PERSPECTIVES FROM SETTINGS OF HOUSEHOLD AIR POLLUTION IN LOW- AND MIDDLE-INCOME COUNTRIES

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HEI Webinar Series
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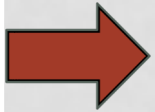
Perspectives from settings of household air pollution

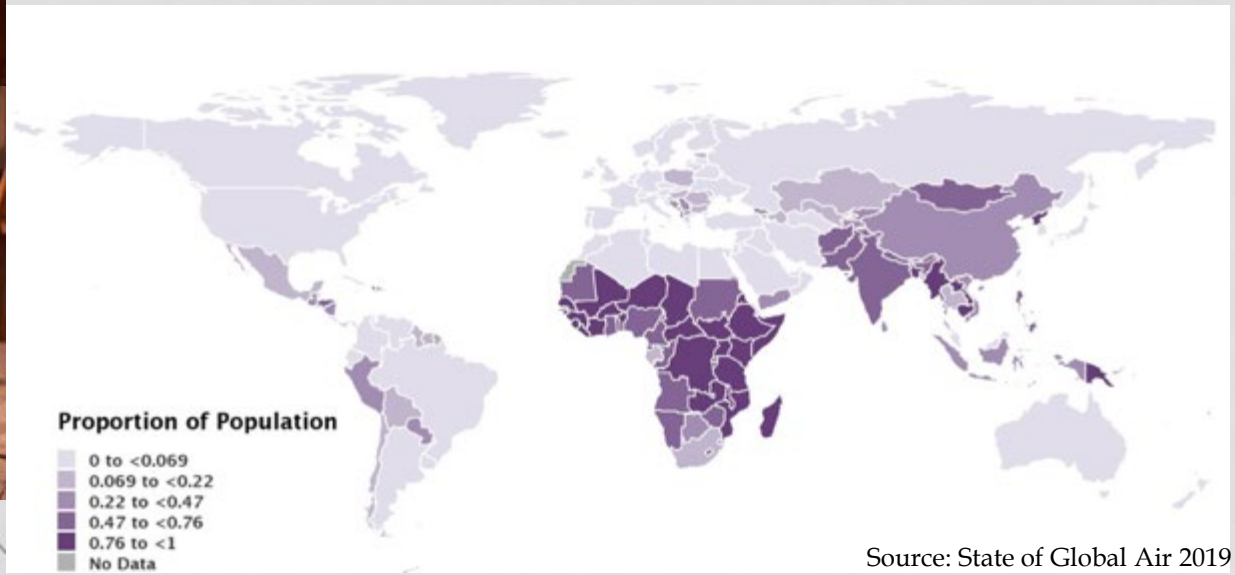


What is household air pollution?

- Causal inference methods in household air pollution
- Role of big data in household air pollution and health

Photos: GACC, 2017; HEI 2018

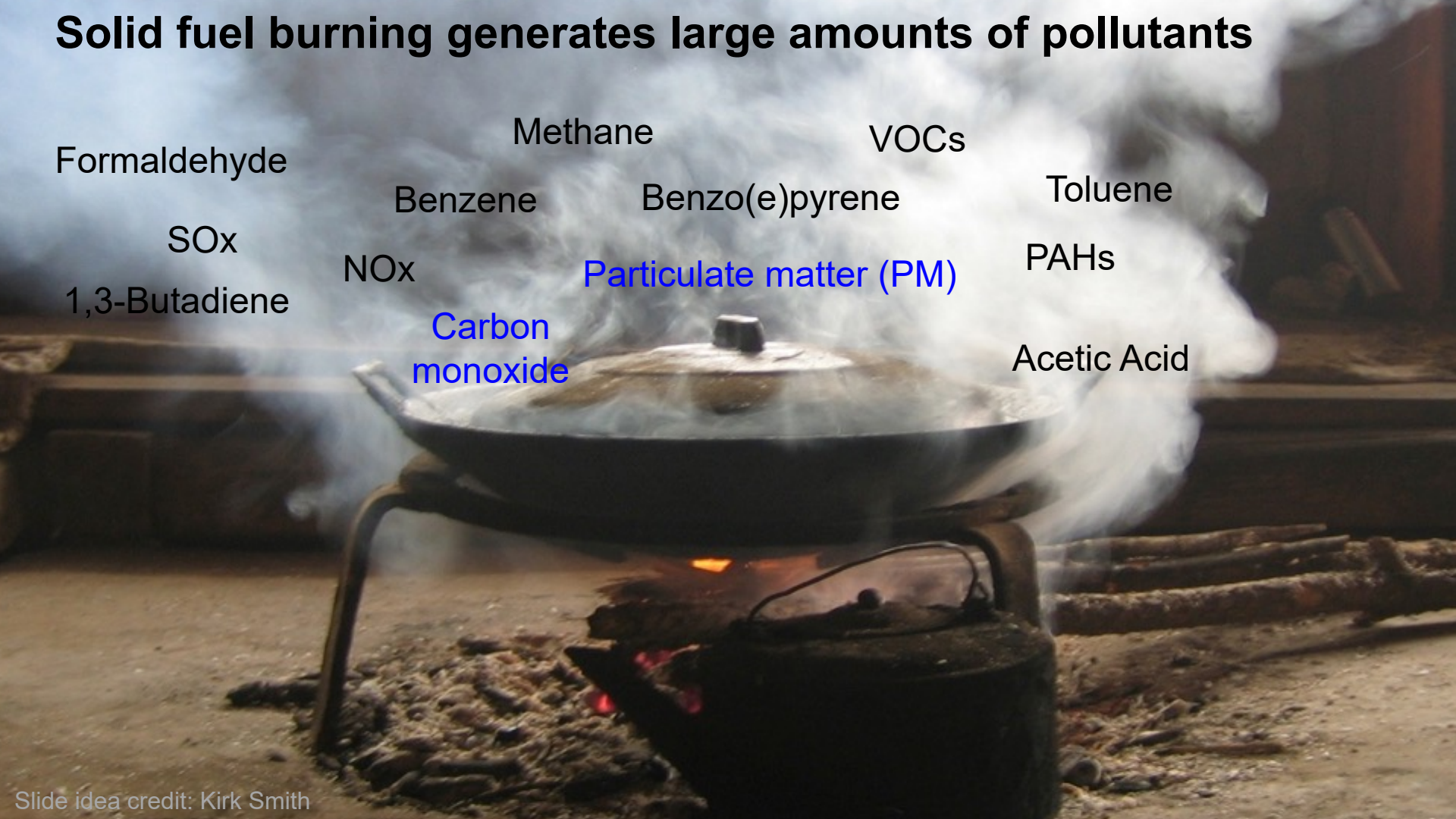
Proportion of population primarily cooking with biomass or coal (solid fuel) stoves in 2017*



