Omaha Public Power District

**OPPD BOARD OF DIRECTORS**

**BOARD MEETING MINUTES**

**November 20, 2025**

The regular meeting of the Board of Directors of the Omaha Public Power District ("OPPD" or "District") was held on November 20, 2025, at 5:00 p.m. at the Omaha Douglas Civic Center, 1819 Farnam Street, 2nd Floor Legislative Chamber, Omaha, Nebraska and via WebEx audio and video conference.

Joining in person were Directors A. E. Bogner, M. J. Cavanaugh, C. C. Moody, M. G. Spurgeon and E. H. Williams. M. R. Core joined virtually. S. E. Howard and J. L. Hudson were absent. Also present were L. J. Fernandez, President and Chief Executive Officer, and Messrs. S. Bruckner and T. Thalken, of the Fraser Stryker law firm, General Counsel for the District, E. H. Lane, Sr. Board Operations Specialist, and other members of the OPPD Board meeting logistics support staff. Vice-Chair M. G. Spurgeon presided, and E. H. Lane recorded the minutes. Members of the executive leadership team joining in person included S. M. Focht, C.V. Fleener, T. D. McAreavey, T. R. Via and B. R. Underwood.

***Board Agenda Item 1: Chair Opening Statement***

Vice-Chair Spurgeon gave a brief opening statement, including reminders for using the WebEx audio and video conferencing platform.

***Board Agenda Item 2: Safety Briefing***

Josh Clark, Manager, Protective Services, provided safety reminders.

***Board Agenda Item 3: Guidelines for Participation***

Vice-Chair Spurgeon then presented the guidelines for the conduct of the meeting and instructions on the public comment process in the room and using WebEx audio and video conferencing features.

***Board Agenda Item 4: Roll Call***

Ms. Lane took roll call of the Board. All members were present in person, with the exception of M. R. Core who joined virtually, and S. E. Howard and J. L. Hudson who were absent.

***Board Agenda Item 5: Announcement regarding public notice of meeting***

Ms. Lane read the following:

> *"Notice of the time and place of this meeting was publicized by notifying the area news media; by publicizing same in the Omaha World Herald and Nebraska Press Association, OPPD Outlets newsletter, oppd.com and social media; by displaying such notice on the first level of the OPPD administrative offices; and by e-mailing such notice to each of the District's Directors on November 14, 2025.*

> *A copy of the proposed agenda for this meeting has been maintained, on a current basis, and is readily available for public inspection in the office of the District's Corporate Secretary.*
>
> *Additionally, a copy of the Open Meetings Act is available for inspection on oppd.com."*

***Board Consent Action Items***:

6. Approval of the September 2025 Financial Report, October 2025 Meeting Minutes, and November 20, 2025 Agenda

It was moved and seconded that the Board approve the consent action items.

Vice-Chair Spurgeon asked for public comment in person and on WebEx. There were no comments.

Thereafter, the vote was recorded as follows: Bogner – Yes; Cavanaugh – Yes; Core – Abstain; Howard – Absent; Hudson – Absent; Moody – Yes; Spurgeon – Yes; Williams – Yes. The motion carried (5-0).

***Board Agenda Item 11: President's Report***

CEO Fernandez next presented the following information:

- October 2025 Baseload Generation
- October 2025 Balancing Generation
- October 2025 Renewables
- Heat the Streets Run & Walk for Warmth – March 7
- Community Resource Fair
- Community Volunteering
- In Memoriam – Edward A. Ruhnka

***Board Agenda Item 12: Opportunity for comment on other items of District Business***

Vice-Chair Spurgeon asked for comments from the public in the room on other items of District business. There were 34 comments.

David Corbin, 1002 N. 49th St, representing the Nebraska Sierra Club, provided comments on concerns regarding potential health effects of burning coal.

David Begley, 4611 S. 96th Street, Omaha provided comments on power reliability and issues with renewable energy and presented materials which are attached to the minutes.

April Thompson, 5863 S. 104th Ave, provided comments on concerns regarding potential health effects of burning coal and asthma rates in North Omaha.

Joe Giitter, 1146 Mayberry Plaza, provided comments on the recommendation for the North Omaha Station and "brain drain" and presented materials which are attached to the minutes.

John Pollack, 1412 N. 35th Street, Omaha, provided comments on the winter SPP requirements, reliability of power plants and provided a weather update.

Vern Carlson, 800 Buckboard Blvd, Papillion, provided comments on concerns as to heavy use of water by data centers and renewable energy.

Sandy Lehr, 9737 Brentwood Rd, Omaha, representing Citizens Climate Lobby, provided comments on reducing carbon emissions and environmental responsibility.

Jennifer Glazer, 105 S. 93rd Ave, Omaha, provided comments urging the board to refuel/retire the North Omaha Station.

Kay Carne, 143 White Deer Ln, provided comments on concerns relating to potentialo health effects of burning coal.

Crystal Edwards, 1148 S. 93rd Ave, provided comments urging the board to refuel/retire North Omaha Station.

Isabella Jascot, 3214 Campbell Ct, Bellevue High School, provided comments on her view of the pathology of alleged health effects of burning coal.

Jonathon Paetz, 17226 Williams Cir., Omaha, provided comments on SD-7 and environmental justice, and presented materials which are attached to the minutes.

Jane O'Connor, 5412 Charles St, provided comments on the Attorney General's lawsuit and the health assessment of North Omaha Station emissions performed on behalf of OPPD.

Robert Dyer, 3308 N. 53rd St, provided comments on North Omaha Station decision.

Dr. Grace Kelly, 3308 N. 53rd St, provided comments on concerns as to whether there are subsidies of large customers and over long term potential health impacts of burning coal.

Cole Whitrock, 32nd and Hamilton St, provided comments on the financial aspect of closing North Omaha station.

Dan DiLeo, 5817 S.176th St, Omaha, provided comments on the health assessment of North Omaha Station emissions,

T. Michael Williams, Mt. Moriah Baptist Church, provided comments on keeping a promise to refuel/retire North Omaha station.

Roger Carroll, 417 N. 38th Ave, provided comments on a low voltage study and concerns regarding health effects of burning coal, and presented materials which are attached to these minutes.

Steven Dickerson, 5214 Cass St, representing the Students for Sustainability, provided comments on OPPD's guiding principles and the North Omaha communities' wellbeing.

Claire Vossman, 9701 S. 20th St., Bellevue, provided comments on concerns regarding the potential health effects of coal burning on the North Omaha community.

Mele Mason, 9632 N. 34th St, provided comments on retiring the North Omaha coal plant.

Liz Veazey, 912 N. 49th St., provided comments on ending coal generation in North Omaha, and utilizing other resources such as voltage regulators, rooftop solar and distributed energy storage.

Adam Sundberg, 3425 California St., provided comments on environmental justice and environmental super fund sites.

Annette Harris, 2851 Iowa St, Florence, provided comments on his concerns as to higher levels of asthma and respiratory illnesses in North Omaha.

Terrell McKinney, 5319 N. 30th St, representing BOLD Alliance, provided comments on the lack of respectful engagement with the North Omaha community and refueling/retiring North Omaha Station.

Nancy Gaarder, 2720 Iowa St, provided comments on tree trimming and Greener Together program in North Omaha, the upcoming IRP and presented materials which are attached to these minutes.

Bonnie Mercer, 510 S. 58th St, Omaha, provided comments on lack of transparency of the proposed extension of coal burning in North Omaha.

Ryan Wishart, 912 N. 49th St, provided comments on not serving data centers until North Omaha station stops burning coal.

Nate Austic, 9380 Western Ave, provided comments on speaking with residents of North Omaha and running for Nebraska state legislature.

Samantha Gentry, 7418 Joseph Ave, La Vista, provided comments on opposing keeping the coal plant open.

Scott Williams, Rosewood Dr., Lincoln, NE, provided comments on efforts of the board and ELT to run a reliable grid, distributed energy, and refueling/retiring North Omaha Station.

Linda Johnson, 3716 Mason St, Omaha, provided comments of support for the previous public comments and standing with the North Omaha station.

Kate Carlson, Papillion, provided comments on respiratory illnesses in North Omaha and expressed support for the North Omaha community.

Vice-Chair Spurgeon asked for comments from the public online on other items of District business. There was one comment.

Ken Winston, Lincoln, NE, representing the Nebraska Sierra Club, provided comments on solar projects, demand side energy management, and refueling/retiring the North Omaha Station.

There being no further business, the meeting adjourned at 6:49 p.m.

Signed by:
S. M. Focht
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S. M. Focht
Vice President – Corporate Strategy & Governance and Assistant Secretary

DocuSigned by:
Erin H. Lane
965CE2363A0A42C...

E. H. Lane
Sr. Board Operations Specialist

David Bogley



# Billionaire Bill Gates calls for climate strategy pivot ahead of COP30

By **Sharon Kits Kimathi**

October 28, 2025 12:04 AM CDT · Updated 8 hours ago

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Feedback



Bill Gates speaks at the annual Bloomberg Philanthropies Global Forum in Manhattan, New York City, U.S., September 24, 2025.REUTERS/Caitlin Ochs/File Photo Purchase Licensing Rights

## Summary

Gates urges leaders to focus on adaptation, health

COP30 climate talks in Brazil start in early November

Gates says temperature goal not the best measure of progress

Key Points

LONDON, Oct 28 (Reuters) - Billionaire investor and philanthropist Bill Gates called on world leaders on Tuesday to adapt to extreme weather and focus on improving health outcomes rather than temperature reduction targets ahead of the COP30 climate talks in Brazil.

COP30 will be held November 10-21 in the port city of Belem in Brazil's lower Amazon region. Countries are due to present updated national climate commitments and assess progress on renewable energy targets agreed at previous summits.

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Feedback

The world has spent the last decade working towards the goals of the Paris Agreement, aiming to limit global warming to well below 2 degrees Celsius above the pre-industrial average by mid-century - something that remains well off-track.

While climate change was serious, it was "not civilization-ending", Gates posted on his personal blog. He wrote that rather than focus on temperature as the best measure of progress, climate resilience would be better built by strengthening health and prosperity.

— low rates, reliable power

He called for a shift in focus toward improving human welfare, particularly in vulnerable regions, through investments in energy access, healthcare, and agricultural resilience.

These areas, he argued, offered more equitable benefits than temperature goals and should be central to climate strategies discussed at COP30.

Gates, who has invested billions to accelerate clean technology innovation through his climate-focused venture network, Breakthrough Energy, also challenged policymakers and donors to scrutinise whether climate aid was being spent effectively.

...ged them to use data to maximise impact, and called on investors to back companies developing ...gh-impact clean technologies so they could more quickly lower costs.

OPPD Board 20NOV2025

Comment: OPPD must keep Promises to Community.

1. Low voltage warnings brought up at the OPPD's pre-meeting have been present for years and the corporation has had years to address those warnings. The corporation did not mention concerns previously. We are concerned these warnings are only being brought up now to justify continuing status quo coal operations at North Omaha Power Station.
2. The sudden concern about low voltage warnings despite having years to address has the appearance of a support of the status quo.
3. "When making use of natural resources, we should be concerned
   3.1. for their protection and consider the cost entailed – environmentally and socially
   3.2. as an essential part of the overall expenses incurred" (Pope Benedict XVI,"
   3.3. 2010 World Day of Peace Message, no 25."
4. Release OPPD study purporting the North Omaha coal units do not significantly threaten human health.We support moving away from coal at the North Omaha Station. We emphasize that OPPD keep their promises to the community.
5. Fight the attorney general's lawsuit.
6. We support OPPD moving away from coal at the North Omaha Power Station.
7. We emphasize that OPPD keep its promise to the community.

Roger Carroll
417 N 38 Avenue
Omaha, NE 68131

For clean air in North Omaha

N46 Mayberry

My name is Joseph Giitter. I own a small business in downtown Omaha. I also have nearly 40 years of experience in the energy industry. Much of that experience was in related to risk assessment, including performing risk assessments, teaching risk management at MIT, and serving as the Director of Risk Assessment at the Nuclear Regulatory Commission for seven years. I was also one of those kids from North Omaha who grew up with asthma. Last night I had a chance to go through the slide package that were presented to the board on Tuesday. It was entitled: Strategic Risk: North Omaha Recommendation. As someone who devoted a career to risk assessment, I found that aspects of the presentation that were far from convincing and in some places downright troubling. In the risk assessment there is something called the Texas sharpshooter fallacy. The Texas sharpshooter fallacy describes a situation where someone shoots holes in the side of the barn and then draws a circle around the holes that are clustered together to draw inferences from randomness. On its surface, the OPPD strategic risk assessment has the appearance of an analysis that justifies a decision that has already been made rather than a rigorous strategic risk assessment. Let me briefly highlight some of my concerns:

The study suggests that the North Omaha Station is somehow necessary to prevent blackouts as evidenced by an increase in low voltage alarms. However, as an engineer I can tell you that there are many possible causes for low voltage alarms. It could be generator-specific issue,
like a faulty automatic voltage regulator or an equipment failure caused by poor maintenance. But the assessment would have us believe that these are all grid stability issues.

And let's put things in perspective. The Southwest Power Pool has a capacity of approximately 66 thousand MW and the coal plant is about 350 MW—about half of one percent of the generation capacity in the power pool. When OPPD shut down the Fort Calhoun nuclear plant the rationale was that they would be more of a purchaser of power and less of a generator. How does that philosophy play into this decision?

One of the arguments made for not converting the coal plants to natural gas is that the gas supply would not be available during the winter months. What it failed to mention is that the projected peak load for the summer is about 800 MW higher than the projected peak load for the winter so that argument is specious.

I was also concerned about the independence of the Human Health and Ecological Risk assessment because it was conducted by a company that has a vested interest in the continued operation of the coal plant. What was most ironic is that the study did not look appear to consider the impacts and consequences of global warming although it did acknowledge that there has been an increase in severe weather events. The idea that you need fossil fuels to fight global warming caused by fossil fuels seems like circular logic to me.

Finally, I want to address the topic of brain drain. I directed a documentary film, called Car-Centric earlier this year. The documentary addresses the fact that Omaha is one of the most Car-Centric cities in America and, in fact, we rank 99/100 in the U.S. Climate Transportation Index. But one of the major observations I had when making that film is that many of our best and brightest young people decide first where they want to live before they decide on what job they want. And how their city addresses environmental issues is hugely important to them. The idea that OPPD is reneging on their previous commitment and putting people's health at risk to provide a couple of hundred low tech jobs at data centers is appalling to them. I urge you to watch the documentary film called, Exposing the Dark Side of America's AI Data Center Explosion on Youtube. It puts a national spotlight on how OPPD reneged on its commitment to move toward net zero because of the data centers. The Washington Post had a similar article. So, my challenge to the board is, what side of history are you going to be on?

# O P P D   P R O J E CT

## November 20, 2025

# OMAHA SAFETY NET RESILIENCE

# RESILIENCE MONITORING REPORT

Paul J. Nelson M.S. M.D.

Population Health

DESIGN EPISTEMOLOGY

www.nationalhealthusa.net/prospectus/design-epistemo-logy/

REFERENCES TODAY

Sanja D Zarkovic, et al, (2024). DEFINING POWER SYSTEM HEALTH -- FRAMEWORK AND PROCESS

TOWARD A SYSTEM HEALTH INDEX.

Alessia Rochira, et al, (2023). THE INTERPLAY OF COMMUNITY RESILIENCE POTENTIAL,

TRUST IN THE FUTURE AND SOCIAL WELL-BEING.

Narayan Bhusal, et al, (2024). HISTORICAL POWER OUTAGES OF THE US AND

SOCIAL VULNERABILITY INDEX.

Biying Ding & Lei Ding, (2025). POPULATION DENSITY AND URBAN RESILIENCE

IN CHINESESE MEGA-CITIES: EVIDENCE OF A MEDIUM-DENSITY TRAP.

# O P P D P R O J E CT

November 20, 2025

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IN CHINESESE MEGA-CITIES: EVIDENCE OF A MEDIUM-DENSITY TRAP.

# Defining Power System Health - Framework and Process towards a System Health Index

2024

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**Abstract**

The health index has traditionally been devised and calculated for individual assets within a power system. This index provides vital details about an asset's overall health and allows for a standardized comparison among various assets. However, the intricate nature of power systems poses significant challenges when trying to adapt this methodology for a broader, global power system health index. To tackle this obstacle, this paper proposes an innovative framework for evaluating power system health. The framework's primary purpose is either to monitor the performance of a power system within a defined jurisdiction (such as a country, region, or utility) over time and identify trends/changes or to compare the performance across various jurisdictions. This paper further presents a comprehensive overview of key concepts that play a vital role in determining power system health. These include the driving factors, performance metrics, and associated costs, all of which are under the careful supervision of asset management. Special attention is given to the physical dimensions of the security of electricity supply, which represent the performance-based aspect of power system health and constitute the foundation for the power system health index. Each performance-based dimension is thoroughly reviewed, and a list of relevant key performance indicators is provided for every dimension.

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*Keywords:* Power system health, asset management, security of supply, health index, data analysis

## 1. Introduction

The power system is a complex enterprise, where multiple agents take different responsibilities and roles within it. Modern societies are highly dependent on it and want to reap the benefits of the power system 100% of the time. However, as every complex system, the power system as well has its weak and strong points, needs to be maintained, reinforced, changed and it needs to evolve over time. Therefore, it comes as no surprise to think about the health and well-being of the power system.

The advent of power system health emerged in the 90s under the name "The well-being analysis" proposed by Billinton et al. [1, 2, 3, 4]. The basic idea of well-being analysis is to combine deterministic and probabilistic approaches. Deterministic approaches are said to be easier for power system planners and operators to understand and apply, but they do not reflect the stochastic nature of the power system. Billinton's idea was to map system operating states (normal, alert, emergency and extreme emergency) into well-being states, such as health, marginal and at risk (Figure 1). In the healthy state, everything is within limits and there is sufficient margin to satisfy deterministic criteria. In the marginal state, the system is operating within limits, but there is no longer sufficient margin to satisfy the acceptable deterministic criterion. In the risk state, equipment or system constraints are violated and load may be curtailed [1].

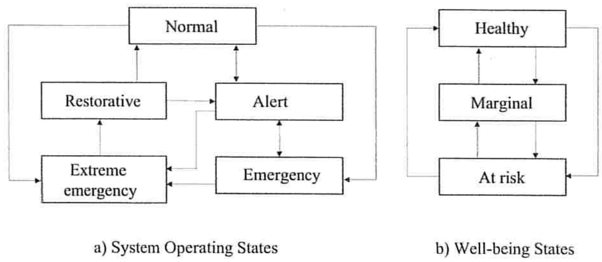


Figure 1: Mapping of operating states into well-being states [1].

Based on the well-being analysis, authors in [5] and [6] propose a probabilistic Power System Health Index (PSHI), in order to assess the health of the whole system. They describe several power system health indices based on two categories - adequacy and security, that take into consideration different aspects, such as frequency, voltage, overload, etc. The main idea of probabilistic PSHI is to create a tool for efficient monitoring, decision making and rapid judgment of different situations within the power system. However, the authors point out the impediments of the complex mathematical models needed to combine all relevant features that define power system health. Additionally, it is noted that this algorithm will be extended to achieve the eventual purpose, which is the development of an integrated health index when assessing highly complicated power system.

The health index has predominantly been defined and calculated for a single asset in the power system (e.g. power transformer), rather than the whole system [7, 8, 9, 10]. Component's health index represents the overall condition of an asset, usually obtained through observations, field inspections, site and laboratory testing [7]. Health index can provide useful insight into the overall health of the utility asset, which can further be used to justify investments, maintenance and replacement plans [8]. Moreover, this index can be used to compare different assets in a consistent fashion. The computation of the health index is based on different techniques, but the most common approach is the weighting of the condition monitoring information by a weight factor. When all possible condition information are available and collected, the health index calculation can combine the data into one single score, which is further transformed into a linguistic expression [8].

The idea of translating the component's health index into a system's health index seems quite appealing, not just to monitor the system performance and propose suitable actions, but also to compare and improve the health of different systems on different levels (e.g. international, regional, local) in a sustainable manner. However, the power system's inherent complexity poses significant challenges for quantifying health at a global scale, as previously emphasized [5, 6].

This issue brings us to the question: if we consider the complexity of the power system, is it even possible to quantitatively assess health in an integrated and holistic way? Moreover, how to deal with complex mathematical models, which are hard to understand, maintain and update with new volumes of data? In [11] authors deal with a complexity dilemma, where they try to assess the security of electricity supply with two different models associated with different levels of complexity: deterministic capacity balances and probabilistic simulations. They demonstrate that, under realistic assumptions, the optimal model design is not reached by ever-increasing model complexity. Additionally, time-intensive and complex modeling approaches do not guarantee reliable predictions of the future.

While we acknowledge the importance of mathematical models, our perspective, based on our research, suggests that in certain contexts, a systematic framework might be more intuitive or actionable, and we want to highlight its potential merits. The framework would involve the identification of all relevant factors needed to define power system health and dimensions that can contribute to the formulation of a global power system health index.

The health of a power system is directly related to the security of the electricity supply, which is considered a fundamental requirement for modern societies [12]. Security of electricity supply is defined as the ability of the electrical power system to provide electricity to end-users with a specified level of continuity and quality in a sustainable manner, relating to the existing standards and contractual agreements at the points of delivery [13]. It very much reflects the performance of the power system, which is essential for power system health analysis. In essence, a healthy power system is one that functions optimally, is maintained appropriately, and operates with a level of efficiency and reliability that ensures the steady provision of power to all consumers.

The security of supply in general (without explicitly focusing on electricity) has been investigated by many scholars. All of them tried to define all relevant aspects and dimensions of security of supply and to quantify energy security by proposing different indicators [14, 15, 16, 17, 18, 19]. In [20] authors develop a framework that specifically focuses on the electricity sector of a single jurisdiction. This framework includes 12 different dimensions that determine the security of the electricity supply. They argue that all dimensions are important and they do not make any attempt to prioritize the different dimensions. However, in [21] they evaluate interdependencies between these dimensions by using Cross Impact Analysis. They derive an influence diagram to visualize the interdependencies and a scatter plot to categorize the dimensions as independent, driver, connector or outcome.

Even though the work presented in [20, 21] is both comprehensive and flexible, we want to emphasize the dimensions that are related to the physical aspect of the security of supply or the system performance. Good performance of the power system is essential for maintaining customer satisfaction, meeting regulatory requirements, and ensuring the overall health of the power system. The performance-based dimensions of security of supply represent the basis of the power system health framework that we are proposing and constitute the foundation for the power system health indicator. Moreover, we want to define the relationship among these performance-based dimensions in order to give a comprehensive view of power system health.

The main contributions of this work are:

- Defining power system health key factors and providing multiple principles of power system health.

- Conducting a meticulous literature review focused on key concepts related to the security of electricity supply, i.e. performance-based dimensions of security of supply.
- Devising a classification schema, intended to systematically interlink performance-based dimensions, enhancing comprehensibility and insight into their relationships.
- Proposing key performance indicators for each dimension, designed to contribute to the global power system health index.
- Unifying all defined factors, aspects, and dimensions under the general power system health framework.

This paper gives a comprehensive overview of relevant concepts that can help in defining power system health and it is structured as follows: Section 2 presents power system health principles and defines important concepts within power system health. Section 3 gives special focus to physical dimensions of security of electricity supply, which represent the performance-based aspect of power system health and constitute the foundation for the power system health index. In Section 4, all important indicators are listed. The last section discusses and concludes the work.

## 2. Power system health principles

Defining the health of the power system is an ambitious and complex goal, where many aspects need to be considered, many stakeholders consulted, and future scientific and technological advances taken into account [22].

If we look at medical sciences, the World Health Organization (WHO) gave a formal definition of health in 1948, where health is "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" [23]. This definition has been widely criticized ever since, mostly due to the fact that this is a utopian concept that is neither operational nor measurable. Moreover, the term "complete well-being" is so extreme that it is nearly impossible to achieve. However, no other formal definition has been accepted for almost 3/4 of a century [24].

According to [24], health may be seen as the contingent result of actions, choices, intentions, embedded in a network of social ideas, expectations, social practices, and institutions/utilities. Moreover, one unique perspective on the health of any system cannot exist - health embodies as many definitions as there are people who use it. Each definition can depend on a different theory, event, aim and application and each definition can contribute to pursuing a specific knowledge or a target. On the other hand, the definition of health can have many implications in practice, policy, promotion and ability to make appropriate health decisions [24].

There are three very important and interconnected factors when defining the power system health and those are: drivers, performance and cost. When it comes to comparing systems between countries, regions or even utilities. there are different priorities and needs that drive the changes in the power system - whether it is a need to expand the existing power system, upgrade existing substation with automation or react promptly in the case of some extreme weather event. An increase in performance should always be the goal. However, there is always a trade-off between cost and performance, and every change, improvement or upgrade is limited by the level of available investments. In order to find a globally optimal trade-off among certain objectives a set of different activities can be performed. These activities constitute asset management, which can be seen as a fourth important factor in defining power system health. Asset management deals with strategic planning, operation, maintenance and utilization of resources while providing high-level and cost-effective service required by customers and in general, helps prioritize a decision-making process [25].

We propose several principles of power system health. Throughout the paper, we will evaluate the relevance and applicability of these principles, taking into consideration their varying context.

*Principle 1:* Power system health represents the interrelation of key factors, such as drivers, performance and cost, overseen by asset management (Figure 2).

*Principle 2:* Power system health must be seen as an ongoing, iterative, and dynamic process, that goes hand-in-hand with technological and societal development.

*Principle 3:* Power system health must be seen as the capability, to be sustainable and able to quickly overcome any disturbance, to deal with climate changes, society's needs, to be robust, reliable, resilient and continuously provide high-quality service.

*Principle 4:* Power system health must take into account the priorities, values, needs, aspirations, and goals of both utilities and customers.

*Principle 5:* Power system health must be operational and measurable by different indicators, where each indicator can be related to different perspectives on health.

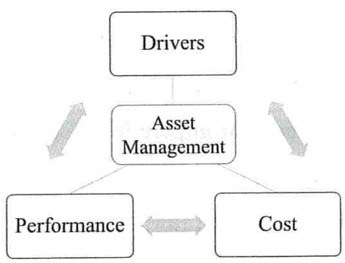


Figure 2: Power system health key factors.

### *2.1. Drivers*

In order to address principles 2 and 4, it is necessary to identify drivers that initiate changes and influence the design and scope of the power system. They can include:

- Society: Society expects a reliable and affordable power supply that is available 24/7. These expectations drive the need for continuous improvements in power system performance [21]. Moreover, an informed and engaged society can influence decision-making processes related to power system planning and operation, asking for increased transparency, public consultation, and involvement in shaping energy policies and strategies [26]. Finally, society's acceptance and adoption of new technologies, such as electric vehicles, smart appliances, and energy storage systems, can drive the need for power system upgrades, demand-side management, and grid modernization.

- Demand growth: Increases in power demand can place additional stress on the system, necessitating upgrades or capacity expansion.

- Technological advancements: New technologies can improve the efficiency, reliability, and sustainability of power systems, creating a need for upgrades and integration.

- Environmental factors: Climate change, extreme weather events, or other environmental factors can affect the power system health and drive the need for adaptive measures.

- Regulatory requirements: Regulatory requirements and methods can differ between countries and industry bodies. Nevertheless, the goal of the regulation should be to set up the rules that will manage electricity supply safely, at acceptable levels of quality, at reasonable tariffs and to the benefit of all customers [27]. Moreover, regulatory authorities use different incentives to attract investment, promote maintenance and efficient operation of existing infrastructure and facilities, and ensure adequate rewards for innovation and technological progress [28].

- Aging infrastructure: As power system equipment ages, its performance may degrade, creating the need for maintenance or replacement.

- Safety: Ensuring the safety of both the public and utility personnel is a critical aspect of power system management [29]. Safety considerations may drive decisions about equipment design, maintenance, and operation. They can also influence regulatory requirements and industry standards that power systems must adhere to.

- Geopolitical factors: Geopolitical tensions can impact the availability and prices of energy resources. This may drive the need for diversifying energy sources or pursuing energy independence to ensure a stable and secure power supply. On the other hand, international collaborations and partnerships can help drive the adoption of new technologies and best practices, and develop integrated electricity markets [14, 20, 21].

### *2.2. Performance*

Based on Principle 3, in order to capture the power system health capability, it is necessary to assess the performance of the power system. There are multiple physical dimensions of security of supply that are directly related to the performance. These dimensions represent the basis of the power system health framework that we are proposing and constitute the foundation for the power system health index. They are:

- Reliability
- Resilience
- Robustness
- Vulnerability
- Stability
- Power quality

A graphical representation of performance-based dimensions is presented in Figure 3.


Figure 3: Performance-based dimensions of security of supply.

Each one of these dimensions is defined in Section 3. Moreover, Section 3 is devoted to explaining the relationship among them in order to give a comprehensive view of power system health.

*2.3. Cost*

When defining power system health, it is essential to consider various costs that can impact the financial sustainability and efficiency of the power system. Some key costs to consider include:

- Capital costs that are associated with the construction, installation, and commissioning of new power system infrastructure (power plants, lines, substations, equipment). Capital costs can also include the costs of upgrading or retrofitting existing infrastructure to improve performance.

- Operational and maintenance costs include the expenses associated with the routine operation and maintenance of power system assets. Effective maintenance strategies, such as preventive or predictive maintenance, can help reduce these costs and improve power system health.

- Damage costs refer to the monetary value of the negative impacts caused by power system incidents, failures, or outages. The damage costs can be measured in terms of Customer Interruption Cost (CIC) on an aggregated system level. The interruption costs represent the economical losses for the customers that are exposed to electricity supply interruptions. The size of these economical losses depends largely on the composition of the customers that experience interruptions [30]. The Value of Lost Load (VOLL) metrics can also be used to quantify the costs of service interruptions.

To improve service continuity and to reduce the probability of supply interruption, it is necessary to increase investments during the planning and/or operating phase in the power system [31]. However, in practice, it is crucial to optimize the investments, since overinvestment can lead to unnecessary expenditures, while underinvestment can lead to an unacceptable level of continuity and unreliable supply [12]. The optimal level of performance or security of supply can be found by minimizing total costs, which are comprised of the cost for ensuring the security of supply and the expected damages due to the supply disruption, as shown in Figure 4 [31].

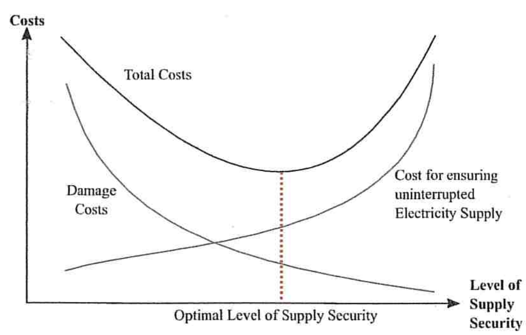


Figure 4: Optimal Level of Supply Security [31].

### 2.4. Asset management

Asset management can be considered an overarching concept that encompasses aspects of power system health.

There have been numerous attempts to define asset management:

- Asset management is the practice of acquiring, using, and disposing of assets by taking into consideration related risks and costs over their entire life cycle and making the most of their economic benefit [25].
- The asset management of transmission and distribution business operating in an electricity market involves the central key decision-making for the network business to maximize long-term profits, whilst delivering high service levels to customers, with acceptable and manageable risks [32].
- Asset management is the set of disciplines, methods, procedures and tools derived from business objectives aimed at optimizing the whole-life business impact of costs, performance and risk exposures associated with the availability, efficiency, quality, longevity and regulatory/safety/environmental compliance of an organization's assets [29].

In [33, 34], asset management forms a bridge between system planning and operation. However, we believe that asset management provides a structured framework for decision-making and resource allocation and effectively balances costs, risks, opportunities and performance through the following activities such as: planning, investment, maintenance, operation, condition monitoring and diagnostics, data-driven decision-making, etc. [35, 36]. Thus, asset management can be seen as a set of different activities or actions, which are performed in order to find a globally optimal trade-off among certain objectives [25]. Moreover, asset management supports power system health Principle 4, playing a vital role in establishing priorities, identifying needs, and defining goals imposed by utilities and customers.

