A COUNTERFACTUAL APPROACH FOR IMPACT EVALUATION

HARVARD
School of Public Health

Department of Epidemiology
Miguel-Angel Luque-Fernandez,PhD

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OUTLINE

1. INTRODUCTION
   - IE Definitions
   - IE Characteristics
   - Differences between IE M&E OR
2. COUNTERFACTUAL FRAMEWORK
   - History, definition and justification
   - What is a causal effect?
3. IE DESIGNS & METHODS
   - IE Designs: methods
   - IE controversies and myths
   - The best design
4. CASE STUDIES
   - Pre/post surveys
   - MSM

IMPACT EVALUATION

Impact Evaluation Definitions

World Bank

"A systematic identification of the **effects** *positive or negative, intended or not on individual households, institutions, and the environment* **caused** *by a given development activity such a* **program or project***"*
http://web.worldbank.org

Impact Evaluation Definitions

US Environmental Protection Agency

"A form of evaluation that assess the **net effect** of a program by **comparing program outcomes** with an estimate of **what would have happened in the absence of the program**"
http://www.epa.gov/evaluate/impact-eval/index.htm

IE characteristics

Impact Evaluation

- **Impact Evaluation (IE)** assesses changes than can be attributed to a particular **intervention**.
- **IE** involves **COUNTERFACTUAL** analysis (**CAUSAL mechanism**), that is, *a comparison between what actually happened and what would have happened in the absence of the intervention*.

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- The main purpose of **IE** is to improve **evidence-based** policy making by means of providing **effectiveness** evaluations of public health interventions.

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Differences

Impact Evaluation

IE is the general framework where **Monitoring and Evaluation** (ME) and **Operational Research** (OR) are integrated.

- **ME** involves **evaluating** data available from the project over time in terms of goals, indicators and outcomes.
- **OR** seeks for tools that can enhance the quality of the **project**. The key element of **OR** is that the **research questions** are generated by identifying the constraints and challenges encountered during the implementation of program activities.

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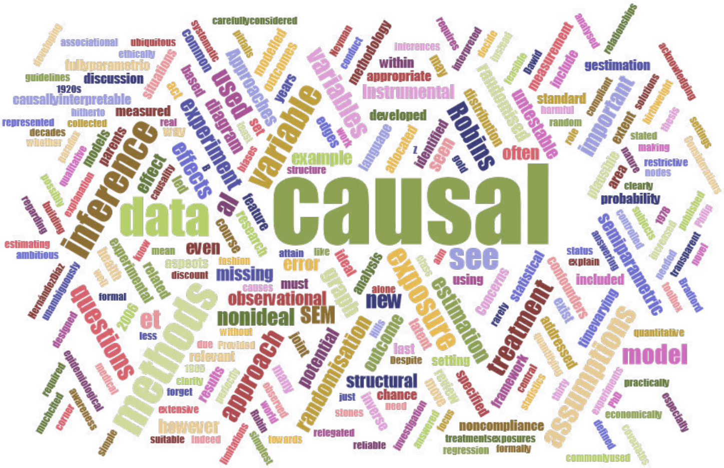
COUNTERFACTUAL FRAMEWORK



Counterfactual framework

When an RCT is not possible

- This framework was developed first by statisticians (Rubin, 1983) and econometricians (Heckman, 1978) as a new approach for the estimation of **causal effects** from observational data.
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The challenge of IE

Counterfactual

The main challenge across different types of **IE** is to find a **good counterfactual** -namely, *the situation a participating subject would have experienced had he or she not been exposed to the program*.

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Causal effects in the real world

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The Outcomes for the treated and control individuals are:

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The Potential Outcomes for an individual i if he/she received treatment or control are:

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The counterfactual is **not observed**.
So the challenge of an **IE** is to create a convincing and reasonable comparison group for beneficiaries in light of this **missing data**.

Total Causal Effect

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$$\mathbf{ATE} = [\mathbf{E}(Y_i(1) \mid T = 1) - \mathbf{E}(Y_i(0) \mid T = 0)] + \mathbf{B}$$

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In an ideal world, we would see this:

$Unit_i$	X_i^1	X_i^2	X_i^3	T_i	$Y_i(0)$	$Y_i(1)$	$Y_i(1) - Y_i(0)$
1	2	1	503	0	693	75	-698
2	7	1	985	0	111	108	-3
3	8	2	830	1	944	102	-842
4	3	1	938	1	14	111	97

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In the real world, this is what we see:

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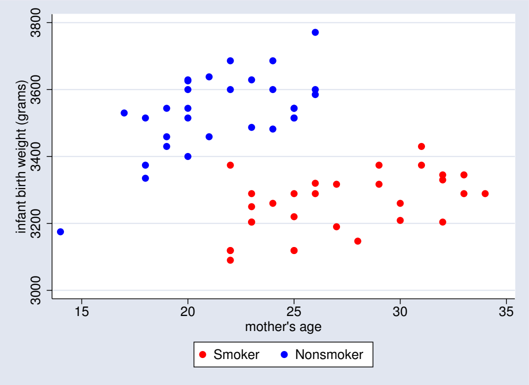

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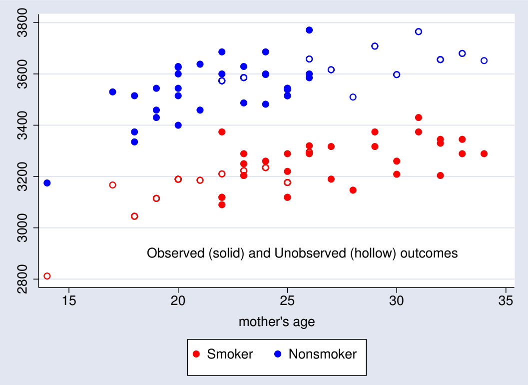

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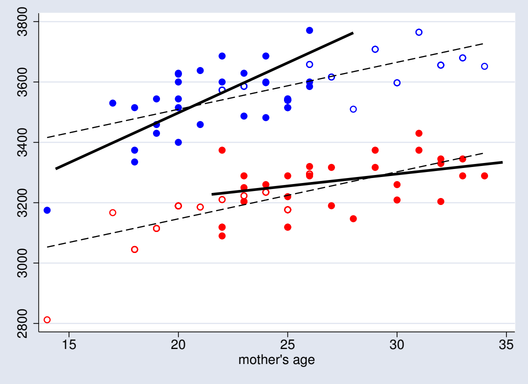

Causal effect in an EXPERIMETAL study

The solution to the fundamental problem of Causal inference

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Causal effects in OBSERVATIONAL studies

When randomization is unethical or infeasible

Causal effect is biased (B):

$$\textbf{ATE} + \textbf{B}$$

Type of bias

1. Observed: The treatment assignment is not random.
2. Unobserved: Unobserved factors associated with both the treatment and the effect.

