HANDBOOK OF GEOSPATIAL ARTIFICIAL INTELLIGENCE

Edited by
Song Gao, Yingjie Hu,
and Wenwen Li

CRC Press
Taylor & Francis Group

Handbook of Geospatial Artificial Intelligence

This comprehensive handbook covers Geospatial Artificial Intelligence (GeoAI), which is the integration of geospatial studies and AI machine (deep) learning and knowledge graph technologies. It explains key fundamental concepts, methods, models, and technologies of GeoAI and discusses the recent advances, research tools, and applications that range from environmental observation and social sensing to natural disaster responses. As the first single volume on this fast-emerging domain, *Handbook of Geospatial Artificial Intelligence* is an excellent resource for educators, students, researchers, and practitioners utilizing GeoAI in fields such as information science, environment and natural resources, geosciences, and geography.

Features

- Provides systematic introductions and discussions of GeoAI theory, methods, technologies, applications, and future perspectives
- Covers a wide range of GeoAI applications and case studies in practice
- Offers supplementary materials such as data, programming code, tools, and case studies
- Discusses the recent developments of GeoAI methods and tools
- Includes contributions written by top experts in cutting-edge GeoAI topics

This book is intended for upper-level undergraduate and graduate students from different disciplines and those taking GIS courses in geography or computer sciences as well as software engineers, geospatial industry engineers, GIS professionals in non-governmental organizations, and federal/state agencies who use GIS and want to learn more about GeoAI advances and applications.

Taylor & Francis
Taylor & Francis Group
http://taylorandfrancis.com

Handbook of Geospatial Artificial Intelligence

Edited by

Song Gao, Yingjie Hu, and Wenwen Li

CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

Designed cover image: © iStock Photos

First edition published 2024
by CRC Press
2385 NW Executive Center Drive, Suite 320, Boca Raton FL 33431

and by CRC Press
4 Park Square, Milton Park, Abingdon, Oxon, OX14 4RN

CRC Press is an imprint of Taylor & Francis Group, LLC

Library of Congress Cataloging-in-Publication Data

Names: Gao, Song (Geography teacher) editor. | Hu, Yingjie, editor.
Title: Handbook of geospatial artificial intelligence / Edited by Song Gao,
Yingjie Hu, and Wenwen Li.
Other titles: Geospatial artificial intelligence
Description: Boca Raton, FL : CRC Press, 2024. | Includes bibliographical
references and index.
Identifiers: LCCN 2023030356 (print) | LCCN 2023030357 (ebook) | ISBN
9781032311661 (hardback) | ISBN 9781032311678 (paperback) | ISBN
9781003308423 (ebook)
Subjects: LCSH: Geospatial data. | Artificial intelligence.
Classification: LCC G70.217.G46 H26 2024 (print) | LCC G70.217.G46
(ebook) | DDC 910.285/63--dc23/eng/20231016
LC record available at https://lccn.loc.gov/2023030356
LC ebook record available at https://lccn.loc.gov/2023030357

ISBN: 978-1-032-31166-1 (hbk)
ISBN: 978-1-032-31167-8 (pbk)
ISBN: 978-1-003-30842-3 (ebk)

DOI: 10.1201/9781003308423

Typeset in Nimbus font
by KnowledgeWorks Global Ltd.

Publisher's note: This book has been prepared from camera-ready copy provided by the authors.

Contents

Acknowledgments

The editors would like to sincerely thank all the chapter authors and reviewers for their valuable contributions to this GeoAI handbook. The editors would like to thank Professor Michael F. Goodchild and Professor Krzysztof Janowicz for their valuable comments and guidance on the organization of this handbook. The editors would also like to thank the following students from the University of Wisconsin-Madison: Yuchi Ma, Jacob Kruse, Yuhan Ji, and Dong Gai for their editorial assistance in all parts of this handbook.

Foreword

Michael F. Goodchild
Department of Geography, University of California, Santa Barbara
good@geog.ucsb.edu

It's a great honor for me to be asked to contribute a foreword to this *Handbook of Geospatial Artificial Intelligence*. GeoAI has very quickly become a major topic of new research and development in geography, geographic information science (GIScience), and in many of the disciplines that concern themselves with the complex patterns and processes that can be found in the geographic domain (that is, the surface and near-surface of the Earth). To this old dog, it represents not only an exciting set of new tricks, but a reinvigoration of the old field of geographic science in directions that are fundamentally different from what came before. It benefits from a perfect storm of trends: the availability of many new sources of data, from remote sensing, social media, and sensor networks; access to almost unlimited resources of computational power; and the emergence of powerful new methods of data analysis and machine learning.

More fundamentally, GeoAI reflects a radical shift in our approach to understanding the geographic domain. Half a century ago the geographic sciences modeled themselves on the senior sciences of physics and chemistry in searching for universal principles (Bunge, 1966). These principles should apply everywhere and at all times, just like Mendeleev's periodic table of the elements. They should also be simple, in accordance with the principle known as Occam's Razor: when two hypotheses might explain the same phenomenon, one should adopt the simpler. The use of Newton's law of gravitation to explain how human communications tend to diminish with increasing distance provides an excellent example, and led to extensive research on the modeling of social interaction. The fact that such models will never provide perfect fits to actual geographic data was inconvenient, but their estimates were nevertheless fit for use in a host of applications. Moreover, the models provided a norm or standard that would be helpful in identifying exceptions, anomalies, and special cases.

By the mid-1980s, however, this attempt to pursue geographic science by emulating physics had run its course. The geographic world was clearly too complex for a set of mechanistic explanations, and more powerful techniques would be needed if we were to discover patterns and identify processes. Some pursued techniques that abandoned universality by adopting what we have come to call place-based methods, which allow explanations to vary across space or time, or both (e.g., Geographically Weighted Regression; Fotheringham, Brunsdon, and Charlton, 2002). Others began to build analysis engines that would explore entire sets of models rather than a few narrowly defined hypotheses. Openshaw, for example, built a series of what he termed geographical analysis machines that would give the data an increasing role in driving the model selection process; much later this approach became enshrined in the principle of the Fourth Paradigm, "Let the data speak for themselves" (Hey, Tansley, and Tolle, 2009). Openshaw was an early user of the term artificial intelligence, and his ideas were collected in an appropriately titled but prescient book that was published shortly before the turn of the century (Openshaw and Openshaw, 1997). In a similar vein, Dobson began writing about what he called automated geography (Dobson, 1983); both he and Openshaw argued that the computer should become increasingly engaged in the research process.

Several decades later these ideas are entering the mainstream of the geographic sciences, but with an important difference. While both Dobson and Openshaw were trained in the domain-specific techniques of geographic analysis, today's methods of machine learning draw from no particular domain science, but instead apply basic approaches that are essentially the same whatever the subject matter. Thus one of the most urgent needs in GeoAI is for techniques that incorporate the general principles that we know to be true of the geographic domain: spatial dependence, spatial heterogeneity, scaling, etc. But while they may appear to be neutral, applying equally well to any domain, techniques such as neural networks and their more recent developments such as DCNN (deep convolutional neural networks) may to some extent emulate rudimentary ideas about the workings of the human brain and its instinctive search for patterns. It seems somewhat ironic that in rejecting the simple mechanistic models of classical physics, we have gravitated to the vastly more complex but similarly mechanistic world of neural networks. Moreover, as some of the chapters of this collection show, the use of DCNN to analyze imagery explicitly invokes the geographic concept of spatial dependence, or what we know familiarly as Tobler's First Law of Geography. This shift in the conceptual framework for geographic science, from Newtonian mechanics to neural networks, has led to another that is equally fundamental. Science has always been concerned with explanation and understanding and has treated description and prediction as somewhat inferior but nevertheless useful byproducts. Results that fall short of explaining might be described somewhat pejoratively as "journalistic", "curve-fitting", or "mere description". Yet much of the very rapid growth of data science and machine learning has been driven by the apparent commercial success of these approaches in prediction, and while vigorous efforts have been made to extract understanding and replicability from these techniques, the results thus far are disappointing. This is not to say that search and classification over vast digital archives are not important contributions to science when driven by GeoAI, but they nevertheless fall short of the ultimate and traditional aims of explanation and understanding and might be better understood as hypothesis-generating rather than hypothesis-confirming. In short, this new discipline of GeoAI not only introduces some valuable techniques, but also challenges our approach to science in very fundamental ways. I hope this Foreword provides a context to what is to follow, and helps the reader to understand the very significant shift in the geographic sciences that it heralds.

BIBLIOGRAPHY

Bunge, W. (1966) *Theoretical Geography*. Lund: Gleerup.

Dobson, J.E. (1983) Automated geography. *The Professional Geographer*. 35(2): 135–143.

Fotheringham, A.S., C. Brunsdon, and M. Charlton (2002) *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Hoboken, NJ: Wiley.

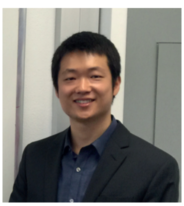
Hey, T., S. Tansley, and K. Tolle, editors (2009) *The Fourth Paradigm: Data-Intensive Scientific Discovery*. Redmond, WA: Microsoft Research.

Openshaw, S. and C. Openshaw (1997) *Artificial Intelligence in Geography*. Chichester: Wiley.

Editors

Song Gao
University of Wisconsin-Madison
song.gao@wisc.edu

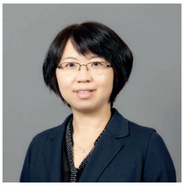
Song Gao is an associate professor and the Director of Geospatial Data Science Lab at the University of Wisconsin-Madison. He holds a PhD in geography at the University of California, Santa Barbara, an MS in cartography and GIS at Peking University, and a BS with honors at the School of Geography, Beijing Normal University. His main research interests include geospatial data science and GeoAI approaches to human mobility and social sensing. He is the (co-)author of 80 peer-reviewed articles in international journals and conference proceedings. He is the (co-)PI of multiple research grants from NSF, WARF, Microsoft AI for earth and geospatial industry, and the recipient of various fellowships and research and teaching awards at national/international levels such as the Waldo Tobler Young Researcher Award in GIScience, UCGIS Early-Mid Career Research Award, and AAG SAM Emerging Scholar Award. He serves as an associate editor for IJGIS (presently) and Annals of GIS (2018–2022) and the editorial board member for *Scientific Reports, Scientific Data, Geoinformatica, TGIS*, and *CaGIS*. He is one of lead organizers for the AAG Symposium on GeoAI and Deep Learning, GeoAI workshops at ACM SIGSPATIAL, and GeoAI webinars at CPGIS.



Yingjie Hu
University at Buffalo
yhu42@buffalo.edu

Yingjie Hu is an associate professor in the Department of Geography at the University at Buffalo (UB). He is also an adjunct professor in the Department of Computer Science and Engineering at UB and an affiliate professor of the UB AI and Data Science Institute. His major research area is in GeoAI. More specifically, his research integrates geospatial data, spatial analysis, and AI methods to understand human–environment interactions and to address some of the challenging problems facing our society, such as those related to natural disasters, public health, and ecosystem conservation. He holds a PhD from the Department of Geography at the University of California Santa Barbara. He received his MS and BS degrees from East China

Normal University. He is the author of over 50 peer-reviewed articles in top international journals and conferences. He and his work received awards at international, national, and university levels, including Waldo-Tobler Young Researcher Award, GIScience 2018 Best Full Paper Award, UB Exceptional Scholar: Young Investigator Award, Jack and Laura Dangermond GIS Graduate Fellow Award, and AAG International Geographic Information Fund Award. His research was also covered by major media such as CNN, NPR, Reuters, and VOA News.



Wenwen Li
Arizona State University
wenwen@asu.edu

Wenwen Li is a full professor in the School of Geographical Sciences and Urban Planning at Arizona State University, where she leads the Cyberinfrastructure and Computational Intelligence Lab. Her research interests lie in the field of geographic information science, focusing on cyberinfrastructure, big data, and GeoAI for data-intensive environmental and social sciences. Li's work has found applications in various scientific disciplines, including polar science, climatology, public health, hydrology, and urban studies. She has received research support from multiple funding agencies such as the National Science Foundation (NSF), United States Geological Survey (USGS), and Open Geospatial Consortium. Li served as the Chair of the Association of American Geographers (AAG)'s cyberinfrastructure specialty group from 2013 to 2014 and currently holds the position of Chair of the Research Committee of the University Consortium of Geographic Information Science. In recognition of her contributions, Li received The NSF CAREER award in 2015 and the NSF Mid-Career Advancement Award in 2021. She was also honored as an elected AAG Fellow in 2023.

Contributors

Joynal Abedin
Texas A&M University

Daniel S. Adams
Oak Ridge National Laboratory

Taylor Anderson
George Mason University

Leila Arras
Fraunhofer Heinrich Hertz Institute

Samantha T. Arundel
U.S. Geological Survey

Sarah Bardin
Arizona State University

Filip Biljecki
National University of Singapore

Heng Cai
Texas A&M University

Guofeng Cao
University of Colorado Boulder

Muhao Chen
University of Southern California

Weiye Chen
University of Maryland, College Park

Tao Cheng
University College London

Ximeng Cheng
Fraunhofer Heinrich Hertz Institute

Yao-Yi Chiang
University of Minnesota, Twin Cities

Helen Couclelis
University of California, Santa Barabra

Kitty Currier
University of California, Santa Barbara

Chunyuan Diao
University of Illinois Urbana-Champaign

Philipe A. Dias
Oak Ridge National Laboratory

Weiwei Duan
University of Southern California

Jiaxin Feng
University of Washington

Colby K. Fisher
Hydronos Labs

Tyler J. Frazier
Oak Ridge National Laboratory

Sébastien Gambs
Université du Québec à Montréal

Song Gao
University of Wisconsin-Madison

Michael F. Goodchild
University of California, Santa Barbara

Zhining Gu
Arizona State University

Sreelekha Guggilam
Oak Ridge National Laboratory

Tianci Guo
University of Illinois Urbana-Champaign

James Haworth
University College London

Erhu He
University of Pittsburgh

Pascal Hitzler
Kansas State University

Tyler D. Hoffman
Arizona State University

Yingjie Hu
University at Buffalo

Krzysztof Janowicz
University of Vienna
University of California, Santa Barbara

Xiaowei Jia
University of Pittsburgh

Yuhao Kang
University of Wisconsin-Madison

Hamdi Kavak
George Mason University

Peter Kedron
Arizona State University

Jina Kim
University of Minnesota, Twin Cities

Joon-Seok Kim
Oak Ridge National Laboratory

Craig A. Knoblock
University of Southern California

Thomaz Kobayashi-Carvalhaes
Oak Ridge National Laboratory

Monique M. Kuglitsch
Fraunhofer Heinrich Hertz Institute

Gaurish Lakhanpal
Adlai E. Stevenson High School

Ni Lao
Google

Stefan Leyk
University of Colorado Boulder

Wenwen Li
Arizona State University

Zekun Li
University of Minnesota, Twin Cities

Ziyuan Li
University of Connecticut

Yunlei Liang
University of Wisconsin-Madison

Binbin Lin
Texas A&M University

Yijun Lin
University of Minnesota, Twin Cities

Zilong Liu
University of Vienna

Dalton Lunga
Oak Ridge National Laboratory

Jackie Ma
Fraunhofer Heinrich Hertz Institute

Gengchen Mai
University of Georgia

Debayan Mandal
Texas A&M University

Kevin G. McKeehan
U.S. Geological Survey

Grant McKenzie
McGill University

Ali Mostafavi
Texas A&M University

Min Namgung
University of Minnesota, Twin Cities

Shawn Newsam
University of California, Merced

Mustafa Can Ozkan
University College London

Dieter Pfoser
George Mason University

Abhishek Potnis
Oak Ridge National Laboratory

Jinmeng Rao
University of Wisconsin-Madison

Dean Rehberger
Michigan State University

Amira Roess
George Mason University

Wojciech Samek
Fraunhofer Heinrich Hertz Institute
Technische Universität Berlin

Zachary Schellin
Fraunhofer Heinrich Hertz Institute

Basel Shbita
University of Southern California

Meilin Shi
University of Vienna

Cogan Shimizu
Wright State University

Shirly Stephen
University of California, Santa Barbara

Kai Sun
University at Buffalo

Johannes H. Uhl
University of Colorado Boulder

Marc Vischer
Fraunhofer Heinrich Hertz Institute

Sarah E. Walters
Oak Ridge National Laboratory

Carson Woody
Oak Ridge National Laboratory

Yiqun Xie
University of Maryland, College Park

Mingzheng Yang
Texas A&M University

Chishan Zhang
University of Illinois Urbana-Champaign

Hongyu Zhang
McGill University

Bo Zhao
University of Washington

Bing Zhou
Texas A&M University

Ryan Zhenqi Zhou
University at Buffalo

Di Zhu
University of Minnesota, Twin Cities

Jiawei Zhu
Central South University

Rui Zhu
University of Bristol

Lei Zou
Texas A&M University

Andreas Züfle
Emory University

Section I

Historical Roots of GeoAI

1 Introduction to Geospatial Artificial Intelligence (GeoAI)

Song Gao
GeoDS Lab, Department of Geography, University of Wisconsin-Madison

Yingjie Hu
GeoAI Lab, Department of Geography, University at Buffalo

Wenwen Li
CICI Lab, School of Geographical Sciences and Urban Planning, Arizona State University

CONTENTS

1.1 INTRODUCTION

It is not often that geography is touched by a development having the potential to affect substantially all of the practical, technical, methodological, theoretical and philosophical aspects of our work. – Couclelis (1986)

Geospatial artificial intelligence (GeoAI) is an interdisciplinary field that has received much attention from both academia and industry (Chiappinelli, 2022; Gao, 2021; Hu *et al.*, 2019a; Li, 2020; Richter and Scheider, 2023). It incorporates a wide range of research topics related to both geography and AI, such as developing intelligent computer programs to mimic human perception of the environment and spatial reasoning, discovering new knowledge about geographic phenomena, and advancing our understanding of human-environment interactions and the Earth systems. While diverse, GeoAI research shares a common focus on spatial contexts and has a root

DOI: 10.1201/9781003308423-1

in geography and geographic information science (GIScience). Three major factors have promoted the fast development of GeoAI: advancements in AI theories and methods, the availability of various geospatial big data, and improvements in computing hardware (e.g., the graphics processing unit, GPU) and computing capability. New research is also emerging along with the latest AI technologies, such as large language models, ChatGPT, and other AI foundation models.

The integration of geography and AI can be traced back to the early work by Couclelis (1986); Openshaw and Openshaw (1997); Smith (1984). Before the recent disruptive GeoAI research, many AI methods and techniques have already been integrated and improved in geospatial research. These AI methods and techniques include artificial neural networks (ANN), heuristic search, knowledge-based expert systems, neurocomputing, and artificial life (e.g., cellular automata) in the 1980s; genetic programming, fuzz logics, and hybrid intelligent systems in the 1990s; as well as ontology, web semantics, and geographic information retrieval (GIR) in the 2000s. Since around 2010, deep learning started to demonstrate outstanding performance with breakthroughs made in training DNNs (Glorot and Bengio, 2010). In 2012, the deep neural network, AlexNet, achieved the best performance in the ImageNet Large Scale Visual Recognition Challenge (Krizhevsky *et al.*, 2012). In the following years, the impact of deep learning reached many domains outside of computer science (LeCun *et al.*, 2015) including geography and earth sciences (Reichstein *et al.*, 2019).

Noticing the fast development of deep learning and its potential in geospatial research, we organized a series of workshops and symposiums starting in 2017 to promote GeoAI research in conferences such as the Annual meetings of the American Association of Geographers (AAG) and ACM SIGSPATIAL (Hu *et al.*, 2019a). In addition, we also organized special issues in journals, such as the special issue on *Artificial Intelligence Techniques for Geographic Knowledge Discovery* in the *International Journal of Geographical Information Science* (Janowicz *et al.*, 2020), the special issue on *Symbolic and subsymbolic GeoAI: Geospatial knowledge graphs and spatially explicit machine learning* in the journal *Transactions in GIS* (Mai *et al.*, 2022a), and the special issue on *Geospatial Artificial Intelligence* in the journal *GeoInformatica* (Gao *et al.*, 2023).

As we are preparing this handbook for 2022 and 2023, there already exists novel GeoAI research on improving individual and population health (Kamel Boulos *et al.*, 2019; Zhou *et al.*, 2022b), enhancing community resilience in natural disasters (Scheele *et al.*, 2021; Wang *et al.*, 2020; Zhou *et al.*, 2022a), enabling automated and intelligent terrain mapping (Arundel *et al.*, 2020; Li and Hsu, 2020; Wang and Li, 2021), predicting spatiotemporal traffic flows (Li *et al.*, 2021a; Zhang *et al.*, 2020), forecasting the impacts of climate change on ecosystems (Ma *et al.*, 2022; Reichstein *et al.*, 2019), building smart and connected communities and cities (Wang and Biljecki, 2022; Ibrahim *et al.*, 2021a), supporting humanitarian mapping (Chen *et al.*, 2018; Lunga *et al.*, 2018), extracting knowledge from historic maps (Chiang *et al.*, 2020), automatic transferring map styles in Cartography (Kang *et al.*, 2019), and enhancing geoprivacy protection (Kamel Boulos *et al.*, 2022; Rao *et al.*, 2021). In addition to using GeoAI to address societal challenges, much research has also been devoted to methodological developments, such as incorporating spatial principles into AI models to develop spatially explicit models (Mai *et al.*, 2022a; Xie *et al.*, 2021), advancing spatial interpolation and prediction methods (Zhu *et al.*, 2020), better representing geographic features in embedding space (Mai *et al.*, 2022b; Yan *et al.*, 2017), and increasing the explainability of GeoAI models (Cheng *et al.*, 2021; Hsu and Li, 2023; Xing and Sieber, 2023; Zheng and Sieber, 2022).

While many studies exist, they are scattered in the literature and, consequently, it is difficult for scholars and students new to GeoAI to grasp a quick view of the field and learn some of the possible applications. This Handbook of GeoAI aims to fill such a gap. In the following, we provide an overview of this book.

1.2 OVERVIEW OF THE GEOAI HANDBOOK

In this handbook, we first review the historical roots for AI in geography and GIScience in **Section I: Historical Roots of GeoAI** (Chapters 1–3). Then, we introduce the foundations and recent developments in GeoAI methods and tools in **Section II: GeoAI Methods** (Chapters 4–10). These chapters cover topics on methodological foundations (deep neural networks and knowledge graphs), spatial image processing, spatial representation learning, intelligent spatial prediction and interpolation, spatial heterogeneity-aware deep learning, explainability in GeoAI, and spatial cross-validation for GeoAI models. **Section III: GeoAI Applications** (Chapters 11–17) presents various GeoAI applications in cartography and mapping, transportation, humanitarian assistance, smart disaster response, public health, agriculture, and urban sensing. Lastly, **Section IV: Perspectives for the Future of GeoAI** (Chapters 18–22) offers perspectives for future developments of GeoAI, including replicability and reproducibility, privacy and ethics, humanistic aspects, forward thinking on geospatial knowledge graph, and other future GeoAI directions. In the following, we briefly summarize each chapter.

Chapter 2 *GeoAI's Thousand-Year History* by H. Couclelis introduces the origin of the concept of GeoAI throughout history, evident in ancient Greek mythology with tales like that of the giant Talos and other artificial beings. Transitioning closer to the present, particularly with the inception of Turing's contributions to the field, this chapter provides a brief overview of the advancements in AI spanning the past seventy years. It distinguishes between two interpretations of AI in geography: a broad interpretation and a more geographically specific one. Then, it discusses different flavors of GeoAI: Program, Neural Nets, Speculations, and Being Human.

Chapter 3 *Philosophical Foundations of GeoAI* by K. Janowicz presents some of the fundamental assumptions and principles that could form the philosophical foundation of GeoAI and spatial data science. Instead of reviewing the well-established characteristics of spatial data (analysis), including interaction, neighborhoods, and autocorrelation, the chapter highlights themes such as sustainability, bias in training data, diversity in schema knowledge, and the (potential lack of) neutrality of GeoAI systems from a unifying ethical perspective. Reflecting on our profession's ethical implications will assist us in conducting potentially disruptive research more responsibly, identifying pitfalls in designing, training, and deploying GeoAI-based systems, and developing a shared understanding of the benefits but also potential dangers of AI research across academic fields.

Chapter 4 *GeoAI Methodological Foundations: Deep Neural Networks and Knowledge Graphs* by Gao et al. provides an overview of the methodological foundations of GeoAI, with a focus on the use of deep learning and knowledge graphs. It covers a range of key concepts and architectures related to convolutional neural networks, recurrent neural networks, transformers, graph neural networks, generative adversarial networks, reinforcement learning, and knowledge graphs. The goal of this chapter is to highlight the importance and ways of incorporating spatial thinking and principles into the development of spatially explicit AI models and geospatial knowledge graphs.

Chapter 5 *GeoAI for Spatial Image Processing* by Arundel et al. presents an overview of the history of (digital) image processing, GeoAI-based image processing applications, and the role of GeoAI in advancing image processing methods and research. The chapter also discusses the challenges to using GeoAI for image processing regarding training data annotation, the issues of scale, resolution, and change in space over time. Finally, the authors share thoughts on future research on geometric algebra, addressing explainability and ethical issues, combining GeoAI and physical modeling, and using knowledge base as input/constraint for GeoAI models.

Chapter 6 *Spatial Representation Learning in GeoAI* by Mai et al. introduces the concept of spatial representation learning (SRL), which is a set of techniques that use deep neural networks (DNNs) to encode and featurize various types of spatial data in the forms of points, polylines, polygons, graphs, etc. This chapter discusses existing works, key challenges, and uniqueness of SRL on various types of spatial data and highlights the unique challenges of developing AI models for geospatial data.

Chapter 7 *Intelligent Spatial Prediction and Interpolation Methods* by Zhu and Cao presents the GeoAI motivations of spatial data representation, spatial structure measuring, and the spatial relationship modeling throughout the workflow of spatial prediction in the context of leveraging AI techniques. This chapter reviews GeoAI for spatial prediction and interpolation methods, with a particular focus on two major fields: geostatistics and spatial regression. Challenges are also discussed around uncertainty, transferability, and interpretability.

Chapter 8 *Heterogeneity-Aware Deep Learning in Space: Performance and Fairness* by Xie et al. examines a fundamental attribute of spatial data– spatial heterogeneity, and depicts the phenomenon that data distributions are non-stationary over space. Ignorance of heterogeneity in space not only decreases the prediction performance of the models but also has an impact on the fairness of results – which has become a major consideration for the responsible use of GeoAI. This chapter summarizes recent heterogeneity-aware and fairness-aware methods that target on addressing the heterogeneity challenge for spatial data.

Chapter 9 *Explainability in GeoAI* by Cheng et al., which is contextualized in debates on the usefulness of AI versus traditional methods in solving geospatial problems, gives an overview of established XAI methods (e.g., gradient-based methods and decomposition-based methods) and their basic principles. Moreover, the chapter highlights the benefits of applying XAI methods for GeoAI applications based on several use cases and discusses explicit challenges and opportunities for applying XAI methods in GeoAI.

Chapter 10 *Spatial Cross-Validation for GeoAI* by Sun et al. reviews spatial cross-validation (CV) methods and discusses how spatial CV is different from random CV. This chapter suggests that random CV could lead to an overestimate of model performance on geographic data, due to the existence of spatial autocorrelation. Spatial CV can help address this issue by splitting the data spatially rather than randomly. Four main spatial CV methods identified from the literature are discussed, and two examples based on real-world data are used to demonstrate these methods in comparison with random CV.

Chapter 11 *GeoAI for the Digitization of Historical Maps* by Chiang et al. overviews cutting-edge AI methods and systems for processing historical maps to generate valuable data, insights, and knowledge. Historical maps capture past landscapes' natural and anthropogenic features. In the past decade, numerous maps have been digitized and made publicly accessible. This chapter highlights recently published research findings from the authors across various domains, including the semantic web, big data, data mining, machine learning, document understanding, natural language processing, remote sensing, and geographic information systems.

Chapter 12 *Spatiotemporal AI for Transportation* by Cheng et al. reviews important application domains of Spatiotemporal AI in transport. Spatiotemporal AI has played an important role in transportation research since the latter part of the 20th century and has facilitated various tasks in intelligent transportation systems. This chapter reviews data-driven prediction of traffic variables, optimization of traffic networks using reinforcement learning, and computer vision for sensing complex urban environments. It concludes with some directions for future research in Spatiotemporal AI for transportation.

Chapter 13 *GeoAI for Humanitarian Assistance* by Dias et al. discusses existing and prospective GeoAI tools to support humanitarian practices. Humanitarian assistance is essential to saving lives and alleviating the suffering of populations during crises caused by conflict, violence, and natural disasters. This chapter covers relevant topics on ethical principles, actors, and data sources, in addition to methodological applications on population mapping, built environment characterization, vulnerability and risk analysis, and agent-based modeling.

Chapter 14 *GeoAI for Disaster Response* by Zou et al. presents a convergence of GeoAI and disaster response with three focuses: (1) establishing a comprehensive paradigm that expounds upon the diverse applications of GeoAI with geospatial big data toward enhancing disaster response efforts; (2) exhibiting the employment of GeoAI in disaster response through the analysis of social media data during the 2017 Hurricane Harvey with advanced Natural Language Processing models; and (3) identifying the challenges and opportunities associated with the complete realization of GeoAI's potential in disaster response research and practice.

Chapter 15 *GeoAI for Public Health* by Züfle et al. focuses on using GeoAI for infectious disease spread prediction. Research interest in GeoAI for public health has been fueled by the increased availability of rich data sources. This chapter (1) motivates the need for AI-based solutions in public health by showing the heterogeneity of human behavior related to health, (2) provides a brief survey of current state-of-the-art solutions using AI for infectious disease spread prediction, (3) describes a use-case of using large-scale human mobility data to inform AI models for the prediction of infectious disease spread in a city, and (4) provides future research directions.

Chapter 16 *GeoAI for Agriculture* by Zhang et al. reviews the development of GeoAI in agriculture. As yield estimation is one of the most important topics, the main focus of the chapter is introducing GeoAI-based conceptual framework of crop yield estimation. The framework comprises the preparation of geospatial modeling inputs, GeoAI-based yield estimation models, as well as feature importance and uncertainty analysis. Using the U.S. Corn Belt as a case study, three GeoAI models for county-level crop yield estimation and uncertainty quantification are discussed.

Chapter 17 *GeoAI for Urban Sensing* by F. Biljecki provides a high-level overview of the applications of GeoAI for urban sensing. Urban sensing has been an important topic in the past decades, and research has been amplified in the last several years with the emergence of new urban data sources and advancements in GeoAI. This chapter reviews four examples of GeoAI applied for urban sensing, which span a variety of data sources, techniques developed, and application domains such as urban sustainability. It also discusses several challenges and future opportunities as well as ethics and data quality issues.

Chapter 18 *Reproducibility and Replicability in GeoAI* by Kedron et al. examines how the reproducibility and replicability of research relates to the development and use of GeoAI. This chapter first defines reproductions and replications in the context of GeoAI research. It then offers guidance for researchers interested in enhancing the reproducibility of GeoAI studies, giving particular attention to some of the unique challenges presented when studying phenomena using spatial data and GeoAI. Looking to the future, this chapter presents several lines of reproduction and replication-related inquiry that researchers could pursue to quicken the development of GeoAI.

Chapter 19 *Privacy and Ethics in GeoAI* by McKenzie et al. discusses the unique privacy and ethical concerns associated with AI techniques used for analyzing geospatial information. This chapter provides an overview of data privacy within the field of GeoAI and describes some of the most common techniques and leading application areas through which data privacy and GeoAI are converging. Finally, the authors suggest a number of ways that privacy within GeoAI can improve and highlight emerging topics within the field.

Chapter 20 *A Humanistic Future of GeoAI* by Zhao and Feng states the need for a humanistic rewire of GeoAI, emphasizing ethical, inclusive, and human-guided development. As GeoAI becomes increasingly integrated into our daily lives, it is crucial to ensure that it benefits society and the environment while upholding essential ethical principles. This chapter discusses the importance of examining GeoAI practices, particularly on marginalized communities and nonhuman entities, to identify potential ethical and social issues and address them proactively.

Chapter 21 *Fast Forward from Data to Insight: (Geographic) Knowledge Graphs and Their Applications* by Janowicz et al. introduces what knowledge graphs are, how they relate to GeoAI research such as knowledge engineering and representation learning, discuss their value proposition for geography and the broader geosciences, outline application areas for knowledge graphs across domains, and introduce the *KnowWhereGraph* as an example of a geospatially centered, highly heterogeneous graph consisting of billions of graph statements extracted from 30 different data layers at the intersection between humans and the environment.

Chapter 22 *Forward Thinking on GeoAI* by S. Newsam discusses the importance of continued interaction between the communities that make up the GeoAI field, the challenges of interdisciplinary research, the role of industry especially with regard to ethics, near- to medium-term opportunities, and some interesting recent developments in generative AI models.

1.3 RESEARCH QUESTIONS AND REFLECTIONS ON THE DEVELOPMENT OF GEOAI

The key question that drives the developments and contributions in GeoAI is why (geo-)spatial is interesting and important in AI research. One answer might be because geographic location or spatial context is often the key for linking heterogeneous datasets that have been intensively used for training advanced AI models (Hu *et al.*, 2019b; Li and Hsu, 2022). Smith (1984) summarizes the applicability of AI to geographic problem-solving, research, and practices with a focus on individual and aggregated intelligent spatial decision-making from both cognitive and engineering perspectives. The cognitive approach focuses on the understanding of human cognitive system and decision-making process modeling while the engineering approach focuses on the development of computer programs that have capabilities for understanding, processing, and generating human-like intelligence (e.g., natural language and vision). A systematic approach might be needed to integrate both. Several geospatial research streams might benefit from the use of AI, including (1) individual decision-making in spatial contexts such as the "cognitive maps" of environments for way-finding; (2) modeling of human behavior or human-environment interactions using symbolic representational approach that can mitigate local language variations; (3) text-based and image-based GIR and discovery; (4) development of neural network-based GeoAI models that rely on fewer statistical assumptions; (5) A hybrid modeling approach that integrates earth system process modeling with data-driven machine learning approaches; and (6) intelligent spatial prediction in environments inaccessible or with limited scientific observations.

These research directions remain valid today. While AI has been advancing so fast, making geographers speed up their research to follow the most recent technological trends, we may also need to pause and reflect on what we have learned in the past few years and what would be GeoAI's research agenda in the next 5–10 years? The following questions may help the community to collectively develop a road map for the next decade of GeoAI research:

- What are the key geographic research questions that we can now address better using AI than traditional approaches?

- What are the unsolved geospatial problems that can now be solved with AI?
- What are the implications of the fast-evolving field of AI to the future research and education landscape of computational geography, human geography, and physical geography?
- Are there any new theories or intelligent approaches for building spatial models and data analysis pipelines in geographic information systems?
- What are the spatial effects that we can extract from machine learning approaches (Li, 2022)?
- How can we replicate a GeoAI model developed in one location to another given the underlying spatial heterogeneity of geographic phenomena (Goodchild and Li, 2021)?
- What kinds of datasets and procedures are required to train a large geospatial foundation model (Mai *et al.*, 2023) and how is it different from general foundation models?
- How to detect deep fakes in AI-generated geospatial data and maps (Zhao *et al.*, 2021)?
- How to mitigate the energy consumption and air pollution issues caused by training large GeoAI models and move toward sustainable AI development (Van Wynsberghe, 2021)?
- What are the ethical issues on the development of artificial general intelligence (AGI) in spatial reasoning and trustworthy decision-making?
- How GeoAI can be a force for social good (Taddeo and Floridi, 2018) and digital resilience (Wright, 2016)?
- What are the best practices to develop responsible GeoAI while mitigating invisible risks and addressing the ethics, empathy, and equity issues (Nelson *et al.*, 2022)?
- Last but not the least, what is the science of GeoAI?

1.4 SUMMARY

AI technologies are advancing rapidly, and new methods and use cases in GeoAI are constantly emerging. As GeoAI researchers, we should not purely hunt for latest AI technologies (Openshaw and Openshaw, 1997) but should focus on addressing geographic problems and solving grand challenges facing our society as well as achieving sustainable goals. We also need research efforts toward the development of responsible, unbiased, explainable, and sustainable GeoAI models to support geographic knowledge discovery and beyond (Janowicz *et al.*, 2020, 2022; Li *et al.*, 2021b). This handbook is completed in the middle of 2023. While we cannot summarize all GeoAI research in this one handbook, we hope that it provides a snapshot of current GeoAI research and helps stimulate future studies in the coming years.

1.5 A LIST OF GEOAI TOOLS AND RESOURCES

Here, we list a set of open-source datasets, tools, and resources that might be useful for students interested in GeoAI. The following list is not exhaustive and is intended to serve as a starting point for exploration rather than a complete collection.

DATASETS

- *GeoImageNet*: https://github.com/ASUcicilab/GeoImageNet, a multi-source natural feature (e.g., basins, bays, islands, lakes, ridges, and valleys) benchmark dataset for GeoAI and supervised machine learning (Li *et al.*, 2022).

- *BigEarthNet*: https://bigearth.net, a benchmark archive consisting of over 590k pairs of Sentinel-1 and Sentinel-2 image patches that were annotated with multi-labels of the CORINE Land Cover types to support deep learning studies in earth remote sensing (Sumbul *et al.*, 2019).

- *EarthNets*: https://earthnets.github.io, an open-source platform that links to hundreds of datasets, pre-trained deep learning models, and various tasks in Earth Observation (Xiong *et al.*, 2022).

- *Microsoft Building Footprints*: https://www.microsoft.com/maps/building-footprints, Microsoft Maps & Geospatial teams released open building footprints datasets in GeoJSON format in United States, Canada, Australia, as well as many countries in Africa and South America.

- *ArcGIS Living Atlas*: https://livingatlas.arcgis.com, a large collection of geographic information (including maps, apps, and GIS data layers) from around the globe. It also includes a set of pretrained deep learning models for geospatial applications such as land use classification, tree segmentation, and building footprint extraction.

- *MoveBank*: https://www.movebank.org, a publicly archived platform containing over 300 datasets that describe movement behavior of 11k animals.

  •*Geolife GPS Trajectories*: https://www.microsoft.com/research/publication/geolife-gps-trajectory-dataset-user-guide, this open dataset contains 17,621 GPS trajectories by 182 users in a period of over three years with activity labels such as shopping, sightseeing, dining, hiking, and cycling (Zheng *et al.*, 2010).

- *Travel Flows*: https://github.com/GeoDS/COVID19USFlows, a multiscale dynamic origin-to-destination population flow dataset (aggregated at three geographic scales: census tract, county, and state; updated daily and weekly) in the U.S. during the COVID-19 pandemic (Kang *et al.*, 2020).

