

Modeling the health impacts of time-varying climate factors: heat and mortality

Josiah Kephart, PhD MPH
Assistant Professor
Drexel University

SALURBAL Meeting, Mexico City
March 2023

(special thanks to Prof. Brisa Sanchez)

Introduction

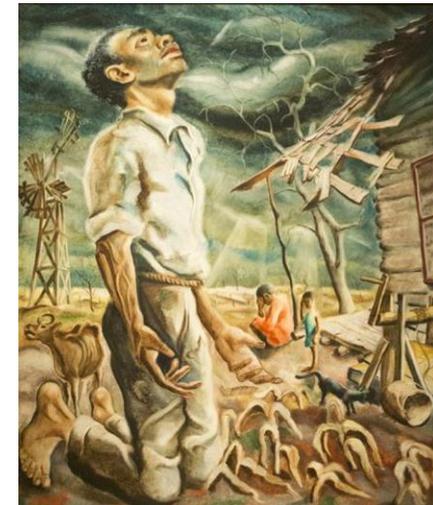
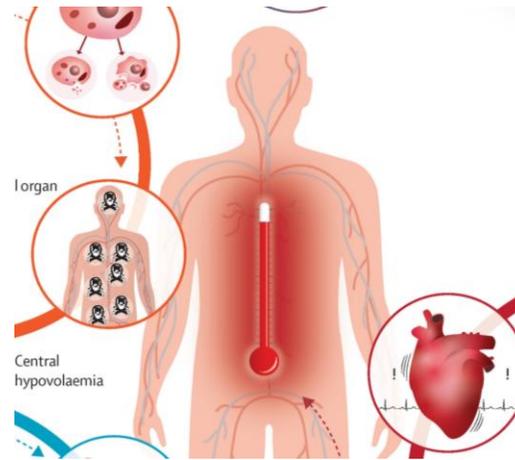
1. Common challenges in climate and health research
 - Example: Heat and mortality
2. Distributed lag non-linear models (DLNM)
3. Demonstration: MS85, heat and mortality
4. Resources



Climate and health: common challenges

CDMX
2023

1. Effects not always immediate
 - Time-scale: ???



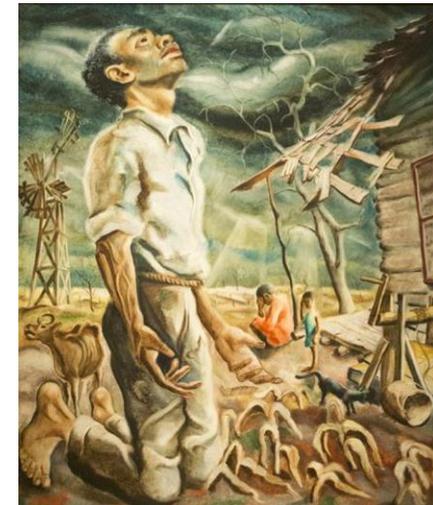
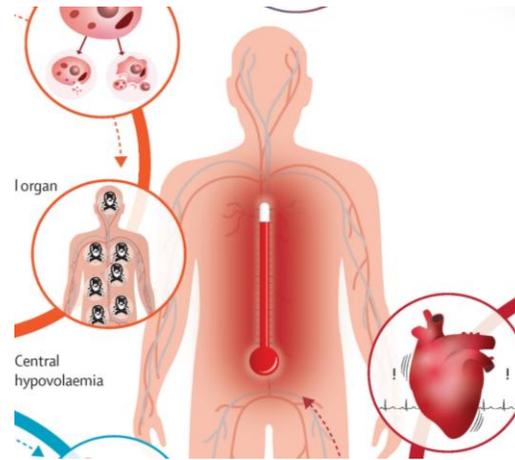
Wikimedia commons. Joseph Vorst.



Climate and health: complex associations

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2023

1. Effects not always immediate
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2. Weather vs. climate?

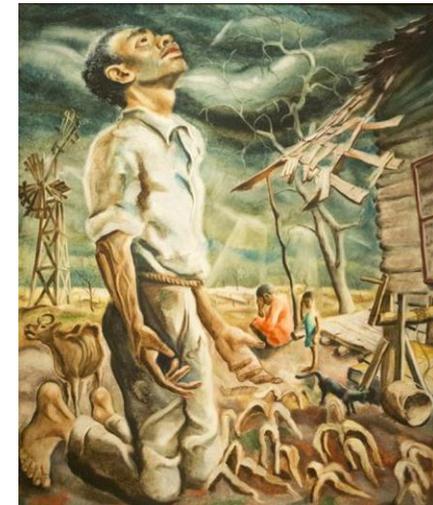
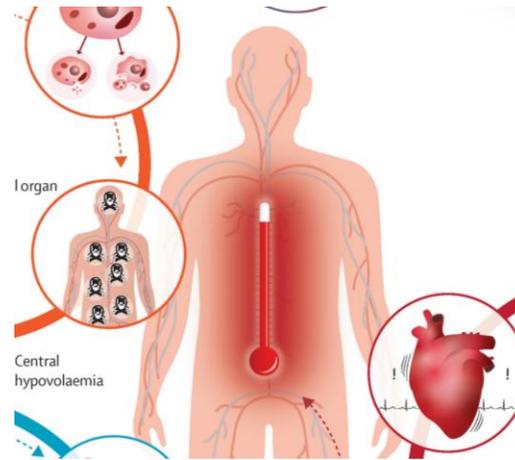


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Climate and health: complex associations

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1. Effects not always immediate
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3. Dramatic differences in exposure profiles by area

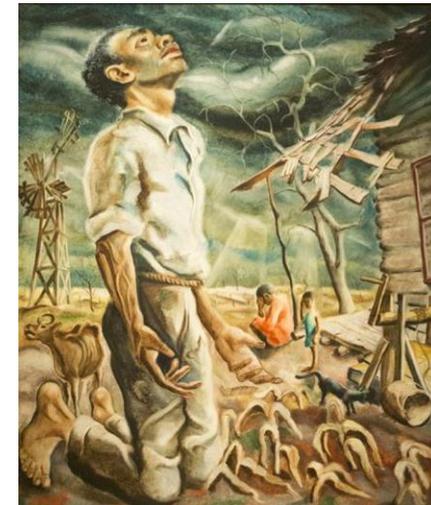
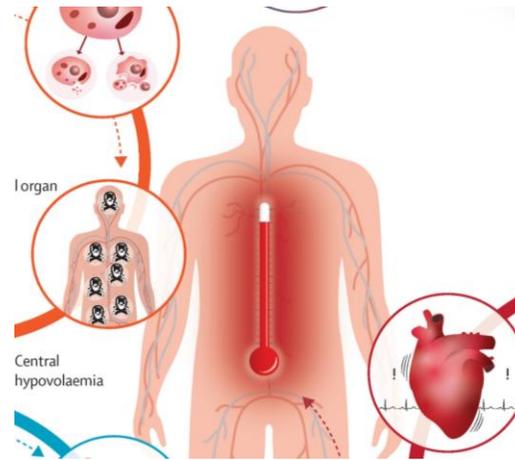


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Climate and health: complex associations

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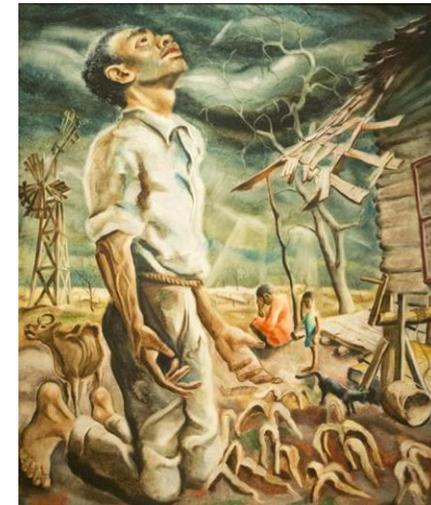
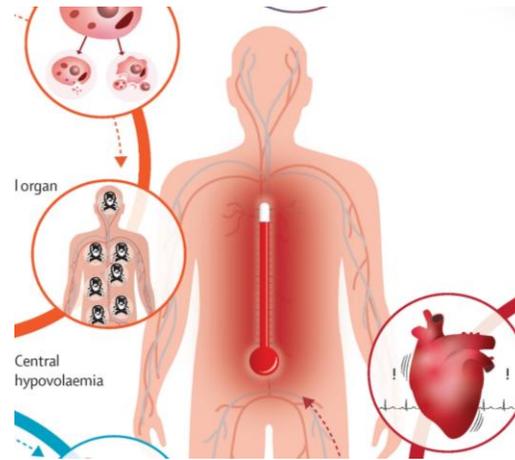
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4. Wide range of presentation and outcomes (direct and indirect)



Climate and health: complex associations

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1. Effects not always immediate
 - Time-scale: ???
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3. Dramatic differences in exposure profiles by area
4. Wide range of presentation and outcomes (direct and indirect)
5. Exposure added to underlying vulnerabilities



Heat: growing challenge to urban health

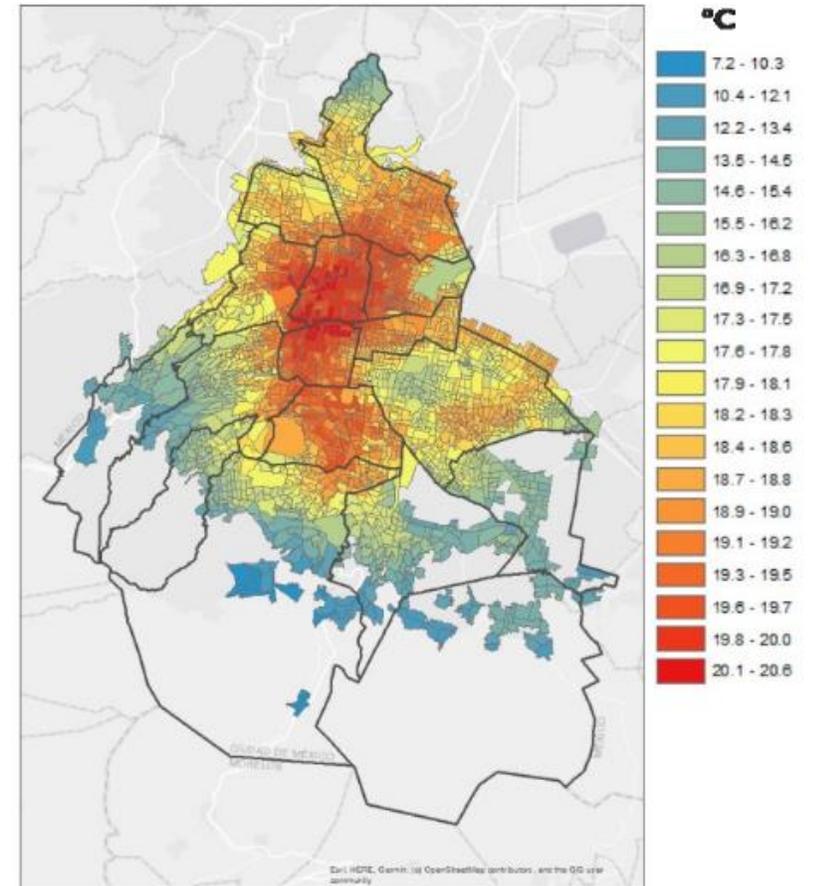
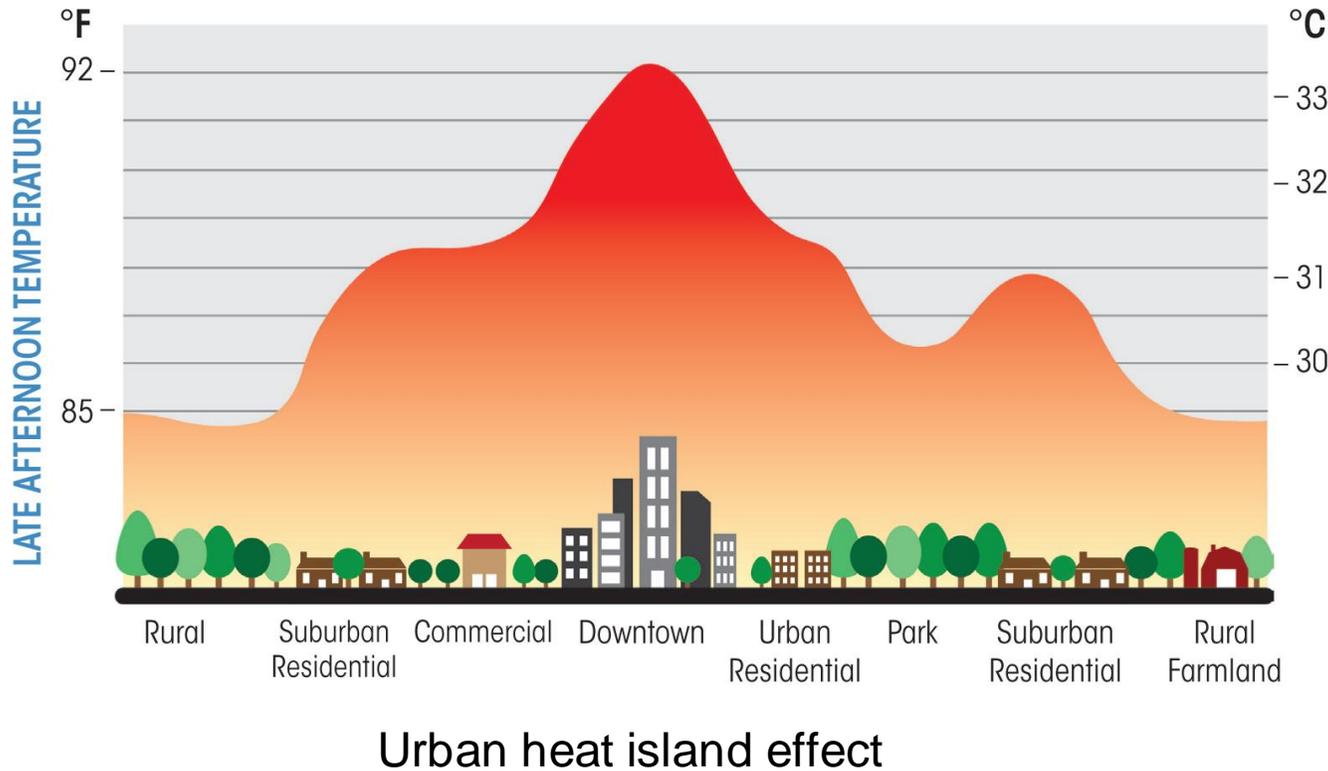


