

Understanding the impact of COVID- 19 and other diseases

Instructions: Click on the link to access each author's presentation.

Chair: Martha María Téllez-Rojo

Participants:

Arturo Erdély: A polynomial regression model for excess mortality in Mexico 2020-2022 due to the COVID-19 pandemic

Feysal Muhammed: Impact of the first COVID-19 lockdown on HIV diagnosis in England

Oyelola Adegboye: Modelling local variations across small geographical areas of COVID-19 Pandemic: A machine learning approach

Anteneh Bezabih Ali: A Cohort Study of COVID-19 Patients: Hawassa University Referral Hospital, Ethiopia

Melkamu A Zeru: Spatial pattern and predictors of malaria in Ethiopia: Application of auto logistics regression



A polynomial regression model for excess mortality in Mexico 2020-2022 due to the COVID-19 pandemic

Dr. Arturo Erdely (UNAM)



Joint work with

Dr. Andreu Comas-García (UASLP)



Outline

1. Data
2. Methods
3. Results

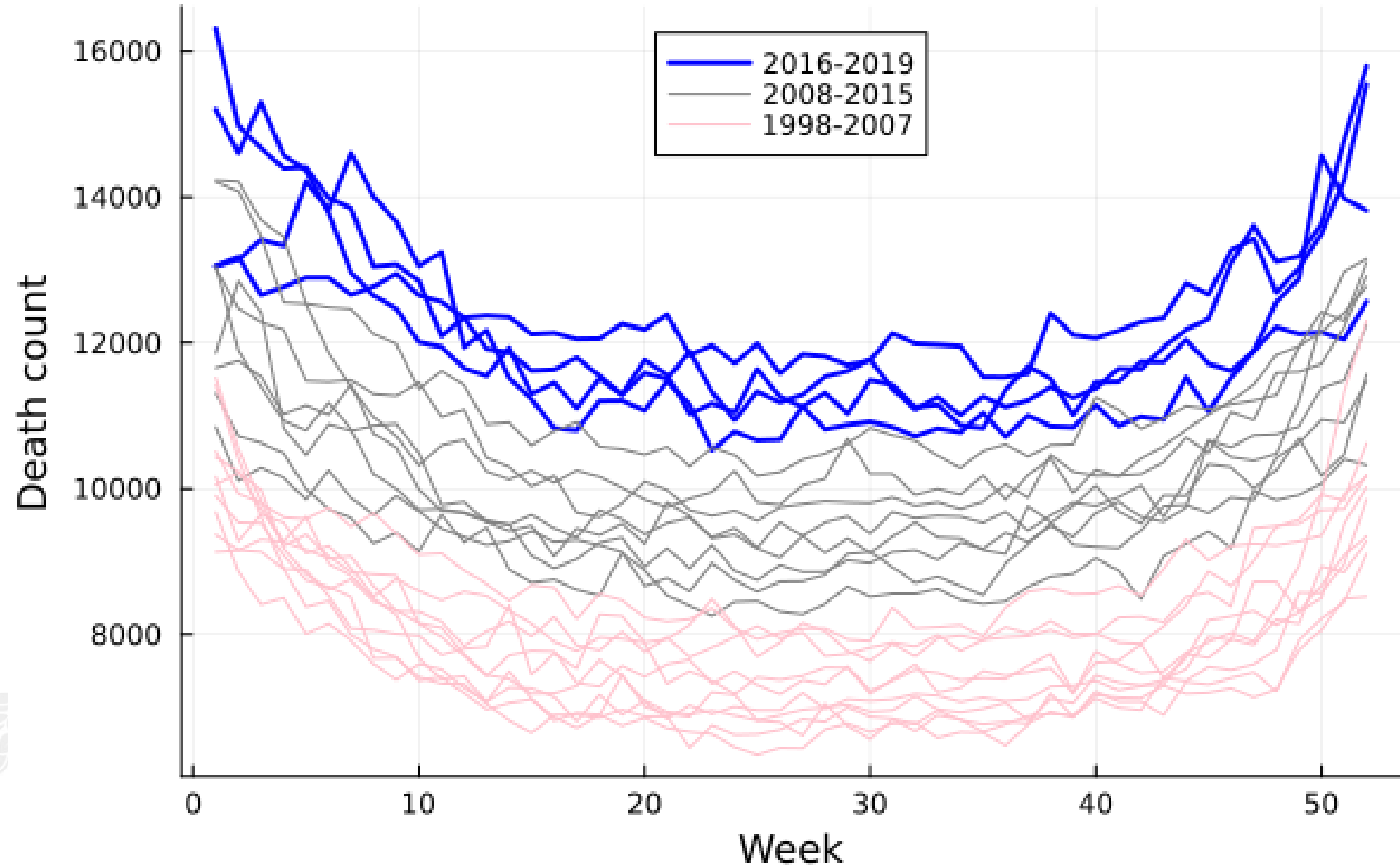


Data sources

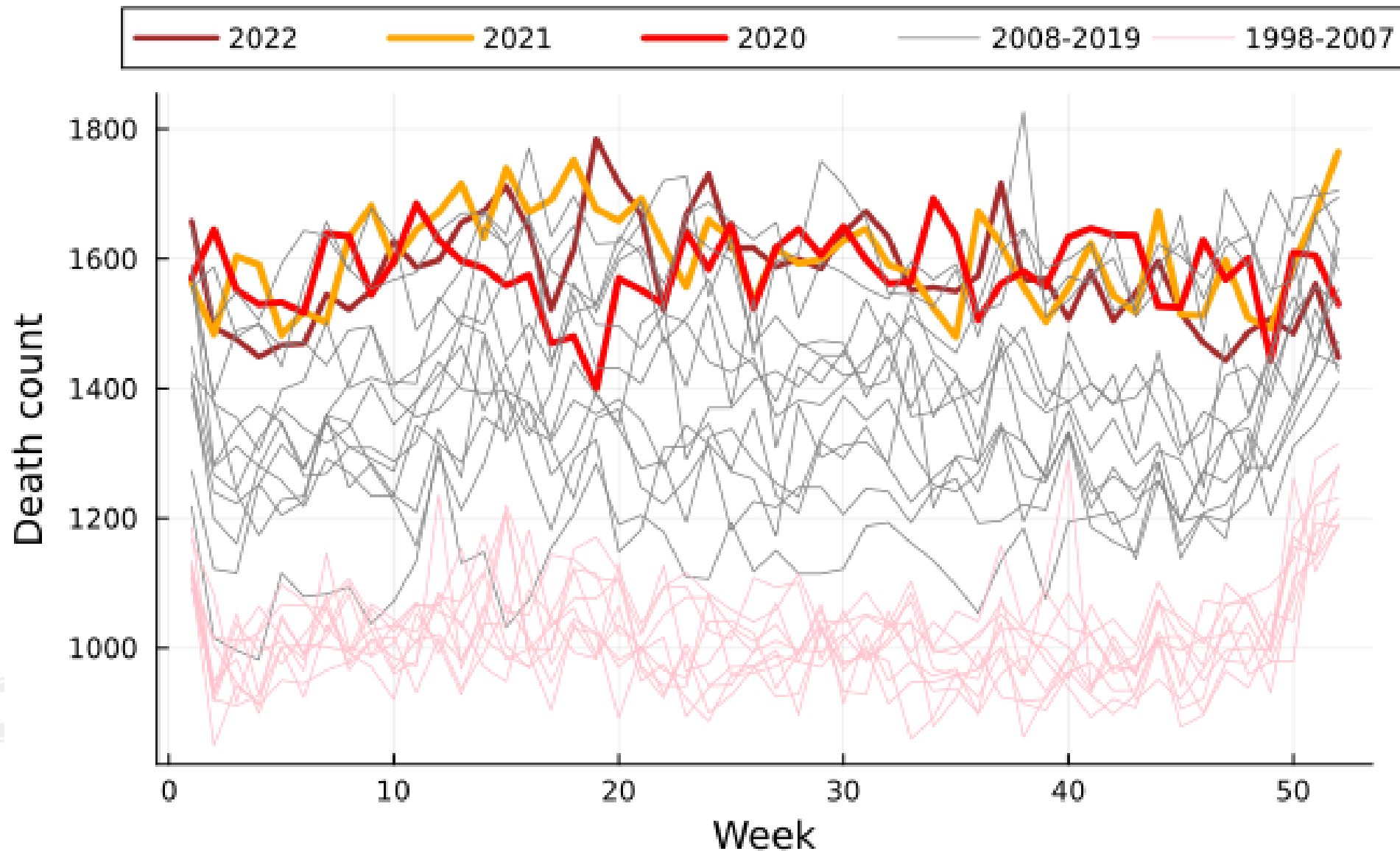
- National death registry database of Mexico (INEGI)
- Pre-pandemic yearly per week distribution of illness-related deaths
- Population projections by CONAPO adjusted by INEGI census 2020



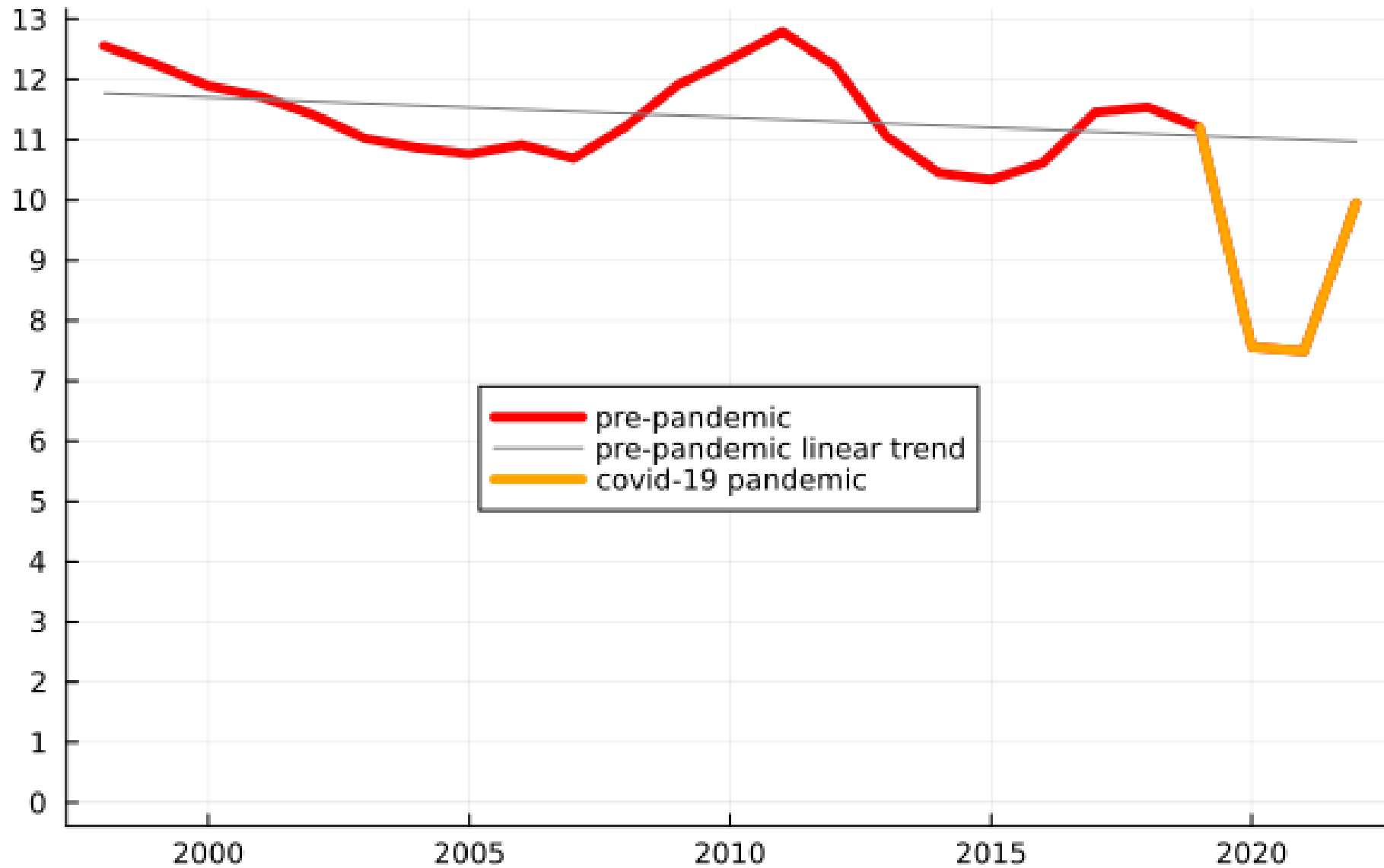
illness deaths in Mexico



non-illness deaths in Mexico



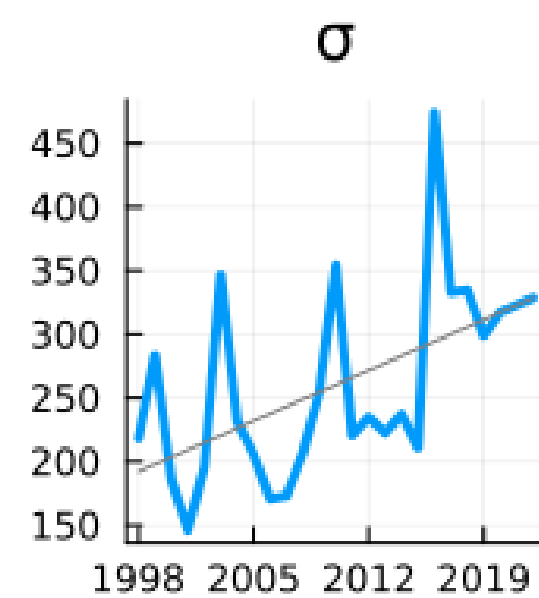
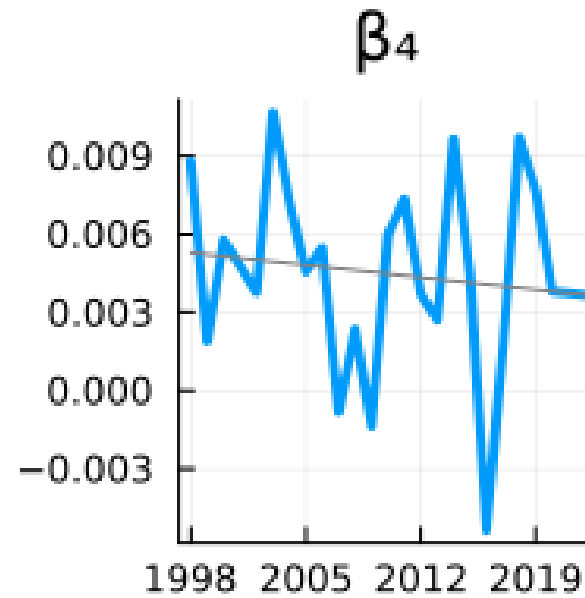
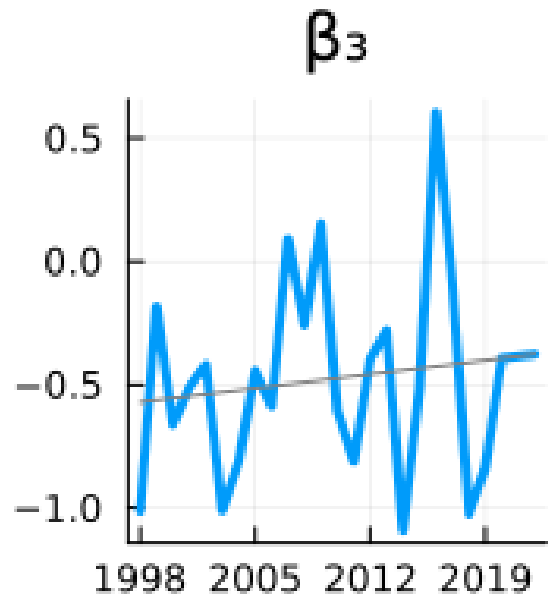
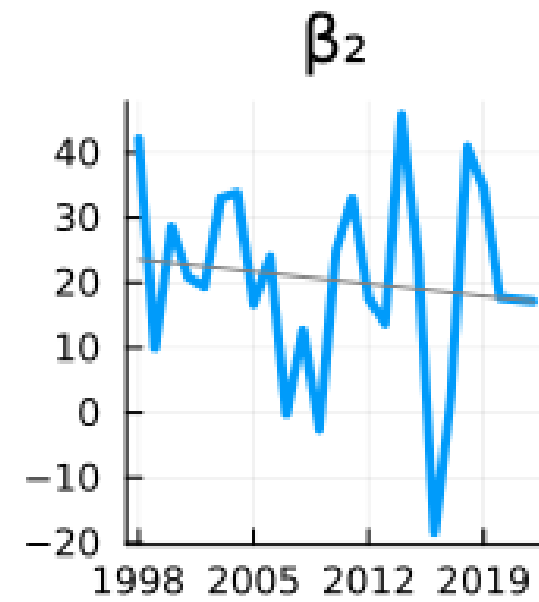
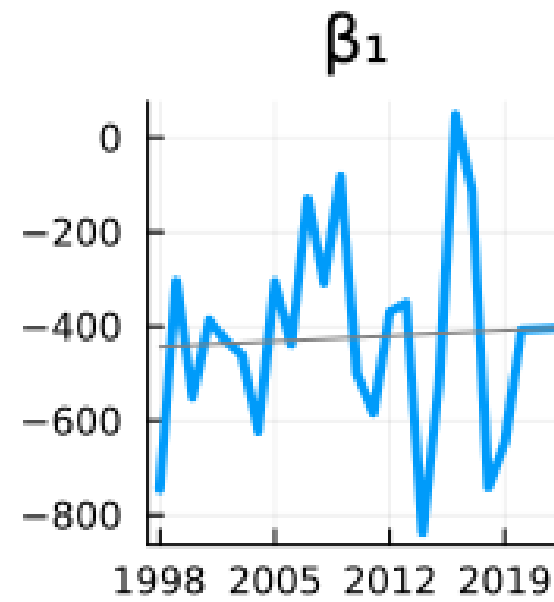
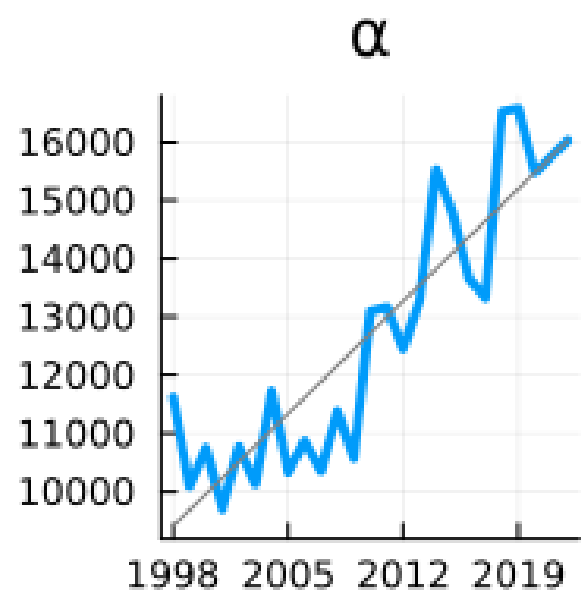
% of non-illness deaths (1998-2022)