All the actions associated with the topology and structural changes that improve reliability, robustness and resilience can be classified as planning or hardening measures [37]. On the contrary, the tools that provide the operators with more control capability on the available resources can be regarded as operational measures. Operational measures can provide immediate solutions to

Table 1: Asset management actions [37], [38], [39], [40], [41].

| Planning/Hardening Strategies | Maintenance Strategies | Operational Strategies |
|---|---|---|
| Undergrounding distribution and transmission lines | Enhancing vegetation management | Network reconfiguration-based methods |
| Building redundant transmission/distribution routes | Condition monitoring | Automatic feeder switching |
| Upgrading poles and other structures with stronger materials | Preventive maintenance | Disaster response and risk management |
| Elevating substations and facilities | Predictive maintenance | Load restoration-based approaches |
| Adding backup generators | Component replacement | Distributed energy systems and decentralized control |
| Installing remote control switches | | Adaptive wide-area protection and control schemes |
| Determining optimal locations and sizes of battery energy storage units | | Microgrids |
| Determining optimal locations of renewable energy sources (RES) | | Intentional islanding |
| Optimal placement of relays | | Utilization of mobile emergency resources and energy storage |
| Optimal allocation of black start resources | | Advanced visualization and situation awareness systems |
| Developing protocols for encrypted communication of critical data | | |
| Integrated electricity and natural gas transportation system planning | | |

reduce the impact of adverse events on the power grid [38]. Effective maintenance strategies are essential for ensuring the longevity, reliability, and safety of the power system. Maintenance is a combination of all technical, administrative and managerial actions during the life-cycle of an item intended to retain it in or restore it to, a state in which it can perform the required function [35].

Based on the literature review from [37], [38], [39], [40], [41], Table 1 shows examples of possible planning, maintenance and operational actions used for performance improvement.

## 3. Performance-based dimensions of security of electricity supply

This section provides a comprehensive overview and literature review of performance-based dimensions of the security of electricity supply. Moreover, it presents a unique perspective on the relationship among these dimensions, which are graphically represented in Figure 3.

### *3.1. Reliability*

Reliability is a very important physical aspect of the security of supply. Reliability represents the probability that an electric power system can perform a required function under given conditions for a given time interval; it quantifies the ability of the electric power system to provide adequate electric service on a nearly continuous basis to its consumers [42].

Quite often, reliability and security of supply are identified as the same concept: quantifying reliability means quantifying security of supply. Moreover, aspects of reliability defined in [31] are the same ones defined for the security of supply [43] (Figure 5 is inspired by [31, 43] and it was shown in this form in [30]):

- Long-term aspect or system adequacy: If a supply is disrupted because the existing supply capacity is unable to meet demand, we have an adequacy of supply problem or a long-term problem. Long-term security requires investment to maintain the supply chain (production, transmission, distribution) and a supply capacity large enough to meet demand during normal conditions [18]. System adequacy can be subdivided into generation adequacy and grid adequacy [43]. Generation adequacy is the availability of generating (and importing) capacity to meet demand. Grid adequacy is defined as the systems' ability to transport sufficient electricity from the generation site to the consumption site, i.e. the availability of network infrastructure to meet demand. This infrastructure covers transmission and distribution systems as well as cross-border interconnections.

- Short-term aspect or system security: If a supply capacity is adequate, but supply is disrupted due to events such as technical failures, extreme weather conditions, terrorist attacks, or strikes, we have a continuity of supply problem or a short-term problem. Short-term or system security of electricity supply focuses on the system's ability to react promptly due to sudden changes in the network. Continuity of supply is related to the actual delivery of electricity and includes the ability to overcome short-term failures of individual components [13].

A related concept to reliability is availability, which is according to [44] the ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided.

Reliability, as a physical dimension, is a well-researched area with many

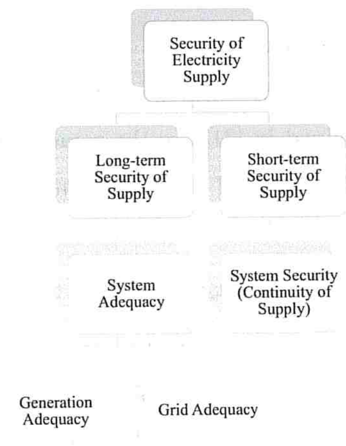


Figure 5: Security of electricity supply overview [30].

developed metrics and methods for the planning and operation of the power system. However, the reliability of the electricity supply is primarily concerned with the duration and frequency of service interruptions. Thus, reliability of supply is a customer-oriented quantity that does not consider the origin or the causes of interruptions [27].

As the power system started to change and develop into a more complex enterprise, more threats started to emerge. It was inevitable that the concept of reliability will branch out, and moreover, that new concepts will emerge - concepts that fill in the gaps missed by reliability.

### *3.2. Resilience*

Reliability and availability are not the only concepts related to the security of supply. In recent years, many studies have been devoted to researching the resilience of the power system, which adds a new dimension to the physical concept of security of supply [45, 46, 38, 47, 37, 39].

According to [48], power system resilience is the ability to limit the extent, severity, and duration of system degradation following an extreme event. Another possible definition describes resilience as the ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event [49].

These extreme or disruptive events are characterized by a low frequency of occurrence but with significant consequences [48]. In [46], extreme events are divided into four major categories based on their origins and impacts on power systems: technical cascading failures, extreme natural events, cyber and physical attacks, and space weather. However, in [45], this division includes only natural and man-made (anthropogenic) disasters, which can cause a lot of harm to physical and cyber components of the system, as well as personnel. Natural disasters (usually caused by weather and earth) involve different kinds of storms, earthquakes, floods, volcanic eruptions, and pandemics, while man-made (anthropogenic) disasters include acts of war, coordinated criminal activity, terrorism, [45].

In [37] it is stated that the concept of resiliency can be studied from short-term and long-term perspectives (Figure 6 is inspired by [37]). In the short-term aspect, the main features of electrical infrastructure are robustness, resourcefulness and rapid recovery. Robustness refers to the ability of the power system to absorb a shock and continue to operate, resourcefulness is the ability of the power system to skillfully manage a crisis and rapid recovery represents the ability of the power system to quickly restore service to a normal state [38]. The short-term features mainly depend on operational strategies, i.e. the operator's ability to react promptly and to make appropriate decisions with available resources in emerging situations [37]. In the long-term aspect, system adaptation (adaptability) to new threats has been considered as the key feature for achieving a more resilient system. Adaptability is defined as the ability to incorporate lessons learned from past events to improve resilience [38]. In other words, adaptability should use experience from past events as a guide in future planning and decision-making strategies.

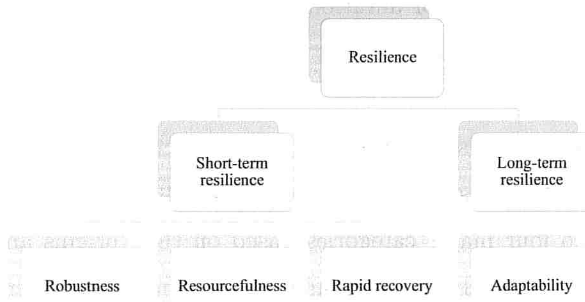


Figure 6: Resilience overview (inspired by [37]).

*Reliability vs. Resilience*

Reliability and resilience are both very much relevant concepts in relation to the power grid. They do interlink, but in many aspects they are distinct.

First of all, reliability is the probability that the system will perform its function over a long period of time under a given condition, i.e. it represents the time average performance of the system [46]. On the other hand, resilience is associated with the time-varying condition of the system over a short period of time [46]. While reliability evaluates the power system states, resilience evaluates both states and transition times between states. Moreover, while reliability is concerned only with customer interruption time, resilience includes infrastructure recovery time as well [39].

In some sense, as a simplified view, reliability can be seen as a binary view of system performance, where the system is either functional or not [50] (Figure 7). On the other hand, the effectiveness of a resilient infrastructure depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event. This suggests the idea that there is a flexible continuum between functional and failed, which goes beyond the stiff binary view related to reliability [50] (Figure 8).

Traditional reliability methods measure the performance of system but they do not take into consideration the origins of events [51]. Additionally, widely accepted reliability metrics (SAIDI, SAIFI, CAIDI), often exclude major outages caused by extreme events [52]. On the other hand, resilience indices determine the system resiliency by comparing the performance of a system before and after disruptions without focusing on specific system features [51].

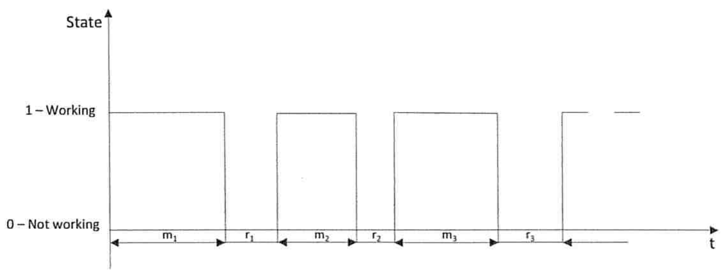


Figure 7: Reliability basis [53].

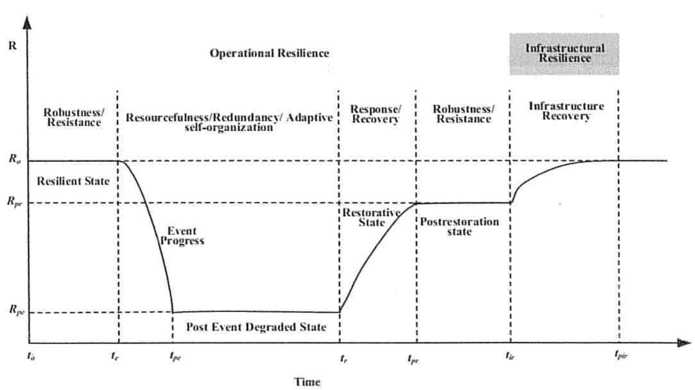


Figure 8: Resilience curve [38],[39].

### 3.3. Robustness

According to [54], robustness represents the ability of the network to withstand an unexpected disturbance without degradation in performance and it quantifies the damage that occurs as a result of such disturbance.

*Robustness vs. Resilience*

Robustness and resilience are related terms. However, as already mentioned, the concept of resilience is broader and it encompasses not only robustness but also resourcefulness, adaptability and rapid recovery [54]. Robustness is a necessary but not sufficient condition to make the power grid resilient. In other words, a power grid that lacks robustness will often collapse before recovery, thus having small or even no resilience.

### *3.4. Vulnerability*

So far, all defined aspects related to the security of supply were positive ones, i.e. defined as a strength of the power system. However, the word that can nicely stipulate the system's weakness is vulnerability.

In [54], robustness and vulnerability are defined as the opposite concepts and they are often used to measure to what extent a power grid has high reliability or low reliability, respectively. Moreover, vulnerability is defined as the performance drop when a disruptive event emerges. Similarly, authors in [55] define vulnerability as the system's inadequate ability to withstand an unwanted situation, limit the consequences, and recover and stabilize after the occurrence of the situation. A review of major approaches used to analyze vulnerability in power systems is given in [56].

In [57], a very interesting view on vulnerability is given, with three different aspects: energy shortage, capacity shortage, and power system failures. Energy shortage deals with the power system's inability to cover the energy consumption, due to, for example, reduced generation (scarcity of primary energy), long-term outage of major plants or the unavailability of major interconnections. It is classified as a long-term problem that can last from one month up to several years. Capacity shortage represents the power system's inability to cover instantaneous demand, due to a lack of available generation and/or transmission capacity. This is normally a short-term problem, that usually lasts for a few hours. Power system failures happen when a power system component's ability to perform its function is interrupted or reduced. The failure can lead to a fault, and the fault may further lead to a power system forced outage or blackout.

Besides power system failure, definitions of energy shortage and capacity shortage very much resemble the long- and short-term aspect of the security of supply. However, we define the security of supply as a higher-level concept that encompasses vulnerability.

In [58] a comprehensive framework for vulnerability analysis is given which classifies aspects of the vulnerability of a power system according to four dimensions: 1) susceptibility; 2) coping capacity; 3) threats; 4) criticality. The first two are considered internal dimensions of the system, while the last two are external dimensions of the system. Moreover, power system vulnerability and resilience are presented as dual or inverse concepts, meaning that low vulnerability implies high resilience and vice versa [58].

Since robustness is a subset of resilience, we do not agree with [54], but rather with [58]. Thus, we are accepting vulnerability as the opposite concept of resilience.

### *3.5. Stability*

The power system is stable when the system is able to restore to its initial condition or reach another steady state (acceptable in terms of operational standards) after experiencing a disturbance. To be more exact, according to [59, 60], power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact. Thus, stability deals with the continuing operation of the system following a disturbance [46].

There are three types of stability [59]:

- Rotor angle stability refers to the ability of synchronous machines to remain in synchronism after being subjected to a disturbance [59].

- Voltage stability refers to the ability of a power system to maintain steady voltages at all buses in the system, or to keep the magnitudes of bus voltages within a certain limit, after being subjected to a disturbance [59, 61].

- Frequency stability refers to the ability of a power system to maintain steady frequency following a disturbance and to maintain/restore equilibrium between system generation and load, with minimum unintentional loss of load [59].

Revised and extended report on power system stability defines two more categories of stability and these are resonance stability and converter-driven stability [60].

Depending on the nature of the disturbance, but also on the time period, stability can be divided into transient and dynamic stability [61]. Transient stability is defined as system's ability to survive a large disturbance (e.g. fault, sudden change in generation, load, system configuration) without loss of synchronism. On the other hand, dynamic stability is the ability of a power system to return to its initial state or reach another steady state nearby after a small disturbance [61]. Any oscillation that happens after such disturbance should die out in several seconds for a strong and dynamically stable system. Otherwise, the system has a bad dynamic characteristic (oscillation is decaying slowly) or the system is dynamically unstable (lasting oscillation) [61].

*Stability vs. Resilience*

The concepts of stability and resilience are similar to each other in the sense that they are both related to the time-varying performance evaluation of the system in the operation condition [46, 59]. However, there are a few differences between them. Stability deals with the continuing operation of the system following a disturbance, while resilience deals with quickly recovering after a disturbance. In simple words, stability tries to answer the question "how long can the system perform before it collapses?", while resilience tries to answer the question "how long does it take for the system to bounce back after it collapses?". When a system is stable, it may not be resilient. The reason is that the concept of stability is defined and assessed for credible contingencies, which have a reasonably high probability of occurrence, while resilience is associated with extreme events (low probability of occurrence, but catastrophic impact) [46].

### *3.6. Power Quality*

According to some researchers, power quality can be seen as the health index of the grid [8]. However, this is a quite heavy statement, with certain gaps in its view. Power quality can be defined as the study of powering and grounding electronic systems in order to maintain the integrity of the power supplied to the system [62]. Moreover, the power quality can be seen as the grid's ability to supply a clean and stable power supply [63]. Good power quality refers to a power supply that is always available, has a pure noise-free, sinusoidal wave shape, and is within voltage and frequency tolerances [63]. Poor power quality can, among many things, affect the accuracy of utility metering, can cause protective relays to malfunction, can result in equipment downtime and/or damage, thus in a loss of productivity and can result in increased costs due to the preceding effects.

Below are listed some of the examples of poor power quality [63, 64, 65]:

- Poor power factor: an excess of reactive power in the system that does not perform any real work and as such is wasteful and costly.
- Harmonics: multiples of the supply frequency, caused by e.g. power electronic loads such as variable speed drives and UPS systems.
- Network unbalance: different line voltages, caused by single-phase loads, phase-to-phase loads and unbalanced three-phase loads like welding equipment.
- Transients: rapid changes in the sinusoidal wave that occur in both voltage and current waveforms, caused by switching devices, starting and stopping high power equipment.

- Voltage variations: discrepancy between line and nominal voltage for a shorter period (e.g. dips, sags, swells, brownouts), caused by e.g. network faults, switching of capacitive loads and excessive loading.
- Flicker: random or repetitive variations in the voltage, caused by e.g. mills, welding equipment and shredders.
- Oscillations (resonances): the flow of electrical energy that changes direction periodically, e.g. between the magnetic field of an inductor and the electric field of a capacitor.

*Power quality vs. Stability*

Power system stability and power quality are by definition distinct concepts. However, they are interconnected, since issues in one area can impact the other. When system stability is compromised, it can lead to power quality issues. For instance, voltage or frequency instability can result in voltage sags, swells, or flickers, impacting the quality of power supplied to consumers [65]. Additionally, when the system undergoes a significant disturbance (like the tripping of a large generator), it can cause frequency deviations from the nominal value (50/60 Hz), directly affecting the power quality experienced by users. Conversely, poor power quality can impact power system stability. For example, harmonics and transient disturbances can affect the performance of power system components, such as generators and transformers, potentially destabilizing the system.

## 4. Quantifying power system health

As suggested in Principle 5, health must be operational and measurable by clear, concrete, and definite processes to become a useful concept in real situations. The whole purpose of defining and evaluating power system health is twofold:

- Being able to monitor the performance of the system in one jurisdiction (utility, region, country) throughout time.

- Being able to compare the performance between different jurisdictions (utilities, regions, countries).

This clearly implicates two possible approaches for power system health assessment:

1. Identify important dimensions of power system health, associate indicators per dimension and monitor their change over time.

2. Aggregate all associated indicators into one health index and use it for comparison between different jurisdictions.

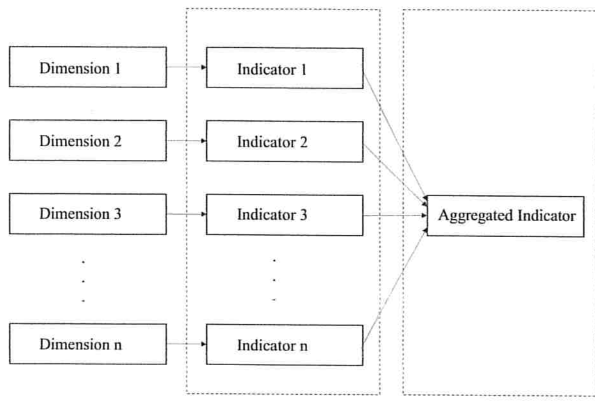


Figure 9: Power system health framework.

An aggregated indicator could help in obtaining a global picture of power system health and identifying the best or the worst practices when comparing different regions [14]. However, the aggregated indicator can hide under- or over-performance of one dimension, i.e. "a good performance on one dimension will not necessarily compensate a poor performance on another one" [20].

It is important to assess the power system health using both approaches 1. and 2. since they complement each other.

In order to assess the various dimensions of power system health, several performance indicators can be utilized to measure and evaluate each dimension (see Table 2). Some criteria on how to choose the relevant indices are given

Table 2: Power system health indicators.

| Indicator | Reliability | Resilience/Vulnerability | Stability | Power Quality |
|---|---|---|---|---|
| System Average Interruption Frequency Index (SAIFI) [67] | ✓ | ✓ | | |
| System Average Interruption Duration Index (SAIDI) [67] | ✓ | ✓ | | |
| Customer Average Interruption Duration Index (CAIDI) [67] | ✓ | ✓ | | |
| Energy Not Supplied (ENS) [67] | ✓ | ✓ | | |
| Asset age and condition (The age and condition of critical components, which can affect the likelihood of failures) | ✓ | ✓ | | |
| Restoration time (The time it takes to restore power after a major event or disturbance) | | ✓ | | |
| Herfindahl-Hirschman Index (HHI): Diversification of energy sources [68] | | ✓ | | |
| Percentage of load served during an event (The portion of the total load that remains served during a disturbance) | | ✓ | | |
| Network sensitivity approach (SG) [69] | | | ✓ | |
| Frequency nadir [70] | | | ✓ | |
| Rate of change of frequency (RoCoF) [70] | | | ✓ | |
| System Average RMS Variation Frequency Index (SARFIx) [71] | | | | ✓ |
| System Instantaneous Average RMS Variation Frequency Index (SIARFIx) [71] | | | | ✓ |
| System Momentary Average RMS Variation Frequency Index (SMARFIx) [71] | | | | ✓ |
| System Temporary Average RMS Variation Frequency Index (STARFIx) [71] | | | | ✓ |

in [66]. It is important to use indices that represent system performance, or that can be aggregated on a system level. Moreover, we are proposing ex-post indicators that allow the evaluation of actual results and outcomes. Unlike ex-ante indicators which are based on forecasts and predictions, ex-post indicators are grounded in actual data, making them less speculative and more reliable. Ex-post indicators provide evidence of actual performance, which can hold parties accountable for their actions and promote transparency in decision-making and implementation processes.

As already mentioned, reliability is the dimension with plenty of developed and tested metrics [31, 67]. In order to obtain reliability indicators it is necessary to collect data about past outages, including the number of customers affected, the duration of outages, and the cause of outages. For example, in Sweden, the electricity network companies annually report information about power outages to the Energy Market Inspectorate [72]. This report is publicly available and provides an overview of the current situation, historical trends and specific shortcomings [73]. Moreover, it provides the values of certain reliability indices between specific regions and some information about power quality. Complementary to EI, the Swedish Energy Companies (Energiföretagen Sverige) annually publishes outage statistics derived from facultative reports from the DSOs. This dataset is commonly known as DARWin [74].

Since vulnerability and resilience are opposite concepts, the same indicators can be used for these two dimensions. There are certain challenges with the quantification of resilience/vulnerability. First of all, measuring these two dimensions is very dependent on the type of disruptive event. Secondly, these events have a low frequency of occurrence - thus, obtaining adequate statistical parameters and historical data is a significant obstacle [49]. Moreover, simulation of such events only provides limited insights [20].

It is not uncommon to use certain reliability indices for quantifying resilience, e.g. ENS [75] or SAIDI [55], causing overlapping of indices between dimensions. It has been shown that the system is more vulnerable if it is dependent on one or very few generation technologies [20]. Thus, the Herfindahl-Hirschman index (HHI) that measures the diversification of energy sources can be used as a resilience/vulnerability indicator. For example, an overview of the various energy sources utilized in Sweden is presented in [76], and this data can be used to calculate the Herfindahl-Hirschman Index (HHI). Additionally, the time needed for power restoration after a major disturbance and the portion of the total load that remains served during a disturbance can help in quantifying the resilience/vulnerability of the system.

Even though power system stability can be divided into angle, frequency, and voltage stability, studies on angle stability are already very mature [77]. However, voltage instability is still a serious issue, that can cause major blackouts in the system [78]. Additionally, many TSOs put great emphasis on frequency quality (avoiding frequency instability) due to the concern of reduced system inertia (lower inertia is commonly associated with larger frequency fluctuations following a disturbance [79]). Therefore, when it comes to evaluating power system health, the focus here is only on voltage and frequency stability.

Authors in [78] give a comprehensive list of voltage stability indices that are in general divided into line, bus and overall voltage stability indices. Since it is essential to look at the power system as a whole, we have included an overall stability indicator, that is simple, accurate and fast in conducting voltage stability analysis - Network sensitivity approach (SG) [69]. The calculation of SG is based on total active power generation, total active power demand and total reactive power demand. The system approaches to its collapse point when SG increments gradually, causing a sharp rise to infinite values [78, 69].

In order to assess frequency stability, frequency nadir and rate of change of frequency (RoCoF) can be used. The frequency nadir represents the minimum value reached by the system frequency following a disturbance and it indicates immediate danger and can be counteracted with measures such as load shedding [70]. RoCoF indicates the severity and speed of frequency changes, highlighting potential issues with system inertia and dynamic response. Recently, frequency recordings have become publicly available, facilitating the calculation of frequency stability indicators [80, 81].

There are multiple aspects of power quality that can be considered and measured. However, since the emphasis is on assessing power quality on the global/system level, SARFIx index and its variations are chosen in the assessment of power system health. SARFIx is related to short-duration voltage variations and represents the mean number of RMS voltage variation events that occur during a determinate period of time for a customer, with a voltage magnitude below x% for sags or above x% for swells [82]. SIARFIx, SMARFIx and STARFIx are the same index as SARFIx, but are limited to events that last from 0.5-30 cycles, from 30 cycles to 3 seconds, and from 3 seconds to 60 seconds, respectively [71]. The issue with quantifying power quality is data availability. Namely, power quality data are collected by the transmission or distribution system operator (TSO or DSO) using different sensors throughout the system, which also include sensitive customer data. To mitigate the risk of spreading sensitive data, the power quality data are usually hard to obtain or unavailable.

After defining and evaluating power system health indicators, they could be aggregated in one global power system health index for one jurisdiction (country, region, utility). Different aggregation techniques are presented in, e.g. [83] or [14].

## 5. Conclusion

This study tackles new ideas and paradigms about power system health. The essence of power system health transcends mere reliability metrics, aiming to encapsulate a multifaceted view of the power system's overall performance and well-being. The focus of this work is to present a conceptual framework of power system health, identify important factors, and propose relevant indicators. Moreover, we suggest several principles of power system health that complement each other. Even though the topic is comprehensive and exhaustive, it is necessary to be presented in a holistic and integrated way, since it is beneficial not only for energy companies but also for authorities, customers, and society in general.

Moving forward, the next steps should include bridging the gap between the theoretical framework and practical applications. A core aspect of this is the development of a universally accepted protocol or standard for data collection, addressing the concerns of confidentiality and competitiveness, while ensuring transparency and objectivity. Collaborations with utilities and regulatory bodies will be crucial in this regard. Furthermore, there is a need to explore advanced data analytics and machine learning techniques to effectively handle and process large volumes of data. By integrating these initiatives, we aim to pave the way for a more adaptive power system that can meet the dynamic needs of the 21st century.

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# Population Density and Urban Resilience in Chinese Mega-Cities: Evidence of a Medium-Density Trap

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**Abstract:** Urban resilience has become a central framework for advancing sustainable development in the context of escalating urban risks. To investigate the role of population density in shaping resilience, panel data from 114 large Chinese cities covering the period 2006–2021 (excluding the COVID-19 years to avoid potential distortions) were analyzed. A multidimensional urban resilience evaluation system was constructed, encompassing five key domains: economy, society, institutions, environment, and infrastructure. Resilience levels were assessed through the entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), while a panel threshold regression model was applied to capture potential nonlinearities in the density–resilience relationship. Results demonstrate that urban resilience in China has exhibited a sustained upward trajectory, largely driven by advances in infrastructure provision and economic capacity. However, population density exerts a nonlinear "double-threshold effect". At low levels of density, the effect on resilience is statistically insignificant; within a medium-density range, a pronounced negative impact emerges, constituting a "medium-density trap"; and at high densities, the adverse effects are attenuated, suggesting that urban systems may gradually adapt to intensified population pressures. This trap is most evident in regional center cities and rapidly developing urban areas, where governance capacity, infrastructure investment, and resource allocation have lagged behind demographic expansion. These findings highlight the stage-dependent vulnerabilities embedded in urbanization processes and indicate that resilience is not solely a function of density itself but also of institutional capacity and infrastructural adequacy. Differentiated governance strategies are therefore required, including targeted improvements in public infrastructure, strengthened institutional and administrative capacities, and the optimization of spatial configurations to accommodate density-specific challenges. By identifying the thresholds at which population density alters resilience trajectories, this study contributes to a deeper theoretical understanding of urban vulnerability and offers actionable insights for policymakers seeking to enhance resilience under conditions of rapid urban growth and high-density development.

**Keywords:** Urban resilience; Population density; Evaluation system; Threshold regression; Medium-density trap

## 1 Introduction

Amid rising global risks and increasing urban complexity, urban resilience has become a key indicator for assessing a city's capacity to achieve sustainable development [1, 2]. It reflects a city's ability to withstand and recover from disasters and public health crises as well as its adaptability to maintain essential functions under continuous change [3, 4]. As high-density development and compound risks intensify, balancing risk management and functional performance has become a major challenge for urban planning and governance [5].

Population density is a core structural factor shaping urban resilience, influencing land use patterns, resource allocation, infrastructure capacity, and environmental pressures [6]. Moderate density can enhance infrastructure efficiency, promote social cohesion, and improve resource utilization, strengthening a city's capacity to absorb and adapt to external disturbances [7, 8]. In contrast, excessive density often correlates with higher pollution levels, infrastructure overload, and increased psychological stress from noise and environmental discomfort [9–11]. Low-density sprawl, on the other hand, is linked to spatial fragmentation, underutilized land, and inefficiencies in public service delivery, which together undermine urban resilience [12].

Existing studies have indicated that the relationship between population density and urban resilience is not strictly linear; the direction and intensity of this effect may vary significantly across different density intervals [13–15], implying that threshold effects may exist rather than a simple one-way response pattern. Particularly during the transition from low to high density, differences in systemic pressure and regulatory capacity across different phases may lead to fluctuations in resilience performance. While some research has preliminarily revealed such nonlinear associations, the mechanisms underlying these patterns, especially across different types of cities and density stages, remain underexplored and lack systematic empirical validation.

Based on this, the study takes 114 prefecture-level and above cities in China as the research sample. It constructs an urban resilience index system covering the five dimensions mentioned above, evaluates resilience levels using the entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method, and applies panel regression and threshold regression models to explore the nonlinear effects and underlying mechanisms of population density on urban resilience and its subsystems. The goal is to provide theoretical support and policy recommendations for managing urban population density and advancing resilience-oriented urban development.

## 2 Related Works

The study of urban resilience has evolved into a comprehensive multi-dimensional framework encompassing five key dimensions: economic, social, environmental, institutional, and infrastructural. Within this framework, population density is a central structural factor influencing all subsystems.

In the economic system, moderate population density can help optimize resource allocation and promote the effective concentration of production factors, thereby enhancing a city's capacity to respond to economic fluctuations and external shocks. On one hand, higher density facilitates information exchange and collaboration among firms, stimulating innovation and industrial synergy, which contributes to faster recovery and greater adaptability of the economic system [7, 8, 16]. On the other hand, excessive density may constrain production space, increase operational costs, and intensify pressure on small and medium-sized enterprises, ultimately undermining economic stability and resilience [17].

In the social system, moderate population density can facilitate neighborhood interaction and the accumulation of social capital, thereby enhancing community-based mutual support and the ability to respond to unexpected events [18]. However, when population concentration is high and spatial distribution is uneven, it may lead to strained public resource allocation and weakened community identity, triggering social isolation, competition for resources, and group tensions, which in turn exacerbate disparities in resilience across communities [19, 20].

Population density plays a critical role in shaping a city's capacity to cope with environmental risks by influencing land use patterns, energy consumption structures, and ecological spatial layouts [21, 22]. A moderately high density is more conducive to the deployment of ecological infrastructure such as green transportation systems, centralized energy supply, and rainwater recycling, thereby enhancing urban adaptability to climate change and natural hazards [23]. Despite these benefits, when population density exceeds ecological carrying thresholds, it often intensifies air pollution, urban heat island effects, and green space degradation, weakening urban ecosystems' self-regulation and recovery capacity [14, 15].

Higher population density places greater demands on urban institutional systems such as disaster response, public service delivery, and interdepartmental coordination [24]. In densely populated areas, the urgency and complexity of governance often drive improvements in risk early-warning and emergency response mechanisms, thereby enhancing institutional adaptability and responsiveness [25]. Nevertheless, in the absence of effective coordination mechanisms, such complexity can also lead to fragmented administration and delayed policy implementation, ultimately undermining the stability of institutional structures [26].

Regarding infrastructure resilience, population density is crucial in shaping urban systems' spatial configuration and emergency response capacity. Densely populated cities are more likely to develop networked and large-scale infrastructure layouts, enhancing the operational efficiency and responsiveness of essential services such as water supply, electricity, transportation, communications, and healthcare [27, 28]. Nevertheless, when density becomes excessive, these systems may face overload risks. The failure of a single critical node can lead to cascading disruptions, exposing vulnerabilities in the overall resilience of urban infrastructure [15].

In summary, although their emphases differ, domestic and international studies have examined the complex relationship between population density and urban resilience. International research, primarily based on experiences from Europe, North America, and the Middle East, has emphasized the vulnerabilities of high-density cities in relation to public service provision, traffic congestion, and environmental carrying capacity [11, 18] . It has also stressed the importance of infrastructural resilience and ecological restoration in mitigating these risks [19, 23]. By contrast, studies in the Chinese context have focused more on the challenges of rapid urbanization, particularly the lag in public service expansion and governance capacity during the medium-density stage [12, 14]. These differences suggest that the mechanisms through which density shapes resilience in Chinese cities may diverge from those observed in developed economies, owing to distinct developmental trajectories and institutional contexts. Engaging more directly with international scholarship can help to identify the generalizable aspects of the density–resilience relationship, while at the same time underscoring the distinctive significance of the "medium-density trap" as a phenomenon characterizing large Chinese cities.