Figura 7. Mapa de temperaturas superficiales nocturnas

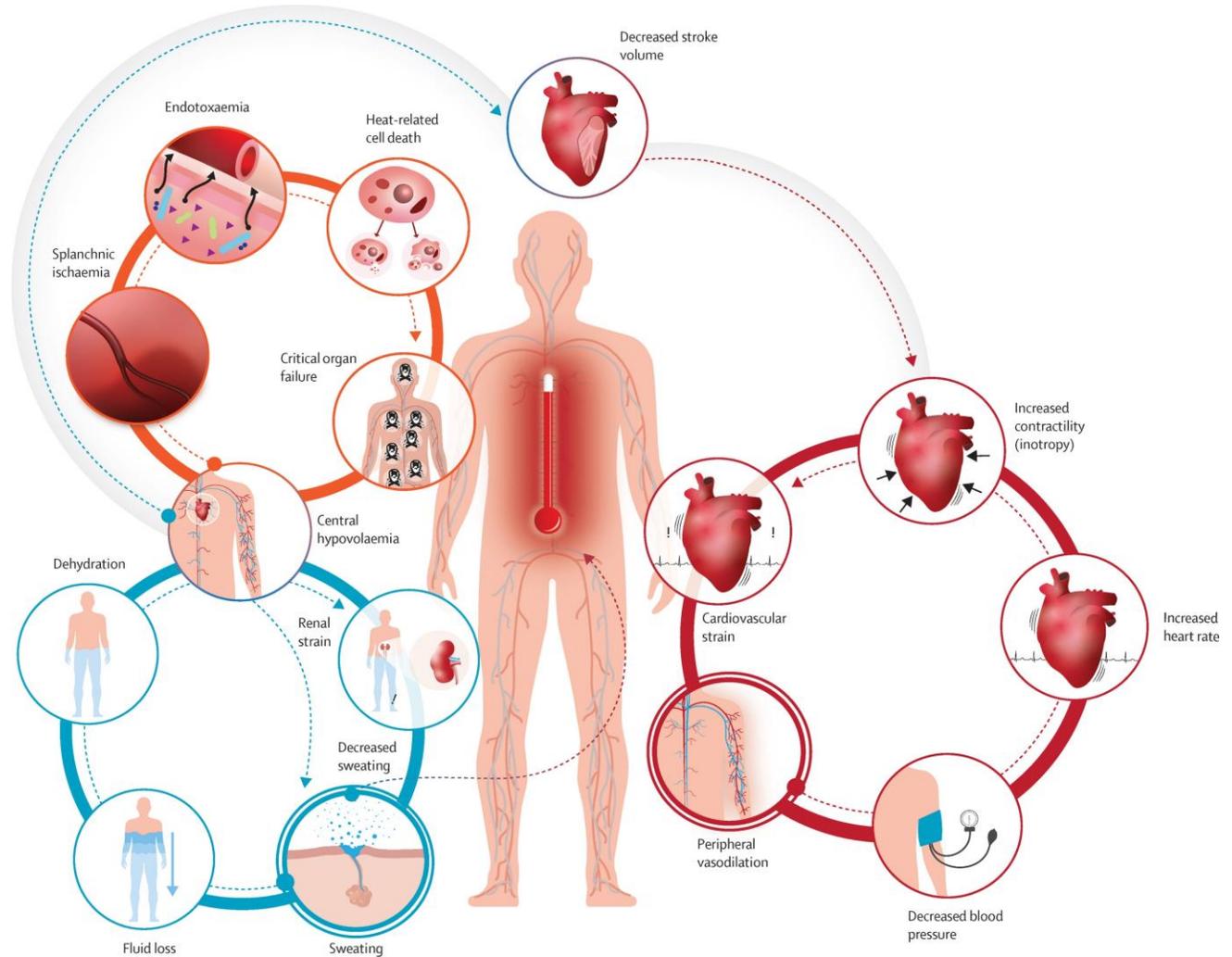


Heat effects the body systemically

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- Dehydration
 - Renal strain
- Cardiovascular strain
 - Vasodilation
 - Decreased blood pressure
 - Increased heart rate
- Cell death
 - Organ failure
- Others....

(Distinct health impacts from cold)



Temperature and health: common challenges

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1. Effects not always immediate
 - up to 21 days after exposure
2. Weather vs. climate
 - Setting up analysis for policy impact
3. Dramatic differences in exposure by area
 - Climate (between city)
 - Urban heat island (within city)
4. Wide range of presentation and outcomes
 - All-cause mortality, CV, respiratory, homicide, drowning, etc.
5. Exposure added to underlying vulnerabilities
 - Age
 - SES: occupation, air conditioning, etc
 - Underlying disease
 - (mixed findings about gender and correlation with age)

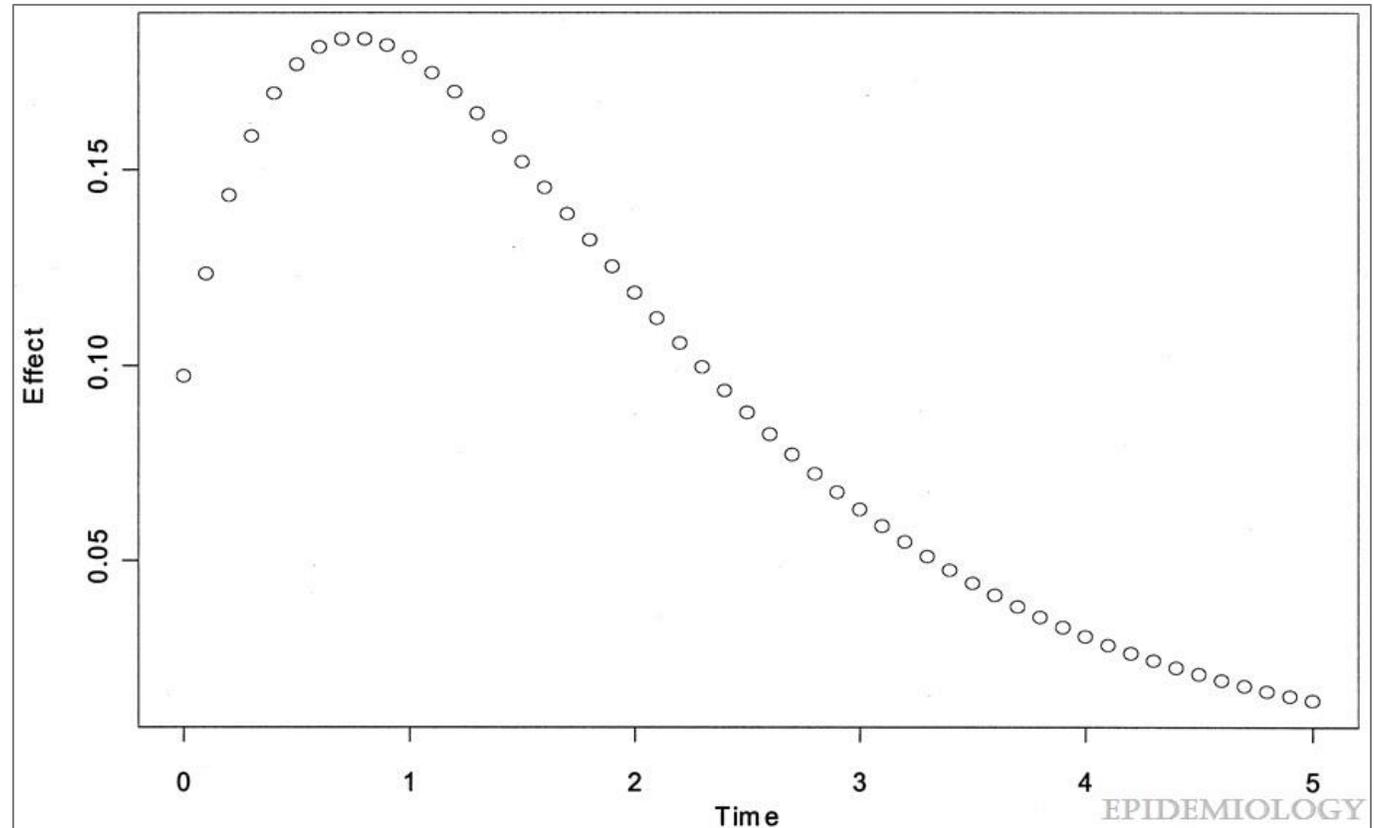


Addressing non-linear exposure-health lags: distributed lag non-linear models

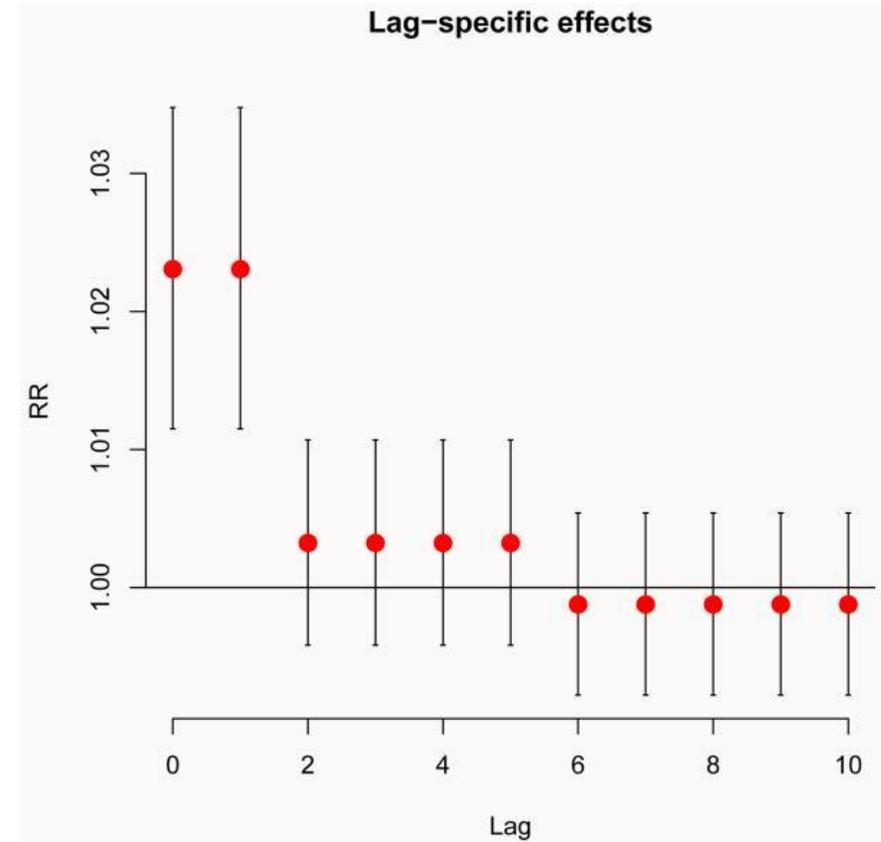
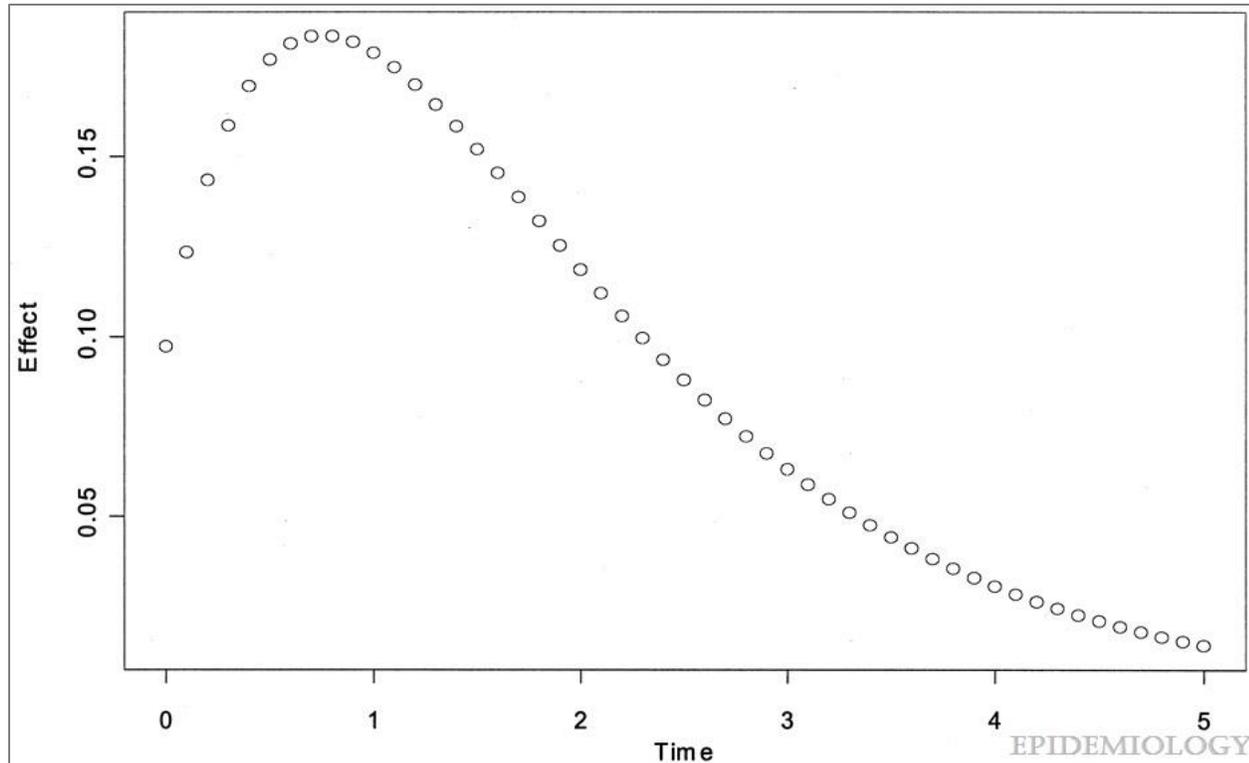