Source: State of Global Air 2019

*These do not account for secondary fuel use or for solid fuel stoves used for other purposes other than heating

Solid fuel burning generates large amounts of pollutants

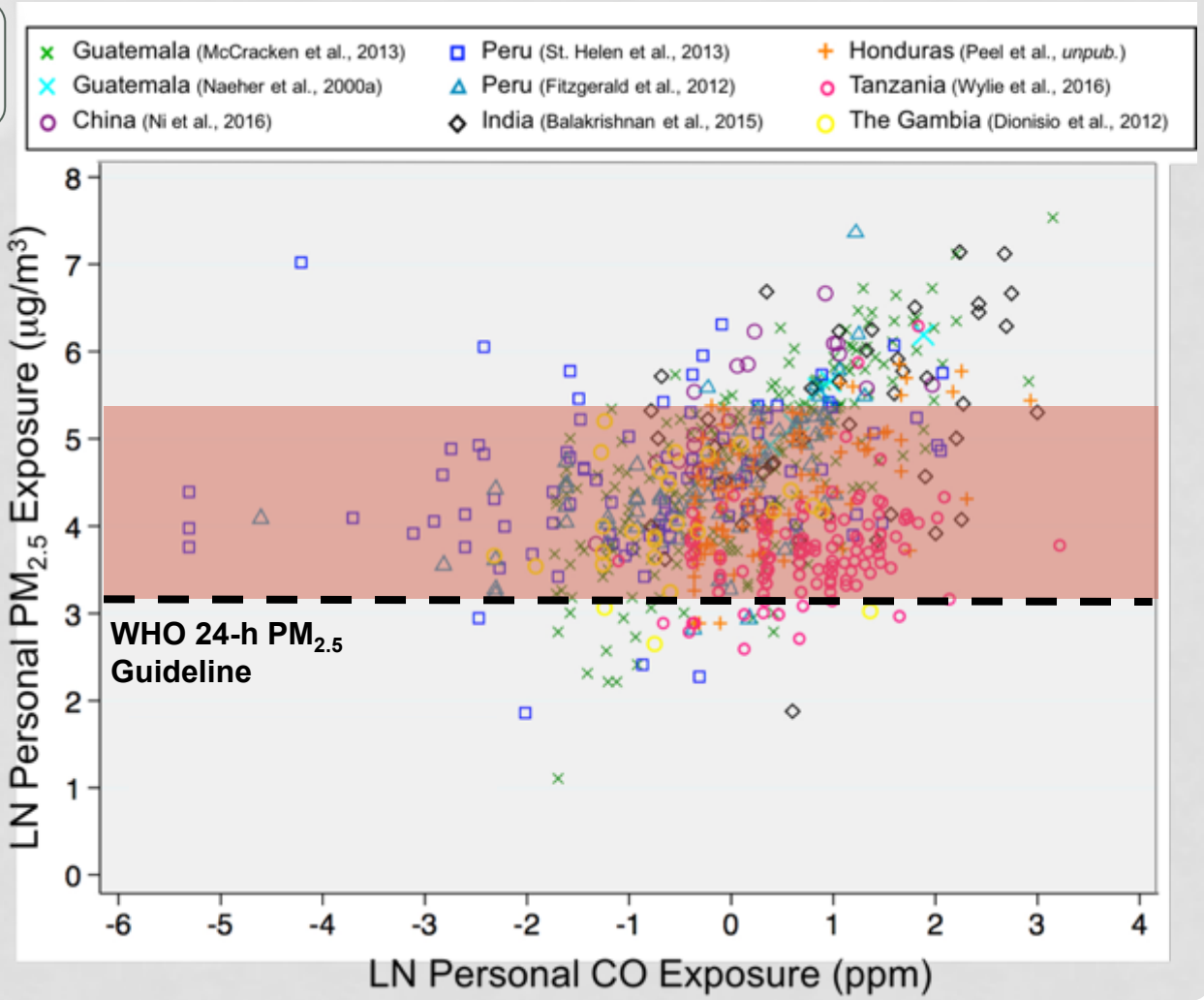


Slide idea credit: Kirk Smith

Outdoor & household ranges overlap

Range of average exposures to $PM_{2.5}$ in settings of **household air pollution** (n=15 studies): **40-186 µg/m³**

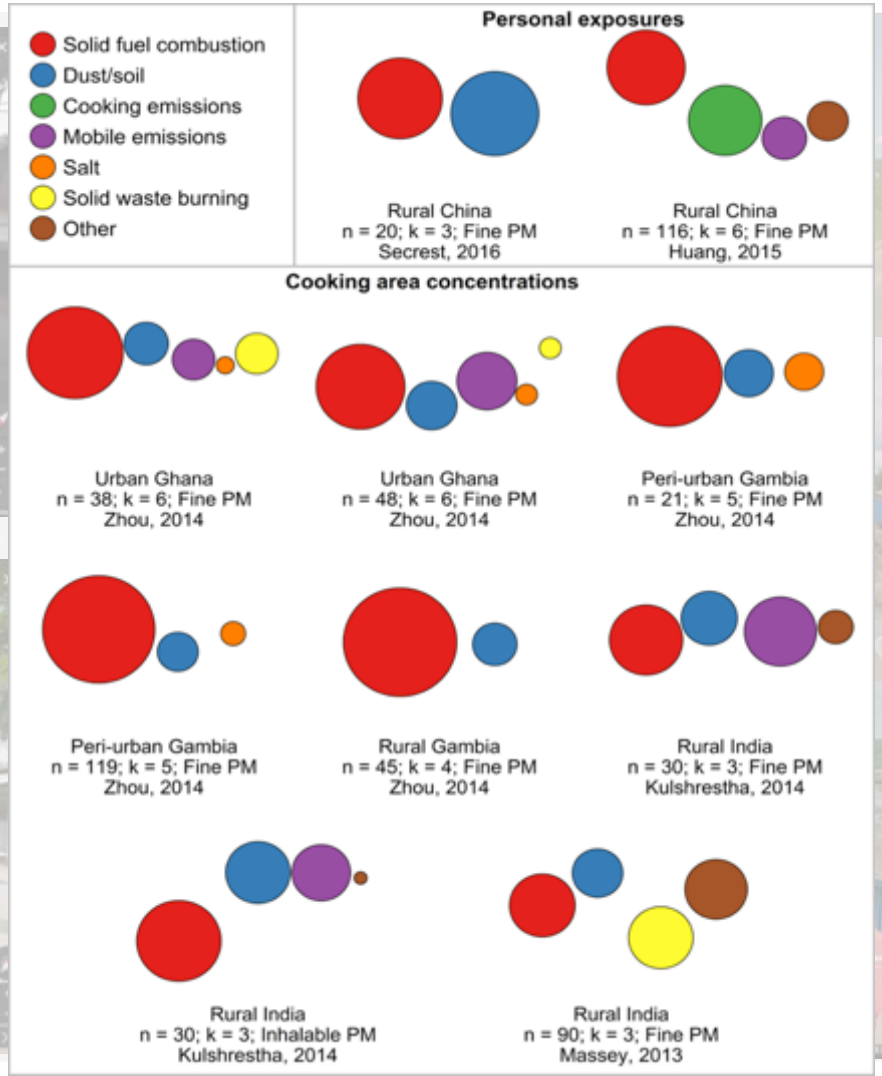
Range of average yearly **outdoor $PM_{2.5}$** in the world's 500 most polluted cities: **27-173 µg/m³**