TOOLS, LIBRARIES AND FRAMEWORKS

- *Scikit-learn*: https://scikit-learn.org, consists of simple and efficient machine learning tools, including classificaiton, regression, clustering, dimension reduction, data preprocessing and model evaluation metrics in Python.
- *PyTorch*: https://pytorch.org, a computational framework for building machine and deep learning models in Python.
- *Tensorflow*: https://www.tensorflow.org, another computational framework for building machine and deep learning models.
- *Keras*: https://keras.io, an effective high-level neural network Application Programming Interface (API) in Python and it is easy for most machine and deep learning beginners to learn and use.
- *Hugging Face*: https://huggingface.co, AI community that builds, trains and deploys state of the art models (e.g., generative pre-trained transformers) powered by the reference open source in machine and deep learning.
- *Google Earth Engine*: https://earthengine.google.com, a multi-petabyte catalog of satellite imagery and geospatial datasets with planetary-scale analysis capabilities and the Earth Engine API for geocomputation and analsis is available in JavaScript and Python, e.g., the *geemap* package by Wu (2020).
- *ArcGIS GeoAI Toolbox*: https://pro.arcgis.com/en/pro-app/latest/tool-reference/geoai, contains ready-to-use tools for training and using machine/deep learning models that perform classification and regression on geospatial feature layers, imagery, tabular and text datasets.

COMPUTING PLATFORMS

- *Google Colab*: https://research.google.com/colaboratory, an open platform for developing machine learning models, data analysis and education resources with easy-to-use Web interface powered by cloud computing.
- *CyberGISX*: https://cybergisxhub.cigi.illinois.edu, an open platform for developing and sharing open educational resources (e.g., Jupyter Notebooks) on computationally intensive and reproducible geospatial analytics and workflows powered by CyberGIS middleware and cyberinfrastructure (Baig *et al.*, 2022; Wang *et al.*, 2013).

ACKNOWLEDGMENTS

Song Gao acknowledges the support by the National Science Foundation funded AI institute (Award No. 2112606) for Intelligent Cyberinfrastructure with Computational Learning in the Environment (ICICLE) and the H.I. Romnes Faculty Fellowship provided by the University of Wisconsin-Madison Office of the Vice Chancellor for Research and Graduate Education with funding from the Wisconsin Alumni Research Foundation. Wenwen Li would like to thank the support by the National Science Foundation (Award No. 2120943 and 1853864). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding agencies.

BIBLIOGRAPHY

Arundel, S.T., Li, W., and Wang, S., 2020. GeoNat v1.0: A dataset for natural feature mapping with artificial intelligence and supervised learning. *Transactions in GIS*, 24 (3), 556–572.

Baig, F., *et al.*, 2022. Cybergis-cloud: A unified middleware framework for cloud-based geospatial research and education. *In*: *Practice and Experience in Advanced Research Computing*, 1–4.

Chen, J., *et al.*, 2018. Deep learning from multiple crowds: A case study of humanitarian mapping. *IEEE Transactions on Geoscience and Remote Sensing*, 57 (3), 1713–1722.

Cheng, X., *et al.*, 2021. A method to evaluate task-specific importance of spatio-temporal units based on explainable artificial intelligence. *International Journal of Geographical Information Science*, 35 (10), 2002–2025.

Chiang, Y.Y., *et al.*, 2020. *Using Historical Maps in Scientific Studies: Applications, Challenges, and Best Practices*. Springer.

Chiappinelli, C., 2022. Think tank: GeoAI reveals a glimpse of the future. *Esri's WhereNext Magazine*, 1–6.

Couclelis, H., 1986. Artificial intelligence in geography: Conjectures on the shape of things to come. *The Professional Geographer*, 38 (1), 1–11.

Gao, S., 2021. *Geospatial Artificial Intelligence (GeoAI)*. Oxford University Press.

Gao, S., *et al.*, 2023. Special issue on geospatial artificial intelligence. *GeoInformatica*, 1–4.

Glorot, X. and Bengio, Y., 2010. Understanding the difficulty of training deep feedforward neural networks. *In*: *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*. JMLR Workshop and Conference Proceedings, 249–256.

Goodchild, M.F. and Li, W., 2021. Replication across space and time must be weak in the social and environmental sciences. *Proceedings of the National Academy of Sciences*, 118 (35), e2015759118.

Hsu, C.Y. and Li, W., 2023. Explainable GeoAI: can saliency maps help interpret artificial intelligence's learning process? An empirical study on natural feature detection. *International Journal of Geographical Information Science*, 1–25.

Hu, Y., *et al.*, 2019a. GeoAI at ACM SIGSPATIAL: progress, challenges, and future directions. *Sigspatial Special*, 11 (2), 5–15.

Hu, Y., *et al.*, 2019b. Artificial intelligence approaches. *The Geographic Information Science & Technology Body of Knowledge*.

Ibrahim, M.R., Haworth, J., and Cheng, T., 2021. Urban-i: From urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision. *Environment and Planning B: Urban Analytics and City Science*, 48 (1), 76–93.

Janowicz, K., *et al.*, 2020. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *International Journal of Geographical Information Science*, 34 (4), 625–636.

Janowicz, K., Sieber, R., and Crampton, J., 2022. GeoAI, counter-AI, and human geography: A conversation. *Dialogues in Human Geography*, 12 (3), 446–458.

Kamel Boulos, M.N., *et al.*, 2022. Reconciling public health common good and individual privacy: new methods and issues in geoprivacy. *International Journal of Health Geographics*, 21 (1), 1.

Kamel Boulos, M.N., Peng, G., and VoPham, T., 2019. An overview of GeoAI applications in health and healthcare. *International Journal of Health Geographics*, 18, 1–9.

Kang, Y., *et al.*, 2020. Multiscale dynamic human mobility flow dataset in the u.s. during the covid-19 epidemic. *Scientific Data*, 1–13.

Kang, Y., Gao, S., and Roth, R.E., 2019. Transferring multiscale map styles using generative adversarial networks. *International Journal of Cartography*, 5 (2-3), 115–141.

Krizhevsky, A., Sutskever, I., and Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. *In*: F. Pereira, C. Burges, L. Bottou and K. Weinberger, eds. *Advances in Neural Information Processing Systems*. vol. 25, 1–10.

LeCun, Y., Bengio, Y., and Hinton, G., 2015. Deep learning. *Nature*, 521 (7553), 436–444.

Li, M., *et al.*, 2021a. Prediction of human activity intensity using the interactions in physical and social spaces through graph convolutional networks. *International Journal of Geographical Information Science*, 35 (12), 2489–2516.

Li, W., 2020. GeoAI: Where machine learning and big data converge in GIScience. *Journal of Spatial Information Science*, (20), 71–77.

Li, W. and Hsu, C.Y., 2020. Automated terrain feature identification from remote sensing imagery: a deep learning approach. *International Journal of Geographical Information Science*, 34 (4), 637–660.

Li, W. and Hsu, C.Y., 2022. GeoAI for large-scale image analysis and machine vision: Recent progress of artificial intelligence in geography. *ISPRS International Journal of Geo-Information*, 11 (7), 385.

Li, W., Hsu, C.Y., and Hu, M., 2021b. Tobler's First Law in GeoAI: A spatially explicit deep learning model for terrain feature detection under weak supervision. *Annals of the American Association of Geographers*, 111 (7), 1887–1905.

Li, W., *et al.*, 2022. GeoImageNet: a multi-source natural feature benchmark dataset for GeoAI and supervised machine learning. *GeoInformatica*, 1–22.

Li, Z., 2022. Extracting spatial effects from machine learning model using local interpretation method: An example of shap and xgboost. *Computers, Environment and Urban Systems*, 96, 101845.

Lunga, D., *et al.*, 2018. Domain-adapted convolutional networks for satellite image classification: A large-scale interactive learning workflow. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 11 (3), 962–977.

Ma, Y., *et al.*, 2022. Forecasting vegetation dynamics in an open ecosystem by integrating deep learning and environmental variables. *International Journal of Applied Earth Observation and Geoinformation*, 114, 103060.

Mai, G., *et al.*, 2022a. Symbolic and subsymbolic GeoAI: Geospatial knowledge graphs and spatially explicit machine learning. *Transactions in GIS*, 26 (8), 3118–3124.

Mai, G., *et al.*, 2022b. A review of location encoding for GeoAI: methods and applications. *International Journal of Geographical Information Science*, 36 (4), 639–673.

Mai, G., *et al.*, 2023. On the opportunities and challenges of foundation models for geospatial artificial intelligence. *arXiv preprint arXiv:2304.06798*.

Nelson, T., Goodchild, M., and Wright, D., 2022. Accelerating ethics, empathy, and equity in geographic information science. *Proceedings of the National Academy of Sciences*, 119 (19), e2119967119.

Openshaw, S. and Openshaw, C., 1997. *Artificial Intelligence in Geography*. John Wiley & Sons, Inc.

Rao, J., *et al.*, 2021. A privacy-preserving framework for location recommendation using decentralized collaborative machine learning. *Transactions in GIS*, 25 (3), 1153–1175.

Reichstein, M., *et al.*, 2019. Deep learning and process understanding for data-driven earth system science. *Nature*, 566 (7743), 195–204.

Richter, K.F. and Scheider, S., 2023. Current topics and challenges in geoai. *KI-Kunstliche Intelligenz*, 1–6.

Scheele, C., Yu, M., and Huang, Q., 2021. Geographic context-aware text mining: enhance social media message classification for situational awareness by integrating spatial and temporal features. *International Journal of Digital Earth*, 14 (11), 1721–1743.

Smith, T.R., 1984. Artificial intelligence and its applicability to geographical problem solving. *The Professional Geographer*, 36 (2), 147–158.

Sumbul, G., *et al.*, 2019. Bigearthnet: A large-scale benchmark archive for remote sensing image understanding. *In*: *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, 5901–5904.

Taddeo, M. and Floridi, L., 2018. How AI can be a force for good. *Science*, 361 (6404), 751–752.

Van Wynsberghe, A., 2021. Sustainable ai: Ai for sustainability and the sustainability of AI. *AI and Ethics*, 1 (3), 213–218.

Wang, J., Hu, Y., and Joseph, K., 2020. Neurotpr: A neuro-net toponym recognition model for extracting locations from social media messages. *Transactions in GIS*, 24 (3), 719–735.

Wang, J. and Biljecki, F., 2022. Unsupervised machine learning in urban studies: A systematic review of applications. *Cities*, 129, 103925.

Wang, S., *et al.*, 2013. Cybergis software: a synthetic review and integration roadmap. *International Journal of Geographical Information Science*, 27 (11), 2122–2145.

Wang, S. and Li, W., 2021. GeoAI in terrain analysis: Enabling multi-source deep learning and data fusion for natural feature detection. *Computers, Environment and Urban Systems*, 90, 101715.

Wright, D.J., 2016. Toward a digital resilience. *Elementa: Science of the Anthropocene*, 4.

Wu, Q., 2020. geemap: A python package for interactive mapping with google earth engine. *Journal of Open Source Software*, 5 (51), 2305.

Xie, Y., *et al.*, 2021. Spatial-net: A self-adaptive and model-agnostic deep learning framework for spatially heterogeneous datasets. *In*: *Proceedings of the 29th International Conference on Advances in Geographic Information Systems*. 313–323.

Xing, J. and Sieber, R., 2023. The challenges of integrating explainable artificial intelligence into geoai. *Transactions in GIS*, 27 (3), 1–20.

Xiong, Z., *et al.*, 2022. Earthnets: Empowering ai in earth observation. *arXiv preprint arXiv:2210.04936*.

Yan, B., *et al.*, 2017. From itdl to place2vec: Reasoning about place type similarity and relatedness by learning embeddings from augmented spatial contexts. *In*: *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 1–10.

Zhang, Y., *et al.*, 2020. A novel residual graph convolution deep learning model for short-term network-based traffic forecasting. *International Journal of Geographical Information Science*, 34 (5), 969–995.

Zhao, B., *et al.*, 2021. Deep fake geography? when geospatial data encounter artificial intelligence. *Cartography and Geographic Information Science*, 48 (4), 338–352.

Zheng, Y., *et al.*, 2010. Geolife: A collaborative social networking service among user, location and trajectory. *IEEE Data Eng. Bull.*, 33 (2), 32–39.

Zheng, Z. and Sieber, R., 2022. Putting humans back in the loop of machine learning in canadian smart cities. *Transactions in GIS*, 26 (1), 8–24.

Zhou, B., *et al.*, 2022a. Victimfinder: Harvesting rescue requests in disaster response from social media with bert. *Computers, Environment and Urban Systems*, 95, 101824.

Zhou, R.Z., *et al.*, 2022b. Deriving neighborhood-level diet and physical activity measurements from anonymized mobile phone location data for enhancing obesity estimation. *International Journal of Health Geographics*, 21 (1), 1–18.

Zhu, D., *et al.*, 2020. Spatial interpolation using conditional generative adversarial neural networks. *International Journal of Geographical Information Science*, 34 (4), 735–758.

Introduction to Geospatial Artificial Intelligence (GeoAI)

Arundel, S.T. , Li, W. , and Wang, S. , 2020. GeoNat v1.0: A dataset for natural feature mapping with artificial intelligence and supervised learning. Transactions in GIS, 24 (3), 556–572.

Baig, F. , *et al.* , 2022. Cybergis-cloud: A unified middleware framework for cloud-based geospatial research and education. *In*: *Practice and Experience in Advanced Research Computing*, 1–4.

Chen, J. , *et al.* , 2018. Deep learning from multiple crowds: A case study of humanitarian mapping. IEEE Transactions on Geoscience and Remote Sensing, 57 (3), 1713–1722.

Cheng, X. , *et al.* , 2021. A method to evaluate task-specific importance of spatio-temporal units based on explainable artificial intelligence. International Journal of Geographical Information Science, 35 (10), 2002–2025.

Chiang, Y.Y. , *et al.* , 2020. Using Historical Maps in Scientific Studies: Applications, Challenges, and Best Practices. Springer.

Chiappinelli, C. , 2022. Think tank: GeoAI reveals a glimpse of the future. Esri's WhereNext Magazine, 1–6.

Couclelis, H. , 1986. Artificial intelligence in geography: Conjectures on the shape of things to come. The Professional Geographer, 38 (1), 1–11.

Gao, S. , 2021. Geospatial Artificial Intelligence (GeoAI). Oxford University Press.

Gao, S. , *et al.* , 2023. Special issue on geospatial artificial intelligence. GeoInformatica, 1–4.

Glorot, X. and Bengio, Y. , 2010. Understanding the difficulty of training deep feedforward neural networks. *In*: *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*. JMLR Workshop and Conference Proceedings, 249–256.

Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. Proceedings of the National Academy of Sciences, 118 (35), e2015759118.

Hsu, C.Y. and Li, W. , 2023. Explainable GeoAI: can saliency maps help interpret artificial intelligence's learning process? An empirical study on natural feature detection. International Journal of Geographical Information Science, 1–25.

Hu, Y. , *et al.* , 2019a. GeoAI at ACM SIGSPATIAL: progress, challenges, and future directions. Sigspatial Special, 11 (2), 5–15.

Hu, Y. , *et al.* , 2019b. Artificial intelligence approaches. The Geographic Information Science & Technology Body of Knowledge.

Ibrahim, M.R. , Haworth, J. , and Cheng, T. , 2021a. Urban-i: From urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision. Environment and Planning B: Urban Analytics and City Science, 48 (1), 76–93.

Janowicz, K. , *et al.* , 2020. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science, 34 (4), 625–636.

Janowicz, K. , Sieber, R. , and Crampton, J. , 2022. GeoAI, counter-AI, and human geography: A conversation. Dialogues in Human Geography, 12 (3), 446–458.

Kamel Boulos, M.N. , *et al.* , 2022. Reconciling public health common good and individual privacy: new methods and issues in geoprivacy. International Journal of Health Geographics, 21 (1), 1.

Kamel Boulos, M.N. , Peng, G. , and VoPham, T. , 2019. An overview of GeoAI applications in health and healthcare. International Journal of Health Geographics, 18, 1–9.

Kang, Y. , *et al.* , 2020. Multiscale dynamic human mobility flow dataset in the u.s. during the covid-19 epidemic. Scientific Data, 1–13.

Kang, Y. , Gao, S. , and Roth, R.E. , 2019. Transferring multiscale map styles using generative adversarial networks. International Journal of Cartography, 5 (2–3), 115–141.

Krizhevsky, A. , Sutskever, I. , and Hinton, G.E. , 2012. Imagenet classification with deep convolutional neural networks. *In*: F. Pereira , C. Burges , L. Bottou and K. Weinberger , eds. Advances in Neural Information Processing Systems. vol. 25, 1–10.

LeCun, Y. , Bengio, Y. , and Hinton, G. , 2015. Deep learning. Nature, 521 (7553), 436–444.

Li, M. , *et al.* , 2021a. Prediction of human activity intensity using the interactions in physical and social spaces through graph convolutional networks. International Journal of Geographical Information Science, 35 (12), 2489–2516.

Li, W. , 2020. GeoAI: Where machine learning and big data converge in GIScience. Journal of Spatial Information Science, (20), 71–77.
Li, W. and Hsu, C.Y. , 2020. Automated terrain feature identification from remote sensing imagery: a deep learning approach. International Journal of Geographical Information Science, 34 (4), 637–660.
Li, W. and Hsu, C.Y. , 2022. GeoAI for large-scale image analysis and machine vision: Recent progress of artificial intelligence in geography. ISPRS International Journal of Geo-Information, 11 (7), 385.
Li, W. , Hsu, C.Y. , and Hu, M. , 2021b. Tobler's First Law in GeoAI: A spatially explicit deep learning model for terrain feature detection under weak supervision. Annals of the American Association of Geographers, 111 (7), 1887–1905.
Li, W. , *et al.* , 2022. GeoImageNet: a multi-source natural feature benchmark dataset for GeoAI and supervised machine learning. GeoInformatica, 1–22.
Li, Z. , 2022. Extracting spatial effects from machine learning model using local interpretation method: An example of shap and xgboost. Computers, Environment and Urban Systems, 96, 101845.
Lunga, D. , *et al.* , 2018. Domain-adapted convolutional networks for satellite image classification: A large-scale interactive learning workflow. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11 (3), 962–977.
Ma, Y. , *et al.* , 2022. Forecasting vegetation dynamics in an open ecosystem by integrating deep learning and environmental variables. International Journal of Applied Earth Observation and Geoinformation, 114, 103060.
Mai, G. , *et al.* , 2022a. Symbolic and subsymbolic GeoAI: Geospatial knowledge graphs and spatially explicit machine learning. Transactions in GIS, 26 (8), 3118–3124.
Mai, G. , *et al.* , 2022b. A review of location encoding for GeoAI: methods and applications. International Journal of Geographical Information Science, 36 (4), 639–673.
Mai, G. , *et al.* , 2023. On the opportunities and challenges of foundation models for geospatial artificial intelligence. *arXiv preprint arXiv:2304.06798*.
Nelson, T. , Goodchild, M. , and Wright, D. , 2022. Accelerating ethics, empathy, and equity in geographic information science. Proceedings of the National Academy of Sciences, 119 (19), e2119967119.
Openshaw, S. and Openshaw, C. , 1997. Artificial Intelligence in Geography. John Wiley & Sons, Inc.
Rao, J. , *et al.* , 2021. A privacy-preserving framework for location recommendation using decentralized collaborative machine learning. Transactions in GIS, 25 (3), 1153–1175.
Reichstein, M. , *et al.* , 2019. Deep learning and process understanding for data-driven earth system science. Nature, 566 (7743), 195–204.
Richter, K.F. and Scheider, S. , 2023. Current topics and challenges in geoai. KI-Kunstliche Intelligenz, 1–6.
Scheele, C. , Yu, M. , and Huang, Q. , 2021. Geographic context-aware text mining: enhance social media message classification for situational awareness by integrating spatial and temporal features. International Journal of Digital Earth, 14 (11), 1721–1743.
Smith, T.R. , 1984. Artificial intelligence and its applicability to geographical problem solving. The Professional Geographer, 36 (2), 147–158.
Sumbul, G. , *et al.* , 2019. Bigearthnet: A large-scale benchmark archive for remote sensing image understanding. *In*: *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium* . IEEE, 5901–5904.
Taddeo, M. and Floridi, L. , 2018. How AI can be a force for good. Science, 361 (6404), 751–752.
Van Wynsberghe, A. , 2021. Sustainable ai: Ai for sustainability and the sustainability of AI. AI and Ethics, 1 (3), 213–218.
Wang, J. , Hu, Y. , and Joseph, K. , 2020. Neurotpr: A neuro-net toponym recognition model for extracting locations from social media messages. Transactions in GIS, 24 (3), 719–735.
Wang, J. and Biljecki, F. , 2022. Unsupervised machine learning in urban studies: A systematic review of applications. Cities, 129, 103925.
Wang, S. , *et al.* , 2013. Cybergis software: a synthetic review and integration roadmap. International Journal of Geographical Information Science, 27 (11), 2122–2145.

Wang, S. and Li, W. , 2021. GeoAI in terrain analysis: Enabling multi-source deep learning and data fusion for natural feature detection. Computers, Environment and Urban Systems, 90, 101715.
Wright, D.J. , 2016. Toward a digital resilience. Elementa: Science of the Anthropocene, 4.
Wu, Q. , 2020. geemap: A python package for interactive mapping with google earth engine. Journal of Open Source Software, 5 (51), 2305.
Xie, Y. , *et al.* , 2021. Spatial-net: A self-adaptive and model-agnostic deep learning framework for spatially heterogeneous datasets. *In*: *Proceedings of the 29th International Conference on Advances in Geographic Information Systems* . 313–323.
Xing, J. and Sieber, R. , 2023. The challenges of integrating explainable artificial intelligence into geoai. Transactions in GIS, 27 (3), 1–20.
Xiong, Z. , *et al.* , 2022. Earthnets: Empowering ai in earth observation. *arXiv preprint arXiv:2210.04936*.
Yan, B. , *et al.* , 2017. From itdl to place2vec: Reasoning about place type similarity and relatedness by learning embeddings from augmented spatial contexts. *In*: *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* , 1–10.
Zhang, Y. , *et al.* , 2020. A novel residual graph convolution deep learning model for short-term network-based traffic forecasting. International Journal of Geographical Information Science, 34 (5), 969–995.
Zhao, B. , *et al.* , 2021. Deep fake geography? when geospatial data encounter artificial intelligence. Cartography and Geographic Information Science, 48 (4), 338–352.
Zheng, Y. , *et al.* , 2010. Geolife: A collaborative social networking service among user, location and trajectory. IEEE Data Eng. Bull., 33 (2), 32–39.
Zheng, Z. and Sieber, R. , 2022. Putting humans back in the loop of machine learning in canadian smart cities. Transactions in GIS, 26 (1), 8–24.
Zhou, B. , *et al.* , 2022a. Victimfinder: Harvesting rescue requests in disaster response from social media with bert. Computers, Environment and Urban Systems, 95, 101824.
Zhou, R.Z. , *et al.* , 2022b. Deriving neighborhood-level diet and physical activity measurements from anonymized mobile phone location data for enhancing obesity estimation. International Journal of Health Geographics, 21 (1), 1–18.
Zhu, D. , *et al.* , 2020. Spatial interpolation using conditional generative adversarial neural networks. International Journal of Geographical Information Science, 34 (4), 735–758.

GeoAI's Thousand-Year History

Bushwick, S. , 2023. Tech talks to animals: Portable sensors and artificial intelligence are helping researchers to talk back to non-humans. Scientific American, 05, 26–27.
Couclelis, H. , 1986a. Artificial Intelligence in geography: Conjectures on the shape of things to come. The Professional Geographer, 38 (1), 1–11.
Couclelis, H. , 1986b. A theoretical framework for alternative models of spatial decision and behavior. Annals of the Association of American Geographers, 76 (1), 95–113.
Dunsany, L. , 1951. The Last Revolution. Talos Press edition.
Freeth, T. , *et al.* , 2021. A model of the Cosmos in the ancient Greek Antikythera mechanism. Scientific Reports, 11 (1), 1–15.
Langton, C.G. , *et al.* , 1991. Artificial Life II. Addison-Wesley Longman Publishing Co., Inc.
Mayor, A. , 2018. Gods and Robots: Myths, Machines, and Ancient Dreams of Technology. Princeton University Press.
Openshaw, S. and Openshaw, C. , 1997. Artificial Intelligence in Geography. John Wiley & Sons, Inc.
Simon, H.A. , 2019. The Sciences of the Artificial, Reissue of the Third Edition with a New Introduction by John Laird. MIT Press.
Smith, T.R. , 1984. Artificial Intelligence and its applicability to geographical problem solving. The Professional Geographer, 36 (2), 147–158.

Philosophical Foundations of GeoAI: Exploring Sustainability, Diversity, and Bias in GeoAI and Spatial Data Science

Abhayaratna, J. , *et al.* , 2021. *The Responsible Use of Spatial Data*. W3C.

Bender, E.M. , *et al.* , 2021. On the dangers of stochastic parrots: Can language models be too big? *In*: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* . 610–623.

Bolukbasi, T. , *et al.* , 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. Advances in Neural Information Processing Systems, 29.

Bommasani, R. , *et al.* , 2021. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*.

Cavoukian, A. , 2009. Privacy by Design. Canadian Electronic Library.

Feng, M. , *et al.* , 2019. Relative space-based gis data model to analyze the group dynamics of moving objects. ISPRS Journal of Photogrammetry and Remote Sensing, 153, 74–95.

Goodchild, M. , *et al.* , 2022. A white paper on locational information and the public interest. American Association of Geographers.

Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. Proceedings of the National Academy of Sciences, 118 (35), e2015759118.

Gupta, U. , *et al.* , 2022. Chasing carbon: The elusive environmental footprint of computing. IEEE Micro, 42 (4), 37–47.

Hagendorff, T. , 2020. The ethics of AI ethics: An evaluation of guidelines. Minds and Machines, 30 (1), 99–120.

Hendler, J. , *et al.* , 2008. Web science: an interdisciplinary approach to understanding the web. Communications of the ACM, 51 (7), 60–69.

Hogan, A. , *et al.* , 2021. Knowledge graphs. ACM Computing Surveys (CSUR), 54 (4), 1–37.

Hsu, C.Y. and Li, W. , 2023. Explainable GeoAI: can saliency maps help interpret artificial intelligence's learning process? An empirical study on natural feature detection. International Journal of Geographical Information Science, 1–25.

Janowicz, K. , *et al.* , 2014. Towards geographic information observatories. *In*: GIO@ GIScience. 1–5.

Janowicz, K. , *et al.* , 2020. GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond.

Janowicz, K. , *et al.* , 2022a. Know, know where, knowwheregraph: A densely connected, cross-domain knowledge graph and geo-enrichment service stack for applications in environmental intelligence. AI Magazine, 43 (1), 30–39.

Janowicz, K. , *et al.* , 2022b. Diverse data! diverse schemata? Semantic Web, 13 (1), 1–3.

Janowicz, K. , Sieber, R. , and Crampton, J. , 2022c. GeoAI, counter-AI, and human geography: A conversation. Dialogues in Human Geography, 12 (3), 446–458.

Janowicz, K. , *et al.* , 2015. Why the data train needs semantic rails. AI Magazine, 36 (1), 5–14.

Janowicz, K. , *et al.* , 2018. Debiasing knowledge graphs: Why female presidents are not like female popes. *In*: *ISWC (P&D/Industry/BlueSky)*.

Janowicz, K. , *et al.* , 2022d. Six giscience ideas that must die. AGILE: GIScience Series, 3, 7.

Jonas, H. , 1985. The Imperative of Responsibility: In Search of an Ethics for the Technological Age. University of Chicago press.

Kedron, P. , *et al.* , 2021. Reproducibility and replicability: opportunities and challenges for geospatial research. International Journal of Geographical Information Science, 35 (3), 427–445.

Keßler, C. and McKenzie, G. , 2018. A geoprivacy manifesto. Transactions in GIS, 22 (1), 3–19.

Kounadi, O. and Leitner, M. , 2014. Why does geoprivacy matter? the scientific publication of confidential data presented on maps. Journal of Empirical Research on Human Research Ethics, 9 (4), 34–45.

Krumm, J. , 2009. A survey of computational location privacy. Personal and Ubiquitous Computing, 13, 391–399.

Li, W. , Hsu, C.Y. , and Hu, M. , 2021. Tobler's First Law in GeoAI: A spatially explicit deep learning model for terrain feature detection under weak supervision. Annals of the American Association of Geographers, 111 (7), 1887–1905.

Li, Z. , 2022. Extracting spatial effects from machine learning model using local interpretation method: An example of shap and xgboost. Computers, Environment and Urban Systems, 96, 101845.
Liu, P. and Biljecki, F. , 2022. A review of spatially-explicit GeoAI applications in Urban Geography. International Journal of Applied Earth Observation and Geoinformation, 112, 102936.
Liu, Z. , *et al.* , 2022. Geoparsing: Solved or biased? an evaluation of geographic biases in geoparsing. AGILE: GIScience Series, 3, 9.
Mai, G. , *et al.* , 2022. A review of location encoding for GeoAI: methods and applications. International Journal of Geographical Information Science, 36 (4), 639–673.
McKenzie, G. , *et al.* , 2022. Privyto: A privacy-preserving location-sharing platform. Transactions in GIS, 26 (4), 1703–1717.
Mehrabi, N. , *et al.* , 2021. A survey on bias and fairness in machine learning. ACM Computing Surveys (CSUR *)*, 54 (6), 1–35.
Mellander, C. , *et al.* , 2015. Night-time light data: A good proxy measure for economic activity? PloS One, 10 (10), e0139779.
Miller, H.J. , 2017. Geographic information science i: Geographic information observatories and opportunistic giscience. Progress in Human Geography, 41 (4), 489–500.
Moor, J.H. , 1985. What is computer ethics? Metaphilosophy, 16 (4), 266–275.
Moor, J.H. , 1997. Towards a theory of privacy in the information age. ACM Sigcas Computers and Society, 27 (3), 27–32.
Nüst, D. , *et al.* , 2018. Reproducible research and giscience: an evaluation using agile conference papers. PeerJ, 6, e5072.
Openshaw, S. , 1984. The modifiable areal unit problem. Concepts and Techniques in Modern Geography.
O'Sullivan, D. and Unwin, D. , 2003. Geographic Information Analysis. John Wiley & Sons.
Papadakis, E. , *et al.* , 2022. Explainable artificial intelligence in the spatial domain (X-GeoAI). Transactions in GIS, 26 (6), 2413–2414.
Peppoloni, S. and Di Capua, G. , 2017. Geoethics: ethical, social and cultural implications in geosciences. Annals of Geophysics.
Phillips, P.J. , *et al.* , 2020. Four principles of explainable artificial intelligence. *Gaithersburg, Maryland*, 18.
Rocher, L. , Hendrickx, J.M. , and De Montjoye, Y.A. , 2019. Estimating the success of re-identifications in incomplete datasets using generative models. Nature Communications, 10 (1), 1–9.
Scheider, S. and Kuhn, W. , 2015. How to talk to each other via computers: Semantic interoperability as conceptual imitation. *Applications of Conceptual Spaces: The Case for Geometric Knowledge Representation*, 97–122.
Schwartz, R. , *et al.* , 2020. Green AI. Communications of the ACM, 63 (12), 54–63.
Shankar, S. , *et al.* , 2017. No classification without representation: Assessing geodiversity issues in open data sets for the developing world. *arXiv preprint arXiv:1711.08536*.
Stinson, C. , 2022. Algorithms are not neutral: Bias in collaborative filtering. AI and Ethics, 2 (4), 763–770.
The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems , 2019. Ethically aligned design: A vision for prioritizing human well-being with autonomous and intelligent systems, first edition. IEEE.
Van Wynsberghe, A. , 2021. Sustainable AI: AI for sustainability and the sustainability of AI. AI and Ethics, 1 (3), 213–218.
Wang, S. , Schlobach, S. , and Klein, M. , 2011. Concept drift and how to identify it. Journal of Web Semantics, 9 (3), 247–265.
Wiedmann, T.O. , *et al.* , 2015. The material footprint of nations. Proceedings of the National Academy of Sciences, 112 (20), 6271–6276.
Wilkinson, M.D. , *et al.* , 2016. The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data, 3 (1), 1–9.
Wu, C.J. , *et al.* , 2022. Sustainable AI: Environmental implications, challenges and opportunities. Proceedings of Machine Learning and Systems, 4, 795–813.
Xing, J. and Sieber, R. , 2023. The challenges of integrating explainable artificial intelligence into GeoAI. Transactions in GIS, 27 (3), 1–20.

GeoAI Methodological Foundations: Deep Neural Networks and Knowledge Graphs

Al-Najjar, H.A. , *et al.* , 2021. A new integrated approach for landslide data balancing and spatial prediction based on generative adversarial networks (gan). Remote Sensing, 13 (19), 4011.

Arjovsky, M. , Chintala, S. , and Bottou, L. , 2017. Wasserstein generative adversarial networks. *In*: *International Conference on Machine Learning* . PMLR, 214–223.

Bashmal, L. , *et al.* , 2018. Siamese-gan: Learning invariant representations for aerial vehicle image categorization. Remote Sensing, 10 (2), 351.

Battle, R. and Kolas, D. , 2011. Geosparql: enabling a geospatial semantic web. Semantic Web Journal, 3 (4), 355–370.

Bengio, Y. , Simard, P. , and Frasconi, P. , 1994. Learning long-term dependencies with gradient descent is difficult. IEEE Transactions on Neural Networks, 5 (2), 157–166.

Berragan, C. , *et al.* , 2022. Transformer based named entity recognition for place name extraction from unstructured text. International Journal of Geographical Information Science, 1–20.

Bihlo, A. , 2021. A generative adversarial network approach to (ensemble) weather prediction. Neural Networks, 139, 1–16.

Biljecki, F. and Ito, K. , 2021. Street view imagery in urban analytics and gis: A review. Landscape and Urban Planning, 215, 104217.

Cai, L. , *et al.* , 2020. Traffic transformer: Capturing the continuity and periodicity of time series for traffic forecasting. Transactions in GIS, 24 (3), 736–755.

Chen, X. , *et al.* , 2016. Infogan: Interpretable representation learning by information maximizing generative adversarial nets. Advances in Neural Information Processing Systems, 29.

Chen, Y. , *et al.* , 2021. Ssd-gan: Measuring the realness in the spatial and spectral domains. *In* : *Proceedings of the AAAI Conference on Artificial Intelligence* . vol. 35, 1105–1112.

Cheng, G. , *et al.* , 2020. Remote sensing image scene classification meets deep learning: Challenges, methods, benchmarks, and opportunities. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 3735–3756.

Chiang, Y.Y. , *et al.* , 2020. Training deep learning models for geographic feature recognition from historical maps. *In*: Using Historical Maps in Scientific Studies. Springer, 65–98.

Cho, K. , *et al.* , 2014. On the properties of neural machine translation: Encoder-decoder approaches. *arXiv preprint arXiv:1409.1259*.

Chung, J. , *et al.* , 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*.

Clementini, E. , 2019. A conceptual framework for modelling spatial relations. Information Technology and Control, 48 (1), 5–17.

Cohn, A.G. and Hazarika, S.M. , 2001. Qualitative spatial representation and reasoning: An overview. Fundamenta informaticae, 46 (1), 1–29.

Dai, K. , *et al.* , 2022. Mstcgan: Multi-scale time conditional generative adversarial network for long-term satellite image sequence prediction. IEEE Transactions on Geoscience and Remote Sensing.

Deng, J. , *et al.* , 2009. Imagenet: A large-scale hierarchical image database. *In*: *2009 IEEE Conference on Computer Vision and Pattern Recognition* . IEEE, 248–255.

Duan, W. , *et al.* , 2020. Automatic alignment of contemporary vector data and georeferenced historical maps using reinforcement learning. International Journal of Geographical Information Science, 34 (4), 824–849.

Feng, Y. , Thiemann, F. , and Sester, M. , 2019. Learning cartographic building generalization with deep convolutional neural networks. ISPRS International Journal of Geo-Information, 8 (6), 258.

Fritz, S. , *et al.* , 2017. A global dataset of crowdsourced land cover and land use reference data. Scientific Data, 4 (1), 1–8.

Ganapathi Subramanian, S. and Crowley, M. , 2018. Using spatial reinforcement learning to build forest wildfire dynamics models from satellite images. Frontiers in ICT, 5, 6.

Gao, H. , *et al.* , 2018a. Object classification using cnn-based fusion of vision and lidar in autonomous vehicle environment. IEEE Transactions on Industrial Informatics, 14 (9), 4224–4231.

Gao, S. , 2021. Geospatial Artificial Intelligence (GeoAI). Oxford Bibliographies, (1), 1–16.
Gao, Y. , Jiang, D. , and Xu, Y. , 2018b. Optimize taxi driving strategies based on reinforcement learning. International Journal of Geographical Information Science, 32 (8), 1677–1696.
Getis, A. , 2009. Spatial weights matrices. Geographical Analysis, 41 (4), 404–410.
Gong, S. , *et al.* , 2022. Spatio-temporal travel volume prediction and spatial dependencies discovery using gru, gcn and bayesian probabilities. *In*: *2022 7th International Conference on Big Data Analytics (ICBDA)* . IEEE, 130–136.
Goodchild, M.F. , 2004. The validity and usefulness of laws in geographic information science and geography. Annals of the Association of American Geographers, 94 (2), 300–303.
Goodfellow, I. , Bengio, Y. , and Courville, A. , 2016. Deep Learning. MIT Press.
Goodfellow, I. , *et al.* , 2014. Generative adversarial nets. *In*: Z. Ghahramani , M. Welling , C. Cortes , N. Lawrence and K. Weinberger , eds. Advances in Neural Information Processing Systems. Curran Associates, Inc., vol. 27.
Guo, D. , *et al.* , 2022. Deepssn: A deep convolutional neural network to assess spatial scene similarity. Transactions in GIS, 26 (4), 1914–1938.
Hamilton, W. , Ying, Z. , and Leskovec, J. , 2017. Inductive representation learning on large graphs. Advances in Neural Information Processing Systems, 30.
Hart, G. and Dolbear, C. , 2013. Linked Data: A Geographic Perspective. Taylor & Francis.
Hawelka, B. , *et al.* , 2014. Geo-located twitter as proxy for global mobility patterns. Cartography and Geographic Information Science, 41 (3), 260–271.
He, K. , *et al.* , 2017. Mask r-cnn. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 2961–2969.
He, K. , *et al.* , 2016. Deep residual learning for image recognition. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 770–778.
Helber, P. , *et al.* , 2018. Introducing eurosat: A novel dataset and deep learning benchmark for land use and land cover classification. *In*: *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* . IEEE, 204–207.
Hochreiter, S. and Schmidhuber, J. , 1997. Long short-term memory. Neural Computation, 9 (8), 1735–1780.
Hogan, A. , *et al.* , 2021. Knowledge graphs. ACM Computing Surveys (CSUR), 54 (4), 1–37.
Hu, S. , *et al.* , 2021. Urban function classification at road segment level using taxi trajectory data: A graph convolutional neural network approach. Computers, Environment and Urban Systems, 87, 101619.
Hu, X. , *et al.* , 2022. Gazpne2: A general place name extractor for microblogs fusing gazetteers and pretrained transformer models. IEEE Internet of Things Journal, 9 (17), 16259–16271.
Hu, Y. , *et al.* , 2013. A geo-ontology design pattern for semantic trajectories. *In*: *International Conference on Spatial Information Theory* . Springer, 438–456.
Huang, G. , *et al.* , 2017. Densely connected convolutional networks. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 4700–4708.
Janelle, D.G. and Goodchild, M.F. , 2011. Concepts, principles, tools, and challenges in spatially integrated social science. The SAGE Handbook of GIS and Society, 27–45.
Janowicz, K. , 2012. Observation-driven geo-ontology engineering. Transactions in GIS, 16 (3), 351–374.
Janowicz, K. , *et al.* , 2020. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science, 34 (4), 625–636.
Janowicz, K. , *et al.* , 2022. Know, know where, knowwheregraph: A densely connected, cross-domain knowledge graph and geo-enrichment service stack for applications in environmental intelligence. AI Magazine, 43 (1), 30–39.
Janowicz, K. , *et al.* , 2010. Semantic enablement for spatial data infrastructures. Transactions in GIS, 14 (2), 111–129.
Jiang, W. and Luo, J. , 2022. Graph neural network for traffic forecasting: A survey. Expert Systems with Applications, 117921.
Kaelbling, L.P. , Littman, M.L. , and Moore, A.W. , 1996. Reinforcement learning: A survey. Journal of Artificial Intelligence Research, 4, 237–285.
Kang, Y. , Gao, S. , and Roth, R.E. , 2019. Transferring multiscale map styles using generative adversarial networks. International Journal of Cartography, 5 (2–3), 115–141.