## 3 Theoretical Mechanism Analysis

### 3.1 Conceptual Definition

In existing studies, the notion of "optimal density" is typically understood as the level of population agglomeration that balances the benefits of concentration with the costs of congestion, thereby maximizing social welfare or economic efficiency [29, 30]. This notion reflects a single-point optimum in terms of static equilibrium. Related to this argument is the concept of the "nonlinear effects of density", which suggests that the relationship between population density and urban development performance may exhibit an inverted U-shape or segmented pattern, revealing differences in marginal effects across stages [31].

Against this backdrop, this study introduces the concept of the "medium-density trap" to describe a stage-specific dilemma that may arise as cities evolve from low-density to high-density conditions. Specifically, when population density enters a certain range, cumulative pressures may emerge simultaneously across the economic, social, ecological, infrastructural, and governance dimensions, while the corresponding support and regulatory capacities fail to expand in parallel. As a result, urban resilience may stagnate or even decline. Urban resilience is understood as a multi-dimensional coupled system that encompasses the economic, social, ecological, infrastructural, and institutional domains [2, 32].

Accordingly, the "medium-density trap" is not equivalent to the single-point notion of "optimal density", nor is it merely a descriptive reference to the nonlinear form of the density–performance relationship. Rather, it emphasizes a cross-dimensional zone of systemic vulnerability. The purpose of introducing this concept is to provide a theoretical reference for subsequent empirical analysis and policy discussion. In this sense, the concept differentiates itself from "optimal density" and "nonlinear effects" and offers a new explanatory framework for identifying stage-specific vulnerabilities in urban development.

### 3.2 Mechanism of Influence

The impact of population density on urban resilience is not unidirectional or linear, and its mechanisms vary across different density stages. Based on existing studies and theoretical reasoning, the potential pathways can be understood through three stages: low density, medium density, and high density.

In the low-density stage, the concentration of population and economic activities is limited, and economies of scale and network externalities are not yet fully realized. Public services and infrastructure utilization remain relatively inefficient, and governance demands are modest. As a result, the relationship between density and resilience is relatively weak.

As density increases, cities enter the medium-density stage. At this stage, agglomeration effects emerge, but congestion, environmental stress, and governance challenges also intensify. Public service demand grows faster than supply expansion, infrastructure systems approach their capacity limits, pollution and heat island effects accumulate, and governance complexity rises. The convergence of these pressures may heighten systemic vulnerability, leading to what can be termed the "medium-density trap". Thus, the medium-density stage may be associated with greater fragility in urban resilience. This theoretical reasoning provides a framework for subsequent empirical analysis.

Some cities may gradually mitigate density-related pressures in the high-density stage through long-term investments and institutional development. Infrastructure redundancy, public service maturity, ecological restoration, and governance capacity improvements can help moderate negative impacts. However, these outcomes are not universal and depend on resource endowments, governance capacity, and developmental trajectories.

### 3.3 Insights from the Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) posits an inverted U-shaped nonlinear relationship between economic development and environmental quality. In the early stages of development, environmental quality tends to decline as economic growth accelerates. Once development reaches a certain level, environmental quality may gradually improve [33]. This theory reflects the stage-based logic of "agglomeration effects–congestion effects–institutional catch-up" during development.

A similar perspective can be applied to the relationship between population density and urban resilience. In the low-density stage, the effects of density may remain limited. In the medium-density stage, pressures from resource constraints and environmental degradation, combined with institutional lag, may become more pronounced. In the high-density stage, some cities may alleviate negative impacts through governance improvements and technological advancement. This nonlinear and stage-specific framework provides important theoretical insights for interpreting the "medium-density trap". Moreover, the concept of the "middle-income trap" in development economics also highlights the risk of stage-specific stagnation [34], offering a useful analogy for understanding potential dilemmas in spatial agglomeration.

### 3.4 Research Hypotheses

Based on the above analysis, this study proposes the following hypotheses:

Hypothesis 1: Population density and urban resilience may exhibit a nonlinear relationship, with heterogeneous marginal effects across different density stages.

Hypothesis 2: In the low-density stage, the impact of population density on urban resilience may be relatively weak. In the medium-density stage, population density may exert negative effects on resilience, while in the high-density stage, these effects may be moderated.

Hypothesis 3: Population density influences urban resilience through multiple mechanisms, including economic, social, ecological, infrastructural, and institutional dimensions. The "medium-density trap" may represent the outcome of these pressures converging at a specific stage.

## 4 Research Design and Empirical Methods

### 4.1 Urban Resilience Evaluation Index System

Drawing on the theory of sustainable development and previous studies [35, 36], this study conceptualizes urban resilience as comprising five subsystems: economic, social, environmental, institutional, and infrastructural. For each subsystem, a corresponding set of objectives was established. Based on these objectives, 32 specific indicators were selected to construct a comprehensive evaluation system for measuring urban resilience. The detailed indicator framework is presented in Table 1.

**Table 1.** Urban resilience evaluation index system

| Dimension | Target | Indicator | Weight | Attribute |
|---|---|---|---|---|
| A: Economic resilience (0.2404) | Economic development | $A_1$ : GDP per capita | 0.0427 | + |
| | | $A_2$ : Fiscal expenditure per capita | 0.0446 | + |
| | | $A_3$ : General public budget revenue per capita | 0.0553 | + |
| | | $A_4$ : FDI as a share of GDP | 0.0014 | - |
| | Industrial structure | $A_5$ : Tertiary industry as a share of GDP | 0.0221 | + |
| | | $A_6$ : Science and technology expenditure as a share of GDP | 0.0590 | + |
| | | $A_7$ : Education expenditure as a share of GDP | 0.0153 | + |
| B: Social resilience (0.1818) | Social development | $B_1$ : Natural population growth rate | 0.0034 | - |
| | | $B_2$ : Urbanization level | 0.0136 | + |
| | | $B_3$ : Built-up area per capita | 0.0235 | + |
| | Residents' livelihood | $B_4$ : Consumption expenditure per capita | 0.0371 | + |
| | | $B_5$ : Proportion of urban employment | 0.0623 | + |
| | | $B_6$ : Urban employees covered by pension insurance | 0.0419 | + |
| C: Institutional resilience (0.2343) | Urban civilization | $C_1$ : Urban-green space per capita | 0.0242 | + |
| | | $C_2$ : College students per 10,000 people | 0.0441 | + |
| | | $C_3$ : Public library books per 100 people | 0.0602 | + |
| | Medical services | $C_4$ : Hospital density | 0.0767 | + |
| | | $C_5$ : Doctors per capita | 0.0291 | + |
| D: Environmental resilience (0.0308) | Living environment | $D_1$ : Green coverage in built-up area | 0.0025 | + |
| | | $D_2$ : $CO_2$ emissions per capita | 0.0065 | - |
| | | $D_3$ : Average PM2.5 concentration | 0.0082 | - |
| | | $D_4$ : Energy efficiency | 0.0003 | - |
| | Sanitation | $D_5$ :Centralized sewage treatment rate | 0.0060 | + |
| | | $D_6$ : Harmless treatment rate of household waste | 0.0051 | + |
| | | $D_7$ : Comprehensive utilization rate of general industrial solid waste | 0.0022 | + |
| E: Infrastructure resilience (0.3129) | Municipal infrastructure | $E_1$ : Completed investment in municipal utilities | 0.1362 | + |
| | | $E_2$ : Water supply pipeline density | 0.0271 | + |
| | | $E_3$ : Road area per capita $(m^2)$ | 0.0158 | + |
| | | $E_4$ : Buses per 10,000 people | 0.0306 | + |
| | Responsive infrastructure | $E_5$ : Mobile phone users per capita | 0.0320 | + |
| | | $E_6$ : Internet users per capita | 0.0488 | + |
| | | $E_7$ : Drainage pipeline density in built-up areas | 0.0224 | + |

### 4.2 Variable Design and Measurement

The dependent variable is urban resilience (UR). Based on the indicator system described above, we first standardize all indicator data and then apply the entropy-weighted TOPSIS method to calculate the indicator weights. The comprehensive UR score for each city is obtained by aggregating the weighted indicators. The weights and attributes of each indicator are shown in Table 1.

The core explanatory variable is population density (PD). It refers to the number of permanent residents per unit of land area. Considering that the resilience indicators are measured at the city level, and to ensure consistency in statistical scope, this study adopts the internationally accepted method: PD is calculated as the ratio of the year-end permanent population within the administrative boundary of a city to the total land area.

Control variables (CVs). Drawing on previous studies [35, 37], this study includes a set of control variables to account for the potential influence of government policy, economic structure, and market conditions on the relationship between population density and urban resilience. Specifically, four control variables are selected: financial investment (FI), measured by the ratio of general government fiscal expenditure to the city's GDP; industrial structure (IS), represented by the proportion of tertiary industry in the city's GDP; degree of marketization (DM), assessed by the share of private and self-employed workers in total urban employment; and government self-sufficiency capacity (GSC), calculated as the ratio of local general public budget revenue to expenditure.

### 4.3 Research Methods

#### 4.3.1 Panel model

This study employs a panel data regression model to examine the relationship between population density and urban resilience. Specifically, we adopt a fixed effects panel model to control for unobserved heterogeneity across cities. The basic form of the model is expressed as following Eq. (1):

$$UR = B + \alpha_1 PD + CV + \varepsilon_1 \tag{1}$$

where, the variables in the model are defined as follows: $UR$ is the dependent variable, representing urban resilience; $B$ is the intercept term; $PD$ is the core explanatory variable, referring to population density; $\alpha_1$ denotes the regression coefficients, reflecting the influence of the core and control variables on urban resilience; $CV$ is a set of control variables; $\varepsilon_1$ is the error term.

#### 4.3.2 Panel threshold model

The panel regression model is employed to verify whether population density directly impacts urban resilience. If a significant relationship is identified, a panel threshold regression model is applied to further examine whether this effect varies across different population density intervals. The threshold regression model is specified as following Eq. (2):

$$\begin{aligned} UR = K + \beta_1 PD \cdot I\,(PD \leq \gamma_1) + \beta_2 PD \cdot I\,(\gamma_1 < PD \leq \gamma_2) + \cdots + \beta_n PD \cdot I\,(\gamma_{n-1} < PD \leq \gamma_n) + \\ \beta_{n+1} PD \cdot I\,(\gamma_n < PD \leq \gamma_{n+1}) + \alpha_2 CV + \varepsilon_2 \end{aligned} \tag{2}$$

where, $K$ denotes the constant term; $I(\cdot)$ is the indicator function; $\beta$ represents the coefficient of the core explanatory variable; $\gamma$ denotes the threshold value; $CV$ refers to the control variables with $\alpha_2$ as their coefficients; $\varepsilon_2$ is the error term.

### 4.4 Study Area and Data Source

According to the Tabulation on 2020 China Population Census by County [38] and the China Urban-Rural Construction Statistical Yearbook 2022 [39], Chinese cities are classified into mega, very large, and large cities based on the number of permanent residents in built-up areas. This study focuses on large cities with a population of more than one million people in built-up areas. After excluding cities with significant data gaps, a final sample of 114 cities was selected for analysis.

The indicator data are primarily sourced from the China Statistical Yearbook (2006–2021) [40], the China Statistical Yearbook on Environment [41], and various provincial and municipal yearbooks. For missing values, supplementary data were estimated using linear interpolation and trend extrapolation based on historical records.

### 4.5 City Clustering

Based on the average population size levels and land use during the study period, this paper uses SPSS 24.0 for statistical analysis to classify the 114 cities into three major clusters. Cluster 1, consists of 34 national core cities, primarily composed of municipalities, provincial capitals, and economically dominant metropolises such as Beijing, Shanghai, and Shenzhen. These cities typically hold provincial or sub-provincial administrative status, possess administrative advantages, large-scale economies, and well-developed infrastructure systems, and serve as national hubs in innovation, finance, and internationalization. Cluster 2 includes 46 regional center cities and industrially specialized cities, represented by Wenzhou and Luoyang. These cities have moderate economic development levels, with GDP ranging between 300 and 800 billion yuan, and fulfill specialized functional roles within provincial urban systems. Cluster 3 comprises 34 developing cities, including Sanming and Zhaoqing, characterized by smaller economies with GDP typically between 200 and 300 billion yuan, mainly serving localized development needs.

## 5 Empirical Results and Analysis

### 5.1 Temporal Evolution of Urban Resilience in Chinese Large Cities

To better understand the changing relationship and distribution between population density and urban resilience over time, this study uses bivariate kernel density estimation to plot joint distribution maps for four representative years: 2006, 2011, 2016, and 2021 (Figure 1). These maps illustrate the dynamic evolution of the sampled cities across China.

The distribution pattern of the full sample cities remained relatively stable from 2006 to 2021. The central aggregation zone consistently appeared in the range of 1.0 to 1.5 (10,000 people/km$^2$) for population density and 0.1 to 0.2 for resilience scores, indicating that urban resilience across the country generally stayed low to medium. Although a secondary aggregation zone representing high-density and high-resilience cities began to emerge in the upper-right corner of the graphs around 2016 and expanded slightly by 2021, the full sample distribution pattern showed little shift. This overall stability in distribution implies that improvements in urban resilience in China have primarily occurred through localized breakthroughs rather than widespread systemic progress.

From 2006 to 2021, Cluster 1 cities showed a pattern of decreasing population density and increasing resilience. The central density index shifted from 1.0-1.5 to 0.5-1.0, while the resilience index increased from 0.10-0.15 to 0.15-0.25, reflecting progress in system optimization and spatial restructuring. Since 2016, a small sub-aggregation zone has appeared in the lower-right corner of the graph. By 2021, its density rose to 3.0, but resilience remained below 0.1, indicating that some ultra-dense cities lag in resilience building.

The distribution pattern of Cluster 2 cities exhibited relatively slow structural changes. The density index shifted from approximately 1.0 to 1.5, while the resilience index remained stable within the range of 0.10 to 0.20, indicating a generally moderate evolution. The contour of the density surface became gradually more compact, and the shading intensified, suggesting a narrowing gap in resilience levels among cities. However, the central aggregation zone did not shift significantly, nor did any high-resilience sub-aggregation zone emerge. Such a pattern indicates that these cities are still in the early stages of resilience platform development, with relatively weak structural stability.

The distribution of Cluster 3 cities has remained concentrated within a low-density and low-resilience range, approximately 0.5 to 1.5 in population density and 0.10 to 0.20 in resilience index, indicating generally low resilience levels and limited capacity for structural improvement. In 2021, the density-resilience structure exhibited signs of divergence, with two distinct density peaks emerging near 0.5 and 1.5, centered around a resilience index of 0.10 to 0.15. Such divergence suggests that while some cities have made incremental progress alongside population growth, others remain stagnant under low-density conditions due to the lack of effective resilience enhancement mechanisms. The spatial structure of this group remains relatively fragmented, with underdeveloped system foundations and insufficient governance capacity.

Overall, from 2006 to 2021, the evolution of urban resilience in Chinese cities exhibited a general pattern of "stable core with structural differentiation". Cluster 1 cities experienced a "declining density-rising resilience" trajectory; although a few cities achieved high-density breakthroughs, their resilience improvements remained relatively limited. Cluster 2 cities entered an initial stage of population concentration with unstable structural characteristics, while Cluster 3 cities had a weak foundation for resilience building, with emerging differentiation but limited overall progress. In general, the temporal evolution of urban resilience does not clearly align with changes in population density, indicating that resilience improvement is not solely driven by population agglomeration. Instead, it is likely shaped by a combination of governance capacity, resource allocation efficiency, and systemic coordination. Although population density remains a key factor influencing urban resilience, its impact mechanism warrants further investigation across different city types and development stages.

### 5.2 Descriptive Statistics and Multicollinearity Test

Pearson correlation coefficients were first used to assess the relationships among the variables to ensure the robustness of the regression results. The results show that the absolute values of the correlation coefficients between variables in all three models are less than 0.5, indicating relatively weak correlations. Subsequently, variance inflation factors (VIF) were calculated to test for multicollinearity among the explanatory variables. All VIF values were below 5, suggesting no significant multicollinearity in the regression models. Detailed results are presented in Table 2.

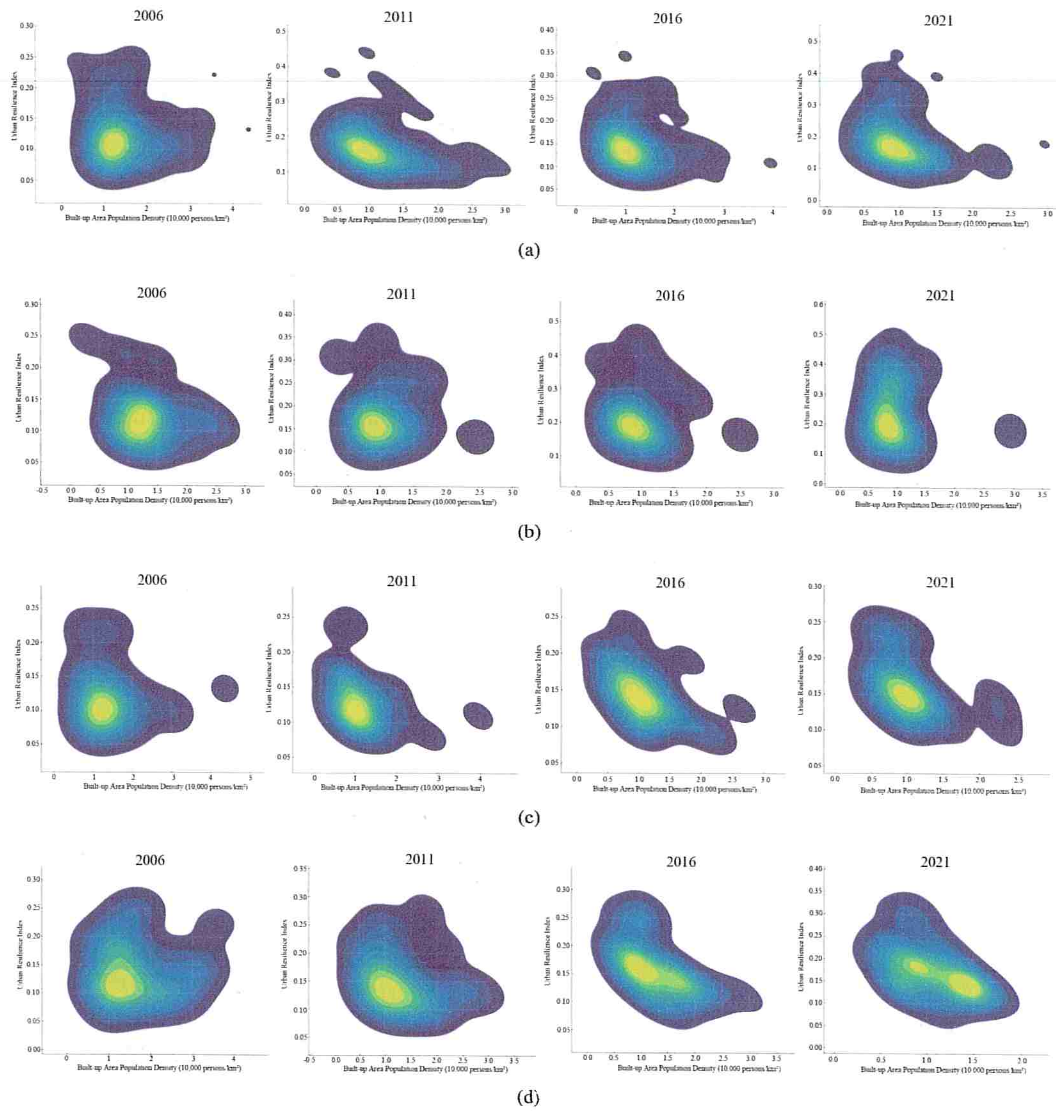



**Figure 1.** Joint distribution maps of Chinese large cities: (a) Joint distribute of full sample cities; (b) Joint distribute of Cluster 1 cities; (c) Joint distribute of Cluster 2 cities; (d) Joint distribute of Cluster 3 cities

**Table 2.** Test results of classification

| Variable | No. | Min | Max | Mean | SD | Median | VIF | PD | FI | IS | DM | GSC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| UR | 1824 | 0.070 | 0.500 | 0.158 | 0.059 | 0.145 | | | | | | |
| PD | 1824 | 0.273 | 4.371 | 1.176 | 0.538 | 1.056 | 1.105 | 1 | | | | |
| FI | 1824 | 0.044 | 1.485 | 0.139 | 0.060 | 0.129 | 1.064 | -0.029 | 1 | | | |
| IS | 1824 | 0.038 | 0.839 | 0.445 | 0.105 | 0.431 | 1.213 | -0.242** | 0.204** | 1 | | |
| DM | 1824 | 0.034 | 12.314 | 1.290 | 0.955 | 1.050 | 1.059 | -0.027 | 0.091** | 0.156** | 1 | |
| GSC | 1824 | 0.069 | 1.541 | 0.610 | 0.215 | 0.607 | 1.170 | -0.247** | -0.071** | 0.264** | -0.124** | 1 |

Note: UR: Urban resilience; PD: Population density; FI: Financial investment; IS: Industrial structure; DM: Degree of marketization; GSC: Government self-sufficiency capacity; SD: Standard deviation; VIF: Variance inflation factors; ** denote significance at the 5% levels.

## 5.3 Panel Regression Results

As shown in Table 3, population density significantly negatively affects urban resilience, with notable heterogeneity across both time and city type. In the full sample, the regression coefficient of population density is -0.023, indicating that population density generally inhibits improvements in resilience. The period-specific results show that this suppressive effect was strongest between 2006 and 2013, with a coefficient of -0.026; it declined to -0.014 in the 2014-2021 period, suggesting that environmental governance and system regulation improvements have somewhat alleviated density-induced pressures. By city cluster, the regression coefficient for Cluster 1 cities is -0.034, indicating the strongest negative effect among the three groups. This result is closely tied to their long-term exposure to ultra-high-density development. Although these cities generally possess advanced infrastructure, efficient resource allocation, and robust governance capacity, prolonged high-density pressure may have led to structural fatigue within their urban systems, significantly undermining resilience. In contrast, Cluster 2 cities have a coefficient of -0.030, reflecting the strain caused by weaker resource carrying capacity and emergency response systems, which render them highly susceptible to the adverse effects of increasing density. Cluster 3 cities show the weakest negative impact, with a coefficient of -0.012, likely due to their relatively low-density levels, and their urban systems have yet to face the pressures of dense development. However, this also suggests that their resilience capacity remains nascent, with limited system responsiveness.

Regarding control variables, financial investment and industrial structure are key drivers of enhanced urban resilience. Financial investment generally shows a positive effect, particularly in earlier years and in larger cities, but its impact weakens in the later period and in some city clusters, where it even turns insignificant or negative. This suggests diminishing marginal returns and uneven effectiveness across contexts. This may be due to inefficient allocation of fiscal resources, low investment returns, or insufficient governmental focus on resilience-building, reflecting the varying effectiveness of fiscal expenditure across different development stages and governance contexts. The coefficient of industrial structure ranges from 0.099 to 0.300 across all models. It is most pronounced in Cluster 1 cities, highlighting the role of industrial upgrading in alleviating resource and environmental constraints and strengthening system resilience. In comparison, the effects of the degree of marketization and government self-sufficiency capacity are relatively limited, with small coefficient fluctuations. Moreover, the constant terms in most models are positive, suggesting a baseline level of resilience embedded in city structures; however, for Cluster 1 cities, the constant is negative, implying that rapid population concentration may have led to the accumulation of structural risks.

**Table 3.** Panel regression results

| Variable | Dependent Variable(UR) | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | Full Sample | | Cluster 1 | Cluster 2 | Cluster 3 |
| | | 2006–2013 | 2014–2021 | | | |
| PD | -0.023*** | -0.026*** | -0.014*** | -0.034** | -0.030** | -0.012* |
| FI | 0.085*** | 0.073*** | -0.064 | 0.572*** | -0.001 | 0.104 |
| IS | 0.201*** | 0.133*** | 0.095*** | 0.300*** | 0.122*** | 0.099 |
| DM | 0.001 | 0.006** | 0.002** | 0.005 | 0.002 | 0.003 |
| GSC | -0.003 | 0.026** | -0.013 | 0.003 | -0.016 | 0.012 |
| Con. | 0.083*** | 0.089*** | 0.157*** | -0.019 | 0.126*** | 0.105*** |
| No. | 1824 | 912 | 912 | 544 | 736 | 544 |

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

### 5.4 Panel Threshold Regression Results

Based on the previous panel regression results, population density generally negatively impacts urban resilience across cities of different scales. However, further investigation is required to determine whether this effect shows heterogeneity in marginal effects. To explore the nonlinear mechanism and evolution pattern of how changes in population density influence urban resilience, this study employs population density as the threshold variable to construct a panel threshold regression model. We use Stata 18.0 to conduct bootstrap threshold effect tests on the full sample and the three city clusters. The results are presented in Table 4.

The full sample, along with Cluster 2 and Cluster 3 cities, revealed a significance double-threshold effect, indicating that the relationship between population density and urban resilience generally exhibits nonlinear characteristics. In contrast, Cluster 1 cities did not show a statistically significant stage-based shift in resilience as density changes. This may be attributed to the fact that resilience improvements in these national core cities depend more on long-term mechanisms such as technological advancement and institutional optimization, making it difficult for short-term density fluctuations to trigger noticeable transitions. Meanwhile, the threshold structures observed in Cluster 2 and Cluster 3 imply that their systems are more sensitive to population density changes and more prone to responsive fluctuations during the process of density adjustment. This reflects both the vulnerability and plasticity of medium and small cities, in stark contrast to the relative stability observed in national core cities.

**Table 4.** Panel threshold regression results

| Sample | Variable | F Statistic | P Value | BS Repetitions | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|---|---|---|
| | | 100.87 | 0.000 | 500 | 56.4855 | 37.8627 | 32.6225 |
| Full sample | PD | 52.01 | 0.034 | 500 | 117.0025 | 46.1675 | 39.0601 |
| | | 48.40 | 0.120 | 500 | 97.2100 | 59.6373 | 50.8404 |
| | | 8.17 | 0.822 | 500 | 60.8424 | 39.9922 | 31.6853 |
| Cluster 1 | PD | 7.074 | 0.742 | 500 | 32.3314 | 26.1071 | 20.5411 |
| | | 6.37 | 0.754 | 500 | 33.2308 | 22.6336 | 18.8853 |
| | | 78.11 | 0.000 | 500 | 50.8453 | 36.8697 | 30.8257 |
| Cluster 2 | PD | 33.08 | 0.040 | 500 | 39.8734 | 31.2160 | 27.9235 |
| | | 10.17 | 0.740 | 500 | 51.9389 | 35.2423 | 27.9541 |
| | | 81.12 | 0.000 | 500 | 45.9509 | 33.9200 | 26.0796 |
| Cluster 3 | PD | 38.86 | 0.012 | 500 | 39.1961 | 28.5654 | 23.5367 |
| | | 26.25 | 0.384 | 500 | 63.0573 | 46.5236 | 39.5706 |

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

5.4.1 Threshold regression results for full-sample cities

Based on the results of the threshold effect test, a double-threshold panel regression model was constructed using population density as the threshold variable. The estimated parameters are presented in Table 5.

**Table 5.** Panel threshold regression results

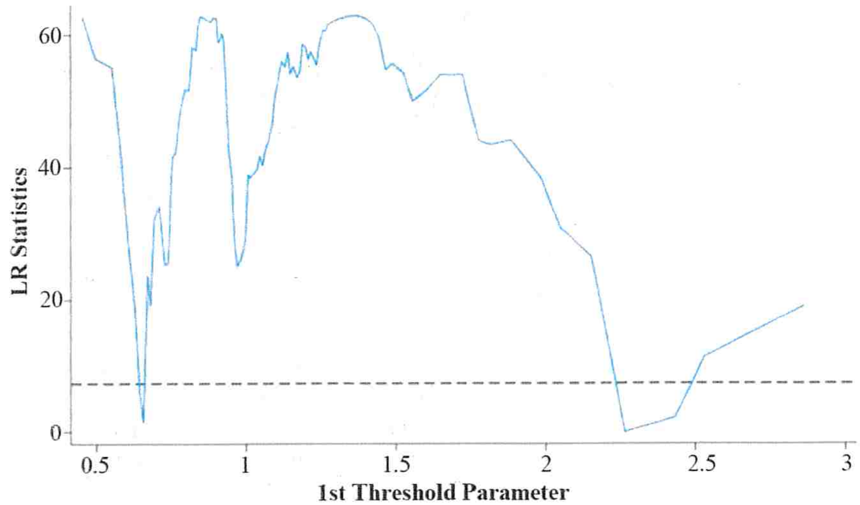
| Variable | Regression Coefficient | T Value | 95% Confidence Interval |
|---|---|---|---|
| $PD \leq 0.869$ | -0.008 | -0.72 | -0.029, 0.014 |
| $0.869 < PD \leq 2.264$ | -0.032*** | -4.41 | -0.047, -0.018 |
| $PD > 2.264$ | -0.014** | -2.64 | -0.025, -0.004 |
| FI | 0.086 | 1.35 | -0.040, 0.213 |
| IS | 0.187*** | 4.94 | 0.112, 0.262 |
| DM | 0.002 | 1.12 | -0.001, 0.005 |
| GSC | -0.002 | -0.11 | -0.038, 0.034 |

Note: Population density is measured as 10,000 people per km$^2$; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

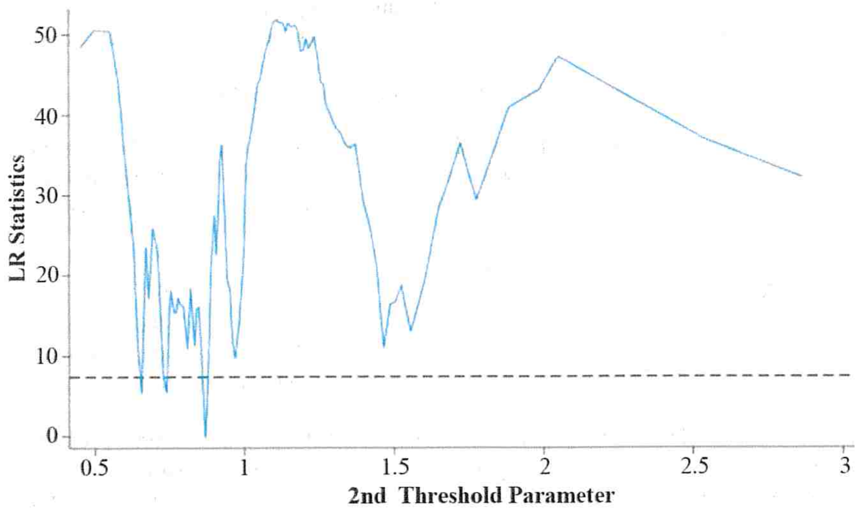
The two identified threshold values for population density are 0.869 and 2.264 (10,000 people/km$^2$), indicating a nonlinear relationship between population density and urban resilience. When population density is below 0.869, the estimated coefficient is -0.008 and statistically insignificant, suggesting that in low-density areas, changes in population density have a limited impact on urban resilience. This could be due to the lack of agglomeration effects, underdeveloped infrastructure and service networks, and relatively fragmented urban systems with low resistance to external shocks. When population density falls between 0.869 and 2.264, the coefficient becomes -0.032 and is statistically significant at the 1% level. This indicates that in medium-density areas, increases in population density significantly suppress urban resilience. During this phase, rapid population agglomeration imposes considerable stress on city operations, overburdening infrastructure and public services. In addition, planning delays and resource misallocations are more pronounced, reducing the system's capacity to respond effectively to risks. When population density exceeds 2.264, the coefficient is -0.014 and remains statistically significant at the 5% level. However, the absolute value is smaller than in the medium-density stage, suggesting that in high-density areas, the negative impact of further density increases is somewhat mitigated. This may reflect improved governance and risk management mechanisms in high-density cities, where intensive development and refined management help reduce negative externalities, although some resilience suppression persists.