Carter et al., Environ Health Perspect 2017

Biomass and coal stoves are a major source contributor to indoor $PM_{2.5}$ & exposures…

…but not the only source or even the largest one.



Secrest et al, *Indoor Air*, 2017

Decades of developing ‘interventions’ with different emissions performance

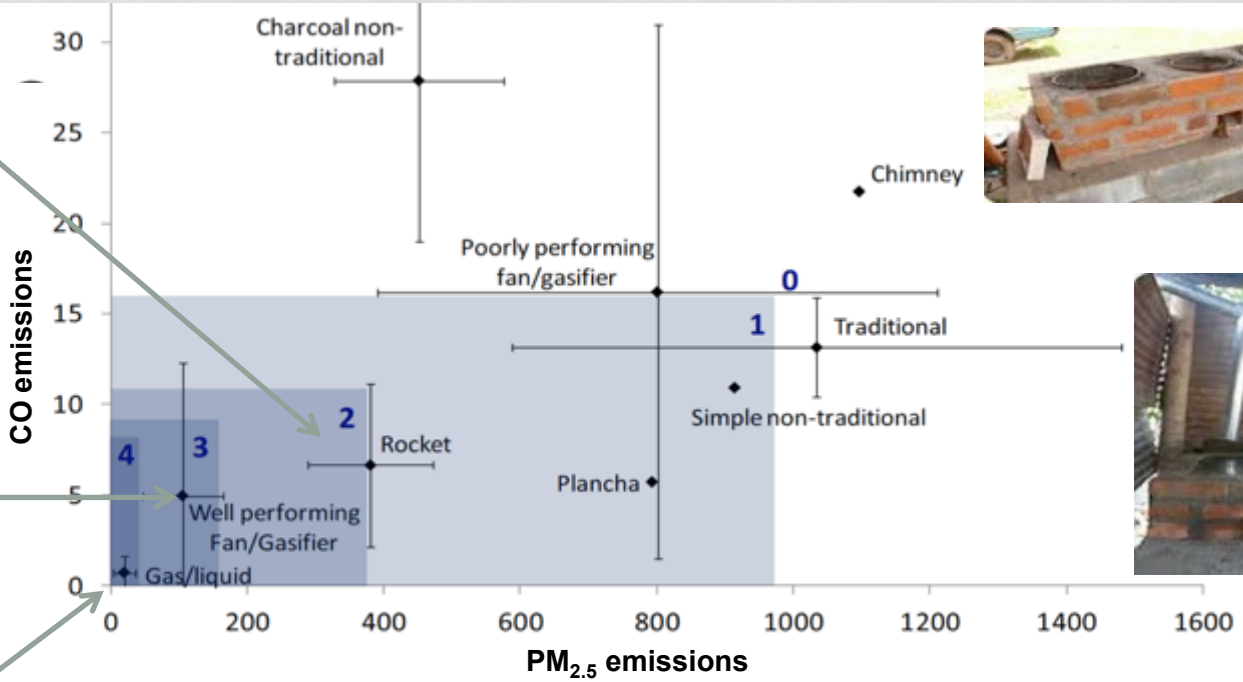


Figure source: Berkeley Air Monitoring Group, Cookstove Emissions Inventory, 2012
Photos: Trees, Water People / Phillips

Perspectives from settings of household air pollution

- What is household air pollution?
- Causal inference methods in household air pollution
- Role of big data in household air pollution and health

Two directions for causal inference in household air pollution

(1) Observational research with personal exposure measurement

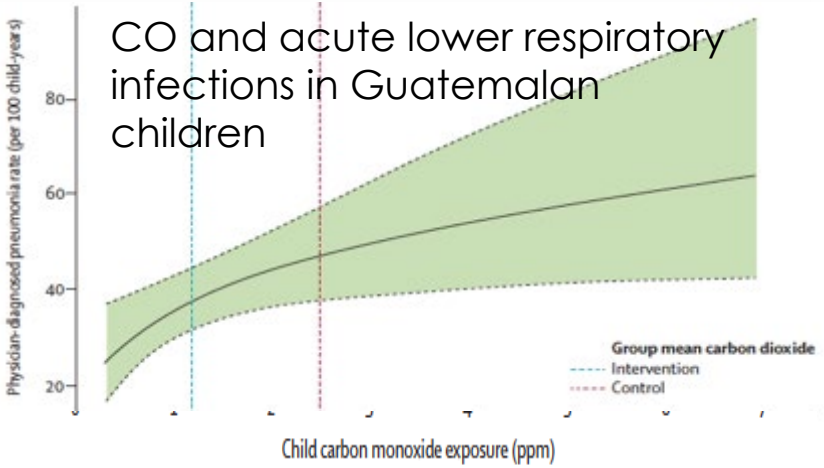
(+) Characterize exposure-response relationships to determine pollution reductions needed to achieve health benefit

Ezzati and Baumgartner, *Lancet*, 2016

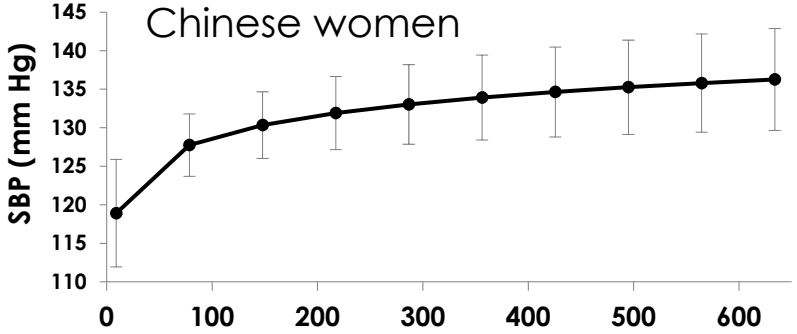
Exposure-response associations for household air pollution

