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Multiscale Drivers of Global Environmental Health

By

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Abstract

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Environmental health's purview, driven by an accelerating transformation of social and ecological systems, has been progressively expanding to encompass a broader array of environment-health relationships. This widening perspective embraces persistent, resurgent, and nascent threats to human health that often operate at multiple scales, generating the attributable burdens of the present as well as the avoidable burdens of the future. Analyzing linkages from the planetary to the individual is a core challenge for evolving environmental health into its "global" incarnation. The complications and uncertainties involved are daunting as causality cascades through multiple scales, prompting global environmental health to expand not only its paradigm but also its toolkit.

In this dissertation, I motivate, develop, and demonstrate three such approaches for investigating multiscale drivers of global environmental health: (1) a causal metric for analyzing contributions and responses to climate change from global to sectoral scales, (2) a conceptual framework for unraveling the influence of environmental change on infectious diseases at regional to local scales, and (3) a mechanistic model for informing the design and evaluation of clean cooking interventions at community to household scales.

The full utility of climate debt as an analytical perspective will remain untapped without causal metrics that can be manipulated by a wide range of analysts, including global environmental health researchers. In *Chapter 2*, I explain how international natural debt (IND) apportions global radiative forcing from fossil fuel carbon dioxide and methane, the two most significant climate altering pollutants, to individual entities − primarily countries but also subnational states and economic sectors, with even finer scales possible − as a function of unique trajectories of historical emissions, taking into account the quite different radiative efficiencies and atmospheric lifetimes of each pollutant. Owing to its straightforward and transparent derivation, IND can readily operationalize climate debt to consider issues of equity and efficiency and drive scenario exercises that explore the response to climate change. Collectively, the analyses presented in this chapter demonstrate how IND can inform a range of key question

at multiple scales, compelling environmental health towards an appraisal of the causes as well as the consequences of climate change.

The environmental change and infectious disease (EnvID) conceptual framework of *Chapter 3* builds on a rich history of prior efforts in epidemiologic theory, environmental science, and mathematical modeling to analyze social and ecological drivers of re/emerging pathogens. EnvID is distinguished by: (1) articulating a flexible and logical system specification; (2) incorporating transmission groupings linked to public health intervention strategies; (3) emphasizing the intersection of proximal environmental characteristics and transmission cycles; (4) incorporating a matrix formulation to identify knowledge gaps and facilitate research integration; and (5) highlighting hypothesis generation amidst dynamic processes. A systems-based approach leverages the reality that studies relevant to environmental change and infectious disease are embedded within a wider web of interactions. As scientific understanding advances, the EnvID framework can help integrate the various factors at play in determining environment–disease relationships and the connections between intrinsically multiscale causal networks.

In *Chapter 4*, the coverage effect mechanistic model functions primarily as a "proof-of-concept" analysis to address whether the efficacy of a clean cooking technology may be determined by the extent of not only household-level use but also community-level coverage. Such coverage dependent efficacy, or a "coverage effect," would transform how interventions are studied and deployed. Ensemble results are consistent with the concept that an appreciable coverage effect from clean cooking interventions can manifest within moderately dense communities. Benefits for users derive largely from direct effects; initially, at low coverage levels, almost exclusively so. Yet, as coverage expands within a user's community, a coverage effect becomes markedly beneficial. In contrast, non-users, despite also experiencing comparable exposure reductions from community-level intervention use, cannot proportionately benefit because their exposures remain overwhelmingly dominated by household-level use of traditional solid fuel cookstoves.

The coverage effect model strengthens the rationale for public health programs and policies to encourage clean cooking technologies with an added incentive to realize high coverage within contiguous areas. The implications of the modeling exercise extend to priorities for data collection, underscoring the importance of outdoor pollution concentrations during, as well as before and/or after, community cooking windows and also routine measurement of ventilation, meteorology, time-activity patterns, and cooking practices. The possibility of a coverage effect necessitates appropriate strategies to estimate not only direct effects but also coverage and total effects to avoid impaired conclusions.

The specter of accelerating social and ecological change challenges efforts to respond to climate change, re/emerging infectious diseases, and household air pollution. Environmental health possesses a verified repertoire of incisive methods but contending with multiscale drivers of risk requires complementary approaches, as well. Integrating causal metrics, conceptual frameworks, and mechanistic models − and the resulting insights − into its analytical arsenal can help global environmental health meet the challenges of today and tomorrow.

… all life is interrelated in an inescapable network of mutuality,
whatever affects one destiny,
affects all destinies …

— Martin Luther King, Jr.

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List of Abbreviations

AAP	ambient air pollution
AERMOD	American Meteorological Society/Environmental Protection Agency Model
AR4	IPCC Fourth Assessment Report
AR5	IPCC Fifth Assessment Report
CALPUFF	California Puff Model
CAP	climate altering pollutant
CARB	Air Resources Board of the California Environmental Protection Agency
CDIAC	Carbon Dioxide Information Analysis Center
CFD	computational fluid dynamics
CH_4	methane
CI	confidence interval
CO_2	carbon dioxide
CO_2(f)	carbon dioxide from fossil fuels and cement manufacture
CRA	Comparative Risk Assessment Project
DALY	disability adjusted life year lost
EDGAR	Emission Database for Global Atmospheric Research
EnvID	Environmental Change and Infectious Disease
EU	European Union (as constituted in 2005)
GDP-PPP	gross domestic product at purchasing power parity
HAP	household air pollution from solid fuel use for cooking
hh	household
HIC	high income country
IER	integrated exposure-response relationship
IND	International Natural Debt, climate debt from CO_2(f) and CH_4 combined
IND_{+LUCF}	climate debt from CO_2(f), CH_4, and LUCF combined
IND_{CH_4}	climate debt from CH_4
IND_{CO_2}	climate debt from CO_2
$IND_{CO_2(f)}$	climate debt from CO_2(f)
IND_{LUCF}	climate debt from LUCF
IPCC	Intergovernmental Panel on Climate Change
ITN	insecticide-treated net
LMIC	low-to-middle income country
LPG-C	liquefied petroleum gas cookstove
LUCF	land use change and forestry

P-G	Pasquill-Gifford
$PM_{2.5}$	particulate matter less than 2.5 μm in aerodynamic diameter
RF	radiative forcing
SUTVA	stable unit treatment value assignment
TSF-C	traditional solid fuel cookstove
U.S. minus CA	United States minus California
UNFCCC	United Nations Framework Convention on Climate Change
USEPA	United States Environmental Protection Agency
WHO	World Health Organization
WSH	water, sanitation, and hygiene

Preface

All research presented in this dissertation was conducted under the auspices of the Graduate Group in Environmental Health Sciences at the University of California, Berkeley.

A version of Chapter 2 have been published in the *Proceedings of the National Academy of Sciences* (*PNAS*) [Smith KR, Desai MA, Rogers JV, and Houghton RA (2013) "Joint CO_2 and CH_4 accountability for global warming" 110(31): E2865-E2874] and *Global Environmental Change* (*GEC*) [Desai MA, Smith KR, and Rogers JV (2015) "Applications of a joint CO_2 and CH_4 climate debt metric: insights into global patterns and priorities" 35(2015): 176-189]. Kirk R. Smith is co-first author on the *PNAS* publication, supervisory author on the *GEC* publication, and originated the concept for the metric elaborated by both publications. I am co-first author on the *PNAS* publication and sole lead author on the *GEC* publication. For the *PNAS* publication, Kirk R. Smith and I jointly designed the project, reviewed and synthesized the literature, developed and demonstrated the metric, and composed the manuscript. Jamesine (V. Rogers) R. Gibson conducted essential preliminary analyses. Richard A. Houghton generously shared the dataset for historical carbon dioxide emissions from land use change and forestry by global region. Jamesine (V. Rogers) R. Gibson and Richard A. Houghton contributed to the editing and revision of the manuscript. For the *GEC* publication, I am responsible for all components: project conceptualization; metric applications and interpretations; and manuscript composition. Kirk R. Smith and Jamesine (V. Rogers) R. Gibson contributed to the editing and revision of the manuscript.

A version of Chapter 3 has been published in *Environmental Health Perspectives* [Eisenberg JNS, Desai MA, Levy K, Bates SJ, Liang S, Naumoff K, and Scott JC (2007) "Environmental determinants of infectious disease: a framework for tracking causal links and guiding public health research" *Environmental Health Perspectives* 115(8): 1216-1223]. Joseph N. S. Eisenberg is supervisory author and devised the initial conceptualization for the framework at the core of the publication. Joseph N. S. Eisenberg and I share co-first authorship and we jointly designed the project, reviewed and synthesized the literature, developed and demonstrated the framework, and composed the manuscript. Karen Levy also provided valuable support for all components of the project. Sarah J. Bates, Song Liang, Kyra (Naumoff) Shields, and James C. Scott contributed to the editing and revision of the manuscript.

For the research described in Chapter 4, I am the lead investigator and solely responsible for all components: project conceptualization; model design, specification, parameterization, execution, and interpretation; and chapter composition. Kirk R. Smith supervised the project with assistance from Joseph N. S. Eisenberg, Robert C. Spear, and Wayne M. Getz.

Chapters 1 and 5 are original and unpublished chapters by the author, Manish A. Desai.

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Completing this dissertation required far more time, effort, compromise, and sacrifice than anyone anticipated. To be clear, I am referring not to myself but to my mentors, colleagues, peers, and friends, all of whom have been stalwart partners of mine.

To paraphrase an ancient saying, I am indebted to my teachers for learning to live well. My advisors, Kirk Smith and Joseph Eisenberg, by their very examples, have taught me much about living with integrity and purpose. Countless, invariably invigorating, discussions with each advisor have been among my most cherished educational experiences. Working with such admirable scholars, who excel at converting talent into impact, has been a privilege and an honor. Most importantly, Kirk and Joe believed in me, seemingly unbelievably, when it mattered most. Kirk's unwavering support, especially during the past year, has been unusually generous. I am profoundly grateful and hope to pay these gifts forward.

I wish also to convey my appreciation for my committee members Bob Spear and Wayne Getz. Amidst ups and downs, including both lengthy quiet and brief intense periods, Bob and Wayne expertly divined when to challenge me and when to reassure me. It is clear why both gentlemen have earned the high distinction of being stellar mentors.

Many others across this incredible campus have been instrumental to this dissertation. In particular, Jack Colford helped lead me onto a doctoral path and Michael Bates helped keep me on it. My fellow students in Environmental Health, Epidemiology, ESPM, and ERG, as well as in other departments, have taught me as much as coursework or research.

The administrative staff of my home department – in particular, Norma Firestone, Maria Hernandez, Michael Murphy, Nancy Smith, and Luis Alvarez – helped smooth obstacles small and large with grace and aplomb. They are unheralded champions, without whom literally nothing could happen.

With respect to *Chapters 2* and *3*, I thank my co-authors, not already mentioned, from the publications which were the bases of those chapters (listed in alphabetical order): Sarah Bates, Jamesine Gibson, Skee Houghton, Karen Levy, Song Liang, Jim Scott, and Kyra Shields. With respect to *Chapter 4*, the following people, not already mentioned, kindly contributed their counsel (listed in alphabetical order): Lucas Bastien, Seema Bhangar, Zoe Chafe, Noor Grewal, Drew Hill, Nick Lam, Jiawen Liao, Tom McKone, David Pennise, and Ajay Pillarisetti.

Deepest bows to Larry Yang, Gina Sharpe, Spring Washam, Mushim Ikeda and my kalyāṇa-mittā for inspiring my mindfulness practice.

I am blessed by a community of friends – near and far, old and new – who truly make life worth living. They are far and away the greatest source of joy in my life. I could not have completed this dissertation without the collective support of these brilliant and compassionate individuals.

My gratitude for my parents and my sister knows no bounds. All of my accomplishments are essentially theirs.

1. Introduction

1.1: Multiscale Drivers of Global Environmental Health

Environmental health's purview, driven by an accelerating transformation of social and ecological systems, has been progressively expanding to encompass a broader array of environment-health relationships (McMichael 2001; Whitmee et al. 2015). This widening perspective embraces persistent, resurgent, and nascent threats to human health that often operate at multiple scales (Myers and Patz 2009; Swinburn et al. 2011; Kovats and Butler 2012; Levy et al. 2012; Myers et al. 2013; Patz et al. 2014), generating the attributable burdens of the present as well as the avoidable burdens of the future (Kovats et al. 2005; Prüss-Ustün et al. 2016). The interplay between social and ecological components of environmental change shapes public health not only through development and sustainability but also through justice and equity (Butler and McMichael 2010; Kleinman 2010; Collins et al. 2011; Cushing et al. 2015; Levy and Patz 2015; Herrick 2016). Collectively, these concerns reveal the complexity of processes by which both traditional and modern environmentally-mediated risks influence human well-being (Smith and Desai 2002).

Analyzing linkages from the planetary to the individual is a core challenge for evolving environmental health into its "global" incarnation (Galea et al. 2010; Ferraro et al. 2015). The complications and uncertainties involved are daunting as causality cascades through multiple scales (Capistrano et al. 2005; Georgopoulos 2008; Sadsad and McDonnell 2014), prompting global environmental health to expand not only its paradigm but also its toolkit. In this dissertation, I motivate, develop, and demonstrate three such approaches for investigating multiscale drivers of global environmental health: (1) a causal metric for analyzing contributions and responses to climate change from global to sectoral scales, (2) a conceptual framework for unraveling the influence of environmental change on infectious diseases at regional to local scales, and (3) a mechanistic model for informing the design and evaluation of clean cooking interventions at community to household scales. Integrating these methods and their insights into its analytical arsenal can help global environmental health meet the challenges of today and tomorrow.

1.2: Metric, Framework, and Model

Environmental health's response to climate change, thus far, has focused primarily on impacts, adaptation, and vulnerability (Portier et al. 2010; Bowen and Friel 2012; IPCC 2014), as well as co-benefits from the control of greenhouse gas emissions (Smith and Haigler 2008; Haines et al. 2009; West et al. 2013). These are vital research streams which justifiably shall remain priorities. Yet in other realms, environmental health seeks not only to characterize the consequences but also mitigate the causes of harmful exposures (Friis 2007). The lack of an accessible means for attributing accountability for climate change at multiple scales has constrained such research in environmental health, as well as other fields (National Research Council 2010).

In *Chapter 2*, I aim to help bridge this gap with a causal metric termed International Natural Debt (IND). IND apportions global radiative forcing from fossil fuel carbon dioxide and methane, the two most significant climate altering pollutants (CAPs), to individual entities − primarily countries but also subnational states and economic sectors, with even finer scales possible − as a function of unique trajectories of historical emissions, taking into account the quite different radiative efficiencies and atmospheric lifetimes of each CAP. Owing to its straightforward and transparent derivation, IND can readily operationalize climate debt to consider issues of equity and efficiency, and drive scenario exercises that explore the response to climate change at multiple scales. The analyses presented in this chapter demonstrate the capacity for climate debt, as captured by IND, to inform a range of key question at multiple scales. In so doing, I present an accessible path for environmental health scientists to pursue the causes as well as the consequences of climate change.

Climate change is among the most prominent examples of a distal environmental change that can affect human health through a series of causal linkages (Altizer et al. 2013). For example, acting through a series of intermediate steps, climate change may alter more proximal environmental characteristics at regional or local scales (Hambling et al. 2011), such as temperature or precipitation, which in turn may perturbate the transmission cycles of an environmentally-mediated infectious disease (Anderson and May 1991; Kraemer and Khan 2010). Systematically interrogating this type of inherently multiscale chain compels a systems-based approach.

In *Chapter 3*, I present the Environmental Change and Infectious Disease (EnvID) conceptual framework which draws on a systems-based structure to organize and evaluate disparate information from a variety of disciplines. The goal of the framework is both to identify knowledge gaps and define research directions, as well as to develop relevant study designs and data analytics so that knowledge about environmental change can be incorporated appropriately into the study and control of re/emerging pathogens. I survey the literature on epidemiologic debates, integrative reviews, and mathematical models to bring into relief the challenges a framework on environmental change and infectious disease endeavors to remedy. On this basis, I explain the EnvID framework's systems-based approach and operationalize its emphases with a putative matrix of plausible relationships between proximal environmental characteristics and transmission cycles. I then apply the framework to a case study, examining a web of interactions surrounding road construction and diarrheal disease in northwestern Ecuador.

A derivative of the systems-based approach advocated by the EnvID framework proves well-suited to the topic of *Chapter 4*. Household air pollution from solid fuel use for cooking (HAP) remains one the world's most significant environmental health challenges, levying an enormous toll on poor families (Smith et al. 2014). Several lines of evidence, viewed in concert, posit that clean cooking interventions may reduce exposure to HAP not only for users but for their neighbors, as well. In turn, the efficacy of interventions may be determined by the extent of both household-level use as well as community-level coverage. Such coverage dependent efficacy, or a "coverage effect," would transform approaches to how interventions are studied and deployed.

In *Chapter 4*, I develop and apply a mechanistic model to study the postulated relationship between community-level coverage of clean cooking interventions and individual-level reductions in exposure to $PM_{2.5}$. Model simulations are intended to help (1) demonstrate whether and to what degree a coverage effect may manifest, (2) explore conditions influencing a relationship between coverage and efficacy, and (3) submit strategies to further enlighten comprehension of a coverage effect. The modeling exercise ventures to be primarily a "proof-of-concept" analysis, and secondarily, an initial first-order approximation and qualitative screening tool. Moreover, the overarching purpose is to encourage approaches that consider − and where or when appropriate, leverage − a coverage effect from clean cooking interventions.

Chapter 5 concludes with synopsis of findings and future steps for these approaches − metric, framework, and model − to investigate multiscale drivers of global environmental health.

1.3: References

Altizer S, Ostfeld RS, Johnson PTJ, Kutz S, and Harvell CD (2013) "Climate change and infectious diseases: from evidence to a predictive framework" *Science* 341(6145): 514-519.

Anderson RM and May RA (1991) Infectious Diseases of Humans: Dynamics and Control Oxford University Press, New York.

Bowen KJ and Friel S (2012) "Climate change adaptation: where does global health fit in the agenda?" *Globalization and Health* 8: 10.

Butler CD and McMichael AJ (2010) "Population health: where demography, environment, and equity converge" *Journal of Public Health* 32(2): 157-158.

Capistrano D, Samper C, Lee MJ, and Raudsepp-Hearne C (2005) Ecosystems and Human Well-being: Multiscale Assessments Island Press, Washington, DC.

Collins SL, Carpenter SR, Swinton SM, Orenstein DE, Childers DL, Gragson TL, Grimm NB, Grove JM, Harlan SL, Kaye JP, Knapp AK, Kofinas GP, Magnuson JJ, McDowell WH, Melack JM, Ogden LA, Robertson GP, Smith MD, and Whitmer AC (2011) "An integrated conceptual framework for long-term social-ecological research" *Frontiers in Ecology and the Environment* 9(6): 351-357.

Cushing L, Morello-Frosch R, Wander M, and Pastor M (2015) "The haves, the have-nots, and the health of everyone: the relationship between social inequality and environmental quality" *Annual Review of Public Health* 36: 193-209.

Ferraro PJ, Hanauer MM, Miteva DA, Nelson JL, Pattanayak SK, Nolte C, and Sims KRE (2015) "Estimating the impacts of conservation on ecosystem services and poverty by integrating modeling and evaluation" *Proceedings of the National Academy of Sciences of the United States of America* 112(24): 7420-7425.

Friis RH (2007) Essentials of Environmental Health Jones & Bartlett, Sudbury, MA.

Galea S, Riddle M, and Kaplan GA (2010) "Causal thinking and complex system approaches in epidemiology" *International Journal of Epidemiology* 39(1): 97-106.

Georgopoulos PG (2008) "A multiscale approach for assessing the interactions of environmental and biological systems in a holistic health risk assessment framework" *Water, Air, & Soil Pollution: Focus* 8(1): 3-21.

Haines A, McMichael AJ, Smith KR, Roberts I, Woodcock J, Markandya A, Armstrong BG, Campbell-Lendrum D, Dangour AD, Davies M, Bruce N, Tonne C, Barrett M, and Wilkinson P (2009) "Public health benefits of strategies to reduce greenhouse-gas emissions: overview and implications for policy makers" *Lancet* 374(9707): 2104-2114.

Hambling T, Weinstein P, and Slaney D (2011) "A review of frameworks for developing environmental health indicators for climate change and health" *International Journal of Environmental Research and Public Health* 8(7): 2854-2875.

Herrick C (2016) "Global health, geographical contingency, and contingent geographies" *Annals of the American Association of Geographers* 106(3): 672-687.

IPCC (2014) "Summary for Policymakers" In Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Editors Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, and White LL, Cambridge University Press, Cambridge, UK**:** 1-32.

Kleinman A (2010) "Four social theories for global health" *Lancet* 375(9725): 1518-1519.

Kovats RS and Butler CD (2012) "Global health and environmental change: linking research and policy" *Current Opinion in Environmental Sustainability* 4(1): 44-50.

Kovats RS, Campbell-Lendrum D, and Matthies F (2005) "Climate change and human health: estimating avoidable deaths and disease" *Risk Analysis* 25(6): 1409-1418.

Kraemer A and Khan MMH (2010) "Global challenges of infectious disease epidemiology" In <u>Modern Infectious Disease Epidemiology: Concepts, Methods, Mathematical Models and Public Health</u>**:** 23-38.

Levy BS and Patz JA (2015) "Climate change, human rights, and social justice" *Annals of Global Health* 81(3): 310-322.

Levy K, Daily G, and Myers SS (2012) "Human health as an ecosystem service: a conceptual framework" In <u>Integrating Ecology and Poverty Reduction: Ecological Dimensions</u> Editors Ingram CJ, DeClerck F, and Rumbaitis del Rio C, Springer New York, New York, NY**:** 231-251.

McMichael AJ (2001) <u>Human Frontiers, Environments and Disease: Past Patterns, Uncertain Futures</u> Cambridge University Press, Cambridge ; New York.

Myers SS, Gaffikin L, Golden CD, Ostfeld RS, H. Redford K, H. Ricketts T, Turner WR, and Osofsky SA (2013) "Human health impacts of ecosystem alteration" *Proceedings of the National Academy of Sciences of the United States of America* 110(47): 18753-18760.

Myers SS and Patz JA (2009) "Emerging threats to human health from global environmental change" *Annual Review of Environment and Resources* 34(1): 223-252.

National Research Council (2010) <u>Monitoring Climate Change Impacts: Metrics at the Intersection of the Human and Earth Systems</u> National Academies Press, Washington, DC.

Patz JA, Frumkin H, Holloway T, Vimont DJ, and Haines A (2014) "Climate change: challenges and opportunities for global health" *Journal of the American Medical Association* 312(15): 1565-1580.

Portier C, Thigpen Tart K, Carter S, Dilworth C, Grambsch A, Gohlke J, Hess J, Howard S, Luber G, Lutz J, Maslak T, Prudent N, Radtke M, Rosenthal J, Rowles T, Sandifer P, Scheraga J, Schramm P, Strickman D, Trtanj J, and Whung P-Y (2010) <u>A Human Health Perspective on Climate Change: A Report Outlining the Research Needs on the Human Health Effects of Climate Change</u> National Institute of Environmental Health Sciences, Research Triangle Park, NC.

Prüss-Ustün A, Wolf J, Corvalán C, Bos R, and Neira M (2016) <u>Preventing Disease through Healthy Environments: A Global Assessment of the Burden of Disease from Environmental Risks</u>, Geneva, CH.

Sadsad R and McDonnell G (2014) "Multiscale modelling for public health management: a practical guide" In <u>Discrete-Event Simulation and System Dynamics for Management Decision Making</u>, John Wiley & Sons Ltd**:** 280-294.

Smith KR, Bruce N, Balakrishnan K, Adair-Rohani H, Balmes J, Chafe Z, Dherani M, Hosgood HD, Mehta S, Pope D, and Rehfuess E (2014) "Millions dead: how do we know and what does it mean? Methods used in the Comparative Risk Assessment of household air pollution" *Annual Review of Public Health* 35: 185-206.

Smith KR and Desai MA (2002) "The contribution of global environmental factors to ill-health" In <u>Environmental Change, Climate, and Health: Issues and Research Methods</u> Editors Martens P and McMichael AJ, Cambridge University Press, New York City**:** 52-95.

Smith KR and Haigler E (2008) "Co-benefits of climate mitigation and health protection in energy systems: scoping methods" *Annual Review of Public Health* 29: 11-25.

Swinburn BA, Sacks G, Hall KD, McPherson K, Finegood DT, Moodie ML, and Gortmaker SL (2011) "The global obesity pandemic: shaped by global drivers and local environments" *The Lancet* 378(9793): 804-814.

West JJ, Smith SJ, Silva RA, Naik V, Zhang Y, Adelman Z, Fry MM, Anenberg S, Horowitz LW, and Lamarque J-F (2013) "Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health" *Nature Climate Change* 3(10): 885-889.

Whitmee S, Haines A, Beyrer C, Boltz F, Capon AG, de Souza Dias BF, Ezeh A, Frumkin H, Gong P, Head P, Horton R, Mace GM, Marten R, Myers SS, Nishtar S, Osofsky SA, Pattanayak SK, Pongsiri MJ, Romanelli C, Soucat A, Vega J, and Yach D (2015) "Safeguarding human health in the Anthropocene epoch: report of the Rockefeller Foundation-Lancet Commission on Planetary Health" *Lancet* 386(10007): 1973-2028.

2. Metric of Climate Debt from Carbon Dioxide and Methane

2.1. Background & Motivation

Environmental health's response to climate change has focused primarily on impacts, adaptation, and vulnerability (Portier et al. 2010; Bowen and Friel 2012; IPCC 2014), as well as co-benefits from the control of greenhouse gas emissions (Haines et al. 2009; West et al. 2013). These are vital research streams which justifiably shall remain priorities. Yet in other realms, environmental health seeks not only to characterize the consequences but also mitigate the causes of harmful exposures (Friis 2007). The lack of an accessible metric for attributing accountability for climate change at multiple scales has constrained such research in environmental health and other disciplines (National Research Council 2010).

2.1.1. Overview

The United Nations Framework Convention on Climate Change (UNFCCC) enjoins countries to act "in accordance with their common but differentiated responsibilities and respective capabilities" (United Nations 1992) "in light of different national circumstances" (UNFCCC, 2014). This guiding principal seeks to engender an equitable, efficient, and ultimately effective international response to climate change (Stone 2004). Efforts to formalize such an approach began with the Brazilian Proposal (UNFCCC, 1997), which emerged during deliberations culminating in the Kyoto Protocol, and continue today as negotiations on a successor treaty progress (Morales 2013). Yet fully implementing a commensurate framework has proven contentious, partly owing to the lack of an acceptable means for estimating accountability for climate change, otherwise known as "climate debt." Moreover, the capacity for a climate debt metric to inform a range of key questions on climate change mitigation, including public health impacts, has been underappreciated.

Discussions about climate debt have generally emphasized disparities between countries in either current or cumulative emissions of carbon dioxide from fossil fuel combustion and cement production (CO_2(f), the "f" referring to fossil carbon), the most important driver of global warming. Neither current nor cumulative emissions fully reflects contributions to climate change, however, because the amount of global warming caused by CO_2(f) at any given moment is actually due to those prior emissions still remaining in the atmosphere at that time, a quantity which is usually intermediate between current and cumulative emissions.

Notably, recent research has also stressed the substantial roles played by other climate altering pollutants (CAPs), the emissions of which, while also exhibiting substantial country-by-country variation, are now garnering attention as additional avenues for intervention (Moore and MacCracken 2009). Chief among these is methane (CH_4), the second most significant CAP (Shindell et al. 2009). Together, CO_2(f) and CH_4 contributed roughly two-thirds of the radiative forcing (RF), or excess energy in the climate system, from all non-aerosol CAPs circulating in the atmosphere during 2005 (Myhre et al. 2013). Yet there is comparatively little in the published climate justice literature incorporating the impact of multiple CAPs in concert, nor the consequent shift in perspective such a joint appraisal would entail (Grübler and Nakićenović 1994; Höhne et al. 2011; den Elzen et al. 2013; Matthews et al. 2014).

In this chapter, I first motivate a straightforward and transparent metric of climate debt termed International Natural Debt or IND (Smith 1991). IND apportions global RF from CO_2(f) and CH_4, the two most significant CAPs, to individual countries as a function of each country's unique trajectory of historical emissions, taking into account the quite different radiative efficiencies and atmospheric lifetimes of each CAP. Hence, IND portrays climate debt in terms of a meaningful parameter for measuring anthropogenic perturbation of the climate system − RF − that resides intermediate along the causal change from source to impact. IND avoids recourse to either computationally intensive methods, such as global climate models, which require specialist knowledge and sophisticated tools to engage (Friman and Linner 2008; Okereke 2010), or time horizons and discount rates, the selection of which have proven problematic for Global Warming Potential and its analogs (Shine 2009; Tol et al. 2012). IND was developed to be accessible and flexible for users, including with regards to inputs and outputs. Thus, IND can be an appropriate vehicle, as data sources improve and climate science advances, for folding additional CAPs and other anthropogenic perturbations to RF, including compensatory actions, into the climate debt paradigm. In sum, I contend that IND meets the criterion of being an insightful "good enough tool" for analyzing responses to climate change (Socolow and Lam 2007).

I develop an IND database[1] that spans 181 countries, 24 dependencies, and the subnational entity of California. California's landmark Global Warming Solutions Act (California State Assembly 2006) expands this state's "tradition of environmental leadership by placing California at the forefront of ... efforts to reduce emissions of greenhouse gases." While acknowledging that "national and international actions are necessary to fully address the issue of global warming," the legislation also argues that "action taken by California will have far-reaching effects by encouraging other states, the federal government, and other countries to act" (California State Assembly 2006). California's leadership provides impetus to include it in IND analyses as one example of how the metric can be leveraged at a subnational scale.

[1] *Database IND* is available at http://www.kirkrsmith.org/s/Desai-Dataset-IND.xlsx.

To characterize both California's and the United States' IND, I contrast the two, using the opportunity to consider uncertainty in IND as well. Subsequently, I survey the global community of nations in total and per capita terms, as well as with respect to economic output and population health in a manner akin to carbon intensity carbon intensity (Knight and Rosa 2011; Jorgenson 2014). I devote extra attention to the CH_4 contribution to IND, since this component of climate debt has been less examined. These characterizations of climate debt serve to highlight equity and efficiency considerations and the relative roles of CO_2(f) versus CH_4 to IND. Descriptive applications can snapshot the global distribution of climate debt along important axes, propose rationales and pathways for decreasing climate debt, and track a county's progress in comparison to itself or other countries.

To investigate the issues posed by excluding or including land use change and forestry (LUCF), an important component of anthropogenic CO_2 flux, I also calculate a combined climate debt metric that consolidates both CO_2(f) and LUCF, as well as CH_4, by global region, as this is the finest geographic scale available for reliable LUCF data. Also at a region-level, I employ IND to bring into relief the stark inequities between countries that are experiencing versus imposing health impacts from climate change, an analysis relevant to burden-sharing among countries.

Next, I show how arguments for reducing CO_2(f) versus CH_4 can be clarified by calculating country-by-country IND under an "aspirational reductions" scenario. In this exercise, I forecast the IND consequences of countries achieving a widely discussed yet ambitious goal of decreasing emissions of CAPs to 80% of 1990 levels by 2050 (Executive Department of the State of California 2005; Parliament of the United Kingdom 2008; European Commission 2011). Under this scenario, for instance, global IND in 2050 would be 93% of its 2005 level with CH_4 comprising 17% of IND instead of 43% as in 2005. This scenario exercise exposes how the composition of IND, determined by the magnitude and timing of historical emissions, constrains a country's capacity to reduce its climate debt, further motivating a globally coordinated approach to mitigating both CAPs.

Lastly, I explore how a question at a sectoral scale can be examined with IND. Energy-related emissions are a major driver of climate debt and among the most discussed targets for mitigation. However, controversy endures about the direction of RF impacts from the expanded use of natural gas (Weber and Clavin 2012; McJeon et al. 2014). I examine this dilemma for California by simulating the change to the state's IND in 2005 that would have occurred from an "alternate histories" scenario during which half of all coal-fired power production had shifted to gas five years prior. The ramifications of this scenario exercise help to elucidate the key parameters and tradeoffs, from the standpoint of climate debt as defined by IND, of selecting between alternative energy sources and their associated infrastructure.

In concert, these characterizations and applications of IND build upon and further extend the purview of climate debt analyses, bringing into relief the consequences of jointly considering CO_2(f) and CH_4, and encouraging global environmental health researchers to investigate the full causal chain from climate change drivers to climate change impacts.

2.1.2. Climate Justice and Historical Accountability

In this subsection, I briefly review the rationale behind the development of climate debt metrics. One reformulation of climate debt is "natural debt," a concept which better reflects physical reality than either current or cumulative emissions by focusing on the amount of a country's or person's past CAP emissions that remain in the atmosphere in any given year (Smith 1991; Smith 1996). A similar notion is "ecological debt" (Baer 2006; Srinivasan et al. 2008). A national debt is built by borrowing financial resources from the future. Similarly, the natural debt is built by borrowing Earth's assimilative capacity from the future, as CAPs are released faster than they can be removed by natural systems. Just as with their national debt, countries have built up their infrastructure and wealth faster than would otherwise have occurred by borrowing against their natural debt. The size of a country's natural debt indicates the degree to which it has avoided diverting resources from other economic activities to CAP control during development, whether consciously or not.

The amount of a CAP remaining in the atmosphere today is not equal to the total amount emitted throughout history since Earth's assimilative capacity removes CAPs from the atmosphere at a rate that varies with, *inter alia*, the physical and chemical characteristics of each CAP. Thus, the most realistic climate debt calculations allow for natural depletion over time, counting only that portion that still survives as the current debt.

An individual country's contribution to the global natural debt serves as a useful measure of its accountability for climate change that more accurately reflects physical reality than current yearly emissions, since the current global natural debt (remaining CAPs in the atmosphere) is what drives climate change. This allocation approach also accords with the "polluter pays principle" from environmental ethics, policy, and law, which says that those who release the pollution into the common environment should be held accountable for the costs of the resulting negative impacts imposed on others and of remediation.

The debut of a natural debt-like metric in international negotiations is attributed to what is termed the "Brazilian Proposal", which recommends use of "net anthropogenic emissions" from 1840 rather than current emissions when calculating accountability for global warming (UNFCCC 1997). This approach was not taken up in the Kyoto Protocol, but remains an option discussed by the UNFCCC; other countries, for example China (Project Team of the Development Research Center of the State Council 2009); and in the scientific literature (Höhne and Blok 2005; Friman and Linner 2008). The approach has raised by various countries, including the BASIC coalition of Brazil, South Africa, India and China.

Incorporating the impacts of additional CAPs into a climate debt metric will help the metric to further reflect physical reality and convey signals regarding the most appropriate control priorities. In addition, as additional CAPs are considered when allocating historic accountability, the spectrum of mitigation strategies to achieve CAP targets will enlarge. There are, however, some conceptual issues with integrating additional CAPs into the climate debt metric in combining CAPs with different RFs and lifetimes. In addition, for non-CO_2(f) CAPs, the available emissions inventories have been much less elaborated than for CO_2(f).

Although the "polluter pays principle" may be conceptually attractive, some observers have expressed discomfort when applied historically to a country's CAP emissions back to the beginnings of the Industrial Revolution (Baer 2006). For an excellent and detailed discussion of the characteristics of different indices for determining just and equitable distributions of CAP emissions and their reductions see Grübler and Nakićenović (1994). Other discussions are found in Hayes and Smith (1993); Ridgley (1996); Cazorla and Toman (2000); and Sagar (2000). In general, two classes of arguments focus on why it is unfair to hold the present accountable for the past: the past was ignorant and the present is ignorant (Beckerman and Pasek 1995; Neumayer 2000; Miller 2009).

Although the first warnings about greenhouse warming appeared in the century before last (Arrhenius 1896), it can be argued that past generations acted out of ignorance in not controlling emissions and thus their descendants should not be penalized (Grubb 1995). Moreover, estimates of the emissions of CAPs become increasingly unreliable the farther back in time one goes, since they depend on records of fossil fuel use, cement production, land use patterns, etc. Even with good estimates by geography, shifting political boundaries and past dominion of one country over others could make it problematic to assign emissions to countries today, even for a CAP such as CO_2(f) for which reasonable emissions data may be available (Grubb et al. 1992).

The counterarguments address why it is unfair not to hold the present accountable for the past, that ignorant or not, we benefitted and ignorance should not be rewarded. People alive today have directly benefited by the actions of their ancestors in borrowing environmental assimilative capacity. The current overall economic standard of living in the United States, for example, would most likely not be as high today if previous U.S. generations had directed more resources to emitting fewer CAPs given the state of technology at the time. In the words of Bhaskar (1995), "..., if current generations in the North accept *assets* from their parents, then it is incumbent upon them to also accept the corresponding *liabilities*" (emphasis in original).

Bhaskar (1995) notes also that because of past ignorance, it is not appropriate to place a moral opprobrium on past generations and their descendants for these actions. It is fair, however, to expect that current generations meet the obligations that come with the benefits they receive. Simply put, it is a matter of repaying one's debts with a fraction of the assets achieved in part by taking on the debts. Similarly, the return from successful investments made in the past for the wrong reasons or even accidently, still is subject to income taxes today.

In addition, if the present generation is to be expected to accept accountability for the future, it must possess a feeling of control over the future. Without any control, there can be no true accountability, because there is no reason to think the values and consequent sacrifices of today will be honored in the future. Consequently, and perhaps paradoxically, in order to impart a perception of control over the future, the present generation must feel somewhat constrained by the past. If this generation dismisses historical accountability, what is to keep the next generation from doing so as well (Smith 1977)?

One of the best ways to encourage this and future generations to more seriously consider the long-term impacts of their activities is to make it clear that they will be held accountable for problems that arise as a result of their decisions, no matter how much ignorance is claimed. With this shift in perspective, they will then be more likely to apply the appropriate caution in their choices. To not do so is to provide great incentive to remain ignorant.

A number of analysts have examined the implications of strategies that achieve just and equitable climate control without considering climate debt (Berk and den Elzen 2001; Toth 2001; Pan 2003; Sugiyama and Deshun 2004; Manne and Stephan 2005; Böhringer and Welsch 2006). Conversely, more sophisticated elaborations of accountability based on historical emissions have also been proposed, such as those related to actual cumulative RF (Labriet and Loulou 2003) or based on weighted temperature changes (Tanaka et al. 2009). These latter approaches, although in a sense more reflective of reality than natural debt, are further along the causal chain from emissions to impact and thus subject to the uncertainties of the complex and evolving models upon which they rely (Smith and Ahuja 1990).

IND therefore endeavors to present a compromise between the over-simplification and somewhat misleading nature of current or cumulative emissions as an accountability metric and the difficult to explain and interpret expressions of climate change impacts resulting from global climate models. IND has the distinct advantage that individuals and organizations can readily duplicate and update the index themselves without contending with differences among global climate models that cannot be quickly resolved even by experts. With the addition of the second major CAP, CH_4, IND is more reflective of physical reality and provides signals related short-lived pollutants that would be otherwise lost.

2.2. Metric Development

2.2.1. Overview

Unless otherwise qualified, "IND" without a subscript specifically refers to climate debt as follows: (1) from both CO_2(f) and CH_4 combined, (2) for the year 2005, and (3) in total not per capita terms. Climate debt from only CO_2(f) or CH_4 is denoted $IND_{CO_2(f)}$ or IND_{CH_4}, respectively, and the percent of IND from CO_2(f) or CH_4 is denoted %CO_2(f) or %CH_4, respectively. To be clear, IND does not include LUCF. Climate debt from LUCF; CO_2(f) and LUCF combined; and CO_2(f), CH_4, and LUCF combined are denoted IND_{LUCF}, IND_{CO_2}, and IND_{+LUCF} (note that IND_{+LUCF} equals the sum of IND and IND_{LUCF}).

I calculated IND for 181 countries, 24 dependencies, and California. For brevity, in this chapter the term "countries" refers to all 206 of these political entities, which together comprised over 99% of the world's population and economy in 2005. IND for the United States was calculated separately for California and an entity termed the United States minus California, abbreviated U.S. minus CA.

IND measures climate debt in terms of RF, defined as the net impact of a factor, including its direct and indirect effects, on the global energy balance. RF, with respect to a CAP, implicitly accounts for the depletion of historical emissions over time by natural processes. Typically, RF is expressed in units of excess energy per surface area (e.g., mW/m^2) and in reference to conditions at a specific point in time relative to pre-industrial conditions. Therefore, expressed in the same units as RF, a given country's IND estimates how many mW/m^2 its still extant past emissions of CO_2(f) and CH_4 are contributing to the climate system in 2005.

The Intergovernmental Panel on Climate Change (IPCC) provides RFs for major CAPs based on anthropogenic emissions since 1750. I continue to use RFs from the Fourth Assessment Report (AR4, Solomon et al. 2007), instead of the more recently released Fifth Assessment Report (AR5, Stocker et al. 2013), because AR4 provides RF values for 2005 (Forster et al. 2007), retaining consistency with time-series of emissions which span 1950−2005.

AR4 reports the RF from CO_2 in 2005, or global IND_{CO_2}, as 1,560 mW/m^2. In order to divide this value among its CO_2(f) and LUCF components, I applied the first two steps of the procedure described in this section to the global-level time-series, which spans the 1850−2005 period, of CO_2(f) and LUCF emissions. In so doing, I calculated that 72% of IND_{CO_2} is attributable to CO_2(f) and the other 28% is attributable to LUCF. In other words, global $IND_{CO_2(f)}$ equals 1,123 mW/m^2 and global IND_{LUCF} equals 437 mW/m^2. AR4 also reports the RF from CH_4 in 2005, or global IND_{CH_4}, as 856 mW/m^2.

Thus, global $IND_{CO_2(f)}$ and IND_{CH_4} sums to a global IND of 1,979 mW/m^2 in 2005. For comparison, the 2005 RF from all non-aerosol CAPs was 2,913 mW/m^2, and the best estimate of net RF from all human activity since the Industrial Revolution − including LUCF, the overall cooling effect of aerosol CAPs, changes in surface albedo from land use, and contrails − is ~1,600 mW/m^2.

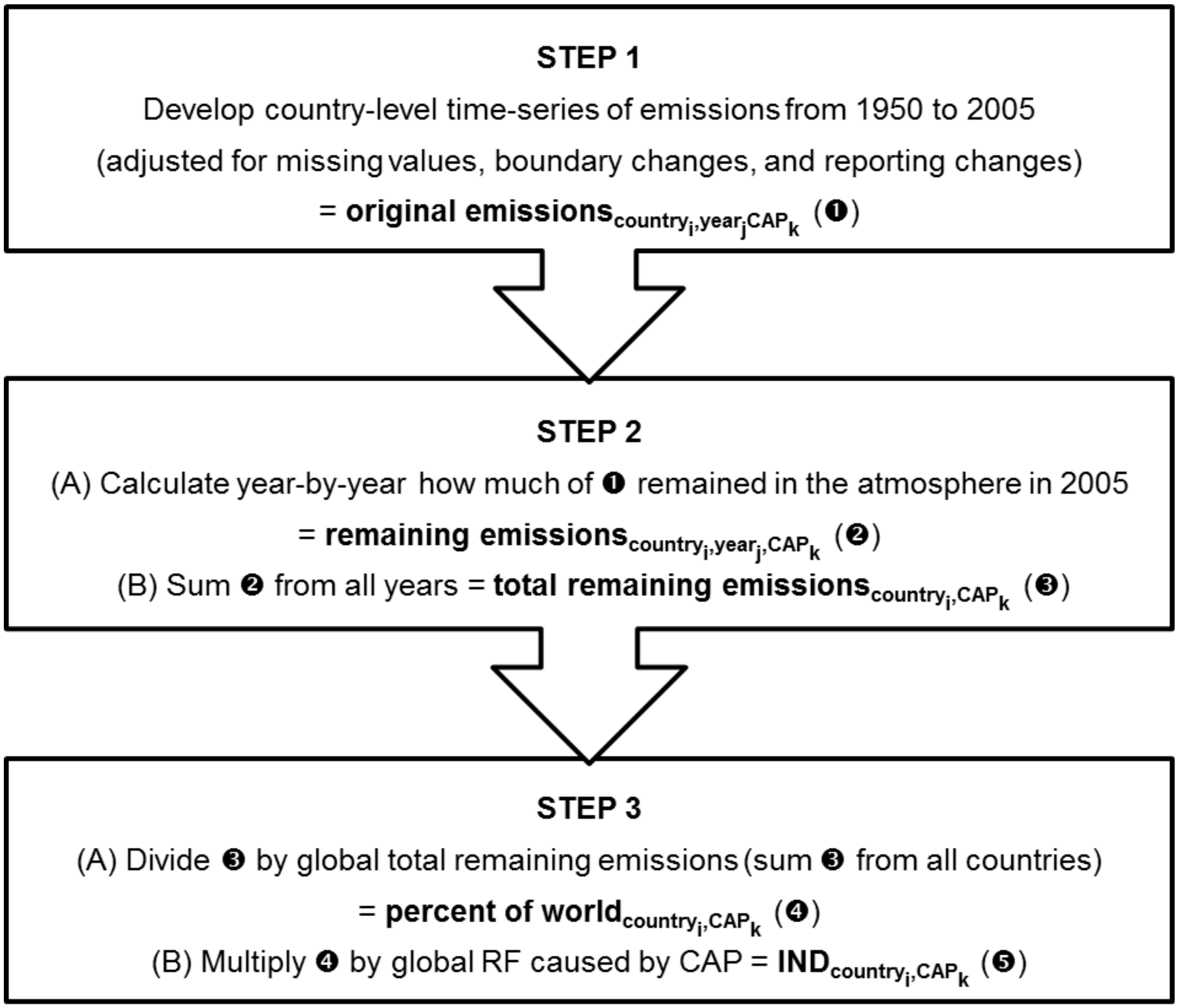


Figure 2.1: Flowchart of Steps to Calculate IND. Summary of procedure to calculate IND from a single CAP and for a single country. See *Section 2.2* for details.

Global $IND_{CO_2(f)}$ and IND_{CH_4} were allocated to countries by the method outlined in *Figure 2.1* and described in detail in the ensuing subsections. As an overview, the steps for a single country and a single CAP were as follows. First, I developed time-series of historical, or "original," emissions from 1950 to 2005. Second, I calculated year-by-year, using the CAP's atmospheric lifetime, how much of these original emissions remained in the atmosphere in 2005 and summed these "remaining" emissions from all years. Third, I divided the country's total remaining emissions by the world's to determine what fraction of global $IND_{CO_2(f)}$ or IND_{CH_4} to assign to the country. Once this procedure was executed for both CAPs, I summed the country's $IND_{CO_2(f)}$ and IND_{CH_4} to generate its IND as well as %CO_2(f) and %CH_4.

A 1950 start year helps to address potential uneasiness associated with historical accountability and practical difficulties in attributing current CAP concentrations to emissions dating back to pre-industrial times. A base year of 1950 was also used by Sagar (2000), but other investigators have gone back to 1915 (Winkler et al. 2002), 1850 (Rosa and Ribeiro 2001), or, in probably the first analysis done, 1800 (Grübler and Fujii 1991). Subak (1993) compares five different approaches to assessing emissions with data going back to 1860. The complexities of systematically determining emissions so long ago and assigning them to current populations, however, are daunting. Shorter periods have also been proposed, e.g., 1990 (Baer 2006).

For the post-1950 timeframe, records are more numerous, detailed, and reliable. In the years following World War II, national boundaries were altered across the globe to mostly resemble their current form and the major colonial empires had begun to dissolve. As a results, IND calculations are subject to fewer assumptions in order to link old national boundaries to current ones. Additionally, by the early 1950s, most of the major global organizations, founded several years prior (e.g., the United Nations and the Bretton Woods institutions), had taken on their modern character, ushering in the present era. Arguably, therefore, 1950 approximately represents the point in world history when a large fraction of the international community first accepted some shared accountability for global action. International commitments focusing on climate change are now expressed through these same 1950-era institutions via the IPCC and UNFCCC.

2.2.2. Step 1 − Develop Time-Series of Original Emissions

To begin, I developed a database of country-level time-series (1950−2005) of original emissions of CO_2(f) and CH_4. The phrase "original emissions" refers to the amount of CAP emitted by a country during a particular year without accounting for any subsequent depletion. The database was derived from datasets which covered as much of the world since 1950 as possible, meeting the spatiotemporal requirement, and also met the following criteria: (1) free and publicly available; (2) frequently updated; (3) well-documented methodologies with estimates of uncertainty; and (4) widely referenced.

Given these criteria, I drew on country-level datasets for CO_2(f) emissions from the Carbon Dioxide Information Analysis Center (CDIAC, Boden et al. 2010) and for CH_4 emissions from the Emission Database for Global Atmospheric Research (EDGAR, 2010b). Both CDIAC and EDGAR were updated with Annex I countries' 1990 to 2005 data from the UNFCCC (2012). Additionally, population data were drawn from the United Nations Department of Social and Economic Affairs, Population Division (2011), and economic data from the World Bank (2012) and World Factbook (United States Central Intelligence Agency 2006).

For California, I drew on datasets of CO_2(f) and CH_4 emissions from the Air Resources Board of the California Environmental Protection Agency (CARB; Air Resources Board of the California Environmental Protection Agency 2007a; Air Resources Board of the California Environmental Protection Agency 2013). I used the earlier inventory for 1990−1999 emissions and the later inventory for 2000−2005 emissions. CO_2(f) emissions from 1960−1989 were drawn from CDIAC (Blasing and Krassovski 2012). Population data were based on intercensal estimates from the Population Estimates Program of the United States Census Bureau (2011), and economic data were obtained from the Bureau of Economic Analysis of the United States Department of Commerce (2006).

The CDIAC and CARB datasets for CO_2(f) included emissions from fossil fuel combustion, cement manufacture, and gas flaring in oil fields, corresponding to Common Reporting Framework categories 1A, 2A1, and 1B2C1, respectively (Houghton et al. 1997). To construct complete and consistent time-series of CO_2(f) emissions, adjustments to the country-level CDIAC dataset were necessary to account for, most notably, changes in the boundaries of countries (see *Appendix A* for details on this and several additional minor adjustments).

Over the 1950−2005, 30% of countries in the database experienced a boundary change unaccounted for by the country-level CDIAC dataset. For unifications, I merged the time-series of the component countries. For partitions, I used cumulative emissions from each component country during the first five years post-partition to proportionally weight the attribution of emissions during pre-partition. Adjustments in one of these two ways affected 14% of all country-years.

The EDGAR and CARB datasets for CH_4 included emissions from energy, industry, agriculture, waste, and wildfires (forest and grassland), corresponding to Common Reporting Framework categories 1, 2, 4, 6, and 5B, respectively (Houghton et al. 1997). EDGAR's CH_4 dataset covers 1970−2005, accurately mapping these historical emissions, with no adjustment necessary, to those countries that existed in 2005. To estimate country-level CH_4 emissions for 1950−1969, I extrapolated individual countries' full 1970−2005 data back to 1950 by least-squares linear regression. If an extrapolated trend became negative, emissions for that and all prior years reverted to zero.

To estimate California's CO_2(f) emissions for 1950−1959 and CH_4 emissions for 1950−1989, a parallel extrapolation was executed using the full 1990−2005 data for CO_2(f) and the full 1970−2005 data for CH_4. The proportional contribution of these extrapolated original emissions to $IND_{CO_2(f)}$ and IND_{CH_4} are provided in the subsection. The full time-series of California's CO_2(f) and CH_4 emissions were subtracted from those for the United States to produce CO_2(f) and CH_4 time-series for the U.S. minus CA.

To reiterate, my purpose is not to calculate the most up-to-date values for IND, but rather, to demonstrate applications of IND and thus encourage a climate debt perspective even as underlying data continually updates. Nonetheless, it is worth noting that post-2005 emissions trajectories will alter the size and distribution of INDs, although, as yet, not in dramatic fashion. Most apparently, CO_2(f) emissions from many low-to-middle income countries (LMICs) have increased more rapidly relative to most high income countries (HICs), whereas CH_4 emissions have increased more-or-less uniformly and gently across the board. Hence, the global balance of IND in 2010, relative to 2005, will shift slightly towards rapidly developing economies, driven by their proportionately faster growth in $IND_{CO_2(f)}$. In per capita terms, the difference between HICs and LMICs generally will narrow, of course, but remain large.

2.2.3. Step 2 − Calculate Total Remaining Emissions

Next, CAP-by-CAP, country-by-country, and year-by-year, I calculated the amount of original emissions that, given depletion over time, remained in the atmosphere in 2005. The phrase "remaining emissions" refers to such amounts. With the database elaborated to include remaining emissions, I summed each country's remaining emissions from each year to calculate country-level total remaining emissions.

Calculations for remaining emissions are based on the impulse response function or lifetime for CO_2 and CH_4. The corresponding equations, which model the decay over time of these two CAPs, are presented in *Equations 2.1* and *2.2*.

Equation 2.1:

$$CO_2 \text{ fraction remaining at time } t \text{ (years)} = 0.186e^{(-t/1.186 \text{ years})} + 0.338e^{(-t/18.51 \text{ years})} + 0.259e^{(-t/172.9 \text{ years})} + 0.217$$

Equation 2.2:

$$CH_4 \text{ fraction remaining at time } t \text{ (years)} = e^{(-t/8.7 \text{ years})}$$

Equation 2.1 is the impulse response function from the Bern Carbon Cycle Model as recommended in AR4 (Joos et al. 2001). *Equation 2.2* utilizes the global CH_4 lifetime reported in AR4 (Denman et al. 2007).

To illustrate the use of these equations and the different decay dynamics of CO_2(f) and CH_4, consider 1000 tonnes of each CAP emitted in 1990. The amount of these original emissions still present in the atmosphere in 2005 would be 605 tonnes of CO_2(f) and 178 tonnes of CH_4. If these 1000 tonnes of each CAP had been emitted in 1950, then remaining in 2005 would be 423 tonnes of CO_2(f) and 2 tonnes of CH_4.

As a result, although the database only extends back to 1950, for CH_4 in particular there would be little difference, only an estimated <0.1% of global total remaining emissions in 2005, were original emissions prior to 1950 included. A comparatively greater fraction of CO_2(f) remaining emissions in 2005 were originally released prior to 1950, but this fraction is nonetheless not vast, given the rapid rise in emissions during recent decades (Houghton 2007). Applying *Equation 2.1* to CDIAC's global time-series of original emissions dating back to 1751, one finds that 87% of anthropogenic CO_2(f) still circulating in the atmosphere during 2005 was emitted subsequent to 1950. Analogous arguments apply to California's pre-1950 CO_2(f) and CH_4 emissions.

The contribution of extrapolated original emissions to total remaining emissions also can be assessed at this stage. By 2005, 1.2% of global total remaining emissions of CH_4 were derived from extrapolated original emissions for 1950−1969. For California, by 2005, 10.0% of its total remaining emissions of CO_2(f) were from the 1950−1959 extrapolated original emissions and 12.4% of its total remaining emissions of CH_4 were from the 1950−1989 extrapolated original emissions.

2.2.4. Step 3 − Determine International Natural Debt

In the final step, I divided each country's total remaining emissions by the global total of remaining emissions (all countries, all years), yielding a "percent of world" for each country. I then multiplied these percentages by the RF for the corresponding CAP to compute country-level $IND_{CO_2(f)}$ or IND_{CH_4}.

I thus parse the total global natural debts of CO_2(f) and CH_4 across countries believing that the practical and theoretical difficulties, in addition to the complications discussed in the *Introduction*, of determining and assigning emissions previous to 1950 would outweigh any minor improvement in nominal accuracy that might result. The distribution derived from the post-1950 period is therefore used as an estimate of the full distribution of remaining CO_2(f) and CH_4 in the atmosphere in 2005.

With all IND measures expressed in the same units as RF, I summed each country's $IND_{CO_2(f)}$ and IND_{CH_4} to compute a combined IND, as well as %CO_2(f) and %CH_4.

2.2.5. Uncertainty

As with other composite metrics, IND is subject to uncertainty from the choices and parameters that are inherent to it (Prather et al. 2009). With respect to the major inputs to IND − RFs, lifetimes, and emissions − each contributes to a different step in the calculation of IND. In this subsection, I discuss uncertainty in these three parameters and explain the methods employed to conduct a formal uncertainty analysis of California's and the United States' IND, $IND_{CO_2(f)}$, and IND_{CH_4}.

Revised estimates of RF would essentially serve to renormalize all countries' $IND_{CO_2(f)}$ or IND_{CH_4} to a different value. Clearly, if one CAP's RF were to shift proportionately more or less than the other, this would alter the relative contribution of $IND_{CO_2(f)}$ and IND_{CH_4} to IND and thereby redistribute countries' INDs. RFs for both CAPs are assessed to have 90% CIs of ±10% for direct effects, and in the case of CH_4, ±20% for its additional indirect effects (Forster et al. 2007).

The effect of uncertainty in lifetimes would be, in a sense, intermediate to that from uncertainty in RFs and emissions. Within calculations for $IND_{CO_2(f)}$ or IND_{CH_4}, a change in lifetime would impact all countries, but late emitters would be affected less than early emitters. Although the multi-compartmental nature of the carbon cycle, among other issues, complicates the presentation of uncertainty for the atmospheric lifetime of CO_2(f), the impulse response functions from the five IPCC assessment reports agree with one another within 15% for simulations over a 100-year timeframe (Joos et al. 2013). The 90% CI for the atmospheric lifetime of CH_4 spans ±15% (Denman et al. 2007).

Emissions inventories likely constitute the greatest source of uncertainty in IND. Uncertainty generally widens as time-series go farther back in time, but the calculation of remaining emissions effectively discounts the weight of older original emissions, partly abating the contribution of these comparatively less certain data to overall uncertainty. Moreover, both $IND_{CO_2(f)}$ and IND_{CH_4} are disproportionately sensitive to emissions from recent years because these emissions have risen rapidly, in the case of CO_2 (f), or not yet decayed away, in the case of CH_4.

The accuracy of time-series of original emissions is also partially a function of economic significance. Countries with high per capita or total economic output are scrutinized by both their own and international data collection agencies with greater rigor. Partly for this reason, whenever appropriate, the fifty countries with the largest INDs are labelled in ensuing figures.

Uncertainty in emissions can only be roughly ascertained through expert opinion or cross-comparisons of competing datasets (Marland et al. 2009). With this caveats in mind, the 95% confidence intervals (CIs) for original emissions of CO_2(f) are judged to range from plus-or-minus several percent for most developed countries, ±15% to 20% for China, and more than ±50% for countries with inadequate statistical infrastructure (Andres et al. 2012). The 90% CIs for original emissions of CH_4 vary depending on source category, from around ±10% for the energy sector to as much as ±100% for the agriculture or waste sectors (Joint Research Centre of the European Commission/PBL Netherlands Environmental Assessment Agency 2010a).

To explore how uncertainty in original emissions affects California's and the U.S. minus CA's INDs, I conducted Monte Carlo simulation analyses to compute the equivalent of 90% CIs. For CO_2(f) time-series, I assumed that emissions estimates for each year were normally distributed with the mean set by the value in the IND database and 95% CIs assumed to be ±10% of the mean. Distributions were truncated at ±100% of the mean. For CH_4 time series, I assumed that emissions estimates for each year were lognormally distributed, since the estimates in the IND database are more likely to be an underestimate than an overestimate according to several lines of evidence (Frey et al. 2006; Fischer and Jeong 2012). As with CO_2(f), the mean was set by the value in the IND database and 90% CIs were assumed, on the left, to be 75% of the mean, and on the right, 175% of the mean. This assumption was intended to reflect a level of uncertainty intermediate to that for energy versus agriculture/waste CH_4 emissions. Distributions were truncated at 33% and 350% of the mean. Furthermore, each individual emissions estimate was assumed to be correlated with the estimate for the year before and the year after according the same correlation coefficients evidenced by the IND database: 0.96 for California's CO_2(f) emissions; 0.95 for U.S. minus CA's CO_2(f) emissions; 0.99 for California's CH_4 emissions; and 0.93 for U.S. minus CA's CH_4 emissions. Simulations were comprised of 3,000 trials each.

The results of this exercise are suggestive but limited. I did not simulate uncertainty simultaneously in all countries' emissions nor in CAP lifetimes, since these scenarios would require repeatedly recalculating the entire database. Furthermore, some studies have suggested that CH_4 emissions might be off by several multiples (Miller et al. 2013; Brandt et al. 2014), which would imply wholesale revisions to central estimates may be necessary, a possibility that I acknowledge but did not model. Alternatives to the structural assumptions embedded within the IND metric were not addressed either.

The analyses that follow are based on central estimates of IND and associated data, with the recognition that there are remaining uncertainties in emissions inventories and other input parameters which will undoubtedly be reduced with time. Accordingly, results are not intended to be definitive but rather first-order approximations that can guide initial decision-making and stimulate further inquiry, even as the particular distribution of global IND across countries may itself change with future refinement.

2.2.6. Land Use Change and Forestry

Most previous CO_2-based climate debt metrics have focused only on emissions from the energy and cement sectors, as reliable databases have been widely available. In reality, human-induced LUCF have also contributed significantly to CO_2 emissions over time. At the country level, it is difficult to attribute LUCF empirically, because of incomplete and uncertain historical records of LUCF sinks and sources, and conceptually, due to the ambiguities of deciding which changes were natural versus human-induced and what credit to assign for avoiding degradation of carbon stocks (Corbera and Schroeder 2011). Nevertheless, attempts have been made (Klein Goldewijk et al. 2011). Also, unlike CO_2(f), there is no appropriate baseline starting point, i.e., the start of the Industrial Revolution (Smith 1994; Ruddiman 2006). LUCF's estimated contribution is therefore reported separately from CO_2(f) in most of the tables and figures that follow. Given these and many other challenges inherent to attributing climate debt from LUCF, a national-level assessment is beyond the scope of this chapter. I do, however, consider the implications of LUCF through a region-level version of IND both with and without LUCF.

