Innovation Management Practices, 2025, 1(1), 0000093
https://doi.org/10.71204/xphyk512

A Survey of Non-radial Directional Distance Function and Global Malmquist-Luenberger Index in Assessing Carbon Emission Performance of Urban Agglomerations

Ruotian Zhuang[1,*]

[1]School of Economics & Management, Tongji University, Shanghai 200092, China; 2230477@tongji.edu.cn

*** Correspondence:**

Ruotian Zhuang

2230477@tongji.edu.cn

Received: 13 March 2025/Accepted: 21 March /Published online: 25 March 2025

Abstract

This survey paper explores an advanced analytical framework that integrates non‑ radial directional distance functions (NDDF) and the Global Malmquist‑ Luenberger (GML) index to assess carbon emission performance and environmental efficiency in urban agglomerations. The study underscores the significance of evaluating carbon emissions, given the substantial contribution of urban centers to global greenhouse gas emissions. By accommodating undesirable outputs, NDDF offer a comprehensive assessment of environmental productivity — crucial for effective policy formulation in urban settings. Integration with the GML index enhances the evaluation of green total factor productivity, offering insights into the interplay between economic growth and environmental sustainability. The paper outlines the methodological framework and discusses case studies that illustrate the practical application of these tools in Chinese urban agglomerations. Challenges such as data availability, methodological limitations, and the integration of socioeconomic factors are addressed, highlighting the need for refined methodologies and policy innovations. The findings emphasize the importance of technological advancements and targeted policies in promoting sustainable urban development. By leveraging these methodologies, urban planners and policymakers can develop effective strategies to enhance environmental efficiency and support the transition towards sustainable urban futures.

Keywords: Carbon Emissions; National Urban Agglomerations; Non-Radial Directional Distance Function; Gml Index

1. Introduction

Urban agglomerations are major sources of greenhouse gas emissions, contributing roughly 70% of global emissions. Assessing carbon emission performance in these areas is important for sustainable development. The rapid growth of urban populations and infrastructures has increased the need for improved methods to monitor productivity changes and evaluate the environmental impacts of urban growth (Wang et al., 2019; Olawumi and Chan, 2018; Liora et al., 2022). In response to these challenges, this study applies non-radial directional distance functions (NDDF) and the Global Malmquist-Luenberger (GML) index to provide a more detailed evaluation of carbon emissions and environmental efficiency in urban settings. Prior research has shown that traditional models do not fully capture the complexity of urban dynamics, particularly when both desirable outputs (such as economic growth) and undesirable outputs (such as carbon emissions) are considered.

This work makes a clear theoretical contribution by integrating NDDF with the GML index, thereby building on and refining existing productivity frameworks. The combined approach offers a fresh perspective on how economic activities and environmental factors interact in urban agglomerations, providing a more accurate analysis of performance than earlier methods. On the practical side, the findings of this study offer actionable insights for urban planners and policymakers. By identifying key drivers of carbon emissions and environmental inefficiencies, the research supports the design of strategies to reduce emissions, improve resource use, and guide sustainable urban development. These results are especially useful for cities facing rapid growth and environmental challenges, as they can inform policy measures aimed at achieving carbon neutrality and better managing urban expansion.

2. Background and Core Concepts

2.1. Global Malmquist-Luenberger Index

The Global Malmquist-Luenberger (GML) index uniquely incorporates both desirable and undesirable outputs (e.g., carbon emissions) into productivity analyses, offering a nuanced evaluation of efficiency and productivity changes over time (Li et al., 2020; Han et al., 2017). Originally defined by Oh (2010) and building on earlier Malmquist indices (Färe et al., 1994), the GML index provides a comprehensive understanding of environmental productivity and reflects the economic and environmental dynamics inherent in urban settings. By assessing green total factor productivity (GTFP), the GML index integrates energy inputs and environmental pollution, thereby establishing a robust framework for evaluating urban environmental efficiency.

