



UNIVERSIDADE FEDERAL DE SANTA CATARINA
CENTRO TECNOLÓGICO
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA DE PRODUÇÃO

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Performance Evaluation of the Water Supply and Sanitation Sector in Brazil

Florianópolis

2025

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Performance Evaluation of the Water Supply and Sanitation Sector in Brazil

Thesis submitted to the Production Engineering Post-Graduate Program from the Federal University of Santa Catarina as a final requirement to obtain a Doctorate degree in Production Engineering, area of concentration Operations Management.

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Florianópolis

2025

Ficha catalográfica gerada por meio de sistema automatizado gerenciado pela BU/UFSC.
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May, Andreia

Performance evaluation of the water supply and
sanitation sector in Brazil / Andreia May ; orientador,
Carlos Ernani Fries, coorientadora, Ana Maria Cunha
Ribeiro dos Santos Ponces Camanho, 2025.
174 p.

Tese (doutorado) - Universidade Federal de Santa
Catarina, Centro Tecnológico, Programa de Pós-Graduação em
Engenharia de Produção, Florianópolis, 2025.

Inclui referências.

1. Engenharia de Produção. 2. Composite indicator. 3.
Benefit-of-the-Doubt. 4. Global Malmquist Index. 5.
Classification and RegressionTrees. I. Fries, Carlos
Ernani. II. Camanho, Ana Maria Cunha Ribeiro dos Santos
Ponces . III. Universidade Federal de Santa Catarina.
Programa de Pós-Graduação em Engenharia de Produção. IV.
Título.

Andreia May

Performance Evaluation of the Water Supply and Sanitation Sector in Brazil

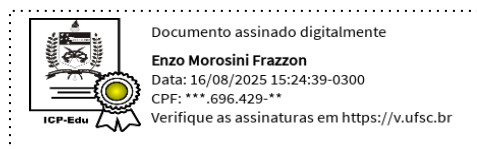
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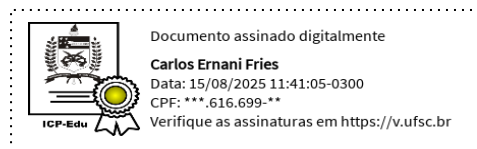
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Florianópolis, 2025

To Mrs. Gerçi,
My mother-in-law, who left us along the way,
but who is present in our thoughts and
hearts every step of the journey.

ACKNOWLEDGEMENTS

That's it! A beautiful and challenging journey is coming to an end. Many people were part of this path, each one contributing in a unique way. Some have been here since the beginning. Others accompanied me through parts of the road. All were essential to the achievement of this goal.

First, I would like to thank my advisors, Prof. Carlos Ernani Fries and Prof. Ana Camanho. It was an honor to work with you. Thank you for sharing your knowledge so precisely and for all the support you gave me.

To the examination committee members, Dr. Hermilio Vilarinho, Dr. Andreia Zanella, and Dr. Nelson Hein, thank you for your willingness to take part in the evaluation of this work and for providing such valuable feedback to improve the study.

To my parents, Neli and Valdir, for being life examples and for teaching me that dedication is the right way to achieve goals, despite daily challenges.

To my life partner, Paulo. I don't think I can find the right words to thank you. You were essential in making all of this come true, from the very beginning. This achievement is also yours.

To my family and friends, who are many and impossible to name one by one, but whose presence and support were fundamental. Thank you for all your encouragement and for patiently listening to my countless reflections about the thesis. To the Universidade Federal de Santa Catarina (UFSC), especially the Graduate Program in Production Engineering (PPGEP), for the opportunity for learning and continuous development.

To the University of Porto, in Portugal, and to all my colleagues there, thank you for the enriching experience, the knowledge shared, and for welcoming me with open arms to such a special place.

To the Brazilian Coordination for the Improvement of Higher Education Personnel (CAPES), for making possible the doctoral exchange period in Portugal, which was essential for the methodological construction of this thesis.

To Companhia Catarinense de Águas e Saneamento (CASAN), the company where I have worked for 21 years and which has taught me much of what I know about basic sanitation.

To all of you, without exception, my most sincere thanks.

ABSTRACT

Performance evaluation in the water supply and sewage sector is essential for promoting efficiency, equity, and sustainability in service provision. In Brazil, where water resources are unevenly distributed and basic sanitation coverage remains a challenge, this evaluation becomes even more critical in the context of recent regulatory changes. The new sanitation legal framework, established by Law No. 14,026/2020, sets ambitious goals for universal access to drinking water and sewage collection and treatment by 2033. In this context, this thesis proposes a multidimensional and integrated approach to assess the performance of water and sewerage services in Brazilian municipalities, considering both temporal evolution and regional heterogeneity. The methodological design combines robust techniques from the field of frontier efficiency analysis and machine learning. Specifically, the Benefit-of-the-Doubt (BoD) model is applied to construct composite performance indicators that integrate financial, operational, and quality dimensions. To address the sensitivity of the BoD scores to outliers, a robust formulation is implemented based on bootstrapping procedures. In addition, the Global Malmquist Index (GMI) is used to analyze performance trends over time, while Classification and Regression Trees (CART) are employed to investigate the determining factors of water distribution losses. The thesis is structured as a compendium of three articles: the first evaluates the evolution of performance in municipalities from Santa Catarina (2009–2021); the second develops a robust ranking for Brazil's 100 most populous cities, incorporating contextual variables; and the third explores factors associated with water losses through classification models. The integrated results highlight not only the persistent challenges faced by the sector, but also the potential for improvement based on benchmarking, data analysis, and evidence-based decision-making. The findings contribute methodologically and empirically to performance assessment in public services, offering practical tools for public managers, regulatory agencies, and policy makers. They also reinforce the importance of using composite indicators and robust evaluation models to guide investments, monitor progress toward universalization goals, and design more efficient and equitable sanitation policies.

Keywords: Data Envelopment Analysis; Water supply. Sewage disposal; Composite indicator; Benefit-of-the-Doubt; Global Malmquist Index, Classification and Regression Trees.

RESUMO

A avaliação de desempenho no setor de abastecimento de água e esgotamento sanitário é essencial para promover eficiência, equidade e sustentabilidade na prestação de serviços. No Brasil, onde os recursos hídricos são distribuídos de forma desigual e a cobertura de saneamento básico continua sendo um desafio, essa avaliação se torna ainda mais crítica no contexto das recentes mudanças regulatórias. O novo marco legal do saneamento, estabelecido pela Lei nº 14.026/2020, estabelece metas ambiciosas para o acesso universal à água potável e à coleta e tratamento de esgoto até 2033. Nesse contexto, esta tese propõe uma abordagem multidimensional e integrada para avaliar o desempenho dos serviços de água e esgotamento sanitário nos municípios brasileiros, considerando tanto a evolução temporal quanto a heterogeneidade regional. O desenho metodológico combina técnicas robustas dos campos da análise de eficiência de fronteira e aprendizado de máquina. Especificamente, o modelo *Benefit-of-the-Doubt* (BoD) é aplicado para construir indicadores compostos de desempenho que integram as dimensões financeira, operacional e de qualidade. Para abordar a sensibilidade das pontuações do BoD a valores extremos (*outliers*), uma formulação robusta baseada em procedimentos de *bootstrapping* é implementada. Além disso, o Índice Global de Malmquist (GMI) é utilizado para analisar comportamentos de desempenho ao longo do tempo, enquanto Árvores de Classificação e Regressão (CART) são empregadas para investigar os fatores determinantes das perdas na distribuição de água. A tese é estruturada como um compêndio de três artigos: o primeiro avalia a evolução do desempenho em municípios catarinenses (2009-2021); o segundo desenvolve um ranking robusto para as 100 cidades mais populosas do Brasil, incorporando variáveis contextuais; e o terceiro explora fatores associados às perdas de água por meio de modelos de classificação. Os resultados integrados destacam não apenas os desafios persistentes enfrentados pelo setor, mas também o potencial de melhoria com base em *benchmarking*, análise de dados e tomada de decisão baseada em evidências. Os resultados contribuem metodológica e empiricamente para a avaliação de desempenho em serviços públicos, oferecendo ferramentas práticas para gestores públicos, agências reguladoras e formuladores de políticas. Eles também reforçam a importância do uso de indicadores compostos e modelos de avaliação robustos para orientar investimentos, monitorar o progresso em direção às metas de universalização e desenvolver políticas de saneamento mais eficientes e equitativas.

Palavras-chave: *Data Envelopment Analysis*; Abastecimento de água. Esgotamento sanitário; Indicador composto; *Benefit-of-the-Doubt*; Índice Malmquist Global, Árvores de Classificação e Regressão.

RESUMO EXPANDIDO

Introdução

O acesso universal a serviços de abastecimento de água e esgotamento sanitário é um dos Objetivos de Desenvolvimento Sustentável (ODS) das Nações Unidas, com metas ambiciosas estabelecidas para 2030. No Brasil, embora existam vastas reservas hídricas, sua distribuição desigual no território, combinada com desafios operacionais e institucionais, impõe barreiras significativas à universalização dos serviços. A promulgação do novo marco legal do saneamento (Lei nº 14.026/2020), que atualizou a Lei nº 11.445/2007, estabeleceu metas rígidas: 99% da população com acesso à água potável e 90% à coleta e tratamento de esgoto até 2033. Nesse cenário, a avaliação de desempenho torna-se um instrumento essencial para monitorar a eficiência dos serviços, apoiar decisões políticas e garantir a adequada aplicação de recursos públicos. A presente tese propõe uma abordagem metodológica robusta e integrada para analisar a performance dos serviços de água e esgoto no Brasil, considerando a evolução temporal, a heterogeneidade regional e a influência de variáveis contextuais.

Objetivos

O objetivo geral desta tese é avaliar o desempenho dos serviços de abastecimento de água e de esgotamento sanitário no Brasil em função das mudanças normativas e legais ocorridas no setor. O alcance do objetivo geral está vinculado à realização dos seguintes objetivos específicos: a) Caracterizar a evolução do setor de abastecimento de água e esgotamento sanitário no Brasil, considerando os marcos regulatórios e normativos; b) Identificar indicadores-chave de desempenho; c) Desenvolver e aplicar um modelo robusto de indicadores compostos, baseado na técnica do *Benefit-of-the-Doubt* (BoD), para avaliar o desempenho dos municípios brasileiros em serviços de saneamento; d) Investigar a evolução temporal do desempenho municipal utilizando o Índice Malmquist Global (GMI), com foco nos componentes de mudança de eficiência e melhores práticas; e) Explorar a influência de variáveis contextuais (exógenas) na eficiência dos serviços de água e esgotamento sanitário; f) Aplicar algoritmos de classificação e regressão (Árvores de Classificação e Regressão) para identificar fatores de perdas de água em sistemas de abastecimento; g) Contribuir para o benchmarking entre municípios e a formulação de políticas públicas mais assertivas no setor de saneamento básico.

Metodologia

A tese adota uma abordagem metodológica quantitativa e aplicada, estruturada em três artigos científicos. As técnicas principais utilizadas foram: i) *Benefit-of-the-Doubt* (BoD): derivado da Análise Envoltória de Dados (DEA), o BoD permite a construção de um indicador composto que sintetiza o desempenho multidimensional de cada município; ii) BoD robusto: a formulação robusta do BoD utiliza *bootstrapping* para reduzir a sensibilidade a *outliers* e melhorar a confiabilidade dos resultados; iii) Índice Malmquist Global: avalia mudanças no desempenho ao longo do tempo, separando os efeitos de melhoria de eficiência e avanço tecnológico; iv) Árvores de Classificação e Regressão (CART): identificam os principais fatores explicativos das perdas de água na distribuição, utilizando algoritmos CHAID e análise de *cluster*. Os dados foram extraídos dos sistemas oficiais do Governo Brasileiro e incluem indicadores

operacionais, financeiros e de qualidade do serviço. A unidade de análise adotada foram os municípios brasileiros.

Resultados e Discussão

O artigo *Evolution of performance in the water and sewage sector in Brazil: a robust directional Benefit-of-the-Doubt assessment of municipalities from Santa Catarina state* avalia a evolução do desempenho dos serviços de abastecimento de água e esgotamento sanitário no estado de Santa Catarina entre 2009 e 2021. Aplicando o BoD e o GMI a 295 municípios catarinenses, foi possível constatar uma perda média de desempenho de 3,3% no período analisado, com ampla variação de resultados entre os municípios. O artigo *From data to decision: a robust ranking of water and sanitation services in Brazil* avaliou o desempenho das 100 cidades mais populosas do Brasil, utilizando variáveis contextuais como tipo e vulnerabilidade da fonte de água, Índice de Desenvolvimento Humano Municipal (IDH-M) e região geográfica. Observou-se que fatores exógenos influenciam significativamente os resultados. A comparação com rankings tradicionais, como o do Instituto Trata Brasil, revelou discrepâncias importantes, mostrando que fatores exógenos afetam os resultados e oferecem uma visão mais realista do desempenho. O artigo *An Analysis of Water Supply System Losses: A Case Study of Santa Catarina State, Brazil* buscou determinar os fatores mais relevantes para as perdas de água em Santa Catarina. Utilizando algoritmos de classificação e regressão, identificou-se que variáveis como índice de consumo de água e macromedicação são importantes para explicar as perdas de água. O modelo desenvolvido apresentou boa capacidade preditiva, contribuindo para a priorização de ações.

Considerações Finais

A tese contribui metodologicamente ao propor uma avaliação de desempenho integrada, robusta e multidimensional, aplicável à realidade do setor de saneamento brasileiro. Os resultados destacam a necessidade de: i) Investimentos mais eficientes e orientados por evidências; ii) Aperfeiçoamento dos sistemas de regulação e monitoramento; iii) Inclusão de indicadores compostos e variáveis contextuais na formulação de políticas públicas; iv) Fortalecimento da gestão municipal, em especial nos pequenos e médios municípios. Do ponto de vista prático, os modelos desenvolvidos podem ser adotados por agências reguladoras, governos e operadores para monitorar o progresso rumo à universalização dos serviços até 2033. A pesquisa também reforça a importância da integração entre análise quantitativa e conhecimento do contexto institucional para a formulação de políticas públicas mais eficazes.

Palavras-chave: *Data Envelopment Analysis*; Abastecimento de água. Esgotamento sanitário; Indicador composto; *Benefit-of-the-Doubt*; Índice Malmquist Global, Árvores de Classificação e Regressão.

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LIST OF ABBREVIATIONS

ABAR	Associação Brasileira de Agências Reguladoras (Brazilian Association of Regulatory Agencies)
ANA	Agência Nacional de Águas e Saneamento Básico (National Water and Basic Sanitation Agency)
ANN	Artificial Neural Network
AR-I	Assurance Regions - I
BoD	Benefit-of-the-Doubt
BPC	Best Practices Change
BPG	Best Practices Gap
CAPES	Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (Coordination for the Improvement of Higher Education Personnel)
CART	Classification and Regression Tree
CASAN	Companhia Catarinense de Águas e Saneamento (Santa Catarina's Water and Sanitation Company)
CESB	State Basic Sanitation Companies
CHAID	Chi-squared Automatic Interaction Detection
CI	Composite Indicator
CRS	Constant Returns to Scale
DAE	Water and Sewage Department
DDF	Directional Distance Function
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
EC	Efficiency Change
EMASA	Empresa Municipal de Água e Saneamento (Municipal Water and Sanitation Company)
ERSAR	Water and Waste Services Regulatory Authority (Portugal)
ES	Exclusively Surface
ETA	Water Treatment Plant
ETE	Sewage Treatment Plant
EU	Exclusively Underground
WEPA	European Workshop on Efficiency and Productivity Analysis

FPI	Färe-Primont Productivity Index
GMI	Global Malmquist Index
HDI	Human Development Index
HDI-M	Municipal Human Development Index
IBGE	Instituto Brasileiro de Geografia e Estatística (Brazilian Institute of Geography and Statistics)
IFORS	International Federation of Operational Research Societies
IIP	Investment by Provider per Receipt Index
IIT	Total Investment by Receipt Index
ILA	Water Connections Index
ILE	Sewage Connections Index
IPD	Distribution Water Loss Index
IPF	Total Revenue Loss Index
IPV	Volumetric Water Loss Index
ITA	Total Water Coverage Index
ITB	Instituto Trata Brasil (Brazilian institute for WSS)
ITE	Total Sewage Coverage Index
ITR	Treated Sewage Referred Consumed Water Index
IUA	Urban Water Coverage Index
IUE	Urban Sewage Coverage Index
IWA	International Water Association
LHMPI	Luenberger-Hicks-Moorsteen Productivity Index
LPI	Luenberger Productivity Indicator
LV	Low-vulnerable
MLPI	Malmquist-Luenberger Productivity Index
MMLPI	Metafrontier Malmquist Luenberger Productivity Index
MMPI	Meta-Malmquist Productivity Index
MPI	Malmquist Productivity Index
MV	Moderately Vulnerable
NRV	Non-Revenue Water
NV	Non-vulnerable
PCA	Principal Component Analysis
PLANASA	National Sanitation Plan

PLANSAB	National Basic Sanitation Plan
PMSB	Municipal Basic Sanitation Plan
PNSR	National Rural Sanitation Plan
PRINT	Programa Institucional de Internacionalização (Institutional Internationalization Program)
PS	Predominantly Superficial
PMPI	Pseudo-Malmquist Productivity Index
PTF	Total Factor Productivity
PU	Predominantly Underground
SAA	Water Supply System
SANEPAR	Paraná's Sanitation Company
SASB	Autonomous Basic Sanitation Service
SDG	Sustainable Development Goal
SFA	Stochastic Frontier Analysis
SINISA	National Basic Sanitation Information System
SNIS	National Sanitation Information System
UFSC	Universidade Federal de Santa Catarina (Federal University of Santa Catarina)
UN	United Nations Organization
UNDP	United Nations Development Program
VMP	Maximum Allowed Value
VRs	Variable Return to Scale
WASH	Water, Sanitation, and Hygiene
WaSCs	Water and Sewage Companies
WoCs	Water Only Companies
WS	Water Supply
WSS	Water Supply and Sewage
WST	Water Source Type
WSV	Water Source Vulnerability
WWD	Wastewater Drainage

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1 INTRODUCTION

This chapter presents a general contextualisation of the main elements that motivate and underpin this research, with a focus on the water supply and sewage sector in Brazil. This is followed by an explanation of the research objectives - both general and specific - as well as the main limitations encountered during the study. Finally, the structure of the thesis is presented, detailing the organisation of the chapters and the methodological steps that guided the research.

1.1 CONTEXTUALISATION

The expansion and efficiency of water supply systems and sewage (WSS) systems are key measures to ensure universal access to drinking water, sanitation and hygiene (WASH), one of the Sustainable Development Goals (SDGs) established by the United Nations (UN). According to the UN (2023), in 2022, 2.2 billion people still did not have drinking water; 3.5 billion people did not have adequate sewage treatment and 2 billion did not even have access to a basic hand-washing facility.

Brazil also faces major challenges. Despite having the largest surface water reserves in the world (Getirana, 2016), the distribution of this resource throughout the country is highly variable and inversely proportional to demand. The Southeast and Northeast regions contribute only 7% and 6% of the total surface water, but include most of the country's population, 39% and 25% respectively (Getirana, 2016). This characteristic requires active management of WSS in order to make water available in the quantity and quality required for the various uses.

Improving water supply and sanitation services also depends on aligning policies, regulations and institutions to achieve the goals of universal access to drinking water, sanitation and hygiene (Mumssen *et al.*, 2018).