Health outcomes with 1+ exposure-response study
Lower respiratory infections (4+)
Blood pressure (4+ studies)
COPD (3+ studies)
Lung cancer (2+ studies)
Diabetes (1 study)
Blood/DNA biomarkers (2 studies)
All cause & cardiovascular mortality (1; abstract only)

CO and acute lower respiratory infections in Guatemalan children



$PM_{2.5}$ and blood pressure in Chinese women

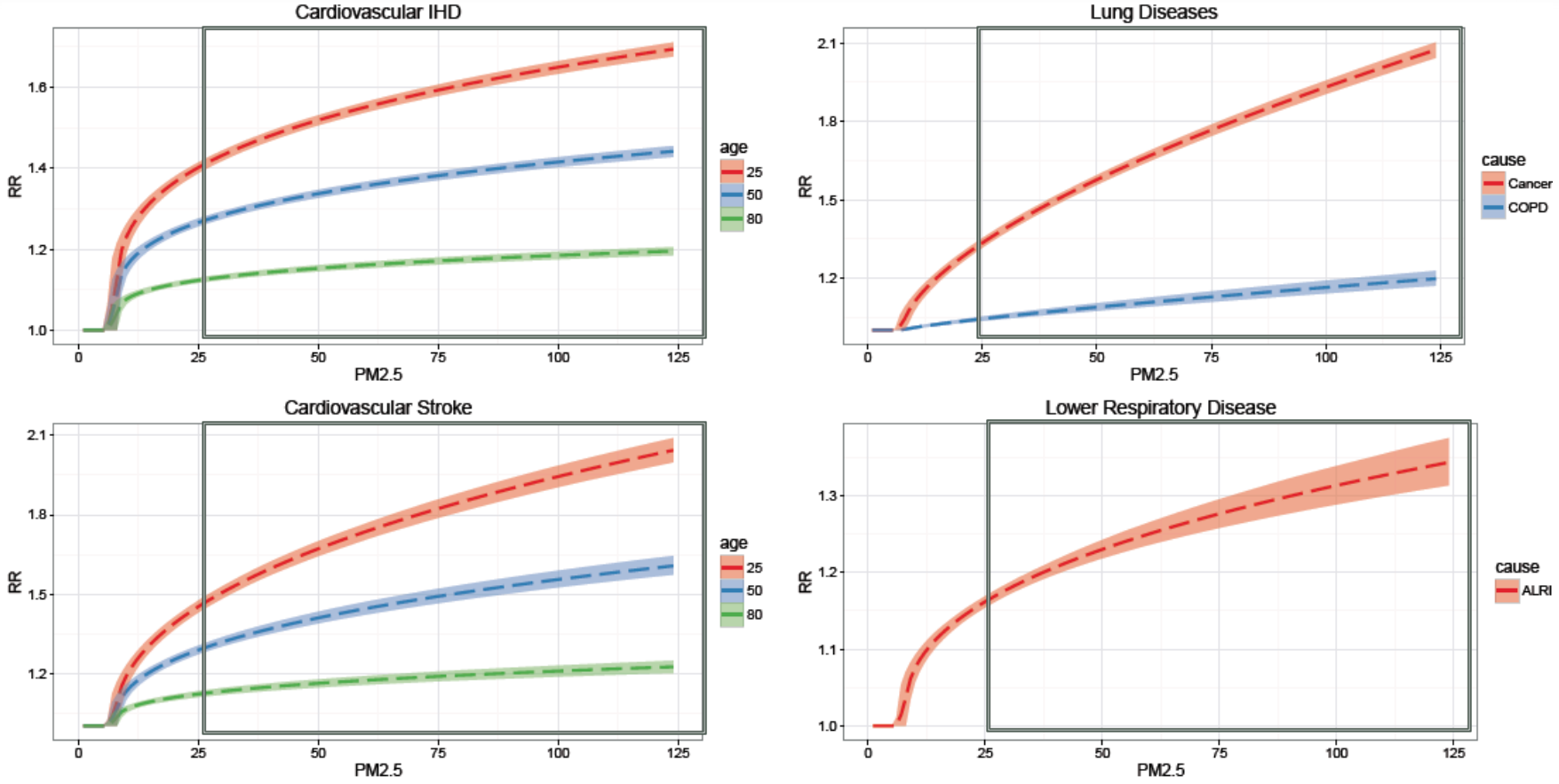


Sources: WHO-IAQ Guidelines, Smith, 2011; Baumgartner, 2011

Measuring exposure to $PM_{2.5}$ is challenging

- Air monitors are expensive, bulky, limited by battery life, and not robust to field conditions; issues of electricity and logistics
- Household (indoor) measurements poorly correlate with exposure in many settings; outdoor monitors fail to capture indoor sources
- Biomarker research is limited and unconvincing

Integrated exposure-response curves for air pollution ($PM_{2.5}$) and health



Sources: Forouzanfar et al. 2015; Burnett et al. 2014

Two directions for causal inference in household air pollution

(1) Observational research with personal exposure measurement

(+) Characterize exposure-response relationships to determine pollution reductions needed to achieve health benefit

(-) Personal exposure assessment is challenging

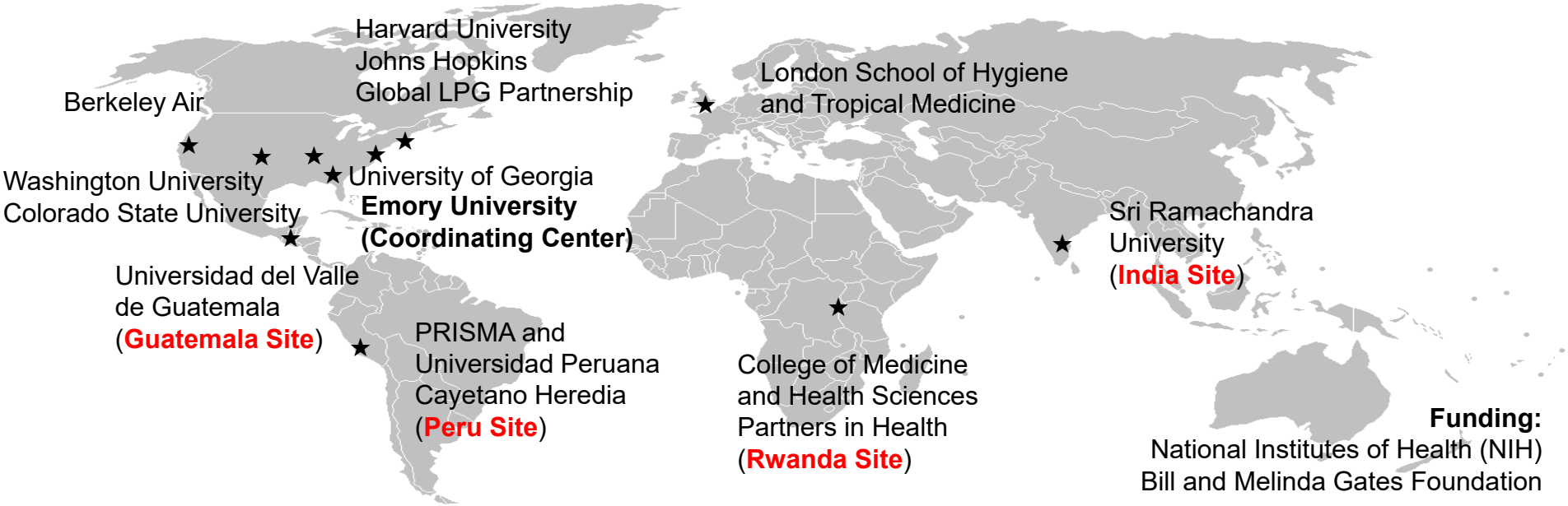
(-) Confounders can be hard to measure well or at all