In summary, the impact of population density on urban resilience exhibits a distinct nonlinear pattern: insignificant in low-density, negative in medium-density, and mitigated in high-density contexts. These findings highlight the need for policymakers to focus on preventing unregulated expansion in medium-density zones, optimizing spatial population distribution, and enhancing urban carrying capacity and system redundancy to strengthen resilience under complex conditions.

To further verify the reliability of the identified thresholds, Figure 2 presents the likelihood ratio functions for the two threshold estimates. Both values fall below the critical value of 7.35 at the 95% confidence level, confirming the statistical validity and robustness of the threshold estimates.




(a)




(b)

**Figure 2.** Double threshold estimates for full sample: (a) First threshold; (b) Second threshold

5.4.2 Threshold regression results for Cluster 2 cities

The threshold regression results for Cluster 2 cities are presented in Table 6 and Figure 3. Compared with the full sample, Cluster 2 cities exhibit a more pronounced and well-defined nonlinear threshold effect. The impact of population density on urban resilience shows strong consistency and structural variation across different density intervals. The two identified thresholds are 0.848 and 2.129, close to the thresholds found in the full sample (0.869 and 2.264). However, the significance levels and magnitudes of the regression coefficients in this cluster reveal a more distinct pattern of negative nonlinear transition.

In the low-density stage, where population density is less than or equal to 0.760, the effect of population density on urban resilience is not statistically significant, with a regression coefficient of 0.001. This is consistent with the results for the full sample, suggesting that in the early stages of urban development, when population agglomeration has not yet formed, cities lack sufficient economies of scale and collaborative networks, and population growth has a limited impact on resilience enhancement. As population density enters the medium-density range, greater than 0.760 and less than or equal to 2.310, the regression coefficient sharply decreases to -0.033 and is significantly negative at the 1% level. This indicates that urban systems face the greatest pressure in this phase. Compared to the full sample, the negative effect is more pronounced in Cluster 2 cities, reflecting more prominent weaknesses in resource allocation, public service provision, and institutional resilience. When population density exceeds 2.310, the negative effect is somewhat alleviated, with a regression coefficient of -0.019, which remains significant at the 5% level. Although this trend aligns with the full-sample findings, the degree of mitigation is less evident, suggesting that Cluster 2 cities have not yet fully developed effective governance and service mechanisms to cope with high-density challenges.

**Table 6.** Cluster 2 panel threshold regression results

| Variable | Regression Coefficient | T Value | 95% Confidence Interval |
|---|---|---|---|
| PD $\leq$ 0.760 | 0.001 | 0.04 | -0.028, 0.029 |
| 0.760 < PD $\leq$ 2.310 | -0.033*** | -3.24 | -0.054, -0.013 |
| PD > 2.310 | -0.019** | -2.35 | -0.035, -0.003 |
| FI | -0.002 | -0.09 | -0.038, 0.034 |
| IS | 0.121*** | 3.05 | 0.041, 0.201 |
| DM | 0.002 | 1.58 | -0.001, 0.006 |
| GSC | -0.005 | -0.26 | -0.045, 0.035 |

Note: Population density is measured as 10,000 people per kmkm$^2$; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

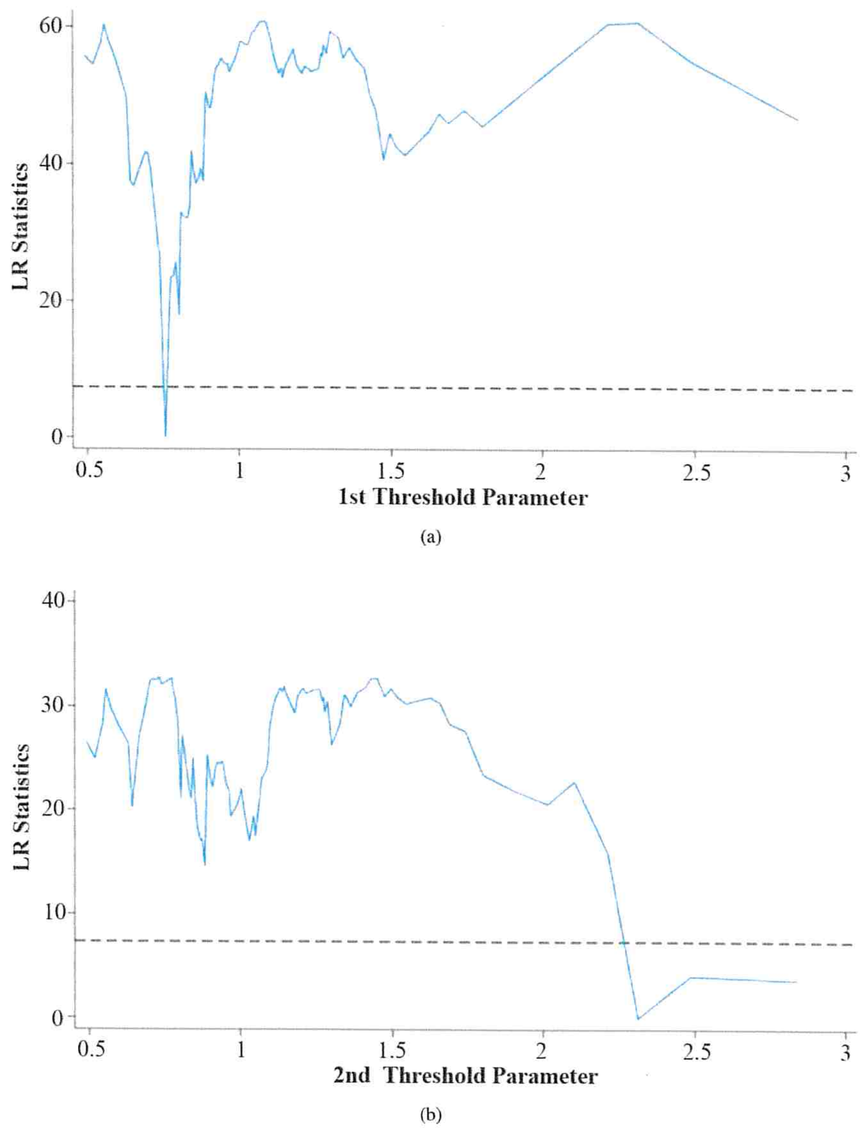



**Figure 3.** Double threshold estimates for Cluster 2: (a) First threshold; (b) Second threshold

Cluster 2 cities experience the most pronounced negative impact during the medium-density stage and exhibit relatively limited system rebound capacity, reflecting a certain degree of stage-specific vulnerability.

**Table 7.** Cluster 3 panel threshold regression results

| Variable | Regression Coefficient | T Value | 95% Confidence Interval |
|---|---|---|---|
| $PD \leq 0.679$ | 0.022 | 1.27 | -0.013, 0.056 |
| $0.679 < PD \leq 2.120$ | -0.033*** | -3.89 | -0.050, -0.016 |
| $PD > 2.120$ | -0.013** | -2.55 | -0.023, -0.003 |
| FI | 0.125 | 1.11 | -0.105, 0.355 |
| IS | 0.086* | 1.81 | -0.010, 0.183 |
| DM | 0.003 | 1.37 | -0.002, 0.008 |
| GSC | 0.000 | -0.00 | -0.039, 0.039 |

Note: Population density is measured as 10,000 people per km$^2$;*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

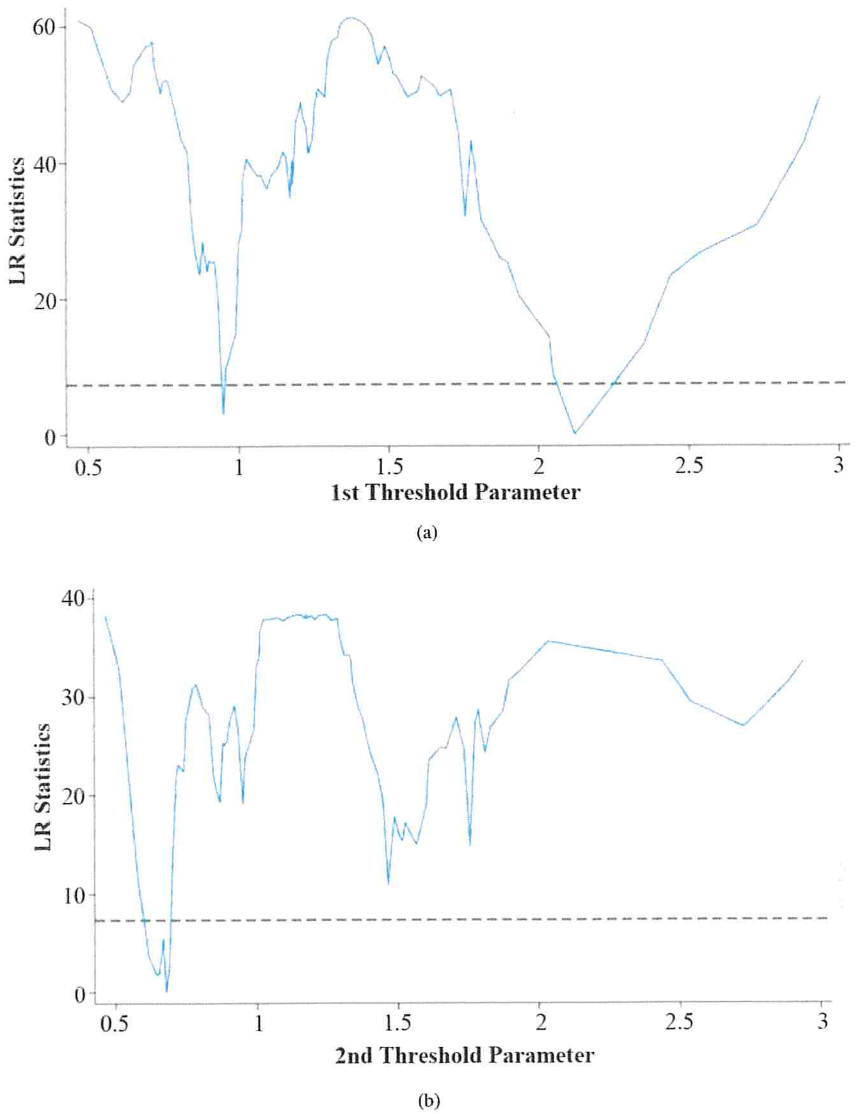



**Figure 4.** Double threshold estimates for Cluster 3: (a) First threshold; (b) Second threshold

5.4.3 Threshold regression results for Cluster 3 cities

The threshold regression results for Cluster 3 cities, as shown in Table 7 and Figure 4, also exhibit clear nonlinearity. However, compared with the full sample and Cluster 2 cities, the threshold effects in Cluster 3 follow a more segmented pattern, characterized by the stages of "potential–pressure–adjustment". The two estimated thresholds are 0.679 and 2.120, slightly lower than those of the full sample and Cluster 2. This suggests that Cluster 3 cities enter the sensitive range of population density at an earlier stage, which may be attributed to their limited resource-carrying capacity and less mature urban systems.

In the low-density stage, where population density does not exceed 0.679, the regression coefficient is 0.022. Although not statistically significant, it shows a positive trend, indicating that some Cluster 3 cities may benefit from a "population dividend". Their relatively abundant land resources and unsaturated infrastructure networks create favorable conditions for expanding urban system functions and enhancing initial resilience. When population density falls between 0.679 and 2.120, the coefficient declines to -0.033 and becomes significantly negative at the 1% level, suggesting that cities in this range face substantial systemic pressure. The combined effects of fiscal constraints, industrial concentration, and lagging governance lead to a marked decline in resilience. Once population density exceeds 2.120, the coefficient drops to -0.013, remaining significantly negative at the 5% level. This implies a modest alleviation of the negative effect, as some cities have begun to establish preliminary coping mechanisms for high-density shocks through governance interventions. However, the overall resilience recovery capacity in Cluster 3 cities remains limited, indicating substantial room for improvement in resilience enhancement.

5.4.4 Comparative analysis of threshold effects

Figure 5 compares the threshold regression results for the full sample and for the second and third clusters of cities, providing a systematic synthesis of the empirical evidence. The findings show that population density has a significant nonlinear impact on urban resilience, with differences across city types in threshold intervals, regression coefficients, and underlying mechanisms. These differences reflect heterogeneity in developmental stages, resource endowments, and governance capacities.

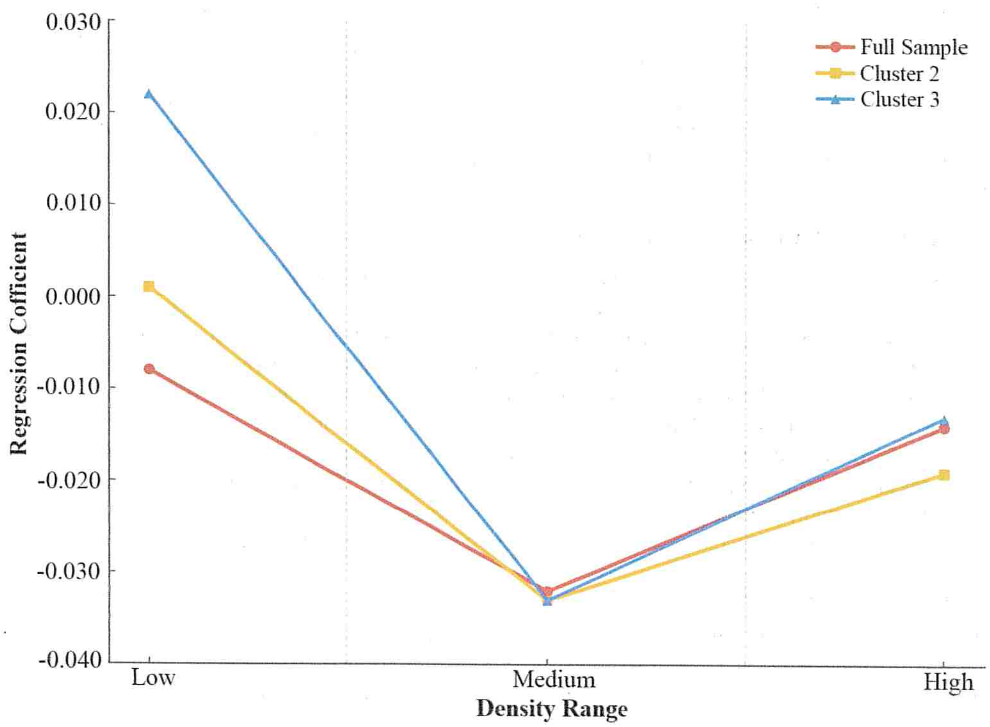



**Figure 5.** Threshold regression results by city cluster

## 6 Discussion

This study identifies the "medium-density trap" as a critical stage-specific barrier to enhancing urban resilience in Chinese cities and demonstrates the nonlinear influence of population density on urban resilience. Within the medium-density range, cities often become systemically vulnerable due to delayed resource allocation, inadequate infrastructure, and limited governance capacity, resulting in a marked decline in resilience. This pattern is most pronounced in the second and third clusters of cities, reflecting weaker institutional flexibility and insufficient support systems. By contrast, the first cluster does not exhibit clear threshold transitions, although the panel regression results still indicate negative density effects. The resilience of these cities appears to be shaped primarily by institutional accumulation and governance inertia, with density fluctuations alone insufficient to induce systemic change in the short term.

Overcoming the "medium-density trap" requires more than isolated efforts by individual cities. It should be embedded within the broader framework of regional spatial restructuring and national institutional arrangements. Urban resilience should be regarded as a systemic outcome of integrated resource management, coordinated governance, and institutional collaboration rather than an independent attribute of single cities. Under resource constraints, resilience enhancement depends on spatial restructuring and institutional reform. These processes in turn strengthen governance capacity and improve the resilience of the urban system as a whole.

### 6.1 Differentiated Pathways for Density Governance

In response to the challenges of the "medium-density trap", a differentiated, stratified, and coordinated mechanism for density governance and resilience enhancement needs to be established.

Regional central cities should continue to strengthen their primacy and regional influence by building systemic resilience and collaborative capacity under high-density conditions. Improving resource allocation efficiency, enhancing public service provision, and expanding green space networks can help reshape the density–resilience relationship in a positive direction, achieving a stable configuration characterized by both high density and high resilience.

Regional sub-central cities represent the critical nodes of density transition and require targeted interventions. With fiscal support, industrial relocation, and institutional incentives, these cities should establish independent and comprehensive service systems and spatial structures, thereby forming new secondary growth poles and generating spillover effects once the trap is overcome.

Ordinary medium-sized cities should avoid the path dependence that equates scale expansion with resilience improvement. Instead, they should adopt compact spatial structures and forward-looking governance approaches. Establishing density monitoring and risk identification mechanisms together with early investment in infrastructure and public services can simultaneously achieve both density control and efficiency gains.

Resource-based cities need to pay particular attention to vulnerabilities associated with industrial monocultures. During the medium-density stage, they should focus on promoting industrial diversification, introducing infrastructural redundancy, and strengthening ecological restoration and environmental governance. These measures can reduce systemic risks and prevent resilience decline under the "medium-density trap".

### 6.2 Practice-Oriented Approaches and Policy Instruments

At the practical level, the above strategies need to be aligned with existing planning and policy instruments. On the one hand, a dynamic monitoring and early-warning system for population density should be established, incorporating key threshold indicators into urban risk management and fiscal budgeting frameworks. On the other hand, policy instruments such as territorial spatial planning, urban regeneration, and intergovernmental fiscal transfers should be embedded in the density–resilience logic, linking infrastructure standards and public service capacity to population density levels to strengthen the coordination between planning indicators and governance capacity.

In addition, infrastructure design in medium-density areas should adopt moderate redundancy strategies. For example, water and electricity systems could be configured at 120 percent of the threshold demand, while around 30 percent of road network capacity should be reserved for emergency access. Such engineering-based resilience measures can substantially enhance the capacity of urban systems to self-regulate and recover under high stress levels.

### 6.3 Avoiding Development Pitfalls

Two common pitfalls must also be avoided. The first is the blind pursuit of urban sprawl, which neglects the coordination of density governance with spatial structure, leading to inefficient land use and resource waste. The second is increasing density without adequate supporting systems, which reduces spatial efficiency and exacerbates systemic risks. These problems indicate that overcoming the "medium-density trap" requires both improvements in urban governance capacity and the strengthening of regional spatial coordination mechanisms together with nationally differentiated policy support systems.

## 7 Conclusions

Based on panel data from 114 large Chinese cities covering the period 2006–2021, this study develops an urban resilience evaluation system encompassing five dimensions: economy, society, institutions, environment, and infrastructure. This study applies the entropy-weighted TOPSIS method and a threshold regression model to examine the nonlinear impact of population density on urban resilience. The main conclusions are as follows:

(1) During the study period, the overall resilience of large cities increased steadily. Infrastructure and the economy made the most significant contributions among the five dimensions, providing the foundation for systemic improvement.

(2) The relationship between population density and resilience follows a three-stage pattern. The effects are insignificant at low density, most negative at medium density, and alleviated at high density. The medium-density stage represents the most vulnerable period for urban resilience. (3) The sensitivity of resilience to changes in density varies across city types. The second and third clusters show more pronounced vulnerability, whereas the first cluster is influenced more strongly by institutional accumulation and governance inertia.

(4) The optimal density for resilience is not a fixed value. It is determined by the dynamic balance between density-induced pressures and the capacity of cities to mitigate them. High resilience is not inherently associated with either low or high density and instead depends on whether cities can effectively overcome the challenges of the medium-density stage.

The dataset used in this study is limited to the period 2006–2021, as data for 2022 and later years have been substantially disrupted by the COVID-19 pandemic, with gaps and abnormal fluctuations that may compromise analytical reliability. In addition, the analysis is restricted to 114 Chinese cities with urban resident populations exceeding one million, so the findings mainly reflect the dynamics of large urban centers. Consequently, the conclusions may not be fully generalizable to medium- or small-sized cities, or to resource-dependent cities with distinct developmental trajectories. Future research should extend both the temporal coverage and the range of city types to evaluate whether the "medium-density trap" exhibits heterogeneous manifestations across different urban contexts.

## Author Contributions

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

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## Data Availability

The panel dataset used in this study was compiled from publicly available official statistical sources, including the Tabulation on 2020 China Population Census by County [38], the China Urban-Rural Construction Statistical Yearbook 2022 [39], the China Statistical Yearbook (2006–2021) [40], and the China Statistical Yearbook on Environment [41]. Processed datasets generated during the current study are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare no conflict of interest.

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# Historical Power Outage of the US and Social Vulnerability Index

2024

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***Abstract*—Several works have been documented in the literature to study the societal impact of power outages through the Social Vulnerability Index (SVI) and power outage data correlation analysis. Since SVI is calculated based on the summed rank of multiple vulnerability factors to disaster, it may include factors that are not relevant to power outages due to extreme events. This work performs a detailed societal vulnerability analysis of power outages by analyzing several vulnerability themes such as socioeconomic status, characteristics of the household, racial and ethnic minority status, and housing type and transportation provided by the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry (CDC/ATSDR). We have performed the power outage analysis with and without an extreme weather outage threshold to study their relation with SVI themes. Although there is some relation between power outages and the SVI themes in the results, there is no strong distinction between the power outage duration and low vs High SVI values.**

***Index Terms*—CDC/ATSDR, EAGLE-I, NWS, Power outage, and Social Vulnerability Index**

## I. Introduction

Extreme weather events have been causing significant disruptions in the power grid system, resulting in widespread power outages and severe infrastructure (e.g., substations, transmission and distribution lines, and power generation plants) damage, leading to inconveniences in critical services (e.g., health care, transportation, and national security), severe economic losses, and adverse effects on the well being of the community [1]–[3]. Monetary losses of major power outage events are billions of dollars every year (25 to 70 billion [4]) to the US economy. Therefore, their social, economic, and technical impact analysis is important to develop the appropriate emergency response and mitigation measures.

To analyze the impact of the major events, the US Department of Energy (DOE) collects power outage data for major power system events [5]. DOE mandates that utility companies in the United States submit major power outage information, which DOE publishes in the OE-417 report. Major events have been defined as events that cause power outages to more than 5,000 customers or more than 300 MW of power demand disruption. Using DOE's major power outage information, several analyses have been documented in the literature studying the impact of weather events on power systems. For example, authors in [6] studied the impact of these events on the power delivery of the United States. The seasonal pattern of power outages has been analyzed in [7].

In addition to the literature on the impact analysis of power outage on power delivery in the United States, numerous work has been documented in the literature to study the societal impact of power outages through SVI and power outage data correlation analysis. Work presented in [8] performs socioeconomic vulnerability impact analysis of severe weather-related power outages. Authors of [8] perform analysis only with Atlantic hurricanes, it does not perform nationwide analysis with other types of weather events such as severe thunderstorms, heat waves, cold waves, snow storms, and flooding. The analysis of [8] is conditioned based on the assumption that outages are caused by extreme outages, ignoring operation-related causes of power outages. The social vulnerability of power outages has been studied in [9]. The work [9] analyzes the power outages caused by all events (weather and nonweather events) and does not perform a detailed social analysis with several social vulnerability themes. The data sources used in [8], [9] are also not available publicly, limiting their replicability for other similar analyses.

In this work, we work around some of the existing problems by mapping weather data obtained from the National Weather Service (NWS) with the publicly available power outages dataset. We used this mapping to develop a threshold to distinguish the power outages caused by extreme weather events. Also, this work performs a detailed societal vulnerability analysis of power outages nationwide at county level resolution by analyzing several vulnerability themes such as socioeconomic status, characteristics of the household, racial and ethnic minority status, and housing type and transportation provided by the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry(CDC/ATSDR SVI). Analyzing each of these individual SVI themes is important as overall SVI is calculated based on the summed rank of multiple vulnerability factors to disaster, it may include factors that are not relevant to power outages due to extreme events and may shadow the relevant themes.

The rest of the paper is presented as follows. Section II provides the overview of the data source and data processing. Section III provides a methodology and the results of the proposed work along with the discussion. Finally, concluding

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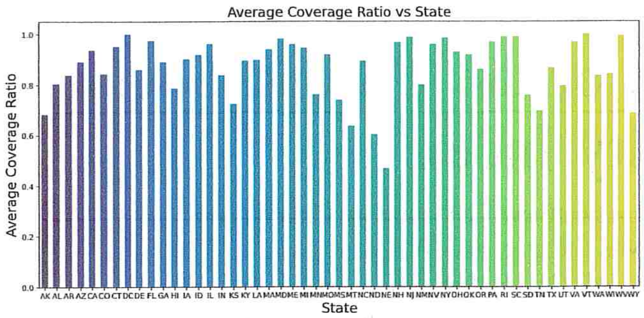


Fig. 1. Average coverage ratio (of coverage ratio between 2018–2022) for different states.

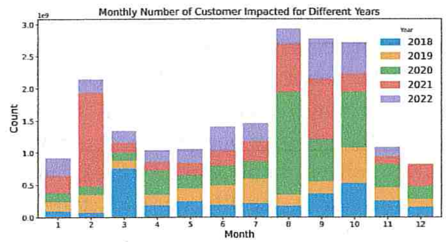


Fig. 2. Number of customers impacted by power outages in the United States from 2018–2022 by month.

remarks are provided in IV.

## II. Data Source

This section provides the source of the data and performs data processing for the proposed work. In this work, we have utilized power outage data from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) platform, SVI CDC/ATSDR, and weather data from NWS.

### A. Power Outage Data: EAGLE-I Data

This work leverages the publicly available power outage data for the United States obtained from ORNL's EAGLE-I platform[1]. EAGLE-I is an interactive geographic information system that allows users to view and map the nation's energy infrastructure and obtain near real-time information updates concerning the electric, petroleum, and natural gas sectors within one visualization platform. The EAGLE-I platform has been collecting county-level power outage datasets from the US power grid from 2014. EAGLE-I datasets are available for academic research. Since data are more complete from 2018, we are using 2018-2022 EAGLE-I data for our analysis.

EAGLE-I datasets are collected based on the voluntary participation of utility companies in the United States. The participation of electric utilities has been increasing over the years, making the dataset more reliable and useful. Fig. 1 shows the state-wide average coverage ratio. The coverage ratio is the ratio between the total number of electrical customers that share data to the total number of electrical customers.

Fig. 2 shows the monthly number of customers impacted by power outages (caused by any kind of cause: weather, operation, cyber, etc.) in the United States from 2018–2022. (Although EAGLE-I started the data collection in 2014, data for some states were not available until 2017; therefore, we are analyzing only 2018–2022 from the EAGLE-I dataset.) This figure shows that a maximum number of cumulative power outages occurred in August, followed by September and October. The possible reason for this trend could be that the outages coincide with tropical storms, thunderstorms, and heat waves. This could also be due to more industry demand (as businesses ramp up after summer breaks) pushing the infrastructure capacity limits towards or above the limit boundary.

[1]https://eagle-i.doe.gov/

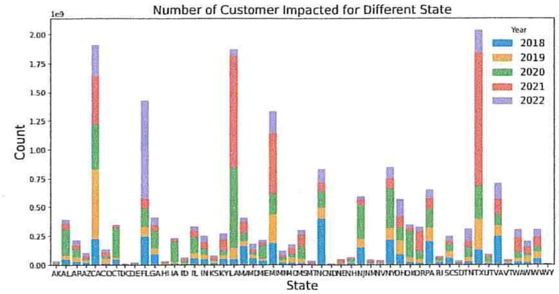


Fig. 3. Number of customers impacted by power outages by state from 2018–2022.

Fig. 3 shows the yearly number of customers impacted by power outages in the United States by state from 2018–2022. This figure shows that the maximum number of cumulative power outages occur in Texas, followed by California and Louisiana. The possible explanation for the maximum number of outages in Texas and California could be because of the significant number of weather events, the power grids running near to or above their capacities, and being significantly more populous states (more population means more customers could be impacted).

Although the number of customers impacted by power outages has changed over the years, drawing conclusions with these limited data from scraping utility websites would be premature. Therefore, more data will be required to draw a concrete conclusion.

### B. Social Vulnerability Index Data

SVI data required for our analysis are obtained from the United States CDC/ATSDR SVI [10]. CDC/ATSDR has defined social vulnerability as "Community's ability to prevent human suffering and financial loss in the event of disaster". The main purpose of the SVI is to help the communities to better prepare before, during, and after hazardous events (extreme weather events, disease outbreaks, and chemical exposure). It provides community-specific and spatially relevant information to health officers and emergency responders.

SVI is a percentile ranking of 16 different variables such as unemployment, racial and ethnic minority status, and disability which are further grouped into four related themes: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and trans-


Fig. 4. Themes and variables of the American community survey, used for computing overall SVI. Source CDC/ATSDR SVI [10]

portation as shown in Fig. 4. SVI provides these rankings for each of the counties of the United States. In our analysis following terminologies are used: RPL_THEME1 for Socioeconomic Status; RPL_THEME2 for Characteristics of Household; RPL_THEME3 for Racial &Ethnic Minority Statys; RPL_THEME4 for Transportation Housing Type; and RPL_THEMES for overall vulnerability index. SVI data are available for the years 2000, 2010, 2014, 2016, 2018, 2020. Since we are performing the analysis on power outage data from 2018-2022, we have averaged the SVI data from 2018 and 2020 for this work.

### C. Weather Data

Weather datasets are obtained from the National Weather Service (NWS), a federal agency of the United States[2]. The NWS provides information about weather, water, climate data, warnings, advisories, history, and forecasts, as well as impact-based decision support systems to protect human life and enhance the US economy. We used the NWS Valid Extend Code (VTEC) archives dataset processed by the Iowa State University Iowa Environmental Mesonet (IEM). This dataset contains information about the geography and life cycle of weather events that occur in the United States, including watches, warnings, advisories, and others. Please refer to the IEM VTEC achieve website for further details on the data[3]. Since "W" (Watch) and "Y" (Advisory) are the most impactful events, we are filtering only the "W" and "Y" type SV events for our analysis.

## III. Methodology and Results

In this section, we provide the power outage and SVI with and without the weather-related outage threshold. In our work, we have mapped the weather outage data with the power outage data to determine the threshold for the outages caused by the extreme weather event. The threshold value is calculated—average power outages from regular causes—to distinguish power outages caused by extreme events from other regular causes (e.g., vegetation and system faults). Fig. 5 displays an example power outage curve. The weather data are only used in this study to calculate the threshold of outages due to extreme weather events. Weather event correlation with SVI is left as future work. The following analysis is performed for this work.

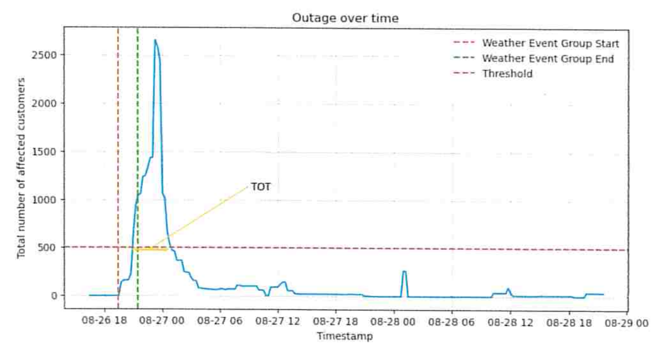


Fig. 5. Power outage pattern of a weather event with the threshold.

### A. Power Outage and SVI without Threshold

Figure 6 shows the Power outage count of different durations vs the cumulative customer impacted. Due to the space limit, we have only provided the results for Theme 1 and Theme 2. The rest of the results are provided in the supplementary file [11]. This plot shows that for Theme 1 (socioeconomic status), theme 2 (characteristics of household), theme 4 (transportation and housing type), and overall theme, there is no clear distinction for all outage duration counts (more than 1 hour, more than 8 hours (medically significant [9]), and more than 24 hours events). For theme 3 (Racial & Ethnic Minority Status), there seem to be more cumulative customers impacted and more events of various duration for more vulnerable communities. In general, there is no strong distinction between outage duration of various sizes vs SVI themes.