Challenge: physiological lag between exposure and outcome

What we might hypothesize for heat and mortality



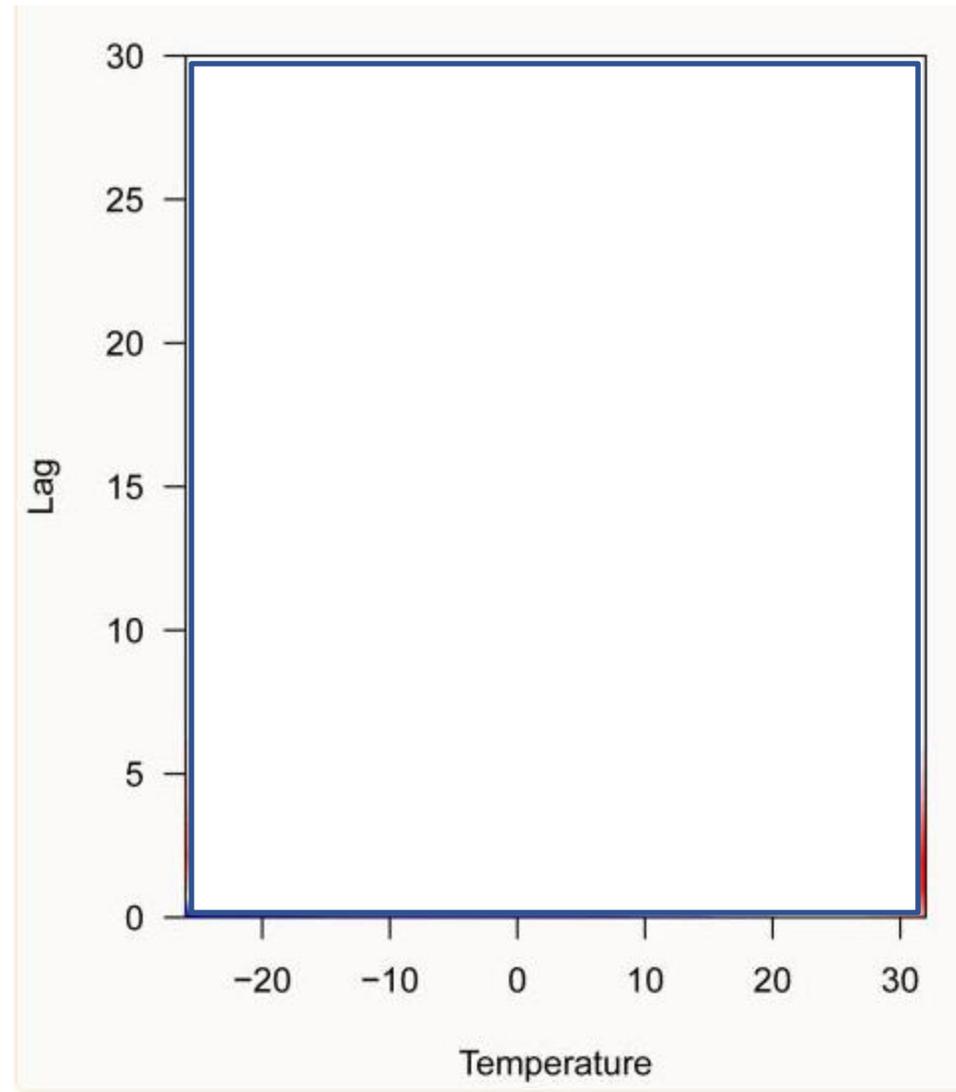
Common approaches have limitations



Example: lagged exposure to heat

Two-dimensions:

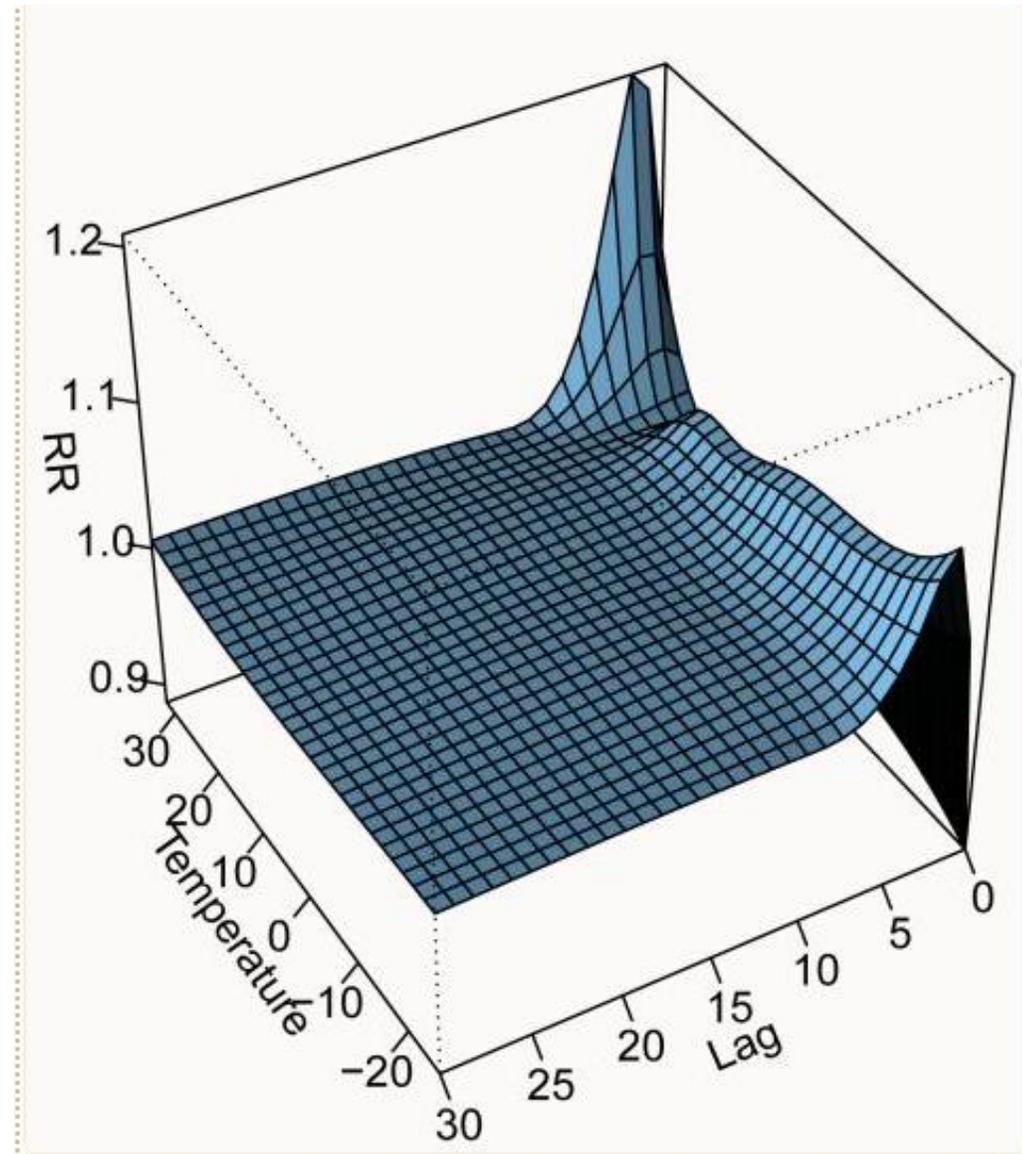
- Temperature
- temporal lag



Example: lagged exposure to heat

Three dimensions, all non-linear:

- Temperature
- temporal lag
- Relative risk

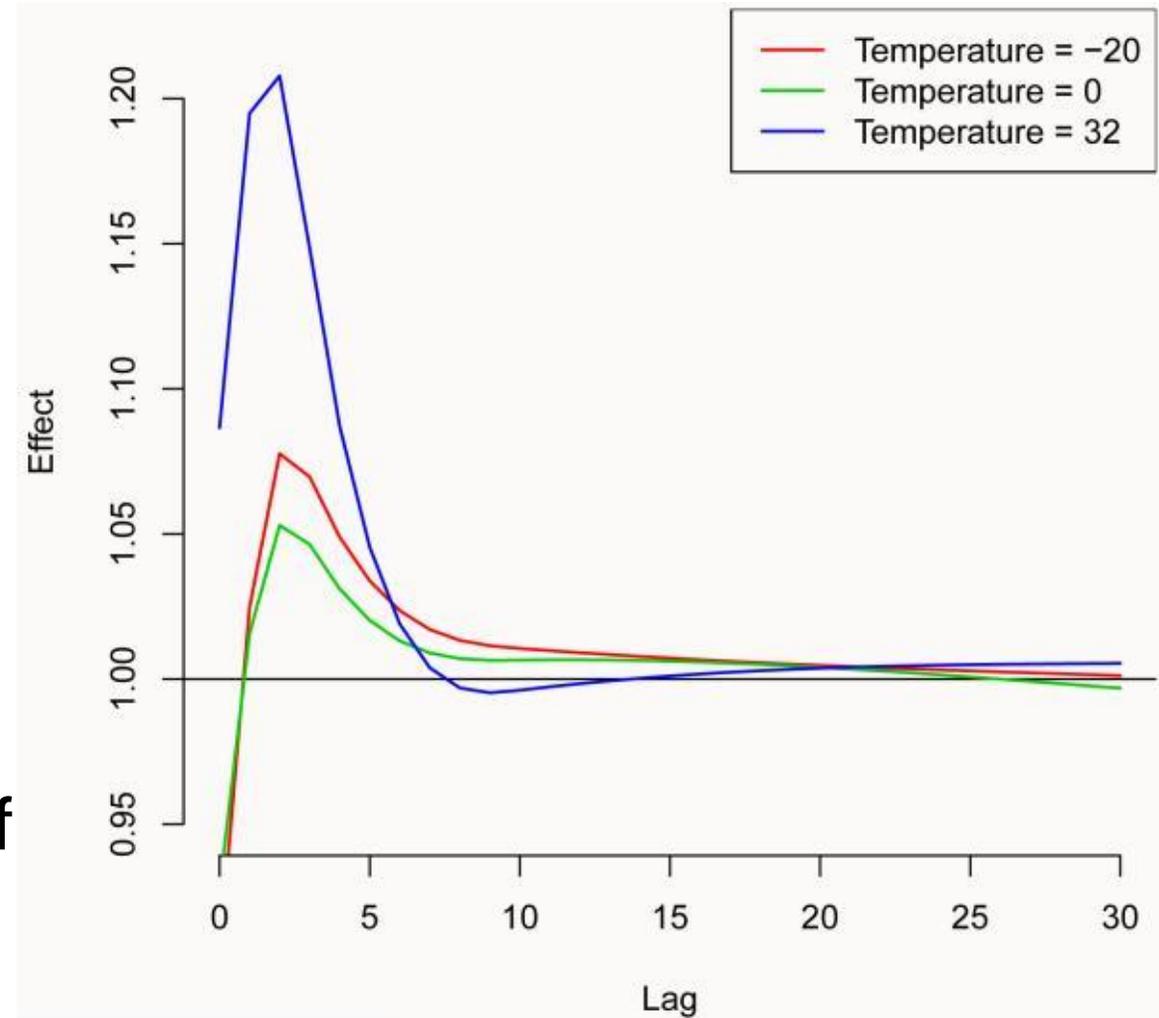


Example: lagged exposure to heat

Associations of lag and RR

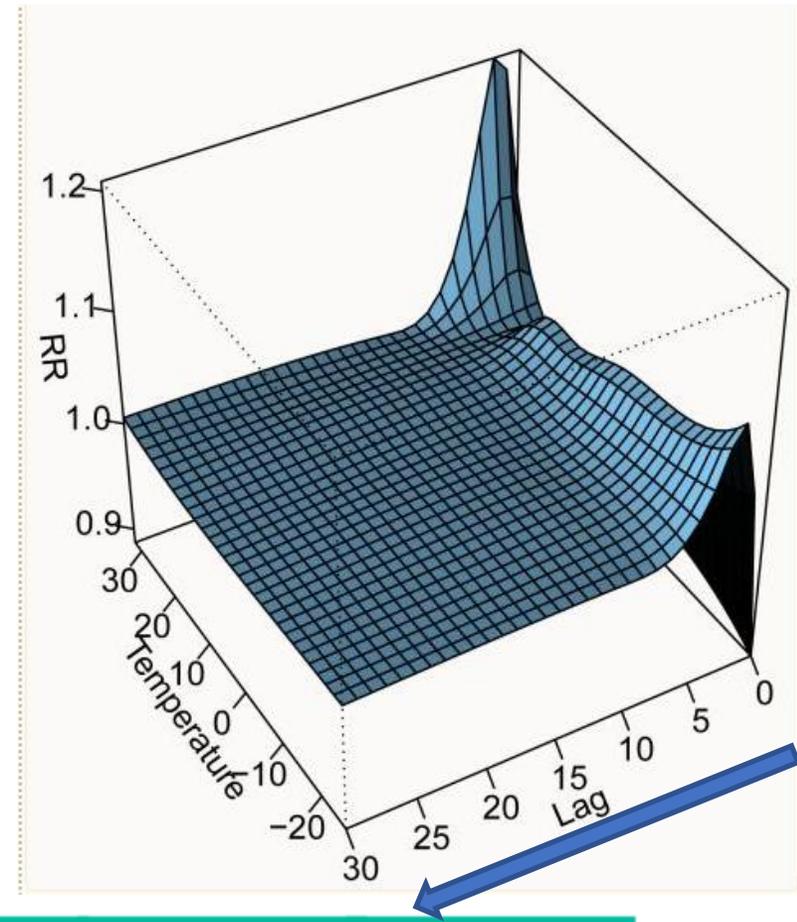
- Non-linear
- Vary by temperature

Need to model joint effect of
1) temperature and 2) lag



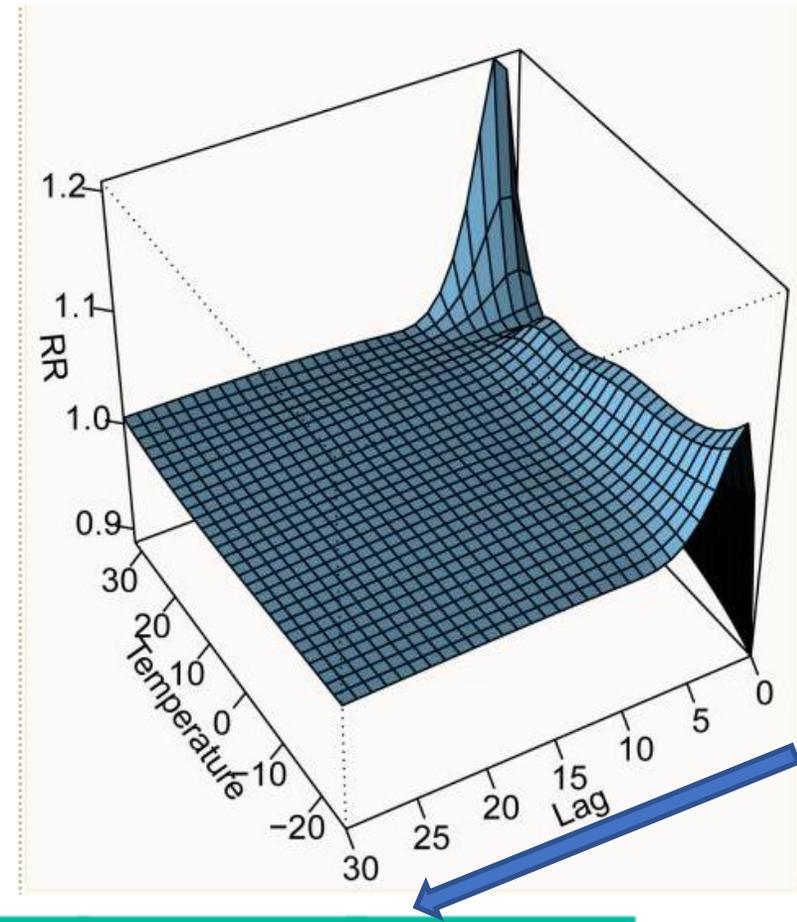
Distributed lag non-linear models

- Start with: joint distribution of relative risk across lags and temperature
- “Sum” relative risk (RR) across all lags
 - While accounting for uncertainty
- Cumulative RR across all lags
- Efficient way to model non-linear effects and uncertainty separately across
 - Lags
 - Temperature