Recent experiences in Brazil regarding the regulation of services and legal and normative updates have sought to improve the sector's performance. The enactment of the basic sanitation legal framework, Law 11.445/2007, was an important step in this direction. Investments and the main indices, such as total sanitation coverage, advanced after the new legislation, but on a smaller scale than was necessary to overcome the deficits in service coverage and increase the efficiency of the systems (Afonso; Almeida, 2020).

In 2020, in order to accelerate the pace of action, Law No. 14.026 (Brazil, 2020a) was enacted, which is an update of Law No. 11.445/2007. Among the main measures of this new law is the universalisation of services, which sets 31 December 2033 as the deadline for providing 99% of the population with treated water and 90% with adequate effluent management.

These indicators, as well as various other pieces of information and indices relating to basic sanitation in Brazil, are published annually by the federal government. In the period between 1995 and 2022, the data is monitored through the National Sanitation Information System (SNIS). In 2023, the SNIS ended its activities with the collection of information on the provision of services for the year 2022. From 2024 onwards, data for the reference years 2023 onwards will be made available through the National Basic Sanitation Information System (SINISA). This update to the official information system aims to meet the requirements of Law 14.026/2020, comprising new data that will be monitored for the management of the systems.

Performance evaluation is an important activity for verifying the fulfilment of these goals and Benefit-of-the-Doubt (BoD) is one of the techniques available for this purpose. BoD is a method derived from Data Envelopment Analysis (DEA) models. BoD was proposed by Cherchye *et al.* (2007) and allows metrics to be analysed together using a composite indicator (CI), providing a holistic view of the situation and benchmarking. The composite indicator aggregates a set of individual indicators with the aim of summarising the performance of the units being assessed, taking into account the multidimensional nature of their activities.

In relation to the literature review, it was found that DEA is a method frequently used in Brazil to evaluate basic sanitation. Previous studies by Carvalho and Sampaio (2015), Macedo (2018) and Tourinho *et al.* (2023), for example, used DEA for this purpose. Carvalho and Sampaio (2015) and Macedo (2018) revealed productivity gains influenced by the institutional changes implemented in Brazil's water and sewage sector.

Tourinho *et al.* (2023) applied two different indices to assess the variation in productivity in Brazil's basic sanitation sector between 2012 and 2019 and to compare productivity levels between Brazilian macro-regions. The results showed a loss of performance of approximately 4% over the period studied.

Another technique used here is the Global Malmquist Index (GMI). The GMI is based on the well-known Malmquist Index, but uses an envelope function of all the

individual technologies in a given period, called the metafrontier, to assess the change in performance over time. The GMI can be broken down into efficiency change and best practice change components. Efficiency change is about improving the use of available resources. Best practice change reflects technological advances or sectoral innovations (Pastor; Lovell, 2005).

Finally, Classification and Regression Trees, a procedure for identifying and classifying relationships between variables in a data set, is used to identify the most relevant cause and effect factors in water losses, one of the most important performance indicators for sanitation companies. The classification tree aims to obtain a classification model by identifying relationships between dependent and independent variables. The algorithm divides the data into a tree model, highlighting the independent variables that provide the maximum segregation of the data according to the dependent variable, in this case water losses (Breiman *et al.*, 2017).

Applying these techniques together offers a new perspective for assessing the performance of sanitation services and identifying the strengths and weaknesses of each Decision Making Unit (DMU), contributing to the diagnosis and planning of WSS. In this study, municipalities were defined as DMUs, so that the results of the research can serve as a subsidy for basic sanitation management at local level, since municipalities are responsible for the ownership of services and for formulating public basic sanitation policy and drawing up sanitation plans.

1.1.1 Panorama in Brazil

The management of the water supply and sanitation sector in Brazil has gone through three significant periods of reform: 1968-1986, characterised by the National Sanitation Plan (PLANASA) and the creation of state-owned companies (CESBs) at state level; 1986-2007, the second period, which promoted the participation of the public sector and established the official source of data on basic sanitation, the National Sanitation Information System (SNIS); and the most recent phase, in which the legal framework for basic sanitation was approved (Law No. 11.445/2007) and its update (Law 14.026/2020) (Mumssen *et al.*, 2018).

Law no. 11.445/2007 listed guidelines for the sector, highlighting the fundamentals of universalisation, which determines access for all people to drinking water and adequate sewage treatment; ownership, which is the responsibility of the

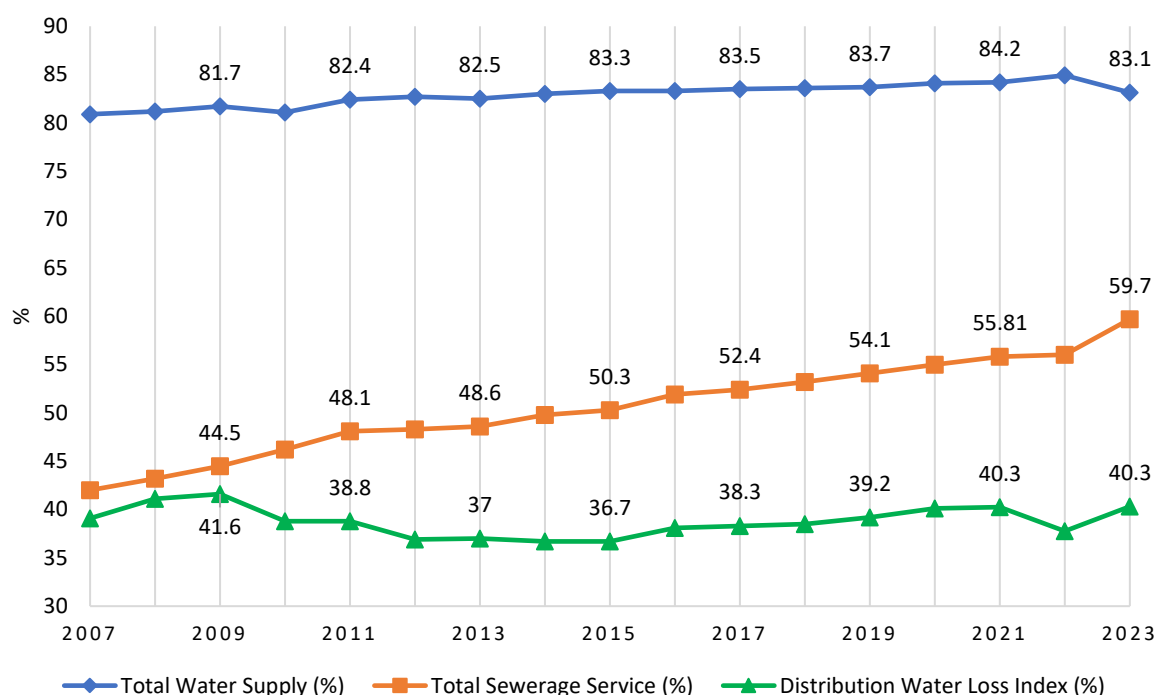
municipality; and regulation of services, carried out by an entity of an autarkic nature endowed with decision-making independence and administrative, budgetary and financial autonomy (Brazil, 2007).

Also in accordance with Law 11.445/2007, Brazilian municipalities should draw up the Municipal Basic Sanitation Plan (PMSB), which is a diagnosis of the situation and planning of services. According to Lisboa *et al* (2013), many municipalities have had difficulties in drawing up their PMSB, mainly due to a lack of financial resources and a shortage of qualified professionals. Data from the Municipal Information Survey, published by Instituto Brasileiro de Geografia e Estatística, IBGE (Brazilian Institute of Geography and Statistics), shows that by 2017, only 2,314 Brazilian municipalities (41.5%) had drawn up municipal plans. Investment in basic sanitation increased sharply in the period following Law 11.445/2007. Between 2007 and 2015, the average annual federal disbursement in sanitation was R\$7.14 billion, while between 2003 and 2006 this amount was approximately R\$1.57 billion per year (Afonso; Almeida, 2020). Despite these developments, resources have not been sufficient to achieve universalisation and system efficiency, as shown in Figure 1 (Brazil, 2009, 2010, 2011, 2012, 2013a, 2014a, 2014b, 2016, 2017, 2018a, 2019a, 2019b, 2020b, 2021a, 2022, 2023b, 2025).

Figure 1 shows that Total Water Supply has gradually increased over the years, resulting in an accumulated variation of +2.2%. The maximum value was obtained in 2022, 84.9%, and the minimum in 2007, 80.9%.

Total Sewerage Service, which refers to municipalities served with water, increased in all the years analysed, from 42.0% in 2007 to 59.7% in 2023.

Figure 1 - Basic sanitation performance in Brazil from 2007 to 2023



Source: prepared by the author based on data from SNIS and SINISA

The Distribution Water Loss Index is an indicator commonly used as a benchmark for efficiency, since it is directly related to the operational and commercial aspects of service providers. This index had the most variations over the period analysed. The best performance was in 2014 and 2015, when it reached a low of 36.7%. The highest value was in 2009, at 41.6%. In 2007, the loss index was not calculated, as the analysis carried out by the Ministry of Cities, through SNIS, focused on the billing loss index.

Faced with the timid progress resulting from Law 11.445/2007, the process of updating the legislation began. The discussions were lengthy and involved the sector's main organisations, bringing up debates on how to provide services to the public, public vs. private, efficiency parameters, cross-subsidisation, among others. In 2020, the sanitation framework was updated through the enactment of Law No. 14.026 (Brazil, 2020a).

Law 14.026/2020 established that the universalisation of services should be achieved by 31 December 2033, i.e. 99% of the population should have access to drinking water and 90% should have sewage collection and treatment. The most recent

figures, for 2022, indicate that these rates are 84.9% and 56%, respectively (Brazil, 2023b). The new law also changed the attributions of the National Water Agency, which was renamed the Agência Nacional de Águas e Saneamento Básico, ANA (National Water and Basic Sanitation Agency). Since then, the ANA has been responsible for issuing reference standards for WSS, which must be used by regulatory bodies in their activities (ANA, 2023).

Water losses are another indicator with specific targets to be met by service providers. Ordinance 490/2021 (Brazil, 2021b) established that in 2034 the rate of water loss per connection must not exceed 216 litres/connection/day. In the event of non-compliance, providers may be denied resources and funding. In 2023, Brazil's result was 348.86 litres/connection/day, or 40.31% (Brazil, 2025).

Although SNIS and SINISA are the official sources of basic sanitation data in Brazil, there are other important government documents that serve as references for studies on the sector, including the National Basic Sanitation Plan (PLANSAB) and the National Rural Sanitation Programme (PNSR).

PLANSAB consists of integrated planning for basic sanitation in Brazil. It has a 20-year horizon, extending from 2014 to 2033. The Plan must be evaluated annually and revised every four years. PLANSAB was approved by Interministerial Ordinance 571/2013 (Brazil, 2013b).

The PNSR (FUNASA, 2019) is dated 2019 and aims to plan appropriate sanitation measures for the Brazilian rural population, covering rural, forest and water populations and indigenous peoples. Given the peculiarities of rural sanitation compared to urban areas, Law 11.445/2007, in its article 48, item VII, established that solutions for serving rural areas must be compatible with their economic and social characteristics.

A significant difference between SNIS, PLANSAB and PNSR, which has caused divergence in data management, concerns individual solutions, such as water supply through springs or sewage treatment through septic tanks, for example. Although PLANSAB and PNSR consider individual solutions to be adequate mechanisms for supplying drinking water and sanitation, they are not included in the SNIS service indices. According to PLANSAB (Brazil, 2023a), total coverage with water and sewage is 94.6% and 75.9%, respectively, figures higher than those presented by SNIS in the 2019 reference year. One of the aims of the implementation of SINISA is to adjust this contradictory information, since the new system includes indicators related to the

service of rural households with water supply and sanitation through alternative solutions.

Since 2018, through Ordinance No. 719 (Brazil, 2018b), Brazil's official basic sanitation data has been audited and certified using a methodology called Acertar. The aim of Acertar is to ensure that the information in SNIS and SINISA, which is self-reporting, is reliable and allows benchmarking between different municipalities and providers. The audits are the responsibility of the regulatory agencies.

Water supply and sewage services have different types of providers in Brazil, consisting of local administration, state-owned companies, municipal companies, local authorities or private companies. The techniques used to treat water and sewage can also vary from one system to another, as will be explained in sections 1.1.2 and 1.1.3.

1.1.2 Water Supply

According to Federal Law No. 14.026/2020 (Brazil, 2020a), the supply of drinking water consists of the activities and the provision and maintenance of infrastructure and operational facilities necessary for the public supply of drinking water, from collection to building connections and their measuring instruments.

Conventional water supply is made up of different stages that guarantee the availability of drinking water for the population, see Figure 2.

Figure 2 - Simplified diagram of a water supply system



Source: adapted from ERSAR (2021)

The following description of the stages of the water supply system follows the Ministry of Cities' Water Supply Guide (Brazil, 2008).

Abstraction, the first stage of the process, involves taking water from surface or underground sources (rivers, lakes, wells, etc.) and directing it to a Water Treatment Plant (WTP). At the WTP, the raw water is subjected to specific potabilisation

processes, the most commonly used of which are coagulation, flocculation, decantation, filtration and disinfection. In coagulation/flocculation, the solids present in the water are agglutinated by adding coagulating chemical reagents such as aluminium sulphate and ferric chloride. The flocs then generated are removed in decantation, which consists of sedimentation by the action of gravity.

Filtration consists of percolating the water through a porous granular medium, usually sand, with one or more layers, installed over a drainage system, capable of retaining and removing the impurities still present in the water. After filtration, the water is disinfected, usually by adding chlorine, to eliminate pathogenic microorganisms.

Once the water has been treated, it is conveyed through pipes and goes to the reservoirs (adduction stage). Reservoirs are buildings designed to receive the treated water and distribute it to households (storage stage). These units are designed to compensate for the difference between the consumption flow and the production flow, ensuring a continuous supply to consumers.

In some cases, water supply and distribution depend on pumping, in order to supply areas with higher water levels. Pumping, when necessary, is carried out by pumping stations using booster pumps (elevation stage).

The distribution network, the final stage of the supply system, has the function of transporting the treated water to the points of consumption (homes, commercial buildings, industries, public places, etc.). It consists of a set of interconnected pipes installed along public roads or pavements. Consumers are connected to the distribution network via water connections.

1.1.3 Sanitary Sewerage

Sanitary sewerage is made up of the activities and the provision and maintenance of infrastructures and operational facilities necessary for the adequate collection, transport, treatment and final disposal of sanitary sewage, from building connections to its final destination for the production of reuse water or its proper discharge into the environment (Brazil, 2020a), as shown in Figure 3.

Figure 3 - Simplified schematic of a sewerage system



Source: adapted from ERSAR (2021)

Sewage is collected through the sewer connection, a structure made up of pipes and fittings, which is responsible for removing sewage from the discharge points and transporting it to the collection network.

The collection network is used to transport sewage to the other units in the system. It is made up of collectors and interceptors. The collectors are pipes that receive sewage from various networks. The sanitary effluent from the collectors goes to the interceptors, which are larger pipes that go to a Sewage Treatment Plant (STP). When there is a need to transport the sewage from a lower level to a higher one, where gravity does not allow this action, pumping stations are installed, where a set of pumps lift the sewage (elevation stage).

Finally, the sewage reaches the STP for proper treatment. At the sewage treatment plant, the effluent goes through various processes that reduce the concentration of organic compounds, nutrients and other elements that make it harmful to the environment. The main stages of a biological sewage treatment process are:

- a) grating, designed to remove the coarse materials present in the raw sewage;
- b) desanding, consisting of a sandpit, where solid debris such as sand and pebbles are removed by sedimentation or flotation;
- c) aeration, a tank in which oxygen is incorporated into the effluent in order to encourage the proliferation of aerobic bacteria responsible for the degradation of organic matter;
- d) decantation, a stage in which the liquid and solid fractions of the effluent are separated, resulting in the sedimentation of biosolids, also called sludge, at the bottom of a tank.

Finally, usually after a disinfection process, the liquid effluent is discharged into a receiving body through a pipe called an outfall. Treated sewage can also be reused for non-potable purposes, such as agriculture. Sewage sludge is usually disposed of in landfill sites, but it can also be reused, as long as it complies with the standards set out in specific regulations (von Sperling, 2005).

1.2 OBJECTIVES

The general aim of this thesis is to assess the performance of water supply and sewage services in Brazil as a result of the regulatory and legal changes that have taken place in the sector.

The achievement of the general objective is linked to the realisation of the following specific objectives:

- a) Characterize the evolution of the water supply and sewerage sector in Brazil, considering regulatory and normative frameworks;
- b) Identify key performance indicators;
- c) Develop and apply a robust composite indicator model, based on the Benefit-of-the-Doubt (BoD) technique, to assess the performance of Brazilian municipalities in sanitation services;
- d) Investigate the temporal evolution of municipal performance using the Global Malmquist Index (GMI), focusing on the components of efficiency change and best practices;
- e) Explore the influence of contextual (exogenous) variables on the efficiency of water and sanitation services;
- f) Apply classification and regression algorithms (Classification and Regression Trees) to identify determining factors of water losses in supply systems;
- g) Contribute to benchmarking among municipalities and the formulation of more assertive public policies in the basic sanitation sector.

1.3 LIMITATIONS

The limitations of the thesis are mainly related to the quality of the data used. Although all the indicators used are referenced in the National Sanitation Information System (SNIS) and the National Basic Sanitation Information System (SINISA), which are official sources of Brazilian basic sanitation data, the information contained therein is self-reporting and may contain errors or inaccuracies.

In order to avoid using indicators with missing or incorrect data, the information was processed according to the methods specified in each of the chapters.

1.4 THESIS STRUCTURE

This doctoral thesis is a compendium of articles, in accordance with Resolution 002/PPGEP/201814 of 07/11/2018 of the Universidade Federal de Santa Catarina (UFSC), which provides for the preparation of a thesis in the form of a collection of articles within the Postgraduate Programme in Production Engineering (PPGEP/UFSC).

The study consists of three articles, the structure of which is shown in Figure 4 and detailed below.

The first chapter comprises the introductory stage of the work, presenting a contextualisation of the subject of the research, the objectives and an explanation of the structure of the thesis and the stages of the research.

Chapter 2 describes the methodological procedures, detailing the methods used to evaluate performance using frontier methods and Classification and Regression Trees.

The third chapter contains the first article in the compendium: *Evolution of performance in the water and sewage sector in Brazil: a robust directional Benefit-of-the-Doubt assessment of municipalities from Santa Catarina state*, published in the journal *Annals of Operations Research*.

The study develops a composite indicator, based on the Benefit-of-the-Doubt (BoD) approach, to estimate the performance of municipalities in the state of Santa Catarina, from 2009 to 2021, in water supply and sewage services. Subsequently, the Global Malmquist Index (GMI) is applied to assess the evolution of municipalities' performance over time.