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1. Experimental: RCT and CRT (considered the gold standard)
2. Classic and Modern Quasi-experimental designs

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2. Classic and Modern Quasi-experimental designs
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IMPACT EVALUATION: case studies

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journal homepage: www.elsevierhealth.com/journals/trst

THE ROYAL SOCIETY OF TROPICAL MEDICINE & HYGIENE

Influence of temperature and rainfall on the evolution of cholera epidemics in Lusaka, Zambia, 2003—2006: analysis of a time series

Miguel Ángel Luque Fernández[a,*], Ariane Bauernfeind[b], Julio Díaz Jiménez[c], Cristina Linares Gil[a], Nathalie El Omeiri[a,d], Dionisio Herrera Guibert[e]

[a] *National Centre of Epidemiology (CNE), Programa de Epidemiología Aplicada de Campo (PEAC), Instituto de Salud Carlos III (ISCIII), C/Sinesio Delgado 6, Pabellón 12, 28029 Madrid, Spain*
[b] *Médecins Sans Frontières (MSF), Brussels Operational Centre, Rue Dupré 94, 1090 Bruxelles, Belgium*
[c] *Escuela Nacional de Sanidad (ENS), Instituto de Salud Carlos III (ISCIII), C/Sinesio Delgado 6, Pabellón 7, 28029 Madrid, Spain*
[d] *European Programme for Intervention Epidemiology Training (EPIET), Stockholm, Sweden*
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KEYWORDS
Cholera;
Epidemics;
Climate;
Mathematical modelling;
Zambia;
Africa

Summary In this study, we aimed to describe the evolution of three cholera epidemics that occurred in Lusaka, Zambia, between 2003 and 2006 and to analyse the association between the increase in number of cases and climatic factors. A Poisson autoregressive model controlling for seasonality and trend was built to estimate the association between the increase in the weekly number of cases and weekly means of daily maximum temperature and rainfall. All epidemics showed a seasonal trend coinciding with the rainy season (November to March). A 1 °C rise in temperature 6 weeks before the onset of the outbreak explained 5.2% [relative risk (RR) 1.05, 95% CI 1.04—1.06] of the increase in the number of cholera cases (2003—2006). In addition, a 50 mm increase in rainfall 3 weeks before explained an increase of 2.5% (RR 1.02, 95% CI 1.01—1.04). The attributable risks were 4.9% for temperature and 2.4% for rainfall. If 6 weeks prior to the beginning of the rainy season an increase in temperature is observed followed by an increase in rainfall 3 weeks later, both exceeding expected levels, an increase in the number of cases of cholera within the following 3 weeks could be expected. Our explicative model could contribute to developing a warning signal to reduce the impact of a presumed cholera epidemic.

Time Series

-Model
TRSTMH-965: No. of Pages 7
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Analysis of the evolution of cholera epidemics in Zambia 5

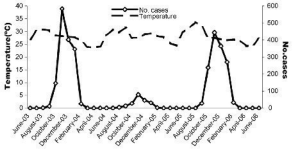

Figure 4 Time plots of number of cholera cases per month and monthly mean temperature (°C) in Lusaka, Zambia, 2003–2006 (Médecins Sans Frontières, unpublished data).

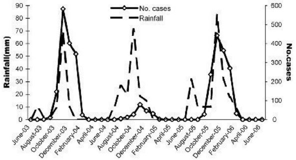

Photo: NOAA

Rita Colwell and colleague Anwar Huq display samples of filtered (left) and unfiltered water. Filtering drinking water helps to remove the zooplankton and reduce cholera by 40 to 50 percent

Jane Olwoch, a senior environmental science lecturer at the University of Pretoria, South Africa, pointed out that besides the biological factors, "Floods caused by heavy rains can contaminate drinking water with the bacterium; in droughts, the bacterium can grow more easily in stagnating water in ponds and rivers."

Researchers in Africa, led by Miguel Angel Luque Fernández from the Institute of Health Carlos III, based in Madrid, Spain, were the first to show a link between higher temperature and rainfall and the incidence of cholera in Zambia in a study published in the Transactions of the Royal Society of Tropical Medicine and Hygiene, in the UK.

Cholera outbreaks between 2003 and 2006 in Zambia showed that a one-degree Celsius rise in temperature six weeks before an outbreak began allowed the bacteria to multiply in enhanced conditions, leading to almost 5 percent more cholera cases, while a 50mm increase in rainfall three weeks ahead of an outbreak pushed up the number of cases by more than 2 percent.

A study in South Africa's coastal province of KwaZulu-Natal in 2008, by researchers from the Environmental Change Institute at the UK-based Oxford University Centre for the Environment, found a similar link between warmer sea water, floods, and cholera outbreaks.

"We know there is an indisputable link between cholera and poverty, poor sanitation, quality of drinking water, but there are biological agents involved in cholera that react to changes in climate," Olwoch said.

"We cannot therefore think that we can solve the cholera problem by ignoring these factors, especially now, when we know very well that our climate is changing."

jk/he

Theme(s): Early Warning, Environment, Health & Nutrition, Natural Disasters, Water & Sanitation,

[This report does not necessarily reflect the views of the United Nations]

Table 2 Association between the number of cholera cases and climate variables: final autoregressive Poisson model including lags of weekly mean temperature and rainfall (Médecins Sans Frontières, unpublished data)[a]

	Coefficient (SE)[b]	RR (95% CI)	% change[c]	AR (%)	*P*-value
Temperature (6 weeks earlier)	0.05 (0.006)	1.05 (1.04–1.06)	5.2	4.7	<0.001
Rainfall (3 weeks earlier)	0.02 (0.01)	1.02 (1.01–1.04)	2.5	1.9	0.011

RR: relative risk; AR: attributable risk.
[a] Adjusted for seasonality.
[b] Standard errors (SE) scaled using square root of Pearson χ^2 based dispersion.
[c] Percent change in expected count for 1 °C increase in temperature and 50 mm in rainfall.

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COMPLEX SURVEYS

Evaluation quali-quantitative du projet «Agents Paludisme»

Enquête de morbi-mortalité due au paludisme dans le district sanitaire de Bongor (Tchad), avril 2008

Miguel Ángel Luque Fernández
Centre Nationale d'épidémiologie, Madrid (Spain)
C/Sinesio Delgado 6, Pabellón 12.
Programa de Epidemiolgía Aplicada de Campo (PEAC)
Field Epidemiolgy Training Program (FETP)
fmiguelangel@isciii.es

MEDECINS SANS FRONTIERES

ENQUÊTE DE COUVERTURE VACCINALE: ENFANTS (12 À 59 MOIS) ET FEMMES (15-45 ANS) EN RDC (LUBUTU) 2009

Instituto de Salud Carlos III

ÉDITIONS UNIVERSITAIRES EUROPÉENNES

Dans les populations à faible couverture vaccinale, les épidémies se produisent régulièrement tous les deux ou trois ans. L'augmentation de la couverture vaccinale entraîne une allongé des périodes inter-épidémiques. Cependant à Lubutu il faut s'attendre dans les années à venir une plus grande proportion des cas parmi les enfants plus âgés de 24 mois. La vaccination permet de réduire l'incidence de la maladie en offrant une immunité aux enfants vulnérables. La morbidité et la mortalité de ces foyers peuvent être particulièrement élevées si ces groupes présentent également des facteurs de risque sous-jacent pour des maladies graves, telles que la suppression immunitaire, la malnutrition et les carences en vitamine A. L'effectivité vaccinale estimée pour la zone rurale (supérieur au 90%) nous indique que la campagne de vaccination menée par Médecins Sans Frontières a eu un impact assez important. Toutefois, pour éviter les épidémies à répétition il faudra continuer de vacciner les nouvelles cohortes d'enfants nés dans la zone de santé dans le cadre du programme de vaccination élargie et reprendre les campagnes de vaccination de masse dans les aires de santé à faible couverture.