### B. Power Outages and SVI with Threshold

In this case, we have analyzed the power outage duration (in minutes) with different values of the SVI index for different sizes of the counties in terms of their population. The results are as shown in Fig 7, in this figure TOT denotes the time duration over the threshold. The average value of county-level TOT calculated is 495 minutes. TOT as shown in 5, is visually indicated by the length of time the power outage curve remains above the threshold line. TOT provides information about the duration of power outages experienced by customers due to extreme events. Lower TOT signifies the power system takes less time to recover from power outages. Q1 and Q4 represent

[2]https://www.weather.gov/

[3]https://mesonet.agron.iastate.edu/info/datasets

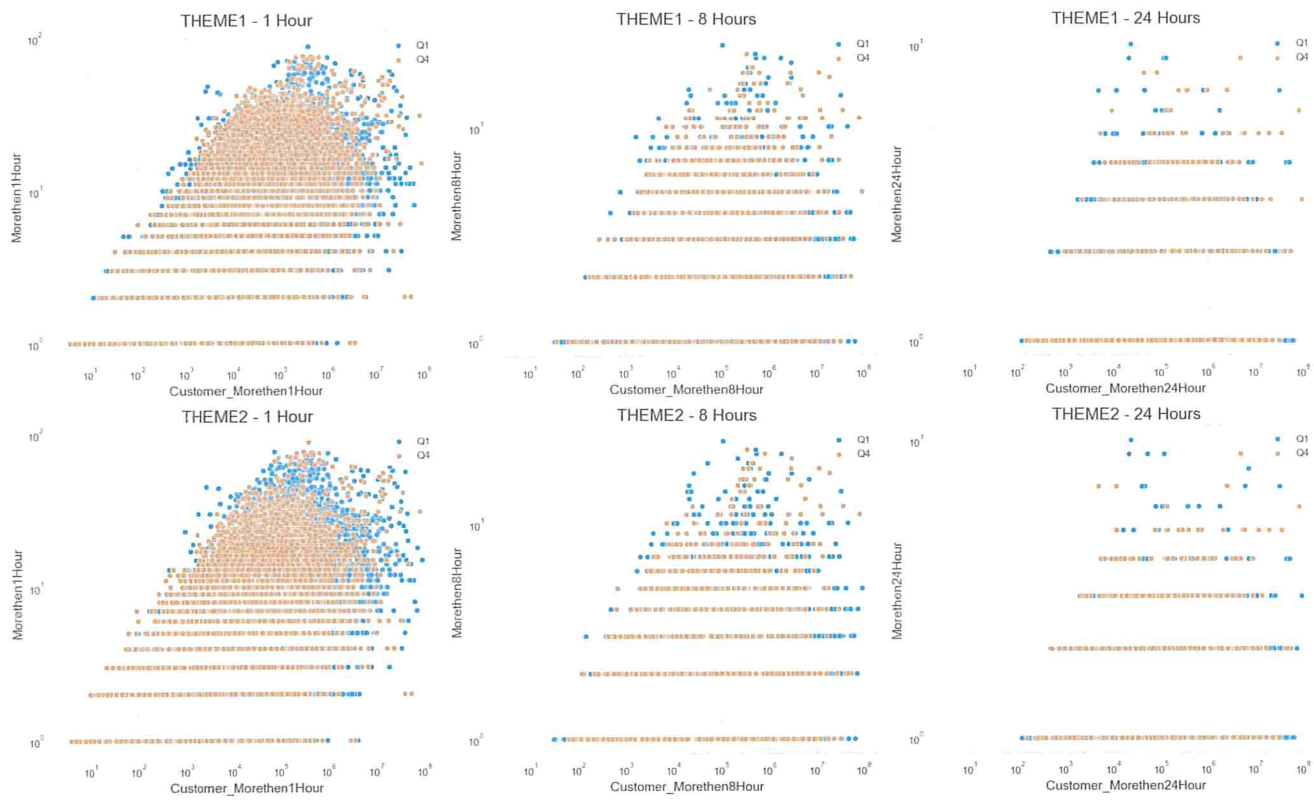


Fig. 6. Outage Duration of More than Various Hours vs SVI Themes. Both low and high SVI counties have higher outage duration, hence do not show a high correlation.

the first(low SVI: 0-0.28: less vulnerable) and fourth (high SVI: 0.77-1: more vulnerable) quartile values of respective SVI themes.

Results in Fig. 7 show that for Theme 1 (socioeconomic status) and Theme 2 (characteristic of household), higher-population cities are more vulnerable. On the other hand for Theme 3 (Racial and Ethnic minority status) and Theme 4 (transportation and housing type), high-population cities are less vulnerable. In terms of power outage duration, there is no clear pattern distinction between the high and low values of SVI themes for different sizes of counties in terms of population. This means there is no clear discrimination between the low SVI counties and high SVI counties in terms of power restoration after a weather event. However, when we look at the individual data points (individual counties), we see the statistics as shown in Fig. 8. The rest of the counties are in the "Q2:[0.28-0.53]" and "Q2:[0.53-0.77]" range (averagely vulnerable) and are not included as we are comparing the more vs less vulnerable counties in terms of SVI themes.

Power outage and SVI on the Continental US map are provided in Fig 9 and Fig 10. The first information that can be extracted from these figures is that even for the same quartile ($Q1[0-0.28]$ or $Q2[0.77-1]$), different SVI themes cover different counties. The Counties with white color in these map indicates that the respective SVI (Theme1, Theme2, Them3, Theme4, and overall) values do not fall in those counties. Fig 9 provides the TOT with low SVI values, this indicates that power outages are generally high in highly populated cities. The result is similar for high SVI values in Fig 9 as well. The possible reason for this is that outage events of the same duration in general impact more population in dense areas resulting overall longer power outage duration. With more power system infrastructure in a densely populated area also has, there is the probability of more infrastructure being damaged due to an event resulting in more power outage duration.

These results show that there is no strong correlation between power outages due to extreme events (distinguished based on the calculated threshold) and the SVI index. Note that the results can expanded to other geographical regions (e.g. Alaska, Hawaii, etc.) of the USA comfortably, although we have provided the results only for the continental US.

## IV. Conclusion

This work performed a detailed societal vulnerability analysis of power outages by analyzing several vulnerability themes such as socioeconomic status, characteristics of the household, racial and ethnic minority status, and housing type and transportation provided by the CDC/ATSDR. This analysis is important as SVI is calculated based on the summed rank of multiple vulnerability factors to disaster, it may include factors that are not relevant to power outages due to extreme events

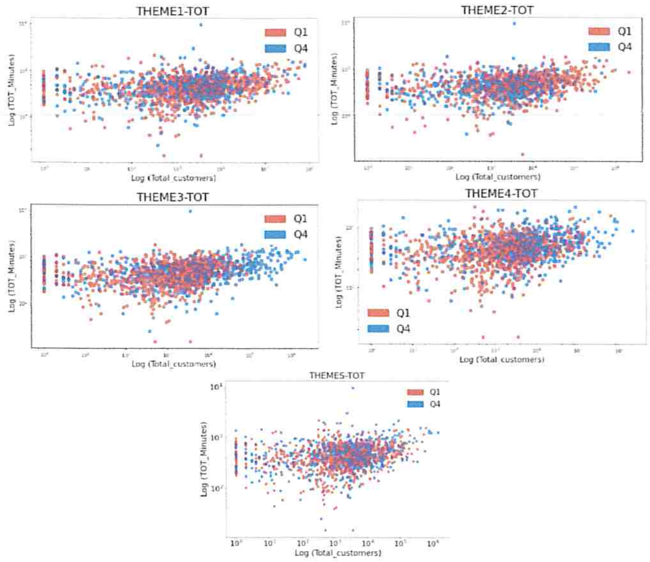


Fig. 7. County level TOT vs Customers. TOT represents the time over the threshold line of the power outage curve as shown in Fig 5. Q1 and Q4 represent the first(0-0.28) and fourth (0.77-1) quartile values of respective SVI themes. Both low and high SVI counties have high TOT with the increasing number of customers impacted.

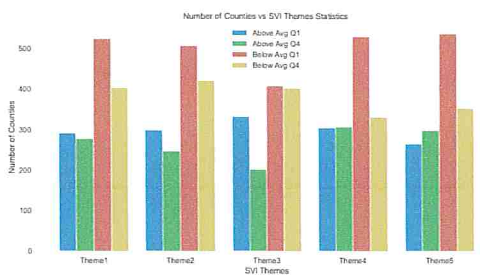


Fig. 8. Number of Counties vs Average TOT Statistics. Q1 and Q4 represent the first(0-0.28) and fourth (0.77-1) quartile values of respective SVI themes.

and may shadow the relevant themes. We performed the power outage analysis with and without an extreme weather outage threshold to study their relation with SVI themes. Although there was some relevance between power outages and the SVI themes in the analysis, there is no strong correlation between the power outage due to extreme events and SVI themes.

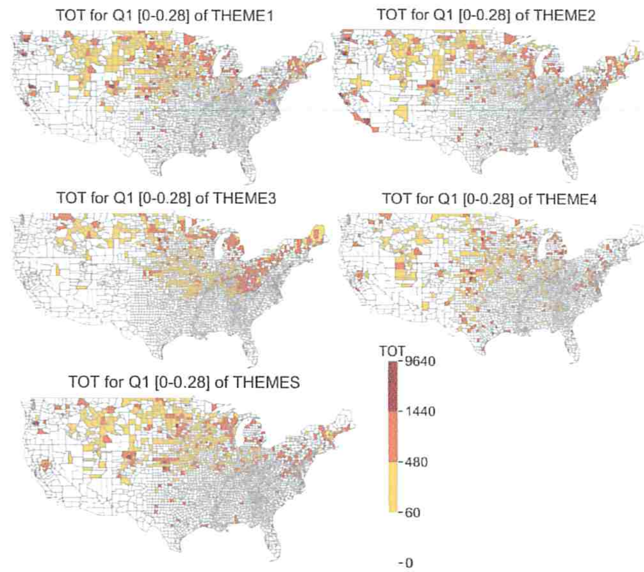


Fig. 9. TOT (in minutes) with Low SVI for Various Theme. TOT represents the time over the threshold line of the power outage curve, see Fig 5.

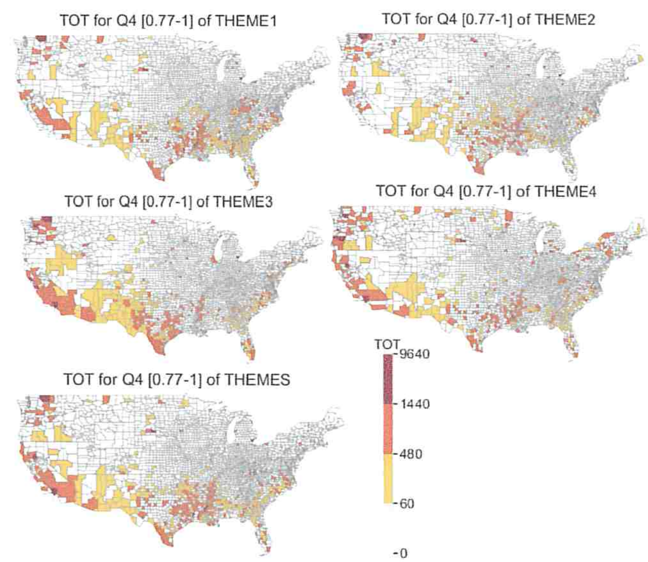


Fig. 10. TOT (in minutes) with High SVI for Various Theme. TOT represents the time over the threshold line of the power outage curve, see Fig 5.

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# Population Density and Urban Resilience in Chinese Mega-Cities: Evidence of a Medium-Density Trap

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**Abstract:** Urban resilience has become a central framework for advancing sustainable development in the context of escalating urban risks. To investigate the role of population density in shaping resilience, panel data from 114 large Chinese cities covering the period 2006–2021 (excluding the COVID-19 years to avoid potential distortions) were analyzed. A multidimensional urban resilience evaluation system was constructed, encompassing five key domains: economy, society, institutions, environment, and infrastructure. Resilience levels were assessed through the entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), while a panel threshold regression model was applied to capture potential nonlinearities in the density–resilience relationship. Results demonstrate that urban resilience in China has exhibited a sustained upward trajectory, largely driven by advances in infrastructure provision and economic capacity. However, population density exerts a nonlinear "double-threshold effect". At low levels of density, the effect on resilience is statistically insignificant; within a medium-density range, a pronounced negative impact emerges, constituting a "medium-density trap"; and at high densities, the adverse effects are attenuated, suggesting that urban systems may gradually adapt to intensified population pressures. This trap is most evident in regional center cities and rapidly developing urban areas, where governance capacity, infrastructure investment, and resource allocation have lagged behind demographic expansion. These findings highlight the stage-dependent vulnerabilities embedded in urbanization processes and indicate that resilience is not solely a function of density itself but also of institutional capacity and infrastructural adequacy. Differentiated governance strategies are therefore required, including targeted improvements in public infrastructure, strengthened institutional and administrative capacities, and the optimization of spatial configurations to accommodate density-specific challenges. By identifying the thresholds at which population density alters resilience trajectories, this study contributes to a deeper theoretical understanding of urban vulnerability and offers actionable insights for policymakers seeking to enhance resilience under conditions of rapid urban growth and high-density development.

**Keywords:** Urban resilience; Population density; Evaluation system; Threshold regression; Medium-density trap

## 1 Introduction

Amid rising global risks and increasing urban complexity, urban resilience has become a key indicator for assessing a city's capacity to achieve sustainable development [1, 2]. It reflects a city's ability to withstand and recover from disasters and public health crises as well as its adaptability to maintain essential functions under continuous change [3, 4]. As high-density development and compound risks intensify, balancing risk management and functional performance has become a major challenge for urban planning and governance [5].

Population density is a core structural factor shaping urban resilience, influencing land use patterns, resource allocation, infrastructure capacity, and environmental pressures [6]. Moderate density can enhance infrastructure efficiency, promote social cohesion, and improve resource utilization, strengthening a city's capacity to absorb and adapt to external disturbances [7, 8]. In contrast, excessive density often correlates with higher pollution levels, infrastructure overload, and increased psychological stress from noise and environmental discomfort [9–11]. Low-density sprawl, on the other hand, is linked to spatial fragmentation, underutilized land, and inefficiencies in public service delivery, which together undermine urban resilience [12].

Existing studies have indicated that the relationship between population density and urban resilience is not strictly linear; the direction and intensity of this effect may vary significantly across different density intervals [13–15], implying that threshold effects may exist rather than a simple one-way response pattern. Particularly during the transition from low to high density, differences in systemic pressure and regulatory capacity across different phases may lead to fluctuations in resilience performance. While some research has preliminarily revealed such nonlinear associations, the mechanisms underlying these patterns, especially across different types of cities and density stages, remain underexplored and lack systematic empirical validation.

Based on this, the study takes 114 prefecture-level and above cities in China as the research sample. It constructs an urban resilience index system covering the five dimensions mentioned above, evaluates resilience levels using the entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method, and applies panel regression and threshold regression models to explore the nonlinear effects and underlying mechanisms of population density on urban resilience and its subsystems. The goal is to provide theoretical support and policy recommendations for managing urban population density and advancing resilience-oriented urban development.

## 2 Related Works

The study of urban resilience has evolved into a comprehensive multi-dimensional framework encompassing five key dimensions: economic, social, environmental, institutional, and infrastructural. Within this framework, population density is a central structural factor influencing all subsystems.

In the economic system, moderate population density can help optimize resource allocation and promote the effective concentration of production factors, thereby enhancing a city's capacity to respond to economic fluctuations and external shocks. On one hand, higher density facilitates information exchange and collaboration among firms, stimulating innovation and industrial synergy, which contributes to faster recovery and greater adaptability of the economic system [7, 8, 16]. On the other hand, excessive density may constrain production space, increase operational costs, and intensify pressure on small and medium-sized enterprises, ultimately undermining economic stability and resilience [17].

In the social system, moderate population density can facilitate neighborhood interaction and the accumulation of social capital, thereby enhancing community-based mutual support and the ability to respond to unexpected events [18]. However, when population concentration is high and spatial distribution is uneven, it may lead to strained public resource allocation and weakened community identity, triggering social isolation, competition for resources, and group tensions, which in turn exacerbate disparities in resilience across communities [19, 20].

Population density plays a critical role in shaping a city's capacity to cope with environmental risks by influencing land use patterns, energy consumption structures, and ecological spatial layouts [21, 22]. A moderately high density is more conducive to the deployment of ecological infrastructure such as green transportation systems, centralized energy supply, and rainwater recycling, thereby enhancing urban adaptability to climate change and natural hazards [23]. Despite these benefits, when population density exceeds ecological carrying thresholds, it often intensifies air pollution, urban heat island effects, and green space degradation, weakening urban ecosystems' self-regulation and recovery capacity [14, 15].

Higher population density places greater demands on urban institutional systems such as disaster response, public service delivery, and interdepartmental coordination [24]. In densely populated areas, the urgency and complexity of governance often drive improvements in risk early-warning and emergency response mechanisms, thereby enhancing institutional adaptability and responsiveness [25]. Nevertheless, in the absence of effective coordination mechanisms, such complexity can also lead to fragmented administration and delayed policy implementation, ultimately undermining the stability of institutional structures [26].

Regarding infrastructure resilience, population density is crucial in shaping urban systems' spatial configuration and emergency response capacity. Densely populated cities are more likely to develop networked and large-scale infrastructure layouts, enhancing the operational efficiency and responsiveness of essential services such as water supply, electricity, transportation, communications, and healthcare [27, 28]. Nevertheless, when density becomes excessive, these systems may face overload risks. The failure of a single critical node can lead to cascading disruptions, exposing vulnerabilities in the overall resilience of urban infrastructure [15].

In summary, although their emphases differ, domestic and international studies have examined the complex relationship between population density and urban resilience. International research, primarily based on experiences from Europe, North America, and the Middle East, has emphasized the vulnerabilities of high-density cities in relation to public service provision, traffic congestion, and environmental carrying capacity [11, 18] . It has also stressed the importance of infrastructural resilience and ecological restoration in mitigating these risks [19, 23]. By contrast, studies in the Chinese context have focused more on the challenges of rapid urbanization, particularly the lag in public service expansion and governance capacity during the medium-density stage [12, 14]. These differences suggest that the mechanisms through which density shapes resilience in Chinese cities may diverge from those observed in developed economies, owing to distinct developmental trajectories and institutional contexts. Engaging more directly with international scholarship can help to identify the generalizable aspects of the density–resilience relationship, while at the same time underscoring the distinctive significance of the "medium-density trap" as a phenomenon characterizing large Chinese cities.

## 3 Theoretical Mechanism Analysis

### 3.1 Conceptual Definition

In existing studies, the notion of "optimal density" is typically understood as the level of population agglomeration that balances the benefits of concentration with the costs of congestion, thereby maximizing social welfare or economic efficiency [29, 30]. This notion reflects a single-point optimum in terms of static equilibrium. Related to this argument is the concept of the "nonlinear effects of density", which suggests that the relationship between population density and urban development performance may exhibit an inverted U-shape or segmented pattern, revealing differences in marginal effects across stages [31].

Against this backdrop, this study introduces the concept of the "medium-density trap" to describe a stage-specific dilemma that may arise as cities evolve from low-density to high-density conditions. Specifically, when population density enters a certain range, cumulative pressures may emerge simultaneously across the economic, social, ecological, infrastructural, and governance dimensions, while the corresponding support and regulatory capacities fail to expand in parallel. As a result, urban resilience may stagnate or even decline. Urban resilience is understood as a multi-dimensional coupled system that encompasses the economic, social, ecological, infrastructural, and institutional domains [2, 32].

Accordingly, the "medium-density trap" is not equivalent to the single-point notion of "optimal density", nor is it merely a descriptive reference to the nonlinear form of the density–performance relationship. Rather, it emphasizes a cross-dimensional zone of systemic vulnerability. The purpose of introducing this concept is to provide a theoretical reference for subsequent empirical analysis and policy discussion. In this sense, the concept differentiates itself from "optimal density" and "nonlinear effects" and offers a new explanatory framework for identifying stage-specific vulnerabilities in urban development.

### 3.2 Mechanism of Influence

The impact of population density on urban resilience is not unidirectional or linear, and its mechanisms vary across different density stages. Based on existing studies and theoretical reasoning, the potential pathways can be understood through three stages: low density, medium density, and high density.

In the low-density stage, the concentration of population and economic activities is limited, and economies of scale and network externalities are not yet fully realized. Public services and infrastructure utilization remain relatively inefficient, and governance demands are modest. As a result, the relationship between density and resilience is relatively weak.

As density increases, cities enter the medium-density stage. At this stage, agglomeration effects emerge, but congestion, environmental stress, and governance challenges also intensify. Public service demand grows faster than supply expansion, infrastructure systems approach their capacity limits, pollution and heat island effects accumulate, and governance complexity rises. The convergence of these pressures may heighten systemic vulnerability, leading to what can be termed the "medium-density trap". Thus, the medium-density stage may be associated with greater fragility in urban resilience. This theoretical reasoning provides a framework for subsequent empirical analysis.

Some cities may gradually mitigate density-related pressures in the high-density stage through long-term investments and institutional development. Infrastructure redundancy, public service maturity, ecological restoration, and governance capacity improvements can help moderate negative impacts. However, these outcomes are not universal and depend on resource endowments, governance capacity, and developmental trajectories.

### 3.3 Insights from the Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) posits an inverted U-shaped nonlinear relationship between economic development and environmental quality. In the early stages of development, environmental quality tends to decline as economic growth accelerates. Once development reaches a certain level, environmental quality may gradually improve [33]. This theory reflects the stage-based logic of "agglomeration effects–congestion effects–institutional catch-up" during development.

A similar perspective can be applied to the relationship between population density and urban resilience. In the low-density stage, the effects of density may remain limited. In the medium-density stage, pressures from resource constraints and environmental degradation, combined with institutional lag, may become more pronounced. In the high-density stage, some cities may alleviate negative impacts through governance improvements and technological advancement. This nonlinear and stage-specific framework provides important theoretical insights for interpreting the "medium-density trap". Moreover, the concept of the "middle-income trap" in development economics also highlights the risk of stage-specific stagnation [34], offering a useful analogy for understanding potential dilemmas in spatial agglomeration.

### 3.4 Research Hypotheses

Based on the above analysis, this study proposes the following hypotheses:

Hypothesis 1: Population density and urban resilience may exhibit a nonlinear relationship, with heterogeneous marginal effects across different density stages.

Hypothesis 2: In the low-density stage, the impact of population density on urban resilience may be relatively weak. In the medium-density stage, population density may exert negative effects on resilience, while in the high-density stage, these effects may be moderated.

Hypothesis 3: Population density influences urban resilience through multiple mechanisms, including economic, social, ecological, infrastructural, and institutional dimensions. The "medium-density trap" may represent the outcome of these pressures converging at a specific stage.

## 4 Research Design and Empirical Methods

### 4.1 Urban Resilience Evaluation Index System

Drawing on the theory of sustainable development and previous studies [35, 36], this study conceptualizes urban resilience as comprising five subsystems: economic, social, environmental, institutional, and infrastructural. For each subsystem, a corresponding set of objectives was established. Based on these objectives, 32 specific indicators were selected to construct a comprehensive evaluation system for measuring urban resilience. The detailed indicator framework is presented in Table 1.

**Table 1.** Urban resilience evaluation index system

| Dimension | Target | Indicator | Weight | Attribute |
|---|---|---|---|---|
| A: Economic resilience (0.2404) | Economic development | $A_1$ : GDP per capita | 0.0427 | + |
| | | $A_2$ : Fiscal expenditure per capita | 0.0446 | + |
| | | $A_3$ : General public budget revenue per capita | 0.0553 | + |
| | | $A_4$ : FDI as a share of GDP | 0.0014 | - |
| | Industrial structure | $A_5$ : Tertiary industry as a share of GDP | 0.0221 | + |
| | | $A_6$ : Science and technology expenditure as a share of GDP | 0.0590 | + |
| | | $A_7$ : Education expenditure as a share of GDP | 0.0153 | + |
| B: Social resilience (0.1818) | Social development | $B_1$ : Natural population growth rate | 0.0034 | - |
| | | $B_2$ : Urbanization level | 0.0136 | + |
| | | $B_3$ : Built-up area per capita | 0.0235 | + |
| | Residents' livelihood | $B_4$ : Consumption expenditure per capita | 0.0371 | + |
| | | $B_5$ : Proportion of urban employment | 0.0623 | + |
| | | $B_6$ : Urban employees covered by pension insurance | 0.0419 | + |
| C: Institutional resilience (0.2343) | Urban civilization | $C_1$ : Urban-green space per capita | 0.0242 | + |
| | | $C_2$ : College students per 10,000 people | 0.0441 | + |
| | | $C_3$ : Public library books per 100 people | 0.0602 | + |
| | Medical services | $C_4$ : Hospital density | 0.0767 | + |
| | | $C_5$ : Doctors per capita | 0.0291 | + |
| D: Environmental resilience (0.0308) | Living environment | $D_1$ : Green coverage in built-up area | 0.0025 | + |
| | | $D_2$ : $CO_2$ emissions per capita | 0.0065 | - |
| | | $D_3$ : Average PM2.5 concentration | 0.0082 | - |
| | | $D_4$ : Energy efficiency | 0.0003 | - |
| | Sanitation | $D_5$ :Centralized sewage treatment rate | 0.0060 | + |
| | | $D_6$ : Harmless treatment rate of household waste | 0.0051 | + |
| | | $D_7$ : Comprehensive utilization rate of general industrial solid waste | 0.0022 | + |
| E: Infrastructure resilience (0.3129) | Municipal infrastructure | $E_1$ : Completed investment in municipal utilities | 0.1362 | + |
| | | $E_2$ : Water supply pipeline density | 0.0271 | + |
| | | $E_3$ : Road area per capita $(m^2)$ | 0.0158 | + |
| | | $E_4$ : Buses per 10,000 people | 0.0306 | + |
| | Responsive infrastructure | $E_5$ : Mobile phone users per capita | 0.0320 | + |
| | | $E_6$ : Internet users per capita | 0.0488 | + |
| | | $E_7$ : Drainage pipeline density in built-up areas | 0.0224 | + |

### 4.2 Variable Design and Measurement

The dependent variable is urban resilience (UR). Based on the indicator system described above, we first standardize all indicator data and then apply the entropy-weighted TOPSIS method to calculate the indicator weights. The comprehensive UR score for each city is obtained by aggregating the weighted indicators. The weights and attributes of each indicator are shown in Table 1.

The core explanatory variable is population density (PD). It refers to the number of permanent residents per unit of land area. Considering that the resilience indicators are measured at the city level, and to ensure consistency in statistical scope, this study adopts the internationally accepted method: PD is calculated as the ratio of the year-end permanent population within the administrative boundary of a city to the total land area.

Control variables (CVs). Drawing on previous studies [35, 37], this study includes a set of control variables to account for the potential influence of government policy, economic structure, and market conditions on the relationship between population density and urban resilience. Specifically, four control variables are selected: financial investment (FI), measured by the ratio of general government fiscal expenditure to the city's GDP; industrial structure (IS), represented by the proportion of tertiary industry in the city's GDP; degree of marketization (DM), assessed by the share of private and self-employed workers in total urban employment; and government self-sufficiency capacity (GSC), calculated as the ratio of local general public budget revenue to expenditure.

### 4.3 Research Methods

4.3.1 Panel model

This study employs a panel data regression model to examine the relationship between population density and urban resilience. Specifically, we adopt a fixed effects panel model to control for unobserved heterogeneity across cities. The basic form of the model is expressed as following Eq. (1):

$$UR = B + \alpha_1 PD + CV + \varepsilon_1 \tag{1}$$

where, the variables in the model are defined as follows: $UR$ is the dependent variable, representing urban resilience; $B$ is the intercept term; $PD$ is the core explanatory variable, referring to population density; $\alpha_1$ denotes the regression coefficients, reflecting the influence of the core and control variables on urban resilience; $CV$ is a set of control variables; $\varepsilon_1$ is the error term.

4.3.2 Panel threshold model

The panel regression model is employed to verify whether population density directly impacts urban resilience. If a significant relationship is identified, a panel threshold regression model is applied to further examine whether this effect varies across different population density intervals. The threshold regression model is specified as following Eq. (2):

$$\begin{aligned} UR = K + \beta_1 PD \cdot I(PD \leq \gamma_I) + \beta_2 PD \cdot I(\gamma_1 < PD \leq \gamma_2) + \cdots + \beta_n PD \cdot I(\gamma_{n-1} < PD \leq \gamma_n) + \\ \beta_{n+1} PD \cdot I(\gamma_n < PD \leq \gamma_{n+1}) + \alpha_2 CV + \varepsilon_2 \end{aligned} \tag{2}$$

where, $K$ denotes the constant term; $I(\cdot)$ is the indicator function; $\beta$ represents the coefficient of the core explanatory variable; $\gamma$ denotes the threshold value; $CV$ refers to the control variables with $\alpha_2$ as their coefficients; $\varepsilon_2$ is the error term.

### 4.4 Study Area and Data Source

According to the Tabulation on 2020 China Population Census by County [38] and the China Urban-Rural Construction Statistical Yearbook 2022 [39], Chinese cities are classified into mega, very large, and large cities based on the number of permanent residents in built-up areas. This study focuses on large cities with a population of more than one million people in built-up areas. After excluding cities with significant data gaps, a final sample of 114 cities was selected for analysis.

The indicator data are primarily sourced from the China Statistical Yearbook (2006–2021) [40], the China Statistical Yearbook on Environment [41], and various provincial and municipal yearbooks. For missing values, supplementary data were estimated using linear interpolation and trend extrapolation based on historical records.

### 4.5 City Clustering

Based on the average population size levels and land use during the study period, this paper uses SPSS 24.0 for statistical analysis to classify the 114 cities into three major clusters. Cluster 1, consists of 34 national core cities, primarily composed of municipalities, provincial capitals, and economically dominant metropolises such as Beijing, Shanghai, and Shenzhen. These cities typically hold provincial or sub-provincial administrative status, possess administrative advantages, large-scale economies, and well-developed infrastructure systems, and serve as national hubs in innovation, finance, and internationalization. Cluster 2 includes 46 regional center cities and industrially specialized cities, represented by Wenzhou and Luoyang. These cities have moderate economic development levels, with GDP ranging between 300 and 800 billion yuan, and fulfill specialized functional roles within provincial urban systems. Cluster 3 comprises 34 developing cities, including Sanming and Zhaoqing, characterized by smaller economies with GDP typically between 200 and 300 billion yuan, mainly serving localized development needs.

## 5 Empirical Results and Analysis

### 5.1 Temporal Evolution of Urban Resilience in Chinese Large Cities

To better understand the changing relationship and distribution between population density and urban resilience over time, this study uses bivariate kernel density estimation to plot joint distribution maps for four representative years: 2006, 2011, 2016, and 2021 (Figure 1). These maps illustrate the dynamic evolution of the sampled cities across China.

The distribution pattern of the full sample cities remained relatively stable from 2006 to 2021. The central aggregation zone consistently appeared in the range of 1.0 to 1.5 (10,000 people/km$^2$) for population density and 0.1 to 0.2 for resilience scores, indicating that urban resilience across the country generally stayed low to medium. Although a secondary aggregation zone representing high-density and high-resilience cities began to emerge in the upper-right corner of the graphs around 2016 and expanded slightly by 2021, the full sample distribution pattern showed little shift. This overall stability in distribution implies that improvements in urban resilience in China have primarily occurred through localized breakthroughs rather than widespread systemic progress.

From 2006 to 2021, Cluster 1 cities showed a pattern of decreasing population density and increasing resilience. The central density index shifted from 1.0-1.5 to 0.5-1.0, while the resilience index increased from 0.10-0.15 to 0.15-0.25, reflecting progress in system optimization and spatial restructuring. Since 2016, a small sub-aggregation zone has appeared in the lower-right corner of the graph. By 2021, its density rose to 3.0, but resilience remained below 0.1, indicating that some ultra-dense cities lag in resilience building.

The distribution pattern of Cluster 2 cities exhibited relatively slow structural changes. The density index shifted from approximately 1.0 to 1.5, while the resilience index remained stable within the range of 0.10 to 0.20, indicating a generally moderate evolution. The contour of the density surface became gradually more compact, and the shading intensified, suggesting a narrowing gap in resilience levels among cities. However, the central aggregation zone did not shift significantly, nor did any high-resilience sub-aggregation zone emerge. Such a pattern indicates that these cities are still in the early stages of resilience platform development, with relatively weak structural stability.