(2) Randomized controlled trials

(+) Free of confounding to measure the pure intervention effects

Ezzati and Baumgartner, *Lancet*, 2016

The Household Air Pollution Intervention Network (HAPIN)



Funding:
National Institutes of Health (NIH)
Bill and Melinda Gates Foundation

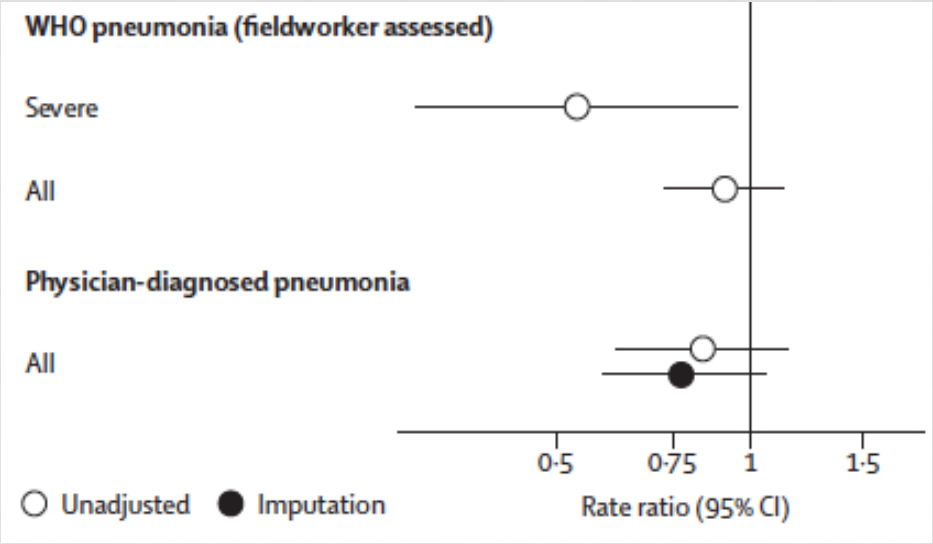
LPG intervention

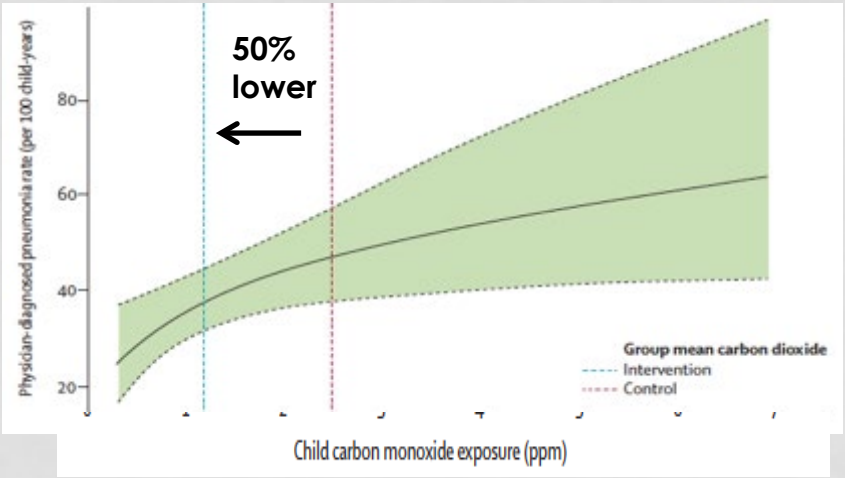
Birth weight
Child severe pneumonia
Child linear growth/stunting
Adult blood pressure

Results from RCTs of clean stove interventions

	Stove provided a benefit to PRIMARY OUTCOME(S) of the trial	Stove provided a benefit to SECONDARY OUTCOME(S) of the trial
Smith, 2011 Guatemala (biomass stove)		E.g., blood pressure, neurocognitive impacts in children, severe pneumonia, biomarkers
Tielsch, abstract Nepal (biomass stove)		
Olopade, 2017; 2018 Nigera (fuel gel-gas)	X	E.g., blood pressure, birth weight and birth outcomes, markers of inflammation
Mortimer, 2017 Malawi (biomass stove)		
Wylie, abstract Ghana (LPG and gasifier)		?
Rosa, 2018 Rwanda (biomass stove)		
Romieu, 2009 Mexico (biomass stove)		
Hanna, 2016 India (biomass stove)		

Incidence of pneumonia in children in the first randomised controlled trial of a (wood chimney) cookstove in Guatemala





Smith et al., *Lancet*, 2011

Incidence of severe pneumonia in children from a cluster randomised controlled trial of a biomass cookstove in Malawi

	Intervention (n=5297)		Control (n=5246)		Incidence rate ratio (95% CI)	P-value
	# Cases	Incidence rate	# Cases	Incidence rate		
Severe pneumonia	186	2.33 (2.00-2.67)	145	1.80 (1.51-2.09)	1.30 (0.99-1.71)	0.06
Air pollution	?	?	?	?	?	

Intervention stoves were used for 0.34 cooking events per day by year 2 of follow-up.