2.2. Interrelationship and Significance in Urban Agglomerations

Urban agglomerations in China, characterized by dense populations and concentrated economic activities, present unique challenges and opportunities for sustainable development. By incorporating undesirable outputs such as carbon emissions, the GML index serves as a comprehensive tool for assessing environmental efficiency and identifying inefficiencies in total factor productivity growth (Li et al., 2020). Direct applications of NDDF in urban energy contexts have been demonstrated by Zhang et al. (2013) and Zhou et al. (2012). Modifications to the basic approach have been proposed by Meng (2019) and Wu et al. (2020), while theoretical advancements linking NDDF with slacks-based measures are provided by Färe and Grosskopf (2010), Färe et al. (2007), and Zhang et al. (2014).

3. Methodological Framework

The methodological framework is crucial to understanding the complexities of Chinese urban agglomerations. Table 1 outlines how NDDF and the GML index are integrated to assess environmental efficiency. Additionally, a comparative overview (as Table 2) highlights the systematic data utilization and holistic methods inherent in these approaches.

Table 1. A synergistic framework for evaluating carbon emission performance and environmental efficiency in urban agglomerations, integrating NDDF and the GML index

Category	Feature	Method
Synergistic Framework for Urban Agglomerations	Environmental Evaluation	NDDF, GML

Table 2. Key benchmarks used in evaluating environmental efficiency and productivity across Chinese urban agglomerations

Benchmark	Size	Domain	Task Format	Metric
GML	561	Environmental Economics	Productivity Measurement	Green Productivity Growth
NDDF	30	Power Generation	Efficiency Evaluation	CO_2 Emissions, Resource Use
MF-NDDF	17	Port Enterprises	Performance Assessment	Carbon Emission Performance

3.1. Integration of Non-Radial Directional Distance Functions

Integrating NDDF involves a systematic process that begins by identifying decision-making units (DMUs) such as cities or provinces and collecting relevant input–output data (Wang et al., 2019). NDDF effectively incorporate both desirable and undesirable outputs, offering a comprehensive assessment of environmental efficiency. They enable analysis of complex relationships between economic activities and environmental impacts by projecting DMUs onto an efficient frontier using exogenous and endogenous directional vectors. Foundational contributions by Chambers et al. (1996), Färe et al. (1989), and Färe et al. (1996), along with Chung et al. (1997), underpin the approach. Extensions linking NDDF with slacks-based measures are provided by Färe and Grosskopf (2010), while further modifications are proposed by Meng (2019), Wu et al. (2020), Färe et al. (2007), and Zhang et al. (2014). Lozano and Soltani (2018) further illustrate a lexicographic approach within the NDDF framework.

3.2. Synergistic Framework for Urban Agglomerations

Combining NDDF with the GML index offers a comprehensive method for evaluating carbon emission performance and environmental efficiency in Chinese urban agglomerations. By integrating NDDF—which account for multiple outputs, including undesirable ones—with the GML index—which measures green productivity growth—the framework captures the complex interplay between economic activities and environmental impacts (Li et al., 2020; Han et al., 2017). This synergistic approach enables policymakers to identify inefficiencies and design targeted strategies to enhance urban sustainability.

4. Carbon Emission Performance in Urban Agglomerations

4.1. Current State of Carbon Emissions

Carbon emission profiles in urban agglomerations exhibit significant heterogeneity due to interactions among technological, economic, and infrastructural factors. Li et al. (2020) identified sectoral variations in productivity changes—especially in carbon-intensive industries—while Tao et al. (2017) demonstrated that technological innovation is a primary driver of performance. Green innovation efficiency further influences emission performance (Zhong et al., 2024).

4.2. Factors Influencing Carbon Emissions

Urban carbon emissions are influenced by economic, technological, and infrastructural factors. Urban sprawl increases emissions by promoting inefficient land use and higher energy demands (Zhou et al., 2012). In contrast, compact urban forms reduce emissions by lowering travel distances and enhancing public transit efficiency. Technological advancements, including cleaner production processes and renewable energy adoption, are crucial for reducing emissions (Shakhbulatov et al., 2019). Additionally, socioeconomic factors—such as higher income levels that lead to increased consumption—contribute to larger carbon footprints (Liora et al., 2022).