Kang, Y. , *et al.* , 2020. A review of urban physical environment sensing using street view imagery in public health studies. Annals of GIS, 26 (3), 261–275.
Kipf, T.N. and Welling, M. , 2016. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*.
Koch, T. and Dugundji, E. , 2020. A review of methods to model route choice behavior of bicyclists: inverse reinforcement learning in spatial context and recursive logit. *In*: *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on GeoSpatial Simulation* . 30–37.
Krizhevsky, A. , Sutskever, I. , and Hinton, G.E. , 2017. Imagenet classification with deep convolutional neural networks. Communications of the ACM, 60 (6), 84–90.
Kuhn, W. , 2005. Geospatial semantics: why, of what, and how? *In*: Journal on Data Semantics iii. Springer, 1–24.
LeCun, Y. , Bengio, Y. , and Hinton, G. , 2015. Deep learning. Nature, 521 (7553), 436–444.
LeCun, Y. , *et al.* , 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86 (11), 2278–2324.
Li, K. , *et al.* , 2020. Object detection in optical remote sensing images: A survey and a new benchmark. ISPRS Journal of Photogrammetry and Remote Sensing, 159, 296–307.
Li, M. , *et al.* , 2021a. Prediction of human activity intensity using the interactions in physical and social spaces through graph convolutional networks. International Journal of Geographical Information Science, 35 (12), 2489–2516.
Li, S. , *et al.* , 2021b. Groupformer: Group activity recognition with clustered spatial-temporal transformer. *In*: *Proceedings of the IEEE/CVF International Conference on Computer Vision* . 13668–13677.
Li, W. , 2020. GeoAI: Where machine learning and big data converge in GIScience. Journal of Spatial Information Science, (20), 71–77.
Li, W. , Hsu, C.Y. , and Hu, M. , 2021c. Tobler's first law in geoai: A spatially explicit deep learning model for terrain feature detection under weak supervision. Annals of the American Association of Geographers, 111 (7), 1887–1905.
Li, W. , *et al.* , 2022. Geoimagenet: a multi-source natural feature benchmark dataset for geoai and supervised machine learning. GeoInformatica, 1–22.
Li, Y. , *et al.* , 2017. Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. *arXiv preprint arXiv:1707.01926*.
Li, Y. , *et al.* , 2018. An aircraft detection framework based on reinforcement learning and convolutional neural networks in remote sensing images. Remote Sensing, 10 (2), 243.
Li, Y. and Moura, J.M. , 2019. Forecaster: A graph transformer for forecasting spatial and time-dependent data. *arXiv preprint arXiv:1909.04019*.
Liang, Y. , *et al.* , 2022. Region2vec: community detection on spatial networks using graph embedding with node attributes and spatial interactions. *In*: *Proceedings of the 30th International Conference on Advances in Geographic Information Systems* . 1–4.
Liang, Y. , *et al.* , 2019. Urbanfm: Inferring fine-grained urban flows. *In*: *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* . 3132–3142.
Lin, D. , *et al.* , 2017. Marta gans: Unsupervised representation learning for remote sensing image classification. IEEE Geoscience and Remote Sensing Letters, 14 (11), 2092–2096.
Liu, Q. , *et al.* , 2016. Predicting the next location: A recurrent model with spatial and temporal contexts. *In*: Thirtieth AAAI Conference on Artificial Intelligence.
Liu, Y. , Ding, J. , and Li, Y. , 2022. Developing knowledge graph based system for urban computing. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Geospatial Knowledge Graphs* . 3–7.
Luo, Y. , *et al.* , 2018. Multivariate time series imputation with generative adversarial networks. Advances in Neural Information Processing Systems, 31.
Mai, G. , *et al.* , 2022a. Symbolic and subsymbolic GeoAI: Geospatial knowledge graphs and spatially explicit machine learning. Transactions in GIS, 26 (8), 3118–3124.
Mai, G. , *et al.* , 2022b. A review of location encoding for geoai: methods and applications. International Journal of Geographical Information Science, 36 (4), 639–673.
Mai, G. , *et al.* , 2019. Multi-scale representation learning for spatial feature distributions using grid cells. *In*: *International Conference on Learning Representations*.
Mai, G. , *et al.* , 2020. Relaxing unanswerable geographic questions using a spatially explicit knowledge graph embedding model. *In*: Geospatial Technologies for Local and Regional Development: Proceedings of the 22nd AGILE Conference on Geographic Information Science

22. Springer, 21–39.
May Petry, L. , *et al.* , 2020. Marc: a robust method for multiple-aspect trajectory classification via space, time, and semantic embeddings. International Journal of Geographical Information Science, 34 (7), 1428–1450.
Mehrabi, N. , *et al.* , 2021. A survey on bias and fairness in machine learning. ACM Computing Surveys, 54 (6), 1–35.
Miller, E. , 1998. An introduction to the resource description framework. D-lib Magazine.
Mirza, M. and Osindero, S. , 2014. Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*.
Mnih, V. , *et al.* , 2016. Asynchronous methods for deep reinforcement learning. *In*: *International Conference on Machine Learning* . PMLR, 1928–1937.
Mnih, V. , *et al.* , 2015. Human-level control through deep reinforcement learning. Nature, 518 (7540), 529–533.
Oono, K. and Suzuki, T. , 2019. Graph neural networks exponentially lose expressive power for node classification. *arXiv preprint arXiv:1905.10947*.
Ouyang, K. , *et al.* , 2018. A non-parametric generative model for human trajectories. In: IJCAI. vol. 18, 3812–3817.
Ouyang, L. , *et al.* , 2022. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*.
Patterson, J. and Gibson, A. , 2017. Deep Learning: A Practitioner's Approach. “O'Reilly Media, Inc.".
Puterman, M.L. , 1990. Markov decision processes. Handbooks in Operations Research and Management Science, 2, 331–434.
Radford, A. , Metz, L. , and Chintala, S. , 2015. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*.
Rao, J. , *et al.* , 2021a. LSTM-TrajGAN: A Deep Learning Approach to Trajectory Privacy Protection. *In*: *11th International Conference on Geographic Information Science (GIScience 2021)* . Schloss Dagstuhl–Leibniz-Zentrumfur Informatik, vol. 177, 12.
Rao, J. , *et al.* , 2022. Measuring network resilience via geospatial knowledge graph: a case study of the US multi-commodity flow network. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Geospatial Knowledge Graphs* . 17–25.
Rao, J. , Gao, S. , and Zhu, X. , 2021b. Vtsv: A privacy-preserving vehicle trajectory simulation and visualization platform using deep reinforcement learning. *In*: *Proceedings of the 4th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery* . 43–46.
Ronneberger, O. , Fischer, P. , and Brox, T. , 2015. U-net: Convolutional networks for biomedical image segmentation. *In*: *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*. Springer, 234–241.
Rui, X. , *et al.* , 2021. Disastergan: Generative adversarial networks for remote sensing disaster image generation. Remote Sensing, 13 (21), 4284.
Rüttgers, M. , *et al.* , 2019. Prediction of a typhoon track using a generative adversarial network and satellite images. Scientific Reports, 9 (1), 1–15.
Schulman, J. , *et al.* , 2015. Trust region policy optimization. *In*: *International Conference on Machine Learning* . PMLR, 1889–1897.
Schulman, J. , *et al.* , 2017. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*.
Shbita, B. , *et al.* , 2020. Building linked spatio-temporal data from vectorized historical maps. *In* : *European Semantic Web Conference* . Springer, 409–426.
Silver, D. , *et al.* , 2016. Mastering the game of go with deep neural networks and tree search. nature, 529 (7587), 484–489.
Srikanth, G. , Nukavarapu, N. , and Durbha, S. , 2021. Deep reinforcement learning interdependent healthcare critical infrastructure simulation model for dynamically varying covid-19 scenario-a case study of a metro city. *In*: *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS* . IEEE, 8499–8502.
Szegedy, C. , *et al.* , 2015. Going deeper with convolutions. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 1–9.
Tang, W. , *et al.* , 2021. Learning disentangled user representation with multi-view information fusion on social networks. Information Fusion, 74, 77–86.

Tobler, W.R. , 1970. A computer movie simulating urban growth in the detroit region. Economic Geography, 46 (sup1), 234–240.

Toutouh, J. , 2021. Conditional generative adversarial networks to model urban outdoor air pollution. *In*: *Smart Cities: Third Ibero-American Congress, ICSC-Cities 2020, San José, Costa Rica, November 9-11, 2020, Revised Selected Papers 3*. Springer, 90–105.

Vaswani, A. , *et al.* , 2017. Attention is all you need. Advances in Neural Information Processing Systems, 30.

Velickovic, P. , *et al.* , 2017. Graph attention networks. *arXiv preprint arXiv:1710.10903*.

Wang, H. , *et al.* , 2019. Learning graph representation with generative adversarial nets. IEEE Transactions on Knowledge and Data Engineering, 33 (8), 3090–3103.

Wang, P. , *et al.* , 2020. Incremental mobile user profiling: Reinforcement learning with spatial knowledge graph for modeling event streams. *In*: *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* . 853–861.

Wang, S. , *et al.* , 2023. Sta-gan: A spatio-temporal attention generative adversarial network for missing value imputation in satellite data. Remote Sensing, 15 (1), 88.

Watkins, C.J. and Dayan, P. , 1992. Q-learning. Machine Learning, 8, 279–292.

Wilkinson, M.D. , *et al.* , 2016. The fair guiding principles for scientific data management and stewardship. Scientific Data, 3 (1), 1–9.

Wu, A.N. and Biljecki, F. , 2022. Ganmapper: geographical data translation. International Journal of Geographical Information Science, 1–29.

Wu, Z. , *et al.* , 2020. A comprehensive survey on graph neural networks. IEEE Transactions on Neural Networks and Learning Systems, 32 (1), 4–24.

Xia, R. , *et al.* , 2014. Supervised hashing for image retrieval via image representation learning. *In:* Twenty-Eighth AAAI Conference on Artificial Intelligence.

Xu, M. , *et al.* , 2020. Spatial-temporal transformer networks for traffic flow forecasting. *arXiv preprint arXiv:2001.02908*.

Yan, B. , *et al.* , 2018. xnet+ sc: Classifying places based on images by incorporating spatial contexts. *In*: *10th International Conference on Geographic Information Science (GIScience 2018)* . Informatik.

Yan, B. , *et al.* , 2019. A spatially explicit reinforcement learning model for geographic knowledge graph summarization. Transactions in GIS, 23 (3), 620–640.

Yang, B. , *et al.* , 2021. St-lbagan: Spatio-temporal learnable bidirectional attention generative adversarial networks for missing traffic data imputation. Knowledge-Based Systems, 215, 106705.

Yoon, J. , Jordon, J. , and Schaar, M. , 2018. Gain: Missing data imputation using generative adversarial nets. *In*: *International Conference on Machine Learning* . PMLR, 5689–5698.

Yu, Y. , *et al.* , 2019. A review of recurrent neural networks: Lstm cells and network architectures. Neural Computation, 31 (7), 1235–1270.

Zhang, B. , *et al.* , 2022. Styleswin: Transformer-based gan for high-resolution image generation. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 11304–11314.

Zhang, F. , *et al.* , 2018a. Measuring human perceptions of a large-scale urban region using machine learning. Landscape and Urban Planning, 180, 148–160.

Zhang, T. , *et al.* , 2018b. Spatial–temporal recurrent neural network for emotion recognition. IEEE Transactions on Cybernetics, 49 (3), 839–847.

Zhang, Y. and Cheng, T. , 2020. Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events. Computers, Environment and Urban Systems, 79, 101403.

Zhao, B. , *et al.* , 2021. Deep fake geography? when geospatial data encounter artificial intelligence. Cartography and Geographic Information Science, 48 (4), 338–352.

Zhao, L. , *et al.* , 2019. T-gcn: A temporal graph convolutional network for traffic prediction. IEEE Transactions on Intelligent Transportation Systems, 21 (9), 3848–3858.

Zhou, B. , *et al.* , 2017. Places: A 10 million image database for scene recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40 (6), 1452–1464.

Zhou, B. , *et al.* , 2014. Learning deep features for scene recognition using places database. Advances in Neural Information Processing Systems, 27.

Zhou, F. , *et al.* , 2021. Improving human mobility identification with trajectory augmentation. GeoInformatica, 25 (3), 453–483.

Zhou, J. , *et al.* , 2020. Graph neural networks: A review of methods and applications. AI Open, 1, 57–81.
Zhu, A.X. , *et al.* , 2018. Spatial prediction based on third law of geography. Annals of GIS, 24 (4), 225–240.
Zhu, D. , *et al.* , 2020a. Spatial interpolation using conditional generative adversarial neural networks. International Journal of Geographical Information Science, 34 (4), 735–758.
Zhu, D. , *et al.* , 2020b. Understanding place characteristics in geographic contexts through graph convolutional neural networks. Annals of the American Association of Geographers, 110 (2), 408–420.
Zhu, J.Y. , *et al.* , 2017a. Unpaired image-to-image translation using cycle-consistent adversarial networks. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 2223–2232.
Zhu, R. , *et al.* , 2021a. Providing humanitarian relief support through knowledge graphs. *In*: *Proceedings of the 11th nowledge Capture Conference* . 285–288.
Zhu, R. , *et al.* , 2022a. Reasoning over higher-order qualitative spatial relations via spatially explicit neural networks. International Journal of Geographical Information Science, 36 (11), 2194–2225.
Zhu, R. , *et al.* , 2022b. Covid-forecast-graph: An open knowledge graph for consolidating covid-19 forecasts and economic indicators via place and time. AGILE: GIScience Series, 3, 21.
Zhu, R. , *et al.* , 2021b. Environmental observations in knowledge graphs. *In*: DaMaLOS. 1–11.
Zhu, X.X. , *et al.* , 2017b. Deep learning in remote sensing: A comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine, 5 (4), 8–36.

GeoAI for Spatial Image Processing

Abhar, K.C. , *et al.* , 2015. Spatial–temporal evolution of aeolian blowout dunes at cape cod. Geomorphology, 236, 148–162.
Acosta, J. and Cherrier, B. , 2021. The transformation of economic analysis at the board of governors of the federal reserve system during the 1960s. Journal of the History of Economic Thought, 43 (3), 323–349.
Al-Mistarehi, B. , *et al.* , 2022. Using machine learning models to forecast severity level of traffic crashes by r studio and arcgis. Frontiers in Built Environment, 8, 54.
Amato, F. , *et al.* , 2020. A novel framework for spatio-temporal prediction of environmental data using deep learning. Scientific Reports, 10 (1), 22243.
Arundel, S.T. , Li, W. , and Wang, S. , 2020. Geonat v1. 0: A dataset for natural feature mapping with artificial intelligence and supervised learning. Transactions in GIS, 24 (3), 556–572.
Arundel, S.T. , Morgan, T.P. , and Thiem, P.T. , 2022. Deep learning detection and recognition of spot elevations on historical topographic maps. Frontiers in Environmental Science, 117.
Barnes, T.J. , 2004. Placing ideas: genius loci, heterotopia and geography's quantitative revolution. Progress in Human Geography, 28 (5), 565–595.
Behnke, S. , 2003. Hierarchical Neural Networks for Image Interpretation. vol. 2766. Springer.
Benos, L. , *et al.* , 2021. Machine learning in agriculture: A comprehensive updated review. Sensors, 21 (11), 3758.
Bhatti, U.A. , *et al.* , 2020. Geometric algebra applications in geospatial artificial intelligence and remote sensing image processing. IEEE Access, 8, 155783–155796.
Bhavsar, P. , *et al.* , 2017. Machine learning in transportation data analytics. *In*: Data Analytics for Intelligent Transportation Systems. Elsevier, 283–307.
Bickel, V.T. , Mandrake, L. , and Doran, G. , 2021. A labeled image dataset for deep learning-driven rockfall detection on the moon and mars. Frontiers in Remote Sensing, 2, 640034.
Bielecki, A. , 2019. Models of Neurons and Perceptrons: Selected Problems and Challenges. Springer.
Blaschke, T. , 2010. Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 65 (1), 2–16.

Bryant, R.G. and Baddock, M.C. , 2021. Remote sensing of aeolian processes. Reference Module in Earth Systems and Environmental Sciences.
Burnett, C. and Blaschke, T. , 2003. A multi-scale segmentation/object relationship modelling methodology for landscape analysis. Ecological Modelling, 168 (3), 233–249.
Campos-Taberner, M. , *et al.* , 2020. Understanding deep learning in land use classification based on sentinel-2 time series. Scientific Reports, 10 (1), 17188.
Cheng, K.S. , Lin, J.S. , and Mao, C.W. , 1996. The application of competitive hopfield neural network to medical image segmentation. IEEE Transactions on Medical Imaging, 15 (4), 560–567.
Chisolm, E. , 2012. Geometric algebra. *arXiv preprint arXiv:1205.5935*.
Church, M. , 2010. The trajectory of geomorphology. Progress in Physical Geography, 34 (3), 265–286.
Cracknell, A. , 1998. Synergy in remote sensing-what's in a pixel? Int. J. Remote Sens, 19, 2025–2057.
Cresswell, T. , 2013. Spatial science and the quantitative revolution. Geographic Thought: A Critical Introduction.
Daranagama, S. and Witayangkurn, A. , 2021. Automatic building detection with polygonizing and attribute extraction from high-resolution images. ISPRS International Journal of Geo-Information, 10 (9), 606.
Dechter, R. , 1986. Learning while searching in constraint-satisfaction problems. *In*: AAAI-86 Proceedings. 178–185.
Dong, G. , *et al.* , 2020. Real-time high-performance semantic image segmentation of urban street scenes. IEEE Transactions on Intelligent Transportation Systems, 22 (6), 3258–3274.
Dosovitskiy, A. , *et al.* , 2020. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*.
Douard, J. , 1996. Review: Reviewed works: Trust in numbers: The pursuit of objectivity in science and public life by theodore m. porter; quantification and the quest for medical certainty by j. rosser mathews. Polit. Life Sci, 15, 350–353.
Duan, W. , *et al.* , 2020. Automatic alignment of contemporary vector data and georeferenced historical maps using reinforcement learning. International Journal of Geographical Information Science, 34 (4), 824–849.
Dyrmann, M. , *et al.* , 2016. Pixel-wise classification of weeds and crops in images by using a fully convolutional neural network. *In*: *Proceedings of the International Conference on Agricultural Engineering, Aarhus, Denmark* . 26–29.
Ellenson, A. , *et al.* , 2020. An application of a machine learning algorithm to determine and describe error patterns within wave model output. Coastal Engineering, 157, 103595.
Escalera, D. , Fraile-Jurado, P. , and Peña Alonso, C. , 2016. *Evaluation of the Impact of Dune Management on the Coast of Huelva Using Repeat Photography Techniques (1986, 2001 and 2015)*. 137–156.
Feizizadeh, B. , *et al.* , 2021. A comparison of the integrated fuzzy object-based deep learning approach and three machine learning techniques for land use/cover change monitoring and environmental impacts assessment. GIScience & Remote Sensing, 58 (8), 1543–1570.
Féret, J.B. , *et al.* , 2019. Estimating leaf mass per area and equivalent water thickness based on leaf optical properties: Potential and limitations of physical modeling and machine learning. Remote Sensing of Environment, 231, 110959.
Fernandes, S. , Duseja, D. , and Muthalagu, R. , 2021. Application of image processing techniques for autonomous cars. Proceedings of Engineering and Technology Innovation, 17, 1.
Fisher, A.R. , *et al.* , 2020. Use of convolutional neural networks for semantic image segmentation across different computing systems.
Fu, K.S. and Mui, J. , 1981. A survey on image segmentation. Pattern Recognition, 13 (1), 3–16.
Gagne II, D.J. , *et al.* , 2019. Interpretable deep learning for spatial analysis of severe hailstorms. Monthly Weather Review, 147 (8), 2827–2845.
Gibson, P.B. , *et al.* , 2021. Training machine learning models on climate model output yields skillful interpretable seasonal precipitation forecasts. Communications Earth & Environment, 2 (1), 159.
Gonzales-Inca, C. , *et al.* , 2022. Geospatial artificial intelligence (geoai) in the integrated hydrological and fluvial systems modeling: Review of current applications and trends. Water, 14

(14), 2211.
Goodchild, M.F. , 2018. Reimagining the history of gis. Annals of GIS, 24 (1), 1–8.
Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. Proceedings of the National Academy of Sciences, 118 (35), e2015759118.
Goodfellow, I. , Bengio, Y. , and Courville, A. , 2016. Deep Learning. MIT Press.
Graff, L.H. and Usery, E.L. , 1993. Automated classification of generic terrain features in digital elevation models. Photogrammetric Engineering and Remote Sensing, 59 (9), 1409–1417.
Gustafsson, K. , Öktem, O. , and Boman, E.J. , 2014. The role of linear algebra in computed tomography.
Hammond, E.H. , 1954. Small-scale continental landform maps. Annals of the Association of American Geographers, 44 (1), 33–42.
Hattersley-Smith, G. , 1966. The symposium on glacier mapping. Canadian Journal of Earth Sciences, 3 (6), 737–741.
Hay, G.J. and Castilla, G. , 2008. Geographic object-based image analysis (geobia): A new name for a new discipline. *Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications*, 75–89.
Hebb, D.O. , 2005. The Organization of Behavior: A Neuropsychological Theory. Psychology press.
Hernández, E. , *et al.* , 2016. Rainfall prediction: A deep learning approach. *In*: Hybrid Artificial Intelligent Systems 2016. Springer, 151–162.
Hoffmann, C. , 2013. Superpositions: Ludwig mach and étienne-jules marey's studies in streamline photography. Studies in History and Philosophy of Science Part A, 44 (1), 1–11.
Honavar, V. , 1995. Symbolic artificial intelligence and numeric artificial neural networks: towards a resolution of the dichotomy. *Computational Architectures Integrating Neural and Symbolic Processes: A Perspective on the State of the Art*, 351–388.
Hopfield, J.J. , 1982. Neural networks and physical systems with emergent collective computational abilities. Proceedings of the National Academy of Sciences, 79 (8), 2554–2558.
Howell, S.B. , 2006. Handbook of ccd Astronomy. vol. 5. Cambridge University Press.
Hsu, C.Y. and Li, W. , 2023. Explainable geoai: can saliency maps help interpret artificial intelligence's learning process? an empirical study on natural feature detection. International Journal of Geographical Information Science, 37 (5), 963–987.
Hsu, C.Y. , Li, W. , and Wang, S. , 2021. Knowledge-driven geoai: Integrating spatial knowledge into multi-scale deep learning for mars crater detection. Remote Sensing, 13 (11), 2116.
Hughes, D. , 2016. Natural Visions: Photography and Ecological Knowledge, 1895-1939. Thesis (PhD). De Montfort University.
Janowicz, K. , *et al.* , 2022. Know, know where, knowwheregraph: A densely connected, cross-domain knowledge graph and geo-enrichment service stack for applications in environmental intelligence. AI Magazine, 43 (1), 30–39.
Kettig, R.L. and Landgrebe, D. , 1976. Classification of multispectral image data by extraction and classification of homogeneous objects. IEEE Transactions on Geoscience Electronics, 14 (1), 19–26.
Khan, A.A. , Laghari, A.A. , and Awan, S.A. , 2021. Machine learning in computer vision: a review. EAI Endorsed Transactions on Scalable Information Systems, 8 (32), e4–e4.
Kirsch, R.A. , 1998. Seac and the start of image processing at the national bureau of standards. IEEE Annals of the History of Computing, 20 (2), 7–13.
Kirsch, R.A. , 2010. Precision and accuracy in scientific imaging. Journal of Research of the National Institute of Standards and Technology, 115 (3), 195.
Kirsch, R.A. , *et al.* , 1957. Experiments in processing pictorial information with a digital computer. *In: Papers and Discussions Presented at the December 9-13, 1957, Eastern Joint Computer Conference: Computers with Deadlines to Meet*. 221–229.
Koc, M. and Acar, A. , 2021. Investigation of urban climates and built environment relations by using machine learning. Urban Climate, 37, 100820.
Kohn, C.F. , 1970. The 1960's: A decade of progress in geographical research and instruction. Annals of the Association of American Geographers, 60 (2), 211–219.
Krizhevsky, A. , Sutskever, I. , and Hinton, G.E. , 2012. Imagenet classification with deep convolutional neural networks. *In*: *Proceedings of NIPS'12*, Red Hook, NY, USA. 1097–1105.

Kucharczyk, M. , *et al.* , 2020. Geographic object-based image analysis: a primer and future directions. Remote Sensing, 12 (12), 2012.
Kurth, T. , *et al.* , 2018. Exascale deep learning for climate analytics. *In*: *SC18: International Conference for High Performance Computing, Networking, Storage and Analysis* . IEEE, 649–660.
Lee, R.S. , 2020. Artificial Intelligence in Daily Life. Springer.
Li, W. , 2020. Geoai: Where machine learning and big data converge in GIScience. Journal of Spatial Information Science, (20), 71–77.
Li, W. , 2022. Geoai in social science. Handbook of Spatial Analysis in the Social Sciences, 291–304.
Li, W. and Arundel, S.T. , 2022. Geoai and the future of spatial analytics. *In*: New Thinking in GIScience. Springer, 151–158.
Li, W. and Hsu, C.Y. , 2020. Automated terrain feature identification from remote sensing imagery: a deep learning approach. International Journal of Geographical Information Science, 34 (4), 637–660.
Li, W. and Hsu, C.Y. , 2022. Geoai for large-scale image analysis and machine vision: Recent progress of artificial intelligence in geography. ISPRS International Journal of Geo-Information, 11 (7), 385.
Li, W. , Hsu, C.Y. , and Hu, M. , 2021a. Tobler's first law in geoai: A spatially explicit deep learning model for terrain feature detection under weak supervision. Annals of the American Association of Geographers, 111 (7), 1887–1905.
Li, W. , *et al.* , 2022a. Real-time geoai for high-resolution mapping and segmentation of arctic permafrost features: the case of ice-wedge polygons. *In*: *Proceedings of the 5th ACM SIGSPATIAL Workshop on AI for Geographic Knowledge Discovery* . 62–65.
Li, W. , *et al.* , 2022b. Geoimagenet: a multi-source natural feature benchmark dataset for geoai and supervised machine learning. GeoInformatica, 1–22.
Li, W. , *et al.* , 2023. Geographvis: a knowledge graph and geovisualization empowered cyberinfrastructure to support disaster response and humanitarian aid. ISPRS International Journal of Geo-Information, 12 (3), 112.
Li, W. , *et al.* , 2022c. Performance benchmark on semantic web repositories for spatially explicit knowledge graph applications. Computers, Environment and Urban Systems, 98, 101884.
Li, W. , *et al.* , 2017. Recognizing terrain features on terrestrial surface using a deep learning model: An example with crater detection. *In*: *Proceedings of the 1st Workshop on Artificial Intelligence and Deep Learning for Geographic Knowledge Discovery* . 33–36.
Li, X. , *et al.* , 2021b. Vehicle detection in very-high-resolution remote sensing images based on an anchor-free detection model with a more precise foveal area. ISPRS International Journal of Geo-Information, 10 (8), 549.
Lin, T.Y. , *et al.* , 2017. Focal loss for dense object detection. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 2980–2988.
Liu, T. , *et al.* , 2020. Superpixel-based shallow convolutional neural network (sscnn) for scanned topographic map segmentation. Remote Sensing, 12 (20), 3421.
Lloyd, C.T. , *et al.* , 2020. Using gis and machine learning to classify residential status of urban buildings in low and middle income settings. Remote Sensing, 12 (23), 3847.
Lundberg, G.A. , 1960. Quantitative methods in sociology: 1920–1960. Social Forces, 39 (1), 19–24.
Mackay, C.D. , 1986. Charge-coupled devices in astronomy. Annual Review of Astronomy and Astrophysics, 24 (1), 255–283.
Magnuson, J.J. , 1990. Long-term ecological research and the invisible present. BioScience, 40 (7), 495–501.
Mahadevkar, S.V. , *et al.* , 2022. A review on machine learning styles in computer vision-techniques and future directions. IEEE Access.
McCarthy, J. , *et al.* , 2006. A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. AI Magazine, 27 (4), 12–12.
McCulloch, W.S. and Pitts, W. , 1943. A logical calculus of the ideas immanent in nervous activity. The Bulletin of Mathematical Biophysics, 5, 115–133.
McFarlane, M.D. , 1972. Digital pictures fifty years ago. Proceedings of the IEEE, 60 (7), 768–770.

Mengwall, S. and Guzewich, S.D. , 2023. Cloud identification in mars daily global maps with deep learning. Icarus, 389, 115252.

Miller, B.A. , *et al.* , 2019. Progress in soil geography i: Reinvigoration. Progress in Physical Geography: Earth and Environment, 43 (6), 827–854.

Milnor, J. , 1941. Picture transmission by submarine cable. Transactions of the American Institute of Electrical Engineers, 60 (3), 105–108.

Minasny, B. and McBratney, A.B. , 2016. Digital soil mapping: A brief history and some lessons. Geoderma, 264, 301–311.

Minsky, M. and Papert, S.A. , 2017. Perceptrons: An Introduction to Computational Geometry. The MIT Press.

Moor, J. , 2006. The dartmouth college artificial intelligence conference: The next fifty years. AI Magazine, 27 (4), 87–87.

Mulyono, S. , *et al.* , 2016. Identifying sugarcane plantation using landsat-8 images with support vector machines. *In*: IOP Conference Series: Earth and Environmental Science. IOP Publishing, vol. 47, 012008.

Naghibi, S.A. , Pourghasemi, H.R. , and Dixon, B. , 2016. Gis-based groundwater potential mapping using boosted regression tree, classification and regression tree, and random forest machine learning models in iran. Environmental Monitoring and Assessment, 188, 1–27.

Nir, D. and Nir, D. , 1990. The ‘quantitative revolution’: Regional geography at its apogee. *Region as a Socio-environmental System: An Introduction to a Systemic Regional Geography*, 43–57.

Olazaran, M. , 1996. A sociological study of the official history of the perceptrons controversy. Social Studies of Science, 26 (3), 611–659.

Pal, N.R. and Pal, S.K. , 1993. A review on image segmentation techniques. Pattern Recognition, 26 (9), 1277–1294.

Quirke, V. and Gaudillière, J.P. , 2008. The era of biomedicine: science, medicine, and public health in britain and france after the second world war. Medical history, 52 (4), 441–452.

Rahmati, O. , *et al.* , 2019. Spatial modeling of snow avalanche using machine learning models and geo-environmental factors: Comparison of effectiveness in two mountain regions. Remote Sensing, 11 (24), 2995.

Redmon, J. and Farhadi, A. , 2018. Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.

Reichstein, M. , *et al.* , 2019. Deep learning and process understanding for data-driven earth system science. Nature, 566 (7743), 195–204.

Ren, S. , *et al.* , 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in Neural Information Processing Systems, 28.

Rogers, G.F. , Malde, H.E. , and Turner, R.M. , 1984. *Bibliography of Repeat Photography for Evaluating Landscape Change*.

Rolnick, D. , *et al.* , 2022. Tackling climate change with machine learning. ACM Computing Surveys (CSUR), 55 (2), 1–96.

Romans, L.E. , 1995. Introduction to Computed Tomography. Lippincott Williams & Wilkins.

Ronneberger, O. , Fischer, P. , and Brox, T. , 2015. U-net: Convolutional networks for biomedical image segmentation. *In*: *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18* . Springer, 234–241.

Rosenblatt, F. , 1958. The perceptron: a probabilistic model for information storage and organization in the brain. Psychological Review, 65 (6), 386.

Rouse, J.W. , *et al.* , 1974. Monitoring vegetation systems in the great plains with erts. NASA Spec. Publ, 351 (1), 309.

Ruggles, S. and Magnuson, D.L. , 2019. The history of quantification in history: The jih as a case study. Journal of Interdisciplinary History, 50 (3), 363–381.

Rumelhart, D.E. , Hinton, G.E. , and Williams, R.J. , 1986. Learning representations by back-propagating errors. Nature, 323 (6088), 533–536.

Sarikan, S.S. and Ozbayoglu, A.M. , 2018. Anomaly detection in vehicle traffic with image processing and machine learning. Procedia Computer Science, 140, 64–69.

Saska, H. , 2010. Anna atkins: Photographs of british algae. Bulletin of the Detroit Institute of Arts, 84 (14), 8–15.

Sexton, N.J. and Love, B.C. , 2022. Reassessing hierarchical correspondences between brain and deep networks through direct interface. Science Advances, 8 (28), eabm2219.
Shirzadi, A. , *et al.* , 2018. Shallow landslide susceptibility mapping. Sensors, 18, 1–28.
Song, H. , *et al.* , 2019. Vision-based vehicle detection and counting system using deep learning in highway scenes. European Transport Research Review, 11, 1–16.
Song, M. , *et al.* , 2016. Spatiotemporal data representation and its effect on the performance of spatial analysis in a cyberinfrastructure environment–a case study with raster zonal analysis. Computers & Geosciences, 87, 11–21.
Starrs, P.F. , 1998. Brinck jackson in the realm of the everyday. Geographical Review, 88 (4), 492–506.
Stegner, W. , 1992. Beyond the Hundredth Meridian: John Wesley Powell and the Second Opening of the West. Penguin.
Stokes, C. , *et al.* , 2013. Formation of mega-scale glacial lineations on the dubawnt lake ice stream bed: 1. size, shape and spacing from a large remote sensing dataset. Quaternary Science Reviews, 77, 190–209.
Talukdar, S. , *et al.* , 2020. Land-use land-cover classification by machine learning classifiers for satellite observations—a review. Remote Sensing, 12 (7), 1135.
Tarran, B. and Ghahramani, Z. , 2015. How machines learned to think statistically. Significance, 12 (1), 8–15.
Tu, K.L. , *et al.* , 2018. Selection for high quality pepper seeds by machine vision and classifiers. Journal of Integrative Agriculture, 17 (9), 1999–2006.
Tucker, C. , Miller, L. , and Pearson, R. , 1973. Measurement of the combined effect of green biomass, chlorophyll, and leaf water on canopy spectroreflectance of the shortgrass prairie. Remote Sensing of Earth Resources.
Vogel, C. , *et al.* , 2019. A delphi study to build consensus on the definition and use of big data in obesity research. International Journal of Obesity, 43 (12), 2573–2586.
Wang, S. and Li, W. , 2021. Geoai in terrain analysis: Enabling multi-source deep learning and data fusion for natural feature detection. Computers, Environment and Urban Systems, 90, 101715.
Weng, Q. , *et al.* , 2018. Land-use scene classification based on a cnn using a constrained extreme learning machine. International Journal of Remote Sensing, 39 (19), 6281–6299.
Wheeler, J.O. , 2001. urban geography in the 1960s. Urban Geography, 22 (6), 511–513.
White, R.A. , *et al.* , 2019. Measurement of vegetation change in critical dune sites along the eastern shores of lake michigan from 1938 to 2014 with object-based image analysis. Journal of Coastal Research, 35 (4), 842–851.
Worboys, M.F. , 1999. Relational databases and beyond. Geographical Information Systems, 1, 373–384.
Wu, H. , *et al.* , 2022. Runoff modeling in ungauged catchments using machine learning algorithm-based model parameters regionalization methodology. Engineering.
Yamashita, R. , *et al.* , 2018. Convolutional neural networks: an overview and application in radiology. Insights into Imaging, 9, 611–629.
Yu, Z. , *et al.* , 2016. Geometric algebra model for geometry-oriented topological relation computation. Transactions in GIS, 20 (2), 259–279.
Yuan, L. , *et al.* , 2012. Geometric algebra method for multidimensionally-unified gis computation. Chinese Science Bulletin, 57, 802–811.
Yuan, L. , Yu, Z. , and Luo, W. , 2019. Towards the next-generation gis: A geometric algebra approach. Annals of GIS, 25 (3), 195–206.
Zhong, L. , Hu, L. , and Zhou, H. , 2019. Deep learning based multi-temporal crop classification. Remote Sensing of Environment, 221, 430–443.
Zhou, P. and Chang, Y. , 2021. Automated classification of building structures for urban built environment identification using machine learning. Journal of Building Engineering, 43, 103008.

Spatial Representation Learning in GeoAI

Acuna, D. , *et al.* , 2018. Efficient interactive annotation of segmentation datasets with Polygon-RNN++. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 859–868.

Alahi, A. , *et al.* , 2016. Social lstm: Human trajectory prediction in crowded spaces. *In*: *Proceedings of the IEEE Conference on CVPR* . 961–971.

Ayush, K. , *et al.* , 2021. Geography-aware self-supervised learning. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 10181–10190.

Bengio, Y. , Courville, A. , and Vincent, P. , 2013. Representation learning: A review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35 (8), 1798–1828.

Berg, T. , *et al.* , 2014. Birdsnap: Large-scale fine-grained visual categorization of birds. *In*: CVPR *2014*. 2011–2018.

Bronstein, M.M. , *et al.* , 2017. Geometric deep learning: going beyond euclidean data. IEEE Signal Processing Magazine, 34 (4), 18–42.

Brown, T. , *et al.* , 2020. Language models are few-shot learners. NIPS *2020*, 33, 1877–1901.

Cai, L. , *et al.* , 2020. Traffic transformer: Capturing the continuity and periodicity of time series for traffic forecasting. Transactions in GIS, 24 (3), 736–755.

Castrejon, L. , *et al.* , 2017. Annotating object instances with a Polygon-RNN. *In*: Proceedings of CVPR'17. 5230–5238.

