



CS patial onfounding & Interference



Where do we go from existing frameworks

JING ZHANG

jing.zhang.2021@bristol.ac.uk

School of Geographical Sciences, University of Bristol

Overview

- **Review of key methodology issues,
ft. : Confounding, interference; PO, SCM.**
- **Research agenda:
Extend existing concepts and frameworks !**

Overview

Disclaimer : POV from someone who believes

**All causal modeling problems are
counterfactual prediction problems.**

- **Review of key methodology issues,
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Overview

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**All causal modeling problems are
counterfactual prediction problems.**

And evaluates models by asking:

Is this good for counterfactual prediction?

**Can we use computational methods to make
it better?**

Spatial Causality: A Systematic Review on Spatial Causal Inference

Kamal Akbari, Stephan Winter, Martin Tomko

Faculty of Engineering and Information Technology, The University of Melbourne, Parkville, Australia

A Review of Spatial Causal Inference Methods for Environmental and Epidemiological Applications

Brian J. Reich¹ and Shu Yang¹ and Yawen Guan² and Andrew B. Giffin¹ and Matthew J. Miller¹ and Ana Rappold³

Rethinking "causality" in Quantitative Human Geography

AUTHORS
Jing Zhang, Levi Wolf

Geography needs to engage with causality

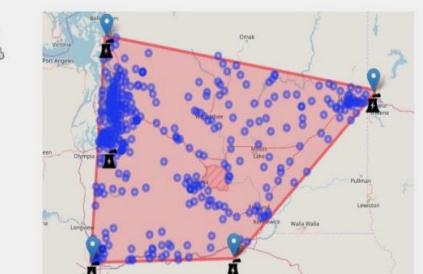
Understanding causal relations is fundamental for science and engineering.

Bringing geographic and causal modeling together is still an **Ongoing** project.

Background: spatial causal modeling



(a)



(b)

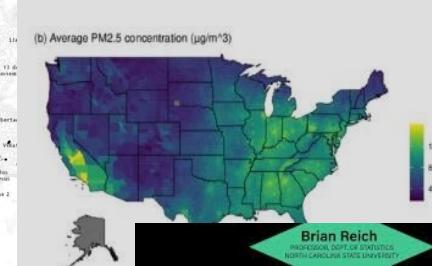
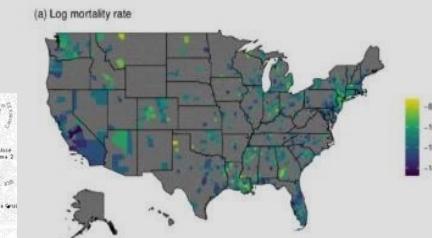
Figure 2:

(a) Grouping of power plants in interference clusters and a Each cluster is depicted with two polygons, the inner poly_i of the power plants, and the outer polygon corresponds to centroids in that cluster. (b) One cl

Corwin M. Zigler^{*}, Georgia Papadogeorgou[†] [Postdoctoral Ass

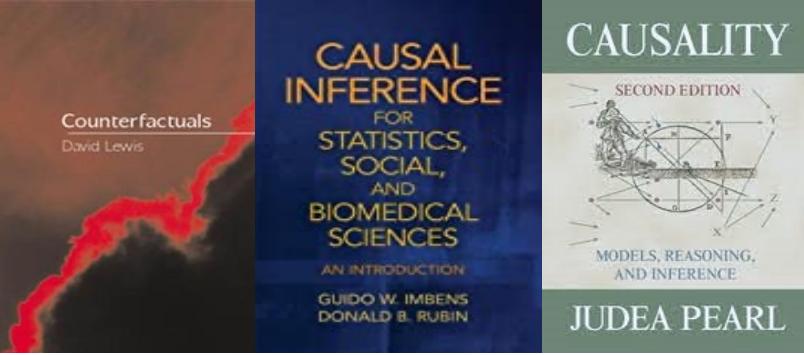
^{*}Department of Statistical Science, Duke University, 206 Old Chem

Figure 3: Plots of the COVID-19/PM_{2.5} data. Panel (a) plots the sample log COVID-19 mortality rate, $\log(Y_i/N_i)$, through May 12, 2020 with gray denoting no observed deaths ($Y_i = 0$); Panel (b) maps the long-term (2000–2016) average fine particulate matter (PM_{2.5}) concentration. Alaska and Hawaii are excluded from the study.



Brian Reich
PROFESSOR, DEPT. OF STATISTICS,
NORTH CAROLINA STATE UNIVERSITY

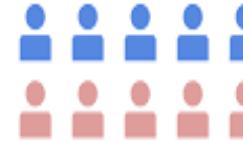
Spatial Causal Inference Using Numerical Models



Standard PO and SCM frameworks

Causation is **difference** making.

Potential Outcomes (PO) : Outcome difference between treated /control. Counterfactuals from randomised treatment.