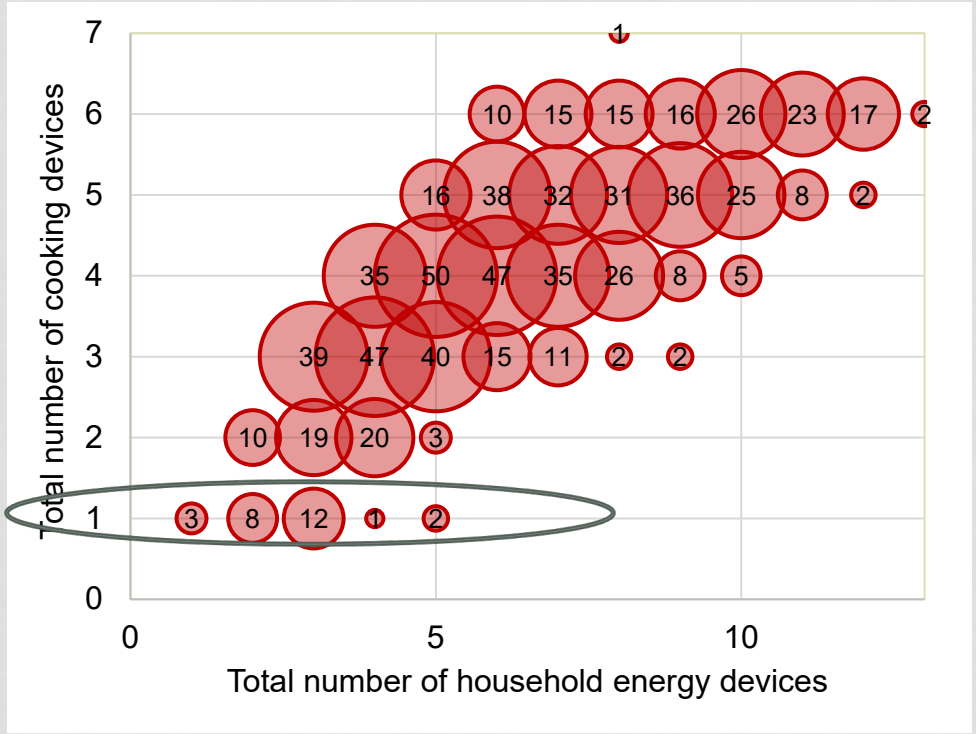
Each intervention stove was replaced or repaired 3.1 times over 2 years, on average.

Mortimer et al, Lancet, 2017

Can a single stove realistically meet the complexity of household energy use demands?

Ownership of household energy devices in rural Chinese homes

3 of 856 homes (0.4%) had 1 household energy device



Carter et al., Nature Sustainability, 2019

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Randomized controlled trials

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Ezzati and Baumgartner, *Lancet*, 2016

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(+) Characterize exposure-response relationships to determine pollution reductions needed to achieve health benefit

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Randomized controlled trials

(+) Free of confounding to measure the pure intervention effects

(-) Not feasible for many health endpoints

(-) Often plagued by low stove adoption, continued use of old stoves, and non-cooking sources

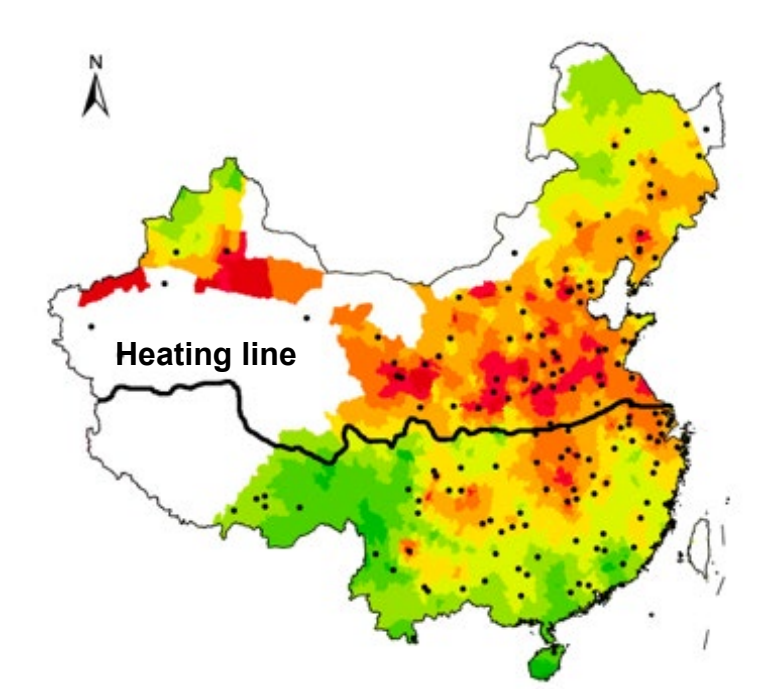
(-) Limited external validity

(-) Policy is already moving ahead

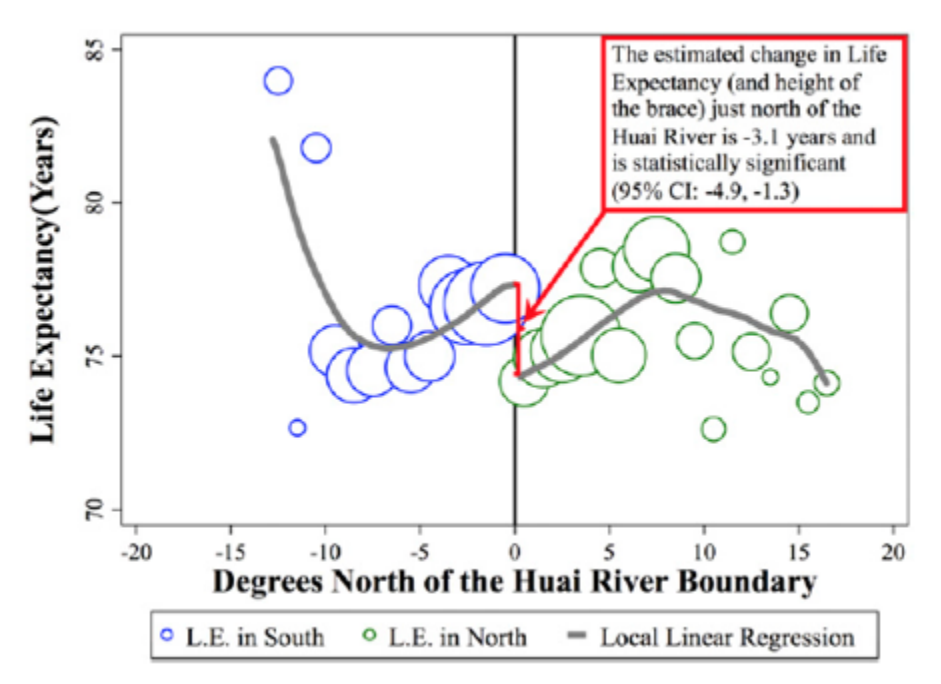
Quasi-experimental approaches

Ezzati and Baumgartner, *Lancet*, 2016

Natural experiment: The effect of the Huai River winter heating policy on air pollution and life expectancy