Distributed lag non-linear models

- Reduces a dimension by collapsing lags into cumulative risk across lag period, for each temperature
 - Makes possible to do meta-analysis of outputs
- Can be applied to a variety of models
 - Case-crossover
 - Conditional Poisson
 - GEE, GLM, GAM families



Example analysis: MS85

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ARTICLES

<https://doi.org/10.1038/s41591-022-01872-6>

nature
medicine



OPEN

City-level impact of extreme temperatures and mortality in Latin America

Josiah L. Kephart ¹✉, Brisa N. Sánchez², Jeffrey Moore², Leah H. Schinasi^{1,3}, Maryia Bakhtsiyarava⁴, Yang Ju⁵, Nelson Gouveia ⁶, Waleska T. Caiffa⁷, Iryna Dronova⁸, Saravanan Arunachalam⁹, Ana V. Diez Roux^{1,2,10} and Daniel A. Rodríguez^{4,10}



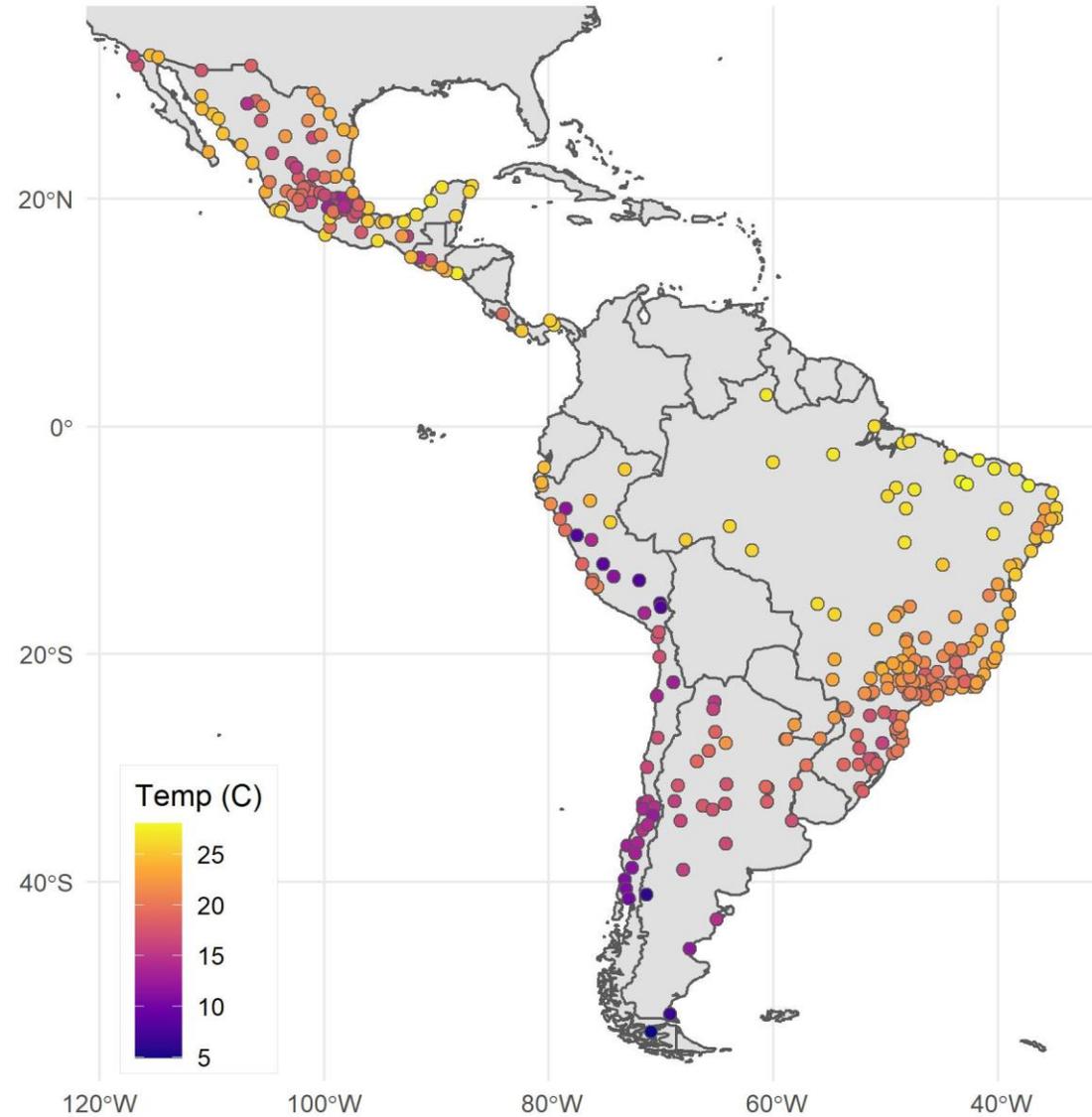
Aims

- 1) What is the relationship between **ambient temperature and all-cause mortality**?
- 2) Does this relationship vary by **age**?
- 3) Does this relationship vary by **cause of death**?
 - Cardiovascular
 - Respiratory Diseases (non-communicable)
 - Respiratory Infections

Study setting

- 326 cities from SALURBAL project
 - Argentina, Brazil, Chile, Costa Rica, El Salvador, Guatemala, Mexico, Panama, Peru
 - >230 million residents
- Exposure: Temperature
 - ERA5-Land, ~9km horizontal grid resolution
 - Population-weighted daily mean temperature
- Outcome: Mortality
 - Individual-level, age and cause of death (ICD-10)
 - Aggregated to city-level daily mortality counts
 - 15 million + deaths
 - 2.9 billion person-years of risk

Annual mean temperature in 326 study cities



Modelling approach: two phases

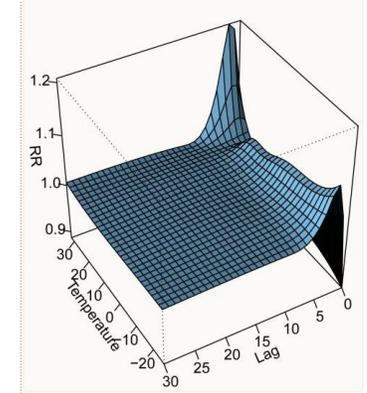
- Phase 1: City-specific estimates
 - Distributed lag non-linear models
- Phase 2: Stabilizing/smooth city curves
 - Meta-analysis of Phase 1 outputs

Phase 1: City-specific estimates

1. Create time series
 - Daily city mean temperature
 - Daily city-wide death count
 - Aggregated by age and cause

Phase 1: City-specific estimates

1. Create time series
2. Conditional Poisson models
 - Distributed lag (0-21 days)
 - Cumulative effect over lag period
 - Nonlinear temperature-mortality
 - Natural cubic spline
 - Knots
 - 10, 75, 90 percentiles
 - min, max
 - Log(annual city population) as offset



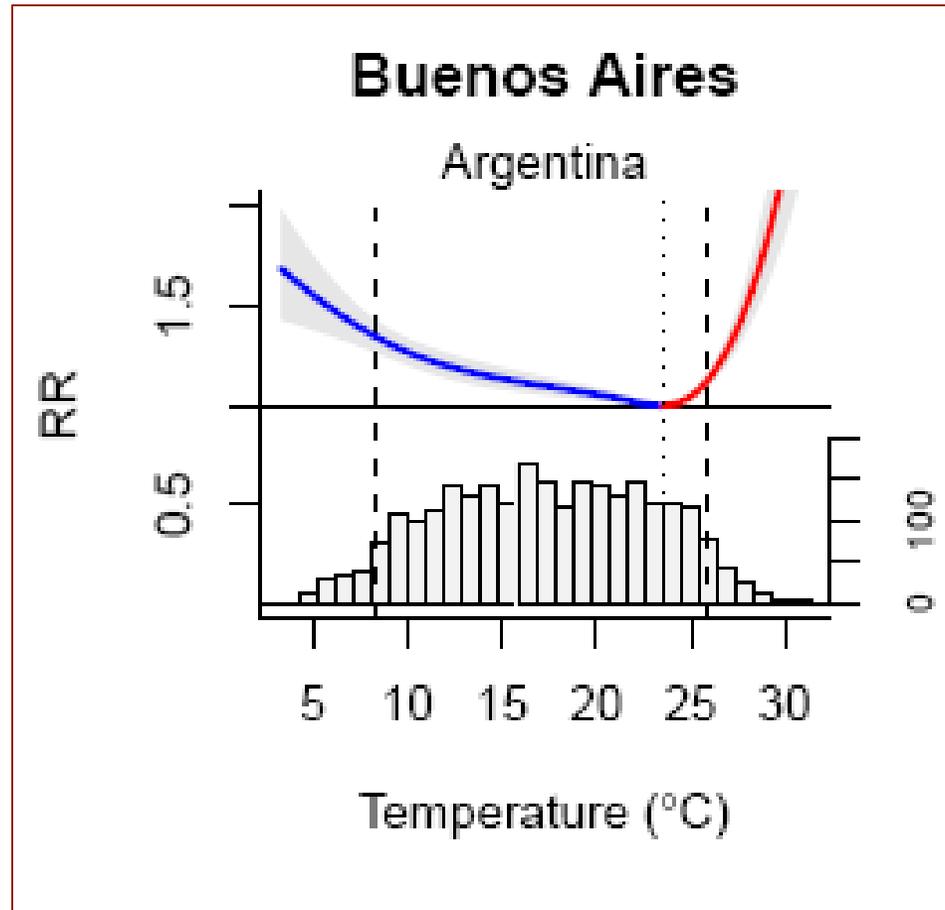
Phase 1: City-specific estimates

1. Create time series
2. Conditional Poisson models
 - Distributed lag (0-21 days)
 - Nonlinear
 - Log(annual city population) as offset
 - Temporal/seasonal adjustment
 - Day of week
 - Calendar month
 - Year
 - Goal: impacts of short-term temperature variability

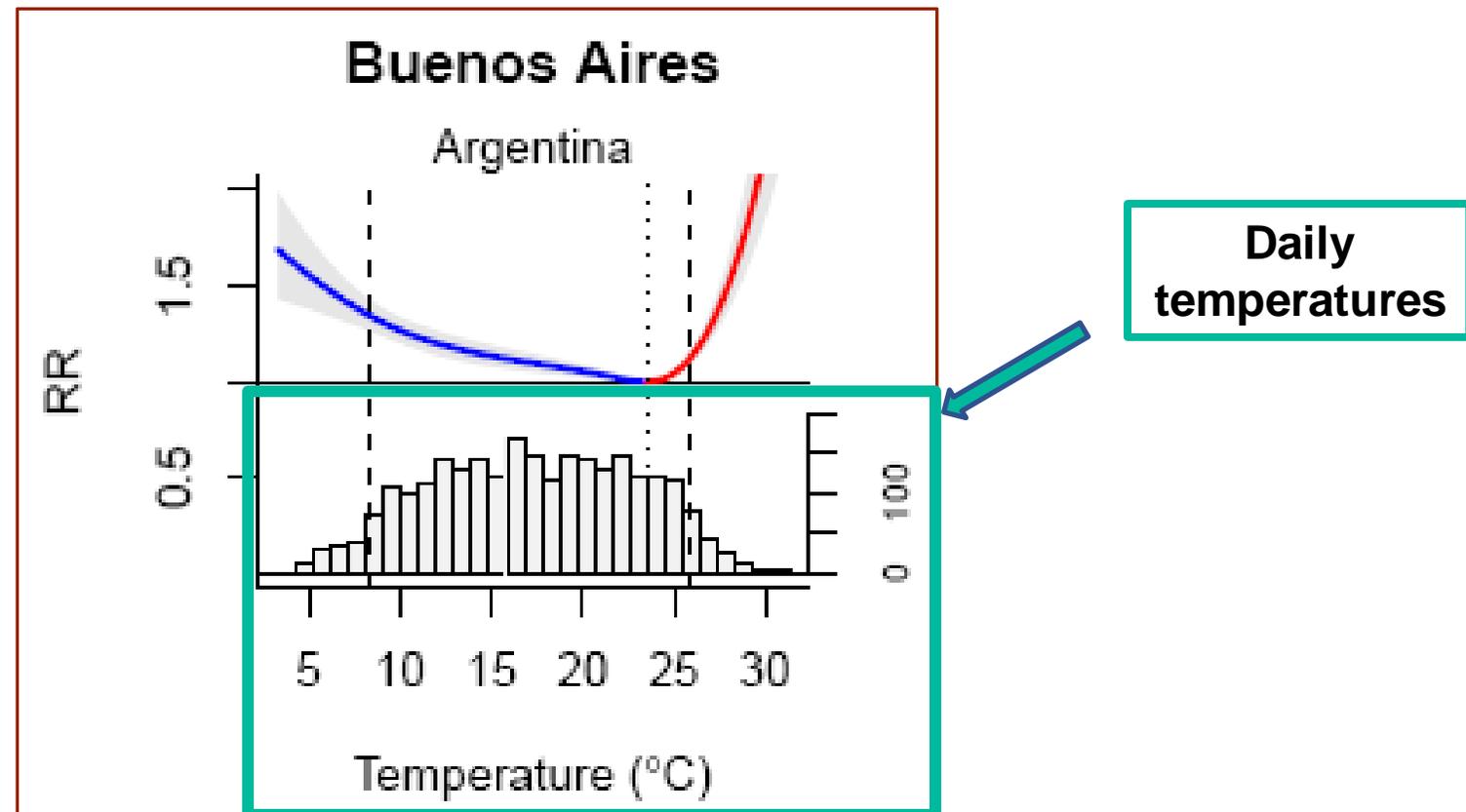
Phase 2: Stabilize city-specific estimates