4.3. Role of Urban Agglomerations in National Carbon Footprint

Chinese urban agglomerations are central to the national carbon landscape due to their concentrated industrial production, transportation, and energy consumption (Li et al., 2020). Oliveira et al. (2014) identified a super linear scaling relationship between urban population size and carbon emissions. Advances in high-resolution mapping (Liu et al., 2024) and spatiotemporal analysis (Shi et al., 2024) provide further insights into emission patterns. Spatial pattern studies (Yu et al., 2024) and methodologies for inventorying emissions (Kennedy et al., 2010; Meng et al., 2014) enhance our understanding of urban contributions to national emissions.

4.4. Evaluating Carbon Emission Performance Using NDDF and GML

The integration of NDDF and the GML index offers a robust framework for evaluating carbon emission performance. NDDF capture both desirable economic outputs and undesirable environmental outputs, while the GML index (Oh, 2010) tracks dynamic changes in green productivity. Applications by Han et al. (2017) and Tao et al. (2017) have validated these methods. Moreover, decomposition analyses (Li et al., 2020; Qu et al., 2022) reveal key drivers of performance, supporting targeted policy interventions.

5. Environmental Efficiency and Sustainable Urban Development

5.1. Conceptualizing Environmental Efficiency

Environmental efficiency reflects an urban system's ability to optimize resource utilization while minimizing environmental impacts, particularly carbon emissions. It is closely linked to green total factor productivity (GTFP), which integrates static and dynamic performance while accounting for undesirable outputs (Chen et al., 2021). Accurate urban boundary definitions (Oliveira et al., 2014) and compact urban forms (Yao et al., 2022) are essential, as they help reduce biases in emissions data and promote lower energy consumption. The integration of NDDF with the GML index has advanced these assessments, providing insights into how economic activities and environmental sustainability interact (Han et al., 2017).

5.2. Factors Influencing Environmental Efficiency

Energy-efficient technologies in industries, buildings, and transportation systems significantly reduce urban carbon footprints (Wu et al., 2022). Regional differences in green innovation efficiency, as highlighted by Zhong et al. (2024), underscore the need for local innovation strategies. Digital technologies, such as blockchain, further enhance resource management and environmental data tracking (Shakhbulatov et al., 2019). Urban areas with service-oriented economies often demonstrate superior environmental efficiency compared to those reliant on heavy, resource-intensive industries (Li et al., 2020). While agglomeration economies can improve resource utilization, larger cities may also generate disproportionately higher emissions (Oliveira et al., 2014). Transitioning to less resource-intensive sectors is therefore key to improving overall efficiency (Tao et al., 2017). Compact urban forms reduce travel distances and support efficient public transit, leading to lower energy consumption and emissions (Yao et al., 2022). Well-developed transportation infrastructure further minimizes reliance on private vehicles, as shown by studies on urban logistics (Qu et al., 2022). Effective policies, including strict emission standards, energy regulations, and carbon pricing, drive improvements in urban environmental performance (Li et al., 2020). Financial incentives and integrated urban planning that coordinate land use, transportation, and economic strategies yield significant benefits (Tao et al., 2017; Yao et al., 2022).

5.3. Environmental Performance Measurement in Urban Agglomerations

Advanced methodologies that integrate NDDF with the GML index enable comprehensive evaluations of environmental efficiency in Chinese urban agglomerations. These methods reveal regional variations influenced by industrial structure, technological capacity, and policy frameworks. Studies have found that eastern coastal agglomerations tend to outperform central and western regions, with temporal trends showing steady improvements driven by innovation (Zhong et al., 2024; Tao et al., 2017; Oliveira et al., 2014).