MIGUEL ANGEL LUQUE FERNANDEZ

Miguel A. Luque-Fernández is Post-doc fellow in the CIDER –Centre for Infectious Diseases Epidemiology and Research- UCT University, Cape Town. He worked as Public Health Researcher and Epidemiologist in Europe, as a field epidemiologist in several African countries and recently with WHO (Global Outbreak Alert and Response Network) in Haiti.

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978-613-1-57979-0

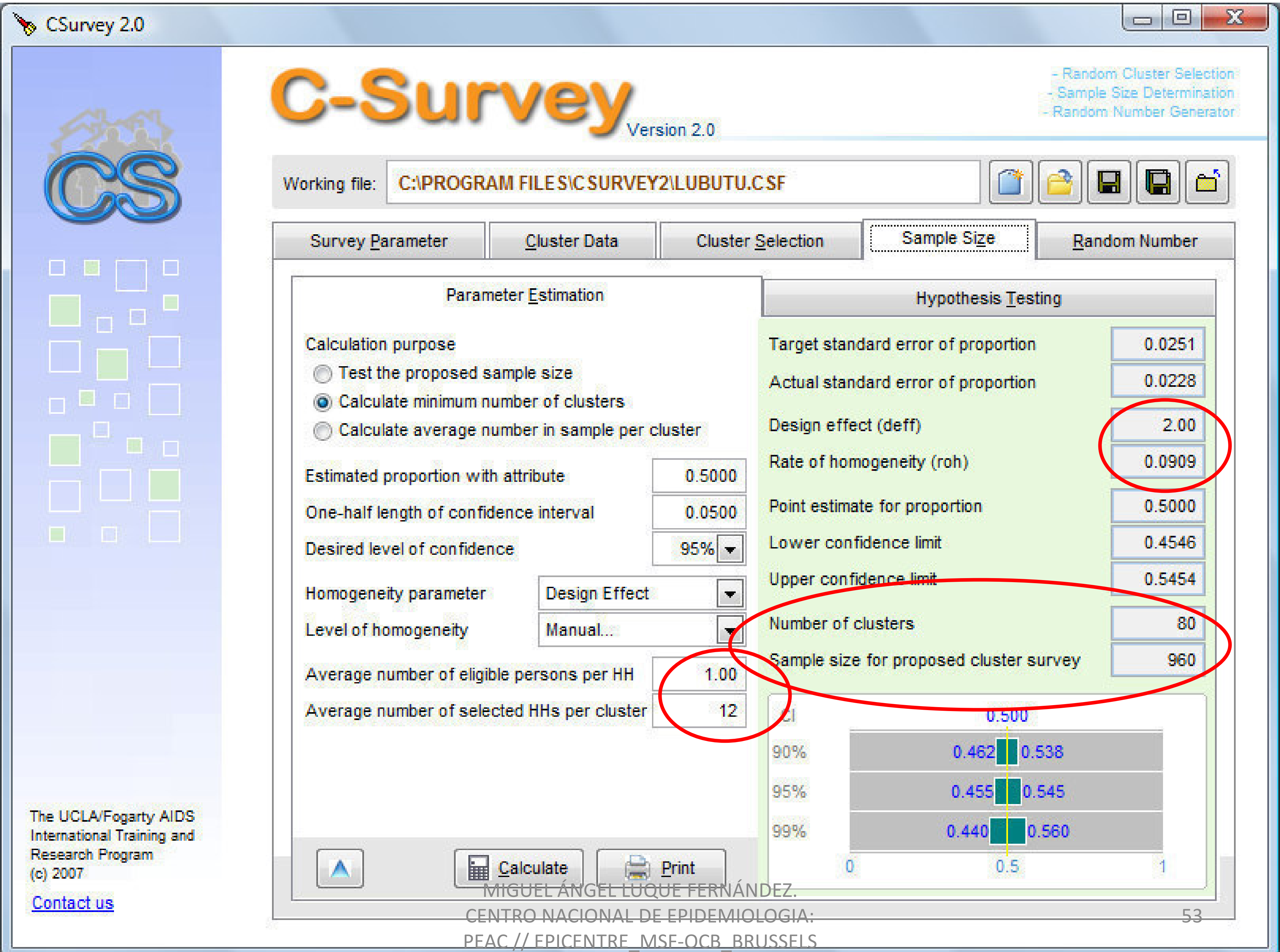
MIGUEL ANGEL LUQUE FERNANDEZ

Couverture Vaccinale à Lubutu 2009

MIGUEL ANGEL LUQUE FERNANDEZ

ENQUÊTE DE COUVERTURE VACCINALE EN RDC (LUBUTU), JUIN 2009

Couverture Vaccinale à Lubutu et efficacité vaccinale à la rougeole, Juin 2009, République Démocratique du Congo


CSurvey 2.0
C-Survey
Version 2.0
- Random Cluster Selection
- Sample Size Determination
- Random Number Generator
Working file:
C:\PROGRAM FILES\CSURVEY2\LUBUTU.CSF
Survey Parameter
Cluster Data
Cluster Selection
Sample Size
Random Number
Parameter Estimation
Hypothesis Testing
Calculation purpose
Test the proposed sample size
Calculate minimum number of clusters
Calculate average number in sample per cluster
Estimated proportion with attribute 0.5000
One-half length of confidence interval 0.0500
Desired level of confidence 95%
Homogeneity parameter Design Effect
Level of homogeneity Manual...
Average number of eligible persons per HH 1.00
Average number of selected HHs per cluster 12
Target standard error of proportion 0.0251
Actual standard error of proportion 0.0228
Design effect (deff) 2.00
Rate of homogeneity (roh) 0.0909
Point estimate for proportion 0.5000
Lower confidence limit 0.4546
Upper confidence limit 0.5454
Number of clusters 80
Sample size for proposed cluster survey 960
CI
0.500
90% 0.462 0.538
95% 0.455 0.545
99% 0.440 0.560
0
0.5
1
Calculate
Print
The UCLA/Fogarty AIDS International Training and Research Program
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Contact us

Data Graphics Statistics User Window Help

Results

```
     WALIKALE   .7236842   .0433469     1.42304
        MAIKO        .75   .0677671     1.26897

NON
    KISANGANI   .3285714    .060998     1.17628
     WALIKALE   .2763158   .0433469     1.42304
        MAIKO        .25   .0677671     1.26897

. svy, vce(linearized): tabulate VACROUG MALROUG, column row obs pearson
(running tabulate on estimation sample)

Number of strata   =         1            Number of obs      =       960
Number of PSUs     =        80            Population size    =       960
                                          Design df          =        79

VACCINE    MALADE DE ROUGEOLE
ROUGEOLE     OUI    NON  Total

      OUI  .5323  .4677      1
           .6815  .6401  .6615
             338    297    635

      NON  .4862  .5138      1
           .3185  .3599  .3385
             158    167    325

    Total  .5167  .4833      1
               1      1      1
             496    464    960

  Key:  row proportions
        column proportions
        number of observations

  Pearson:
    Uncorrected   chi2(1)         =    1.8318
    Design-based  F(1, 79)        =    1.0585     P = 0.3067

.
```

PPV	PCV	ev= (pcv-ppv)/(ppv*(pcv-1)) EV (1)
0.661	0.532	0.4170061

Command

MEDECINS SANS FRONTIERES
ARTSEN ZONDER GRENZEN

Accuracy of mid-upper-arm circumference to detecting severe acute malnutrition measured with the new WHO Growth Standards.