Heat map of PM10 concentrations (red=high)

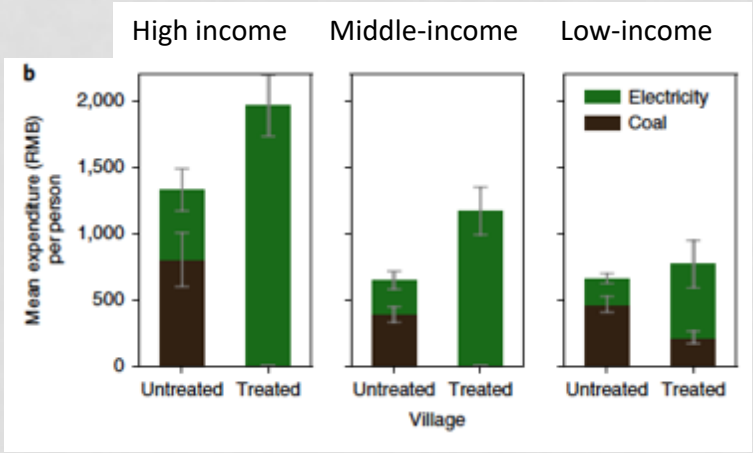


Fitted values from regression of life expectancy and distance from the Huai river

Ebenstein et al, *PNAS* 2017

Cross-sectional evaluation of the Beijing coal ban

- Beijing designated “coal restricted areas” and subsidized electric heat pumps and electricity
- 2017/18: required 2 million people to halt coal use
- Stepped implementation from 2017-2021 in Beijing and northern China (63 million homes)



Barrington-Leigh et al, *Nature Energy* 2019

Large-scale intervention programs provide opportunity for evaluation

ENVIRONMENT & HEALTH

In fight against smog, China bans coal in 28 cities

14 October 2017 10:30 · Global Voices · 6 min read

Donate

By Oiwan Lam

As winter approaches, Beijing is gearing up to fight against smog, and a large number of cities in northern China have issued a ban on coal.

Different from the previous efforts coordinated by the Ministry of Environmental Protection in past years, the Coal Ban, as it is being called, has become an economic policy supervised by a coalition of top authorities. Concrete targets on air quality level — and the number of coal-free districts — have been handed down to 28 cities in northern China.

Perspectives from settings of household air pollution

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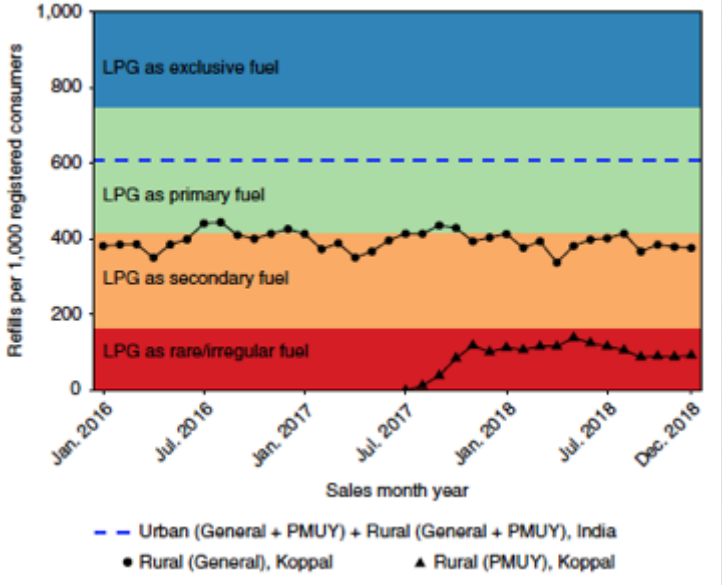
Leveraging fuel data to evaluate space-time trends in fuel and health

nature energy

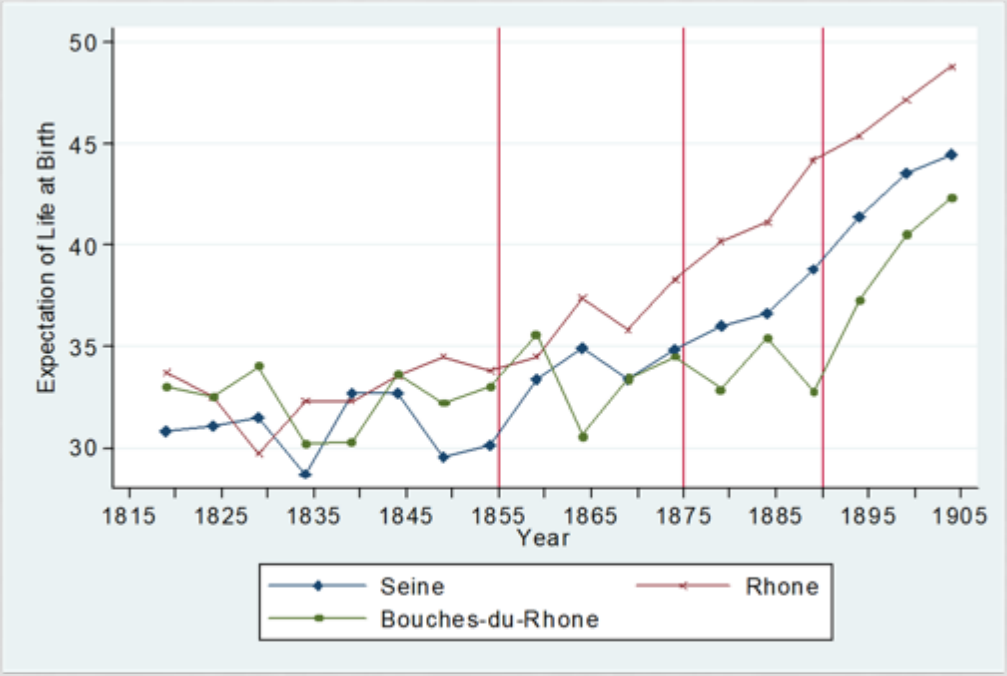
ANALYSIS

Using sales data to assess cooking gas adoption and the impact of India's *Ujjwala* programme in rural Karnataka

Abhishek Kar[1*], Shonali Pachauri[2], Rob Bailis[3] and Hisham Zerriffi[4]