Figure 4 - Thesis structure

Chapter	Description
1 - Introduction	Background, objectives, thesis structure and research stages
2 - Methodological procedures	Methods used
3 - Article 1 - Evolution of performance in the water and sewage sector in Brazil: a robust directional Benefit-of-the-Doubt assessment of municipalities from Santa Catarina state	Article published in the journal Annals of Operations Research in October/2024
4 - Article 2 - From data to decision: a robust ranking of water and sanitation services in Brazil	Article submitted and under review at a high-impact journal
5 - Article 3 - An Analysis of Water Supply System Losses: A Case Study of Santa Catarina State, Brazil	Presented in June/2025 at the International Conference on Industrial Engineering and Operations Management. To be published in the book with the conference proceedings, in October 2025
6 - Discussion of results	Joint analysis and discussion of the results of the articles
7 - Conclusion	Conclusion of the thesis

Source: prepared by the author

The fourth chapter presents the article *From data to decision: a robust ranking of water and sanitation services in Brazil*, which is currently under review at a high-impact journal. This article expands on the methodological approach of the previous publication, adding context variables to the performance assessment. The context variables make it possible to assess the impact of exogenous factors on the performance of water supply and sanitation services in Brazil's 100 largest cities in 2021. In addition, the study provides a new perspective on the most widespread basic sanitation ranking in Brazil, which is published annually by the Instituto Trata Brasil (Brazilian institute for WSS).

The fifth chapter contains the last article in the collection: *An Analysis of Water Supply System Losses: A Case Study of Santa Catarina State, Brazil*. This article was presented at the International Conference on Industrial Engineering and Operations Management, in Orlando, USA, in June 2025. The paper will be published in the book with the conference proceedings, in October 2025.

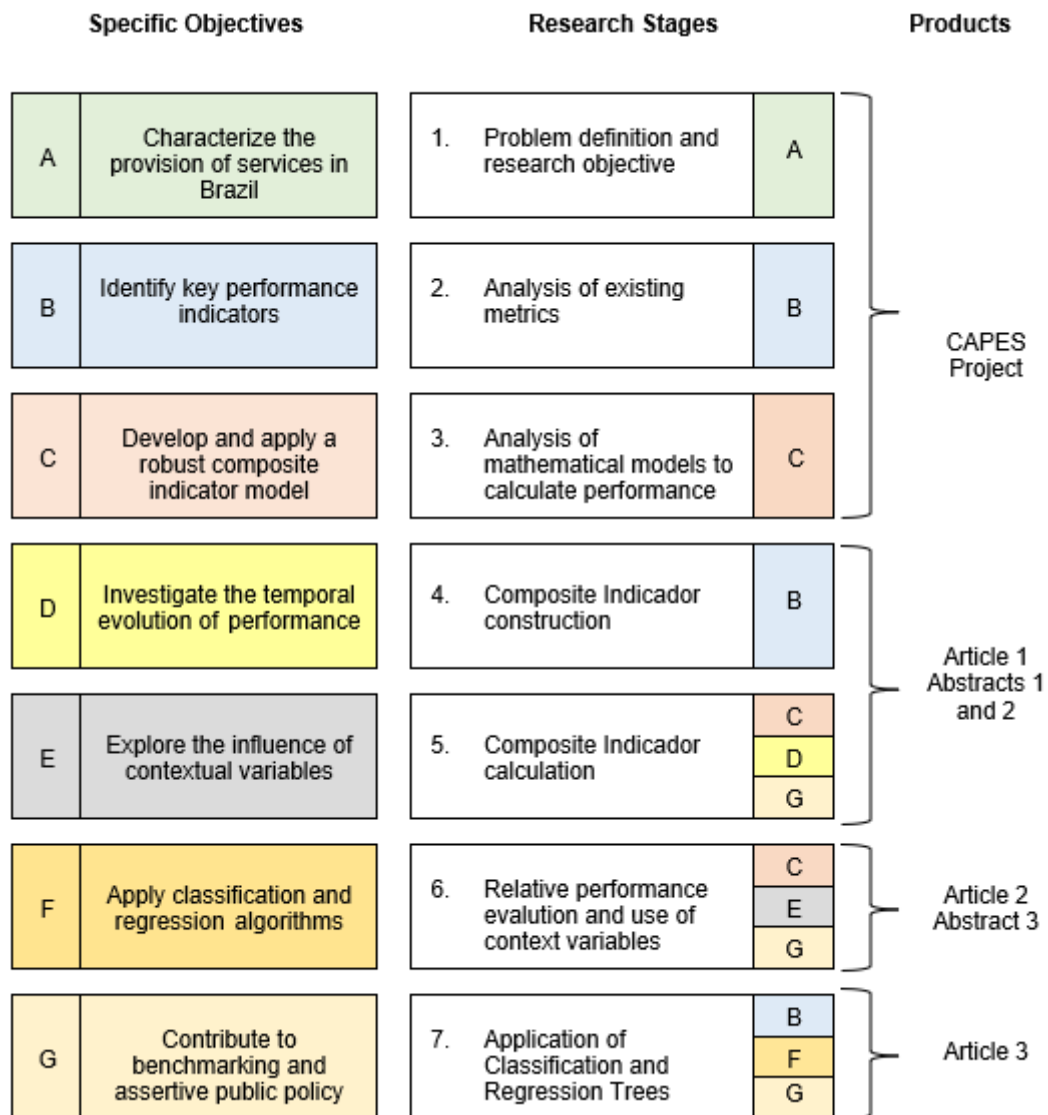
This third article applies statistical models and classification and regression trees to investigate the determinants of water distribution losses in the state of Santa Catarina in 2022.

Chapter 6 is devoted to a joint discussion of the results of the articles. Chapter 7 presents the conclusions of the study. A summary of the articles, including the list of co-authors, is available in Appendix A.

1.5 RESEARCH STAGES

This thesis involves seven distinct stages, which are connected in order to achieve the specific objectives and products, as shown in Figure 5.

Figure 5 - Research stages, specific objectives and products



Source: prepared by the author

1.5.1 Steps 1 to 3: Defining objectives, analysing metrics and mathematical models

Steps 1 to 3 refer to the identification of the problem and the aim of the thesis, as well as the exploratory search for metrics and methods for evaluating the performance of WSS.

Based on the study of the main normative and legal documents relating to basic sanitation in Brazil, it was possible to draw up an initial overview of the sector and identify the most relevant indicators. At the same time, in order to identify the most

recent work on the subject, a literature review was carried out on the main multidisciplinary databases.

It was decided that the thesis should assess the performance of Brazil's water supply and sewage services and check whether the changes in laws and regulations that have taken place since 2007, the year the legal framework for basic sanitation was enacted. Law No. 11.445, had a real impact on the results observed.

The main product of these initial stages of the research was approval in the selection process for a sandwich doctorate under the Programa Institucional de Internacionalização, PRINT (Institutional Internationalisation Programme) of the Universidade Federal de Santa Catarina (UFSC) and the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior, CAPES (Coordination for the Improvement of Higher Education Personnel). In March 2023, he began a six-month sandwich doctorate at the University of Porto in Portugal. The University of Porto is carrying out various studies to assess the performance of Portugal's water sector, several of them in partnership with the Portuguese Water and Waste Services Regulatory Authority, ERSAR. The receiving professor, Dr Ana Camanho, has extensive experience in the field and is the author of more than 100 articles in journals indexed in Web of Science and Scopus.

While at the University of Porto, the Benefit-of-the-Doubt (BoD) technique was studied and applied in the first two articles of the thesis. BoD is a technique derived from Data Envelopment Analysis (DEA). DEA uses a set of sample observations to estimate an efficiency frontier. Through DEA it is possible to assess how efficiently a unit transforms its inputs into outputs, comparing its performance with that of the other units under evaluation. Those that manage to produce more outputs with fewer inputs (or the same outputs with fewer resources) are considered more efficient. In the BoD, inputs are represented by a fictitious unit value and outputs are analysed in aggregate, which is particularly useful in contexts where units have autonomy of action, outputs are heterogeneous and the main focus of the analysis is results.

Similarly, it was found that the Global Malmquist Index (GMI), a circular version of the Malmquist Index, should be the technique adopted for assessing performance over time, allowing comparisons over more than two time intervals, which is not possible using the standard Malmquist Index. The main characteristics of the mathematical models used in the thesis are presented in section 2.

The metrics were analysed based on the fundamental principles of the Legal

Framework, as well as recommendations from the International Water Association (IWA) and the Brazilian Association of Regulatory Agencies (ABAR). Finally, it was identified that the metrics that corresponded to the principles mentioned were available in the National Sanitation Information System (SNIS).

1.5.2 Steps 4 and 5: Construction and calculation of the composite indicator

Steps 4 and 5 consist of constructing and calculating the composite indicator used to assess performance.

The main product of these stages was the publication of the article *Evolution of performance in the water and sewage sector in Brazil: a robust directional Benefit-of-the-Doubt assessment of municipalities from Santa Catarina state*, in the journal *Annals of Operations Research*, in October 2024 (Chapter 3 of the thesis).

Several preliminary studies were carried out before the final version of the article was produced. One of these studies was presented at the International Federation of Operational Research Societies (IFORS), held in Santiago, Chile, in July 2023. The expanded abstract *Data Envelopment Analysis Applied to Indicators of Sanitation Service in Brazil* is available in Appendix B.

Another paper related to the main article was the expanded abstract *Directional Benefit-of-the-Doubt assessment of municipalities from Santa Catarina state*, presented at the XVIII European Workshop on Efficiency and Productivity Analysis (EWEPA), in June 2024, in Faro, Portugal (see Appendix C).

1.5.3 Step 6: Benchmarking and context variables

Stage 6 focused on validating the BoD method for evaluating Brazil's WSS. To do this, a comparison was made between the results of the BoD and the sanitation ranking, a report published annually by the Instituto Trata Brasil (ITB). Applying the BoD to the ITB metrics, the performance of Brazil's 100 most populous municipalities was calculated for the years 2019 to 2021 (Oliveira *et al*, 2021, 2022, 2023).

The results culminated in the article *From data to decision: a robust ranking of water and sanitation services in Brazil*, which is currently being reviewed in a high-impact journal. The extended abstract, *Benchmarking analysis in the Brazilian water*

and sewage sector: a directional Benefit- of-the-Doubt approach, was presented at the XVIII EWEPA in 2024 (see Appendix D).

1.5.4 Step 7: Application of Classification and Regression Trees

Stage 7 takes a different approach to the previous stages for assessing the performance of sanitation services, adding the technique of Classification and Regression Trees.

The application of this technique to the variable of water losses, a key indicator for efficiency in the provision of water supply services, resulted in the third and final article of the thesis: *An Analysis of Water Supply System Losses: A Case Study of Santa Catarina State, Brazil*. This article has been submitted to the International Conference on Industrial Engineering and Operations Management, which will take place in Orlando, USA, in June 2025.

2 METHODOLOGICAL PROCEDURES

This chapter presents the methodological procedures adopted in the thesis in order to answer the research question: What is the performance of water supply and sewage services in Brazil in the face of the legal and regulatory changes to which the sector has been subjected in recent years?

The performance evaluation models using frontier methods and classification and regression trees are described in the following sections.

2.1 PERFORMANCE EVALUATION USING FRONTIER METHODS

Due to the scope and different concepts related to performance evaluation by frontier methods, it is convenient that some terms that guide the subject are previously defined, in order to allow a full understanding of the process (Berg, 2010; Barbosa *et al.*, 2018; Coelli *et al.*, 2005):

Productivity: This refers to the relationship between inputs and outputs (products/services). The output/input ratio serves as an indicator of current performance.

Efficiency: Refers to the ability to achieve a result using as few resources as possible. Related to productivity but involves setting a standard and determining how close the entity under analysis is to achieving these objectives and targets.

Effectiveness: Refers to what is produced, not considering the resources used for this purpose. It refers to the extent to which the organisation under analysis achieves its stated objectives. If the objectives are not quantifiable, success cannot be measured. If the goals are unrealistic, they are meaningless. If objectives are easily achievable, they are not necessary.

Decision-making Unit (DMU): These are production units that convert inputs into outputs (products/services). They can be private sector companies that produce goods, such as a factory, or are active in the service sector, such as a restaurant, for

example. DMUs must carry out similar tasks, converting similar production inputs into comparable products/services.

Performance evaluation can be defined as the process of quantifying the efficiency and effectiveness of a given action (Neely *et al.*, 1995). This process makes it possible to measure goals and objectives and, for this reason, it is used to monitor the services provided, making it possible to anticipate problems and speed up decision-making, whether for structural or structuring measures (Bezerra, 2019). Performance evaluation is also used to support benchmarking processes (Vilanova *et al.*, 2015).

The basic assumptions for calculating efficiency by creating a frontier were described by Farrel in 1957. The mathematical framework for dealing with frontier analysis in a non-parametric way was established 20 years later in the work of Charnes, Cooper and Rhodes (1978). The method became known as Data Envelopment Analysis (DEA).

The model established by Charnes, Cooper and Rhodes is called CCR (an anagram of the authors' names) or CRS (Constant Returns to Scale). This linear programming method determines the weight of the inputs and outputs that maximise the DMU's productivity, taking the most productive DMU in the sample as a reference, as shown in Model 1.

$$\begin{aligned}
 \max_{u,v} e_0 &= \sum_{j=1}^s u_j y_{j_0} \\
 \text{sujeito a: } &\sum_{i=1}^r v_i x_{i_0} = 1 \\
 &\sum_{j=1}^s u_j y_{j_m} \leq \sum_{i=1}^r v_i x_{i_m} \quad m = 1, \dots, n \\
 &v_i \geq 0 \quad i = 1, \dots, r \\
 &u_j \geq 0 \quad j = 1, \dots, s
 \end{aligned} \tag{1}$$

In Model 1, u_j and v_i represent the weights of the s outputs Y and r inputs X of a set of n DMUs. x_{i_0} and y_{j_0} are the i inputs and j outputs of DMU₀. x_{i_m} and y_{j_m} are the i inputs and j outputs of DMU m . DMUs with $e_m = 1$ are operating on the efficiency

frontier, while those with $e_m < 1$ are inefficient when compared to the former. Model 1 has an *input* orientation, i.e. efficiency can be increased by minimising *inputs* given a level of production output.

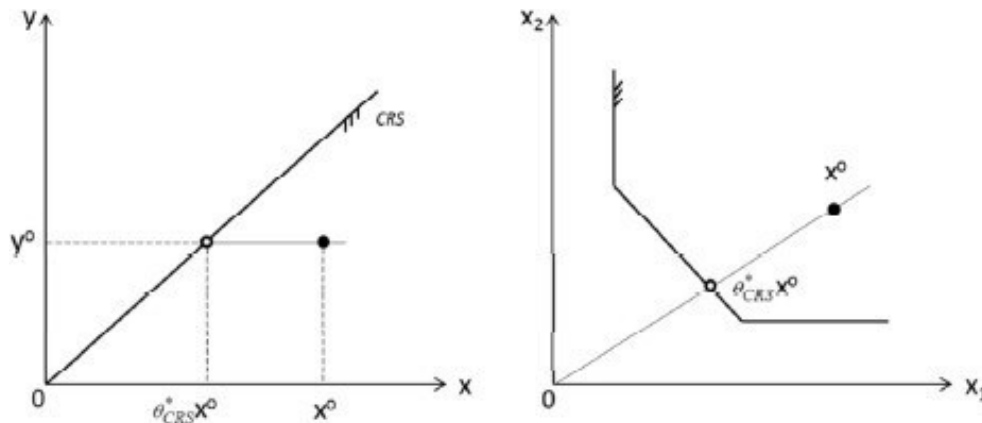
By means of the concept of strong duality in linear programming, the (primal) multiplier model of Model 1 can be converted into the (dual) envelope model. According to Cooper *et al.* (2007), the choice between the multiplier and envelope form is usually a matter of convenience or interest, depending on whether the user is concerned with input/output weights or reference sets and goals. The envelope model is shown in (2).

$$\begin{aligned}
 & \min_{\theta_{CRS}, \lambda} \quad \theta_{CRS} & (2) \\
 & \text{subject to: } \sum_{m=1}^n \lambda_m X_{im} \leq \theta_{CRS} X_{i0} & i = 1, \dots, r \\
 & \sum_{m=1}^n \lambda_m Y_{jm} \geq Y_{j0} & j = 1, \dots, s \\
 & \lambda_m \geq 0 & m = 1, \dots, n
 \end{aligned}$$

In Model 2, λ is a multiplier that defines a point on the frontier estimated from the convex combination of other DMUs in the sample. θ_{CRS} is the scalar that corresponds to the smallest multiplier of the input quantities of DMU o . Essentially, the problem seeks to radially contract the vector of inputs, x_i , while remaining within the feasible set of inputs. The inner limit of this set is a piecewise linear isoquant determined by the observed data points.

The efficiency index obtained with the CRS model is called "*global technical efficiency*". The graphical representation of the production plan of DMU o on the frontier, considering an input x and an output y , and the projection of x_o in the space generated by inputs x_1 and x_2 , the input-orientated CRS model, is shown in Figure 6.

Figure 6 - Representation of technical efficiency, CRS model, input orientation



Source: adapted from Fare, Grosskopf and Lovell (1994)

2.1.1 BoD – Benefit-of-the-Doubt

The Benefit-of-the-Doubt (BoD) model is derived from DEA and was popularised by Cherchye *et al.* (2007). It is equivalent to the original DEA model (Charnes *et al.*, 1978), but the inputs are represented by a fictitious unit value, which guides the DMUs towards maximising results. The outputs are analysed in aggregate, forming Composite Indicators (CI). The CI measures multidimensional metrics that cannot be captured by a single indicator (Nardo *et al.*, 2008).

In the standard BoD approach, outputs should represent desirable results of the production process, so that higher values indicate better performance (e.g. number of consumers). However, in some cases it is appropriate for undesirable indicators, whose lower values indicate better performance, to be considered in the analysis (e.g. billing losses). For this to happen, a Directional Distance Function (DDF) must be applied. BoD DDF allows the simultaneous aggregation of outputs desirable and undesirable.

This thesis adopted the BoD DDF model formulated by Zanella *et al.* (2015), whose envelope formula is shown in Model 3.

$$\text{Minimize } \beta_{j_0} = - \sum_{r=1}^s y_{rj_0} u_r + \sum_{k=1}^l b_{kj_0} p_k + v \quad (3)$$

$$\text{subject to: } \sum_{r=1}^s g_y u_r + \sum_{k=1}^l g_b p_k = 1$$

$$- \sum_{r=1}^s y_{rj} u_r + \sum_{k=1}^l b_{kj} p_k + v \geq 0, \quad j = 1, \dots, n$$

$$v \in \mathbb{R}$$

$$u_r \geq 0, \quad r = 1, \dots, s$$

$$p_k \geq 0, \quad k = 1, \dots, l$$

In Model 3, y_{rj} represents the desirable metrics and b_{kj} represents the undesirable metrics for DMU j ($j=1, \dots, n$). y_{rj_0} and b_{kj_0} are the values of desirable and undesirable metrics observed for DMU j_0 under evaluation. The decision variables of model are the weights, where u_r is associated with the desired outputs r , p_k with the undesired outputs k and v is associated with the fictitious unit input.

The directional distance vector is specified as $(g_y, -g_b)$. It indicates the direction of expansion of the desired outputs and reduction of the undesired ones. The direction vector used in the model can influence the efficiencies to be calculated, so the choice should be made according to the objective of each study. In this thesis, the $(g_y, -g_b)$ were chosen to be equal to $(y_{rj_0}, -b_{kj_0})$, thus each DMU can improve using the values of their own performance metrics, resulting in a proportional interpretation of the value of the composite indicator (Zanella *et al.*, 2015 and Rogge *et al.*, 2017).

The proportional increase in desirable metrics and the proportional decrease in undesirable metrics towards the best practice frontier is represented by β_{j_0} . Finding the optimal result that minimizes β_{j_0} is the objective function of the model BoD DDF.