5.4. Challenges and Opportunities in Environmental Efficiency Improvement

Despite significant methodological advances, challenges remain regarding data availability, inconsistent emissions inventories, and urban boundary definitions (Olawumi and Chan, 2018). Heterogeneity in economic structures and technological capacities requires tailored, region-specific approaches (Elmqvist et al., 2019). Technological innovations and comprehensive policy frameworks, combined with climate resilience strategies, offer promising avenues for future improvement.

6. Case Studies and Applications

This section reviews empirical applications of NDDF and the GML index within Chinese urban agglomerations to assess environmental efficiency and carbon emission performance.

6.1. Case Studies and Benchmarking

NDDF and the GML index have been applied to evaluate environmental efficiency and productivity across Chinese urban agglomerations. For example, Wang et al. (2019) demonstrated dynamic efficiency analyses, while Tao et al. (2017) assessed green total factor productivity in rapidly industrializing regions. Benchmark studies by Yang et al. (2019) and Li et al. (2020) illustrate these approaches.

6.2. Logistics Performance and Carbon Emissions in Yunnan Province

Yang et al. (2019) documented rising logistics-related carbon emissions in Yunnan Province, highlighting the challenge of traditional transport modes that elevate emissions. NDDF and the GML index have been used to assess logistics eco-efficiency, incorporating carbon emissions into performance evaluations. Strategies focus on optimizing logistics networks, adopting cleaner transportation technologies, and promoting intermodal solutions to align with low-carbon development goals. Zhu et al. (2019) underscore that enhancing rail and waterway infrastructure, coupled with smart logistics systems, can significantly reduce emissions.

6.3. Urban Agglomerations in China: A Decadal Analysis

A decade-long analysis of Chinese urban agglomerations reveals that clusters with high industrial activity tend to exhibit higher emissions, whereas service-oriented economies perform better environmentally (Li et al., 2020). Tao et al. (2017) identify technological innovation as a key driver of efficiency improvements, with eastern coastal agglomerations generally outperforming central and western regions. Cleaner production technologies and energy-efficient practices have contributed to notable emission reductions, supporting national decarbonization goals (Zhong et al., 2024). Policy interventions promoting compact urban forms and smart city initiatives further enhance environmental efficiency.

6.4. Benchmarking Environmental Efficiency in the Beijing-Tianjin-Hebei Region

Zhong et al. (2024) applied NDDF and the GML index to assess environmental efficiency in the Beijing-Tianjin-Hebei (BTH) region. Findings reveal that Beijing’s service-oriented economy yields superior efficiency compared to Tianjin and Hebei. Urban form and robust public transit are critical determinants; compact development and efficient transit systems in Beijing contribute significantly to its environmental performance. These insights support the design of targeted policies to mitigate industrial emissions and promote sustainable urban growth.

7. Challenges and Future Directions

Exploring the challenges and future directions in assessing environmental efficiency and carbon emission performance reveals a multifaceted landscape. As Chinese urban agglomerations expand, understanding these intricacies is vital for effective policy formulation and implementation. The following subsections address specific challenges and limitations in this field, emphasizing methodological hurdles and data-related issues for researchers and policymakers. Addressing these challenges is essential for establishing robust frameworks and innovative solutions to enhance urban sustainability.

7.1. Challenges and Limitations

Assessing environmental efficiency and carbon emission performance poses challenges due to the reliance on extensive data and significant computational resources required by methods like the GML index (Lozano and Soltani, 2018). Data availability and accuracy for undesirable outputs remain problematic (Han et al., 2017). Furthermore, disparities between core and peripheral cities and variations in regional infrastructure and economic conditions limit the generalizability of findings. Subjective semantic labels influenced by cultural variances also weaken reliability (Shakhbulatov et al., 2019). Moreover, focusing solely on CO_2 emissions, while neglecting other greenhouse gases, restricts the comprehensiveness of evaluations (Zhong et al., 2024).