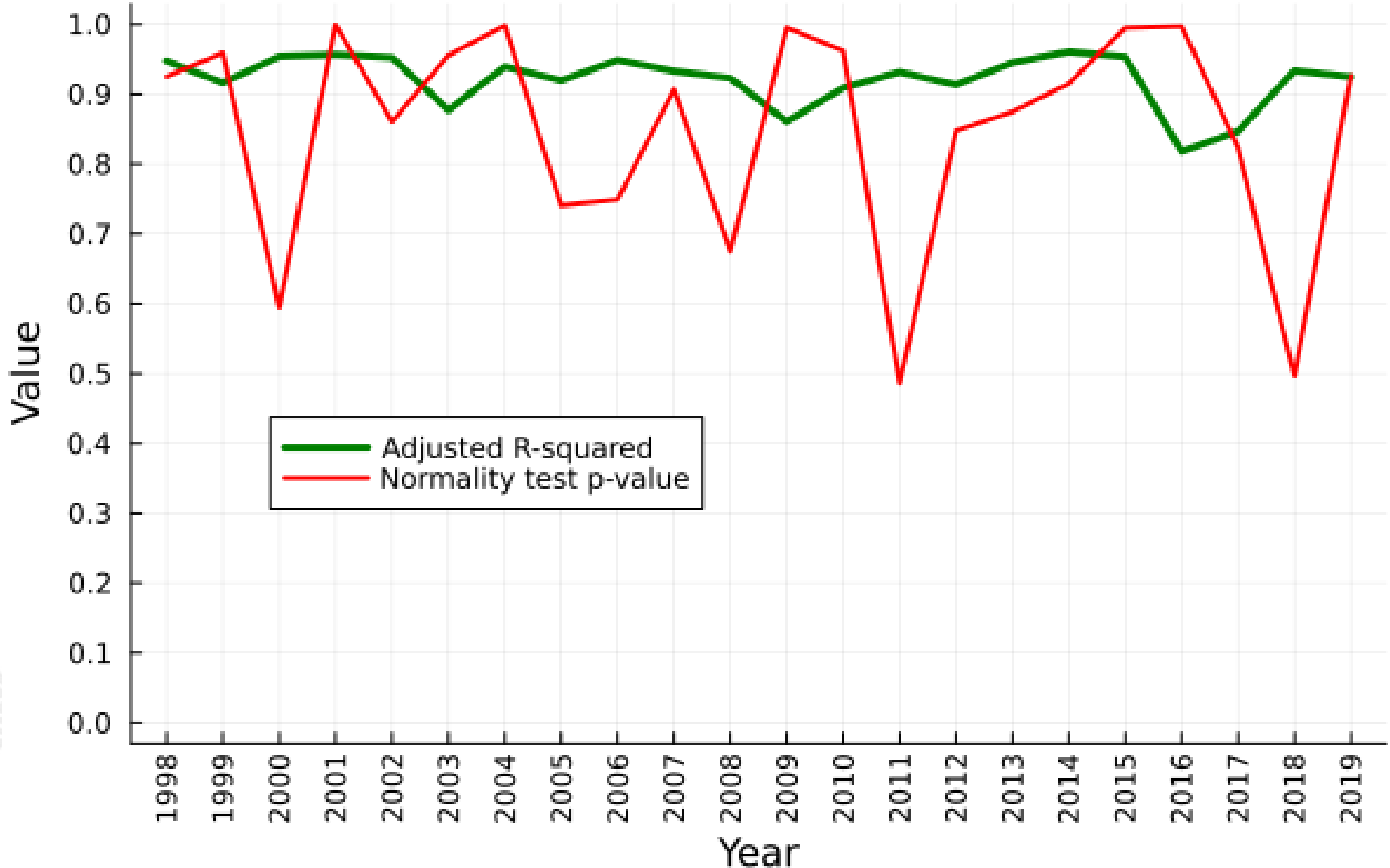
illness-related deaths per week

$$d(w) = \alpha + \beta_1 w + \beta_2 w^2 + \beta_3 w^3 + \beta_4 w^4 + \varepsilon$$

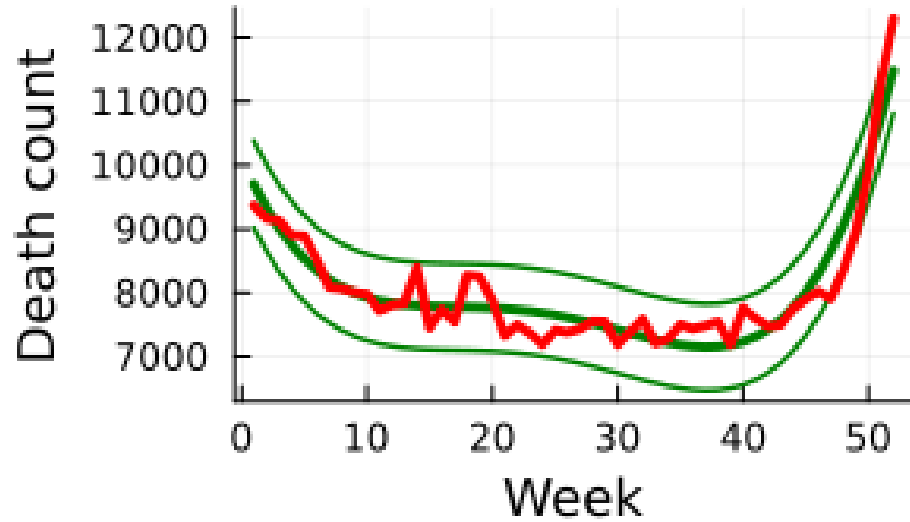
- OLS estimation of parameters
- $w \in \{1, 2, \dots, 52\}$
- $\widehat{d(53)} = \hat{d}(53) \times \frac{\ell}{7} \times \text{avg} \left(\frac{d(53)}{\hat{d}(53) \times \frac{\ell}{7}} \right)$
- $\varepsilon \sim \mathcal{N}(0, \sigma^2)$



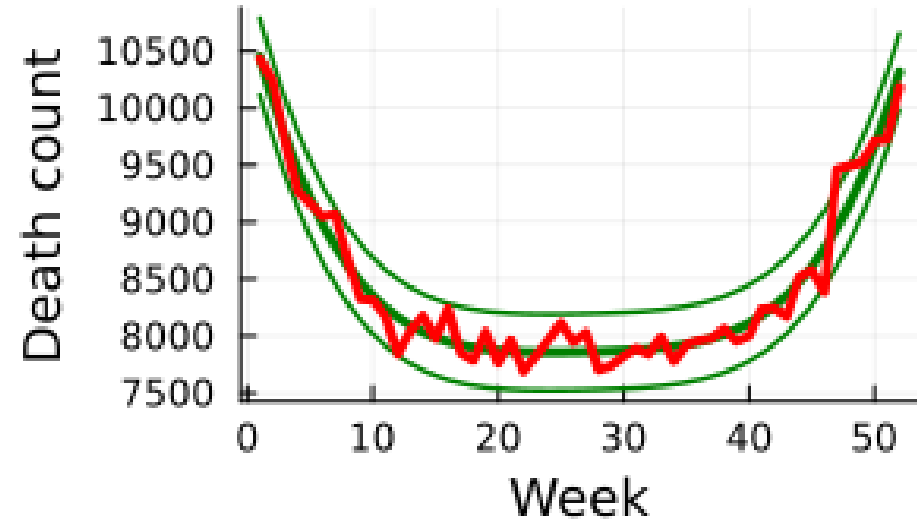
Goodness of fit



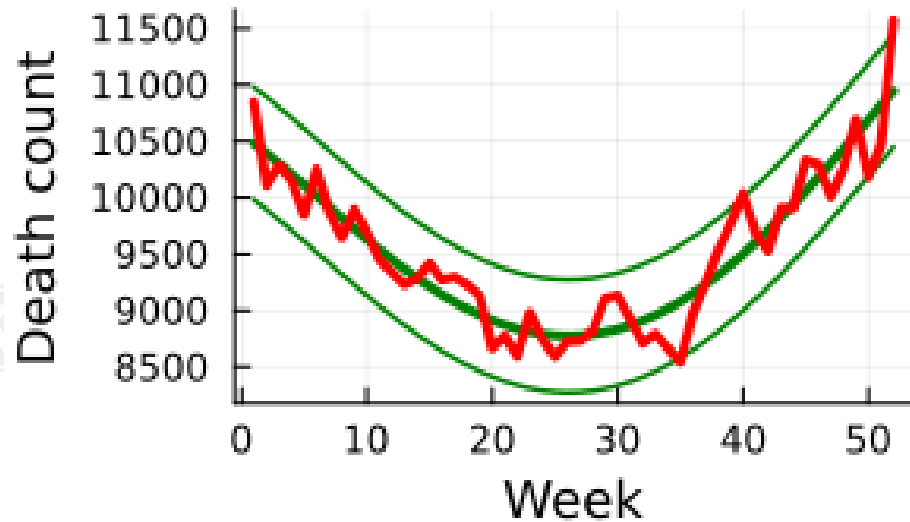
illness deaths (2003)



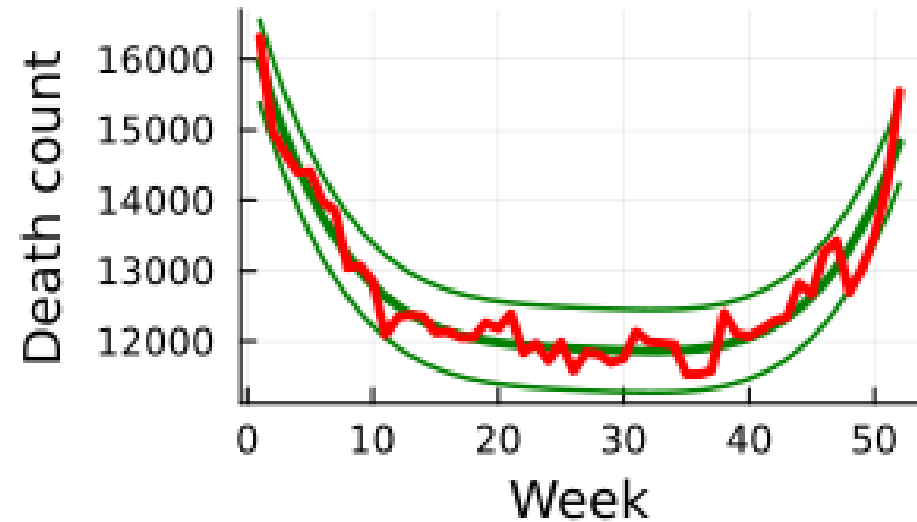
illness deaths (2006)



illness deaths (2009)



illness deaths (2019)



- **Excess mortality**

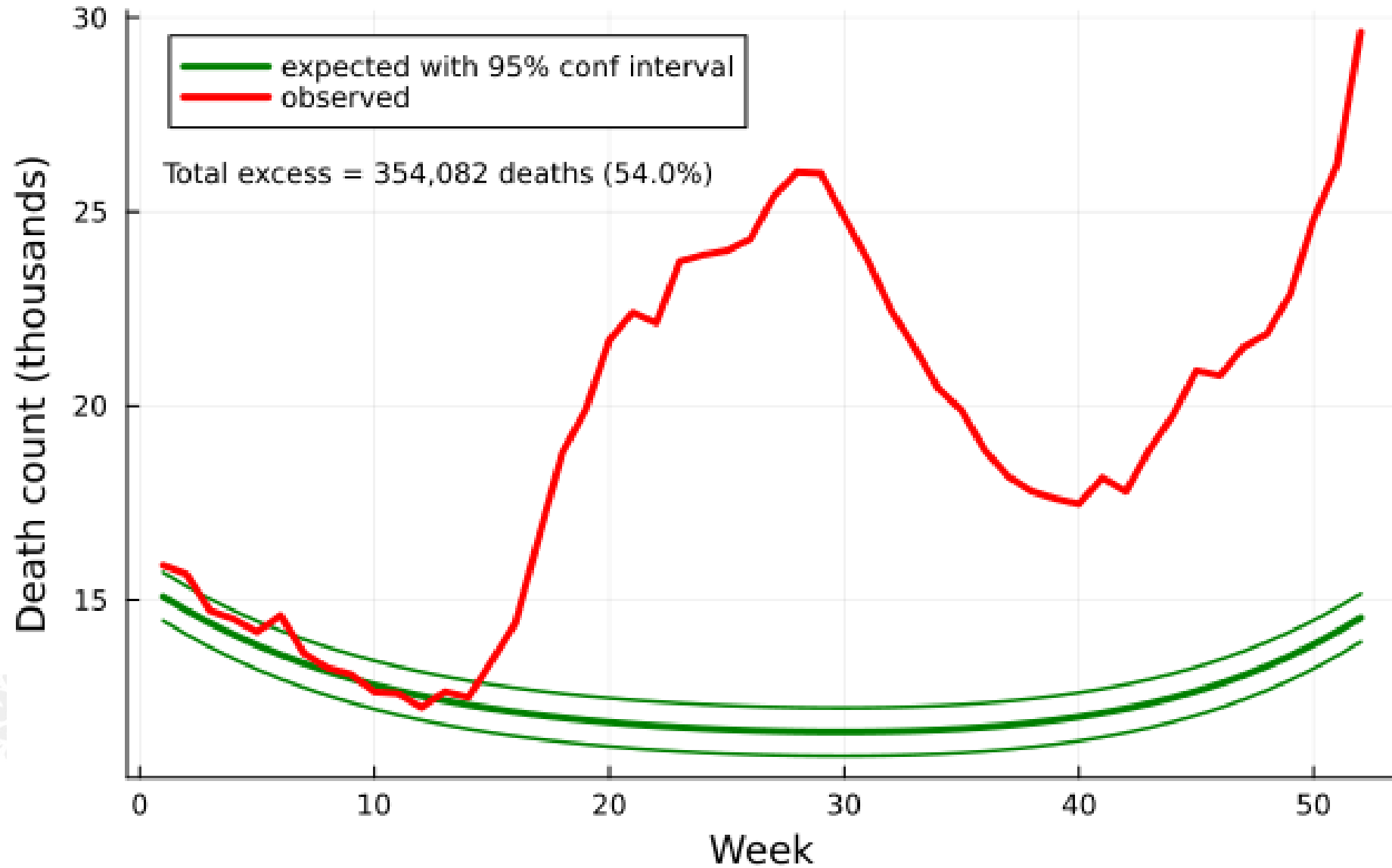
$$\psi = \sum_{w=1}^{52} [d(w) - \hat{d}(w)] + d(53) - \widehat{d(53)}$$

- **in %**

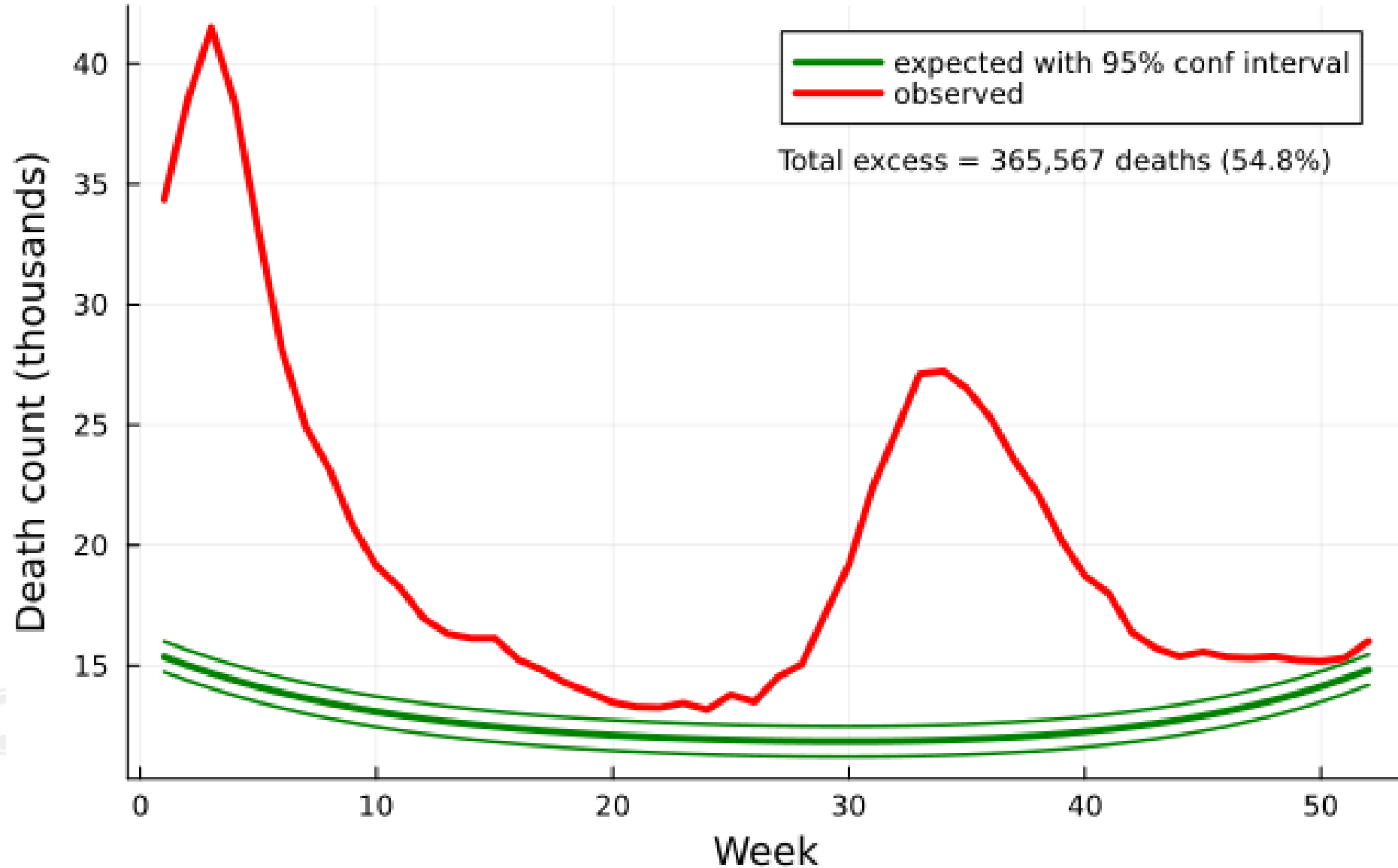
$$\Delta\psi = \frac{\psi}{\sum_{w=1}^{52} \widehat{d(53)}} \times 100\%$$



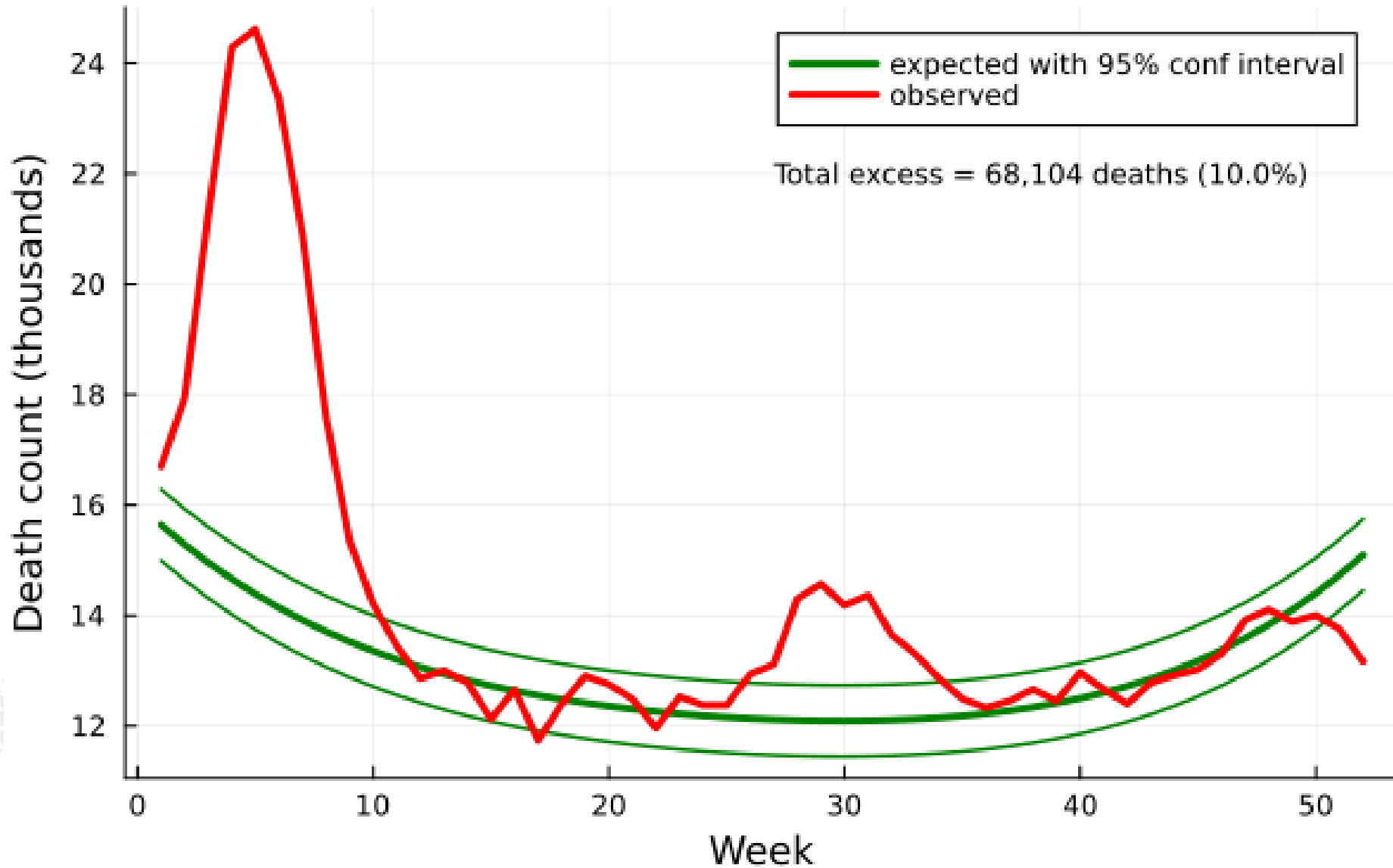
illness total deaths (2020)



illness total deaths (2021)



illness total deaths (2022)