- Stabilize/smooth city-specific curves
 - Small N of daily deaths in many cities
 - Random effects meta-analysis
 - Dependent variables
 - Spline coefficients (N=4) of temp-mortality association
 - Meta-predictors
 - City temp: median, range
 - Country
 - Best Linear Unbiased Prediction (BLUP)
 - Balances raw city-curve with pooled curve

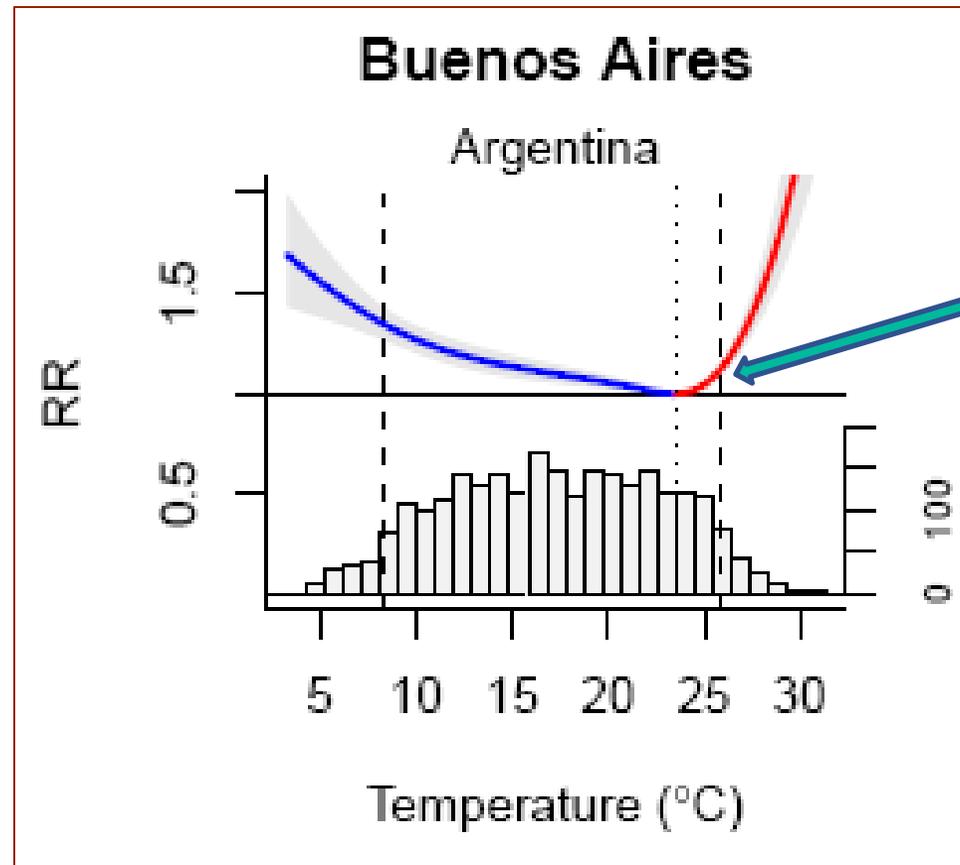
City-specific temperature-mortality curves



For each city: distribution of daily temperatures



For each city: defining optimal temperature



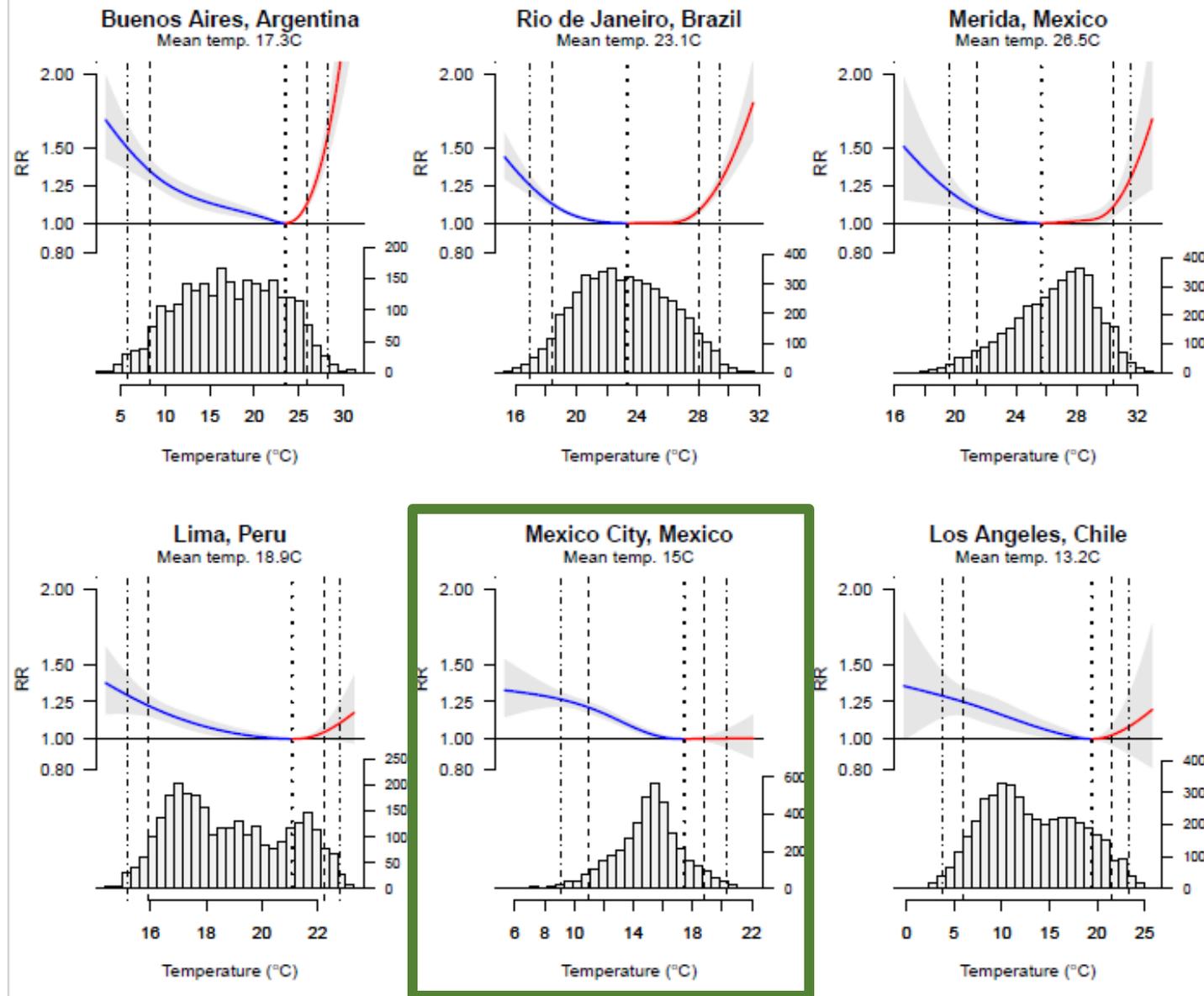
Optimal temperature



For each city: temperature- mortality curve

Wide variation between cities:

- Temp. range
- Temp. variability
- Temp.-mortality curve



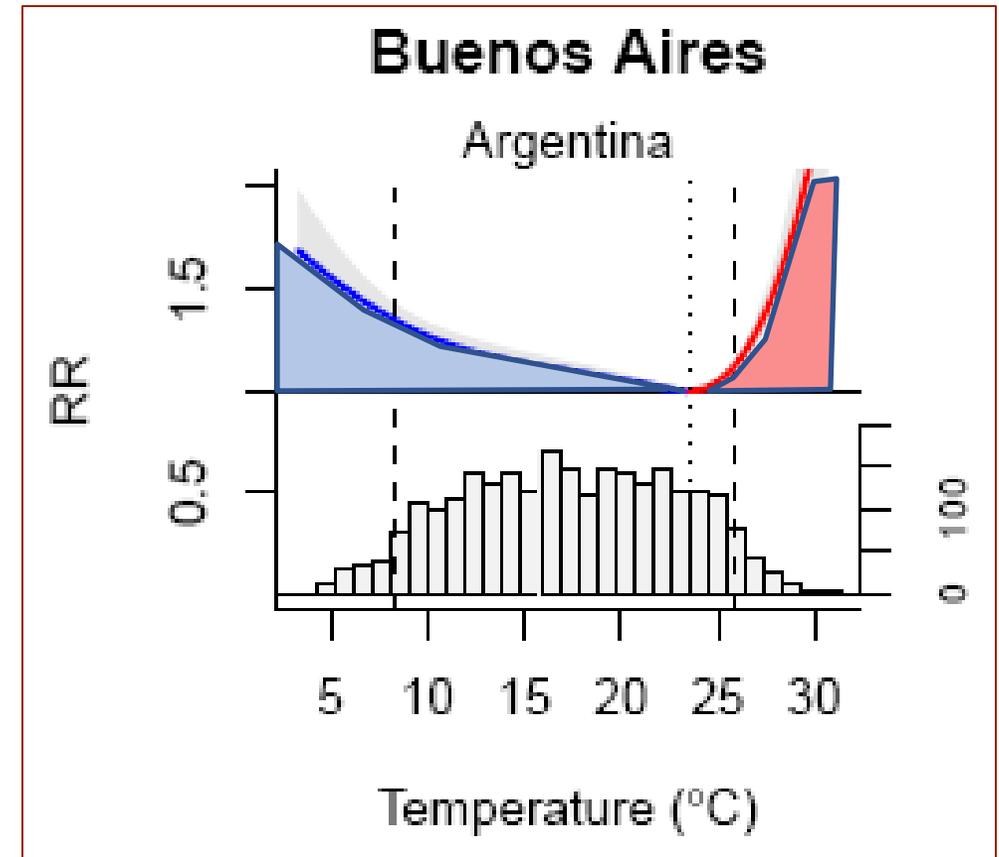
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2023



For each city: temperature-mortality burden

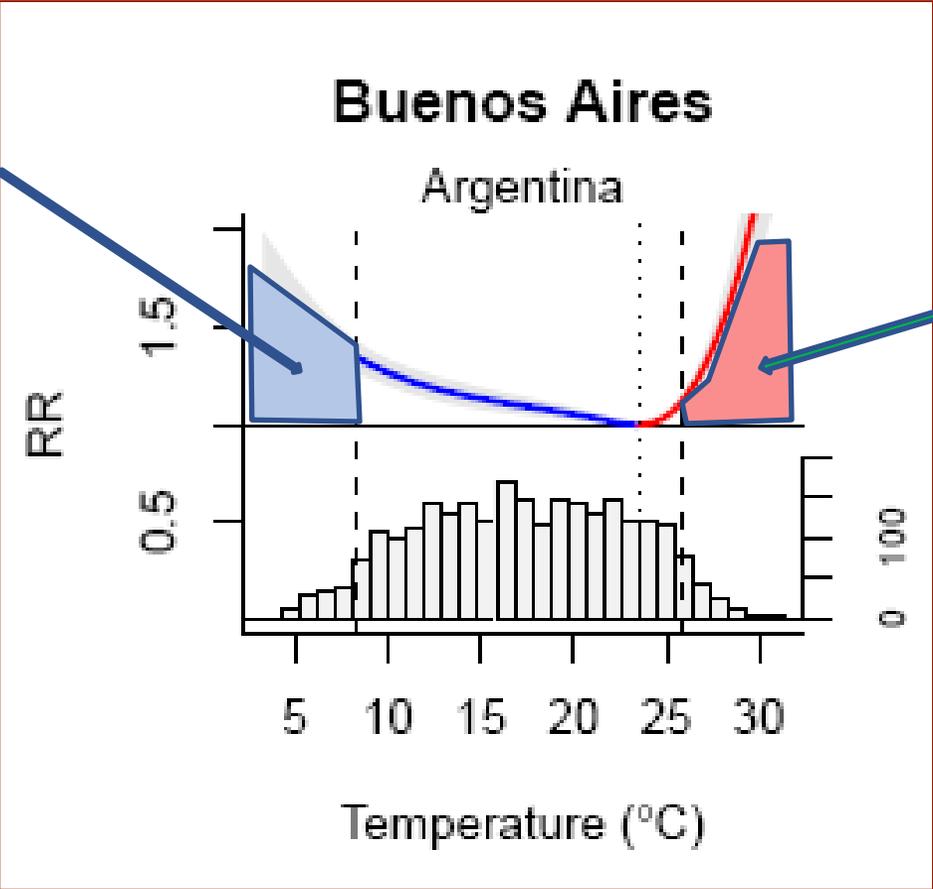
1. Excess death fraction

- % of total deaths explainable by ambient temperature
- Also known as “attributable fraction”



Option: limiting to “extreme” temperatures

Cumulative risk of extreme cold (< 5th percentile)