7.2. Challenges in Measuring Carbon Emission Performance

Measuring carbon emission performance is complicated by the diversity of industrial processes and infrastructural differences across regions such as Yunnan Province (Liora et al., 2022; Oliveira et al., 2014; Qu et al., 2022). Limited and incomplete emissions data—especially in logistics sectors—further impede accurate assessments. Advanced spatial and remote sensing methodologies (Kennedy et al., 2010; Meng et al., 2014; Shan et al., 2022) and high-resolution emission databases (Cai et al., 2018; Chen et al., 2021) offer promising solutions for improving measurement precision.

7.3. Implications for Policy and Practice

Findings on carbon emission performance have significant policy implications. Integrating NDDF and the GML index provides a solid basis for evaluating environmental performance and informing targeted policies (Li et al., 2020; Han et al., 2017). These results underscore the need to promote technological innovation and cleaner production processes. Investments in renewable energy and energy-saving practices are crucial to reduce emissions and improve environmental efficiency. Urban planning that prioritizes compact development and efficient public transit can further reduce energy consumption. Additionally, addressing socioeconomic disparities through sustainable consumption policies is vital for equitable carbon reduction.

7.4. Future Directions and Policy Implications

Future research should focus on refining methodologies to overcome existing limitations and enhance sustainability outcomes. Leveraging cutting-edge technologies and expanding data collection are essential steps (Olawumi and Chan, 2018). Further improvements in the GML index and the incorporation of additional environmental factors will enrich model comprehensiveness and inform policy decisions (Färe et al., 1994). The integration of ICT in urban planning and the development of AI frameworks for carbon monitoring represent promising avenues. Expanding studies to include other pollutants and human capital factors, and refining index systems for green growth in resource-dependent cities, are important future directions. A holistic approach is critical, given that Chinese cities contribute significantly to national emissions and face mounting climate challenges (Kii, 2021; Elmqvist et al., 2019).

7.5. Data Availability and Quality

Reliable data are critical for evaluating environmental efficiency and carbon emissions. Limited access to precise statistics and inconsistent regional classifications complicate analyses (Olawumi and Chan, 2018; Klopp and Petretta, 2017; Lozano and Soltani, 2018). Obtaining accurate data on undesirable outputs is particularly challenging in areas with underdeveloped monitoring systems, potentially skewing assessments (Elmqvist et al., 2019; Tao et al., 2017; Cai et al., 2018; Qu et al., 2022). Enhanced monitoring systems and standardized reporting protocols are essential to improve data quality and support reliable evaluations.

7.6. Methodological Limitations

Although the combined NDDF and GML approaches are robust, they require extensive datasets and significant computational resources (Lozano and Soltani, 2018). Infeasibility issues with cross-period directional distance functions and the exclusion of critical productivity variables reduce measurement completeness, particularly in regions with limited energy statistics (Liora et al., 2022). Additionally, cultural variations in semantic labels and limitations in data granularity hinder consistency. These drawbacks underscore the need for continuous refinement of sustainability methods to address the challenges posed by rapid urbanization, climate risks, and socioeconomic inequalities (Bibri and Krogstie, 2017; Klopp and Petretta, 2017; Kii, 2021; Elmqvist et al., 2019; Huang and Jiang, 2017).

7.7. Integration of Socioeconomic and Lifestyle Factors

Integrating socioeconomic and lifestyle factors is essential for a comprehensive understanding of urban sustainability. Variables such as income, education, and employment significantly influence energy consumption and carbon footprints (Li et al., 2020). Higher income levels are often associated with increased consumption of energy-intensive goods, leading to larger carbon footprints. Understanding these relationships is vital for designing targeted, equitable interventions that promote sustainable behaviors (Han et al., 2017).