EXCESS MORTALITY IN MEXICO 2020 - 2022

Age group	Absolute			Percentage			Rate per 100,000 inhab.		
	point	95% conf. interval		point	95% c. interval		point	95% c. interval	
	estimate	lower	upper	estimate	lower	upper	estimate	lower	upper
0 to 5	-3,753	-4,307	-3,199	-5.3	-6.1	-4.6	-31	-35	-26
6 to 10	-93	-238	52	-1.8	-4.5	1.0	-1	-2	0
11 to 19	693	431	955	4.4	2.7	6.0	4	2	5
20 to 29	10,933	10,593	11,273	30.4	29.5	31.4	54	52	55
30 to 39	33,386	32,858	33,914	52.1	51.3	52.9	182	179	185
40 to 49	77,139	76,281	77,997	57.2	56.5	57.8	470	464	475
50 to 59	136,988	135,645	138,331	55.3	54.7	55.8	1,082	1,071	1,092
60 to 69	206,926	205,121	208,731	59.7	59.2	60.2	2,463	2,441	2,484
70 & older	325,596	320,421	330,771	30.1	29.6	30.6	4,887	4,809	4,965
all ages	787,753	779,834	795,672	39.3	38.9	39.7	626	620	632



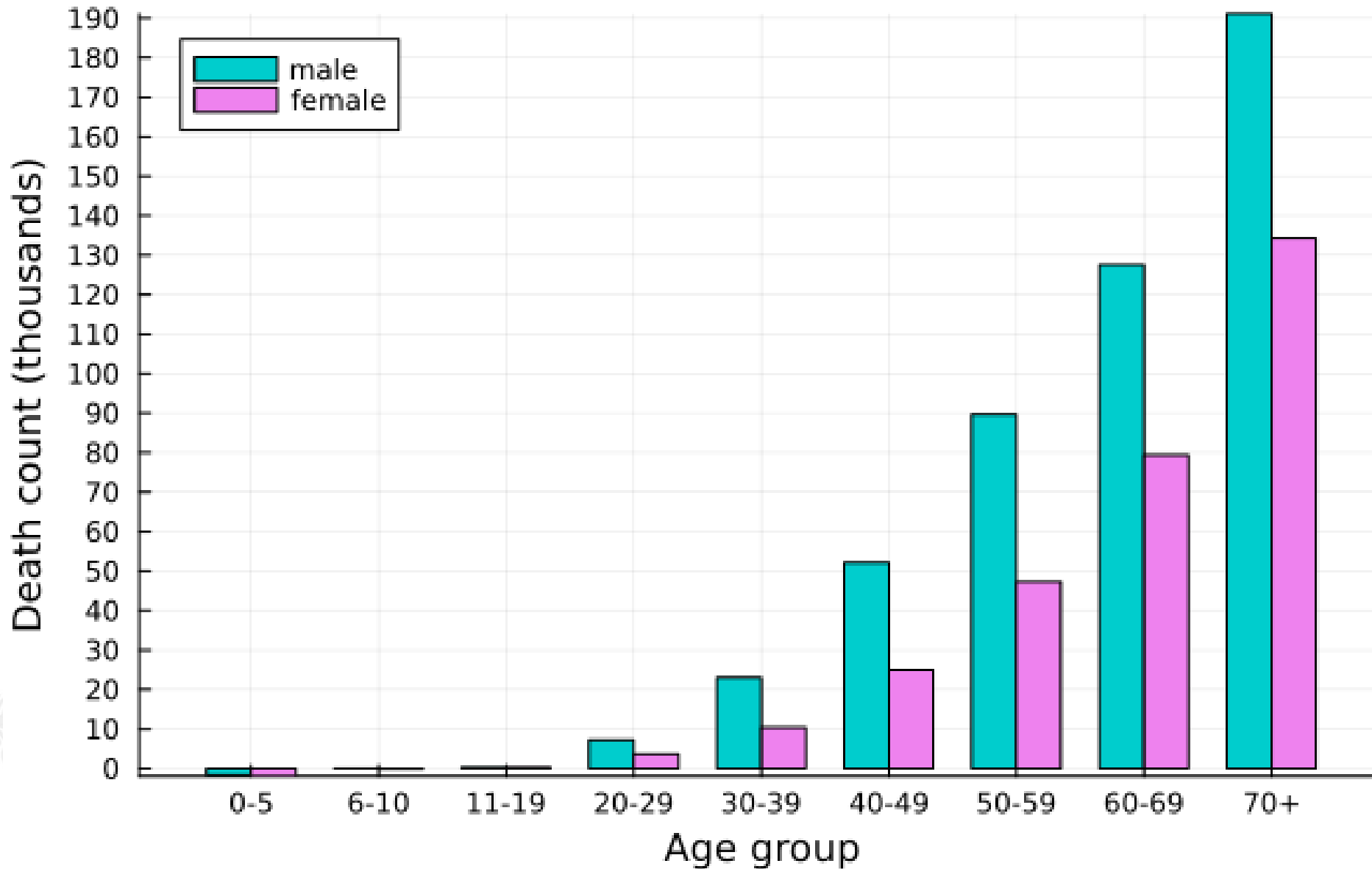


Comunicado de prensa número 644/23
31 de octubre de 2023
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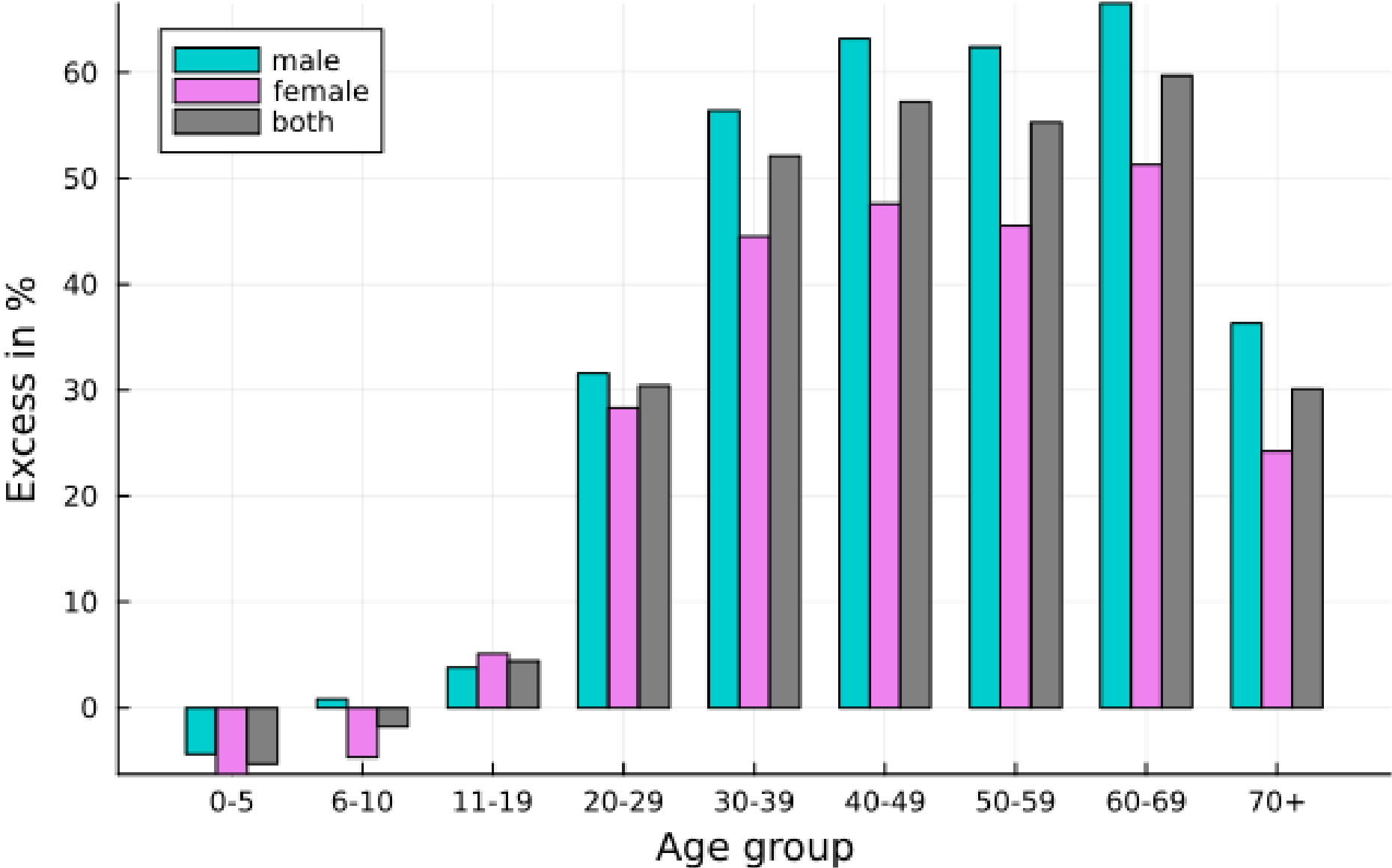
Con base en estos resultados, se tiene un exceso de mortalidad, por todas las causas, de 807 720 con las estimaciones de canales endémicos y de 673 211 mediante el modelo cuasi-Poisson. Esto representa un exceso de 36.19 y 28.45 %, respectivamente. Para los mismos periodos, y como parte de los presentes resultados de exceso de mortalidad, se realizó también la estimación para cada una de las principales afecciones. Así se mostrará en las gráficas subsecuentes.



Excess of mortality 2020-2022



Excess of mortality 2020-2022





Thank you



Impact of the first COVID-19 lockdown on HIV diagnosis in England

Feysal Kemal

Peter Kirwan, Tasnuva Tabassum, James Lester, Pantelis Samartsidis, Alison Brown, Daniela De Angelis, Chiara Chiavenna, Anne Presanis

Outlines of the talk

- Introduction
- Data
- Methods
- Discussions
- Conclusions
- References

Introduction

- STI and HIV prevention and care services have been unavoidably disrupted by the pandemic and its associated interventions, such as *lockdown and other social distancing measures*.
- Services were reconfigured to be increasingly online/by phone, rather than in person, so that the UK March 2020 lockdown is expected to have had a causal effect on HIV diagnosis.
- Assessing the effect of a policy (or intervention) on an outcome requires first estimating the '*counterfactual*', i.e. what would have happened if the intervention had not taken place.

Introduction...

- Time series models to estimate such *counterfactuals* have been used in many applications such as health and Social science [Brodersen et al., 2015].
- In this paper, I aim is to estimate the *magnitude of the effect of the first UK national COVID-19 lockdown on HIV diagnoses*.
- In particular by inferring the counterfactual of how many *new HIV diagnoses* would have occurred in the *absence of the lockdown*, and comparing this with the recorded number of new HIV diagnoses during 2020.

- The HARS dataset records all new HIV diagnoses from 1978 to 2020.
- For the purpose of this study, we concentrate on diagnoses from the period 2004 to 2020.
- We aggregated the HARS dataset by *year, quarters, age group, a combined gender/sexual orientation variable*, and *2 stages of diagnosis*.

Synthetic controls

- The idea behind synthetic control [[Abadie et al., 2010](#)] is to find a control unit, unaffected by the intervention, against which to compare the treated/intervened on unit.
- Rather than use a single control unit, a *weighted sum* of control units (that are all unaffected by the intervention) might be better correlated with the pre-intervention treated unit than a single control time series alone.
- Our “treated unit” is the time series of quarterly new HIV diagnoses affected by the intervention (lockdown).

The causal impact method

- The causal impact method (CIM) was introduced by [Brodersen et al., 2015], using a *Bayesian structural time series (BSTS)* model to estimate the counterfactual against which to compare the treated unit
- Bayesian variable selection using a spike and slab prior is used to decide which control time series $Z_{t,s}$ to include, i.e. how to define the synthetic control.
- The BSTS model is fitted to the pre-intervention period data, then the fitted model is used to predict the counterfactual for the post-intervention period.
- The causal effect is defined as the difference between the counterfactual prediction and the observed treated unit in the post-intervention period.

BSTS model

- BSTS model for the outcome $Y_{t,s}$, the observed number of new HIV diagnoses at time t (quarter-year) for stratum s is given as follows:

$$Y_{t,s} \sim N(\mu_{t,s}, \sigma_{y,t,s}^2)$$

$$\mu_{t,s} = \alpha_s Z_{t,s} + I_{t,s} + \gamma_{t,s}$$

$$I_{t+1,s} \sim N(I_{t,s} + \delta_{t,s}, \sigma_{I,t,s}^2)$$

$$\delta_{t+1,s} \sim N(\delta_{t,s}, \sigma_{\delta,t,s}^2)$$

$$\gamma_{t+1,s} \sim N\left(-\sum_{u=0}^{U-2} \gamma_{t-u,s}, \sigma_{\gamma,t,s}^2\right)$$

- The magnitude of the effect can be defined as the difference between the observed series and the counterfactuals

$$Y_{i,t}(\text{Observed}) - Y_{i,c}(\text{counterfactual})$$

Chosen synthetic control time series

Finding appropriate synthetic controls time series for this application was very challenging

- We checked *three* group of control time series:
- Time series that are likely to be *highly correlated with new HIV diagnoses*, such as *HIV tests, tests and diagnoses for other STIs*.
- *Random terms* in google searches that are unlikely to have been affected by the lockdown, such as *“apple”, “duck”, “google”, “bbc”, etc*
- To help capture the *observed peak hit in 2015* in the MSM group, we also included search terms for events/names that were in the news in 2015 (*Tsipras, Syriza, Syria, Austerity, Greece election, Paris summit*).

Combination of 37 synthetic controls series were selected from google trend data

Results

Estimated posterior probability of an effect

Gender/ sexual orientation	Age group	Late diagnosis (AIDS or CD4 < 350)	Non-late diagnosis (CD4 ≥ 350)
MSM	15-24	56%	64%
	25-34	91%	63%
	35-49	52%	60%
	50+	67%	89%
Other men	15-24	88%	96%
	25-34	64%	59%
	35-49	55%	92%
	50+	98%	71%
Women	15-24	45%	55%
	25-34	51%	58%
	35-49	56%	75%
	50+	87%	91%

Table: Estimated posterior probability of a causal effect of the first COVID-19 lockdown on HIV diagnoses, by gender, sexual orientation, age group, and stage

Results: Counterfactual plots

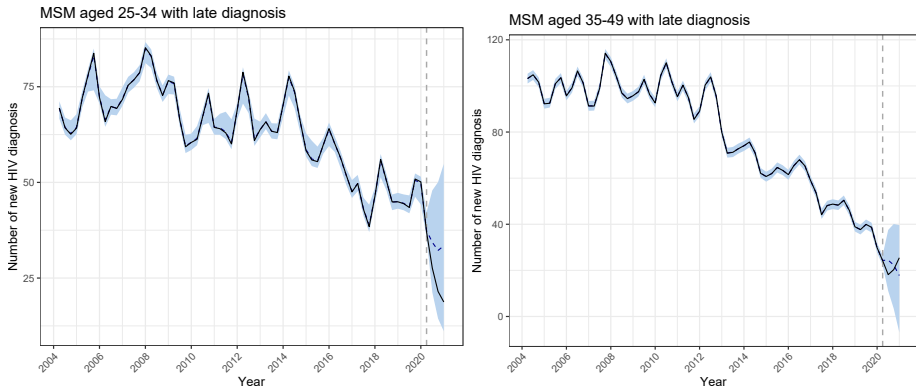
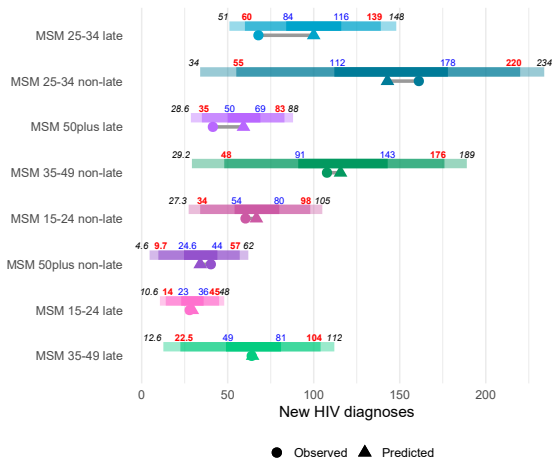


Figure: Counterfactual plots for MSM aged 25-34 (left) and 35-49 (right) with late diagnosis. The black lines show the observed diagnoses, the dashed line is the posterior mean counterfactual diagnoses, and the blue ribbon is the 95% CrI for the counterfactual diagnoses.

Dumbbell plots



Line range indicates the 95%,90% and 50% credible interval for the predicted number of diagnoses

Figure: Dumbbell plots for MSM exposure groups showing the observed vs the counterfactual number of new diagnoses summed over the three quarters after the lockdown ordered by effect size.

- We estimated the effect of the first UK national SARS-CoV-2 pandemic lockdown on HIV diagnoses.
- Due to the small sample sizes in the *age group 50+*, the variability in the difference between the counterfactual and the observed diagnoses is comparatively *high* in this age group.
- There is a higher posterior probability of an effect for those with *non-late diagnosis* compared with late diagnosis among *women*.
- This analysis is the first to formally quantify the effect of the first UK national SARS-CoV-2 pandemic lockdown on HIV diagnoses.

Conclusions

- *Largest effect* is seen in *first calendar quarter after lockdown*, with the effect subsequently reducing as HIV testing, and consequent diagnosis, caught up during the summer of 2020.
- The magnitude of the effect of lockdown on HIV diagnosis *varies* for the *different strata* we considered.
- Public health campaigns which encouraged HIV home testing during the lockdown may also have helped to mitigate the effect.

- A. Abadie, A. Diamond, and J. Hainmueller. Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505, 2010.
- K. H. Brodersen, F. Gallusser, J. Koehler, N. Remy, and S. L. Scott. Inferring causal impact using bayesian structural time-series models. *The Annals of Applied Statistics*, pages 247–274, 2015.

Acknowledgments

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- We also thank UKHSA colleagues in the Blood Safety, Hepatitis, Sexually Transmitted Infections and HIV Division for providing guidance and advice on the data used.