The LUCF dataset was derived from the most recent update to Houghton (Houghton 2003; Houghton 2008) and estimates net CO_2 fluxes resulting from human-induced LUCF at a regional level (see *Figure 2.2* and *Table A8* for region definitions). Once again, I focused on only the 1950−2005 portion of time-series. The methods for calculating the annual LUCF fluxes of CO_2 are described elsewhere in greater detail (e.g., Houghton 1999). Here, I note that the analysis (1) draws on a vast array of land-use statistics from agencies and researchers; (2) models carbon fluxes for multiple native ecosystems per region; (3) accounts for changes in living and dead carbon (above and below ground), harvested wood products, and soils; and (4) incorporates time lags for the decay of biomass and soil carbon and regrowth of secondary forests following wood harvest and agricultural abandonment. Thus, the net flux of CO_2 for a given region-year may be either positive (net CO_2 source) or negative (net CO_2 sink). The LUCF dataset does not include fluxes of CO_2 from ecosystems undisturbed by human activity. Nor does it include the effects of environmental change (e.g., CO_2 fertilization, nitrogen deposition) on CO_2 fluxes.

Historical data on LUCF fluxes are understandably difficult to develop and possess much higher uncertainty than counterpart data on CO_2(f) emissions. For California, I was unable to identify an LUCF dataset that spans the bulk of the 1950−2005 timeframe. The Air Resources Board of the California Environmental Protection Agency (2007b) has generated estimates for 1990−2004 (the LUCF flux was negative for all years). Nonetheless, pre-1990 estimates for California await development. Hence, with respect to LUCF, this chapter does not consider California and the U.S. minus CA separately. Yet despite its more coarse geographic resolution, the LUCF analysis remains informative given the import of LUCF to the global CO_2 budget.

To harmonize the different spatial scales of the datasets (country-level versus region-level), I added IND_{CH_4} for all countries within a region to arrive at region-level IND_{CH_4} values. However, for CO_2(f) I followed a slightly different process to accommodate negative values for LUCF. Within each region, I added member countries' yearly CO_2(f) original emissions to create region-level time-series. Next, I combined region-level CO_2(f) and LUCF time-series, adding or subtracting as warranted, to generate a unified CO_2 time-series. With these CO_2 time-series of original emissions, I then followed the same three-step procedure explained above to generate region-level IND_{CO_2} values. Lastly, summing each region's IND_{CO_2} and IND_{CH_4} yielded its IND_{+LUCF}.

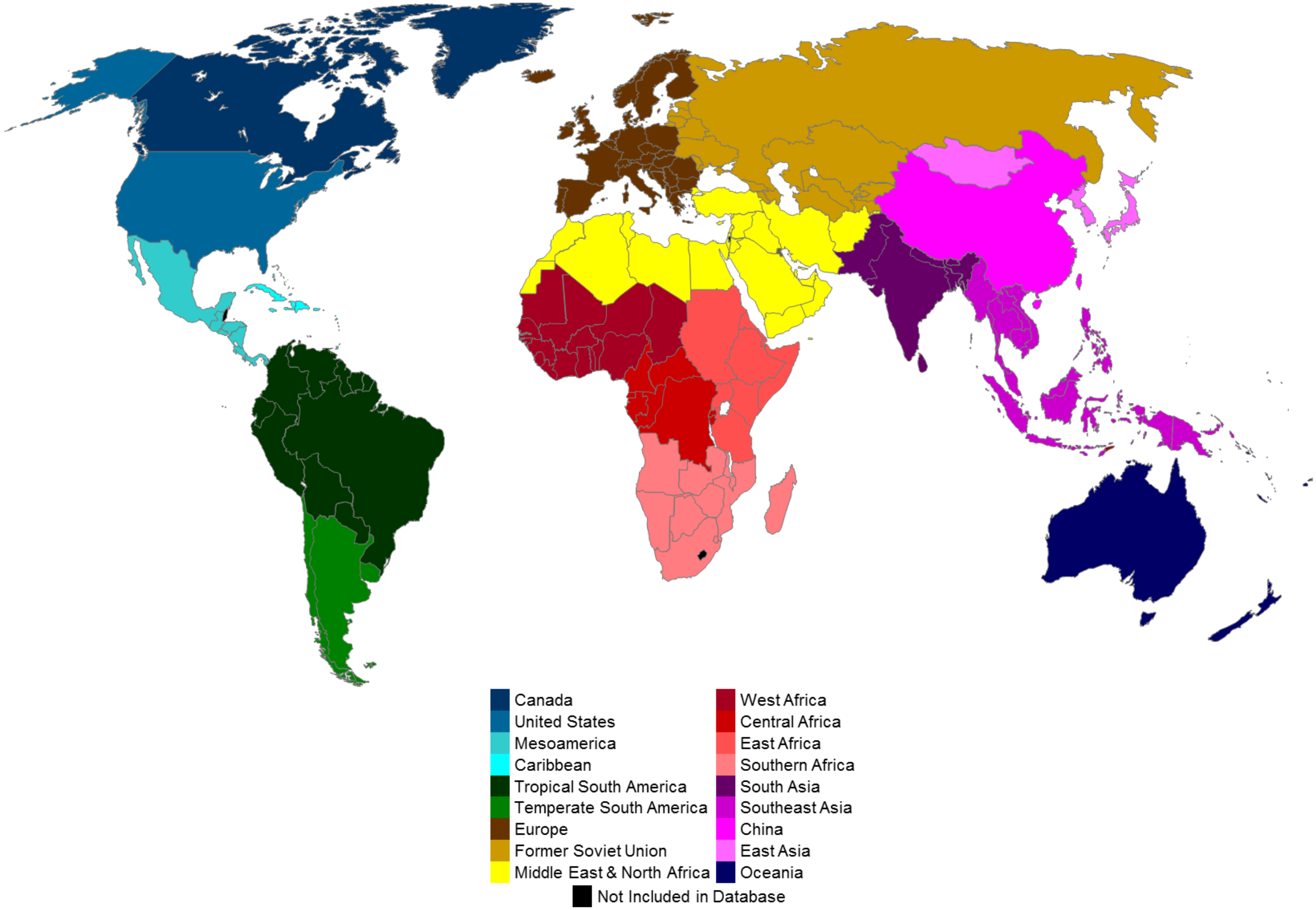


Figure 2.2: Map of Regions for IND_{+LUCF}. Map of the world circa 2005 that distinguishes by color the 18 regions used for calculating IND_{+LUCF}. For list of countries constituting each region see *Table A8*.

2.3. Results & Discussion

2.3.1. California and the United States

Database IND[2] summarizes IND results for all 206 countries, including California, considered in the analysis. *Database IND* includes total and per capita IND, $IND_{CO_2(f)}$, and IND_{CH_4}; current, total original, and total remaining emissions for CO_2(f) and CH_4; and population and income data.

Figure 2.3 focuses on California's and the U.S. minus CA's total (top panel) and per capita (bottom panel) INDs. Ninety percent CIs based on the approach explained in the previous section and discussed further below are represented by error bars in *Figure 2.3* and reported in brackets within the text.

California's total IND is 24.0 mW/m^2 [21.8 mW/m^2, 27.5 mW/m^2] or 1.21% of global total IND. The U.S. minus CA's total IND is 340 mW/m^2 [302 Mw/m^2, 411 mW/m^2] or 17.2% of global total IND. Split into its dual components, California's total $IND_{CO_2(f)}$ is 20.7 mW/m^2 [19.1 mW/m^2, 22.2 mW/m^2], 1.84% of global $IND_{CO_2(f)}$, and its total IND_{CH_4} is 3.27 mW/m^2 [1.47 mW/m^2, 6.28 mW/m^2], 0.383% of global IND_{CH_4}. The U.S. minus CA's $IND_{CO_2(f)}$ is 260 mW/m^2 [241 mW/m^2, 280 mW/m^2], 23.2% of global $IND_{CO_2(f)}$, and its IND_{CH_4} is 79.2 mW/m^2 [44.8 mW/m^2, 142 mW/m^2], 9.25% of global IND_{CH_4}. Consequently, California's %CO_2(f) is higher than that of the U.S. minus CA's, 86.3% versus 76.7%, and conversely its %CH_4 is lower, 13.7% versus 23.3%.

The difference in climate debts accumulated by California and the U.S. minus CA is perhaps best revealed through per capita measures. California's per capita IND is 669 μW/m^2 [575 μW/m^2, 796 μW/m^2], essentially half (51%) that of the U.S. minus CA's per capita IND of 1300 μW/m^2 [1,100 μW/m^2, 1,620 μW/m^2]. California's $IND_{CO_2(f)}$ of 578 μW/m^2 [534 μW/m^2, 621 μW/m^2] and IND_{CH_4} of 91.4 μW /m^2 [41.1 μW/m^2, 175 μW/m^2] are roughly three-fifths (58%) and one-third (30%), respectively, of the U.S. minus CA's $IND_{CO_2(f)}$ of 999 μW/m^2 [924 μW/m^2, 1,070 μW/m^2] and IND_{CH_4} of 303 μW/m^2 [172 μW/m^2, 546 μW/m^2]. These per capita IND values reflect California's more efficient generation of both CO_2(f) and CH_4 emissions in comparison to the U.S. minus CA.

[2] *Database IND* is available at http://www.kirkrsmith.org/s/Desai-Dataset-IND.xlsx.

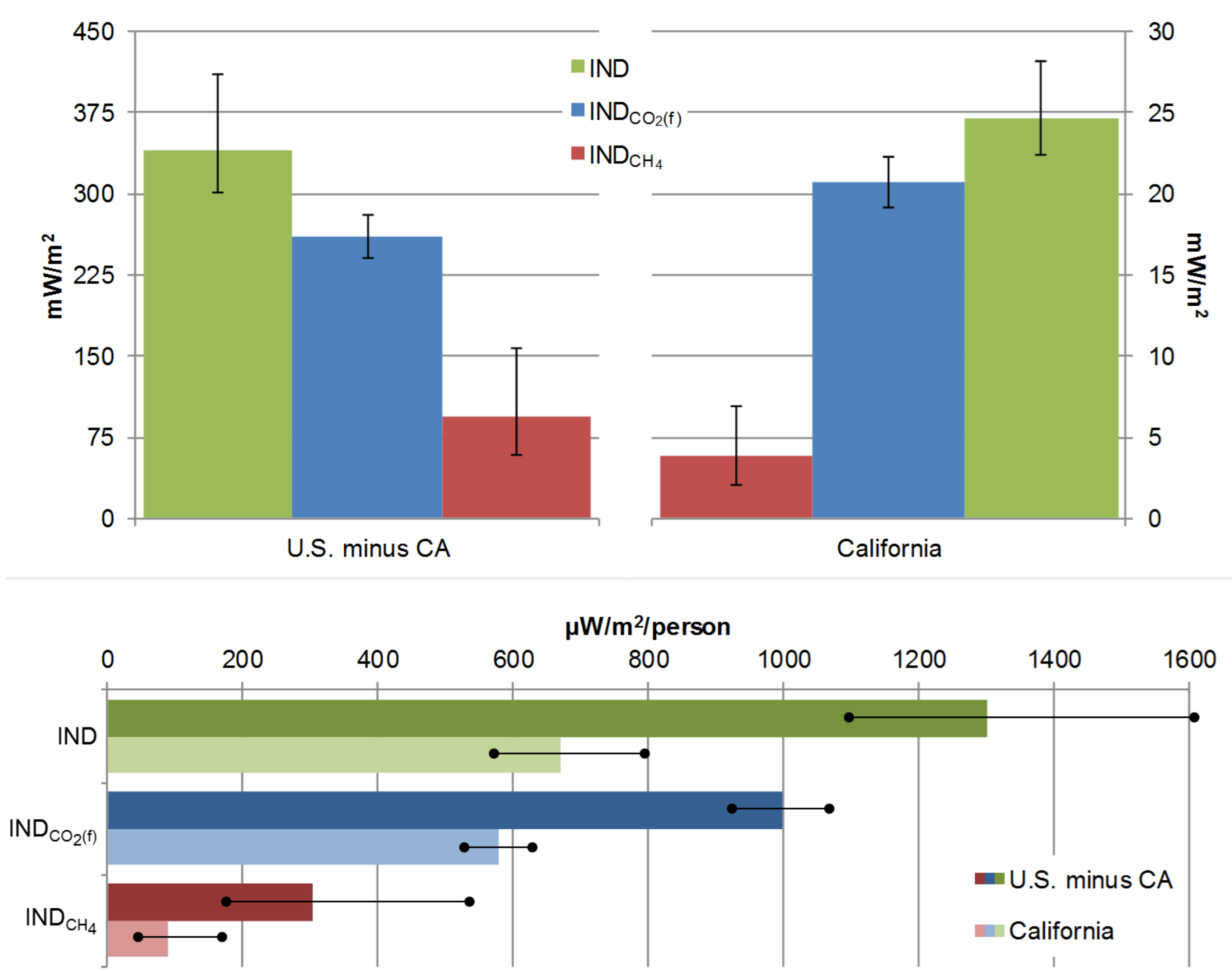


Figure 2.3: Total and Per Capita INDs for U.S. minus CA and California. Two top panels display total IND, $IND_{CO2(f)}$, and IND_{CH4}. Note the different scales used for the U.S. minus CA (left) and California (right). Bottom panel displays per capita IND, $IND_{CO2(f)}$, and IND_{CH4} for the U.S. minus CA (top bars, darker color) and California (bottom bars, lighter color). Error bars (bar ends at top and round ends at bottom) represent 90% confidence intervals (see *Section 2.3.1* for details). Abbreviation: U.S. minus CA = United States minus California.

The 90% CIs reported above help to contextualize IND results for California and the U.S. minus CA. The upper 90% CIs for IND_{CH_4} are farther from central estimates than the lower 90% CIs, reflecting current thinking that CH_4 emissions, and consequently estimates of IND_{CH_4}, are more likely to be underestimates rather than overestimates. For IND_{CH_4}, 90% CIs are wider than central estimates of IND_{CH_4}. For $IND_{CO_2(f)}$, 90% CIs are proportionately much narrower both in comparison to 90% CIs for IND_{CH_4} and central estimates of $IND_{CO_2(f)}$. Ninety-percent CIs for IND are intermediate to those for $IND_{CO_2(f)}$ and IND_{CH_4}, with uncertainty for IND driven more by uncertainty in IND_{CH_4} than $IND_{CO_2(f)}$. The results of this exercise are not to be interpreted as definitive quantifications of uncertainty. At the same time, an appreciation of the magnitude of uncertainty from its most likely significant source − original emissions − can help inform IND-based decision analyses.

Policy to address climate change must nonetheless proceed amidst multiple dimensions of uncertainty. In this chapter, IND analyses are based on current best estimates, with the recognition that remaining uncertainties in emissions inventories and other parameters will be reduced with time. Accordingly, results are intended to be first-order approximations that describe climate debt, guide initial decision-making, demonstrate insightful applications, and stimulate further inquiry, even as the particular specification of IND across countries, including for California and the U.S. minus CA, may itself shift with future refinement.

2.3.2. Characterizations of International Natural Debt

2.3.2.1. Total and Per Capita International Natural Debt

Understanding the global distribution of climate debt as captured by IND begins with characterizing individual countries' total and per capita IND values, including the splits between $\%CO_2(f)$ and $\%CH_4$. Total IND, predictably, spans a vast range incorporating the extremes of population and economic size exhibited by the world's countries, with the U.S. minus CA's 340 mW/m^2 at one end and Niue's 3.51×10^{-4} mW/m^2 at the opposite. As a separate country, California is ranked 18th in the world in total IND, below Iran and above South Africa; 11th in the world in total $IND_{CO_2(f)}$, below France and above Italy; and 48th in the world in total IND_{CH_4}, below Azerbaijan and above the United Arab Emirates. The U.S. minus CA's rankings do not change relative those for the United States. The U.S. minus CA is first with regards to total IND and total $IND_{CO_2(f)}$ but second, flipping positions with China, with regards to total IND_{CH_4}.

Chart *A* of *Figure 2.4* illustrates total world $CO_2(f)$ climate debt, emphasizing the contribution from the ten countries with the largest $IND_{CO_2(f)}$ values plus California. Chart *B* of *Figure 2.4* similarly illustrates total world CH_4 climate debt. LUCF, represented by chart *D* in *Figure 2.4*, is not attributed to individual countries but is included as its own separate chart for comparison. Within *Figure 2.4*, combining chart *A* and chart *B* yields chart *C*, total global IND.

Given $IND_{CO_2(f)}$'s genesis from fossil fuel combustion, the largest debtor countries reflect economic size. The total $IND_{CO_2(f)}$ from the U.S. minus CA alone comprises 23.2% of total global $IND_{CO_2(f)}$ and the next nine countries and California account for an additional 44.5%. Thus, these top $IND_{CO_2(f)}$ debtors collectively account for two-thirds of total global $IND_{CO_2(f)}$.

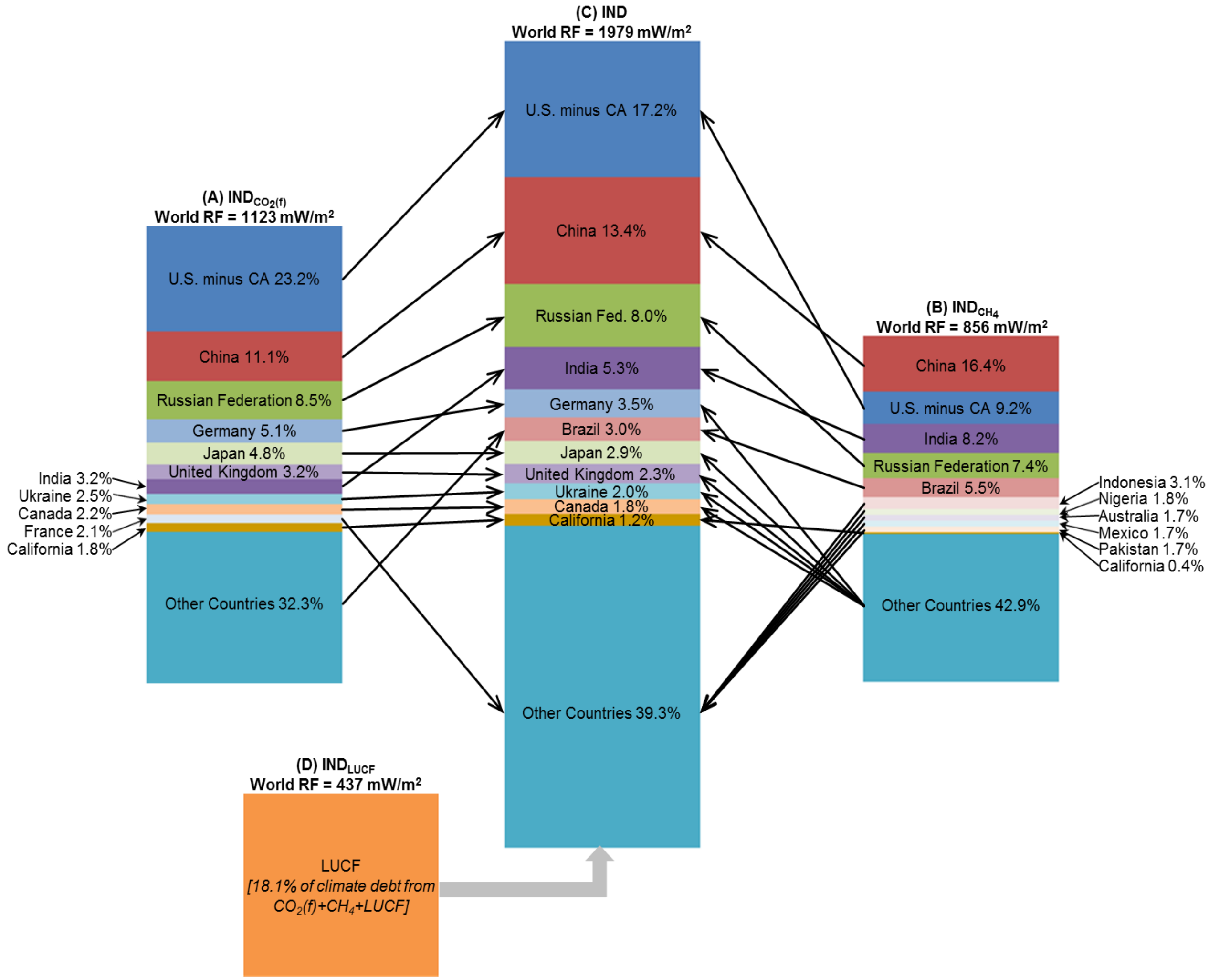


Figure 2.4: Total INDs for Top Debtor Countries. Stacked bar charts represent total world (*A*) $IND_{CO2(f)}$, (*B*) IND_{CH4}, (*C*) IND, and (*D*) IND_{LUCF} climate debt. Chart sizes are proportional to RF. Within charts *A*−*C*, the ten countries with the largest INDs are indicated top-most by individual segments in rank order, followed by California's segment and the remainder of the world represented by the segment "Other Countries". Thin arrows track the change in top ten countries' positions from chart *A* to chart *C* or from chart *B* to chart *C*. The percentages immediately following a segment's name indicate its contribution to total global IND for that chart. IND_{LUCF} is represented separately because it is not a component of $IND_{CO2(f)}$ or IND. Instead, the wide arrow shows how chart *C* would enlarge if LUCF were attributed to countries (or regions) and included in an IND_{+LUCF} metric (as in *Table 2.1*, panel *B*). Data are from *Database IND*. Abbreviation: U.S. minus CA = United States minus California.

IND_{CH_4}, given its link to agriculture, broadly reflects population size. Total IND_{CH_4} from China accounts for 16.4% of total global IND_{CH_4} and the next nine countries plus California account for an additional 40.7% of total global IND. Thus these top $IND_{CO_2(f)}$ debtor countries collectively account for approximately three-fifths of total global $IND_{CO_2(f)}$. These percentages all imply a more even distribution of IND_{CH_4} than $IND_{CO_2(f)}$.

Comparing ranks from chart *A* to chart *C* (see arrows) reveal that the relative contribution of HICs often decreases in going from $IND_{CO_2(f)}$ to IND, for example Japan's 4.8% to 2.9%, while the contribution of LMICs often increases, for example India's 3.2% to 5.3%. The reverse trends hold in comparing ranks from chart *B* to chart *C*. Put another way, %CO_2(f) is often greater for HICs than LMICs and %CH_4 is often greater for LMICs than HICs. In the case of California, it's contribution to global IND_{CH_4} (0.4%) is much lower than its contribution to global $IND_{CO_2(f)}$ (1.8%) or global IND (1.2%).

Just as other metrics related to human welfare, such as income and health, are best judged on a per capita basis, per capita IND indicates the average use of the assimilative capacity of the planet by individuals within a country. Per capita IND varies dramatically across the globe. Comparing opposite extremes, the Falkland Islands' 5050 $\mu W/m^2$/person and Rwanda's 28.8 $\mu W/m^2$/person differ by a factor of nearly 175. California's per capita IND, $IND_{CO_2(f)}$, and IND_{CH_4} are 220%, 334%, and 69.4%, respectively, of the corresponding global averages. These values contrast with the U.S. minus CA's per capita IND, $IND_{CO_2(f)}$, and IND_{CH_4} of 428%, 578%, and 230%, respectively, expressed in the same manner. Viewed from this perspective, California's IND profile is closer to that for the European Union (EU; as constituted in 2005) than that for the U.S. minus CA. The EU possesses per capita IND, $IND_{CO_2(f)}$, and IND_{CH_4}, expressed as percent of global averages, of 206%, 284%, and 104%, respectively. Hence, relative to the EU, California's IND derives comparatively more from $IND_{CO_2(f)}$ than IND_{CH_4}.

Figure 2.5 compares per capita IND for the ten countries (minimum population ten million) with the largest values, California, and the ten most populous LMICs. The divergence in per capita IND between these two sets is striking. Even so, Brazil and Mexico are close to the global average per capita IND. In general, CH_4 constitutes a higher fraction of climate debt in LMICs, primarily due to agriculture. For illustration, the mean percent for the CH_4 proportion among the 10 most populous LMICs is 74%, compared to 28% for the ten countries with the largest values of per capita IND. California's per capita IND, while less than that of the ten countries with the largest values, nonetheless remains large at over twice the global average. California's per capita $IND_{CO_2(f)}$ surpasses that for all ten most populous LMICs, but at the same time, California's IND_{CH_4} falls roughly in the middle of these same countries.

Figure 2.6 helps characterize climate debt, as conceptualized by IND, along several important dimensions, capturing the wide range of climate debts accrued by countries as expressed in terms of both per capita IND (y-axis) and total IND (bubble area). Additionally, bubble slices correspond to %CO_2(f) (red) and %CH_4 (blue). The countries included in the figure, all with a population greater than one million and per capita IND less than 1,500 mW/m^2, span a thirty-fold range of per capita IND. The horizontal line at 305 $\mu W/m^2$/person represents global per capita IND and could be viewed as an initial demarcation between countries, circa 2005, with a surplus of climate debt, above the line, and a deficit of climate debt, below the line.

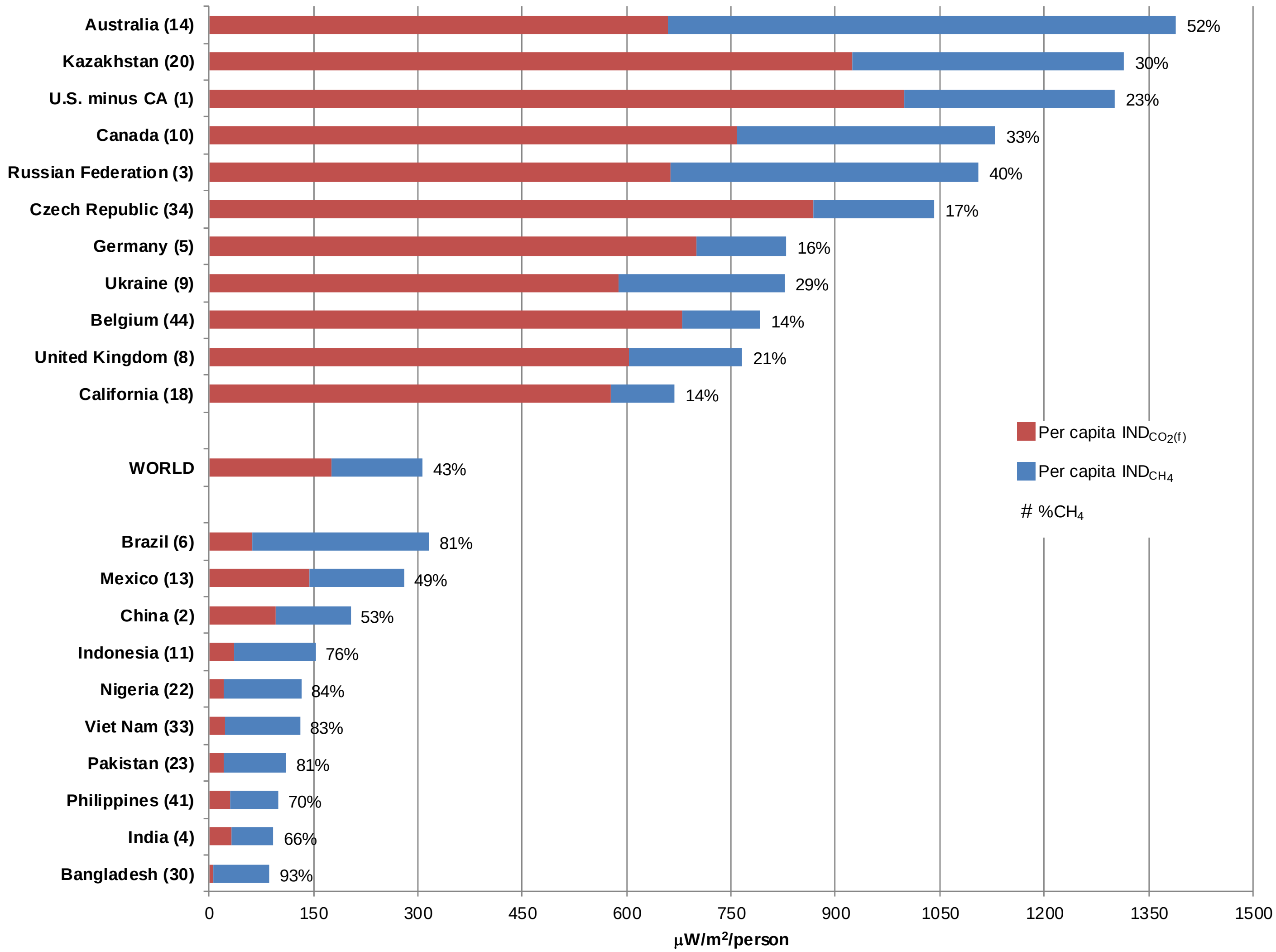


Figure 2.5: Per Capita INDs for Top Debtor Countries, California, World, and Largest Developing Countries. Upper bars list the ten countries, minimum population ten million, with the largest per capita IND, plus California. Together these ten countries and California comprise 11% of global population. The middle bar provides the world average for per capita IND. Lower bars list the 10 most populous developing countries, collectively comprising 55% of global population, with each country's per capita IND. Each bar is divided into $IND_{CO2(f)}$ and IND_{CH4} components, the sum of which equals IND. Numbers in parentheses indicate country rankings for total IND. The value to the right of each bar is the percent of IND from CH_4 ($\%CH_4$). Data are from *Database IND*. Abbreviation: U.S. minus CA = United States minus California.

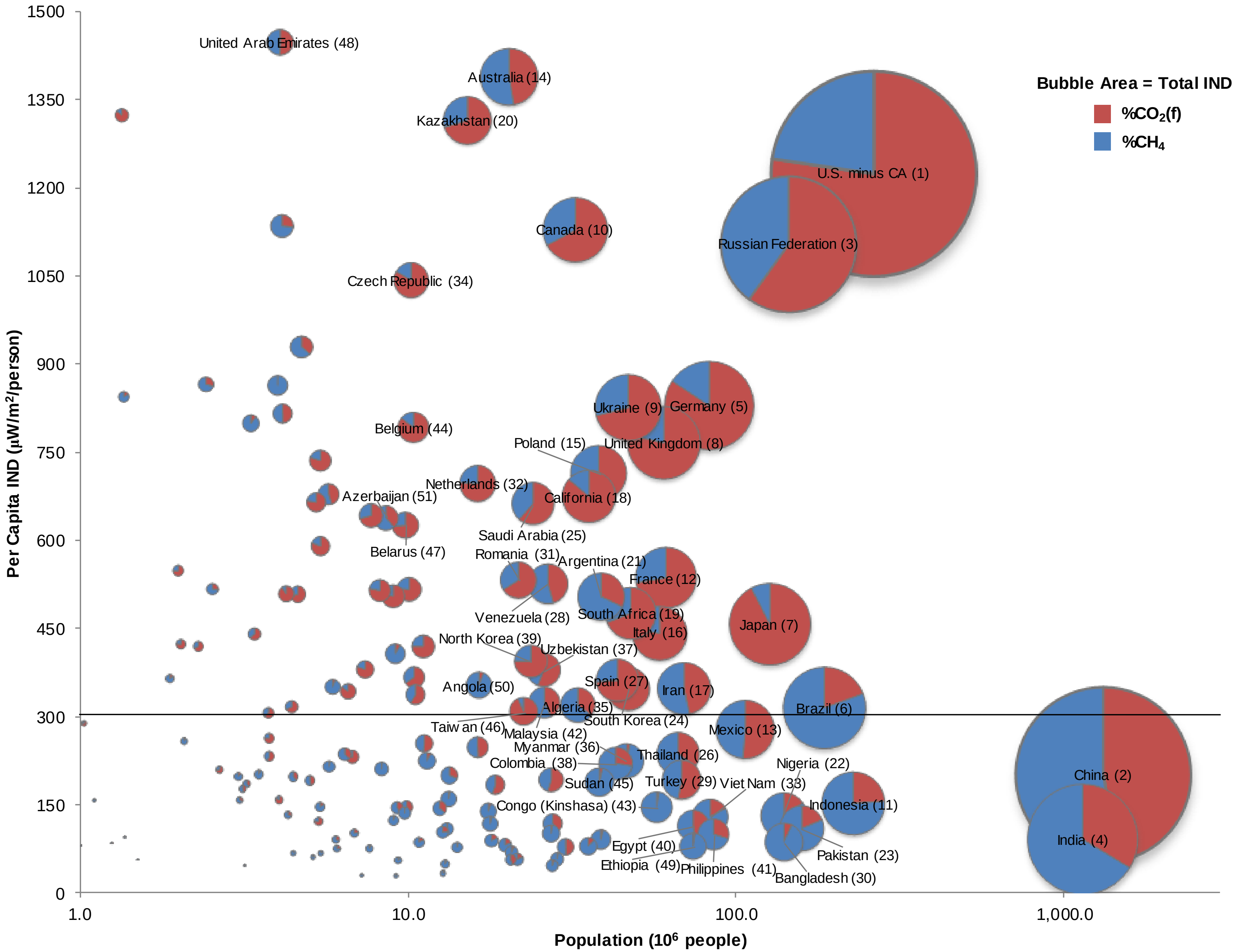

Bubble Area = Total IND
%CO_2(f)
%CH_4
Per Capita IND (µW/m²/person)
Population (10^6 people)
1500
1350
1200
1050
900
750
600
450
300
150
0
1.0
10.0
100.0
1,000.0
United Arab Emirates (48)
Australia (14)
Kazakhstan (20)
U.S. minus CA (1)
Russian Federation (3)
Canada (10)
Czech Republic (34)
Ukraine (9)
Germany (5)
Belgium (44)
Poland (15)
United Kingdom (8)
Netherlands (32)
California (18)
Azerbaijan (51)
Saudi Arabia (25)
Belarus (47)
Romania (31)
Argentina (21)
France (12)
Venezuela (28)
South Africa (19)
Italy (16)
Japan (7)
North Korea (39)
Uzbekistan (37)
Angola (50)
Spain (27)
Iran (17)
Algeria (35)
Brazil (6)
Taiwan (46)
South Korea (24)
Mexico (13)
Malaysia (42)
Myanmar (36)
Thailand (26)
Colombia (38)
Nigeria (22)
Sudan (45)
Turkey (29)
Viet Nam (33)
China (2)
Congo (Kinshasa) (43)
Indonesia (11)
Egypt (40)
Pakistan (23)
India (4)
Ethiopia (49)
Philippines (41)
Bangladesh (30)

Figure 2.6: Total and Per Capita Distribution of IND. Bubble areas (previous page) are proportional to total IND and divided into slices representing $IND_{CO2(f)}$ (red) and IND_{CH4} (blue). Bubble centers are graphed with respect to per capita IND on the y-axis (linear scale) and population on the x-axis (log scale). The axes are truncated to exclude countries with a population less than one million or per capita IND greater than 1500 μW/m^2. Consequently, bubbles for 152 countres from the IND database, plus California, are visible. Labeled are the 51 countries, including California, with the largest INDs in 2005 with ranks given in parentheses. The horizontal line at 305 μW/m^2 represents global per capita IND. Data are from *Database IND*. Abbreviation: U.S. minus CA = United States minus California.

At first glance, most apparent are the four largest bubbles, representing the U.S. minus CA, China, Russian Federation, and India. In aggregate, these four countries accounted for 43.9% of global IND in 2005. Although possessing the largest INDs, these countries have attained their debts through different means. The U.S. minus CA and Russian Federation are both populous and have high per capita INDs, roughly four times the global average, with $IND_{CO_2(f)}$ constituting a majority of IND. China and India, although even more populous, have per capita INDs less than the global average, approximately two-thirds and one-third of the global average, respectively, and IND_{CH_4} comprises a majority of IND. With the addition of Germany and Brazil, these six countries alone would account for over half of global IND in 2005. Overall, *Figure 2.6* brings into relief the distinction between countries with high per capita INDs and high total INDs, hinting at the size and direction of burden sharing between countries that would be most equitable.

Focusing on the fifty countries with largest INDs (labeled with rank in parentheses) and California (also labeled), groupings can be defined by bands based on multiples of global per capita IND. These groupings also identify countries that may be facing similar challenges, given their comparable accumulations of climate debt on a per capita basis, and thus the groupings suggest potential partnerships and networks for sharing technological innovations and policy instruments.

Countries with per capita IND greater than three times the global average (>~900 mW/m^2) include the U.S. minus CA and Russian Federation as well as the five countries from the United Arab Emirates to Czech Republic. Australia and the United Arab Emirates carry more IND_{CH_4} than $IND_{CO_2(f)}$, unlike the other countries in this grouping, reflecting the sizable CH_4 emissions from the agricultural sector for Australia and the energy sector for both countries. The ten countries with per capita IND between two and three times the global average (~600−900 mW/m^2), from Germany to Belarus and including California, exhibit a %CO_2(f) greater than %CH_4 in all cases except Azerbaijan, which has a large natural gas industry. Countries with per capita IND between one and two times the global average (~300−600 mW/m^2), the seventeen countries from France to Taiwan, span a range from possessing markedly more $IND_{CO_2(f)}$ than IND_{CH_4}, as in the case of Japan and Taiwan, to decidedly more IND_{CH_4} than $IND_{CO_2(f)}$, such as for Brazil and Angola, mirroring the diverse economic histories of this group. Finally, there are the seventeen countries with per capita IND less than the global average (<~300 mW/m^2), including China and India plus the group from Mexico to Ethiopia. All but two of these have a %CH_4 greater than %CO_2(f), as the proportionately larger agricultural sectors of these countries would suggest. The two exceptions, Mexico and Turkey, both enjoy a per capita gross domestic product at purchasing power parity (GDP-PPP) higher by a factor of two than the other countries in this final group.

Figure 2.6 captures a number of key features of the global distribution of climate debt, and its simultaneous appraisal of total IND, per capita IND, %CO_2(f), and %CH_4 begins to suggest ways forward. The figure sketches a general pattern of greater %CO_2(f) as per capita IND increases and hence greater %CH_4 as per capita IND decreases, with divergences from this broad trend notwithstanding. Partly explaining this observation is the fact that $IND_{CO_2(f)}$ is strongly linked with economic development while IND_{CH_4} is more evenly distributed with respect to income. Wealthier countries, in addition to accumulating IND_{CH_4}, have amassed substantial $IND_{CO_2(f)}$, and so their total IND and %CO_2(f) all tend to be greater than poorer countries of similar population. The inclusion of IND_{CH_4} narrows the gap in per capita IND between wealthier and poorer countries, but in general the latter still far exceed the former on a per capita basis.

Countries with similar INDs, including with respect to %CO_2(f)/%CH_4, would be logical partners for sharing technological and policy innovations, whereas those with divergent INDs might benefit from Clean Development Mechanism projects (Sutter and Parreño 2007). The size and color of a country's bubble hints at the relative durability of its IND, given that in most cases $IND_{CO_2(f)}$ will contract more slowly than IND_{CH_4}. These two observations are relevant to prioritizing emissions reductions or guiding emissions trading, though both are complex matters with many factors to consider. Furthermore, the location of a country's bubble could help it to track progress, in comparison to itself or others, as its IND changes over time.

Figure 2.7 further establishes the distinction between distributions of per capita $IND_{CO_2(f)}$ and per capita IND_{CH_4} among countries by income, as measured by per capita GDP-PPP. The analysis was limited to countries with populations greater than one million because many small countries have unique circumstances with respect to IND. With the added dimension of per capita GDP-PPP, *Figure 2.7* also expands on the earlier observation that California has less intensively accumulated IND than has the U.S. minus CA, even though California's per capita GDP is slighter higher than that of the U.S. minus CA.

Examining *Figure 2.7*, it is apparent that per capita $IND_{CO_2(f)}$ is relatively closely associated with economic development ($r^2 = 0.55$), with an upward-sloping linear regression line. California's per capita $IND_{CO_2(f)}$ is below the associated trend line, while the U.S. minus CA's per capita $IND_{CO_2(f)}$ is far above it. In contrast, per capita IND is less predictably distributed across the income spectrum ($r^2 = 0.085$). Furthermore, per capita $IND_{CO_2(f)}$ occupies a much broader range of values, with the ratio of highest to lowest more than 1250 (Kuwait : Chad). In comparison, the ratio of highest to lowest per capita IND_{CH_4} is only about 50 (Trinidad & Tobago : Taiwan).

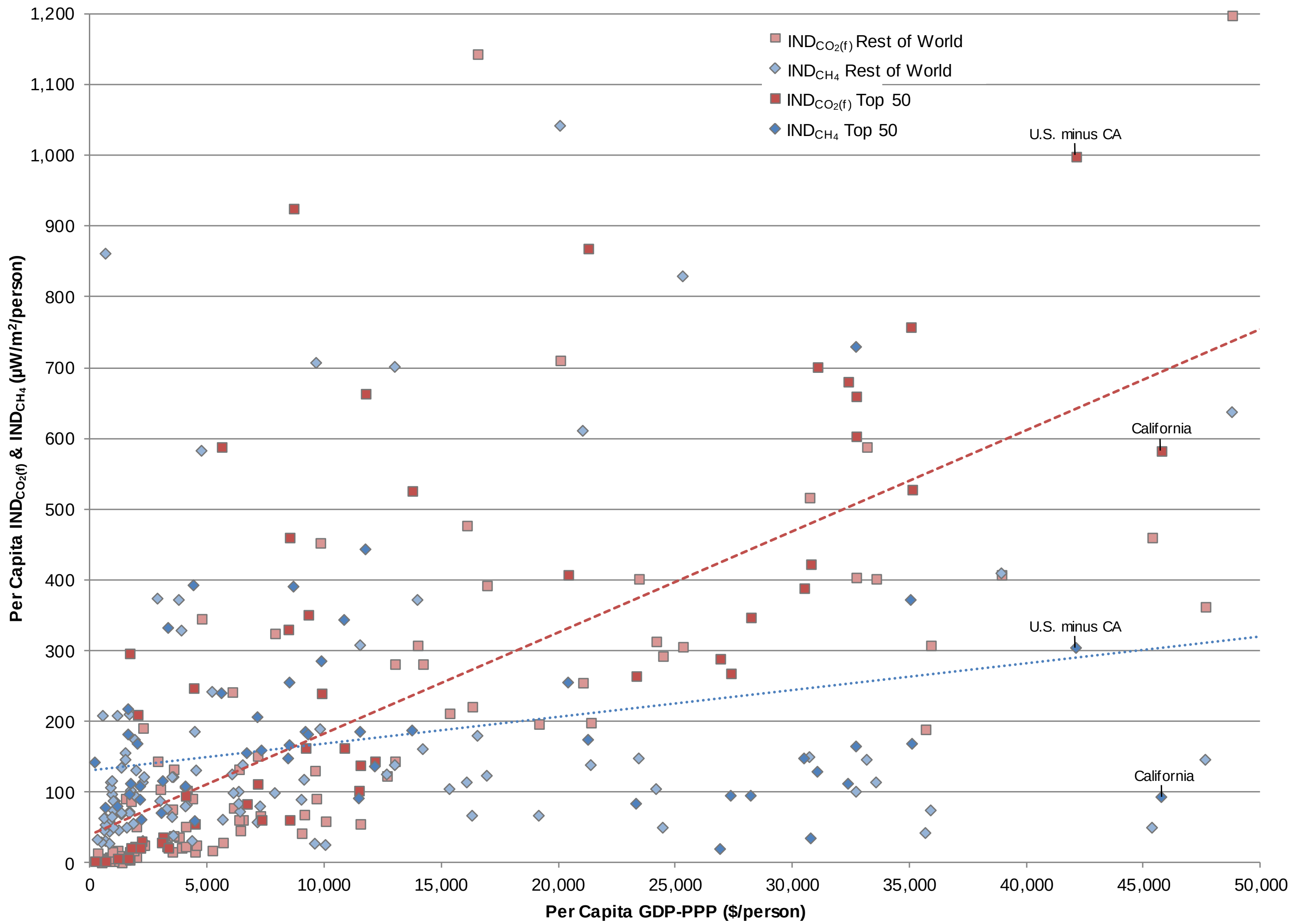


Figure 2.7: Per Capita GDP-PPP by Per Capita $IND_{CO2(f)}$ and Per Capita IND_{CH4}. Data are limited to countries with populations greater than one million (n = 153). Dark blue and dark red points represent per capita $IND_{CO2(f)}$ and IND_{CH4}, respectively, for the 51 countries, including California, with the largest total IND. Light blue and light red points represent the rest of the world. U.S. minus CA and California are labelled for both data series. Linear regression lines are dashed for $IND_{CO2(f)}$ or dotted for IND_{CH4}. Data are from *Database IND*. Abbreviations: GDP-PPP = gross domestic product at purchasing power parity (PPP); U.S. minus CA = United States minus California.

2.3.2.2. Income and Health

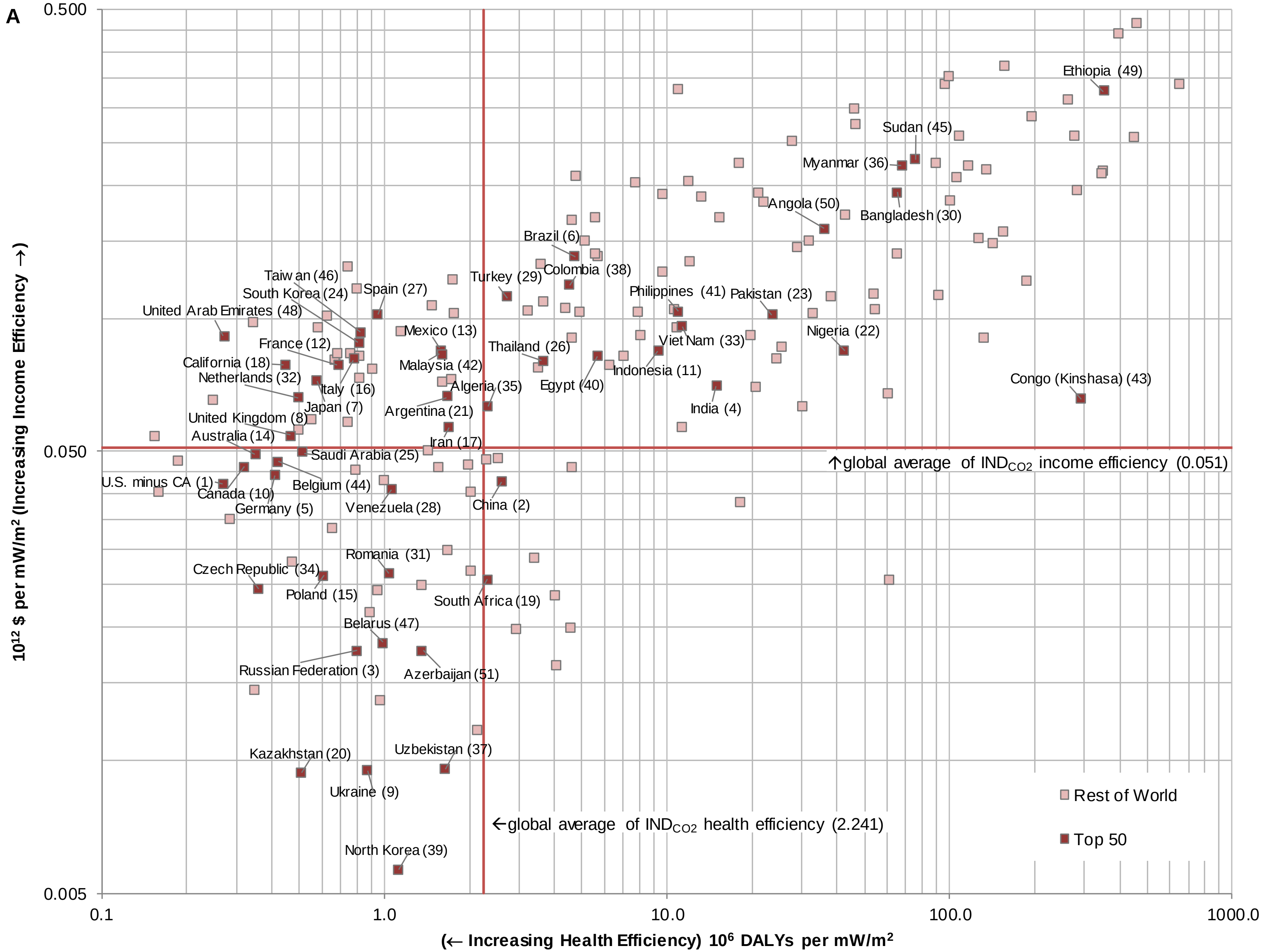
The accrual of climate debt can be conceptualized as a country repeatedly borrowing future resiliency from natural systems in order to progressively better the lot of its citizenry (Smith et al. 1993; Bhaskar 1995; Smith 1996; Srinivasan et al. 2008). Research on various measures of humanity's "environmental footprint" indicates that countries differ in how successfully they have transformed impacts on natural resources into improved conditions for their societies (Knight and Rosa 2011; Jorgenson 2014). Characterizing climate debt in an analogous manner can bring into focus variation in countries' efficiency of climate debt accumulation and pathways for narrowing these differences (McMichael and Butler 2011; Lamb and Rao 2015).

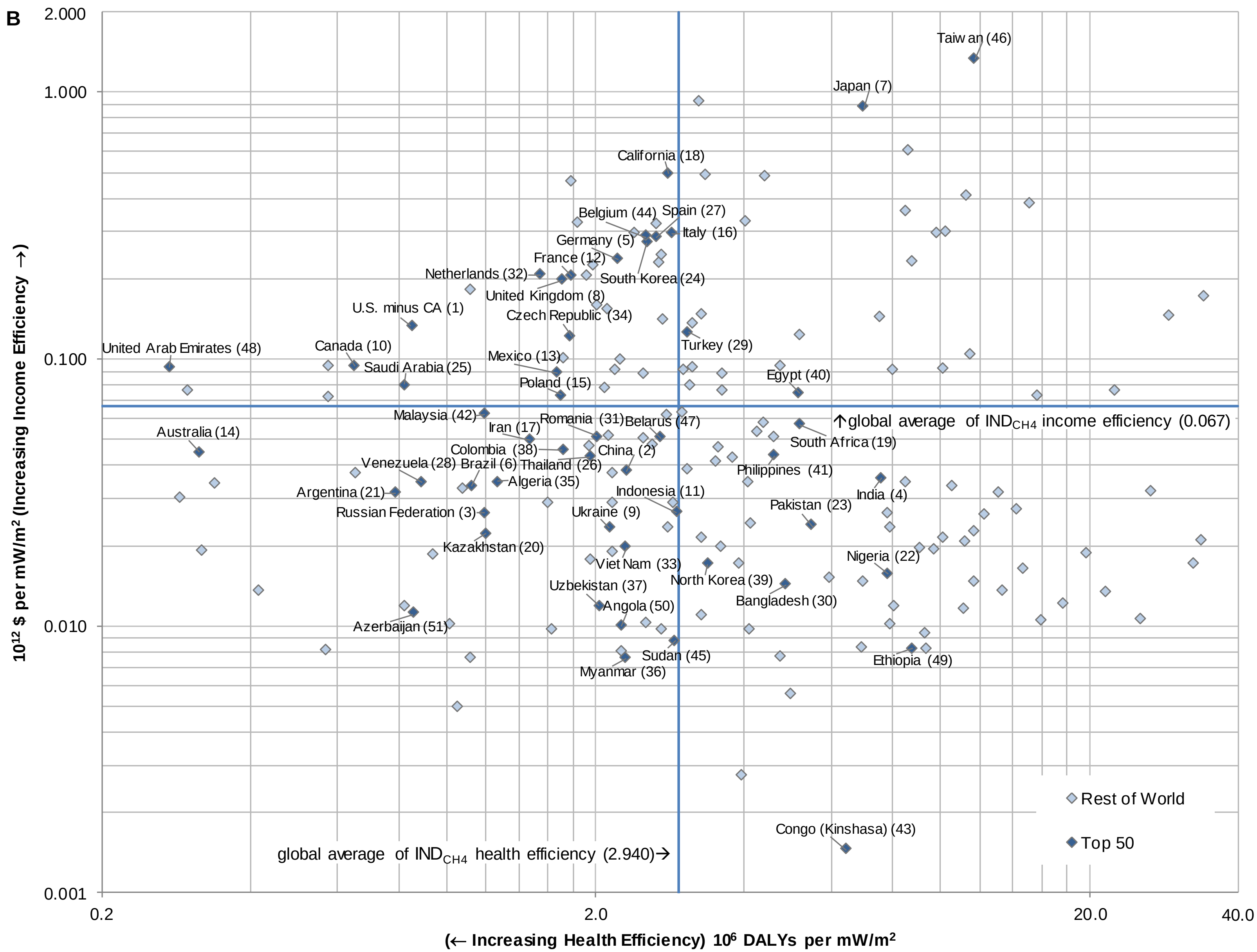
Figure 2.8 examines how "efficiently" countries have translated their consequent climate debt, as measured by IND, into two major indicators of overall well-being: economic output and population health. Although there is a degree of overlap in the activities that generate CO_2(f) and CH_4 emissions, sources differ sufficiently to prompt separate assessments of the efficiencies of $IND_{CO_2(f)}$ (*2A*) and IND_{CH_4} (*2B*). Economic output is gauged by GDP-PPP (United States Central Intelligence Agency 2006; World Bank 2012) and population health by the total amount of ill-health in a country as measured by lost disability-adjusted life years (DALYs) (Global Burden of Disease Study 2010 2012). The DALY, a widely-used metric for lost healthy life years, is a more accurate estimate of lost health than deaths alone since it accounts for both the degree of prematurity in mortality as well as the severity and duration of morbidity.

For California, state-level DALY data were unavailable. In its place, I applied age-specific DALY rates for the United States to the population distribution of California. Summing these results enabled an estimation of California's DALYs, but this approach may only a be a rough approximation. In common with original emissions, I subtracted California's DALYs from those for the United States' to arrive at the U.S. minus CA's DALYs.

Figure 2.8 depicts the efficiency of countries' accumulated investments, enabled by climate debt, in expanding economic output while diminishing ill-health. Twenty-seven countries which lack DALY data, listed in *Table A7*, are missing from *Figure 2.8* (Global Burden of Disease Study 2010 2012). The location of countries with regards to the y-axes is analogous to the notion of carbon intensity (Jorgenson 2014). In other words, the more economic output per unit of climate debt (or "income efficiency'), the more efficiently a country has parlayed its borrowing into national income. Conversely, with regards to the x-axes, the less ill-health per unit of climate debt (or "health efficiency"), the more efficiently a country has converted its borrowing into wellness.

The horizontal and vertical lines represent global average IND efficiencies and define four quadrants of combined income and health efficiency. The most efficient quadrant at top-left marks countries with high income and health efficiencies in comparison to the global average. Correspondingly, the least efficient quadrant at bottom-right hosts countries with low income and health efficiencies in comparison to the global average.


A
10^12 $ per mW/m² (Increasing Income Efficiency →)
(← Increasing Health Efficiency) 10^6 DALYs per mW/m²
0.500
0.050
0.005
0.1
1.0
10.0
100.0
1000.0
↑global average of IND_CO2 income efficiency (0.051)
←global average of IND_CO2 health efficiency (2.241)
Rest of World
Top 50
Ethiopia (49)
Sudan (45)
Myanmar (36)
Bangladesh (30)
Angola (50)
Brazil (6)
Colombia (38)
Turkey (29)
Taiw an (46)
South Korea (24)
Spain (27)
United Arab Emirates (48)
Philippines (41)
Pakistan (23)
Nigeria (22)
Mexico (13)
France (12)
Thailand (26)
Viet Nam (33)
California (18)
Malaysia (42)
Indonesia (11)
Netherlands (32)
Italy (16)
Algeria (35)
Egypt (40)
Congo (Kinshasa) (43)
Japan (7)
Argentina (21)
India (4)
United Kingdom (8)
Australia (14)
Iran (17)
Saudi Arabia (25)
U.S. minus CA (1)
Belgium (44)
Canada (10)
Germany (5)
Venezuela (28)
China (2)
Romania (31)
Czech Republic (34)
Poland (15)
South Africa (19)
Belarus (47)
Russian Federation (3)
Azerbaijan (51)
Kazakhstan (20)
Uzbekistan (37)
Ukraine (9)
North Korea (39)



B
10^12 $ per mW/m² (Increasing Income Efficiency →)
(← Increasing Health Efficiency) 10^6 DALYs per mW/m²
2.000
1.000
0.100
0.010
0.001
0.2
2.0
20.0
40.0
Taiw an (46)
Japan (7)
California (18)
Belgium (44)
Spain (27)
Italy (16)
Germany (5)
France (12)
South Korea (24)
Netherlands (32)
United Kingdom (8)
U.S. minus CA (1)
Czech Republic (34)
Turkey (29)
United Arab Emirates (48)
Canada (10)
Saudi Arabia (25)
Mexico (13)
Poland (15)
Egypt (40)
Malaysia (42)
Romania (31)
Belarus (47)
↑global average of IND$_{CH4}$ income efficiency (0.067)
Australia (14)
Iran (17)
South Africa (19)
Colombia (38)
China (2)
Venezuela (28)
Brazil (6)
Thailand (26)
Philippines (41)
Algeria (35)
Argentina (21)
Indonesia (11)
India (4)
Russian Federation (3)
Ukraine (9)
Pakistan (23)
Kazakhstan (20)
Nigeria (22)
Viet Nam (33)
North Korea (39)
Uzbekistan (37)
Bangladesh (30)
Angola (50)
Azerbaijan (51)
Sudan (45)
Ethiopia (49)
Myanmar (36)
Congo (Kinshasa) (43)
global average of IND$_{CH4}$ health efficiency (2.940)→
Rest of World
Top 50

Figure 2.8: Efficiency of $IND_{CO2(f)}$ and IND_{CH4} by GDP-PPP and DALYs. Figure (previous two pages) plots countries according to the efficiency of their $IND_{CO2(f)}$ (panel *A*) or IND_{CH4} (panel *B*) with regards to income (y-axis, log scale) and health (x-axis, log scale) in 2005. $IND_{CO2(f)}$ or IND_{CH4} income efficiency, defined as the ratio of GDP-PPP divided by $IND_{CO2(f)}$ or IND_{CH4}, respectively, increases to the top of the graph. Conversely, $IND_{CO2(f)}$ or IND_{CH4} health efficiency, defined as the ratio of DALYs divided by $IND_{CO2(f)}$ or IND_{CH4}, respectively, increases to the left of the graph. The horizontal and vertical lines represent global average IND efficiencies and delineate four quadrants of combined income and health efficiency, the most efficient at top-left and the least efficient at bottom-right. Labeled and dark red points represent the 51 countries, including California, with the largest INDs in 2005 and ranks given in parentheses. Not graphed are 27 countries that lacked DALY data (see *Table A7*). In both panels, an additional three countries are off-scale (in 2A: Chad, Mali, and Micronesia; in 2B: Brunei Darussalam, Central African Republic, and Qatar). Light red points represent the remaining 125 countries in the IND database. The intersection of the two lines represents the world as a whole. Data are from *Database IND*. Abbreviations: DALY = disability-adjusted life year; GDP-PPP = gross domestic product at purchasing power parity; U.S. minus CA = United States minus California.

Viewing both log-log plots of *Figure 2.8* side-by-side, it is apparent that the health efficiency of $IND_{CO_2(f)}$ covers a wider range (~10,000×) than IND_{CH_4} (~200×) and conversely the income efficiency of IND_{CH_4} covers a wider range (~2,000×) than $IND_{CO_2(f)}$ (~100×). The distribution of countries, in *Figure 2.8A*, mostly excludes the bottom-right quadrant (low health and low income efficiencies), but in in *Figure 2.8B*, includes all four quadrants. Both distributions raise research questions, for example on the direction of causal relationships between income and health (Bloom and Canning 2000), into which the lens of IND efficiency may provide additional insight.

California, located in the upper-left quadrant, exceeds global averages with respect to both income and health efficiencies for $IND_{CO_2(f)}$. Yet there is room for improvement for California along both axes. In comparison, the U.S. minus CA is less efficient in terms of income, an expected outcome given California's more moderate accumulation of $IND_{CO_2(f)}$, but more efficient in terms of health. A similar relationship between California and the U.S. minus CA exists for IND_{CH_4} efficiencies. California's IND_{CH_4} is exceptionally efficient with respect to income as only two top fifty countries, Japan and Taiwan, are more efficient. With respect to health, California is near the global average for health efficiency of IND_{CH_4}.

Figure 2.8A suggests that, for future $IND_{CO_2(f)}$, "leapfrog" strategies are possible for LMICs currently in the top-right quadrant (low health but high income efficiencies) to shift into the top-left quadrant (high health and high income efficiencies). If these countries maintained or even moderately increased their current CO_2(f) climate debt in order to promote population health, they could catapult to HIC levels of health and economic efficiency. It would be advantageous from a global and country-level perspective, doubly so given health co-benefits (Smith et al. 2014), for these LMICs to avoid the fossil fuel intensive pathway of the suite of countries in the bottom-left quadrant (high health but low income efficiencies). Many HICs, it must also be noted, have room for improvement with respect to the income efficiency of their $IND_{CO_2(f)}$.

Shifting to *Figure 2.8B*, rapidly and dramatically boosting population health in LMICs, the stated objective of initiatives such as Global Health 2035 (Jamison et al. 2013), would also move many countries currently in the bottom-right quadrant (low health and low income efficiencies), into the lower-left quadrant (high health and low income efficiencies). The sizable number of countries currently in the bottom half of the figure, from the perspective of economic output, have inefficiently accumulated IND_{CH_4}, lending additional impetus for research and development into technologies and strategies that either decrease CH_4 emissions, which also has attendant health co-benefits (Shindell et al. 2012), or more effectively convert CH_4 emissions into income gains, and for the countries in the bottom-right quadrant, health gains, as well.