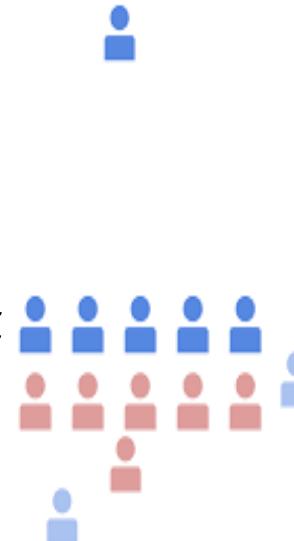


Structural Causal Models (SCM) : Known for its graphical model (DAG) language. Affords more detailed/faithful representation of causal process.

The Spatial dimension is there

Spatial relations complicate the disentanglement

of Non-causal from Causal.



An additional dimension of change, beyond the time dimension against which to foreground causal change/ variation.



The Spatial dimension in PO and SCM

PO

Strength : Closely grounded in measurement.

Limitation : Restricted representation of causal process and abstraction of causal effect.

SCM

Strength : Affords representation of spatial process.

Limitation : Potential complexity hinders communication efficiency and computation tractability.

In brief: Current concepts, Conceptual models

We are still seeking **well fitted** statistical language for spatial causal process, as solid **scaffolding** for spatial causal modeling.

The beta version of DROPS 2 is now publicly available! [Check this page out at DROPS 2 now!](#)

DROPS

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URL: <https://drops.dagstuhl.de/opus/volltexte/2023/18986/>

Zhang, Jing

Causal Effects Under Spatial Confounding and Interference (Short Paper)

pdf-format: [LIPIcs-GIScience-2023-91.pdf \(0.8 MB\)](https://drops.dagstuhl.de/opus/volltexte/2023/18986/LIPIcs-GIScience-2023-91.pdf)

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Zhang, Jing

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Specifically: Confounding, interference

The two concepts are currently pillars of methodological development.

Key interface where theory meets empirics,
abstraction meet measurement.

Confounding and Collapsibility in Causal Inference

Sander Greenland, Judea Pearl, James M. Robins

Statist. Sci. 14(1): 29-46 (February 1999). DOI: 10.1214/ss/1009211805

A causal inference framework for spatial confounding

Brian Gilbert¹, Abhirup Datta¹, Joan A. Casey², Elizabeth L. Ogburn¹

¹ Department of Biostatistics, Johns Hopkins University

² Department of Environmental Health Sciences, Columbia University

Summary of core issues in spatial causal



Journal of the American Statistical Association

ISSN: 0162-1459 (Print) 1537-274X (Online) Journal homepage: <https://www.tandfonline.com/>

Elements of estimation theory for causal effects in the presence of network interference

Daniel L. Sussman*, Edoardo M. Airoldi†

February 14, 2017

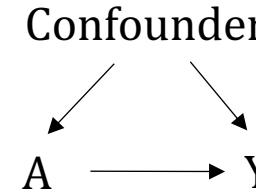
Abstract

Randomized experiments in which the treatment of a unit can affect the outcomes of other units are becoming increasingly common in healthcare, economics, and in the social and information sciences. From a causal inference perspective, the typi-

Toward Causal Inference With Interference

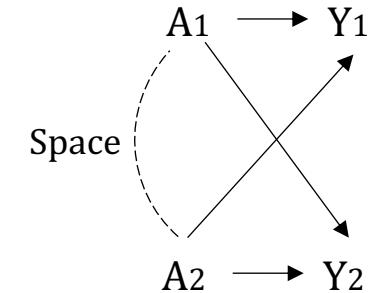
Michael G Hudgens & M. Elizabeth Halloran

Confounding



Classic notion: **Spurious Correlation**
between treatment and outcome due to
influence of common source.

Interference



Classic notion: **Outcome of a unit**
dependent on **treatment of others**.



Specification searches in spatial econometrics:
the relevance of Hendry's methodology

Raymond J.G.M. Florax^{a,e}, , Hendrik Folmer^{b,c}, Sergio J. Rey^{d,e}

For and Against Methodologies: Some Perspectives on Recent Causal and Statistical Inference Debates

Sander Greenland¹

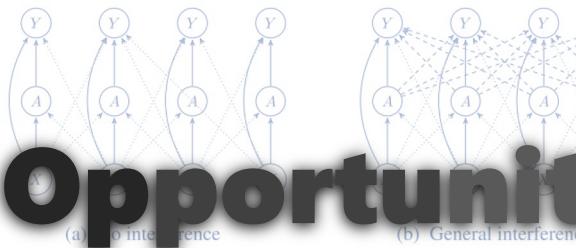
CAUSAL EFFECT UNDER SPATIAL INTERFERENCE

A GENERALISED PROPENSITY SCORE WEIGHTED CONFORMAL APPROACH

Jing Zhang
School of Geographical Sciences
University of Bristol
Bristol, UK
jing.zhang.2021@bristol.ac.uk

ABSTRACT

Estimating causal effect under spatial interference is an important



Challenges and Opportunities

PO

Restricted representation.