Modelling local variations across small geographical areas of COVID-19 Pandemic: A machine learning approach

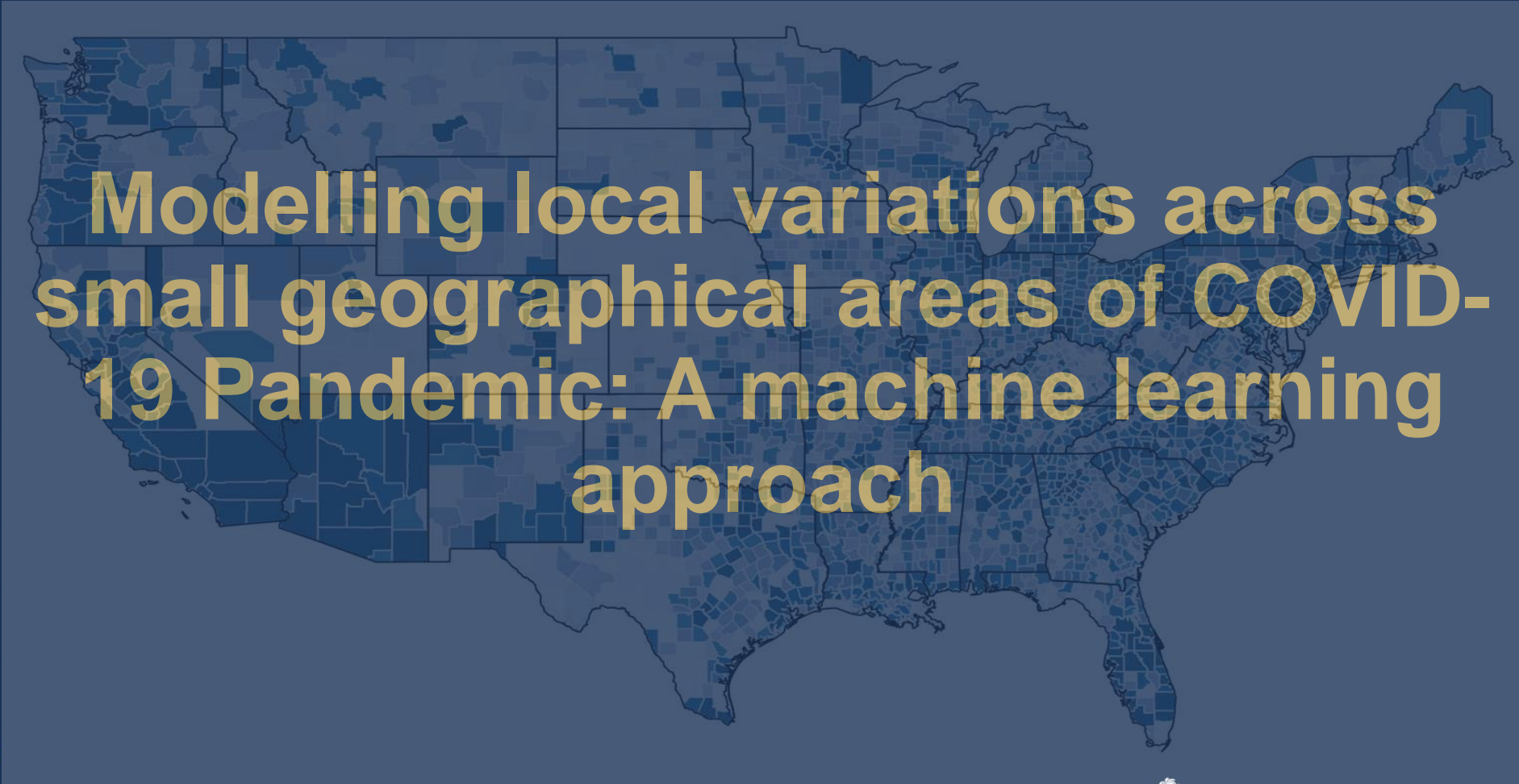
Oyelola Adegboye, PhD

Menzies School of Health Research, Charles Darwin University, Australia

And

Hassan Ajulo, Faith Alele, Theophilus Emeto



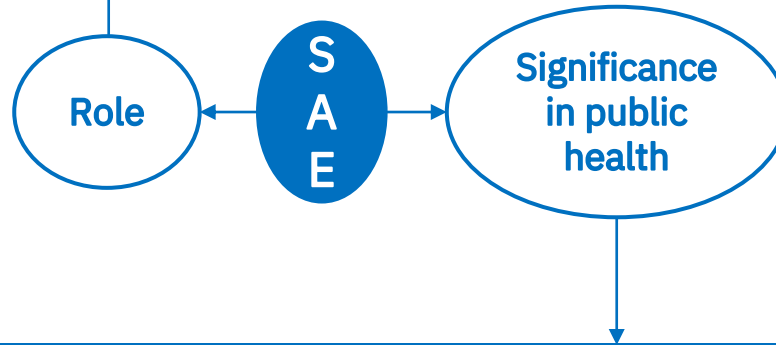


**Modelling local variations across
small geographical areas of COVID-
19 Pandemic: A machine learning
approach**

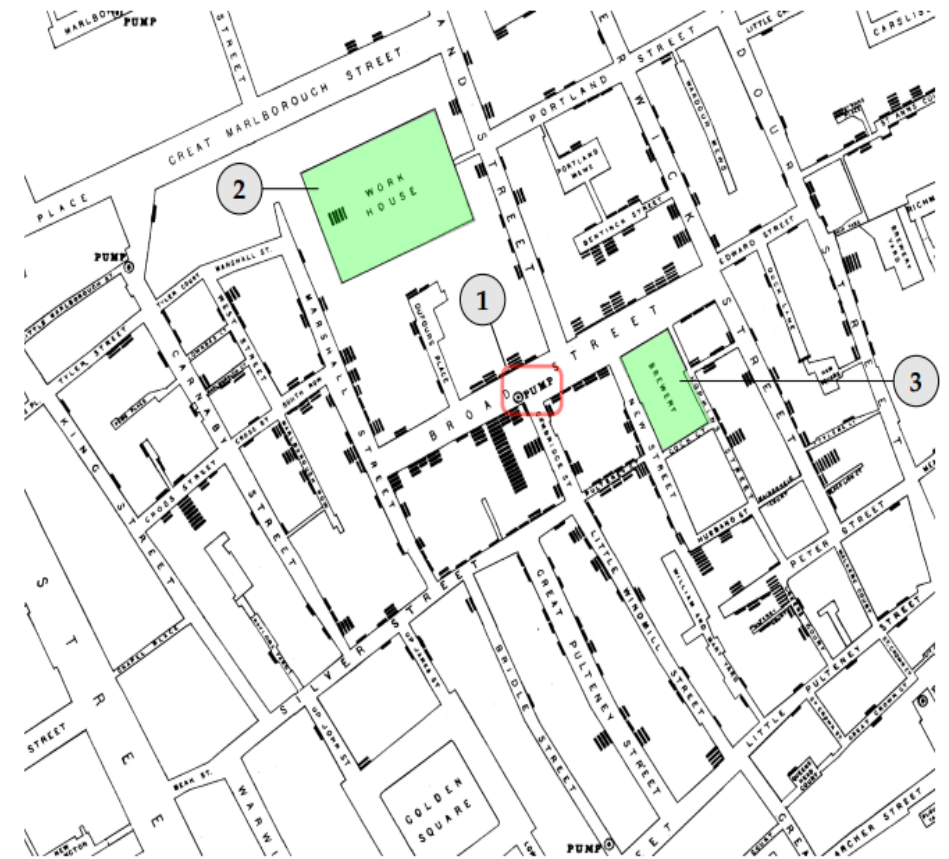


Introduction: Small area estimation (SAE)

Estimation of health-related parameters for small geographic areas (Rao & Molina, 2015)



Provision of insights into localized health disparities, disease prevalence, and risk factors within specific geographic area (Wakefield et al., 2020)



John Snow cholera map adapted from (Erraissi, 2019)

Introduction: Small area estimation (SAE)



John Snow cholera map adapted from (Erraissi, 2019)

SAE categories

A

Design-based
estimation

Function:
Direct sampling

B

Model-based
estimation

Function:
Statistical /
machine learning
(ML) modelling

Study focus:
ML models

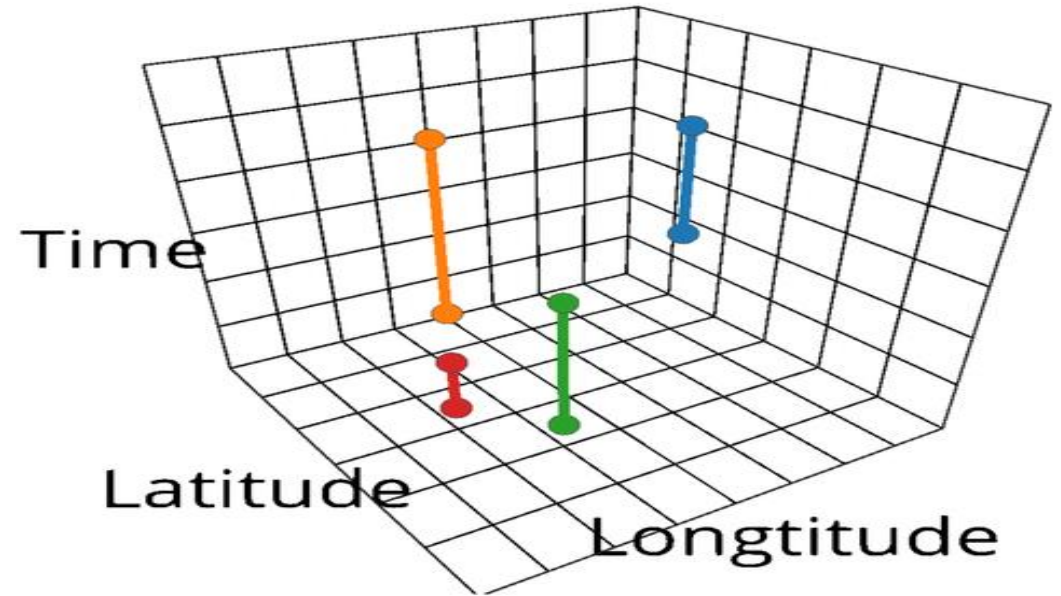
Introduction: ML models

ML models that account for spatial or spatiotemporal context

Spatial and spatiotemporal ML models

- ❑ Luo et al., 2021
- ❑ Draidí et al., 2022
- ❑ Lucas et al., 2022
- ❑ Wang et al., 2023

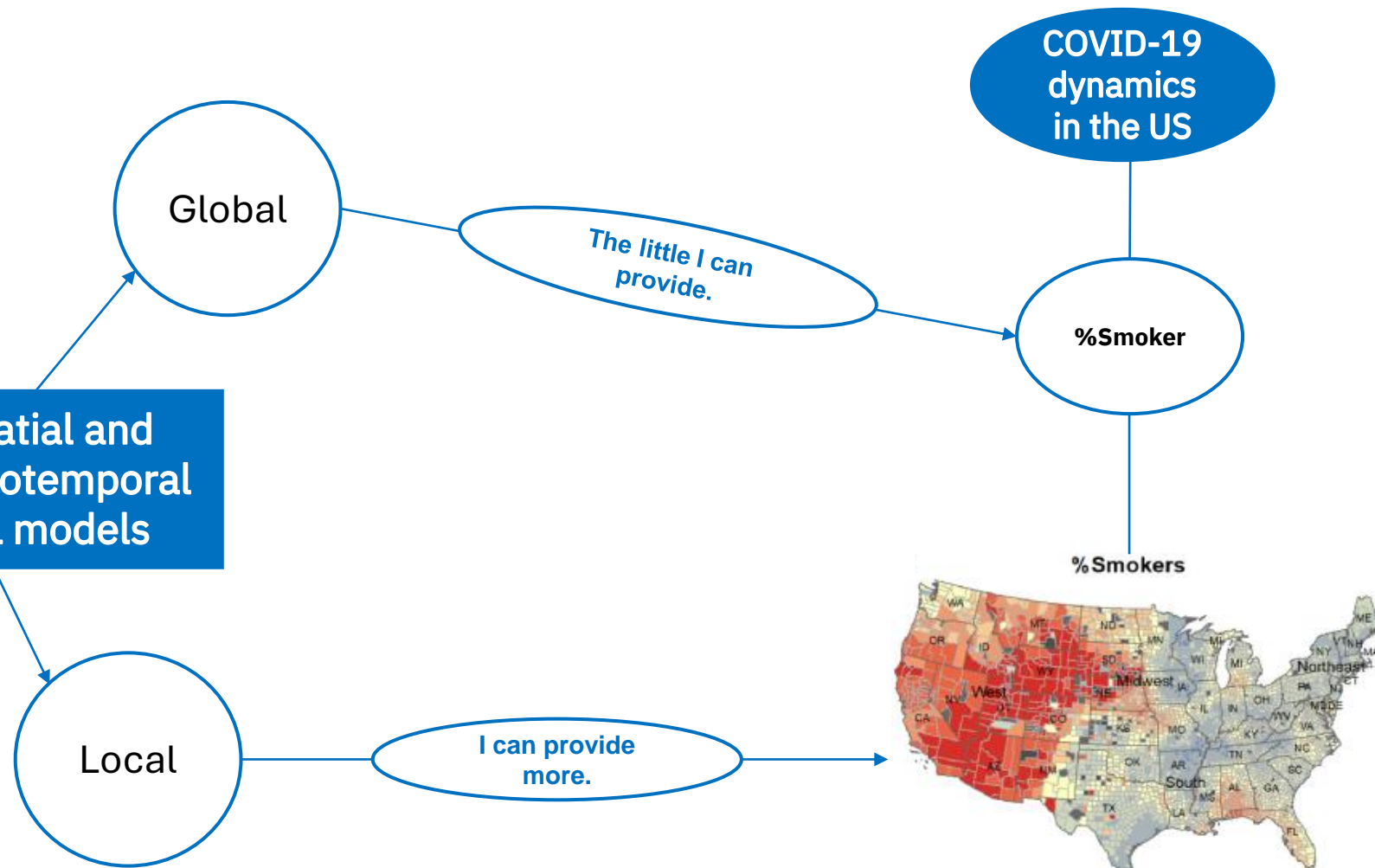
- ❑ Geographically weighted random forest (GRF/GWRF)
- ❑ Spatio-temporal attention network (STAN)
- ❑ Graph wavenet (GWNet)
- ❑ Spatio-temporal prediction network (STG-Net)
- ❑ Cross-location attention-based graph neural networks (ColaGNN)



Credit: Unknown creator

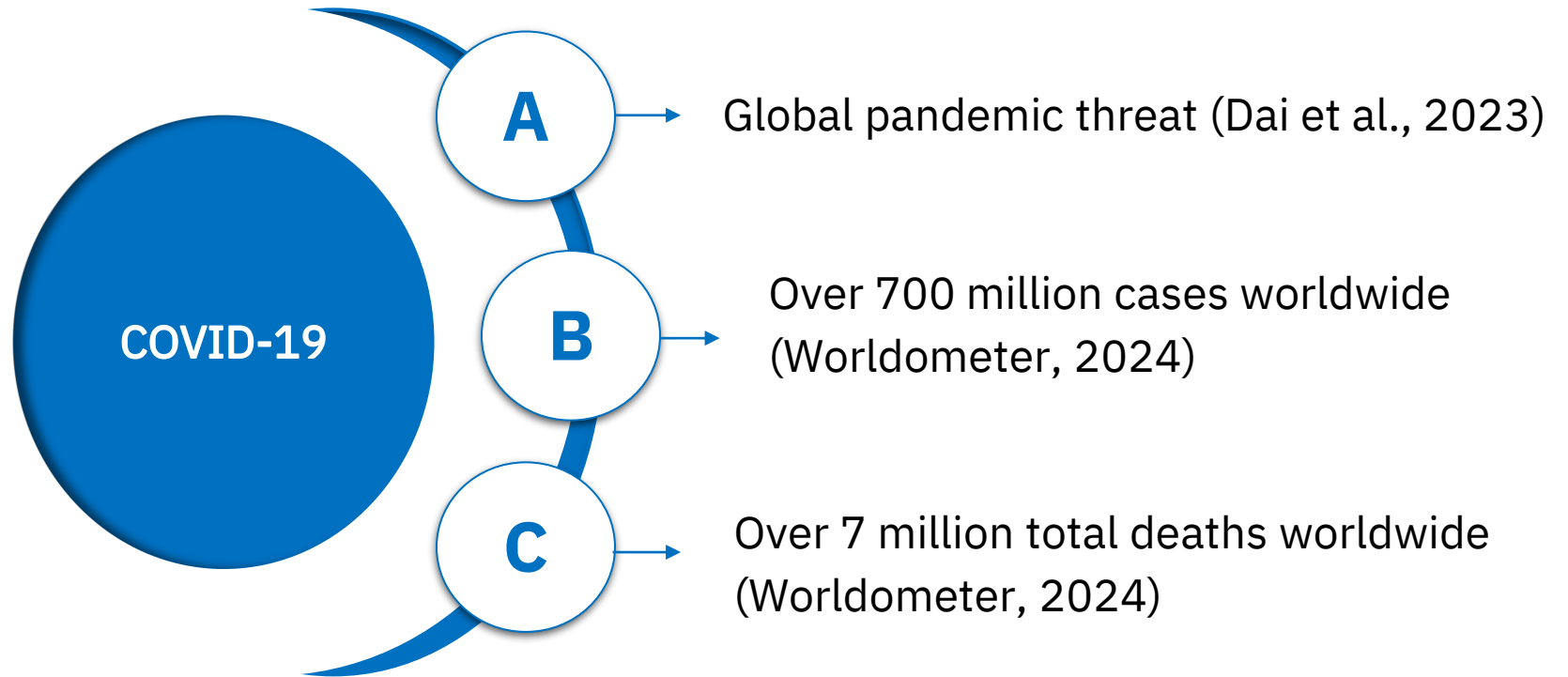
Introduction: ML models

Spatial and spatiotemporal ML models



Source: Adapted from (George et al., 2022)

**Introduction:
Spatial and
spatiotemporal ML
models for COVID-19
studies**



Objectives

2: To model COVID-19 spatial dynamics using composite indicators

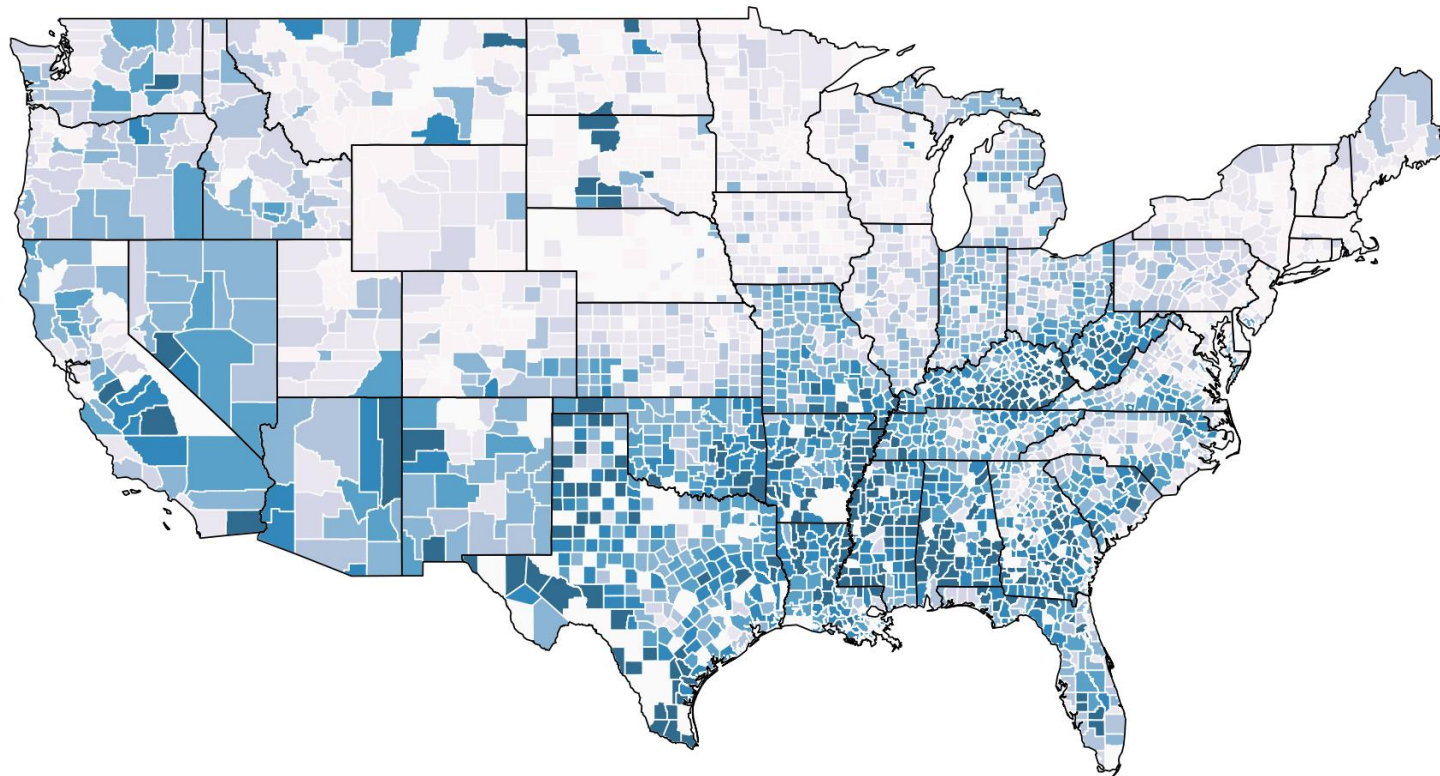
3: To incorporate temporal variation into our model to gain a deeper understanding of COVID-19 spatiotemporal dynamics