7.8. Urban Agglomeration Dynamics

Urban agglomerations evolve through complex interactions among economic activities, population trends, infrastructure development, and environmental impacts (Li et al., 2020). While dense urban areas benefit from shared resources, they also face greater environmental pressures. Compact urban forms and efficient public transit can mitigate these impacts (Yao et al., 2022). Moreover, technological innovations and effective governance are critical for driving low-carbon development, and socioeconomic disparities influence overall resource utilization.

https://doi.org/10.71204/xphyk512

7.9. Technological and Policy Innovations

Technological and policy innovations are central to enhancing urban environmental efficiency. The adoption of smart city technologies—such as digital platforms, ICT-based tools, and blockchain systems—improves urban services and resource management (Shakhbulatov et al., 2019). Transitioning to renewable energy sources significantly reduces fossil fuel reliance and carbon emissions (Han et al., 2017). Policy innovations, including strict emission standards, financial incentives, and integrated urban planning, are essential for sustainable development (Li et al., 2020; Yao et al., 2022).

8. Conclusion

The exploration of non-radial directional distance functions together with the Global Malmquist-Luenberger index underscores their pivotal role in assessing carbon emission performance and environmental efficiency within Chinese urban agglomerations. These methodologies provide a robust framework by incorporating both desirable and undesirable outputs, thereby offering a comprehensive understanding of urban environmental dynamics and productivity evolution. The research emphasizes the critical need for improved production efficiency to enhance the impact of environmental policies and advance sustainable urban development.

The study highlights the importance of implementing targeted interventions and policy reforms to address high-carbon lifestyles, as many consumer groups already exceed carbon footprint benchmarks for 2030 and 2050. Recognizing the potential of alternative data sources is crucial for deepening our understanding of urban dynamics and supporting sustainable development. Moreover, the successful implementation of the Urban Sustainable Development Goal framework relies on local institutional involvement and the adaptation of indicators to meet specific urban needs.

Finally, integrating technological advancements with innovative policy measures is vital for enhancing urban environmental efficiency—especially given the increasing trend of urban concentration and its implications for infrastructure and sustainability strategies. The findings advocate for policies that support green agricultural practices and comprehensive strategies that harmonize economic growth with environmental sustainability.

Author Contributions:

Conceptualization, R.Z.; methodology, R.Z.; software, R.Z.; validation, R.Z.; formal analysis, R.Z.; investigation, R.Z.; resources, R.Z.; data curation, R.Z.; writing—original draft preparation, R.Z.; writing—review and editing, R.Z.; visualization, R.Z.; supervision, R.Z.; project administration, R.Z.; funding acquisition, R.Z. All authors have read and agreed to the published version of the manuscript.

https://doi.org/10.71204/xphyk512

Funding:

This research received no external funding.

Institutional Review Board Statement:

Not applicable.

Informed Consent Statement:

Not applicable.

Data Availability Statement:

Not applicable.

Conflict of Interest:

The authors declare no conflict of interest.

References

Bibri, S. E., & Krogstie, J. (2017). Smart sustainable cities of the future: An extensive interdisciplinary literature review. Sustainable Cities and Society, 31, 183-212.

Cai, B., Liang, S., Zhou, J., et al. (2018). China high-resolution emission database (CHRED) with point emission sources, gridded emission data, and supplementary socioeconomic data. Resources, Conservation and Recycling, 129, 232-239.

Chambers, R. G., Chung, Y., & Färe, R. (1996). Benefit and distance functions. Journal of Economic Theory, 70(2), 407-419.

Chen, J., Gao, M., Cheng, S., et al. (2021). China's city-level carbon emissions during 1992–2017 based on the inter-calibration of nighttime light data. Scientific Reports, 11(1), 33

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. Journal of Environmental Management, 51(3), 229-240.

Cowls, J., Tsamados, A., Taddeo, M., & Floridi, L. (2023). The AI gambit: Leveraging artificial intelligence to combat climate change—Opportunities, challenges, and recommendations. AI & Society, 38(1), 283-307.

Elmqvist, T., Andersson, E., Frantzeskaki, N., McPhearson, T., Olsson, P., Gaffney, O., Takeuchi, K., & Folke, C. (2019). Sustainability and resilience for transformation in the urban century. Nature Sustainability, 2(4), 267-273.