In conjunction with tracking climate debt on its own, the concept of IND efficiency can provide another yardstick by which a country can trace the progression of its climate debt over time either in comparison to itself or in reference to other countries. It must be noted, however, that IND efficiency would improve as long as the rate at which income expands or ill-health contracts exceeds the rate at which climate debt grows. Though such a scenario remains more desirable than its opposite, more efficiently acquiring climate debt may not correspond to mitigating climate change.

Additionally, facilitating the conversion of societal investments, financed partly by climate debt, into income or health gains is often a complex multifactorial process with time lags. There is also a delay between decelerating emissions growth or outright emissions decreases and reducing IND, since IND carries the burden of past emissions that can only be discharged as a function of each CAP's atmospheric lifetime. It follows that the efficiency of IND_{CH_4} would respond more quickly to contracting emissions than the efficiency of $IND_{CO_2(f)}$.

2.3.2.3. Methane International Natural Debt by Sector

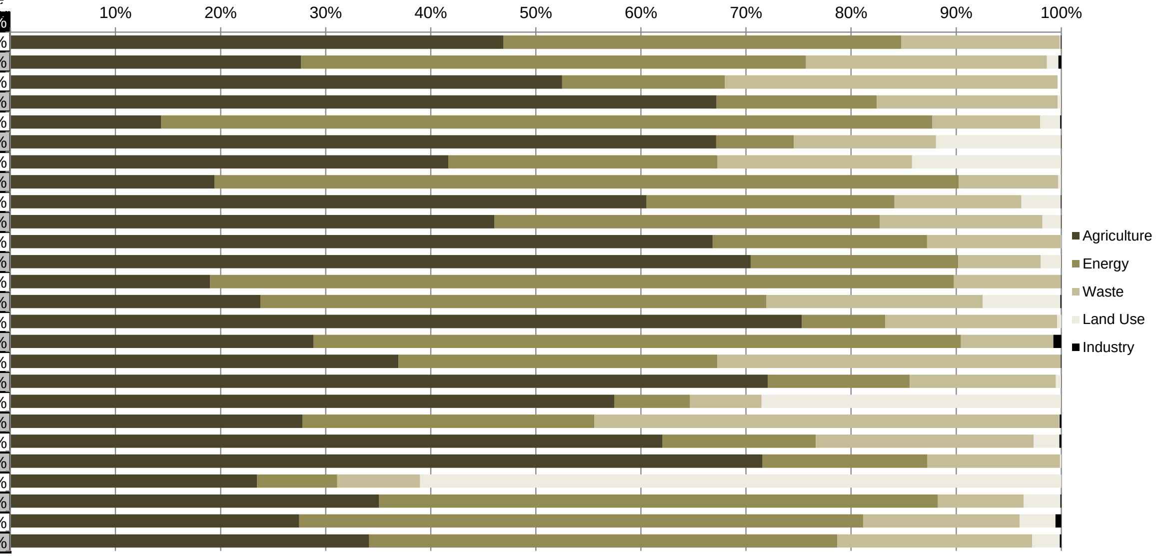
Controlling anthropogenic emissions of CH_4 may present, under certain circumstances, an underappreciated opportunity for climate change mitigation, an insight that motivates a closer examination of IND_{CH_4}. Major sources include ruminant livestock, manure management, and rice cultivation in the agriculture sector; fossil fuel systems in the energy sector; and landfills and wastewater in the waste sector (2006; Reay et al. 2010). Current inventory methodologies are not comprehensive and atmospheric monitoring of CH_4 suggests emissions from unaccounted sources, such as abandoned landfills and oil/gas wells, may be large (Fischer and Jeong 2012; Brandt et al. 2014).

In order to probe IND_{CH_4}, *Figure 2.9* breaks down IND_{CH_4} into its sector-level components. Panel *A* presents the 25 countries with the largest IND_{CH_4} from all sectors combined and panels *B−D* present the top 25 contributors of IND_{CH_4} from the agriculture (*B*), energy (*C*), and waste (*D*) sectors. Rankings for each panel are in the left-most columns, and rankings for total IND are in parentheses. California is included at bottom in all four panels. Collectively, the top 25 countries plus California accounted for 75% of global IND_{CH_4} in 2005.

Global IND_{CH_4} is dominated by the agriculture (45.3%), energy (34.5%), and waste (16.2%) sectors, with much smaller input from land use (3.8%), referring to emissions from forest and grass fires, and industry (<1%). Over half of California's IND_{CH_4} derives from agriculture (52.5%), followed by waste (31.7%) and energy (15.5%). For the U.S. minus CA's IND_{CH_4}, historical emissions from the energy sector (48.0%) contribute the most, followed by agriculture (27.7%) and waste (22.9%), with small contributions from land use (1.1%) and industry (0.3%).

(A) ALL SECTORS

	Total mW/m²	Total % World	Per Capita μW/m² pp	Per Capita % Average
WORLD	856.00	100.00%	131.71	100.00%
1 China (2)	140.23	16.38%	107.24	81.42%
2 United States (1)	82.43	9.63%	277.70	210.84%
3 India (4)	70.02	8.18%	61.42	46.63%
4 Russian Fed. (3)	63.63	7.43%	442.32	335.82%
5 Brazil (6)	47.37	5.53%	254.72	193.39%
6 Indonesia (11)	26.33	3.08%	115.83	87.94%
7 Nigeria (22)	15.55	1.82%	111.23	84.45%
8 Australia (14)	14.88	1.74%	729.35	553.74%
9 Mexico (13)	14.50	1.69%	136.14	103.36%
10 Pakistan (23)	14.20	1.66%	89.54	67.98%
11 Argentina (21)	13.25	1.55%	342.58	260.09%
12 Iran (17)	12.89	1.51%	184.86	140.35%
13 Canada (10)	12.01	1.40%	372.01	282.43%
14 Bangladesh (30)	11.33	1.32%	80.59	61.19%
15 Ukraine (9)	11.23	1.31%	239.35	181.72%
16 Germany (5)	10.69	1.25%	129.57	98.37%
17 Thailand (26)	10.29	1.20%	154.27	117.12%
18 Myanmar (36)	10.04	1.17%	216.71	164.53%
19 United Kingdom (8)	9.85	1.15%	163.67	124.26%
20 France (12)	9.03	1.06%	148.12	112.45%
21 Viet Nam (33)	8.98	1.05%	107.97	81.97%
22 Congo (Kin.) (43)	8.16	0.95%	142.08	107.87%
23 Venezuela (28)	7.62	0.89%	285.78	216.97%
24 Poland (15)	7.17	0.84%	187.92	142.67%
25 South Africa (19)	7.05	0.82%	147.57	112.04%
48 California (18)	3.28	0.38%	91.45	69.43%



(B) AGRICULTURE

	Total mW/m²	Total % World	Per Capita μW/m² pp	Per Capita % Average
WORLD	387.59	45.28%	59.64	100.00%
1 China (2)	65.77	16.97%	50.30	84.34%
2 India (4)	47.04	12.14%	41.27	69.19%
3 Brazil (6)	31.81	8.21%	171.05	286.81%
4 United States (1)	23.63	6.10%	79.60	133.47%
5 Indonesia (11)	10.97	2.83%	48.27	80.94%
6 Pakistan (23)	9.49	2.45%	59.84	100.33%
7 Argentina (21)	9.33	2.41%	241.32	404.64%
8 Russian Fed. (3)	9.13	2.36%	63.48	106.45%
9 Australia (14)	9.01	2.32%	441.51	740.31%
10 Bangladesh (30)	8.53	2.20%	60.68	101.75%
11 Thailand (26)	7.42	1.91%	111.20	186.46%
12 Mexico (13)	6.68	1.72%	62.72	105.16%
13 Viet Nam (33)	6.43	1.66%	77.27	129.56%
14 Sudan (45)	6.02	1.55%	156.79	262.90%
15 Myanmar (36)	5.77	1.49%	124.54	208.82%
16 France (12)	5.61	1.45%	91.93	154.14%
17 Colombia (38)	4.72	1.22%	109.59	183.75%
18 Ethiopia (49)	4.26	1.10%	57.36	96.18%
19 Philippines (41)	4.00	1.03%	46.73	78.35%
20 Germany (5)	3.95	1.02%	47.84	80.22%
21 Ukraine (9)	3.24	0.84%	69.08	115.83%
22 New Zealand	3.05	0.79%	738.02	1237.46%
23 Nigeria (22)	3.02	0.78%	21.61	36.23%
24 Canada (10)	2.86	0.74%	88.56	148.50%
25 United Kingdom (8)	2.74	0.71%	45.48	76.26%
41 California (18)	1.72	0.44%	48.02	80.52%

(C) ENERGY

	Total mW/m²	Total % World	Per Capita μW/m² pp	Per Capita % Average
WORLD	295.62	34.53%	45.49	100.00%
1 China (2)	53.09	17.96%	40.60	89.26%
2 Russian Fed. (3)	46.67	15.79%	324.48	713.34%
3 United States (1)	38.52	13.03%	129.77	285.29%
4 Nigeria (22)	11.01	3.73%	78.77	173.18%
5 India (4)	10.68	3.61%	9.36	20.59%
6 Iran (17)	9.13	3.09%	130.87	287.71%
7 Ukraine (9)	6.92	2.34%	147.40	324.06%
8 Indonesia (11)	6.74	2.28%	29.67	65.23%
9 Canada (10)	5.78	1.96%	179.08	393.69%
10 Algeria (35)	5.78	1.95%	175.68	386.22%
11 Mexico (13)	5.31	1.80%	49.90	109.71%
12 Saudi Arabia (25)	5.30	1.79%	220.65	485.09%
13 Venezuela (28)	4.05	1.37%	151.97	334.10%
14 Poland (15)	3.85	1.30%	100.83	221.66%
15 Australia (14)	3.51	1.19%	172.06	378.27%
16 Brazil (6)	3.50	1.18%	18.83	41.40%
17 Kazakhstan (20)	3.36	1.14%	221.22	486.33%
18 Germany (5)	3.25	1.10%	39.31	86.43%
19 South Africa (19)	3.14	1.06%	65.72	144.48%
20 Malaysia (42)	3.11	1.05%	119.29	262.25%
21 Pakistan (23)	2.90	0.98%	18.26	40.13%
22 U.A.E. (48)	2.77	0.94%	681.69	1498.63%
23 United Kingdom (8)	2.74	0.93%	45.47	99.96%
24 Azerbaijan (51)	2.64	0.89%	307.40	675.80%
25 Argentina (21)	2.62	0.89%	67.66	148.75%
58 California (18)	0.51	0.17%	14.16	31.12%

(D) WASTE

	Total mW/m²	Total % World	Per Capita μW/m² pp	Per Capita % Average
WORLD	139.06	16.24%	21.40	100.00%
1 China (2)	21.16	15.22%	16.18	75.63%
2 United States (1)	19.19	13.80%	64.64	302.08%
3 India (4)	12.06	8.67%	10.58	49.44%
4 Russian Fed. (3)	6.55	4.71%	45.51	212.69%
5 Brazil (6)	6.41	4.61%	34.47	161.10%
6 Indonesia (11)	4.88	3.51%	21.45	100.24%
7 United Kingdom (8)	4.36	3.13%	72.40	338.35%
8 Germany (5)	3.49	2.51%	42.34	197.89%
9 Turkey (29)	3.13	2.25%	45.90	214.50%
10 Canada (10)	2.47	1.78%	76.51	357.58%
11 Italy (16)	2.41	1.73%	41.04	191.79%
12 Mexico (13)	2.24	1.61%	21.07	98.48%
13 France (12)	1.87	1.35%	30.70	143.47%
14 Bangladesh (30)	1.85	1.33%	13.18	61.61%
15 Pakistan (23)	1.81	1.30%	11.41	53.32%
16 Australia (14)	1.80	1.29%	88.09	411.69%
17 Nigeria (22)	1.47	1.06%	10.52	49.18%
18 Philippines (41)	1.44	1.04%	16.87	78.83%
19 Thailand (26)	1.43	1.03%	21.47	100.33%
20 South Korea (24)	1.37	0.99%	29.17	136.31%
21 Iran (17)	1.31	0.94%	18.82	87.94%
22 South Africa (19)	1.31	0.94%	27.38	127.98%
23 Spain (27)	1.31	0.94%	30.08	140.57%
24 Japan (7)	1.19	0.85%	9.41	43.96%
25 Netherlands (32)	1.15	0.82%	70.23	328.23%
29 California (18)	1.04	0.75%	28.96	135.33%

Figure 2.9: IND_{CH4} by Sector. Figure (previous page) presents the 25 countries plus California with the largest total and sectoral debts from IND_{CH4}. Panel *A* focuses in total IND_{CH4}. Stacked bars at left show the percent of each country's IND_{CH4} derived from each sector. The top 10 countries in panel *A* are color-coded so they can be easily tracked in panels *B−D*. Panels *B−D* list the top 25 contributors of IND_{CH4}, plus California, from the agriculture (*B*), energy (*C*), and waste (*D*) sectors. All panels include total and per capita IND_{CH4}, both of which are also expressed as "% World" or "% Average" with respect to the global total or global average, respectively, for that panel. The fraction each sector contributes to global IND_{CH4} is provided in panels *B−D* in the entry for the world (top-most row) under "Total" and "% of World". Numbers in parentheses indicate country rankings for total IND. Additionally, data for California are provided in the bottom-most row of each panel along with California's ranking for that particular sector. Data are from *Database IND*. Abbreviations: pp = per person, U.S. minus CA = United States minus California.

Focusing on panel *A*, the sectoral decomposition of IND_{CH_4} shows a diversity of situations reflecting the distinctive circumstances of each country. Countries with proportionately large contributions to their IND_{CH_4} from the agriculture sector often have had major rice or livestock production, for example California, Argentine, or Bangladesh. Major oil and gas producers typically have proportionately large contributions from the energy sector to their IND_{CH_4}, for example Nigeria and Russia. The waste sector can also be a large contributor to IND_{CH_4}, particularly for California, the United Kingdom, and Germany. Several countries with large areas of tropical forest have sizeable contributions to their IND_{CH_4} from land use, most notably Congo (Kinshasa) but also Myanmar, Indonesia, and Brazil.

China has the largest total IND_{CH_4} from all sectors combined and for each of the separate sectors. However, in each case, China's per capita IND_{CH_4} is 10−25% lower than the global average. India, with the third largest total IND_{CH_4}, follows a similar pattern with even lower per capita IND_{CH_4} values, half the global average for all sectors combined and 20−70% the global average for the separate sectors. On the other hand, the U.S. minus CA, which has the second largest total IND_{CH_4} and is ranked in the top four for the agriculture, energy, and waste sectors, possesses in all instances per capita IND_{CH_4} values much higher than the global average. Similarly, Australia, a medium-sized country from the perspective of population or economic size, is a top 25 contributor to global total IND_{CH_4} from all three sectors and at per capita levels several times the global average.

About half of California's IND_{CH_4} derives from agriculture (52.5%), a third from waste (31.7%), and the remainder from energy (15.5%). Compared globally, the state's IND_{CH_4} from the waste sector is ranked highest (29^{th}), with a per capita value 136% of the global average. California's total IND_{CH_4} for the agriculture and energy sectors are ranked 41^{st} and 58^{th}, respectively, and corresponding per capita values are below global averages. Although California's accumulation of IND_{CH_4} has been modest, CH_4 emissions remain substantial for the state, comprising 8.3% of total CAP emissions in 2012 on a CO_2 equivalent basis (Air Resources Board of the California Environmental Protection Agency 2014). IND would respond more quickly to decreases in CH_4 emissions than CO_2(f) emissions, potentially at lower cost or disruption.

For California and indeed most countries, decreasing emissions by shifting diet preferences for meat, diary, and/or rice would likely be slow, although perhaps engineering genetic or management approaches to reducing emission factors could be achieved more rapidly.

Conversely, remedying poor human and animal waste management or leaks from fossil fuel systems can be achieved with little impact on consumption patterns. Current inventory methodologies are not comprehensive, so there are probably additional CH_4 sources that are not yet accounted for, such as abandoned landfills and oil/gas wells (Wunch et al. 2009). Leakage from fracking operations may also add to future CH_4 inventories. Nonetheless, countries with large agricultural components to their IND_{CH_4} such as California are already experimenting with different feed compositions to minimize enteric fermentation in ruminant livestock (Eckard et al. 2010) or altered flooding and fertilization regimens to curtail methanogenesis in wet rice fields (Jain et al. 2013). Such technological advances, as well as policy ideas, could be shared between countries with similar portfolios of IND_{CH_4}.

2.3.3. Land Use Change and Forestry

In actuality, LUCF has also contributed significantly to anthropogenic CO_2 flux over time. *Table 2.1* presents a preliminary exploration, at a regional level (see *Figure 2.2* and *Table A8* for region definitions), of LUCF's contribution to IND, contrasting IND (Panel A), which does not include LUCF, and IND_{+LUCF} (Panel B), which does. For this analysis, California is subsumed into the United States region. In both panels, the United States, Europe, and China regions possess the largest total values and the Oceania, United States, and Canada regions possess the largest per capita values. As would be expected, assigning accountability for LUCF leads IND_{+LUCF} to be greater than IND for all regions (except the Caribbean). The increases are proportionately much larger, however, in those tropical regions that experienced significant deforestation over 1950−2005 (Tropical South America, Central Africa, West Africa, East Africa, and Southeast Asia), so much so that these regions leapfrog others in both total and per capita IND. Yet, intact tropical forests in these same regions, as well as undisturbed ecosystems in other regions, undoubtedly served as carbon sinks both since 1950 as well as prior. The limited data on California's LUCF net CO_2(f) flux suggest the state served as a carbon sink throughout the period 1990−2004 (Air Resources Board of the California Environmental Protection Agency 2007b).

Although *Table 2.1* draws on the best available LUCF dataset to my knowledge, it must be emphasized that it is difficult to attribute CO_2 flux from LUCF empirically, due to incomplete and uncertain historical records of sinks and sources, and conceptually, owing to ambiguities in deciding which changes were natural versus anthropogenic and what credit to assign for avoiding degradation of carbon stocks (Corbera and Schroeder 2011). Nevertheless, attempts have been made, albeit at regional levels (Klein Goldewijk et al. 2011). Also, unlike CO_2(f), there is no appropriate baseline starting point, i.e., the start of the Industrial Revolution (Smith 1994; Ruddiman 2006). These and other theoretical and methodological obstacles continue to limit the incorporation of LUCF into a robust climate debt metric. Such challenges serve to further motivate research into the carbon cycle across spatial and temporal scales, as well as to highlight the advantage of a less comprehensive but more tractable metric such as IND.

Table 2.1: IND and IND$_{+LUCF}$ by Region

	Population	A: IND[1]						B: IND$_{+LUCF}$[2]					
	Year 2005	Total IND		Per Capita IND		GHG Fraction		Total IND		Per Capita IND		GHG Fraction	
Region[3] (# of Countries)	*10^6 people*	*mW/m^2*	*% of World*	*µW/m^2/ person*	*% of World Ave.*	*CO_2*	*CH_4*	*mW/m^2*	*% World*	*µW/m^2/ person*	*% of World Ave.*	*CO_2*	*CH_4*
WORLD CO_2(f)+CH_4	**6,498.893**	**1979.0**	**100.0%**	**304.5**	**100.0%**	**57%**	**43%**	**2416.0**	**100.0%**	**371.8**	**100.0%**	**65%**	**35%**
Canada (2)	32.341	36.5	1.8%	1129.0	370.7%	67%	33%	48.2	2.0%	1489.5	400.7%	75%	25%
United States (1)	296.820	364.0	18.4%	1226.2	402.6%	77%	23%	394.8	16.3%	1329.9	357.7%	79%	21%
Mesoamerica (7)	145.103	34.3	1.7%	236.3	77.6%	48%	52%	49.4	2.0%	340.2	91.5%	64%	36%
Caribbean (16)	39.081	9.3	0.5%	238.5	78.3%	52%	48%	7.3	0.3%	187.9	50.6%	39%	61%
Trop. South America (10)	313.169	94.5	4.8%	301.8	99.1%	25%	75%	205.0	8.5%	654.5	176.1%	65%	35%
Temp. South America (4)	58.308	26.2	1.3%	449.9	147.7%	33%	67%	34.2	1.4%	586.7	157.8%	48%	52%
Europe (33)	518.902	314.3	15.9%	605.7	198.9%	77%	23%	334.1	13.8%	643.8	173.2%	79%	21%
FSU (15)	284.920	252.9	12.8%	887.8	291.5%	62%	38%	274.6	11.4%	963.7	259.2%	65%	35%
ME & NA (22)	436.970	110.2	5.6%	252.1	82.8%	51%	49%	122.5	5.1%	280.3	75.4%	56%	44%
West Africa (17)	277.322	30.0	1.5%	108.2	35.5%	13%	87%	52.7	2.2%	190.1	51.1%	51%	49%
Central Africa (9)	101.109	17.1	0.9%	169.3	55.6%	4%	96%	39.0	1.6%	385.9	103.8%	58%	42%
East Africa (9)	229.289	23.2	1.2%	101.3	33.2%	4%	96%	37.6	1.6%	164.0	44.1%	41%	59%
Southern Africa (14)	147.553	38.6	2.0%	261.6	85.9%	45%	55%	58.5	2.4%	396.7	106.7%	64%	36%
South Asia (7)	1,487.355	139.7	7.1%	93.9	30.8%	29%	71%	144.1	6.0%	96.9	26.1%	31%	69%
Southeast Asia (12)	565.976	95.7	4.8%	169.0	55.5%	26%	74%	154.3	6.4%	272.6	73.3%	54%	46%
China (4)	1,337.586	273.9	13.8%	204.7	67.2%	49%	51%	323.8	13.4%	242.1	65.1%	56%	44%
East Asia (4)	199.730	85.0	4.3%	425.4	139.7%	86%	14%	92.2	3.8%	461.5	124.2%	87%	13%
Oceania (19)	27.359	33.8	1.7%	1235.0	405.5%	45%	55%	43.8	1.8%	1601.5	430.8%	57%	43%

Notes: [1]Includes climate debt from CO_2(f) and CH_4.; [2] Includes climate debt from CO_2(f), CH_4, and LUCF.; [3] Regions defined in *Figure 2.2* and *Table A8*. Abbreviations: Trop. = Tropical; Temp. = Temperate; FSU = Former Soviet Union; ME & NA = Middle East and North Africa

2.3.4. Applications of International Natural Debt

2.3.4.1. Impact and Accountability: the Example of Health

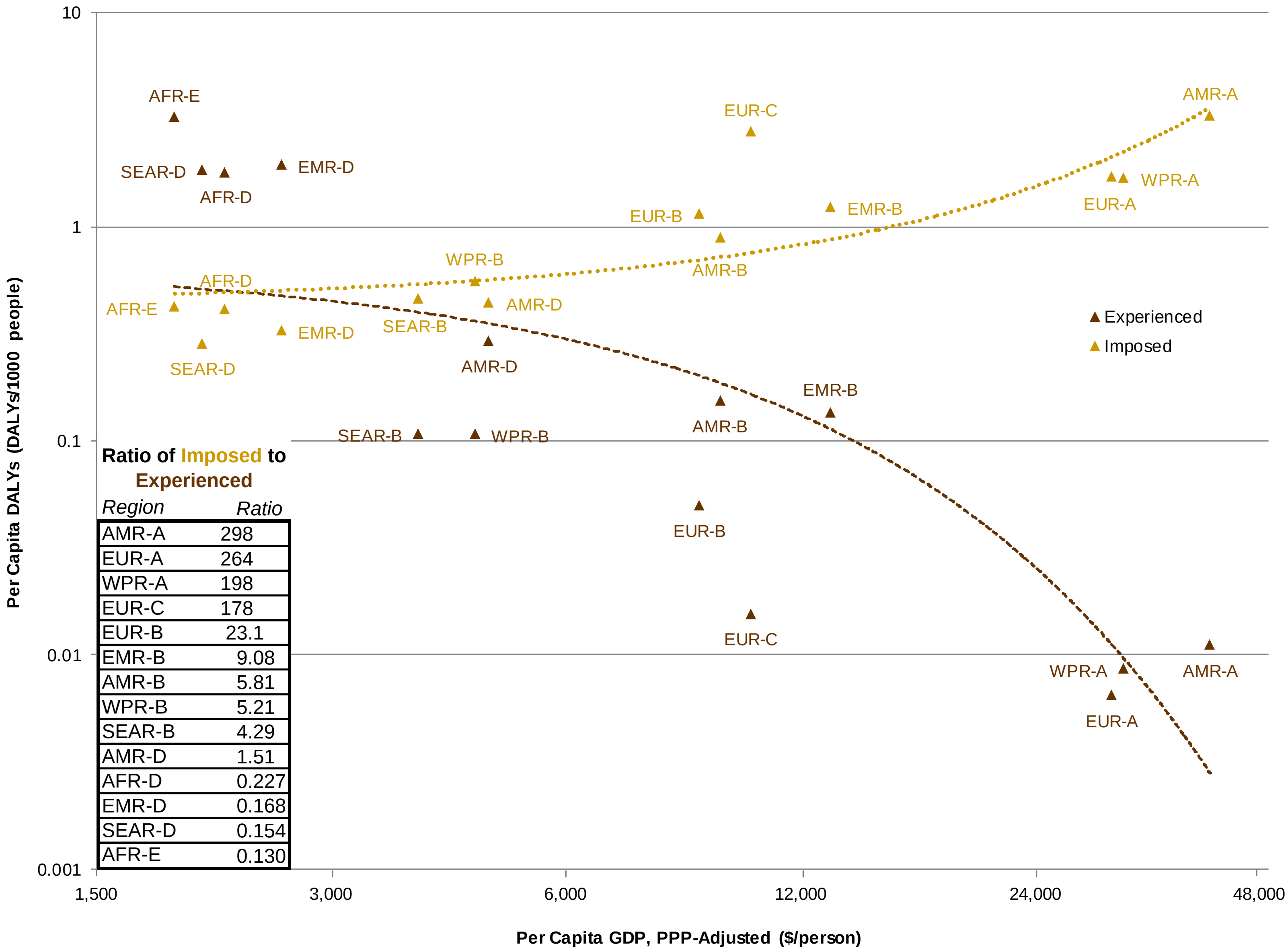
IND can be used to compare the distribution of accountability with the impacts of climate change. A major concern about climate change, for example, is the potential impacts on human health, through shifts in disease patterns (infectious, vector-borne and parasitic), extreme weather events, damage to agriculture, changes in water availability, heat stress, sea-level rise, and other routes (McMichael et al. 2006; Parry et al. 2007). Although knowledge is growing rapidly, only one detailed global assessment of these effects has been published to date as part of the World Health Organization's (WHO) Comparative Risk Assessment (CRA) Project (Ezzati et al. 2004).

Estimates were made of DALYs)in 2000 due to premature death and illness or injury by age, sex, and 14 world regions (defined in *Table A9*) due to anthropogenic climate change (McMichael et al. 2004). California, as a part of the United States, is included within region AMR-A, although California's per capita IND profile is actually closer to that for the EU, the bulk of which constitutes region EUR-A.

In the target year of 2000, the overall impact of 150,000 premature deaths annually worldwide (0.4% of global lost DALYs) is relatively small by comparison with other global risk factors. I use the WHO CRA results in the analysis, nevertheless, since it provides the only currently available consistent set of health effect estimates that allow comparison across regions and risk factors in an equivalent manner. In addition, it seems reasonable to expect that the future patterns of impacts would be similar across the world, given that most of the risk will likely be exerted as exacerbation of local baseline health conditions. It is the future expression of ill-health from climate change (avoidable risk), moreover, that is the main worry, rather than what has happened so far (attributable risk).

The downward trending line in *Figure 2.10* is taken directly from the CRA (McMichael et al. 2004) and shows that the "experienced" health burden from climate change declines with increasing economic development (per capita GDP-PPP) across the 14 CRA regions (for a CO_2(f)-only analog, see Smith and Ezzati (2005)). This trend in experienced health burden is to be expected in that the poorest parts of the world are less able to protect themselves from environmental stresses in general and, partly as a result, experience much higher levels of ill-health from them. The upper line shows the "imposed" health burden or the same total impact distributed according to the 2005 IND per capita for each region, which trends in the reverse direction, i.e., richer regions impose more risk than poorer ones because of their INDs.

The embedded table in *Figure 2.10* compares the ratio of imposed to experienced impacts across regions. The poorest regions impose ~10% of the risk they experience, while the richest − AMR-A and EUR-A − impose ~30,000% (~300 times) the risk they experience, a difference of a factor of ~1000. This is the basis of the often published maps of global health inequity from climate change (Patz et al. 2007). It is noteworthy that all regions above a per capita GDP-PPP of about $2,500 were imposing more health impact than they were experiencing early last decade.



Ratio of Imposed to Experienced

Region	*Ratio*
AMR-A	298
EUR-A	264
WPR-A	198
EUR-C	178
EUR-B	23.1
EMR-B	9.08
AMR-B	5.81
WPR-B	5.21
SEAR-B	4.29
AMR-D	1.51
AFR-D	0.227
EMR-D	0.168
SEAR-D	0.154
AFR-E	0.130

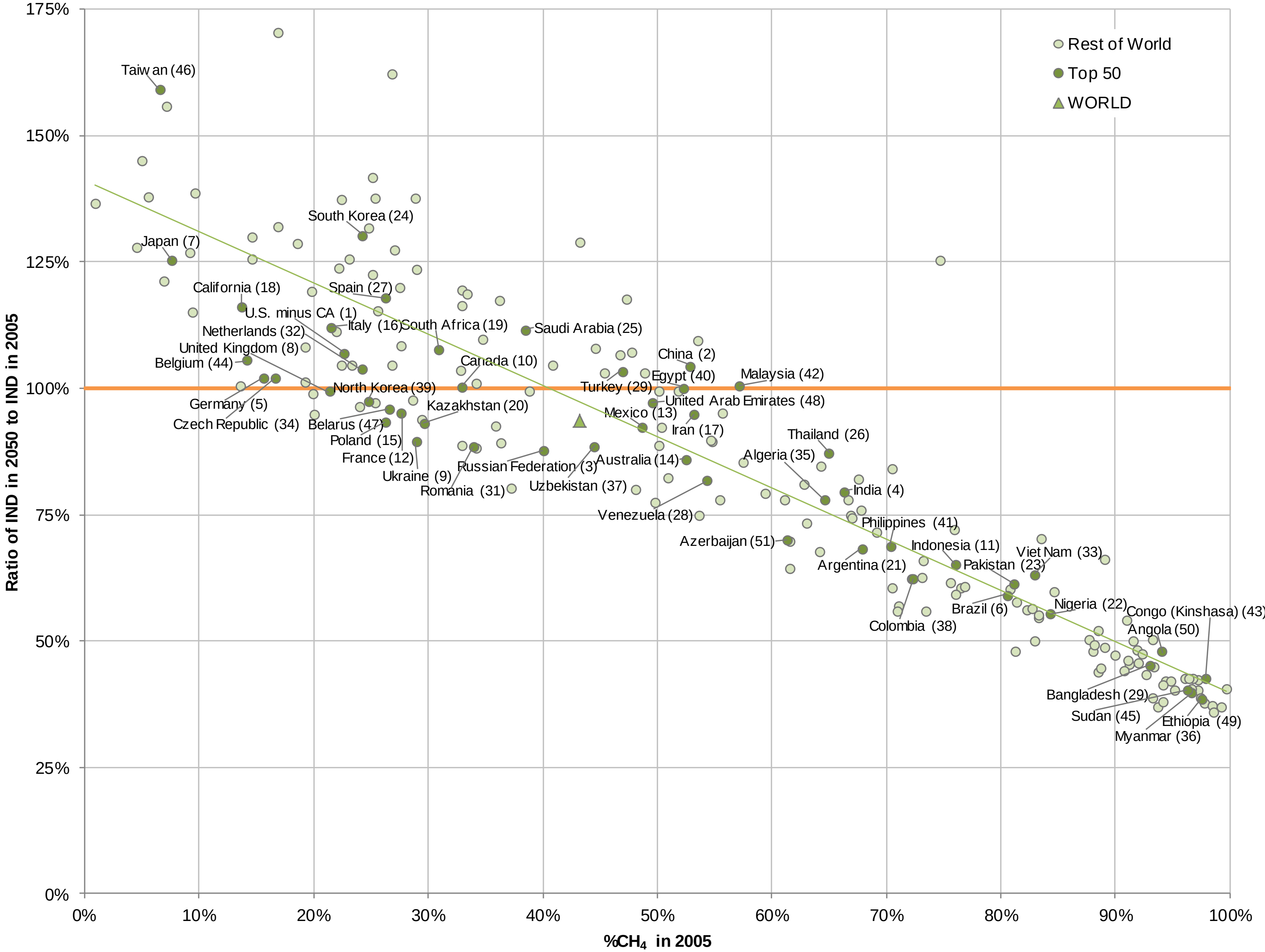
Figure 2.10: Per Capita GDP-PPP by Per Capita Imposed versus Experienced Health Impacts from Climate Change. Figure (previous page) presents all data in terms of 14 WHO regions defined in *Table A7*. The United States, including California, is part of region AMR-A. Each region is located on the x-axis according to its GDP-PPP. With respect to the y-axis, each region is graphed according to its per capita experienced health impacts (brown triangles) and imposed health impacts (yellow triangles), the latter calculated by parsing the global impact by region according to IND. The lower line (brown dashed) is fitted to the per capita GDP-PPP and experienced health impacts data (r^2 = 0.67). The upper line (yellow dotted) is fitted to the per capita GDP-PPP and imposed health impacts data (r^2 = 0.64). Note the logarithmic scale for both axes. The imbedded table shows the ratio of imposed to experienced risk from climate change by region. Data are from *Database IND* and McMichael *et al*. (2004). Abbreviations: DALY = disability-adjusted life year, GDP-PPP = gross domestic product at purchasing power parity;.

2.3.4.2. Aspirational Reductions

IND captures the amount of excess RF in a given year attributable to a country's past activities. Given the relative ease of calculating and interpreting IND-based climate debt, IND lends itself to exploring the implications of mitigation goals and strategies through scenario analyses.

Figure 2.11 conveys how much IND would change under a scenario of "aspirational reductions" in which all countries achieved a proposed goal of decreasing all CAP emissions to 20% of 1990 levels by 2050 (Executive Department of the State of California 2005; Parliament of the United Kingdom 2008; European Commission 2011). The scenario models each country's future time-series of CO_2(f) and CH_4 emissions as a linear decline commencing in 2006 and attaining target emissions rates in 2050. Initial conditions are based on *Database IND*. Implicitly, rising energy demands are met despite economic and population pressures. Over the 2006−2050 timeframe, the scenario assumes that atmospheric lifetimes, direct and indirect effects, and radiative efficiencies hold constant. These assumptions simplify the climate system but enable a reasonably realistic first-order examination.

The results for future RFs are in broad concordance with more sophisticated models that simulate similarly aggressive emissions reduction, such as RCP2.6 utilized in AR5 (van Vuuren et al. 2011). Under the aspirational reductions scenario, global IND in 2050 would be 1,850 mW/m^2 or 93% of its 2005 level. The respective contributions of CO_2(f) and CH_4 to IND would shift from 57% and 43% in 2005 to 83% and 17% in 2050, as would be expected since $IND_{CO_2(f)}$ persists longer than IND_{CH_4}. Owing to the endurance of past and future CO_2 emissions, by 2050 California's IND, as well as that of the U.S. minus CA's, would actually increase to 27 mW/m^2 (1.5% of global IND) and 364 mW/m^2 (20% of global IND), respectively. California, with a larger %CO_2(f) in 2005, would see its IND in 2050 relative to IND in 2005 grow slightly more than the U.S. minus CA: 116% versus 107%.



Rest of World
Top 50
WORLD
Ratio of IND in 2050 to IND in 2005
%CH_4 in 2005
175%
150%
125%
100%
75%
50%
25%
0%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Taiwan (46)
Japan (7)
South Korea (24)
California (18)
Spain (27)
U.S. minus CA (1)
Italy (16)
South Africa (19)
Saudi Arabia (25)
Netherlands (32)
United Kingdom (8)
Belgium (44)
Canada (10)
China (2)
Egypt (40)
Malaysia (42)
North Korea (39)
Turkey (29)
United Arab Emirates (48)
Germany (5)
Kazakhstan (20)
Czech Republic (34)
Belarus (47)
Mexico (13)
Iran (17)
Poland (15)
Thailand (26)
France (12)
Russian Federation (3)
Australia (14)
Algeria (35)
Ukraine (9)
Romania (31)
Uzbekistan (37)
India (4)
Venezuela (28)
Philippines (41)
Azerbaijan (51)
Indonesia (11)
Viet Nam (33)
Argentina (21)
Pakistan (23)
Brazil (6)
Nigeria (22)
Colombia (38)
Congo (Kinshasa) (43)
Angola (50)
Bangladesh (29)
Sudan (45)
Ethiopia (49)
Myanmar (36)

Figure 2.11: IND Consequences of Aspirational Reductions in CAP Emissions. Figure (previous page) depicts the IND consequences of a scenario in which all countries decrease both their CO_2(f) and CH_4 emissions to 20% of 1990 levels by 2050. A country's resulting IND in 2050, measured as a percent of its IND in 2005 (y-axis), is plotted against the country's percent of IND from CH_4 (%CH_4) in 2005 (x-axis). The orange horizontal line represents equal INDs in 2050 and 2005. Countries experiencing an IND increase are above this line and those experiencing an IND decrease are below the line. Labeled dark green points represent the 51 countries, including California, with the largest INDs in 2005 and ranks given in parentheses. One country (Turks & Caicos Islands) is off-scale. Light green points represent the remaining 154 countries. The green triangle represents the world as a whole. The linear regression line (green), calculated using data for all 206 countries, has an r^2 equal to 0.76. Data derived from using *Database IND* as the input for modeling this scenario. Abbreviation: U.S. minus CA = United States minus California.

A sizable minority of countries, including both California and the U.S. minus CA, are located above the orange line which represents INDs that are equal in 2050 and 2005. These countries, despite dramatic emissions decreases, nonetheless would experience a rise in their IND by 2050, and many of these same countries already possess per capita INDs well above the global average in 2005. Such countries have a high %CO_2(f) and/or an unusually steep recent increase in CO_2(f) emissions. The consequent evolution of IND underlines the substantial "hangover" from comparatively persistent CO_2(f) contributions to IND. As a result, for countries above the orange line, the aspirational reductions scenario argues that even more drastic decreases in CO_2(f) emissions would be necessary to allow these countries to lower their INDs by 2050.

A majority of countries are found below the orange line. These countries would lower their INDs by 2050, in some cases quite markedly so. Such countries typically have a high %CH_4 and/or gradually decreasing CO_2(f) emissions. In reality, however, many of these countries are currently poised to increase CO_2(f) emissions during the coming years as their economies continue to develop and populations continue to grow. Most such countries are also carrying INDs lower than the global per capita average in 2005, underscoring the question of how to justly apportion obligations to reduce climate debt across the globe.

Although %CH_4 functions well as a shortcut for locating countries on the graph, countries' outcomes under the scenario are in actuality a consequence of their unique historical emissions trajectories of CO_2(f) and CH_4. This explains the variance in the figure, accounting for differing INDs in 2050 among countries with seemingly comparable compositions to their INDs in 2005. For example, South Korea and Poland share a similar %CH_4 in 2005, 26% and 24%, respectively. In addition, the preponderance of both countries' IND_{CH_4} is comprised of remaining emissions from recent years.

South Korea's and Poland's historical time-series of CO_2(f) emissions, however, differ strikingly from one another and consequently so does the genesis of each's $IND_{CO_2(f)}$. South Korea's CO_2(f) emissions doubled from 1990−2005 and remaining emissions from this period account for three-fourths of its $IND_{CO_2(f)}$. In contrast, Poland's CO_2(f) emissions decreased by a third over the same years, but remaining emissions from the more distant 1970−1989 period account for almost half of its $IND_{CO_2(f)}$.

As a result, though South Korea and Poland have almost identical values for %CO_2(f) in 2005, they begin the aspirational reductions scenario with proportionately much different emissions rates of CO_2(f) in 2005: South Korea's are higher, their decline for the scenario is steeper, and yet their contribution to IND in 2050 is larger. These disparities in historical emissions between South Korea and Poland explain why the former's IND in 2050 expands by 27% while the latter's contracts by 4%.

A similar explanation accounts for the difference between California and Estonia, though the differences between the historical time-series of this pair are not as stark as the pairing of South Korea and Poland. In *Figure 2.11*, Estonia is represented by the light green unlabeled point directly below California but located directly on the orange line. Estonia is thus a country with a similar %CO_2(f) versus %CH_4 split in 2005 to California, but unlike California, with an IND in 2050 that would be essentially unchanged from that in 2005.

Estonia experienced higher CO_2(f) emission in distant decades but more recently, since 1989, has witnessed declining CO_2(f) emissions. Indeed, Estonia's CO_2(f) emissions in 2005 had not been that low since 1955. California, on the other hand, experienced a steady rise in CO_2(f) emissions until 2000 followed by a levelling off over 2001 to 2005. That California's CO_2(f) emissions have been commendably declining on a per capita or per dollar basis, however, does not alter the trajectory of its total IND burden.

Under the aspirational reductions scenario, Estonia starts with an emissions rate of CO_2(f) far below its peak whereas California begins only slightly below its peak. In the case of both countries, the decrease in their CH_4 emissions will also causes a decline in their IND_{CH_4}s. But in Estonia's case, the contribution of its future CO_2(f) emissions to its IND will be balanced by the decay of its past emissions, whereas California will see its IND slowly grow barring even more significant cuts to its CO_2(f) emissions.

Under the aspirational reductions scenario, whether a country's IND contracts or expands is determined by the balance between the country's lowering of IND_{CH_4} and its raising of $IND_{CO_2(f)}$. The modeled decreases in CH_4 emissions lower IND_{CH_4} by 2050 for all countries, verifying the swift response of IND_{CH_4} to a decline in emissions. On the other hand, the modeled decreases in CO_2(f) emissions do not lower $IND_{CO_2(f)}$ for any country, in this case reflecting the enduring legacy of past CO_2(f) emissions. The decreases in CO_2(f) emissions prevent $IND_{CO_2(f)}$ from rising even further, but their insufficiency also make apparent the incentive for simultaneously decreasing emissions of other CAPs while devising viable carbon capture and sequestration technologies (Rubin et al. 2012; Sedjo and Sohngen 2012), as well as the impulse for cautiously appraising geoengineering schemes to manipulate the climate system (Lenton and Vaughan 2009).

For the world as a whole, the rise in IND from countries above the orange line is compensated by the fall in IND from countries below the orange line. Consequently, global IND in 2050 remains very similar to that in 2005. But this seemingly favorable outcome for the aspirational reductions scenario does not advocate for its implementation. A global program of climate stabilization pursued through commensurate decreases in emissions intensity across all countries, on the contrary, would exacerbate already stark inequities.

Instead, the aspirational reduction scenario stresses the different capacities of countries to lower their climate debt and draws a sharp distinction between the potentially divergent evolution of countries' IND. The scenario exercise lays bare the need for coordinated action on both CO_2(f) and CH_4 to address climate change. Firstly, bold decreases in CO_2(f) emissions from countries with a high $\%CO_2$(f) will be necessary to both reduce global $IND_{CO_2(f)}$ and offset increases in CO_2(f) emissions from countries that aspire to attain a prosperous level of development. Secondly, decreases in CH_4 emissions from all countries will also be necessary to rapidly reduce the global IND_{CH_4} and thereby at least postpone and possibly diminish the deleterious impacts of climate change. Therefore, on both counts, the aspirational reductions scenario motivates sharp cuts in both CO_2(f) and CH_4 emissions in order for California to reduce its IND by 2050.

Moreover, the aspirational reductions scenario posits that the global IND in 2005 could serve as a medium-term objective for capping worldwide climate debt from CO_2(f) and CH_4 combined. It follows that the target for global per capita IND in 2050 would be about 215 $\mu W/m^2$/person for the intermediate-fertility population projection from the United Nations Department of Economic and Social Affairs - Population Division (United Nations Department of Economic and Social Affairs - Population Division 2011), similar to the climate debt carried in 2005 by the average Jamaican, Laotian, or Somali. For the UN's low-fertility and high-fertility population projections, global per capita IND in 2050 would be roughly 30 $\mu W/m^2$/person higher or lower, respectively. The target applies equally to countries currently above and below it, and offers a vision of what will be required, as well as what would be achieved, by "convergence" with respect to climate debt.

2.3.4.3. Alternate Histories

The same features of IND which make it an accessible tool for global-level scenario analyses also facilitate the scrutiny of questions at finer scales. As an example of such an analysis, I leverage IND to help define the climate debt contours of the ongoing debate on natural gas in California and across the world. In particular, IND can help to assess the relative impact, in terms of change in RF, from displacing coal-fired electricity generation with gas-fired alternatives.

Much of the opportunity for reducing emissions of both CO_2(f) and CH_4 resides in the energy sector. Hydraulic fracturing or "fracking" has significantly expanded natural gas production in the United States since the mid-2000s. Coupled with the opportune advances in extraction technology has been a favorable economic, regulatory, and strategic environment for natural gas as an energy source. In addition, gas burns more cleanly than oil and especially coal, producing less CO_2(f) per unit energy released, which has led some to pitch natural gas as a "bridge" fuel until renewables become more competitive.

Part of the argument around natural gas concerns whether its greater combustion efficiency might be outweighed by fugitive emissions of CH_4 during extraction, transport, storage, and use (Alvarez et al. 2012; Miller et al. 2013). Although natural processes remove CH_4 from the atmosphere more rapidly than CO_2, the radiative efficiency of CH_4 exceeds that of CO_2 on a per unit mass or carbon atom basis. Studies on the net impacts of natural gas, including those focused on fracking, have found evidence to support claims on both sides of the argument (Weber and Clavin 2012; McJeon et al. 2014).

An analysis based on IND can help define the climate debt contours of this ongoing debate while also highlighting the applicability of IND for scrutinizing questions at finer scales.

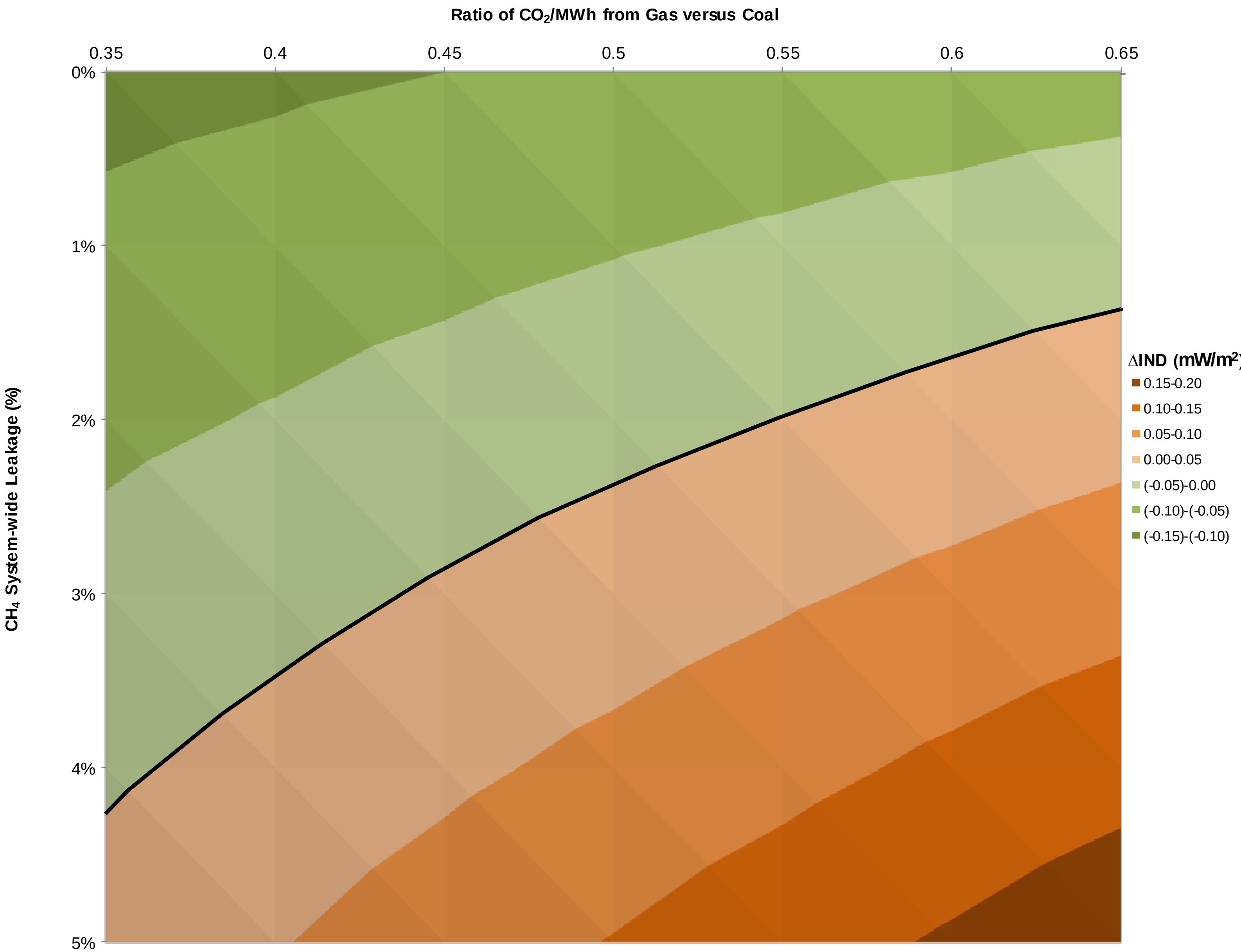
In order to examine the IND implications of shifting California' power production portfolio from coal to gas, I developed an "alternate histories" scenario in which half of the state's coal-fired electricity generation during 2001 to 2005, including imports from other states, was instead produced by natural gas power plants. The scenario considers a range of coal and gas power plant types and a continuum of plausible leakage rates in the natural gas system.

Instead of attempting to forecast the future, I sought to reimagine the past, asking how the California' IND in 2005 would have differed had the fracking revolution occurred earlier. This approach has the benefit of drawing on more reliable existing data, subjected to the hypotheses of the exercise, instead of anticipating less certain circumstances far into the future. Additionally, such a strategy may be useful for situations requiring a near-term assessment, for instance to meet a target or respond to feedbacks (Rignot et al. 2014; van Nes et al. 2015), whereas assessing long-term impacts would require assumptions similar to the aspirational reductions scenario.

The alternate histories scenario drew on *Database IND* and its underlying datasets (Air Resources Board of the California Environmental Protection Agency 2007a; Boden et al. 2010; JRC/PBL, 2010b; Air Resources Board of the California Environmental Protection Agency 2013). In the scenario, CO_2(f) emissions from coal are replaced by those from gas at a proportion ranging from 0.35 to 0.65., thereby accounting for the range of carbon intensity (CO_2 emissions per unit energy) ratios possible given the various types of both coal and gas power plants. The lower value corresponds to a combined cycle gas plant replacing an average coal plant and the higher value corresponds to an average gas plant replacing a super pulverizer coal plant (2012).

For simplicity, I assumed that all coal or gas combusted in a given year was extracted in that same year. In order to capture the full impact of the coal-to-gas alternate history, I expanded the system boundary of California's greenhouse gas emissions inventory in two ways. First, I included decreases in CH_4 emissions consequent to a decline in coal mining caused by diminished demand even though the state's emissions inventory's boundary does not include CH_4 emissions from out-of-state coal mines that supply facilities generating electricity for California. To fill this data gap, I relied on data showing that, during 2001 to 2005, coal mining contributed on average 18.5% of the United States' energy sector's CH_4 emissions (2010b; 2013).

Second, I included increases in CH_4 emissions from fugitive emissions (i.e., leaks) of natural gas anywhere on the pathway from well to plant. Again, current inventory methods do not include such CH_4 emissions that occur out-of-state, except at the site of a power plant that exports electricity to California. System-wide, i.e., well-to-plant, leakage in the natural gas system can be expressed as a percent of the gas being extracted in order to be combusted at gas-fired facilities. In the scenario, leakage spans a range of 0% to 5%, encapsulating a plausible range approximately centered around the United States Environmental Protection Agency's pre-2013 estimate that ~2.25% of natural gas produced over 2001 to 2005 was lost to fugitive emissions (2008). More recently, the United States Environmental Protection Agency revised this fraction downwards, to ~1.5% (2013). Other evidence suggests leakage could be several times higher than either of these values (Miller et al. 2013; Brandt et al. 2014), a concern addressed by the higher end of the leakage range.



Ratio of CO_2/MWh from Gas versus Coal
0.35
0.4
0.45
0.5
0.55
0.6
0.65
0%
1%
2%
3%
4%
5%
CH_4 System-wide Leakage (%)
ΔIND (mW/m^2)
0.15-0.20
0.10-0.15
0.05-0.10
0.00-0.05
(-0.05)-0.00
(-0.10)-(-0.05)
(-0.15)-(-0.10)

Figure 2.12: IND Outcomes from Alternate Histories of a Coal-to-Gas Transition in California. Figure (previous page) depicts the net impact on California's IND in 2005 under a scenario in which 50% of the state's coal-fired electricity generation during 2001 to 2005 had instead been produced by gas power plants. The colored contour bands (contour interval 0.05 mW/m^2) indicate the change in IND between the various combinations of this scenario and reality. The contour bands range from a decrease in IND (green hues) of -0.15 to -0.10 mW/m^2 at top-left to an increase in IND (brown hues) of 0.15 to 0.20 mW/m^2 at bottom-right. The y-axis spans the possible range of carbon intensity ratios for gas versus coal power generation and the x-axis spans a continuum of plausible system-wide leakage rates in the natural gas system (see text). The black curve separates the regions of IND decrease, above the arc, from IND increase, below the arc. Data derived from using *Database IND* as the input for modeling this scenario, with additional data from the Air Resources Board of the California Environmental Protection Agency (2013).

The scenario exercise recalculated CO_2(f) and CH_4 emissions over 2001−2005 for California and then adjusted corresponding global emissions accordingly. This pair of recalculations provided both a new numerator and denominator for re-attributing global $IND_{CO_2(f)}$ and IND_{CH_4} to California.

Figure 2.12 presents the difference between California's IND as calculated under the alternate histories scenario and California's actual IND in 2005 across all combinations of relative carbon intensities (x-axis) and leakage rates (y-axis). As the green-hued contour bands become darker, they incrementally indicate larger falls in IND. Conversely, as the brown-hued contour bands become darker, they incrementally indicate larger rises in IND.

The upper left corner, where natural gas leakage is lowest and combined cycle gas plants replace average coal plants, is the most favorable region of IND outcomes, a decrease of 0.15 to 0.10mW/m^2. The opposite corner, at the bottom-right, where natural gas leakage is highest and average gas plants replace super pulverizer coal plants, is the least favorable region, with IND actually increasing 0.15 to 0.20 mW/m^2. In general, combined cycle gas plants are net positive, with respect to climate debt in 2005, until leakage rates approach the 3% to 4.5% range. For average gas plants to be advantageous from this perspective, leakage rates must be lower, in the 1.5% to 2.5% range.

The IND-based scenario analysis, in which half of California's coal power production was replaced by gas, defines the range of outcomes possible, over the five year period, in terms of climate debt. Clearly, conclusions pivot on the amount of leakage in the natural gas system and the type of gas and coal plants being swapped. Overall, from one set of extremes to the other, as leakage in the natural gas system decreases or as the combustion efficiency of gas plants relative to coal plants increases, electricity generation by natural gas goes from being unfavorable to favorable in terms of climate debt. The alternate histories scenario provides a template for using IND to scrutinize more elaborate decision analyses, including the incorporation of economic costs, a central issue I have left aside for the time-being, as well as longer time horizons.

2.4. Conclusions

IND apportions global radiative forcing from CO_2(f) and CH_4, the two most significant CAPs, to individual entities − primarily countries but also subnational states and economic sectors, with even finer scales possible − as a function of unique trajectories of historical emissions, taking into account the quite different radiative efficiencies and atmospheric lifetimes of each CAP. Owing to its straightforward and transparent derivation, IND can readily operationalize climate debt to consider issues of equity and efficiency, and drive scenario exercises that explore the response to climate change from global to sectoral scales. The analyses presented in this chapter demonstrate the capacity for climate debt, as captured by IND, to inform a range of key question on climate change mitigation. As such, an accessible path exists for public health scientists to pursue the causes and not just the consequences of climate change.

Scrutinizing IND in total and per capita terms exposes and emphasizes variations in the size and composition of climate debt that can help orient burden-sharing, guide mitigation approaches, track progress at multiple scales, and generate hypotheses for further investigation. For example, monitoring California's IND can benchmark the state's progress in comparison to other countries, the U.S. minus CA, or itself over time. California's IND in 2005 reflects its historically efficient generation, relative to the U.S. minus CA, of both CO_2(f) and CH_4 emissions. Yet California's IND nonetheless exceeds the global average by more than a factor of two. Reducing California's contribution to global warming will require determined and coordinated decreases to both its CO_2(f) and CH_4 emissions. IND functions as a natural tool for exploring, in an manageable yet realistic manner, technological and policy options at the level of a subnational state.

At the global level, IND reveals that the bulk of accountability remains with HICs, though there is a shift in balance toward LMICs compared to a CO_2(f)-only perspective. In contrast, compared to HICs, CH_4 reductions in LMICs can result in comparatively rapid reductions in these countries' climate debts, since CH_4 is often a significant portion of LMICs' debt, while helping to slacken the pace of warming over this century. The use of IND to allocate accountability in international negotiations for action on CAP mitigation and adaptation could help enact the "differentiated responsibilities" portion of the UNFCCC (United Nations 1992). By itself, however, IND would be insufficient to determine obligations. Under the "respective capabilities" clause of the UNFCCC (United Nations 1992), actual transfers for remediation or adaptation in an international regime would require implicit or explicit assessment of ability to pay and additional factors including, for instance, promoting access to family planning and adhering to conventions on conservation (Hayes and Smith 1993; Baer 2006).

Similar to other measures of environmental footprint (Knight and Rosa 2011; Jorgenson 2014), the accumulation of IND can be evaluated in comparison to two major indicators of overall well-being – economic output and population health. I put forth a characterization of the "efficiencies" of $IND_{CO_2(f)}$ and IND_{CH_4} in order to explore how effectively countries have accumulated these two forms of climate debt in the pursuit of expanding economic output and diminishing ill-health. For instance, the distribution of the efficiency of $IND_{CO_2(f)}$ hints at the consequence of a "leapfrog" strategy for many LMICs, a number of which have low health but high income efficiencies. If these countries maintained or even moderately increased their

$IND_{CO_2(f)}$ in order to promote population health, they could catapult to HIC levels of both health and income efficiency. In contrast, the sizable number of LMICs which, from the perspective of economic output, have inefficiently accumulated IND_{CH_4}, lends additional impetus for research and development into technologies and strategies that either decrease CH_4 emissions or more effectively convert CH_4 emissions into income gains. Overall, IND efficiency provides another yardstick by which to investigate the distribution and evolution of climate debt across countries as countries also endeavor to achieve other goals (McMichael and Butler 2011; Lamb and Rao 2015).

IND functions as a natural tool for investigating mitigation goals and strategies. As a measure of climate debt, IND accounts for the constraints imposed by the magnitude and timing of past emissions and measures the amount of radiative forcing in a particular year caused by still-extant emissions of multiple CAPs. Scenario exercises, with appropriate attention to their limitations, can help evaluate the future evolution of IND, propose evenhanded approaches to reducing climate debt, and interrogate the choice between mitigating CO_2(f) or CH_4 at several scales.

Under the "aspirational reductions" scenario, countries linearly decrease their CAP emissions to 20% of 1990 levels by 2050, attaining a target commonly discussed for midcentury (European Commission, 2011; Executive Department State of California, 2005; Parliament of the United Kingdom, 2008). Overall, the exercise posits that, assuming intermediate-term fertility projections (United Nations Department of Economic and Social Affairs - Population Division 2011), a medium-term, globally averaged, per capita IND of approximately 215 $\mu W/m^2$/person would stabilize global IND by 2050.

The aspirational reduction scenario explains how the differing capacities of countries to lower their climate debts is a function of historical emissions trajectories of CO_2(f) and CH_4. Thus, the exercise lays bare the need for coordinated action on both CO_2(f) and CH_4 to address climate change. Firstly, bold decreases in CO_2(f) emissions from countries with a high %CO_2(f) will be necessary to both reduce global $IND_{CO_2(f)}$ and offset increases in CO_2(f) emissions from countries aspiring to attain a prosperous level of development. Secondly, decreases in CH_4 emissions from all countries will also be necessary to rapidly reduce global IND_{CH_4} and thereby at least postpone and possibly diminish the deleterious impacts of climate change. Thirdly, the immense challenge of the preceding two recommendations makes apparent the incentive for simultaneously decreasing emissions of other CAPs; devising viable carbon capture and sequestration technologies (Rubin et al. 2012; Sedjo and Sohngen 2012); and appraising, with due caution, geoengineering schemes to manipulate the climate system (Lenton and Vaughan 2009).

Although natural processes remove CH_4 from the atmosphere more rapidly than CO_2, the radiative efficiency of CH_4 exceeds that of CO_2 on a per unit mass or carbon atom basis, complicating decisions to preferentially mitigate one CAP versus the other (Weber and Clavin 2012; McJeon et al. 2014). This question can be pursued at a sectoral level through an "alternate histories" scenario in which half of California's coal-fired power production had been instead generated by natural gas facilities from 2000 to 2005. The scenario incorporates the carbon intensity ratios of different coal-to-gas plant substitutions and a range of plausible well-to-plant leakage rates in the natural gas system. For such a hypothesized shift to have lowered

California's IND in 2005, relative to the state's actual IND that year, combined cycle gas plants would require leakage rates in the 3% to 4.5% range or less, whereas average gas plants, with their lower efficiency, would require leakage rates at most in the 1.5% to 2.5% range.