1: To construct composite indicators

Gaps

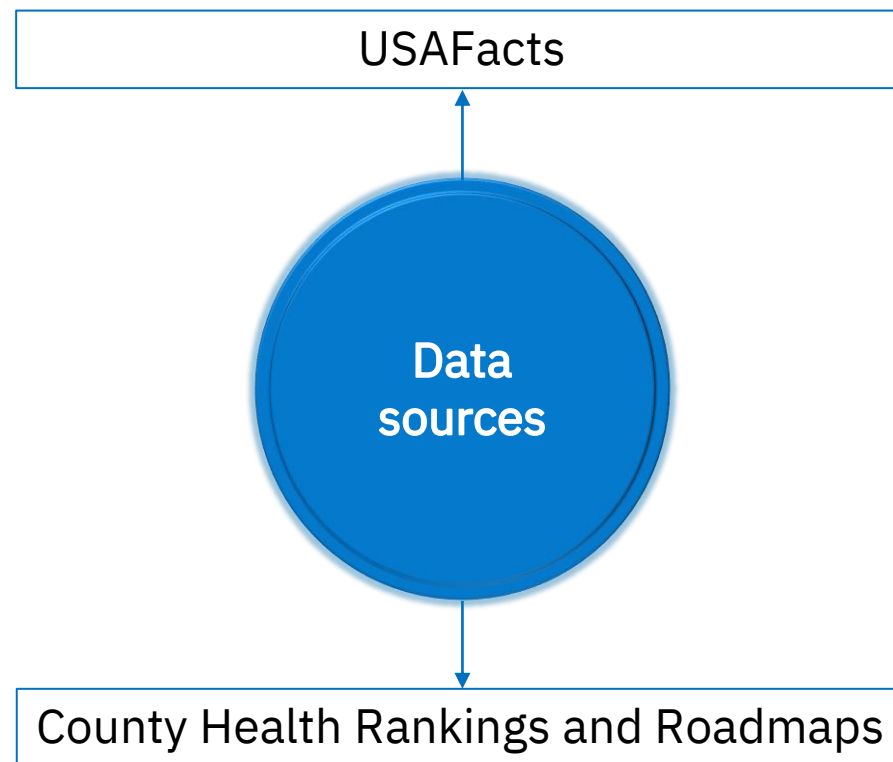
Methods:
Study area

The United States (US)

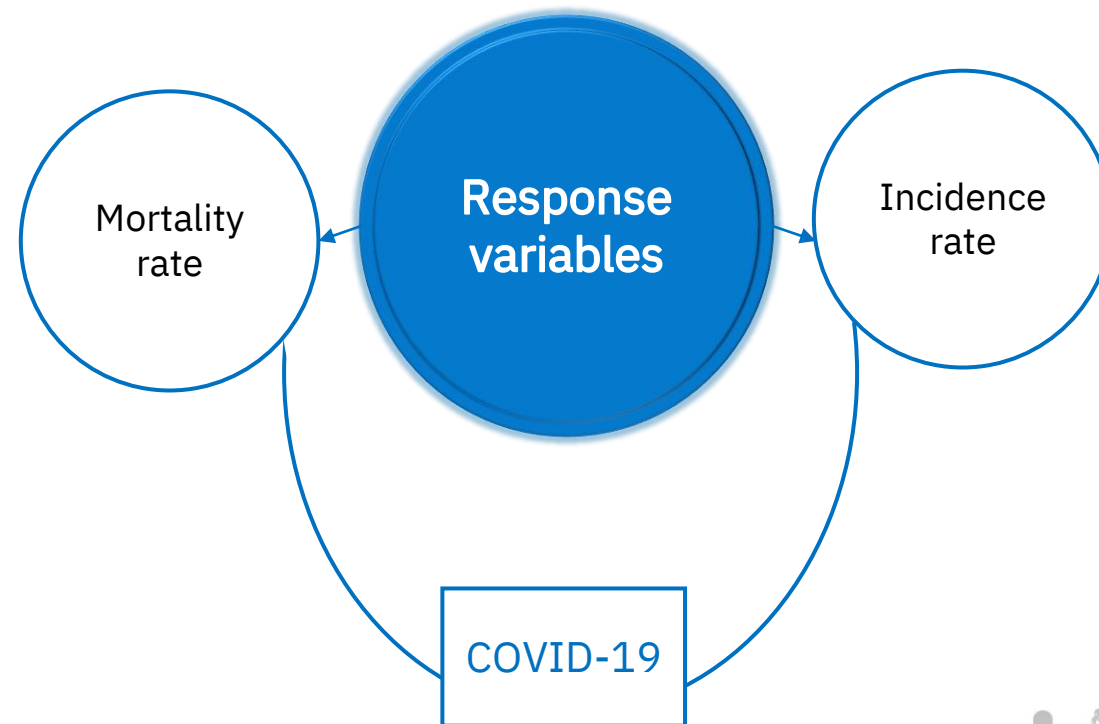


Spatial distribution of percentage of people with fair or poor health
Sources: Author generated map

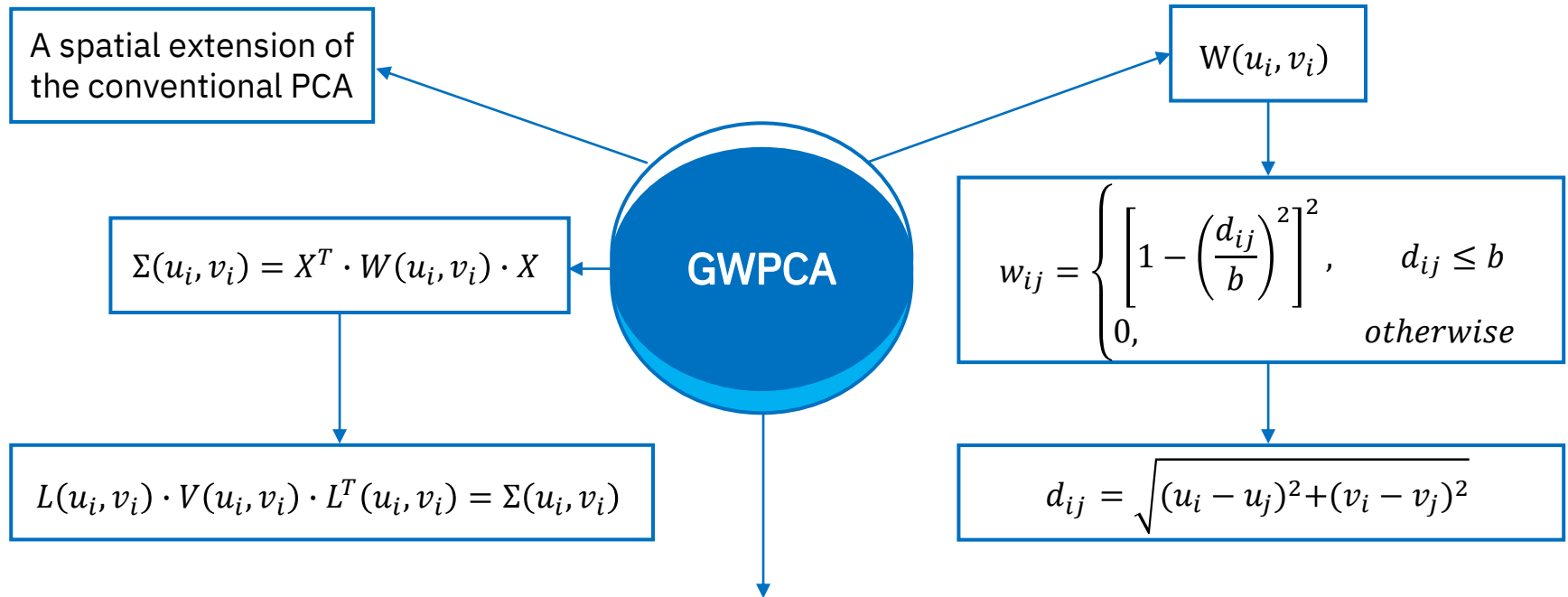
**Methods:
Data sources**



Methods: Data



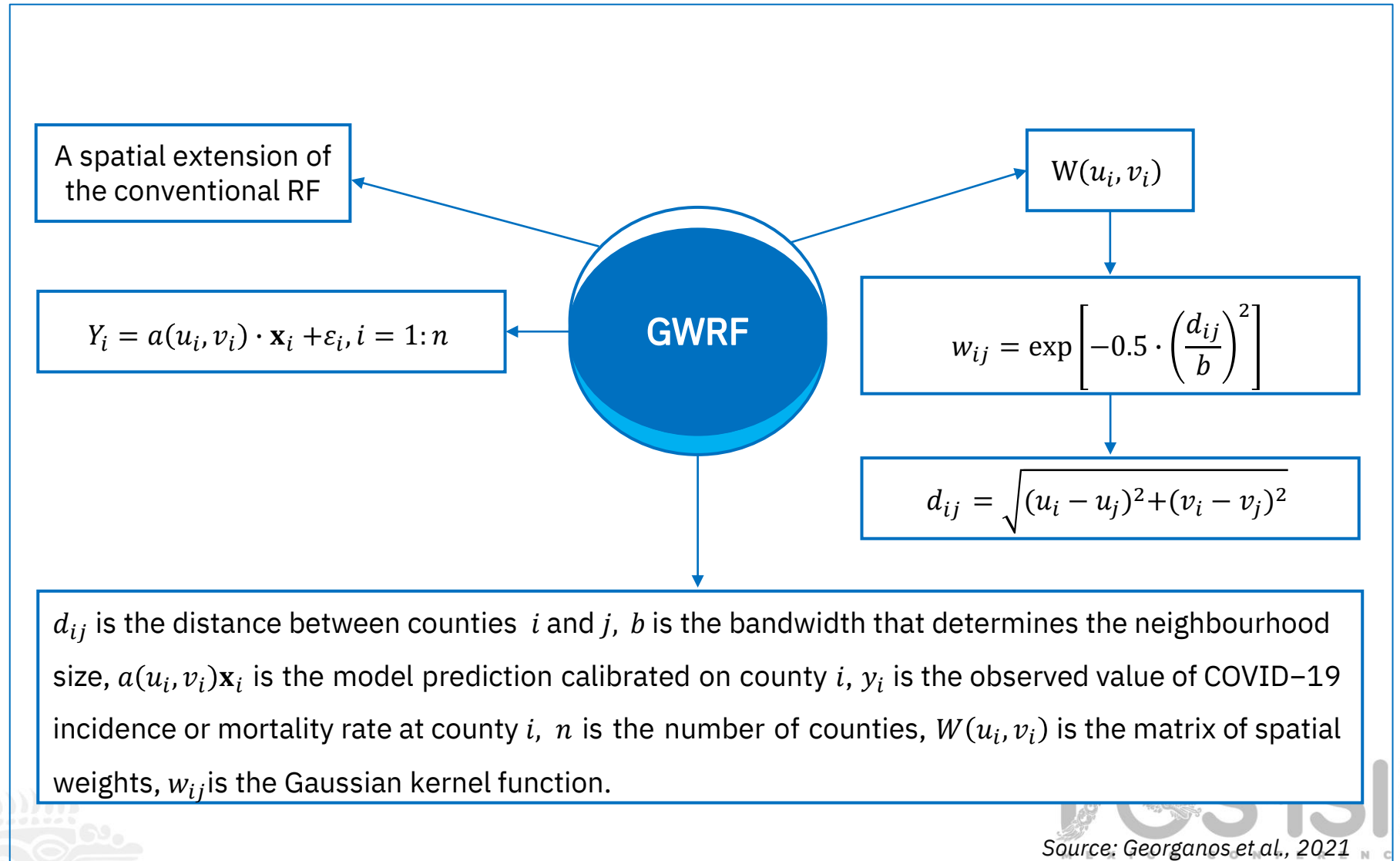
**Methods:
Geographically
weighted principal
component analysis
(GWPCA)**



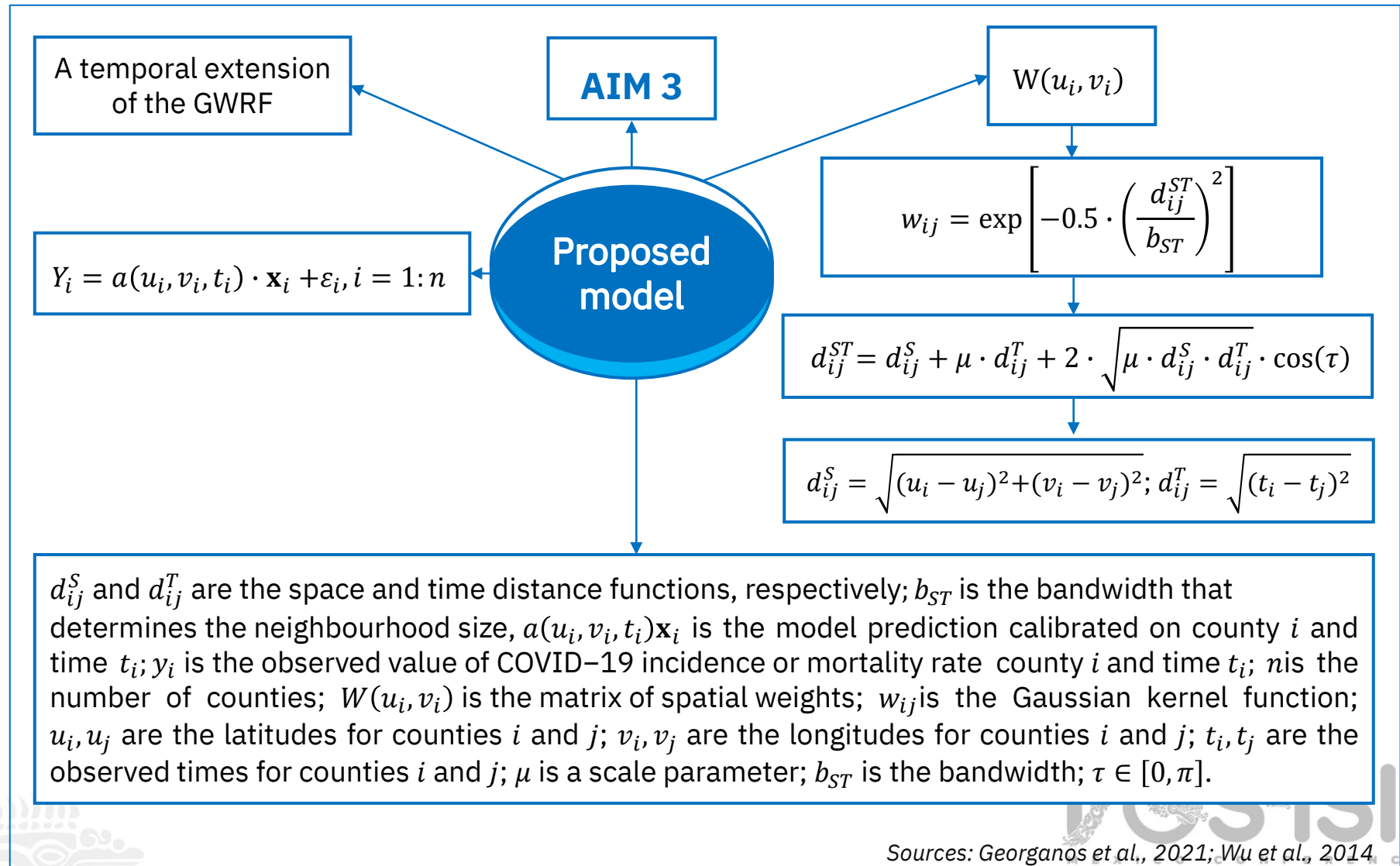
X is the individual indicators matrix, $W(u_i, v_i)$ is the diagonal matrix of spatial weights, w_{ij} is the bi-square kernel function, d_{ij} is the distance between counties i and j , b is the bandwidth that determines the neighbourhood size, $L(u_i, v_i)$ is the matrix of loadings of the individual indicators for each component and $V(u_i, v_i)$ is the diagonal matrix of the variance of the components.

Sources: Harris et al., 2011; Aidoo et al., 2021

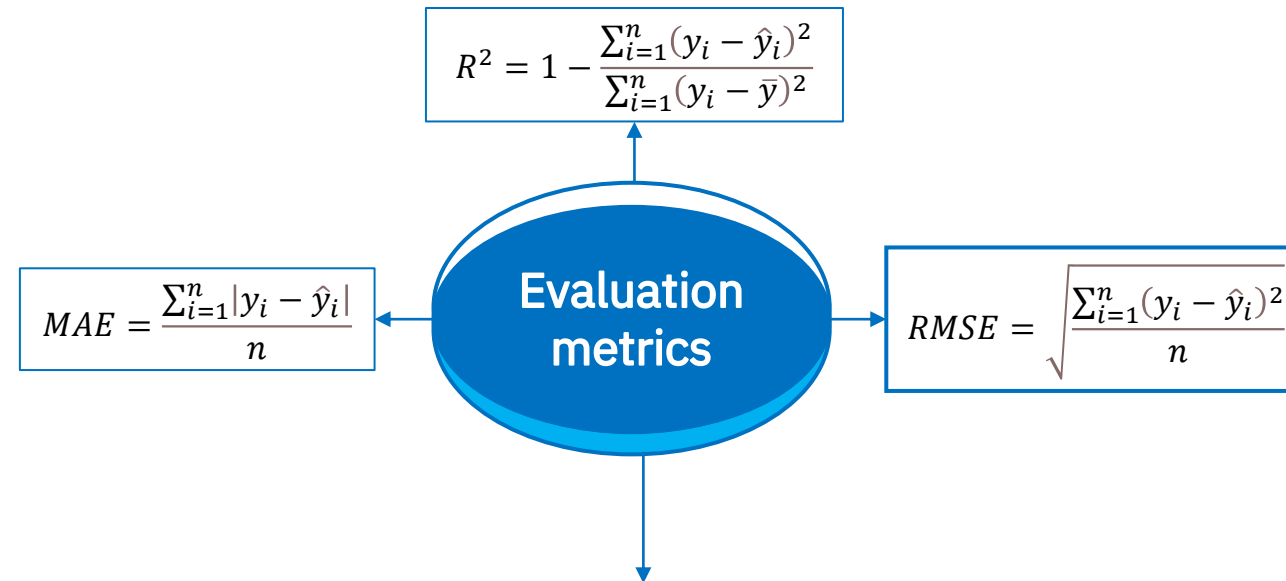
Methods: Geographically weighted random forest (GWRF)



Methods: Proposed model



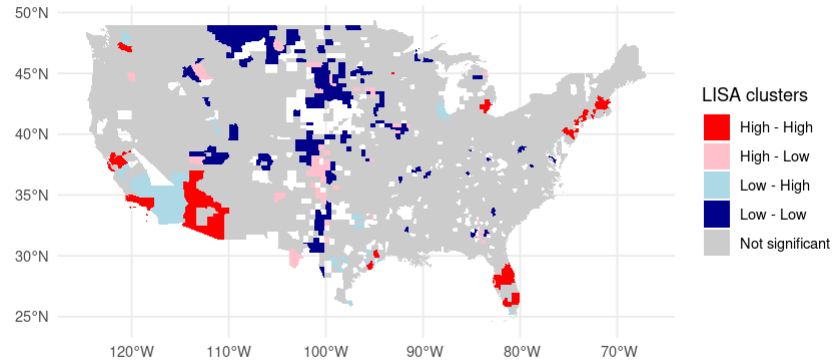
Methods: Evaluation metrics



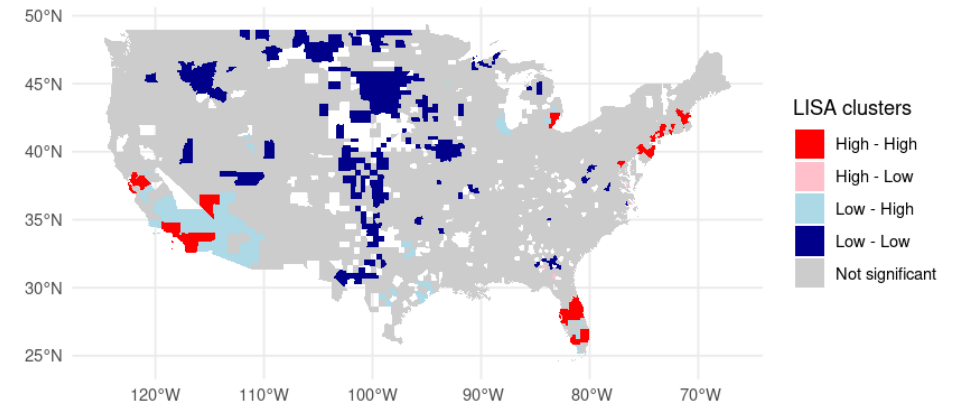
y_i is the observed value of COVID-19 incidence or mortality rate at county i , \hat{y}_i is the predicted value of COVID-19 incidence or mortality rate at county i , \bar{y} is the observed mean of COVID-19 incidence or mortality rate across all counties, and n is the number of counties.