The distribution of Cluster 3 cities has remained concentrated within a low-density and low-resilience range, approximately 0.5 to 1.5 in population density and 0.10 to 0.20 in resilience index, indicating generally low resilience levels and limited capacity for structural improvement. In 2021, the density-resilience structure exhibited signs of divergence, with two distinct density peaks emerging near 0.5 and 1.5, centered around a resilience index of 0.10 to 0.15. Such divergence suggests that while some cities have made incremental progress alongside population growth, others remain stagnant under low-density conditions due to the lack of effective resilience enhancement mechanisms. The spatial structure of this group remains relatively fragmented, with underdeveloped system foundations and insufficient governance capacity.

Overall, from 2006 to 2021, the evolution of urban resilience in Chinese cities exhibited a general pattern of "stable core with structural differentiation". Cluster 1 cities experienced a "declining density-rising resilience" trajectory; although a few cities achieved high-density breakthroughs, their resilience improvements remained relatively limited. Cluster 2 cities entered an initial stage of population concentration with unstable structural characteristics, while Cluster 3 cities had a weak foundation for resilience building, with emerging differentiation but limited overall progress. In general, the temporal evolution of urban resilience does not clearly align with changes in population density, indicating that resilience improvement is not solely driven by population agglomeration. Instead, it is likely shaped by a combination of governance capacity, resource allocation efficiency, and systemic coordination. Although population density remains a key factor influencing urban resilience, its impact mechanism warrants further investigation across different city types and development stages.

### 5.2 Descriptive Statistics and Multicollinearity Test

Pearson correlation coefficients were first used to assess the relationships among the variables to ensure the robustness of the regression results. The results show that the absolute values of the correlation coefficients between variables in all three models are less than 0.5, indicating relatively weak correlations. Subsequently, variance inflation factors (VIF) were calculated to test for multicollinearity among the explanatory variables. All VIF values were below 5, suggesting no significant multicollinearity in the regression models. Detailed results are presented in Table 2.

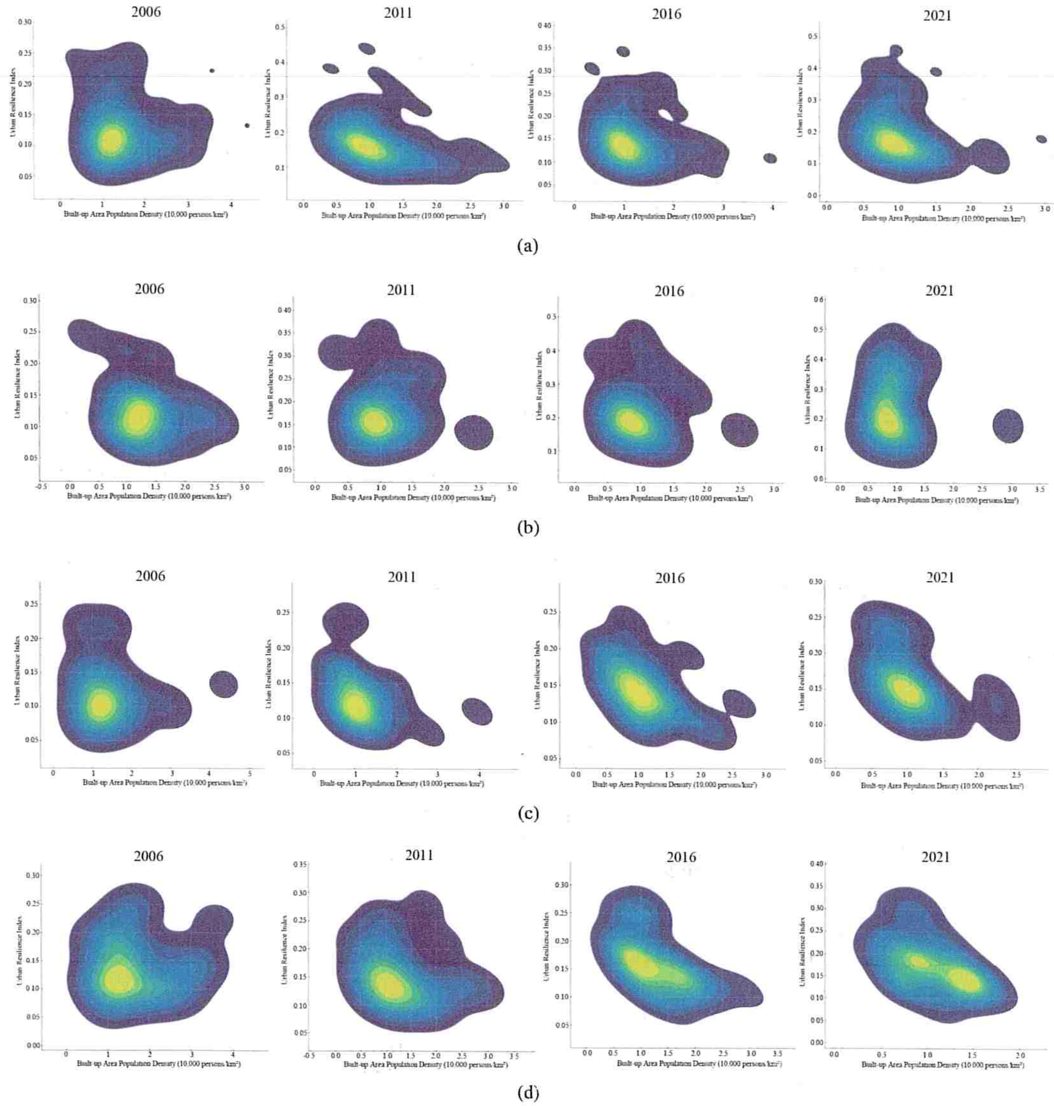


**Figure 1.** Joint distribution maps of Chinese large cities: (a) Joint distribute of full sample cities; (b) Joint distribute of Cluster 1 cities; (c) Joint distribute of Cluster 2 cities; (d) Joint distribute of Cluster 3 cities

**Table 2.** Test results of classification

| Variable | No. | Min | Max | Mean | SD | Median | VIF | PD | FI | IS | DM | GSC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| UR | 1824 | 0.070 | 0.500 | 0.158 | 0.059 | 0.145 | | | | | | |
| PD | 1824 | 0.273 | 4.371 | 1.176 | 0.538 | 1.056 | 1.105 | 1 | | | | |
| FI | 1824 | 0.044 | 1.485 | 0.139 | 0.060 | 0.129 | 1.064 | -0.029 | 1 | | | |
| IS | 1824 | 0.038 | 0.839 | 0.445 | 0.105 | 0.431 | 1.213 | -0.242** | 0.204** | 1 | | |
| DM | 1824 | 0.034 | 12.314 | 1.290 | 0.955 | 1.050 | 1.059 | -0.027 | 0.091** | 0.156** | 1 | |
| GSC | 1824 | 0.069 | 1.541 | 0.610 | 0.215 | 0.607 | 1.170 | -0.247** | -0.071** | 0.264** | -0.124** | 1 |

Note: UR: Urban resilience; PD: Population density; FI: Financial investment; IS: Industrial structure; DM: Degree of marketization; GSC: Government self-sufficiency capacity; SD: Standard deviation; VIF: Variance inflation factors; ** denote significance at the 5% levels.

### 5.3 Panel Regression Results

As shown in Table 3, population density significantly negatively affects urban resilience, with notable heterogeneity across both time and city type. In the full sample, the regression coefficient of population density is -0.023, indicating that population density generally inhibits improvements in resilience. The period-specific results show that this suppressive effect was strongest between 2006 and 2013, with a coefficient of -0.026; it declined to -0.014 in the 2014-2021 period, suggesting that environmental governance and system regulation improvements have somewhat alleviated density-induced pressures. By city cluster, the regression coefficient for Cluster 1 cities is -0.034, indicating the strongest negative effect among the three groups. This result is closely tied to their long-term exposure to ultra-high-density development. Although these cities generally possess advanced infrastructure, efficient resource allocation, and robust governance capacity, prolonged high-density pressure may have led to structural fatigue within their urban systems, significantly undermining resilience. In contrast, Cluster 2 cities have a coefficient of -0.030, reflecting the strain caused by weaker resource carrying capacity and emergency response systems, which render them highly susceptible to the adverse effects of increasing density. Cluster 3 cities show the weakest negative impact, with a coefficient of -0.012, likely due to their relatively low-density levels, and their urban systems have yet to face the pressures of dense development. However, this also suggests that their resilience capacity remains nascent, with limited system responsiveness.

Regarding control variables, financial investment and industrial structure are key drivers of enhanced urban resilience. Financial investment generally shows a positive effect, particularly in earlier years and in larger cities, but its impact weakens in the later period and in some city clusters, where it even turns insignificant or negative. This suggests diminishing marginal returns and uneven effectiveness across contexts. This may be due to inefficient allocation of fiscal resources, low investment returns, or insufficient governmental focus on resilience-building, reflecting the varying effectiveness of fiscal expenditure across different development stages and governance contexts. The coefficient of industrial structure ranges from 0.099 to 0.300 across all models. It is most pronounced in Cluster 1 cities, highlighting the role of industrial upgrading in alleviating resource and environmental constraints and strengthening system resilience. In comparison, the effects of the degree of marketization and government self-sufficiency capacity are relatively limited, with small coefficient fluctuations. Moreover, the constant terms in most models are positive, suggesting a baseline level of resilience embedded in city structures; however, for Cluster 1 cities, the constant is negative, implying that rapid population concentration may have led to the accumulation of structural risks.

**Table 3.** Panel regression results

| Variable | Dependent Variable(UR) | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | Full Sample | | Cluster 1 | Cluster 2 | Cluster 3 |
| | | 2006–2013 | 2014–2021 | | | |
| PD | -0.023*** | -0.026*** | -0.014*** | -0.034** | -0.030** | -0.012* |
| FI | 0.085*** | 0.073*** | -0.064 | 0.572*** | -0.001 | 0.104 |
| IS | 0.201*** | 0.133*** | 0.095*** | 0.300*** | 0.122*** | 0.099 |
| DM | 0.001 | 0.006** | 0.002** | 0.005 | 0.002 | 0.003 |
| GSC | -0.003 | 0.026** | -0.013 | 0.003 | -0.016 | 0.012 |
| Con. | 0.083*** | 0.089*** | 0.157*** | -0.019 | 0.126*** | 0.105*** |
| No. | 1824 | 912 | 912 | 544 | 736 | 544 |

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

### 5.4 Panel Threshold Regression Results

Based on the previous panel regression results, population density generally negatively impacts urban resilience across cities of different scales. However, further investigation is required to determine whether this effect shows heterogeneity in marginal effects. To explore the nonlinear mechanism and evolution pattern of how changes in population density influence urban resilience, this study employs population density as the threshold variable to construct a panel threshold regression model. We use Stata 18.0 to conduct bootstrap threshold effect tests on the full sample and the three city clusters. The results are presented in Table 4.

The full sample, along with Cluster 2 and Cluster 3 cities, revealed a significance double-threshold effect, indicating that the relationship between population density and urban resilience generally exhibits nonlinear characteristics. In contrast, Cluster 1 cities did not show a statistically significant stage-based shift in resilience as density changes. This may be attributed to the fact that resilience improvements in these national core cities depend more on long-term mechanisms such as technological advancement and institutional optimization, making it difficult for short-term density fluctuations to trigger noticeable transitions. Meanwhile, the threshold structures observed in Cluster 2 and Cluster 3 imply that their systems are more sensitive to population density changes and more prone to responsive fluctuations during the process of density adjustment. This reflects both the vulnerability and plasticity of medium and small cities, in stark contrast to the relative stability observed in national core cities.

**Table 4.** Panel threshold regression results

| Sample | Variable | F Statistic | P Value | BS Repetitions | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|---|---|---|
| Full sample | PD | 100.87 | 0.000 | 500 | 56.4855 | 37.8627 | 32.6225 |
| | | 52.01 | 0.034 | 500 | 117.0025 | 46.1675 | 39.0601 |
| | | 48.40 | 0.120 | 500 | 97.2100 | 59.6373 | 50.8404 |
| Cluster 1 | PD | 8.17 | 0.822 | 500 | 60.8424 | 39.9922 | 31.6853 |
| | | 7.074 | 0.742 | 500 | 32.3314 | 26.1071 | 20.5411 |
| | | 6.37 | 0.754 | 500 | 33.2308 | 22.6336 | 18.8853 |
| Cluster 2 | PD | 78.11 | 0.000 | 500 | 50.8453 | 36.8697 | 30.8257 |
| | | 33.08 | 0.040 | 500 | 39.8734 | 31.2160 | 27.9235 |
| | | 10.17 | 0.740 | 500 | 51.9389 | 35.2423 | 27.9541 |
| Cluster 3 | PD | 81.12 | 0.000 | 500 | 45.9509 | 33.9200 | 26.0796 |
| | | 38.86 | 0.012 | 500 | 39.1961 | 28.5654 | 23.5367 |
| | | 26.25 | 0.384 | 500 | 63.0573 | 46.5236 | 39.5706 |

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

5.4.1 Threshold regression results for full-sample cities

Based on the results of the threshold effect test, a double-threshold panel regression model was constructed using population density as the threshold variable. The estimated parameters are presented in Table 5.

**Table 5.** Panel threshold regression results

| Variable | Regression Coefficient | T Value | 95% Confidence Interval |
|---|---|---|---|
| $PD \leq 0.869$ | -0.008 | -0.72 | -0.029, 0.014 |
| $0.869 < PD \leq 2.264$ | -0.032*** | -4.41 | -0.047, -0.018 |
| $PD > 2.264$ | -0.014** | -2.64 | -0.025, -0.004 |
| FI | 0.086 | 1.35 | -0.040, 0.213 |
| IS | 0.187*** | 4.94 | 0.112, 0.262 |
| DM | 0.002 | 1.12 | -0.001, 0.005 |
| GSC | -0.002 | -0.11 | -0.038, 0.034 |

Note: Population density is measured as 10,000 people per km$^2$; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

The two identified threshold values for population density are 0.869 and 2.264 (10,000 people/km$^2$), indicating a nonlinear relationship between population density and urban resilience. When population density is below 0.869, the estimated coefficient is -0.008 and statistically insignificant, suggesting that in low-density areas, changes in population density have a limited impact on urban resilience. This could be due to the lack of agglomeration effects, underdeveloped infrastructure and service networks, and relatively fragmented urban systems with low resistance to external shocks. When population density falls between 0.869 and 2.264, the coefficient becomes -0.032 and is statistically significant at the 1% level. This indicates that in medium-density areas, increases in population density significantly suppress urban resilience. During this phase, rapid population agglomeration imposes considerable stress on city operations, overburdening infrastructure and public services. In addition, planning delays and resource misallocations are more pronounced, reducing the system's capacity to respond effectively to risks. When population density exceeds 2.264, the coefficient is -0.014 and remains statistically significant at the 5% level. However, the absolute value is smaller than in the medium-density stage, suggesting that in high-density areas, the negative impact of further density increases is somewhat mitigated. This may reflect improved governance and risk management mechanisms in high-density cities, where intensive development and refined management help reduce negative externalities, although some resilience suppression persists.

In summary, the impact of population density on urban resilience exhibits a distinct nonlinear pattern: insignificant in low-density, negative in medium-density, and mitigated in high-density contexts. These findings highlight the need for policymakers to focus on preventing unregulated expansion in medium-density zones, optimizing spatial population distribution, and enhancing urban carrying capacity and system redundancy to strengthen resilience under complex conditions.

To further verify the reliability of the identified thresholds, Figure 2 presents the likelihood ratio functions for the two threshold estimates. Both values fall below the critical value of 7.35 at the 95% confidence level, confirming the statistical validity and robustness of the threshold estimates.

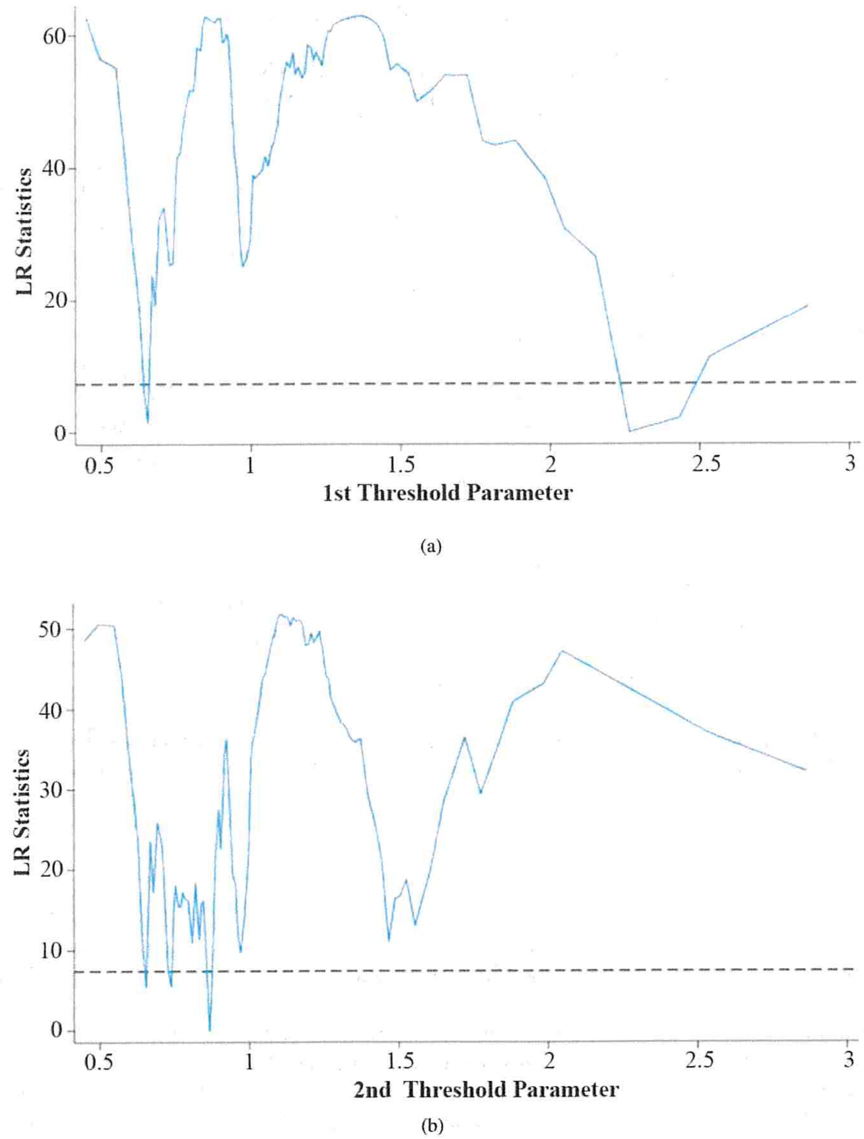


**Figure 2.** Double threshold estimates for full sample: (a) First threshold; (b) Second threshold

5.4.2 Threshold regression results for Cluster 2 cities

The threshold regression results for Cluster 2 cities are presented in Table 6 and Figure 3. Compared with the full sample, Cluster 2 cities exhibit a more pronounced and well-defined nonlinear threshold effect. The impact of population density on urban resilience shows strong consistency and structural variation across different density intervals. The two identified thresholds are 0.848 and 2.129, close to the thresholds found in the full sample (0.869 and 2.264). However, the significance levels and magnitudes of the regression coefficients in this cluster reveal a more distinct pattern of negative nonlinear transition.

In the low-density stage, where population density is less than or equal to 0.760, the effect of population density on urban resilience is not statistically significant, with a regression coefficient of 0.001. This is consistent with the results for the full sample, suggesting that in the early stages of urban development, when population agglomeration has not yet formed, cities lack sufficient economies of scale and collaborative networks, and population growth has a limited impact on resilience enhancement. As population density enters the medium-density range, greater than 0.760 and less than or equal to 2.310, the regression coefficient sharply decreases to -0.033 and is significantly negative at the 1% level. This indicates that urban systems face the greatest pressure in this phase. Compared to the full sample, the negative effect is more pronounced in Cluster 2 cities, reflecting more prominent weaknesses in resource allocation, public service provision, and institutional resilience. When population density exceeds 2.310, the negative effect is somewhat alleviated, with a regression coefficient of -0.019, which remains significant at the 5% level. Although this trend aligns with the full-sample findings, the degree of mitigation is less evident, suggesting that Cluster 2 cities have not yet fully developed effective governance and service mechanisms to cope with high-density challenges.

**Table 6.** Cluster 2 panel threshold regression results

| Variable | Regression Coefficient | T Value | 95% Confidence Interval |
|---|---|---|---|
| PD $\leq$ 0.760 | 0.001 | 0.04 | -0.028, 0.029 |
| 0.760 $<$ PD $\leq$ 2.310 | -0.033*** | -3.24 | -0.054, -0.013 |
| PD $>$ 2.310 | -0.019** | -2.35 | -0.035, -0.003 |
| FI | -0.002 | -0.09 | -0.038, 0.034 |
| IS | 0.121*** | 3.05 | 0.041, 0.201 |
| DM | 0.002 | 1.58 | -0.001, 0.006 |
| GSC | -0.005 | -0.26 | -0.045, 0.035 |

Note: Population density is measured as 10,000 people per kmkm$^2$; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

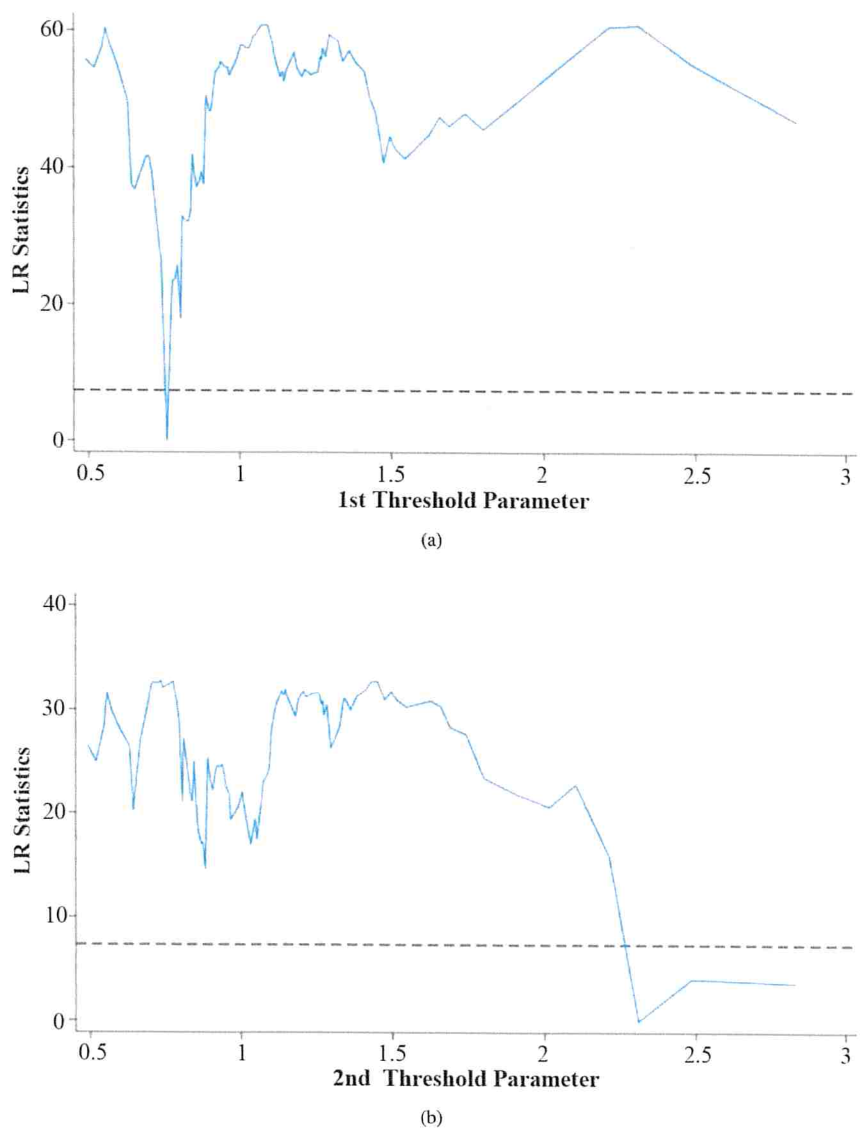


**Figure 3.** Double threshold estimates for Cluster 2: (a) First threshold; (b) Second threshold

Cluster 2 cities experience the most pronounced negative impact during the medium-density stage and exhibit relatively limited system rebound capacity, reflecting a certain degree of stage-specific vulnerability.

**Table 7.** Cluster 3 panel threshold regression results

| Variable | Regression Coefficient | T Value | 95% Confidence Interval |
|---|---|---|---|
| PD $\leq$ 0.679 | 0.022 | 1.27 | -0.013, 0.056 |
| 0.679 $<$ PD $\leq$ 2.120 | -0.033*** | -3.89 | -0.050, -0.016 |
| PD $>$ 2.120 | -0.013** | -2.55 | -0.023, -0.003 |
| FI | 0.125 | 1.11 | -0.105, 0.355 |
| IS | 0.086* | 1.81 | -0.010, 0.183 |
| DM | 0.003 | 1.37 | -0.002, 0.008 |
| GSC | 0.000 | -0.00 | -0.039, 0.039 |

Note: Population density is measured as 10,000 people per km$^2$;*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

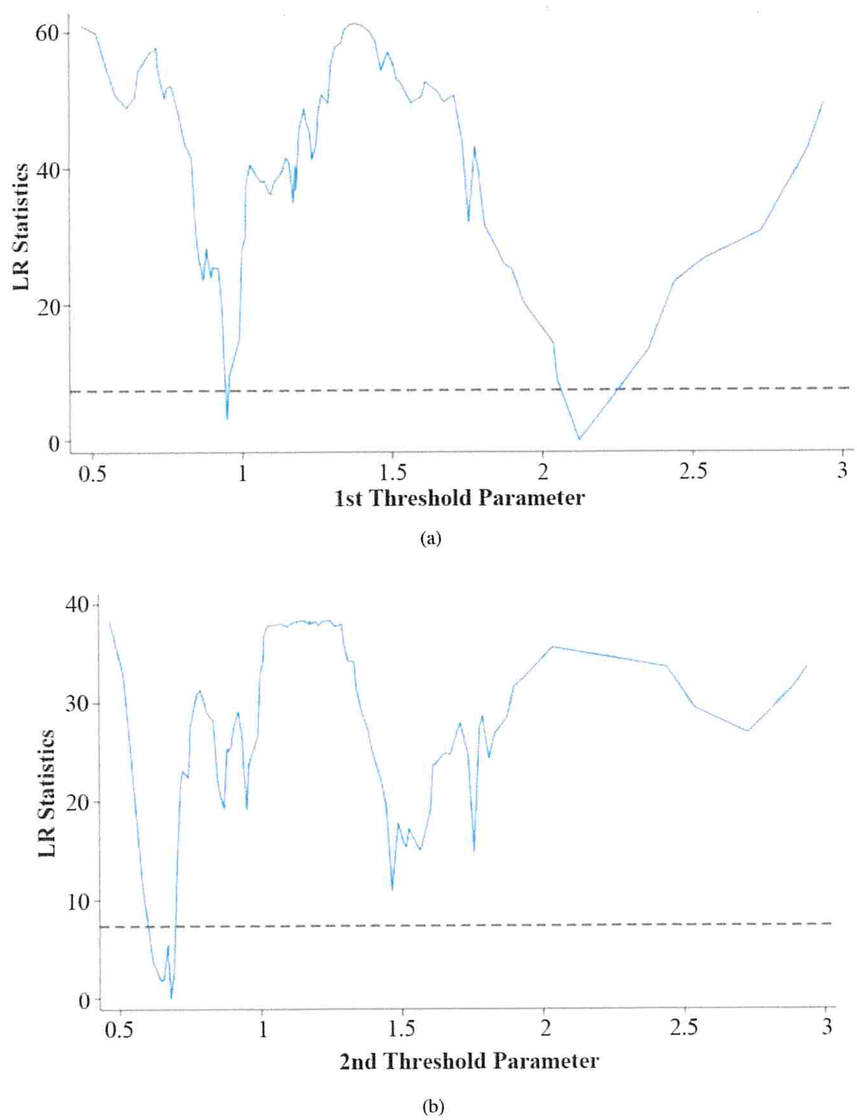


**Figure 4.** Double threshold estimates for Cluster 3: (a) First threshold; (b) Second threshold

5.4.3 Threshold regression results for Cluster 3 cities

The threshold regression results for Cluster 3 cities, as shown in Table 7 and Figure 4, also exhibit clear nonlinearity. However, compared with the full sample and Cluster 2 cities, the threshold effects in Cluster 3 follow a more segmented pattern, characterized by the stages of "potential–pressure–adjustment". The two estimated thresholds are 0.679 and 2.120, slightly lower than those of the full sample and Cluster 2. This suggests that Cluster 3 cities enter the sensitive range of population density at an earlier stage, which may be attributed to their limited resource-carrying capacity and less mature urban systems.

In the low-density stage, where population density does not exceed 0.679, the regression coefficient is 0.022. Although not statistically significant, it shows a positive trend, indicating that some Cluster 3 cities may benefit from a "population dividend". Their relatively abundant land resources and unsaturated infrastructure networks create favorable conditions for expanding urban system functions and enhancing initial resilience. When population density falls between 0.679 and 2.120, the coefficient declines to -0.033 and becomes significantly negative at the 1% level, suggesting that cities in this range face substantial systemic pressure. The combined effects of fiscal constraints, industrial concentration, and lagging governance lead to a marked decline in resilience. Once population density exceeds 2.120, the coefficient drops to -0.013, remaining significantly negative at the 5% level. This implies a modest alleviation of the negative effect, as some cities have begun to establish preliminary coping mechanisms for high-density shocks through governance interventions. However, the overall resilience recovery capacity in Cluster 3 cities remains limited, indicating substantial room for improvement in resilience enhancement.

5.4.4 Comparative analysis of threshold effects

Figure 5 compares the threshold regression results for the full sample and for the second and third clusters of cities, providing a systematic synthesis of the empirical evidence. The findings show that population density has a significant nonlinear impact on urban resilience, with differences across city types in threshold intervals, regression coefficients, and underlying mechanisms. These differences reflect heterogeneity in developmental stages, resource endowments, and governance capacities.

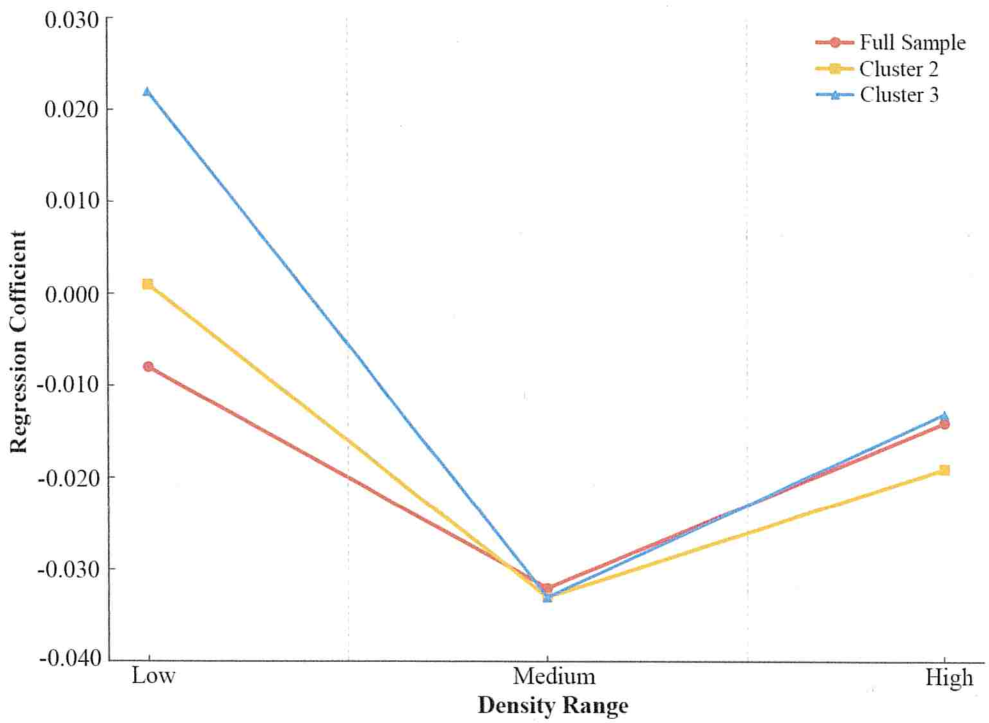


**Figure 5.** Threshold regression results by city cluster

## 6 Discussion

This study identifies the "medium-density trap" as a critical stage-specific barrier to enhancing urban resilience in Chinese cities and demonstrates the nonlinear influence of population density on urban resilience. Within the medium-density range, cities often become systemically vulnerable due to delayed resource allocation, inadequate infrastructure, and limited governance capacity, resulting in a marked decline in resilience. This pattern is most pronounced in the second and third clusters of cities, reflecting weaker institutional flexibility and insufficient support systems. By contrast, the first cluster does not exhibit clear threshold transitions, although the panel regression results still indicate negative density effects. The resilience of these cities appears to be shaped primarily by institutional accumulation and governance inertia, with density fluctuations alone insufficient to induce systemic change in the short term.