IND was developed to be flexible for users, including with regards to data inputs and calculated outputs. IND can be an appropriate vehicle, as data sources improve and climate science advances, for folding additional CAPs, non-CAP anthropogenic perturbations to RF, and mitigative actions into the climate debt paradigm. The incorporation of a "basic needs" allowance (Müller et al. 2009; Costa et al. 2011), as well as approaches that attribute IND on the basis of where good and services were consumed, as opposed to where emissions were produced (Hertwich and Peters 2009; Unger et al. 2010), would further expand the explanatory and analytical power of IND.

Collectively, the analyses presented in this chapter demonstrate how IND in its present form – as well as updated, expanded, or enhanced − can inform a range of key question on climate change mitigation. The published literature on climate debt has often involved either philosophically or technically complex approaches to contemplate or calculate climate debt (Caney 2005; Tanaka et al. 2009; Bell 2011; Höhne et al. 2011). Both of these are valuable streams of scholarship that warrant sustained attention, and have contributed to the development of IND. However, the full utility of climate debt as an analytical perspective will remain untapped without tools such as IND that can be manipulated by a wide range of analysts, including global environmental health researchers. By demonstrating the insights possible from applications of IND, I have sought to broaden the intellectual terrain for climate debt analyses and invite more participatory and inclusive discussions about the consequent implications of such a perspective.

2.5. References

Air Resources Board of the California Environmental Protection Agency (2007a) "1990-2004 Greenhouse Gas Inventory", Sacramento, CA http://www.arb.ca.gov/cc/inventory/archive/archive.htm Accessed 2014 February 23.

Air Resources Board of the California Environmental Protection Agency (2007b) "Land Use, Land Use Change, and Forestry - Net CO_2 Flux", Sacramento, CA http://www.arb.ca.gov/cc/inventory/archive/archive.htm Accessed 2014 February 23.

Air Resources Board of the California Environmental Protection Agency (2013) "Greenhouse Gas Inventory Data - 2000-2011", Sacramento, CA http://www.arb.ca.gov/cc/inventory/data/data.htm Accessed 2014 February 23.

Air Resources Board of the California Environmental Protection Agency (2014) California Greenhouse Gas Emission Inventory: 2000-2012 Air Resources Board of the California Environmental Protection Agency, Sacramento, CA.

Alvarez RA, Pacala SW, Winebrake JJ, Chameides WL, and Hamburg SP (2012) "Greater focus needed on methane leakage from natural gas infrastructure" *Proceedings of the National Academy of Sciences of the United States of America* 109(17): 6435-6440.

Andres RJ, Boden TA, Bréon FM, Ciais P, Davis S, Erickson D, Gregg JS, Jacobson A, Marland G, Miller J, Oda T, Olivier JGJ, Raupach MR, Rayner P, and Treanton K (2012) "A synthesis of carbon dioxide emissions from fossil-fuel combustion" *Biogeosciences* 9(5): 1845-1871.

Arrhenius S (1896) "On the influence of carbonic acid in the air upon the temperature of the ground" *Philosophical Magazine and Journal of Science* 41(251): 237-276.

Baer P (2006) "Adaptation to climate change: who pays whom?" In Fairness in Adaptation to Climate Change Editors Adger N, Huq S, Paavola J, and Mace MJ, MIT Press, Cambridge, MA.

Baer P, Harte J, Haya B, Herzog AV, Holdren J, Hultman NE, Kammen DM, Norgaard RB, and Raymond L (2000) "Climate change: equity and greenhouse gas responsibility" *Science* 289(5488): 2287.

Beckerman W and Pasek J (1995) "The equitable international allocation of tradable carbon emission permits" *Global Environmental Change* 5(5): 405-413.

Bell D (2011) "Global climate justice, historic emissions, and excusable ignorance" *The Monist* 94(3): 391-411.

Berk MM and den Elzen M (2001) "Options for differentiation of future commitments in climate policy: how to realise timely participation to meet stringent climate goals?" *Climate Policy* 1(4): 465-480.

Bhaskar V (1995) "Distributive justice and the control of global warming" In The North, the South, and the Environment: Ecological Constraints and the Global Economy Editors Bhaskar V and Glyn A, Earthscan, London, UK**:** 102-117.

Blasing TJ and Krassovski M (2012) "Estimates of Annual Fossil-Fuel Carbon Emitted for Each State in the U.S.A. and the District of Columbia for Each Year from 1960 through 2010" Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, TN http://cdiac.ornl.gov/CO2_Emission/timeseries/usa Accessed 2014 April 15.

Bloom DE and Canning D (2000) "The health and wealth of nations" *Science* 287: 1207-1209.

Boden TA, Marland G, and Andres RJ (2010) "Global, Regional, and National Fossil-Fuel CO_2 Emissions" Carbon Dioxide Information Analysis Center, Oak Ridge National

Laboratory, U.S. Department of Energy, Oak Ridge, TN http://cdiac.esd.ornl.gov/trends/emis/tre_coun.htm Accessed 2011 April 15.
Böhringer C and Welsch H (2006) "Burden sharing in a greenhouse: egalitarianism and sovereignty reconciled" *Applied Economics* 38(9): 981-996.
Bowen KJ and Friel S (2012) "Climate change adaptation: where does global health fit in the agenda?" *Globalization and Health* 8: 10.
Brandt AR, Heath GA, Kort EA, O'Sullivan F, Pétron G, Jordaan SM, Tans P, Wilcox J, Gopstein AM, Arent D, Wofsy S, Brown NJ, Bradley R, Stucky GD, Eardley D, and Harriss R (2014) "Methane leaks from North American natural gas systems" *Science* 343(6172): 733-735.
Bureau of Economic Analysis of the United States Department of Commerce (2006) "Gross Domestic Product by State, Advance 2005 and Revised 1998-2004", Washington, DC http://www.bea.gov/regional/histdata/releases/0606gsp/index.cfm Accessed 2014 April 15.
California State Assembly (2006) "California Global Warming Solutions Act (Assembly Bill 32)", Sacramento, CA.
Caney S (2005) "Cosmopolitan justice, responsibility, and global climate change" *Leiden Journal of International Law* 18(4): 747-775.
Cazorla M and Toman M (2000) International Equity and Climate Change Policy Resources for the Future, Washington, DC.
Corbera E and Schroeder H (2011) "Governing and implementing REDD+" *Environmental Science & Policy* 14(2): 89-99.
Costa L, Rybski D, and Kropp JP (2011) "A human development framework for CO_2 reductions" *PLOS ONE* 6(12): e29262.
den Elzen MGJ, Olivier JGJ, Höhne N, and Janssens-Maenhout G (2013) "Countries' contributions to climate change: effect of accounting for all greenhouse gases, recent trends, basic needs and technological progress" *Climatic Change* 121(2): 397-412.
Denman KL, Brasseur G, Chidthaisong A, Ciais P, Cox PM, Dickinson RE, Hauglustaine D, Heinze C, Holland E, Jacob D, Lohmann U, Ramachandran S, da Silva Dias PL, Wofsy SC, and Zhang X (2007) "Couplings between changes in the climate system and biogeochemistry" In Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Editors Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, and Miller HL, Cambridge University Press, New York, NY**:** 499-588.
Eckard RJ, Grainger C, and de Klein CAM (2010) "Options for the abatement of methane and nitrous oxide from ruminant production: a review" *Livestock Science* 130(1-3): 47-56.
European Commission (2011) "Roadmap for moving to a competitive low carbon economy in 2050" COM(2011) 112 final.
Executive Department of the State of California (2005) "Executive Order # S-03-05".
Ezzati M, Rodgers AD, Lopez AD, and Murray CJL, Editors (2004). Comparative Quantification of Health Risks: Global and Regional Burden of Disease due to Selected Major Risk Factors World Health Organization, Geneva, CH.
Fischer M and Jeong S (2012) Inverse Modeling to Verify California's Greenhouse Gas Emission Inventory California Air Resources Board of the California Environmental Protection Agency, Sacramento, CA: #09-348.

Forster P, Ramaswamy V, Artaxo P, Berntsen T, Betts R, Fahey DW, Haywood J, Lean J, Lowe DC, Myhre G, Nganga J, Prinn R, Raga G, Schulz M, and Van Dorland R (2007) "Changes in atmospheric constituents and in radiative forcing" In Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Editors Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, and Miller HL, Cambridge University Press, New York, NY**:** 129-234.

Frey C, Penman J, Hanle L, S. M, and Ogle S (2006) "Uncertainties" In 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 1: General Guidance and Reporting Editors Paciornik N and Rypdal K, Institute for Global Environmental Strategies, Hayama, JP**:** 3.1-3.66.

Friis RH (2007) Essentials of Environmental Health Jones & Bartlett, Sudbury, MA.

Friman M and Linner BO (2008) "Technology obscuring equity: historical responsibility in UNFCCC negotiations" *Climate Policy* 8(4): 339-354.

Global Burden of Disease Study 2010 (2012) "Global Burden of Disease Study 2010, Results by Cause 1990-2010" Institute for Health Metrics and Evaluation, Seattle, WA http://ghdx.healthmetricsandevaluation.org/record/global-burden-disease-study-2010-gbd-2010-results-cause-1990-2010 Accessed 2013 October 12.

Grubb M (1995) "Seeking fair weather: Ethics and the international debate on climate change" *International Affairs* 71(3): 463-496.

Grubb M, Sebenius J, Maglhaes A, and Subak S (1992) "Sharing the burden" In Confronting Climate Change: Risks, Implications, and Responses Editor Mintzer IM, Cambridge University Press, Cambridge, UK.

Grübler A and Fujii Y (1991) "Inter-generational and spatial equity issues of carbon accounts" *Energy* 16(11-12): 1397-1416.

Grübler A and Nakićenović N (1994) International Burden Sharing in Greenhouse Gas Reduction International Institute for Applied Systems Analysis, Laxenburg, AT.

Haines A, McMichael AJ, Smith KR, Roberts I, Woodcock J, Markandya A, Armstrong BG, Campbell-Lendrum D, Dangour AD, Davies M, Bruce N, Tonne C, Barrett M, and Wilkinson P (2009) "Public health benefits of strategies to reduce greenhouse-gas emissions: overview and implications for policy makers" *Lancet* 374(9707): 2104-2114.

Hayes P and Smith KR, Editors (1993). The Global Greenhouse Regime: Who Pays? Science, Economics and North-South Politics in the Climate Change Convention Earthscan Publications/United Nations University Press, London, UK.

Hertwich EG and Peters GP (2009) "Carbon footprint of nations: a global, trade-linked analysis" *Environmental Science & Technology* 43(16): 6414-6420.

Höhne N and Blok K (2005) "Calculating historical contributions to climate change - discussing the "Brazilian Proposal"" *Climatic Change* 71(1-2): 141-173.

Höhne N, Blum H, Fuglestvedt J, Skeie RB, Kurosawa A, Hu GQ, Lowe J, Gohar L, Matthews B, de Salles ACN, and Ellermann C (2011) "Contributions of individual countries' emissions to climate change and their uncertainty" *Climatic Change* 106(3): 359-391.

Houghton JT, Meira Filho LG, Lim B, Treanton K, Mamaty I, Bonduki Y, Griggs DJ, and Callender BA, Editors (1997). Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories Intergovernmental Panel on Climate Change, Organisation for Economic Cooperation and Development, and International Energy Agency, Paris, FR.

Houghton R (2008) "Carbon Flux to the Atmosphere from Land-Use Changes: 1850-2005. TRENDS: A Compendium of Data on Global Change" Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, TN http://cdiac.ornl.gov/trends/landuse/houghton/houghton.html Accessed 2012 March 31.

Houghton RA (1999) "The annual net flux of carbon to the atmosphere from changes in land use 1850-1990" *Tellus Series B-Chemical and Physical Meteorology* 51(2): 298-313.

Houghton RA (2003) "Revised estimates of the annual net flux of carbon to the atmosphere from changes in land use and land management 1850-2000" *Tellus Series B-Chemical and Physical Meteorology* 55(2): 378-390.

IPCC (2014) "Summary for Policymakers" In Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Editors Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, and White LL, Cambridge University Press, Cambridge, UK**:** 1-32.

Jain N, Dubey R, Dubey DS, Singh J, Khanna M, Pathak H, and Bhatia A (2013) "Mitigation of greenhouse gas emission with system of rice intensification in the Indo-Gangetic Plains" *Paddy and Water Environment*: 1-9.

Jamison DT, Summers LH, Alleyne G, Arrow KJ, Berkley S, Binagwaho A, Bustreo F, Evans D, Feachem RGA, Frenk J, Ghosh G, Goldie SJ, Guo Y, Gupta S, Horton R, Kruk ME, Mahmoud A, Mohohlo LK, Ncube M, Pablos-Mendez A, Reddy KS, Saxenian H, Soucat A, Ulltveit-Moe KH, and Yamey G (2013) "Global health 2035: a world converging within a generation" *The Lancet* 382(9908): 1898-1955.

Joint Research Centre of the European Commission/PBL Netherlands Environmental Assessment Agency (2010a) "EDGAR Documentation Uncertainty" http://themasites.pbl.nl/en/themasites/edgar/documentation/uncertainties/index.html Accessed 2012 July 15.

Joint Research Centre of the European Commission/PBL Netherlands Environmental Assessment Agency (2010b) "Emission Database for Global Atmospheric Research, release version 4.1" http://edgar.jrc.ec.europa.eu Accessed 2011 April 15.

Joos F, Prentice IC, Sitch S, Meyer R, Hooss G, Plattner GK, Gerber S, and Hasselmann K (2001) "Global warming feedbacks on terrestrial carbon uptake under the Intergovernmental Panel on Climate Change (IPCC) emission scenarios" *Global Biogeochemical Cycles* 15(4): 891-907.

Joos F, Roth R, Fuglestvedt JS, Peters GP, Enting IG, von Bloh W, Brovkin V, Burke EJ, Eby M, Edwards NR, Friedrich T, Frölicher TL, Halloran PR, Holden PB, Jones C, Kleinen T, Mackenzie FT, Matsumoto K, Meinshausen M, Plattner GK, Reisinger A, Segschneider J, Shaffer G, Steinacher M, Strassmann K, Tanaka K, Timmermann A, and Weaver AJ (2013) "Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: a multi-model analysis" *Atmospheric Chemistry and Physics* 13(5): 2793-2825.

Jorgenson AK (2014) "Economic development and the carbon intensity of human well-being" *Nature Climate Change* 4: 186-189.

Klein Goldewijk K, Beusen A, van Drecht G, and de Vos M (2011) "The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years" *Global Ecology and Biogeography* 20(1): 73-86.

Knight KW and Rosa EA (2011) "The environmental efficiency of well-being: a cross-national analysis" *Social Science Research* 40(3): 931-949.

Labriet M and Loulou R (2003) "Coupling climate damages and GHG abatement costs in a linear programming framework" *Environmental Modeling and Assessment* 8(3): 261-274.

Lamb WF and Rao ND (2015) "Human development in a climate-constrained world: What the past says about the future" *Global Environmental Change* 33: 14-22.

Lenton TM and Vaughan NE (2009) "The radiative forcing potential of different climate geoengineering options" *Atmospheric Chemistry and Physics* 9(15): 5539-5561.

Manne AS and Stephan G (2005) "Global climate change and the equity–efficiency puzzle" *Energy* 30(14): 2525-2536.

Marland G, Hamal K, and Jonas M (2009) "How uncertain are estimates of CO_2 emissions?" *Journal of Industrial Ecology* 13(1): 4-7.

Matthews HD, Graham TL, Keverian S, Lamontagne C, Seto D, and Smith TJ (2014) "National contributions to observed global warming" *Environmental Research Letters* 9(1): 014010.

McJeon H, Edmonds J, Bauer N, Clarke L, Fisher B, Flannery BP, Hilaire J, Krey V, Marangoni G, Mi R, Riahi K, Rogner H, and Tavoni M (2014) "Limited impact on decadal-scale climate change from increased use of natural gas" *Nature* 514(7523): 482-485.

McMichael AJ and Butler CD (2011) "Promoting global population health while constraining the environmental footprint" *Annual Review of Public Health* 32(1): 179-197.

McMichael AJ, Campbell-Lendrum D, Kovats S, Edwards S, Wilkinson P, Wilson T, Nicholls R, Hales S, Tanser F, Le Sueur D, Schlesinge M, and Andronova N (2004) "Global climate change" In <u>Comparative Quantification of Health Risks: Global and Regional Burden of Disease Due to Selected Major Risk Factors</u> Editors Ezzati M, Rodgers A, Lopez A, and Murray C, World Health Organization, Geneva, CH**:** 1543-1649.

McMichael AJ, Woodruff RE, and Hales S (2006) "Climate change and human health: present and future risks" *Lancet* 367(9513): 859-869.

Miller D (2009) "Global justice and climate change: How should responsibilities be distributed?" <u>The Tanner Lectures on Human Values</u> Delivered at Tsinghua University,, Beijing, CN.

Miller SM, Wofsy SC, Michalak AM, Kort EA, Andrews AE, Biraud SC, Dlugokencky EJ, Eluszkiewicz J, Fischer ML, Janssens-Maenhout G, Miller BR, Miller JB, Montzka SA, Nehrkorn T, and Sweeney C (2013) "Anthropogenic emissions of methane in the United States" *Proceedings of the National Academy of Sciences of the United States of America* 110(50): 20018-20022.

Moore FC and MacCracken MC (2009) "Lifetime-leveraging: An approach to achieving international agreement and effective climate protection using mitigation of short-lived greenhouse gases" *International Journal of Climate Change Strategies and Management* 1(1): 42-62.

Morales A (2013) "U.S., EU, reject Brazilian call for climate equity metric" Bloomberg News http://www.bloomberg.com/news/2013-11-15/u-s-eu-reject-brazilian-call-for-climate-equity-metric.html Accessed 2014 February 15.

Müller B, Höhne N, and Ellermann C (2009) "Differentiating (historic) responsibilities for climate change" *Climate Policy* 9(6): 593-611.

Murray CJL and Lopez AD, Editors (1996). The Global Burden of Disease: a Comprehensive Assessment of Mortality and Disability from Diseases, Injuries, and Risk Factors in 1990 and Projected to 2020 Harvard School of Public Health on behalf of the World Health Organization and the World Bank, Cambridge, MA.

Myhre G, Shindell D, Bréon F-M, Collins W, Fuglestvedt J, Huang J, Koch D, Lamarque J-F, Lee D, Mendoza B, Nakajima T, Robock A, Stephens G, Takemura T, and Zhang H (2013) "Anthropogenic and natural radiative forcing" In Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Editors Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, and Midgley PM, Cambridge University Press, New York, NY**:** 659-740.

National Research Council (2010) Monitoring Climate Change Impacts: Metrics at the Intersection of the Human and Earth Systems National Academies Press, Washington, DC.

Neumayer E (2000) "In defence of historical accountability for greenhouse gas emissions" *Ecological Economics* 33(2): 185-192.

Okereke C (2010) "Climate justice and the international regime" *Wiley Interdisciplinary Reviews: Climate Change* 1(3): 462-474.

Pan J (2003) "Emissions rights and their transferability" *International Environmental Agreements: Politics, Law and Economics* 3: 1-16.

Parliament of the United Kingdom (2008) "Climate Change Act of 2008".

Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, and Hanson CE, Editors (2007). Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, Cambridge, UK.

Patz JA, Gibbs HK, Foley JA, Rogers JV, and Smith KR (2007) "Climate change and global health: Quantifying a growing ethical crisis" *EcoHealth* 4(4): 397-404.

Population Estimates Program of the United States Census Bureau (2011) "Population Estimates: Historical Data" United States Census Bureau, Washington, DC http://www.census.gov/popest/data/historical/index.html Accessed 2014 May 3.

Portier C, Thigpen Tart K, Carter S, Dilworth C, Grambsch A, Gohlke J, Hess J, Howard S, Luber G, Lutz J, Maslak T, Prudent N, Radtke M, Rosenthal J, Rowles T, Sandifer P, Scheraga J, Schramm P, Strickman D, Trtanj J, and Whung P-Y (2010) A Human Health Perspective on Climate Change: A Report Outlining the Research Needs on the Human Health Effects of Climate Change National Institute of Environmental Health Sciences, Research Triangle Park, NC.

Prather MJ, Penner JE, Fuglestvedt JS, Kurosawa A, Lowe JA, Hohne N, Jain AK, Andronova N, Pinguelli L, de Campos CP, Raper SCB, Skeie RB, Stott PA, van Aardenne J, and Wagner F (2009) "Tracking uncertainties in the causal chain from human activities to climate" *Geophysical Research Letters* 36(5): L05707.

Project Team of the Development Research Center of the State Council (2009) "Greenhouse gas emissions reduction: A theoretical framework and global solution" In China's New Place in A World in Crisis Editors Garnaut R, Song L, and Wood WT, Australian National University Press, Canberra, AU**:** 389-408.

Reay D, Smith P, and van Amstel A, Editors (2010). Methane and Climate Change Earthscan, London, UK.

Ridgley MA (1996) "Fair sharing of greenhouse gas burdens" *Energy Policy* 24(6): 517-529.
Rignot E, Mouginot J, Morlighem M, Seroussi H, and Scheuchl B (2014) "Widespread, rapid grounding line retreat of Pine Island, Thwaites, Smith, and Kohler glaciers, West Antarctica, from 1992 to 2011" *Geophysical Research Letters* 41(10): 3502-3509.
Rosa LP and Ribeiro SK (2001) "The present, past, and future contributions to global warming of CO_2 emissions from fuels" *Climatic Change* 48(2): 289-307.
Rubin ES, Mantripragada H, Marks A, Versteeg P, and Kitchin J (2012) "The outlook for improved carbon capture technology" *Progress in Energy and Combustion Science* 38(5): 630-671.
Ruddiman RF (2006) Plows, Plagues, and Petroleum Princeton University Press, Princeton.
Sagar AD (2000) "Wealth, responsibility, and equity: Exploring an allocation framework for global GHG emissions" *Climatic Change* 45(3): 511-527.
Sedjo R and Sohngen B (2012) "Carbon sequestration in forests and soils" *Annual Review of Resource Economics* 4(1): 127-144.
Shindell D, Kuylenstierna JC, Vignati E, van Dingenen R, Amann M, Klimont Z, Anenberg SC, Muller N, Janssens-Maenhout G, Raes F, Schwartz J, Faluvegi G, Pozzoli L, Kupiainen K, Hoglund-Isaksson L, Emberson L, Streets D, Ramanathan V, Hicks K, Oanh NT, Milly G, Williams M, Demkine V, and Fowler D (2012) "Simultaneously mitigating near-term climate change and improving human health and food security" *Science* 335(6065): 183-189.
Shindell DT, Faluvegi G, Koch DM, Schmidt GA, Unger N, and Bauer SE (2009) "Improved attribution of climate forcing to emissions" *Science* 326(5953): 716-718.
Shine KP (2009) "The global warming potential - the need for an interdisciplinary retrial" *Climatic Change* 96(4): 467-472.
Smith KR (1977) The Interaction of Time and Technology University of California, Berkeley.
Smith KR (1991) "Allocating responsibility for global warming: the natural debt index" *Ambio* 20(2): 95-96.
Smith KR (1994) "Pre-industrial missing carbon and current greenhouse responsibilities" *Chemosphere* 29(5): 1135-1143.
Smith KR (1996) "The natural debt North and South" In Climate Change: Developing Southern Hemisphere Perspectives Editors Giambelluca T and Henderson-Sellers A, John Wiley & Sons, New York, NY**:** 423-448.
Smith KR and Ahuja DR (1990) "Toward a greenhouse equivalence index - the Total Exposure analogy" *Climatic Change* 17(1): 1-7.
Smith KR and Ezzati M (2005) "How environmental health risks change with development: the epidemiologic and environmental risk transitions revisited" *Annual Review of Environment and Resources* 30: 291-333.
Smith KR, Swisher J, and Ahuja DR (1993) "Who pays (to solve the problem and how much)?" In The Global Greenhouse Regime: Who Pays? Science, Economics and North-South Politics in the Climate Change Convention Editors Hayes P and Smith KR, Earthscan Publications/United Nations University Press, London**:** 70-98.
Smith KR, Woodward A, Campbell-Lendrum D, Chadee D, Honda Y, Liu Q, Olwoch J, Revich B, and Sauerborn R (2014) "Human health: impacts, adaptation,and co-benefits" In Climate Change 2014: Impacts, Adaptation, and Vulnerability.Volume I: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Editors Field CB, Barros V, Dokken DJ,

Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Kissel ES, MacCracken S, and White L, Cambridge University Press, New York, NY.
Socolow RH and Lam SH (2007) "Good enough tools for global warming policy making" *Philosophical Transactions of the Royal Society of London. Series A: Mathematical and Physical Sciences* 365(1853): 897-934.
Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, and Miller HL, Editors (2007). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, New York, NY.
Srinivasan UT, Carey SP, Hallstein E, Higgins PAT, Kerr AC, Koteen LE, Smith AB, Watson R, Harte J, and Norgaard RB (2008) "The debt of nations and the distribution of ecological impacts from human activities" *Proceedings of the National Academy of Sciences of the United States of America* 105(5): 1768-1773.
Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, and Midgley PM, Editors (2013). Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, New York, NY.
Stone CD (2004) "Common but differentiated responsibilities in international law" *American Journal of International Law* 98: 276-301.
Subak S (1993) "Assessing emissions: five approaches compared" In The Global Greenhouse Regime: Who Pays? Science, Economics and North-South Politics in the Climate Change Convention Editors Hayes P and Smith KR, Earthscan Publications/United Nations University Press, London, UK**:** 51-69.
Sugiyama T and Deshun L (2004) "Must developing countries commit quantified targets? Time flexibility and equity in climate change mitigation" *Energy Policy* 32(5): 697-704.
Sutter C and Parreño JC (2007) "Does the current Clean Development Mechanism (CDM) deliver its sustainable development claim? An analysis of officially registered CDM projects" *Climatic Change* 84(1): 75-90.
Tanaka K, O’Neill BC, Rokityanskiy D, Obersteiner M, and Tol RSJ (2009) "Evaluating Global Warming Potentials with historical temperature" *Climatic Change* 96(4): 443-466.
Tol RSJ, Berntsen TK, O’Neill B, C., Fuglestvedt JS, and Shine KP (2012) "A unifying framework for metrics for aggregating the climate effect of different emissions" *Environmental Research Letters* 7(4): 044006.
Toth FL (2001) "Decision analysis for climate change: Development, equity and sustainability concerns" *International Journal of Global Environmental Issues* 1(2): 223-240.
Unger N, Bond TC, Wang JS, Koch DM, Menon S, Shindell DT, and Bauer S (2010) "Attribution of climate forcing to economic sectors" *Proceedings of the National Academy of Sciences of the United States of America* 107(8): 3382-3387.
United Nations (1992) Framework Convention on Climate Change, New York, NY: #FCCC/INFORMAL/84 GE.05-62220 (E) 200705.
United Nations Department of Economic and Social Affairs - Population Division (2011) "World Population Prospects, 2010 Revision" http://esa.un.org/unpd/wpp/Excel-Data/population.htm Accessed 2011 June 05.
United Nations Framework Convention on Climate Change (1997) "Implementation of the Berlin Mandate", New York, NY.

United Nations Framework Convention on Climate Change (2012) "Greenhouse Gas Inventory Data" http://unfccc.int/ghg_data/items/3800.php Accessed 2012 April 01.
United Nations Framework Convention on Climate Change (2014) "Decision 1/CP.20 Lima Call for Climate Action", Lima, PE.
United States Central Intelligence Agency (2006) "The World Factbook 2006", Washington, DC http://www.allcountries.org/wfb2006/ Accessed 2012 October 10.
United States Environmental Protection Agency (2006) Global Anthropogenic Non-CO_2 Greenhouse Gas Emissions: 1990-2020 Office of Atmospheric Programs, Climate Change Division, U.S. Environmental Protection Agency, Washingon DC.
United States Environmental Protection Agency (2008) Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2006 United States Environmental Protection Agency, Washington, DC.
United States Environmental Protection Agency (2012) "eGRID2012 Version 1.0" United States Environmental Protection Agency, Washington, DC http://www.epa.gov/cleanenergy/energy-resources/egrid/ Accessed 2013 October 10.
United States Environmental Protection Agency (2013) Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2011 United States Environmental Protection Agency, Washington, DC.
van Nes EH, Scheffer M, Brovkin V, Lenton TM, Ye H, Deyle E, and Sugihara G (2015) "Causal feedbacks in climate change" *Nature Climate Change* 5(5): 445-448.
van Vuuren DP, Stehfest E, den Elzen MGJ, Kram T, van Vliet J, Deetman S, Isaac M, Goldewijk KK, Hof A, Beltran AM, Oostenrijk R, and van Ruijven B (2011) "RCP2.6: exploring the possibility to keep global mean temperature increase below 2°C" *Climatic Change* 109(1-2): 95-116.
Weber CL and Clavin C (2012) "Life cycle carbon footprint of shale gas: review of evidence and implications" *Environmental Science & Technology* 46(11): 5688-5695.
West JJ, Smith SJ, Silva RA, Naik V, Zhang Y, Adelman Z, Fry MM, Anenberg S, Horowitz LW, and Lamarque J-F (2013) "Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health" *Nature Climate Change* 3(10): 885-889.
Winkler H, Spalding-Fecher R, and Tyani L (2002) "Comparing developing countries under potential carbon allocation schemes" *Climate Policy* 2(4): 303-318.
World Bank (2012) "World Development Indicators: GDP, PPP (constant 2005 international $)" The World Bank http://data.worldbank.org/ Accessed 2012 October 10.
Wunch D, Wennberg PO, Toon GC, Keppel-Aleks G, and Yavin YG (2009) "Emissions of greenhouse gases from a North American megacity" *Geophysical Research Letters* 36(15): L15810.

3. Framework for Environmental Change and Infectious Disease

3.1. Introduction

Climate change is among the most prominent examples of a distal environmental change that can affect human health through a series of causal linkages (Altizer et al. 2013). For example, acting through a series of intermediate steps, climate change may alter more proximal environmental characteristics at regional or local scales, such as temperature or precipitation, (Hambling et al. 2011), which in turn shift the transmission dynamics of an environmentally-mediated infectious disease (Anderson and May 1991; Kraemer and Khan 2010). Systematically interrogating this type of inherently multiscale chain motivates a systems-based approach.

3.1.1. Overview

Over the past two decades, global environmental health scientists have increasingly discovered that the recent emergence or re-emergence of infectious diseases has an origin in environmental change (Morse 1995; Patz et al. 2000; Jones et al. 2008; Wallinga et al. 2010; Kilpatrick and Randolph 2012; Gebreyes et al. 2014; Mackey et al. 2014). These multiscale environmental changes encompass social processes such as urbanization, transportation, and migration (Balcan et al. 2009), as well as ecological processes such as agricultural intensification, water development, energy use, biodiversity loss, and as *Chapter 2* explored, climate change (Aguirre and Tabor 2008). Concern surrounding these trends has inspired much exploratory research, since these phenomena are often anthropogenic, interrelated, and accelerating. Yet there remains a pressing need to more clearly define the causal relationships leading from a distal environmental change to alterations in more proximal environmental characteristics and disease transmission cycles, which eventually lead to a shift in the prevalence, distribution, or severity of an infectious disease.

In this chapter, I focus on the intermediary relationships between proximal environmental characteristics and transmission cycles. The environmental sciences have traditionally focused on the linkages between distal environmental changes and their effects on proximal environmental characteristics, whereas the public health sciences have focused on the linkages between transmission cycles and disease burden. I motivate and develop a framework for leveraging the wealth of prior research in both realms by highlighting the relationships between these two modes of scholarship. These links are conveniently defined through a matrix formulation in which system elements from one component are mapped onto system elements from another component. The matrix cells can then be used to provide information on what is known about the particular link. This matrix formulation is consistent with a dynamic systems approach that accounts for feedbacks, a central feature of complex systems (Bar-Yam 1997).

The Environmental Change and Infectious Disease (EnvID) framework (*Figure 3.1*) uses a systems-based structure to integrate and analyze disparate information from a variety of disciplines. My ultimate goal is to identify knowledge gaps and define research directions, as well as to develop relevant study designs and approaches for data analysis so that knowledge about environmental change can be incorporated appropriately into the study and control of infectious diseases. In the ensuing section, I survey the literature on contemporary frameworks of environmental change and infectious disease. Next, I motivate and describe the EnvID framework. I then use this framework to generate a putative matrix of plausible relationships between proximal environmental characteristics and transmission cycles. This matrix can be used to assess the strengths and weaknesses of existing knowledge, and thus prioritize avenues for future research.

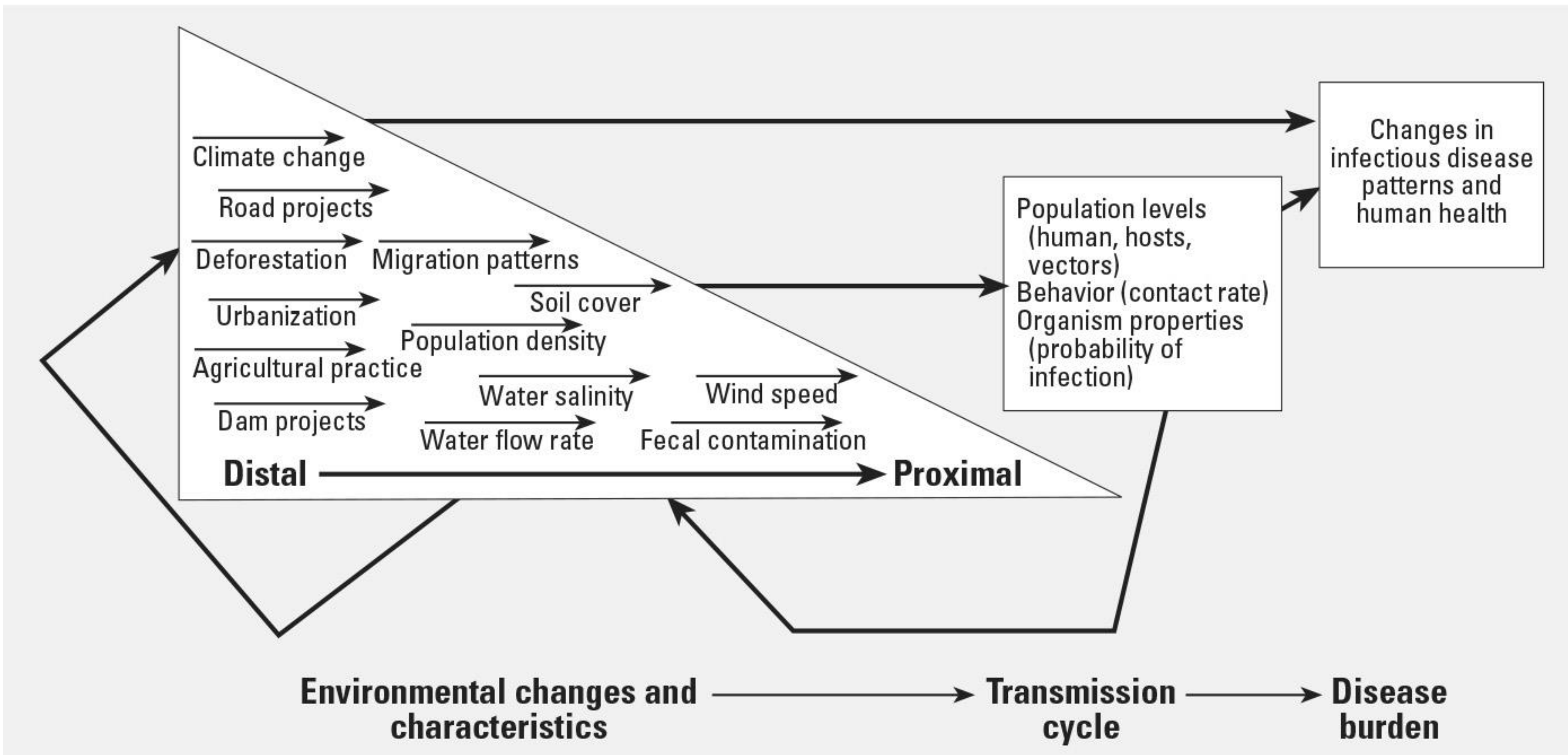


Figure 3.1: Environmental Determinants of Infectious Disease (EnvID) Framework

3.2. Environmental Change and Infectious Disease

During the modern era of public health, attention to the natural and built environment has fluctuated, reflecting wider trends in biomedical thought and praxis (Porter 1999; McMichael 2001). In the 19th century, the progenitors of public health instituted a suite of interventions that astutely reflected perceived linkages between environmental conditions and poor health. Campaigns that focused on sanitation, hygiene, housing, and nutrition led to unparalleled leaps in health and longevity (Szreter 1988). Despite a flawed rationale based on theories of *miasma* or *contagion*, these campaigns effectively controlled many significant communicable pathogens (Cipolla 1992). Moreover, their success demonstrated the utility of intervening further up the causal chain, even in the absence of comprehensive knowledge (Smith and Desai 2002).

Subsequent advances in germ theory gradually overshadowed the environment as a major cause of disease. In the 20th century, public health strategies for the control of infectious disease progressed along a reductionist trajectory that emphasized vaccines, antibiotics, pesticides, and barriers to infection. These technologies resulted in further improvements in the public's health and deservedly continue to influence much of biomedicine.

However, a growing body of literature on environmental change and infectious disease has emerged, returning public health to its roots (Epstein 1995; Daily and Ehrlich 1996; Gratz 1999). Overviews on the topic have permeated a growing array of academic fields (Price-Smith 1999; Cohen 2000; Kombe and Darrow 2001; Anderson 2004) and popular literature (Garrett 1994). These commentaries have raised interest and stimulated research, but understanding how environmental change impacts an infectious disease process remains a challenge. This challenge hinders efforts to translate research into public health policy and practice.

In order to help bridge this gap, I highlight three threads of scholarship that link environmental change and infectious disease: (1) debates on the future of epidemiology; (2) integrative reviews on environmental change and infectious disease; and (3) mathematical models of disease transmission. I draw and build upon the major themes and converging concerns and approaches within these threads.

3.2.1. Debates on the Future of Epidemiology

Suggestions that public health move from a discipline concerned primarily with risk factors at the individual level toward one concerned with multiple levels and types of causation have prompted vigorous discussions. Several themes within these debates on the future of epidemiology offer guidance for the study of environmental change and infectious disease.

3.2.1.1. Strengths and Weaknesses of Risk Factor Analysis

Risk factor analysis has become virtually synonymous with modern epidemiology. It supplies the theoretical and methodological foundation for studying relationships at an individual level, and within this realm, provides the basis for testing causal hypotheses. Although risk factor analysis has enjoyed much success, its limitations have come to light in recent years (Pearce 1996; Susser 1998). In response, more valid and precise techniques which better account for bias and error have been developed (Robins et al. 2000; Greenland 2001; Lash and Fink 2003); where others have advocated of the risk factor approach, stressed the role of apparently inexplicable results in eventually guiding discovery (Savitz 1994; Greenland et al. 2004).

Although such refinement and reflection have addressed some weaknesses of risk factor analysis, others have emerged. For example, although the individual level may be an important scale for probing certain public health questions, risk factor analysis is challenged by the complexity of fundamental causes, including social and ecological drivers (Krieger and Zierler 1996; Pimentel et al. 1998), gene-environment interactions (Hunter 2005), and life-course trajectories (Susser and Terry 2003). Risk-factor analysis, even with modification, faces limits in its capacity to examine causal mechanisms at multiple scales (Susser and Susser 1996a); it may adeptly explain who is at risk but not why risks exist or differ within and between populations (Rose 1985; Krieger 1994; Susser 2004).

3.2.1.2. Causal Inference for Infectious Disease

Yet other critiques have questioned the appropriateness of placing causal inference on potential outcomes at the individual level, the underlying premise of risk factor analysis; i.e., the traditional analytical approach in epidemiology assumes independence of outcomes, and is therefore an inherently individual-level analysis (Plowright et al. 2008). This model hinges on the conjecture that populations are simple collections of individuals, and the nature or arrangement of interactions between individuals does not alter patterns of risk (Koopman and Lynch 1999). The propagation of exposures and outcomes through a population, however, is intrinsic to most communicable pathogens and plainly violates the so-called stability assumption, which requires independence among individuals' exposure and outcome status (Rubin 1991; Halloran and Struchiner 1995). Disease (e.g., cholera) influences exposure (e.g., contaminated water source), which in turn influences outcome (e.g., more cholera), and so on, via transmission. It is not simply an individual's exposure to water which alone determines the individual's outcome, but rather the exposure and outcome status of all other individuals in possible prior contact with the same water source (Eisenberg et al. 1996).

Feedbacks among exposures and outcomes generate context-dependent effects. Population level effects are not equivalent to the sum of individual level effects, and individual level effects depend on the distribution of population level effects. Herd immunity and threshold density are two well-known examples of this phenomenon. Moreover, feedbacks are also integral to many wider causal webs of environment and disease (*Figure 3.1*). In complex systems, inappropriate inferences based on potential outcomes can severely distort the interpretation of effects and misdirect the application of interventions (Jacquez et al. 1994; Halloran and Struchiner 1995; Eisenberg et al. 2003). Risk-factor analysis for infectious disease can sometimes be partially salvaged through conditioning on transmission potential (Haber 1999) or employing counterfactuals (Robins et al. 2000), but results from both experimental and observational studies warrant cautious scrutiny prior to generalization.

3.2.1.3. New Paradigms for Epidemiologic Research

The impetus to understand causality within complex systems has inspired the search for new paradigms that do not abandon conventional research, but rather situate it within the study of processes. Several more sophisticated approaches have been proposed, some of the more influential of which include eco-epidemiology (Susser and Susser 1996b), social-ecologic systems perspectives (McMichael et al. 1999), and eco-social theory (Krieger 2001). These efforts all utilize a systems- based approach to extend the purview of causation across axes of space, time, and organizational level and propose to interrelate research at different scales through feedbacks and interactions.

3.2.2. Integrative Reviews on Environmental Change and Infectious Disease

In recent years, research on the linkages between environmental change and infectious disease has proliferated, embracing multiple types and levels of anthropogenic disturbance, pathogenic process, and scientific approach. Integrative reviews on environmental change and infectious disease have played a critical role for the nascent field by distilling results from disparate sources. I do not systematically assess these integrative reviews, and many worthwhile publications are overlooked. Instead, I concentrate on three emerging trends within this literature of notable import to future projects and syntheses.

In parallel to the debates on the future of epidemiology, in recent years integrative reviews on environmental change and infectious disease have proliferated. I concentrate on three emerging trends within this literature.

3.2.2.1. Conceptual Frameworks

A set of integrative reviews articulate conceptual frameworks for comprehensively organizing knowledge about systems of interacting components that link fundamental drivers to disease resurgence through an interplay of subsystems (e.g. social, economic, biological, physical; Barrett et al. 1998; Cohen 1998; McMichael et al. 1998; Daszak et al. 2000; Mayer 2000; Weiss and McMichael 2004; Harrus and Baneth 2005; Wilcox and Colwell 2005; Bonds et al. 2010). Some existing conceptual frameworks could also be applied to environmental change and infectious disease. Particularly germane are frameworks for climate change (Colwell 1996; Patz et al. 1996; McMichael and Butler 2004; Parham et al. 2015), globalization (Woodward et al. 2001; Chapman 2009), social epidemiology (Diez Roux 2000; Subramanian 2004; Gislason 2013), and environmental health (Black 2000; Parkes et al. 2003; Mellor et al. 2016). The various conceptual frameworks reveal the exceptional complexity and difficulties of their subject matter, such as striking a balance between the general versus the specific, and difficulty in assessing validity and relevance to decision-making bodies. Still, conceptual frameworks undoubtedly encourage critical thought and shape the evolution of the field.

3.2.2.2. Interdisciplinarity and Integration

Virtually all integrative reviews are, at least to some extent, interdisciplinary since the study of environmental change and infectious disease clearly requires expertise from numerous fields. Most integrative reviews include various biomedical sciences but selectively emphasize certain social or ecological sciences, with more recent work displaying greater inclusivity and deeper collaboration. In addition, integrative reviews that reference the gradually growing number of case studies on sustainable development (Shahi et al. 1997; Corvalan et al. 1999) or ecosystem approaches (Forget and Lebel 2001; Patz et al. 2004; Corvalan et al. 2005; Parkes et al. 2005) bridge scientists, policy-makers, activists, and citizens.

3.2.2.3. Categorization Schemes

Explicitly or implicitly, many integrative reviews deploy particular typologies to categorize environmental changes and/or infectious diseases. Most schemes do not emphasize the most salient features of environment-disease relationships. Infectious diseases are commonly grouped according to scientific taxonomy or clinical symptoms, which might be useful for purposes of diagnosis and treatment, but do not correspond reliably to environmental drivers. Wilson (2001) groups infectious diseases by transmission cycle, an approach I adopt here. Proposed typologies of environmental change are similarly elusive due to their complex causes and consequences. Still, the tentative discrimination of environmental changes along continuums of spatial extent, temporal persistence, distal to proximal action, and social versus ecological impact could more usefully translate linkages, as they are identified, to a putative causal network.

3.2.3. Mathematical Models of Disease Transmission

Mathematical models of disease transmission began to be developed nearly a century ago with work on mass action (Ross 1915) and threshold densities (Kermack and McKendrick 1933), with subsequent elaboration from mathematical and population biologists (Anderson and May 1991). Ecologists, epidemiologists, and mathematicians are increasingly deploying transmission models towards informing study designs, effect estimates, and intervention strategies (Levin et al. 1999; Eisenberg et al. 2002). From the extensive literature on transmission models, I underscore two important and related conclusions: transmission models are instructive as a well-developed systems-based approach; and transmission models can themselves be incorporated into wider studies of environmental change.

3.2.3.1. Systems-Based Approach

The overt consideration of feedbacks and interactions within and between populations in a transmission model allows for a consideration of infectious diseases as inherently dynamic and interdependent processes, and thus causality as context-dependent and systems-based (Koopman 2004). Transmission models elucidate the relationships governing the creation and distribution of risks by disentangling individual level effects and population level effects (Halloran et al. 1991).

The insights enabled by this analysis are often nuanced. For example, altering the pattern of connections between exposed and unexposed individuals may impact the level of infection within a population more so than altering the exposure status of individuals in that population (Koopman and Longini 1994). If a core group is sustaining infection in a larger group, targeting interventions based on individual-level risk factors will not, in general, address the principle cause of disease (Jacquez et al. 1988; Sattenspiel 2000; Christley et al. 2005; Verdasca et al. 2005).

3.2.3.2. Transmission Models within Wider Systems

The influence of social and ecological contexts on disease transmission has been recognized for diseases spread through direct contact (e.g., sexually transmitted diseases (STDs) and air-borne diseases; Rothenberg et al. 1998; Klovdahl et al. 2001; Shen et al. 2004), diseases with environmental reservoirs (e.g., water-borne diseases; Colwell 2004; Eisenberg et al. 2005), and diseases for which land use change modulates vector populations (e.g., vector-borne diseases; Lindblade et al. 2000; Ostfeld and Keesing 2000). Transmission models can serve as conceptual or analytical instruments to analyze the interactions between environmental contexts and transmission cycle components (McMichael 1997; Brooker et al. 2002; Smith et al. 2005; Ortblad et al. 2015).

3.2.4. Preliminary Synthesis

These three threads of scholarship all advocate a gradual shift towards a systems-based approach. The emerging epidemiologic paradigms, spurred by debates on the future of epidemiology, and the conceptual frameworks, distilled from integrative reviews on environmental change and infectious disease, are essentially extensions of the systems perspective intrinsic to mathematical models of disease transmission that spans the gulf from distal environmental change to disease burden by leveraging interdisciplinarity and sound causal inference.

I propose a series of steps, derived from these three threads, towards constructing a more robust scaffold. An initial step defines flexible and logical classifications of environment and disease that can readily translate to causal webs. These classifications or components form the basis of the framework. A second step begins to integrate transmission with environment by examining the intersection of proximal environmental characteristics and transmission cycles and acknowledging the useful but limited insights of risk factor analysis. Here I detail some of the connections that exist between environment and health. A third step develops causal networks with explicit feedbacks and interactions that highlight the dynamic properties of this large-scale environmental process.

3.3. The Framework

The EnvID framework encompasses three interlocking components: environment, transmission, and disease. There has been a tendency to delineate environmental changes into those that are social, such as urbanization, and those that are ecological, such as deforestation, but in actuality any process affecting human health has both social and ecological components that are inextricably linked. These changing environmental processes may affect the transmission cycles of infectious pathogens. I present six transmission groups that each relate to the environment in distinct ways. Disease burden is determined by incidence and severity of infection, which is in part a function of the transmission cycle.

An initial step in operationalizing this framework I propose a matrix formulation to move both backwards, towards fundamental drivers, and forwards, towards disease burden. A matrix as describe in this section can provide an explicit description of the interconnections between system elements. In this manner the matrix defines one component of the system and provides a means to summarize what is known and what is unknown about that component. This section describes each of the three main EnvID components, with a focus on the linkage between proximal environmental characteristics and transmission cycles.

3.3.1. Framework Description

3.3.1.1. Environmental Change

Although the environment represents the first component of the systems-based EnvID framework, the environment is itself a system of interacting components. I choose to disaggregate the environment into distal environmental changes that act on disease transmission through multiple intermediate steps and proximal environmental characteristics that directly affect disease transmission.

The list of distal environmental changes in *Table 3.1* includes anthropogenic changes that affect landscape ecology, human ecology, and human-created environments, as well as natural perturbations and natural disasters. There are clear interactions among these distal factors and their effects. For example, climate change may impact the characteristics of El Niño, roads may contribute to urbanization, deforestation may amplify climate change, and the impacts of natural disasters might be augmented by anthropogenic changes such as loss of wetlands (Martens and McMichael 2002).

The distal changes are larger in temporal and spatial scale than the more proximal environmental characteristics that they influence. Proximal environmental characteristics are defined as directly measurable physical, chemical, biological, or social components of the environment, including populations and traits of relevant organisms. Proximal environmental characteristics can have a direct influence on the environment of the organisms in question (pathogen, vector, host, or human), and thus may directly affect the transmission cycle of an infectious disease.

Table 3.1: Distal Environmental Changes and Infectious Diseases

	Description	*Infectious Disease*
Energy Use	exposure to immune suppressing air-borne pollutants	bacterial and viral pneumonias tuberculosis
Urbanization	migration to and growth within towns, interplay between humans and domesticated animals	dengue fever fecal-oral pathogens tuberculosis influenza, SARS, avian flu
Antibiotic Use	selective pressure for emergence of antibiotic resistance	multi-drug resistant tuberculosis *S. typhimurium*
Water Projects	water flow changes due to dam construction and irrigation networks	malaria schistosomiasis
Agricultural Intensification	changing crop and animal management practices, fertilizer and biocide use, use of genetically modified organisms	*Cryptosporidium* pathogenic *E. coli*
Deforestation	loss of forest cover, changing water flow patterns, human encroachment along and into forested areas	malaria Lyme disease hemorrhagic fevers sexually transmitted diseases
Transportation Projects	construction of roads, increasing access to both towns and remote areas	malaria sexually transmitted diseases
Natural Perturbations	large-scale climatic and other changes such as El Niño events	cholera leptospirosis
Natural Disasters	localized landscape changes caused by earthquakes, tsunamis, wildfires, etc.	water-mediated infections
Climate Change	changing temperature and precipitation patterns	vector-borne infections water-borne infections food-borne infections

Distal changes affect disease only through a series of causal linkages. For example, a dam does not change health directly; rather, a dam causes changes in water flow, which may affect mosquito habitat, which in turn can affect transmission potential of malaria. A new road may affect disease through major demographic shifts that ultimately lead to increased sexual activity and STD incidence. The causal linkages between distal and proximal, therefore, represent a continuum, and the labeling of a factor as distal or proximal is relative. However, by focusing on *measurable* proximal environmental characteristics studies can more clearly and definitively describe the causal linkages that changes in the environment have on disease transmission.

3.3.1.2. Transmission Cycles

The impact of proximal environmental characteristics on disease burden is mediated through the dynamics of transmission cycles. I categorize pathogens into one of six transmission system groups based on their distinct relationships with the environment (*Figure 3.2*).

The first group (I) includes person-to-person transmitted diseases, wherein "contact" between humans is the principle mode of transmission, through intimate proximity (e.g. casual contact or droplet spray) or bodily fluid exchange (Mandell et al. 2000). In this group, humans are the only host and the environment does not serve as a reservoir for the pathogen. The second group (II) includes all vector-borne diseases in which humans play an important role in the transmission cycle. Transmission occurs through contact between humans and vectors (defined here as arthropods that move pathogens from one host to another). The third group includes infectious diseases for which the environment (e.g., food, water, soil, etc.) plays a significant role in a pathogen's transmission cycle. In the first subtype (IIIa), transmission occurs between humans and the environment directly; no other host animals are involved. In the second subtype (IIIb), non-human hosts mediate transmission, although the environment remains an integral part of the transmission chain. The fourth group (IV) includes all pathogens that cause zoonotic diseases. The transmission cycles of all zoonotic diseases share two key features; humans are dead-end hosts and no person-to-person transmission is possible. Subtype IVa includes vector-borne zoonotic diseases. Non-vector-borne zoonotic diseases in which pathogens are transmitted indirectly through the environment or host-to-host are included in subtype IVb.

Although each of these six transmission cycles describe a different mechanism of transmission, they share common attributes; i.e., all are affected by the population level and/or density of the host and/or vector, and all are driven by a transmission potential governed by a number of biological and environmental characteristics. The transmission rate from one host to another can be thought of as the product of two processes: contact rate and infectivity. The contact rate quantifies the interaction between hosts or between a host and the environment and is generally determined by host behavior and properties of the environment. Infectivity, or probability of infection given contact, is a function of both the virulence of the pathogen and the immune status of the host. Environmental changes can affect population levels of the host, vector, or environmental stage of the pathogen, as well as the transmission rate at which pathogens move between hosts, vectors and environment.

3.3.1.3. Disease Patterns and Disease Burden

Understanding how environmental change affects disease transmission and incidence does not address the crucial public health concern of disease burden. For example, high levels of rotavirus disease exist in both developed and developing countries, but the mortality rates in developing countries are much higher than in developed countries (Parashar et al. 2003). In addition, environmental change can affect disease burden directly without necessarily influencing transmission. If environmental change affects nutrition, for example, this can in turn affect disease severity. Disease burden can also feedback to transmission cycles, as people who are more seriously sick may have higher pathogen loads.

Transmission group	Transmission pathway	Modes of transmission	Environmental factors	Transmission cycle
I. Directly transmitted diseases				
AIDS, gonorrhea, syphilis, chlamydia Measles, rubella, smallpox, pertussis, diphtheria Influenza, severe acute respiratory syndrome (SARS) Tuberculosis	Human–human	Fluid exchange (intercourse, transfusion) Physical touch Droplet spray Airborne	Pathogens cannot survive long in the environment Factors governing transmission: close personal contact	Humans Humans
II. Vectorborne diseases				
Malaria Dengue fever Onchocerciasis Trypanosomiasis, filariasis	Human–vector	Vector biting a host (human or nonhuman)	Pathogens survive outside host in arthropod vectors; humans are the only host Factors governing transmission: biting rate, vector survivorship, host-seeking behavior	Humans Vector Host
IIIa. Environmentally mediated diseases—no nonhuman host				
Cholera Diseases caused by hepatitis A, hepatitis E, rotavirus, enteroviruses, noroviruses, typhoid fever, shigelosis, amebiasis, ascaris, trichurus, hookworm, strongyloides	Human–environment Environment–human	Water ingestion Food ingestion Dermal contact Inhalation	Pathogens survive long periods of time in the environment Cholera has free-living stage	Humans Environment
IIIb. Environmentally mediated diseases—nonhuman host				
Same as IIIa, except for some bacteria infection that occurs through consumption of infected meat Diseases caused by tapeworms, *Escherichia coli,* salmonelosis	Human–environment Environment–human Animal–environment		Same as IIIa, except nonhuman hosts can be infected and transmit pathogens or infect humans through consumption of meat	Humans Environment Host
IVa. Zoonotic diseases				
Lyme disease Yellow fever, West Nile virus, Japanese encephalitis Bubonic plague	Zoonotic transmission; vectorborne with nonhuman hosts; humans are dead-end hosts	Vectorborne biting nonhuman hosts	Pathogens survive outside host in arthropod vectors; humans are the only host Factors governing transmission: biting rate, vector survivorship, host-seeking behavior, host ecology	Host Vector ↓ Human
IVb. Zoonotic diseases				
Rabies Hantavirus, toxoplasmosis trichanelosis Anthrax Botulism, tetnus	Zoonotic transmission (involves nonhuman hosts); humans are dead-end hosts	Same as those in groups I, II, and III	Factors governing transmission: nonhuman host ecology	Host Environment ↓ Human

Figure 3.2: Transmission Cycle Groupings

3.3.2. Proximal Characteristics to Transmission Cycles

Many studies have focused on the association between specific proximal changes in the environment and health, and how these proximal characteristics influence transmission. Since proximal environmental changes often affect transmission processes directly, experiments can be designed to elucidate these mechanistic relationships. These proximal environmental characteristic/transmission cycle relationships can be mapped using a tabular "transmission matrix," in which the environmental proximal characteristics are represented as rows and the transmission cycle characteristics are represented as columns (*Figure 3.3*).

The transmission matrix organization is consistent with two paradigms prevalent in the literature. First, the classic paradigm of infectious disease transmission depicts the agent, host, and environment as each representing one node of a triangle. The matrix columns represent the host and agent nodes. They consist of population/demographic factors such as density, virulence, and immune status, as well as those factors that influence the rate of transmission from one host to another, such as ingestion rate, vector biting rate, and human-to-human contact rates. The matrix rows represent the environment node that consists of those specific proximal environmental characteristics that can affect host/agent properties.

The proximal environmental characteristics represented as rows in *Figure 3.3* were chosen to encompass: physio-chemical characteristics associated with air, water, and climate; ecological characteristics of plants and animals; genetic characteristics of pathogens; and human characteristics associated with short and long-term human migratory patterns, human contact with the environment, and social structure. Again, each row may not be relevant for every infectious disease, and the list is not meant to be definitive. The choice of columns is based on the transmission paradigm elaborated above. This paradigm suggests that disease incidence is proportional to the population level of all organisms that can harbor the pathogen, and the transmission rate, which is the product of: (1) the rate of contact between hosts or between a host and the environment; and (2) the probability of infection given contact. The matrix columns therefore represent factors needed to estimate the transmission rate, and the matrix rows represent those environmental factors that can impact the transmission potential by modifying factors represented in the columns. Each cell represents the potential for a proximal environmental characteristic to affect a component of the transmission cycle. Different portions of the matrix (columns and rows) will apply to the different transmission groups outlined in *Figure 3.2*.