The CI value associated with DMU j_0 can be obtained as $1/(1+\beta_{j_0})$. The CI score ranges from 0 to 1, where 1 represents the best level of performance and indicates that the DMU under evaluation is located on the frontier of best practices.

The BoD approach allows the incorporation of weight restrictions in order to reflect the relative importance of each output. The weight restriction model proposed by Zanella *et al.* (2015), Assurance Regions I (AR-I) type restrictions, was adopted in

this thesis, according to Inequations 4. The restrictions shown in (4) allow the relative importance of the output indicators to be expressed in percentage terms. To do this, an "artificial" DMU is used which represents the average values of the outputs of the analysed sample, and the weight restrictions are imposed on this artificial DMU, instead of restricting the virtual outputs of a DMU j . The use of AR-I constraints makes it possible to construct a single frontier for the evaluation of all DMUs and represents the ideal choice for composite indicators and benchmarking (Zanella *et al.*, 2015).

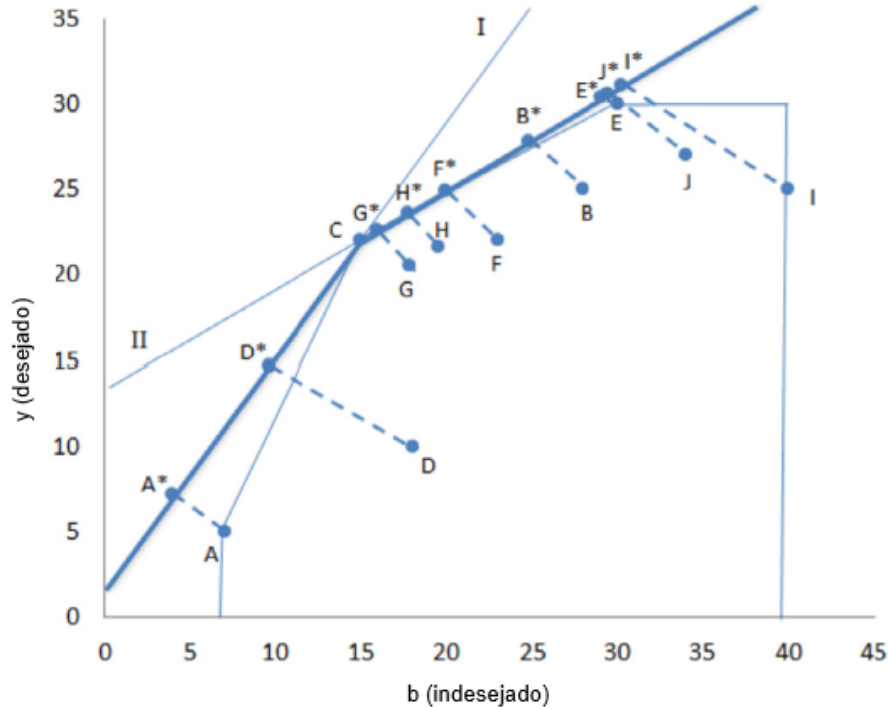
$$\begin{aligned} \frac{u_r \bar{y}_r}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_r, & r = 1, \dots, s \\ \frac{p_k \bar{b}_k}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_k, & k = 1, \dots, l \end{aligned} \quad (4)$$

In Inequations 4, the parameters ϕ_r and ϕ_k represent the lower limits of the weights for the desirable and undesirable indicators, respectively.

Figure 7 illustrates the use of AR-I weight restrictions for an analysis involving 10 DMUs and the imposition of a 40% restriction on the desired (y) and undesired (b) outputs.

In Figure 7, the restrictions on desirable and undesirable outputs are represented by segments I and II, respectively. The slope of the efficient frontier must lie between the slopes of these segments to ensure that both outputs are weighted by at least 40% in the evaluation. The efficiency frontier used for the evaluation of all DMUs is defined by the segments in bold. The projection of the DMUs onto the frontier is also illustrated in the graph.

Figure 7 - Example of an AR-I weight restriction application



Source: adapted from Zanella *et al.*(2015)

Another advantage of using BoD for the construction of CIs is that it allows extracting the strengths and weaknesses of each DMU by analysing the magnitude of the virtual weights of the optimal solution. Virtual weights are the result of the product of each DMU's observed output by the associated optimal weight. Higher virtual weights indicate the strengths and the lower ones indicate the weaknesses of the DMU under assessment.

However, magnitude of virtual weights cannot be interpreted directly as the relative importance of the indicators in the case of a BoD DDF, as this model aims to optimise weights for desirable and undesirable metrics in opposite directions, as indicated in the objective function of Model 4. In order to overcome this limitation, Vilarinho *et al.* (2023b) proposed determining the relative strengths of each DMU by means of the values associated with the specification of the AR-I weight restrictions, estimated considering the 'average DMU' for the sample under evaluation, as shown in Inequations 5. This approach makes it possible for the relative weights of both desirable and undesirable indicators to correspond to the magnitude of the respective virtual weight, providing important information about the performance of one DMU in relation to the others.

According to Cherchye *et al.* (2007), the BoD technique minimises critical observations about the "imputed" weighting of weights, and the ease of interpreting the results allows for greater dissemination of information and knowledge. However, some authors, including Nardo *et al.* (2008) and Daraio and Simar (2005) mention the sensitivity of the score to extreme values or outliers and the difficulty in carrying out statistical inference as disadvantages of applying the BoD method. In order to overcome these limitations, Cazals *et al.* (2002) and Daraio and Simar (2007) proposed a robust approach to calculating the CI, as will be seen in section 2.1.1.1.

2.1.1.1 Robust Benefit-of-the-Doubt (BoD) approach

The robust BoD approach is based on a bootstrapping sampling procedure. In this way, each DMU is evaluated B times in relation to a randomly drawn sample of size m , taking into account the replacement of the set of units from the original sample of DMUs. The variable B must be a large number, so the effects of extreme values are minimised in the average calculation of the CI.

The robust composite indicator $CI_{j_0}^m$ is shown in Equation 5, where $CI_{j_0}^{b,m}$ is the composite indicator of DMU j_0 under evaluation calculated using sub-sample b .

$$CI_{j_0}^m = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m} \quad (5)$$

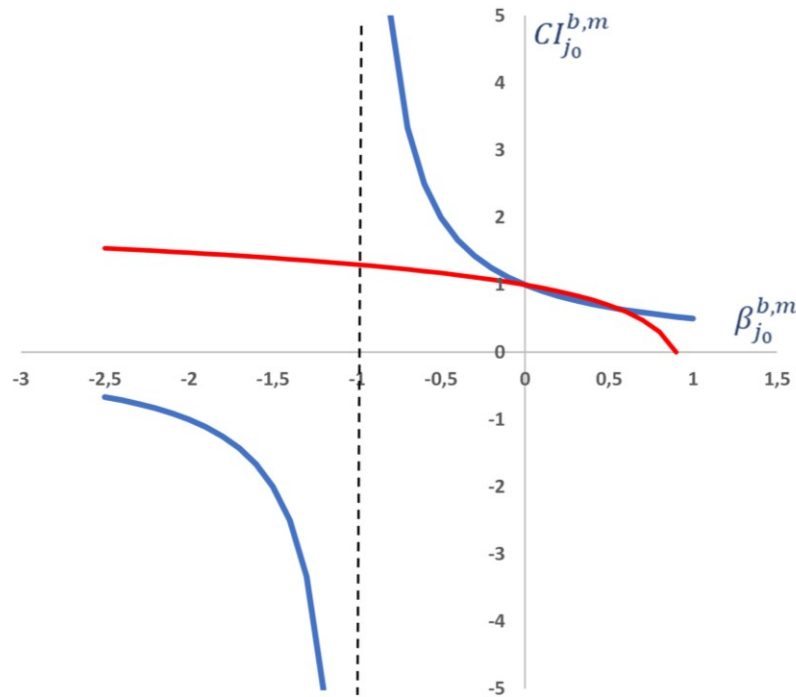
When the scores are calculated, it may occur in some samples that the DMU j_0 is not included in b . Therefore, the results may indicate that j_0 is more efficient than all the DMUs in the sample. In this case, $\beta_{j_0}^{b,m}$ (see Model 3) will have a negative value and the DMU can be classified as super performing. However, this cannot happen when $CI_{j_0}^{b,m}$ is obtained from the expression $1/(1 + \beta_{j_0})$. According to Mergoni *et al.* (2022), one solution to this problem is to modify the calculation of $CI_{j_0}^{b,m}$ as shown in Equation 6.

$$CI_{j_0}^{b,m} = \frac{1}{1 + \beta_{j_0}^{b,m}}, \quad \text{se } \beta_{j_0}^{b,m} \geq 0; \quad (6)$$

$$CI_{j_0}^{b,m} = \log_{10}(1 - \beta_{j_0}^{b,m}) + 1, \quad \text{se } \beta_{j_0}^{b,m} < 0$$

As shown in Figure 8, the proposed formulation when $\beta_{j_0}^{b,m} < 0$ follows a similar trend to the original formulation for positive values of $\beta_{j_0}^{b,m}$, allowing the value of $CI_{j_0}^{b,m}$ to increase proportionally as the performance of DMUs improves (Vilarinho *et al.*, 2023a).

Figure 8 - Comparison between the expressions used to calculate the robust BoD



$$CI_{j_0}^{b,m} = \begin{cases} \frac{1}{1 + \beta_{j_0}^{b,m}}, & \text{if } \beta_{j_0}^{b,m} \geq 0 \Rightarrow \text{In Blue} \\ \log_{10}(1 - \beta_{j_0}^{b,m}) + 1, & \text{if } \beta_{j_0}^{b,m} < 0 \Rightarrow \text{In Red} \end{cases}$$

Source: Vilarinho *et al.* (2023a)

For the selection of m , Daraio and Simar (2007) suggest carrying out a sensitivity analysis using various values of m and assessing the number of units with super performance.

2.1.2 Malmquist Index

The Malmquist Index (MI) is a technique used to assess changes in productivity over time. It was introduced by Caves *et al.* (1982) and developed by Färe *et al.* (1989), named after the researcher Sten Malmquist. In 1953, Malmquist proposed the use of distance functions to evaluate the productive efficiency of a DMU in different periods, taking into account technological variations and the quantity of inputs and outputs. The technique is based on Shephard's (1970) distance functions, which measure the technical efficiency of a DMU at a single point in time in relation to a production frontier.

The IM calculation requires the estimation of two Shephard distance functions within the period under analysis and two mixed-period Shepard distance functions. Equation 7 shows the distance functions considering the input orientation and the mixed period.

$$D_i^t(x^{t+1}, y^{t+1}) = \max \left\{ \delta : \left(\frac{x^{t+1}}{\delta}, y^{t+1} \right) \in \theta^t \right\} \quad (7)$$

$$D_i^{t+1}(x^t, y^t) = \max \left\{ \delta : \left(\frac{x^t}{\delta}, y^t \right) \in \theta^{t+1} \right\}$$

In Equation 7, δ represents an input efficiency scaling factor. In the first mixed period, the distance function measures the maximum proportional reduction in inputs needed to make a DMU (x^{t+1}, y^{t+1}) , in period $t+1$, efficient in relation to the technology Φ^t . The second mixed period measures the maximum reduction proportional input required to make a DMU (x^t, y^t) , in the time period t , efficient in relation to the technology Φ^{t+1} (Oliveira, 2018).

In 1985, Färe *et al.* noted that Shephard distance functions can be estimated using DEA CRS models. In 1992, Färe *et al.* defined an input-oriented productivity index based on the geometric mean of Malmquist indices referring to technology in time periods t and $t+1$, as shown in Equation 8.

$$IM_i^{t,t+1} = \left[\frac{D_i^t(x^t, y^t)}{D_i^t(x^{t+1}, y^{t+1})} \frac{D_i^{t+1}(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \right]^{\frac{1}{2}} \quad (8)$$

Färe *et al.* (1992) also pointed out that the index in Equation 8 can be broken down into two separate indices: an *Efficiency Change Index* ($EC_i^{t,t+1}$) and a *Technological Change Index* ($TC_i^{t,t+1}$), such that $IM_i^{t,t+1} = E_i^{t,t+1} \times T_i^{t,t+1}$, as shown in Equation 9 and in Equation 10.

$$EC_i^{t,t+1} = \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \quad (9)$$

$$TC_i^{t,t+1} = \left[\frac{D_i^{t+1}(x^t, y^t)}{D_i^t(x^t, y^t)} \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^{t+1}, y^{t+1})} \right]^{1/2} \quad (10)$$

The efficiency change (Equation 9) measures the distance of the DMU from the frontier in two periods. The technological change (Equation 10) measures the Frontier Shift (FS) between periods t and $t+1$.

The name "efficiency change" was originally coined in the context of efficiency studies based on DEA models. In a BoD framework, the name "performance change" would be more appropriate, since only production levels (the outputs) are considered in the evaluation, as opposed to a transformation process involving inputs and outputs. However, it was decided to stick with this terminology throughout the thesis, as it is already well established in previous studies on the subject.

The values of $IM^{t,t+1}$ and its components can be greater, equal to or less than 1. These values indicate, respectively, growth, stagnation or decline in performance between periods t and $t+1$.

Evaluating changes in performance over time seeks to understand the main actions that have led to positive results, with a view to repeating and improving them. As such, it will also be explored throughout this thesis to help analyse the water supply and sewage sector.

2.1.2.1 Global Malmquist Index

The Global Malmquist Index (GMI) is the method adopted in this thesis to analyse the change in performance over time. The GMI is an alternative formulation to the original Malmquist Index (see section 2.1.3) and, unlike the Malmquist Index (MI),

the GMI satisfies the circular property.

In the original formulation of the MI, the value of the index between time period t and $t+2$ cannot be derived from the values of the productivity index between t and $t+1$, as well as $t+1$ and $t+2$. However, the GMI, proposed by Pastor and Lovell (2005), evaluates efficiency considering a metafrontier formed from data from all units in all periods, which allows the non-circularity limitation of the original Malmquist Index to be overcome. The GMI assumes that each period p has its own technology T^p ($p = 1, 2, \dots, t, t+1, \dots, P$), but it is possible to specify a meta-technology $T^M = \bigcup_{p=1}^P T^p$ which involves all the individual period technologies. The formulation GMI for a multiple input and output configuration is shown in Equation 11.

$$GMI^{t,t+1} = \frac{E^M(X^{t+1}, Y^{t+1})}{E^M(X^t, Y^t)} \quad (11)$$

$E^M(X^t, Y^t)$ corresponds to the DEA efficiency score of a DMU in period t with an *input-output* vector (X^t, Y^t) calculated in relation to the metatechnology frontier T^M . Similarly, $E^M(X^{t+1}, Y^{t+1})$ is the DEA score of the DMU considering the *input-output* vector (X^{t+1}, Y^{t+1}) in period $t+1$.

Following Camanho *et al.* (2023), the GMI of Equation 11 can be adapted to the context of a BoD assessment as shown in Equation 12.

$$GMI^{t,t+1} = \frac{CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^M(\mathbb{1}, Y^t, B^t)} \quad (12)$$

$CI^M(\mathbb{1}, Y^t, B^t)$ and $CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})$ correspond to the indicator scores of Composite Indicator calculated in relation to the technology metafrontier T^M with data from period t and $t+1$, respectively. The data is represented by the unit vector of the input (dummy), desirable outputs Y and undesirable outputs B observed in a given time interval for the DMU under evaluation, represented by $(\mathbb{1}, Y, B)$. The CI scores are obtained from the β resulting from the application of the mathematical expressions in (6).

The Global Malmquist Index can be broken down into the Efficiency Change

Index (EC) and the Best Practices Change Index (BPC), as shown in Equation 13 (Pastor and Lovell, 2005).

$$\begin{aligned}
 GMI^{t,t+1} &= \frac{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^t(\mathbb{1}, Y^t, B^t)} \\
 &\quad \times \left(\frac{CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})} \times \frac{CI^t(\mathbb{1}, Y^t, B^t)}{CI^M(\mathbb{1}, Y^t, B^t)} \right) \\
 &= \frac{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^t(\mathbb{1}, Y^t, B^t)} \times \left(\frac{\frac{CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})}}{\frac{CI^M(\mathbb{1}, Y^t, B^t)}{CI^t(\mathbb{1}, Y^t, B^t)}} \right) \\
 &= EC^{t,t+1} \times \frac{BPG^{t+1,M}(\mathbb{1}, Y^{t+1}, B^{t+1})}{BPG^{t,M}(\mathbb{1}, Y^t, B^t)} \\
 &= EC^{t,t+1} \times BPC^{t,t+1}
 \end{aligned} \tag{13}$$

$EC^{t,t+1}$ measures the evolution of the distance to the border of the DMU under evaluation between period t and $t+1$. $EC^{t,t+1} \geq 1$ indicates greater proximity to the frontier in $t+1$ than in t .

$BPG^{t,M}(\mathbb{1}, Y^t, B^t)$ is the best practice gap between the frontiers of T^M e T^t . The ratio between $CI^M(\mathbb{1}, Y^t, B^t)$ and $CI^t(\mathbb{1}, Y^t, B^t)$ results in the BPG.

In turn, $BPC^{t,t+1}$ reflects the change in best practice between t and $t+1$, calculated as the ratio between $BPG^{t+1,M}(\mathbb{1}, Y^{t+1}, B^{t+1})$ and $BPG^{t,M}(\mathbb{1}, Y^t, B^t)$. $BPC^{t,t+1} > 1$ indicates that the frontier in period $t+1$ is closer to the metafrontier than it was in period t . On the other hand, $BPC^{t,t+1} < 1$ indicates that the frontier at $t+1$ is further away from the metatechnology than the frontier at t .

The circular property of GMI allows comparisons to be made involving more than two time periods, as shown in Equation 14 and applied by Camanho *et al.* (2023).

$$GMI^{t,t+2} = GMI^{t,t+1} \times GMI^{t+1,t+2} \tag{14}$$

Equation 14 indicates that the index estimating the evolution of performance between t and $t+2$ is equal to the product of the index comparing t with $t+1$ and the index comparing $t+1$ with $t+2$. The same property applies to the EC and BPC components.

2.2 CLASSIFICATION AND REGRESSION TREES

Classification and Regression Trees are a technique for representing the relationships existing in a set of data, divided into subgroups in the form of a hierarchy, in order to classify them. The technique aims to identify the independent variables that provide the maximum segregation of data according to the dependent variable. The most commonly used algorithms are C4.5 (Quinlan, 1993), Chi-squared Automatic Interaction Detection (CHAID) (Kass, 1980) and Classification and Regression Trees (CART), as well as their various adaptations and extensions (Breiman *et al.*, 2017).

The CHAID approach used in this study is based on χ -squared association tests, which determine the significance of the relationship between two categorical variables. The test compares the observed frequencies with the expected frequencies, checking whether the distribution of one variable varies significantly with the category of the other (Ture *et al.*, 2009). Equation 15 describes the relationship between the outcome (dependent variable) y and the characteristics (independent variables) x in classification trees (Molnar, 2025).

$$\hat{f}(x) = \sum_{m=1}^M c_m I\{x \in R_m\} \quad (15)$$

In Equation 15, $\hat{f}(x)$ refers to the prediction function of a classification tree partitioned into M regions R_m . Each region corresponds to a leaf of the tree, and the function associates with each region a fixed value c_m , which is the predicted response for any input x that falls in that region.

$I\{x \in R_m\}$ is the indicator function that returns 1 if x is in the R_m subset and 0, otherwise.