Miguel Ángel Luque Fernández

Accuracy of MUAC in the Detection of Severe Wasting With the New WHO Growth Standards

AUTHORS: Miguel Ángel Luque Fernández, MA, MPH, FETP, Pascale Delchevalerie, MSc, and Michel Van Herp, MD, MPH

Medical Department, Brussels Operational Center, Doctors Without Borders, Brussels, Belgium

KEY WORDS
malnutrition, anthropometry, mid-upper-arm circumference, diagnostic errors, epidemiology

ABBREVIATIONS
MUAC—mid-upper-arm circumference
NCHS—National Center for Health Statistics
WHO—World Health Organization
CI—confidence interval

Dr Luque Fernández's current affiliation is the Brussels-Capital Health and Social Observatory, Research Centre for the Joint College Services of the Joint Community Commission, Brussels, Belgium.

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Address correspondence to Miguel Ángel Luque Fernández, MA, MPH, FETP, Médecins Sans Frontières OCB-Belgique, Medical Department, Rue Dupré 97, 1090 Jette, Brussels, Belgium. E-mail: miguel.angel.luque@brussels.msf.org or watzilei@hotmail.com

PEDIATRICS (ISSN Numbers: Print, 0031-4005; Online, 1098-4275).

FINANCIAL DISCLOSURE: *The authors have indicated they have no financial relationships relevant to this article to disclose.*

WHAT'S KNOWN ON THIS SUBJECT: MUAC measurements are used to screen rapidly for malnutrition among children 6 to 59 months of age. With the introduction of a new growth curve for children by the WHO in 2006, an evaluation of MUAC diagnostic accuracy is needed.

WHAT THIS STUDY ADDS: This study confirms the need to change the MUAC cutoff value from <110 mm to <115 mm. This change is needed to maintain the same diagnostic accuracy and to identify children at greatest risk of death resulting from severe wasting.

abstract

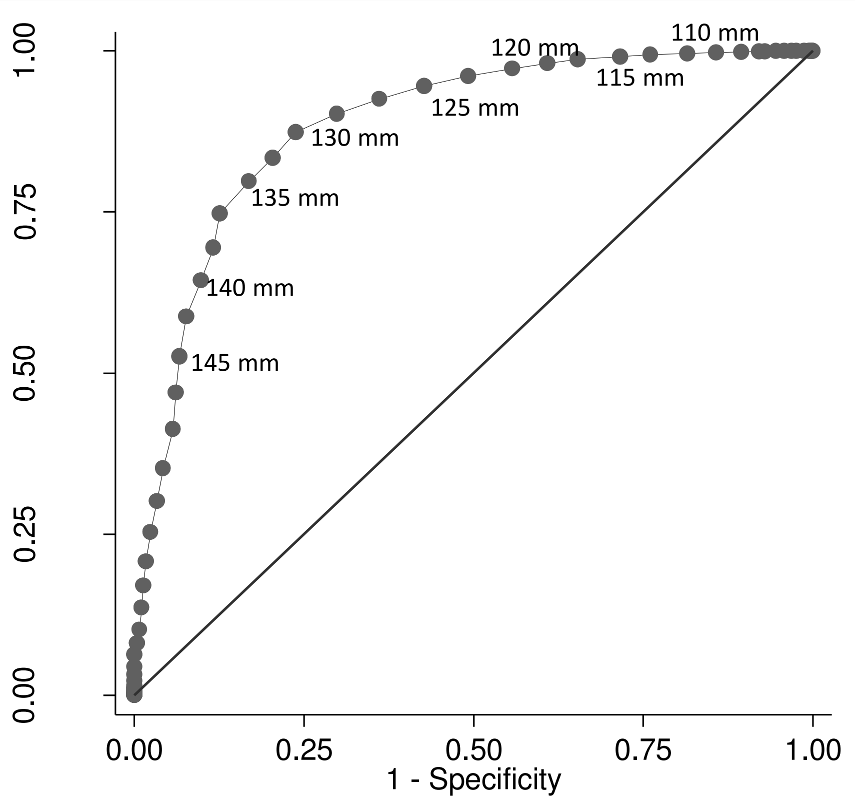
OBJECTIVES: The objectives of this study were to estimate the accuracy of using mid-upper-arm circumference (MUAC) measurements to diagnose severe wasting by comparing the new standards from the World Health Organization (WHO) with those from the US National Center for Health Statistics (NCHS) and to analyze the age independence of the MUAC cutoff values for both curves.

METHODS: We used cross-sectional anthropometric data for 34 937 children between the ages of 6 and 59 months, from 39 nutritional surveys conducted by Doctors Without Borders. Receiver operating characteristic curves were used to examine the accuracy of MUAC diagnoses. MUAC age independence was analyzed with logistic regression models.

RESULTS: With the new WHO curve, the performance of MUAC measurements, in terms of sensitivity and specificity, deteriorated. With different cutoff values, however, the WHO standards significantly improved the predictive value of MUAC measurements over the NCHS standards. The sensitivity and specificity of MUAC measurements were the most age independent when the WHO curve, rather than the NCHS curve, was used.

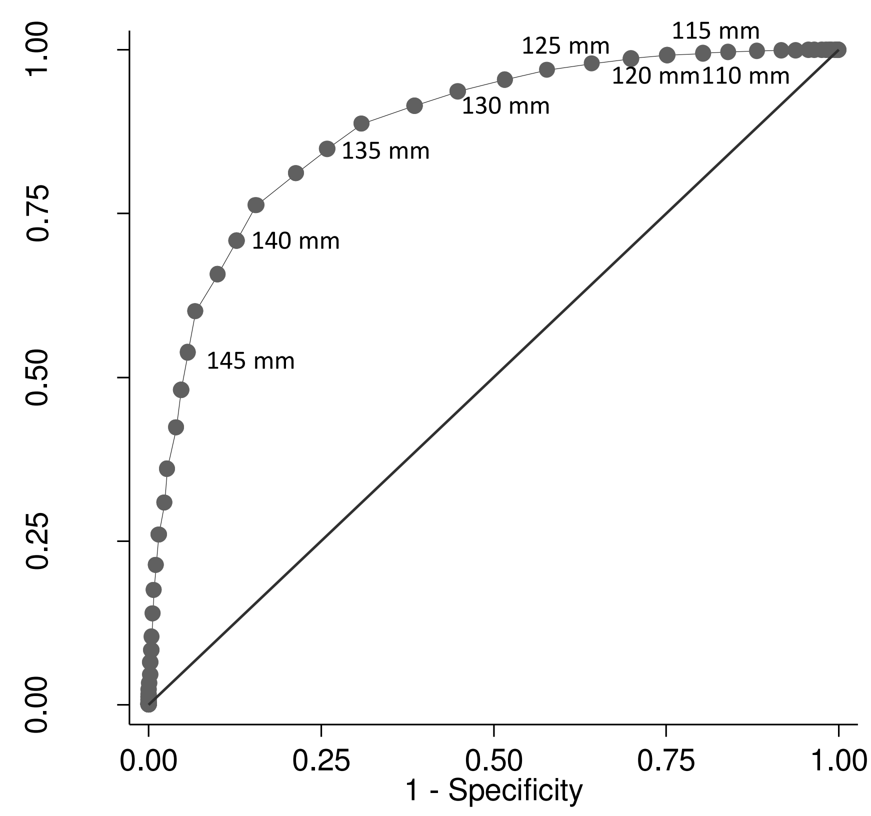
CONCLUSIONS: This study confirms the need to change the MUAC cutoff value from <110 mm to <115 mm. This increase of 5 mm produces a large change in sensitivity (from 16% to 25%) with little loss in specificity, improves the probability of diagnosing severe wasting, and reduces false-negative results by 12%. This change is needed to maintain the same diagnostic accuracy as the old curve and to identify the children at greatest risk of death resulting from severe wasting. *Pediatrics* 2010;126:e195–e201