Proximal Environmental Characteristics		Population Size				Organism Properties		Human-Human Contact		Human-Vector Contact		Human Environment Contact				
		Pathogen	Vector	Host	Human	Pathogen Virulence	Host Immune Status	Sexual Contact	Close Contact	Biting rate	Host Seeking	Water ingestion	Dermal Contact	Inhalation	Food Ingestion	Biting
Water	Presence/Absence															
	Flow Rate															
	Nutrient Content															
	Chemical Composition (Inorganic Pollution)															
	Fecal Matter Content (Organic Pollution)															
	Salinity															
	Turbidity															
Climate	Temperature															
	Precipitation															
	Humidity															
	Cloud Cover/Sunlight Exposure															
	Wind Speed															
Air	Particulates															
	Chemical Composition															
Animals	Diversity (Non-Domesticated)															
	Magnitude (Non-Domesticated)															
	Density (Non-Domesticated)															
	Pets															
	Livestock															
Plants	Diversity (Non-Domesticated)															
	Magnitude (Non-Domesticated)															
	Density (Non-Domesticated)															
	Crop Cover															
Genetic	Prevalence of antibiotic resistance genes															
	Prevalence of GMO genes															
	Prevalence of virulence factors															
Human Practice	Migration															
	Travel															
	Human Contact with Environment															
Human Environment	Physical Barriers to Exposure															
	Living Structures															
	Sanitation Infrastructure															
	Density															
	Other Structures															

Figure 3.3: Matrix for Mapping Relationships between Proximal Environmental Characteristics and Transmission Cycles. Abbreviation: GMO = genetically modifed organisms

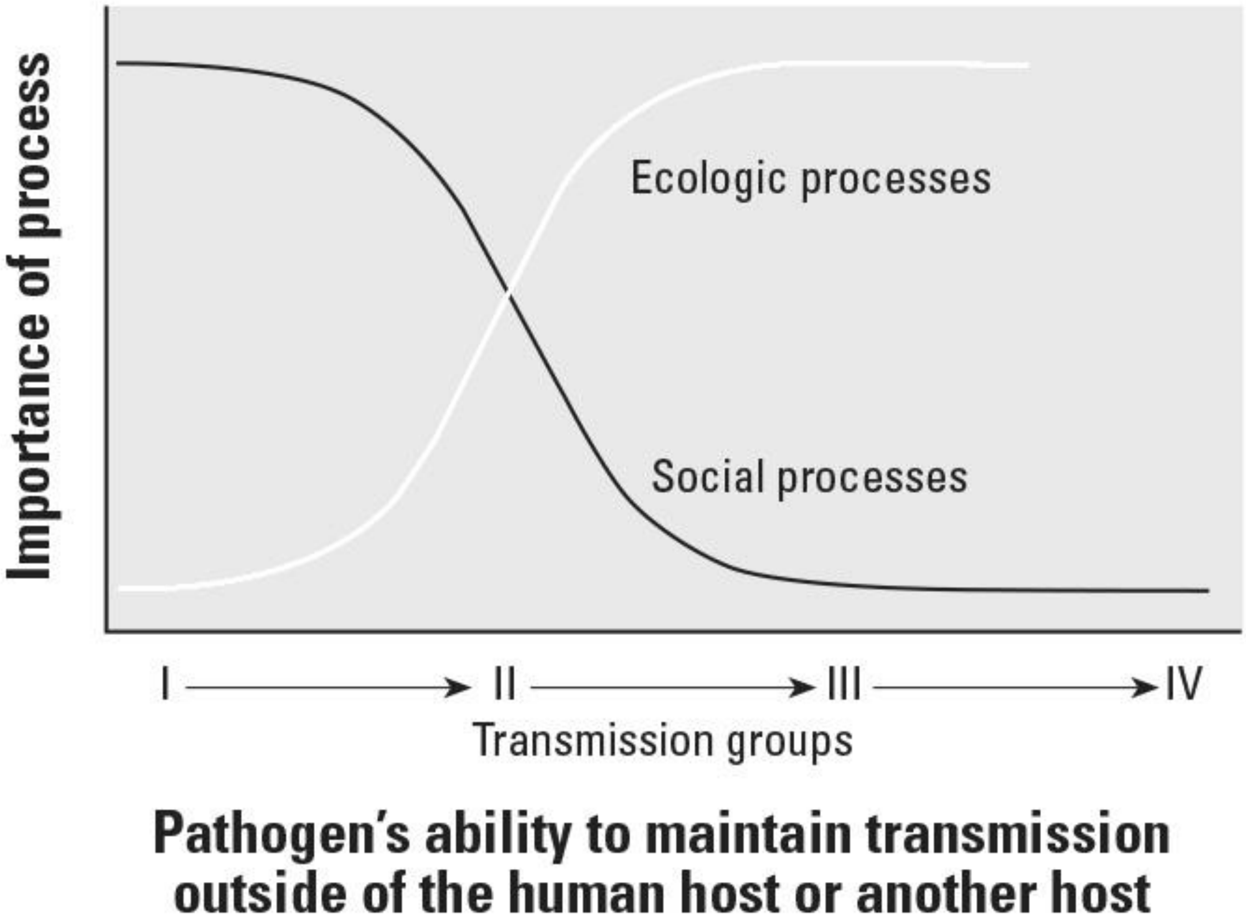


Figure 3.4: Importance of Ecological versus Social Processes from Different Transmission Groups

Environmental change will obviously impact disease patterns differently depending on the transmission cycle of a particular pathogen (*Figure 3.2*). Because diseases in Transmission Group I are directly transmitted between humans they are most influenced by the proximal changes in the environment that affect human social structure, such as conditions of severe overcrowding, social changes affected by access to transportation, and migration and travel patterns. However, many of these pathogens can survive in the environment for hours or more and therefore other physiochemical characteristics of the environment may also play a role. Environmental change can impact transmission of diseases in Transmission Group II through its effects on proximal factors associated with vector ecology, such as vector biting behavior, mortality, and population density, or through social changes that can increase human contact with vectors. Because all pathogens in Transmission Group III can survive in the environment and some have non-human hosts, environmental change impacts transmission through modifying human exposure to contaminated media such as drinking water, recreational water, and food, animal hosts, and other infectious individuals. Since this class of pathogens consists of both vector-borne and environmentally mediated pathogens, The contact patterns of Transmission Group IV are similar to those of Group II and III, but transmission is sustained in non-human hosts, so environmental factors associated with the ecology of these non-human hosts and their relationships to pathogens is most salient.

These differences in the role of social and ecologic processes in mediating environmental change between the six transmission groups is represented in *Figure 3.4*. Environmental change impacts those diseases caused by pathogens within Transmission Group I via mechanisms that are primarily mediated by social processes. In contrast, those changes impact diseases caused by Group IV pathogens via mechanisms primarily mediated by non-human ecological processes. Both ecological and social processes influence group II and III pathogens.

3.4. Application of EnvID

The EnvID framework can be used in several ways. For example, it can be used to assess all possible impacts of environmental factors on a single infectious disease. A formal use of this framework would be to conduct a systematic review evaluating the weight of evidence on how the environment affects representative pathogens for each of the transmission groups. The framework can also be used to guide a particular research question exploring the impacts of a distal environmental change on a particular disease. It provides a structured way to conceptualize the causal network, which can guide research approaches.

To illustrate this latter approach, I present a short case study here that examines the proposed causal linkages between road development and diarrheal disease. In 1996, the Ecuadorian government began a 100 km road construction project to link the southern Colombian border with the Ecuadorian coast. The road was completed in 2001 but secondary roads continue to be built, linking additional villages to the paved road. These roads provide a faster and cheaper mode of transportation compared with rivers and have led to major changes in the ecology and social structure of the region (Sierra 1999). While there is evidence that road construction affects the incidence of vector-borne and sexually transmitted diseases (Birley 1995) the impact that environmental changes from road construction have on diarrheal disease remains largely unexplored. A proximal environmental characteristic−transmission cycle matrix of this environmental change/infectious disease example illustrates that there is strong risk factor evidence for the relationship between the proximal factors of water quality as well as sanitation and hygiene levels and transmission of enteric pathogens. There are fewer studies that demonstrate a relationship between distal social factors such as crowding or general social infrastructure and distal ecological factors such as regional scale water patterns with diarrheal disease (Mackey et al. 2014).

Road development represents a comparatively distal environmental change that can impact both ecological processes, such as deforestation, biodiversity, and hydroecology, as well as social processes, such as migration, demographics, and infrastructure. Deforestation can cause major changes in watershed characteristics and potential local climate change, which can affect the transmission of enteric pathogens (Curriero et al. 2001). Perhaps more important than ecological processes, social processes such as migration that are facilitated by roads can increase the rate of pathogen introduction into a region. Road proximity affects short-term travel patterns, thereby resulting in continual reintroduction of new pathogen strains into communities. New communities are created along roads and existing communities can rapidly increase in density. These changes in social structures of communities often create or are accompanied by inadequate infrastructure, which affects hygiene and sanitation levels, and in turn the likelihood of transmission of enteric pathogens. Roads can also increase flows of consumer goods such as processed food, material goods, and medicines, and may also provide communities with increased access to health care, health facilities, and health information. *Figure 3.5* illustrates a mapping of the distal environmental change, due to road proximity, to the proximal environmental factors associated with water sanitation and hygiene that directly influences disease transmission.

The framework and matrix help elucidate the necessary interdisciplinary research elements and approaches needed to study environmental impacts of road development on diarrheal disease transmission in this Ecuadorian landscape. The research question requires a design that examines and integrates processes at multiple spatial and temporal scales using regional, village-wide, individual, and molecular-level data, and systems-based models to integrate these data. Epidemiological study designs are complemented by hydrology and water quality studies, remote sensing and geographic information system technologies, social network analysis, ethnography, and molecular strain typing of to elucidate pathogen flow across the landscape. The scale and inherent dimensionality of the problem requires this systems-based analytic model approach to examine relationships between environmental, social, and biological change to explain the detection of the relationship between road access and infection.

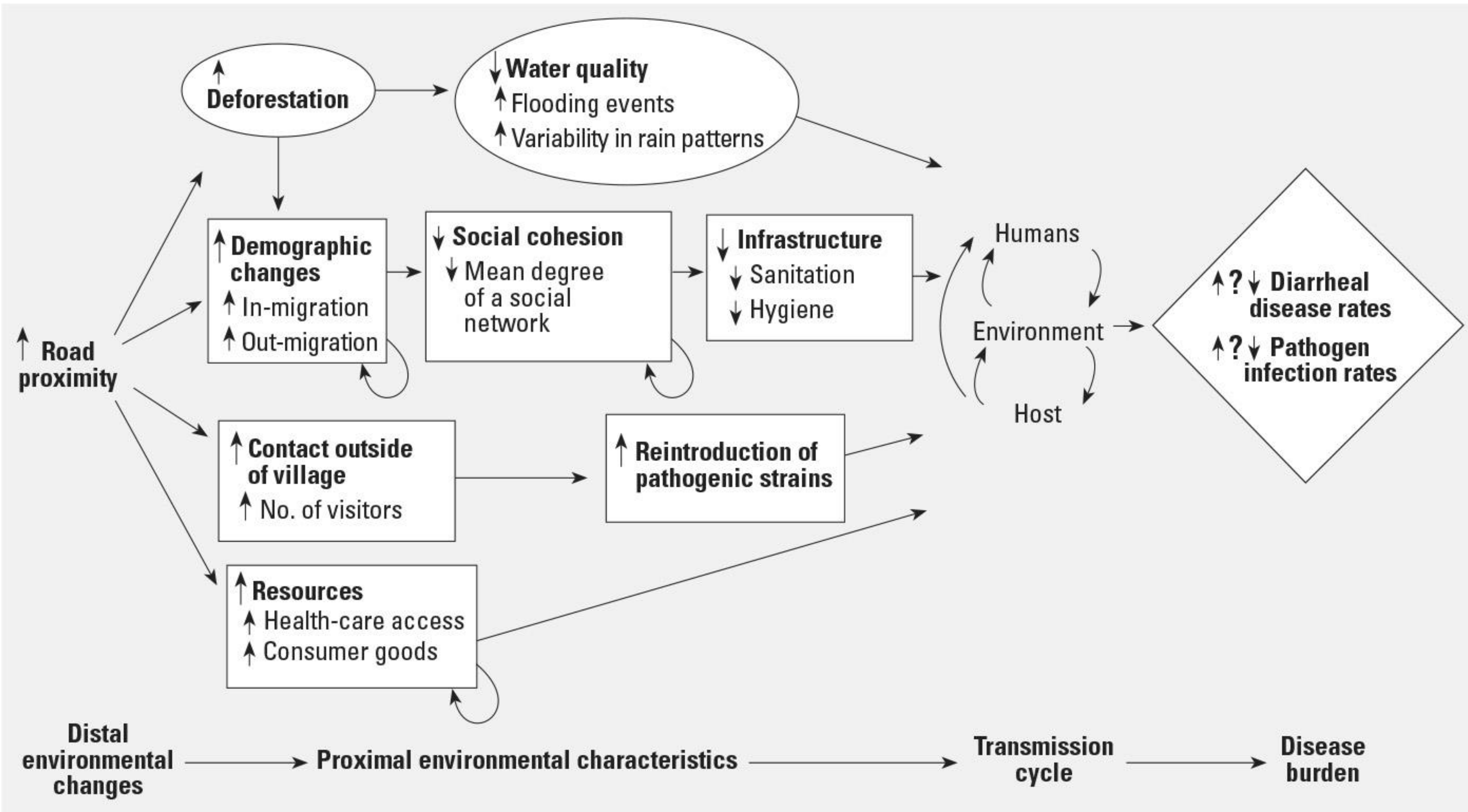


Figure 3.5: Causal Diagram of the Relationship between Transportation Projects and Diarrheal Disease.

3.5. Conclusion

As public health moves more towards examining how ecological and social processes affect disease transmission, and more specifically, towards examining the fundamental role of environmental change in creating the landscape of human disease, a systems-based framework is needed from which to integrate and analyze data obtained from the disparate but relevant fields of study involved. As the review of contemporary frameworks suggests, the inherent multi-dimensionality of these problems precludes the use of standard analytic approaches.

The EnvID framework of *Chapter 2* builds on a rich history of prior conceptualizations of environmental change and infectious disease by: (1) articulating a flexible and logical system specification; (2) incorporating transmission groupings linked to public health intervention strategies; (3) emphasizing the intersection of proximal environmental characteristics and transmission cycles; (4) incorporating a matrix formulation to identify knowledge gaps and facilitate an integration of research; and (5) highlighting hypothesis generation amidst dynamic processes. The EnvID framework endeavors to identify source of disputes or uncertainty and prioritizes avenues for resolution. As scientific understanding advances, the EnvID framework can help integrate the various factors at play in determining environment–disease relationships and the connections between intrinsically multiscale causal networks.

A systems-based approach serves to leverage the reality that studies on environmental change and infectious disease are embedded within a wider web of interactions. This systems-based approach can be initially operationalized by the proposed matrix formulation. The matrix formulation provides a succinct approach to characterizing the system, providing information on the interrelatedness of the different system components and defining research needs. Data needs for the matrix often will be a combination of site-specific data, collected specifically for the systems-based analysis, and data from the literature, which always need to be assessed with respect to quality and appropriateness. The matrix can be additionally used to (1) inform theoretical simulation studies on broader system dynamics, (2) guide the development of more focused and informative empiric studies, and (3) integrate and contextualize both theoretical and empirical with processes upstream and downstream. In *Chapter 4*, I pursue such a project, focusing on household-level energy use and community-level $PM_{2.5}$ exposure, a major intervention point and risk factor, respectively, for childhood pneumonias.

The challenge for future studies on environmental change and infectious disease will be to develop new approaches for thinking about processes at the system level that in turn will elicit new study designs and data analyses. Given the increasingly explicit nature of the connections between proximal environmental change and well-being (Dye 2014), the EnvID framework can help synthesize these connections to spur this important nexus of environment and health forward.

3.6. References

Aguirre AA and Tabor GM (2008) "Global factors driving emerging infectious diseases" *Annals of the New York Academy of Sciences* 1149: 1-3.

Anderson RM and May RA (1991) Infectious Diseases of Humans: Dynamics and Control Oxford University Press, New York.

Anderson W (2004) "Natural histories of infectious disease: ecological vision in twentieth-century biomedical science." *Osiris* 19: 39-61.

Balcan D, Colizza V, Gonçalves B, Hu H, Ramasco JJ, and Vespignani A (2009) "Multiscale mobility networks and the spatial spreading of infectious diseases" *Proceedings of the National Academy of Sciences* 106(51): 21484-21489.

Bar-Yam Y (1997) Dynamics of Complex Systems Addison-Wesley, Reading, MA.

Barrett R, Kuzawa CW, McDade T, and Armelagos GJ (1998) "Emerging and re-emerging infectious diseases: the third epidemiologic transition" *Annual Review of Anthropology* 27: 247-271.

Birley MH (1995) The Health Impact Assessment of Development Projects H.M.S.O., London.

Black H (2000) "Environmental and public health: pulling together the pieces" *Environmental Health Perspectives* 108(11): A513-515.

Bonds MH, Keenan DC, Rohani P, and Sachs JD (2010) "Poverty trap formed by the ecology of infectious diseases" *Proceedings of the Royal Society, B, Biological Sciences* 277(1685): 1185-1192.

Brooker S, Hay SI, and Brundy DAP (2002) "Tools from ecology: useful for evaluating risk models?" *Trends in Parasitology* 18(2): 70-74.

Chapman AR (2009) "Globalization, human rights, and the social determinants of health" *Bioethics* 23(2): 97-111.

Christley RM, Pinchbeck GL, Bowers RG, Clancy D, French NP, Bennett R, and Turner J (2005) "Infection in social networks: using network analysis to identify high-risk individuals" *American Journal of Epidemiology* 162(10): 1024-1031.

Cipolla CM (1992) Miasmas and Disease: Public Health and the Environment in the Pre-Industrial Age Yale University Press, New Haven.

Cohen ML (1998) "Resurgent and emergent disease in a changing world" *British Medical Bulletin* 54(3): 523-532.

Cohen ML (2000) "Changing patterns of infectious disease" *Nature* 406(6797): 762-767.

Colwell RR (1996) "Global climate change and infectious diseases: the cholera paradigm" *Science* 274(5295): 2025-2031.

Colwell RR (2004) "Infectious disease and environment: cholera as a paradigm for waterborne disease" *International Microbiology* 7(4): 285-289.

Corvalan CF, Hales S, and McMichael AJ (2005) Ecosystems and Human Well-Being: Health Synthesis World Health Organization, Geneva, CH.

Corvalan CF, Kjellstrom T, and Smith KR (1999) "Health, environment and sustainable development: identifying links and indicators to promote action" *Epidemiology* 10(5): 656-660.

Curriero FC, Patz JA, Rose JB, and Lele S (2001) "The association between extreme precipitation and waterborne disease outbreaks in the United States, 1948–1994" *American Journal of Public Health* 91(8): 1194-1199.

Daily GC and Ehrlich PR (1996) "Global change and human susceptibility to disease" *Annual Review of Energy and the Environment* 21: 125-144.

Daszak P, A. CA, and Hyatt AD (2000) "Emerging infectious diseases of wildlife - threats to biodiversity and human health" *Science* 287(5452): 443-449.
Diez Roux AV (2000) "Multilevel analysis in public health research" *Annual Review of Public Health* 21: 171-192.
Dye C (2014) "After 2015: infectious diseases in a new era of health and development" *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* 369(1645): 20130426.
Eisenberg JN, Brookhart MA, Rice G, Brown M, and Colford JM, Jr. (2002) "Disease transmission models for public health decision making: analysis of epidemic and endemic conditions caused by waterborne pathogens" *Environmental Health Perspectives* 110(8): 783-790.
Eisenberg JN, Lei X, Hubbard AH, Brookhart MA, and Colford JM, Jr. (2005) "The role of disease transmission and conferred immunity in outbreaks: analysis of the 1993 Cryptosporidium outbreak in Milwaukee, Wisconsin" *American Journal of Epidemiology* 161(1): 62-72.
Eisenberg JN, Seto EY, Olivieri AW, and Spear RC (1996) "Quantifying water pathogen risk in an epidemiological framework" *Risk Analysis* 16(4): 549-563.
Eisenberg JNS, Lewis BL, Porco TC, Hubbard AH, and Colford J, J. M. (2003) "Bias due to secondary transmission in estimation of attributable risk from intervention trials" *Epidemiology* 14(4): 442-450.
Epstein PR (1995) "Emerging diseases and ecosystem instability: new threats to public health" *American Journal of Public Health* 85(2): 168-172.
Forget G and Lebel J (2001) "An ecosystem approach to human health" *International Journal of Occupational and Environmental Health* 7(2 Suppl): S3-38.
Garrett L (1994) The Coming Plague: Newly Emerging Diseases in a World out of Balance Farrar, Straus and Giroux, New York, NY.
Gebreyes WA, Dupouy-Camet J, Newport MJ, Oliveira CJB, Schlesinger LS, Saif YM, Kariuki S, Saif LJ, Saville W, Wittum T, Hoet A, Quessy S, Kazwala R, Tekola B, Shryock T, Bisesi M, Patchanee P, Boonmar S, and King LJ (2014) "The global One Health paradigm: challenges and opportunities for tackling infectious diseases at the human, animal, and environment interface in low-resource settings" *PLOS Neglected Tropical Diseases* 8(11): e3257.
Gislason MK (2013) "Expanding the social: moving towards the ecological in social studies of health" In Ecological Health: Society, Ecology and Health**:** 3-22.
Gratz NG (1999) "Emerging and resurging vector-borne diseases" *Annual Review of Entomology* 44: 51-75.
Greenland S (2001) "Sensitivity analysis, Monte Carlo risk analysis, and Bayesian uncertainty assessment" *Risk Analysis* 21(4): 579-583.
Greenland S, Gago-Dominguez M, and Castelao JE (2004) "The value of risk-factor ("black-box") epidemiology" *Epidemiology* 15(5): 529-535.
Haber M (1999) "Estimation of the direct and indirect effects of vaccination" *Statistics and Medicine* 18(16): 2101-2109.
Halloran ME, Haber M, Longini IM, and Struchiner CJ (1991) "Direct and indirect effects in vaccine efficacy and effectiveness" *American Journal of Epidemiology* 133(4): 323-331.
Halloran ME and Struchiner CJ (1995) "Causal inference in infectious diseases" *Epidemiology* 6(2): 142-151.

Harrus S and Baneth G (2005) "Drivers for the emergence and re-emergence of vector-borne protozoal and bacterial diseases" *International Journal of Parasitology* 35(11-12): 1309-1318.

Hunter DJ (2005) "Gene-environment interactions in human diseases" *Nature Reviews Genetics* 6(4): 287-298.

Jacquez JA, Koopman JS, Simon CP, and Longini IMJ (1994) "Role of the primary infection in epidemics of HIV infection in gay cohorts" *Journal of Acquired Immune Deficiency Syndromes* 7(11): 1169-1184.

Jacquez JA, Simon CP, Koopman J, Sattenspiel L, and Perry T (1988) "Modeling and analyzing HIV transmission: the effect of contact patterns" *Mathematical Biosciences* 92(2): 119-199.

Jones KE, Patel NG, Levy MA, Storeygard A, Balk D, Gittleman JL, and Daszak P (2008) "Global trends in emerging infectious diseases" *Nature* 451(7181): 990-993.

Kermack KO and McKendrick AG (1933) "Contributions to the mathematical theory of epidemics - III. Further studies of the problem of endemicity" *Proceedings of the Royal Society of London, Series A, Containing Papers of a Mathematical and Physical Character* 141(843): 94-122.

Kilpatrick AM and Randolph SE (2012) "Drivers, dynamics, and control of emerging vector-borne zoonotic diseases" *Lancet* 380(9857): 1946-1955.

Klovdahl AS, Graviss EA, Yaganehdoost A, Ross MW, Wanger A, Adams GJ, and Musser JM (2001) "Networks and tuberculosis: an undetected community outbreak involving public places" *Social Science & Medicine* 52(5): 681-694.

Kombe GC and Darrow DM (2001) "Revisiting emerging infectious diseases: the unfinished agenda" *Journal of Community Health* 26(2): 113-122.

Koopman J (2004) "Modeling infection transmission" *Annual Review of Public Health* 25: 303-326.

Koopman JS and Longini IM (1994) "The ecological effects of individual exposures and nonlinear disease dynamics in populations" *American Journal of Public Health* 84(5): 836-842.

Koopman JS and Lynch JW (1999) "Individual causal models and population systems models in epidemiology" *American Journal of Public Health* 89: 1170-1174.

Krieger N (1994) "Epidemiology and the web of causation: has anyone seen the spider?" *Social Science & Medicine* 39(7): 887-903.

Krieger N (2001) "Theories for social epidemiology in the 21st century: an ecosocial perspective" *International Journal of Epidemiology* 30(4): 668-677.

Krieger N and Zierler S (1996) "What explains the public's health? A call for epidemiologic theory" *Epidemiology*: 107-109.

Lash TL and Fink AK (2003) "Semi-automated sensitivity analysis to assess systematic errors in observational data" *Epidemiology* 14(4): 451-458.

Levin BR, Lipsitch M, and Bonhoeffer S (1999) "Population biology, evolution, and infectious disease: convergence and synthesis" *Science* 283(5403): 806-809.

Lindblade KA, Walker ED, Onapa AW, Katungu J, and Wilson ML (2000) "Land use change alters malaria transmission parameters by modifying temperature in a highland area of Uganda" *Tropical Medicine & International Health* 5(4): 263-274.

Mackey TK, Liang BA, Cuomo R, Hafen R, Brouwer KC, and Lee DE (2014) "Emerging and reemerging neglected tropical diseases: a review of key characteristics, risk factors, and the policy and innovation environment" *Clinical Microbiology Reviews* 27(4): 949-979.

Mandell G, Douglas R, Bennett J, and Dolin R (2000) Mandell, Douglas, and Bennett's Principles and Practice of Infectious Diseases Churchill Livingstone, Philadelphia, PA.

Martens P and McMichael A, Editors (2002). Environmental Change, Climate and Health: Issues and Research Methods Cambridge University Press, New York City.

Mayer JD (2000) "Geography, ecology and emerging infectious diseases" *Social Science & Medicine* 50(7-8): 937-952.

McMichael AJ (1997) "Integrated assessment of potential health impact of global environmental change: prospects and limitations" *Environmental Modeling and Assessment* 2: 129-137.

McMichael AJ (2001) Human Frontiers, Environments and Disease: Past Patterns, Uncertain Futures Cambridge University Press, Cambridge ; New York.

McMichael AJ, Bolin B, Costanza R, Daily GC, Folke C, Lindahl-Kiessling K, Lindgren E, and Niklasson B (1999) "Globalization and the sustainability of human health" *Bioscience* 49(3): 205-210.

McMichael AJ and Butler CD (2004) "Climate change, health, and development goals" *Lancet* 364(9450): 2004-2006.

McMichael AJ, Patz J, and Kovats RS (1998) "Impacts of global environmental change on future health and health care in tropical countries" *British Medical Bulletin* 54(2): 475-488.

Mellor JE, Levy K, Zimmerman J, Elliott M, Bartram J, Carlton E, Clasen T, Dillingham R, Eisenberg J, Guerrant R, Lantagne D, Mihelcic J, and Nelson K (2016) "Planning for climate change: the need for mechanistic systems-based approaches to study climate change impacts on diarrheal diseases" *Science of The Total Environment* 548–549: 82-90.

Morse SS (1995) "Factors in the emergence of infectious diseases" *Emerging Infectious Diseases* 1(1): 7-15.

Ortblad KF, Salomon JA, Barnighausen T, and Atun R (2015) "Stopping tuberculosis: a biosocial model for sustainable development" *Lancet* 386(10010): 2354-2362.

Ostfeld RS and Keesing F (2000) "Biodiversity and disease risk: the case of Lyme disease" *Conservation Biology* 14: 722-729.

Parashar UD, Hummelman EG, Bresee JS, Miller MA, and Glass RI (2003) "Global illness and deaths caused by rotavirus disease in children" *Emerging Infectious Disease* 9(5): 565.

Parham PE, Waldock J, Christophides GK, Hemming D, Agusto F, Evans KJ, Fefferman N, Gaff H, Gumel A, LaDeau S, Lenhart S, Mickens RE, Naumova EN, Ostfeld RS, Ready PD, Thomas MB, Velasco-Hernandez J, and Michael E (2015) "Climate, environmental, and socio-economic change: weighing up the balance in vector-borne disease transmission" *Philosophical Transactions of the Royal Society of London, Series B, Biological Sciences* 370(1665).

Parkes M, Panelli R, and Weinstein P (2003) "Converging paradigms for environmental health theory and practice" *Environmental Health Perspectives* 111(5): 669-675.

Parkes MW, Bienen L, Breilh J, Hsu L-N, McDonald M, Patz JA, Rosenthal JP, Sahani M, Sleigh A, Waltner-Toews D, and Yassi A (2005) "All hands on deck: transdisciplinary approaches to emerging infectious disease" *EcoHealth* 2(4): 258-272.

Patz J, Graczyk TK, Geller N, and Vittor AY (2000) "Effects of environmental change on emerging parasitic diseases" *International Journal of Parasitology* 30(12-13): 1395-1405.

Patz JA, Daszak P, Tabor GM, Aguirre AA, Pearl M, Epstein J, Wolfe ND, Kilpatrick AM, Foufopoulos J, Molyneux D, and Bradley DJ (2004) "Unhealthy landscapes: Policy recommendations on land use change and infectious disease emergence" *Environmental Health Perspectives* 112(10): 1092-1098.

Patz JA, Epstein PR, Burke TA, and Balbus JM (1996) "Global climate change and emerging infectious diseases" *Journal of the American Medical Association* 275(3): 217-223.

Pearce N (1996) "Traditional epidemiology, modern epidemiology, and public health" *American Journal of Public Health* 86(5): 678-683.

Pimentel D, Tort M, D'Anna L, Krawic A, Berger J, Rossman J, Mugo F, Doon N, Shriberg M, Howard E, Lee S, and Talbot J (1998) "Ecology of increasing disease" *Bioscience* 48(10): 817-826.

Plowright RK, Sokolow SH, Gorman ME, Daszak P, and Foley JE (2008) "Causal inference in disease ecology: investigating ecological drivers of disease emergence" *Frontiers in Ecology and the Environment* 6(8): 420-429.

Porter D (1999) Health, Civilization, and the State: A History of Public Health from Ancient to Modern Times Routledge, London, UK.

Price-Smith A (1999) "Ghosts of Kigali: infectious disese and global stability at the turn of the century" *International Journal* Summer 1999: 426-442.

Robins JM, Hernan MA, and Brumback B (2000) "Marginal structural models and causal inference in epidemiology" *Epidemiology* 11(5): 550-560.

Rose G (1985) "Sick individuals and sick populations" *International Journal of Epidemiology* 14(1): 32-38.

Ross R (1915) "Some *a priori* pathometric equations" *British Medical Journal* 1: 546-547.

Rothenberg RB, Potterat JJ, Woodhouse DE, Muth SQ, Darrow WW, and Klovdahl AS (1998) "Social network dynamics and HIV transmission" *AIDS* 12(12): 1529-1536.

Rubin DB (1991) "Practical implications of modes of statistical inference for causal effects and the critical role of the assignment mechanism" *Biometrics* 47(4): 1213-1234.

Sattenspiel L (2000) "Tropical environments, human activities, and the transmission of infectious diseases" *American Journal of Physical Anthropology* Suppl 31: 3-31.

Savitz DA (1994) "In defense of black box epidemiology" *Epidemiology* 5(5): 550-552.

Shahi GS, Levy BS, Binger A, Kjellstrom T, and Lawrence R, Editors (1997). International Perspectives on Environment, Development, and Health: Toward A Sustainable World Springer Publishing Company, New York City.

Shen Z, Ning F, Zhou W, He X, Lin C, Chin DP, Zhu Z, and Schuchat A (2004) "Superspreading SARS events, Beijing, 2003" *Emerging Infectious Diseases* 10(2): 256-260.

Sierra R (1999) "Traditional resource-use systems and tropical deforestation in a multi-ethnic region in North-West Ecuador" *Environmental Conservation* 26(02): 136-145.

Smith KF, Dobson AP, McKenzie FE, Real LA, Smith DL, and Wilson ML (2005) "Ecological theory to enhance infectious disease control and public health policy" *Frontiers in Ecology and the Environment.* 3(1): 29-37.

Smith KR and Desai MA (2002) "The contribution of global environmental factors to ill-health" In Environmental Change, Climate, and Health: Issues and Research Methods Editors Martens P and McMichael AJ, Cambridge University Press, New York City**:** 52-95.

Subramanian SV (2004) "The relevance of multilevel statistical methods for identifying causal neighborhood effects" *Social Science & Medicine* 58(10): 1961-1967.

Susser E (2004) "Eco-epidemiology: Thinking outside the black box" *Epidemiology* 15(5): 519-520.
Susser E and Terry MB (2003) "A conception-to-death cohort" *Lancet* 361(9360): 797-798.
Susser M (1998) "Does risk factor epidemiology put epidemiology at risk? Peering into the future" *Journal of Epidemiology and Community Health* 52: 608-611.
Susser M and Susser E (1996a) "Choosing a future for epidemiology: I. Eras and paradigms" *American Journal of Public Health* 86(5): 668-673.
Susser M and Susser E (1996b) "Choosing a future for epidemiology: II. From black box to Chinese boxes and eco-epidemiology" *American Journal of Public Health* 86(5): 674-677.
Szreter S (1988) "The importance of social intervention in Britain's mortality decline c.1885-1914: a reinterpretation of the role of public health" *Social History of Medicine* 1: 1-37.
Verdasca J, Telo da Gama MM, Nunes A, Bernardino NR, Pacheco JM, and Gomes MC (2005) "Recurrent epidemics in small world networks" *Journal of Theoretical Biology* 233(4): 553-561.
Wallinga J, van Boven M, and Lipsitch M (2010) "Optimizing infectious disease interventions during an emerging epidemic" *Proceedings of the National Academy of Sciences of the United States of America* 107(2): 923-928.
Weiss RA and McMichael AJ (2004) "Social and environmental risk factors in the emergence of infectious diseases" *Nature Medicine* 10(12 Suppl): S70-76.
Wilcox B and Colwell R (2005) "Emerging and reemerging infectious diseases: biocomplexity as an interdisciplinary paradigm" *EcoHealth* 2(4): 244-257.
Wilson ML (2001) "Ecology and infectious disease" In Ecosystem Change and Public Health: A Global Perspective Editors Aron JL and Patz JA, Johns Hopkins University Press, Baltimore**:** 283-324.
Woodward D, Drager N, Beaglehole R, and Lipson D (2001) "Globalization and health: a framework for analysis and action" *Bulletin of the World Health Organization* 79(9): 875-881.

4. Model of Postulated Coverage Effect from Clean Cooking Interventions

4.1. Background & Motivation

The overarching theme throughout this dissertation has been to motivate, develop, and demonstrate approaches for investigating multiscale drivers of global environmental health. The IND metric of climate debt from *Chapter 1* addressed global to sectoral scales. The EnvID framework for environmental change and infectious disease from *Chapter 2* addressed regional to local scales. Now, in Chapter 3, I focus on community to household scales with a mechanistic model of clean cooking interventions.

4.1.1. Household Air Pollution from Solid Fuel Use

Household air pollution from solid fuel use for cooking (HAP) remains one the world's most significant environmental health challenges. Approximately three billion people rely on biomass fuels (wood, dung, crop waste, charcoal, etc.) or coal as their primary energy source for cooking[3] (Bonjour et al. 2013). These solid fuels, used in inefficiently combusting and inadequately vented traditional cookstoves, generate extraordinary indoor concentrations of health-damaging aerosols and gases (Balakrishnan and Mehta 2014). HAP has been causatively linked with a range of cardiovascular and respiratory diseases in adults, as well as pneumonias in children, resulting in approximately four million premature deaths and over 100 million lost disability-adjusted life years annually (Lim et al. 2012; Smith et al. 2014). Current estimates of disease burden do not yet include accumulating evidence of additional risks from HAP (Bruce and Smith 2014). Women and children experience the greatest exposures to HAP but men are also significantly impacted (Adair-Rohani et al. 2016). The vast bulk of this avoidable burden is borne by poor families in low-to-middle income countries (LMICs).

[3] Solid fuel use for heating (Chafe et al. 2015) and kerosene use for cooking, heating, and lighting (Lam et al. 2012) are additional sources of household air pollution, incurring attendant risks, but are not discussed further here.

Nevertheless, the present moment is a time for cautious optimism. Owing to a renewed focus from the global health community, efforts to encourage cleaner burning alternatives to traditional solid fuel cookstoves (TSF-Cs) are proliferating (Martin et al. 2013; Rosenthal 2015; Amegah and Jaakkola 2016). Clean cooking interventions center primarily on two types of technologies: "improved" cookstoves (Barnes et al. 2012; Anenberg et al. 2013) and modern cookstove-cookfuel combinations (Smith and Sagar 2014; Smith 2015). Improved cookstoves are designed to burn solid fuels with more efficiency and/or less pollution than TSF-Cs. A promising but loosely defined category, improved cookstoves have encountered challenges with adoption, correct use, and maintenance (Lewis and Pattanayak 2012; Rehfuess et al. 2014b; Shankar et al. 2014). Relatedly and crucially, though many improved cookstoves perform well during laboratory tests, none has yet demonstrated a consistent capacity to attain recommended pollutant levels during actual sustained household use (Rehfuess et al. 2014a; Sambandam et al. 2015; Thomas et al. 2015).

Thus, the most promising strategy to achieve healthy indoor air quality remains enabling access to modern cookstoves and cookfuels, in particular, liquefied petroleum gas cookstoves (LPG-Cs) and electricity powered induction cookers − provided, of course, that these options are safe, reliable, and affordable (Bruce et al. 2015). The question of how to best facilitate the use of clean cooking interventions, however, is complicated by the substantial constraints faced by poorer households (Jeuland et al. 2015), as well as by the multilateral consortia, development agencies, and governments programs which seek to aid them. Households and organizations interested in clean cooking interventions must decide how to best distribute their inevitably limited resources, a decision which will inform the nature of scale-up schemes − e.g., based on commercial markets (Bailis et al. 2009), antenatal clinics (Mukhopadhyay et al. 2012; Jack et al. 2015), or subsidized distribution (Tripathi et al. 2015) − and consequently "coverage" or the extent of intervention use within a given community or region.

Notably, several lines of evidence, considered in concert, posit that clean cooking interventions may reduce exposure to HAP not only for users but for their neighbors, as well. In turn, the efficacy[4] of an intervention may be determined by the extent of both household-level use as well as community-level coverage. Such coverage dependent efficacy, or a "coverage effect," would transform how interventions are studied and deployed. The systems-based approach advocated in *Chapter 3* lends itself to investigating questions surrounding a postulated coverage effect from clean cooking interventions to mitigate HAP. In this chapter, I pursue a mechanistic modeling exercise to help bring into relief the conditions under which a coverage effect may manifest and the consequent implications for research and policy.

4.1.2. Relationship between Household and Ambient Air Pollution

Ambient air pollution (AAP) is also a major environmental health concern, responsible for roughly three million premature deaths and nearly 75 million lost disability-adjusted life years annually (Lim et al. 2012; Apte et al. 2015). The definition for AAP differs from that for

[4] I use the term "efficacy" throughout for consistency and because the chapter is a theoretical exercise. However, the principles explored herein apply to both controlled and real-world conditions.

HAP in that the former refers to air pollution in a general place (the outdoors), whereas the latter refers to air pollution from a specific source (household cooking with solid fuels). Thus, AAP arises from many different emission sources, including the energy, industrial, transportation, agricultural, commercial, and residential sectors, as well as geologic processes (e.g., wind-swept desert dust) and vegetation fires of both natural and anthropogenic origin.

Recent modeling advances (Brauer et al. 2012; Brauer et al. 2016) have refined estimates of worldwide ambient exposure to fine particulate matter (≤ 2.5 μm in aerodynamic diameter; $PM_{2.5}$), a major toxic air pollutant and an indicator for adverse impacts from air pollution more generally. Enhanced resolution models (1°×1° or finer) channel inputs from emissions inventories, remote sensing measurements, and air quality monitoring stations through a global chemical transport model. The resulting concentrations can be integrated with spatially-resolved population distributions and associated time-activity patterns to yield estimates of exposure. In this manner, Lelieveld et al. (2015) attributed one-third of global ambient $PM_{2.5}$, on a population-exposure weighted basis, to energy use by the residential and commercial sectors, mostly for cooking and heating. In a more specific study, Chafe et al. (2014) found HAP accounted for 12% of population-exposure weighted ambient $PM_{2.5}$. In both studies, the impact of residential/household combustion was highest, several times the global average, in South Asia and East Asia, and growing fastest in Sub-Saharan Africa − the three regions with the largest numbers of TSF-C users.

Although models of this scope necessarily entail extensive simplifications, they nonetheless posit that a substantial portion of AAP exposures may be due to HAP sources. Indeed, for this reason, the Global Burden of Disease Study 2010 attributed a portion of the total disease burden from air pollution to both HAP and AAP (~16%; Lim et al. 2012), a practice consistent with how attributable risk operates (Walter 1978). The growing recognition that HAP and AAP are often interrelated issues, especially for many LMICs, advocates for a commensurate research agenda (Balakrishnan et al. 2014).

Vexingly, empirical research on HAP and AAP have historically not been well integrated. Projects on HAP have understandably prioritized the indoor environment, whereas projects on AAP have customarily overlooked the locales within which HAP predominates: rural villages, and to a lesser extent, urban slums. Still, a handful of field studies have considered HAP in the context of AAP and offer suggestive insights. In the earliest such work, Smith et al. (1983) gauged ambient total suspended particulate concentrations during evening cooking periods within four villages in Gujarat. The startling result, ~2 mg/m^3, an extremely high concentration, established that AAP from TSF-Cs warranted scrutiny. Additional data from the same project, presented in a landmark book on HAP (Smith 1987), indicated that concentrations dropped sharply at the village edge. Smith (1987) also recognized that many of the same factors, such as meteorology, that influence ambient concentrations from more typically studied sources would also apply to household sources.

Three ensuing studies offer suggestive insights into the relationship between HAP and AAP. First, in the city of Pune, Smith et al. (1994) monitored daily outdoor PM_{10} at 60 sites in several poorer neighborhoods. Concentrations were an order of magnitude higher in neighborhoods using TSF-C versus LPG-C, emphasizing the role of predominant cooking technology on AAP at a daylong and community scale. Second, in highland Guatemala, Naeher et al. (2000) collected real-time ambient $PM_{2.5}$ readings along street-level transects in a half-dozen villages within which the major $PM_{2.5}$ source was HAP. Concentrations were ~three-fold greater in villages with high versus low residential density (~10 versus ~1 household/ha). Third, in New Delhi, Saksena et al. (2003) measured respirable suspended particulate concentrations inside and outside 40 households in two different slum according to micro-environmental sampling scheme. Concentrations were elevated by ~1.5× in households located in the slum with high versus low background concentrations as qualitatively ascertained by the authors. Although limited in number and pilot by design, this trio of studies nevertheless enrich the conclusions of the recent global-level models by proposing potential key mechanisms for conceptualizing how a coverage effect from clean cooking interventions may arise.

4.1.3. Considering a Coverage Effect

Clean cooking interventions, implicitly or explicitly, have usually been presumed to attenuate exposure to air pollution from only a single exposure pathway − emissions from a household's own cooking activities. Exposures to air pollution originating from other sources, such as from another household, are not assessed. Moreover, benefits are assumed only to accrue for inhabitants of the household using the intervention. In many cases, these assumptions may well hold. But the trio of studies described at the end of the previous section submit intriguing snapshots to the contrary. Not only may HAP give rise to non-negligible, near-field, outdoor air pollution, but in turn, this AAP may then also contribute to indoor air pollution.

In settings and circumstances conforming to this description, the exposure (and eventually health) outcomes for individuals will not be independent of the intervention status of neighbors. An underappreciated but core feature of such a system is that, as coverage of a clean cooking intervention expands within a community, exposure to $PM_{2.5}$ and other pollutants from HAP progressively declines for other users (and possibly non-users), as well. Therefore, a coverage effect would be anticipated because the clean cooking intervention reduces exposure both directly, for inhabitants of households using the intervention, and indirectly, for all community residents via reduced emissions vented into the outdoors. Coverage effects would accumulate as coverage expands, with each additional intervention household contributing another increment of benefit. The nature of associated exposure-response relationships would then determine the degree to which the intervention, by reducing exposure through its combined effects, will translate into a diminution of risk at the individual level and a contraction of disease burden at the community level.

As an illustration, consider a characteristically drafty poor household, which possesses no indoor sources of $PM_{2.5}$ besides a cookstove, in two extremes of locales and under two scenarios. To begin, imagine the household is exceedingly distant from any neighbors or any regional sources of $PM_{2.5}$ emissions. For the inhabitants of this household, exposure to HAP would be exclusively determined by the household's cooking technology. The notion of a coverage effect would be irrelevant. In essence, current thinking about clean cooking interventions embodies this assumption.

Now, imagine the same household is wedged inside a dense informal settlement, again with no regional sources of $PM_{2.5}$ emissions wafting into the community. Here, all of the household's neighbors use TSF-Cs. The household's inhabitants' $PM_{2.5}$ exposure, in this case, might be strongly affected by its neighbors' cookstove use, even if the household itself uses, as an example, LPG-C. Inhabitants of the household could be exposed to $PM_{2.5}$ not only from their own cookstove, but while outdoors they could be exposed to the exfiltration of emissions from their neighbors' cookstoves, and while indoors they could also be exposed to the infiltration of these same emissions into their household.

Lastly, imagine the same household in either locale but downwind of a constantly operating coal-fired power plant. Even if the household in the informal settlement and all of its neighbors use LPG-Cs, the household's inhabitants, and indeed all community residents, must contend with $PM_{2.5}$ exposures from the power plant while they are outdoors as well as indoors. The same holds true for the former case, the isolated household.

Lending further credence to this thought experiment is a more recent and sophisticated study. Working in a Dhaka slum distant from roadways, Salje et al. (2013) assessed indoor daily minute-by-minute $PM_{2.5}$ levels for 257 households, some of which used TSF-Cs and others LPG-Cs/induction cookers. Previously, the authors had observed that even households without TSF-Cs or other obvious indoor emission sources still experienced high $PM_{2.5}$ concentrations. Median daily average $PM_{2.5}$ concentrations confirmed this observation: 101 $\mu g/m^3$ for TSF-C households versus 79 $\mu g/m^3$ for LPG-Cs/induction cooker households. Probing further with a statistical model, Salje et al. (2013) computed that the highest probability of $PM_{2.5}$ concentrations exceeding 1000 $\mu g/m^3$ − for both groups of households − occurred during community cooking periods. These results are consistent with the conjecture that even households using modern cooking technologies may still be subjected to neighborhood HAP or to emissions from TSF-Cs within their communities (Moschandreas et al. 2002). It would follow that expanding coverage of LPG-Cs or induction cookers would help ameliorate exposure to $PM_{2.5}$ for all residents of the community.

My use of the terms "coverage" and "community," which denote idealized notions, warrants clarification. In order to isolate the effect of TSF-Cs and clean cooking technologies, I maintain the assumptions of the preceding thought experiment − there are no other household or community sources of air pollution besides cooking and all households possess only a single cookstove – for the following discussion.

"Coverage" is intended to express the level of intervention use within a community. I define coverage simplistically as the percentage of households within a community that use the clean cooking intervention. This definition has the decided advantage of being easy to explain but its application in the field would require caution. A more realistic coverage metric, in order to account for multiple cookstoves per household, among other factors, might quantify the fraction of total community cooking energy, events, or time that employ the intervention. Coverage also functions as a convenient shorthand for the degree to which exposure to HAP is reduced within a community. In the absence of any coverage effect, this may not be problematic, but in the presence of a postulated coverage effect, equating coverage with a reduction in exposure to HAP would be more complicated, and thus using coverage as a surrogate for efficacy could be at least subtly misleading.

By "community," I refer to a collection of households connected by an environmental feature that communicates exposure (Gurarie and Seto 2009); in this case, given the emphasis on

HAP, a shared community airshed[5] within which airborne pollution initially disperses. The ground-level boundaries of a community defined in this manner and the geographic units of village or slum are identical. But the volume of a community airshed can only be loosely delineated since it varies over time and space with inconstant and porous boundaries. Furthermore, the degree to which different households are connected naturally differs based on many factors, most apparently distance and prevalent wind direction. Nonetheless, connectivity would be enhanced where and when local emission sources predominate.

A community airshed interacts with indoor environments, as well. Within less prosperous communities throughout LMICs, houses are generally constructed with open architectures and of porous materials. These structures are therefore exceedingly drafty. Ventilation facilitates connectivity with the larger airshed through exfiltration and infiltration. The elderly, women, and the young, especially in rural locales, may not move about as widely, and so these groups' exposures may be primarily determined by air quality in their household and home community airshed. Conversely, for urban locales or for individuals who spend significant time away from their home community airshed, the opposite may be the case. Estimating total exposure would necessitate either personal monitoring or an approximation of complex spatiotemporal patterns of human activity and pollutant concentrations in all relevant environments.

Airsheds, it must be noted, exist on multiple, nested, scales. The specter of climate change has focused global attention on the largest shared airshed, the planetary atmosphere. With regards to HAP, residential density and background concentration help determine, respectively, the connectivity of households within a community airshed and the connectivity of communities within a regional airshed. Neither factor is amenable to easy manipulation. In other words, residential density and background concentration can be presumed to act as external constraints on the emergence and strength of any coverage effect from clean cooking interventions.

4.1.4. A Mechanistic Modeling Approach

The preponderance of exposure to HAP is experienced by those households using TSF-Cs. However, global-level models and local-level studies suggest that the impact of HAP may spread farther afield. These observations, coupled with common-sense reasoning, propose that, at least under certain conditions, coverage effects may play a vital role in shaping benefits from clean cooking technologies. Yet thus far, few efforts have considered the conditions for and consequences of a coverage effect, despite the possible implications for the design and interpretation of interventions studies and the planning and evaluation of intervention programs.

As always, carefully collected field measurements will be the true barometer for appraising a coverage effect. Still, it remains the case that empirical data are inevitably limited to descriptions of specific places and times, and as a result, may not offer clear guidance on the identification of causes or generalizability to alternative scenarios. Disentangling a coverage effect will require apportioning averted and extant $PM_{2.5}$ exposures to categories which are, in practice, exceedingly difficult if not impossible to distinguish. Perhaps a gold standard could be

[5] To be clear, "community airshed" refers to the surface layer of the atmosphere within which emissions vented by households initially disperse. This may be a smaller scale than is often implied by "airshed" used in other contexts.

inferred through sustained personal and area monitoring, along with gathering much other relevant information, across a continuum of coverage levels. The requirements for such an undertaking will clearly be demanding.

Mechanistic models can prove indispensable to guiding these efforts and extending their conclusions to other settings and circumstances (Gall et al. 2013). Models of this nature have been utilized by public health scientists since at least the early-20th century (Ross 1915; Kermack and McKendrick 1927; Sutton 1932; Bosanquet and Pearson 1936). A mechanistic model synthesizes current understanding by specifying, in mathematical and algorithmic terms, a chain of logic about how processes and parameters interact to govern a system. Given thorough verification and validation, a mechanistic model can thereby help to explain past and predict future outcomes of interest (Garnett et al. 2011).

Mechanistic modeling can be particularly useful for examining system behavior beyond what may be readily observable, for example, to assess questions for which experimental or observational studies are overly controversial, costly, or complicated (Alper and Geller 2015); to explore the ramifications of variability and uncertainty in process or parameter space (Cullen and Frey 1999); or to portray the theoretical counterfactual with regards to causal inference based on potential outcomes (Neyman 1923; Rubin 1974; Holland 1986). Yet ideally, mechanistic models and field data work together in mutually constitutive fashion. Models are calibrated and validated by data, and in turn, data are targeted and interpreted by models. Over time, conceptual, statistical, and mechanistic models can gradually help bring the empirical and the theoretical into alignment.

Just as with any analysis, suitable attention must be paid to a mechanistic model's assumptions and applicability. Unavoidable simplifications may be both a boon, by deliberately isolating the consequences of specific components of a system, or a curse, by inadvertently neglecting pivotal aspects of the reality. An appreciation of the scope of a mechanistic model is equally critical, or results risk being overgeneralized. Accordingly, the tasks are to identify a sufficiently parsimonious but robust model for the question at hand and to draw conclusions commensurate with the limitations of the modeling exercise (Getz 1998; Johnson and Omland 2004). Given the great number of model structures available, as well as the choices inherent to evaluating any modeling exercise, this may be an appropriate juncture to recall that, paraphrasing the aphorism, all models – conceptual, statistical, mechanistic – are wrong … but some are useful (Box and Draper 1987).

In this chapter, I develop and apply a mechanistic model to investigate the postulated relationship between community-level coverage of LPG-Cs and individual-level reductions in exposure to $PM_{2.5}$. Model simulations are intended to help (1) demonstrate whether and to what degree a coverage effect may manifest, (2) explore conditions influencing a relationship between coverage and efficacy, and (3) submit strategies to further enlighten comprehension of a coverage effect. The modeling exercise ventures to be primarily a "proof-of-concept" analysis, and secondarily, an initial first-order approximation and qualitative screening tool. Moreover, the overarching purpose is to encourage approaches that consider − and where or when appropriate, leverage − a coverage effect from clean cooking interventions.

4.1.5. Overview of Dispersion Models

Mechanistic modeling approaches to air pollutant dispersion are diverse and numerous, reflecting the import of air quality to human well-being across a spectrum of settings and circumstances. In this section, I outline features of the three major categories of dispersion models, located along a continuum of sophistication, and discuss the applicability of each category to modeling primary $PM_{2.5}$ mass concentrations (henceforth, simply "$PM_{2.5}$ concentrations") derived from cookstoves at the scale of a household or community in an LMIC. Within such a domain, a net change to $PM_{2.5}$ concentration, either from aerosol dynamics (i.e., losses from coagulation or gains from phase-change at the margins of the size class) or multi-pollutant chemistry (i.e., formation of secondary particulate matter), would be negligible in most cases (Morawska et al. 2013), and consequently, modeling approaches for these processes are not considered here. At wider scales, as these processes become more significant and even dominant (Gelencsér et al. 2007; Fine et al. 2008), dispersion models may be integrated with modules for aerosol dynamics and/or multi-pollutant chemistry (e.g., see Byun and Schere 2006).

At one extreme of sophistication are computational fluid dynamic (CFD) models. CFD models approximate solutions to the Navier-Stokes equations for dissipative fluid flow by using various numerical methods for closure and discretization within a three-dimensional mesh architecture (Ferziger and Perić 2002). CFD models are valued for their capacity to adeptly handle multiscale turbulence, fine resolutions, and complex environments. Provided with well-defined boundary conditions and detailed input data, CFD models can achieve reasonable agreement with experimental or empirical results (Gousseau et al. 2011; Tilley et al. 2011). Yet, this potential accuracy must be balanced against a workflow far more demanding than for alternatives with respect to model specification, parameterization, execution, and interpretation (Lateb et al. 2015). Moreover, because each CFD model is designed to simulate a unique scenario, results may be difficult to generalize. Standardized procedures for validating and verifying CFD models (Oberkampf and Trucano 2002), with their more complicated but seemingly realistic appearing output, remain ongoing (Britter and Schatzmann 2007). Nonetheless, CFD models are rapidly proliferating to address air quality questions at moderate spatial and temporal scales for both indoor and outdoor environments (Yan et al. 2009; Habilomatis and Chaloulakou 2015). Applications of relevance to LMIC settings remain, however, rare. As mathematical and computational innovation progresses, CFD models certainly hold considerable promise for providing tailored insights into the core concerns of this chapter (Pepper and Carrington 2009; Blocken et al. 2013), but to do so will require the support of exceptionally detailed site-specific data, as well.

At an intermediate level of sophistication are the dispersion models based on Gaussian or Lagrangian approaches (Collett and Oduyemi 1997). This category of models is widely used to serve research, risk assessment, and regulatory purposes for simulating, in particular, ambient air quality (Holmes and Morawska 2006). There are dozens of such models, each tailored to particular applications. For example, models in this category may be integrated with different algorithms for approximating turbulence; pre-processing inputs (e.g., terrain, to set source and receptor heights, or meteorology, to model wind and temperature gradients); and post-processing outputs (e.g., to transform results into the spatiotemporal scale of interest). A Gaussian plume model describes a concentration field under relatively stable meteorological and emissions conditions. Pollutant dispersal in the vertical and horizontal directions follows a normal distribution modified by downwind distance and atmospheric turbulence. The American Meteorological Society/Environmental Protection Agency Model or AERMOD, the current recommended United States Environmental Protection Agency (USEPA) Gaussian model, extends its applicability by accounting for factors such as Monin-Obukhov length based on land use, plume reflection by the ground surface or an inversion layer, and dry or wet deposition (Cimorelli et al. 2005). A Lagrangian puff model tracks plume parcels as they disperse across a landscape, utilizing a moving reference frame and random walk process to map pathlines. The California Puff Model or CALPUFF, the current recommended USEPA Lagrangian model, includes a capacity to address more complicated scenarios such as complex terrains or coastal regions with alternating sea and land breezes (Scire et al. 2000).

Although constituting a grouping with an active and ample user base, this category of air pollution models is infrequently applied to scales similar to that of a typical neighborhood. AERMOD and CALPUFF generally utilize horizontal grids of several-to-tens of kilometers ("local scale") or tens-to-hundreds of kilometers ("regional scale"), with resolution also restricted by the level of detail in terrain or meteorology (Dresser and Huizer 2011). At such scales, simulating the planetary boundary layer becomes important, and methods for doing so differ among models. Most of the handful of efforts to apply AERMOD, CALPUFF, and related models to sub-kilometer near-fields have witnessed poor agreement with field measurements (Isakov et al. 2004; Donaldson et al. 2008; Sivacoumar et al. 2009; Kim 2010; Cohan et al. 2011; Thatcher and Kirchstetter 2011). Tight calibration with field measurements has been shown to improve model predictions in at least one instance (Isakov and Venkatram 2006). Models in this category designed to simulate emissions from roadways, for which comparatively fine resolutions are key, perform better (Vardoulakis et al. 2003). However, the concentration fields from quasi-constant line-sources versus intermittent and distributed volume-sources would be expected to differ considerably. Gaussian and Lagrangian models may be able to better address the sub-kilometer near-field through still evolving approaches such as multiple nested grids and plume-in-grid models (Karamchandani et al. 2011). Hence, with further refinement in future, this category of models may become well-suited to engage HAP's impact on AAP, provided that topographic, meteorological, and built environment data, which heretofore has not been routinely collected during studies on air pollution in villages and slums, becomes more available.

At the other extreme of sophistication are the relatively straightforward mass-balance models which, as the name implies, rely on the principle that pollutant mass is conserved within a defined region (Jacob 1999). In such a compartment, alternatively termed a zone or box, $PM_{2.5}$ concentration is regulated, at minimum, by emission and transport processes, and optionally by reactions and/or deposition. For each compartment, these processes are collectively described by a single, first-order, ordinary differential equation (Nazaroff 2004). The solution to this differential equation depicts the consequent temporal evolution of pollutant concentration within the compartment. In implementation, the differential equation is either solved analytically, or for more complex models, numerically, incorporating time-varying parameters and/or discontinuous events as necessary. Multiple compartments representing, for instance, rooms within a building, can be linked together, provided that flow between compartments can be reasonably estimated.

This latter method can also be extended such that a matrix of hypothetical air parcels comprising a volume are described by a system of advection-diffusion partial differential equations – an approach referred to as an Eulerian model.

Notably, mass-balance models assume that pollutants are instantaneously and homogenously mixed throughout the entire volume of a compartment. Addressing this core assumption, which often does not comport to the real world, could involve the use of a mixing factor (Jayjock et al. 2000) or multiple sub-compartments (Furtaw et al. 1996). But such remedies introduce their own issues: mathematical inconsistencies, in the case of mixing factors (Nicas 1996), and potentially challenging-to-characterize parameters, in the case of sub-compartments (Nicas et al. 2009).

Nevertheless, mass-balance model naturally lend themselves to many purposes. In the early-00s, USEPA developed a multi-compartment mass-balance model for simulating inhalation exposure to air pollution within indoor environments (Guo 2000) which has witnessed recent application (Wang 2009; Motlagh et al. 2011; McCready et al. 2012). Mass-balance models have also proven useful for scenarios in which it can be reasonably argued that spatial heterogeneity in $PM_{2.5}$ concentrations regresses to central values, such as for long averaging times or large sample sizes. Still, mass-balance models must be applied with careful but appropriate attention to their limitations, especially for conditions in which imperfect mixing may predominate.

4.2. Model Development

4.2.1. Mass-Balance Models for Household Cookfuel Combustion

Mass-balance models, their caveats notwithstanding, continue to enjoy currency not only with regards to air pollution (Hellweg et al. 2009; Zhang et al. 2010; Bond et al. 2011) and environmental health (Mason 2006; Breivik et al. 2007; Knaebel et al. 2016) but also across the environmental sciences (Minasny et al. 2008; Pellicciotti et al. 2014; Ofir et al. 2016). For indoor $PM_{2.5}$, single-compartment mass-balance models have achieved sufficient agreement with empirical data to be used for simulating concentrations from secondhand smoke (Ott 1999; Klepeis and Nazaroff 2006) and occupational sources (Ten Berge 2000; Nicas 2008), as well as to estimate the effectiveness of interventions such as portable air purifiers (Lee et al. 2015) and air filtration systems (Zhao et al. 2015). Applications for modeling indoor concentrations of $PM_{2.5}$ of outdoor origin have also been common (Mohammed et al. 2015), including one study on naturally ventilated schoolrooms in Delhi (Goyal and Khare 2011). For outdoor $PM_{2.5}$, single-compartment mass-balance models, by leveraging long averaging times and large sample sizes, have been utilized relatively recently to determine intake fractions from non-point sources within urban areas (Marshall et al. 2005; Stevens et al. 2007; Humbert et al. 2011; Apte et al. 2012).

With respect to $PM_{2.5}$ arising from solid fuel combustion in LMICs, Smith et al. (1983) first used a mass-balance model to derive initial estimates for the concentrations experienced by women villagers in Gujarat, followed soon thereafter by a similar effort undertaken in Nepal by Davidson et al. (1986). Mass-balance models have also been utilized to back-calculate emission rates for cookstoves (Prasad et al. 1985) and kerosene lamps (Schare and Smith 1995). More recently, Johnson et al. (2011) deployed a single-compartment mass-balance model with a focus on India to simulate daily indoor $PM_{2.5}$ concentrations from different cooking technologies. In this study, the authors were especially cognizant of variability in key parameters driving indoor $PM_{2.5}$ concentrations. As a result, they drew on cookstove tests (for stove power, thermal efficiency, and emission factors) and empirical data (for household volumes, ventilation rates, and energy requirements) to set parameter means, assumed parameters vary lognormally, and then conducted simple Monte Carlo runs by sampling across the outlined parameter distributions. The approach led to reasonable agreement for TSF-Cs-using, indoor cooking, one-room households as appraised by the output from a statistical model based on a vast number of field measurements (Balakrishnan et al. 2013). Given the wide diversity of conditions present on the subcontinent, this is a somewhat surprising but reassuring result.

In fact, factors beyond those parenthetically listed above would also be anticipated to impact indoor $PM_{2.5}$ concentrations. These include fuel characteristics: type, quality, preparation, or moisture content; non-cooking-related stove use: water purification, area heating, or animal feed; other indoor $PM_{2.5}$ sources: tobacco smoke, resuspension, kerosene lamps, incense, etc.; and emissions of $PM_{2.5}$ from outdoor sources which penetrate households: trash or crop burning, wildfires, transportation, industry, etc. Perhaps most importantly, households commonly use more than one cookstove, also referred to as "stacking," and thus the number, type, condition, and use of all cookstoves will collectively determine indoor $PM_{2.5}$ concentrations (Ruiz-Mercado et al. 2011; Ruiz-Mercado and Masera 2015). Yet the results of the single-compartment mass-balance model of Johnson et al. (2011), which awaits further validation and verification, does intimate that these other sources of variability, though they may be vital to accurately explaining and predicting $PM_{2.5}$ concentrations within many particular settings or circumstances, may be less important at a regional or country level. Indeed, the approach, with only slight modification, contributed towards the development of the World Health Organization's (WHO's) Indoor Air Quality Guidelines for Household Fuel Combustion (Johnson 2014; World Health Organization 2014b).