Färe, R., & Grosskopf, S. (2010). Directional distance functions and slacks-based measures of efficiency. European Journal of Operational Research, 200(1), 320-322.

Färe, R., Grosskopf, S., & Norris, M. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. American Economic Review, 84(1), 66–83.

Färe, R., Grosskopf, S., & Pasurka, C. A. (2007). Environmental production functions and environmental directional distance functions. Energy, 32(7), 1055-1066.

Färe, R., Grosskopf, S., & Tyteca, D. (1996). An activity analysis model of the environmental performance of firms—Application to fossil-fuel-fired electric utilities. Ecological Economics, 18(2), 161-175.

Färe, R., Grosskopf, S., Lovell, C. A. K., et al. (1989). Multilateral productivity comparisons when some outputs are undesirable: A non-parametric approach. Review of Economics and Statistics, 71(1), 90-98.

Han, Z.-L., Xia, K., Guo, J.-K., Sun, C.-Z., & Deng, Z. (2017). Research of the level and spatial differences of land-sea coordinate development in coastal areas based on the Global-Malmquist-Luenberger index. Journal of Natural Resources, 32(8), 1271-1285.

Huang, G., & Jiang, Y. (2017). Urbanization and socioeconomic development in Inner Mongolia in 2000 and 2010: A GIS analysis. Sustainability, 9, 1-11.

Jedwab, R., & Völker, D. (2015). Urbanization without growth in historical perspective. Explorations in Economic History, 58, 1-21.

Kennedy, C., Steinberger, J., Gasson, B., et al. (2010). Methodology for inventorying greenhouse gas emissions from global cities. Energy Policy, 38(9), 4828-4837.

Kii, M. (2021). Projecting future populations of urban agglomerations around the world and through the 21st century. npj Urban Sustainability, 1(1), 10.

Klopp, J. M., & Petretta, D. L. (2017). The urban sustainable development goal: Indicators, complexity and the politics of measuring cities. Cities, 63, 92-97.

Li, Y., Li, J., Gong, Y., Wei, F., & Huang, Q. (2020). CO_2 emission performance evaluation of Chinese port enterprises: A modified meta-frontier non-radial directional distance function approach. Transportation Research Part D: Transport and Environment, 89, 102605.

Liora, N., Poupkou, A., Papadogiannaki, S., Parliari, D., Giama, E., Pieretti, G. A., Da Rugna, L. C., Susanetti, L., Bressan, M., Becerra Villanueva, J. A., et al. (2022). A methodology for carbon footprint estimations of research project activities—A scenarios analysis for reducing carbon footprint. Atmosphere, 14(1), 6.

Liu, Z., Han, L., & Liu, M. (2024). High-resolution carbon emission mapping and spatial-temporal analysis based on multi-source geographic data: A case study in Xi'an City, China. Environmental Pollution, 361, 124879.

Lozano, S., & Soltani, N. (2018). DEA target setting using lexicographic and endogenous directional distance function approaches. Journal of Productivity Analysis, 50, 55-70.

Meng, F. (2019). Carbon emissions efficiency and abatement cost under inter-region differentiated mitigation strategies: A modified DDF model. Physica A: Statistical Mechanics and its Applications, 532, 121888.

Meng, L., Graus, W., Worrell, E., et al. (2014). Estimating CO_2 emissions at urban scales by DMSP/OLS nighttime light imagery: Methodological challenges and a case study for China. Energy, 71, 468-478.

Oh, D. H. (2010). A global Malmquist-Luenberger productivity index. Journal of Productivity Analysis, 34(3), 183-197.

Olawumi, T. O., & Chan, D. W. M. (2018). A scientometric review of global research on sustainability and sustainable development. Journal of Cleaner Production, 183, 231-250.