If x falls on sheet R_i , then the predicted value for x will be c_i , which is the average of the actual values (dependent variable) of the training data that also fell on that sheet.

The results obtained using CHAID are presented graphically and are easy to analyse and read. Interpreting classification and regression trees involves a comprehensive understanding of their structure, the logic of their divisions and the implications of their predictions. The results can be used to generate individual probability scores for the individuals in the sample belonging to a given node. As the

segments or response of interest are defined by combinations of predictor variables, new cases can be classified to a certain segment by the values of these variables. Thus, the probabilities for new cases can be estimated (Silveira *et al.*, 2011).

3 EVOLUTION OF PERFORMANCE IN THE WATER AND SEWAGE SECTOR IN BRAZIL: A ROBUST DIRECTIONAL BENEFIT-OF-THE-DOUBT ASSESSMENT OF MUNICIPALITIES FROM SANTA CATARINA STATE

This chapter presents the final version of the article published in the journal *Annals of Operations Research*, in October 2024.

Abstract

The water supply and sewage sector (WSS) is essential for promoting health and providing the population with drinking water and the adequate disposal of effluents. Assessing the evolution of performance in WSS allows for highlighting the best and worst results achieved, identifying benchmarks, and pinpointing sources of improvement for water services. Brazil has a large population and immense freshwater reserves that are unevenly distributed throughout the territory. This situation emanates a challenge that requires efficient management of water resources. This study develops a composite indicator framework based on the robust Benefit-of-the-Doubt (BoD) approach to estimate the performance of municipalities of the Brazilian State of Santa Catarina from 2009 to 2021, considering financial, operational, and quality dimensions associated with the provision of WSS services. Subsequently, the Global Malmquist Index (GMI) is applied to assess the performance evolution of the municipalities over time. The BoD results enable the quantification of the relative contribution of each sub-indicator to the performance score, allowing the assessment of the strengths and weaknesses of each municipality. The GMI results show an average performance loss of 3.3% in Santa Catarina state and considerable variability among municipalities, with scores ranging from losses of 54.2% to gains of 109.3% in the period analysed.

Keywords: Data envelopment analysis; Water supply and sewage sector; Composite indicator; Benefit-of-the-Doubt; Global Malmquist index.

3.1 INTRODUCTION

Universal access to drinking Water, Sanitation, and Hygiene (WASH) is one of the sustainable development goals (SDG) established by the United Nations to be achieved by 2030. However, in 2022, 2.2 billion people still lacked safely managed drinking water, 3.5 billion people did not have safely managed sanitation, and 2 billion lacked a basic handwashing facility (UN, 2023). Given the urgency to change this scenario, it is crucial to increase the priority of policies promoting adequate water supply and adequate sewage treatment worldwide. This challenge requires expanding services while continually seeking to make the available structures more efficient.

The effectiveness of the policies depends on both the identification and dissemination of best practices, as well as the ability to implement new approaches that reinforce endogenous drivers for reform. These may include incentives issued at the national level or rooted in government programs and local policies managed by regional administrations. However, the lack of data and information is often an initial barrier to policy compliance and implementation. When authorities have access to robust data and analytical frameworks, such as benchmarking methods, they can establish an adequate baseline and adopt mechanisms that imitate competition and encourage greater efficiency (Mumssen and Saltiel, 2018).

The WSS sector is affected by infrastructure economics, economic policies, and the behaviour of institutions and society. The integrated analysis of these factors enables the offering of various technical solutions that consider a broader context. This comprehensive approach, suggested by Mumssen and Saltiel (2018), seeks to derive WSS objectives by learning lessons from what has worked or not worked, considering differing contextual realities of countries.

Brazil holds the world's largest surface renewable water reserve, although the availability of this resource across its territory is highly variable. The southeastern and northeastern Brazilian regions contribute only 7% and 6% of the total surface water, but include most of the country's population, 39% and 25%, respectively (Getirana, 2016). In other words, water demand and availability across the country are inversely proportional, requiring active management of WSS resources. Furthermore, Brazil's recent experiences in WSS regulation and policy, in addition to the organization of an extensive national system for water and sanitation data (SNIS) database, establish favorable conditions for analysing municipalities' performance and evaluating productivity changes over time.

The case study explored in the paper encompasses nearly three hundred municipalities in the Brazilian state of Santa Catarina. It involves cities of varying sizes and a spectrum of water and sewage systems, ranging from the most basic to the most advanced. This diversity effectively characterizes the authentic challenges service providers face in the region.

Data envelopment analysis (DEA) is a benchmarking technique that can be applied to monitor efficiency and the evolution of productivity in the water supply and sewage (WSS) sector. This nonparametric method quantifies the best and worst results of the sector, identifying areas for intervention. The Benefit-of-the-Doubt (BoD)

approach, proposed by Cherchye *et al.* (2007), is a framework derived from DEA that enables the construction of composite indicators. A composite indicator aggregates individual indicators of different dimensions to summarize the performance of the units under assessment.

The analysis of performance of WSS services requires the use of metrics representing various dimensions - financial, quality, and operational. These metrics, reflecting both desired and undesired aspects, can be synthesised in a composite indicator that provides a comprehensive assessment of performance. This paper aims to apply the BoD technique to municipalities of Santa Catarina State in Brazil to presents a holistic view of the use of the infrastructures, the quality of the services provided, and their value for money.

To overcome the limitations of score sensitivity to extreme values, a robust approach of the BoD is employed in this study.

In the robust approach, a bootstrapping sampling procedure is conducted, ensuring that the composite indicator score of each unit is an outcome of a high number of calculations.

This research also applies the global Malmquist index (GMI) to study performance trends over time. In particular, this approach enables the assessment of the impact of WSS regulatory and normative updates on utility performance. However, changes in the WSS sector are not immediately reflected in the results of the indicators, as there is often a time lag until these changes become effective. This situation is mitigated through an analysis of data spanning more than a decade, considering data collected for four-year periods.

Finally, identifying specific municipalities' strengths and weaknesses is explored to assist the effective allocation of improvement efforts. This requires the analysis of the relative importance of each dimension in the optimization process leading to the estimation of the BoD Composite Indicator score.

Using a robust Benefit-of-the-Doubt technique, the global Malmquist index (GMI), and identifying strengths and weaknesses in the water sector stands out as a novel and unique approach not found in existing literature. This combination offers a fresh perspective for examining the evolution of performance in the Brazilian WSS sector.

The remaining parts of this paper are structured as follows: Sect. 3.2 presents a brief literature review. An overview of the water supply and sewage sector in Brazil

is presented in Sect. 3.3. The proposed methodology is explained in Sect. 3.4. The case study is introduced in Sect. 3.5. Section 3.6 discusses the results. Finally, the study's conclusions are presented in Sect. 3.7.

3.2 LITERATURE REVIEW

The studies of performance in water and sewage systems have become more frequent in recent years. The increased demand for efficiency in the sector, combined with stricter legal and regulatory requirements, are some factors that can explain this growing interest. Research on performance change over time follow the same growth trend. It aims to identify key factors that contribute to positive outcomes, with the intention of replicating and enhancing successes.

Table 1 summarizes WSS studies on performance change over time, providing an expanded version of the literature review presented by Tourinho *et al.* (2023).

In recent studies, the representation of the WSS activity required the specification of desirable and undesirable outputs (Maziotis *et al.*, 2017; See and Ma, 2018; Ananda and Pawsey, 2019; Sala-Garrido *et al.*, 2019; Mocholi-Arce *et al.*, 2021; Maziotis *et al.*, 2021). Undesirable outputs mean that higher values indicate that the performance is worse (for example, CO₂ produced in the combustion of fossil fuel). The opposite occurs for desirable outputs, where higher values reveal better performance. The simultaneous modelling of desirable and undesired outputs requires the use of a directional distance function (DDF) approach.

Table 1 - Summary of water and sewage services studies on performance change over time, expanded from Tourinho *et al.* (2023)

Reference	Country	Method	Sample	Period
Portela <i>et al.</i> (2011)	England and Wales	Meta-Malmquist productivity index (MMPI)	22 water companies	1993–2007
Witte <i>et al.</i> (2011)	Belgium and Netherlands	Malmquist productivity index (MPI)	52 water utilities	1999–2005
Molinos-Senante <i>et al.</i> (2014)	England and Wales	Luenberger productivity index (LPI) and MPI	22 water companies	2001–2008
Carvalho and Sampaio (2015)	Brazil	MPI	27 Water and sewage companies (WaSCs)	2006 and 2011
Molinos-Senante <i>et al.</i> (2015)	Chile	LPI	18 WaSCs	1997–2013
Maziotis <i>et al.</i> (2017)	England and Wales	Malmquist-Luenberger productivity index (MLPI)	12 Water only companies (WoCs)	2001–2008
Molinos-Senante <i>et al.</i> (2017)	England and Wales	Färe-Primont productivity index (FPI)	12 WoCs and 10 WaSCs	2001–2008
Guerrini <i>et al.</i> (2018)	Italy	LPI and MPI	136 water companies	2009–2014
Macedo (2018)	Brazil	MPI	18 WaSCs	2004–2015
Molinos-Senante and Maziotis (2018)	England and Wales	SFA (Stochastic Frontier Analysis)	11 WoCs and 10 WaSCs	1996–2019
Sala-Garrido <i>et al.</i> (2018)	Chile	Luenberger-Hicks-Moorsteen (LHMPI) and LPI productivity index	23 water utilities	2010–2016
See and Ma (2018)	Malaysia	Metafrontier Malmquist Luenberger productivity index (MMLPI)	14 state water utilities	1999–2012
Ananda and Pawsey (2019)	Australia	MLPI	50 WaSCs	2009–2016
Sala-Garrido <i>et al.</i> (2019)	Chile	MMLPI	22 water companies	2010–2016
Molinos-Senante <i>et al.</i> (2020)	Chile	MPI (with SFA)	22 private water companies	2007–2015
Maziotis <i>et al.</i> (2021)	Chile	LHMPI	20 WaSCs	2007–2018
Mocholi-Arce <i>et al.</i> (2021)	England and Wales	MMLPI	7 WoCs and 10 WaSCs	2001–2018
Tourinho <i>et al.</i> (2023)	Brazil	MPI and Pseudo-Malmquist productivity index (PMPI)	283 largest municipalities in Brazil	2012–2019
Pereira <i>et al.</i> (2023)	Portugal	Robust conditional order-m DEA	10 WoCs and 12 WaSCs	2017–2021

Source: the author

DDF models were introduced by Chambers *et al.* (1996). This approach allows the simultaneous expansion of outputs and contraction of inputs according to a directional vector.

It can be noted that only a few countries have studies in the WSS sector focused on performance change over time. The studies reviewed indicate that the techniques more frequently applied for this purpose are the Malmquist productivity index (MPI), applied with DEA models, and the Luenberger productivity indicator (LPI), applied with DDF models.

Extensions of these approaches have also been proposed to answer specific challenges posed by the empirical applications.

As noted by Pastor and Lovell (2005) and Oh (2010), the MPI and LPI fail the circular property. In other words, the direct comparison between two periods, t and $t + 2$, does not provide the same index as the indirect comparison through a third period, $t + 1$ (Rebelo, 2010). To overcome this problem a metafrontier formed by all DMUs from all the periods under assessment is used, as in Tourinho *et al.* (2023), Mocholi-Arce *et al.* (2021), Sala-Garrido *et al.* (2019), and See and Ma (2018).

Whilst DEA focuses on the production process transforming resources (inputs) into products (outputs), involving the estimation of an efficiency score, BoD composite indicators are centered on the evaluation of the achievement of goals, representing an effectiveness score. In the BoD formulation (Cherchye *et al.*, 2007) the input is replaced by a dummy variable equal to one for all decision making units (DMUs) under assessment. In the presence of both desirable and undesirable outputs, the BoD approach has been extended by Zanella *et al.* (2015) to enable the construction of Composite Indicators using a directional distance function (DDF). This type of formulation is known as the directional BoD approach.

Henriques *et al.* (2020) and Vilarinho *et al.* (2023b) applied a BoD model to support regulation in the WSS sector in Portugal. These studies used performance indicators collected by the Portuguese regulatory authority for the water and waste sectors (ERSAR) to evaluate the quality of service provided to users and the asset management of the operators, respectively. The results from Henriques *et al.* (2020) showed that six wholesale operators and thirteen retail operators were found to be outstanding according to the quality of service. In relation to the study of Vilarinho *et al.* (2023b), specifically for asset management, it was concluded that the direct

management model was unfavorable concerning developing structured management systems, whilst urban environments favor managerial advancement.

In Brazil, there are no studies that applied the BoD approach to performance assessment in WSS sector. The DEA model was used by Carvalho and Sampaio (2015), Macedo (2018) and Tourinho *et al.* (2023). The input of these studies were the expenses associated with the provision of services (representing the financial dimension). The outputs were mostly related to the assets of companies or municipalities (number of connections, network length, among others, all representing desirable features). Carvalho and Sampaio (2015) and Macedo (2018) applied the Malmquist productivity index to evaluate the productivity change over time. Both studies revealed productivity gains mainly influenced by the movement of the frontier (frontier shift effect) caused by the institutional changes implemented in Brazilian WSS sector.

Tourinho *et al.* (2023) applied a MPI to assess productivity change in the period 2012–2019, and a Pseudo-Malmquist productivity index (PMPI) to compare productivity levels across Brazilian macro-regions. The PMPI required the specification of a reference metafrontier that considered the three macro-regions in all years analyzed. The results showed a productivity loss of approximately 4% from 2012 to 2019. This decline in productivity was mostly due to an increase in the average distance to the frontier, as revealed by the efficiency change score lower than one.

According to the literature review, to the best of our knowledge, no studies applied a robust Benefit-of-the-Doubt (BoD) approach to assess performance change over time in conjunction with the global Malmquist index (GMI) in the WSS sector. This paper also extends the existing literature by considering operational and quality features to complement the financial dimension of utility activity. These three dimensions are intrinsically related, as the result of one directly affects the performance of the others and, consequently, the sector as a whole. The composition of the sample, based on municipalities instead of providers, and the varying sizes of the municipalities also contribute to a comprehensive and realistic performance evaluation of the Brazilian WSS sector.

3.3 THE WATER AND SEWAGE SECTOR IN BRAZIL

As exposed by Mumssen and Saltiel (2018), WSS management in Brazil has gone through three significant reform periods: 1968–1986, characterized by a central national water supply and sanitation plan (PLANASA) and the establishment of state-level state-owned WSS companies (CESBs); 1986-2007, the second period, that promoted public sector participation and established the official source of data on basic sanitation, the national system for water and sanitation data (SNIS); and the most recent phase, whereby the approval of a new basic sanitation guideline (Law No 11,445/2007) and its update (Law No 14,026/2020).

The laws of this third period established that the set of public services, infrastructure, and operational installations for drinking water supply, sewage collection and treatment, solid waste management and, urban rainwater drainage are the four pillars of basic sanitation in Brazil (Brazil, 2007, 2020a).

According to Law No 11,445/2007 the municipalities are the entities responsible for the provision of basic sanitation services. They can provide services themselves, hire companies providers, and enter municipal partnerships, among other options. The provision of these services must be planned by the municipalities through the preparation of the municipal basic sanitation plan (PMSB). Law No 11,445/2007 also established the creation of regulatory entities, which must issue standards on the technical, economic, and social dimensions of service provision.

The main updates in Law No 14,026/2020 are the establishment of regionalized service provision and expansion of water supply and sewerage systems. The regionalization establishes that states must group their municipalities into regions, with their specific governance structures. The municipalities and the state jointly exercise the management functions of basic sanitation policy. The goal of universalizing WSS services means that 99% of the population should have access to potable water, and 90% should have proper sewage management by 2033 (Brazil, 2020a).

Quantitative targets for reducing water losses were established by Ordinance No 490/2021 (Brazil, 2021b). The goals are more stringent as the years go by, reaching 216 l/connection/day in 2034. In case of non-compliance, resources and financing may be denied to service providers. The most recent data on water losses in Brazil is from 2021: 325.4 l/connection/day (Brazil, 2022). To achieve the water loss goal, the service

providers have the challenge of reducing water losses annually by around 10 l/connection/day until 2034.

Regulatory agencies are responsible for overseeing adherence to these goals. WSS regulation was established in 2007, and since that, some states founded regulatory agencies while some municipalities have created their agencies or joined regional agencies. Brazil currently has 89 regulatory agencies. The state of Santa Catarina, for example, has six agencies. Since the enactment of Law No 14,026/2020, the national water and basic sanitation agency (ANA) has assumed the responsibility of editing reference standards for WSS sector. These general rules must be observed by the basic sanitation regulatory entities in their activities (ANA, 2023).

According to SNIS (Brazil, 2022), in 2021, the total population served with water supply in Brazil was approximately 177 million inhabitants, which represents 84.2% of coverage with the public network, considering urban and rural populations. The urban coverage is about 93.5%, serving 167 million inhabitants living in urban areas. The 2021 total and urban sewage coverage were 55.8% and 64.1%, respectively.

It is important to note that SNIS has the limitation of not considering the individual solutions in its indicators. Individual solutions consist of alternative means of access to water supply and final disposal of sewage in locations that are not directly served by the public network. Therefore, water supply fountains or sewage treatment by septic tanks, for example, are ignored in Brazil's official data (Brazil, 2023b). This situation has caused some controversy in WSS management since other government documents, such as the national basic sanitation plan (PLANSAB) and the national rural sanitation plan (PNSR), consider individual solutions to be appropriate, especially in rural areas. According to PLANSAB (Brazil, 2020d), total water coverage is 94.5% instead of the 84.2% shown by SNIS. The total sewage coverage in PLANSAB is 74.3%, a difference of 18.5% from the SNIS data (55.8%). Until new guidance is provided, the rule outlined in Decree No. 11,599/2023 remains in effect. This entails the exclusion of individual systems from Brazil's WSS official data.

Since 2018, by Ordinance no. 719 (Brazil, 2018b), SNIS data has a methodology for auditing and certification known as Acertar. The objective of Acertar is to ensure that SNIS information, which is self-declaratory, is reliable and allows for benchmarking between different municipalities and providers. Audits are carried out by

regulatory agencies to ensure that, by 2024, all SNIS data will be analyzed to assess its reliability and accuracy.

Water supply and sewage services in Brazil are provided by various entities, including local administrations, government-controlled companies, municipal companies, autarchies (an autonomous Brazilian service with its own legal personality, assets and revenue, to carry out activities typical of Public Administration) and, private companies. Discussions regarding public versus private providers and their efficiency are very latent in Brazil, especially after the promulgation of Law No. 14,026/2020. The scenario of WSS in Brazil should be observed in the coming years as the legal ruling provisions are being reviewed. In this context, benchmarking studies and the analysis of the evolution of performance over time are relevant and timely.

3.4 METHODOLOGY

This section presents the BoD framework, which underlies the evaluation of water and sewage systems performance conducted in this study. It also explains the global Malmquist index (GMI), an alternative formulation to the original Malmquist index (MI) that is estimated using a metafrontier. The GMI components, efficiency change and best practice change are also discussed.

3.4.1 The BoD setting

The performance assessment conducted in this study involves the construction of a composite indicator (CI), according to the Benefit-of-the-Doubt (BoD) framework popularized by Cherchye *et al.* (2007). The composite indicator aggregates a set of individual indicators, also referred to as sub-indicators, with the objective of summarizing the performance of DMUs considering the multi-dimensional nature of their activities. The standard BoD formulation is equivalent to an original DEA model (Charnes *et al.*, 1978), with a dummy input equal to one and multiple desirable outputs.