Chami, I. , *et al.* , 2022. Machine learning on graphs: A model and comprehensive taxonomy. Journal of Machine Learning Research, 23 (89), 1–64.

Chen, D. , *et al.* , 2017. Reading wikipedia to answer open-domain questions. *arXiv preprint arXiv:1704.00051*.

Chen, Y. , Liu, S. , and Wang, X. , 2021. Learning continuous image representation with local implicit image function. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 8628–8638.

Chu, G. , *et al.* , 2019. Geo-aware networks for fine-grained recognition. *In*: *Proceedings of the IEEE International Conference on Computer Vision Workshops* . 0–0.

Cong, Y. , *et al.* , 2022. Satmae: Pre-training transformers for temporal and multi-spectral satellite imagery. *In*: Advances in Neural Information Processing Systems.

Das, R. , *et al.* , 2019. Multi-step retriever-reader interaction for scalable open-domain question answering. *In*: International Conference on Learning Representations.

DeAngelis, D.L. and Yurek, S. , 2017. Spatially explicit modeling in ecology: a review. Ecosystems, 20 (2), 284–300.

Dosovitskiy, A. , *et al.* , 2020. An image is worth 16x16 words: Transformers for image recognition at scale. *In*: International Conference on Learning Representations.

Dupont, E. , *et al.* , 2021. Coin: Compression with implicit neural representations. *arXiv preprint arXiv:2103.03123*.

Gao, R. , *et al.* , 2019. Learning grid cells as vector representation of self-position coupled with matrix representation of self-motion. *In*: *Proceedings of ICLR 2019*.

Girshick, R. , 2015. Fast r-cnn. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 1440–1448.

Goodchild, M. , 2001. Issues in spatially explicit modeling. Agent-Based Models of Land-Use and Land-Cover Change, 13–17.

Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. PNAS, 118 (35).

Goodfellow, I. , *et al.* , 2020. Generative adversarial networks. Communications of the ACM, 63 (11), 139–144.

Guo, M.H. , *et al.* , 2022. Attention mechanisms in computer vision: A survey. Computational Visual Media, 1–38.

Gupta, J. , *et al.* , 2021. Spatial variability aware deep neural networks (svann): A general approach. ACM Transactions on Intelligent Systems and Technology (TIST), 12 (6), 1–21.

Ha, D. and Eck, D. , 2018. A neural representation of sketch drawings. *In*: International Conference on Learning Representations.

Hamilton, W.L. , Ying, R. , and Leskovec, J. , 2017. Representation learning on graphs: Methods and applications. *arXiv preprint arXiv:1709.05584*.

Hamzei, E. , Tomko, M. , and Winter, S. , 2022. Translating place-related questions to geosparql queries. *In*: *Proceedings of the ACM Web Conference 2022* . 902–911.
Haw, D.J. , *et al.* , 2020. Strong spatial embedding of social networks generates nonstandard epidemic dynamics independent of degree distribution and clustering. Proceedings of the National Academy of Sciences, 117 (38), 23636–23642.
He, K. , *et al.* , 2022. Masked autoencoders are scalable vision learners. *In*: *Proceedings of the IEEE/CVF Conference on CVPR* . 16000–16009.
He, Y. , *et al.* , 2021. Spatial-temporal super-resolution of satellite imagery via conditional pixel synthesis. Advances in Neural Information Processing Systems, 34, 27903–27915.
Hoffart, J. , *et al.* , 2013. Yago2: A spatially and temporally enhanced knowledge base from wikipedia. Artificial Intelligence, 194, 28–61.
Holt, D. , *et al.* , 1996. Aggregation and ecological effects in geographically based data. Geographical Analysis, 28 (3), 244–261.
Horner, M.W. and Murray, A.T. , 2002. Excess commuting and the modifiable areal unit problem. Urban Studies, 39 (1), 131–139.
Hu, Y. , *et al.* , 2015. Metadata topic harmonization and semantic search for linked-data-driven geoportals: A case study using arcgis online. Transactions in GIS, 19 (3), 398–416.
Janowicz, K. , *et al.* , 2020. Geoai: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond.
Janowicz, K. , *et al.* , 2022. Know, know where, knowwheregraph: A densely connected, cross-domain knowledge graph and geo-enrichment service stack for applications in environmental intelligence. AI Magazine, 43 (1), 30–39.
Jean, N. , *et al.* , 2019. Tile2vec: Unsupervised representation learning for spatially distributed data. *In*: *Proceedings of the AAAI Conference on Artificial Intelligence* . vol. 33, 3967–3974.
Jiang, C. , *et al.* , 2019a. DDSL: Deep differentiable simplex layer for learning geometric signals. *In*: *Proceedings of the IEEE/CVF International Conference on Computer Vision* . 8769–8778.
Jiang, C.M. , *et al.* , 2019b. Convolutional neural networks on non-uniform geometrical signals using euclidean spectral transformation. *In*: International Conference on Learning Representations.
Karpukhin, V. , *et al.* , 2020. Dense passage retrieval for open-domain question answering. *In*: *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)* . 6769–6781.
Kenton, J.D.M.W.C. and Toutanova, L.K. , 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. *In*: *Proceedings of NAACL-HLT.* 4171–4186.
Kingma, D.P. and Welling , M., 2013. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*.
Kuhn, W. , *et al.* , 2021. The semantics of place-related questions. Journal of Spatial Information Science, (23), 157–168.
Li, W. , 2020. Geoai: Where machine learning and big data converge in GIScience. Journal of Spatial Information Science, (20), 71–77.
Li, W. , Hsu, C.Y. , and Hu, M. , 2021. Tobler's first law in geoai: A spatially explicit deep learning model for terrain feature detection under weak supervision. Annals of the American Association of Geographers, 111 (7), 1887–1905.
Li, Y. , *et al.* , 2018a. Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. *In*: International Conference on Learning Representations.
Li, Y. , *et al.* , 2018b. PointCNN: Convolution on x-transformed points. Advances in Neural Information Processing Systems, 31.
Li, Y. , *et al.* , 2018c. Deep learning for remote sensing image classification: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8 (6), e1264.
Liang, J. , *et al.* , 2020. Polytransform: Deep polygon transformer for instance segmentation. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 9131–9140.
Mac Aodha, O. , Cole, E. , and Perona, P. , 2019. Presence-only geographical priors for fine-grained image classification. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 9596–9606.
Mai, G. , *et al.* , 2022a. Towards a foundation model for geospatial artificial intelligence (vision paper). *In*: *Proceedings of the 30th International Conference on Advances in Geographic Information Systems* . 1–4.

Mai, G. , *et al.* , 2022b. Symbolic and subsymbolic geoai: Geospatial knowledge graphs and spatially explicit machine learning. Transactions in GIS, 26 (8), 3118–3124.

Mai, G. , *et al.* , 2020a. Se-kge: A location-aware knowledge graph embedding model for geographic question answering and spatial semantic lifting. Transactions in GIS, 24 (3), 623–655.

Mai, G. , *et al.* , 2022c. A review of location encoding for geoai: methods and applications. International Journal of Geographical Information Science, 36 (4), 639–673.

Mai, G. , *et al.* , 2020b. Multi-scale representation learning for spatial feature distributions using grid cells. In: *The Eighth International Conference on Learning Representations*. openreview.

Mai, G. , *et al.* , 2021. Geographic question answering: challenges, uniqueness, classification, and future directions. AGILE: GIScience Series, 2, 1–21.

Mai, G. , *et al.* , 2022d. Towards general-purpose representation learning of polygonal geometries. GeoInformatica, 1–52.

Mai, G. , *et al.* , 2022e. Sphere2vec: Multi-scale representation learning over a spherical surface for geospatial predictions. *arXiv preprint arXiv:2201.10489*.

Mai, G. , *et al.* , 2019. Relaxing unanswerable geographic questions using a spatially explicit knowledge graph embedding model. *In*: *AGILE 2019*. Springer, 21–39.

Manas, O. , *et al.* , 2021. Seasonal contrast: Unsupervised pre-training from uncurated remote sensing data. *In*: *Proceedings of the IEEE/CVF International Conference on Computer Vision* . 9414–9423.

Maturana, D. and Scherer, S. , 2015. Voxnet: A 3d convolutional neural network for real-time object recognition. *In*: *2015 IEEE/RSJ IROS*. IEEE, 922–928.

Mikolov, T. , *et al.* , 2013. Distributed representations of words and phrases and their compositionality. Advances in Neural Information Processing Systems, 26.

Mildenhall, B. , *et al.* , 2021. Nerf: Representing scenes as neural radiance fields for view synthesis. Communications of the ACM, 65 (1), 99–106.

Musleh, M. , Mokbel, M.F. , and Abbar, S. , 2022. Let's speak trajectories. *In*: *Proceedings of the 30th ACM SIGSPATIAL* . 1–4.

Nickel, M. , *et al.* , 2015. A review of relational machine learning for knowledge graphs. Proceedings of the IEEE, 104 (1), 11–33.

Niemeyer, M. and Geiger, A. , 2021. Giraffe: Representing scenes as compositional generative neural feature fields. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 11453–11464.

Pennington, J. , Socher, R. , and Manning, C.D. , 2014. Glove: Global vectors for word representation. *In*: *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* . 1532–1543.

Qi, C.R. , *et al.* , 2017a. Pointnet: Deep learning on point sets for 3d classification and segmentation. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 652–660.

Qi, C.R. , *et al.* , 2017b. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. Advances in Neural Information Processing Systems, 30.

Qi, Y. , *et al.* , 2019. A hybrid model for spatiotemporal forecasting of pm2. 5 based on graph convolutional neural network and long short-term memory. Science of the Total Environment, 664, 1–10.

Rahimi, A. and Recht, B. , 2007. Random features for large-scale kernel machines. Advances in Neural Information Processing Systems, 20.

Rao, J. , *et al.* , 2020. LSTM-TrajGAN: A deep learning approach to trajectory privacy protection. In: GIScience *2020*. 12:1–12:17.

Rumelhart, D.E. , Hinton, G.E. , and Williams, R.J. , 1986. Learning representations by back-propagating errors. Nature, 323 (6088), 533–536.

Schuster, M. and Paliwal, K.K. , 1997. Bidirectional recurrent neural networks. IEEE Transactions on Signal Processing, 45 (11), 2673–2681.

Soni, A. and Boddhu, S. , 2022. Finding map feature correspondences in heterogeneous geospatial datasets. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Geospatial Knowledge Graphs* . 7–16.

Su, H. , *et al.* , 2015. Multi-view convolutional neural networks for 3d shape recognition. *In*: *ICCV 2015*. 945–953.

Sutskever, I. , Vinyals, O. , and Le, Q.V. , 2014. Sequence to sequence learning with neural networks. Advances in Neural Information Processing Systems, 27.

Tancik, M. , *et al.* , 2020. Fourier features let networks learn high frequency functions in low dimensional domains. Advances in Neural Information Processing Systems, 33, 7537–7547.

Tang, K. , *et al.* , 2015. Improving image classification with location context. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 1008–1016.

Tenzer, M. , *et al.* , 2022. Meta-learning over time for destination prediction tasks. *In*: *Proceedings of the 30th International Conference on Advances in Geographic Information Systems* . 1–10.

Terry, J.C.D. , Roy, H.E. , and August, T.A. , 2020. Thinking like a naturalist: Enhancing computer vision of citizen science images by harnessing contextual data. Methods in Ecology and Evolution, 11 (2), 303–315.

Tobler, W.R. , 1970. A computer movie simulating urban growth in the detroit region. Economic Geography, 46 (sup1), 234–240.

Trisedya, B.D. , Qi, J. , and Zhang, R. , 2019. Entity alignment between knowledge graphs using attribute embeddings. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 33, 297–304.

Vaswani, A. , *et al.* , 2017. Attention is all you need. Advances in Neural Information Processing Systems, 30.

Veer, R.V. , Bloem, P. , and Folmer, E. , 2018. Deep learning for classification tasks on geospatial vector polygons. *arXiv preprint arXiv:1806.03857*.

Wang, L. , *et al.* , 2019a. Graph attention convolution for point cloud semantic segmentation. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 10296–10305.

Wang, Q. , *et al.* , 2017. Knowledge graph embedding: A survey of approaches and applications. IEEE Transactions on Knowledge and Data Engineering, 29 (12), 2724–2743.

Wang, Y. , *et al.* , 2019b. Dynamic graph CNN for learning on point clouds. ACM Transactions on Graphics (tog), 38 (5), 1–12.

Wu, W. , Qi, Z. , and Fuxin, L. , 2019. Pointconv: Deep convolutional networks on 3d point clouds. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 9621–9630.

Wu, Z. , *et al.* , 2020. A comprehensive survey on graph neural networks. IEEE Transactions on Neural Networks and Learning Systems, 32 (1), 4–24.

Xie, Y. , *et al.* , 2021. A statistically-guided deep network transformation and moderation framework for data with spatial heterogeneity. *In*: *2021 IEEE International Conference on Data Mining (ICDM)* . IEEE, 767–776.

Yan, B. , *et al.* , 2017. From itdl to place2vec: Reasoning about place type similarity and relatedness by learning embeddings from augmented spatial contexts. *In*: *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 1–10.

Yan, X. , *et al.* , 2021. Graph convolutional autoencoder model for the shape coding and cognition of buildings in maps. International Journal of Geographical Information Science, 35 (3), 490–512.

Yan, X. , *et al.* , 2019. A graph convolutional neural network for classification of building patterns using spatial vector data. ISPRS Journal of Photogrammetry and Remote Sensing, 150, 259–273.

Yang, J. , *et al.* , 2021. Implicit transformer network for screen content image continuous super-resolution. Advances in Neural Information Processing Systems, 34.

Yang, L. , *et al.* , 2022. Dynamic mlp for fine-grained image classification by leveraging geographical and temporal information. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 10945–10954.

Yin, Y. , *et al.* , 2019. Gps2vec: Towards generating worldwide gps embeddings. *In*: *Proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 416–419.

Yu, W. and Chen, Y. , 2022. Filling gaps of cartographic polylines by using an encoder–decoder model. IJGIS, 1–26.

Zhang, K. , 2021. Implicit neural representation learning for hyperspectral image super-resolution. *arXiv preprint arXiv:2112.10541*.

Zhong, E.D. , *et al.* , 2020. Reconstructing continuous distributions of 3d protein structure from cryo-em images. *In*: *ICLR 2020*.
Zhu, R. , *et al.* , 2022. Reasoning over higher-order qualitative spatial relations via spatially explicit neural networks. International Journal of Geographical Information Science, 36 (11), 2194–2225.

Intelligent Spatial Prediction and Interpolation Methods

Anselin, L. , 1988. Spatial Econometrics: Methods and Models. vol. 4. Springer Science & Business Media.
Anselin, L. , 1992. Space and applied econometrics: introduction. Regional Science and Urban Economics, 22 (3), 307–316.
Anselin, L. , 2010. Thirty years of spatial econometrics. Papers in Regional Science, 89 (1), 3–25.
Anselin, L. and Bera, A.K. , 1998. Spatial dependence in linear regression models with an introduction to spatial econometrics. Statistics Textbooks and Monographs, 155, 237–290.
Anselin, L. and Rey, S.J. , 2014. Modern Spatial Econometrics in Practice: A Guide to Geoda, Geodaspace and Pysal. GeoDa Press LLC.
Arbia, G. , 2014. A primer for spatial econometrics with applications in r. Springer.
Arjovsky, M. , Chintala, S. , and Bottou, L. , 2017. Wasserstein Generative Adversarial Networks. *In*: *Proceedings of the 34th International Conference on Machine Learning* , July. PMLR, 214–223.
Bai, J. , *et al.* , 2021. A3t-gcn: Attention temporal graph convolutional network for traffic forecasting. ISPRS International Journal of Geo-Information, 10 (7), 485.
Besag, J. , 1974. Spatial interaction and the statistical analysis of lattice systems. Journal of the Royal Statistical Society: Series B (Methodological), 36 (2), 192–225.
Bui, K.H.N. , Cho, J. , and Yi, H. , 2021. Spatial-temporal graph neural network for traffic forecasting: An overview and open research issues. Applied Intelligence, 1–12.
Burrough, P.A. , McDonnell, R.A. , and Lloyd, C.D. , 2015. Principles of Geographical Information Systems. Oxford University Press.
Caers, J. , 2002. Multiple-point geostatistics: A quantitative vehicle for integrating geologic analogs into Stanford University, Stanford Center for Reservoir Forecasting. 1–24.
Cao, G. , Kyriakidis, P.C. , and Goodchild, M.F. , 2011a. A multinomial logistic mixed model for the prediction of categorical spatial data. International Journal of Geographical Information Science.
Cao, G. , Kyriakidis, P. , and Goodchild, M. , 2013. On spatial transition probabilities as continuity measures in categorical fields. *arXiv preprint arXiv:1312.5391*.
Cao, G. , Kyriakidis, P.C. , and Goodchild, M.F. , 2011b. Combining spatial transition probabilities for stochastic simulation of categorical fields. International Journal of Geographical Information Science, 25 (11), 1773–1791.
Cao, G. , Yoo, E.H. , and Wang, S. , 2014. A statistical framework of data fusion for spatial prediction of categorical variables. Stochastic Environmental Research and Risk Assessment, 28 (7), 1785–1799.
Carle, S.F. and Fogg, G.E. , 1996. Transition probability-based indicator geostatistics. Mathematical Geology, 28 (4), 453–476.
Chen, L. , *et al.* , 2019a. Quantifying the scale effect in geospatial big data using semi-variograms. PloS One, 14 (11), e0225139.
Chen, R. , *et al.* , 2019b. A hybrid CNN-LSTM model for typhoon formation forecasting. GeoInformatica, 23 (3), 375–396.
Chiles, J.P. and Delfiner, P. , 1999. Geostatistics: Modeling Spatial Uncertainty. vol. 136. Wiley-Interscience.
Chu, X. , *et al.* , 2021. Twins: Revisiting the design of spatial attention in vision transformers. Advances in Neural Information Processing Systems, 34, 9355–9366.
Cressie, N. , 2015. Statistics for Spatial Data. John Wiley & Sons.

Dai, Z. , *et al.* , 2022. Geographically convolutional neural network weighted regression: a method for modeling spatially non-stationary relationships based on a global spatial proximity grid. International Journal of Geographical Information Science, 0 (0), 1–22.

Dale, M.R. and Fortin, M.J. , 2014. Spatial Analysis: A Guide for Ecologists. Cambridge University Press.

Darmofal, D. , 2015. Spatial Analysis for the Social Sciences. Cambridge University Press.

Defferrard, M. , Bresson, X. , and Vandergheynst, P. , 2016. Convolutional neural networks on graphs with fast localized spectral filtering. *In*: Advances in Neural Information Processing Systems. 3844–3852.

Diggle, P.J. , Tawn, J.A. , and Moyeed, R.A. , 1998. Model-based Geostatistics. Applied Statistics, 47 (3), 299–350.

Draxl, C. , *et al.* , 2015a. Overview and Meteorological Validation of the Wind Integration National Dataset Toolkit. National Renewable Energy Lab.(NREL), Golden, CO (United States).

Draxl, C. , *et al.* , 2015b. The wind integration national dataset (wind) toolkit. Applied Energy, 151, 355–366.

Du, Z. , *et al.* , 2020. Geographically neural network weighted regression for the accurate estimation of spatial non-stationarity. International Journal of Geographical Information Science, 34 (7), 1353–1377.

Fischer, M.M. , 1998. Computational neural networks: a new paradigm for spatial analysis. Environment and Planning A, 30 (10), 1873–1891.

Fischer, M.M. and Wang, J. , 2011. Spatial Data Analysis: Models, Methods and Techniques. Springer Science & Business Media.

Fotheringham, A.S. , Yang, W. , and Kang, W. , 2017. Multiscale geographically weighted regression (mgwr). Annals of the American Association of Geographers, 107 (6), 1247–1265.

Gal, Y. , 2016. Uncertainty in Deep Learning. *PhD Thesis*.

Gal, Y. and Ghahramani, Z. , 2016. Dropout as a Bayesian approximation: Representing model uncertainty in deep learning. *In*: International Conference on Machine Learning. 1050–1059.

Gao, S. , 2020. A review of recent researches and reflections on geospatial artificial intelligence. Geomatics and Information Science of Wuhan University, 45 (12), 1865–1874.

Goodchild, M.F. , 2004a. Giscience, geography, form, and process. Annals of the Association of American Geographers, 94 (4), 709–714.

Goodchild, M.F. , 2004b. The validity and usefulness of laws in geographic information science and geography. Annals of the Association of American Geographers, 94 (2), 300–303.

Goodchild, M.F. , 2008. Statistical perspectives on geographic information science. Geographical Analysis, 40 (3), 310–325.

Goodchild, M.F. , 2020. How well do we really know the world? Uncertainty in GIScience. Journal of Spatial Information Science, (20), 97–102.

Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. Proceedings of the National Academy of Sciences, 118 (35).

Goovaerts, P. , 2005. Geostatistical analysis of disease data: estimation of cancer mortality risk from empirical frequencies using poisson kriging. International Journal of Health Geographics, 4 (1), 1–33.

Griffith, D.A. and Paelinck, J.H.P. , 2011. Non-standard Spatial Statistics and Spatial Econometrics. Springer Science & Business Media.

Hu, S. , *et al.* , 2021. Urban function classification at road segment level using taxi trajectory data: A graph convolutional neural network approach. Computers, Environment and Urban Systems, 87, 101619.

Janowicz, K. , *et al.* , 2020. Geoai: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science, 34 (4), 625–636.

Jean, N. , *et al.* , 2016. Combining satellite imagery and machine learning to predict poverty. Science, 353 (6301), 790–794.

Karras, T. , *et al.* , 2018. Progressive growing of gans for improved quality, stability, and variation. 26.

Kedron, P. , *et al.* , 2021. Reproducibility and replicability: Opportunities and challenges for geospatial research. International Journal of Geographical Information Science, 35 (3), 427–445.

Kelejian, H.H. and Prucha, I.R. , 1998. A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. The Journal of Real Estate Finance and Economics, 17 (1), 99–121.
Kelejian, H.H. and Prucha, I.R. , 1999. A generalized moments estimator for the autoregressive parameter in a spatial model. International Economic Review, 40 (2), 509–533.
Kelejian, H.H. and Prucha, I.R. , 2007. The relative efficiencies of various predictors in spatial econometric models containing spatial lags. Regional Science and Urban Economics, 37 (3), 363–374.
King, J. , Clifton, A. , and Hodge, B.M. , 2014. Validation of Power Output for the Wind Toolkit. National Renewable Energy Lab.(NREL), Golden, CO (United States).
Kipf, T.N. and Welling, M. , 2017. Semi-supervised classification with graph convolutional networks. *In*: International Conference on Learning Representations.
Kitanidis, P.K. and Shen, K.F. , 1996. Geostatistical interpolation of chemical concentration. Advances in Water Resources, 19 (6), 369–378.
Kleiber, W. and Nychka, D. , 2012. Nonstationary modeling for multivariate spatial processes. Journal of Multivariate Analysis, 112, 76–91.
Klemmer, K. and Neill, D.B. , 2021. Auxiliary-task learning for geographic data with autoregressive embeddings. *In*: *Proceedings of the 29th International Conference on Advances in Geographic Information Systems* . 141–144.
Kyriakidis, P.C. , 2004. A geostatistical framework for area-to-point spatial interpolation. Geographical Analysis, 36, 259–289.
Lam, N.S.N. , 1983. Spatial interpolation methods: a review. The American Cartographer, 10 (2), 129–150.
LeCun, Y. , Bengio, Y. , and Hinton, G. , 2015. Deep learning. Nature, 521 (7553), 436–444.
Ledig, C. , *et al.* , 2017. Photo-realistic single image super-resolution using a generative adversarial network. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 4681–4690.
Lehmann, A. , Overton, J.M. , and Leathwick, J.R. , 2002. Grasp: generalized regression analysis and spatial prediction. Ecological Modelling, 157 (2–3), 189–207.
LeSage, J. and Pace, R.K. , 2009. Introduction to Spatial Econometrics. Chapman and Hall/CRC.
LeSage, J.P. , 1997. Regression analysis of spatial data. Journal of Regional Analysis and Policy, 27 (1100-2016-89650), 83–94.
LeSage, J.P. and Fischer, M.M. , 2008. Spatial growth regressions: model specification, estimation and interpretation. Spatial Economic Analysis, 3 (3), 275–304.
Li, W. and Hsu, C.Y. , 2020. Automated terrain feature identification from remote sensing imagery: a deep learning approach. International Journal of Geographical Information Science, 34 (4), 637–660.
Li, W. , Hsu, C.Y. , and Hu, M. , 2021. Tobler's first law in geoai: A spatially explicit deep learning model for terrain feature detection under weak supervision. Annals of the American Association of Geographers, 111 (7), 1887–1905.
Lieberman-Cribbin, W. , Draxl, C. , and Clifton, A. , 2014. Guide to Using the Wind Toolkit Validation Code. National Renewable Energy Lab.(NREL), Golden, CO (United States).
Lim, B. , *et al.* , 2017. Enhanced deep residual networks for single image super-resolution. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops* . 136–144.
Liu, P. and De Sabbata, S. , 2021. A graph-based semi-supervised approach to classification learning in digital geographies. Computers, Environment and Urban Systems, 86, 101583.
Liu, Y. , *et al.* , 2018. Improve ground-level pm2. 5 concentration mapping using a random forests-based geostatistical approach. Environmental Pollution, 235, 272–282.
Lu, B. , *et al.* , 2014. Geographically weighted regression with a non-euclidean distance metric: a case study using hedonic house price data. International Journal of Geographical Information Science, 28 (4), 660–681.
Mennis, J. and Guo, D. , 2009. Spatial data mining and geographic knowledge discovery—an introduction. Computers, Environment and Urban Systems, 33 (6), 403–408.
Miller, H.J. , 2004. Tobler's first law and spatial analysis. Annals of the association of American geographers, 94 (2), 284–289.

Oliver, M.A. and Webster, R. , 1990. Kriging: a method of interpolation for geographical information systems. International Journal of Geographical Information System, 4 (3), 313–332.
Ord, K. , 1975. Estimation methods for models of spatial interaction. Journal of the American Statistical Association, 70 (349), 120–126.
Paciorek, C.J. and Schervish, M.J. , 2006. Spatial Modelling Using a New Class of Nonstationary Covariance Functions. Environmetrics (London, Ont.), 17 (5), 483–506.
Paelinck, J.H. , *et al.* , 1979. Spatial Econometrics. vol. 1. Saxon House.
Parks, B.O. , Steyaert, L.T. , and Goodchild, M.F. , 1993. Environmental Modeling with gis. Oxford University Press.
Pearl, J. , 2019. The seven tools of causal inference, with reflections on machine learning. Communications of the ACM, 62 (3), 54–60.
Raissi, M. , Perdikaris, P. , and Karniadakis, G.E. , 2019. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686–707.
Reichstein, M. , *et al.* , 2019. Deep learning and process understanding for data-driven earth system science. Nature, 566 (7743), 195–204.
Ripley, B. , 1981. Spatial Statistics. New York: John Wiley & Sons.
Scheider, S. and Huisjes, M.D. , 2019. Distinguishing extensive and intensive properties for meaningful geocomputation and mapping. International Journal of Geographical Information Science, 33 (1), 28–54.
Sengupta, M. , *et al.* , 2018. The national solar radiation data base (nsrdb). Renewable and Sustainable Energy Reviews, 89, 51–60.
Shepard, D. , 1968. A two-dimensional interpolation function for irregularly-spaced data. *In*: *Proceedings of the 1968 23rd ACM National Conference* . 517–524.
Solow, A.R. , 1986. Mapping by simple indicator kriging. Mathematical Geology, 18 (3), 335–352.
Strebelle, S. , 2002. Conditional simulation of complex geological structures using multiple-point statistics. Mathematical Geology, 34 (1), 1–21.
Tobler, W. , 2004. On the first law of geography: A reply. Annals of the Association of American Geographers, 94 (2), 304–310.
Tobler, W.R. , 1970. A computer movie simulating urban growth in the detroit region. Economic Geography, 46 (sup1), 234–240.
Ulyanov, D. , Vedaldi, A. , and Lempitsky, V. , 2018. Deep Image Prior. *In*: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* .
van den Boogaart, K.G. and Schaeben, H. , 2002. Kriging of regionalized directions, axes, and orientations i. directions and axes. Mathematical Geology, 34 (5), 479–503.
Van Westen, C.J. , Castellanos, E. , and Kuriakose, S.L. , 2008. Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. Engineering Geology, 102 (3–4), 112–131.
Wang, H. and Yeung, D.Y. , 2020. A Survey on Bayesian Deep Learning. ACM Computing Surveys, 53 (5), 108:1–108:37.
Wang, Q. , Shi, W. , and Atkinson, P.M. , 2016. Area-to-point regression kriging for pan-sharpening. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 151–165.
Wang, X. , *et al.* , 2018. Esrgan: Enhanced super-resolution generative adversarial networks. *In* : *Proceedings of the European Conference on Computer Vision (ECCV) Workshops* . 0–0.
Whittle, P. , 1954. On stationary processes in the plane. Biometrika, 434–449.
Wu, S. , *et al.* , 2021a. Geographically and temporally neural network weighted regression for modeling spatiotemporal non-stationary relationships. International Journal of Geographical Information Science, 35 (3), 582–608.
Wu, Y. , *et al.* , 2021b. Inductive graph neural networks for spatiotemporal kriging. *In*: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 35, 4478–4485.
Xiao, L. , *et al.* , 2021. Predicting vibrancy of metro station areas considering spatial relationships through graph convolutional neural networks: The case of Shenzhen, China. Environment and Planning B: Urban Analytics and City Science, 48 (8), 2363–2384.
Xie, Y. , *et al.* , 2021. A statistically-guided deep network transformation and moderation framework for data with spatial heterogeneity. *In*: *2021 IEEE International Conference on Data Mining (ICDM)* . IEEE, 767–776.

Yan, B. , *et al.* , 2017. From ITDL to Place2Vec: Reasoning about place type similarity and relatedness by learning embeddings from augmented spatial contexts. *In*: *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 1–10.
Yan, X. , *et al.* , 2019. A graph convolutional neural network for classification of building patterns using spatial vector data. ISPRS Journal of Photogrammetry and Remote Sensing, 150, 259–273.
Zhang, H. , *et al.* , 2019. Self-attention generative adversarial networks. *In*: *International Conference on Machine Learning* . PMLR, 7354–7363.
Zhang, Y. , *et al.* , 2020. A novel residual graph convolution deep learning model for short-term network-based traffic forecasting. International Journal of Geographical Information Science, 34 (5), 969–995.
Zhang, Y. and Yu, W. , 2022. Comparison of dem super-resolution methods based on interpolation and neural networks. Sensors, 22 (3), 745.
Zhang, Y. , Yu, W. , and Zhu, D. , 2022. Terrain feature-aware deep learning network for digital elevation model superresolution. ISPRS Journal of Photogrammetry and Remote Sensing, 189, 143–162.
Zhao, L. , *et al.* , 2019. T-GCN: A temporal graph convolutional network for traffic prediction. IEEE Transactions on Intelligent Transportation Systems.
Zhu, A.X. , *et al.* , 2018. Spatial prediction based on third law of geography. Annals of GIS, 24 (4), 225–240.
Zhu, D. , *et al.* , 2020a. Spatial interpolation using conditional generative adversarial neural networks. International Journal of Geographical Information Science, 34 (4), 735–758.
Zhu, D. , Gao, S. , and Cao, G. , 2022. Towards the intelligent era of spatial analysis and modeling. In: *Proceedings of the 5th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery* . 10–13.
Zhu, D. , *et al.* , 2021. Spatial regression graph convolutional neural networks: A deep learning paradigm for spatial multivariate distributions. GeoInformatica, 1–32.
Zhu, D. , *et al.* , 2020b. Understanding place characteristics in geographic contexts through graph convolutional neural networks. Annals of the American Association of Geographers, 110 (2), 408–420.

Heterogeneity-Aware Deep Learning in Space: Performance and Fairness

Alasadi, J. , Al Hilli, A. , and Singh, V.K. , 2019. Toward fairness in face matching algorithms. *In* : *Proceedings of the 1st International Workshop on Fairness, Accountability, and Transparency in MultiMedia* . 19–25.
Atluri, G. , Karpatne, A. , and Kumar, V. , 2018. Spatio-temporal data mining: A survey of problems and methods. ACM Computing Surveys (CSUR), 51 (4), 1–41.
Bao, H. , *et al.* , 2020. Covid-gan: Estimating human mobility responses to covid-19 pandemic through spatio-temporal conditional generative adversarial networks. *In*: *Proceedings of the 28th International Conference on Advances in Geographic Information Systems* . 273–282.
Ben-David, S. , *et al.* , 2007. Analysis of representations for domain adaptation. Advances in Neural Information Processing Systems, 19, 137.
Brunsdon, C. , Fotheringham, A.S. , and Charlton, M. , 1999. Some notes on parametric significance tests for geographically weighted regression. Journal of Regional Science, 39 (3), 497–524.
Chen, T. , *et al.* , 2020. A simple framework for contrastive learning of visual representations. *In* : *International Conference on Machine Learning* . PMLR, 1597–1607.
Du, M. , *et al.* , 2021. Fairness via representation neutralization. Advances in Neural Information Processing Systems, 34, 12091–12103.
Du, M. , *et al.* , 2020. Fairness in deep learning: A computational perspective. IEEE Intelligent Systems, 36 (4), 25–34.
Finn, C. , Abbeel, P. , and Levine, S. , 2017. Model-agnostic meta-learning for fast adaptation of deep networks. *In*: *International Conference on Machine Learning* . PMLR, 1126–1135.

Finn, C. , *et al.* , 2016. Deep spatial autoencoders for visuomotor learning. *In*: *2016 IEEE International Conference on Robotics and Automation (ICRA)* . IEEE, 512–519.
Fotheringham, A.S. , Yang, W. , and Kang, W. , 2017. Multiscale geographically weighted regression (mgwr). Annals of the American Association of Geographers, 107 (6), 1247–1265.
Gao, Y. , *et al.* , 2019. Incomplete label multi-task deep learning for spatio-temporal event subtype forecasting. *In*: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 33, 3638–3646.
Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. Proceedings of the National Academy of Sciences, 118 (35).
Gupta, J. , *et al.* , 2020. Towards spatial variability aware deep neural networks (svann): A summary of results. *In*: *ACM SIGKDD Workshop on Deep Learning for Spatiotemporal Data, App. & Sys.*
Gupta, J. , *et al.* , 2021. Spatial variability aware deep neural networks (svann): A general approach. ACM Trans. Intell. Syst. Technol., 12 (6).
He, E. , *et al.* , 2022. Sailing in the location-based fairness-bias sphere. In: *Proceedings of the 30th International Conference on Advances in Geographic Information Systems* . 1–10.
He, E. , *et al.* , 2023. Physics guided neural networks for time-aware fairness: An application in crop yield prediction. In: AAAI Conference on Artificial Intelligence.
He, K. , *et al.* , 2016. Deep residual learning for image recognition. *In*: *CVPR*. 770–778.
Jean, N. , *et al.* , 2019. Tile2vec: Unsupervised representation learning for spatially distributed data. *In*: *Proceedings of the AAAI Conference on Artificial Intelligence* . vol. 33, 3967–3974.
Jia, X. , *et al.* , 2019. Spatial context-aware networks for mining temporal discriminative period in land cover detection. *In*: *SDM*. SIAM, 513–521.
Jiang, Z. , *et al.* , 2019. Spatial ensemble learning for heterogeneous geographic data with class ambiguity. ACM Trans. on Intelligent Sys. and Tech. (TIST *)*, 10 (4).
Jiang, Z. , *et al.* , 2017. Spatial ensemble learning for heterogeneous geographic data with class ambiguity: A summary of results. *In*: *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 1–10.
Jo, E.S. and Gebru, T. , 2020. Lessons from archives: Strategies for collecting sociocultural data in machine learning. *In*: *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* . 306–316.
Kamishima, T. , Akaho, S. , and Sakuma, J. , 2011. Fairness-aware learning through regularization approach. *In*: *2011 IEEE 11th International Conference on Data Mining Workshops* . IEEE, 643–650.
Kaya, A. , *et al.* , 2019. Analysis of transfer learning for deep neural network based plant classification models. Computers and Electronics in Agriculture, 158, 20–29.
Kilbertus, N. , *et al.* , 2018. Blind justice: Fairness with encrypted sensitive attributes. *In*: *International Conference on Machine Learning* . PMLR, 2630–2639.
Krizhevsky, A. , Sutskever, I. , and Hinton, G.E. , 2012. Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097–1105.
Kulldorff, M. , *et al.* , 2007. Multivariate scan statistics for disease surveillance. Statistics in Medicine, 26 (8), 1824–1833.
Li, Z. , *et al.* , 2023. Point-to-region co-learning for poverty mapping at high resolution using satellite imagery. *In*: AAAI Conference on Artificial Intelligence.
Liu, X.P. , *et al.* , 2019. Risk assessment using transfer learning for grassland fires. Agricultural and Forest Meteorology, 269, 102–111.
Ma, J. , *et al.* , 2019. Improving air quality prediction accuracy at larger temporal resolutions using deep learning and transfer learning techniques. Atmospheric Environment, 214, 116885.
Mai, G. , *et al.* , 2022. A review of location encoding for geoai: methods and applications. International Journal of Geographical Information Science, 36 (4), 639–673.
Mehrabi, N. , *et al.* , 2021. A survey on bias and fairness in machine learning. ACM Computing Surveys (CSUR), 54 (6), 1–35.
Morales, A. , *et al.* , 2020. Sensitivenets: Learning agnostic representations with application to face images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43 (6), 2158–2164.