NCHS



Area under ROC curve = 0.82 95%CI=(0.79-0.83)

WHO



Area under ROC curve = 0.80 95%CI=(0.79-0.82)

Crisis 2008, Hyperinflation

Source: www.wealthdaily.com

Cholera Epidemic in Zimbabwe

100,000 cases **4,000 deaths**

Source: The Guardian and The Nytimes

G Model
TRSTMH-1423; No. of Pages 8
ARTICLE IN PRESS

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journal homepage: http://www.elsevier.com/locate/trstmh

Descriptive spatial analysis of the cholera epidemic 2008–2009 in Harare, Zimbabwe: a secondary data analysis

Miguel Ángel Luque Fernández[a,*], Peter R. Mason[b], Henry Gray[c], Ariane Bauernfeind[a], Jean François Fesselet[d], Peter Maes[c]

[a] *Médecins Sans Frontières, Medical department (Brussels Operational Center), 94, rue Dupre, 1090 Brussels, Belgium*
[b] *Biomedical Research and Training Institute, University of Zimbabwe College of Health Sciences, Harare, Zimbabwe*
[c] *Médecins Sans Frontières, Medical Department, Water, Hygiene and Sanitation Unit, Brussels Operational Centre, Belgium*
[d] *Médecins Sans Frontières, Public health department, Water, Hygiene and Sanitation Unit, Amsterdam Operational Centre, Holland*

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ABSTRACT

This ecological study describes the cholera epidemic in Harare during 2008-2009 and identifies patterns that may explain transmission. Rates ratios of cholera cases by suburb were calculated by a univariate regression Poisson model and then, through an Empirical Bayes modelling, smoothed rate ratios were estimated and represented geographically. Mbare and southwest suburbs of Harare presented higher rate ratios. Suburbs attack rates ranged from 1.2 (95% CI = 0.7–1.6) cases per 1000 people in Tynwald to 90.3 (95% CI = 82.8–98.2) in Hopley. The identification of this spatial pattern in the spread, characterised by low risk in low density residential housing, and a higher risk in high density south west suburbs and Mbare, could be used to advocate for improving water and sanitation conditions and specific preparedness measures in the most affected areas.

1. Introduction

On 20 August 2008 an outbreak of 118 cholera cases was declared in St. Mary's and Zengeza wards of Chitungwiza, a large urban centre on the outskirts of Harare.[1–5] *Vibrio cholerae* El Tor 01 was isolated from 18 (30%) of the 59 specimens collected, thus supporting the clinical evidence for an outbreak.[2] Two months after this initial outbreak, a second wave of cases was reported with numerous suburbs being affected within the city of Harare and within every province of the country. This was the largest and most extensive outbreak of cholera recorded in Zimbabwe and indeed in Africa, affecting rural and urban areas with more than 100 000 cases and 4000 deaths, about half of which occurred in the urban centres of Harare and Chitungwiza.[2–7]

During the 2008–2009 Zimbabwe cholera epidemic the country was in economic crisis and the health care system had become dysfunctional, with most government hospitals unable to provide services or closed due to a lack of essential medical supplies. Many staff in health structures had not been paid, and many were unable to report for duty. Water supplies were irregular and sanitation systems had collapsed. The reason for this was a lack of maintenance of the system, with frequent power interruptions affecting pumping stations.[8–11]

By 2008, Chitungwiza had been without adequate water supply water for more than two years. People had become dependent on shallow wells that were at risk of contamination because of the lack of sewage disposal.[1,9,11] On 1 December 2008, problems with the main pumping station meant that, without prior warning, the water supply was shut off for Harare, leaving large populations without

* Corresponding author.
E-mail addresses: miguel.angel.luque@brussels.msf.org, watzilei@hotmail.com (M.Á. Luque Fernández).

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doi:10.1016/j.trstmh.2010.10.001

Environmental Risk Factors

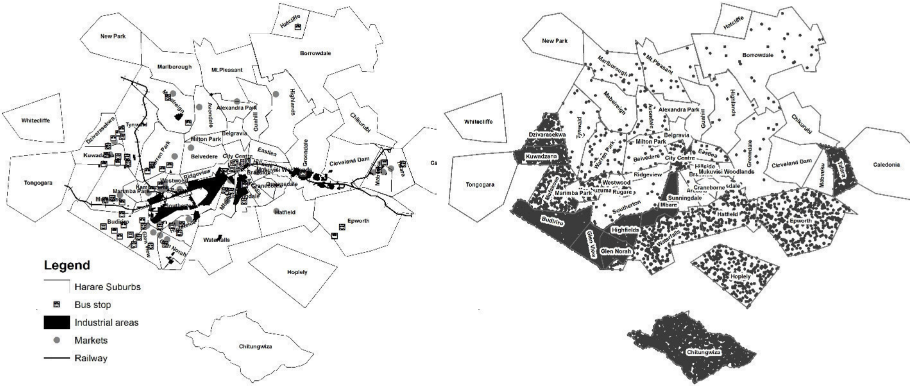
Source: Medécins Sans Frontiéres (MSF)
http://www.zimbabwesituation.com

Environment Risk Factors: Housing

Mbare House

Mount Pleasant House

Environment Risk Factors: Population mobility and Sanitation



Pearsons Coefficient of Correlation $= \color{red}{0.31}$

Source: Luque Fernndez M,et al. Descriptive spatial analysis of the cholera epidemic 20082009 in Harare, Zimbabwe: a secondary data analysis. Trans R Soc Trop Med Hyg (2010)

BMC Public Health

RESEARCH ARTICLE **Open Access**

Elevation and cholera: an epidemiological spatial analysis of the cholera epidemic in Harare, Zimbabwe, 2008-2009

Miguel A Luque Fernandez[1*], Michael Schomaker[1], Peter R Mason[2], Jean F Fesselet[3], Yves Baudot[4], Andrew Boulle[1] and Peter Maes[5]

Abstract

Background: In highly populated African urban areas where access to clean water is a challenge, water source contamination is one of the most cited risk factors in a cholera epidemic. During the rainy season, where there is either no sewage disposal or working sewer system, runoff of rains follows the slopes and gets into the lower parts of towns where shallow wells could easily become contaminated by excretes. In cholera endemic areas, spatial information about topographical elevation could help to guide preventive interventions. This study aims to analyze the association between topographic elevation and the distribution of cholera cases in Harare during the cholera epidemic in 2008 and 2009.