Introduction of safe water and life expectancy in cities in France

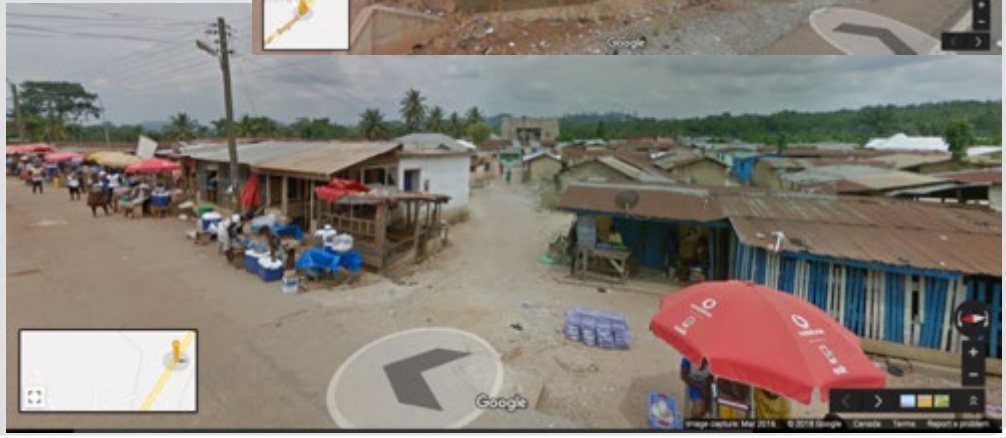


Source: Preston and van de Walle (1978)

Use of imagery and satellite data for exposure estimation

Small scale industry, traffic, road dust, biomass burning, diesel-powered equipment: rural Ghana

Traffic, roadside cooking with biomass, dust, other urban sources: peri-urban Dhaka

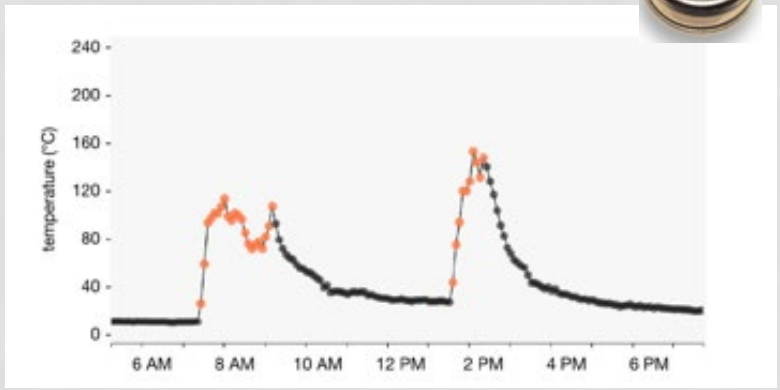


Use of sensors to evaluate compliance in use of LPG and abandonment of biomass stoves in the HAPIN trial

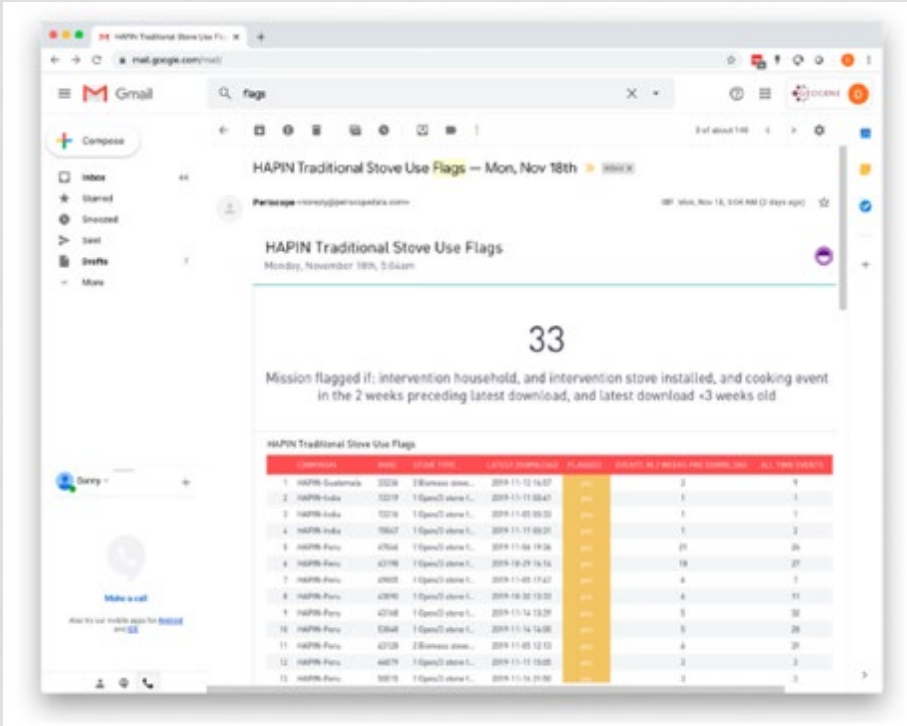
Article

An Integrated Sensor Data Logging, Survey, and Analytics Platform for Field Research and Its Application in HAPIN, a Multi-Center Household Energy Intervention Trial

Daniel Lawrence Wilson [1,2,*], Kendra N. Williams [3,4] and Ajay Pillarisetti [5,*,†]
on behalf of the HAPIN Investigators



Use of machine learning techniques to develop algorithms that detect rises in surface temperature associated with stove use events



Weekly email sent to trial researchers that identifies potentially non-compliant households

Wilson et al., *Sustainability,* 2020

Low-cost air pollution sensors for large-scale long-term monitoring

Environment International

journal homepage: www.elsevier.com/locate/envint

Full length article

Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates?

Nuria Castell [a,*], Franck R. Dauge [a], David Broday [b], Alena Bartonova [a]

[a] NILU – Norwegian Institute for Air Research, Kjeller, Norway
[b] Faculty of Civil and Environmental Engineering, Technion -

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Validating novel air pollution sensors to improve exposure estimates for epidemiological analyses and citizen science

Michael Jerrett[a,*], David
Ronald C. Cohen[d], Estel
Tom Cole-Hunter[b], Mar

Environment International

journal homepage: www.elsevier.com/locate/envint

Review

The rise of low-cost sensing for managing air pollution in cities

Prashant Kumar [a,b,*], Lidia Morawska [c], Claudio Martani [d], George Biskos [e,f,g], Marina Neophytou [h], Silvana Di Sabatino [i], Margaret Bell [j], Leslie Norford [k], Rex Britter [l]

Policy and research implications

- Actions to reduce household air pollution are warranted, not least because exposures are very high
- Leveraging natural experiments and policy evaluation can move focus beyond single stove interventions to assess more complex, contextualised, and realistic energy interventions
- Evaluation of whether clean energy programs policies achieve intended benefits and avoid harm, and whether benefits reach the most vulnerable, remains a need
- Big data still in its infancy in household air pollution; data availability and logistics in low-resource settings are a challenge