Oliveira, E. A., Andrade Jr., J. S., & Makse, H. A. (2014). Large cities are less green. Scientific Reports, 4, 4235.

Qu, Y., Xie, H., & Liu, X. (2022). Measurement of environmental sustainability in China: Based on Global Malmquist-Luenberger model. In 2022 3rd International Conference on Big Data and Social Sciences (ICBDSS 2022) . Atlantis Press, 1022-1029.

Shakhbulatov, D., Arora, A., Dong, Z., & Rojas- Cessa, R. (2019). Blockchain implementation for analysis of carbon footprint across food supply chain. In 2019 IEEE International Conference on Blockchain (Blockchain). IEEE, 546551.

Shan, Y., Guan, Y., Hang, Y., et al. (2022). City- level emission peak and drivers in China. Science Bulletin, 67(18), 1910–1920.

Shi, J., Dai, X. Y., & Chen, G. J. (2024). Spatiotemporal analysis of carbon emissions based on night- time light data in western provinces of China. Light Engineering, 32(2), 152.

Tao, F., Zhang, H., Hu, J., & Xia, X. H. (2017). Dynamics of green productivity growth for major Chinese urban agglomerations. Applied Energy, 196, 170-179.

Wang, K., Xian, Y., Lee, C.Y., Wei, Y.M., & Huang, Z. (2019). On selecting directions for directional distance functions in a non- parametric framework: A review. Annals of Operations Research, 278, 43-76.

Wang, Y., Wang, J., Liu, Y., et al. (2022). Calibrations of urbanization level in China. China CDC Weekly, 4(6), 111-115.

Wu, C.-J., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., Chang, G., Aga, F., Huang, J., Bai, C., et al. (2022). Sustainable AI: Environmental implications, challenges and opportunities. Proceedings of Machine Learning and Systems, 4, 795-813.

Wu, F., Zhou, P., & Zhou, D. Q. (2020). Modeling carbon emission performance under a new joint production technology with energy input. Energy Economics, 92, 104963.

Yang, J., Tang, L., Mi, Z., Liu, S., Li, L., & Zheng, J. (2019). Carbon emissions performance in logistics at the city level. Journal of Cleaner Production, 231, 1258-1266.

Yao, Y., Pan, H., Cui, X., & Wang, Z. (2022). Do compact cities have higher efficiencies of agglomeration economies? A dynamic panel model with compactness indicators. Land Use Policy, 115, 106005.

Yu, T., Shu, T., & Xu, J. (2024). Spatial pattern and evolution of China's urban agglomerations. Frontiers of Urban and Rural Planning, 2(1), 7.

Zhang, N., & Choi, Y. (2013). Total- factor carbon emission performance of fossil fuel power plants in China: A metafrontier non- radial Malmquist index analysis. Energy Economics, 40, 549-559.

Zhang, N., Kong, F., Choi, Y., et al. (2014). The effect of size- control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants. Energy Policy, 70, 193-200.

Zhang, N., Zhou, P., & Choi, Y. (2013). Energy efficiency, CO_2 emission performance and technology gaps in fossil fuel electricity generation in Korea: A metafrontier non- radial directional distance function analysis. Energy Policy, 56, 653-662.

Zhong, C., Yu, M., Zhang, Z., & Lu, M. (2024). Green innovation efficiency measurement of manufacturing industry in the Beijing-Tianjin-Hebei region of China based on super- EBM model and Malmquist- Luenberger index. Frontiers in Energy Research, 12, 1337188.

Zhou, P., Ang, B. W., & Wang, H. (2012). Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. European Journal of Operational Research, 221(3), 625-635.

Zhou, P., Delmas, M. A., & Kohli, A. (2017). Constructing meaningful environmental indices: A non-parametric frontier approach. Journal of Environmental Economics and Management, 85, 21-34.

Zhu, J., Zhou, D., Pu, Z., & Sun, H. (2019). A study of regional power generation efficiency in China: Based on a non-radial directional distance function model. Sustainability, 11(3), 659.