Methods: We developed an ecological study using secondary data. First, we described attack rates by suburb and then calculated rate ratios using whole Harare as reference. We illustrated the average elevation and cholera cases by suburbs using geographical information. Finally, we estimated a generalized linear mixed model (under the assumption of a Poisson distribution) with an Empirical Bayesian approach to model the relation between the risk of cholera and the elevation in meters in Harare. We used a random intercept to allow for spatial correlation of neighboring suburbs.

Results: This study identifies a spatial pattern of the distribution of cholera cases in the Harare epidemic, characterized by a lower cholera risk in the highest elevation suburbs of Harare. The generalized linear mixed model showed that for each 100 meters of increase in the topographical elevation, the cholera risk was 30% lower with a rate ratio of 0.70 (95% confidence interval=0.66-0.76). Sensitivity analysis confirmed the risk reduction with an overall estimate of the rate ratio between 20% and 40%.

Conclusion: This study highlights the importance of considering topographical elevation as a geographical and environmental risk factor in order to plan cholera preventive activities linked with water and sanitation in endemic areas. Furthermore, elevation information, among other risk factors, could help to spatially orientate cholera control interventions during an epidemic.

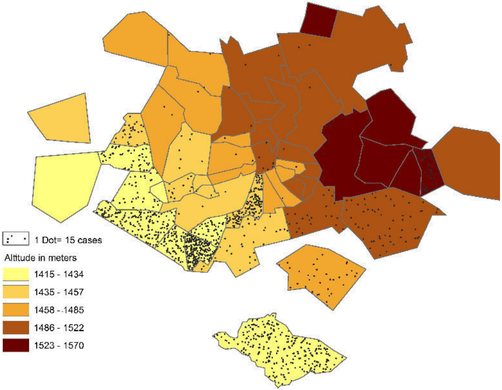
Background

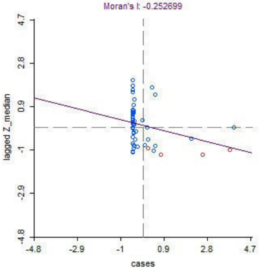
On the 20th of August 2008, an outbreak of 118 cases was declared at St. Mary's and Zenenga wards of Chitungwiza, a large urban centre on the outskirts of Harare [1,2]. *Vibrio Cholerae El Tor 01* was isolated from 18 (30%) of the 59 specimens submitted for examination, thus supporting the clinical evidence for an outbreak [3].

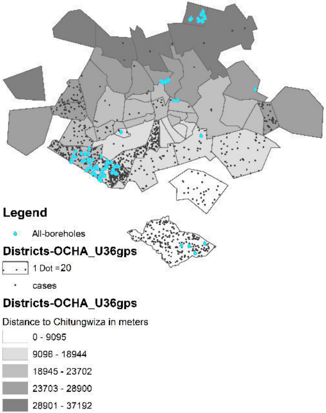
Following this initial outbreak in Chitungwiza, a second wave of infections was reported a few months later with numerous wards being affected and a rapid transmission of the infections to the whole city of Harare. This is one of the largest and most extensive outbreaks of cholera yet recorded in Zimbabwe affecting rural and urban areas [1-4].

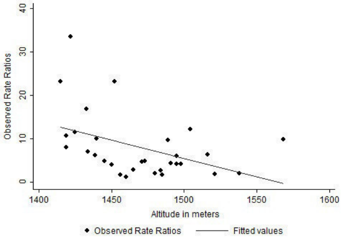
*Correspondence: Miguel.luquefernandez@uct.ac.za
[1]Centre of Infectious Disease Epidemiology and Research (CIDER), University of Cape Town, Cape Town, South Africa
Full list of author information is available at the end of the article

Elevation and Cholera






Legend
All-boreholes
Districts-OCHA_U36gps
1 Dot =20
cases
Districts-OCHA_U36gps
Distance to Chitungwiza in meters
0 - 9095
9096 - 18944
18945 - 23702
23703 - 28900
28901 - 37192


Observed Rate Ratios
0
10
20
30
40
1400
1450
1500
1550
1600
Altitude in meters
Observed Rate Ratios
Fitted values

Reinforcing Retention in Care: RCC

Patient Adherence Clubs: A New Model of Care to Reinforce Long-Term Retention on Antiretrovirals

Department of Infectious Disease Epidemiology and Research, CIDER-UCT

MA.LuqueFernandez[1], *G.VanCutsem*[1,2] , *E.Goemaere*[1,2], *K.Hilderbrand*[1,2], *M.Schomaker*[1], *N.Mantangana*[3], *S.Mathee*[3], *V.Dubula*[4], *A.Boulle*[1]
UCT-CIDER[1], MSF-South Africa[2], Provincial Government of the Western Cape[3] and Treatment Campaign[4]

February 24, 2012

Justification

- The number of patients initiating antiretroviral treatment (ART) in resource-limited settings continues to increase, leading to concerns that conventional health systems will become increasingly overloaded.
- More effective models of ART delivery and new strategies of retention in care have been identified as the most urgent operations research priorities in HIV.

Justification

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- Community adherence groups has been suggested to be one of these new strategies aiming to improve the quality of services delivery and retention in care.

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H.I.V.
POSITIVE
HIV
POSITIVE

1.2 ART ADHERENCE CLUBS IN A NUTSHELL

ART adherence clubs (ART clubs) are a long term retention model of care catering for stable ART patients. 30 stable patients meet and are facilitated by a non-clinical staff member who provides quick clinical assessment, referral where necessary, peer support and distribution of pre-packed ART every 2 months. Once a year, a clinician provides follow up clinical management.

COUNSELLOR/ PEER EDUCATOR RUN

Every 2 months

1. Quick clinical assessment
2. Collection of 2 month ART supply
3. Quick optimized group support
4. Simplified monitoring

See ART club short film - Annexure 1.

NURSE SUPPORTED

Once a year

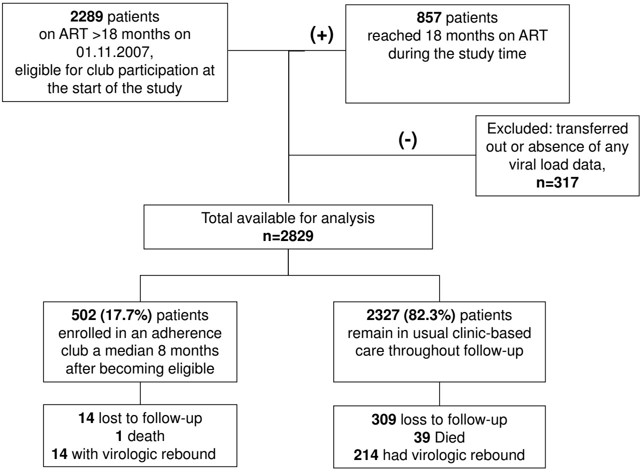
1. Blood taken for CD4 and viral load
2. Clinical consultation with clinician

1.1 WHY ART ADHERENCE CLUBS?

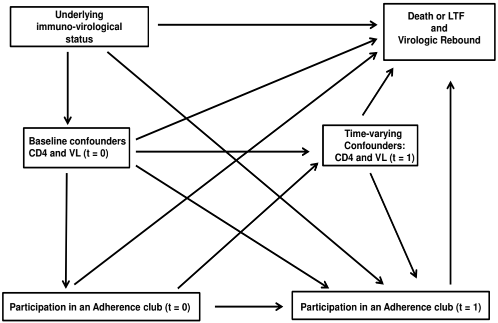
South Africa’s National Strategic Plan 2012-2016 targets:

- 80% of all patients eligible on ART by 2016: estimated at more than 3 million patients
- 70% retained in care 5 years after treatment initiation

By mid 2011, 1.79 million patients were initiated on ART with retention in care estimated at less than 60% at 4 years.