Overcoming the "medium-density trap" requires more than isolated efforts by individual cities. It should be embedded within the broader framework of regional spatial restructuring and national institutional arrangements. Urban resilience should be regarded as a systemic outcome of integrated resource management, coordinated governance, and institutional collaboration rather than an independent attribute of single cities. Under resource constraints, resilience enhancement depends on spatial restructuring and institutional reform. These processes in turn strengthen governance capacity and improve the resilience of the urban system as a whole.

### 6.1 Differentiated Pathways for Density Governance

In response to the challenges of the "medium-density trap", a differentiated, stratified, and coordinated mechanism for density governance and resilience enhancement needs to be established.

Regional central cities should continue to strengthen their primacy and regional influence by building systemic resilience and collaborative capacity under high-density conditions. Improving resource allocation efficiency, enhancing public service provision, and expanding green space networks can help reshape the density–resilience relationship in a positive direction, achieving a stable configuration characterized by both high density and high resilience.

Regional sub-central cities represent the critical nodes of density transition and require targeted interventions. With fiscal support, industrial relocation, and institutional incentives, these cities should establish independent and comprehensive service systems and spatial structures, thereby forming new secondary growth poles and generating spillover effects once the trap is overcome.

Ordinary medium-sized cities should avoid the path dependence that equates scale expansion with resilience improvement. Instead, they should adopt compact spatial structures and forward-looking governance approaches. Establishing density monitoring and risk identification mechanisms together with early investment in infrastructure and public services can simultaneously achieve both density control and efficiency gains.

Resource-based cities need to pay particular attention to vulnerabilities associated with industrial monocultures. During the medium-density stage, they should focus on promoting industrial diversification, introducing infrastructural redundancy, and strengthening ecological restoration and environmental governance. These measures can reduce systemic risks and prevent resilience decline under the "medium-density trap".

### 6.2 Practice-Oriented Approaches and Policy Instruments

At the practical level, the above strategies need to be aligned with existing planning and policy instruments. On the one hand, a dynamic monitoring and early-warning system for population density should be established, incorporating key threshold indicators into urban risk management and fiscal budgeting frameworks. On the other hand, policy instruments such as territorial spatial planning, urban regeneration, and intergovernmental fiscal transfers should be embedded in the density–resilience logic, linking infrastructure standards and public service capacity to population density levels to strengthen the coordination between planning indicators and governance capacity.

In addition, infrastructure design in medium-density areas should adopt moderate redundancy strategies. For example, water and electricity systems could be configured at 120 percent of the threshold demand, while around 30 percent of road network capacity should be reserved for emergency access. Such engineering-based resilience measures can substantially enhance the capacity of urban systems to self-regulate and recover under high stress levels.

### 6.3 Avoiding Development Pitfalls

Two common pitfalls must also be avoided. The first is the blind pursuit of urban sprawl, which neglects the coordination of density governance with spatial structure, leading to inefficient land use and resource waste. The second is increasing density without adequate supporting systems, which reduces spatial efficiency and exacerbates systemic risks. These problems indicate that overcoming the "medium-density trap" requires both improvements in urban governance capacity and the strengthening of regional spatial coordination mechanisms together with nationally differentiated policy support systems.

## 7 Conclusions

Based on panel data from 114 large Chinese cities covering the period 2006–2021, this study develops an urban resilience evaluation system encompassing five dimensions: economy, society, institutions, environment, and infrastructure. This study applies the entropy-weighted TOPSIS method and a threshold regression model to examine the nonlinear impact of population density on urban resilience. The main conclusions are as follows:

(1) During the study period, the overall resilience of large cities increased steadily. Infrastructure and the economy made the most significant contributions among the five dimensions, providing the foundation for systemic improvement.

(2) The relationship between population density and resilience follows a three-stage pattern. The effects are insignificant at low density, most negative at medium density, and alleviated at high density. The medium-density stage represents the most vulnerable period for urban resilience. (3) The sensitivity of resilience to changes in density varies across city types. The second and third clusters show more pronounced vulnerability, whereas the first cluster is influenced more strongly by institutional accumulation and governance inertia.

(4) The optimal density for resilience is not a fixed value. It is determined by the dynamic balance between density-induced pressures and the capacity of cities to mitigate them. High resilience is not inherently associated with either low or high density and instead depends on whether cities can effectively overcome the challenges of the medium-density stage.

The dataset used in this study is limited to the period 2006–2021, as data for 2022 and later years have been substantially disrupted by the COVID-19 pandemic, with gaps and abnormal fluctuations that may compromise analytical reliability. In addition, the analysis is restricted to 114 Chinese cities with urban resident populations exceeding one million, so the findings mainly reflect the dynamics of large urban centers. Consequently, the conclusions may not be fully generalizable to medium- or small-sized cities, or to resource-dependent cities with distinct developmental trajectories. Future research should extend both the temporal coverage and the range of city types to evaluate whether the "medium-density trap" exhibits heterogeneous manifestations across different urban contexts.

## Author Contributions

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

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## Data Availability

The panel dataset used in this study was compiled from publicly available official statistical sources, including the Tabulation on 2020 China Population Census by County [38], the China Urban-Rural Construction Statistical Yearbook 2022 [39], the China Statistical Yearbook (2006–2021) [40], and the China Statistical Yearbook on Environment [41]. Processed datasets generated during the current study are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare no conflict of interest.

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*OWH Public Pulse published Sunday, October 19,2025*

**Addressing Misinformation**

On October 9, State Attorney General Mike Hilgers said that he's filed a lawsuit against Omaha Public Power District (OPPD) over its plans to refuel and retire electric units at its North Omaha Station (WOWT).

Because of increased energy demands for Meta and Google data centers in 2023, the OPPD Board delayed replacement of the two-remaining coal-fired units to 2026.
Attorney General Hilger also reports that the North Omaha Station is not producing unhealthy air per the federal government or Douglas County (WOWT). His assessment of air quality in North Omaha is suspect because the closest EPA monitor in Omaha that tracks coal pollutants is at 4102 Woolworth Ave which is five miles away from the plant (Nebraska Public Media).

I would like to take this opportunity to inform everyone there are multiple sources that identify health implications related to coal burning.

According to the 2024 Community Health Needs Assessment (Douglas County Health and partners), 12.5% of metro adults have asthma, while 18.2% of Northeast Omaha adults have asthma. Area trends have increased by 4.5% in the past 9 years.

The Child and Adolescent Health Needs Assessment document reports while our Metro Area rate is lower than the National benchmark of 18.4%, Northeast Omaha's rates are 23.4%.
Higher rates of premature death, heart attacks and strokes, and preterm births are also associated with ozone smog and particle pollution.

The American Lung Association's 26th annual "State of the Air" report assesses ozone and particle pollution levels across the U.S. The Omaha metro area:

- **Ground-level Ozone Pollution:** Ranked 29th worst out of 228 nationally, with 8.2 unhealthy days per year (grade F).
- **Particle Pollution:** Ranked 104th worst out of 223, with 1.8 unhealthy days per year (grade C).
- **Year-Round Particle Pollution:** Ranked 89th worst nationally with pollution levels below federal standards.

The report highlights environmental disparities, noting that people of color are over twice as likely as white individuals to live in areas with failing grades for all pollution measures.

In conclusion, I would like to bring attention to Pope Leo's words "Where the most vulnerable of our brothers and sisters are the first to suffer the devastating effects of climate change, deforestation and pollution, care for creation becomes an expression of our faith and humanity."

Jane O'Connor

Omaha, NE

11/20/2025 OPPD Board Meeting

Jonathan Paetz
17226 William Cir
Omaha, NE. 68130

At the October 16, 2025 Board Meeting, a public comment was made against SD-7, as related to the proposed conversion to natural gas and shut down of three units at the North Omaha Station (NOS) and in support of the Attorney Generals lawsuit against OPPD.

The individual said, they were mystified by the fact that, if the NOS is such a health risk to the residents of North Omaha, why aren't the residents of Nebraska City complaining about whatever health risk the Nebraska City Station (NCS) is generating.

While the health impacts of each resident are difficult to quantify, here are a couple facts as to why the residents of Nebraska City may not be complaining about the emissions from the Nebraska City Station.

The information on power generation load and emission data I am going to site is available to download from the US EPA website, which I have reference in my written comments.

**The first fact:**
The NCS is located 6 miles southeast of Nebraska City. The NOS is within the city of Omaha.

**The second fact:**
The Plant Specific Buffer Distance from an emission source, is defined as the maximum concentration radius. A radius is determined for each power plant by averaging the distances to the ten highest concentrations around a source.
https://experience.arcgis.com/experience/4d419ce790aa42e8b42228f824024cc4/page/home

The EPA references the number of residents within the plant specific buffer for each permitted site:

North Omaha Station – approximately 3,300 residents live within the 0.8-mile defined buffer radius

Nebraska City Station – 59 residents live within the 2.8-mile defined buffer radius. So the 2.8 mile radius does not even reach Nebraska City.

OPPD has stated that the emissions from NOS are below the permit requirements and emit half, or less than half, of the maximum allowed limits from the EPA.

**The third fact:**
Despite the fact that the Nebraska City station is twice as large, in terms of MW production than the NOS, when you measure the annual emissions in pounds emitted per MWh of energy

produced, instead of tons emitted, annual emission rates from 2015 to 2024 in lbs/MWh are higher at North Omaha than Nebraska City: https://campd.epa.gov/data

Sulfur Dioxide ($SO_2$) emissions are 40% to 90% higher than NCS
Nitrogen Oxide (NOx) emissions are 75% to 100% higher than NCS
Carbon Dioxide ($CO_2$) emissions are 1% to 12% higher than NCS

During this period, the gross load MWh generation at North ~~Omaha (running 3 natural gas and 2 coal units)~~ was 90 to 135% lower than Nebraska City.

Remember only Units 4 and 5 burn coal at North Omaha, with a total generation capacity of 350 MW compared to 1300 MW at NCS.

I have not reviewed the permits for each station, but I suspect that the North Omaha Station has a higher permit emission rate than Nebraska City. The North Omaha units were constructed in the 1960's, compared to NC station units in 1979 and 2009. Older coal fired power plants typically have less stringent emission standards than newer stations.

So even though North Omaha meets the air-quality permit standards and is emitting less than half allowed by their permit, those emissions, on a lbs/MWh basis, are greater and potentially impact more residents than the Nebraska City Station.

I am in favor of eliminating coal from the NOS, but if OPPD votes to extend the operation of the coal units, I would appreciate OPPD perform a study to determine how best to reduce the emission load from the NOS to be comparable with the NCS. At the very least, it should be our obligation to put North Omaha residents on par with Nebraska City.

Thank you

| Station | Year | Gross Load (MWh) | SO2 Mass (short tons) | CO2 Mass (short tons) | NOx Mass (short tons) | Heat Input (mmBtu) |
|---|---|---|---|---|---|---|
| NE | 2000 | 3,651,388.50 | 12,640.16 | 3,966,587.07 | 5,990.85 | 38,903,721.31 |
| NE | 2001 | 3,519,240.75 | 11,798.85 | 3,873,052.60 | 5,991.42 | 37,845,111.89 |
| NE | 2002 | 3,663,534.00 | 11,509.22 | 3,904,853.91 | 6,107.79 | 38,335,920.91 |
| NE | 2003 | 3,780,240.75 | 11,729.58 | 4,061,113.67 | 6,010.29 | 39,703,386.24 |
| NE | 2004 | 3,845,050.00 | 16,124.89 | 4,113,684.01 | 6,309.45 | 40,143,212.40 |
| NE | 2005 | 3,697,936.00 | 16,704.52 | 3,957,606.18 | 6,238.58 | 38,676,965.51 |
| NE | 2006 | 3,758,084.75 | 14,314.97 | 4,065,696.37 | 6,259.42 | 39,689,186.96 |
| NE | 2007 | 3,629,877.94 | 14,749.43 | 3,842,084.14 | 6,124.66 | 37,517,239.60 |
| NE | 2008 | 3,828,988.19 | 15,011.74 | 4,210,262.25 | 6,455.18 | 40,378,142.01 |
| NE | 2009 | 3,311,480.65 | 13,159.18 | 3,689,137.37 | 5,745.56 | 35,228,017.74 |
| NE | 2010 | 3,530,101.98 | 10,515.15 | 4,065,276.27 | 6,765.23 | 38,820,663.94 |
| NE | 2011 | 3,629,188.37 | 14,069.35 | 4,058,799.60 | 6,742.00 | 38,736,187.41 |
| NE | 2012 | 3,305,317.04 | 11,377.16 | 3,677,848.54 | 5,571.68 | 35,111,946.97 |
| NE | 2013 | 3,575,234.25 | 12,236.96 | 3,960,179.09 | 6,257.51 | 37,830,803.02 |
| NE | 2014 | 3,330,467.65 | 11,244.87 | 3,714,819.67 | 5,778.80 | 35,503,184.98 |
| NE | 2015 | 3,358,473.56 | 13,892.11 | 3,668,223.79 | 5,841.77 | 35,040,706.32 |
| NE | 2016 | 2,239,335.69 | 8,902.07 | 2,355,407.44 | 3,818.42 | 22,511,203.43 |
| NE | 2017 | 2,089,437.48 | 7,896.91 | 2,221,834.47 | 3,639.10 | 21,427,237.25 |
| NE | 2018 | 1,930,833.96 | 7,285.16 | 2,078,468.78 | 3,392.51 | 19,895,842.15 |
| NE | 2019 | 2,054,346.11 | 5,792.82 | 2,331,026.91 | 3,343.14 | 22,610,485.21 |
| NE | 2020 | 1,947,105.11 | 5,446.63 | 2,105,599.71 | 3,176.27 | 20,227,757.29 |
| NE | 2021 | 1,797,516.86 | 5,825.99 | 1,963,480.51 | 2,850.09 | 18,869,681.42 |
| NE | 2022 | 1,947,972.45 | 5,479.06 | 2,085,302.84 | 2,932.69 | 20,381,689.41 |
| NE | 2023 | 1,724,355.03 | 4,314.54 | 1,737,643.60 | 2,476.68 | 17,473,256.92 |
| NE | 2024 | 1,233,422.94 | 2,935.19 | 1,275,409.19 | 1,779.08 | 13,013,745.53 |

NOS - North Omaha Station (OPPD)

https://campd.epa.gov/data

| Station | Year | Gross Load (MWh) | SO2 Mass (short tons) | CO2 Mass (short tons) | NOx Mass (short tons) | Heat Input (mmBtu) |
|---|---|---|---|---|---|---|
| NE | 2000 | 4,686,781.25 | 15,227.12 | 4,634,285.80 | 9,253.80 | 45,168,470.10 |
| NE | 2001 | 4,950,436.75 | 16,205.49 | 4,910,417.38 | 9,481.61 | 47,859,791.55 |
| NE | 2002 | 4,349,606.50 | 12,819.65 | 4,196,582.88 | 8,213.73 | 40,902,361.78 |
| NE | 2003 | 5,055,104.25 | 15,052.01 | 4,966,427.93 | 10,214.97 | 48,405,745.78 |
| NE | 2004 | 4,747,600.75 | 15,592.75 | 4,558,116.98 | 9,347.97 | 44,426,102.50 |
| NE | 2005 | 4,896,714.25 | 17,550.18 | 4,966,129.50 | 9,994.53 | 48,402,869.98 |
| NE | 2006 | 4,782,250.25 | 14,993.60 | 4,703,183.45 | 9,402.44 | 45,839,960.63 |
| NE | 2007 | 4,492,016.05 | 14,173.35 | 4,459,194.57 | 9,484.47 | 43,461,945.18 |
| NE | 2008 | 5,265,440.33 | 17,498.41 | 5,167,077.32 | 10,271.36 | 49,536,240.66 |
| NE | 2009 | 8,594,668.08 | 19,074.38 | 8,770,042.91 | 15,136.93 | 83,656,645.06 |
| NE | 2010 | 8,852,580.79 | 14,295.58 | 8,506,116.45 | 8,830.27 | 81,103,348.24 |
| NE | 2011 | 9,807,247.63 | 17,334.40 | 9,595,501.57 | 6,288.96 | 91,490,307.85 |
| NE | 2012 | 10,276,573.54 | 16,765.90 | 9,921,057.60 | 6,160.92 | 94,594,399.12 |
| NE | 2013 | 10,350,366.74 | 16,910.74 | 10,214,003.76 | 6,427.38 | 97,400,333.38 |
| NE | 2014 | 9,502,353.27 | 16,134.23 | 9,407,657.27 | 5,629.57 | 89,738,543.97 |
| NE | 2015 | 9,302,249.49 | 18,547.06 | 9,218,735.41 | 5,935.33 | 87,987,796.45 |
| NE | 2016 | 9,764,404.95 | 14,722.06 | 9,214,968.52 | 5,287.19 | 87,921,260.36 |
| NE | 2017 | 9,366,275.35 | 15,950.18 | 9,343,763.60 | 6,053.14 | 89,169,617.74 |
| NE | 2018 | 9,811,777.99 | 17,209.70 | 9,726,483.82 | 5,834.91 | 92,789,688.57 |
| NE | 2019 | 7,396,692.33 | 10,386.36 | 7,457,451.31 | 4,149.27 | 71,213,328.08 |
| NE | 2020 | 8,316,439.92 | 11,479.65 | 8,770,945.50 | 5,317.41 | 83,716,848.54 |
| NE | 2021 | 7,579,326.80 | 9,465.40 | 7,515,046.66 | 4,303.59 | 71,768,066.36 |
| NE | 2022 | 7,766,376.20 | 10,199.84 | 7,584,304.04 | 4,599.34 | 72,396,274.52 |
| NE | 2023 | 6,491,607.99 | 10,616.33 | 6,479,756.45 | 4,234.20 | 61,884,642.76 |
| NE | 2024 | 6,508,639.55 | 7,967.88 | 6,448,384.96 | 3,632.73 | 61,584,933.93 |

**NCS - Nebraska City Station (OPPD)**
https://campd.epa.gov/data

| Station | Year | Gross Load (MWh) | $SO_2$ Mass (short tons) | $SO_2$ [1] (lbs/MWh) | $CO_2$ Mass (short tons) | $CO_2$ [1] (lbs/MWh) | $NO_x$ Mass (short tons) | $NO_x$ [1] (lbs/MWh) | Heat Input (mmBtu) |
|---|---|---|---|---|---|---|---|---|---|
| NOS | 2000 | 3,651,388.50 | 12,640.16 | 6.92 | 3,966,587.07 | 2,172.65 | 5,990.85 | 3.28 | 38,903,721.31 |
| NOS | 2001 | 3,519,240.75 | 11,798.85 | 6.71 | 3,873,052.60 | 2,201.07 | 5,991.42 | 3.40 | 37,845,111.89 |
| NOS | 2002 | 3,663,534.00 | 11,509.22 | 6.28 | 3,904,853.91 | 2,131.74 | 6,107.79 | 3.33 | 38,335,920.91 |
| NOS | 2003 | 3,780,240.75 | 11,729.58 | 6.21 | 4,061,113.67 | 2,148.60 | 6,010.29 | 3.18 | 39,703,386.24 |
| NOS | 2004 | 3,845,050.00 | 16,124.89 | 8.39 | 4,113,684.01 | 2,139.73 | 6,309.45 | 3.28 | 40,143,212.40 |
| NOS | 2005 | 3,697,936.00 | 16,704.52 | 9.03 | 3,957,606.18 | 2,140.44 | 6,238.58 | 3.37 | 38,676,965.51 |
| NOS | 2006 | 3,758,084.75 | 14,314.97 | 7.62 | 4,065,696.37 | 2,163.71 | 6,259.42 | 3.33 | 39,689,186.96 |
| NOS | 2007 | 3,629,877.94 | 14,749.43 | 8.13 | 3,842,084.14 | 2,116.92 | 6,124.66 | 3.37 | 37,517,239.60 |
| NOS | 2008 | 3,828,988.19 | 15,011.74 | 7.84 | 4,210,262.25 | 2,199.15 | 6,455.18 | 3.37 | 40,378,142.01 |
| NOS | 2009 | 3,311,480.65 | 13,159.18 | 7.95 | 3,689,137.37 | 2,228.09 | 5,745.56 | 3.47 | 35,228,017.74 |
| NOS | 2010 | 3,530,101.98 | 10,515.15 | 5.96 | 4,065,276.27 | 2,303.21 | 6,765.23 | 3.83 | 38,820,663.94 |
| NOS | 2011 | 3,629,188.37 | 14,069.35 | 7.75 | 4,058,799.60 | 2,236.75 | 6,742.00 | 3.72 | 38,736,187.41 |
| NOS | 2012 | 3,305,317.04 | 11,377.16 | 6.88 | 3,677,848.54 | 2,225.41 | 5,571.68 | 3.37 | 35,111,946.97 |
| NOS | 2013 | 3,575,234.25 | 12,236.96 | 6.85 | 3,960,179.09 | 2,215.34 | 6,257.51 | 3.50 | 37,830,803.02 |
| NOS | 2014 | 3,330,467.65 | 11,244.87 | 6.75 | 3,714,819.67 | 2,230.81 | 5,778.80 | 3.47 | 35,503,184.98 |
| NOS | 2015 | 3,358,473.56 | 13,892.11 | 8.27 | 3,668,223.79 | 2,184.46 | 5,841.77 | 3.48 | 35,040,706.32 |
| NOS | 2016 | 2,239,335.69 | 8,902.07 | 7.95 | 2,355,407.44 | 2,103.67 | 3,818.42 | 3.41 | 22,511,203.43 |
| NOS | 2017 | 2,089,437.48 | 7,896.91 | 7.56 | 2,221,834.47 | 2,126.73 | 3,639.10 | 3.48 | 21,427,237.25 |
| NOS | 2018 | 1,930,833.96 | 7,285.16 | 7.55 | 2,078,468.78 | 2,152.92 | 3,392.51 | 3.51 | 19,895,842.15 |
| NOS | 2019 | 2,054,346.11 | 5,792.82 | 5.64 | 2,331,026.91 | 2,269.36 | 3,343.14 | 3.25 | 22,610,485.21 |
| NOS | 2020 | 1,947,105.11 | 5,446.63 | 5.59 | 2,105,599.71 | 2,162.80 | 3,176.27 | 3.26 | 20,227,757.29 |
| NOS | 2021 | 1,797,516.86 | 5,825.99 | 6.48 | 1,963,480.51 | 2,184.66 | 2,850.09 | 3.17 | 18,869,681.42 |
| NOS | 2022 | 1,947,972.45 | 5,479.06 | 5.63 | 2,085,302.84 | 2,141.00 | 2,932.69 | 3.01 | 20,381,689.41 |
| NOS | 2023 | 1,724,355.03 | 4,314.54 | 5.00 | 1,737,643.60 | 2,015.41 | 2,476.68 | 2.87 | 17,473,256.92 |
| NOS | 2024 | 1,233,422.94 | 2,935.19 | 4.76 | 1,275,409.19 | 2,068.08 | 1,779.08 | 2.88 | 13,013,745.53 |

| Station | Year | Gross Load (MWh) | $SO_2$ Mass (short tons) | $SO_2$ [1] (lbs/MWh) | $CO_2$ Mass (short tons) | $CO_2$ [1] (lbs/MWh) | $NO_x$ Mass (short tons) | $NO_x$ [1] (lbs/MWh) | Heat Input (mmBtu) |
|---|---|---|---|---|---|---|---|---|---|
| NCS | 2000 | 4,686,781.25 | 15,227.12 | 6.50 | 4,634,285.80 | 1,977.60 | 9,253.80 | 3.95 | 45,168,470.10 |
| NCS | 2001 | 4,950,436.75 | 16,205.49 | 6.55 | 4,910,417.38 | 1,983.83 | 9,481.61 | 3.83 | 47,859,791.55 |
| NCS | 2002 | 4,349,606.50 | 12,819.65 | 5.89 | 4,196,582.88 | 1,929.64 | 8,213.73 | 3.78 | 40,902,361.78 |
| NCS | 2003 | 5,055,104.25 | 15,052.01 | 5.96 | 4,966,427.93 | 1,964.92 | 10,214.97 | 4.04 | 48,405,745.78 |
| NCS | 2004 | 4,747,600.75 | 15,592.75 | 6.57 | 4,558,116.98 | 1,920.18 | 9,347.97 | 3.94 | 44,426,102.50 |
| NCS | 2005 | 4,896,714.25 | 17,550.18 | 7.17 | 4,966,129.50 | 2,028.35 | 9,994.53 | 4.08 | 48,402,869.98 |
| NCS | 2006 | 4,782,250.25 | 14,993.60 | 6.27 | 4,703,183.45 | 1,966.93 | 9,402.44 | 3.93 | 45,839,960.63 |
| NCS | 2007 | 4,492,016.05 | 14,173.35 | 6.31 | 4,459,194.57 | 1,985.39 | 9,484.47 | 4.22 | 43,461,945.18 |
| NCS | 2008 | 5,265,440.33 | 17,498.41 | 6.65 | 5,167,077.32 | 1,962.64 | 10,271.36 | 3.90 | 49,536,240.66 |
| NCS | 2009 | 8,594,668.08 | 19,074.38 | 4.44 | 8,770,042.91 | 2,040.81 | 15,136.93 | 3.52 | 83,656,645.06 |
| NCS | 2010 | 8,852,580.79 | 14,295.58 | 3.23 | 8,506,116.45 | 1,921.73 | 8,830.27 | 1.99 | 81,103,348.24 |
| NCS | 2011 | 9,807,247.63 | 17,334.40 | 3.54 | 9,595,501.57 | 1,956.82 | 6,288.96 | 1.28 | 91,490,307.85 |
| NCS | 2012 | 10,276,573.54 | 16,765.90 | 3.26 | 9,921,057.60 | 1,930.81 | 6,160.92 | 1.20 | 94,594,399.12 |
| NCS | 2013 | 10,350,366.74 | 16,910.74 | 3.27 | 10,214,003.76 | 1,973.65 | 6,427.38 | 1.24 | 97,400,333.38 |
| NCS | 2014 | 9,502,353.27 | 16,134.23 | 3.40 | 9,407,657.27 | 1,980.07 | 5,629.57 | 1.18 | 89,738,543.97 |
| NCS | 2015 | 9,302,249.49 | 18,547.06 | 3.99 | 9,218,735.41 | 1,982.04 | 5,935.33 | 1.28 | 87,987,796.45 |
| NCS | 2016 | 9,764,404.95 | 14,722.06 | 3.02 | 9,214,968.52 | 1,887.46 | 5,287.19 | 1.08 | 87,921,260.36 |
| NCS | 2017 | 9,366,275.35 | 15,950.18 | 3.41 | 9,343,763.60 | 1,995.19 | 6,053.14 | 1.29 | 89,169,617.74 |
| NCS | 2018 | 9,811,777.99 | 17,209.70 | 3.51 | 9,726,483.82 | 1,982.61 | 5,834.91 | 1.19 | 92,789,688.57 |
| NCS | 2019 | 7,396,692.33 | 10,386.36 | 2.81 | 7,457,451.31 | 2,016.43 | 4,149.27 | 1.12 | 71,213,328.08 |
| NCS | 2020 | 8,316,439.92 | 11,479.65 | 2.76 | 8,770,945.50 | 2,109.30 | 5,317.41 | 1.28 | 83,716,848.54 |
| NCS | 2021 | 7,579,326.80 | 9,465.40 | 2.50 | 7,515,046.66 | 1,983.04 | 4,303.59 | 1.14 | 71,768,066.36 |
| NCS | 2022 | 7,766,376.20 | 10,199.84 | 2.63 | 7,584,304.04 | 1,953.11 | 4,599.34 | 1.18 | 72,396,274.52 |
| NCS | 2023 | 6,491,607.99 | 10,616.33 | 3.27 | 6,479,756.45 | 1,996.35 | 4,234.20 | 1.30 | 61,884,642.76 |
| NCS | 2024 | 6,508,639.55 | 7,967.88 | 2.45 | 6,448,384.96 | 1,981.48 | 3,632.73 | 1.12 | 61,584,933.93 |

**NOS - North Omaha Station (OPPD)**

**NCS - Nebraska City Station (OPPD)**

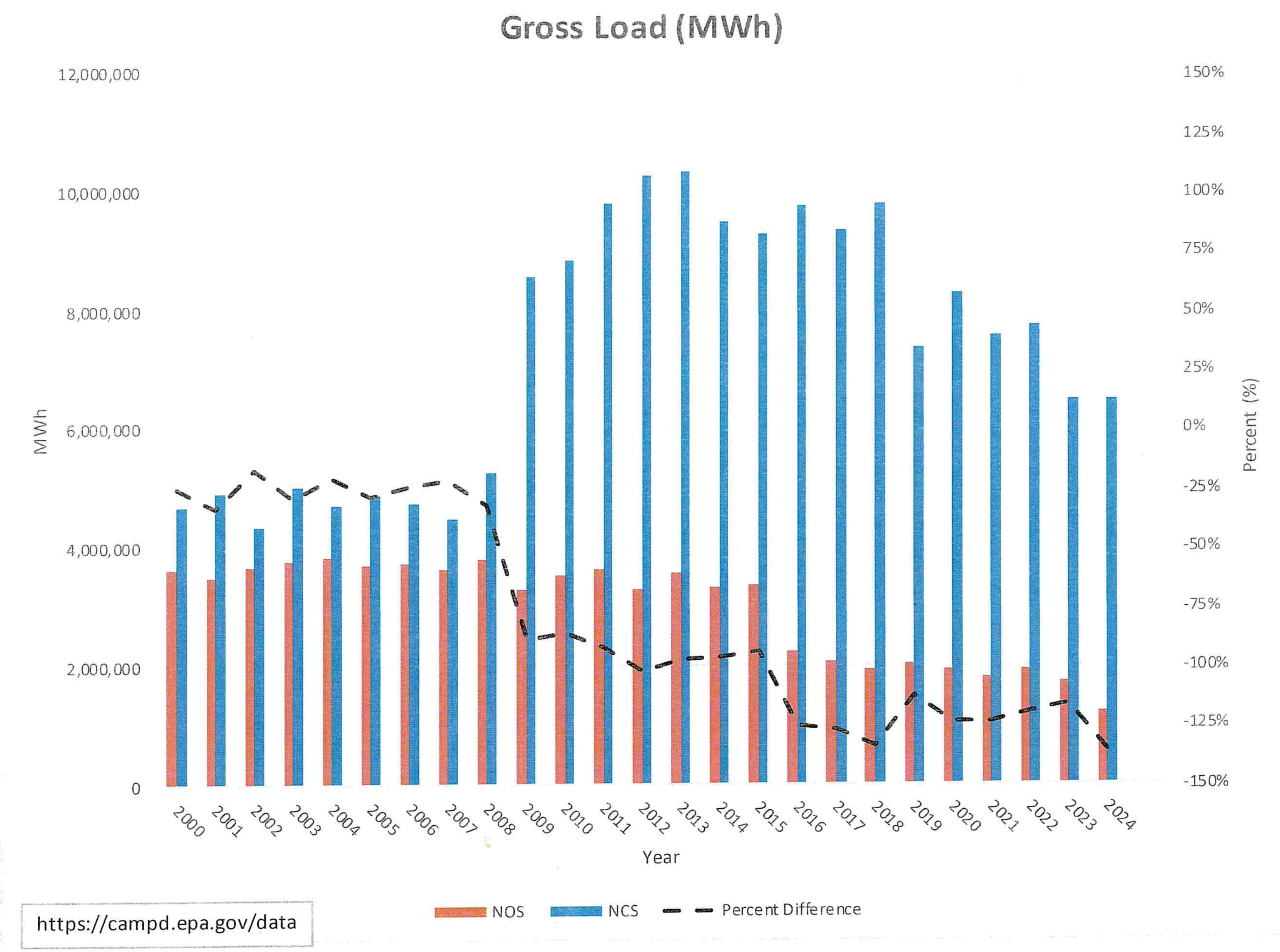
**1 - (short tons x 2000 lbs/ton)/ MWh**