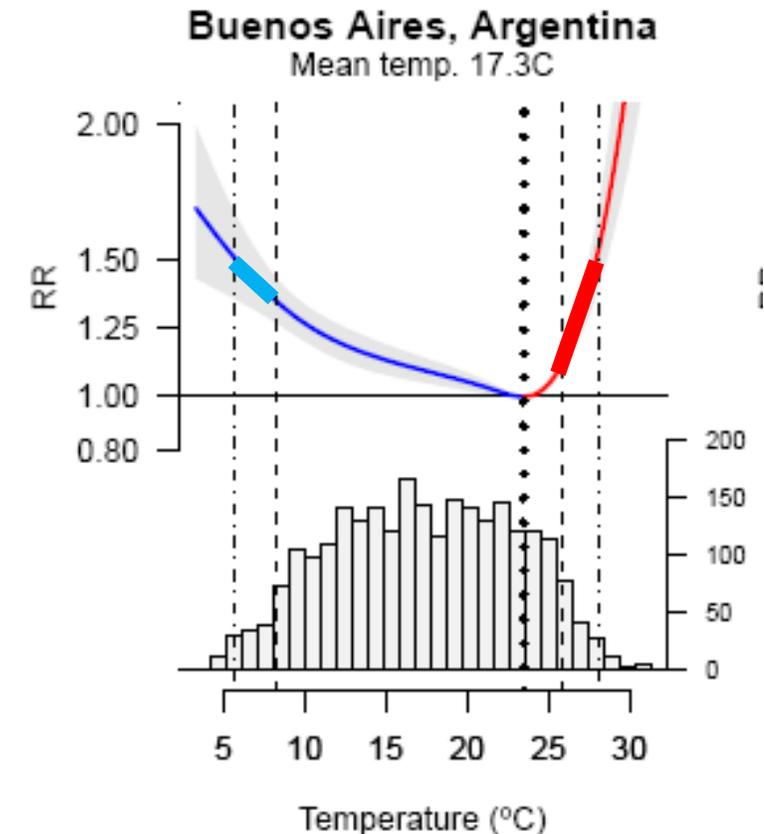


Cumulative risk of extreme heat (> 95th percentile)



Methods: Outputs

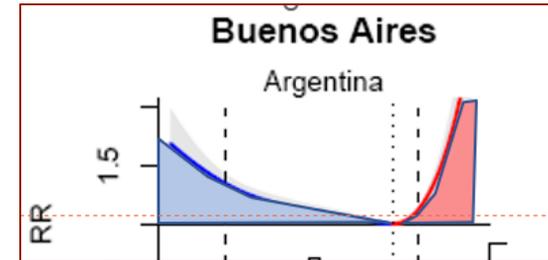
- 1) Excess death fraction
- 2) Change in **relative risk per 1°C change** under extreme temperatures
 - Change in RR / change in degrees,
 - Extreme heat
 - P95 vs. P99
 - Extreme cold
 - P5 vs. P1



Combine city outputs into overall effects

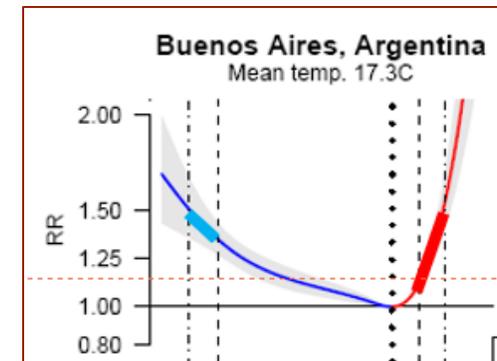
1. Excess death fraction

- Sum deaths across cities
 - Heat (> optimal temp.)
 - Cold (< optimal temp.)
 - Extreme heat (> P95)
 - Extreme cold (< P5)



2. Change in relative risk per 1°C change under extreme temps

- Meta-analysis of city effects
 - Extreme heat: P95 vs. P99
 - Extreme cold: P5 vs. P1



Results: excess death fractions (%)

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Percent of total deaths explainable by ambient temperatures

Heat*

All	<u>0.67%</u>	(0.58% to 0.74%)
Age 65+	<u>0.81%</u>	(0.75% to 0.86%)

Cold*

All	<u>5.09%</u>	(4.64% to 5.47%)
Age 65+	<u>6.82%</u>	(6.41% to 7.18%)

*Cumulative effect of temperatures above/below the city-specific optimal temperature



Understanding heat vs. cold

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Percent of total deaths explainable by ambient temperatures (excess death fraction)

Heat*

All **0.67%** (0.58% to 0.74%)

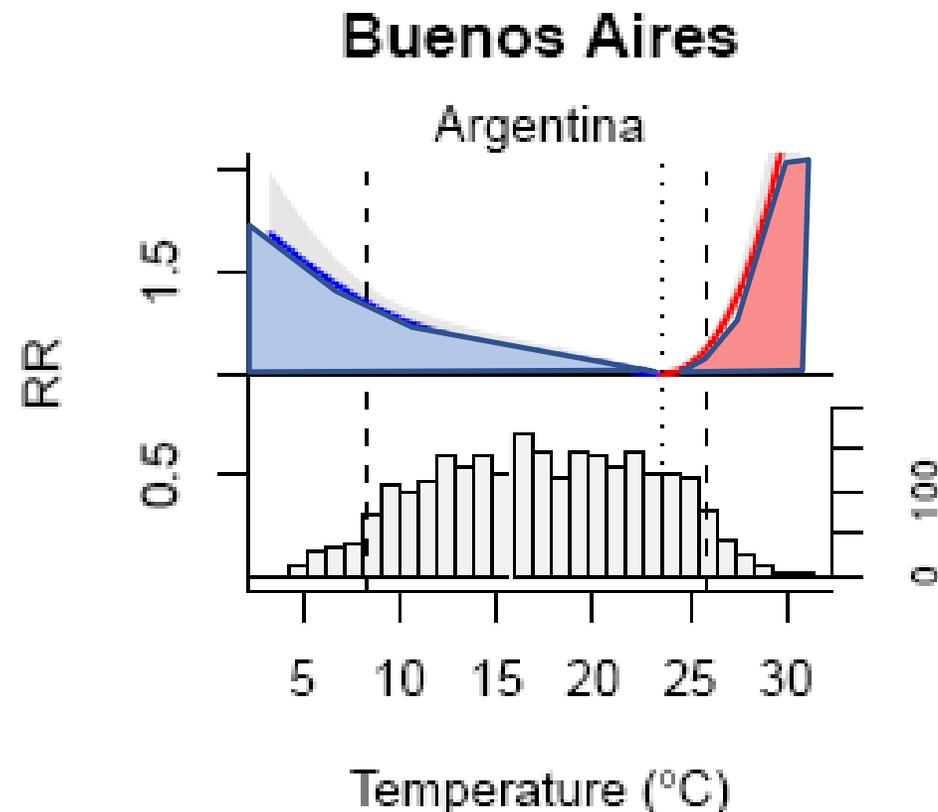
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*Cumulative effect of temperatures above/below the city-specific optimal temperature



Results: excess death fractions (%)

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	All Heat	Extreme Heat ²	All Cold	Extreme Cold ³
All Cause				
All Ages	0.67% (0.58, 0.74)	0.42% (0.38, 0.45)	5.09% (4.64, 5.47)	1.03% (0.99, 1.06)
Ages 65+	0.81% (0.75, 0.86)	0.55% (0.5, 0.59)	6.82% (6.41, 7.18)	1.36% (1.31, 1.39)
Cardiovascular				
All Ages	0.69% (0.64, 0.74)	0.38% (0.36, 0.4)	8.43% (7.79, 9.01)	1.52% (1.48, 1.55)
Ages 65+	0.75% (0.68, 0.82)	0.42% (0.38, 0.44)	9.35% (8.35, 10.13)	1.66% (1.59, 1.71)
Respiratory Disease				
All Ages	1.1% (1.02, 1.18)	0.54% (0.5, 0.57)	9.62% (8.55, 10.39)	1.58% (1.51, 1.63)
Ages 65+	1.28% (1.13, 1.4)	0.61% (0.55, 0.65)	9.31% (8.71, 9.78)	1.64% (1.56, 1.69)
Respiratory Infections				
All Ages	1.56% (1.28, 1.81)	0.81% (0.77, 0.84)	10.53% (9.68, 11.2)	1.92% (1.86, 1.97)
Ages 65+	1.84% (1.67, 1.95)	0.98% (0.92, 1.02)	11.79% (10.3, 12.8)	2.01% (1.9, 2.07)



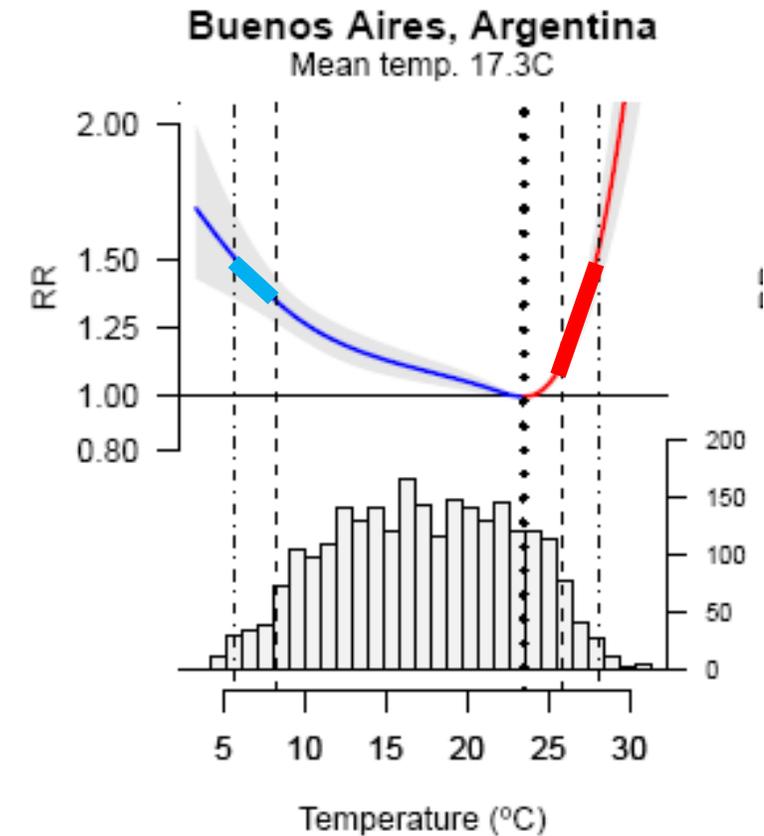
Change in relative risk of mortality per 1°C increase above 95th percentile daily temperature

RR per degree hotter than 95% percentile

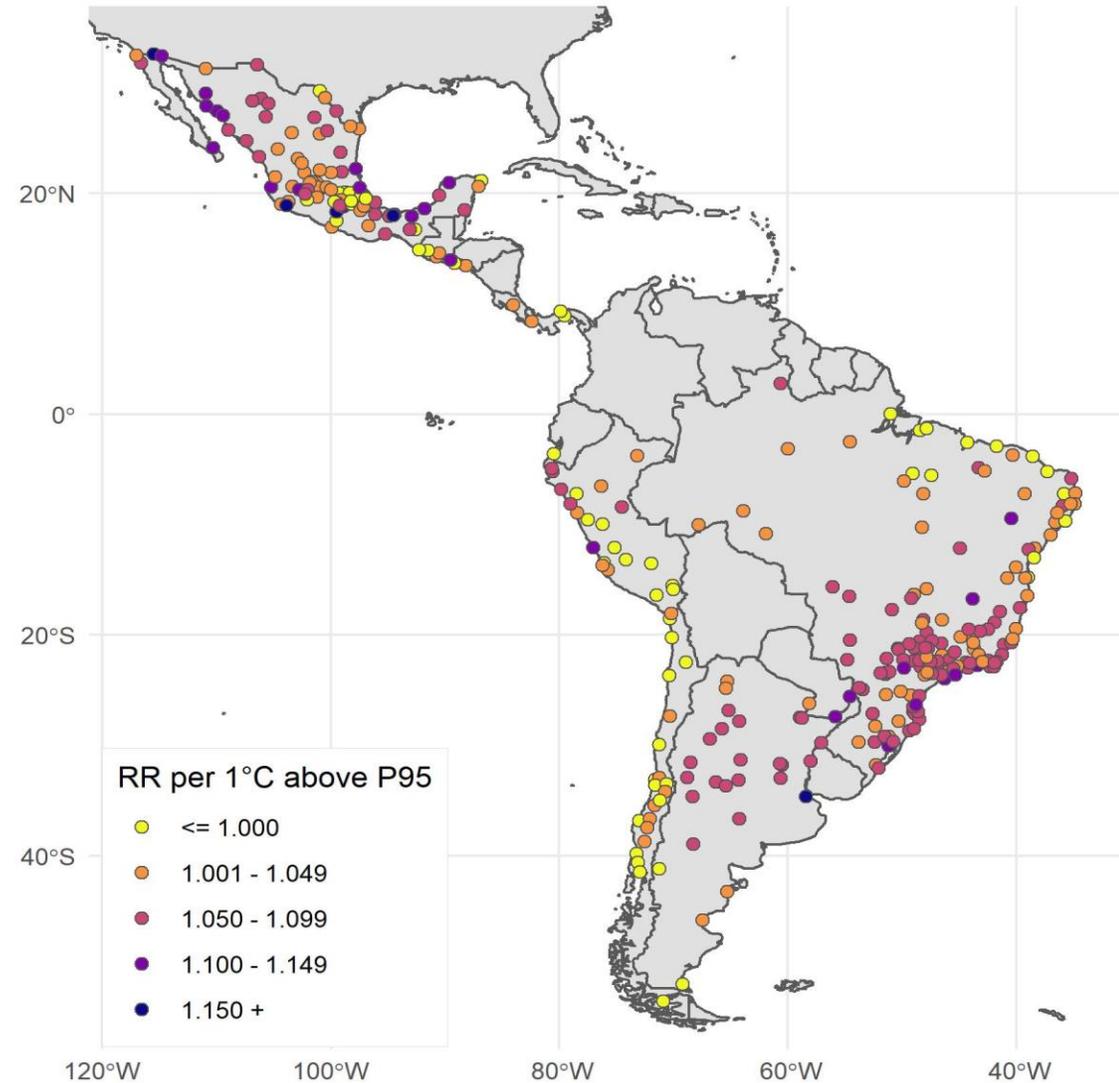
5.7% (4.6 to 6.7)