2289 patients on ART >18 months on 01.11.2007, eligible for club participation at the start of the study
(+)
857 patients reached 18 months on ART during the study time
(-)
Excluded: transferred out or absence of any viral load data, n=317
Total available for analysis n=2829
502 (17.7%) patients enrolled in an adherence club a median 8 months after becoming eligible
2327 (82.3%) patients remain in usual clinic-based care throughout follow-up
14 lost to follow-up
1 death
14 with virologic rebound
309 loss to follow-up
39 Died
214 had virologic rebound

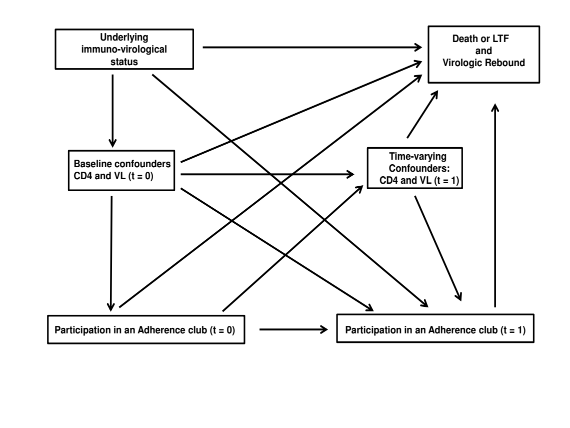
Direct Acyclic Graph



Time dependent confounding

- Past CD4 and viral load predict current and future treatment.
- Current CD4 and viral load predict current and future outcome, **depending on past treatment**.

Direct Acyclic Graph



Time dependent confounding

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Inverse-probability-of-treatment weights: stabilized version

$$(Y_i(1), Y_i(0)) \perp T_i \mid X_i$$

Inverse-probability-of-treatment weights: stabilized version

$$(Y_i(1), Y_i(0)) \perp T_i \mid X_i$$

$$W(t) = \prod_{t=0}^{t} \frac{f\left[P(t) \mid \bar{P}(t-1), V\right]}{f\left[P(t) \mid \bar{P}(t-1), V, \bar{L}(t)\right]}$$

Inverse-probability-of-treatment weights: stabilized version

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$$W(t) = \prod_{t=0}^{t} \frac{f\left[P(t) \mid (\text{Past treatment}), (\text{Baseline})\right]}{f\left[P(t) \mid (\text{Past treatment}), (\text{Baseline}), (\text{Time dependent})\right]}$$

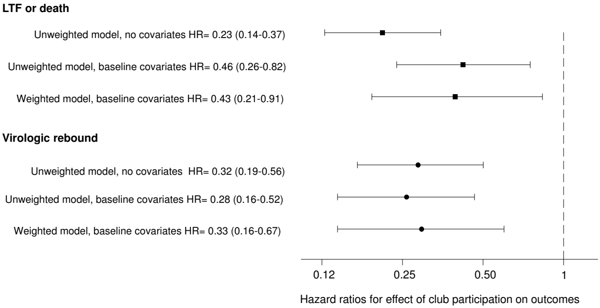
Inverse-probability-of-treatment weights: stabilized version

$$(Y_i(1), Y_i(0)) \perp T_i \mid X_i$$

$$W(t) = \prod_{t=0}^{t} \frac{f\left[P(t) \mid \bar{P}(t-1), V\right]}{f\left[P(t) \mid \bar{P}(t-1), V, \bar{L}(t)\right]}$$

$$W(t) = \prod_{t=0}^{t} \frac{f\left[P(t) \mid (\text{Past treatment}),(\text{Baseline})\right]}{f\left[P(t) \mid (\text{Past treatment}),(\text{Baseline}),(\text{Time dependent})\right]}$$

Adherence club of patients effect



Weighted models with baseline covariates estimate parameters of marginal structural model. Weights adjust for confounding due to measured time-dependent covariates.

MSF acknowledges the following partnerships that contributed significantly to the ART adherence club model pilot:

Western Cape Government

TAC TREATMENT ACTION CAMPAIGN

THIS CITY WORKS FOR YOU

MSF Khayelitsha Office
Tel: +27 (0) 21 364 5490
www.msf.org.za

Effectiveness of Patient Adherence Groups as a Model of Care for Stable Patients on Antiretroviral Therapy in Khayelitsha, Cape Town, South Africa

Miguel Angel Luque-Fernandez[1*¤], Gilles Van Cutsem[1,2], Eric Goemaere[1,2], Katherine Hilderbrand[1,2], Michael Schomaker[1], Nompumelelo Mantangana[3], Shaheed Mathee[3], Vuyiseka Dubula[4], Nathan Ford[1,5], Miguel A. Hernán[6,7], Andrew Boulle[1]

1 Centre for Infectious Disease Epidemiology and Research, School of Public Health and Family Medicine, University of Cape Town, Cape Town, South Africa, **2** Médecins sans Frontières, Cape Town, South Africa, **3** Khayelitsha Community Health Centre, Department of Health, Provincial Government of the Western Cape, Cape Town, South Africa, **4** Treatment Action Campaign, Cape Town, South Africa, **5** Médecins sans Frontières, Geneva, Switzerland, **6** Departments of Epidemiology and Biostatistics, Harvard School of Public Health, Boston, Massachusetts, United States of America, **7** Division of Health Sciences and Technology, Harvard-Massachusetts Institute of Technology, Boston, Massachusetts, United States of America

Abstract

Background: Innovative models of care are required to cope with the ever-increasing number of patients on antiretroviral therapy in the most affected countries. This study, in Khayelitsha, South Africa, evaluates the effectiveness of a group-based model of care run predominantly by non-clinical staff in retaining patients in care and maintaining adherence.

Methods and Findings: Participation in ''adherence clubs'' was offered to adults who had been on ART for at least 18 months, had a current CD4 count >200 cells/ml and were virologically suppressed. Embedded in an ongoing cohort study, we compared loss to care and virologic rebound in patients receiving the intervention with patients attending routine nurse-led care from November 2007 to February 2011. We used inverse probability weighting to estimate the intention-to-treat effect of adherence club participation, adjusted for measured baseline and time-varying confounders. The principal outcome was the combination of death or loss to follow-up. The secondary outcome was virologic rebound in patients who were virologically suppressed at study entry. Of 2829 patients on ART for >18 months with a CD4 count above 200 cells/µl, 502 accepted club participation. At the end of the study, 97% of club patients remained in care compared with 85% of other patients. In adjusted analyses club participation reduced loss-to-care by 57% (hazard ratio [HR] 0.43, 95% CI = 0.21–0.91) and virologic rebound in patients who were initially suppressed by 67% (HR 0.33, 95% CI = 0.16–0.67).

Discussion: Patient adherence groups were found to be an effective model for improving retention and documented virologic suppression for stable patients in long term ART care. Out-of-clinic group-based models facilitated by non-clinical staff are a promising approach to assist in the long-term management of people on ART in high burden low or middle-income settings.