The BoD model based on a Directional Distance Function (DDF) was first proposed by Zanella *et al.* (2015). It allows the simultaneous adjustment of both desirable and undesirable outputs without requiring the adjustment of measurement scales. The multiplier formulation of the directional BoD model is shown in (1).

$$\text{Minimize } \beta_{j_0} = - \sum_{r=1}^s y_{rj_0} u_r + \sum_{k=1}^l b_{kj_0} p_k + v \quad (1)$$

$$\text{sujeito a: } \sum_{r=1}^s g_y u_r + \sum_{k=1}^l g_b p_k = 1$$

$$- \sum_{r=1}^s y_{rj} u_r + \sum_{k=1}^l b_{kj} p_k + v \geq 0, \quad j = 1, \dots, n$$

$$v \in \mathbb{R}$$

$$u_r \geq 0, \text{ para } r = 1, \dots, s$$

$$p_k \geq 0, \text{ para } k = 1, \dots, l$$

In this directional BoD model, y_{rj} represents the desirable variables and b_{kj} represents the undesirable variables for DMU j ($j=1, \dots, n$), where n indicates the number of DMUs under assessment. The parameters y_{rj_0} e b_{kj_0} are the values of desirable and undesirable variables observed for the DMU j_0 under assessment.

The decision variables of the model are the weights, where u_r is associated to the desirable outcomes r , p_k with the undesirable outcomes k and v is associated with the dummy input.

The directional distance vector is specified as $(g_y, -g_b)$. It indicates the direction of expansion of desired outputs and reduction of undesired ones towards the optimal condition. The direction vector used in the model can influence the computed scores, so the choice must be made according to the objective of the respective study. In this work the values of $(g_y, -g_b)$ were chosen as being equal to $(y_{rj_0}, -b_{kj_0})$, following Zanella *et al.* (2015) and Rogge *et al.* (2017). In this case, each DMU can improve using the values of its output metrics, resulting in a proportional expansion of desirable metrics and contraction of undesirable ones. Therefore, the improvement is proportional to the DMU's observed values. Because the directional distance vector specifies the direction of improvement for desirable and undesirable outputs in opposite directions, there is no need to transform the scale of undesirable metrics to convert them into desirable ones.

The model's objective function, expressed by the variable β_{j_0} , represents the maximal feasible expansion of desirable factors and contraction of undesirable factors that can be achieved simultaneously.

The value of the composite indicator (CI) associated with DMU j_0 can be obtained as $1/(1 + \beta_{j_0})$. It ranges from 0 to 1, where 1 represents the best performance level and indicates that DMU under assessment is in the best-practice frontier. Actually, in the robust approach, CI can present values higher than 1, what will be better explained in Sect. 3.4.2.

Also, this model allows the incorporation of weight restrictions to reflect the relative importance of the outputs and prevent assessments that could disregard certain indicators by assigning them a weight equal to zero. There are several kinds of weight restrictions for DEA models, as discussed in Wong *et al.* (1990), Allen *et al.* (1997), Sarrico and Dyson (2004), among others.

In this study, the weight restrictions used are in the form of assurance regions type I (ARI), as proposed by Zanella *et al.* (2015). The AR-I weight restrictions displayed in (2) use an “artificial” DMU that is composed of the average values of the outputs observed in the sample, being $(\bar{y}_r)$ for the average of the desirable outputs and $(\bar{b}_k)$ for the average of the undesirable outputs. The parameters ϕ_r and ϕ_k represent the lower bounds of the weights for desirable and undesirable indicators, respectively.

According to Zanella *et al.* (2015), the use of these AR-I restrictions presents the advantage of allowing the assessment of the performance of all DMUs against the same frontier, as well as the interpretation of the magnitude of the weights bounds as the relative importance of a given output dimension in percentage terms. In this study, only the lower bounds of the output weights are considered in the Directional BoD model:

$$\begin{aligned} \frac{u_r \bar{y}_r}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_r, & r = 1, \dots, s \\ \frac{p_k \bar{b}_k}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_k, & k = 1, \dots, l \end{aligned} \quad (2)$$

Another advantage of using BoD for the construction of CIs is that it allows extracting the strengths and weaknesses of each DMU by analysing the magnitude of the virtual weights of the optimal solution. Virtual weights are the result of the product of each DMU's observed output by the associated optimal weight. Higher virtual weights indicate the strengths and the lower ones indicate the weaknesses of the DMU under assessment.

As exposed by Vilarinho *et al.* (2024) in DDF-based BoD models, the magnitude of virtual weights cannot be interpreted directly as the relative importance of the indicators because, in these cases, the virtual weights for the desirable and undesirable outputs present different signs in the model objective function. To address this limitation, the relative strengths of each DMU are estimated by the normalised values associated with the specification of the weight restrictions, as shown in mathematical expressions (2). In this case, a higher magnitude of the relative virtual weights signals a strength both for desirable and undesirable indicators. This method is applied in this study to identify the strengths and weaknesses of the DMUs and to allocate improvement efforts more effectively.

3.4.2 Robust approach for the composite indicator calculation

Previous literature (see Nardo *et al.* (2008), Daraio and Simar (2005), among others) discussed some limitations related to the use of the BoD approach: the score sensitivity to extreme values, the sample size, and the difficulty in performing statistical inference. In order to overcome the sensitivity to outliers, Cazals *et al.* (2002), Daraio and Simar (2007) proposed a robust composite indicator approach for BoD computations.

In the robust composite indicator approach, a bootstrapping sampling procedure is performed. This way each DMU is evaluated B times for a sample of size m randomly drawn with replacement from the original set of DMUs. The variable B is often a high number then the effects of extreme values are minimized on the average composite indicator CI calculation. The robust composite indicator results from the average of the various composite indicators generated for all B samples of size m . The robust composite indicator $CI_{j_0}^m$ is shown in (3), where $CI_{j_0}^{b,m}$ is the composite indicator of the DMU j_0 under assessment calculated using sub-sample b .

$$CI_{j_0}^m = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m} \quad (3)$$

In case the DMU j_0 is not included in b , the results may eventually indicate that it is more efficient than all the DMUs in the sample. If this happens, the DMUs are classified as “super-performing” and its score, β_{j_0} , have a value greater than 1. So $\beta_{j_0}^{b,m}$ (see 1) displays a negative value and the value of $CI_{j_0}^{b,m}$, obtained from the expression $1/(1 + \beta_{j_0})$, does not reflect the performance improvement expected for a better-performing DMU. According to Mergoni *et al.* (2022), a solution to this problem is modifying the calculation of $CI_{j_0}^{b,m}$ as shown in (4).

$$CI_{j_0}^{b,m} = \frac{1}{1 + \beta_{j_0}^{b,m}}, \quad se \beta_{j_0}^{b,m} \geq 0; \quad (4)$$

$$CI_{j_0}^{b,m} = \log_{10}(1 - \beta_{j_0}^{b,m}) + 1, \quad se \beta_{j_0}^{b,m} < 0$$

As presented by Vilarinho *et al.* (2023a), the proposed formulation when $\beta_{j_0}^{b,m} < 0$ follows a similar trend as the original formulation for positive values of $\beta_{j_0}^{b,m}$, allowing the value of $CI_{j_0}^{b,m}$ to proportionally increases as the performance of the DMUs improves. Therefore, the robust composite indicators in this study are computed using the expressions in (4), following Mergoni *et al.* (2022).

3.4.3 Global Malmquist Index

The global Malmquist index (GMI) is the method adopted in this paper to explore the evolution of performance over time. The GMI is an alternative formulation to the original Malmquist index (MI) introduced by Färe *et al.* (1994). The main advantage of the GMI is that it satisfies the circular property, which requires defining a metafrontier that envelops all data.

According to Battese and Rao (2002) and Battese *et al.* (2004), the metafrontier is an envelope function of the frontiers of different time period technologies, by which comparable technical efficiencies can be estimated. It assumes each period p has its own technology T^p ($p = 1, 2, \dots, t, t+1, \dots, P$), but it is possible to specify a metatechnology T^M equivalent to the convex hull of T^p , that envelops all individual period technologies.

Based on this concept, Pastor and Lovell (2005) proposed the GMI with a technology formed from data of all units in all periods that allows to overcome the limitation of non-circularity of the original Malmquist index. Afsharian and Ahn (2015) highlighted several drawbacks in the work of Pastor and Lovell (2005). These include potential loss of information regarding the role of each contemporaneous technology, possible infeasibility arising from convex combinations of observations across time periods, and the possibility of changes in the GMI when incorporating new time periods. Despite these limitations, we believe that the water sector does not experience rapid technological or environmental changes. Furthermore, the application of GMI did not cause infeasibilities in the cross-period analyses of this work.

Therefore, in this context, employing a global convex set provides sufficient information to effectively assess performance changes. The GMI formulation for a multi-input multi-output setting is shown in (5). $E^M(X^t, Y^t)$ is the DEA efficiency score of a DMU in period t with an input–output vector (X^t, Y^t) computed in relation to the frontier of the metatechnology T^M . Similarly, $E^M(X^{t+1}, Y^{t+1})$ is the DEA score of the DMU considering the input and output vector (X^{t+1}, Y^{t+1}) observed in period $t + 1$.

$$GMI^{t,t+1} = \frac{E^M(X^{t+1}, Y^{t+1})}{E^M(X^t, Y^t)} \quad (5)$$

Following Camanho *et al.* (2023), this index in Equation (5) can be adapted to the context of a BoD evaluation as shown in Equation (6). Even though these authors, did not use a DDF-based BoD model, but rather a standard-DEA-based BoD model, the GMI can be still computed. This is possible because a performance measurement ($CI_{j_0}^{b,m}$) is obtained from Equation (4) for both periods t and $t + 1$ in a manner similar to that of a standard DEA-based BoD.

$$GMI^{t,t+1} = \frac{CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^M(\mathbb{1}, Y^t, B^t)} \quad (6)$$

where $CI^M(\mathbb{1}, Y^t, B^t)$ and $CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})$ corresponds to the CI scores estimated against the metafrontier of technology T^M with data from period t and $t + 1$, respectively. In the context of this study, the data is represented by the vector of the dummy input, desirable outputs (Y) and undesirable outputs (B) observed in a given time period for

the DMU j_0 under assessment, represented by $(\mathbb{1}, Y, B)$. These CI scores are obtained from the directional BoD estimate β obtained at the optimal solution to model (1), using formula (4) (see Subsection 3.4.2).

Following (Pastor and Lovell, 2005), the global Malmquist index can be decomposed into the components of efficiency change (EC) and best-practice change (BPC), as shown in (7):

$$\begin{aligned}
 GMI^{t,t+1} &= \frac{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^t(\mathbb{1}, Y^t, B^t)} \\
 &\quad \times \left(\frac{CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})} \times \frac{CI^t(\mathbb{1}, Y^t, B^t)}{CI^M(\mathbb{1}, Y^t, B^t)} \right) \\
 &= \frac{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^t(\mathbb{1}, Y^t, B^t)} \times \left(\frac{\frac{CI^M(\mathbb{1}, Y^{t+1}, B^{t+1})}{CI^{t+1}(\mathbb{1}, Y^{t+1}, B^{t+1})}}{\frac{CI^M(\mathbb{1}, Y^t, B^t)}{CI^t(\mathbb{1}, Y^t, B^t)}} \right) \\
 &= EC^{t,t+1} \times \frac{BPG^{t+1,M}(\mathbb{1}, Y^{t+1}, B^{t+1})}{BPG^{t,M}(\mathbb{1}, Y^t, B^t)} \\
 &= EC^{t,t+1} \times BPC^{t,t+1}
 \end{aligned} \tag{7}$$

$EC^{t,t+1}$ is the efficiency change component that measures the evolution of the distance to the frontier for the DMU under assessment between period t and $t+1$. $EC^{t,t+1} \geq 1$ indicates greater proximity to the frontier in $t+1$ than in t .

The name “efficiency change” was originally coined in the context of efficiency studies based on DEA models. In a BoD framework, the name “performance change” would be more appropriate, as only output levels are considered in the assessment, as opposed to a transformation process involving inputs and outputs. However, we have chosen to retain this terminology as it is well established in studies evaluating performance change over time.

$BPG^{t,M}(\mathbb{1}, Y^t, B^t)$ is the best practice gap between the frontiers of technologies T^M and T^t . The ratio between $CI^M(\mathbb{1}, Y^t, B^t)$ and $CI^t(\mathbb{1}, Y^t, B^t)$ results in BPG.

In turn, $BPC^{t,t+1}$ is the change in the best practice gap between t and $t+1$, calculated by the ratio $BPG^{t+1,M}(\mathbb{1}, Y^{t+1}, B^{t+1})$ over $BPG^{t,M}(\mathbb{1}, Y^t, B^t)$. $BPC^{t,t+1} > 1$ indicates that the frontier in period $t+1$ is closer to the metatechnology than it was in

period t . On the other hand, $BPC^{t,t+1} < 1$ indicates that the frontier in $t+1$ is further away from the metatechnology than the frontier in t .

The circular property of GMI allows comparisons involving more than two time periods, as shown in (8) and applied by Camanho *et al.* (2023):

$$GMI^{t,t+2} = GMI^{t,t+1} \times GMI^{t+1,t+2} \quad (8)$$

Expression (8) indicates that the index estimating the evolution of performance between t to $t+2$ is equal to the product of the index comparing t to $t+1$ and the index comparing $t+1$ to $t+2$. The same property applies to the components EC and BPC .

3.5 CASE STUDY

This section details the case study of this research. Subsection 3.5.1 describes the primary data set containing the variables collected by SNIS (Brazil, 2022) that are used to construct the composite indicator. Subsection 3.5.2 presents the main descriptive statistics of each metric of the composite indicator.

3.5.1 Variable selection

The variable selection is based on the fundamental principles of Brazilian basic sanitation guideline, Law No14,026/2020, and inspired by research conducted by the international water association (IWA), the Brazilian association of regulatory agencies (ABAR), as well as the studies reviewed in Sect. 3.2.

Brazilian Law No 14,026/2020, establishes among its fundamental principles the universal access and effective service provision; safety, quality, regularity and continuity; reduction of water losses and promotion of energy efficiency.

According to IWA (Alegre *et al.*, 2016), water supply and sewerage services should adhere to the principles of universal access, continuity, quality of service, efficiency, and equitable tariffs.

Aligning with these principles, ABAR (Júnior; de Castro, 2006) emphasizes that metrics reflecting water supply and sewerage coverage, water loss control,

drinking water quality, and sewage treatment should be used to evaluate WSS performance.

The data utilized in this study were sourced from SNIS, and a detailed description is presented in Table 2.

Financial performance is crucial to ensure the continuity of service provision and to guarantee the necessary funds for maintenance and expansion of water and sewerage systems. This is achieved by balancing revenues and expenses. The operational revenues of the financial performance index (IN012) include the annual billed amount resulting from the application of tariffs and/or fees arising from the provision of WSS services. Invoiced amounts resulting from the sale of water, raw or treated, exported from wholesale to other distribution agents are also considered. Total expenses include staff, chemicals, electricity, third party services, expenses incurred with profits and debt service charges (including expenses arising from monetary and exchange rate variations), expenses with depreciation of fixed operational assets (machinery, equipment and installations in service) and expenses with amortization of deferred assets (installation expenses and organization that contributes to the result of more than one exercise), among others.

Treated sewage referred consumed water index (IN046) refers to treatment of total sewage generated. It rarely reaches rates above 90%, as not all water generates sewage. It can exceed 100% in situations of rainwater infiltration into sewage networks (Brazil, 2022). This variable summarizes both information about sewerage coverage and its effective treatment, since in some situations sewage can be collected but discarded without previous treatment.

Water losses correspond to the difference between the total volume of drinking water produced at the treatment plants (plus water imported from other systems, if applicable) and the sum of volumes measured by hydrometers installed at customers' properties (in addition to estimated consumption volume for connections without a hydrometer or with a non-functional hydrometer, if applicable). Water loss is directly related to operational and commercial performance since total water losses may result from issues in these two areas. These issues include leaks, reservoir overflows, measurement errors, consumer fraud and others (Brazil, 2022). Some of the factors that contribute to water losses include (i) low institutional and management capacity of the systems, (ii) limited availability of resources for investments, (iii) a culture of increasing supply and individual consumption without concern for conservation and

rational use, (iv) and pragmatic decisions to expand hydraulic load and extend networks to more peripheral areas of the systems without proper engineering studies (Miranda, 2006). The linear water losses index (IN050) also demonstrates the accuracy of the technical registration of the water network extension. If this data is not accurate, IN050 tends to present worse results.

Total water coverage index (IN055) is aligned with the principle of universal access to drinking water. It corresponds to the proportion of the total population that is effectively served with public water networks, including those located in areas not considered urban. The calculation does not consider individual or alternative solutions, such as wells, springs, cisterns and fountains.

WSS is a massive consumer of energy, consequently electricity is one of the main operating costs of water and sewerage systems. Energy moves electromechanical equipment, especially pumps, which are installed in many operational units, such as capturing raw water, distributing water to higher consumption points and aerating sewage in treatment tanks, for example. Although the energy tariff value cannot be directly controlled by the WSS provider, there are devices/tools available in the Brazilian energy sector that can reduce these costs and improve the capacity of obtaining the same service with less energy consumption, the called energy efficiency. According to Feldman (2009), energy efficiency can be achieved by installing new technology, improving system design, installing variable speed of pump and reducing leakages. Other alternatives are the installation of solar panels, energy use of methane from effluents and, acquisition of energy through the Mercado Livre de Energia (free energy market, in English), that is an environment that allows large consumers to negotiate the purchase of energy directly with generators and suppliers. If energy efficiency is greater, the total costs of WSS will be lower, consequently, the financial performance will be better.

Table 2 - Description of SNIS indicators used in the composite indicator

Variable Code	Variable description		Scale	Variable definition	Type	Dimension	Sub-sector
IN012	Financial performance index		%	Ratio of operational income to total expenses for services	Desirable	Financial	WS, WWD
IN046	Treated sewage referred consumed water index		%	Ratio between the volume of treated sewage in relation to the volume of water consumed	Desirable	Quality	WWD
IN050	Linear water losses index		m³/km per day	Volume of water losses per km of distribution network length	Undesirable	Quality	WS
IN055	Total water coverage index		%	Ratio of the total population served with water supply to the total resident	Desirable	Quality	WS
IN060	Energy spending		Brazilian real per kWh	Electric energy expenditure per kWh	Undesirable	Operational	WS, WWD
IN071-A	Water supply interruptions index (*)		%	Ratio between the number of dwelling units that have had at least one water supply interruption in the course of a year in relation to the total of active dwelling units	Undesirable	Operational	WS
IN084	Out-of-standard total coliform analysis incidence		%	Ratio between the quantity of samples for total coliforms with non-standard results and the quantity of analyzed samples	Undesirable	Quality	WS
IN102	Total equivalent staff productivity index		connection per employee	Number of connections served by each employee	Desirable	Operational	WS, WWD

Source: the author

WS - Water supply. WWD - Wastewater drainage

*Adapted from SNIS.