RR per degree colder than 5th percentile

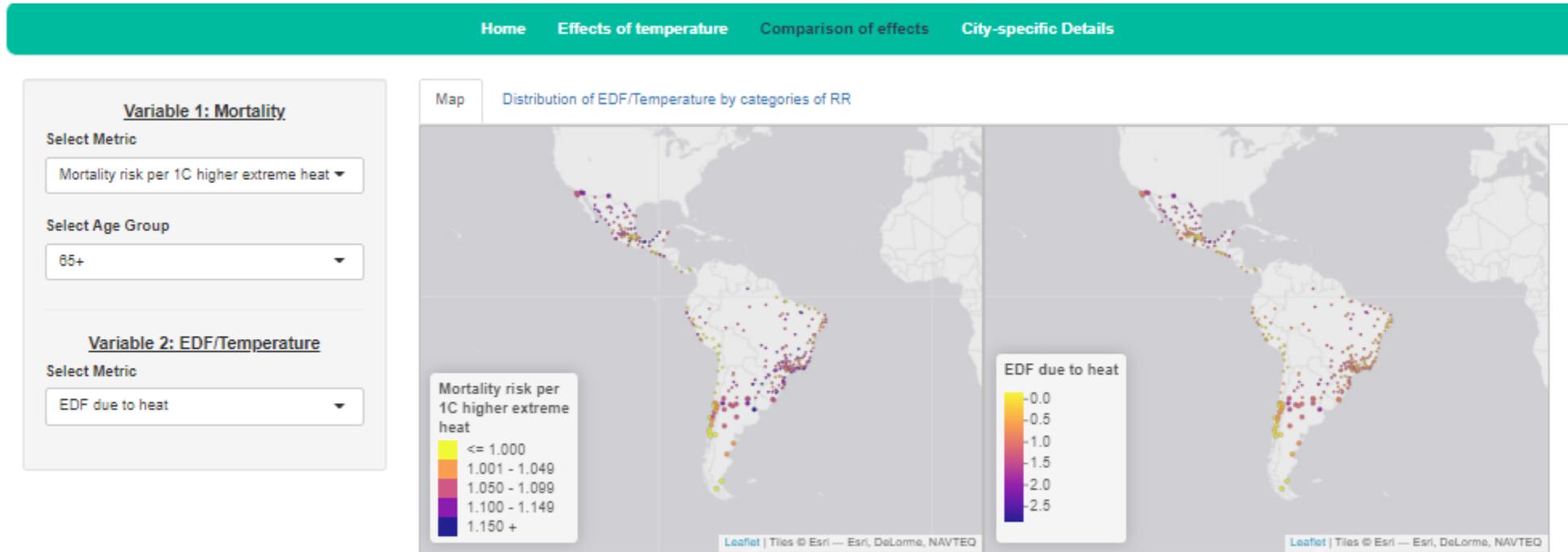
3.4% (2.8 to 4.0)



Change in relative risk of mortality per 1°C increase while under **extreme heat**



Interactive app for city-specific findings



drexel-uhc.shinyapps.io/MS85/



Summary of MS85 findings

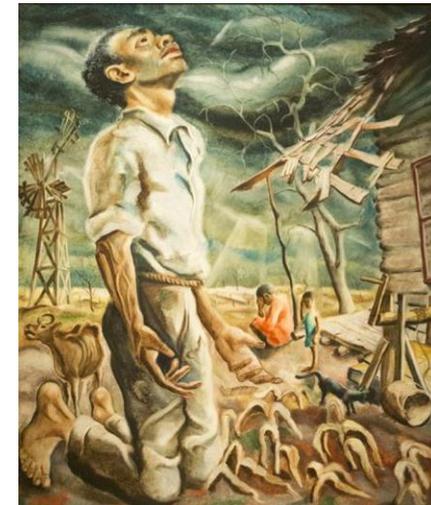
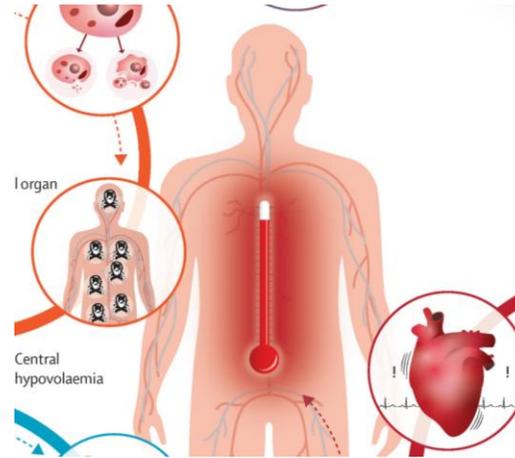
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- Ambient temperature is a major driver of mortality in Latin American cities
- Older individuals are especially vulnerable
- **Small** increases in extreme heat temperature → **steep** increases in mortality
- Marginal increases in extreme heat will likely have a substantial impact on mortality, particularly among older individuals.
- Impact of temperatures on mortality varies spatially, local understanding is critical for effective mitigation planning

Dealing with analytical challenges

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1. Effects not always immediate
 - Distributed lags
2. Weather vs climate
 - Adjusted extensively to focus on short-term variation only
3. Differential exposure by area
 - City-level associations pooled via meta-analysis
4. Wide range of presentation and outcomes
 - All and cause-specific death
5. Exposure added to underlying vulnerabilities
 - Stratify by age & cause of death



Wikimedia commons. Joseph Vorst.

When to use distributed lag non-linear models

- Benefits
 - Allow for cumulative effects across lags
 - Capture effects at lags where effect may not be statistically significant
 - Reduce dimensions, allowing standard meta-analysis techniques (city -> overall)
 - R packages available
- Challenges
 - More complex than common methods
 - Computationally intense
- BEST FOR: exposures with unknown lagged effects that are unlikely to be linear



Resources

- *Distributed Lag Linear and Non-Linear Models in R: The Package dlnm:*
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3191524/>
- Stabilizing curves via meta-analysis
<https://doi.org/10.1186/1471-2288-13-1>
- Two-stage analyses (combine city estimates via meta-analysis)
<https://doi.org/10.1002/sim.5471>
[https://doi.org/10.1016/S0140-6736\(14\)62114-0](https://doi.org/10.1016/S0140-6736(14)62114-0)

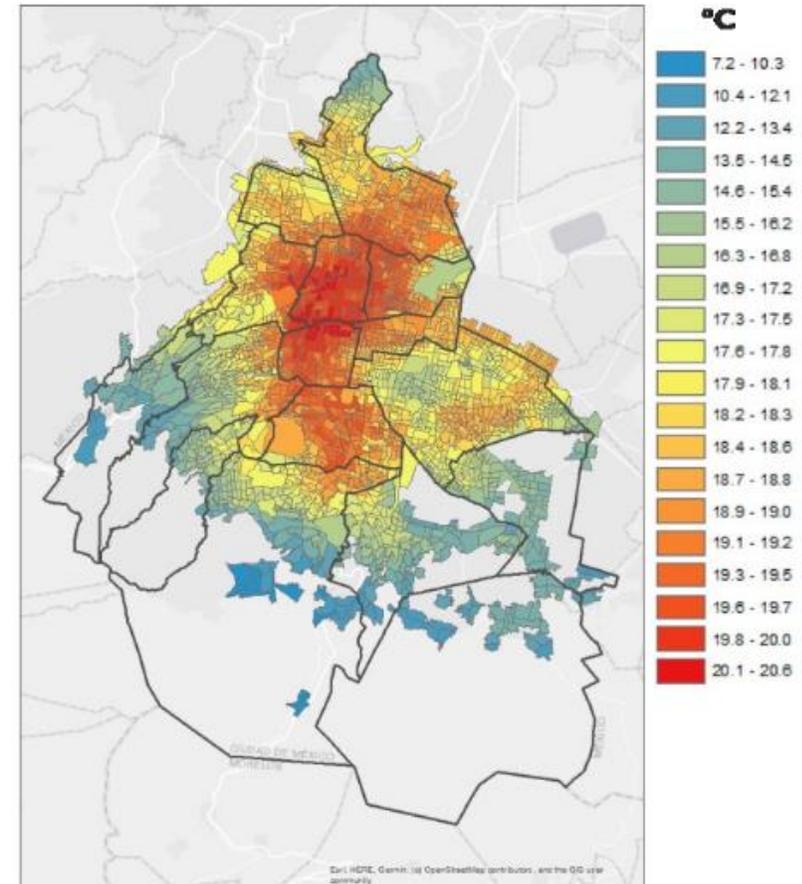


Figura 7. Mapa de temperaturas superficiales nocturnas



Within-city disparities in climate risks: floods

(MS218: work in progress)



SALURBAL Flood Project Aims

- **MS218**

- **Aim 1:** Characterize differential exposure to floods by social factors and features of the urban environment

- Cumulative exposure, cross-sectional

- **Aim 2:** Examine excess all-cause and cause-specific mortality due to exposure to floods

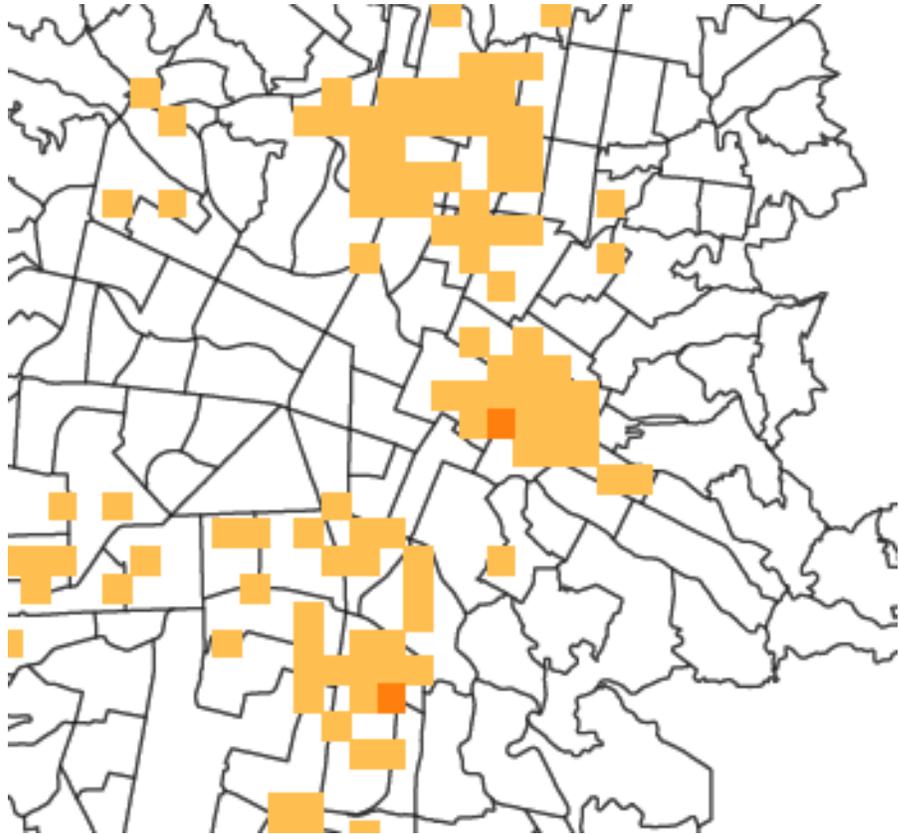
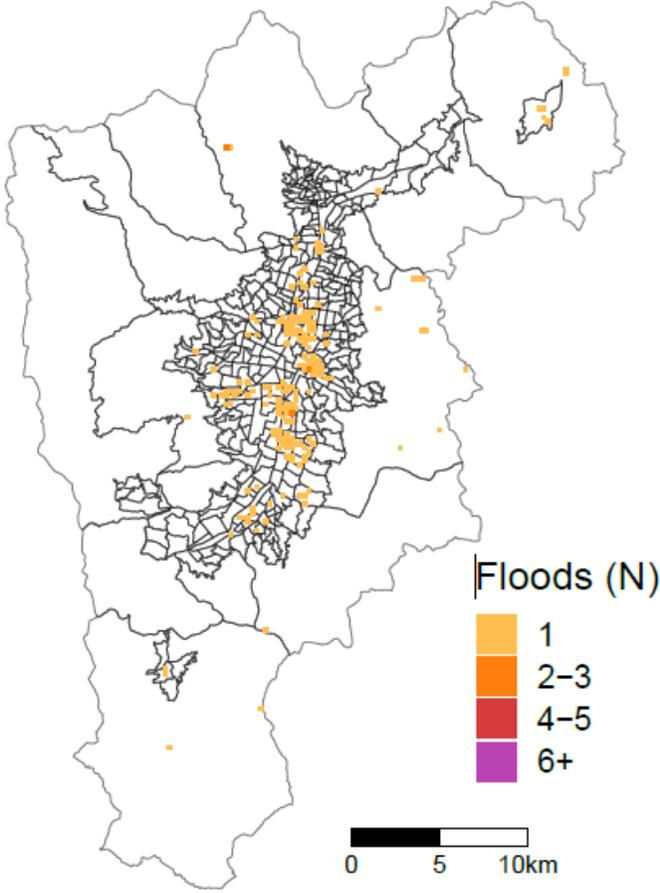


Global Flood Database

- 2000-2018
- 918 global flood events
- 250m x 250m resolution (L3!)
- Metrics
 - Maximum water extant beyond standing water extant (requires high confidence)
 - Flood duration in days
 - Dates



Global Flood Database



Approach

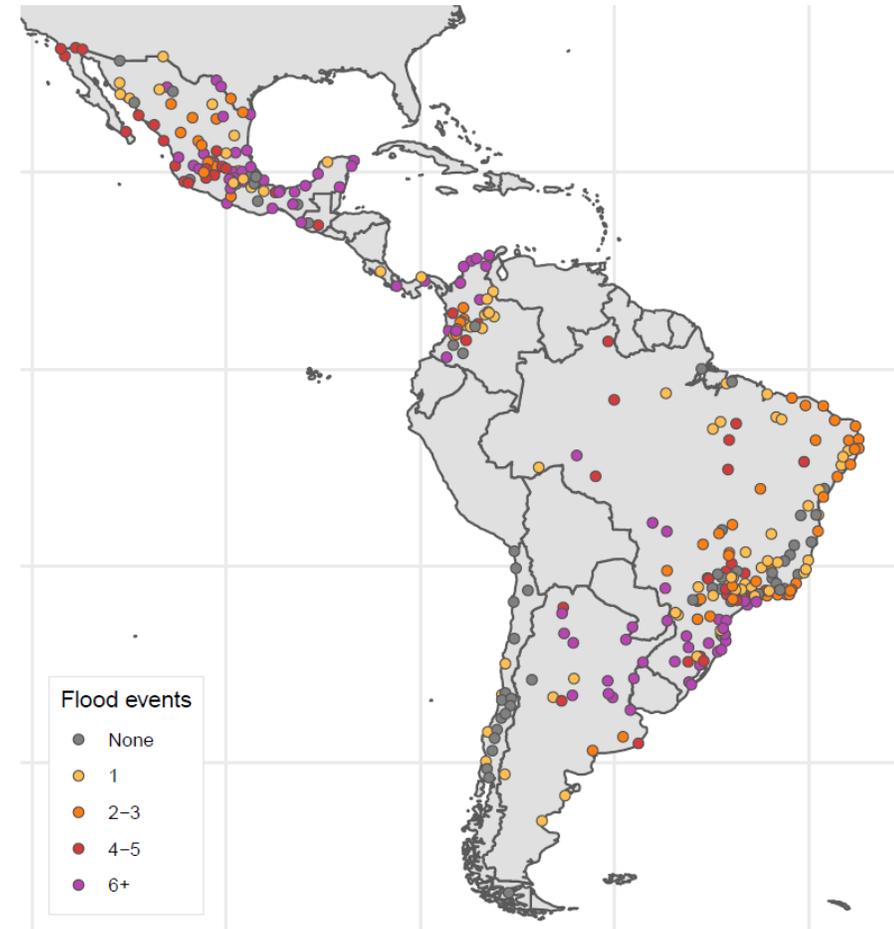
1. Link flood raster data to SALURBAL L3's
 1. (process 918 global raster files using JavaScript)
2. Merge with SALURBAL BEC and SEC L3 data
3. Describe disparities in flood exposure by education
 - Slope Index of Inequality (in progress)
4. Describe associations with urban environment