Citation: Luque-Fernandez MA, Van Cutsem G, Goemaere E, Hilderbrand K, Schomaker M, et al. (2013) Effectiveness of Patient Adherence Groups as a Model of Care for Stable Patients on Antiretroviral Therapy in Khayelitsha, Cape Town, South Africa. PLoS ONE 8(2): e56088. doi:10.1371/journal.pone.0056088

Editor: David W. Dowdy, Johns Hopkins Bloomberg School of Public Health, United States of America

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Competing Interests: The authors have declared that no competing interests exist.

* E-mail: miguel.luquefernandez@uct.ac.za

¤ Current address: Department of Epidemiology, Harvard School of Public Health, Boston, Massachusetts, United States of America

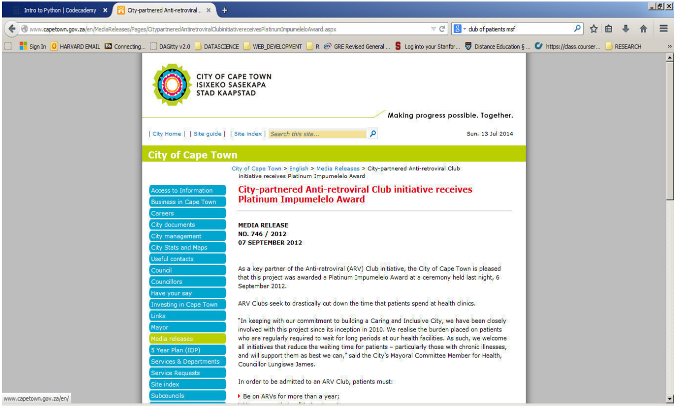
Introduction

Retaining patients in lifelong HIV care is a major challenge in many countries in sub-Saharan Africa, where antiretroviral treatment (ART) has been rapidly scaled up to some 5 million people as of the end of 2010. [1] In recent years in South Africa, an increasing proportion of patients on ART are being lost to follow-up (LTF) as overall the numbers on treatment increase. [2] Although up to a third of adult patients lost to care are estimated to have died, the majority are alive: without treatment, they are at increased risk of morbidity and mortality. [3].

Decentralization of services and task-shifting aspects of care to nurses and non-clinical staff, including patients, has been found to be feasible with good clinical outcomes.[4–12] However, such approaches are reaching their limits as increasing numbers of patients are initiated on ART. Accessible and flexible ART services that differentiate between the needs of clinically ill patients starting ART, and clinically stable patients who have been on ART for some time, have been suggested as important strategies for maintaining and improving retention and quality of care. [13].

Patient support groups have long been recognized as an important adjunct to clinical care that encouraged retention and

Award


Intro to Python | Codecademy
City-partnered Anti-retroviral...
www.capetown.gov.za/en/MediaReleases/Pages/CitypartneredAntiretroviralClubinitiativereceivesPlatinumImpumeleloAward.aspx
club of patients msf
Sign In
HARVARD EMAIL
Connecting...
DAGitty v2.0
DATASCIENCE
WEB_DEVELOPMENT
R
GRE Revised General ...
Log into your Stanfor...
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https://class.courser...
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STAD KAAPSTAD
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City of Cape Town > English > Media Releases > City-partnered Anti-retroviral Club initiative receives Platinum Impumelelo Award
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Useful contacts
Council
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Investing in Cape Town
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Media releases
5 Year Plan (IDP)
Services & Departments
Service Requests
Site index
Subcouncils
City-partnered Anti-retroviral Club initiative receives Platinum Impumelelo Award
MEDIA RELEASE
NO. 746 / 2012
07 SEPTEMBER 2012
As a key partner of the Anti-retroviral (ARV) Club initiative, the City of Cape Town is pleased that this project was awarded a Platinum Impumelelo Award at a ceremony held last night, 6 September 2012.
ARV Clubs seek to drastically cut down the time that patients spend at health clinics.
"In keeping with our commitment to building a Caring and Inclusive City, we have been closely involved with this project since its inception in 2010. We realise the burden placed on patients who are regularly required to wait for long periods at our health facilities. As such, we welcome all initiatives that reduce the waiting time for patients – particularly those with chronic illnesses, and will support them as best we can," said the City's Mayoral Committee Member for Health, Councillor Lungiswa James.
In order to be admitted to an ARV Club, patients must:
Be on ARVs for more than a year;
www.capetown.gov.za/en/


JOIN THE
CLUB

References

Some important references

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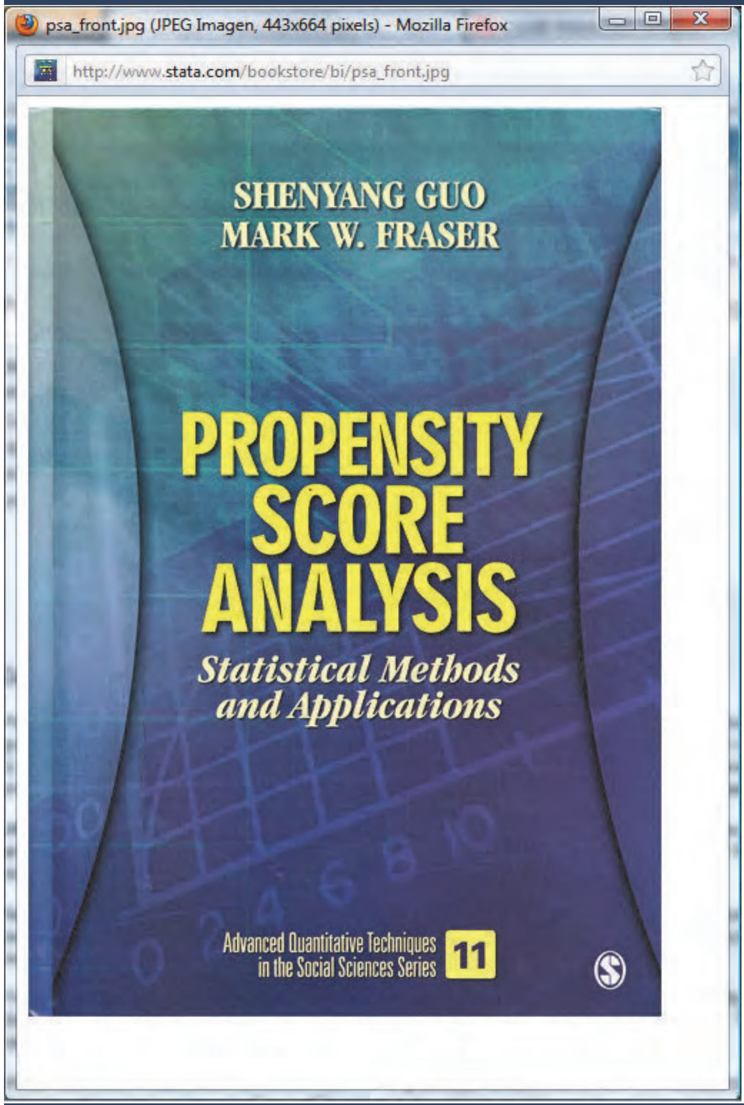
MOSTLY HARMLESS ECONOMETRICS

An Empiricist's Companion

Joshua D. Angrist and Jörn-Steffen Pischke



Two excellent resources to learn more about PSA

Pweto DRC 2003

THANKS

mluquefe@hsph.harvard.edu