The regularity of water system operation is related to the principle of continuity and the quality of service. The Water Supply Interruptions index (IN071-A) reflects interruptions resulting from issues in water supply units (from production to distribution). The most common causes of these interruptions include power outage and repairs in the water system. However, interruptions resulting from problems in drinking water production, network pressure and undersizing of plumbing, which in SNIS constitutes the indicator IN073 (dwelling units affected by shutdowns), were not considered due to the insufficient amount of information available in for this study. In order to allow the water supply interruptions index (IN071-A) to increase according to a greater number of water system stops and affected dwelling units, the indicator was adjusted to a percentage unit and identified as IN071-A (Adapted). The total amount of active dwelling units used in this adaptation corresponds to AG003 metric code from SNIS. It is important to note that IN071-A provides information about interruptions lasting six hours or more.

The presence of pathogenic organisms in water is a serious problem and requires permanent control of distributed water. However, identifying the infectious agent is not simple because the number of different possible pathogens is large and their concentration in potable water is too small for direct enumeration to be possible. Therefore, the presence of pathogens is determined with indirect evidence by testing total coliform bacteria (Edberg and Smith, 1989). Total coliforms come from the same sources as pathogenic organisms, are relatively easy to identify, are usually present in larger numbers than dangerous pathogens, and respond water treatment similarly to many pathogens, so testing for total coliform bacteria is a reasonable indication of whether other pathogenic bacteria are present in water (NYS, 2023). Out-of-standard total coliform analysis incidence (IN084) is related to the principle of drinking water quality. It refers to the compliance with Brazilian water potability standards for human consumption, in accordance with Ordinance No. 888/2021 (Brazil, 2021b), from the Brazilian ministry of health. The ordinance establishes maximum values (VMP) of total coliforms allowed in water depending on the size of the system. For example, the VMP in water systems or collective alternative solutions that supply from 20,000 inhabitants is 'absence in 100ml in 95% of the samples examined in the month'.

The total equivalent staff productivity index (IN102) represents staff productivity depending on the number of water and sewage connections per employee. In Brazil, in 2021, the average value was 372.5 connection/employee. Values lower than the

average may indicate employee under performance, so the variable was considered desirable as the goals established by Brazil's Law No. 14,026/2020 tend to increase investments in the sector and, consequently, demand greater staff productivity.

3.5.2 Data collection

The data of water supply and sewage services used in this study were obtained from the national system for water and sanitation data (SNIS). SNIS is provided in a yearly basis and is the official source of basic sanitation data in Brazil. This study employs the metrics collected by SNIS during thirteen years, from 2009 to 2021, for the state of Santa Catarina, a federative unit in southern Brazil. Santa Catarina has 295 municipalities and a population of over 7,6 million inhabitants (IBGE, 2022). The water and sewage services in Santa Catarina are provided by the local administrations, government-controlled companies, municipal companies, autarchies and private companies.

In some cases, municipalities are served by more than one provider. This usually occurs when one company manages water services and the other manages sewerage services. There are also cases of different water companies serving specific regions of the same municipality. Previous studies on the evaluation of performance of Brazilian water and sewage services, as Tourinho *et al.* (2023), considered a sample only with municipalities with a single water supply and sanitation company to avoid the bias of associating the volumes to a particular municipality. To accomplish the objectives of this study, a decision was made to aggregate the data from all service providers in municipalities with multiple providers, and subsequently recalculate the indicators. This approach facilitates a comprehensive evaluation from the municipality's perspective in terms of goal attainment.

Table 3 displays the primary descriptive statistics for the data associated with the metrics composing the composite indicator.

Data collection was based on an unbalanced panel sample, where the number of municipalities is not the same in each of the years analyzed. In 2021 the number of municipalities was 291. In the years 2017, 2013 and 2009 the number of municipalities in the sample was 284, 283 and 273, respectively. In a total of 29.480 observations considered to be valid, 2.5% resulted from replacing missing values. The variables with more missing data were IN060 (related to electricity expenses), IN071-A (related to

water system stops) and IN102 (related to staff productivity). Data from years 2009 and 2010 showed the highest number of missing instances.

Table 3 - Descriptive statistics of the variables

Variable	Statistics	2009	2013	2017	2021
IN012 - Financial performance index (%)	Average	98.2	99.1	89.8	95.0
	Std. Dev	45.1	23.3	22.3	21.8
	Minimum	0.0	0.0	12.6	0.0
	Maximum	408.9	239.7	366.6	246.6
IN046 - Treated sewage referred consumed water index (%)	Average	3.9	4.9	7.5	10.7
	Std. Dev	6.8	8.3	12.3	16.5
	Minimum	0.0	0.0	0.0	0.0
	Maximum	100.0	100.0	100.0	100.0
IN050 - Linear water losses index (m ³ /day/km)	Average	11.7	11.8	11.9	11.1
	Std. Dev	8.0	7.3	7.3	6.9
	Minimum	0.0	0.0	0.0	0.0
	Maximum	115.1	111.3	82.1	185.1
IN055 - Total water coverage index (%)	Average	62.9	65.5	69.5	74.2
	Std. Dev	21.1	19.2	19.8	19.1
	Minimum	9.4	11.8	13.5	16.3
	Maximum	100.0	100.0	100.0	100.0
IN060 - Energy spending index (Brazilian real/kWh)	Average	0.4	0.4	0.7	1.1
	Std. Dev	0.2	0.1	0.3	0.6
	Minimum	0.0	0.0	0.1	0.1
	Maximum	1.0	0.8	1.8	4.1
IN071-A - Water supply interruptions index (%)	Average	52.2	18.1	14.2	7.3
	Std. Dev	46.8	24.0	21.3	11.7
	Minimum	0.0	0.0	0.0	0.0
	Maximum	100.0	100.0	100.0	100.0
IN084 - Out-of-standard total coliform analysis incidence (%)	Average	6.5	2.7	3.6	2.2
	Std. Dev	9.1	2.8	4.4	2.3
	Minimum	0.0	0.0	0.0	0.0
	Maximum	100.0	100.0	100.0	100.0
IN102 - Total equivalent staff productivity index (connection/employee)	Average	267.3	250.6	246.0	236.6
	Std. Dev	136.6	89.9	85.6	87.2
	Minimum	0.0	0.0	0.0	0.0
	Maximum	1,263.4	1,019.5	763.7	878.0

Source: the author

Missing data substitution was performed in accordance with the procedure recommended by Kuosmanen (2002). Among the desirable variables, only IN012 (related to financial performance) and IN102 presented missing values, which were replaced by zero. Among the undesirable indicators only variable IN050 (related to water loss) had no missing data. For the variables IN071-A and IN084 (related to out-of-standard water quality) the value of 100% was assigned to missing data instances. For IN060, whose scale is Brazilian real/kWh and not %, the procedure indicated by Oliveira *et al.* (2020) was adopted and blank instances were replaced by the mean value of the indicator plus three times its standard deviation. This different approach to IN060 was necessary as the 2021 indicator for the municipality of Presidente Nereu

pointed to a probable data management error, whose value was almost ninety times higher than the data available from the other DMUs.

3.5.3 Descriptive statistics

The individual analysis of descriptive statistics of the variables allows a first view of WSS in Brazil in the period studied. The data available in Table 3 show that efforts to universalize WSS services have been successful and sewage treatment (IN046) and water supply coverage (IN055) have evolved gradually.

The pursuit for higher quality in services is also yielding positive results, as evidenced by the indicators related to water supply interruptions (IN071-A) and out-of-standard water quality (IN084), which have gradually decreased.

Financial performance (IN012), water losses (IN050) and staff productivity (IN102) show stability, with no significant variations over time.

On the other hand, the energy spending has significantly increased throughout the period. This is likely a consequence of the Brazilian Tariff Flag System, which was implemented in 2015, resulting in an almost 50% increase in energy tariffs in that year. The flag system is activated when there is a restriction to energy generation by hydroelectric plants, which provide cheaper energy. The green flag indicates that conditions for generating hydroelectric energy are favorable and the tariff has no increases. For the other flags, there are increases in tariff values which are proportional to the energy generation costs (Brazil, 2022). A positive side effect of the increase in energy tariffs is that, since then, the topic of energy efficiency has become recurrent in WSS.

3.5.4 Data treatment

Data treatment for this study occurred in four distinct stages, as follows:

1. For each year, a robust composite indicator is generated according to the methodology described in Sect. 3.4.2;
2. For the metafrontier with all data in all years, a robust composite indicator is generated according to the methodology described in Sect. 3.4.2;

3. Based on the results of the composite indicators for each year and for the metafrontier, the global Malmquist index (GMI) is calculated as explained in Sect. 3.4.3. The GMI is used to determine performance change in the period considered, spanning from 2009 to 2021 considering intervals of four years;
4. Finally, the strengths and weaknesses of each municipality were estimated based on the relative importance of each variable to the DMU performance score, based on the values of the AR-I weight restriction presented in subsection 3.4.1. The procedure follows the method proposed by Vilarinho *et al.* (2024), which considers the value of the virtual weights associated with the ‘average DMU’.

3.6 RESULTS AND DISCUSSION

This section begins with a brief discussion of the results of the robust composite indicator, which reveal the relative position of municipalities’ performance. The discussion follows with a characterisation of the evolution of performance at the municipality level in the period 2009–2021 and finalises with an overview of each indicator’s contribution to the final result achieved by each municipality.

3.6.1 Robust composite indicator’ results

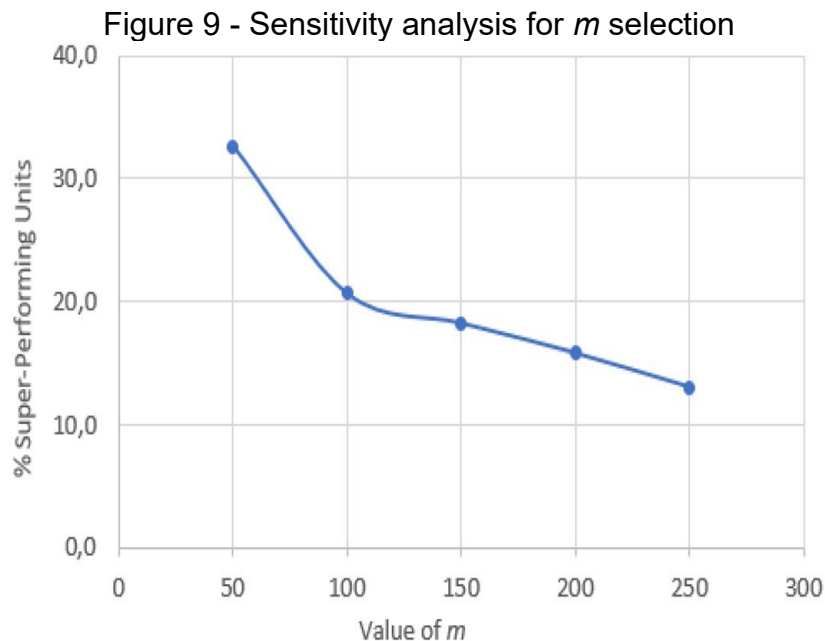
This subsection discusses the findings associated with the estimation of the robust BoD composite indicator, which reveal the relative position of municipalities regarding their performance in each of the four years analysed.

As the composite indicator considered both desirable and undesirable outputs, a Directional BoD model was computed adopting the formulation presented in (1). Regarding the weight restrictions shown in (2), different values of ϕ_r and ϕ_k ranging from 1% to 5% were tested, and the results remained stable.

After running this sensitivity analysis, the value of 1% was chosen since it is the option that allows greater flexibility for analysis, allowing more accurate detection of weaknesses, and, simultaneously, preventing assessments that could disregard certain indicators by assigning them weights equal to zero (Vilarinho *et al.*, 2023a). For all indicators, the values of ϕ_r and ϕ_k were set for the same value of 1%. This approach avoids pre-assigning any relative importance and allows differences in importance to emerge naturally from the optimization process.

For the robust composite indicator, the values of the parameters m and B must be determined. B is often a high number, and for this study, the value of 2,000 was employed for B . Daraio and Simar (2007) explain that there are no fixed rules to select the value of m . Following those authors, a sensitivity analysis using several levels of m and evaluating the number of super-performing units for 2021 was performed to decide the value of bootstrapping sample size m .

Figure 9 shows the graph with the resulting percentage of “super-performing” DMUs in the robust composite indicator computations for several values of m . These findings led to the choice of $m=150$. At this value, the proportion of “super-performing” units reduces, whereas it remains relatively stable at higher values. The same value of m was used for the four years analysed. The results were obtained using packages *Rglpk* (Hornik *et al.*, 2012) and *lpSolve* (Berkelaar, 2015) in R software.



Source: the author

Table 4 shows the average performance results and statistics of all municipalities in the sample. Best and worst ranked municipalities are shown in Table 5. Appendix 8 shows the composite indicator results for all DMUs and all years analysed.

Table 4 - Average performance results and statistics

Year	2009	2013	2017	2021
Average C/I^t	0.801	0.830	0.869	0.872
Std. dev	0.111	0.111	0.094	0.105
Minimum	0.524	0.597	0.570	0.549
Maximum	1.151	1.235	1.185	1.257

Source: the author

Looking at the results in Table 4 it can be seen that the average score increased progressively from 2009 to 2021, indicating a greater proximity of DMUs to the best-practice frontier and convergence within the WSS sector. However, despite the progress evidenced by the results, the average values of the composite indicator (below 90%) denote the existence of potential for improvement. Furthermore, the frontier is only spanned by 12% of the municipalities in 2009, 13% in 2013, 17% in 2017 and, 18% in 2021.

The ranks shown in Table 5 mean that, based on the data available, these municipalities represent the best and worst observed performance in the period considered. The composite indicator scores C/I^t reveal that there is a significant difference in performance between the best and worst-ranked municipalities. This reflects the great challenges of advancing in basic sanitation, since it encompasses municipalities with characteristics that are very different from each other. The goals of WSS sector in Santa Catarina can be reached more easily if the peculiarities of each region and each municipality in the state are considered in the decision-making process.

Balneário Camboriú ranked twice in the first place of the composite indicator ranking, in 2009 and 2017. In 2013 it ranked 7th (1,122) and in 2021 in 17th position (1,056). Balneário Camboriú is 12th most populous municipality in Santa Catarina, with a total population of more than 139 thousand inhabitants (IBGE, 2022). The city also stands out for its human development index (HDI), which was 2nd in Santa Catarina (0.845) and 4th in Brazil, according to the latest available data from 2010 (IBGE, 2023). In relation to WSS indicators, Balneário Camboriú performed better than the average of other municipalities in Santa Catarina in almost all variables. The only exceptions were the financial performance in 2021 (88.51%), electricity expenses in 2013 (0.82 R\$/kWh) and staff productivity. In this last indicator, Balneário Camboriú results were lower than the average in the four years analyzed. However, urbanism in Balneário Camboriú is characterized by being extremely verticalized, which can influence the

results of staff productivity, that is expressed in connections and not in dwelling or apartments (Spode *et al.*, 2021). WSS services in Balneário Camboriú are provided by a municipal company, Empresa Municipal de água e Saneamento (EMASA).

Porto União secured a position among the top five in the composite indicator ranking twice, specifically in 2009 and 2013. It ranked 19th in 2017 (1,027) and 51st in 2021 (1,006). Porto União is located in the north of Santa Catarina, bordering the state of Paraná. Given its border characteristic, there is collaboration between the states for the provision of WSS services in Porto União. The state company of Paraná (SANEPAR) is responsible for serving approximately 97% of the population, representing around 32,000 inhabitants (IBGE, 2022). The state company of Santa Catarina (CASAN) is responsible for services in just one location in Porto União, called Santa Cruz do Timbó, serving around 900 inhabitants of this municipality. Individual analysis of descriptive statistics shows that Porto União had better performance than the other municipalities in almost all variables, with the exception of water loss index (IN050), whose values were slightly higher than the average in all years analyzed.

Table 5 - Composite indicator (C/I) results for top 5 in the ranking and bottom 5 municipalities in the ranking

2009			2013			2017			2021		
Munic. (j)	C/I	Rank	Munic. (j)	C/I	Rank	Munic. (j)	C/I	Rank	Munic. (j)	C/I	Rank
Balneário Camboriú	1.151	1	Bandeirante	1.235	1	Balneário Camboriú	1.185	1	Sul Brasil	1.257	1
Porto União	1.148	2	Ibiam	1.229	2	Bom Jardim da Serra	1.170	2	Rio Rufino	1.213	2
Angelina	1.141	3	União do Oeste	1.151	3	Zortéa	1.158	3	Tijucas	1.163	3
Camboriú	1.101	4	Urussanga	1.127	4	Pedras Grandes	1.122	4	Paraíso	1.162	4
São Ludgero	1.093	5	Porto União	1.126	5	Vargem	1.094	5	Santa Helena	1.150	5
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Major Gercino	0.564	269	Painel	0.617	279	Santa Rosa de Lima	0.636	280	Irati	0.592	287
União do Oeste	0.562	270	Frei Rogério	0.614	280	Santa Terezinha do Progresso	0.614	281	Presidente Nereu	0.590	288
Papanduva	0.545	271	Ouro Verde	0.610	281	Presidente Nereu	0.614	282	Major Gercino	0.582	289
Rio Rufino	0.531	272	São José do Cerrito	0.605	282	Alto Bela Vista	0.605	282	Serra Alta	0.573	290
Nova Itaberaba	0.524	273	Presidente Castello Branco	0.597	283	Arvoredo	0.570	284	Imaruí	0.549	291

Source: the author

Staff productivity (IN102) consistently presented zero values throughout all years. This is likely due to the fact that Porto União does not have employees stationed locally, but rather in União da Vitória, a city in Paraná, with which its WSS services are integrated. Porto União is also a municipality that stands out for its HDI (0.786), ranking 21st in Santa Catarina and 87th in Brazil (IBGE, 2023).

The lower rank position of the classification of Balneário Camboriú and Porto União tends to be a consequence of the evolution of the performance of other DMUs, since the two municipalities remained super-performing in all years analyzed.

On the opposite side of the table, the municipality of Major Gercino appears twice among the bottom five positions in the composite indicator ranking, in 2009 and 2021. In 2013, it ranked 240th (CI=0.699) and, in 2017, 277th (CI=0.664). Major Gercino is a small town, with 3,214 inhabitants (IBGE, 2022). Its HDI is 0.698 (237th in Santa Catarina and 1969th in Brazil) (IBGE, 2023). This municipality's best performance occurs in water system interruptions index (IN071-A), with no interruptions being reported in 2013, 2017 and 2021. Universalization of WSS services is still a distant goal from being achieved in Major Gercino, considering the SNIS data criteria, as discussed in Sect. 3.3. The sewage treatment referred to the water consumed (IN046) was equal to zero and the water supply coverage was 35.38%, in 2021. WSS services are provided by the state company of Santa Catarina, CASAN.

The municipality of Presidente Nereu was also twice positioned among the lowest ranking in the composite indicator assessment, ranking 282nd in 2017 and 288th in 2021. In the earlier assessments, it secured the 194th position in 2009 (with a score of 0.728) and the 270th position in 2013 (with a score of 0.641). Presidente Nereu is another small city in Santa Catarina (2,301 inhabitants), with an average HDI (0.737) whose services are provided by CASAN (IBGE (2022) and IBGE (2023)), and for which WSS universalization is also far from being achieved. Presidente Nereu's sewage treatment referred to the water consumed (IN046) was equal to zero and its water supply coverage (IN055) was 43.09%, in 2021. A positive aspect about this municipality's performance is that no water supply interruption, indicated by IN071-A, was reported in the years analyzed.