Imprecision arising from the mass-balance model's inability to factor in the many variables that influence indoor $PM_{2.5}$ concentrations is amplified by the mass-balance model's well-mixed assumption. Mass-balance models cannot readily capture heterogeneity in pollutant concentrations within an individual compartment. Considering $PM_{2.5}$ from household cookfuel combustion[6] for illustration, concentrations would be expected to exhibit substantial spatial variation both indoors and outdoors. Indoors, concentrations are higher closer to the cookstove and vertically stratified to at least some degree (Kandpal et al. 1995). Outdoors, concentrations would be anticipated to be higher proximate to $PM_{2.5}$ sources, such as homes actively combusting solid cookfuels. Upwind homes would be projected to impact air quality more than downwind homes. Furthermore, at the scale of a household or community, many features, both natural and human-made, complicate wind-flow fields, and hence pollutant transport, by introducing zones of recirculation, stagnation, and acceleration. Indoor examples would include household layout, including the number, size, location, arrangement, and use of rooms, doors, windows, eaves, and chimneys. Outdoor examples would include local geography, including the position of households relative to one another and environmental attributes. Accordingly, $PM_{2.5}$ concentrations, especially over brief timespans or for a small number of households or communities, might be expected to vary spatially, perhaps markedly, for a multiplicity of reasons.

4.2.2. Coverage Effect Model − Overview

Despite caveats, a mass-balance modeling approach lends itself well to the core pursuit of this chapter, a theoretical investigation of whether and to what extent a coverage effect may manifest from clean cooking interventions to reduce exposure to $PM_{2.5}$. For these objectives, the success of a modeling exercise hinges not on its predictive power in a strict statistical sense, but instead, on its capacity to clarify and generalize the consequences of processes and parameters understood to govern $PM_{2.5}$ emissions, concentrations, and exposures (Caswell 1988; Servedio et al. 2014). Given this criteria, the simplified context of a mass-balance model is both an advantage and a disadvantage. Mass-balance models involve comparatively few assumptions, which eases specification, parameterization, execution, and interpretation, and allows for mechanisms to be isolated and results to be interrogated in a relatively straightforward and

[6] "Household cookfuel combustion" refers to cooking with any type of combustible cookfuel − solid, liquid, or gas. Thus, as used in this chapter, the phrase includes cooking with either a TSF-C or LPG-C.

transparent manner. But mass-balance models demand judicious use given their intrinsic assumptions and simplifications, discussed in general and in detail throughout this section.

The coverage effect model endeavors to translate into a mathematical and algorithmic formulation the essential mechanisms that control air pollution from household cookfuel combustion. The model depicts a community of 100 households, each with one woman and one child. Households exclusively use either a TSF-C or LPG-C. For simplicity, there is only one cookstove per household, no other cookstove use besides meal preparation, and no other indoor source of $PM_{2.5}$. Indoor $PM_{2.5}$ concentrations are a function of a household's use of either TSF-C or LPG-C, as well as infiltration of $PM_{2.5}$ from outdoors. Outdoor $PM_{2.5}$ concentration, in turn, is a function of exfiltration from the mix of TSF-C and LPG-C used within the community, with no other outdoor sources of $PM_{2.5}$ endogenous to the community itself, and a background concentration from regional sources exogenous to the community. One hundred separate single-compartment mass-balance models simulate indoor $PM_{2.5}$ concentrations for each household. These household models are nested within a single-compartment mass-balance model that simulates outdoor $PM_{2.5}$ concentrations for the community airshed. For parameterization and calibration, the coverage effect model, to the degree feasible, focuses on Indian or neighboring South Asian contexts, as this is the country and global region that bears the highest burden from HAP (Balakrishnan et al. 2011a; Rohra and Taneja 2016).

Four scenarios are modeled: two residential densities, representative of moderately dense rural and urban locations, or a "village" and "slum", respectively; and two background concentrations, representative of low and high regional emissions of $PM_{2.5}$. Community-level LPG-C coverage is modeled from 0% (the counterfactual) to 100% in 5% increments. Each model iteration, by drawing new parameters for house volumes and ventilation rates, constitutes a unique community that then experiences simulations at each coverage level increment for one year at a time. For each day within a simulation year, parameters for average temperature and average windspeed are resampled and then transformed into quasi-sinusoidal diurnal patterns. Meteorology contributes to the calculation of plume rise, which sets the height for the vertical dimension of the community airshed. Emission rates and the timing of events related to cooking and time-activity patterns also vary daily within assumed distributions.

To minimize less critical sources of variation, the model does not simulate seasonal effects, for instance in background concentration, fuel availability, cooking intensity, or time-activity patterns. Conversely, the model assumes no autocorrelation within parameters or correlation between parameters, choices which may increase overall variability.

One thousand iterations of each scenario yield ensemble distributions of $PM_{2.5}$ concentrations for indoor and outdoor environments and $PM_{2.5}$ exposures for women and children. As appropriate, results are stratified by scenario, coverage, and TSF-C versus LPG-C.

The coverage effect model is coded in R 3.2.3 (R Core Team 2015) using the Microsoft R Open enhanced distribution and its associated Intel Math Kernel Library (Microsoft R Application Network 2015). The script utilizes the following packages not included in base installations: 'deSolve' (Soetaert et al. 2012), 'doParallel' (Revolution Analytics and Weston 2015a), 'doRNG' (Gaujoux 2014), 'foreach' (Revolution Analytics and Weston 2015b), 'ggplot2' (Wickham 2009), 'reshape2' (Wickham 2007), 'plyr' (Wickham 2011), 'triangle' (Carnell 2013), and 'truncdist' (Novomestky and Nadarajah 2011).

4.2.3. Coverage Effect Model − Details

4.2.3.1. Residential Densities and Background Concentrations

The two residential density scenarios are based on a ~100 households per hectare (hh/ha) rural village in Haryana (Ajay Pillarisetti, personal communication, 2016 Feb 16) and a ~400 hh/ha urban slum in Dhaka (Angeles et al. 2009). In implementation, the model is specified in terms of a linear dimension (L; row #1 of *Table 4.1*), referring to both the length and width of a community. The low and high residential densities correspond to linear dimensions of 100 m and 50 m, respectively. Data on residential density, unfortunately, is far less common than that for comparatively crude measures of population density which encompass both inhabited areas and also areas devoted to every other purpose from cultivation to commerce. Within South Asia, there are communities with residential densities less than 100 hh/ha and greater than 400 hh/ha. The values used for the coverage effect model scenarios are moderate, viz. they are not outliers, but their representativeness cannot be readily quantified. In rural areas where habitations are scattered instead of clustered in hamlets or a village center, residential densities may be far lower than 100 hh/ha. In such locales, a much less connected community airshed would render any coverage effect negligible. In urban areas where high-rise developments predominate, residential density may be far higher than 400 hh/ha. But ventilation rates in modern buildings are generally quite low and again a community airshed would be, as a result, much less connected, attenuating any coverage effect.

The two background concentrations which model $PM_{2.5}$ concentrations from regional sources (C_{reg}; row #2 of *Table 4.1*) are based on annual averages reported for the 140 South Asian cities present in the WHO Ambient Air Pollution in Cities Database (2014a). Within this region, as elsewhere, ambient air pollution monitoring stations are virtually always located in or near urban areas. Crudely, without weighing by population or exposure, the low value of 10 $\mu g/m^3$ corresponds to the 1st percentile (Thimpu) and the high value of 100 $\mu g/m^3$ to the 95th percentile (Ahmedabad). The low value also corresponds to the WHO guideline for annual average $PM_{2.5}$ concentration both outdoors and indoors (World Health Organization 2006; World Health Organization 2014b). Consequently, 10 $\mu g/m^3$ often serves as the explicit or implicit counterfactual for many investigations of ambient and household air pollution, including comparative risk assessments (Lim et al. 2012). Many populous cities of the Indo-Gangetic Plain experience annual average $PM_{2.5}$ concentrations above the high value, for example, Karachi (117 $\mu g/m^3$), Delhi (153 $\mu g/m^3$), and Patna (149 $\mu g/m^3$). Typically, the low value would be more representative of rural villages and the high value urban slums. Yet this is not always the case. Rural areas may experience high background concentrations in the tens of $\mu g/m^3$ or more (Balakrishnan et al. 2013), whereas urban areas may experience low background concentrations in the teens (e.g., Pondicherry).

In reality, $PM_{2.5}$ concentration from regional sources would most likely fluctuate episodically in response to natural or human events, and systematically in a diurnal and/or seasonal fashion. Since patterns would vary from site-to-site and cannot be easily generalized, the coverage model adopts time-invariant constant value for background concentration.

4.2.3.2. Cooking Events and Time-Activity Patterns

The coverage effect model makes use of common-sense assumptions to craft cooking start times, cooking durations, and time-activity patterns (*Table 4.2*), each of which varies on a daily basis for each household according to a uniform distribution. Cooking start times and durations help determine concentrations. Time-activity patterns do likewise for exposures. There are three cooking events with the start times commencing within a two-hour timeframe with a uniform distribution: morning (5 a.m. to 7 a.m.); mid-day (11 a.m. to 1 p.m.), and evening (5 p.m. to 7 p.m.). Cooking continues for anywhere from 45 to 90 minutes, a duration understood to meet energy requirements for the vast majority of meals (Johnson and Chiang 2015a).

With respect to time-activity patterns, women and children ("individuals") are assumed to be together at all times follow the same patterns. For neonates and infants, groups which experience the bulk of the disease burden from pneumonias associated with HAP (Bruce et al. 2013), this is a reasonable assumption. As children age, the correlation between their time-activity patterns and their mothers' gradually weakens. Sampling from a uniform distribution, individuals move outdoors 30 to 90 minutes after the morning meal, return indoors 30 to 90 minutes before the mid-day meal, move outdoors again 30 to 90 minutes after the mid-day meal, and return indoors again 30-90 minutes before the evening meal. The delays both before and after cooking events simulate time devoted to meal-related and other household tasks. The two outdoor periods, one in the morning and one in the afternoon, simulate time spent away from home, not indoors in other households, but outdoors within the community. To be clear, the model does not incorporate movement outside the residential area of the village or slum, a constraint which makes this schema less appropriate for individuals who work or otherwise frequently travel away from their communities.

4.2.3.3. Indoor Concentrations

The coverage effect model's single-compartment abstraction of a house equates to a single, common, room for all household activities – cooking, studying, relaxing, sleeping, etc. One-room houses remain widespread among the socioeconomic strata most likely to use traditional fuels. The 2011 Indian Census tabulated that 37% of the country's households live in a one-room house; 32% and 31% of all households reside in a two-room or three-plus room house, respectively (Office of the Registrar General and Census Commissioner 2012). A multiple room house would not be much more challenging to simulate, but a one-room house obviously necessitates fewer assumptions and parameters.

The coverage effect model parameterizes median ventilation rate (α; row #3 of *Table 4.1*) at 20 air exchanges per hour (1/hr) (Bhangar 2006; Brant et al. 2009; Brant et al. 2010; Balakrishnan et al. 2011b). Ventilation rate is lognormally distributed, truncated at a minimum corresponding to modern homes (6.7/hr), and a maximum corresponding to the outdoors (60/hr). The impact of this draftiness on indoor air quality, holding all other variables constant, is not immediately apparent. For an isolated household, increasing ventilation would likely decrease indoor $PM_{2.5}$ concentration, as a test kitchen study discovered (Grabow et al. 2013). Understandably, behavioral and technological interventions that target ventilation are consequently being contemplated (Johnson and Chiang 2015b). However, enhancing ventilation for a household using an LPG-C that is subject to emissions from either its neighbors or regional sources could, in fact, increase exposure. Similarly, enhancing ventilation for a household using a TSF-C that is proximate to other households may levy costs as well as benefits, although this is a complicated calculus, the conclusions of which are likely specific to a site.

Household volume (V; row #3 of *Table 4.1*) exhibits a direct relationship with indoor $PM_{2.5}$ concentration since larger volumes dilute pollution more than smaller volumes. Median household volume (V; row #4 of *Table 4.1*) is 30 m^3 (Bhangar 2006; Brant et al. 2009; Brant et al. 2010; Balakrishnan et al. 2011b) equivalent to a cube roughly three meters in all dimensions. House volume is lognormally distributed with a minimum of 10 m^3 and a maximum of 90 m^3.

Emission rates for TSF-Cs ($E_{TSF\text{-}C}$; row # 5 in *Table 4.1*) and LPG-Cs ($E_{LPG\text{-}C}$; row # 6 in *Table 4.1*) are based on laboratory tests (Jetter et al. 2012; Edwards 2014). On one hand, this is a standardized approach, but on the other hand, test conditions may not reproduce real-world use since emission rates for TSF-Cs vary for a myriad of reasons (International Organization for Standardization 2012). Jetter et al. (2012) provides measurements for a three-stone traditional cookstove combusting wood fuel at high versus low output and minimally versus carefully tended situations. The coverage effect model uses the simple average of these four values, 65825 μg/min, as the median emission rate for TSF-Cs. The median emission rate for LPG-Cs is set by measurements from Edwards (2014) at 730 μg/min (a remarkable 90× lower than TSF-Cs). Both emission rates are lognormally distributed, truncated at 0.5× and 1.5× the medians.

As noted, ventilation rates and house volumes values are resampled only at the start of each simulation, and as a result, each simulation constitutes a different community. The coverage effect model resamples emissions rates for every household daily during the year-long simulations. Resampling attempts to model changes in emission rates owing to host of reasons from fuel quality to number of guests. Even within the same household, emission rates can vary over the course of a day but the coverage effect model disregards this variability. Lognormal distributions characterize many environmental variables (Limpert et al. 2001), hence their use for all four indoor compartment parameters.

The differential equation describing the rate of change per unit time of the indoor $PM_{2.5}$ concentration for household i ($C_{in,i}$) is presented in *Equation 4.1*. The three right-hand terms signify, in sequence, (1) infiltration of outdoor air (C_{out}) at the ventilation rate (α_i), (2) $PM_{2.5}$ emissions from TSF-C or LPG-C ($E_{TSF\text{-}C|LPG\text{-}C,i}$) into the house's volume (V_i), and (3) exfiltration of indoor air out at the ventilation rate (α_i). Implementation of *Equation 4.1* is covered in the next section.

Equation 4.1: Indoor $PM_{2.5}$ Concentrations

$$\frac{dC_{in,i}}{dt} = \alpha_i C_{out} + \frac{E_{TSF\text{-}C|LPG\text{-}C,i}}{V_i} - \alpha_i C_{in,i}$$

Equation 4.1 does not model chimney use or indoor deposition. Chimneys are among the most self-evident of clean cooking interventions but the focus of the coverage effect model is on

LPG-C interventions. Chimneys could be modeled by a fraction, *f*, multiplied by the second term. In that case, $1 - f$ multiplied by the cookstove emission rate would be directly vented outdoors. By assuming that deposition is negligible, the coverage effect model asserts, not unreasonably, that $PM_{2.5}$ removal is dominated by ventilation. Alternatively, deposition could be modeled as a fourth term on the right-hand side of the equation with an appropriate loss rate multiplied by the indoor $PM_{2.5}$ concentration.

Concentrations calculated by *Equation 4.1* represent a mechanistic modeling analog to area monitoring, data which are frequently collected as part of studies on air pollution from household cookfuel combustion.

4.2.3.4. Outdoor Concentrations

The coverage effect model's single-compartment abstraction of a community airshed requires calculating the corresponding volume. The community airshed is intended to represent the volume within which plumes of $PM_{2.5}$, originally emitted by cookstove combustion and eventually emanated by drafty houses, might be reasonably expected to disperse outdoors. The horizontal dimensions of the community airshed are effectively set by residential density. Determining the height of the vertical dimension, however, is a more complicated enterprise.

Single-compartment mass-balance models applied to urban domains rely on atmospheric mixing depths, as reported by meteorological instruments, for setting vertical dimension heights. At such a scale of many kilometers or more, emission plumes gradually disperses to this approximate height. Mixing depths can range from several tens of meters, for example during an atmospheric inversion on a winter early-morning, to several kilometers, for example during an unstable atmosphere on a summer mid-afternoon. However, within a village or slum scale of 50 to 100 m in horizontal distance, emission plumes are very unlikely to rise to the mixing depth. A zeroth order approach might be to assume a constant height to which plumes rise within the community airshed. But there is no obvious way to set such a height beyond the anecdotal or arbitrary. The coverage effect model, instead, relies on the physics of plume rise (Hanna 1982).

Outdoor plume rise can be described by Newtonian equations of motion (Macdonald 2003). Briggs formulated a suite of semi-empirical and semi-mechanistic solutions to the equations of motion for plume rise (Briggs 1975) which have been widely adopted, most prominently by the USEPA Industrial Source Complex (ISC) family of dispersion models (United States Environmental Protection Agency 1995; Schnelle and Dey 2000), the previously widely-used precursor to AERMOD. Recent efforts to model dispersion from amorphous sources such as wildfires (Achtemeier et al. 2011) or pool fires (Fisher et al. 2001) have also leveraged the Briggs Equations. The Briggs Equations require the calculation of a plume's buoyancy and momentum fluxes, coupled with information on environmental conditions, particularly temperature, windspeed, and atmospheric stability class, to calculate the plume's centerline height as a function of distance from the source (see *Appendix B* for full complement of Briggs Equations).

Table 4.1: Model Parameters

#	Parameter	Definition	Units	Distribution	Expectation	Type	Dispersion	Type	Min	Max
1	L	linear dimension (length and width of community)	m	fixed	n/a	n/a	n/a	n/a	50*	100*
2	C_{reg}	background concentration ($PM_{2.5}$ from regional sources)	$\mu g/m^3$	fixed	n/a	n/a	n/a	n/a	10	100
3	α	air exchange rate of house	1/min	lognormal	0.333	median	0.5	COV	0.111	1
4	V	volume of house	m^3	lognormal	30	median	0.5	COV	10	90
5	$E_{TSF\text{-}C}$	$PM_{2.5}$ emission rate for traditional biomass cookstove	μg/min	lognormal	65825	median	0.2	COV	32913	98738
6	E_{LPG}	$PM_{2.5}$ emission rate for liquid petroleum gas cookstove	μg/min	lognormal	730	median	0.2	COV	365	1095
7	T	ambient temperature	°C	triangular	25	mode	8.167	variance	18	32
8	$t_{T_{max}}$	time of maximum ambient temperature	min (time)	uniform	840 (14:00)	mean	1200	variance	780 (13:00)	900 (15:00)
9	U	windspeed	m/min	Weibull	60	mode	30	variance	33.333	100
10	$t_{U_{max}}$	time of maximum windspeed	min (time)	uniform	840 (14:00)	mean	1200	variance	780 (13:00)	900 (15:00)
11	h	height of plume rise	m	calculated parameter see *Section 4.2.3.4* and *Appendix B* for details						

Abbreviations: $PM_{2.5}$ = fine particulate matter; COV = coefficient of variation; hh = households.

Note: *For a community of 100 households, these values correspond to 400 hh/ha or 100 hh/ha, respectively. See *Section 4.2* for sources.

Table 4.2: Model Events

Event	*Definition*	*Units*	*Distribution*	*Expectation*	*Type*	*Dispersion*	*Type*	*Min*	*Max*
cooking start time	time at which emissions begin	min (time)	uniform	360 (06:00) 720 (12:00) 1080 (18:00)	mean	1200	variance	300 (05:00) 660 (11:00) 1020 (17:00)	420 (07:00) 780 (13:00) 1140 (19:00)
cooking duration	duration of emissions	min (time)	uniform	67.5	mean	168.75	variance	45	90
time-activity pattern	individual is outdoors '*x*' minutes after/before cooking event stops/starts*	min (time)	uniform	45	mean	300	variance	30	90

Note: *Individuals are outdoors only between morning and midday meals and between midday and evening meals; otherwise, they are indoors.

In order to employ the Briggs Equations, two simplifying assumptions must be made: (1) the plume is advected by the mean windspeed over its depth and (2) the plume's density is equal to that of ambient air. Two additional assumptions must be made for plumes emanating in the context of the coverage effect model. First, a plume temperature must be established. The value assumed, 313°K (40°C), is based on the observation that cookstove smoke cools significantly while indoors but remains modestly warmer than indoor temperature. Second, an exit velocity must be imputed which, for a volume source such as a household, necessitates an assumption about the area of all vents via which emissions exit. Vent area– doors, windows, and eaves – is assumed to be 2 m^2 for the median house volume of 30 m^3 and scales linearly with volume. It follows that house volume times ventilation rate divided by vent area yields an exit velocity. As an example, the median values of model parameters leads to an exit velocity of 0.083 m/s.

In practice, using the Briggs Equations, of which there are four sets, requires establishing whether atmospheric stability is unstable or stable and whether the plume is buoyancy or momentum dominated. For simplicity, the coverage effect model assumes atmospheric stability is unstable during the day (5 a.m. to 7 p.m.) and stable during the night (7 p.m. to 5 a.m.). Given the slow exit velocity for emissions emanating from drafty houses, plumes are usually buoyancy dominated, the exception being exceptionally hot days. If the distance at which final plume rise occurs is less than the average distance between two randomly selected houses (Mathai et al. 1999), 50 or 25 m in the village or slum residential density scenarios, respectively, then this value is retained. Otherwise, the calculated plume rise at 50 or 25 m is employed.

The Briggs Equations utilize ambient temperature and ground-level windspeed, and the latter variable is also used directly in the differential equation for outdoor $PM_{2.5}$ concentration. The coverage effect model draws on annual daily averages from a 1997 to 2012 time-series of meteorological data for Lucknow (WeatherSpark 2016). Lucknow was chosen because it lies in the approximate geographical center of Uttar Pradesh, the most populous state of India. Extreme values of neither temperature nor windspeed are considered. Instead, sinusoidal patterns during the course of a day allow for high/low temperatures ±7°C relative to the daily average and high/low windspeeds ±50% of the daily average.

Each day's average temperature (T; row #6 in *Table 4.1*) is sampled from a triangular distribution with a mean of 25°C, minimum of 18°C, and maximum of 32°C. These values correspond to Lucknow's annual mean, lowest daily average, and highest daily average temperatures, respectively (WeatherSpark 2016). The diurnal temperature pattern is replicated by a cosine curve from 6 a.m. to 6 p.m. and a linear decline from 6 p.m. to 6 a.m. as proposed by Ephrath et al. (1996). An hour-long adjustment period from 12 a.m. to 1 a.m. harmonizes curves between consecutive days. Maximum temperature occurs sometime between 1 p.m. and 3 p.m. (t_{Tmax}; row #8 in *Table 4.1*), sampled daily from a uniform distribution, and minimum temperature always happens at 6 a.m.

Each day's average windspeed is sampled from a Weibull distribution (Justus et al. 1978) with shape and scale parameters that equate to a mean of 3.6 km/hr (60 m/min), truncated at a minimum of 2.0 km/hr (33.3 m/min) and maximum of 6.0 km/hr (100 m/min). As with temperature, these values correspond to Lucknow's annual mean, lowest daily average, and highest daily average windspeeds, respectively (WeatherSpark 2016). Windspeeds are usually gauged at a reference height of 10 m, so these values are adjusted to ground-level (1.5 m) windspeeds (U; row #9 in *Table 4.1*) by employing a logarithmic wind profile with a roughness length of 0.2 m (Gowen et al. 2004). The diurnal wind pattern is replicated by a cosine curve as proposed by Guo et al. (2016). Again, as with temperature, an hour-long adjustment period from 12 a.m. to 1 a.m. harmonizes curves between consecutive days. Maximum windspeed happens sometime between 1 p.m. and 3 p.m. ($t_{U_{max}}$; row #10 in *Table 4.1*), sampled daily from a uniform distribution, and minimum windspeed occurs twelve hours prior.

Both temperature and windspeed, it should be noted, exert dual opposing influences on plume rise. The consequent impacts on $PM_{2.5}$ concentration are not easy to unravel. Ambient temperature and plume buoyancy have an inverse relationship. As temperature declines, buoyancy enhances, so plumes rises higher (and vice versa). But at lower temperatures, atmospheric inversions are more likely. Inversions cap the height of plumes from regional sources, thereby boosting background concentration. With wind, higher windspeeds evacuate plumes from the community airshed more rapidly, but in doing so, limit the time available for plumes to rise. Conversely, lower windspeeds allow plumes to persist longer within the community airshed, but as a result, plumes also rise higher and dilute within a larger volume.

Plume rise, as ascertained by the Briggs Equations, is the centerline height above the emission source. So, the height of the emission source must be added to the result of the Briggs Equations. The coverage effect model uses 1.5 m, the midpoint of a single story hut, as the height of all emission sources. Additionally, the vertical dispersion of the plume, which entrains ambient air, expanding as it rises, must also be added to the result. The coverage effect model relies on the power law specification of the vertical dispersion coefficients for a Gaussian plume model to calculate this additional height (Turner 1970; United States Environmental Protection Agency 1995). There are separate dispersion coefficient curves for each of the six Pasquill-Gifford (P−G) atmospheric stability classes (Gifford 1961; Pasquill 1961). For simplicity, the coverage effect assumes daytime (5 a.m. to 7 p.m.) atmospheric stability is consistently P-G class B or moderately unstable, and nighttime (7 p.m. to 5 a.m.) atmospheric stability is consistently P-G class D or slightly stable (see *Appendix B* for equations to calculate vertical dispersion coefficients).

Based on procedure just explained, the vertical dimension of the community airshed (h; row #11 in *Table 4.1*), recalculated at each time-step, varies from ~5 m to ~17 m for the village residential density and from ~4 m to ~16 m for the slum residential density. The three-to-four-fold difference between low and high heights stresses the importance of plume rise to outdoor $PM_{2.5}$ concentration at a sub-kilometer scale.

The differential equation describing the rate of change per unit time of outdoor $PM_{2.5}$ concentration for the community airshed (C_{out}) is presented in *Equation 4.2*. The four right-hand terms signify, in sequence, (1) inflow of background concentration from regional sources of $PM_{2.5}$ (C_{reg}) at the exchange rate of ground-level windspeed (U) over linear dimension (L), (2) emissions vented by all households (summation from i = 1 to 100 of $\alpha_i V_i C_{in,i}$) and diluted by community airshed volume (L^2h), (3) outflow of community airshed $PM_{2.5}$ at the exchange rate of ground-level windspeed over linear dimension, and (4) dilution of community airshed $PM_{2.5}$ by incremental growth of community airshed height ($1/h \times dh/dt$). The ϕ acts as a binary switch to address expansion and contraction of the vertical dimension of the community airshed (Stevens et al. 2007). If height is increasing, ϕ is unity. Otherwise, ϕ is zero, preventing $PM_{2.5}$ from being artificially condensed because height decreases.

Equation 4.2: Outdoor $PM_{2.5}$ Concentration

$$\frac{dC_{out}}{dt} = \frac{U}{L} C_{reg} + \frac{\sum_{i=1}^{100} \alpha_i V_i C_{in,i}}{L^2 h} - \frac{U}{L} C_{out} - C_{out} \phi \frac{1}{h} \frac{dh}{dt}$$

In implementation, there is one *Equation 4.1* per household, each of which is coupled to *Equation 4.2*. All equations are numerically integrated using Euler's Method. Comparisons to simulations using the analytical solution and fourth-order Runge-Kutta Method reveal discretization errors between these three approaches are less than 1%. The combination of the coverage effect model's one-minute time-step and 50 or 100 m linear domain prevents it from handling sustained high windspeeds events (Lakshmanan et al. 2009) during which the residence time of an air parcel drops below the time-step.

Concentrations calculated by *Equation 4.2* represent a mechanistic modeling analog to ambient monitoring, data which, at present, are infrequently collected as part of studies on air pollution from household cookfuel combustion.

4.2.3.5. Exposures

Time-activity patterns and indoor/outdoor concentrations are tracked on a minute-by-minute basis. Combining this information yields the exposure for each individual, equivalent to the time-weighted average of concentrations experienced indoors and outdoors. Formally, exposure is expressed as the average annual $PM_{2.5}$ concentration experienced by an individual.

Exposures calculated in this fashion represent a mechanistic modeling analog to personal monitoring, data which are often collected as part of studies on air pollution from household cookfuel combustion. Personal monitoring, however, is less common than area monitoring, since adherence to continually wearing cumbersome equipment can be taxing.

4.2.4. Coverage Effect Model − Core Assumption

The core assumption of a mass-balance modeling approach is that pollution instantaneously and homogenously mixes within a compartment, be that compartment a household or a community. Most apparently, concentrations would be, in reality, higher closer to sources (cookstoves or TSF-C-using households). Complicated wind-flow fields, as discussed in *Section 4.2.1*, introduce further heterogeneity. But the well-mixed assumption leads to several additional complications to consider.

For the household-level model, the ratio of personal exposure to area concentration is assumed to be simply unity for all inhabitants. Field studies which simultaneously conducted both personal and area monitoring found varying ratios between these two measures for different age-sex subpopulations: 0.24 to 1.02 for women, 0.39 to 0.84 for children, and 0.27 to 0.85 for men (Balakrishnan and Mehta 2014). Since subjects do not remain in one micro-environment all the time, however, these results do not necessarily violate the ratio of one assumption. A related issue is that women tending cookstoves would be expected to experience higher exposures than children or men. Field studies which simultaneous monitored personal exposure for both women and children have not arrived at a consistent conclusion about the magnitude of differences between the two groups (e.g., Smith et al. 2010; Baumgartner et al. 2011). The pooled analysis of Balakrishnan and Mehta (2014) suggests that the global average of children's exposure to $PM_{2.5}$ may be, on balance, ~80% that of women's. Certainly, each age-sex subpopulation's exposure will be differentially influenced by complex interactions between household-level variables and time-activity profiles in a site-specific fashion. Although field studies suggest that children's personal exposures may well be less than either area concentrations or women's personal exposures, the model makes no compensatory adjustment given continued uncertainty about why − including where, when, and to what degree − these measures differ.

For the community airshed-level model, the well-mixed assumption equates to a "spatially implicit" conceptualization with regards to household location. Households are spatially linked insofar as they share the community airshed. But, besides assigning a residential density to a community, the model ignores the precise location of households relative to one another. Within the community airshed, just as within a house, all locations are equivalent with respect to $PM_{2.5}$ concentrations. As a result, at least three additional assumptions underpin the model's spatially implicit structure. Firstly, households using TSF-C and LPG-C are uniformly distributed within the community such that there are no clusters of high or low emissions households. Secondly, wind direction varies more-or-less uniformly over all compass points such that there is no distinction between upwind and downwind houses. Thirdly, individuals do not preferentially spend time outdoors in areas with low or high emissions, for instance mostly upwind or downwind or primarily proximate to households using TSF-C or LPG-C. Clearly, these assumptions are unlikely to uphold in most, if not all, locations and situations but provide a starting point for analysis.

Alternatively, this trio of assumptions could be relaxed and replaced by a different interpretation. For exposures conveyed via the shared community airshed, the model reproduces the average experience of individuals. In other words, the model acknowledges that concentrations are higher near clusters of TSF-C-use and downwind areas, lower near clusters of LPG-C-use and upwind areas, and intermediate in between. These distinctions are smoothed out by imposing a mean concentration field on the outdoor compartment.

For the coverage effect model, several of its features may partially but not fully alleviate shortcomings with the spatially implicit suite of assumptions. Simulations are run over the course of one year. Furthermore, each simulation represents a unique community and each scenario-coverage combination is simulated 1000 times. Both the long averaging times of individual simulations and large number of total simulations may attenuate the magnitude of heterogeneities in exposures. Nevertheless, no approach fully avoids spatial indeterminancy (Kwan 2012). It remains imperative to recall that the coverage effect model does not aspire to fully recreate reality, but rather, merely distill the more salient features of an idealized system, relevant to a postulated coverage effect, into a tractable form for analysis.

4.3. Results & Discussion

The coverage effect model emphasizes four scenarios which differ from one another in residential density and/or background concentration (see *Section 4.2.3.1*). For ease of discussion in this section, the scenarios are designated by the letters A−D as in *Table 4.3*.

Table 4.3: Scenario Letter Designations

	Low Emission Regional Sources	**High Emission Regional Sources**	
Village	Scenario A	Scenario B	**Residential Density 100 hh/ha**
Slum	Scenario C	Scenario D	**Residential Density 400 hh/ha**
	Background Concentration 10 μg/m^3	**Background Concentration 100 μg/m^3**	

Also recall that each model iteration represented a unique community that experienced simulations at each coverage level increment for one year at a time. One thousand iterations of each scenario produced the ensemble distributions of results covered in this section.

4.3.1. Concentrations

Figures 4.1A−D present box plots by coverage level for annual average $PM_{2.5}$ concentrations in three environments: indoors for households using either LPG-Cs (top panel) or TSF-Cs (middle panel), and outdoors (bottom panel). Letters designations correspond to scenarios. Results are the equivalent of year-long area monitoring in all three environments.

In all scenarios, for each additional increment of coverage, $PM_{2.5}$ concentrations improve modestly for indoor LPG-C environments and outdoors, whereas they remain high and seemingly less diminished for indoor TSF-C environments. (Note the different scales for the middle panel versus the top and bottom panels.) In all three environments, the declines are roughly linear. Since concentrations decrease as a function of coverage, these results lend credence to the emergence of a coverage effect.

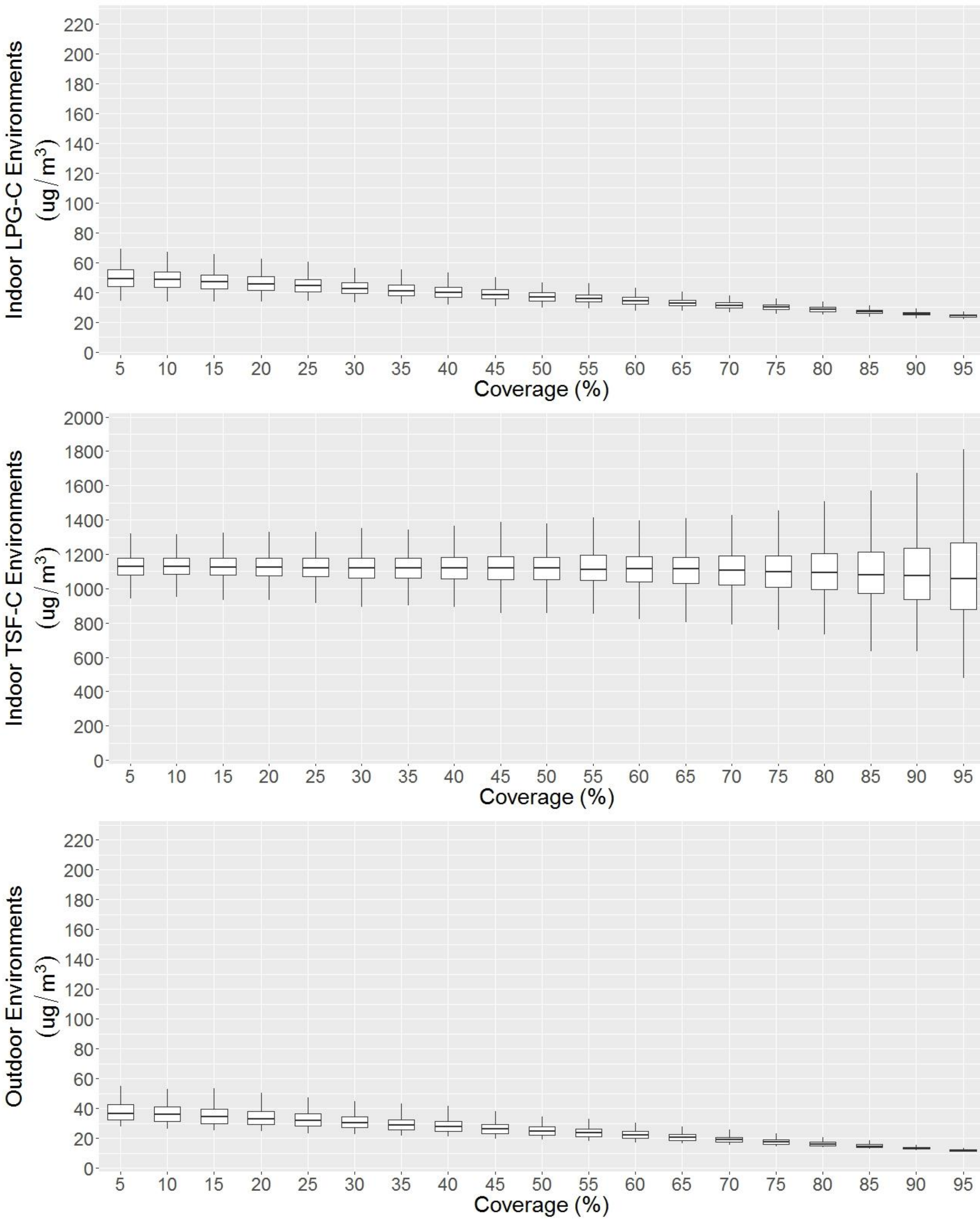


Figure 4.1A: Annual Average $PM_{2.5}$ Concentrations by Coverage − Scenario A. For scenario A, residential density is 100 hh/ha and background concentration is 10 µg/m^3. For each box plot, medians are represented by the middle dark segment, 75th and 25th percentiles by top and bottom hinges, respectively, and 97.5th and 2.5th percentiles by top and bottom whiskers, respectively. Indoor LPG-C (top panel) and outdoor (bottom panel) environments share the same y-axis scale, whereas indoor TSC-C (middle panel) uses a different y-axis scale. These y-axis scales are consistent across *Figures 4.1A−D*.

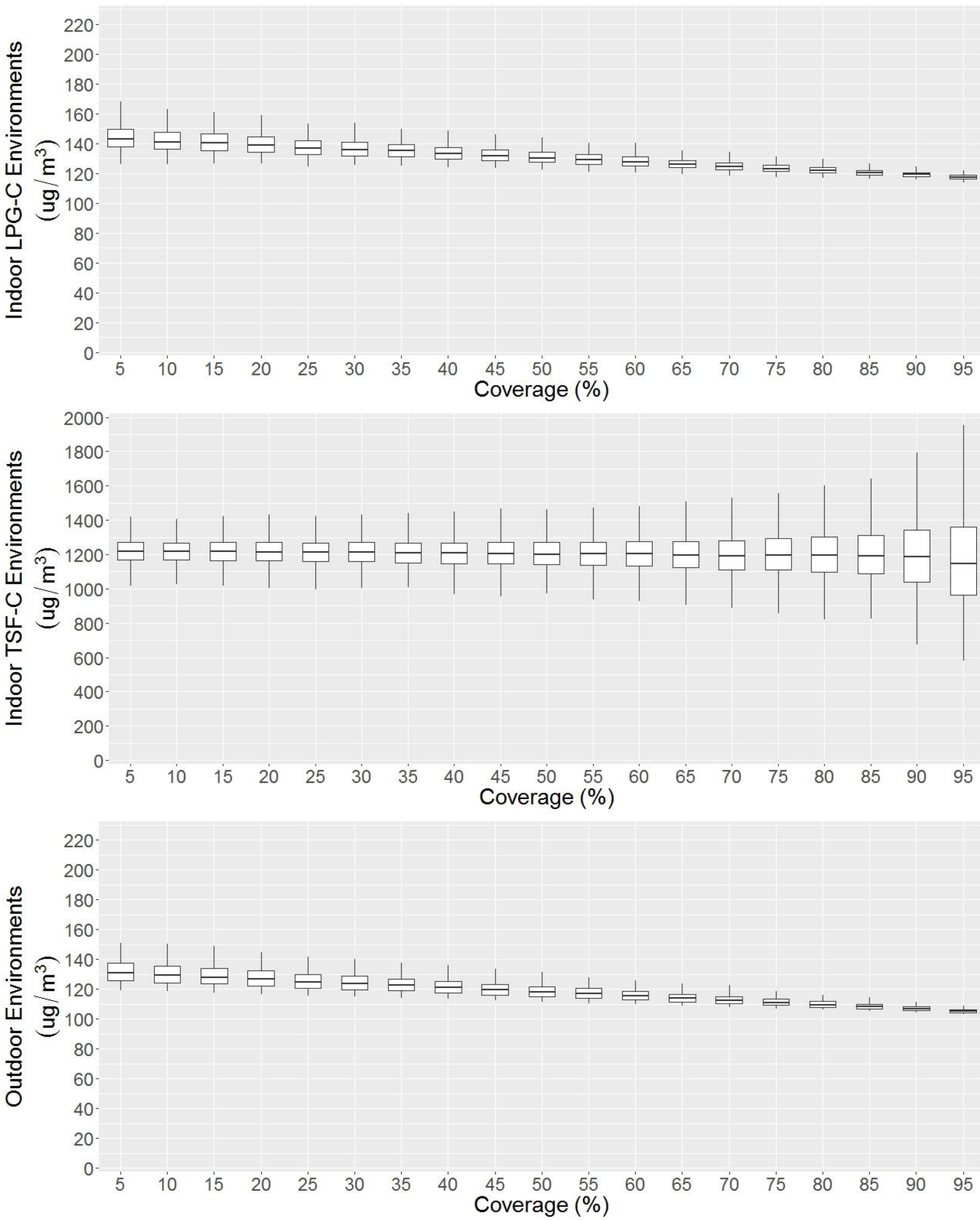


Figure 4.1B: Annual Average $PM_{2.5}$ Concentrations by Coverage − Scenario B. For scenario B, residential density is 100 hh/ha and background concentration is 100 µg/m^3. For each box plot, medians are represented by the middle dark segment, 75th and 25th percentiles by top and bottom hinges, respectively, and 97.5th and 2.5th percentiles by top and bottom whiskers, respectively. Indoor LPG-C (top panel) and outdoor (bottom panel) environments share the same y-axis scale, whereas indoor TSC-C (middle panel) uses a different y-axis scale. These y-axis scales are consistent across *Figures 4.1A−D*.

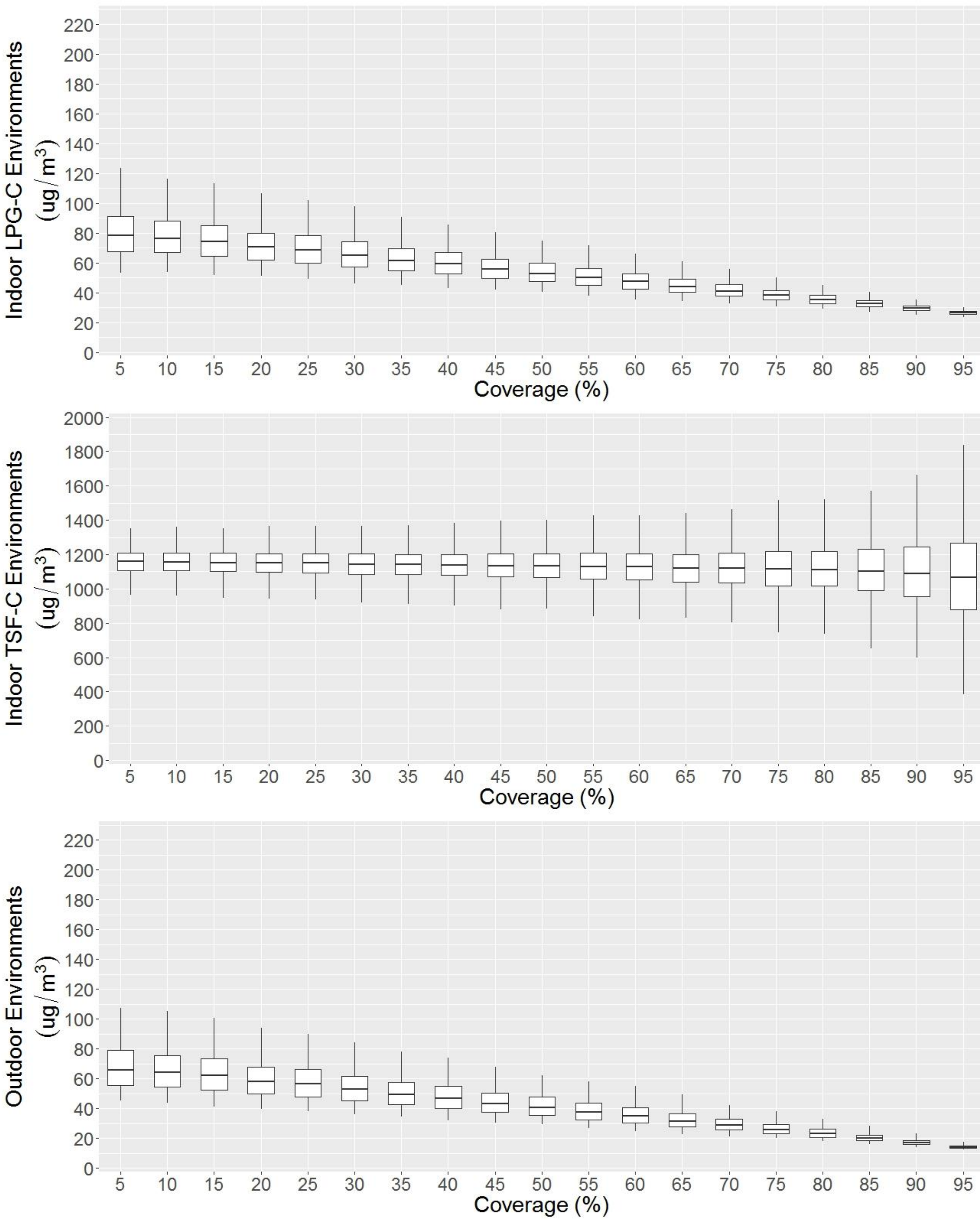


Figure 4.1C: Annual Average $PM_{2.5}$ Concentrations by Coverage − Scenario C. For scenario C, residential density is 400 hh/ha and background concentration is 10 μg/m^3. For each box plot, medians are represented by the middle dark segment, 75th and 25th percentiles by top and bottom hinges, respectively, and 97.5th and 2.5th percentiles by top and bottom whiskers, respectively. Indoor LPG-C (top panel) and outdoor (bottom panel) environments share the same y-axis scale, whereas indoor TSC-C (middle panel) uses a different y-axis scale. These y-axis scales are consistent across *Figures 4.1A−D*.

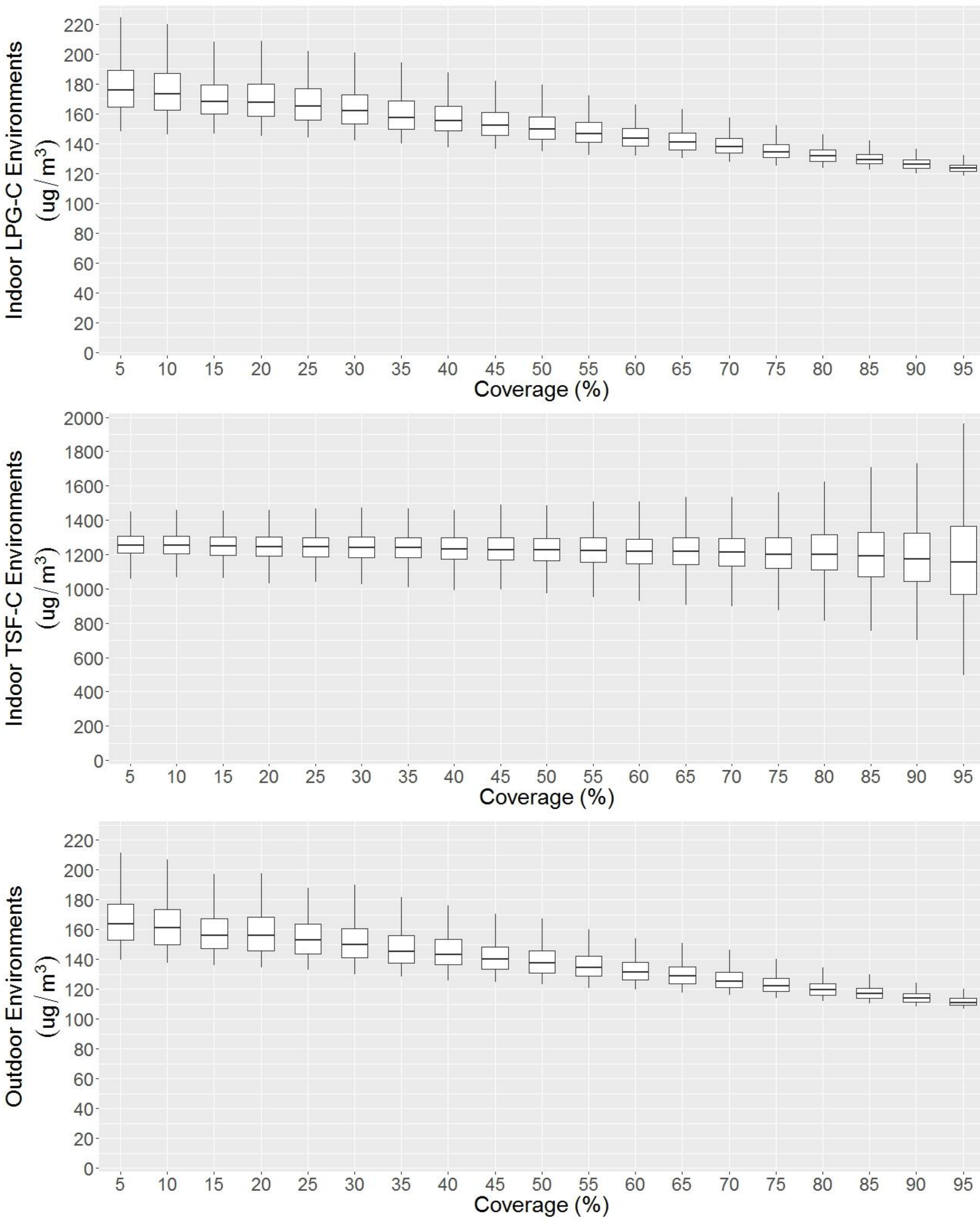


Figure 4.1D: Annual Average $PM_{2.5}$ Concentrations by Coverage − Scenario D. For scenario D, residential density is 400 hh/ha and background concentration is 100 μg/m^3. For each box plot, medians are represented by the middle dark segment, 75th and 25th percentiles by top and bottom hinges, respectively, and 97.5th and 2.5th percentiles by top and bottom whiskers, respectively. Indoor LPG-C (top panel) and outdoor (bottom panel) environments share the same y-axis scale, whereas indoor TSC-C (middle panel) uses a different y-axis scale. These y-axis scales are consistent across *Figures 4.1A−D*.

Table 4.4 focuses on mean results at the extremes of coverage. As communities transition from 5% to 95% coverage, mean annual average $PM_{2.5}$ concentrations in all three environments drop by similar amounts for scenarios A and B or for scenarios C and D. In absolute terms, the declines are greater for scenarios C and D than scenarios A and B. Residential density is higher for scenarios C and D. As a result, increasing coverage levels within these communities has a proportionately larger effect within the smaller volumes of these community airsheds, which are therefore more "shared." It follows that the slope, or decrease in concentration per unit increase in coverage, is steeper in scenarios C and D.

Table 4.4: Mean Annual Average $PM_{2.5}$ Concentrations

Coverage	*Indoor LPG-C*	*Indoor TSF-C*	*Outdoor*	*Indoor LPG-C*	*Indoor TSF-C*	*Outdoor*	↙(µg/m^3)
5%	A 50 (7.2)	1132 (73)	38 (6.6)	B 144 (8.1)	1222 (75)	132 (7.5)	**Residential Density 100 hh/ha**
95%	24 (1.0)	1100 (306)	12 (0.5)	118 (1.5)	1205 (329)	106 (1.3)	
Percent Difference	51%	3%	68%	18%	1%	20%	
5%	C 80 (14.7)	1159 (73)	68 (14.2)	D 178 (16.2)	1258 (74)	164 (15.9)	**Residential Density 400 hh/ha**
95%	27 (1.3)	1113 (320)	14 (1.1)	124 (2.8)	1199 (314)	111 (2.9)	
Percent Difference	67%	4%	79%	30%	5%	33%	
	Background Concentration 10 µg/m^3			**Background Concentration 100 µg/m^3**			

Note: Letters in upper-left of each quadrant correspond to scenario letter designations. Standard deviations are in parentheses.

In relative terms, the declines from 5% to 95% coverage are greater for scenarios A and C than scenarios B and D. The lower background concentrations for scenarios A and C translate into smaller denominators for calculating proportional impacts. For scenarios A and C, this floor is sufficiently low that average communities at 95% coverage approach the WHO's Interim-2 $PM_{2.5}$ guideline (25 µg/m^3) within indoor LPG-C environments and attaint the Interim-3 $PM_{2.5}$ guideline (15 µg/m^3) in outdoor environments (World Health Organization 2006). Indoor TSF-C environments, with mean concentrations above 1000 µg/m^3 in all scenarios and at all coverage levels, cannot benefit as much, in relative terms, from coverage effects in the tens of µg/m^3, even though such benefits do materialize to a similar extent, in absolute terms, as those in indoor LPG-C environments.

4.3.1.1 Variability

The presentation of concentration results lends itself to a discussion of model variability. Distributions for all three environments are unimodal and somewhat positively/right skewed in all cases. Means are slightly greater than medians, but not strictly due to the skew, a commonplace but erroneous conclusion owing to an outdated rule-of-thumb (von Hippel 2005). In any case, the trends for medians, plotted in *Figures 4.1A−D*, differ subtly from those for underlying means, which are listed for 5% and 95% coverage in *Table 4.4*.

Sampling across parameter distributions drawn, as much as possible, from South Asian contexts was a deliberate modeling choice intended to capture the spectrum of conditions such as they may exist. Distributions of model results thereby attempt to approximate the range of outcomes which might be expected in the real world. This variability, therefore, does not correspond to error, uncertainty, or other unexplained "noise." On the contrary, in appraising model results, variability informs the generalizability of central values by characterizing the frequency with which other outcomes may be realized. The distributions for concentrations displayed in *Figures 4.1A−D* suggest that a coverage effect may be rather difficult to discern for indoor TSF-C environments. Conversely, for indoor LPG-C and outdoor environments, enhanced benefits from a coverage effect may be more easily discernable, more so for scenarios C and D than scenarios A and B, but in all cases with greater likelihood at larger differences in coverage.

Both *Figures 4.1A−D* and *Table 4.4* show that as coverage expands for the model's communities, variability in annual average $PM_{2.5}$ concentrations for indoor TSF-C environments also widens substantially. The reverse occurs for indoor LPG-C and outdoor environments. Variability is wider at higher coverage levels for indoor TSF-C environments because there are fewer TSF-C-using households. Extreme values in the sampling of parameter distributions, particularly emission rates and cooking durations, become relatively more influential. For the outdoor environment, variability narrows at higher coverage levels because, although a single TSF-C-using household contributes more to ambient $PM_{2.5}$ concentrations than its LPG-C-using counterpart, the proportionate contribution via exfiltration from indoor TSF-C environments diminishes. Narrower variability in indoor LPG-C environments at higher coverage levels is explained by the greater number of households using LPG-Cs and the variability trend in outdoor environments.

4.3.1.2. Validity

Concentration results provide opportunity to qualitatively validate the coverage effect model. Because ambient air pollution (AAP) is rarely monitored in rural villages, modeled concentrations for the outdoor compartment can only be validated against field measurements from urban slums. To my knowledge, there are no pooled estimates from multiple studies, so I rely instead on reports from two publications. The previously discussed study on a Delhi slum by Saksena et al. (2003) measured outdoor respirable particulate matter during 4-hour sampling periods, observing concentrations of 150−380 $\mu g/m^3$. Also working in a Delhi slum, Kulshreshtha et al. (2008) monitored outdoor $PM_{2.5}$ during 6-hour sampling periods, finding concentrations of 53−287 μg/m^3. The best point of comparison against these measured results are the modeled results for scenario D, for which concentrations are 111 μg/m^3 and 164 μg/m^3 at 95% and 5% coverage, respectively. On the basis of these limited comparisons, measured and modeled results seem to roughly agree.

Modeled concentrations for indoor environments can be validated against pooled estimates of field measurements for 24-48 hour kitchen concentrations as reported for the World Health Organization's Southeast Asia Region (Balakrishnan and Mehta 2014), the region providing many model parameters. The measured results, by drawing on data from multiple studies, span a range of residential densities, background concentrations, and other relevant factors. Since it is unclear which of the model's coverage levels would be most appropriate for comparison, I have chosen to use the range of modeled results for 5% and 95% coverage levels across all four scenarios. This choice thereby encompasses maximum and minimum coverage effects.

For LPG-C indoor environments, modeled results are 24−124 μg/m^3 versus a measured result of 72 μg/m^3 (standard deviation = 41 μg/m^3). For TSF-C indoor environments, modeled results are 1132−1258 μg/m^3 versus a measured result of 826 μg/m^3 (standard deviation = 1038 μg/m^3) . Hence, there appears to be broad concordance between modeled and measured results for indoor LPG-C environments. But for indoor TSF-C environments, modeled results are perhaps one-third higher than measured results.

Although the source of the discrepancy is undoubtedly multifactorial, aspects of model parameterization may warrant re-examination, especially household characteristics and TSF-C emission rates. The single-compartment specification and well-mixed assumption of the coverage effect model may also merit re-evaluation. Since the indication is that the coverage effect model overestimates indoor TSF-C $PM_{2.5}$ concentrations, an alternative formulation might immediately vent the initially most buoyant fraction of TSF-C emissions to the outdoors. The effect of doing so would be to elevate outdoor concentrations, a portion of which would again contribute to indoor concentrations but to a lesser extent.

The discrepancy between modeled and measured results for indoor TSF-C environments is not sufficiently vast so as to militate against use of the coverage effect model as currently developed. Pooled estimates of field measurements, after all, exhibit a wide standard deviation. The measured results include multiple-room households and other locations and situations for which lower concentrations, compared to the system simulated by the coverage effect model, would be expected. The model does perform acceptably for indoor LPG-C and outdoor environments, though the possibility that this agreement may be merely coincidental cannot be dismissed. For indoor TSF-C and LPG-C environments, the coverage effect model concurs with the modeled results of Johnson et al. (2011) and Johnson (2014). For these reasons, and given the exploratory nature of the modeling exercise, I proceed, mindful that further calibration and validation of the coverage effect model will be requisite for application to specific settings and circumstances.

4.3.2. Exposures

Combining time-activity patterns with concentrations in different environments enables calculation of exposures. *Figures 4.2A-B* and *4.2C-D* present violin plots by coverage level for annual average $PM_{2.5}$ exposure, measured in the same units as concentration ($\mu g/m^3$), for individuals (women and children) living in households using either LPG-C (left-hand panels) or TSF-C (right-hand panels). Once again, letters designations correspond to scenarios. The width of the violin plot conveys the distribution's density, akin to a histogram sliced in half. Results are the equivalent of year-long personal monitoring of individuals.

As with concentrations, for each additional increment of coverage, $PM_{2.5}$ exposures improve moderately for individuals living in households using LPG-C ("LPG-C users"), whereas $PM_{2.5}$ exposures remain high and ostensibly less diminished for individuals living in households using TSF-Cs ("TSF-C users"). Note the different scales for the left-hand versus right-hand panels. In both cases, the declines are approximately linear. In all scenarios, exposures diminish as coverage expands, and thus these results evidence a coverage effect.

4.3.2.1. Causal Inference for Coverage Effects

These results, at first glance, appear to enable easy estimation of intervention efficacy as measured by reductions in $PM_{2.5}$ exposures. In order to better interpret what these findings truly measure, an appreciation of the relevant principles of causal inference will prove helpful. Generically, estimating the causal relationship between a treatment (e.g., a clean cooking technology) and an outcome (e.g., exposure to $PM_{2.5}$) is accomplished by comparing units (individual, households, communities, etc.) receiving the treatment ("users," e.g., LPG-C users) with those not receiving the treatment ("non-users" or "controls," e.g., TSF-C users). A fundamental assumption accompanies such a comparison − the potential outcomes of units are unaffected by the treatment assignment of other units. This is the so-called stable unit treatment value assignment (SUTVA) assumption (Rubin 1990), also known as the stability assumption (Halloran and Struchiner 1995), underpinning the Neyman-Rubin theory of causal inference prevalent in epidemiology and many other disciplines (Neyman 1923; Rubin 1974; Holland 1986).

The SUTVA assumption obviously does not hold for contexts in which treatment effects spread between units connected by environmental features or social networks − "dependent happenings" as aptly coined a century ago (Ross 1916). If the effect of an intervention disperses between units assumed to be independent, then an estimate of efficacy based on an uncritical comparison of users and non-users will be biased (Eisenberg et al. 2003). Violations of SUTVA, referred to as interference (Cox 1958), may be viewed as a flaw to be avoided or neutralized through compensatory strategies in study design or data analysis. Or, interference may also create effects of interest.