Results

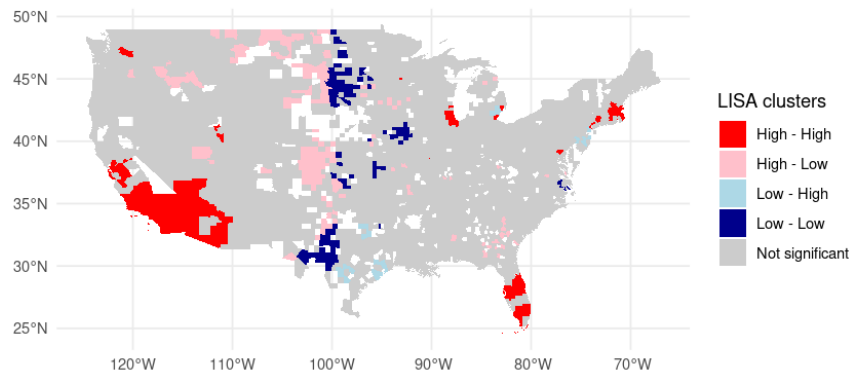
LISA Map for Demographic Indicator



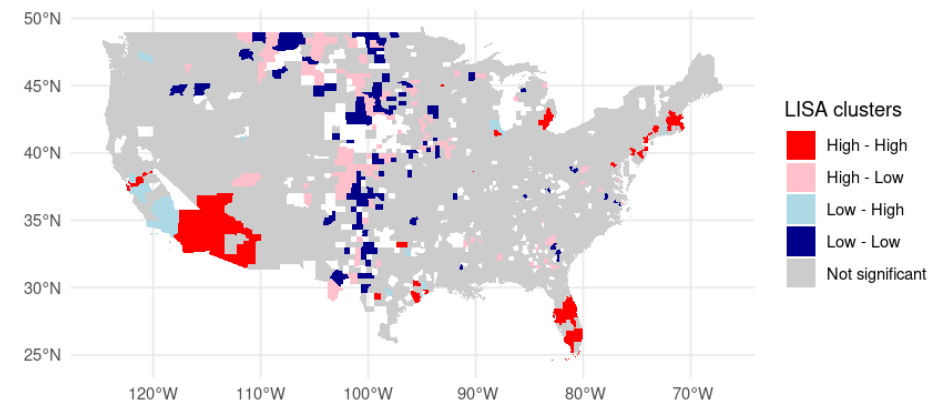
LISA Map for Environmental Indicator



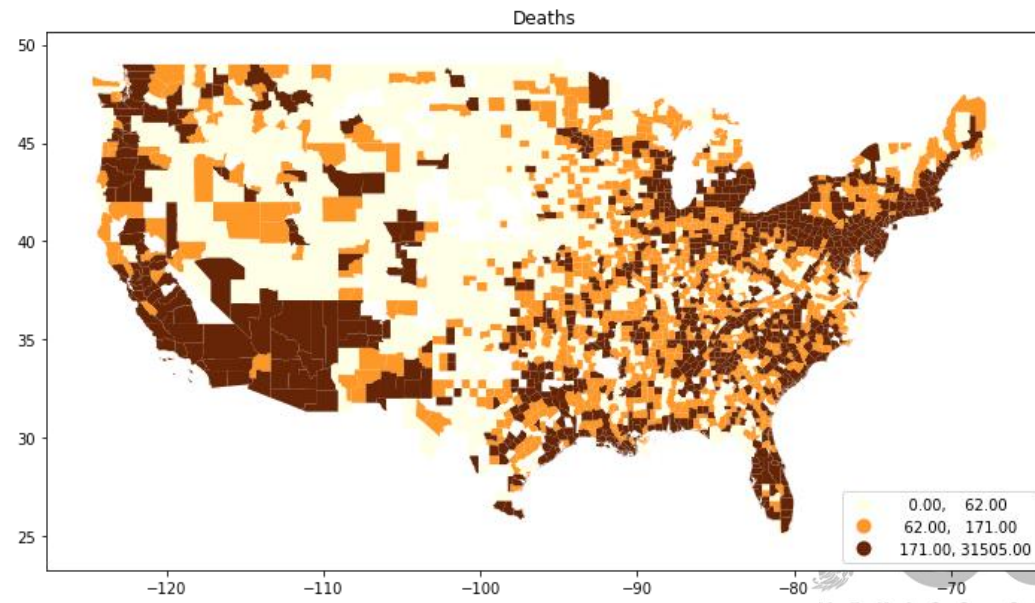
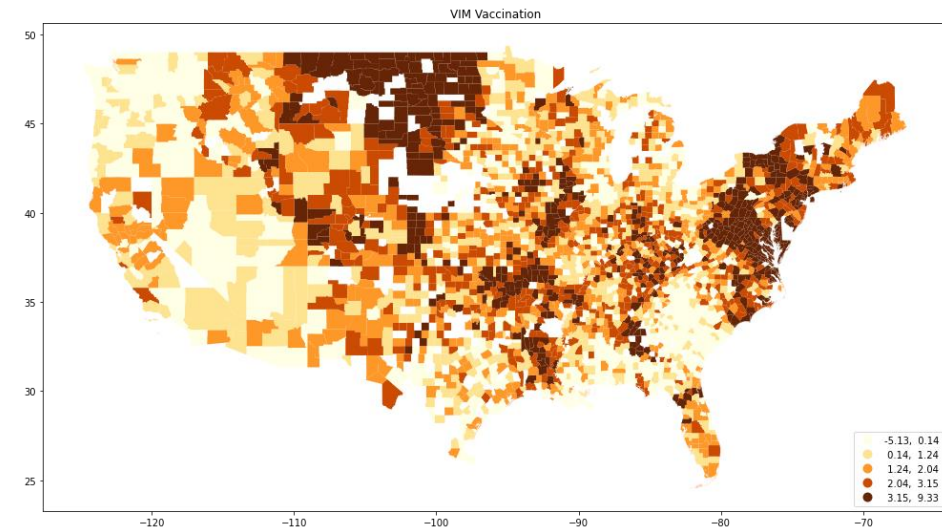
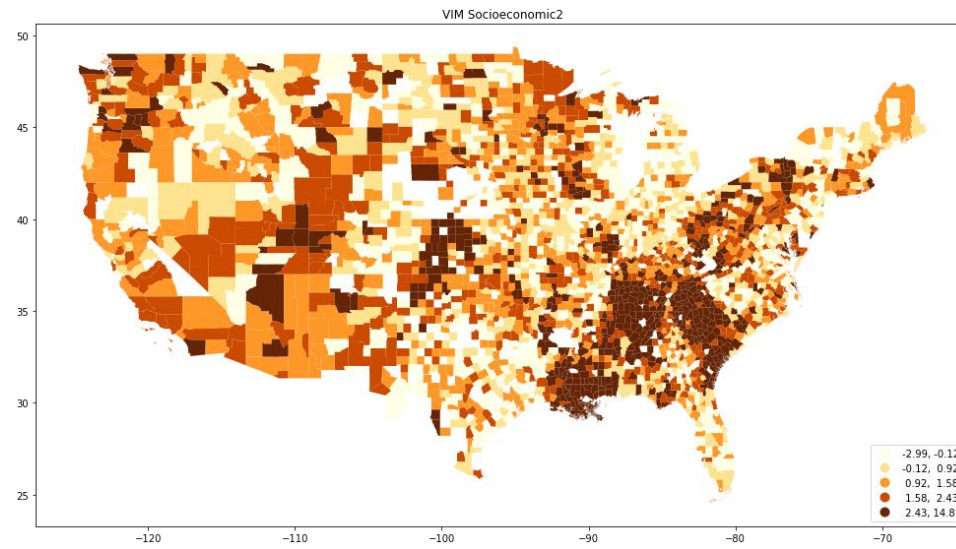
LISA Map for Vaccination Indicator



LISA Map for Socioeconomic 1 Indicator



Results



References

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- George Grekousis, Zhixin Feng, Ioannis Marakakis, Yi Lu, Ruoyu Wang (2022). Ranking the importance of demographic, socioeconomic, and underlying health factors on US COVID-19 deaths: A geographical random forest approach, *Health & Place*, Volume 74, 102744, ISSN 1353-8292.



Thank you





A Cohort Study of COVID-19 Patients: Hawassa University Referral Hospital, Ethiopia

Anteneh Bezabih, Marissa LeB., Abebe A. Natnael, Asfaw G. Zeytu

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Oslo University Hospital

Hawassa University Comprehensive Specialized Hospital

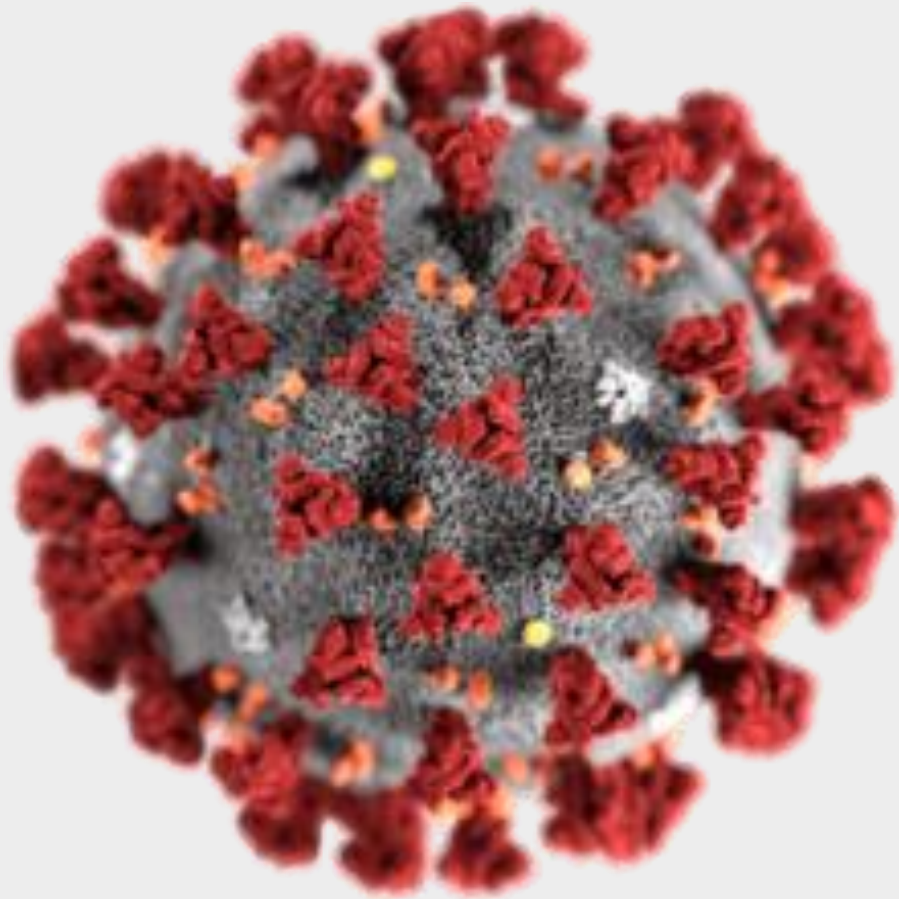
Addis Ababa University School of Public Health



Presentation Overview

- **Background**
 - **Objectives and Study Design**
- **Study Variables**
- **Methods**
- **Result and Discussion**
- **Conclusion**
- **References**





Introduction

- A novel severe acute respiratory syndrome is brought on by the coronavirus, an infectious pathogen.
- Since the 1960s, when human coronaviruses were first identified.
- The COVID-19 pandemic has had significant impact on global health, leading to widespread morbidity and mortality.
- Global mortality has already exceeded 6.7 million ^[1]

By March 28, 2023



Regions	Total cases	Death	Recovered	Active cases
World wide	683, 429, 692	6, 827, 784	656, 415, 256	20, 186, 652
Europe	247, 664, 499	2, 029, 182	243, 290, 731	2, 344, 536
N. America	125, 557, 878	1, 620, 839	121, 078, 499	2, 858, 540
Asia	215, 158, 026	1, 540, 337	199, 753, 408	13, 864, 281
S. America	68, 261, 922	1, 352, 159	66, 388, 794	520, 969
Africa	12, 809, 031	258, 646	12, 080,302	470, 083
Oceania	13, 977, 665	26, 606	13, 822, 816	128, 243
Ethiopia	500,272	7,573	487,530	5,341



Deaths

United States

Brazil

India

Russia

Mexico

Remains the front-line nation, with overall **1,151,642**

699,917

530,841

397,146

333,449

Intro cont...

- Although the infection burden is high in Europe, Americas, and West Pacific,
 - we need to pay attention to the continent of Africa, in particular, highly populous nations like Ethiopia, where most nations face resource challenges in terms of
 - skilled human,
 - economic, and
 - logistical facilities to control the prevalence of the pandemic.



Objectives and Study Design

- To determine clinical and demographic characteristics, as well as risk factors for in-hospital mortality, are assessed in HUCSH, Ethiopia

Specifically,

- Describe the baseline characteristics by Outcome Status.
- Identify the effect of different risk factors on the mortality of patients with COVID-19 by stratifying different covariates
- Estimate the effect of covariates on covid-19 patients to wards mortality

Study design and population

- A hospital-based retrospective cohort study was conducted using medical records
- 804 COVID-19 patients at HUCSH, COVID-19 isolation and treatment center
- From 24/9/2020 to 26/11/2021 were considered as study population

Variables of the Study

The survival outcome

- Time from admission to discharge,(in days)
- The observed event, **(Death or Censored).**

Demography Variables

- Age Category
- Sex
- Severity
- Source of Reporting

Symptoms variables

- Like Fever,
- Cough,
- Shortness of breath
- body weakness
- Chest pain...

Comorbidity Variables

- CVC,
- Hypertension,
- Diabetes,
- HIV,
- Renal Disease .



Statistical analysis

- Descriptive statistics and chi-square test
- Kaplan-Meier plot with various covariates for non-parametric estimation
- the cox regression analysis for the time to death was applied.
- The Cox model

$$h(t) = h_0(t)e^{\{\beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p\}}$$

The hazard function can be interpreted as the risk of dying at time t .

where,

- t - the survival time
- $h(t)$ - the hazard function determined by a set of p covariates (X_1, X_2, \dots, X_p)
- $(\beta_1, \beta_2, \dots, \beta_p)$ measure the impact (i.e., the effect size) of covariates.
- the term h_0 is called the baseline hazard. The 't' in $h(t)$ reminds us that the hazard may vary over time.
- two-sided tests with a significance threshold of less than 0.05 were used.

Result and Discussion

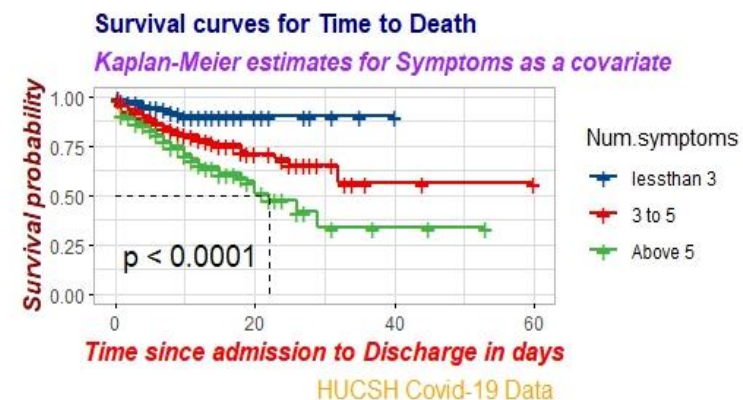
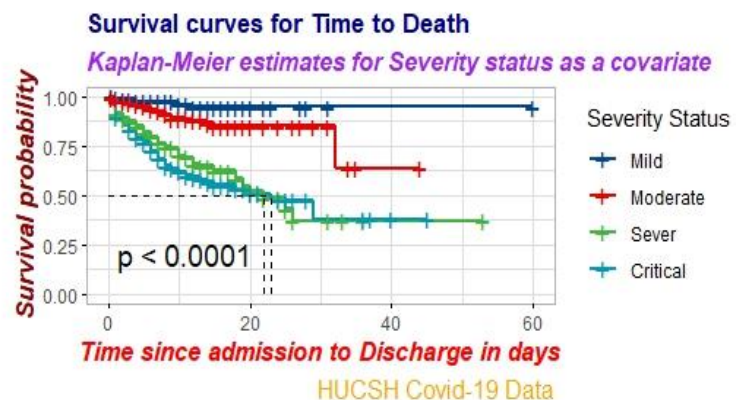
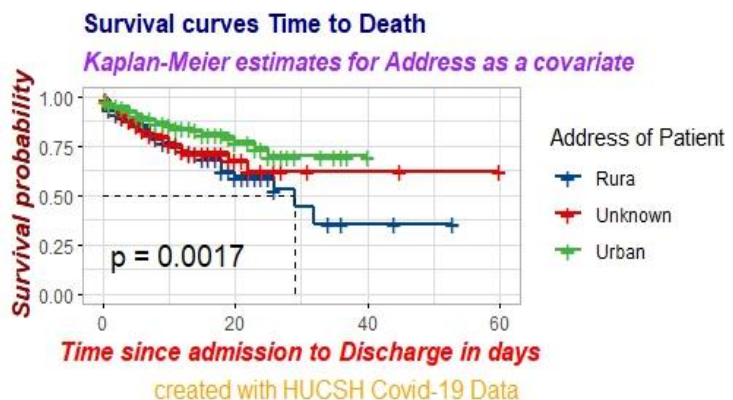
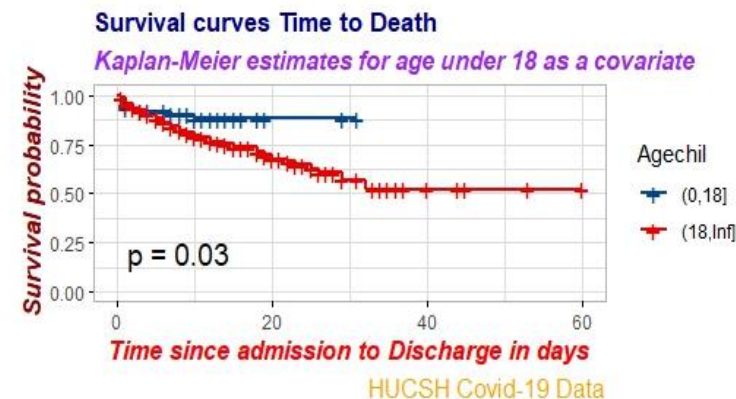
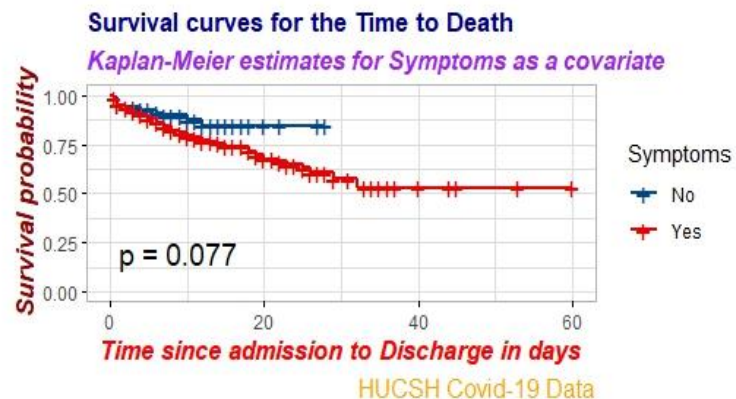
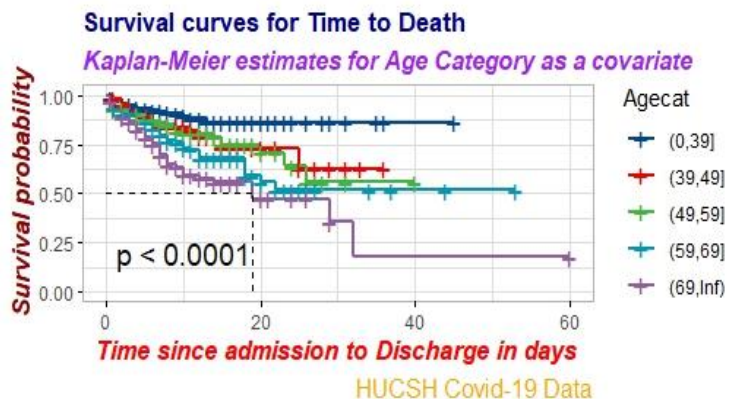
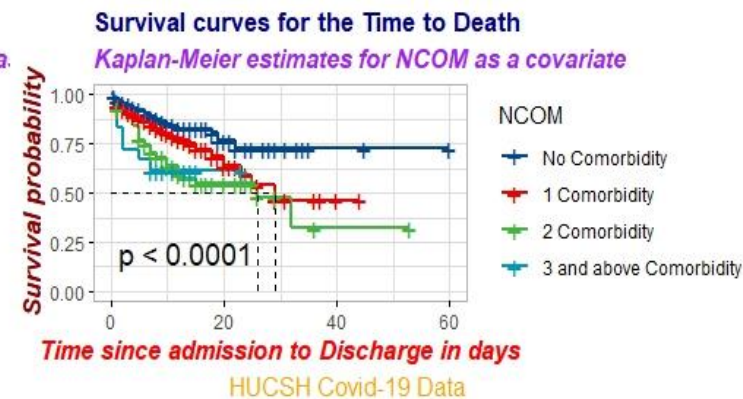
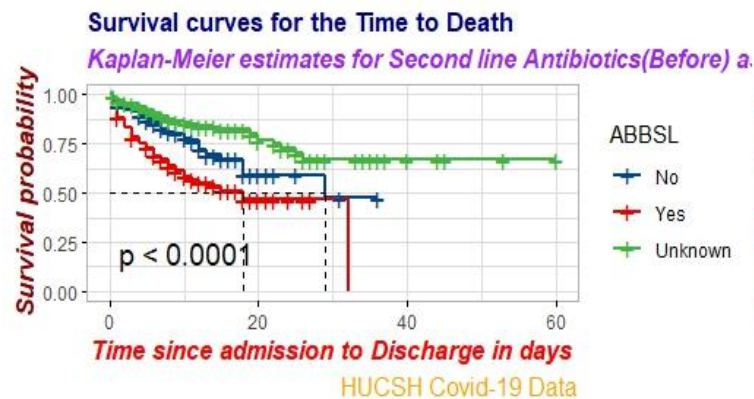
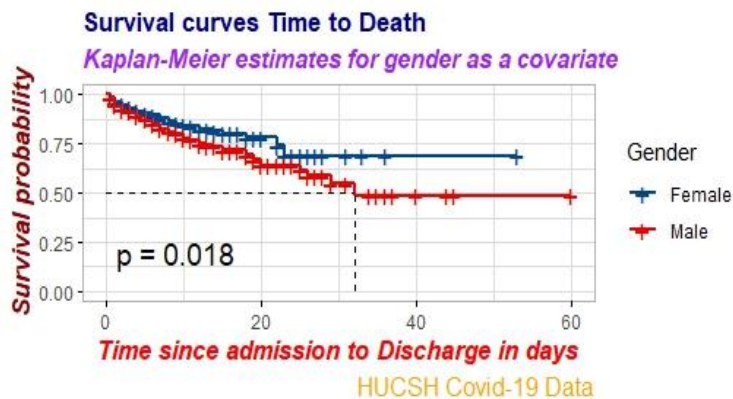
Demographic Characteristics of the study population