Unable to generalise over confounding & interference.

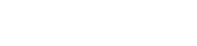
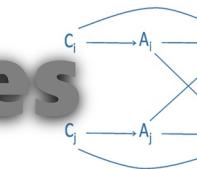
Packing spatial complexity in auxiliary tasks:

Bespoke causal estimands.

Flexible counterfactual prediction.

Model specification search.

Research agenda



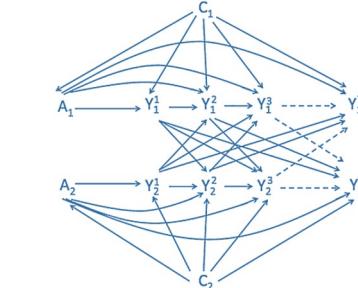
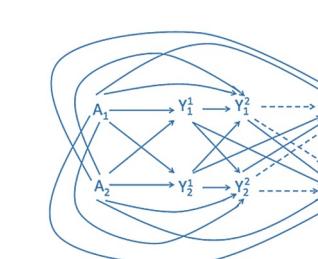
International Statistical Review (2021), Vol. 3, 469-474 doi: 10.1111/rssc.12452

A Review of Spatial Causal Inference Methods for Environmental and Epidemiological Applications

Brian J. Reich¹ and Shu Yang² and Yawen Guan³ and Andrew B. Gaffin⁴ and Matthew J. Miller⁵ and Ann Rappold⁶

Causal Diagrams for Interference

Elizabeth L. Ogburn and Tyler J. VanderWeele



Beyond Structural Causal Models: Causal Constraints Models

Tineke Blom
Informatics Institute
University of Amsterdam

Stephan Bongers
Informatics Institute
University of Amsterdam

Joris M. Mooij
Informatics Institute
University of Amsterdam

Research agenda

Challenges and Opportunities

SCM

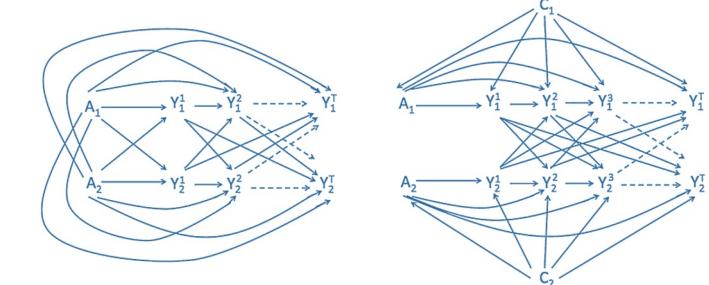
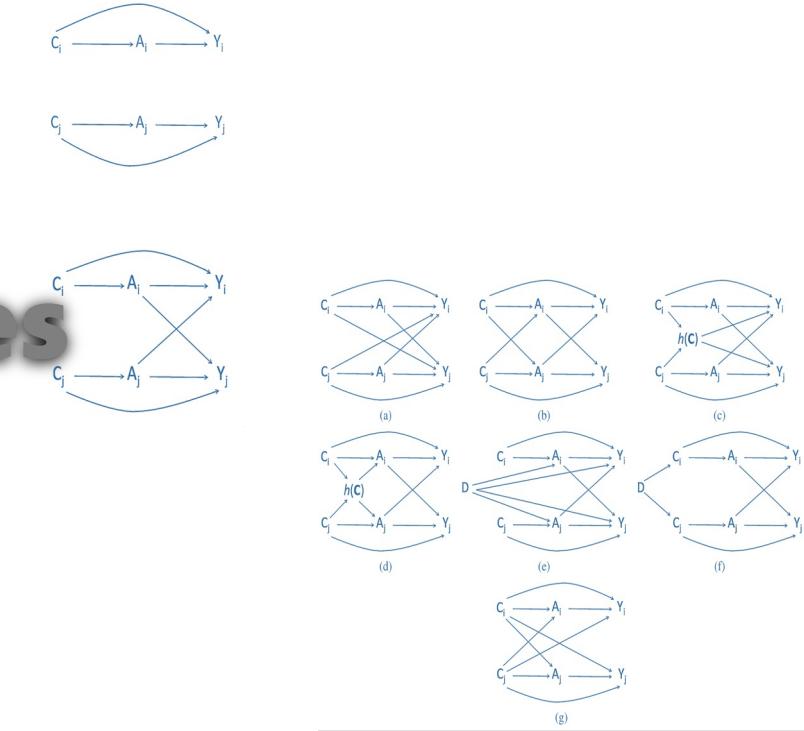
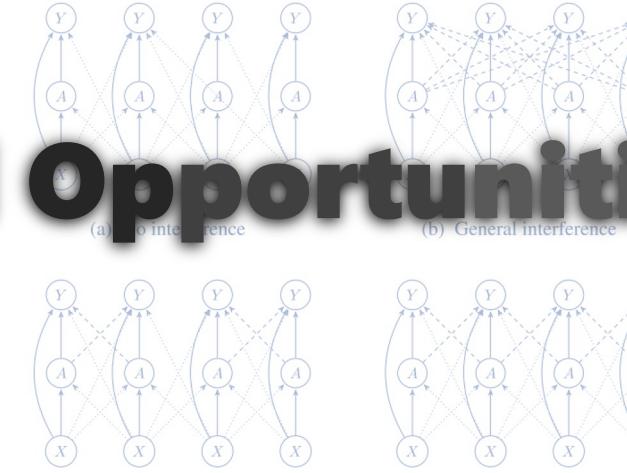
Potential complexity.