The canonical example of worthwhile interference from an intervention – a coverage effect in the parlance of this chapter − is herd immunity from vaccination programs (Fine 1993). As discussed in *Chapter 3*, infectious diseases are intrinsically dependent happenings because the incidence of infection depends on the prevalence of infection. Thus, beyond vaccination,

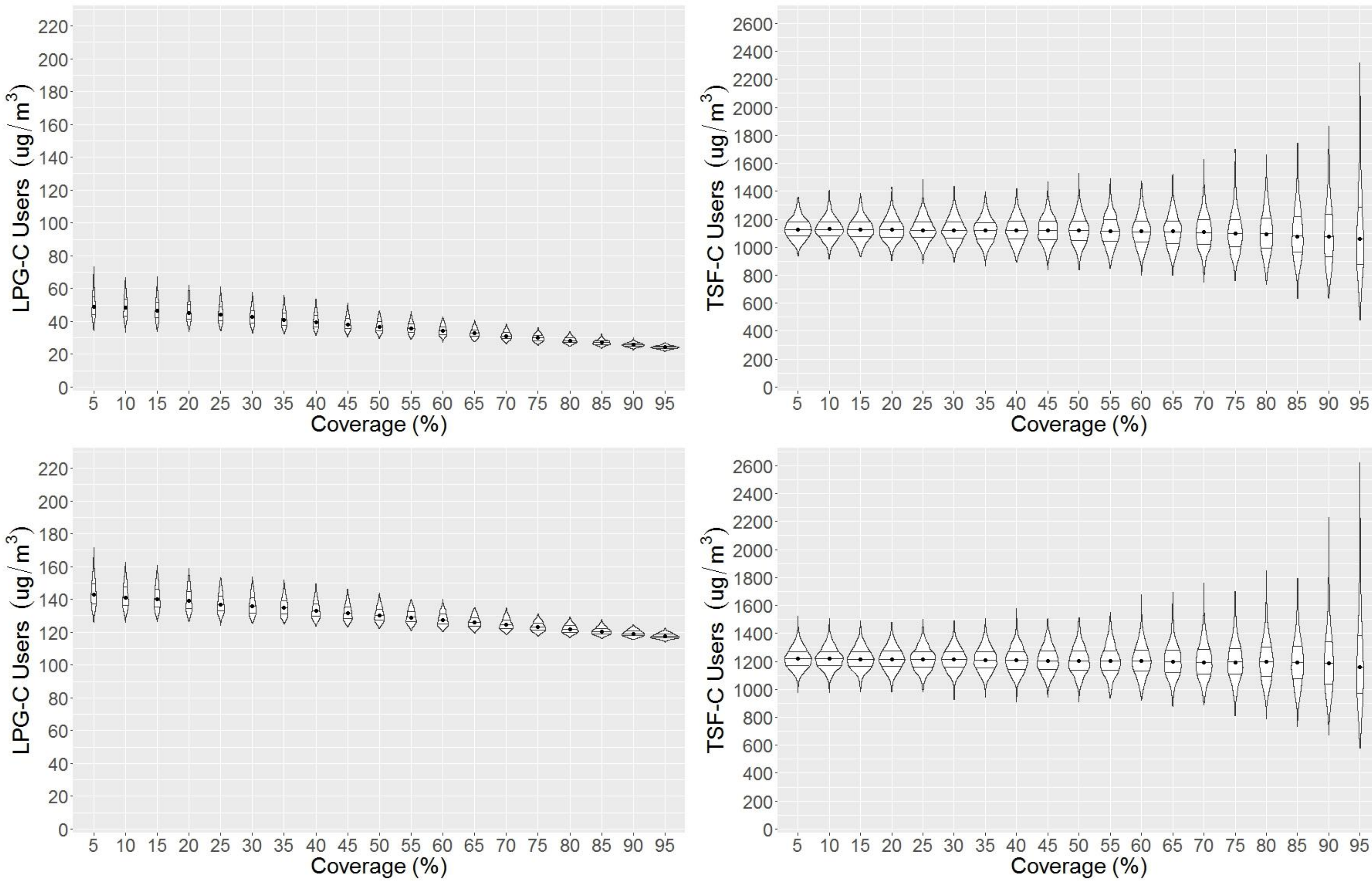


Figure 4.2A-B: Annual Average $PM_{2.5}$ Exposure by Coverage − Scenarios A and B. For scenarios A (top panels) and B (bottom panels), background concentrations are 10 and 100 μg/m^3, respectively. Residential density is 100 hh/ha for both scenarios. For each violin plot, medians are represented by the middle dark dot, 75th and 25th percentiles by top and bottom segments, respectively, and 97.5th and 2.5th percentiles by top and bottom tips, respectively. Left and right panels use different y-axis scales. These y-axis scales are consistent across *Figures 4.2A−D*.

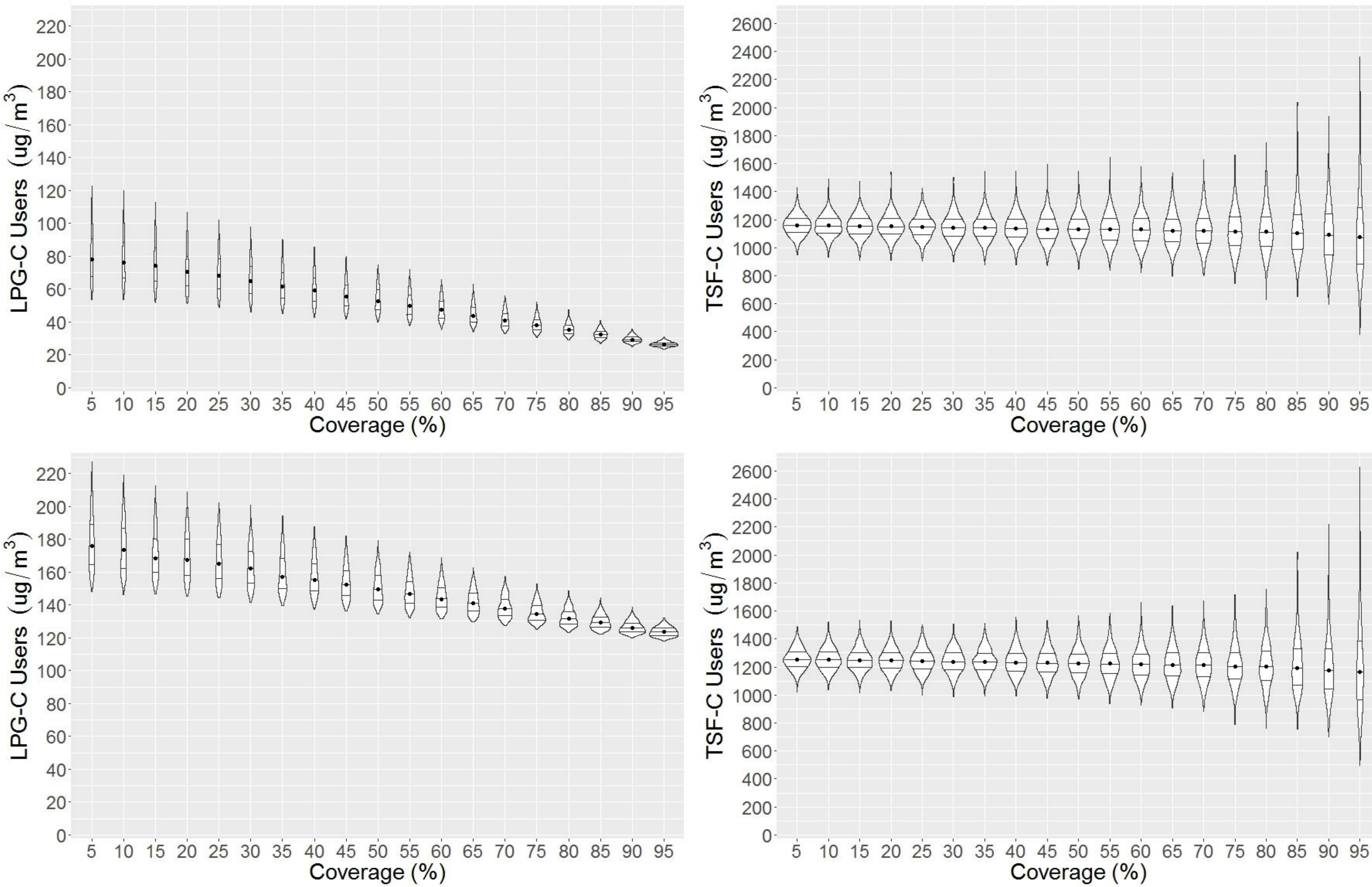


Figure 4.2A-B: Annual Average $PM_{2.5}$ Exposure by Coverage − Scenarios C and D. For scenarios C (top panels) and D (bottom panels), background concentrations are 10 and 100 µg/m3, respectively. Residential density is 400 hh/ha for both scenarios. For each violin plot, medians are represented by the middle dark dot, 75th and 25th percentiles by top and bottom segments, respectively, and 97.5th and 2.5th percentiles by top and bottom tips, respectively. Left and right panels use different y-axis scales. These y-axis scales are consistent across *Figures 4.2A−D*.

several other interventions targeting infectious diseases reveal coverage effects. Experimental and observational studies have suggested that expanding community-level coverage of insecticide-treated bednets (ITNs) for malaria control enhances protection for users and non-users alike (Howard et al. 2000; Hawley et al. 2003; Klinkenberg et al. 2010; Larsen et al. 2014). Similarly, field studies have proposed that community-level coverage of sanitation can help explain stunting and wasting (Spears et al. 2013; Andres et al. 2014; Fuller et al. 2016), diarrheal disease (Root 2001; Genser et al. 2006; Barreto et al. 2007), and infant mortality (Geruso and Spears 2015). Coverage effects have been explored widely with respect to interventions targeting water, sanitation, and hygiene (WSH; Eisenberg et al. 2012; Wolf et al. 2014; Ejemot-Nwadiaro et al. 2015). This is a complex realm, and mixed or null results have also been reported (Mausezahl et al. 2009; Clasen et al. 2014; Patil et al. 2014), perhaps highlighting the value of devoting due attention to location and situation specific nuances.

Environmental proximity is not the only conduit of interference. Interventions that target "contagious" behaviors may give rise to coverage effects transmitted by social proximity (Christakis and Fowler 2009). In fact, many of the social sciences have contemplated coverage effects¸ including education (Rosenbaum 2007), political science (Sinclair et al. 2012), and in particular, economics (Manski 1993; Sobel 2006). Economists have long recognized the significance of externalities, a similar but broader concept than interference in several regards. Just as externalities can be either positive or negative, interference may also be beneficial or harmful. Coverage effect, as defined in this chapter, is strictly beneficial interference attributable to an intervention. On the other hand, the contribution of a household's TSF-C use to its neighbors' $PM_{2.5}$ exposures could be regarded as harmful interference or a negative externality. In fact, AAP is such a classic instance of a negative externality that it is taught as such in undergraduate textbooks (Tietenberg 1992). Economics teaches that negative externalities can be discouraged by compensatory or punitive measures such as taxes or regulation, whereas positive externalities can be encouraged through subsidies (Baumol and Blinder 1988). Heretofore, HAP has not been viewed in this light. I do not pursue this line of reasoning further but simply note the idea may deserve further deliberation.

Comparing LPG-C and TSF-C users within any scenario-coverage combination would seem to characterize the efficacy of the intervention in reducing $PM_{2.5}$ exposures for LPG-C users. And in practice, intervention efficacy is often measured this way. However, should a coverage effect be prevalent, this comparison actually measures both the reduction in exposure from household-level LPG-C use and an additional reduction in exposure from community-level LPG-C use. Disentangling the effect of the intervention at the household-level from the effect of the intervention program at the community-level requires a different approach (Hayes et al. 2000; Hudgens and Halloran 2008; van der Laan 2014).

Much as there are compensatory strategies for avoiding or neutralizing interference, there are also techniques for deliberately bringing into relief effects of interest born by "spillovers," yet another term for interference (Benjamin-Chung et al. 2015). This is not merely an academic exercise but an undertaking to understand the full impact of an intervention. In an influential exposition, Halloran and Struchiner (1991) extended the potential outcomes framework to encompass dependent happenings by defining comparisons that enable estimation of an intervention's direct effect, indirect effect, and total effect.

I will use the LPG-C intervention program simulated by the coverage effect model to define this trio of effects. Direct effect is the difference between the outcomes in LPG-C users and what the outcomes would have been had the LPG-C users been TSF-C users, without any other change to the intervention program including coverage level. A direct effect is what a straight comparison between LPG-C and TSC-F users in the same community would estimate. Indirect effect is the difference between the outcomes in TSF-C users and what the outcomes would have been for TSF-C users had there been no intervention program in the community at all. An indirect effect, as Halloran and Struchiner (1991) refer to it, if beneficial, is equivalent to this chapter's coverage effect. Although the most efficient method to calculate a coverage effect involves comparing TSF-C users (for other strategies, see Haber 1999), LPG-C users also experience an equivalent coverage effect. Total effect is the difference between the outcomes in LPG-C users and what the outcomes would have been had LPG-C users been TSF-C users without there being an intervention program in the community. A total effect is the sum of a direct effect and a coverage effect. The referent group for estimating coverage and total effects is realized by the modeling exercise through the 0% coverage level, or theoretical counterfactual, simulated in all iterations.

4.3.2.2. Coverage Effects from LPG-C Interventions

Table 4.5 focuses on mean annual average $PM_{2.5}$ exposures for LPG-C and TSF-C users at select coverage levels: 0%, 5%, 25%, 50%, 75%, 95%, and 100%. *Table 4.5* includes estimates for total, direct, and coverage effects based on the procedure outlined in the previous section. Variability in model results means that estimates for this trio themselves vary, but trends are clear and disaggregating effects permits a number of insights.

Contrasting coverage effects among the four scenarios, *Table 4.5* reveals the pattern noted for concentration results and the same explanation applies here. Higher residential density facilitates a coverage effect in absolute terms, whereas elevated background concentration dampens a coverage effect in relative terms. Among the four, scenario B, with its lower density and higher background, experiences the smallest coverage effect.

As would be expected, for individuals living in a household which switches from TSF-C to LPG-C, the vast bulk of their consequent reduction in exposure to $PM_{2.5}$ is caused by the direct effect, or their household-level LPG-C use. Nevertheless, as coverage expands within the community, the coverage effect increases, signaling the progressively growing importance of community-level LPG-C use to exposure reduction for LPG-C users. For the average LPG-C user in scenarios A−D, as coverage goes from 5% to 95%, the coverage effect contributes an additional exposure reduction of, roughly, 50%, 20%, 70%, or 30%, respectively. For a household already using LPG-C, the coverage effect may be quite substantial.

Table 4.5: Mean Annual Average $PM_{2.5}$ Exposures and Coverage Effects

Coverage	LPG-C Users	Total Effect	Direct Effect	Coverage Effect	TSF-C Users	LPG-C Users	Total Effect	Direct Effect	Coverage Effect	TSF-C Users	↙(µg/m³)
0%	A				1133	B				1222	
5%	50	1083	1082	2	1132	144	1078	1078	1	1221	
25%	45	1088	1081	7	1126	138	1085	1078	6	1216	Residential Density 100 hh/ha
50%	37	1096	1083	13	1120	131	1091	1078	14	1208	
75%	30	1103	1077	26	1107	123	1099	1081	18	1205	
95%	24	1109	1076	33	1100	118	1105	1088	17	1205	
100%	23	1110	1080	31		116	1106	1080	26		
0%	C				1163	D				1262	
5%	80	1083	1079	4	1159	178	1084	1080	4	1258	
25%	70	1094	1081	13	1150	167	1095	1080	15	1247	Residential Density 400 hh/ha
50%	54	1109	1083	26	1137	151	1111	1079	32	1230	
75%	39	1125	1086	39	1124	135	1127	1078	48	1214	
95%	27	1136	1086	50	1113	124	1138	1075	63	1199	
100%	24	1139	1083	57		121	1141	1079	63		
	Background Concentration 10 µg/m³					**Background Concentration 100 µg/m³**					

Note: Letters in upper-left of each quadrant correspond to scenario letter designations. LPG-C users benefit from both direct and coverage effects which sum to a total effect. TSF-C users benefit only from a coverage effect. Direct effects at 100% coverage are set to the average of the other coverage levels.

TSF-C users also experience the benefits of a coverage effect (the dashed column divider in *Table 4.5* seeks to convey this). As coverage expands, TSF-C users are subjected to less $PM_{2.5}$ from community-level TSF-C use, but this coverage effect remains swamped by the enormous exposures still caused by household-level TSF-C use. For the average TSF-C user in scenarios A−D, as coverage goes from 5% to 95%, coverage effects provide only a slight exposure reduction of several percentage points. Exposure for TSF-C users, as would be expected, continues to be dominated by their households' TSF-C use.

Direct effects for LPG-C users are very similar for all scenario-coverage combinations. This finding confirms the logic that, for an isolated household's inhabitants, exposure to $PM_{2.5}$ from LPG-C versus TSF-C would differ by a fixed amount. In the context of a community, however, both LPG-C and TSF-C users also experience a coverage effect and to a similar degree. Hence, comparing the exposures experienced by LPG-C and TSF-C users in the same community would obscure the combined benefits of both household-level and community-level LPG-C use. Relying on the direct effect as a measure of intervention efficacy underestimates actual efficacy (i.e., total effect). The miscalculation is only slight at low coverage but increases as coverage expands.

As elucidated by the coverage effect model, an LPG-C intervention program is distinct from other public health interventions that also exhibit coverage effects, though some features are shared. Perhaps the closest analogs may be a leaky vaccine or ITNs. In these two cases, as with LPG-C, direct effects confer the chief benefits but coverage effects supplement protection for users as coverage expands within relevant communities. However, non-users can greatly benefit from a leaky vaccine (Halloran et al. 1991) or ITN (Desai and Eisenberg 2007; Killeen et al. 2007; Le Menach et al. 2007) program if coverage levels are high enough. In contrast, though TSF-C users do experience a coverage effect, it is insufficient to be beneficial. At the opposite extreme of LPG-C interventions may be a sanitation program, an intervention which appears to be almost entirely efficacious owing to coverage effects (Eisenberg et al. 2007; Luby 2014). Most fecal-oral infections can be transmitted through multiple pathways (Conant 2005) which may partly explain why the other two arms of WSH – safe water and proper hygiene – inconsistently demonstrate coverage effects (Dangour et al. 2013). This may sound a cautionary note for coverage effects from LPC-C, since exposure to $PM_{2.5}$ also occurs via multiple pathways.

4.3.2.3. Cooking Events and Time-Activity Patterns Revisited

The observant reader will have noticed that the values in *Table 4.5* at 5% and 95% coverage are nearly identical to those in *Table 4.4*. For all intents and purposes, results for concentrations and exposures are equivalent, including with regards to trend lines and measures of dispersion. Thus, before continuing, I address why the coverage effect model's results for concentration and exposure are so similar and what this suggests about choices in model development and the nature of a coverage effect.

For communities experiencing average daily windspeeds of ~3.6 km/hr (60 m/min) and possessing linear dimensions of ~50−100 m, the residence time of an air parcel is on the order of minutes. Similarly, for households exhibiting ventilation rates of ~20/hr (0.333/min), the residence time of an air parcel is also on the order of minutes. Thus, cookstove emissions exit the household relatively rapidly. Upon entering the ambient air, these emissions either exit the community airshed swiftly, or a portion enters another household, once again exiting rapidly, and so on. The point being that during community cooking windows, concentrations rise and fall quickly, returning to background, both within indoor and outdoor environments. Cooking start times and durations are stretched out over the community cooking window, so the rise and fall of concentrations can be somewhat elongated, but essentially the contribution of HAP to elevating $PM_{2.5}$ concentrations within the community airshed and neighbors' households is transient.

A corollary of these dynamics is that concentrations and thus potential exposures are far and away at their highest in all environments, regardless of cookstove technology or coverage level, during community cooking windows. Outside these time periods, concentrations in all environments – including inside households, given high ventilation rates − revert to background. Thus, from the perspective of potential exposure, it makes little difference whether an individual is indoors or outdoors for much of the night, mid-morning, or mid-afternoon.

The coverage effect model employs a simple algorithm for time-activity patterns. Women and children are indoors during their household's cooking events and for a period both before and after cooking events. Thus, when they are outdoors, ambient $PM_{2.5}$ concentrations have very likely returned to near background levels. Given this approach to time-activity patterns, exposures are so dominated by indoor concentrations that the distributions of exposures and indoor concentrations are exceedingly similar. Women and children are nonetheless subjected to

HAP from their neighbors, but via the infiltration of elevated ambient $PM_{2.5}$ concentrations into their households during community cooking windows.

The proportion of exposure occurring indoors versus outdoors averages ~90% versus ~10% for LPG-C users and >99% versus <1% for TSF-C users for all scenario-coverage combinations. LPG-C users witness a very slight decline in the fraction of exposure occurring indoors (less than a couple percent points) as coverage expands. For all simulations, time spent indoors versus outdoors is similar, ~75% versus ~25%, over the course of a solar day.

The algorithms for cooking events and especially time-activity patterns explain the near-equivalency of exposures and indoor concentrations. I chose to use a straightforward and transparent approach for cooking events and time-activity patterns so as not to eclipse the influence of other variables such as residential density and background concentration, as well as to ensure generalizability. In reality, the timing of cooking events and human movement between micro-environments will obviously be quite variable, distinct to an even individual level, and challenging to characterize. Perhaps for this reason, there are few, if any, evidence-based strategies with wide applicability for coding cooking events and time-activity patterns.

Of the two, cooking events, for which there is a two hour window for commencing cookstove use, seems less problematic. Time-activity patterns are arguably overly simplistic. Children in particular, but women as well, likely move between indoor and outdoor environments more than assumed. A different scheme for time-activity patterns could be easily instituted since the model calculates concentrations in all indoor and outdoor environments. However, if cooking events were kept as currently modeled, then the effect of simulating more time spent outdoors during community cooking windows would be to enhance the coverage effect. This is because individuals would experience proportionately less exposure from their households' cookstove use and more exposure from their neighbors' (e.g., this may be the case for individuals working outdoors within the community airshed during community cooking windows). As a result, the model could be viewed as conservative with regards to its estimates of coverage effects.

The transiency of elevated $PM_{2.5}$ concentrations attributable to HAP in all environments comports with the physics of plume rise and dispersion. Yet public health researchers and practitioners working in villages and slums have anecdotally reported sustained high ambient $PM_{2.5}$ concentrations. If these observations coincided with community cooking windows, the explanation seems apparent. But at least some of these observations probably indicate sizeable emissions from non-cooking-related sources within communities and/or emissions from regional sources. Regional sources, it should be mentioned, could include both primary and secondary $PM_{2.5}$ from HAP generated upwind by other communities. Complex wind-flow fields, for example building downwash, may temporarily concentrate emissions, as well. The related anecdotal observation of high ambient $PM_{2.5}$ concentrations during morning hours or wintertime inversions may be partially explained by low boundary layer mixing heights which effectively condense regional air pollution into a smaller volume. But under calm winds or cool temps, community sources such as HAP could disperse more not less (see *Section 4.2.3.4*). Unless the community cooking window spans the day, HAP from within the village or slum itself would seem an unlikely source for sustained high ambient $PM_{2.5}$ concentrations.

4.4. Implications

4.4.1. Insights from the Coverage Effect Model

The coverage effect model functions primarily as a "proof-of-concept" analysis, and secondarily, as an initial first-order approximation and qualitative screening tool. Ensemble results are consistent with the concept that an appreciable coverage effect from LPG-C interventions can manifest within moderately dense communities. Benefits for LPG-C users derive largely from direct effects; initially, at low coverage levels, almost exclusively so. Yet, as coverage expands within an LPG-C user's community, a coverage effect becomes increasingly beneficial. In contrast, TSF-C users, despite also experiencing comparable exposure reductions from community-level LPG-C use, cannot proportionately benefit because their $PM_{2.5}$ exposures remain overwhelmingly dominated by household-level TSF-C use.

To a first-order approximation, the magnitude of coverage benefits would be expectedly slight compared to the direct benefits of LPG-C adoption (~1000 $\mu g/m^3$). But once a household switches to LPG-C, the additional exposure reduction attributable to their neighbors' uptake of LPG-C may be quite significant. Given a low background concentration (10 $\mu g/m^3$) and residential densities representative of a moderately dense village (100 hh/ha; scenario A) or a slum (400 hh/ha; scenario C), inhabitants of typical households using LPG-C could experience a coverage effect that further halves exposure to $PM_{2.5}$ as coverage expands from 5% to 95%. Should background concentrations be high (100 $\mu g/m^3$; scenarios B and D), exposure could still be reduced by another quarter.

The absolute reduction, ~25-30 $\mu g/m^3$ at village residential densities and ~50-60 $\mu g/m^3$ at slum residential densities, may seem modest in the context of the exposures experienced by TSF-C users, which routinely exceed 1000 $\mu g/m^3$. But an AAP abatement program purporting similar reductions in concentration or exposure would entertain widespread consideration. To put the magnitude of the coverage effect in context, a reduction in AAP $PM_{2.5}$ on an average annual basis of 60 $\mu g/m^3$ is equivalent to the difference between Beijing and Lhasa, and a 30 $\mu g/m^3$ reduction corresponds to the difference between Johannesburg and Mauritius (World Health Organization 2014a).

These quantitative results are intended only to be cautiously suggestive of average outcomes under idealized conditions. Recall that model processes incorporate a number of simplifications owing to the objective of isolating effects from household fuel combustion. As noted, for this reason, the model assumes no other household or community $PM_{2.5}$ sources and no cookstove stacking. Model processes are also constrained by the adoption of a single-compartment mass-balance approach and its intrinsic well-mixed assumption. In addition, model parameters emulate poorer communities in northern India, potentially restricting extrapolation to other locations and situations. Furthermore, output distributions overlap at lower residential densities, higher background concentrations, and intermediate coverage levels. In spite of these limitations, circumscriptions, and variability, the model's mean $PM_{2.5}$ concentrations qualitatively comport with field measurements of indoor LPG-C and urban outdoor environments. Moreover, trends are robust across scenarios, outlining generalizable principles.

In particular, the coverage effect model strengthens the rationale for public health programs and policies to encourage clean cooking technologies with an added incentive to realize high coverage within contiguous areas. As a screening tool, the model suggests that coverage effects would be anticipated to be more prominent at the higher residential densities found in urban locales. Here, economic and institutional factors are more easily conducive to enabling access to LPG-C and induction cookers. Yet, given the findings of Salje et al. (2013), the impetus for expanding coverage, so that coverage effect are maximized, persists. Below ~100 hh/ha, coverage effects decline as plumes disperse within ever larger volumes and the well-mixed assumption becomes less tenable. But in rural locales where dwellings are clustered in hamlets or a village center, leveraging a coverage effect could help households and communities approach or attain air quality guidelines.

Background concentrations from regional sources of $PM_{2.5}$ temper benefits from not only a coverage effect but also the direct effect of LPG-C use. Non-cooking-related community or household sources of $PM_{2.5}$ would incur similar consequences. The impact of other $PM_{2.5}$ sources besides household fuel combustion may help explain why improved cookstove, LPG-C, or induction cooker campaigns sometimes do not translate into expected reductions in exposure. An additional explanation could be the absence of a coverage effects should uptake of the intervention be sparse. Unraveling the real-world implications of a coverage effect will require thoughtful approaches to interventions studies and programs.

4.4.2. Data Collection and Effect Estimation

The implications of the coverage effect model extend to identifying priorities for collecting data and strategies for estimating effects. The brief residence time of air parcels within a household or community airshed means that community residents are exposed to their neighbors' HAP predominantly during community cooking windows. The importance of community cooking windows to exposure would hold whether an individual is outdoors, where emissions exfiltrate out of households, or indoors, where elevated outdoor concentrations infiltrate into households. Much as indoor concentrations are most often monitored during cooking events, the coverage effect model would advocate for monitoring outdoor concentrations during, as well as before and/or after, community cooking windows. Contrasting the resulting measurements would yield an indicator of the fraction of local AAP due to community HAP and the fraction of indoor concentrations attributable to neighbors' TSF-C use. Routine measurement of outdoor air pollution as part of investigations on HAP would help avoid exposure misattribution. My proposal glosses over the many details that a genuine protocol would require. But the point remains that distinguishing outdoor $PM_{2.5}$ attributable to HAP from other community or regional sources will be essential to judging the potential and actual benefits from cleaning cooking interventions, including the role of a coverage effect.

Relatedly, the modeling exercise recommends regular measurement of physical parameters related to ventilation and meteorology, especially for contexts amenable to a coverage effect. Ventilation rates, although not easy to gauge, are paramount among these (Desai et al. 2011; Mukhopadhyay et al. 2014). In essence, ventilation rates connect indoor and outdoor environments and thereby shape connectivity within, and possibly even between, communities.

The residents of communities within which drafty homes are the norm may be consequently subjected to $PM_{2.5}$ sources from their community and region indoors as well as outdoors. Several additional variable, important for estimating plume dispersal but easier to measure than ventilation rates, are lamentably infrequently assessed. These include the temperature of vented cookstove emissions, total area of household vents, ambient temperature, and ground-level windspeed. These parameters may improve the explanatory and predictive power of statistical models for exposure, in addition to being core inputs for air pollution dispersion models.

The coverage effect model reinforces the importance of a total exposure perspective (Smith 1988; Girman et al. 1989) and information on two behavioral parameters would facilitate such an orientation. Time-activity patterns, also discussed in *Section 4.3.2.3*, are pivotal to establishing the balance between exposure to various air pollution sources in various microenvironments (Ezzati and Kammen 2002; Barnes et al. 2005). Detailed information on cooking practices (Clark et al. 2015), especially the commonplace use of multiple cookstoves (Kumar et al. 2016), would inform a more comprehensive metric of coverage, for instance, the fraction of total community cooking energy, events, or time that employ a clean cooking technology. Time-activity patterns and cooking practices are challenging to characterize but the lack of this data restricts the capacity of statistical and mechanistic models to accurately estimate and attribute exposures.

The possibility of a coverage effect equates to a potential for SUTVA violation (see *Section 4.3.2.1*). Accordingly, strategies to estimate not only direct effects but also coverage and total effects can help avoid impaired conclusions. This is especially true with respect to assuming that the benefits of clean cooking intervention will transfer from one coverage level to another. Using scenario A (see *Table 4.5*) as an example of real-world conditions, if the exposures experienced by LPG-C users in a community with full coverage were assumed to apply to LPG-C users in a community with 25% coverage, the expected exposure (23 $\mu g/m^3$) would be nearly half as much as reality (45 $\mu g/m^3$). Correspondingly, health benefits would be unlikely to materialize to the extent anticipated.

As previously explained, an estimate of the coverage effect, and therefore the total effect, cannot be ascertained by comparing LPG-C and TSF-C users contemporaneously within the same community (this estimates the direct effect). Instead, LPG-C and TSF-C users must be compared across both communities and coverage levels, using cluster (Donner and Klar 2004) or multilevel designs (Subramanian 2004), or within the same community but across coverage levels, using pre-post (Harris et al. 2006) or step-wedge designs (Hemming et al. 2015). A number of variants and subtleties exist to these approaches (see excellent discussion in Benjamin-Chung et al. 2015) but none has been commonly applied to HAP or clean cooking interventions.

4.4.3. Model Refinements and Extensions

Exposure results from the coverage effect model could be transformed into incidence rates by sampling the integrated exposure-response relationship (IER) for $PM_{2.5}$ exposure. The IER was developed as part of the comparative risk assessment component of the Global Burden of Disease Study 2010 (Lim et al. 2012). As its name declares, the IER integrated exposure-response relationships across the continuum of $PM_{2.5}$ exposures – ambient air pollution, secondhand tobacco smoke, household air pollution, and active smoking – to produce unified exposure-response curves, spanning several orders of magnitude of $PM_{2.5}$ concentration, for major associated health impacts (Burnett et al. 2014). Although an intriguing extension of the coverage effect model, applying IERs to small population sizes would entail navigating a series of complications (e.g., background burdens, covariate distributions, vital dynamics, etc.) which may introduce problematic uncertainties and limit the applicability of conclusions. Nonetheless, as a theoretical exercise to better understand how coverage effects may express in terms of protective efficacy or attributable burden, the idea has merit (Goodkind et al. 2014; Pillarisetti et al. 2016).

The coverage effect model, as currently formulated, appears reasonably robust and valid as an instrument for informing implementation science (Lobb and Colditz 2013). Relatively modest refinements may well be adequate to the task of considering the coverage effect hypothesis amidst more diverse but still generalizable conditions. With regards to improving exposure estimates, the priorities for elaborating the coverage effect model would include incorporating diurnally-varying background concentrations, cookstove stacking, non-cooking-related $PM_{2.5}$ sources, seasonal patterns, and autocorrelation within or correlation between parameters. As relevant empirical data becomes more widely available, the model would profit from being calibrated to rural ambient concentrations, time-activity patterns, and age-sex specific exposures.

Modeling a wider variety of locations and situations could be accomplished by altering how the coverage effect model simulates air pollution dispersal in households and community airsheds. Outdoor cooking could be simulated by a zone directly above the cookstove (Furtaw et al. 1996) and multi-room houses by extra zones for other rooms. Simulation of the outdoor environment could leverage anticipated advances in near-field Gaussian and Lagrangian models as discussed in *Section 4.1.5*. Enacting these updates, of course, would require commensurate data, for example air flow and human movement between multiple zones or more detailed meteorology.

To better capture heterogeneity in $PM_{2.5}$ concentrations and human exposures, more ambitious extensions of the coverage effect model would progress towards a "spatially explicit" approach based on cell or grid environment (Getz et al. 2015) or a "spatially realistic" approach based on a geographic information system (Jerrett et al. 2010). These structures would be conducive to simulating Eulerian air pollution dispersion with three-dimensional plumes driven by variable environmental conditions, including wind direction and temperature gradients, as well as more complex patterns of human movement. The ramifications of a community airshed and connectivity among households (e.g., upwind versus downwind houses or clusters of LPG-C versus TSF-C users) could be explored. Modeling of this nature could eventually serve as a site-specific vehicle for integrating and evaluating causal hypotheses and field measurements much as in other domains (Spear 2002). However, it must be stressed, models that generate seemingly more realistic output are not necessarily better at modeling reality. Issues pertaining to calibration and validation persist but are more complicated for sophisticated models. Moreover, there often exists a trade-off between specificity and generalizability.

This chapter's focus on a coverage effect from clean cooking interventions also raises hypotheses about air pollution more generally. Just as a coverage effect may exist within communities, there may well be a parallel phenomenon between communities. In fact, over regional scales, both primary and secondary $PM_{2.5}$ from household combustion can markedly impact ambient concentrations in downwind communities (Liu et al. 2016). As a result, one could conceptualize a region-level coverage effect and possible rationale to initially target rolling out or scaling up clean cooking interventions in those communities that exert a greater influence on other communities' exposures. This logic would apply, of course, to any source of AAP. In a sense, the benefits from abatement programs for AAP are intrinsically coverage effects. Beneficiaries may not only, and perhaps not even primarily, be users, but instead, residents of the surrounding community (1st level coverage effect), wider region (2nd level coverage effect), and even cross-boundary or global communities (3rd level coverage effect). Comprehensively analyzing clean cooking interventions and HAP may well inspire a multiscale perspective that extends beyond household and community to broader scales.

In conclusion, I have put forth an argument that greater attention be paid to the potential benefits, especially for users of clean cooking interventions, of a coverage effect. Momentum to mitigate HAP has risen before only to fall, partly owing to misplaced expectations. Understanding coverage effects can help ensure effective and efficient strategies for addressing HAP, one of the world's most significant environmental health challenges. For any particular case in the real world, the many sources of natural variability will determine the actual strength and significance of a coverage effect. This chapter closes with encouragement for this more nuanced but essential task, one for public health researchers and practitioners in the field to pursue in dialogue and collaboration with their modeling colleagues, given the import of leveraging a coverage effect.

4.5. References

Achtemeier GL, Goodrick SA, Liu Y, Garcia-Menendez F, Hu Y, and Odman MT (2011) "Modeling smoke plume-rise and dispersion from Southern United States prescribed burns with Daysmoke" *Atmosphere* 2(3): 358.

Adair-Rohani H, Lewis J, Mingle J, and Gumy S (2016) Burning Opportunity: Clean Household Energy for Health, Sustainable Development, and Wellbeing of Women and Children World Health Organization, Geneva, CH.

Alper J and Geller A, Editors (2015). How Modeling Can Inform Strategies to Improve Population Health: Workshop Summary National Academies Press, Washington, DC.

Amegah AK and Jaakkola JJ (2016) "Household air pollution and the sustainable development goals" *Bulletin of the World Health Organization* 94(3): 215-221.

Andres L, Briceño B, Chase C, and Echenique JA (2014) Sanitation and Externalities: Evidence from Early Childhood Health in Rural India World Bank, Washington, DC: #6737.

Anenberg SC, Balakrishnan K, Jetter J, Masera O, Mehta S, Moss J, and Ramanathan V (2013) "Cleaner cooking solutions to achieve health, climate, and economic cobenefits" *Environmental Science & Technology* 47(9): 3944-3952.

Angeles G, Lance P, Barden-O'Fallon J, Islam N, Mahbub A, and Nazem NI (2009) "The 2005 census and mapping of slums in Bangladesh: design, select results and application" *International Journal of Health Geographics* 8(1): 1-19.

Apte JS, Bombrun E, Marshall JD, and Nazaroff WW (2012) "Global intraurban intake fractions for primary air pollutants from vehicles and other distributed sources" *Environmental Science & Technology* 46(6): 3415-3423.

Apte JS, Marshall JD, Cohen AJ, and Brauer M (2015) "Addressing global mortality from ambient $PM_{2.5}$" *Environmental Science & Technology* 49(13): 8057-8066.

Bailis R, Cowan A, Berrueta V, and Masera O (2009) "Arresting the killer in the kitchen: the promises and pitfalls of commercializing improved cookstoves" *World Development* 37(10): 1694-1705.

Balakrishnan K, Cohen A, and Smith KR (2014) "Addressing the burden of disease attributable to air pollution in India: the need to integrate across household and ambient air pollution exposures" *Environmental Health Perspectives* 122(1): A6-7.

Balakrishnan K, Ghosh S, Ganguli B, Sambandam S, Bruce N, Barnes DF, and Smith KR (2013) "State and national household concentrations of $PM_{2.5}$ from solid cookfuel use: results from measurements and modeling in India for estimation of the global burden of disease" *Environmental Health* 12(1): 77.

Balakrishnan K and Mehta S (2014) World Health Organization Indoor Air Quality Guidelines: Household Fuel Combustion - Evidence Review 5: Population Levels of Household Air Pollution and Exposures World Health Organization, Geneva, CH.

Balakrishnan K, Ramaswamy P, Sambandam S, Thangavel G, Ghosh S, Johnson P, Mukhopadhyay K, Venugopal V, and Thanasekaraan V (2011a) "Air pollution from household solid fuel combustion in India: an overview of exposure and health related information to inform health research priorities" *Global Health Action* 4: 5638.

Balakrishnan K, Thangavel G, Ghosh S, Sambandam S, Mukhopadhyay K, Adair-Rohani H, Bruce N, and Smith KR (2011b) "Global Database of Household Air Pollution Measurements " World Health Organization, Geneva, CH http://www.who.int/indoorair/health_impacts/databases_iap/en/ Accessed 2015 Nov 01.

Barnes B, Mathee A, and Moiloa K (2005) "Assessing child time-activity patterns in relation to indoor cooking fires in developing countries: a methodological comparison" *International Journal of Hygiene and Environmental Health* 208(3): 219-225.
Barnes DF, Kumar P, and Openshaw K (2012) Cleaner Hearths, Better Homes: New Stoves for India and the Developing World Oxford University Press, New Delhi, IN.
Barreto ML, Genser B, Strina A, Teixeira MG, Assis AMO, Rego RF, Teles CA, Prado MS, Matos SMA, Santos DN, dos Santos LA, and Cairncross S (2007) "Effect of city-wide sanitation programme on reduction in rate of childhood diarrhoea in northeast Brazil: assessment by two cohort studies" *Lancet* 370(9599): 1622-1628.
Baumgartner J, Schauer JJ, Ezzati M, Lu L, Cheng C, Patz J, and Bautista LE (2011) "Patterns and predictors of personal exposure to indoor air pollution from biomass combustion among women and children in rural China" *Indoor Air* 21(6): 479-488.
Baumol WJ and Blinder AS (1988) Economics: Principles and Policy Harcourt Brace Jovanovich, Orlando, FL.
Benjamin-Chung J, Abedin J, Berger D, Clark A, Falcao L, Jimenez V, Konagaya E, Tran D, Arnold B, Hubbard A, Luby S, Miguel E, and Colford J (2015) The Identification and Measurement of Health-Related Spillovers in Impact Evaluations: a Systematic Review International Initiative for Impact Evaluation, London, UK.
Bhangar S (2006) Indoor Air Quality of Households with Improved and Traditional Stoves in Kaldari, India [masters thesis] University of California, Berkeley, Berkeley, CA.
Blocken B, Tominaga Y, and Stathopoulos T (2013) "CFD simulation of micro-scale pollutant dispersion in the built environment" *Building and Environment* 64: 225-230.
Bond TC, Zarzycki C, Flanner MG, and Koch DM (2011) "Quantifying immediate radiative forcing by black carbon and organic matter with the Specific Forcing Pulse" *Atmospheric Chemistry and Physics* 11(4): 1505-1525.
Bonjour S, Adair-Rohani H, Wolf J, Bruce NG, Mehta S, Pruss-Ustun A, Lahiff M, Rehfuess EA, Mishra V, and Smith KR (2013) "Solid fuel use for household cooking: country and regional estimates for 1980-2010" *Environmental Health Perspectives* 121(7): 784-790.
Bosanquet CH and Pearson JL (1936) "The spread of smoke and gases from chimneys" *Transactions of the Faraday Society* 32: 1249-1263.
Box GE and Draper NR (1987) Empirical Model-Building and Response Surfaces John Wiley & Sons, New York, NY.
Brant S, Johnson M, Pennise D, and Charron D (2010) Controlled Cooking Test Evaluation of the B1200 and G3300 Cookstoves in Tamil Nadu, South India Berkeley Air Monitoring Group and Department of Environmental Health Engineering, Sri Ramachandra University, Berkeley, CA.
Brant S, Pennise D, and Charron D (2009) Monitoring and Evaluation of the B1100 and S2100 Cookstoves in South India Berkeley Air Monitoring Group and Department of Environmental Health Engineering, Sri Ramachandra University, Berkeley, CA.
Brauer M, Amann M, Burnett RT, Cohen A, Dentener F, Ezzati M, Henderson SB, Krzyzanowski M, Martin RV, Van Dingenen R, van Donkelaar A, and Thurston GD (2012) "Exposure assessment for estimation of the global burden of disease attributable to outdoor air pollution" *Environmental Science & Technology* 46(2): 652-660.
Brauer M, Freedman G, Frostad J, van Donkelaar A, Martin RV, Dentener F, Dingenen Rv, Estep K, Amini H, Apte JS, Balakrishnan K, Barregard L, Broday D, Feigin V, Ghosh S, Hopke PK, Knibbs LD, Kokubo Y, Liu Y, Ma S, Morawska L, Sangrador JLT, Shaddick

G, Anderson HR, Vos T, Forouzanfar MH, Burnett RT, and Cohen A (2016) "Ambient air pollution exposure estimation for the Global Burden of Disease 2013" *Environmental Science & Technology* 50(1): 79-88.

Breivik K, Sweetman A, Pacyna JM, and Jones KC (2007) "Towards a global historical emission inventory for selected PCB congeners - a mass balance approach update" *Science of The Total Environment* 377(2–3): 296-307.

Briggs GA (1975) "Plume rise predictions" In Lectures on Air Pollution and Environmental Impact Analyses Editor Haugen DA, American Meteorological Society, Boston, MA**:** 59-111.

Britter R and Schatzmann M (2007) Background and Justification Document to Support the Model Evaluation Guidance and Protocol - COST Action 732 COST Office, Brussels, Belgium.

Bruce N, Pope D, Rehfuess E, Balakrishnan K, Adair-Rohani H, and Dora C (2015) "WHO indoor air quality guidelines on household fuel combustion: strategy implications of new evidence on interventions and exposure–risk functions" *Atmospheric Environment* 106: 451-457.

Bruce N and Smith KR (2014) World Health Organization Indoor Air Quality Guidelines: Household Fuel Combustion - Evidence Review 4: Health Effects of Household Air Pollution Exposure World Health Organization, Geneva, CH.

Bruce NG, Dherani MK, Das JK, Balakrishnan K, Adair-Rohani H, Bhutta ZA, and Pope D (2013) "Control of household air pollution for child survival: estimates for intervention impacts" *BMC Public Health* 13(Suppl 3): S8.

Burnett RT, Pope CA, Ezzati M, Olives C, Lim SS, Mehta S, Shin HH, Singh G, Hubbell B, Brauer M, Anderson HR, Smith KR, Balmes JR, Bruce NG, Kan H, Laden F, Pruss-Ustun A, Turner MC, Gapstur SM, Diver WR, and Cohen A (2014) "An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure" *Environmental Health Perspectives* 122(4): 397-403.

Byun D and Schere KL (2006) "Review of the governing equations, computational algorithms, and other components of the Models-3 Community Multiscale Air Quality (CMAQ) modeling system" *Applied Mechanics Reviews* 59(2): 51-77.

Carnell R (2013) "triangle: Provides the Standard Distribution Functions for the Triangle Distribution (Version 0.8)" https://CRAN.R-project.org/package=triangle Accessed 2016 May 01.

Caswell H (1988) "Theory and models in ecology: a different perspective" *Ecological Modelling* 43(1): 33-44.

Chafe Z, Brauer M, Héroux M-E, Klimont Z, Lanki T, Salonen RO, and Smith KR (2015) Residential Heating with Wood and Coal: Health Impacts and Policy Options in Europe and North America World Health Organization, Regional Office for Europe, Copenhagen, DK.

Chafe ZA, Brauer M, Klimont Z, Van Dingenen R, Mehta S, Rao S, Riahi K, Dentener F, and Smith KR (2014) "Household cooking with solid fuels contributes to ambient $PM_{2.5}$ air pollution and the burden of disease" *Environmental Health Perspectives* 122(12): 1314-1320.

Christakis NA and Fowler JH (2009) Connected: The Surprising Power of Our Social Networks and How They Shape Our Lives Little, Brown, and Company, New York, NY.

Cimorelli AJ, Perry SG, Venkatram A, Weil JC, Paine RJ, Wilson RB, Lee RF, Peters WD, and Brode RW (2005) "AERMOD: A dispersion model for industrial source applications; Part I: General model formulation and boundary layer characterization" *Journal of Applied Meteorology* 44(5): 682-693.

Clark ML, Heiderscheidt JM, and Peel JL (2015) "Integrating behavior change theory and measures into health-based cookstove interventions: a proposed epidemiologic research agenda" *Journal of Health Communication* 20 Suppl 1: 94-97.

Clasen T, Boisson S, Routray P, Torondel B, Bell M, Cumming O, Ensink J, Freeman M, Jenkins M, Odagiri M, Ray S, Sinha A, Suar M, and Schmidt W-P (2014) "Effectiveness of a rural sanitation programme on diarrhoea, soil-transmitted helminth infection, and child malnutrition in Odisha, India: a cluster-randomised trial" *Lancet Global Health* 2(11): e645-653.

Cohan A, Wu J, and Dabdub D (2011) "High–resolution pollutant transport in the San Pedro Bay of California" *Atmospheric Pollution Research* 2(3): 237-246.

Collett RS and Oduyemi K (1997) "Air quality modelling: a technical review of mathematical approaches" *Meteorological Applications* 4(3): 235-246.

Conant J (2005) Sanitation and Cleanliness for a Healthy Environment Hesperian Foundation, Berkeley, CA.

Cox DR (1958) Planning of Experiments Wiley, Oxford, UK.

Cullen A and Frey H (1999) Use of Probabilistic Techniques in Exposure Assessment: A Handbook for Dealing with Variability and Uncertainty in Models and Inputs Springer, New York, NY.

Dangour AD, Watson L, Cumming O, Boisson S, Che Y, Velleman Y, Cavill S, Allen E, and Uauy R (2013) "Interventions to improve water quality and supply, sanitation and hygiene practices, and their effects on the nutritional status of children" *Cochrane Database of Systematic Reviews* 8: CD009382.

Davidson CI, Lin SF, Osborn JF, Pandey MR, Rasmussen RA, and Khalil MAK (1986) "Indoor and outdoor air pollution in the Himalayas" *Environmental Science & Technology* 20(6): 561-567.

Desai M and Eisenberg J (2007) "ITN interventions across environmental and transmission settings: the fundamental role of spatial connectivity in determining effectiveness" Presented at 2007 Annual Meeting of the American Society of Tropical Medicine and Hygiene November 4-8, Philadelphia PA *American Journal of Tropical Medicine and Hygiene* 77(6 Suppl): 895.

Desai M, Rehfuess E, Mehta S, and Smith K (2011) "Indoor smoke from solid fuels" In Environmental Burden of Disease Associated with Inadequate Housing Editors Braubach M, Jacobs DE, and Ormandy D, World Health Organization, Regional Office for Europe**:** 165-172.

Donaldson I, Harrison D, and Hill J (2008) Performance of AERMOD vs. CALPUFF on Fugitive Emission Sources in the Nearfield Trinity Consultants, Dallas, TX: #816.

Donner A and Klar N (2004) "Pitfalls of and controversies in cluster randomization trials" *American Journal of Public Health* 94(3): 416-422.

Edwards R (2014) World Health Organization Indoor Air Quality Guidelines: Household Fuel Combustion - Evidence Review 2: Emissions of Health-Damaging Pollutants from Household Stoves World Health Organization, Geneva, CH.

Eisenberg JNS, Lewis BL, Porco TC, Hubbard AH, and Colford J, J. M. (2003) "Bias due to secondary transmission in estimation of attributable risk from intervention trials" *Epidemiology* 14(4): 442-450.
Eisenberg JNS, Scott JC, and Porco T (2007) "Integrating disease control strategies: balancing water sanitation and hygiene interventions to reduce diarrheal disease burden" *American Journal of Public Health* 97(5): 846-852.
Eisenberg JNS, Trostle J, Sorensen RJD, and Shields KF (2012) "Toward a systems approach to enteric pathogen transmission: from individual independence to community interdependence" *Annual Review of Public Health* 33: 239-257.
Ejemot-Nwadiaro RI, Ehiri JE, Arikpo D, Meremikwu MM, and Critchley JA (2015) "Hand washing promotion for preventing diarrhoea" *Cochrane Database of Systematic Reviews* 9: CD004265.
Ephrath JE, Goudriaan J, and Marani A (1996) "Modelling diurnal patterns of air temperature, radiation wind speed and relative humidity by equations from daily characteristics" *Agricultural Systems* 51(4): 377-393.
Ezzati M and Kammen DM (2002) "The health impacts of exposure to indoor air pollution from solid fuels in developing countries: knowledge, gaps, and data needs" *Environmental Health Perspectives* 110(11): 1057-1068.
Ferziger JH and Perić M (2002) Computational Methods for Fluid Dynamics Springer Berlin, DE.
Fine PE (1993) "Herd immunity: history, theory, practice" *Epidemiologic Reviews* 15(2): 265-302.
Fine PM, Sioutas C, and Solomon PA (2008) "Secondary particulate matter in the United States: insights from the Particulate Matter Supersites Program and related studies" *Journal of the Air & Waste Management Association* 58(2): 234-253.
Fisher BEA, Metcalfe E, Vince I, and Yates A (2001) "Modelling plume rise and dispersion from pool fires" *Atmospheric Environment* 35(12): 2101-2110.
Fuller JA, Villamor E, Cevallos W, Trostle J, and Eisenberg JNS (2016) "I get height with a little help from my friends: herd protection from sanitation on child growth in rural Ecuador" *International Journal of Epidemiology*.
Furtaw EJ, Pandian MD, Nelson DR, and Behar JV (1996) "Modeling indoor air concentrations near emission sources in imperfectly mixed rooms" *Journal of the Air & Waste Management Association* 46(9): 861-868.
Gall ET, Carter EM, Earnest CM, and Stephens B (2013) "Indoor air pollution in developing countries: research and implementation needs for improvements in global public health" *American Journal of Public Health* 103(4): e67-72.
Garnett GP, Cousens S, Hallett TB, Steketee R, and Walker N (2011) "Mathematical models in the evaluation of health programmes" *Lancet* 378(9790): 515-525.
Gaujoux R (2014) "doRNG: Generic Reproducible Parallel Backend for 'foreach' Loops (Version 1.6)" https://CRAN.R-project.org/package=doRNG Accessed 2016 Apr 15.
Gelencsér A, May B, Simpson D, Sánchez-Ochoa A, Kasper-Giebl A, Puxbaum H, Caseiro A, Pio C, and Legrand M (2007) "Source apportionment of $PM_{2.5}$ organic aerosol over Europe: primary/secondary, natural/anthropogenic, and fossil/biogenic origin" *Journal of Geophysical Research: Atmospheres* 112(D23).

Genser B, Strina A, Teles CA, Prado MS, and Barreto ML (2006) "Risk factors for childhood diarrhea incidence: dynamic analysis of a longitudinal study" *Epidemiology* 17(6): 658-667.

Geruso M and Spears D (2015) Neighborhood Sanitation and Infant Mortality National Bureau of Economic Research, Cambridge MA: #21184.

Getz WM (1998) "An introspection on the art of modeling in population ecology" *BioScience* 48(7): 540-552.

Getz WM, Salter RM, and Sippl-Swezey N (2015) "Using Nova to construct agent-based models for epidemiological teaching and research" In Proceedings of the 2015 Winter Simulation Conference Editors Yilmaz L, Chan WKV, Moon I, Roeder TMK, Macal C, and Rossetti MD**:** 3490-3501.

Gifford FA (1961) "Use of routine meteorological observations for estimating atmospheric dispersion" *Nuclear Safety* 2(4): 47-57.

Girman JR, Jenkins PL, and Wesolowski JJ (1989) "Indoor air quality the role of total exposure in air pollution control strategies" *Environment International* 15(1): 511-515.

Goodkind AL, Coggins JS, and Marshall JD (2014) "A spatial model of air pollution: the impact of the concentration-response function" *Journal of the Association of Environmental and Resource Economists* 1(4): 451-479.

Gousseau P, Blocken B, and van Heijst GJF (2011) "CFD simulation of pollutant dispersion around isolated buildings: On the role of convective and turbulent mass fluxes in the prediction accuracy" *Journal of Hazardous Materials* 194: 422-434.

Gowen T, Karantonis P, and Rofail T (2004) "Converting bureau of meteorology wind speed data to local wind speeds at 1.5m above ground level" In Proceedings of the Annual Conference of the Australian Acoutical Society Editors Mee DJ, Hooker RJ, and Hillock IDM, Australian Acoustical Society, Gold Coast, AU**:** 57-61.

Goyal R and Khare M (2011) "Indoor air quality modeling for PM10, $PM_{2.5}$, and PM1.0 in naturally ventilated classrooms of an urban Indian school building" *Environmental Monitoring and Assessment* 176(1-4): 501-516.

Grabow K, Still D, and Bentson S (2013) "Test kitchen studies of indoor air pollution from biomass cookstoves" *Energy for Sustainable Development* 17(5): 458-462.

Guo Z (2000) Simulation Tool Kit for Indoor Air Quality and Inhalation Exposure (IAQX) Version 1.0 User's Guide U.S. Environmental Protection Agency, Research Triangle Park, NC.

Guo Z, Chang C, and Wang R (2016) "A novel method to downscale daily wind statistics to hourly wind data for wind erosion modelling" In Geo-Informatics in Resource Management and Sustainable Ecosystem Editors Bian F and Xie Y, Springer Berlin Heidelberg, Berlin, Heidelberg**:** 611-619.

Gurarie D and Seto EYW (2009) "Connectivity sustains disease transmission in environments with low potential for endemicity: modelling schistosomiasis with hydrologic and social connectivities" *Journal of the Royal Society Interface* 6(35): 495-508.

Haber M (1999) "Estimation of the direct and indirect effects of vaccination" *Statistics and Medicine* 18(16): 2101-2109.

Habilomatis G and Chaloulakou A (2015) "A CFD modeling study in an urban street canyon for ultrafine particles and population exposure: the intake fraction approach" *Science of the Total Environment* 530–531: 227-232.

Halloran ME, Haber M, Longini IM, and Struchiner CJ (1991) "Direct and indirect effects in vaccine efficacy and effectiveness" *American Journal of Epidemiology* 133(4): 323-331.
Halloran ME and Struchiner CJ (1991) "Study designs for dependent happenings" *Epidemiology* 2(5): 331-338.
Halloran ME and Struchiner CJ (1995) "Causal inference in infectious diseases" *Epidemiology* 6(2): 142-151.
Hanna SR (1982) Handbook of Atmospheric Diffusion United States Department of Energy, Springfield, VA.
Harris AD, McGregor JC, Perencevich EN, Furuno JP, Zhu J, Peterson DE, and Finkelstein J (2006) "The use and interpretation of quasi-experimental studies in medical informatics" *Journal of the American Medical Informatics Association* 13(1): 16-23.
Hawley WA, Phillips-Howard PA, ter Kuile FO, Terlouw DJ, Vulule JM, Ombok M, Nahlen BL, Gimnig JE, Kariuki SK, Kolczak MS, and Hightower AW (2003) "Community-wide effects of permethrin-treated bed nets on child mortality and malaria morbidity in western Kenya" *American Journal of Tropical Medicine and Hygiene* 68(4 Suppl): 121-127.
Hayes RJ, Alexander ND, Bennett S, and Cousens SN (2000) "Design and analysis issues in cluster-randomized trials of interventions against infectious diseases" *Statistical Methods in Medical Research* 9(2): 95-116.
Hellweg S, Demou E, Bruzzi R, Meijer A, Rosenbaum RK, Huijbregts MAJ, and McKone TE (2009) "Integrating human indoor air pollutant exposure within life cycle impact assessment" *Environmental Science & Technology* 43(6): 1670-1679.
Hemming K, Haines TP, Chilton PJ, Girling AJ, and Lilford RJ (2015) "The stepped wedge cluster randomised trial: rationale, design, analysis, and reporting" *BMJ* 350.
Holland PW (1986) "Statistics and causal inference" *Journal of the American Statistical Association* 81(396): 945-960.
Holmes NS and Morawska L (2006) "A review of dispersion modelling and its application to the dispersion of particles: an overview of different dispersion models available" *Atmospheric Environment* 40(30): 5902-5928.
Howard SC, Omumbo J, Nevill C, Some ES, Donnelly CA, and Snow RW (2000) "Evidence for a mass community effect of insecticide-treated bednets on the incidence of malaria on the Kenyan coast" *Transactions of the Royal Society of Tropical Medicine and Hygiene* 94(4): 357-360.
Hudgens MG and Halloran ME (2008) "Toward causal inference with interference" *Journal of the American Statistical Association* 103(482): 832-842.
Humbert S, Marshall JD, Shaked S, Spadaro JV, Nishioka Y, Preiss P, McKone TE, Horvath A, and Jolliet O (2011) "Intake fraction for particulate matter: recommendations for life cycle impact assessment" *Environmental Science & Technology* 45(11): 4808-4816.
International Organization for Standardization (2012) International Workshop Agreement 11:2012: Guidelines for Evaluating Cookstove Performance International Organisation for Standardization, Geneva, CH.
Isakov V, Sax T, Venkatram A, Pankratz D, Heumann J, and Fitz D (2004) "Near-field dispersion modeling for regulatory applications" *Journal of the Air & Waste Management Association* 54(4): 473-482.
Isakov V and Venkatram A (2006) "Resolving neighborhood scale in air toxics modeling: a case study in Wilmington, CA" *Journal of the Air & Waste Management Association* 56(5): 559-568.

Jack DW, Asante KP, Wylie BJ, Chillrud SN, Whyatt RM, Ae-Ngibise KA, Quinn AK, Yawson AK, Boamah EA, Agyei O, Mujtaba M, Kaali S, Kinney P, and Owusu-Agyei S (2015) "Ghana randomized air pollution and health study (GRAPHS): study protocol for a randomized controlled trial" *Trials* 16(1): 1-10.
Jacob DJ (1999) "Simple models" In Introduction to Atmospheric Chemistry, Princeton University Press, Princeton, NJ**:** 22-34.
Jayjock MA, Lynch J, and Nelson DI (2000) Risk Assessment Principles for the Industrial Hygienist American Industrial Hygiene Association, Falls Church, VA.
Jerrett M, Gale S, and Kontgis C (2010) "Spatial modeling in environmental and public health research" *International Journal of Environmental Research and Public Health* 7(4): 1302-1329.
Jetter J, Zhao Y, Smith KR, Khan B, Yelverton T, Decarlo P, and Hays MD (2012) "Pollutant emissions and energy efficiency under controlled conditions for household biomass cookstoves and implications for metrics useful in setting international test standards" *Environmental Science & Technology* 46(19): 10827-10834.
Jeuland M, Pattanayak SK, and Bluffstone R (2015) "The economics of household air pollution" *Annual Review of Resource Economics* 7(1): 81-108.
Johnson JB and Omland KS (2004) "Model selection in ecology and evolution" *Trends in Ecology & Evolution* 19(2): 101-108.
Johnson M (2014) World Health Organization Indoor Air Quality Guidelines: Household Fuel Combustion - Evidence Review 3: Model for Linking Household Energy Use with Indoor Air Quality World Health Organization, Geneva, CH.
Johnson M, Lam N, Brant S, Gray C, and Pennise D (2011) "Modeling indoor air pollution from cookstove emissions in developing countries using a Monte Carlo single-box model" *Atmospheric Environment* 45(19): 3237-3243.
Johnson MA and Chiang RA (2015a) "Quantitative guidance for stove usage and performance to achieve health and environmental targets" *Environmental Health Perspectives* 123(8): 820-826.
Johnson MA and Chiang RA (2015b) "Quantitative stove use and ventilation guidance for behavior change strategies" *Journal of Health Communication* 20: 6-9.
Justus CG, Hargraves WR, Mikhail A, and Graber D (1978) "Methods for estimating wind speed frequency-distributions" *Journal of Applied Meteorology* 17(3): 350-353.
Kandpal JB, Maheshwari RC, and Kandpal TC (1995) "Indoor air pollution from domestic cookstoves using coal, kerosene and LPG" *Energy Conversion and Management* 36(11): 1067-1072.
Karamchandani P, Vijayaraghavan K, and Yarwood G (2011) "Sub-grid scale plume modeling" *Atmosphere* 2(3): 389.
Kermack KO and McKendrick AG (1927) "Contributions to the mathematical theory of epidemics - I" *Proceedings of the Royal Society of London, Series A, Containing Papers of a Mathematical and Physical Character* 115(772): 700-721.
Killeen GF, Smith TA, Ferguson HM, Mshinda H, Abdulla S, Lengeler C, and Kachur SP (2007) "Preventing childhood malaria in Africa by protecting adults from mosquitoes with insecticide-treated nets" *PLOS Medicine* 4(7): e229.
Kim HS (2010) Neighborhood Scale Air Quality Modeling in Corpus Christi Using AERMOD and CALPUFF [masters thesis] Univeristy of Texas at Austin, Austin, TX.