- A mean age of 44.8 ± 20.6 (median=45, [0.006, 100]) years
- 512 (64.1%) men and 289 (34.9%) female
- An average of 10.9 ± 7.17 days take from **admission to discharge**, from [0.5,60] days.
An average of 16.5 ± 8.42 , [1, 63] days from the **onset of symptoms** to discharge
The onset of their symptoms to **admission** on average 5.92 ± 5.22 days, with [0.5,51] days.
- Over 78% of patients reported more than three symptoms, and 90% of patients had at least one symptom.
 - Chest pain (68.9%), cough (68.7%), shortness of breath (65.7%), and fever (57.6%) were the most prevalent symptoms
- Also, 24.1% of patients had severe illnesses, 21.4% had critical illnesses, 30.0% had moderate illnesses, and 24.5% had mild illnesses.

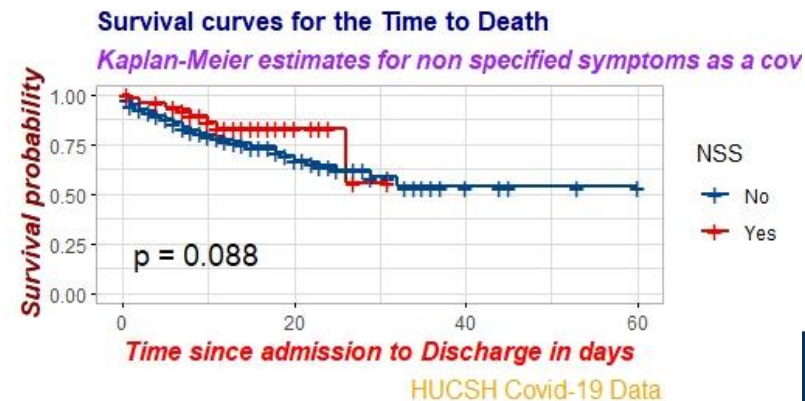
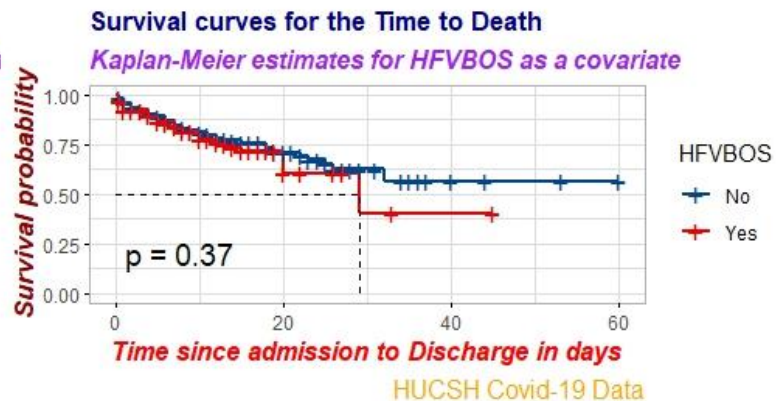
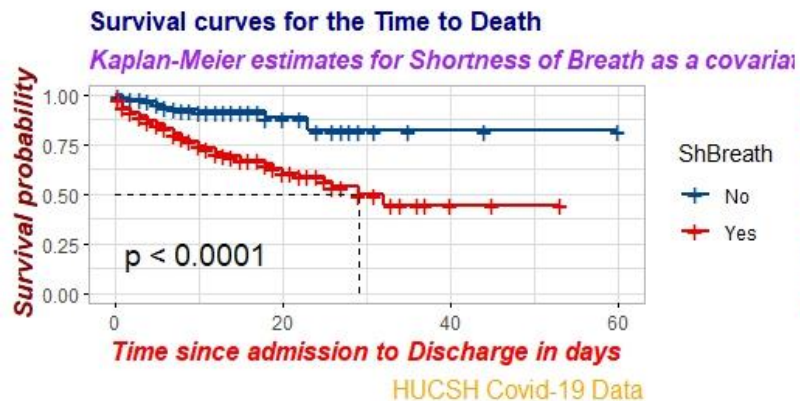
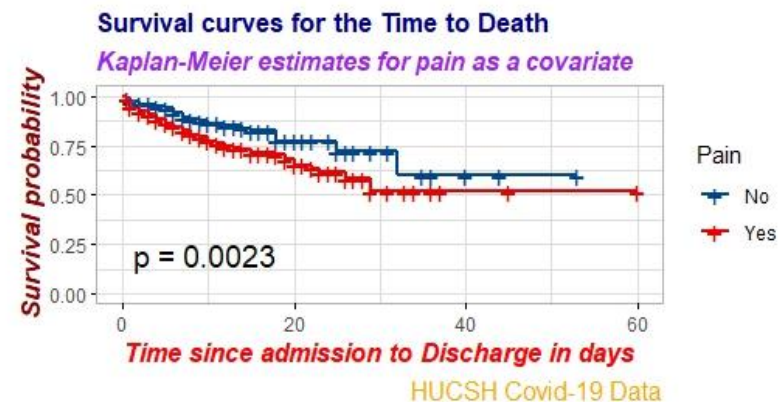
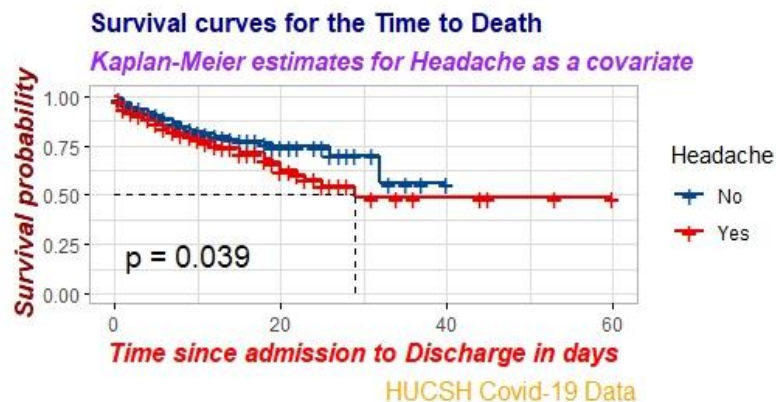
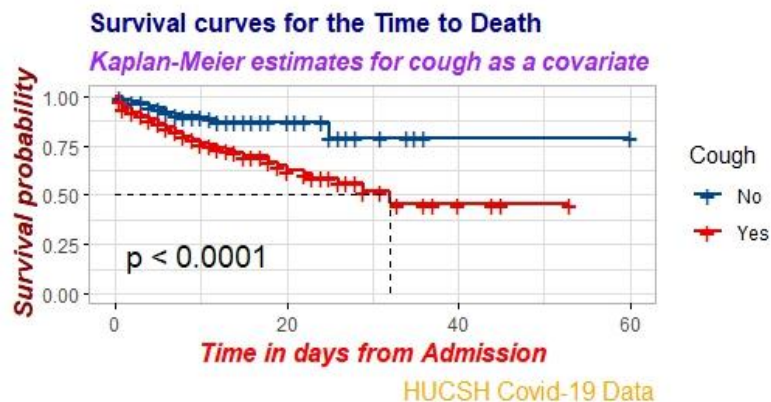
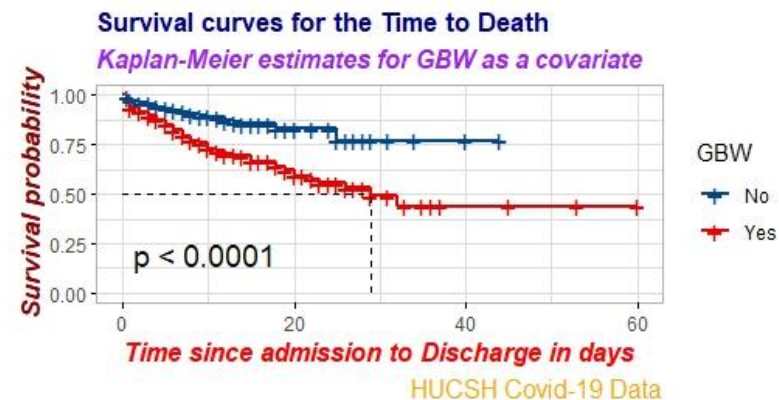
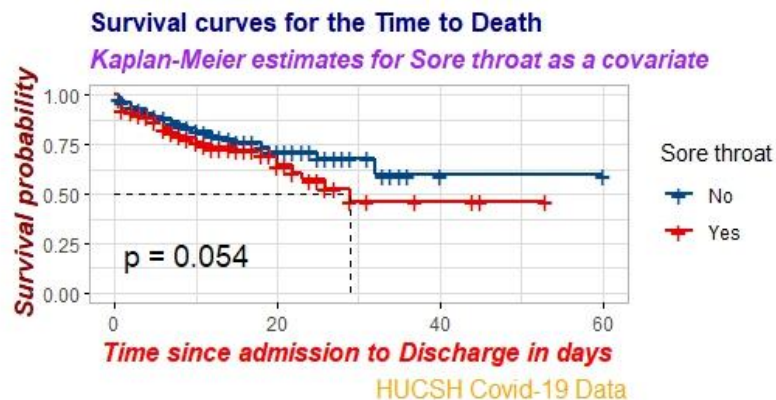
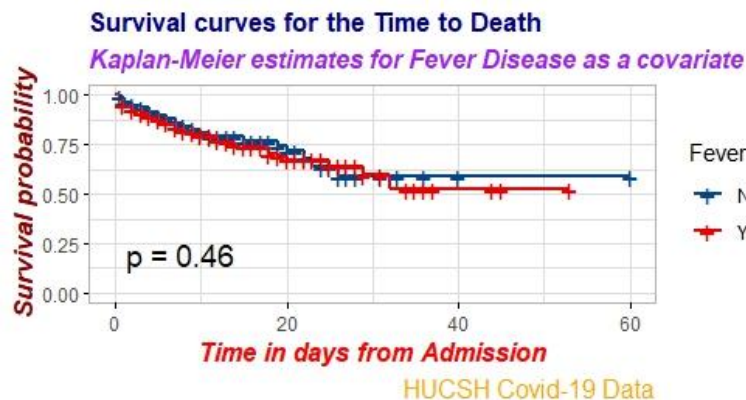
Comorbidities

- Of the 804 patients, 395 (49.1%) had at least one or more coexisting medical conditions comorbidities.
 - 291(36.2%) reported having one comorbidity,
 - 84 (10.4%) two comorbidities and 18 (2.2%) three or more comorbidities.
- 180 (22.4%) had diseases related to cardiovascular
- About 42(5.2%) experienced various forms of trauma
- While 40(5%) experienced other respiratory problems
- 22(2.7%) renal disease/urological conditions
 - Diabetes mellitus (128, 15.9%),
 - Hypertension (122, 15.2%),
 - cancer (30, 3.7%), and RVI/HIV (25, 3.1%) were the most common coexisting conditions among the study participant patients

KM Plots demography and other

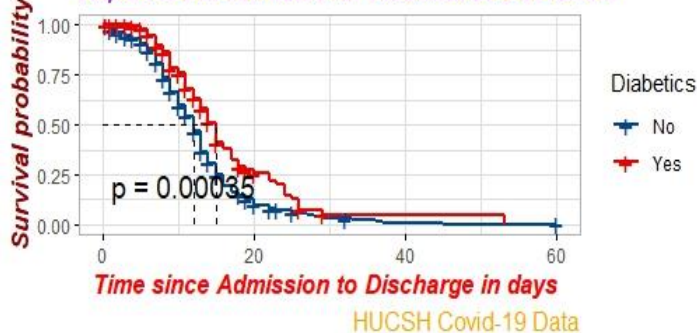


KM Plots symptoms

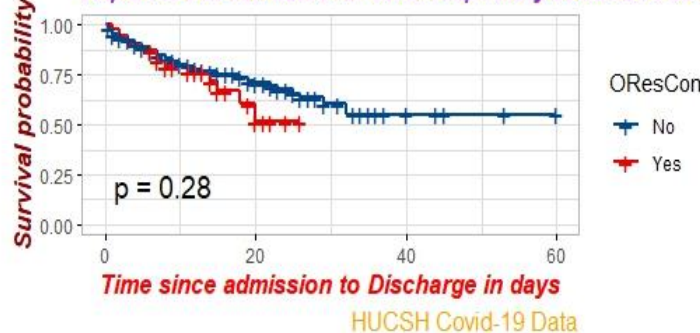


KM Plots comorbidities

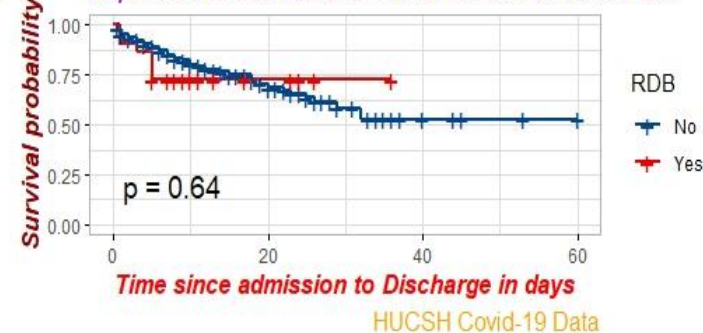
Survival curves for the Time to Death
Kaplan-Meier estimates for Diabetics as a covariate



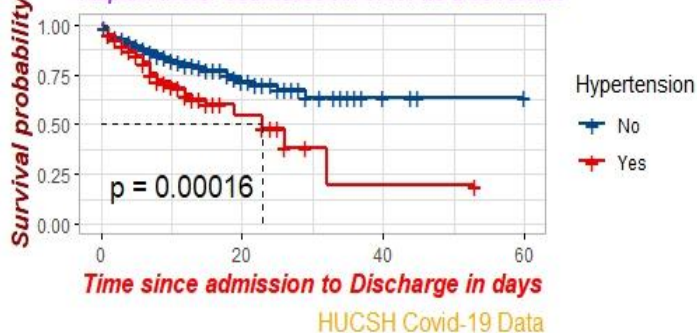
Survival curves for the Time to Death
Kaplan-Meier estimates for other respiratory conditions as a



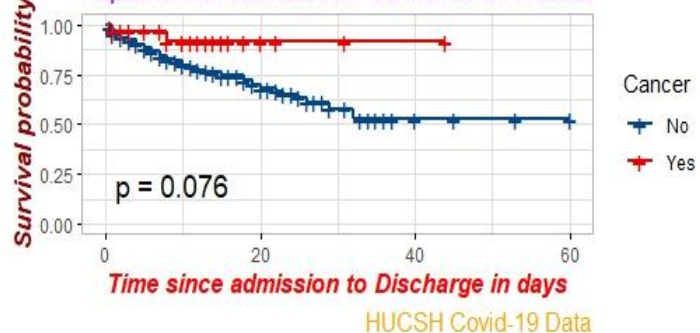
Survival curves for the Time to Death
Kaplan-Meier estimates for Renal disease as a covariate



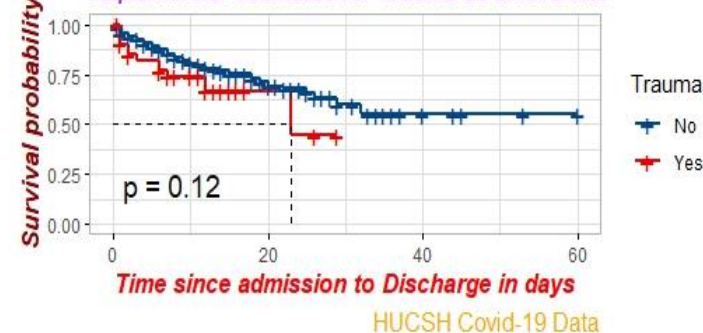
Survival curves for the Time to Death
Kaplan-Meier estimates for HTN as a covariate



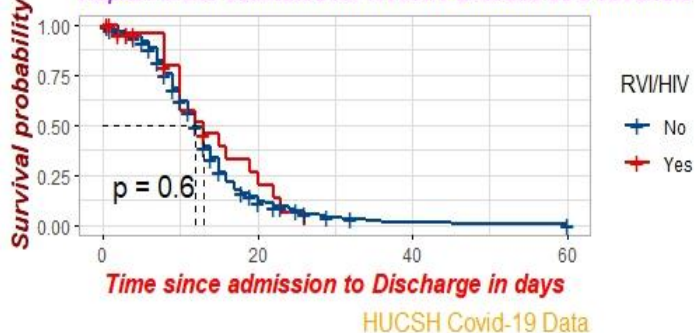
Survival curves for the Time to Death
Kaplan-Meier estimates for Cancer as a covariate



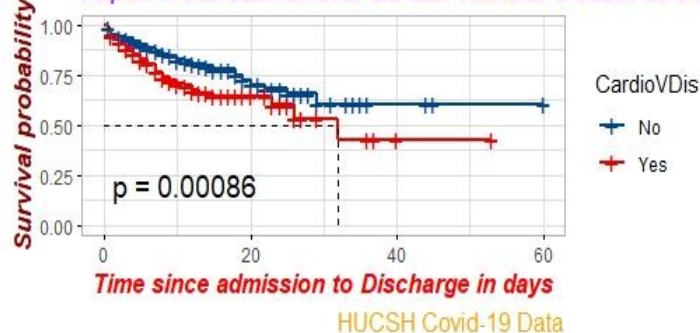
Survival curves for the Time to Death
Kaplan-Meier estimates for Traoma as a covariate



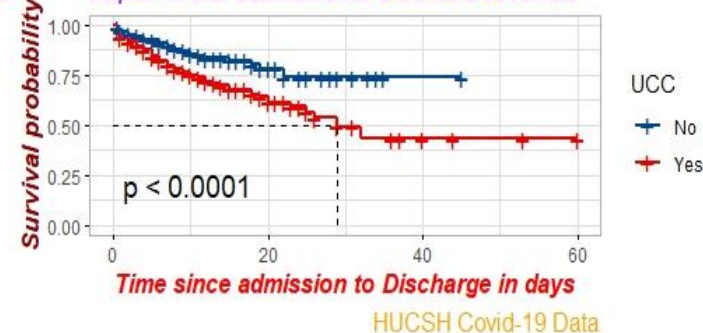
Survival curves for the Time to Death
Kaplan-Meier estimates for RVI/HIV Disease as a covariate