Neill, D.B. , 2012. Fast subset scan for spatial pattern detection. Journal of the Royal Statistical Society, 74 (2), 337–360.
Neill, D.B. , McFowland III, E. , and Zheng, H. , 2013. Fast subset scan for multivariate event detection. Statistics in Medicine, 32 (13), 2185–2208.
NPR , 2019. Supreme court rules partisan gerrymandering is beyond the reach of federal courts.
Pan, S.J. , *et al.* , 2010. Domain adaptation via transfer component analysis. IEEE Transactions on Neural Networks, 22 (2), 199–210.
Pan, S.J. and Yang, Q. , 2009. A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22 (10), 1345–1359.
Serna, I. , *et al.* , 2020. Sensitiveloss: Improving accuracy and fairness of face representations with discrimination-aware deep learning. *arXiv preprint arXiv:2004.11246*.
Shekhar, S. , Feiner, S.K. , and Aref, W.G. , 2015. Spatial computing. Communications of the ACM, 59 (1), 72–81.
Shekhar, S. and Xiong, H. , 2007. Encyclopedia of gis. Springer Science & Business Media.
Steed, R. and Caliskan, A. , 2021. Image representations learned with unsupervised pre-training contain human-like biases. *In*: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* . 701–713.
Sweeney, C. and Najafian, M. , 2020. Reducing sentiment polarity for demographic attributes in word embeddings using adversarial learning. *In*: *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* . 359–368.
Vilalta, R. and Drissi, Y. , 2002. A perspective view and survey of meta-learning. Artificial Intelligence Review, 18 (2), 77–95.
Wang, M. and Deng, W. , 2018. Deep visual domain adaptation: A survey. Neurocomputing, 312, 135–153.
Wei, Z. , *et al.* , 2021. Large-scale river mapping using contrastive learning and multi-source satellite imagery. Remote Sensing, 13 (15), 2893.
Xie, Y. , *et al.* , 2023a. Harnessing heterogeneity in space with statistically-guided meta-learning. Knowledge and Information Systems, 65, 2699–2729.
Xie, Y. , *et al.* , 2021a. A statistically-guided deep network transformation and moderation framework for data with spatial heterogeneity. *In*: *2021 IEEE International Conference on Data Mining (ICDM)* . IEEE, 767–776.
Xie, Y. , *et al.* , 2022a. Statistically-guided deep network transformation to harness heterogeneity in space (extended abstract). In: L.D. Raedt, ed. *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence* , *IJCAI-22*, 7, 5364–5368.
Xie, Y. , *et al.* , 2022b. Fairness by “where”: A statistically-robust and model-agnostic bi-level learning framework. Proceedings of the AAAI Conference on Artificial Intelligence, 36 (11), 12208–12216.
Xie, Y. , *et al.* , 2021b. Spatial-net: A self-adaptive and model-agnostic deep learning framework for spatially heterogeneous datasets. *In*: *Proceedings of the 29th International Conference on Advances in Geographic Information Systems* . 313–323.
Xie, Y. , *et al.* , 2023b. Auto-cm: Unsupervised deep learning for satellite imagery composition and cloud masking using spatio-temporal dynamics. *In:* AAAI Conference on Artificial Intelligence.
Xie, Y. , Shekhar, S. , and Li, Y. , 2022c. Statistically-robust clustering techniques for mapping spatial hotspots: A survey. ACM Computing Surveys (CSUR *)*, 55 (2), 1–38.
Yan, A. and Howe, B. , 2019. Fairst: Equitable spatial and temporal demand prediction for new mobility systems. *In*: *Proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 552–555.
Yang, K. , *et al.* , 2020. Towards fairer datasets: Filtering and balancing the distribution of the people subtree in the imagenet hierarchy. *In*: *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* . 547–558.
Yao, H. , *et al.* , 2019. Learning from multiple cities: A meta-learning approach for spatial-temporal prediction. *In*: The World Wide Web Conference. 2181–2191.
Yuan, Z. , Zhou, X. , and Yang, T. , 2018. Hetero-convlstm: A deep learning approach to traffic accident prediction on heterogeneous spatio-temporal data. *In*: *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* . 984–992.

Zafar, M.B. , *et al.* , 2017. Fairness beyond disparate treatment & disparate impact: Learning classification without disparate mistreatment. *In*: *Proceedings of the 26th International Conference on World Wide Web* . 1171–1180.
Zhang, H. and Davidson, I. , 2021. Towards fair deep anomaly detection. *In*: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* . 138–148.

Explainability in GeoAI

Achtibat, R. , *et al.* , 2022. From “Where" to “What": Towards human-understandable explanations through concept relevance propagation. *arXiv preprint arXiv:2206.03208*.
Anders, C.J. , *et al.* , 2022. Finding and removing Clever Hans: Using explanation methods to debug and improve deep models. Information Fusion, 77, 261–295.
Arras, L. , *et al.* , 2019a. Explaining and Interpreting LSTMs. *In*: Explainable AI: Interpreting, Explaining and Visualizing Deep Learning. Lecture Notes in Computer Science, vol. 11700. 211–238.
Arras, L. , *et al.* , 2017. Explaining recurrent neural network predictions in sentiment analysis. *In* : *Proceedings of the EMNLP'17 Workshop on Computational Approaches to Subjectivity, Sentiment & Social Media Analysis* . 159–168.
Arras, L. , *et al.* , 2019b. Evaluating recurrent neural network explanations. *In*: *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP* . 113–126.
Arras, L. , Osman, A. , and Samek, W. , 2022. CLEVR-XAI: A benchmark dataset for the ground truth evaluation of neural network explanations. Information Fusion, 81, 14–40.
Assael, Y.M. , *et al.* , 2016. LipNet: End-to-end sentence-level lipreading. *arXiv preprint arXiv:1611.01599*.
Bach, S. , *et al.* , 2015. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. PloS ONE, 10 (7), e0130140.
Başağaoğlu, H. , *et al.* , 2022. A review on interpretable and explainable artificial intelligence in hydroclimatic applications. Water, 14 (8), 1230.
Berner, C. , *et al.* , 2019. Dota 2 with large scale deep reinforcement learning. *arXiv preprint arXiv:1912.06680*.
Beven, K.J. , 2011. Rainfall-Runoff Modelling: The primer. John Wiley & Sons.
Blöschl, G. , 2006. Rainfall-runoff modeling of ungauged catchments. *In*: Encyclopedia of Hydrological Sciences. John Wiley & Sons, Ltd, Ch. 133.
Castelvecchi, D. , 2016. Can we open the black box of AI? Nature News, 538 (7623), 20.
Cheng, X. , Doosthosseini, A. , and Kunkel, J. , 2022. Improve the deep learning models in forestry based on explanations and expertise. Frontiers in Plant Science, 1531.
Cheng, X. , *et al.* , 2021a. A method to evaluate task-specific importance of spatio-temporal units based on explainable artificial intelligence. International Journal of Geographical Information Science, 35 (10), 2002–2025.
Cheng, X. , *et al.* , 2021b. Multi-scale detection and interpretation of spatio-temporal anomalies of human activities represented by time-series. Computers, Environment and Urban Systems, 88, 101627.
Dorhöfer, G. , Hannappel, S. , and Voigt, H.J. , 2001. Die hydrogeologische Übersichskarte von Deutschland (HÜK 200). Die hydrogeologische Übersichskarte von Deutschland (HÜK 200), 47 (3 4), 153–159.
Erhan, D. , *et al.* , 2009. Visualizing higher-layer features of a deep network. University of Montreal, 1341 (3), 1.
Fel, T. , *et al.* , 2022a. Harmonizing the object recognition strategies of deep neural networks with humans. *Advances in Neural Information Processing Systems (NeurIPS)*.
Fel, T. , *et al.* , 2022b. CRAFT: Concept recursive activation factorization for explainability. *arXiv preprint arXiv:2211.10154*.
Fong, R.C. and Vedaldi, A. , 2017. Interpretable explanations of black boxes by meaningful perturbation. *ICCV 2017*, 3449–3457.

GeoBasis-DE/BKG , 2012. CORINE Land Cover 5 ha, Stand 2012 (CLC5-2012). Accessed: (2023/02/28), Available from: https://gdz.bkg.bund.de/index.php/default/corine-land-cover-5-ha-stand-2012-clc5-2012.html.

GeoBasis-DE/BKG , 2021. Digitales Geländemodell Gitterweite 200 m. Accessed: (2023/02/28), Available from: https://mis.bkg.bund.de/trefferanzeige?docuuid=eaaa67a1-5ecb-4e57-af38-b5f1d6d57e2a#metadata_info.

Hedström, A. , *et al.* , 2023. Quantus: An explainable AI toolkit for responsible evaluation of neural network explanations and beyond. Journal of Machine Learning Research, 24 (34), 1–11.

Hilburn, K.A. , Ebert-Uphoff, I. , and Miller, S.D. , 2021. Development and interpretation of a neural-network-based synthetic radar reflectivity estimator using GOES-R satellite observations. Journal of Applied Meteorology and Climatology, 60 (1), 3–21.

Hinton, G.E. , Osindero, S. , and Teh, Y.W. , 2006. A fast learning algorithm for deep belief nets. Neural Computation, 18 (7), 1527–1554.

Hinton, G.E. and Salakhutdinov, R.R. , 2006. Reducing the dimensionality of data with neural networks. Science, 313 (5786), 504–507.

Holzinger, A. , *et al.* , 2022. Explainable ai methods - a brief overview. *In*: *xxAI - Beyond Explainable AI*. Lecture Notes in Artificial Intelligence, vol. 13200. Springer, 13–38.

Huang, J. , *et al.* , 2022a. ConceptExplainer: Interactive explanation for deep neural networks from a concept perspective. IEEE Transactions on Visualization and Computer Graphics, 29 (1), 831–841.

Huang, Q. , *et al.* , 2022b. GraphLIME: Local interpretable model explanations for graph neural networks. IEEE Transactions on Knowledge and Data Engineering.

Iten, R. , *et al.* , 2020. Discovering physical concepts with neural networks. Physical Review Letters, 124 (1), 010508.

Janowicz, K. , *et al.* , 2020. GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science, 34 (4), 625–636.

Kim, B. , *et al.* , 2018. Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (TCAV). *In*: ICML. vol. 80, 2673–2682.

Kratzert, F. , *et al.* , 2018. Rainfall– runoff modelling using long short-term memory (LSTM) networks. Hydrology and Earth System Sciences, 22 (11), 6005–6022.

Kratzert, F. , *et al.* , 2019. Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. Hydrology and Earth System Sciences, 23 (12), 5089–5110.

Krizhevsky, A. , Sutskever, I. , and Hinton, G.E. , 2017. ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60 (6), 84–90.

Krug, D. , Stegger, U. , and Eberhardt, E. , 2015. Bodenübersichtskarte 1:200.000 (BÜK200) – Status 2015. *In*: *Jahrestagung der DBG 2015: Unsere Böden - unser Leben*, München.

Lapuschkin, S. , *et al.* , 2019. Unmasking Clever Hans predictors and assessing what machines really learn. Nature Communications, 10 (1), 1–8.

LeCun, Y. , Bengio, Y. , and Hinton, G. , 2015. Deep learning. Nature, 521 (7553), 436–444.

Li, Z. , 2022. Extracting spatial effects from machine learning model using local interpretation method: An example of SHAP and XGBoost. Computers, Environment and Urban Systems, 96, 101845.

Liu, P. and Biljecki, F. , 2022. A review of spatially-explicit GeoAI applications in Urban Geography. International Journal of Applied Earth Observation and Geoinformation, 112, 102936.

Liu, Y. , *et al.* , 2012. Urban land uses and traffic ‘source-sink areas': Evidence from GPS-enabled taxi data in Shanghai. Landscape and Urban Planning, 106 (1), 73–87.

Lundberg, S.M. , *et al.* , 2020. From local explanations to global understanding with explainable AI for trees. Nature Machine Intelligence, 2 (1), 56–67.

Lundberg, S.M. and Lee, S.I. , 2017. A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30.

Mamalakis, A. , Barnes, E.A. , and Ebert-Uphoff, I. , 2022a. Investigating the fidelity of explainable artificial intelligence methods for applications of convolutional neural networks in geoscience. Artificial Intelligence for the Earth Systems, 1 (4), e220012.

Mamalakis, A. , Ebert-Uphoff, I. , and Barnes, E.A. , 2022b. Explainable artificial intelligence in meteorology and climate science: Model fine-tuning, calibrating trust and learning new science.

In: International Workshop on Extending Explainable AI Beyond Deep Models and Classifiers. Springer, 315–339.
Matin, S.S. and Pradhan, B. , 2021. Earthquake-induced building-damage mapping using Explainable AI (XAI). Sensors, 21 (13), 4489.
Mayer, K.J. and Barnes, E.A. , 2021. Subseasonal forecasts of opportunity identified by an explainable neural network. Geophysical Research Letters, 48 (10), e2020GL092092.
McGovern, A. , *et al.* , 2019. Making the black box more transparent: Understanding the physical implications of machine learning. Bulletin of the American Meteorological Society, 100 (11), 2175–2199.
Miller, T. , 2019. Explanation in artificial intelligence: Insights from the social sciences. Artificial Intelligence, 267, 1–38.
Montavon, G. , *et al.* , 2019. Layer-wise relevance propagation: An overview. *In*: *Explainable AI: Interpreting, Explaining and Visualizing Deep Learning*. Lecture Notes in Computer Science, vol. 11700. Springer, 193–209.
Montavon, G. , *et al.* , 2017. Explaining nonlinear classification decisions with deep Taylor decomposition. Pattern Recognition, 65, 211–222.
Montavon, G. , Samek, W. , and Müller, K.R. , 2018. Methods for interpreting and understanding deep neural networks. Digital Signal Processing, 73, 1–15.
Peel, M.C. and McMahon, T.A. , 2020. Historical development of rainfall-runoff modeling. Wiley Interdisciplinary Reviews: Water, 7 (5).
Poerner, N. , Roth, B. , and Schütze, H. , 2018. Evaluating neural network explanation methods using hybrid documents and morphosyntactic agreement. *In*: *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics* . 340–350.
Reichstein, M. , *et al.* , 2019. Deep learning and process understanding for data-driven Earth system science. Nature, 566 (7743), 195–204.
Ribeiro, M.T. , Singh, S. , and Guestrin, C. , 2016. “Why should I trust you?": Explaining the predictions of any classifier. *In*: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* , KDD ‘16. 1135–1144.
Rieckmann, A. , *et al.* , 2022. Causes of Outcome Learning: a causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology, 51 (5), 1622–1636.
Roscher, R. , *et al.* , 2020. Explainable machine learning for scientific insights and discoveries. IEEE Access, 8, 42200–42216.
Ross, A.S. , Hughes, M.C. , and Doshi-Velez, F. , 2017. Right for the right reasons: Training differentiable models by constraining their explanations. *In*: *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence* . 2662–2670.
Russakovsky, O. , *et al.* , 2015. ImageNet large scale visual recognition challenge. International Journal of Computer Vision, 115 (3), 211–252.
Samek, W. , *et al.* , 2019. *Explainable AI: Interpreting, Explaining and Visualizing Deep Learning*. Lecture Notes in Computer Science, vol. 11700. Springer Nature.
Samek, W. , *et al.* , 2021. Explaining deep neural networks and beyond: A review of methods and applications. Proceedings of the IEEE, 109 (3), 247–278.
Schnake, T. , *et al.* , 2020. Higher-order explanations of graph neural networks via relevant walks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44, 7581–7596.
Schölkopf, B. , 2022. Causality for Machine Learning, 1st ed. New York, NY, USA: Association for Computing Machinery, 765–804.
Schramowski, P. , *et al.* , 2020. Making deep neural networks right for the right scientific reasons by interacting with their explanations. Nature Machine Intelligence, 2 (8), 476–486.
Selvaraju, R.R. , *et al.* , 2017. Grad-CAM: Visual explanations from deep networks via gradient-based localization. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 618–626.
Silver, D. , *et al.* , 2016. Mastering the game of Go with deep neural networks and tree search. Nature, 529 (7587), 484–489.
Simonyan, K. , Vedaldi, A. , and Zisserman, A. , 2014. Deep inside convolutional networks: Visualising image classification models and saliency maps. *In*: *Proceedings of the International Conference on Learning Representations (ICLR)* . ICLR.
Sitterson, J. , *et al.* , 2018. An overview of rainfall-runoff model types. *International Congress on Environmental Modelling and Software*.

Smilkov, D. , *et al.* , 2017. SmoothGrad: removing noise by adding noise. *In*: *ICML*.
Sundararajan, M. , Taly, A. , and Yan, Q. , 2017. Axiomatic attribution for deep networks. *In*: *Proceedings of the 34th International Conference on Machine Learning - Volume 70* , ICML'17. 3319–3328.
Toms, B.A. , Barnes, E.A. , and Ebert-Uphoff, I. , 2020. Physically interpretable neural networks for the Geosciences: Applications to Earth system variability. Journal of Advances in Modeling Earth Systems, 12 (9).
Toms, B.A. , Barnes, E.A. , and Hurrell, J.W. , 2021. Assessing decadal predictability in an Earth-system model using explainable neural networks. Geophysical Research Letters, 48 (12), e2021GL093842.
Van Der Knijff, J. , Younis, J. , and De Roo, A. , 2010. LISFLOOD: a GIS-based distributed model for river basin scale water balance and flood simulation. International Journal of Geographical Information Science, 24 (2), 189–212.
Weber, L. , *et al.* , 2023. Beyond explaining: Opportunities and challenges of XAI-based model improvement. Information Fusion, 92, 154–176.
Xing, J. and Sieber, R. , 2021. Integrating XAI and GeoAI. *In*: GIScience 2021 Short Paper Proceedings. UC Santa Barbara: Center for Spatial Studies.
Xing, X. , *et al.* , 2020. Mapping human activity volumes through remote sensing imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 5652–5668.
Yang, Y. , *et al.* , 2018. Explaining therapy predictions with layer-wise relevance propagation in neural networks. *In*: *2018 IEEE International Conference on Healthcare Informatics (ICHI)* . IEEE, 152–162.
Yeom, S.K. , *et al.* , 2021. Pruning by explaining: A novel criterion for deep neural network pruning. Pattern Recognition, 115, 107899.
Zeiler, M.D. and Fergus, R. , 2014. Visualizing and understanding convolutional networks. *In*: *Computer Vision–ECCV 2014: 13th European Conference* . 818–833.
Zhang, F. , *et al.* , 2019. Social sensing from street-level imagery: A case study in learning spatio-temporal urban mobility patterns. ISPRS Journal of Photogrammetry and Remote Sensing, 153, 48–58.
Zink, M. , *et al.* , 2017. A high-resolution dataset of water fluxes and states for Germany accounting for parametric uncertainty. Hydrology and Earth System Sciences, 21 (3), 1769–1790.
Zintgraf, L.M. , *et al.* , 2017. Visualizing deep neural network decisions: Prediction difference analysis. *In*: *ICLR 2017*.
Zou, Q. , *et al.* , 2015. Deep learning based feature selection for remote sensing scene classification. IEEE Geoscience and Remote Sensing Letters, 12 (11), 2321–2325.

Spatial Cross-Validation for GeoAI

Airola, A. , *et al.* , 2019. The spatial leave-pair-out cross-validation method for reliable auc estimation of spatial classifiers. Data Mining and Knowledge Discovery, 33, 730–747.
Brenning, A. , 2012. Spatial cross-validation and bootstrap for the assessment of prediction rules in remote sensing: The r package sperrorest. *In*: *2012 IEEE International Geoscience and Remote Sensing Symposium* . IEEE, 5372–5375.
Brenning, A. , 2023. Spatial machine-learning model diagnostics: a model-agnostic distance-based approach. International Journal of Geographical Information Science, 37 (3), 584–606.
Browne, M.W. , 2000. Cross-validation methods. Journal of Mathematical Psychology, 44 (1), 108–132.
Burman, P. , 1989. A comparative study of ordinary cross-validation, v-fold cross-validation and the repeated learning-testing methods. Biometrika, 76 (3), 503–514.
Chang, T. , *et al.* , 2022. The role of alcohol outlet visits derived from mobile phone location data in enhancing domestic violence prediction at the neighborhood level. Health & Place, 73, 102736.
Crosby, H. , Damoulas, T. , and Jarvis, S.A. , 2020. Road and travel time cross-validation for urban modelling. International Journal of Geographical Information Science, 34 (1), 98–118.

Da Silva, T.P. , Parmezan, A.R. , and Batista, G.E. , 2021. A graph-based spatial cross-validation approach for assessing models learned with selected features to understand election results. *In*: *2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA)* . IEEE, 909–915.

Diniz-Filho, J.A.F. , Bini, L.M. , and Hawkins, B.A. , 2003. Spatial autocorrelation and red herrings in geographical ecology. Global ecology and Biogeography, 12 (1), 53–64.

Fotheringham, A.S. , 2009. “the problem of spatial autocorrelation” and local spatial statistics. Geographical Analysis, 41 (4), 398–403.

Gao, S. , *et al.* , 2017. A data-synthesis-driven method for detecting and extracting vague cognitive regions. International Journal of Geographical Information Science, 31 (6), 1245–1271.

Géron, A. , 2022. Hands-on Machine Learning with Scikit-Learn, Keras, and Tensorflow. “O'Reilly Media, Inc.".

Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. Proceedings of the National Academy of Sciences, 118 (35), e2015759118.

Hijmans, R.J. , 2012. Cross-validation of species distribution models: removing spatial sorting bias and calibration with a null model. Ecology, 93 (3), 679–688.

Karasiak, N. , 2020. Museo toolbox: A python library for remote sensing including a new way to handle rasters. Journal of Open Source Software, 5 (48), 1978.

Karasiak, N. , *et al.* , 2022. Spatial dependence between training and test sets: another pitfall of classification accuracy assessment in remote sensing. Machine Learning, 111 (7), 2715–2740.

Karasiak, N. , *et al.* , 2019. Statistical stability and spatial instability in mapping forest tree species by comparing 9 years of satellite image time series. Remote Sensing, 11 (21), 2512.

Meyer, H. and Pebesma, E. , 2021. Predicting into unknown space? estimating the area of applicability of spatial prediction models. Methods in Ecology and Evolution, 12 (9), 1620–1633.

Meyer, H. and Pebesma, E. , 2022. Machine learning-based global maps of ecological variables and the challenge of assessing them. Nature Communications, 13 (1), 2208.

Meyer, H. , *et al.* , 2018. Improving performance of spatio-temporal machine learning models using forward feature selection and target-oriented validation. Environmental Modelling & Software, 101, 1–9.

Montello, D.R. , Friedman, A. , and Phillips, D.W. , 2014. Vague cognitive regions in geography and geographic information science. International Journal of Geographical Information Science, 28 (9), 1802–1820.

Muscarella, R. , *et al.* , 2014. Enm eval: An r package for conducting spatially independent evaluations and estimating optimal model complexity for maxent ecological niche models. Methods in Ecology and Evolution, 5 (11), 1198–1205.

Pohjankukka, J. , *et al.* , 2017. Estimating the prediction performance of spatial models via spatial k-fold cross validation. International Journal of Geographical Information Science, 31 (10), 2001–2019.

Roberts, D.R. , *et al.* , 2017. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. Ecography, 40 (8), 913–929.

Schratz, P. , *et al.* , 2021. mlr3spatiotempcv: Spatiotemporal resampling methods for machine learning in r. *arXiv preprint arXiv:2110.12674*.

Tobler, W.R. , 1970. A computer movie simulating urban growth in the detroit region. Economic Geography, 46 (sup1), 234–240.

Valavi, R. , *et al.* , 2018. blockcv: An r package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. Biorxiv, 357798.

Zhou, R.Z. , *et al.* , 2022. Deriving neighborhood-level diet and physical activity measurements from anonymized mobile phone location data for enhancing obesity estimation. International Journal of Health Geographics, 21 (1), 1–18.

GeoAI for the Digitization of Historical Maps

Allord, G.J. , Fishburn, K.A. , and Walter, J.L. , 2014. Standard for the us geological survey historical topographic map collection. US Geological Survey: Reston, VA, USA, 3.

Athanasiou, S. , *et al.* , 2014. Geoknow: making the web an exploratory place for geospatial knowledge. ERCIM News, 96 (12–13), 119–120.

Battle, R. and Kolas, D. , 2011. Geosparql: enabling a geospatial semantic web. Semantic Web Journal, 3 (4), 355–370.

Bhushan Damodaran, B. , *et al.* , 2018. An entropic optimal transport loss for learning deep neural networks under label noise in remote sensing images. *arXiv e-prints*, arXiv–1810.

Boeing, G. , 2017. Osmnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Computers, Environment and Urban Systems, 65, 126–139.

Bone, C. , *et al.* , 2016. A geospatial search engine for discovering multi-format geospatial data across the web. International Journal of Digital Earth, 9 (1), 47–62.

Burghardt, K. , *et al.* , 2022. Road network evolution in the urban and rural united states since 1900. Computers, Environment and Urban Systems, 95, 101803.

Carion, N. , *et al.* , 2020. End-to-end object detection with transformers. *In*: *European Conference on Computer Vision* . Springer, 213–229.

Chan, T. and Zhu, W. , 2005. Level set based shape prior segmentation. *In: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)* . IEEE, vol. 2, 1164–1170.

Chen, L.C. , *et al.* , 2018. Encoder-decoder with atrous separable convolution for semantic image segmentation. *In*: *Proceedings of the European Conference on Computer Vision (ECCV)* . 801–818.

Chen, X. , *et al.* , 2021. Text recognition in the wild: A survey. ACM Computing Surveys (CSUR), 54 (2), 1–35.

Chiang, Y.Y. , 2015. Querying historical maps as a unified, structured, and linked spatiotemporal source: Vision paper. SIGSPATIAL '15, New York, NY, USA. Association for Computing Machinery. Available from: https://doi.org/10.1145/2820783.2820887.

Chiang, Y.Y. , *et al.* , 2020. Using Historical Maps in Scientific Studies: Applications, Challenges, and Best Practices. Springer.

Chiang, Y.Y. , Leyk, S. , and Knoblock, C.A. , 2014. A survey of digital map processing techniques. ACM Computing Surveys (CSUR), 47 (1), 1–44.

Chiron, G. , *et al.* , 2017. Icdar2017 competition on post-ocr text correction. In: 2017 ICDAR. vol. 01, 1423–1428.

Devlin, J. , *et al.* , 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. *In*: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)* , June, Minneapolis, Minnesota. ACL, 4171–4186.

Duan, W. , *et al.* , 2017. Automatic alignment of geographic features in contemporary vector data and historical maps. *In*: *Proceedings of the 1st Workshop on Artificial Intelligence and Deep Learning for Geographic Knowledge Discovery* . 45–54.

Duan, W. , *et al.* , 2021a. Guided generative models using weak supervision for detecting object spatial arrangement in overhead images. *In*: *2021 IEEE International Conference on Big Data (Big Data)* . IEEE, 725–734.

Duan, W. , *et al.* , 2021b. A label correction algorithm using prior information for automatic and accurate geospatial object recognition. *In*: *2021 IEEE International Conference on Big Data (Big Data)* . IEEE, 1604–1610.

Florczyk, A.J. , *et al.* , 2019. Ghsl data package 2019. Luxembourg, EUR, 29788 (10.2760), 290498.

Goodchild, M.F. , 2007. Citizens as sensors: the world of volunteered geography. GeoJournal, 69 (4), 211–221.

Gupta, A. , Vedaldi, A. , and Zisserman, A. , 2016. Synthetic data for text localisation in natural images. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 2315–2324.

Hosseini, K. , *et al.* , 2022. Mapreader: a computer vision pipeline for the semantic exploration of maps at scale. *In*: *Proceedings of the 6th ACM SIGSPATIAL International Workshop on Geospatial Humanities* . 8–19.

Huang, M. , *et al.* , 2022. Swintextspotter: Scene text spotting via better synergy between text detection and text recognition. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 4593–4603.

Jaderberg, M. , *et al.* , 2014. Synthetic data and artificial neural networks for natural scene text recognition. *arXiv preprint arXiv:1406.2227*.

Kang, J. , *et al.* , 2021. Noise-tolerant deep neighborhood embedding for remotely sensed images with label noise. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 2551–2562.

Lan, Z. , *et al.* , 2020. ALBERT: A lite BERT for self-supervised learning of language representations. *In*: *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net. Available from: https://openreview.net/forum?id=H1eA7AEtvS.

Levenshtein, V. , 1966. Binary codes capable of correcting deletions, insertions, and reversals. *In*: Soviet Physics Doklady. Soviet Union, vol. 10, 707–710.

Lewis, M. , *et al.* , 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *In*: *Proceedings of the 58th Annual Meeting of the ACL* , July. ACL, 7871–7880.

Leyk, S. , *et al.* , 2020. Two centuries of settlement and urban development in the united states. Science Advances, 6 (23), eaba2937.

Li, H. , Liu, J. , and Zhou, X. , 2018. Intelligent map reader: A framework for topographic map understanding with deep learning and gazetteer. IEEE Access, 6, 25363–25376.

Li, Z. , *et al.* , 2020. An Automatic Approach for Generating Rich, Linked Geo-Metadata from Historical Map Images. New York, NY, USA: Association for Computing Machinery, 3290–3298.

Li, Z. , *et al.* , 2021. Synthetic map generation to provide unlimited training data for historical map text detection. *In*: *Proceedings of the 4th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery* . 17–26.

Li, Z. , *et al.* , 2022. Spabert: A pretrained language model from geographic data for geo-entity representation. *In*: *EMNLP-findings*.

Liu, X. , *et al.* , 2018. Fots: Fast oriented text spotting with a unified network. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 5676–5685.

Liu, Y. , *et al.* , 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Liu, Y. , *et al.* , 2020. Abcnet: Real-time scene text spotting with adaptive bezier-curve network. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 9809–9818.

Long, S. , He, X. , and Yao, C. , 2021. Scene text detection and recognition: The deep learning era. International Journal of Computer Vision, 129 (1), 161–184.

Namgung, M. and Chiang, Y.Y. , 2022. Incorporating spatial context for post-ocr in map images. *In*: *Proceedings of the 5th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery* . 14–17.

Nguyen, T. , *et al.* , 2020. Neural machine translation with bert for post-ocr error detection and correction. *In*: *Proceedings of the ACM/IEEE JCDL* , New York, NY, USA. ACM, 333–336.

Rothe, S. , Narayan, S. , and Severyn, A. , 2020. Leveraging pre-trained checkpoints for sequence generation tasks. Transactions of the Association for Computational Linguistics, 8, 264–280.

Rumsey, D. and Williams, M. , 2002. Historical Maps in GIS. Cartography Associates.

Sanh, V. , *et al.* , 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *arXiv preprint arXiv:1910.01108*.

Shbita, B. , *et al.* , 2022. Building spatio-temporal knowledge graphs from vectorized topographic historical maps. *Semantic Web*, (Preprint), 1–23.

Song, B. and Chan, T. , 2002. A fast algorithm for level set based optimization. UCLA Cam Report, 2 (68).

Soper, E. , Fujimoto, S. , and Yu, Y. , 2021. BART for post-correction of OCR newspaper text. *In*: *Proceedings of W-NUT 2021*, November, Online. ACL, 284–290.

Uhl, J.H. , 2021. How the U.S. was mapped - visualizing 130 years of topographic mapping in the conterminous U.S. Available from: https://doi.org/10.6084/m9.figshare.17209433.v3.

Uhl, J.H. and Duan, W. , 2020. Automating information extraction from large historical topographic map archives: New opportunities and challenges. *Handbook of Big Geospatial Data*

, 509–522.
Uhl, J.H. , *et al.* , 2018. Map archive mining: visual-analytical approaches to explore large historical map collections. ISPRS International Journal of Geo-Information, 7 (4), 148.
Uhl, J.H. , *et al.* , 2022a. Towards the automated large-scale reconstruction of past road networks from historical maps. Computers, Environment and Urban Systems, 94, 101794.
Uhl, J.H. , *et al.* , 2022b. Unmapped terrain and invisible communities: Analyzing topographic mapping disparities across settlements in the united states from 1885 to 2015. July. Zenodo. Available from: https://doi.org/10.5281/zenodo.6789259.
Uhl, J.H. , *et al.* , 2021. Combining remote-sensing-derived data and historical maps for long-term back-casting of urban extents. Remote Sensing, 13 (18), 3672.
Vrandečić, D. and Krötzsch, M. , 2014. Wikidata: a free collaborative knowledgebase. Communications of the ACM, 57 (10), 78–85.
Wang, H. and Song, M. , 2011. Ckmeans. 1d. dp: optimal k-means clustering in one dimension by dynamic programming. The R Journal, 3 (2), 29.
Wang, T. , *et al.* , 2012. End-to-end text recognition with convolutional neural networks. *In*: *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)* . IEEE, 3304–3308.
Weinman, J. , *et al.* , 2019. Deep neural networks for text detection and recognition in historical maps. *In*: *Proceedings of IEEE ICDAR '19*. IEEE, 902–909.
Wu, S. , *et al.* , 2019. Road extraction from very high resolution images using weakly labeled openstreetmap centerline. ISPRS International Journal of Geo-Information, 8 (11), 478.
Xia, Z. , *et al.* , 2022. Vision transformer with deformable attention. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 4794–4803.
Yang, S. , *et al.* , 2019. Exploring pre-trained language models for event extraction and generation. *In*: *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* , July, Florence, Italy. ACL, 5284–5294.
Zhang, X. , *et al.* , 2022. Text spotting transformers. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* . 9519–9528.
Zhu, X. , *et al.* , 2020. Deformable detr: Deformable transformers for end-to-end object detection. *arXiv preprint arXiv:2010.04159*.

Spatiotemporal AI for Transportation

Asad, M.H. , *et al.* , 2022. Pothole detection using deep learning: A real-time and ai-on-the-edge perspective. Advances in Civil Engineering, 2022, e9221211.
Basso, R. , *et al.* , 2022. Dynamic stochastic electric vehicle routing with safe reinforcement learning. Transportation Research Part E: Logistics and Transportation Review, 157, 102496.
Chen, C. , *et al.* , 2020. An intelligent path planning scheme of autonomous vehicles platoon using deep reinforcement learning on network edge. IEEE Access, 8, 99059–99069.
Cheng, T. , Haworth, J. , and Wang, J. , 2012. Spatio-temporal autocorrelation of road network data. Journal of Geographical Systems, 14, 389–413.
Cheng, T. , Zhang, Y. , and Haworth, J. , 2022. Network spacetime ai: Concepts, methods and applications. Journal of Geodesy and Geoinformation Science, 5 (3), 78.
Chu, T. , *et al.* , 2019. Multi-agent deep reinforcement learning for large-scale traffic signal control. IEEE Transactions on Intelligent Transportation Systems, 21 (3), 1086–1095.
Edrisi, A. , Bagherzadeh, K. , and Nadi, A. , 2022. Applying markov decision process to adaptive dynamic route selection model. *In*: *Proceedings of the Institution of Civil Engineers Transport* . vol. 175, 359–372.
Fayyad, J. , *et al.* , 2020. Deep learning sensor fusion for autonomous vehicle perception and localization: A review. Sensors, 20 (15), 4220.
Grunitzki, R. , de Oliveira Ramos, G. , and Bazzan, A.L.C. , 2014. Individual versus difference rewards on reinforcement learning for route choice. *In*: *2014 Brazilian Conference on Intelligent Systems* . IEEE, 253–258.
Hassan, L.A.H. , Mahmassani, H.S. , and Chen, Y. , 2020. Reinforcement learning framework for freight demand forecasting to support operational planning decisions. Transportation

Research Part E: Logistics and Transportation Review, 137, 101926.
Ibrahim, M.R. , Haworth, J. , and Cheng, T. , 2019. Weathernet: Recognising weather and visual conditions from street-level images using deep residual learning. ISPRS International Journal of Geo-Information, 8 (12), 549.
Ibrahim, M.R. , Haworth, J. , and Cheng, T. , 2021a. Urban-i: From urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision. Environment and Planning B: Urban Analytics and City Science, 48 (1), 76–93.
Ibrahim, M.R. , *et al.* , 2021b. Cyclingnet: Detecting cycling near misses from video streams in complex urban scenes with deep learning. IET Intelligent Transport Systems, 15 (10), 1331–1344.
Ibrahim, M.R. , *et al.* , 2020. Cycling near misses: a review of the current methods, challenges and the potential of an ai-embedded system. Transport Reviews, 41 (3), 304–328.
Irannezhad, E. , Prato, C.G. , and Hickman, M. , 2020. An intelligent decision support system prototype for hinterland port logistics. Decision Support Systems, 130, 113227.
Jindal, I. , *et al.* , 2018. Optimizing taxi carpool policies via reinforcement learning and spatio-temporal mining. *In*: *2018 IEEE International Conference on Big Data* . 1417–1426.
Kamarianakis, Y. and Prastacos, P. , 2003. Forecasting traffic flow conditions in an urban network: Comparison of multivariate and univariate approaches. Transportation Research Record, 1857 (1), 74–84.
Kang, Y. , Lee, S. , and Do Chung, B. , 2019. Learning-based logistics planning and scheduling for crowdsourced parcel delivery. Computers & Industrial Engineering, 132, 271–279.
Karlaftis, M.G. and Vlahogianni, E.I. , 2011. Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. Transportation Research Part C: Emerging Technologies, 19 (3), 387–399.
Khadilkar, H. , 2018. A scalable reinforcement learning algorithm for scheduling railway lines. IEEE Transactions on Intelligent Transportation Systems, 20 (2), 727–736.
Kiela, K. , *et al.* , 2020. Review of v2x–iot standards and frameworks for its applications. Applied Sciences, 10 (12), 4314.
Li, X. and Chen, D. , 2022. A survey on deep learning-based panoptic segmentation. Digital Signal Processing, 120, 103283.
Liu, Q. and Xu, J. , 2012. Traffic signal timing optimization for isolated intersections based on differential evolution bacteria foraging algorithm. Procedia-Social and Behavioral Sciences, 43, 210–215.
Matos, G.P. , *et al.* , 2021. Solving periodic timetabling problems with sat and machine learning. Public Transport, 13 (3), 625–648.
Miletic, M. , *et al.* , 2022. A review of reinforcement learning applications in adaptive traffic signal control. IET Intelligent Transport Systems, 16 (10), 1269–1285.
Mo, Y. , *et al.* , 2022. Review the state-of-the-art technologies of semantic segmentation based on deep learning. Neurocomputing, 493, 626–646.
Mostafa, T.S. and Talaat, H. , 2010. Intelligent geographical information system for vehicle routing (igis-vr): A modeling framework. *In*: *13th International IEEE Conference on Intelligent Transportation Systems* . IEEE, 801–805.
Pal, S.K. , *et al.* , 2021. Deep learning in multi-object detection and tracking: state of the art. Applied Intelligence, 51, 6400–6429.
Ren, Y. , *et al.* , 2020. A hybrid integrated deep learning model for the prediction of citywide spatio-temporal flow volumes. International Journal of Geographical Information Science, 34 (4), 802–823.
Ren, Y. , Cheng, T. , and Zhang, Y. , 2019. Deep spatio-temporal residual neural networks for road-network-based data modeling. International Journal of Geographical Information Science, 33 (9), 1894–1912.
Rosenfeld, A. , 1988. Computer vision: basic principles. Proceedings of the IEEE, 76 (8), 863–868.
Shi, D. , *et al.* , 2019. Optimal transportation network company vehicle dispatching via deep deterministic policy gradient. *In: Wireless Algorithms, Systems, and Applications: 14th International Conference, WASA 2019* , *Honolulu, HI, USA* , *June 24–26, 2019.* Springer, 297–309.
Silver, D. , *et al.* , 2016. Mastering the game of go with deep neural networks and tree search. Nature, 529 (7587), 484–489.