Klepeis NE and Nazaroff WW (2006) "Modeling residential exposure to secondhand tobacco smoke" *Atmospheric Environment* 40(23): 4393-4407.

Klinkenberg E, Onwona-Agyeman KA, McCall PJ, Wilson MD, Bates I, Verhoeff FH, Barnish G, and Donnelly MJ (2010) "Cohort trial reveals community impact of insecticide-treated nets on malariometric indices in urban Ghana" *Transactions of the Royal Society of Tropical Medicine and Hygiene* 104(7): 496-503.

Knaebel A, Scheringer M, Stehle S, and Schulz R (2016) "Aquatic exposure predictions of insecticide field concentrations using a multimedia mass-balance model" *Environmental Science & Technology* 50(7): 3721-3728.

Kulshreshtha P, Khare M, and Seetharaman P (2008) "Indoor air quality assessment in and around urban slums of Delhi City, India" *Indoor Air* 18(6): 488-498.

Kumar P, Chalise N, and Yadama GN (2016) "Dynamics of sustained use and abandonment of clean cooking systems: study protocol for community-based system dynamics modeling" *International Journal for Equity in Health* 15(1): 1-8.

Kwan M-P (2012) "The uncertain geographic context problem" *Annals of the Association of American Geographers* 102(5): 958-968.

Lakshmanan N, Gomathinayagam S, Harikrishna P, Abraham A, and Ganapathi SC (2009) "Basic wind speed map of India with long-term hourly wind data" *Current Science* 96(7): 911-922.

Lam NL, Smith KR, Gauthier A, and Bates MN (2012) "Kerosene: a review of household uses and their hazards in low- and middle-income countries" *Journal of Toxicology and Environmental Health, Part B* 15(6): 396-432.

Larsen DA, Hutchinson P, Bennett A, Yukich J, Anglewicz P, Keating J, and Eisele TP (2014) "Community coverage with insecticide-treated mosquito nets and observed associations with all-cause child mortality and malaria parasite infections" *American Journal of Tropical Medicine and Hygiene* 91(5): 950-958.

Lateb M, Meroney RN, Yataghene M, Fellouah H, Saleh F, and Boufadel MC (2015) "On the use of numerical modelling for near-field pollutant dispersion in urban environments - a review" *Environmental Pollution*.

Le Menach A, Takala S, McKenzie FE, Perisse A, Harris A, Flahault A, and Smith DL (2007) "An elaborated feeding cycle model for reductions in vectorial capacity of night-biting mosquitoes by insecticide-treated nets" *Malaria Journal* 6: 10.

Lee W-C, Catalano PJ, Yoo JY, Park CJ, and Koutrakis P (2015) "Validation and application of the mass balance model to determine the effectiveness of portable air purifiers in removing ultrafine and submicrometer particles in an apartment" *Environmental Science & Technology* 49(16): 9592-9599.

Lelieveld J, Evans JS, Fnais M, Giannadaki D, and Pozzer A (2015) "The contribution of outdoor air pollution sources to premature mortality on a global scale" *Nature* 525(7569): 367-371.

Lewis JJ and Pattanayak SK (2012) "Who adopts improved fuels and cookstoves? A systematic review" *Environmental Health Perspectives* 120(5): 637-645.

Lim SS, Vos T, Flaxman AD, Danaei G, Shibuya K, Adair-Rohani H, Amann M, Anderson HR, Andrews KG, Aryee M, Atkinson C, Bacchus LJ, Bahalim AN, Balakrishnan K, Balmes J, Barker-Collo S, Baxter A, Bell ML, Blore JD, Blyth F, Bonner C, Borges G, Bourne R, Boussinesq M, Brauer M, Brooks P, Bruce NG, Brunekreef B, Bryan-Hancock C, Bucello C, Buchbinder R, Bull F, Burnett RT, Byers TE, Calabria B, Carapetis J, Carnahan E, Chafe Z, Charlson F, Chen H, Chen JS, Cheng AT-A, Child JC, Cohen A, Colson KE, Cowie BC, Darby S, Darling S, Davis A, Degenhardt L, Dentener F, Des Jarlais DC, Devries K, Dherani M, Ding EL, Dorsey ER, Driscoll T, Edmond K, Ali SE, Engell RE, Erwin PJ, Fahimi S, Falder G, Farzadfar F, Ferrari A, Finucane MM, Flaxman S, Fowkes FGR, Freedman G, Freeman MK, Gakidou E, Ghosh S, Giovannucci E, Gmel G, Graham K, Grainger R, Grant B, Gunnell D, Gutierrez HR, Hall W, Hoek HW, Hogan A, Hosgood HD, 3rd, Hoy D, Hu H, Hubbell BJ, Hutchings SJ, Ibeanusi SE, Jacklyn GL, Jasrasaria R, Jonas JB, Kan H, Kanis JA, Kassebaum N, Kawakami N, Khang Y-H, Khatibzadeh S, Khoo J-P, Kok C, Laden F, Lalloo R, Lan Q, Lathlean T, Leasher JL, Leigh J, Li Y, Lin JK, Lipshultz SE, London S, Lozano R, Lu Y, Mak J, Malekzadeh R, Mallinger L, Marcenes W, March L, Marks R, Martin R, McGale P, McGrath J, Mehta S, Mensah GA, Merriman TR, Micha R, Michaud C, Mishra V, Mohd Hanafiah K, Mokdad AA, Morawska L, Mozaffarian D, Murphy T, Naghavi M, Neal B, Nelson PK, Nolla JM, Norman R, Olives C, Omer SB, Orchard J, Osborne R, Ostro B, Page A, Pandey KD, Parry CDH, Passmore E, Patra J, Pearce N, Pelizzari PM, Petzold M, Phillips MR, Pope D, Pope CA, 3rd, Powles J, Rao M, Razavi H, Rehfuess EA, Rehm JT, Ritz B, Rivara FP, Roberts T, Robinson C, Rodriguez-Portales JA, Romieu I, Room R, Rosenfeld LC, Roy A, Rushton L, Salomon JA, Sampson U, Sanchez-Riera L, Sanman E, Sapkota A, Seedat S, Shi P, Shield K, Shivakoti R, Singh GM, Sleet DA, Smith E, Smith KR, Stapelberg NJC, Steenland K, Stockl H, Stovner LJ, Straif K, Straney L, Thurston GD, Tran JH, Van Dingenen R, van Donkelaar A, Veerman JL, Vijayakumar L, Weintraub R, Weissman MM, White RA, Whiteford H, Wiersma ST, Wilkinson JD, Williams HC, Williams W, Wilson N, Woolf AD, Yip P, Zielinski JM, Lopez AD, Murray CJL, Ezzati M, AlMazroa MA, and Memish ZA (2012) "A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010" *Lancet* 380(9859): 2224-2260.

Limpert E, Stahel WA, and Abbt M (2001) "Log-normal distributions across the sciences: keys and clues" *Bioscience* 51(5): 341-352.

Liu J, Mauzerall DL, Chen Q, Zhang Q, Song Y, Peng W, Klimont Z, Qiu X, Zhang S, Hu M, Lin W, Smith KR, and Zhu T (2016) "Air pollutant emissions from Chinese households: a major and underappreciated ambient pollution source" *Proceedings of the National Academy of Sciences* (early edition).

Lobb R and Colditz GA (2013) "Implementation science and its application to population health" *Annual Review of Public Health* 34(1): 235-251.

Luby S (2014) "Is targeting access to sanitation enough?" *The Lancet Global Health* 2(11): e619-e620.

Macdonald R (2003) Theory And Objectives of Air Dispersion Modelling University of Waterloo, Waterloo, ON.

Manski CF (1993) "Identification of endogenous social effects: the reflection problem" *The Review of Economic Studies* 60(3): 531-542.

Marshall JD, Teoh SK, and Nazaroff WW (2005) "Intake fraction of nonreactive vehicle emissions in US urban areas" *Atmospheric Environment* 39(7): 1363-1371.

Martin WJ, II, Glass RI, Araj H, Balbus J, Collins FS, Curtis S, Diette GB, Elwood WN, Falk H, Hibberd PL, Keown SEJ, Mehta S, Patrick E, Rosenbaum J, Sapkota A, Tolunay HE, and

Bruce NG (2013) "Household air pollution in low- and middle-income countries: health risks and research priorities" *PLOS Medicine* 10(6): e1001455.
Mason IG (2006) "Mathematical modelling of the composting process: a review" *Waste Management* 26(1): 3-21.
Mathai AM, Moschopoulos P, and Pederzoli G (1999) "Random points associated with rectangles" *Rendiconti del Circolo Matematico di Palermo* 48(1): 163-190.
Mausezahl D, Christen A, Pacheco GD, Tellez FA, Iriarte M, Zapata ME, Cevallos M, Hattendorf J, Cattaneo MD, Arnold B, Smith TA, and Colford JM, Jr. (2009) "Solar drinking water disinfection (SODIS) to reduce childhood diarrhoea in rural Bolivia: a cluster-randomized, controlled trial" *PLOS Medicine* 6(8): e1000125.
McCready D, Arnold SM, and Fontaine DD (2012) "Evaluation of potential exposure to formaldehyde air emissions from a washing machine using the IAQX model" *Human and Ecological Risk Assessment* 18(4): 832-854.
Microsoft R Application Network (2015) "Microsoft R Open: The Enhanced R Distribution" Microsoft Corporation, Mountain View, CA https://mran.revolutionanalytics.com/open/ Accessed 2016 Jan 05.
Minasny B, McBratney AB, and Salvador-Blanes S (2008) "Quantitative models for pedogenesis - a review" *Geoderma* 144(1-2): 140-157.
Mohammed MOA, Song WW, Ma WL, Li WL, Ambuchi JJ, Thabit M, and Li YF (2015) "Trends in indoor–outdoor $PM_{2.5}$ research: A systematic review of studies conducted during the last decade (2003–2013)" *Atmospheric Pollution Research* 6(5): 893-903.
Morawska L, Afshari A, Bae GN, Buonanno G, Chao CYH, Hänninen O, Hofmann W, Isaxon C, Jayaratne ER, Pasanen P, Salthammer T, Waring M, and Wierzbicka A (2013) "Indoor aerosols: from personal exposure to risk assessment" *Indoor Air* 23(6): 462-487.
Moschandreas DJ, Watson J, D'Abreton P, Scire J, Zhu T, Klein W, and Saksena S (2002) "Chapter three: methodology of exposure modeling" *Chemosphere* 49(9): 923-946.
Motlagh MS, Kalhor M, and Arya FK (2011) "Comparison of numerical simulation of NOx with modeling of IAQX in indoor environments" *Iranian Journal of Health and Environment* 4(2): 125-136.
Mukhopadhyay K, Ramasamy R, Mukhopadhyay B, Ghosh S, Sambandam S, and Balakrishnan K (2014) "Use of ventilation-index in the development of exposure model for indoor air pollution - a review" *Open Journal of Air Pollution* 3(33-41).
Mukhopadhyay R, Sambandam S, Pillarisetti A, Jack D, Mukhopadhyay K, Balakrishnan K, Vaswani M, Bates MN, Kinney PL, Arora N, and Smith KR (2012) "Cooking practices, air quality, and the acceptability of advanced cookstoves in Haryana, India: an exploratory study to inform large-scale interventions" *Global Health Action* 5.
Naeher LP, Smith KR, Leaderer BP, Mage D, and Grajeda R (2000) "Indoor and outdoor $PM_{2.5}$ and CO in high- and low-density Guatemalan villages" *Journal of Exposure Analysis and Environmental Epidemiology* 10: 544-551.
Nazaroff WW (2004) "Indoor particle dynamics" *Indoor Air* 14: 175-183.
Neyman JS (1923) "Sur les applications de la theorie des probabilites aux experiences agricoles: assai des principes" *Roczniki Nauk Rolniczych* 10: 1-51.
Nicas M (1996) "Estimating exposure intensity in an imperfectly mixed room" *American Industrial Hygiene Association Journal* 57(6): 542-550.

Nicas M (2008) "Application of mathematical modeling to estimate air contaminant exposure " In Modern Industrial Hygiene Editor JL P, American Conference of Governmental Industrial Hygienists, Cincinnati, OH**:** 357-406.

Nicas M, Boelter FW, Simmons CE, Scheff P, and Berman L (2009) "A three-zone model for welding fume concentrations" *Journal of Occupational and Environmental Hygiene* 6(10): D69-D71.

Novomestky F and Nadarajah S (2011) "truncdist: Truncated Random Variables (Version 1.0.1)" https://CRAN.R-project.org/package=truncdist Accessed 2016 May 01.

Oberkampf WL and Trucano TG (2002) "Verification and validation in computational fluid dynamics" *Progress in Aerospace Sciences* 38(3): 209-272.

Office of the Registrar General and Census Commissioner (2012) "Houselisting and Housing Data" Ministry of Home Affairs, Government of India, New Delhi, IN http://www.censusindia.gov.in/2011census/hlo/HLO_Tables.html Accessed 2016 Apr 15.

Ofir E, Gal G, Goren M, Shapiro J, and Spanier E (2016) "Detecting changes to the functioning of a lake ecosystem following a regime shift based on static food-web models" *Ecological Modelling* 320: 145-157.

Ott WR (1999) "Mathematical models for predicting indoor air quality from smoking activity" *Environmental Health Perspectives* 107(Suppl 2): 375-381.

Pasquill F (1961) "The estimation of the dispersion of windborne material" *The Meteorological Magazine* 90(1063): 33-49.

Patil SR, Arnold BF, Salvatore AL, Briceno B, Ganguly S, Colford JM, Jr., and Gertler PJ (2014) "The effect of India's total sanitation campaign on defecation behaviors and child health in rural Madhya Pradesh: a cluster randomized controlled trial" *PLOS Medicine* 11(8): e1001709.

Pellicciotti F, Carenzo M, Bordoy R, and Stoffel M (2014) "Changes in glaciers in the Swiss Alps and impact on basin hydrology: current state of the art and future research" *Science of the Total Environment* 493: 1152-1170.

Pepper DW and Carrington D (2009) Modeling Indoor Air Pollution Imperial College Press, London, UK.

Pillarisetti A, Mehta S, and Smith KR (2016) "HAPIT, the household air pollution intervention tool, to evaluate the health benefits and cost-effectiveness of clean cooking interventions" In Broken Pumps and Promises: Incentiving Impact in Environmental Health Editor Thomas EA, Springer, Cham, CH**:** 147-169.

Prasad KK, Sangen E, and Visser P (1985) "Woodburning cookstoves" In Advances in Heat Transfer Editors Hartnett JP and Irvine TF, Elsevier, Amsterdam, NL**:** 159-317.

R Core Team (2015) "R: A Language and Environment for Statistical Computing" R Foundation for Statistical Computing, Vienna, Austria https://www.R-project.org/ Accessed 2015 Oct 01.

Rehfuess E, Pope D, and Bruce N (2014a) World Health Organization Indoor Air Quality Guidelines: Household Fuel Combustion - Evidence Review 6: Impact of Interventions on Household Air Pollution Concentrations and Personal Exposure World Health Organization, Geneva, CH.

Rehfuess EA, Puzzolo E, Stanistreet D, Pope D, and Bruce NG (2014b) "Enablers and barriers to large-scale uptake of improved solid fuel stoves: a systematic review" *Environmental Health Perspectives* 122(2): 120-130.

Revolution Analytics and Weston S (2015a) "doParallel: Foreach Parallel Adaptor for the 'parallel' Package (Version 1.0.10)" https://CRAN.R-project.org/package=doParallel Accessed 2016 Apr 15.
Revolution Analytics and Weston S (2015b) "foreach: Provides Foreach Looping Construct for R (Version 1.4.3)" https://CRAN.R-project.org/package=doParallel Accessed 2016 Apr 15.
Rohra H and Taneja A (2016) "Indoor air quality scenario in India - an outline of household fuel combustion" *Atmospheric Environment* 129: 243-255.
Root GP (2001) "Sanitation, community environments, and childhood diarrhoea in rural Zimbabwe" *Journal of Health, Population, and Nutrition* 19(2): 73-82.
Rosenbaum PR (2007) "Interference between units in randomized experiments" *Journal of the American Statistical Association* 102(477): 191-200.
Rosenthal J (2015) "The real challenge for cookstoves and health: more evidence" *EcoHealth* 12(1): 8-11.
Ross R (1915) "Some *a priori* pathometric equations" *British Medical Journal* 1: 546-547.
Ross R (1916) "An application of the theory of probabilities to the study of *a priori* pathometry. Part I" *Proceedings of the Royal Society of London A: Mathematical, Physical, and Engineering Sciences* 92(638): 204-230.
Rubin DB (1974) "Estimating causal effects of treatments in randomized and nonrandomized studies" *Journal of Educational Psychology* 66(5): 688-701.
Rubin DB (1990) "Formal mode of statistical inference for causal effects" *Journal of Statistical Planning and Inference* 25(3): 279-292.
Ruiz-Mercado I and Masera O (2015) "Patterns of stove use in the context of fuel-device stacking: rationale and implications" *EcoHealth* 12(1): 42-56.
Ruiz-Mercado I, Masera O, Zamora H, and Smith KR (2011) "Adoption and sustained use of improved cookstoves" *Energy Policy* 39(12): 7557-7566.
Saksena S, Singh PB, Prasad RK, Prasad R, Malhotra P, Joshi V, and Patil RS (2003) "Exposure of infants to outdoor and indoor air pollution in low-income urban areas - a case study of Delhi" *Journal of Exposure Analysis and Environmental Epidemiology* 13(3): 219-230.
Salje H, Gurley ES, Homaira N, Ram PK, Haque R, Petri W, Moss WJ, Luby SP, Breysse P, and Azziz-Baumgartner E (2013) "Impact of neighborhood biomass cooking patterns on episodic high indoor particulate matter concentrations in clean fuel homes in Dhaka, Bangladesh" *Indoor Air* 24(2): 213-220.
Sambandam S, Balakrishnan K, Ghosh S, Sadasivam A, Madhav S, Ramasamy R, Samanta M, Mukhopadhyay K, Rehman H, and Ramanathan V (2015) "Can currently available advanced combustion biomass cook-stoves provide health relevant exposure reductions? Results from initial assessment of select commercial models in India" *EcoHealth* 12(1): 25-41.
Schare S and Smith KR (1995) "Particulate emission rates of simple kerosene lamps" *Energy for Sustainable Development* 2(2): 32-35.
Schnelle KK and Dey PR (2000) Atmospheric Dispersion Modeling Compliance Guide McGraw-Hill, New York, NY.
Scire JS, Strimaitis DG, and Yamartino. RJ (2000) A User’s Guide for the CALPUFF Dispersion Model Earth Tech, Inc. , Concord, MA.

Servedio MR, Brandvain Y, Dhole S, Fitzpatrick CL, Goldberg EE, Stern CA, Van Cleve J, and Yeh DJ (2014) "Not just a theory - the utility of mathematical models in evolutionary biology" *PLoS Biology* 12(12): e1002017.
Shankar A, Johnson M, Kay E, Pannu R, Beltramo T, Derby E, Harrell S, Davis C, and Petach H (2014) "Maximizing the benefits of improved cookstoves: moving from acquisition to correct and consistent use" *Global Health, Science, and Practice* 2(3): 268-274.
Sinclair B, McConnell M, and Green DP (2012) "Detecting spillover effects: design and analysis of multilevel experiments" *American Journal of Political Science* 56(4): 1055-1069.
Sivacoumar R, Mohan Raj S, Chinnadurai SJ, and Jayabalou R (2009) "Modeling of fugitive dust emission and control measures in stone crushing industry" *Journal of Environmental Monitoring* 11(5): 987-997.
Smith KR (1987) Biofuels, Air Pollution, and Health: A Global Review Plenum, New York.
Smith KR (1988) "Air pollution: assessing total exposure in developing countries" *Environment: Science and Policy for Sustainable Development* 30(10): 16-35.
Smith KR (2015) "Changing paradigms in clean cooking" *EcoHealth* 12(1): 196-199.
Smith KR, Aggarwal AL, and Dave RM (1983) "Air pollution and rural biomass fuels in developing countries: a pilot village study in India and implications for research and policy" *Atmospheric Environment* 17(11): 2343-2362.
Smith KR, Apte MG, Yuqing M, Wongsekiarttirat W, and Kulkarni A (1994) "Air pollution and the energy ladder in Asian cities" *Energy* 19(5): 587-600.
Smith KR, Bruce N, Balakrishnan K, Adair-Rohani H, Balmes J, Chafe Z, Dherani M, Hosgood HD, Mehta S, Pope D, and Rehfuess E (2014) "Millions dead: how do we know and what does it mean? Methods used in the Comparative Risk Assessment of household air pollution" *Annual Review of Public Health* 35: 185-206.
Smith KR, McCracken JP, Thompson L, Edwards R, Shields KN, Canuz E, and Bruce N (2010) "Personal child and mother carbon monoxide exposures and kitchen levels: methods and results from a randomized trial of woodfired chimney cookstoves in Guatemala (RESPIRE)" *Journal of Exposure Science & Environmental Epidemiology* 20(5): 406-416.
Smith KR and Sagar A (2014) "Making the clean available: escaping India's chulha trap" *Energy Policy* 75: 410-414.
Sobel ME (2006) "What do randomized studies of housing mobility demonstrate?" *Journal of the American Statistical Association* 101(476): 1398-1407.
Soetaert K, Cash J, and Mazzia F (2012) "Solving Ordinary Differential Equations in R" In Solving Differential Equations in R, Springer-Verlag, Berlin, DE 41-80.
Spear R (2002) "Mathematical modeling in environmental health" *Environmental Health Perspectives* 110(7): A382.
Spears D, Ghosh A, and Cumming O (2013) "Open defecation and childhood stunting in India: an ecological analysis of new data from 112 districts" *PLOS ONE* 8(9): e73784.
Stevens G, de Foy B, West JJ, and Levy JI (2007) "Developing intake fraction estimates with limited data: comparison of methods in Mexico City" *Atmospheric Environment* 41(17): 3672-3683.
Subramanian SV (2004) "The relevance of multilevel statistical methods for identifying causal neighborhood effects" *Social Science & Medicine* 58(10): 1961-1967.

Sutton OG (1932) "A theory of eddy diffusion in the atmosphere" *Proceedings of the Royal Society of London A: Mathematical, Physical, and Engineering Sciences* 135(826): 143-165.
Ten Berge WF (2000) Mathematical Models for Estimating Occupational Exposure to Chemicals American Industrial Hygiene Association, Falls Church, VA.
Thatcher T and Kirchstetter T (2011) Assessing Near-Field Exposures from Distributed Residential Wood Smoke Combustion Sources Air Resources Board of the California Environmental Protection Agency, Sacramento, CA: #07-308.
Thomas E, Wickramasinghe K, Mendis S, Roberts N, and Foster C (2015) "Improved stove interventions to reduce household air pollution in low and middle income countries: a descriptive systematic review" *BMC Public Health* 15: 650.
Tietenberg TH (1992) Environmental and Natural Resource Economics HarperCollins, New York, NY
Tilley N, Rauwoens P, and Merci B (2011) "Verification of the accuracy of CFD simulations in small-scale tunnel and atrium fire configurations" *Fire Safety Journal* 46(4): 186-193.
Tripathi A, Sagar AD, and Smith KR (2015) "Promoting clean and affordable cooking: smarter subsidies for LPG" *Economic & Political Weekly* 50(48): 81-84.
Turner DB (1970) Workbook of Atmospheric Dispersion Estimates Environmental Protection Agency, Research Triangle Park, NC.
United States Environmental Protection Agency (1995) User's Guide for the Industrial Source Complex (ICS3) Dispersion Models: Volume II - Description of Model Algorithms U.S. Environmental Protection Agency, Research Triangle Park, NC.
van der Laan MJ (2014) "Causal inference for a population of causally connected units" *Journal of Causal Inference* 2(1): 13-74.
Vardoulakis S, Fisher BEA, Pericleous K, and Gonzalez-Flesca N (2003) "Modelling air quality in street canyons: a review" *Atmospheric Environment* 37(2): 155-182.
von Hippel PT (2005) "Mean, median, and skew: correcting a textbook rule" *Journal of Statistics Education* 13(2): www.amstat.org/publications/jse/v13n12/vonhippel.html.
Walter SD (1978) "Calculation of attributable risks from epidemiological data" *International Journal of Epidemiology* 7(2): 175-182.
Wang WH (2009) "Assessment for inside building dispersion of aerosol from an outdoor radiological release" *Kerntechnik* 74(1-2): 79-82.
WeatherSpark (2016) "Average Weather for Lucknow, India" https://weatherspark.com/averages/33937/Lucknow-Uttar-Pradesh-India Accessed 2016 Feb 15.
Wickham H (2007) "Reshaping data with the 'reshape' package" *Journal of Statistical Software* 21(12): 1-20.
Wickham H (2009) ggplot2: Elegant Graphics for Data Analytics Springer-Verlag, New York, NY.
Wickham H (2011) "The split-apply-combine strategy for data analysis" *Journal of Statistical Software* 40(1): 1-29.
Wolf J, Pruss-Ustun A, Cumming O, Bartram J, Bonjour S, Cairncross S, Clasen T, Colford JM, Jr., Curtis V, De France J, Fewtrell L, Freeman MC, Gordon B, Hunter PR, Jeandron A, Johnston RB, Mausezahl D, Mathers C, Neira M, and Higgins JPT (2014) "Assessing the impact of drinking water and sanitation on diarrhoeal disease in low- and middle-income

settings: systematic review and meta-regression" *Tropical Medicine & International Health* 19(8): 928-942.
World Health Organization (2006) Air Quality Guidelines Global Update 2005: Particulate Matter, Ozone, Nitrogen Dioxide, and Sulfur Dioxide World Health Organization, Geneva, CH.
World Health Organization (2014a) "Ambient Air Pollution in Cities Database 2014" World Health Organization, Geneva, CH http://www.who.int/phe/health_topics/outdoorair/databases/cities/en/ Accessed 2016 Feb 15.
World Health Organization (2014b) Indoor Air Quality Guidelines: Household Fuel Combustion World Health Organization, Geneva, CH.
Yan W, Zhang Y, Sun Y, and Li D (2009) "Experimental and CFD study of unsteady airborne pollutant transport within an aircraft cabin mock-up" *Building and Environment* 44(1): 34-43.
Zhang J, Bai Z, and Ding X (2010) "Indoor-outdoor relationship for airborne particulate matter of outdoor origin in exposure assessment: a review of recent studies" *Journal of Environment and Health* 27(8): 737-741.
Zhao D, Azimi P, and Stephens B (2015) "Evaluating the long-term health and economic impacts of central residential air filtration for reducing premature mortality associated with indoor fine particulate matter ($PM_{2.5}$) of outdoor origin" *International Journal of Environmental Research and Public Health* 12(7): 8448-8479.

5. Conclusion

In this dissertation, I motivated, developed, and demonstrated three approaches for investigating multiscale drivers of global environmental health: (1) a causal metric for analyzing contributions and responses to climate change from global to sectoral scales, (2) a conceptual framework for unraveling the influence of environmental change on infectious disease at regional to local scales, and (3) a mechanistic model for informing the design and evaluation of clean cooking interventions at community to household scales.

The full utility of climate debt as an analytical perspective will remain untapped without causal metrics that can be manipulated by a wide range of analysts, including global environmental health researchers. *Chapter 2* explains how IND apportions global radiative forcing from CO_2(f) and CH_4, the two most significant CAPs, to individual entities − primarily countries but also subnational states and economic sectors, with even finer scales possible − as a function of unique trajectories of historical emissions, taking into account the quite different radiative efficiencies and atmospheric lifetimes of each CAP. Owing to its straightforward and transparent derivation, IND can readily operationalize climate debt to consider issues of equity and efficiency and drive scenario exercises that explore the response to climate change at multiple scales. Collectively, the analyses presented in this chapter demonstrate how IND can inform a range of key questions, compelling environmental health towards an appraisal of the causes as well as the consequences of climate change.

The environmental change and infectious disease (EnvID) conceptual framework of *Chapter 3* builds on a rich history of prior efforts in epidemiologic theory, environmental science, and mathematical modeling to analyze social and ecological drivers of re/emerging pathogens. EnvID is distinguished by: (1) articulating a flexible and logical system specification; (2) incorporating transmission groupings linked to public health intervention strategies; (3) emphasizing the intersection of proximal environmental characteristics and transmission cycles; (4) incorporating a matrix formulation to identify knowledge gaps and facilitate research integration; and (5) highlighting hypothesis generation amidst dynamic processes. A systems-based approach leverages the reality that studies relevant to environmental change and infectious disease are embedded within a wider web of interactions. As scientific understanding advances, the EnvID framework can help integrate the various factors at play in determining environment–disease relationships and the connections between intrinsically multiscale causal networks.

In *Chapter 4*, the coverage effect mechanistic model functions primarily as a "proof-of-concept" analysis to address whether the efficacy of a clean cooking technology may be determined by the extent of not only household-level use but also community-level coverage. Such coverage dependent efficacy, or a "coverage effect," would transform how interventions are studied and deployed. Ensemble results are consistent with the concept that an appreciable coverage effect from LPG-C interventions can manifest within moderately dense communities. Benefits for LPG-C users derive largely from direct effects; initially, at low coverage levels, almost exclusively so. Yet, as coverage expands within an LPG-C user's community, a coverage effect becomes markedly beneficial. In contrast, TSF-C users, despite also experiencing comparable exposure reductions from community-level LPG-C use, cannot proportionately benefit because their $PM_{2.5}$ exposures remain overwhelmingly dominated by household-level TSF-C use.

The coverage effect model strengthens the rationale for public health programs and policies to encourage clean cooking technologies with an added incentive to realize high coverage within contiguous areas. The implications of the modeling exercise extend to priorities for data collection, underscoring the importance of outdoor $PM_{2.5}$ concentrations during, as well as before and/or after, community cooking windows and also routine measurement of ventilation, meteorology, time-activity patterns, and cooking practices. The possibility of a coverage effect equates to a potential for SUTVA violation, necessitating strategies to estimate not only direct effects but also coverage and total effects to avoid impaired conclusions.

A postulated coverage effect from clean cooking interventions also raises hypotheses about air pollution more generally. Just as a coverage effect may exist within communities, there may well be a parallel phenomenon between communities. Arguably, the benefits from abatement programs for AAP are intrinsically coverage effects. Beneficiaries may not only, and perhaps not even primarily, be users, but instead, residents of the surrounding community (1^{st} level coverage effect), wider region (2^{nd} level coverage effect), and even cross-boundary or global communities (3^{rd} level coverage effect). Of course, if the specific form of air pollution being considered is CO_2(f) or CH_4, then the analysis has come full circle.

The specter of accelerating social and ecological change challenges efforts to respond to climate change, re/emerging infectious diseases, and household air pollution. Environmental health possesses a verified repertoire of incisive methods but contending with multiscale drivers of risk requires complementary approaches, as well. Integrating metrics, frameworks, and models − and the resulting insights − into its analytical arsenal can help global environmental health meet the challenges of today and tomorrow.

Appendix A

A1. Legend for Database IND

Workbook[7] reports IND and associated data with respect to the year 2005 for 206 countries, a number which includes California as a distinct entity. In all worksheets, countries are presented sorted by population size with population data provided (Population Estimates Program of the United States Census Bureau 2011; United Nations Department of Social and Economic Affairs, Population Division 2011). All data types are presented as total and per capita values, accompanied, for total values, with percent of world ("% World"); for per capita values, with percent of world average ("% Average"); and for both, global ranks (1 to 206). The first tab provides data on IND (including $\%CO_2$(f) and $\%CH_4$), $IND_{CO_2(f)}$, and IND_{CH_4}. The second tab provides data on current (2005), total original, and total remaining emissions of CO_2(f) and CH_4 (Air Resources Board of the California Environmental Protection Agency 2007a; Air Resources Board of the California Environmental Protection Agency 2013; Boden et al. 2010; Joint Research Centre of the European Commission/PBL Netherlands Environmental Assessment Agency 2010b; United Nations Framework Convention on Climate Change 2012). The third tab provides data on GDP-PPP and DALYs (Global Burden of Disease Study 2010 2012; World Bank 2012; Bureau of Economic Analysis of the United States Department of Commerce 2006; United States Central Intelligence Agency 2006). The 51 countries with the largest total IND, a list which includes California, are highlighted in the first three tabs. The fourth tab provides data on IND_{CH_4} from all sectors combined and disaggregated by sector. The 25 countries with the largest total IND_{CH_4}, plus California, are highlighted in this tab. Abbreviations: $\%CH_4$ = percent of IND from CH_4; $\%CO_2$(f) = percent of IND from CO_2(f); CH_4 = methane; CO_2(f) = carbon dioxide from fossil fuels and cement manufacture; DALYs = disability-adjusted life years lost; IND = International Natural Debt, climate debt from CO_2(f) and CH_4 combined; IND_{CH_4} = climate debt from CH_4; $IND_{CO_2(f)}$ = climate debt from CO_2(f); GDP-PPP = gross domestic product at purchasing power parity; pp = per person; U.S. minus CA = United States minus California.

[7] *Database IND* is available at http://www.kirkrsmith.org/s/Desai-Dataset-IND.xlsx

A2. Adjustments to Emissions Datasets

Adjustments were required for the CDIAC dataset (Boden et al. 2010) to account for unifications and partitions, affecting 14% of all country-year original emissions data. Additionally, for a comparatively small number of country-years, the CDIAC dataset was adjusted to address missing data, negative values, and a reporting change for the United States and its dependencies. These are other adjustments are detailed below.

Unifications − CDIAC

- For unifications, listed in Table A1, I merged the time-series of component countries to create the time-series for the merged country.

Table A1: CDIAC − Country Unifications

Component Countries (Pre-Unification)	*Merged Country (Post-Unification)*
Japan 1952−1972 Ryukyu Islands 1952−1972	Japan 1952−1972
Panama 1950−1979 Panama Canal Zone 1950−1979	Panama 1950−1979
North Vietnam 1955−1969 South Vietnam 1955−1969	Viet Nam 1955−1969
North Yemen 1950−1990 South Yemen 1950−1990	Yemen 1950−1990
Peninsular Malaysia 1957−1969 Sarawak 1957−1969 Sabah 1957−1969	Malaysia 1957−1969
Tanganyika 1950−1959 Zanzibar 1950−1959	Tanzania 1950−1959
West Germany 1950−1990 East Germany 1950−1990	Germany 1950−1990

Partitions − CDIAC

- For partitions, listed in *Table A2*, I used cumulative emissions from each component country during the first five years post-partition to proportionally weight the attribution of emissions from the merged country during pre-partition.

Table A2: CDIAC − Country Partitions

Merged Country (Pre-Partition)	*Component Countries (Post-Partition)*
Ethiopia 1950−1993	Eritrea 1950−1993 Ethiopia 1950−1993
Indonesia 1950−2001	Indonesia 1950−2001 Timor-Leste 1950−2001
Czechoslovakia 1950−1991	Czech Republic Slovakia
East & West Pakistan 1950−1971	Bangladesh 1950−1971 Pakistan 1950−1971
French Equatorial Africa[1] 1950−1958	Central African Republic 1950−1958 Chad 1950−1958 Congo (Brazzaville) 1950−1958 Gabon 1950−1958
French Indo-China 1950−1954	Cambodia 1950−1954 Laos 1950−1954 Viet Nam 1950−1954
French West Africa 1950−1957	Benin 1950−1957 Burkina Faso 1950−1957 Côte d'Ivoire 1950−1957 Guinea 1950−1957 Mali 1950−1957 Mauritania 1950−1957 Niger 1950−1957 Senegal 1950−1957
Leeward Islands 1950−1956	Anguilla[2] 1950−1956 Antigua & Barbuda[2] 1950−1956 British Virgin Islands 1950−1956 Montserrat 1950−1956 Saint Kitts & Nevis 1950−1956
Malaya-Singapore 1950−1956	Malaysia 1950−1956 Singapore 1950−1956

Merged Country (Pre-Partition)	*Component Countries (Post-Partition)*
Rhodesia-Nyasaland 1950−1963	Malawi 1950−1963 Zambia 1950−1963 Zimbabwe 1950−1963
Rwanda-Urundi 1950−1961	Burundi 1950−1961 Rwanda 1950−1961
Saint Kitts, Nevis, and Anguilla 1957−1980	Anguilla[2] 1957−1980 Saint Kitts & Nevis 1957−1980
USSR 1950−1991	Armenia 1950−1991 Azerbaijan 1950−1991 Belarus 1950−1991 Estonia 1950−1991 Georgia 1950−1991 Kazakhstan 1950−1991 Kyrgyzstan 1950−1991 Latvia 1950−1991 Lithuania 1950−1991 Moldova 1950−1991 Russian Federation 1950−1991 Tajikistan 1950−1991 Turkmenistan 1950−1991 Ukraine 1950−1991 Uzbekistan 1950−1991
Yugoslavia 1950−1991	Bosnia & Herzegovina 1950−1991 Croatia 1950−1991 Macedonia 1950−1991 Serbia & Montenegro 1950−1991 Slovenia 1950−1991

[1]Although French Equatorial Africa included Cameroon, the CDIAC dataset reports a full time-series for Cameroon. Hence, for the purposes of partition calculations, Cameroon is not included here.

[2]These countries or dependencies are included in the CDIAC dataset but missing from the EDGAR dataset and thus not included in the IND database. Data for these entities, however, was required for partition calculations.

Missing Years − CDIAC

- A missing year is defined as an annual total of zero. Missing years, which comprised 4.3% of all country-year original emissions data, are summarized in *Table A3*.
- Missing years that occurred in the middle of a time-series were replaced by linear interpolation based on the nearest non-zero years. Missing years that occurred at the start of a time-series were replaced by linear extrapolation of the full range of reported data by the least squares method. If an extrapolated trend became negative, emissions reverted to zero for that and all prior years. It is for this reason that missing years and replaced years differ in *Table A3*.

Table A3: CDIAC − Missing Years

Country or Dependency	*Missing Years*	*Middle or Start*	*Replaced Years*
Anguilla[1]	1981−1996	Start	1992−1996
American Samoa	1950−1953	Start	1952−1953
Bhutan	1950−1969	Start	none
Botswana	1950−1971	Start	1969−1971
British Virgin Islands[2]	1957−1961	Start	1961
Comoros	1950−1958	Start	1958
Cook Islands	1950−1968	Start	1950−1968
Falkland Islands	1968−1969	Middle	1968−1968
French Polynesia	1950−1954	Start	none
Kiribati	1950−1960	Start	1950−1960
Macau SAR	1950−1953	Start	1950−1953
Maldives	1950−1970	Start	none
Mali	1958	Start	1958
Marshall Islands	1950−1989	Start	1970−1989
Mauritania	1958	Start	1958
Micronesia[3]	1950−1998	Start	none
Montserrat[2]	1957−1961	Start	none
Namibia	1950−1989	Start	none
Nauru	1950−1963	Start	1950−1963
Niue[4]	1950−1969	Start	1950−1969
Niue[4]	1977	Middle	1977
Oman	1950−1963	Start	none
Palau	1950−1954	Start	1950−1954
Saint Helena[4]	1950−1967	Start	1959−1967
Saint Helena[4]	1969−1980	Middle	1969−1980
Sao Tome & Principe	1950	Start	none
Seychelles	1950−1962	Start	none
Solomon Islands	1950−1951	Start	none
Somalia	1996−1999	Middle	1996−1999

Country or Dependency	*Missing Years*	*Middle or Start*	*Replaced Years*
Turks & Caicos Islands	1950−1994	Start	none
United Arab Emirates	1950−1958	Start	none
Vanuatu	1950−1961	Start	1950−1961
Wallis & Futuna Islands[3]	1950−2000	Start	none
Western Sahara	1950−1969	Start	1950−1969

[1]Anguilla is excluded from the database but its time-series was necessary for the partition calculations for Leeward Islands and Saint Kitts, Nevis, & Anguilla.

[2]For British Virgin Islands and Montserrat, 1950−1956 is covered by Leeward Islands. However, interpolation remained infeasible after the partition calculation for Leeward Islands. Thus, extrapolation was used to replace 1957−1961.

[3]Reported data for Micronesia and Wallis & Futuna Islands was insufficient for extrapolation (only 7 and 5 years, respectively). Hence, these missing years were left uncorrected.

[4]Niue and Saint Helena each possessed two different sets of missing years. Interpolation was performed first and extrapolation second.

A2.4. Negative Values − CDIAC

- A small number of negative values for original emissions were reported at the source level (solid, liquid, or gas fossil fuel; flaring; or cement). Negative values affected 0.2% of all country-year original emissions data. These negative values were replaced by linear interpolation based on the nearest adjacent non-negative data for that source category. See *Table A4.*
- In one case (Iran 1950 liquid source category), the negative value occurred at the start of the time-series. In this instance the value was set to zero.
- Replacing negative values in source categories eliminated the previously negative total original emissions for a handful of country-years − Iran 1950, Saudi Arabia 1951 & 1952, and Kuwait 1952 & 1953.

Table A4: CDIAC − Negative Values

Country or Dependency	*Source*	*Year*	*Negative Value*	*Interpolated Value*
Iran	Liquid	1950	-5,965.67	0.00
Saudi Arabia	Liquid	1951	-348.33	3588.44
Saudi Arabia	Liquid	1952	-172.33	2032.56
Kuwait	Liquid	1952	-436.33	546.33
Kuwait	Liquid	1953	-51.33	975.33
Switzerland	Liquid	1956	-3.67	0.00
Switzerland	Liquid	1957	-3.67	0.00
Switzerland	Liquid	1958	-3.67	0.00
Switzerland	Liquid	1959	-3.67	0.00
Switzerland	Liquid	1960	-3.67	0.00
Switzerland	Liquid	1961	-3.67	0.00
Switzerland	Liquid	1962	-3.67	0.00
Switzerland	Liquid	1963	-3.67	0.00
Switzerland	Liquid	1964	-3.67	0.00
Switzerland	Liquid	1966	-3.67	1.22
Trinidad and Tobago	Liquid	1963	-370.33	4222.78
Kuwait	Liquid	1968	-726.00	1873.67
Senegal	Liquid	1968	-179.67	540.22
Libya	Gas	1977	-146.67	498.67
Brunei Darussalam	Liquid	1981	-590.33	670.08
Brunei Darussalam	Liquid	1982	-572.00	665.50
Brunei Darussalam	Liquid	1983	-29.33	660.92
Panama	Liquid	1985	-113.67	24.44
United Arab Emirates	Liquid	1996	-14,498.00	28898.22
United Arab Emirates	Liquid	1997	-14,025.00	32712.78
United States Virgin Islands	Solid	1952	-3.67	0.00

A2.5. Reporting Change − CDIAC

- CDIAC includes original emissions for American Samoa, Guam, Puerto Rico, and United States Virgin Islands within the United States' totals. However, these dependencies' original emissions were reported separately until 2003 and the corresponding dependency-specific time-series remain available from CDIAC. Hence, original emissions from the four dependencies during 1950−2002 were subtracted from the United States' original emissions for 1950−2002, yielding an adjusted time-series for the United States. This reporting change affected 1.9% of all country-year original emissions.
- UNFCCC data were used for the United States' original emissions, prior to subtraction, for 1990 to 2005. Thus for those years the reporting change procedure is identical to that for UNFCCC adjustment.
- The situation for 2003−2005 was unique but follows an analogous procedure to a partition. For a given source category, the cumulative original emissions during 1998−2002 (the final five years of separate reporting) were used to determine proportional weights for the attribution of 2003−2005 original emissions.
- CDIAC reports original emissions for American Samoa in 2003, unlike with the other three dependencies, whose time-series end at 2002. For consistency with calculations, this data was ignored and American Samoa's time-series is reset to end with 2002 (difference in reported versus calculated emissions only ~1%).

A2.6. 1991 Kuwaiti Oil Fires − CDIAC

- 1991 Kuwaiti Oil Fires were included with Kuwait's energy sector category emissions for 1991.

A2.7. UNFCCC Notes − CDIAC

- UNFCCC data, reported according to IPCC codes, were mapped to CDIAC source categories according to the scheme in *Table A5* below.
- CDIAC's flaring emissions data refer strictly to the practice employed in oil fields. The UNFCCC's procedure, as outlined in the Revised 1996 IPCC Guidelines (Houghton et al. 1997), includes three subcategories for flaring: oil, gas, and combined, with the last subcategory referring to situations in which flaring from oil versus gas cannot be (or simply was not) separated. For the purposes of reporting GHG inventories, these three subcategories do not overlap.
- Most Annex I countries either (1) report flaring from oil and gas separately, and report nothing as combined; or (2) report all flaring as combined, and report nothing for either oil or gas. Canada and France are the exceptions to this practice, reporting data for all three categories. As a result, I use one of the two − oil flaring or combined flaring − and in the case of Canada and France sum these two categories.
- UNFCCC adjustments overwrite the results of partition calculations for 1990 and 1991 for the countries of Belarus, Estonia, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Russian Federation, Slovakia, Slovenia, and Ukraine.
- In order to avoid circular references in partition calculations, CDIAC data were not updated for 1990 and 1991. UNFCCC adjustments were utilized from 1992 to 2005 for partition calculations. Note, however, that if any partition countries were updated by UNFCCC adjustments, then the sums of emissions for daughter countries, being a mix of UNFCCC and CDIAC data, will not equal the emissions for the mother country, which are from CDIAC, for the years 1990 and 1991.

Table A5: Mapping of CO_2(f) Source Categories between CDIAC and UNFCCC

CDIAC	*UNFCCC*
Solids	Solid Fuels (Reference Approach)
Liquids	Liquid Fuels (Reference Approach)
Gas	Gaseous Fuels (Reference Approach)
Cement Production	2.A.1 Cement Production (Sectoral Approach)
Gas Flaring	1.B.2.C.2.1. Oil Flaring + 1.B.2.C.2.3 Combined Flaring (Sectoral Approach)

A2.8. UNFCCC Adjustments − CDIAC and EDGAR

- An additional adjustment was necessary because Annex I countries that possess dependencies report original emissions to UNFCCC for both the parent country and its dependencies combined. In such instances, to avoid double-counting, CDIAC or EDGAR data for the dependencies were subtracted from UNFCCC data (United Nations Framework Convention on Climate Change 2012) for the parent country. *Table A6*, based on 2011 National Inventory Reports to the UNFCCC, summarizes the ruling countries and dependencies for which adjustments were necessary. For each GHG, 3.6% of all country-years were adjusted in this fashion.

Table A6: Parent Countries and Dependencies for CDIAC to UNFCCC Adjustment

Ruling Country	*Dependency*
Denmark	Faeroe Islands
	Greenland
France	French Guiana
	French Polynesia
	Guadeloupe
	Martinique
	New Caledonia
	Réunion
	Wallis & Futuna Islands
New Zealand	Cook Islands
	Niue
United Kingdom	British Virgin Islands
	Falkland Islands
	Gibraltar
	Montserrat
	Saint Helena
	Turks & Caicos Islands
United States	American Samoa
	Guam
	Puerto Rico
	United States Virgin Islands

A3. Other Tables

Additional tables follow that list country inclusion/exclusion for *Figure 2.8*, *Figure 2.10*, and *Table 2.1*.

Table A7: Countries Missing from *Figure 2.8*

Missing Country or Dependency	*DALY Data Merged With or DALY Data Missing*
American Samoa	United States
British Virgin Islands	United Kingdom
Cook Islands	New Zealand
Faeroe Islands	Denmark
Falkland Islands	United Kingdom
French Guiana	France
French Polynesia	France
Gibraltar	United Kingdom
Greenland	Denmark
Guadeloupe	France
Guam	United States
Hong Kong SAR	*Missing*
Macau SAR	*Missing*
Martinique	France
Montserrat	United Kingdom
Nauru	*Missing*
New Caledonia	France
Niue	New Zealand
Palau	*Missing*
Puerto Rico	United States
Réunion	France
Saint Helena	United Kingdom
Saint Kitts & Nevis	*Missing*
Turks & Caicos Islands	United Kingdom
United States Virgin Islands	United States
Wallis & Futuna Islands	France
Western Sahara	*Missing*

Table A8: LUCF Region Definitions for *Table 2.1*

Region	Member Country
Canada	Canada
	Greenland
United States	
Mesoamerica	Costa Rica
	El Salvador
	Guatemala
	Honduras
	Mexico
	Nicaragua
	Panama
Caribbean	British Virgin Islands
	Cuba
	Dominican Republic
	Grenada
	Guadeloupe
	Haiti
	Jamaica
	Martinique
	Montserrat
	Puerto Rico
	Saint Kitts & Nevis
	Saint Lucia
	Saint Vincent & Grenadines
	Trinidad & Tobago
	Turks & Caicos Islands
	United States Virgin Islands
Tropical South America	Bolivia
	Brazil
	Colombia
	Ecuador
	French Guiana
	Guyana
	Paraguay
	Peru
	Suriname
	Venezuela
Temperate South America	Argentina
	Chile
	Falkland Islands
	Uruguay
Europe	Albania
	Austria
	Belgium
	Bosnia & Herzegovina
	Bulgaria
	Croatia
	Czech Republic
	Denmark
	Faeroe Islands
	Finland
	France
	Germany
	Greece
	Gibraltar
	Hungary
	Iceland
	Ireland
	Italy
	Luxembourg
	Macedonia
	Malta
	Netherlands
	Norway
	Poland
	Portugal
	Romania
	Serbia & Montenegro
	Slovakia
	Slovenia
	Spain
	Sweden
	Switzerland
	United Kingdom
Former Soviet Union	Armenia
	Azerbaijan
	Belarus
	Estonia
	Georgia
	Kazakhstan
	Kyrgyzstan
	Latvia
	Lithuania
	Moldova
	Russian Federation
	Tajikistan
	Turkmenistan
	Ukraine
	Uzbekistan
Middle East & North Africa	Afghanistan
	Algeria
	Bahrain
	Cyprus
	Egypt
	Iran
	Iraq
	Israel
	Jordan
	Kuwait
	Lebanon
	Libya
	Morocco
	Oman
	Qatar
	Saudi Arabia
	Syria
	Tunisia
	Turkey
	United Arab Emirates
	Western Sahara
	Yemen
West Africa	Benin
	Burkina Faso
	Cape Verde
	Chad
	Côte d'Ivoire
	Gambia
	Ghana
	Guinea
	Guinea-Bissau
	Liberia
	Mali
	Mauritania
	Niger
	Nigeria
	Senegal
	Sierra Leone
	Togo
Central Africa	Burundi
	Cameroon
	Central African Republic
	Congo (Brazzaville)
	Congo (Kinshasa)
	Equatorial Guinea
	Gabon
	Rwanda
	Sao Tome & Principe
East Africa	Djibouti
	Eritrea
	Ethiopia
	Kenya
	Seychelles
	Somalia
	Sudan
	Tanzania

Uganda
Southern Africa
Angola
Botswana
Comoros
Madagascar
Malawi
Mauritius
Mozambique
Namibia
Réunion
Saint Helena
South Africa
Swaziland
Zambia
Zimbabwe
South Asia
Bangladesh
Bhutan
India
Maldives
Nepal
Pakistan
Sri Lanka
Southeast Asia
Brunei Darussalam
Cambodia
Indonesia
Laos
Malaysia
Myanmar
Papua New Guinea
Philippines
Singapore
Thailand
Timor-Leste
Viet Nam
China
China
Hong Kong SAR
Macau SAR
Taiwan
East Asia
Japan
Mongolia
North Korea
South Korea
Oceania
Australia
American Samoa
Cook Islands
Fiji
French Polynesia
Guam
Kiribati
Marshall Islands
Micronesia
Nauru
New Caledonia
New Zealand
Niue
Palau
Samoa
Solomon Islands
Tonga
Vanuatu
Wallis & Futuna Islands

Table A9: WHO Region Definitions for *Figure 2.10*

WHO Region
Member Country

AFR-D
Algeria
Angola
Benin
Burkina Faso
Cameroon
Cape Verde
Chad
Comoros
Equatorial Guinea
Gabon
Gambia
Ghana
Guinea
Guinea-Bissau
Liberia
Madagascar
Mali
Mauritania
Mauritius
Niger
Nigeria
Sao Tome & Principe
Senegal
Seychelles
Sierra Leone
Togo
AFR-E
Botswana
Burundi
Central African Republic
Congo (Brazzaville)
Congo (Kinshasa)
Côte d'Ivoire
Eritrea
Ethiopia
Kenya
Malawi
Mozambique
Namibia
Rwanda
South Africa
Swaziland
Tanzania
Uganda
Zambia
Zimbabwe
AMR-A
Canada
Cuba
United States
AMR-B
Argentina
Brazil
Chile
Colombia
Costa Rica
Dominican Republic
El Salvador
Grenada
Guyana
Honduras
Jamaica
Mexico
Panama
Paraguay
Saint Kitts & Nevis
Saint Lucia
Saint Vincent & Grenadines
Suriname
Trinidad & Tobago
Uruguay
Venezuela
AMR-D
Bolivia
Ecuador
Guatemala
Haiti
Nicaragua
Peru
EMR-B
Bahrain
Cyprus

Iran
Jordan
Kuwait
Lebanon
Libya
Oman
Qatar
Saudi Arabia
Syria
Tunisia
United Arab Emirates

EMR-D

Afghanistan
Djibouti
Egypt
Iraq
Morocco
Pakistan
Somalia
Sudan
Yemen

EUR-A

Austria
Belgium
Croatia
Czech Republic
Denmark
Finland
France
Germany
Greece
Iceland
Ireland
Israel
Italy
Luxembourg
Malta
Netherlands
Norway
Portugal
Slovenia
Spain
Sweden
Switzerland
United Kingdom

EUR-B

Albania
Armenia
Azerbaijan
Bosnia & Herzegovina
Bulgaria
Georgia
Kyrgyzstan
Macedonia*
Poland
Romania
Serbia & Montenegro*
Slovakia
Tajikistan
Turkey
Turkmenistan
Uzbekistan

EUR-C

Belarus
Estonia
Hungary
Kazakhstan
Latvia
Lithuania
Moldova
Russian Federation
Ukraine

SEAR-B

Indonesia
Sri Lanka
Thailand

SEAR-D

Bangladesh
Bhutan
India
Maldives
Myanmar
Nepal
North Korea

WPR-A

Australia
Brunei Darussalam
Japan
New Zealand
Singapore

WPR-B

Cambodia
China
Cook Islands
Fiji
Kiribati
Laos
Malaysia
Marshall Islands
Micronesia
Mongolia
Nauru
Niue
Palau
Papua New Guinea
Philippines
Samoa
Solomon Islands
South Korea
Tonga
Vanuatu
Viet Nam

IN IND, NOT IN WHO

American Samoa
British Virgin Islands
Faeroe Islands
Falkland Islands
French Guiana
French Polynesia
Gibraltar
Greenland
Guadeloupe
Guam
Hong Kong SAR
Macau SAR
Martinique
Montserrat
New Caledonia
Puerto Rico
Réunion
Saint Helena
Serbia & Montenegro
Taiwan
Timor-Leste
Turks & Caicos Islands
United States Virgin Islands
Wallis & Futuna Islands
Western Sahara

IN WHO, NOT IN IND

Antigua and Barbuda
Bahamas
Barbados
Belize
Dominica
Grenadines
Lesotho
Monaco
San Marino
Tuvalu

*In lieu of WHO's former use of Yugoslavia, Serbia & Montenegro and Macedonia were placed in EUR-B

A4. References

Boden TA, Marland G, and Andres RJ (2010) "Global, Regional, and National Fossil-Fuel CO_2 Emissions" Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, TN http://cdiac.esd.ornl.gov/trends/emis/tre_coun.htm Accessed 2011 April 15.

Houghton JT, Meira Filho LG, Lim B, Treanton K, Mamaty I, Bonduki Y, Griggs DJ, and Callender BA, Editors (1997). Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories Intergovernmental Panel on Climate Change, Organisation for Economic Cooperation and Development, and International Energy Agency, Paris, FR.

United Nations Framework Convention on Climate Change (2012) "Greenhouse Gas Inventory Data" http://unfccc.int/ghg_data/items/3800.php Accessed 2012 April 01.

Appendix B

B1. Briggs Equations

Based on equations reported in United States Environmental Protection Agency (1995) and Schnelle and Dey (2000).

<u>Notation</u>

g	= gravitational constant (9.8 m/sec^2)
s	= stability parameter (0.2 °K/m)
β	= entrainment parameter (0.6; unit-less)
u	= windspeed (m/sec)
v_s	= stack velocity (m/sec)
d_s	= stack diameter (m)
ΔT	= temperature difference between stack and ambient air (°K)
T_a	= ambient temperature (°K)
T_s	= stack temperature (°K)
V	= volume (m^3)
α	= ventilation rate (1/sec)
F_b	= buoyancy flux (m^4/s^3)
F_m	= momentum flux (m^4/s^3)
x_f	= distance to final rise (m)
h_f	= height at final rise (m)
h_x	= height at distance *x* less than final rise (m)

<u>Flux</u>

Equation B1.1: Buoyancy Flux

$$F_b = gv_s \frac{d_s^2}{4}\left(\frac{T_s - T_a}{T_s}\right)$$

Equation B1.2: Momentum Flux

$$F_m = \frac{v_s^2 d_s^2}{4}\left(\frac{T_a}{T_s}\right)$$

Buoyancy versus Momentum
If $\Delta T > (\Delta T)_c$, then flux is buoyancy dominated, otherwise flux is momentum dominated.

Equation B1.3: Buoyancy Versus Momentum for P-G Classes A-D

$$(\Delta T)_c = \frac{0.0297 T_s v_s^{1/3}}{d_s^{2/3}}$$

Equation B1.4: Buoyancy Versus Momentum for P-G Classes E-F

$$(\Delta T)_c = 0.01958 T_s v_s s^{1/2}$$

Buoyancy Dominated P-G Classes A-D

Equation B1.5: Distance to Final Rise for Buoyancy Dominated P-G Classes A-D

$$x_f = 49 F_b^{5/8}$$

Equation B1.6: Height at Final Rise for Buoyancy Dominated P-G Classes A-D

$$h_f = \frac{1.6 F_b^{1/3} (x_f)^{2/3}}{u}$$

Equation B1.7: Height at Distance Less Than Final Rise for Buoyancy Dominated P-G Classes A-D

$$h_x = \frac{1.6 F_b^{1/3} (x)^{2/3}}{u}$$

Buoyancy Dominated P-G Classes E-F

Equation B1.8: Distance to Final Rise for Buoyancy Dominated P-G Classes E-F

$$x_f = 2.0715 \frac{u}{s^{1/2}}$$

Equation B1.9: Height at Final Rise for Buoyancy Dominated P-G Classes E-F

$$h_f = 2.6 \left(\frac{F_b}{us} \right)^{1/3}$$

Equation B1.10: Height at Distance Less Than Final Rise for Buoyancy Dominated P-G Classes E-F

$$h_x = \frac{1.6 F_b^{1/3} (x)^{2/3}}{u}$$

<u>Momentum Dominated P-G Classes A-D</u>

Equation B1.11: Distance to Final Rise for Momentum Dominated P-G Classes A-D

$$x_f = 49F_b^{5/8}$$

Equation B1.12: Height at Final Rise for Momentum Dominated P-G Classes A-D

$$h_f = \frac{3d_s v_s}{u}$$

Equation B1.13: Height at Distance Less Than Final Rise for Momentum Dominated P-G Classes A-D

$$h_x = \left(\frac{3F_m x}{(\beta u)^2} \right)^{1/3}$$

<u>Momentum Dominated P-G Classes E-F</u>

Equation B1.14: Distance to Final Rise for Momentum Dominated P-G Classes E-F

$$x_f = 0.5 \frac{\pi u}{\sqrt{s}}$$

Equation B1.15: Height at Final Rise for Momentum Dominated P-G Classes E-F

$$h_f = 1.5 \left(\frac{F_m}{u\sqrt{s}} \right)^{1/3}$$

Equation B1.16: Height at Distance Less Than Final Rise for Momentum Dominated P-G Classes E-F

$$h_x = \left(3F_m \frac{\sin(x\sqrt{s}/u)}{\beta^2 u \sqrt{s}} \right)^{1/3}$$

B2. Vertical Dispersion Coefficient Equations

Based on parameters reported in Turner (1970) and United States Environmental Protection Agency (1995).

Notation

σ_z	= vertical dispersion coefficient (m)
x	= distance downwind (km)

P-G Class B

Equation B2.1: Vertical Dispersion Coefficient for P-G Class B

$\sigma_z = 90.673x^{0.93198}$

P-G Class E

Equation B2.2: Vertical Dispersion Coefficient for P-G Class E

$\sigma_z = 24.26x^{0.8366}$

B3. References

Schnelle KK and Dey PR (2000) Atmospheric Dispersion Modeling Compliance Guide McGraw-Hill, New York, NY.

Turner DB (1970) Workbook of Atmospheric Dispersion Estimates Environmental Protection Agency, Research Triangle Park, NC.

United States Environmental Protection Agency (1995) User's Guide for the Industrial Source Complex (ICS3) Dispersion Models: Volume II - Description of Model Algorithms U.S. Environmental Protection Agency, Research Triangle Park, NC.