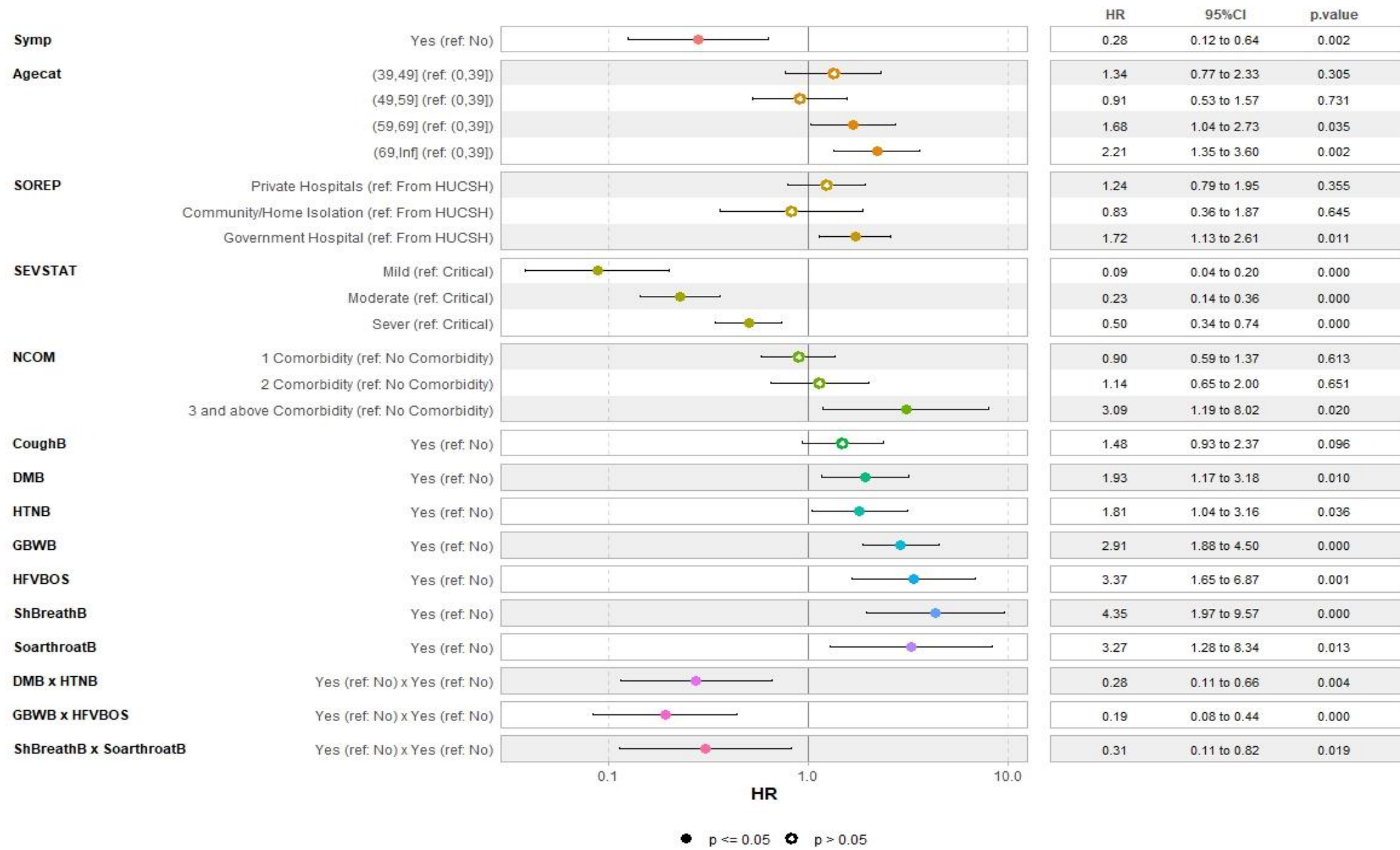


Survival curves for the Time to Death
Kaplan-Meier estimates for Cardiac Vascular Disease as a co



Survival curves for the Time to Death
Kaplan-Meier estimates for UCC as a covariate





Result and Discussion cont...

- 173 (21.5%) death occurred
- From the total study population
 - more than 40% were aged less than 40
 - 562(69.9%) were from HUCSH different wards
- The mean (SD) and median length of stay from **admission to death** were 6.63(5.98) and 5[0.5, 32]days, respectively [28, 31, 32, 61, 62].
- The mean (SD) and median duration of stay from the time of the **first symptom** to **admission** were 5.92 (5.22) and 5[0, 51]respectively [29, 44, 45, 49, 51, 54, 55, 56, 59].
 - Malaysian patients took (3 days)when their symptoms started,
 - German patients took double the median time (10 days).
- Fever, Cough, Shortness of breath, sore throat, headache, GBW, Chest Pain, NSSB, Health facility visit, severity, and number of symptoms have a significant association with the source of reporting
- Similarly, the number of comorbidities, CVCB, Diabetes and hypertension were significantly associated with the source

Result and Discussion

There is a clear relationship between old age and a higher risk of dying.

Africa region [74], South Africa [75], China [35], Brazil [62], Norway [76], the Netherlands [31], Malaysia [50], Canada [37], and Ethiopia [17].

- More than three comorbidities had a higher risk of dying. [34, 35, 37, 56].
- As the severity level rises from mild to critical, the probability of death also significantly rises. Meta-analyses on sub-Saharan Africa and Congo [77, 78].
- Diabetes increases more than doubles the chance of death [34, 35, 37, 56, 62, 79].
- The interaction of shortness of breath and sore throat increases the risk of death.
- The interaction of general body weakness and a history of visiting the hospital earlier decreases the risk of death.
- The interaction of diabetes and hypertension cooperate to reduce mortality risk.
 - Further explanation is required with regard to the hospital's care or the interaction effect of the treatments.

Conclusion

- This study characterized a large cohort of hospitalized COVID-19 patients in Ethiopia and showed that
 - Similar to high-income countries, Older age groups, sex, severity, co-morbidities, and the number of symptoms upon admission were associated with an increased risk of in-hospital death.
 - Source of reporting, (Government give attention for medium hospitals)
 - HUCSH give attention to patients in different wards
 - Hawassa city health office should raise awareness about pre-diagnosis to the community and make them get tested
 - The average age was remarkably low.
 - Additionally, a greater number of comorbidity, shortness of breath, sore throat, general body weakness, diabetes, and patients who visit health facilities before onset had a higher risk of dying due to covid-19 disease.
 - On the other hand, patients who show symptoms decrease the risk of death.

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Thank you





Spatial Patterns and Predictors of Malaria in Ethiopia: Application of Auto logistic Regression

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Conten^{tes}

- **Introduction**
- **Data and Methodology**
- **Results**
- **Conclusion**
- **Recommendations**



Introduction

- Malaria is a severe health threat in the World, mainly in Africa including Ethiopia.
- An estimated of 1.5 billion cases and 7.6 million death due malaria were recorded globally in 2020.
- Malaria is the most public tropical disease and is still prevalent in tropical and subtropical regions including Ethiopia.
- Malaria is a severe health threat in the World, mainly in Africa including Ethiopia.

Cont'd ...

- Malaria is a serious health problem in Ethiopia, affecting the socio-economic and health status of the country at large.
- Based EMIS-2015, nearly 60% of Ethiopia's population lives in the malaria region,
- and 68% of the country's population are at high risk of spreading malaria.
- Morbidity and mortality associated with malaria cases are characterized by spatial variations across the county.

Cont'd ...

- The values of two similar units in space tend to be more similar than would be predicted by chance.
- As a result, models that overlook SAC may be incorrect due to overestimation of environmental variable's importance.
- Morbidity and mortality associated with malaria cases are characterized by spatial variations across the county.
- Malaria incidences and geographic risk factors for malaria are often positively auto correlated.

Cont'd ...

- Malaria is a serious health problem in Ethiopia, affecting the socio-economic and health status of the country at large.
- Therefore, this study was aimed to investigate the spatial patterns and predictors of malaria distribution in Ethiopia.

Data and Methodology

- A weighted sample of 15,239 individuals with rapid diagnosis test obtained from the Central Statistical Agency and Ethiopia malaria indicator survey of 2015.
- Global Moran's I and Moran scatter plots were used in determining the distribution of malaria cases.

Cont'd . . .

- Whereas, the auto logistics spatial binary regression model was used to investigate the predictors of malaria.
- One of the most extensively utilized models for modeling spatially linked binary data is the **auto logistics spatial regression** model.
- It's a variant of the generalized logistic regression model with a spatial autocorrelation term in the form of Euclidean distance.

Cont'd . . .

- Models that included the spatial autocorrelation effect were important to the response variable which,
- resulting in accurate results in estimating the spatial distribution of malaria illnesses
- Improving model accuracy
- and Adaptability.



Where,

π_i denotes the probability of an event occurring for every region;

X_i is independent variable

Auto covi is the auto covariate variable,

β and r are the coefficient of explanatory variable and coefficient of fixed auto covariate variable in the equation.

i is the index of geographical region (cluster) respectively.

➤ In this study, we restricted our attention to a constant auto regression coefficient ($r_{ii} = r$)

for all geographic indexes that can express the conditional probability of the occurrence of malaria disease as:

$$\pi_i = \frac{\exp(x'_i\beta + rAutocov_i)}{1 + \exp(x'_i\beta + rAutocov_i)} \quad \text{Where } Auto\ cov_i = \frac{\sum_{j=1}^{k_i} W_{ij}D_j}{\sum_{j=1}^{k_i} W_{ij}}$$

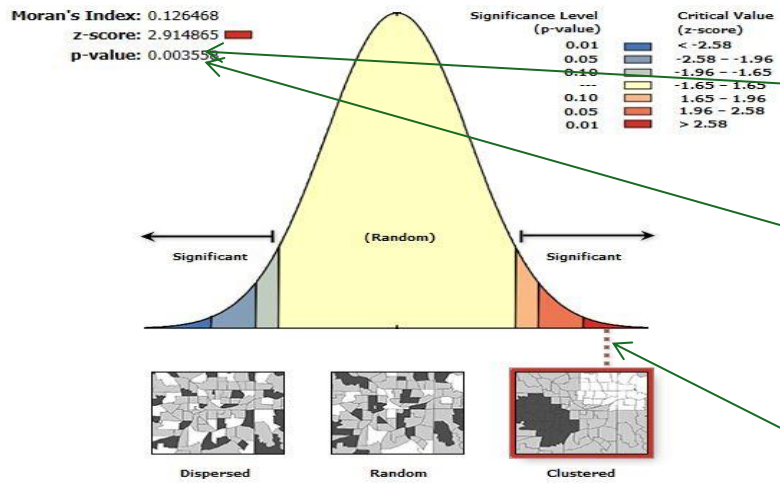
$$W_{ij} = \begin{cases} 1 & \text{if centroid of } j \text{ is one of the } k \text{ nearest centroids to that of } i \\ 0 & \text{otherwise} \end{cases}$$

Results

- Among the weighed sample of 15,239 individuals included in this study, 2876 were had malaria cases, 1951(67.84%) households were in rural.
- Among 8362 females, about 510(17.73%) had malaria cases
- Among 6878 male, 2366(15.53%) have malaria cases.
- 1218(42.35%) were Illiterate ,

Cont'd . . .

- About 1879(65.33%) malaria case were used surface water,
- 32(1.11%) were used tanker water,
- The remaining 965 (33.56%) were had other sources of water.



➤ The Moran's I p-value of is less than 0.05, implies that there exists a significant spatial autocorrelation in risk of malaria disease between regions of the country.

➤ Moran's I index value was positive and indicate, the spatial distribution of malaria disease was significantly

clustered between zones of the country ($p - value < 0.05$)

Fig 1: Spatial Autocorrelation of malaria

The malaria rapid diagnosis test was clustered as high risk in

- Northern Amhara.
- Southwestern parts of Oromiya,
- Western parts of Gambela.
- Eastern and middle parts of Tigray.
- Western part of Afar,
- and central part of Somali regional states of Ethiopia

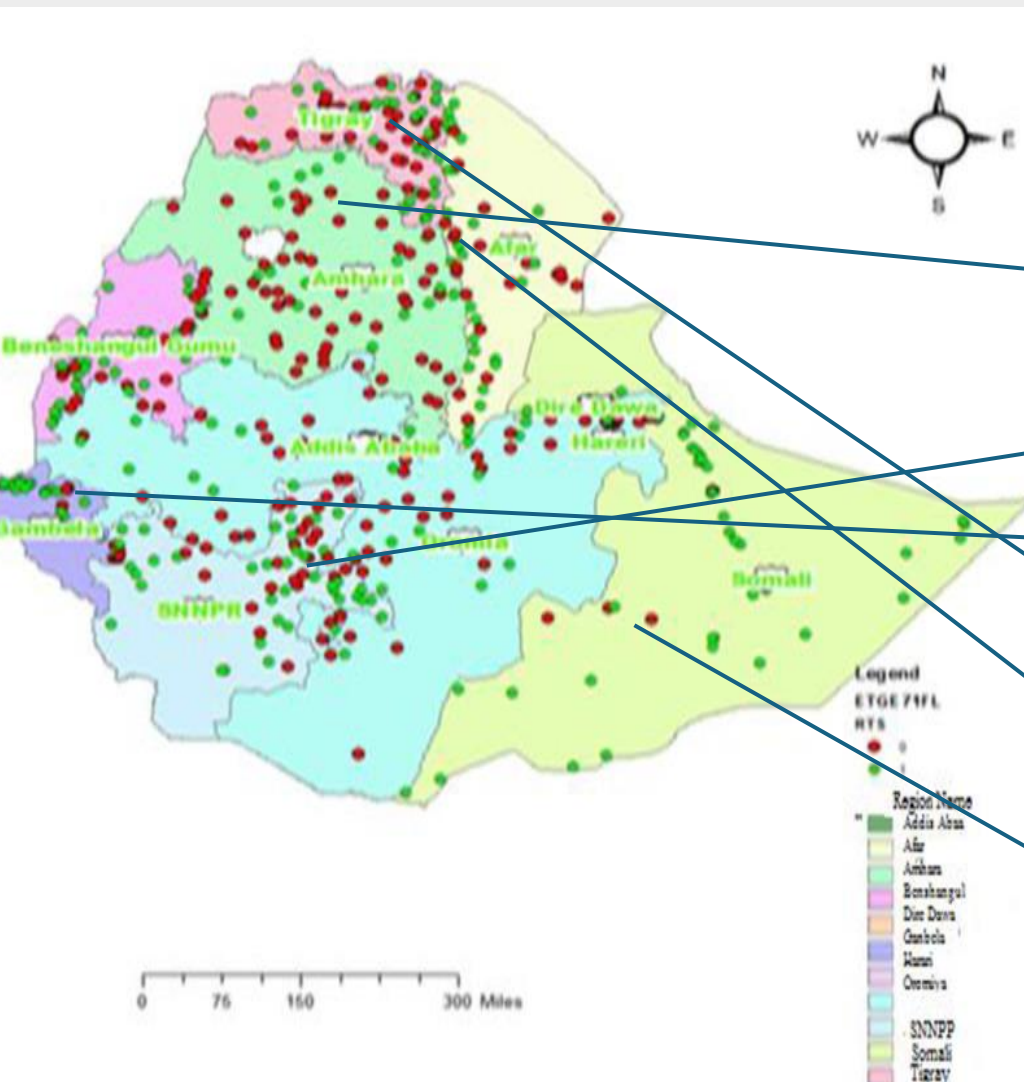
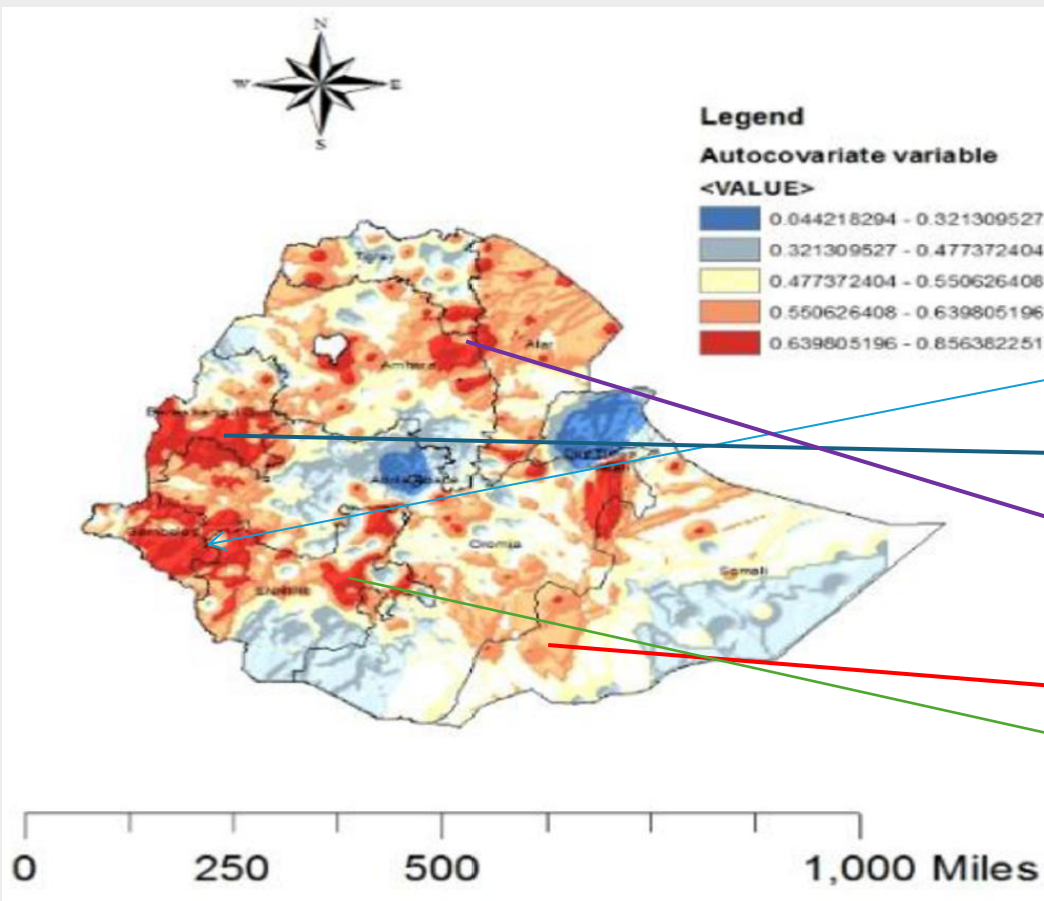


Fig 2: Spatial distribution of Malaria in Ethiopia



➤ Spatial autocorrelation of malaria is almost predictable as human populations live in spatial clusters rather than in random distributions of regions.

➤ Gambella,

➤ Beneshangul Gumuz,

➤ The common boundary of Afar and Amhara,

➤ The west part of Somalia

➤ and Oromiya in the south and east region were at high risk.

Fig 3: Predicted spatial effects from the malaria case in Ethiopia, from EMIS 2015.

Cont'd . . .

The spatial effect had a positive significant effect on malaria cases,

where districts with **lower levels of patient** status were usually surrounded by districts with **lower levels of patient** status.

and that districts with a **higher incidence of malaria cases** were usually surrounded by districts with a **higher incidence of malaria**.

From the model result the transmission of malaria infection by:

- the mosquitoes over space
- The effects of socio-economic
- The demographic variables
- Geographic variable
- types of toilet use and place of residence
- Source of water used

are highly associated with transmission of malaria that determines the survival of mosquito over large areas/malaria cases



Conclusions

- Considering the space variations and factors would be useful for the prevention, control and ultimately achieve elimination targets in the area.
- Spatial clustering of malaria cases has occurred in all regions, but the risk of clustering was different across the regions/areas.
- protected anti-mosquito net was reducing the risk of malaria incidence.

Cont'd . . .

- The risk of malaria was found to be higher for those who live in soil floor-type houses as compared to those who lived in cement or ceramics floor type.
- To provide clean drinking water, proper hygiene and maintaining the good condition of a house is essential in controlling the transmission of malaria.

Recommendations

- Concerned body shall use spatial statistics results for **monitoring and identifying high-rate malaria affected regions** and helpful when implementing preventative measures.
- Being able to determine areas and predict malaria onset can help policies makers to target actions at the right time and at the right places.

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Thank you