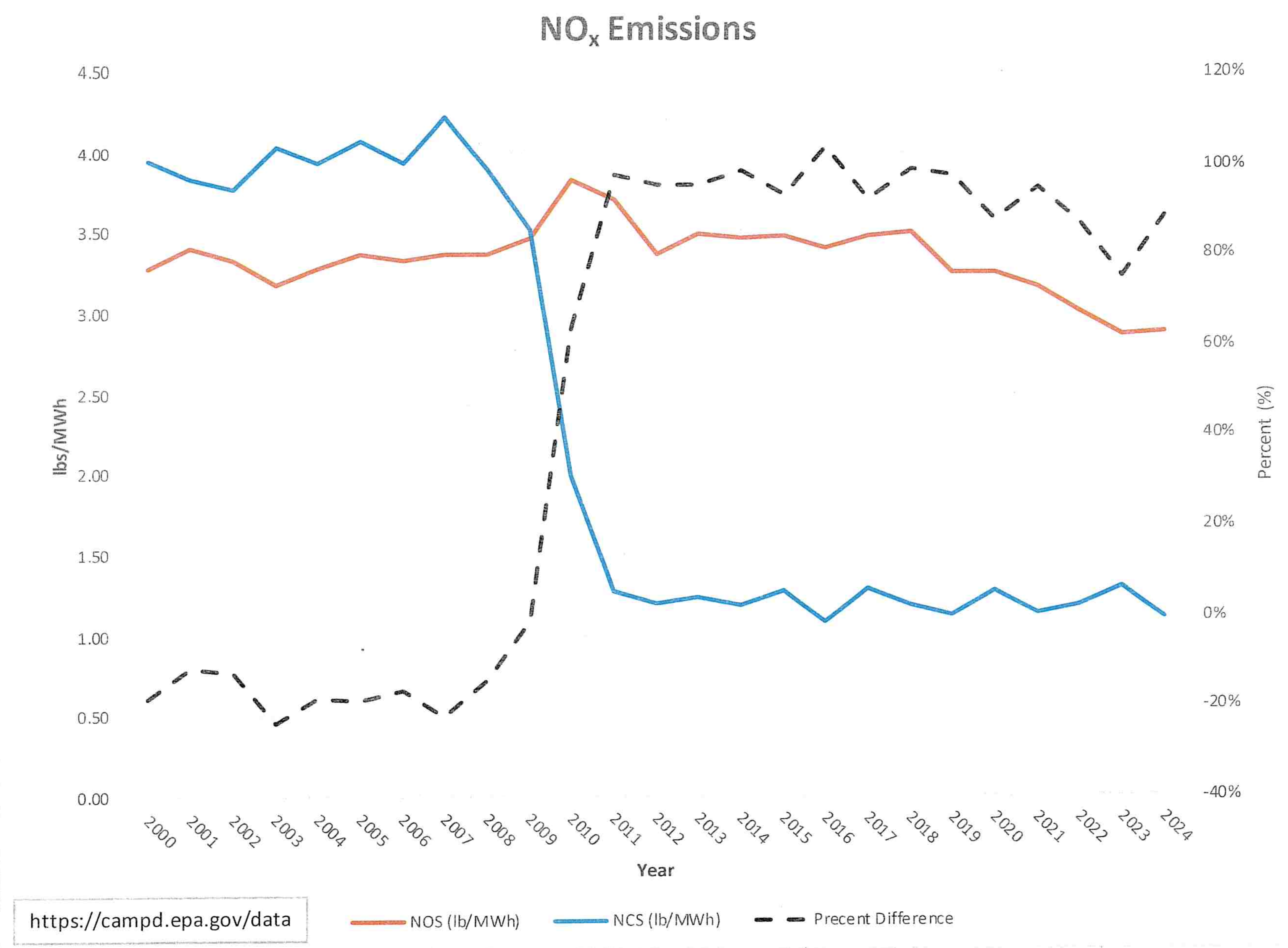
https://campd.epa.gov/data

| Gross Load | SO2 | | CO2 | | NOx | |
|---|---|---|---|---|---|---|
| NOS (MWh) - NCS (MWh) | NOS (tons) - NCS (tons)) | NOS (lbs/MWh) - NCS (lbs/MWh) | NOS (tons- NCS (tons)) | NOS (lbs/MWh) - NCS (lbs/MWh) | NOS (tons) - NCS (tons)) | NOS (lbs/MWh) - NCS (lbs/MWh) |
| -25% | -19% | 6% | -16% | 9% | -43% | -18% |
| -34% | -31% | 2% | -24% | 10% | -45% | -12% |
| -17% | -11% | 6% | -7% | 10% | -29% | -12% |
| -29% | -25% | 4% | -20% | 9% | -52% | -24% |
| -21% | 3% | 24% | -10% | 11% | -39% | -18% |
| -28% | -5% | 23% | -23% | 5% | -46% | -19% |
| -24% | -5% | 19% | -15% | 10% | -40% | -17% |
| -21% | 4% | 25% | -15% | 6% | -43% | -22% |
| -32% | -15% | 16% | -20% | 11% | -46% | -15% |
| -89% | -37% | 57% | -82% | 9% | -90% | -1% |
| -86% | -30% | 59% | -71% | 18% | -26% | 63% |
| -92% | -21% | 75% | -81% | 13% | 7% | 97% |
| -103% | -38% | 71% | -92% | 14% | -10% | 95% |
| -97% | -32% | 71% | -88% | 12% | -3% | 95% |
| -96% | -36% | 66% | -87% | 12% | 3% | 98% |
| -94% | -29% | 70% | -86% | 10% | -2% | 93% |
| -125% | -49% | 90% | -119% | 11% | -32% | 104% |
| -127% | -68% | 76% | -123% | 6% | -50% | 92% |
| -134% | -81% | 73% | -130% | 8% | -53% | 99% |
| -113% | -57% | 67% | -105% | 12% | -22% | 97% |
| -124% | -71% | 68% | -123% | 3% | -50% | 87% |
| -123% | -48% | 89% | -117% | 10% | -41% | 95% |
| -120% | -60% | 73% | -114% | 9% | -44% | 87% |
| -116% | -84% | 42% | -115% | 1% | -52% | 75% |
| -136% | -92% | 64% | -134% | 4% | -69% | 88% |

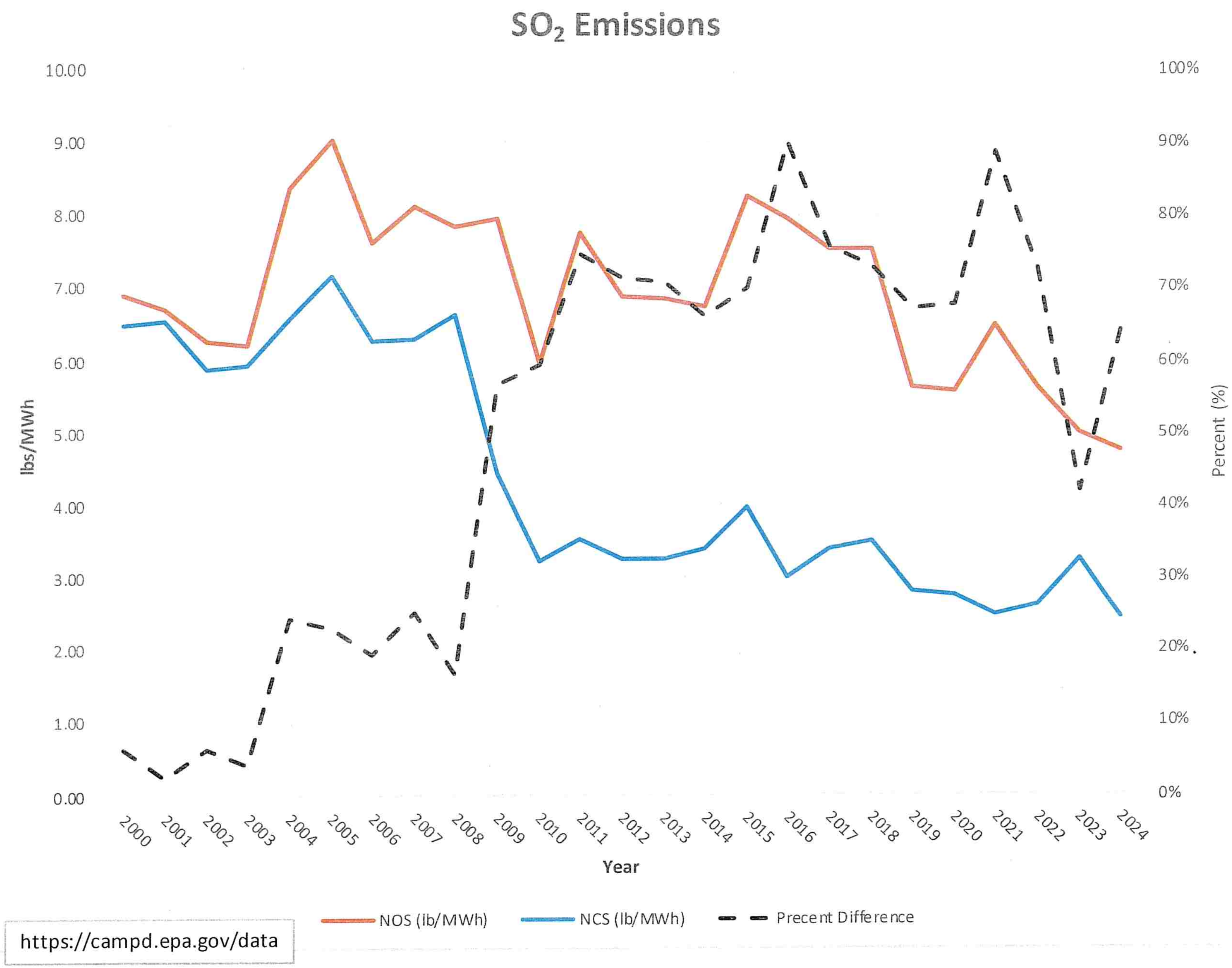
Note :

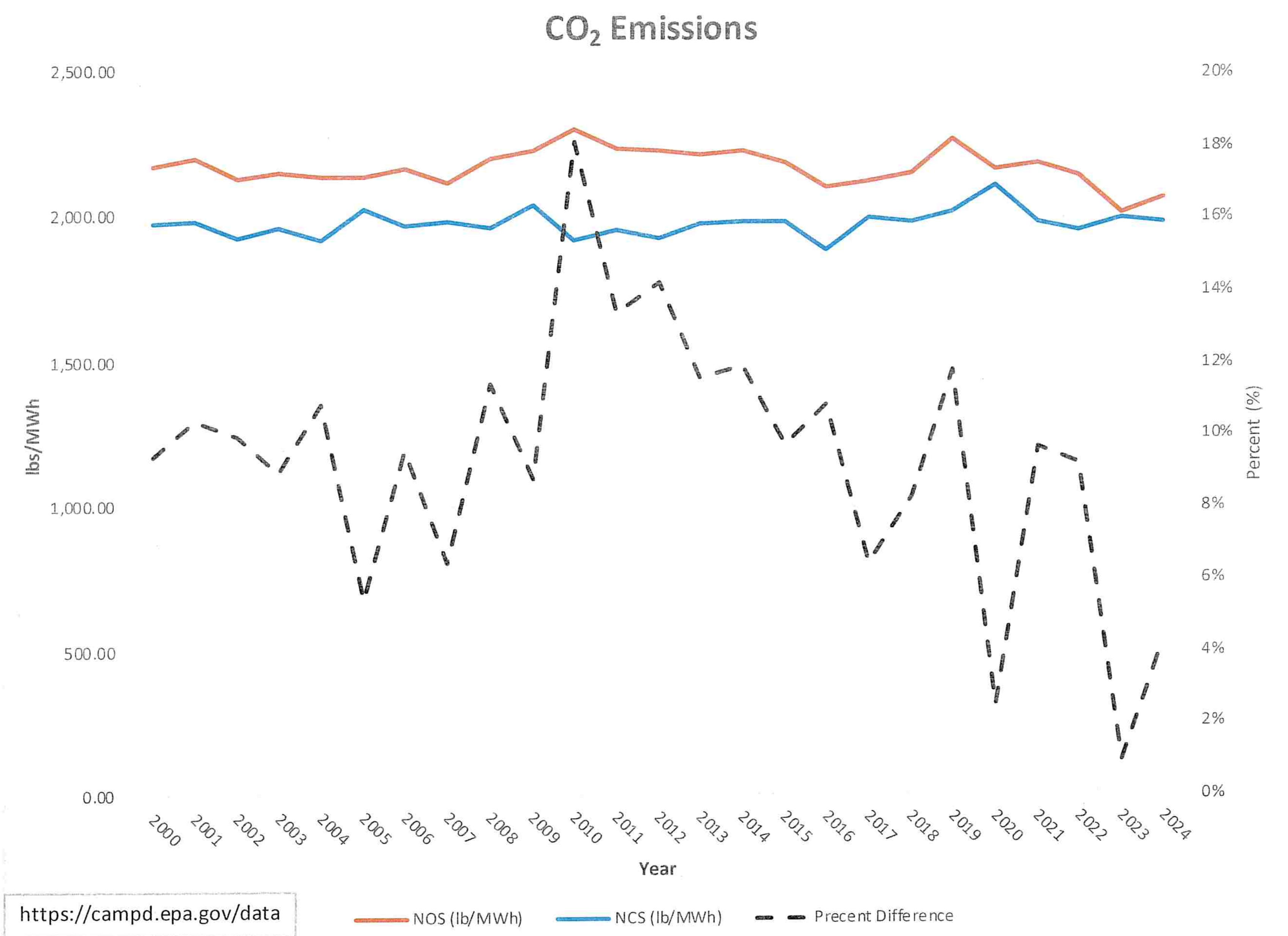
Percent Difference = (NOS - NCS)/((NOS + NCS)/2)


Gross Load (MWh)
12,000,000
10,000,000
8,000,000
6,000,000
4,000,000
2,000,000
0
MWh
150%
125%
100%
75%
50%
25%
0%
-25%
-50%
-75%
-100%
-125%
-150%
Percent (%)
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year
NOS
NCS
Percent Difference
https://campd.epa.gov/data

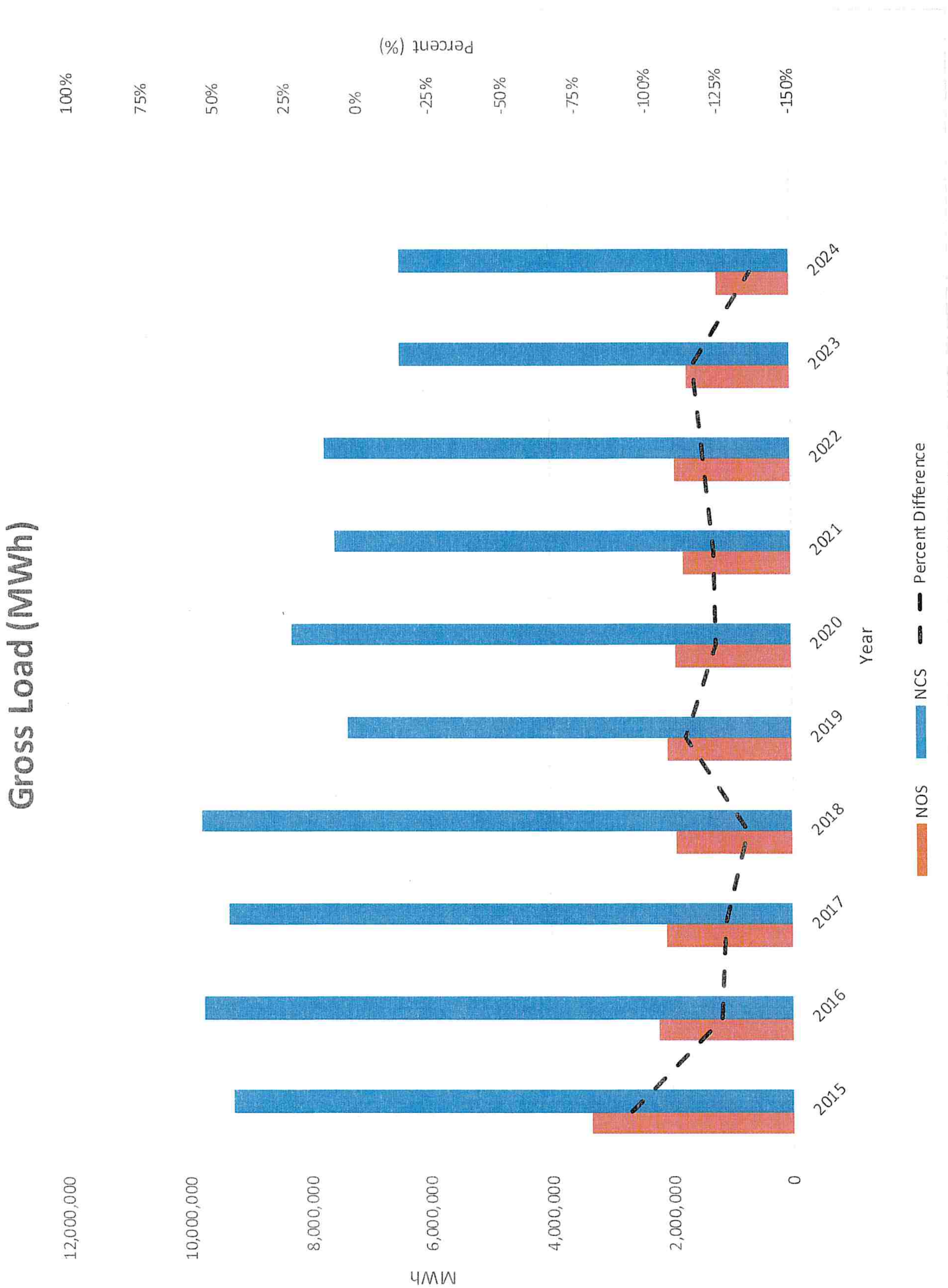


NOx Emissions
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
lbs/MWh
120%
100%
80%
60%
40%
20%
0%
-20%
-40%
Percent (%)
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year
https://campd.epa.gov/data
NOS (lb/MWh)
NCS (lb/MWh)
Precent Difference

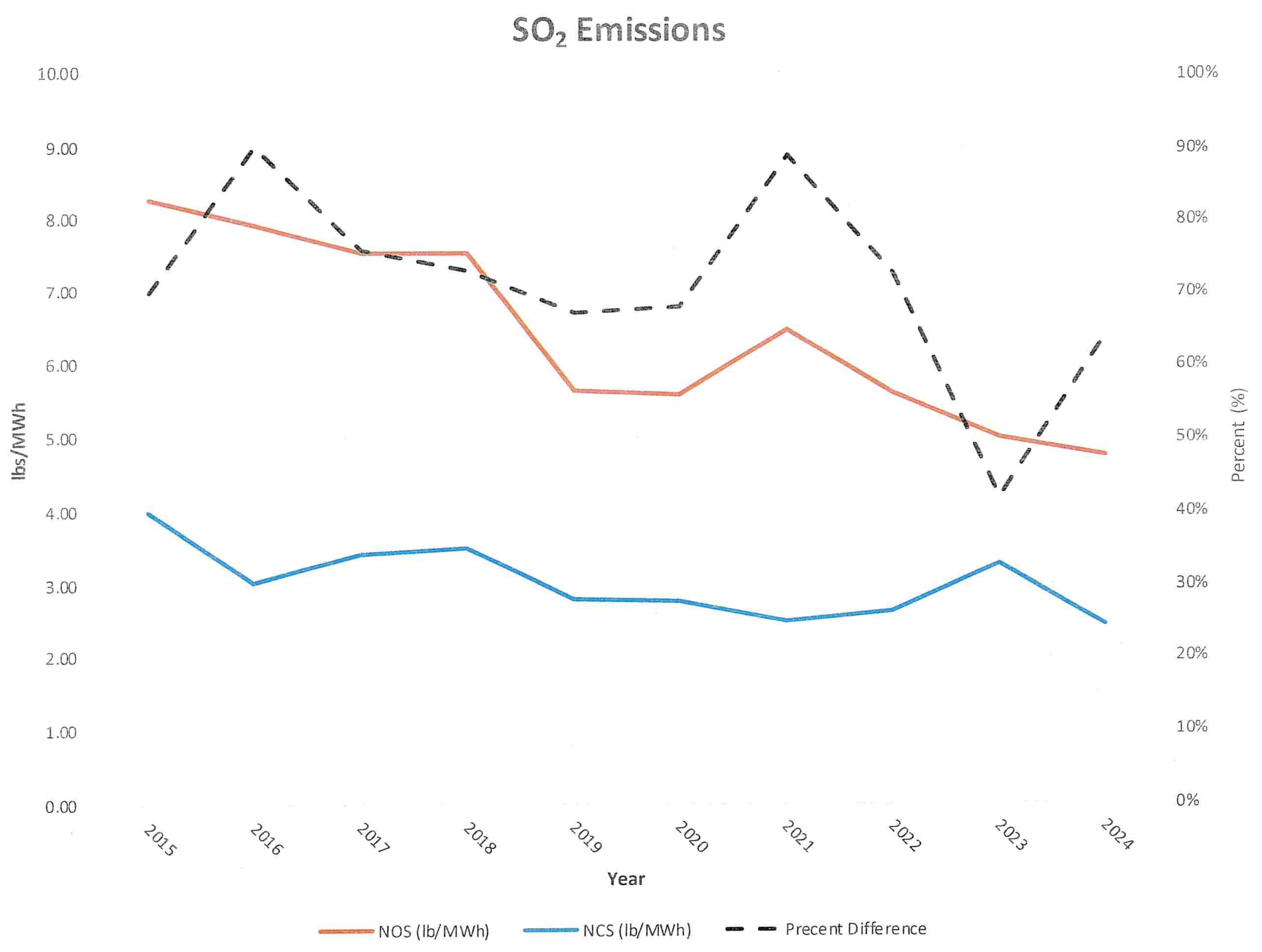

SO2 Emissions
lbs/MWh
10.00
9.00
8.00
7.00
6.00
5.00
4.00
3.00
2.00
1.00
0.00
Percent (%)
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024
Year
NOS (lb/MWh)
NCS (lb/MWh)
Precent Difference
https://campd.epa.gov/data



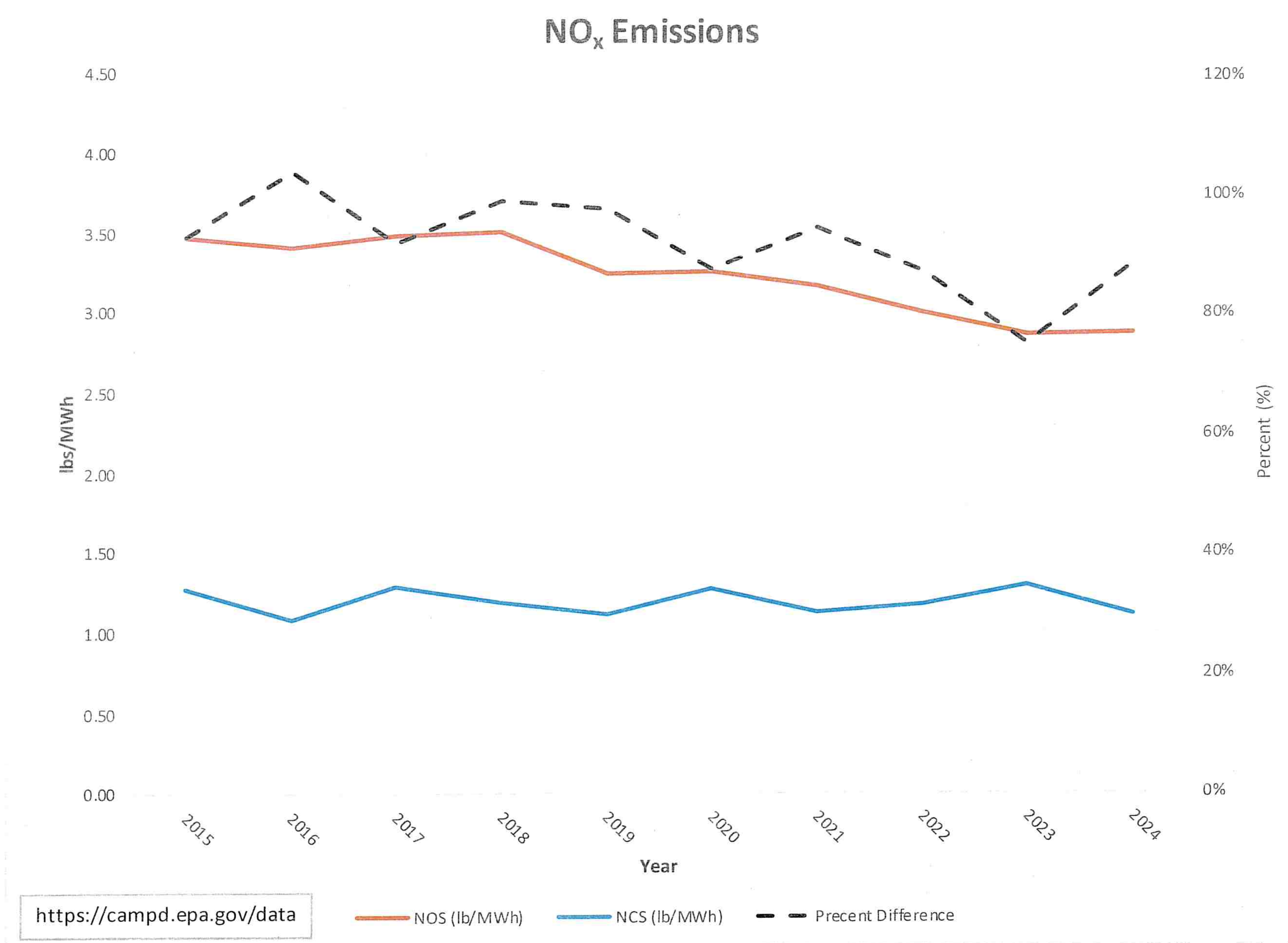
CO2 Emissions
2,500.00
2,000.00
1,500.00
1,000.00
500.00
0.00
lbs/MWh
20%
18%
16%
14%
12%
10%
8%
6%
4%
2%
0%
Percent (%)
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year
https://campd.epa.gov/data
NOS (lb/MWh)
NCS (lb/MWh)
Precent Difference

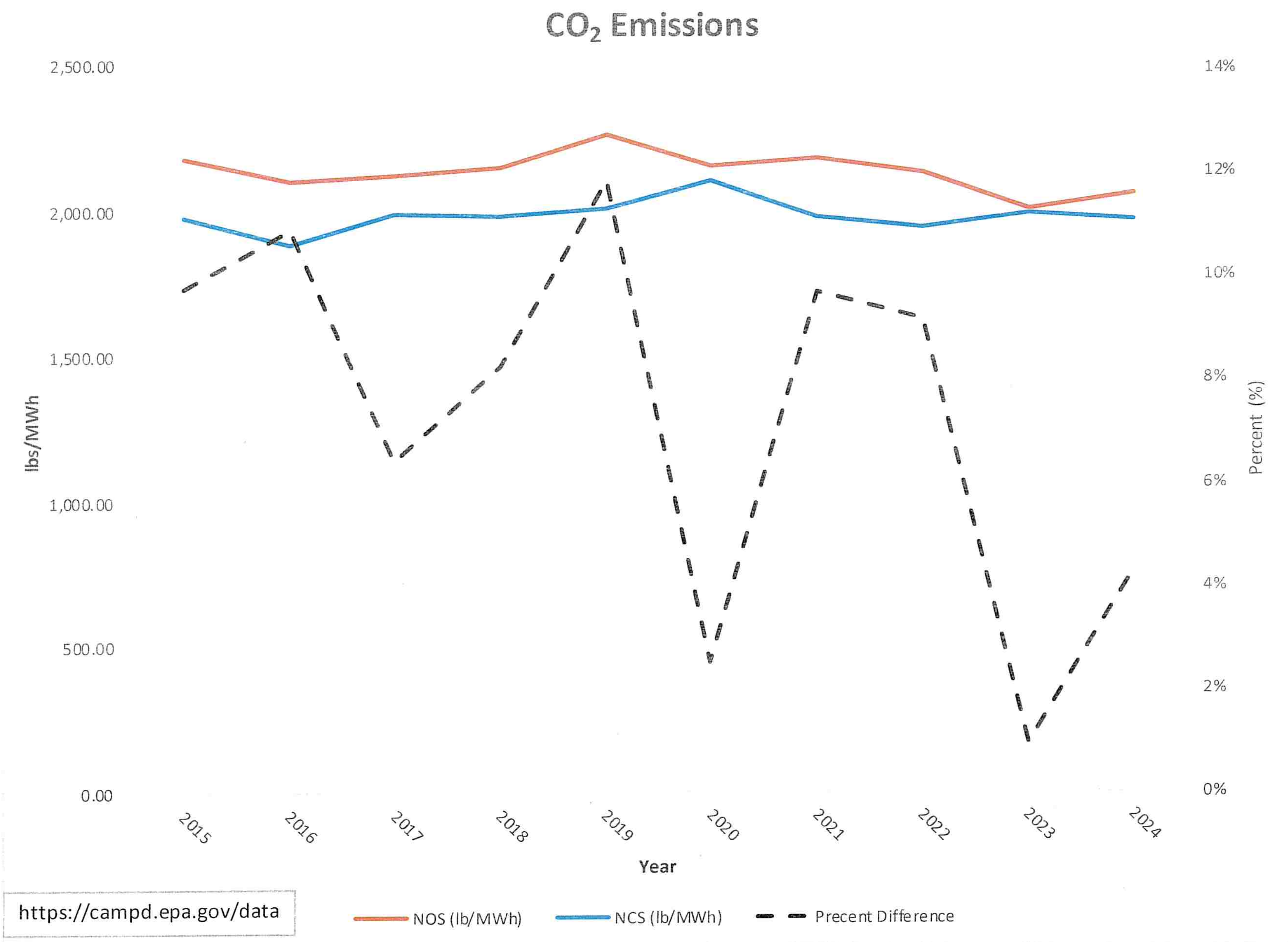


Gross Load (MWh)
MWh
12,000,000
10,000,000
8,000,000
6,000,000
4,000,000
2,000,000
0
Percent (%)
100%
75%
50%
25%
0%
-25%
-50%
-75%
-100%
-125%
-150%
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year
NOS
NCS
Percent Difference



SO2 Emissions
10.00
9.00
8.00
7.00
6.00
5.00
4.00
3.00
2.00
1.00
0.00
lbs/MWh
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Percent (%)
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year
NOS (lb/MWh)
NCS (lb/MWh)
Precent Difference


NO$_x$ Emissions
lbs/MWh
Percent (%)
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
120%
100%
80%
60%
40%
20%
0%
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year
https://campd.epa.gov/data
NOS (lb/MWh)
NCS (lb/MWh)
Precent Difference


CO2 Emissions
2,500.00
2,000.00
1,500.00
1,000.00
500.00
0.00
lbs/MWh
14%
12%
10%
8%
6%
4%
2%
0%
Percent (%)
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year
https://campd.epa.gov/data
NOS (lb/MWh)
NCS (lb/MWh)
Precent Difference