Confounding & interference tends to lead to
unidentifiable models.

Packing spatial complexity in the nodes/ skeleton:

Handling high dimensional data.

Generative models and uncertainty quantification.



Title
Operationalizing Spatial Causal Inference

Permalink
<https://escholarship.org/uc/item/2sh2c3w0>

Authors
Hoffman, Tyler D.
Kedron, Peter

Rethinking causality in quantitative human geography

Jing "Mirah" Zhang^{1*}

Levi John Wolf¹

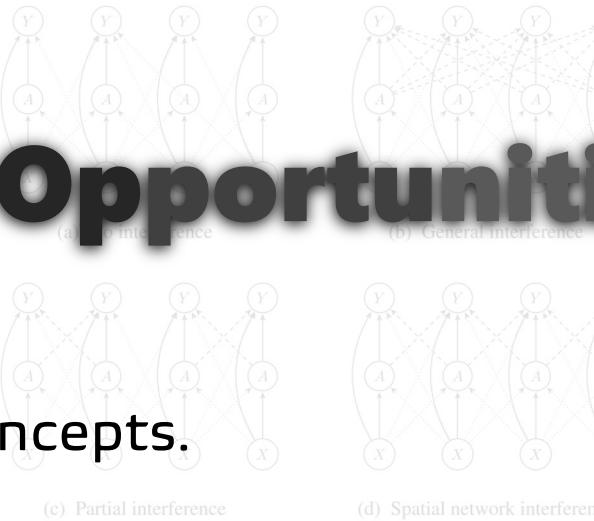
Research agenda

Challenges and Opportunities

Theories

Refining existing theory and concepts.

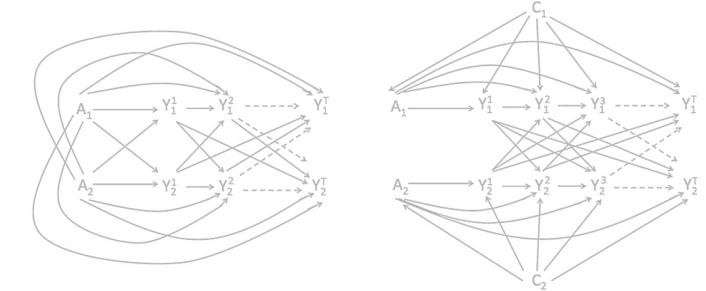
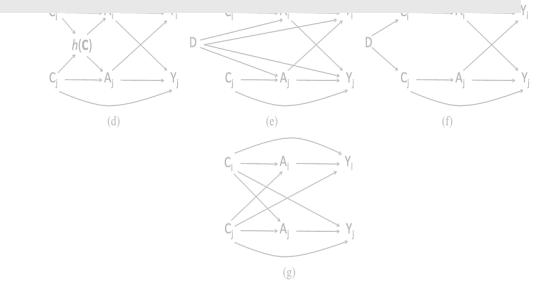
New directions, e.g. information theoretic definitions/ measurements of causality for geographic systems.



Information flow and causality as rigorous notions *ab initio*
X. San Liang
Phys. Rev. E **94**, 052201 – Published 1 November 2016

Advances in Complex Systems | Vol. 11, No. 01, pp. 17-41 (2008) | Physics and Mathematics
INFORMATION FLOWS IN CAUSAL NETWORKS
NIHAT AY and DANIEL POLANI

<https://doi.org/10.1142/S0219525908001465> | Cited by: 156



**Recap:
On analytical concepts
and conceptual models.**

**Causal modeling problems are
counterfactual prediction problems.**

**Ample space for
further development**

CSpatial Confounding & Interference Where do we go from existing frameworks

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jing.zhang.2021@bristol.ac.uk

Twitter @MirahJZ

Slides from the talk



Law and causality in quantitative geography



Conformal prediction for spatial causal inference