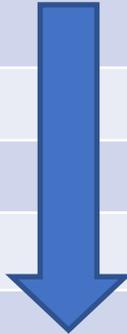
Study neighborhoods

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- 47,187 neighborhoods
- 326 cities
- 8 countries
 - AR, BR, CL, CO, CR, GT, MX, PA
- 235.9 million people

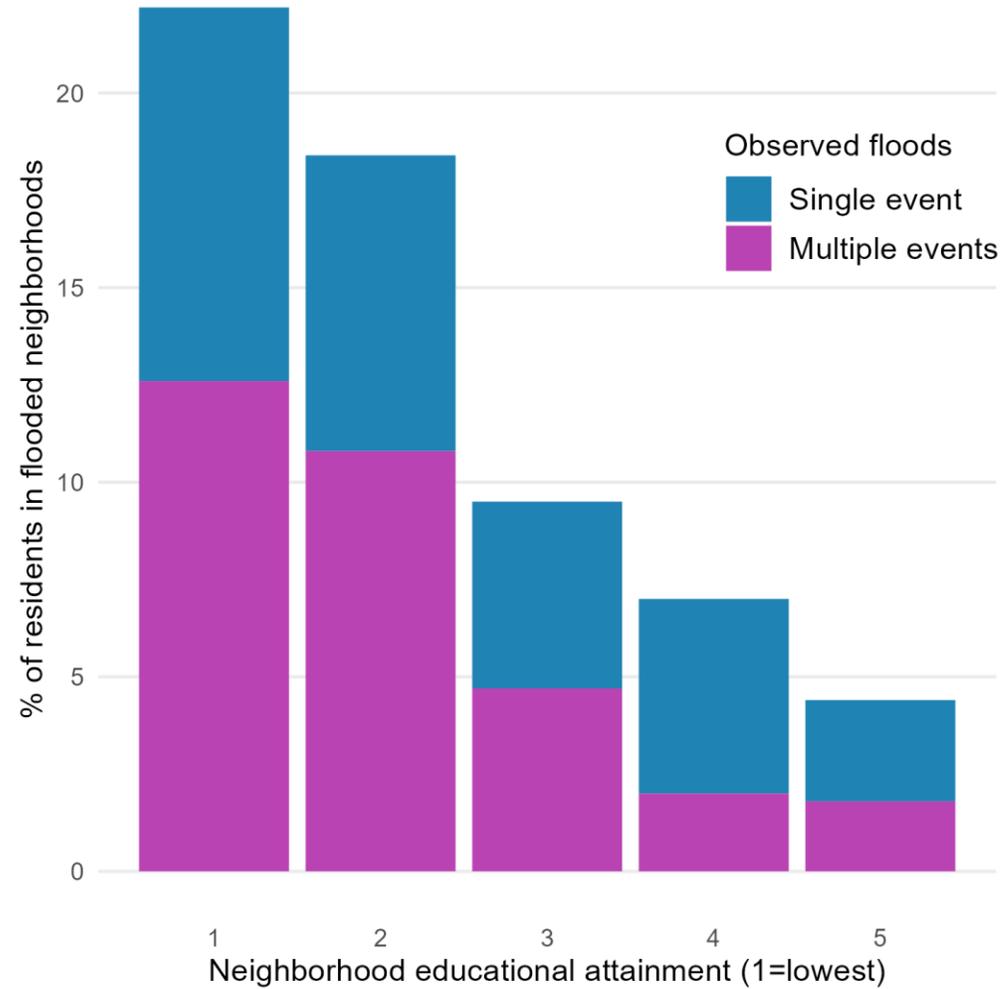


	Total, neighborhoods	Study Population (millions)	% of study population living in flood- prone neighborhoods
Overall	47,187	235.9	15.9%
By educational attainment			
1st quintile (lowest)	9,428	102.6	<u>22.2 %</u>
2nd	9,439	46.1	18.3 %
3rd	9,444	33.8	9.4 %
4th	9,439	31.8	7.0 %
5th quintile (highest)	9,437	21.6	<u>4.3 %</u>



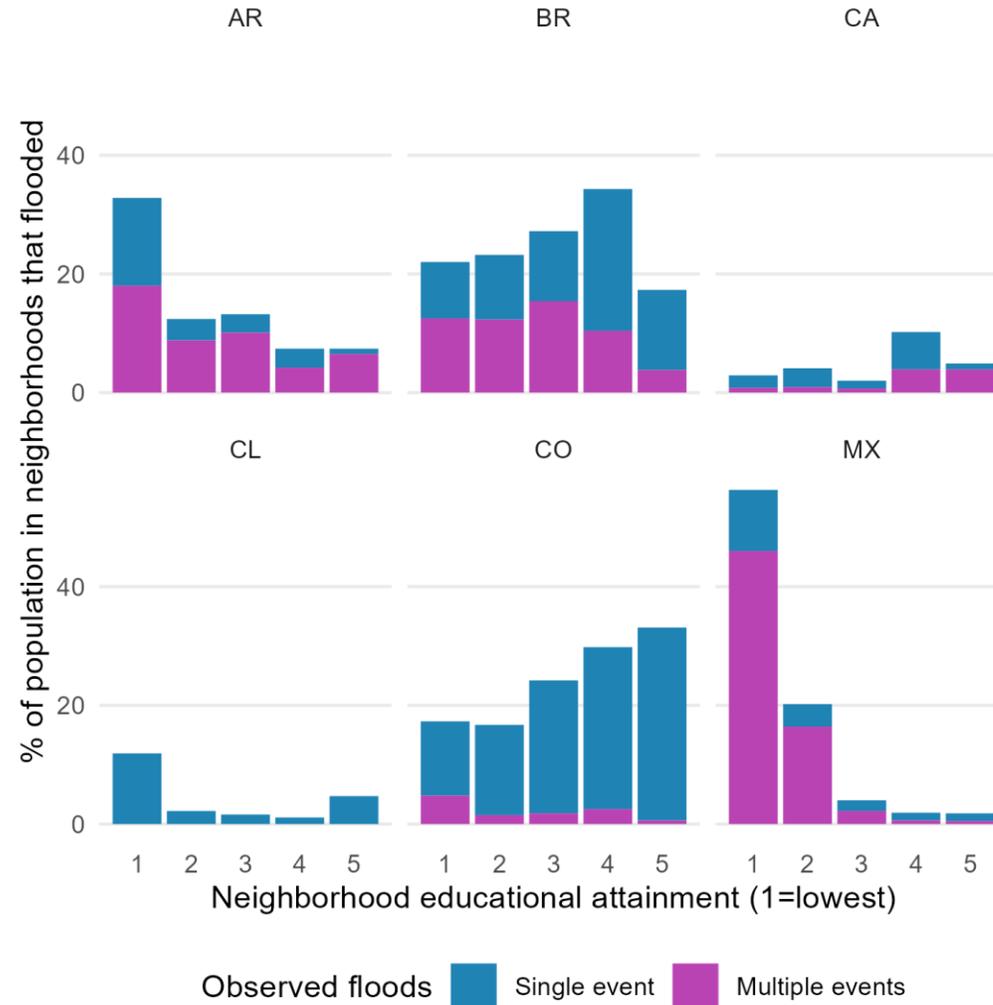
Flooding in Urban Latin America
2000-2018, 47,235 neighborhoods

Major educational
disparities in
neighborhood exposure
to flooding



Flooding in Urban Latin America
2000-2018, 47,235 neighborhoods

Variation within countries,
but disparity consistent for
multiple floods



Associations with urban environment

Table 3. Odds ratio of neighborhood flooding associated with a one-unit z-score increase in neighborhood- and city-level

		Univariable		Multivariable	
		Estimate	95% CI	Estimate	95% CI
Neighborhood- Level	Population density*	0.17	0.15, 0.20	0.42	0.36, 0.49
	Education	0.66	0.63, 0.69	0.79	0.74, 0.84
	Intersection density	0.40	0.36, 0.45	0.80	0.73, 0.87
	Greenness	2.02	2.02, 2.02	1.57	1.44, 1.70
	Distance from city center	1.52	1.46, 1.59	1.20	1.13, 1.26
	Coastal (<1 km)	48.7	39.9, 59.4	67.91	54.74, 84.26
	Altitude	1.00	0.99, 1.00	1.00	1.00, 1.00
	Slope	1.02	1.00, 1.03	0.93	0.91, 0.95

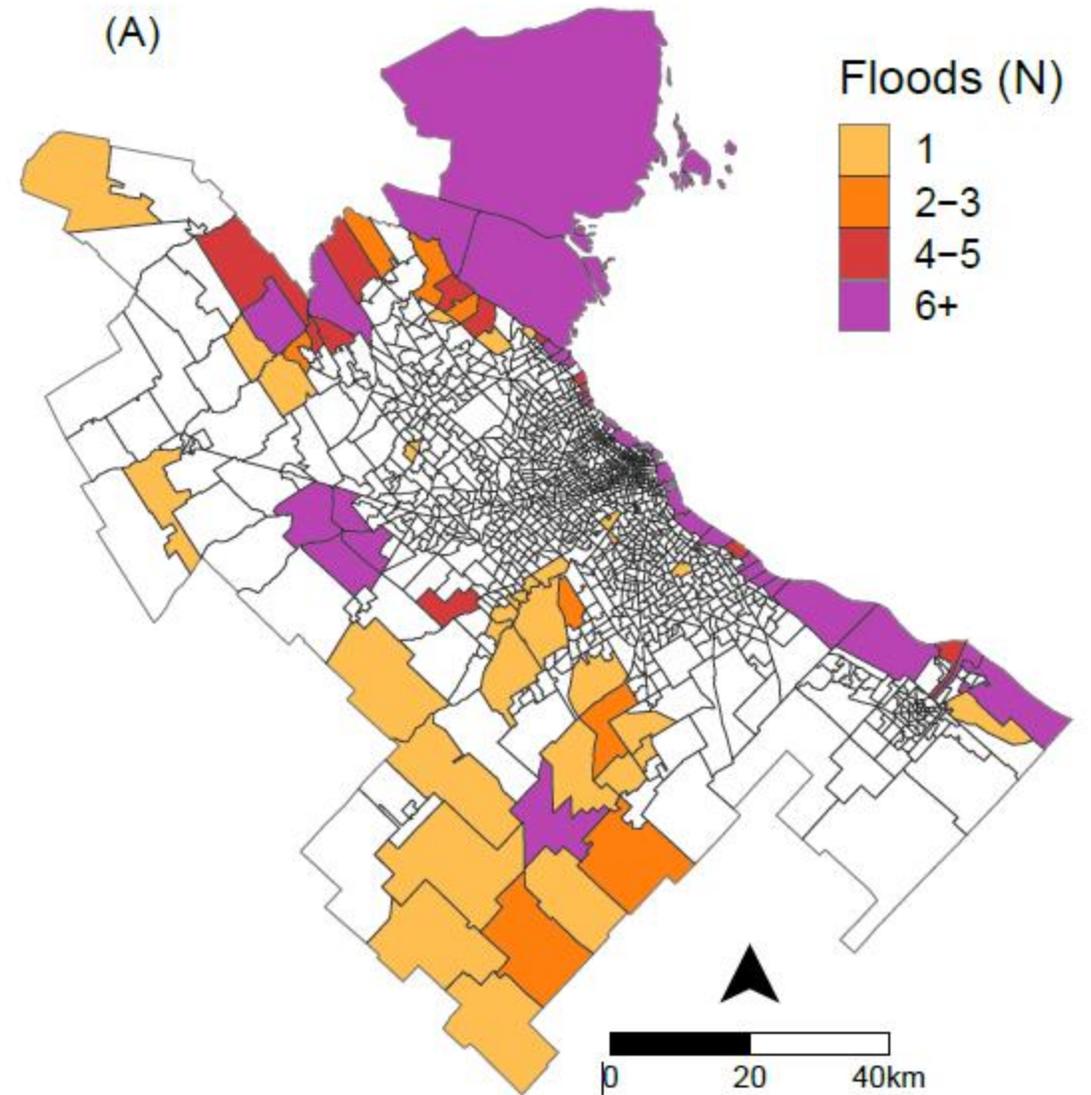


		Univariable		Multivariable	
		Estimate	95% CI	Estimate	95% CI
City-level	Population size	0.94	0.81, 1.09	1.13	0.95, 1.34
	Population density	0.85	0.66, 1.10	0.85	0.66, 1.09
	Education	1.04	0.76, 1.41	1.08	0.80, 1.48
	Intersection density	0.85	0.72, 1.00	0.84	0.69, 1.02
	Greenness/vegetation	1.42	1.42, 1.42	1.14	0.89, 1.45
	GDP - SEI	1.21	1.02, 1.44	1.08	0.92, 1.27
	Climate				
	Temperate	Ref	Ref	Ref	Ref
	Arid	0.69	0.39, 1.22	0.82	0.43, 1.56
Tropical	1.65	1.10, 2.46	1.09	0.72, 1.63	



Summary of associations with urban environment

- Neighborhoods features associated with flooding
 - Coastal***
 - Lower density (population and intersection)
 - Lower education
 - More green
 - Further from city center
 - Flatter slope
- City features
 - No associations with city features



In summary

- Lowest education neighborhoods were **5x more likely** to experience flooding than highest education neighborhoods
- Coastal neighborhoods and peripheral n'hoods with lower density and more green experienced more flooding



Next up: health analyses

