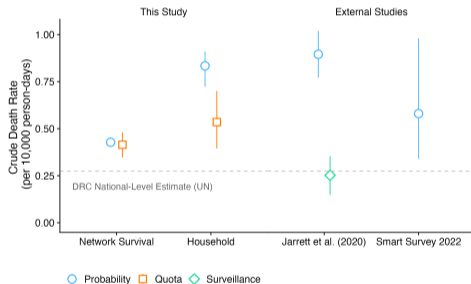
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Where to next...?


- ▶ We need more **rigorous assessment** of household mortality survey and network survival method in different settings
 - ▶ Surveillance sites, verification visits, etc.
- ▶ Streamlining into a “off-the-shelf” module that can easily be added onto existing surveys

Thank You

► Questions?



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