Smith, B.L. and Demetsky, M.J. , 1997. Traffic flow forecasting: comparison of modeling approaches. Journal of Transportation Engineering, 123 (4), 261–266.
Smith, B.L. , Williams, B.M. , and Oswald, R.K. , 2002. Comparison of parametric and nonparametric models for traffic flow forecasting. Transportation Research Part C: Emerging Technologies, 10 (4), 303–321.
Sutton, R.S. and Barto, A.G. , 2018. Reinforcement Learning: An Introduction. MIT Press.
Tamagawa, D. , Taniguchi, E. , and Yamada, T. , 2010. Evaluating city logistics measures using a multi-agent model. Procedia-Social and Behavioral Sciences, 2 (3), 6002–6012.
Tang, J. , Li, S. , and Liu, P. , 2021. A review of lane detection methods based on deep learning. Pattern Recognition, 111, 107623.
Van Lint, J. , Hoogendoorn, S. , and van Zuylen, H.J. , 2005. Accurate freeway travel time prediction with state-space neural networks under missing data. Transportation Research Part C: Emerging Technologies, 13 (5–6), 347–369.
Veres, M. and Moussa, M. , 2019. Deep learning for intelligent transportation systems: A survey of emerging trends. IEEE Transactions on Intelligent Transportation Systems, 21 (8), 3152–3168.
Vikharev, S. and Liapustin, M. , 2019. Reinforcement learning cases for passengers behavior modeling. *In*: *AIP Conference Proceedings* . AIP Publishing, vol. 2142, 170020.
Vlahogianni, E.I. , Karlaftis, M.G. , and Golias, J.C. , 2014. Short-term traffic forecasting: Where we are and where we're going. Transportation Research Part C: Emerging Technologies, 43, 3–19.
Wali, S.B. , *et al.* , 2019. Vision-based traffic sign detection and recognition systems: Current trends and challenges. Sensors, 19 (9), 2093.
Walraven, E. , Spaan, M.T. , and Bakker, B. , 2016. Traffic flow optimization: A reinforcement learning approach. Engineering Applications of Artificial Intelligence, 52, 203–212.
Wang, J. , *et al.* , 2019. A survey of vehicle to everything (v2x) testing. Sensors, 19 (2), 334.
Wang, J. and Sun, L. , 2020. Dynamic holding control to avoid bus bunching: A multi-agent deep reinforcement learning framework. Transportation Research Part C: Emerging Technologies, 116, 102661.
Wei, H. , *et al.* , 2021. Recent advances in reinforcement learning for traffic signal control: A survey of models and evaluation. ACM SIGKDD Explorations Newsletter, 22 (2), 12–18.
Welch, T.F. and Widita, A. , 2019. Big data in public transportation: a review of sources and methods. Transport Reviews, 39 (6), 795–818.
Williams, B.M. and Hoel, L.A. , 2003. Modeling and forecasting vehicular traffic flow as a seasonal arima process: Theoretical basis and empirical results. Journal of Transportation Engineering, 129 (6), 664–672.
Wu, Y. and Tan, H. , 2016. Short-term traffic flow forecasting with spatial-temporal correlation in a hybrid deep learning framework. *arXiv preprint arXiv:1612.01022*.
Xiao, Y. , *et al.* , 2020. A review of object detection based on deep learning. Multimedia Tools and Applications, 79, 23729–23791.
Yang, M. , *et al.* , 2020. Inferring passengers' interactive choices on public transits via MA-AL: Multi-agent apprenticeship learning. *In*: *Proceedings of the Web Conference 2020* . 1637–1647.
Yang, Z. and Pun-Cheng, L.S. , 2018. Vehicle detection in intelligent transportation systems and its applications under varying environments: A review. Image and Vision Computing, 69, 143–154.
Yao, G. , Lei, T. , and Zhong, J. , 2019. A review of convolutional-neural-network-based action recognition. Pattern Recognition Letters, 118, 14–22.
Yu, B. , Yin, H. , and Zhu, Z. , 2018. Spatio-temporal graph convolutional networks: a deep learning framework for traffic forecasting. *In*: *Proceedings of the 27th International Joint Conference on Artificial Intelligence* . 3634–3640.
Yu, X. and Marinov, M. , 2020. A study on recent developments and issues with obstacle detection systems for automated vehicles. Sustainability, 12 (8), 3281.
Zhang, H. , *et al.* , 2019a. A comprehensive survey of vision-based human action recognition methods. Sensors, 19 (5), 1005.
Zhang, S. , *et al.* , 2019b. Graph convolutional networks: A comprehensive review. Computational Social Networks, 6 (1), 11.
Zhang, Y. , Cheng, T. , and Ren, Y. , 2019c. A graph deep learning method for short-term traffic forecasting on large road networks. Computer-Aided Civil and Infrastructure Engineering, 34

(10), 877–896.
Zhao, Z. , *et al.* , 2017. Lstm network: A deep learning approach for short-term traffic forecast. IET Intelligent Transport Systems, 11 (2), 68–75.
Zhou, Y. , Fu, R. , and Wang, C. , 2020. Learning the car-following behavior of drivers using maximum entropy deep inverse reinforcement learning. Journal of Advanced Transportation, 2020 (4752651), 1–13.

GeoAI for Humanitarian Assistance

Abel, G.J. , *et al.* , 2019. Climate, conflict and forced migration. Global Environmental Change, 54, 239–249.
Alegana, V.A. , *et al.* , 2015. Fine resolution mapping of population age-structures for health and development applications. Journal of The Royal Society Interface, 12 (105), 20150073.
Alfons, A. , *et al.* , 2011. Simulation of close-to-reality population data for household surveys with application to EU-SILC. Statistical Methods & Applications, 20, 383–407.
Arndt, J. and Lunga, D. , 2020. Sampling subjective polygons for patch-based deep learning land-use classification in satellite images. *In*: *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium* . 1953–1956.
Arndt, J. and Lunga, D. , 2021. Large-scale classification of urban structural units from remote sensing imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 2634–2648.
Batty, M. , 2007. Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals. Boston: The MIT Press.
Beckman, R.J. , Baggerly, K.A. , and McKay, M.D. , 1996. Creating synthetic baseline populations. Transportation Research Part A: Policy and Practice, 30 (6), 415–429.
Beine, M. and Jeusette, L. , 2021. A meta-analysis of the literature on climate change and migration. Journal of Demographic Economics, 87 (3), 293–344.
Benenson, I. and Torrens, P.M. , 2004. Geosimulation: Automata-Based Modeling of Urban Phenomena. London: John Wiley & Sons, Ltd.
Bhaduri, B. , *et al.* , 2007. Landscan usa: a high-resolution geospatial and temporal modeling approach for population distribution and dynamics. GeoJournal, 69 (1), 103–117.
Black, R. , *et al.* , 2011a. The effect of environmental change on human migration. Global Environmental Change, 21, S3–S11.
Black, R. , *et al.* , 2011b. Migration as adaptation. Nature, 478 (7370), 447–449.
Blumenstock, J. , 2018. Don't forget people in the use of big data for development.
Bosco, C. , *et al.* , 2017. Exploring the high-resolution mapping of gender-disaggregated development indicators. Journal of The Royal Society Interface, 14 (129), 20160825.
Burris, J.W. , *et al.* , 2013. Uncertainty quantification techniques for population density estimates derived from sparse open source data. *In*: *Proc. SPIE 8747, Geospatial InfoFusion III* . vol. 8747, 254–258.
Burris, J.W. , *et al.* , 2015. Machine learning for the activation of contraflows during hurricane evacuation. *In*: *2015 IEEE Global Humanitarian Technology Conference (GHTC)* . vol. 1, 254–258.
Carvalhaes, T. , *et al.* , 2022a. A spatially non-stationary approach to identify multi-dimensional push factors for international emigration. *Social Science Research Network*.
Carvalhaes, T. , *et al.* , 2022b. Integrating spatial and ethnographic methods for resilience research: A thick mapping approach for hurricane maria in puerto rico. *Annals of the American Association of Geographers*.
Carvalhaes, T.M. , *et al.* , 2021. An overview & synthesis of disaster resilience indices from a complexity perspective. International Journal of Disaster Risk Reduction, 57, 102165.
Casali, Y. , Aydin, N.Y. , and Comes, T. , 2022. Machine learning for spatial analyses in urban areas: a scoping review. Sustainable Cities and Society, 85, 104050.
Coppi, G. , Moreno Jimenez, R. , and Kyriazi, S. , 2021. Explicability of humanitarian ai: a matter of principles. Journal of International Humanitarian Action, 6 (1), 1–22.

Crooks, A. , *et al.* , 2021. Agent-based modeling and the city: A gallery of applications. *In*: W. Shi , M.F. Goodchild , M. Batty , M.P. Kwan and A. Zhang , eds. Urban Informatics. Singapore: Springer, Ch. 46, 885–910.

Cutter, S.L. and Finch, C. , 2008. Temporal and spatial changes in social vulnerability to natural hazards. Proceedings of the National Academy of Sciences, 105 (7), 2301–2306.

de Blasio, G. , D'Ignazio, A. , and Letta, M. , 2022. Gotham city. Predicting 'corrupted' municipalities with machine learning. Technological Forecasting and Social Change, 184, 122016.

Dias, P. , *et al.* , 2022a. Human-machine collaboration for reusable and scalable models for remote sensing imagery analysis. *Presented at the ICML 2022 Workshop on Human-Machine Collaboration and Teaming*.

Dias, P. and Lunga, D. , 2022. Embedding ethics and trustworthiness for sustainable AI in earth sciences: Where do we begin? *In*: *IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium* . 4639–4642.

Dias, P. , *et al.* , 2022b. Model assumptions and data characteristics: Impacts on domain adaptation in building segmentation. IEEE Transactions on Geoscience and Remote Sensing, 60, 1–18.

Dodgson, K. , *et al.* , 2020. A framework for the ethical use of advanced data science methods in the humanitarian sector. *Data Science and Ethics Group*.

Durst, D. , Lämmel, G. , and Klüpfel, H. , 2014. Large-scale multi-modal evacuation analysis with an application to hamburg. *In*: Pedestrian and Evacuation Dynamics 2012. Springer, 361–369.

Epstein, J.M. and Axtell, R.L. , 1996. Growing Artificial Societies: Social Science from the Bottom Up. Boston: The MIT Press.

Feitosa, F.F. , Le, Q.B. , and Vlek, P.L. , 2011. Multi-agent simulator for urban segregation (masus): A tool to explore alternatives for promoting inclusive cities. Computers, Environment and Urban Systems, 35 (2), 104–115.

Flowerdew, R. and Aitkin, M. , 1982. A method of fitting the gravity model based on the poisson distribution. Journal of Regional Science, 22 (2), 191–202.

Fotheringham, A.S. , *et al.* , 2004. The Development of a Migration Model for England and Wales: Overview and Modelling Out-Migration. Environment and Planning A: Economy and Space, 36 (9), 1633–1672.

Fotheringham, A.S. , Yang, W. , and Kang, W. , 2017. Multiscale Geographically Weighted Regression. Annals of the American Association of Geographers, 107 (6), 1247–1265.

Fotheringham, A. , 1983. A new set of spatial-interaction models: The theory of competing destinations. Environment and Planning A: Economy and Space, 15 (1), 15–36.

Frazier, T. and Alfons, A. , 2012. Generating a close-to-reality synthetic population of ghana. Social Science Research Network, 15.

Garcia, A.J. , *et al.* , 2014. Modeling internal migration flows in sub-Saharan Africa using census microdata. Migration Studies, 3 (1), 89–110.

Gething, P. , *et al.* , 2015. Creating spatial interpolation surfaces with DHS data. *DHS Spatial Analysis Reports*, No. 11, pp. 86.

Helbing, D. and Molnar, P. , 1995. Social force model for pedestrian dynamics. Physical Review E, 51 (5), 4282–4286.

Jayachandran, S. , Biradavolu, M. , and Cooper, J. , 2023. Using machine learning and qualitative interviews to design a five-question survey module for women's agency. World Development, 161, 106076.

Knippenberg, E. , Jensen, N. , and Constas, M. , 2019. Quantifying household resilience with high frequency data: Temporal dynamics and methodological options. World Development, 121, 1–15.

Kraemer, M.U.G. , *et al.* , 2019. Utilizing general human movement models to predict the spread of emerging infectious diseases in resource poor settings. Scientific Reports, 9 (5151).

Kuffer, M. , *et al.* , 2022. The missing millions in maps: Exploring causes of uncertainties in global gridded population datasets. ISPRS International Journal of Geo-Information, 11 (7), 403.

Kuner, C. , *et al.* , 2020. *Handbook on Data Protection in Humanitarian Action*. International Committee of the Red Cross.

Lai, S. , *et al.* , 2019. Exploring the use of mobile phone data for national migration statistics. Palgrave Communications, 5 (34), 89–110.

Lämmel, G. , Klüpfel, H. , and Nagel, K. , 2009. The matsim network flow model for traffic simulation adapted to large-scale emergency egress and an application to the evacuation of the indonesian city of padang in case of a tsunami warning. *In*: Pedestrian Behavior. Emerald Group Publishing Limited, 245–265.
Le, Q.B. , Park, S.J. , and Vlek, P.L. , 2010. Land use dynamic simulator (ludas): A multi-agent system model for simulating spatio-temporal dynamics of coupled human–landscape system. Ecological Informatics, 5 (3), 203–221.
Leslie, D. , 2019. Understanding artificial intelligence ethics and safety. *arXiv preprint arXiv:1906.05684*.
Li, W. , 2020. Geoai: Where machine learning and big data converge in GIScience. Journal of Spatial Information Science, (20), 71–77.
Luca, M. , *et al.* , 2020. Deep learning for human mobility: a survey on data and models. *CoRR*, abs/2012.02825.
Lunga, D. , *et al.* , 2021. Resflow: A remote sensing imagery data-flow for improved model generalization. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 10468–10483.
Lunga, D. , *et al.* , 2020. Apache spark accelerated deep learning inference for large scale satellite image analytics. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 271–283.
Lunga, D. , *et al.* , 2022. GeoAI at ACM SIGSPATIAL: The New Frontier of Geospatial Artificial Intelligence Research.
Martnez-Rivera, W. , *et al.* , 2022. A treatment-effect model to quantify human dimensions of disaster impacts: the case of hurricane maria in puerto rico. Natural Hazards, 1–36.
McAuliffe, M. and Triandafyllidou, A. , 2020. World Migration Report 2022. Geneva: International Organization for Migration (IOM).
McLeman, R. , *et al.* , 2016. Environmental migration and displacement: What we know and don't know. *In*: *Laurier Environmental Migration Workshop*.
Milán-Garca, J. , *et al.* , 2021. Climate change-induced migration: a bibliometric review. Globalization and Health, 17 (1), 74.
Miller, E.J. , 2021. Transportation modeling. *In*: W. Shi , M.F. Goodchild , M. Batty , M.P. Kwan and A. Zhang , eds. Urban Informatics. Singapore: Springer, Ch. 46, 911–931.
Mitchell, M. , 1998. An Introduction to Genetic Algorithms. Boston: The MIT Press.
Munnich, R. and Schurle, J. , 2003. On the simulation of complex universes in the case of applying the german microcensus. *DACSEIS Research Paper Series, No. 4, 2003*, No. 4, pp. 22.
Nagel, K. and Schreckenberg, M. , 1992. A cellular automaton model for freeway traffic. Journal de Physique, 2 (12), 2221–2229.
Newman, M.E.J. , 2003. The structure and function of complex networks. SIAM Review, 45 (2), 167–256.
Ortiz, D.A. , 2020. Geographic information systems (gis) in humanitarian assistance: a meta-analysis. Pathways: A Journal of Humanistic and Social Inquiry, 1 (2), 4.
Pagels, H. , 1989. The Dreams of Reason. USA: Simon & Schuster, Inc.
Pandey, B. , Brelsford, C. , and Seto, K.C. , 2022. Infrastructure inequality is a characteristic of urbanization. Proceedings of the National Academy of Sciences, 119 (15), e2119890119.
Persello, C. , *et al.* , 2022. Deep learning and earth observation to support the sustainable development goals: Current approaches, open challenges, and future opportunities. IEEE Geoscience and Remote Sensing Magazine, 10 (2), 172–200.
Pizzi, M. , Romanoff, M. , and Engelhardt, T. , 2020. AI for humanitarian action: Human rights and ethics. International Review of the Red Cross, 102 (913), 145–180.
Presner, T. , Shepard, D. , and Kawano, Y. , 2014. Hypercities Thick Mapping in the Digital Humanities. UCLA Previously Published Works. UCLA eScholarship.
Quinn, J.A. , *et al.* , 2018. Humanitarian applications of machine learning with remote-sensing data: review and case study in refugee settlement mapping. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376 (2128), 20170363.
Reddy, T.A. , 2020. Resilience of complex adaptive systems: A pedagogical framework for engineering education and research. ASME Journal of Engineering for Sustainable Buildings and Cities, 1 (2), 021004.

Sallah, K. , *et al.* , 2017. Mathematical models for predicting human mobility in the context of infectious disease spread: introducing the impedance model. International Journal of Health Geographics, 16 (42).
Saprykin, A. , Chokani, N. , and Abhari, R.S. , 2022. Accelerating agent-based demand-responsive transport simulations with gpus. Future Generation Computer Systems, 131, 43–58.
Schiavina, M. , *et al.* , 2022. GHSL Data Package 2022 GHS-BUILT-S R2022A - GHS built-up surface grid, derived from Sentinel-2 composite and Landsat, multitemporal (1975-2030).
Schindler, J. , 2013. About the uncertainties in model design and their effects: An illustration with a land-use model. Journal of Artificial Societies and Social Simulation, 16 (4), 6.
Spielman, S.E. , *et al.* , 2020. Evaluating social vulnerability indicators: criteria and their application to the social vulnerability index. Natural Hazards, 100 (1), 417–436.
Stewart, R. , *et al.* , 2016. A bayesian machine learning model for estimating building occupancy from open source data. Natural Hazards, 81.
Sumbul, G. , *et al.* , 2019. BigEarthNet: A Large-Scale Benchmark Archive For Remote Sensing Image Understanding. *CoRR*, arxiv.org/abs/1902.06148.
Taubenbock, H. , *et al.* , 2009. "last-mile" preparation for a potential disaster – interdisciplinary approach towards tsunami early warning and an evacuation information system for the coastal city of padang, indonesia. Natural Hazards and Earth System Sciences, 9 (4), 1509–1528.
Tsegai, D. and Le, Q.B. , 2010. District-level spatial analysis of migration flows in ghana: Determinants and implications for policy. *ZEF-Discussion Papers on Development Policy*, No. 144, pp. 18.
Utazi, C. , *et al.* , 2018. High resolution age-structured mapping of childhood vaccination coverage in low and middle income countries. Vaccine, 36 (12), 1583–1591.
Verjee, F. , 2005. The application of geomatics in complex humanitarian emergencies. Journal of Humanitarian Assistance.
Villamor, G.B. , *et al.* , 2014. Biodiversity in rubber agroforests, carbon emissions, and rural livelihoods: An agent-based model of land-use dynamics in lowland sumatra. Environmental Modelling & Software, 61, 151–165.
Vinuesa, R. , *et al.* , 2020. The role of artificial intelligence in achieving the sustainable development goals. Nature Communications, 11 (1), 1–10.
Waddell, P. , 2002. Urbansim: Modeling urban development for land use, transportation, and environmental planning. Journal of the American Planning Association, 68 (3), 297–314.
Wardrop, N. , *et al.* , 2018. Spatially disaggregated population estimates in the absence of national population and housing census data. Proceedings of the National Academy of Sciences, 115 (14), 3529–3537.
Wesolowski, A. , *et al.* , 2013. The use of census migration data to approximate human movement patterns across temporal scales. PLOS ONE, 8 (1), 1–8.
Wilson, A. , 1971. A family of spatial interaction models, and associated developments. Environment and Planning A: Economy and Space, 3 (1), 1–32.
Wisetjindawat, W. , *et al.* , 2013. Modeling disaster response operations including road network vulnerability. Journal of the Eastern Asia Society for Transportation Studies, 10, 196–214.
Yang, H.L. , *et al.* , 2018. Building extraction at scale using convolutional neural network: Mapping of the united states. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11 (8), 2600–2614.

GeoAI for Disaster Response

British Geological Survey . (2023). ALARMS — *Assessment of Landslides using Acoustic Real-time Monitoring Systems*. British Geological Survey. Retrieved March 21, 2023, from https://www.bgs.ac.uk/geology-projects/geophysical-tomography/technologies/
Cai, H. , N. S. Lam , Y. Qiang , L. Zou , R. M. Correll , and V. Mihunov (2018). A synthesis of disaster resilience measurement methods and indices. International Journal of Disaster Risk Reduction *31* , 844–855.
Deng, H. , D. P. Aldrich , M. M. Danziger , J. Gao , N. E. Phillips , S. P. Cornelius , and Q. R. Wang (2021). High-resolution human mobility data reveal race and wealth disparities in disaster evacuation patterns. Humanities and Social Sciences Communications *8* (1), 1–8.

Devlin, J. , M.-W. Chang , K. Lee , and K. Toutanova (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
Dong, E. , H. Du , and L. Gardner (2020). An interactive web-based dashboard to track covid-19 in real time. The Lancet Infectious Diseases *20* (5), 533–534.
Dong, L. and J. Shan (2013). A comprehensive review of earthquake-induced building damage detection with remote sensing techniques. ISPRS Journal of Photogrammetry and Remote Sensing *84* , 85–99.
Gao, S. , J. Rao , Y. Kang , Y. Liang , and J. Kruse (2020). Mapping county-level mobility pattern changes in the united states in response to covid-19. SIGSpatial Special *12* (1), 16–26.
Gao, S. , J. Rao , X. Liu , Y. Kang , Q. Huang , and J. App (2019). Exploring the effectiveness of geomasking techniques for protecting the geoprivacy of twitter users. Journal of Spatial Information Science (19), 105–129.
Hu, T. , S. Wang , B. She , M. Zhang , X. Huang , Y. Cui , J. Khuri , Y. Hu , X. Fu , X. Wang , et al. (2021). Human mobility data in the covid-19 pandemic: characteristics, applications, and challenges. International Journal of Digital Earth *14* (9), 1126–1147.
Huang, X. , C. Wang , and Z. Li (2018). A near real-time flood-mapping approach by integrating social media and post-event satellite imagery. Annals of GIS *24* (2), 113–123.
Janowicz, K. , S. Gao , G. McKenzie , Y. Hu , and B. Bhaduri (2020). Geoai: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science *34* (4), 625–636.
Jiang, Y. , Z. Li , and S. L. Cutter (2019). Social network, activity space, sentiment, and evacuation: what can social media tell us? Annals of the American Association of Geographers *109* (6), 1795–1810.
Kryvasheyeu, Y. , H. Chen , N. Obradovich , E. Moro , P. Van Hentenryck , J. Fowler , and M. Cebrian (2016). Rapid assessment of disaster damage using social media activity. Science Advances *2* (3), e1500779.
Lam, N. S.-N. , Y. J. Xu , K.-B. Liu , D. E. Dismukes , M. Reams , R. K. Pace , Y. Qiang , S. Narra , K. Li , T. A. Bianchette , et al. (2018). Understanding the mississippi river delta as a coupled natural-human system: Research methods, challenges, and prospects. Water *10* (8), 1054.
Lee, C.-C. , M. Maron , and A. Mostafavi (2022). Community-scale big data reveals disparate impacts of the texas winter storm of 2021 and its managed power outage. Humanities and Social Sciences Communications *9* (1), 1–12.
Li, L. , Y. Fan , M. Tse , and K.-Y. Lin (2020). A review of applications in federated learning. Computers & Industrial Engineering *149* , 106854.
Li, Z. , C. Wang , C. T. Emrich , and D. Guo (2018). A novel approach to leveraging social media for rapid flood mapping: a case study of the 2015 south carolina floods. Cartography and Geographic Information Science *45* (2), 97–110.
Lin, B. , L. Zou , N. Duffield , A. Mostafavi , H. Cai , B. Zhou , J. Tao , M. Yang , D. Mandal , and J. Abedin (2022). Revealing the linguistic and geographical disparities of public awareness to covid-19 outbreak through social media. International Journal of Digital Earth *15* (1), 868–889.
Martin, Y. , Z. Li , and S. L. Cutter (2017). Leveraging twitter to gauge evacuation compliance: Spatiotemporal analysis of hurricane matthew. PLoS One *12* (7), e0181701.
Mihunov, V. V. , N. H. Jafari , K. Wang , N. S. Lam , and D. Govender (2022). Disaster impacts surveillance from social media with topic modeling and feature extraction: Case of hurricane harvey. International Journal of Disaster Risk Science *13* (5), 729–742.
Mihunov, V. V. , N. S. Lam , L. Zou , Z. Wang , and K. Wang (2020). Use of twitter in disaster rescue: lessons learned from hurricane harvey. International Journal of Digital Earth *13* (12), 1454–1466.
Nelson, T. , M. Goodchild , and D. Wright (2022). Accelerating ethics, empathy, and equity in geographic information science. Proceedings of the National Academy of Sciences *119* (19), e2119967119.
Nex, F. , D. Duarte , F. G. Tonolo , and N. Kerle (2019). Structural building damage detection with deep learning: Assessment of a state-of-the-art cnn in operational conditions. Remote Sensing *11* (23), 2765.
Ray, P. P. , M. Mukherjee , and L. Shu (2017). Internet of things for disaster management: State-of-the-art and prospects. IEEE Access *5* , 18818–18835.

Simonyan, K. and A. Zisserman (2015). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Song, X. , R. Shibasaki , N. J. Yuan , X. Xie , T. Li , and R. Adachi (2017). Deepmob: learning deep knowledge of human emergency behavior and mobility from big and heterogeneous data. ACM Transactions on Information Systems (TOIS) *35* (4), 1–19.

Song, X. , Q. Zhang , Y. Sekimoto , and R. Shibasaki (2014). Prediction of human emergency behavior and their mobility following large-scale disaster. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* , pp. 5–14.

Wang, J. , Y. Hu , and K. Joseph (2020). Neurotpr: A neuro-net toponym recognition model for extracting locations from social media messages. Transactions in GIS *24* (3), 719–735.

Wang, K. , N. S. Lam , L. Zou , and V. Mihunov (2021). Twitter use in hurricane isaac and its implications for disaster resilience. ISPRS International Journal of Geo-Information *10* (3), 116.

Yabe, T. , Y. Zhang , and S. V. Ukkusuri (2020). Quantifying the economic impact of disasters on businesses using human mobility data: a bayesian causal inference approach. EPJ Data Science *9* (1), 36.

Yuan, F. and R. Liu (2020). Mining social media data for rapid damage assessment during hurricane matthew: Feasibility study. Journal of Computing in Civil Engineering *34* (3), 05020001.

Zhai, W. and Z.-R. Peng (2020). Damage assessment using google street view: Evidence from hurricane michael in mexico beach, florida. Applied Geography *123* , 102252.

Zhang, B. , Z. Chen , D. Peng , J. A. Benediktsson , B. Liu , L. Zou , J. Li , and A. Plaza (2019). Remotely sensed big data: Evolution in model development for information extraction [point of view]. Proceedings of the IEEE *107* (12), 2294–2301.

Zhao, F. and C. Zhang (2020). Building damage evaluation from satellite imagery using deep learning. In *2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science (IRI)* , pp. 82–89. IEEE.

Zhou, B. , L. Zou , Q. Y. Hu, Yingjie , and D. Goldberg (2023). Topobert: Plug and play toponym recognition module harnessing fine-tuned bert. *arXiv preprint arXiv:2301.13631*.

Zhou, B. , L. Zou , A. Mostafavi , B. Lin , M. Yang , N. Gharaibeh , H. Cai , J. Abedin , and D. Mandal (2022). Victimfinder: Harvesting rescue requests in disaster response from social media with bert. Computers, Environment and Urban Systems *95* , 101824.

Zou, L. , N. S. Lam , H. Cai , and Y. Qiang (2018). Mining twitter data for improved understanding of disaster resilience. Annals of the American Association of Geographers *108* (5), 1422–1441.

Zou, L. , N. S. Lam , S. Shams , H. Cai , M. A. Meyer , S. Yang , K. Lee , S.-J. Park , and M. A. Reams (2019). Social and geographical disparities in twitter use during hurricane harvey. International Journal of Digital Earth *12* (11), 1300–1318.

Zou, L. , D. Liao , N. S. Lam , M. A. Meyer , N. G. Gharaibeh , H. Cai , B. Zhou , and D. Li (2023). Social media for emergency rescue: An analysis of rescue requests on twitter during hurricane harvey. International Journal of Disaster Risk Reduction *85* , 103513.

GeoAI for Public Health

Abdulkareem, S.A. , 2019. Enhancing Agent-Based Models with Artificial Intelligence for Complex Decision Making. Thesis (PhD). University of Twente.

Abdulkareem, S.A. , *et al.* , 2019. Bayesian networks for spatial learning: a workflow on using limited survey data for intelligent learning in spatial agent-based models. Geoinformatica, 23 (2), 243–268.

Aboubakr, H.A. and Magdy, A. , 2020. On improving toll accuracy for COVID-like epidemics in underserved communities using user-generated data. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Modeling and Understanding the Spread of COVID-19* . 32–35.

Adhikari, B. , *et al.* , 2021. The 4th international workshop on epidemiology meets data mining and knowledge discovery (epidamik 4.0@ kdd2021). *In*: *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining* . 4104–4105.

Adhikari, B. , *et al.* , 2019. Epideep: Exploiting embeddings for epidemic forecasting. *In*: *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* . 577–586.

Adhikari, B. , *et al.* , 2022. epidamik 5.0: The 5th international workshop on epidemiology meets data mining and knowledge discovery. *In*: *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* . 4850–4851.

Adiga, A. , *et al.* , 2020. Mathematical models for COVID-19 pandemic: a comparative analysis. Journal of the Indian Institute of Science, 100 (4), 793–807.

Agarwal, R. and Banerjee, A. , 2020. Infection risk score: Identifying the risk of infection propagation based on human contact. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Modeling and Understanding the Spread of COVID-19* . 1–10.

Agusto, F.B. , *et al.* , 2020. To isolate or not to isolate: The impact of changing behavior on COVID-19 transmission. *medRxiv*.

Ajayakumar, J. , Curtis, A. , and Curtis, J. , 2021. A clustering environment for real-time tracking and analysis of COVID-19 case clusters. *In*: *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology (SpatialEpi 2021)* . 1–9.

Alam, M. , Tanaka, M. , and Tanimoto, J. , 2019. A game theoretic approach to discuss the positive secondary effect of vaccination scheme in an infinite and well-mixed population. Chaos, Solitons & Fractals, 125, 201–213.

Anderson, T. and Dragićević, S. , 2020. Neat approach for testing and validation of geospatial network agent-based model processes: case study of influenza spread. International Journal of Geographical Information Science, 1–30.

Anderson, T. , *et al.* , 2022. *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology (SpatialEpi 2022)* . ACM.

Anderson, T. , *et al.* , 2021a. *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology (SpatialEpi 2021)* . ACM.

Anderson, T. , Yu, J. , and Züfle, A. , 2021b. The 1st acm sigspatial international workshop on modeling and understanding the spread of COVID-19. SIGSPATIAL Special, 12 (3), 35–40.

Aron, J.L. and Schwartz, I.B. , 1984. Seasonality and period-doubling bifurcations in an epidemic model. Journal of Theoretical Biology, 110 (4), 665–679.

Azad, F.T. , *et al.* , 2022. Sirtem: Spatially informed rapid testing for epidemic modeling and response to COVID-19. ACM Transactions on Spatial Algorithms and Systems, 8 (4), 1–43.

Baldassare, M. , 1978. Human spatial behavior. Annual Review of Sociology, 4 (1), 29–56.

Barrett, C. , *et al.* , 2011. Economic and social impact of influenza mitigation strategies by demographic class. Epidemics, 3 (1), 19–31.

Bauch, C. , d'Onofrio, A. , and Manfredi, P. , 2013. Behavioral epidemiology of infectious diseases: an overview. *In*: Modeling the Interplay Between Human Behavior and the Spread of Infectious Diseases. Springer, 1–19.

Behera, S. , Dogra, D.P. , and Satpathy, M. , 2022. Effect of migrant labourer inflow on the early spread of COVID-19 in odisha: A case study. ACM Transactions on Spatial Algorithms and Systems, 8 (4), 1–18.

Bertsimas, D. and Kallus, N. , 2020. From predictive to prescriptive analytics. Management Science, 66 (3), 1025–1044.

Bharti, N. , 2021. Linking human behaviors and infectious diseases. Proceedings of the National Academy of Sciences, 118 (11).

Bian, L. , 2004. A conceptual framework for an individual-based spatially explicit epidemiological model. Environment and Planning B: Planning and Design, 31 (3), 381–395.

Blei, D.M. , Ng, A.Y. , and Jordan, M.I. , 2003. Latent dirichlet allocation. Journal of Machine Learning Research, 3 (Jan), 993–1022.

Bobashev, G. , *et al.* , 2020. Geospatial forecasting of COVID-19 spread and risk of reaching hospital capacity. SIGSPATIAL Special, 12 (2), 25–32.

Bossert, A. , *et al.* , 2020. Limited containment options of COVID-19 outbreak revealed by regional agent-based simulations for south africa. *arXiv preprint arXiv:2004.05513*.

Brearcliffe, D.K. and Crooks, A. , 2021. Creating intelligent agents: Combining agent-based modeling with machine learning. *In*: *Proceedings of the 2020 Conference of The Computational Social Science Society of the Americas* . Springer, 31–58.

Brooks, L.C. , *et al.* , 2018. Nonmechanistic forecasts of seasonal influenza with iterative one-week-ahead distributions. PLoS Computational Biology, 14 (6), e1006134.

Burke, D.S. , *et al.* , 2006. Individual-based computational modeling of smallpox epidemic control strategies. Academic Emergency Medicine, 13 (11), 1142–1149.
Burtner, S. and Murray, A.T. , 2022. Covid-19 and minimizing micro-spatial interactions. ACM Transactions on Spatial Algorithms and Systems, 8 (3), 1–17.
Cabana, E. , *et al.* , 2022. Using mobile network data to color epidemic risk maps. *In*: *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology* . 35–44.
Cardoso, M. , *et al.* , 2021. Modeling the geospatial evolution of COVID-19 using spatio-temporal convolutional sequence-to-sequence neural networks. *ACM Transactions on Spatial Systems and Algorithms*.
CDC , 2020. Contact tracing for COVID-19. *Centers for Disease Control and Prevention*.
Chai, D. , Wang, L. , and Yang, Q. , 2018. Bike flow prediction with multi-graph convolutional networks. *In*: *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 397–400.
Chao, D.L. , *et al.* , 2010. Flute, a publicly available stochastic influenza epidemic simulation model. PLoS Comput Biol, 6 (1), e1000656.
Chen, E. and McKenzie, G. , 2021. Mobility response to COVID-19-related restrictions in new york city. *In*: *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology (SpatialEpi 2021)* . 10–13.
Chen, L.C. , *et al.* , 2006. Model alignment of anthrax attack simulations. Decision Support Systems, 41 (3), 654–668.
Coro, G. and Bove, P. , 2022. A high-resolution global-scale model for COVID-19 infection rate. ACM Transactions on Spatial Algorithms and Systems, 8 (3), 1–24.
Cramer, E.Y. , *et al.* , 2022. Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the united states. Proceedings of the National Academy of Sciences, 119 (15), e2113561119.
Davies, N.G. , *et al.* , 2020. Age-dependent effects in the transmission and control of COVID-19 epidemics. *MedRxiv*.
Del Valle, S.Y. , Mniszewski, S.M. , and Hyman, J.M. , 2013. Modeling the impact of behavior changes on the spread of pandemic influenza. *In*: Modeling the Interplay Between Human Behavior and the Spread of Infectious Diseases. Springer, 59–77.
Deng, S. , *et al.* , 2020. Cola-gnn: Cross-location attention based graph neural networks for long-term ili prediction. *In*: *Proceedings of the 29th ACM International Conference on Information & Knowledge Management* . 245–254.
Dignum, F. , *et al.* , 2020. Analysing the combined health, social and economic impacts of the corovanvirus pandemic using agent-based social simulation. *arXiv preprint arXiv:2004.12809*.
Dong, Y. , Yu, C. , and Xia, L. , 2020. Hierarchical reinforcement learning for epidemics intervention. *In*: *First International KDD Workshop for Prescriptive Analytics for the Physical World (PAPW 2020)*.
D'Orazio, M. , Bernardini, G. , and Quagliarini, E. , 2020. How to restart? an agent-based simulation model towards the definition of strategies for COVID-19" second phase" in public buildings. *arXiv preprint arXiv:2004.12927*.
Elarde, J. , *et al.* , 2021. Change of human mobility during COVID-19: A united states case study. PloS One, 16 (11), e0259031.
Elsaka, T. , *et al.* , 2021. Correlation analysis of spatio-temporal arabic COVID-19 tweets. In: *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology (SpatialEpi 2021)* . 14–17.
Fan, Z. , *et al.* , 2020. Human mobility based individual-level epidemic simulation platform. SIGSPATIAL Special, 12 (1), 34–40.
Fan, Z. , *et al.* , 2022. Human mobility-based individual-level epidemic simulation platform. ACM Transactions on Spatial Algorithms and Systems, 8 (3), 1–16.
Fanticelli, H.C. , *et al.* , 2022. Data-driven mobility analysis and modeling: Typical and confined life of a metropolitan population. *ACM Transactions on Spatial Systems and Algorithms*.
Frazzetto, D. , *et al.* , 2019. Prescriptive analytics: a survey of emerging trends and technologies. The VLDB Journal, 28 (4), 575–595.
Frias-Martinez, E. , Williamson, G. , and Frias-Martinez, V. , 2011. An agent-based model of epidemic spread using human mobility and social network information. *In*: *2011 IEEE Third International Conference on Social Computing* . IEEE, 57–64.

Fu, F. , *et al.* , 2011. Imitation dynamics of vaccination behaviour on social networks. Proceedings of the Royal Society B: Biological Sciences, 278 (1702), 42–49.
Funk, S. , *et al.* , 2015. Nine challenges in incorporating the dynamics of behaviour in infectious diseases models. Epidemics, 10, 21–25.
Funk, S. , Salathé, M. , and Jansen, V.A. , 2010. Modelling the influence of human behaviour on the spread of infectious diseases: a review. Journal of the Royal Society Interface, 7 (50), 1247–1256.
Gao, S. , *et al.* , 2020. Mapping county-level mobility pattern changes in the united states in response to COVID-19. SIGSPATIAL Special, 12 (1), 16–26.
Ginsberg, J. , *et al.* , 2009. Detecting influenza epidemics using search engine query data. Nature, 457 (7232), 1012–1014.
Golledge, R.G. , 1997. Spatial Behavior: A Geographic Perspective. Guilford Press.
Gollwitzer, A. , *et al.* , 2020. Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. Nature Human Behaviour, 1–12.
Halder, N. , Kelso, J.K. , and Milne, G.J. , 2010. Developing guidelines for school closure interventions to be used during a future influenza pandemic. BMC Infectious Diseases, 10 (1), 221.
Hehman, E. , *et al.* , 2019. Establishing construct validity evidence for regional measures of explicit and implicit racial bias. Journal of Experimental Psychology: General, 148 (6), 1022.
Hehman, E. , Ofosu, E.K. , and Calanchini, J. , 2020. Using environmental features to maximize prediction of regional intergroup bias. Social Psychological and Personality Science, 1948550620909775.
Hoertel, N. , *et al.* , 2020. A stochastic agent-based model of the sars-cov-2 epidemic in france. Nature Medicine, 1–5.
Holmdahl, I. and Buckee, C. , 2020. Wrong but useful—what COVID-19 epidemiologic models can and cannot tell us. New England Journal of Medicine.
Imran, M. , Qazi, U. , and Ofli, F. , 2022. Tbcov: two billion multilingual COVID-19 tweets with sentiment, entity, geo, and gender labels. Data, 7 (1), 8.
Islam, S. , *et al.* , 2021. Spatiotemporal prediction of foot traffic. In: *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Location-Based Recommendations, Geosocial Networks and Geoadvertising* . 1–8.
Jing, Q.L. , *et al.* , 2020. Household secondary attack rate of COVID-19 and associated determinants in Guangzhou, China: a retrospective cohort study. The Lancet Infectious Diseases.
Kang, Y. , *et al.* , 2020. Multiscale dynamic human mobility flow dataset in the us during the COVID-19 epidemic. Scientific Data, 7 (1), 1–13.
Karl, S. , *et al.* , 2014. A spatial simulation model for dengue virus infection in urban areas. BMC Infectious Diseases, 14 (1), 1–17.
Kavak, H. , *et al.* , 2018. Big data, agents, and machine learning: towards a data-driven agent-based modeling approach. *In*: *Proceedings of the Annual Simulation Symposium* . 1–12.
Kiamari, M. , *et al.* , 2020. Covid-19 risk estimation using a time-varying sir-model. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Modeling and Understanding the Spread of COVID-19* . 36–42.
Kim, J.S. , Jin, H. , and Züfle, A. , 2020a. Expert-in-the-loop prescriptive analytics using mobility intervention for epidemics. *In*: *First International KDD Workshop for Prescriptive Analytics for the Physical World (PAPW 2020).*
Kim, J.S. , *et al.* , 2019. Advancing simulation experimentation capabilities with runtime interventions. *In*: SpringSim 2019. IEEE, 1–11.
Kim, J.S. , *et al.* , 2020b. Location-based social simulation for prescriptive analytics of disease spread. SIGSPATIAL Special, 12 (1), 53–61.
Kim, J.S. , *et al.* , 2020c. Covid-19 ensemble models using representative clustering. SIGSPATIAL Special, 12 (2), 33–41.
Klompas, M. , Baker, M.A. , and Rhee, C. , 2020. Airborne transmission of sars-cov-2: theoretical considerations and available evidence. *JAMA*.
Laato, S. , *et al.* , 2020. Unusual purchasing behavior during the early stages of the COVID-19 pandemic: The stimulus-organism-response approach. Journal of Retailing and Consumer Services, 57, 102224.

Lamperti, F. , Roventini, A. , and Sani, A. , 2018. Agent-based model calibration using machine learning surrogates. Journal of Economic Dynamics and Control, 90, 366–389.
Lee, B.Y. , *et al.* , 2010. A computer simulation of vaccine prioritization, allocation, and rationing during the 2009 h1n1 influenza pandemic. Vaccine, 28 (31), 4875–4879.
Lepenioti, K. , *et al.* , 2020. Prescriptive analytics: Literature review and research challenges. International Journal of Information Management, 50, 57–70.
Li, Y. , *et al.* , 2015. Traffic prediction in a bike-sharing system. *In*: *Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 1–10.
Lopes, G.R. , *et al.* , 2022. Multimaps: a tool for decision-making support in the analyzes of multiple epidemics. *In*: *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology* . 22–25.
López, L. , Fernández, M. , and Giovanini, L. , 2020. Influenza epidemic model using dynamic social networks of individuals with cognition maps. MethodsX, 7, 101030.
Lorch, L. , *et al.* , 2022. Quantifying the effects of contact tracing, testing, and containment measures in the presence of infection hotspots. ACM Transactions on Spatial Algorithms and Systems, 8 (4), 1–28.
Lukens, S. , *et al.* , 2014. A large-scale immuno-epidemiological simulation of influenza a epidemics. BMC Public Health, 14 (1), 1–15.
Manfredi, P. and D'Onofrio, A. , 2013. Modeling the Interplay Between Human Behavior and the Spread of Infectious Diseases. Springer Science & Business Media.
Mao, L. , 2014. Modeling triple-diffusions of infectious diseases, information, and preventive behaviors through a metropolitan social network—an agent-based simulation. Applied Geography, 50, 31–39.
Marathe, M. and Vullikanti, A.K.S. , 2013. Computational epidemiology. Communications of the ACM, 56 (7), 88–96.
Mehrab, Z. , *et al.* , 2021. Evaluating the utility of high-resolution proximity metrics in predicting the spread of COVID-19. *ACM Transactions on Spatial Systems and Algorithms*.
Mei, S. , *et al.* , 2013. Individual decision making can drive epidemics: a fuzzy cognitive map study. IEEE Transactions on Fuzzy Systems, 22 (2), 264–273.
Merler, S. , *et al.* , 2015. Spatiotemporal spread of the 2014 outbreak of ebola virus disease in liberia and the effectiveness of non-pharmaceutical interventions: a computational modelling analysis. The Lancet Infectious Diseases, 15 (2), 204–211.
Mokbel, M. , Abbar, S. , and Stanojevic, R. , 2020. Contact tracing: Beyond the apps. SIGSPATIAL Special, 12 (2), 15–24.
Mokbel, M. , *et al.* , 2022. Mobility data science (dagstuhl seminar 22021). *In*: *Dagstuhl reports*. Schloss Dagstuhl-Leibniz-Zentrum für Informatik.
Nardin, L.G. , *et al.* , 2016. Planning horizon affects prophylactic decision-making and epidemic dynamics. PeerJ, 4, e2678.
Oruc, B.E. , *et al.* , 2021. Homebound by covid19: the benefits and consequences of non-pharmaceutical intervention strategies. BMC Public Health, 21 (1), 1–8.
Painter, M. and Qiu, T. , 2020. Political beliefs affect compliance with COVID-19 social distancing orders. *Available at SSRN 3569098.*
Pan, Z. , *et al.* , 2019. Urban traffic prediction from spatio-temporal data using deep meta learning. *In*: *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* . 1720–1730.
Pechlivanoglou, T. , *et al.* , 2022. Microscopic modeling of spatiotemporal epidemic dynamics. *In*: *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology* . 11–21.
Pejó, B. and Biczók, G. , 2020. Corona games: Masks, social distancing and mechanism design. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Modeling and Understanding the Spread of COVID-19* . 24–31.
Pesavento, J. , *et al.* , 2020. Data-driven mobility models for COVID-19 simulation. *In*: *Proceedings of the 3rd ACM SIGSPATIAL Workshop on Advances in Resilient and Intelligent Cities, Seattle, WA, USA* .
Pew Research Center , 2000. Most Americans Say Coronavirus Outbreak Has Impacted Their Lives, March 2020.
Qazi, U. , Imran, M. , and Ofli, F. , 2020. Geocov19: a dataset of hundreds of millions of multilingual COVID-19 tweets with location information. SIGSPATIAL Special, 12 (1), 6–15.

Ramchandani, P. , Paich, M. , and Rao, A. , 2017. Incorporating learning into decision making in agent based models. *In*: EPIA Conference on Artificial Intelligence. Springer, 789–800.
Ray, E.L. , *et al.* , 2020. Ensemble forecasts of coronavirus disease 2019 (COVID-19) in the us. *medRxiv.*
Reich, N.G. , *et al.* , 2019. A collaborative multiyear, multimodel assessment of seasonal influenza forecasting in the united states. Proceedings of the National Academy of Sciences, 116 (8), 3146–3154.
Rizzo, C. , *et al.* , 2013. Survey on the likely behavioural changes of the general public in four european countries during the 2009/2010 pandemic. *In*: Modeling the Interplay Between Human Behavior and the Spread of Infectious Diseases. Springer, 23–41.
Rizzo, S.G. , 2020. Balancing precision and recall for cost-effective epidemic containment. *In*: *First International KDD Workshop for Prescriptive Analytics for the Physical World (PAPW 2020).*
Rodrguez, A. , *et al.* , 2022. Data-centric epidemic forecasting: A survey. *arXiv preprint arXiv:2207.09370*.
Russell, S. and Norvig, P. , 2005. Ai a modern approach. Learning, 2 (3), 4.
Sajjadi, S. , Hashemi, A. , and Ghanbarnejad, F. , 2021. Social distancing in pedestrian dynamics and its effect on disease spreading. Physical Review E, 104 (1), 014313.
Samet, H. , *et al.* , 2020. Using animation to visualize spatio-temporal varying COVID-19 data. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Modeling and Understanding the Spread of COVID-19* . 53–62.
Schneider, C.M. , *et al.* , 2013. Unravelling daily human mobility motifs. Journal of The Royal Society Interface, 10 (84), 20130246.
Sert, E. , Bar-Yam, Y. , and Morales, A.J. , 2020. Segregation dynamics with reinforcement learning and agent based modeling. Scientific Reports, 10 (1), 1–12.
Siettos, C. , *et al.* , 2015. Modeling the 2014 ebola virus epidemic–agent-based simulations, temporal analysis and future predictions for liberia and sierra leone. PLoS Currents, 7.
Silva, P.C. , *et al.* , 2020. Covid-abs: An agent-based model of COVID-19 epidemic to simulate health and economic effects of social distancing interventions. Chaos, Solitons & Fractals, 139, 110088.
Susarla, A. , *et al.* , 2022. Spatiotemporal disease case prediction using contrastive predictive coding. *In*: *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology* . 26–34.
Sydora, C. , *et al.* , 2022. Building occupancy simulation and analysis under virus scenarios. ACM Transactions on Spatial Algorithms and Systems, 8 (3), 1–20.
Tanaka, M. and Tanimoto, J. , 2020. Is subsidizing vaccination with hub agent priority policy really meaningful to suppress disease spreading? Journal of Theoretical Biology, 486, 110059.
Taskesen, E. , 2019. distfit. https://github.com/erdogant/distfit.
Thakur, G. , *et al.* , 2020. Covid-19 joint pandemic modeling and analysis platform. In: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Modeling and Understanding the Spread of COVID-19* . 43–52.
Vallejo, M. , Corne, D.W. , and Rieser, V. , 2013. Evolving urbanisation policies-using a statistical model to accelerate optimisation over agent-based simulations. *In*: ICAART (2). Citeseer, 171–181.
Van Bavel, J.J. , *et al.* , 2020. Using social and behavioural science to support COVID-19 pandemic response. Nature Human Behaviour, 1–12.
Venkatramanan, S. , *et al.* , 2018. Using data-driven agent-based models for forecasting emerging infectious diseases. Epidemics, 22, 43–49.
Volkova, S. , *et al.* , 2017. Forecasting influenza-like illness dynamics for military populations using neural networks and social media. PloS One, 12 (12), e0188941.
Wang, X. , *et al.* , 2017. Predicting the city foot traffic with pedestrian sensor data. In: *Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services* . 1–10.
Wang, Z. and Cruz, I.F. , 2020. Analysis of the impact of COVID-19 on education based on geotagged twitter. *In*: *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Modeling and Understanding the Spread of COVID-19* . 15–23.
Weill, J.A. , *et al.* , 2020. Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. Proceedings of the National Academy of Sciences, 117 (33),

19658–19660.
Williams, A.D. , *et al.* , 2011. An individual-based simulation of pneumonic plague transmission following an outbreak and the significance of intervention compliance. Epidemics, 3 (2), 95–102.
Wu, Y. , *et al.* , 2018. Deep learning for epidemiological predictions. *In*: *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval* . 1085–1088.
Xiong, L. , *et al.* , 2020. React: Real-time contact tracing and risk monitoring using privacy-enhanced mobile tracking. SIGSPATIAL Special, 12 (2), 3–14.
Ye, W. and Gao, S. , 2022. Understanding the spatiotemporal heterogeneities in the associations between COVID-19 infections and both human mobility and close contacts in the united states. *In*: *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Spatial Computing for Epidemiology* . 1–9.
Zakaria, C. , *et al.* , 2022. Analyzing the impact of COVID-19 control policies on campus occupancy and mobility via wifi sensing. ACM Transactions on Spatial Algorithms and Systems, 8 (3), 1–26.
Zhao, L. , *et al.* , 2019. T-gcn: A temporal graph convolutional network for traffic prediction. IEEE Transactions on Intelligent Transportation Systems, 21 (9), 3848–3858.
Züfle, A. and Anderson, T. , 2020. Introduction to this special issue: Modeling and understanding the spread of COVID-19: (part i). SIGSPATIAL Special, 12 (1), 1–2.
Züfle, A. , Anderson, T. , and Gao, S. , 2022a. Introduction to the special issue on understanding the spread of COVID-19, part 1.
Züfle, A. , Gao, S. , and Anderson, T. , 2022b. Introduction to the special issue on understanding the spread of COVID-19, part 2.

GeoAI for Agriculture

Anagnostis, A. , *et al.* , 2021. A deep learning approach for anthracnose infected trees classification in walnut orchards. Computers and Electronics in Agriculture, 182, 105998.
Archontoulis, S.V. , *et al.* , 2020. Predicting crop yields and soil-plant nitrogen dynamics in the us corn belt. Crop Science, 60 (2), 721–738.
Barbosa, A. , *et al.* , 2020. Modeling yield response to crop management using convolutional neural networks. Computers and Electronics in Agriculture, 170, 105197.
Barnes, W.L. , Xiong, X. , and Salomonson, V.V. , 2003. Status of terra modis and aqua modis. Advances in Space Research, 32 (11), 2099–2106.
Benos, L. , Bechar, A. , and Bochtis, D. , 2020. Safety and ergonomics in human-robot interactive agricultural operations. Biosystems Engineering, 200, 55–72.
Breiman, L. , 2001. Random forests. Machine Learning, 45, 5–32.
Challinor, A.J. , *et al.* , 2014. A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change, 4 (4), 287–291.
Chlingaryan, A. , Sukkarieh, S. , and Whelan, B. , 2018. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and Electronics in Agriculture, 151, 61–69.
Conrad, Z. , *et al.* , 2018. Relationship between food waste, diet quality, and environmental sustainability. PloS One, 13 (4), e0195405.
Coopersmith, E.J. , *et al.* , 2014. Machine learning assessments of soil drying for agricultural planning. Computers and Electronics in Agriculture, 104, 93–104.
Crane-Droesch, A. , 2018. Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. Environmental Research Letters, 13 (11), 114003.
Dadsetan, S. , *et al.* , 2021. Detection and prediction of nutrient deficiency stress using longitudinal aerial imagery. *In*: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 35, 14729–14738.
Diao, C. , 2019. Innovative pheno-network model in estimating crop phenological stages with satellite time series. ISPRS Journal of Photogrammetry and Remote Sensing, 153, 96–109.
Diao, C. , 2020. Remote sensing phenological monitoring framework to characterize corn and soybean physiological growing stages. Remote Sensing of Environment, 248, 111960.

Diao, C. and Li, G. , 2022. Near-surface and high-resolution satellite time series for detecting crop phenology. Remote Sensing, 14 (9), 1957.
Diao, C. , *et al.* , 2021. Hybrid phenology matching model for robust crop phenological retrieval. ISPRS Journal of Photogrammetry and Remote Sensing, 181, 308–326.
Drusch, M. , *et al.* , 2012. Sentinel-2: Esa's optical high-resolution mission for gmes operational services. Remote Sensing of Environment, 120, 25–36.
Feng, Y. , *et al.* , 2017. Modeling reference evapotranspiration using extreme learning machine and generalized regression neural network only with temperature data. Computers and Electronics in Agriculture, 136, 71–78.
Folberth, C. , *et al.* , 2019. Spatio-temporal downscaling of gridded crop model yield estimates based on machine learning. Agricultural and Forest Meteorology, 264, 1–15.
Gal, Y. and Ghahramani, Z. , 2015. Bayesian convolutional neural networks with bernoulli approximate variational inference. *arXiv preprint arXiv:1506.02158*.
Gal, Y. and Ghahramani, Z. , 2016. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In: *Proceedings of PMLR* , 1050–1059.
Garca Pereira, A. , *et al.* , 2020. Data acquisition and processing for geoai models to support sustainable agricultural practices.
Grassini, P. , *et al.* , 2015. High-yield maize–soybean cropping systems in the us corn belt. *In*: Crop Physiology. Elsevier, 17–41.
Hamida, A.B. , *et al.* , 2018. 3-d deep learning approach for remote sensing image classification. IEEE Transactions on Geoscience and Remote Sensing, 56 (8), 4420–4434.
Hengl, T. , *et al.* , 2017. Soilgrids250m: Global gridded soil information based on machine learning. PLoS One, 12 (2), e0169748.
Islam, N. , *et al.* , 2021. Early weed detection using image processing and machine learning techniques in an australian chilli farm. Agriculture, 11 (5), 387.
Jeffries, G.R. , *et al.* , 2020. Mapping sub-field maize yields in Nebraska, USA by combining remote sensing imagery, crop simulation models, and machine learning. Precision Agriculture, 21, 678–694.
Jeong, J.H. , *et al.* , 2016. Random forests for global and regional crop yield predictions. PloS One, 11 (6), e0156571.
Jiang, H. , *et al.* , 2020a. A deep learning approach to conflating heterogeneous geospatial data for corn yield estimation: A case study of the us corn belt at the county level. Global Change Biology, 26 (3), 1754–1766.
Jiang, Z. , *et al.* , 2020b . Predicting county-scale maize yields with publicly available data. Scientific Reports, 10 (1), 1–12.
Johann, A.L. , *et al.* , 2016. Soil moisture modeling based on stochastic behavior of forces on a no-till chisel opener. Computers and Electronics in Agriculture, 121, 420–428.
Jumrani, K. and Bhatia, V.S. , 2018. Impact of combined stress of high temperature and water deficit on growth and seed yield of soybean. Physiology and Molecular Biology of Plants, 24 (1), 37–50.
Kang, Y. , *et al.* , 2020. Comparative assessment of environmental variables and machine learning algorithms for maize yield prediction in the us midwest. Environmental Research Letters, 15 (6), 064005.
Kattenborn, T. , *et al.* , 2021. Review on convolutional neural networks (cnn) in vegetation remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 173, 24–49.
Kendall, A. and Gal, Y. , 2017. What uncertainties do we need in bayesian deep learning for computer vision? Advances in Neural Information Processing Systems, 30.
Khaki, S. and Wang, L. , 2019. Crop yield prediction using deep neural networks. Frontiers in Plant Science, 10, 621.
Lencucha, R. , *et al.* , 2020. Government policy and agricultural production: a scoping review to inform research and policy on healthy agricultural commodities. Globalization and Health, 16, 1–15.
Li, Z. , Zhang, Z. , and Zhang, L. , 2021. Improving regional wheat drought risk assessment for insurance application by integrating scenario-driven crop model, machine learning, and satellite data. Agricultural Systems, 191, 103141.
Lin, T. , *et al.* , 2020. Deepcropnet: a deep spatial-temporal learning framework for county-level corn yield estimation. Environmental Research Letters, 15 (3), 034016.

Lobell, D.B. , *et al.* , 2015. A scalable satellite-based crop yield mapper. Remote Sensing of Environment, 164, 324–333.
Ma, Y. , *et al.* , 2021. Corn yield prediction and uncertainty analysis based on remotely sensed variables using a bayesian neural network approach. Remote Sensing of Environment, 259, 112408.
Maestrini, B. , *et al.* , 2022. Mixing process-based and data-driven approaches in yield prediction. European Journal of Agronomy, 139, 126569.
Maimaitijiang, M. , *et al.* , 2020. Soybean yield prediction from uav using multimodal data fusion and deep learning. Remote Sensing of Environment, 237, 111599.
Meng, T. , *et al.* , 2017. Analyzing temperature and precipitation influences on yield distributions of canola and spring wheat in saskatchewan. Journal of Applied Meteorology and Climatology, 56 (4), 897–913.
Menze, B.H. , *et al.* , 2009. A comparison of random forest and its gini importance with standard chemometric methods for the feature selection and classification of spectral data. BMC Bioinformatics, 10, 1–16.
Mobiny, A. , *et al.* , 2021. Dropconnect is effective in modeling uncertainty of bayesian deep networks. Scientific Reports, 11 (1), 1–14.
Mohammadi, K. , *et al.* , 2015. Extreme learning machine based prediction of daily dew point temperature. Computers and Electronics in Agriculture, 117, 214–225.
Morellos, A. , *et al.* , 2016. Machine learning based prediction of soil total nitrogen, organic carbon and moisture content by using vis-nir spectroscopy. Biosystems Engineering, 152, 104–116.
Müller, C. , *et al.* , 2021. Exploring uncertainties in global crop yield projections in a large ensemble of crop models and cmip5 and cmip6 climate scenarios. Environmental Research Letters, 16 (3), 034040.
Muruganantham, P. , *et al.* , 2022. A systematic literature review on crop yield prediction with deep learning and remote sensing. Remote Sensing, 14 (9), 1990.
Nahvi, B. , *et al.* , 2016. Using self-adaptive evolutionary algorithm to improve the performance of an extreme learning machine for estimating soil temperature. Computers and Electronics in Agriculture, 124, 150–160.
Nassani, A.A. , *et al.* , 2019. Management of natural resources and material pricing: Global evidence. Resources Policy, 64, 101500.
Nembrini, S. , König, I.R. , and Wright, M.N. , 2018. The revival of the gini importance? Bioinformatics, 34 (21), 3711–3718.
Nguyen, G. , *et al.* , 2019. Machine learning and deep learning frameworks and libraries for large-scale data mining: a survey. Artificial Intelligence Review, 52, 77–124.
Patil, A.P. and Deka, P.C. , 2016. An extreme learning machine approach for modeling evapotranspiration using extrinsic inputs. Computers and Electronics in Agriculture, 121, 385–392.
Pourmohammadali, B. , *et al.* , 2019. Effects of soil properties, water quality and management practices on pistachio yield in rafsanjan region, southeast of iran. Agricultural Water Management, 213, 894–902.
Raun, W.R. , *et al.* , 2002. Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. Agronomy Journal, 94 (4), 815–820.
Russello, H. , 2018. Convolutional neural networks for crop yield prediction using satellite images. *IBM Center for Advanced Studies*.
Saha, D. , Basso, B. , and Robertson, G.P. , 2021. Machine learning improves predictions of agricultural nitrous oxide (n2o) emissions from intensively managed cropping systems. Environmental Research Letters, 16 (2), 024004.
Schwalbert, R. , *et al.* , 2020. Mid-season county-level corn yield forecast for us corn belt integrating satellite imagery and weather variables. Crop Science, 60 (2), 739–750.
Shahhosseini, M. , Hu, G. , and Archontoulis, S.V. , 2020. Forecasting corn yield with machine learning ensembles. Frontiers in Plant Science, 11, 1120.
Shahhosseini, M. , *et al.* , 2021. Coupling machine learning and crop modeling improves crop yield prediction in the us corn belt. Scientific Reports, 11 (1), 1–15.
Shirani, H. , *et al.* , 2015. Determining the features influencing physical quality of calcareous soils in a semiarid region of iran using a hybrid pso-dt algorithm. Geoderma, 259, 1–11.

Shridhar, K. , Laumann, F. , and Liwicki, M. , 2019. A comprehensive guide to bayesian convolutional neural network with variational inference. *arXiv preprint arXiv:1901.02731*.
Sishodia, R.P. , Ray, R.L. , and Singh, S.K. , 2020. Applications of remote sensing in precision agriculture: A review. Remote Sensing, 12 (19), 3136.
Sun, J. , *et al.* , 2019. County-level soybean yield prediction using deep cnn-lstm model. Sensors, 19 (20), 4363.
Terliksiz, A.S. and Altỳlar, D.T. , 2019. Use of deep neural networks for crop yield prediction: A case study of soybean yield in lauderdale county, Alabama, USA. *In*: *2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)* . IEEE, 1–4.
Thayer, A.W. , *et al.* , 2020. Integrating agriculture and ecosystems to find suitable adaptations to climate change. Climate, 8 (1), 10.
Tian, H. , *et al.* , 2021. An lstm neural network for improving wheat yield estimates by integrating remote sensing data and meteorological data in the Guanzhong plain, PR China. Agricultural and Forest Meteorology, 310, 108629.
Van Klompenburg, T. , Kassahun, A. , and Catal, C. , 2020. Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, 177, 105709.
VoPham, T. , *et al.* , 2018. Emerging trends in geospatial artificial intelligence (geoai): potential applications for environmental epidemiology. Environmental Health, 17 (1), 1–6.
Wang, X. , *et al.* , 2020. Winter wheat yield prediction at county level and uncertainty analysis in main wheat-producing regions of China with deep learning approaches. Remote Sensing, 12 (11), 1744.
Wang, Y. , *et al.* , 2021. A new attention-based cnn approach for crop mapping using time series sentinel-2 images. Computers and Electronics in Agriculture, 184, 106090.
Woo, S. , *et al.* , 2018. Cbam: Convolutional block attention module. *In*: *Proceedings of the European Conference on Computer Vision (ECCV)* . 3–19.
Yao, Y. , *et al.* , 2012. Active canopy sensor-based precision n management strategy for rice. Agronomy for Sustainable Development, 32, 925–933.
Yoosefzadeh-Najafabadi, M. , Tulpan, D. , and Eskandari, M. , 2021. Using hybrid artificial intelligence and evolutionary optimization algorithms for estimating soybean yield and fresh biomass using hyperspectral vegetation indices. Remote Sensing, 13 (13), 2555.
You, J. , *et al.* , 2017. Deep gaussian process for crop yield prediction based on remote sensing data. In: *Proceedings of the AAAI Conference on Artificial Intelligence* . vol. 31.
Zhang, J. , *et al.* , 2021. Identification of cucumber leaf diseases using deep learning and small sample size for agricultural internet of things. International Journal of Distributed Sensor Networks, 17 (4), 15501477211007407.
Zhang, S. , *et al.* , 2020. Plant species recognition methods using leaf image: Overview. Neurocomputing, 408, 246–272.
Zhong, L. , *et al.* , 2019. Deep learning based winter wheat mapping using statistical data as ground references in Kansas and Northern Texas, US. Remote Sensing of Environment, 233, 111411.
Ziliani, M.G. , *et al.* , 2022. Early season prediction of within-field crop yield variability by assimilating cubesat data into a crop model. Agricultural and Forest Meteorology, 313, 108736.

GeoAI for Urban Sensing

Abirami, S. and Chitra, P. , 2022. Probabilistic air quality forecasting using deep learning spatial–temporal neural network. GeoInformatica, 27 (2), 199–235.
Andris, C. and Lee, S. , 2021. Romantic relationships and the built environment: a case study of a U.S. college town. Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 1–22.
Arjunan, P. , *et al.* , 2021. Operational characteristics of residential air conditioners with temporally granular remote thermographic imaging. *In*: *BuildSys ‘21: Proceedings of the 8th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation* . 184–187.
Bai, Y. , *et al.* , 2022. Knowledge distillation based lightweight building damage assessment using satellite imagery of natural disasters. GeoInformatica, 27 (2), 237–261.

Biljecki, F. and Ito, K. , 2021. Street view imagery in urban analytics and GIS: A review. Landscape and Urban Planning, 215, 104217.

Bódis, K. , *et al.* , 2019. A high-resolution geospatial assessment of the rooftop solar photovoltaic potential in the European Union. Renewable and Sustainable Energy Reviews, 114, 109309.

Byun, G. and Kim, Y. , 2022. A street-view-based method to detect urban growth and decline: A case study of Midtown in Detroit, Michigan, USA. PLOS ONE, 17 (2), e0263775.

Calabrese, F. , *et al.* , 2013. Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. Transportation Research Part C: Emerging Technologies, 26, 301–313.

Chen, L.C. , *et al.* , 2018. Encoder-decoder with atrous separable convolution for semantic image segmentation. *In*: *Proceedings of the European Conference on Computer Vision (ECCV)* . 801–818.

Chen, M. , *et al.* , 2023. Artificial intelligence and visual analytics in geographical space and cyberspace: Research opportunities and challenges. Earth-Science Reviews, 104438.

Chen, S. and Biljecki, F. , 2023. Automatic assessment of public open spaces using street view imagery. Cities, 137, 104329.

Chen, X. and Biljecki, F. , 2022. Mining real estate ads and property transactions for building and amenity data acquisition. Urban Informatics, 1 (1), 12.

Cordts, M. , *et al.* , 2016. The cityscapes dataset for semantic urban scene understanding. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 3213–3223.

Das, S. , Sun, Q.C. , and Zhou, H. , 2022. GeoAI to implement an individual tree inventory: Framework and application of heat mitigation. Urban Forestry & Urban Greening, 74, 127634.

deSouza, P. , *et al.* , 2020. Air quality monitoring using mobile low-cost sensors mounted on trash-trucks: Methods development and lessons learned. Sustainable Cities and Society, 60, 102239.

Ding, X. , Fan, H. , and Gong, J. , 2021. Towards generating network of bikeways from Mapillary data. Computers, Environment and Urban Systems, 88, 101632.

Dobler, G. , *et al.* , 2021. The urban observatory: A multi-modal imaging platform for the study of dynamics in complex urban systems. Remote Sensing, 13 (8), 1426.

Duarte, F. and Ratti, C. , 2021. What urban cameras reveal about the city: The work of the senseable city lab. *In*: Urban Informatics. Springer Singapore, 491–502.

Gao, S. , *et al.* , 2023. Special issue on geospatial artificial intelligence. GeoInformatica, 27 (2), 133–136.

Gao, S. , *et al.* , 2021. User-generated content: A promising data source for urban informatics. *In*: Urban Informatics. Springer Singapore, 503–522.

Garrido-Valenzuela, F. , Cats, O. , and van Cranenburgh, S. , 2023. Where are the people? Counting people in millions of street-level images to explore associations between people's urban density and urban characteristics. Computers, Environment and Urban Systems, 102, 101971.

Ghahramani, M. , Zhou, M. , and Wang, G. , 2020. Urban sensing based on mobile phone data: approaches, applications, and challenges. IEEE/CAA Journal of Automatica Sinica, 7 (3), 627–637.

Hamilton, W. , Ying, Z. , and Leskovec, J. , 2017. Inductive representation learning on large graphs. Advances in Neural Information Processing Systems, 30.

Han, J.Y. , Chen, Y.C. , and Li, S.Y. , 2022. Utilising high-fidelity 3D building model for analysing the rooftop solar photovoltaic potential in urban areas. Solar Energy, 235, 187–199.

He, X. and He, S.Y. , 2023. Using open data and deep learning to explore walkability in Shenzhen, China. Transportation Research Part D: Transport and Environment, 118, 103696.

Hochreiter, S. and Schmidhuber, J. , 1997. Long short-term memory. Neural Computation, 9 (8), 1735–1780.

Hou, Y. and Biljecki, F. , 2022. A comprehensive framework for evaluating the quality of street view imagery. International Journal of Applied Earth Observation and Geoinformation, 115, 103094.

Hsu, C.Y. and Li, W. , 2023. Explainable GeoAI: can saliency maps help interpret artificial intelligence's learning process? an empirical study on natural feature detection. International Journal of Geographical Information Science, 37 (5), 963–987.

Hu, Y. , *et al.* , 2015. Extracting and understanding urban areas of interest using geotagged photos. Computers, Environment and Urban Systems, 54, 240–254.
Ibrahim, M.R. , Haworth, J. , and Cheng, T. , 2020. Understanding cities with machine eyes: A review of deep computer vision in urban analytics. Cities, 96, 102481.
Janowicz, K. , 2023. Philosophical foundations of geoai: Exploring sustainability, diversity, and bias in geoai and spatial data science.
Janowicz, K. , *et al.* , 2019. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science, 34 (4), 625–636.
Jayathissa, P. , *et al.* , 2019. Is your clock-face cozie? A smartwatch methodology for the in-situ collection of occupant comfort data. Journal of Physics: Conference Series, 1343 (1), 012145.
Ju, Y. , Dronova, I. , and Delclòs-Alió, X. , 2022. A 10 m resolution urban green space map for major Latin American cities from Sentinel-2 remote sensing images and OpenStreetMap. Scientific Data, 9 (1).
Juhász, L. and Hochmair, H.H. , 2016. User contribution patterns and completeness evaluation of Mapillary, a crowdsourced street level photo service. Transactions in GIS, 20 (6), 925–947.
Kang, Y. , *et al.* , 2023. Assessing differences in safety perceptions using GeoAI and survey across neighbourhoods in Stockholm, Sweden. Landscape and Urban Planning, 236, 104768.
Kang, Y. , *et al.* , 2020a. Multiscale dynamic human mobility flow dataset in the U.S. during the COVID-19 epidemic. Scientific Data, 7 (1).
Kang, Y. , Gao, S. , and Roth, R.E. , 2019. Transferring multiscale map styles using generative adversarial networks. International Journal of Cartography, 5 (2-3), 115–141.
Kang, Y. , *et al.* , 2020b. A review of urban physical environment sensing using street view imagery in public health studies. Annals of GIS, 26 (3), 261–275.
Kang, Y. , *et al.* , 2021. Human settlement value assessment from a place perspective: Considering human dynamics and perceptions in house price modeling. Cities, 118, 103333.
Kruse, J. , *et al.* , 2021. Places for play: Understanding human perception of playability in cities using street view images and deep learning. Computers, Environment and Urban Systems, 90, 101693.
Lai, W.W.L. , 2021. Underground utilities imaging and diagnosis. *In*: Urban Informatics. Springer Singapore, 415–438.
Li, M. , *et al.* , 2022. Marked crosswalks in US transit-oriented station areas, 2007–2020: A computer vision approach using street view imagery. Environment and Planning B: Urban Analytics and City Science, 50 (2), 350–369.
Li, W. , 2020. GeoAI: Where machine learning and big data converge in GIScience. Journal of Spatial Information Science, (20).
Li, W. and Hsu, C.Y. , 2022. GeoAI for Large-Scale Image Analysis and Machine Vision: Recent Progress of Artificial Intelligence in Geography. ISPRS International Journal of Geo-Information, 11 (7), 385.
Liang, X. and Andris, C. , 2021. Measuring McCities: Landscapes of chain and independent restaurants in the United States. Environment and Planning B: Urban Analytics and City Science, 49 (2), 585–602.
Liu, P. and Biljecki, F. , 2022. A review of spatially-explicit GeoAI applications in Urban Geography. International Journal of Applied Earth Observation and Geoinformation, 112, 102936.
Liu, P. , *et al.* , 2023a. Towards human-centric digital twins: Leveraging computer vision and graph models to predict outdoor comfort. Sustainable Cities and Society, 93, 104480.
Liu, X. , *et al.* , 2019. Inside 50,000 living rooms: an assessment of global residential ornamentation using transfer learning. EPJ Data Science, 8 (1).
Liu, Y. , *et al.* , 2015. Social sensing: A new approach to understanding our socioeconomic environments. Annals of the Association of American Geographers, 105 (3), 512–530.
Liu, Y. , *et al.* , 2023b. An interpretable machine learning framework for measuring urban perceptions from panoramic street view images. iScience, 26 (3), 106132.
Lu, Y. , *et al.* , 2023. Assessing urban greenery by harvesting street view data: A review. Urban Forestry & Urban Greening, 83, 127917.
Luo, J. , *et al.* , 2022a. Semantic Riverscapes: Perception and evaluation of linear landscapes from oblique imagery using computer vision. Landscape and Urban Planning, 228, 104569.

Luo, J. , *et al.* , 2022b. Water View Imagery: Perception and evaluation of urban waterscapes worldwide. Ecological Indicators, 145, 109615.
Ma, D. , *et al.* , 2019. The State of Mapillary: An Exploratory Analysis. ISPRS International Journal of Geo-Information, 9 (1), 10.
Ma, N. , *et al.* , 2023. Learning building occupants' indoor environmental quality complaints and dissatisfaction from text-mining Booking.com reviews in the United States. Building and Environment, 237, 110319.
Mart, P. , Serrano-Estrada, L. , and Nolasco-Cirugeda, A. , 2019. Social media data: Challenges, opportunities and limitations in urban studies. Computers, Environment and Urban Systems, 74, 161–174.
Martin, M. , *et al.* , 2022. Infrared thermography in the built environment: A multi-scale review. Renewable and Sustainable Energy Reviews, 165, 112540.
O'Keeffe, K.P. , *et al.* , 2019. Quantifying the sensing power of vehicle fleets. Proceedings of the National Academy of Sciences, 116 (26), 12752–12757.
Pang, H.E. and Biljecki, F. , 2022. 3D building reconstruction from single street view images using deep learning. International Journal of Applied Earth Observation and Geoinformation, 112, 102859.
Piadyk, Y. , *et al.* , 2023. StreetAware: A high-resolution synchronized multimodal urban scene dataset. Sensors, 23 (7), 3710.
Psyllidis, A. , *et al.* , 2022. Points of interest (POI): a commentary on the state of the art, challenges, and prospects for the future. Computational Urban Science, 2 (1).
Richter, K.F. and Scheider, S. , 2023. Current topics and challenges in geoAI. *KI - Künstliche Intelligenz*.
Rottensteiner, F. , *et al.* , 2014. Results of the ISPRS benchmark on urban object detection and 3D building reconstruction. ISPRS Journal of Photogrammetry and Remote Sensing, 93, 256–271.
Shahtahmassebi, A.R. , *et al.* , 2021. Remote sensing of urban green spaces: A review. Urban Forestry & Urban Greening, 57, 126946.
Shi, W. , 2021. Introduction to urban sensing. *In*: Urban Informatics. Springer Singapore, 311–314.
Shin, D. , *et al.* , 2015. Urban sensing: Using smartphones for transportation mode classification. Computers, Environment and Urban Systems, 53, 76–86.
Song, Y. , *et al.* , 2023. Advances in geocomputation and geospatial artificial intelligence (GeoAI) for mapping. International Journal of Applied Earth Observation and Geoinformation, 103300.
Tartarini, F. , Miller, C. , and Schiavon, S. , 2022. Cozie Apple: An iOS mobile and smartwatch application for environmental quality satisfaction and physiological data collection.
Tu, W. , *et al.* , 2021. User-generated content and its applications in urban studies. *In*: Urban Informatics. Springer Singapore, 523–539.
Wilson, J.P. , *et al.* , 2020. A Five-Star Guide for Achieving Replicability and Reproducibility When Working with GIS Software and Algorithms. Annals of the American Association of Geographers, 111 (5), 1311–1317.
Wu, A.N. and Biljecki, F. , 2021. Roofpedia: Automatic mapping of green and solar roofs for an open roofscape registry and evaluation of urban sustainability. Landscape and Urban Planning, 214, 104167.
Wu, W.B. , *et al.* , 2023. A first Chinese building height estimate at 10 m resolution (CNBH-10 m) using multi-source earth observations and machine learning. Remote Sensing of Environment, 291, 113578.
Xie, E. , *et al.* , 2021. SegFormer: Simple and efficient design for semantic segmentation with transformers. Advances in Neural Information Processing Systems, 34.
Xing, J. and Sieber, R. , 2023. The challenges of integrating explainable artificial intelligence into GeoAI. *Transactions in GIS*.
Xu, S. , *et al.* , 2022a. Detecting spatiotemporal traffic events using geosocial media data. Computers, Environment and Urban Systems, 94, 101797.
Xu, Y. , *et al.* , 2022b. Perception of urban population characteristics through dietary taste patterns based on takeout data. Cities, 131, 103910.
Yan, Y. , *et al.* , 2020. Volunteered geographic information research in the first decade: a narrative review of selected journal articles in GIScience. International Journal of Geographical

Information Science, 34 (9), 1–27.
Yang, J. , *et al.* , 2021. The financial impact of street-level greenery on New York commercial buildings. Landscape and Urban Planning, 214, 104162.
Yang, Y. , *et al.* , 2023. Embracing geospatial analytical technologies in tourism studies. *Information Technology & Tourism*.
Yap, W. , Chang, J.H. , and Biljecki, F. , 2022. Incorporating networks in semantic understanding of streetscapes: Contextualising active mobility decisions. *Environment and Planning B: Urban Analytics and City Science*, 239980832211388.
Zhang, F. , *et al.* , 2023a. Street-level imagery analytics and applications. ISPRS Journal of Photogrammetry and Remote Sensing, 199, 195–196.
Zhang, F. , *et al.* , 2020. Uncovering inconspicuous places using social media check-ins and street view images. Computers, Environment and Urban Systems, 81, 101478.
Zhang, Y. , Liu, P. , and Biljecki, F. , 2023b. Knowledge and topology: A two layer spatially dependent graph neural networks to identify urban functions with time-series street view image. ISPRS Journal of Photogrammetry and Remote Sensing, 198, 153–168.
Zhang, Z. , *et al.* , 2022. Vectorized rooftop area data for 90 cities in China. Scientific Data, 9 (1).
Zhao, T. , *et al.* , 2023. Sensing urban soundscapes from street view imagery. Computers, Environment and Urban Systems, 99, 101915.

Reproducibility and Replicability in GeoAI

Abadi, M. , *et al.* , 2015. Tensorflow: Large-scale machine learning on heterogeneous systems. *arXiv preprint arXiv:1603.04467*.
Arnold, B. , *et al.* , 2019. The turing way: a handbook for reproducible data science. *Zenodo*.
Barba, L.A. , 2018. Terminologies for reproducible research. *arXiv preprint arXiv:1802.03311*.
Brdar, S. , *et al.* , 2016. Unveiling spatial epidemiology of hiv with mobile phone data. Scientific Reports, 6 (1), 19342.
Brinckman, A. , *et al.* , 2019. Computing environments for reproducibility: Capturing the “whole tale”. Future Generation Computer Systems, 94, 854–867.
Brunsdon, C. , 2017. Quantitative methods ii: Issues of inference in quantitative human geography. Progress in Human Geography, 41 (4), 512–523.
Chard, K. , *et al.* , 2020. Toward enabling reproducibility for data-intensive research using the whole tale platform. *In*: Parallel Computing: Technology Trends. IOS Press, 766–778.
Couclelis, H. , 1986. Artificial intelligence in geography: Conjectures on the shape of things to come. The Professional Geographer, 38 (1), 1–11.
Crigger, E. and Khoury, C. , 2019. Making policy on augmented intelligence in health care. AMA Journal of Ethics, 21 (2), 188–191.
Davidson, S.B. and Freire, J. , 2008. Provenance and scientific workflows: challenges and opportunities. *In*: *Proceedings of the 2008 ACM SIGMOD International Conference on Management of Data* . 1345–1350.
Dsouza, A. , *et al.* , 2021. Worldkg: A world-scale geographic knowledge graph. *In*: *Proceedings of the 30th ACM International Conference on Information & Knowledge Management* . 4475–4484.
Duque, J.C. , Anselin, L. , and Rey, S.J. , 2012. The max-p-regions problem. Journal of Regional Science, 52 (3), 397–419.
Emsley, I. and De Roure, D. , 2017. A framework for the preservation of a docker container. International Journal of Digital Curation, 12 (2), 125–135.
Goodchild, M.F. , *et al.* , 2021. Introduction: Forum on reproducibility and replicability in geography. Annals of the American Association of Geographers, 111 (5), 1271–1274.
Goodchild, M.F. and Li, W. , 2021. Replication across space and time must be weak in the social and environmental sciences. Proceedings of the National Academy of Sciences, 118 (35), e2015759118.
Goodman, S.N. , Fanelli, D. , and Ioannidis, J.P. , 2016. What does research reproducibility mean? Science Translational Medicine, 8 (341), 341ps12–341ps12.

Gundersen, O.E. , Gil, Y. , and Aha, D.W. , 2018. On reproducible ai: Towards reproducible research, open science, and digital scholarship in ai publications. AI Magazine, 39 (3), 56–68.

Gundersen, O.E. and Kjensmo, S. , 2018. State of the art: Reproducibility in artificial intelligence. *In*: *The AAAI Conference on Artificial Intelligence* . vol. 32.

Haibe-Kains, B. , *et al.* , 2020. Transparency and reproducibility in artificial intelligence. Nature, 586 (7829), E14–E16.

Hartter, J. , *et al.* , 2013. Spatially explicit data: stewardship and ethical challenges in science. PLoS Biology, 11 (9), e1001634.

Hastie, T. , *et al.* , 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. vol. 2. Springer.

Hey, A.J. , *et al.* , 2009. The Fourth Paradigm: Data-Intensive Scientific Discovery. vol. 1. Microsoft Research.

Holler, J. and Kedron, P. , 2022. Mainstreaming metadata into research workflows to advance reproducibility and open geographic information science. The Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 48, 201–208.

Hutson, M. , 2018. Artificial intelligence faces reproducibility crisis. Science, 359 (6377), 725–726.

Janowicz, K. , *et al.* , 2020. Geoai: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond.

Janowicz, K. , Sieber, R. , and Crampton, J. , 2022. Geoai, counter-ai, and human geography: A conversation. Dialogues in Human Geography, 12 (3), 446–458.

Jupyter, P. , *et al.* , 2018. Binder 2.0-reproducible, interactive, sharable environments for science at scale. *In*: *Proceedings of the 17th Python in Science Conference* . 113–120.

Kang, Y. , Gao, S. , and Roth, R. , 2022. A review and synthesis of recent geoai research for cartography: Methods, applications, and ethics. *In*: *Proceedings of AutoCarto* . 2–4.

Kapoor, S. and Narayanan, A. , 2022. Leakage and the reproducibility crisis in ml-based science. *arXiv preprint arXiv:2207.07048*.

Kaufman, S. , *et al.* , 2012. Leakage in data mining: Formulation, detection, and avoidance. ACM TKDD, 6 (4), 1–21.

Kedron, P. , *et al.* , 2021a. Reproducibility and replicability in geographical analysis. Geographical Analysis, 53 (1), 135–147.

Kedron, P. , *et al.* , 2022. Reproducibility, replicability, and open science practices in the geographical sciences. *OSF, Center for Open Science*, 1–10.

Kedron, P. , *et al.* , 2021b. Reproducibility and replicability: opportunities and challenges for geospatial research. International Journal of Geographical Information Science, 35 (3), 427–445.

Konkol, M. , Kray, C. , and Pfeiffer, M. , 2019. Computational reproducibility in geoscientific papers: Insights from a series of studies with geoscientists and a reproduction study. International Journal of Geographical Information Science, 33 (2), 408–429.

Leipzig, J. , *et al.* , 2021. The role of metadata in reproducible computational research. Patterns, 2 (9), 100322.

Li, W. , 2020. Geoai: Where machine learning and big data converge in GIScience. Journal of Spatial Information Science, (20), 71–77.

Li, W. , 2022. Geoai in social science. Handbook of Spatial Analysis in the Social Sciences, 291–304.

Li, W. and Hsu, C.Y. , 2022. Geoai for large-scale image analysis and machine vision: Recent progress of artificial intelligence in geography. ISPRS International Journal of Geo-Information, 11 (7), 385.

Lin, T.Y. , Belongie, S. , and Hays, J. , 2013. Cross-view image geolocalization. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* . 891–898.

Liu, P. and Biljecki, F. , 2022. A review of spatially-explicit geoai applications in urban geography. International Journal of Applied Earth Observation and Geoinformation, 112, 102936.

Mai, G. , *et al.* , 2022. A review of location encoding for geoai: methods and applications. International Journal of Geographical Information Science, 36 (4), 639–673.

Miller, H.J. and Wentz, E.A. , 2003. Representation and spatial analysis in geographic information systems. Annals of the Association of American Geographers, 93 (3), 574–594.

Missier, P. , Belhajjame, K. , and Cheney, J. , 2013. The w3c prov family of specifications for modelling provenance metadata. *In*: *Proceedings of the 16th International Conference on Extending Database Technology* . 773–776.

National Academies of Sciences , Engineering, and Medicine and others, 2019. Reproducibility and Replicability in Science. National Academies Press.

Nüst, D. , *et al.* , 2018. Reproducible research and giscience: an evaluation using agile conference papers. PeerJ, 6, e5072.

Nüst, D. and Hinz, M. , 2019. Containerit: Generating dockerfiles for reproducible research with r. Journal of Open Source Software, 4 (40), 1603.

Nüst, D. and Pebesma, E. , 2021. Practical reproducibility in geography and geosciences. Annals of the American Association of Geographers, 111 (5), 1300–1310.

Openshaw, S. , 1984. The modifiable areal unit problem. Concepts and Techniques in Modern Geography, 60–69.

Openshaw, S. and Openshaw, C. , 1997. Artificial Intelligence in Geography. John Wiley & Sons, Inc.

Parasidis, E. , Pike, E. , and McGraw, D. , 2019. A belmont report for health data. The New England Journal of Medicine, 380 (16), 1493–1495.

Paszke, A. , *et al.* , 2019. Pytorch: An imperative style, high-performance deep learning library. Advances in Neural Information Processing Systems, 32.

Plesser, H.E. , 2018. Reproducibility vs. replicability: a brief history of a confused terminology. Frontiers in Neuroinformatics, 11, 76.

Rey, S.J. and Franklin, R.S. , 2022. Handbook of Spatial Analysis in the Social Sciences. Edward Elgar Publishing.

Smith, T.R. , 1984. Artificial intelligence and its applicability to geographical problem solving. The Professional Geographer, 36 (2), 147–158.

Stewart, A.J. , *et al.* , 2022. Torchgeo: deep learning with geospatial data. *In*: *Proceedings of the 30th International Conference on Advances in Geographic Information Systems* . 1–12.

Tullis, J.A. and Kar, B. , 2021. Where is the provenance? ethical replicability and reproducibility in GIScience and its critical applications. Annals of the American Association of Geographers, 111 (5), 1318–1328.

Wang, S. and Li, W. , 2021. Geoai in terrain analysis: Enabling multi-source deep learning and data fusion for natural feature detection. Computers, Environment and Urban Systems, 90, 101715.

Watada, J. , *et al.* , 2019. Emerging trends, techniques and open issues of containerization: a review. IEEE Access, 7, 152443–152472.

Wilkinson, M.D. , *et al.* , 2016. The fair guiding principles for scientific data management and stewardship. Scientific Data, 3 (1), 1–9.

Wilson, J.P. , *et al.* , 2021. A five-star guide for achieving replicability and reproducibility when working with gis software and algorithms. Annals of the American Association of Geographers, 111 (5), 1311–1317.

Workman, S. , Souvenir, R. , and Jacobs, N. , 2015. Wide-area image geolocalization with aerial reference imagery. *In*: *Proceedings of the IEEE International Conference on Computer Vision* . 3961–3969.

Yao, X. , *et al.* , 2020. Spatial origin-destination flow imputation using graph convolutional networks. IEEE Transactions on Intelligent Transportation Systems, 22 (12), 7474–7484.

Yin, D. , *et al.* , 2017. A cybergis-jupyter framework for geospatial analytics at scale. *In*: *Proceedings of the Practice and Experience in Advanced Research Computing on Sustainability, Success and Impact* . 1–8.

Zhou, F. , *et al.* , 2021. Land deformation prediction via slope-aware graph neural networks. In: AAAI Conference on Artificial Intelligence. vol. 35, 15033–15040.

Zhu, D. , *et al.* , 2021. Spatial regression graph convolutional neural networks: A deep learning paradigm for spatial multivariate distributions. GeoInformatica, 26, 645–676.

Privacy and Ethics in GeoAI

Acar, A. , *et al.* , 2018. A survey on homomorphic encryption schemes: Theory and implementation. ACM Computing Surveys, 51 (4), 1–35.

Adams, B. and Janowicz, K. , 2012. On the geo-indicativeness of non-georeferenced text. *In*: *Proceedings of the International AAAI Conference on Web and Social Media* . vol. 6, 375–378.

Alanwar, A. , *et al.* , 2017. Proloc: Resilient localization with private observers using partial homomorphic encryption. *In*: *Proceedings of the 16th ACM/IEEE International Conference on Information Processing in Sensor Networks* . 41–52.

Andrés, M.E. , *et al.* , 2013. Geo-indistinguishability: Differential privacy for location-based systems. *In*: *Proceedings of the 2013 ACM SIGSAC Conference on Computer & Communications Security* . 901–914.

Armstrong, M.P. , Rushton, G. , and Zimmerman, D.L. , 1999. Geographically masking health data to preserve confidentiality. Statistics in Medicine, 18 (5), 497–525.

Armstrong, M.P. , Tsou, M.H. , and Seidl, D.E. , 2018. 1.28-geoprivacy. *In*: Comprehensive Geographic Information Systems. Elsevier Inc, 415–430.

Arumugam, S. and Bhargavi, R. , 2019. A survey on driving behavior analysis in usage based insurance using big data. Journal of Big Data, 6, 1–21.

Beckman, R.J. , Baggerly, K.A. , and McKay, M.D. , 1996. Creating synthetic baseline populations. Transportation Research Part A: Policy and Practice, 30 (6), 415–429.

Boerman, S.C. , Kruikemeier, S. , and Zuiderveen Borgesius, F.J. , 2017. Online behavioral advertising: A literature review and research agenda. Journal of Advertising, 46 (3), 363–376.

Brunila, M. , *et al.* , 2022. Drift: E2ee spatial feature sharing & instant messaging. *In*: *Proceedings of the 6th ACM SIGSPATIAL International Workshop on Location-Based Recommendations, Geosocial Networks and Geoadvertising* . 1–11.

Burgess, M. , 2022. How gdpr is failing. *Wired Magazine*.

Charleux, L. and Schofield, K. , 2020. True spatial k-anonymity: Adaptive areal elimination vs. adaptive areal masking. Cartography and Geographic Information Science, 47 (6), 537–549.

Clarke, R. , 2009. Privacy impact assessment: Its origins and development. Computer Law & Security Review, 25 (2), 123–135.

Crawford, K. and Schultz, J. , 2014. Big data and due process: Toward a framework to redress predictive privacy harms. BCL Rev., 55, 93.

Cunningham, T. , Cormode, G. , and Ferhatosmanoglu, H. , 2021. Privacy-preserving synthetic location data in the real world. *In*: *17th International Symposium on Spatial and Temporal Databases* . 23–33.

Dakalbab, F. , *et al.* , 2022. Artificial intelligence & crime prediction: A systematic literature review. Social Sciences & Humanities Open, 6 (1), 100342.

Dhar, S. and Varshney, U. , 2011. Challenges and business models for mobile location-based services and advertising. Communications of the ACM, 54 (5), 121–128.

Dobson, J.E. and Fisher, P.F. , 2003. Geoslavery. IEEE Technology and Society Magazine, 22 (1), 47–52.

Dressel, J. and Farid, H. , 2018. The accuracy, fairness, and limits of predicting recidivism. Science Advances, 4 (1), eaao5580.

Dubber, M.D. , Pasquale, F. , and Das, S. , 2020. The Oxford Handbook of Ethics of AI. Oxford Handbooks.

Dwork, C. , 2006. Differential privacy. *In*: *Automata, Languages and Programming: 33rd International Colloquium, ICALP 2006, Venice, Italy, July 10-14, 2006, Proceedings, Part II 33* . Springer, 1–12.

Finn, R.L. , Wright, D. , and Friedewald, M. , 2013. Seven types of privacy. European Data Protection: Coming of Age, 3–32.

Fontes, C. , *et al.* , 2022. Ai-powered public surveillance systems: why we (might) need them and how we want them. Technology in Society, 71, 102137.

Gambs, S. , Killijian, M.O. , and del Prado Cortez, M.N. , 2014. De-anonymization attack on geolocated data. Journal of Computer and System Sciences, 80 (8), 1597–1614.

Ghinita, G. , *et al.* , 2010. A reciprocal framework for spatial k-anonymity. Information Systems, 35 (3), 299–314.

Grekousis, G. and Liu, Y. , 2021. Digital contact tracing, community uptake, and proximity awareness technology to fight covid-19: a systematic review. Sustainable Cities and Society,

71, 102995.
Griffith, D.A. , 2018. Uncertainty and context in geography and giscience: reflections on spatial autocorrelation, spatial sampling, and health data. Annals of the American Association of Geographers, 108 (6), 1499–1505.
Guha, S. , *et al.* , 2012. Koi: A location-privacy platform for smartphone apps. *In*: NSDI. vol. 12, 14.
Harmanci, A. and Gerstein, M. , 2016. Quantification of private information leakage from phenotype-genotype data: linking attacks. Nature Methods, 13 (3), 251–256.
Hasan, R. , *et al.* , 2020. Automatically detecting bystanders in photos to reduce privacy risks. *In* : *2020 IEEE Symposium on Security and Privacy (SP)* . IEEE, 318–335.
Hojati, M. , *et al.* , 2021. Decentralized geoprivacy: leveraging social trust on the distributed web. International Journal of Geographical Information Science, 35 (12), 2540–2566.
Janowicz, K. , *et al.* , 2019. Using semantic signatures for social sensing in urban environments. *In*: Mobility Patterns, Big Data and Transport Analytics. Elsevier, 31–54.
Jiang, H. , *et al.* , 2021. Location privacy-preserving mechanisms in location-based services: A comprehensive survey. ACM Computing Surveys, 54 (1), 1–36.
Jiang, J. , *et al.* , 2019. A survey on location privacy protection in wireless sensor networks. Journal of Network and Computer Applications, 125, 93–114.
Jobin, A. , Ienca, M. , and Vayena, E. , 2019. The global landscape of ai ethics guidelines. Nature Machine Intelligence, 1 (9), 389–399.
Kamel Boulos, M.N. , Peng, G. , and VoPham, T. , 2019. An overview of geoai applications in health and healthcare. International Journal of Health Geographics, 18, 1–9.
Keßler, C. and McKenzie, G. , 2018. A geoprivacy manifesto. Transactions in GIS, 22 (1), 3–19.
Kim, J.W. , *et al.* , 2021. A survey of differential privacy-based techniques and their applicability to location-based services. Computers & Security, 111, 102464.
Kounadi, O. and Leitner, M. , 2014. Why does geoprivacy matter? the scientific publication of confidential data presented on maps. Journal of Empirical Research on Human Research Ethics, 9 (4), 34–45.
Kounadi, O. and Leitner, M. , 2016. Adaptive areal elimination (aae): A transparent way of disclosing protected spatial datasets. Computers, Environment and Urban Systems, 57, 59–67.
Kounadi, O. , *et al.* , 2020. A systematic review on spatial crime forecasting. Crime Science, 9 (1), 1–22.
Kumar, D. and Jakhar, S.D. , 2022. Artificial intelligence in animal surveillance and conservation. Impact of Artificial Intelligence on Organizational Transformation, 73–85.
Liu, B. , *et al.* , 2018. Location privacy and its applications: A systematic study. IEEE Access, 6, 17606–17624.
Liu, Y. , *et al.* , 2017. Point-of-interest demand modeling with human mobility patterns. *In*: *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* . 947–955.
Mayson, S.G. , 2019. Bias in, bias out. The Yale Law Journal, 128 (8), 2218–2300.
McKenzie, G. , Janowicz, K. , and Seidl, D. , 2016. Geo-privacy beyond coordinates. *In*: *Geospatial Data in a Changing World: Selected Papers of the 19th AGILE Conference on Geographic Information Science* . Springer, 157–175.
McKenzie, G. and Mwenda, K. , 2021. Identifying regional variation in place visit behavior during a global pandemic. Journal of Spatial Information Science, 1 (23), 95–124.
McKenzie, G. , *et al.* , 2022. Privyto: A privacy-preserving location-sharing platform. *Transactions in GIS*.
Mittelstadt, B. , 2019. Principles alone cannot guarantee ethical ai. Nature Machine Intelligence, 1 (11), 501–507.
Mökander, J. and Floridi, L. , 2021. Ethics-based auditing to develop trustworthy ai. Minds and Machines, 31 (2), 323–327.
Munir, K. , *et al.* , 2019. Cancer diagnosis using deep learning: a bibliographic review. Cancers, 11 (9), 1235.
Munjal, K. and Bhatia, R. , 2022. A systematic review of homomorphic encryption and its contributions in healthcare industry. Complex & Intelligent Systems, 1–28.
Naik, N. , *et al.* , 2022. Legal and ethical consideration in artificial intelligence in healthcare: who takes responsibility? Frontiers in Surgery, 266.

Narayanan, A. and Shmatikov, V. , 2008. Robust de-anonymization of large sparse datasets. *In* : *2008 IEEE Symposium on Security and Privacy (sp 2008)* . IEEE, 111–125.
Naylor, C.D. , 2018. On the prospects for a (deep) learning health care system. JAMA, 320 (11), 1099–1100.
Nelson, T. , Goodchild, M. , and Wright, D. , 2022. Accelerating ethics, empathy, and equity in geographic information science. Proceedings of the National Academy of Sciences, 119 (19), e2119967119.
Nikolenko, S.I. , 2021. Synthetic Data for Deep Learning. vol. 174. Springer.
Olteanu, A.M. , *et al.* , 2016. Quantifying interdependent privacy risks with location data. IEEE Transactions on Mobile Computing, 16 (3), 829–842.
Pan, X. , *et al.* , 2020. Privacy risks of general-purpose language models. *In*: *2020 IEEE Symposium on Security and Privacy (SP)* . IEEE, 1314–1331.
Pedersen, D.M. , 1979. Dimensions of privacy. Perceptual and Motor Skills, 48 (3_suppl), 1291–1297.
Pensa, R.G. , Di Blasi, G. , and Bioglio, L. , 2019. Network-aware privacy risk estimation in online social networks. Social Network Analysis and Mining, 9, 1–15.
Rao, J. , *et al.* , 2020. LSTM-TrajGAN: A Deep Learning Approach to Trajectory Privacy Protection. *In*: K. Janowicz and J.A. Verstegen , eds. 11th International Conference on Geographic Information Science (GIScience 2021) - Part I, Dagstuhl, Germany. Schloss Dagstuhl–Leibniz-Zentrum für Informatik, Leibniz International Proceedings in Informatics (LIPIcs), vol. 177, 12:1–12:17. Available from: https://drops.dagstuhl.de/opus/volltexte/2020/13047.
Rao, J. , *et al.* , 2021. A privacy-preserving framework for location recommendation using decentralized collaborative machine learning. Transactions in GIS, 25 (3), 1153–1175.
Ribeiro-Navarrete, S. , Saura, J.R. , and Palacios-Marqués, D. , 2021. Towards a new era of mass data collection: Assessing pandemic surveillance technologies to preserve user privacy. Technological Forecasting and Social Change, 167, 120681.
Richardson, D.B. , *et al.* , 2015. Replication of scientific research: addressing geoprivacy, confidentiality, and data sharing challenges in geospatial research. Annals of GIS, 21 (2), 101–110.
Riederer, C. , *et al.* , 2016. Linking users across domains with location data: Theory and validation. *In*: *Proceedings of the 25th International Conference on World Wide Web* . 707–719.
Seidl, D.E. , Jankowski, P. , and Tsou, M.H. , 2016. Privacy and spatial pattern preservation in masked gps trajectory data. International Journal of Geographical Information Science, 30 (4), 785–800.
Stahl, B.C. and Wright, D. , 2018. Ethics and privacy in ai and big data: Implementing responsible research and innovation. IEEE Security & Privacy, 16 (3), 26–33.
Stevens, R. , *et al.* , 2012. Investigating user privacy in android ad libraries. *In*: Workshop on Mobile Security Technologies (MoST). vol. 10, 195–197.
Sun, G. , *et al.* , 2019. Location privacy preservation for mobile users in location-based services. IEEE Access, 7, 87425–87438.
Swanlund, D. , Schuurman, N. , and Brussoni, M. , 2020. Maskmy. xyz: An easy-to-use tool for protecting geoprivacy using geographic masks. Transactions in GIS, 24 (2), 390–401.
Sweeney, L. , 2002. k-anonymity: A model for protecting privacy. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 10 (05), 557–570.
Thompson, S.A. and Warzel, C. , 2019. Twelve million phones, one dataset, zero privacy. *In*: Ethics of Data and Analytics. Auerbach Publications, 161–169.
Tobler, W.R. , 1970. A computer movie simulating urban growth in the detroit region. Economic Geography, 46 (sup1), 234–240.
Vaishya, R. , *et al.* , 2020. Artificial intelligence (ai) applications for covid-19 pandemic. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14 (4), 337–339.
Verhelst, H.M. , Stannat, A. , and Mecacci, G. , 2020. Machine learning against terrorism: how big data collection and analysis influences the privacy-security dilemma. Science and Engineering Ethics, 26, 2975–2984.
VoPham, T. , *et al.* , 2018. Emerging trends in geospatial artificial intelligence (geoai): potential applications for environmental epidemiology. Environmental Health, 17 (1), 1–6.
Wang, Q. , *et al.* , 2019. Learning from synthetic data for crowd counting in the wild. *In*: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* .

8198–8207.
Wang, R. , *et al.* , 2016. A de-anonymization attack on geo-located data considering spatio-temporal influences. *In*: *Information and Communications Security: 17th International Conference, ICICS 2015, Beijing, China, December 9–11, 2015, Revised Selected Papers 17* . Springer, 478–484.
Zhang, H. , *et al.* , 2010. Privacy issues and user attitudes towards targeted advertising: A focus group study. *In*: Proceedings of the Human Factors and Ergonomics Society Annual Meeting. SAGE Publications Sage CA: Los Angeles, CA, vol. 54, 1416–1420.
Zhang, H. and McKenzie, G. , 2022. Rehumanize geoprivacy: from disclosure control to human perception. GeoJournal, 1–20.
Zhao, B. , *et al.* , 2021. Deep fake geography? when geospatial data encounter artificial intelligence. Cartography and Geographic Information Science, 48 (4), 338–352.
Zhong, Y. , *et al.* , 2015. You are where you go: Inferring demographic attributes from location check-ins. *In*: *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining* . 295–304.

A Humanistic Future of GeoAI

Anika Berger , Teresa Schofield , Amy Pickens , Johannes Reiche , and Y. Gou , 2022. Looking for the quickest signal of deforestation? Turn to GFW's integrated alerts. *Global Forest Watch* .
Buolamwini, J. , and T. Gebru . 2018. Gender shades: Intersectional accuracy disparities in commercial gender classification. In Proceedings of the 1st Conference on Fairness, Accountability and Transparency, eds. A. F. Sorelle and W. Christo , 77–91. Proceedings of Machine Learning Research: PMLR.
Esri-AAG , 2023. GeoMentors - supporting K-12 geography and GIS education.
Foderaro, L. W. , 2017. Navigation apps are turning quiet neighborhoods into traffic nightmares. *The New York Times*.
Heaven, W. D. , 2020. Predictive policing algorithms are racist. They need to be dismantled. *MIT Technology Review*.
Huang, Z. , 2021. AI in urban planning: 3 ways it will strengthen how we plan for the future. *Urban Redevelopment Authority* .
Joseph, D. , 2018. How Red Cross uses data during global disasters. *Mapillary* .
Labbe, M. , 2021. Energy consumption of AI poses environmental problems. *TechTarget* .
Mcilwain, C. , 2020. AI has exacerbated racial bias in housing. Could it help eliminate it instead? *MIT Technology Review*.
Michaux, S. , 2019. Farming for the future: UGA leads the way in precision agriculture. *University of Georgia Research* .
Microsoft , 2023. Using AI for good with Microsoft AI.
Netzley, L. , 2023. Artificial intelligence used to reduce traffic congestion. *Downtown Los Angeles News*.
Torres, D. L. , J. N. Turnes , P. J. Soto Vega , R. Q. Feitosa , D. E. Silva , J. Marcato Junior , and C. Almeida , 2021. Deforestation detection with fully convolutional networks in the Amazon forest from Landsat-8 and Sentinel-2 images. Remote Sensing, 13 (24), 5084.
Uddin, K. , M. A. Matin , and F. J. Meyer , 2019. Operational flood mapping using multi-temporal Sentinel-1 SAR images: A case study from Bangladesh. Remote Sensing, 11 (13), 1581.
USGIF , 2023. USGIF K-12 educational outreach. Accessed on March 31 2023, available from https://usgif.org/k-12.
Weston, M. A. , C. O'Brien , K. N. Kostoglou , and M. R. E. Symonds , 2020. Escape responses of terrestrial and aquatic birds to drones: Towards a code of practice to minimize disturbance. Journal of Applied Ecology, 57 (4), 777–785.
Women+ in Geospatial , 2023. Accessed on March 31 2023, available from https://womeningeospatial.org.
Zastrow, M. , 2014. Crisis mappers turn to citizen scientists. Nature, 515 (7527), 321–321.
Zhao, B. , 2022. Humanistic GIS: Toward a research agenda. Annals of the American Association of Geographers, 112 (6), 1576–1592.

Fast Forward from Data to Insight: (Geographic) Knowledge Graphs and Their Applications

Allemang, D. and Hendler, J. , 2011. Semantic Web for the Working Ontologist: Effective Modeling in RDFs and OWL. Elsevier.

Amini, R. , Zhou, L. , and Hitzler, P. , 2020. Geolink cruises: A non-synthetic benchmark for co-reference resolution on knowledge graphs. *In*: *Proceedings of the 29th ACM International Conference on Information & Knowledge Management* . 2959–2966.

Baranzini, S. , *et al.* , 2022. A biomedical open knowledge network harnesses the power of ai to understand deep human biology. AI Magazine, 43 (1), 46–58.

Battle, R. and Kolas, D. , 2011. Geosparql: enabling a geospatial semantic web. Semantic Web Journal, 3 (4), 355–370.

Bizer, C. , Heath, T. , and Berners-Lee, T. , 2011. Linked data: The story so far. *In*: Semantic Services, Interoperability and Web Applications: Emerging Concepts. IGI global, 205–227.

Bordes, A. , *et al.* , 2013. Translating embeddings for modeling multi-relational data. Advances in Neural Information Processing Systems, 26.

Cox, S. , *et al.* , 2017. Time ontology in owl. W3C Recommendation, 19.

Fisher, J. , *et al.* , 2020. Debiasing knowledge graph embeddings. *In*: *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)* . 7332–7345.

Frank, A.U. , 1997. Spatial ontology: A geographical information point of view. Spatial and Temporal Reasoning, 135–153.

Gangemi, A. and Presutti, V. , 2009. Ontology design patterns. *In*: Handbook on Ontologies. Springer, 221–243.

Hart, G. and Dolbear, C. , 2013. Linked Data: A Geographic Perspective. Taylor & Francis.

Hitzler, P. and Krisnadhi, A. , 2016. On the roles of logical axiomatizations for ontologies. *In*: P. Hitzler , A. Gangemi , K. Janowicz , A. Krisnadhi and V. Presutti , eds. Ontology Engineering with Ontology Design Patterns - Foundations and Applications. Studies on the Semantic Web, vol. 25. IOS Press, 73–80.

Hitzler, P. , Krotzsch, M. , and Rudolph, S. , 2009. Foundations of Semantic Web Technologies. CRC Press.

Hogan, A. , *et al.* , 2021. Knowledge graphs. ACM Computing Surveys (CSUR), 54 (4), 1–37.

Hu, Y. , 2018. Geo-text data and data-driven geospatial semantics. Geography Compass, 12 (11), e12404.

Hu, Y. , *et al.* , 2013. A geo-ontology design pattern for semantic trajectories. *In*: Spatial Information Theory: 11th International Conference, COSIT 2013, Scarborough, UK, September 2-6, 2013. Proceedings 11. Springer, 438–456.

Janowicz, K. , *et al.* , 2019. Sosa: A lightweight ontology for sensors, observations, samples, and actuators. Journal of Web Semantics, 56, 1–10.

Janowicz, K. , *et al.* , 2022. Know, know where, knowwheregraph: A densely connected, cross-domain knowledge graph and geo-enrichment service stack for applications in environmental intelligence. AI Magazine, 43 (1), 30–39.

Janowicz, K. , *et al.* , 2012. Geospatial semantics and linked spatiotemporal data–past, present, and future. Semantic Web, 3 (4), 321–332.

Janowicz, K. , *et al.* , 2015. Why the data train needs semantic rails. AI Magazine, 36 (1), 5–14.

Janowicz, K. , *et al.* , 2018. Debiasing knowledge graphs: Why female presidents are not like female popes. *In*: *ISWC (P&D/Industry/BlueSky)*.

Johnson, J.M. , *et al.* , 2022. Knowledge graphs to support real-time flood impact evaluation. AI Magazine, 43 (1), 40–45.

Kuhn, W. , 2005. Geospatial semantics: why, of what, and how? *In*: Journal on Data Semantics III. Springer, 1–24.

Kuhn, W. , *et al.* , 2021. The semantics of place-related questions. Journal of Spatial Information Science, (23), 157–168.

Kuhn, W. , Kauppinen, T. , and Janowicz, K. , 2014. Linked data-a paradigm shift for geographic information science. *In*: Geographic Information Science: 8th International Conference, GIScience 2014, Vienna, Austria, September 24-26, 2014. Proceedings 8. Springer, 173–186.

Lehmann, J. , *et al.* , 2015. Dbpedia–a large-scale, multilingual knowledge base extracted from wikipedia. Semantic Web, 6 (2), 167–195.

Li, W. , Song, M. , and Tian, Y. , 2019. An ontology-driven cyberinfrastructure for intelligent spatiotemporal question answering and open knowledge discovery. ISPRS International Journal of Geo-Information, 8 (11), 496.

Li, W. , *et al.* , 2023. Geographvis: a knowledge graph and geovisualization empowered cyberinfrastructure to support disaster response and humanitarian aid. ISPRS International Journal of Geo-Information, 12 (3), 112.

Mai, G. , *et al.* , 2022. Symbolic and subsymbolic geoai: Geospatial knowledge graphs and spatially explicit machine learning. Transactions in GIS, 26 (8), 3118–3124.

Mai, G. , *et al.* , 2020. Se-kge: A location-aware knowledge graph embedding model for geographic question answering and spatial semantic lifting. Transactions in GIS, 24 (3), 623–655.

Polleres, A. , *et al.* , 2020. A more decentralized vision for linked data. Semantic Web, 11 (1), 101–113.

Purves, R.S. , *et al.* , 2018. Geographic information retrieval: Progress and challenges in spatial search of text. Foundations and Trends in Information Retrieval, 12 (2-3), 164–318.

Scheider, S. and Kuhn, W. , 2015. How to talk to each other via computers: Semantic interoperability as conceptual imitation. Applications of Conceptual Spaces: The Case for Geometric Knowledge Representation, 97–122.

Scheider, S. , *et al.* , 2020. Ontology of core concept data types for answering geo-analytical questions. Journal of Spatial Information Science, (20), 167–201.

Shbita, B. , *et al.* , 2020. Building linked spatio-temporal data from vectorized historical maps. *In* : The Semantic Web: 17th International Conference, ESWC 2020, Heraklion, Crete, Greece, May 31–June 4, 2020, Proceedings 17. Springer, 409–426.

Shimizu, C. , *et al.* , 2022. Ontology design facilitating Wikibase integration – and a worked example for historical data. CoRR, abs/2205.14032.

Shimizu, C. , Hammar, K. , and Hitzler, P. , 2023. Modular ontology modeling. Semantic Web, 14 (3), 459–489.

Shimizu, C. , *et al.* , 2020. The enslaved ontology: Peoples of the historic slave trade. J. Web Semant., 63, 100567.

Smith, B. and Mark, D.M. , 2001. Geographical categories: an ontological investigation. International Journal of Geographical Information Science, 15 (7), 591–612.

Stadler, C. , *et al.* , 2012. Linkedgeodata: A core for a web of spatial open data. Semantic Web, 3 (4), 333–354.

Vrandečić, D. and Krötzsch, M. , 2014. Wikidata: a free collaborative knowledgebase. Communications of the ACM, 57 (10), 78–85.

Vrandečić, D. , Pintscher, L. , and Krötzsch, M. , 2023. Wikidata: The making of. *In: Companion Proceedings of the ACM Web Conference 2023* . 615–624.

Wang, Q. , *et al.* , 2017. Knowledge graph embedding: A survey of approaches and applications. IEEE Transactions on Knowledge and Data Engineering, 29 (12), 2724–2743.

Wiafe-Kwakye, K. , Hahmann, T. , and Beard, K. , 2022. An ontology design pattern for spatial and temporal aggregate data (stad).

Wilkinson, M.D. , *et al.* , 2016. The fair guiding principles for scientific data management and stewardship. Scientific Data, 3 (1), 1–9.

Yan, B. , *et al.* , 2017. From itdl to place2vec: Reasoning about place type similarity and relatedness by learning embeddings from augmented spatial contexts. *In*: *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* . 1–10.

Zacharopoulou, D. , *et al.* , 2022. A web-based application to support the interaction of spatial and semantic representation of knowledge. AGILE: GIScience Series, 3, 70.

Zhu, R. , *et al.* , 2021. Providing humanitarian relief support through knowledge graphs. *In*: *Proceedings of the 11th on Knowledge Capture Conference* . 285–288.

Zhu, R. , *et al.* , 2016. Spatial signatures for geographic feature types: Examining gazetteer ontologies using spatial statistics. Transactions in GIS, 20 (3), 333–355.

Zhu, R. , *et al.* , 2022. Covid-forecast-graph: An open knowledge graph for consolidating covid-19 forecasts and economic indicators via place and time. AGILE: GIScience Series, 3, 21.

Goodchild, M. , 2001. Issues in spatially explicit modeling. *In*: D.C. Parker , T. Berger and S.M. Manson , eds. Agent-Based Models of Land-Use and Land-Cover Change Report and Review of an International Workshop, October. 12–15.

Janowicz, K. , *et al.* , 2020. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science, 34 (4), 625–636.

Lunga, D. , *et al.* , 2022. GeoAI at ACM SIGSPATIAL: The New Frontier of Geospatial Artificial Intelligence Research. SIGSPATIAL Special, 13 (3), 21–32.

Richarson, L.F. , 1961. The problem of contiguity: An appendix to statistics of deadly quarrels. General Systems Yearbook, 6, 139–187.

Wang, W. , *et al.* , 2022. Image as a Foreign Language: BEiT Pretraining for All Vision and Vision-Language Tasks. arXiv:2208.10442.