The municipalities of União do Oeste and Rio Rufino exhibit a very peculiar pattern in the composite indicator ranking, advancing many positions from one period to the next. In 2009 União do Oeste was among the lowest ranked, but in 2013 it had advanced to the 3rd position. In 2017, the municipality ranked 50th (with a score of

1,000) and, in 2021, it held the 49th position (with a score of 1,009). In 2009 the indicators IN012 (financial performance) and IN102 (staff productivity) of União do Oeste were replaced according to the procedures detailed in subsection 3.5.2. In the following years there was no need to replace information, indicating an improvement in data management and the consequent evolution of the municipality's position in the ranking. União do Oeste is also a small city in Santa Catarina with 2,774 inhabitants and an average HDI (0.705), with services provided by CASAN (IBGE (2022) and IBGE (2023)). While sewage treatment (IN046) and water supply coverage (IN055) were also identified as this municipality's weak points, there was a significant increase in water coverage between 2017 and 2021, with the index rising from 59.08% to 73.69%.

Rio Rufino was in the lowest positions in 2009 and advanced to the 2nd in 2021. In 2009, IN012 (financial performance) and IN102 (staff productivity) were missing and needed to be replaced. In 2013, the municipality did not provide data for SNIS. In 2017 Rio Rufino ranked 252nd (with a score of 0.743). The large variation in positions in the composite indicator rankings and the absence of valid data in 2013 do not allow to conclude if the evolution in the ranking is the result of real advances in the provision of services or a reflection of inefficiency in data management. It is important to note that SNIS data collection is self-declaratory. Rio Rufino has only 2,397 inhabitants and its HDI is one of the lowest in Santa Catarina (IBGE (2022) and IBGE (2023)). This municipality presented a composite indicator score of 0.653. Sewage treatment related to consumed water (IN046) and water supply coverage (IN055) showed up also as weaknesses in this municipality, reaching 0.0% and 50.4% in 2021, respectively. Water system outages also pose a challenge for this municipality, reaching 25% in 2021. However, a positive aspect is its financial performance in 2017 and 2021, which were quite superior the state average at 141.78% and 122.3%, respectively. The responsibility of WSS services lie with a local provider under public law, Serviço Autônomo de Saneamento Básico (SASB).

3.6.2 Results of the global Malmquist index and its components

The results of the global Malmquist index (GMI) provide an overview of the evolution of water supply and sewerage services in Santa Catarina's municipalities for the period 2009–2021. Table 6 shows the average results for GMI and its components, efficiency change (EC) and best practice change (BPC).

Table 6 - Average results for the global Malmquist index, efficiency change and best practice change

Period	2009/2021	2009/2013	2013/2017	2017/2021
GMI	0.967	0.996	0.957	1.017
EC	1.083	1.030	1.049	1.006
BPC	0.893	0.967	0.912	1.011

Source: the author

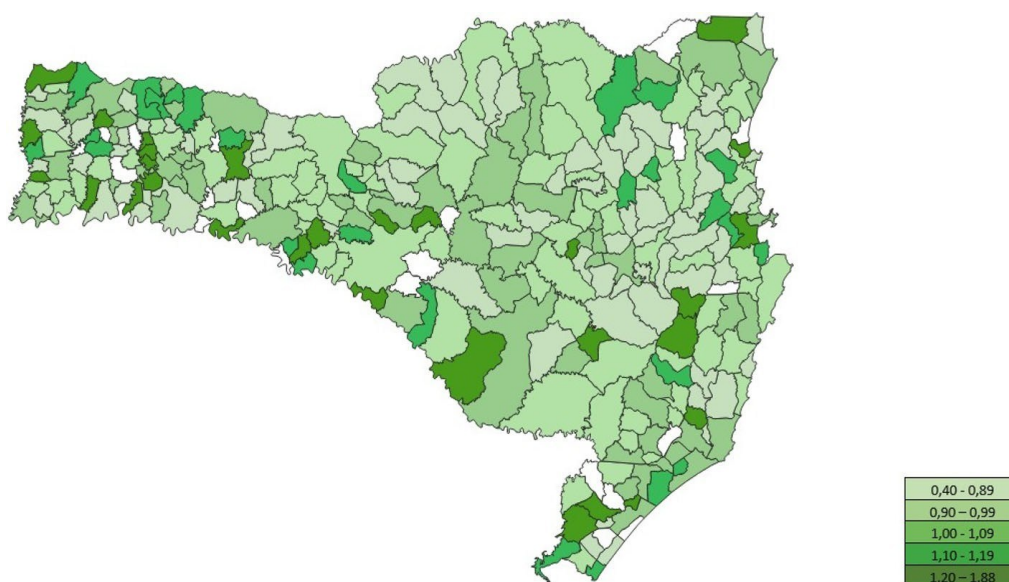
The average score of the global Malmquist index (GMI) is equal to 0.967, and reveals a performance loss of approximately 3% between 2009 and 2021. This result is mostly attributable to a decline of the performance frontier, reflected by BPC lower than one. As the performance frontier decreased, the DMUs' average distance to the frontier reduced, reflected by EC higher than one (1.083). As shown in Table 6, BPC and EC tend to have opposite trends, except in the period 2017–2021, where EC, BPC and GMI values were very close to one, indicating a scenario of stability.

This result aligns with the conclusions revealed by Tourinho *et al.* (2023) regarding productivity change in Brazilian water services from 2012 to 2019, as exposed in Sect. 3.2. The authors hypothesized that the unusual pattern of the best-practices trend could be attributed to the period of macroeconomic instability experienced by Brazil from 2011 onwards. The results of this study corroborate the authors' findings. The period from 2013 to 2017 corresponds to the lowest GMI observed in Santa Catarina. Coincidentally, it was during this period that the financial performance index retracted around 10% (see Sect. 3.5.1). Electricity expenses also increased by almost 90% in this period, significantly impacting the sector.

Moreover the profound legal changes that occurred in Brazil in a short period of time (see Sect. 3.3), may have contributed to a scenario of instability in the WSS. Firstly, these changes required many adaptations (organizational, technical, operational, among others) by providers to comply with new legal and regulatory requirements. Additionally, the scarcity of financial resources from 2011 onwards meant that investments for expanding and improving water supply and sewerage were insufficient to meet the goals of universalization and quality. After that, discussions to update Law No 11,445/2007, which lasted more than two years, caused many debates and generated a climate of uncertainty and insecurity in the sector. The stability indicated by the GMI from 2017 to 2021 may be an evidence that the two previous periods, 2009–2013 and 2013–2017, will be known in the future as a transition phase, something that can be investigated in future studies.

Figure 10 shows the spatial distribution of GMI in Santa Catarina. The map reveals that there is no GMI performance standard in the state. Moreover, no concentration of municipalities with high or low performance in a specific region exists.

Figure 10 - GMI of Santa Catarina's municipalities from 2009 to 2021



Source: the author

According to the GMI results of all DMUs, presented in Appendix 8, over 50% of the municipalities have a GMI values below one, reinforcing the downward trend in performance that occurred in this period.

Table 7 shows the evolution of performance achievements of best and worst ranked municipalities.

Rio Rufino was the municipality with the greatest performance improvement from 2009 to 2021, with a magnitude of performance change of 109%. This behavior is aligned with Rio Rufino composite indicator results and the respective conclusions, as discussed in Subsection 3.6.1.

Anitápolis also had a notable evolution of performance, superior to 88%. Anitápolis is a small municipality, with about 3,600 inhabitants (IBGE, 2022) and HDI equals 0.674 (IBGE, 2023). WSS services in Anitápolis are responsibility of an autarchy, the Departamento de Água e Esgoto (DAE). One of the highlights in the evolution of Anitápolis is the IN102 (related to staff productivity). The municipality evolved more than 250% in this regard.

Table 7 - Evolution of performance achievements of the five best and five worst Santa Catarina's municipalities in the period 2009/2021

Municipality	2009/2021				2009/2013	2013/2017	2017/2021
	GMI	EC	BPC	Rank	GMI	GMI	GMI
Rio Rufino	2.093	2.287	0.915	1	—	—	1.603
Anitápolis	1.876	1.895	0.990	2	1.304	1.269	1.134
Ibiam	1.775	1.777	0.999	3	2.064	0.572	1.504
União do Oeste	1.577	1.796	0.878	4	2.065	0.700	1.091
Rancho Queimado	1.536	1.465	1.049	5	1.598	1.063	0.904
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Entre Rios	0.551	0.714	0.771	268	—	—	0.903
Ermo	0.547	0.641	0.854	269	0.733	0.759	0.983
Botuverá	0.537	0.757	0.709	270	0.596	0.893	1.009
Serra Alta	0.505	0.538	0.940	271	0.993	0.832	0.612
Imaruí	0.458	0.503	0.909	272	0.763	0.738	0.813

Source: the author

On the opposite side of the table lies the municipality of Imaruí. This city has approximately 12.000 inhabitants (IBGE, 2022) and HDI of 0.667 (IBGE, 2023). The water supply and sewerage are managed by the direct public administration of Imaruí. The municipality also appears to have problems in data management as IN060 (related to energy expenses) needed to be replaced in all years analyzed. IN012 (related to financial performance) was just not replaced in 2017. The sewage treatment (IN046) and water supply coverage (IN055) are weaknesses in Imaruí's WSS, with values of 0% and 32.77% in 2021, respectively. The positive aspect of the Imaruí WSS is IN084 (related to water quality) as none of the water samples showed the presence of Total Coliform.

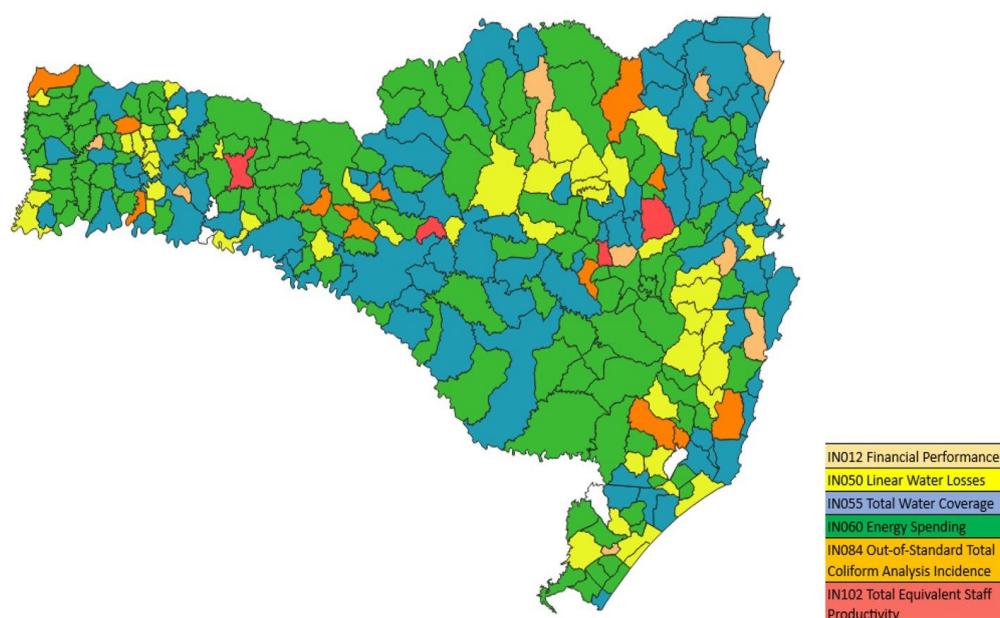
A direct comparison at the municipal level with the findings from the study by Tourinho et al. (2023) reveals that Balneário Camboriú exhibited similar results in both studies, with a marginal difference of just 1.5%. In contrast, the difference in the results of Blumenau, Chapecó, Concórdia and Florianópolis exceeded 20%. Additionally, despite securing the best GMI in Tourinho *et al.* (2023) with a score of 1.10, São Bento do Sul only ranked 88th in this study, attaining a score of 1.024.

3.6.3 Strengths and weaknesses analysis

The determination of the relative importance of each variable to the performance of each DMU, based on the analysis of the AR-I weight restrictions, was

carried out in this study to identify the strengths and weaknesses of each municipality. Figure 11 shows the spatial distribution of strengths in Santa Catarina in 2021.

Figure 11 - Strengths of Santa Catarina's municipalities in 2021

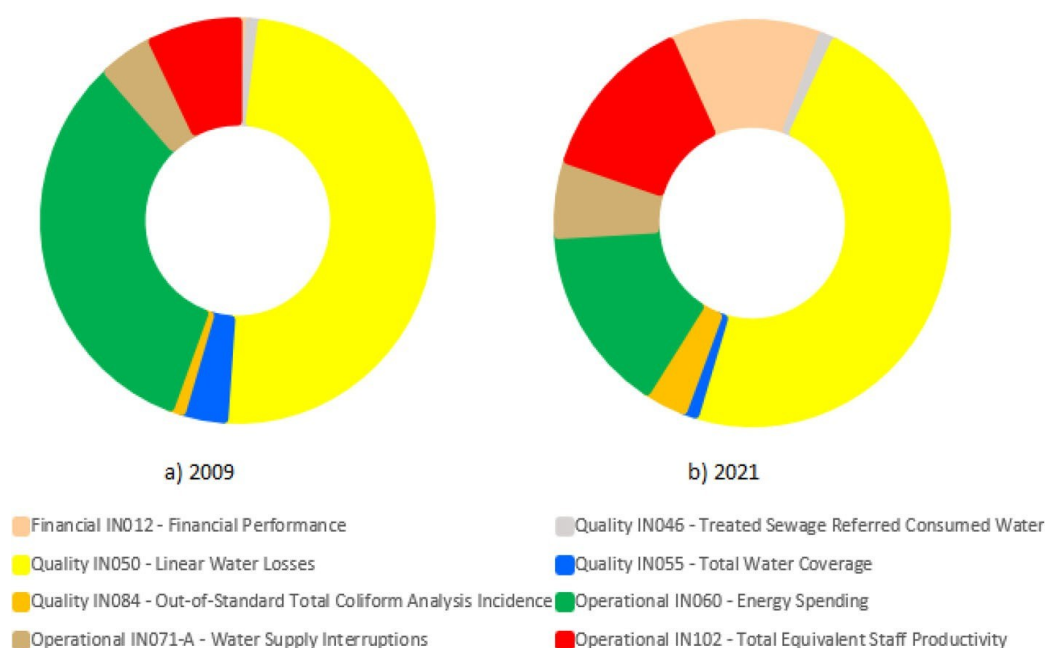


Source: the author

Through the map it is possible to note that total water coverage (IN055) and energy spending (IN060) are the main strengths of the state. The water coverage was the main strength in some of the largest municipalities, such as Blumenau, Chapecó, Criciúma, Florianópolis, Jaraguá do Sul, Joinville and Lages. In the opposite direction, the variables treated sewage referred to consumed water (IN046) and water supply interruptions (IN071-A) were not identified as the main strength by any municipality.

As an example, the case of Anitápolis, the second municipality that improved performance the most over time, will be presented. Figure 12 shows the contribution of each variable to Anitápolis performance in years 2009 and 2021.

Figure 12 - Contribution of each variable from the municipality of Anitápolis



Source: the author

It is evident from Fig. 4 that in 2009 the quality dimension was the most relevant for the municipality, followed closely by the operational dimension. In terms of quality, IN050 (related to water losses) was Anitápolis greatest strength, representing around 50% of the relative contributions of all indicators. In the operational aspect, IN060 (related to electricity expenses) was its greatest strength, despite the metric value was replaced from missing instances. The financial performance index (IN012) also was replaced from missing instances and contributed just 1%, resulting from the calculation of the left-hand side of the weight restriction, as shown in Subsection 3.6.1.

In 2021, IN060 continued to be the second largest strength, but with a smaller contribution than that observed in 2009. Water losses represented the main strength of Anitápolis both in 2009 and 2021. The fact that the two main strengths are undesired variables indicates that the municipality may be adopting effective actions to reduce energy consumption and to mitigate water losses, becoming a benchmark for other municipalities with similar characteristics that need to evolve in these indicators.

According to Table 8 the water losses for Anitápolis in 2021 were higher than in 2009, but even so it remained to be a positive aspect of this municipality, since its value is about nine times lower than the state average.

Table 8 - Performance and relative importance (RI) of the metrics in the assessment of Anitápolis

Code	Variable description	2009		2013		2017		2021	
		Value	RI (%)	Value	RI (%)	Value	RI (%)	Value	RI (%)
IN012	Financial performance (%)	0.00*	1.00	0.02	1.00	139.59	22.62	189.24	12.79
IN046	Treated sewage referred consumed water (%)	0.00	1.00	0.00	1.00	0.00	1.15	0.00	1.17
IN050	Linear water losses (m ³ /day/Km)	1.24	49.13	4.94	17.41	2.40	39.39	1.66	47.71
IN055	Total water coverage (%)	37.15	3.53	41.58	8.83	47.08	1.02	50.57	1.03
IN060	Energy spending (R\$/kWh)	0.98*	32.75	0.20	51.09	0.57	14.62	0.51	14.97
IN071-A	Water supply interruptions (%)	0.00	4.36	0.00	4.16	18.70	2.14	9.35	6.05
IN084	Out-of-standard total coliform analysis incidence (%)	100.00	1.00	100.00	1.00	2.50	3.32	1.11	3.36
IN102	Total equivalent staff Productivity (connection/employee)	140.00	7.23	417.71	15.51	480.12	15.74	507.84	12.92

Source: the author

*Replaced data from missing instances.

The analysis of the relative importance of the indicators in Table 8 also allows to point out that the variables related to the universalization of services (IN046 and IN055) constitute the main challenges of the municipality's WSS.

The integrated evaluation of the results of the BoD, GMI and virtual weights of Anitápolis reaffirms the progressive evolution of the municipality's performance.

3.7 CONCLUSIONS

This study assesses the evolution of performance in municipalities of Santa Catarina State in Southern Brazil for the provision of water supply and sewage services. The BoD technique is used to synthesize eight metrics that reflect the financial, operational, and quality dimensions of WSS into a composite indicator.

The framework adopted is organised in three stages. The first stage used a robust directional BoD model to overcome the limitation related to sensitivity to extreme values that can bias the results from basic DEA applications. The eight indicators to be aggregated reflect desired and undesired aspects of the WSS requiring the use of a directional distance functions in the BoD computation.

The second stage involved the estimation of the global Malmquist index (GMI) and its components, efficiency change (EC) and best practice change (BPC). This allowed the assessment of performance change over time and determining whether the performance changes were related to the general development of the sector in terms of the maximum performance levels observed at the frontier or to the convergence of the municipalities under analysis towards the frontier.

The third stage was the identification of the strengths and weaknesses of each municipalities via the analysis of the values of the virtual weight restrictions at the optimal solution to the Directional BoD linear programming model.

The unprecedented integrated application of these three methods in WSS analysis provides a holistic picture of the sector, starting with a state-level overview and reaching specific results by municipalities. Consequently, factual guidelines to increase performance and achieve goals may be pursued.

The study's findings shows the existence of significant room for improvement in Santa Catarina's WSS. Several municipalities did not reach the intended performance levels, corresponding to the best practices observed in peers. Urgent changes are necessary so that the universalization and quality goals imposed by Brazilian Law no. 14,026/2020 are met. The same applies to the sustainable development goals established by the United Nations.

Subsequent studies could use the most recent data to continue evaluating performance and to check whether the stability of the 2017–2021 period characterizes a transition phase for effective advances in the sector. Contextual variables can also be used to evaluate the effects of exogenous factors on the results.

The main limitations of the study are based on the available data set. Even though the data is provided by an official source, the information collected is self-declared by providers, which in some specific cases may compromise the reliability.

In conclusion, the approach proposed in this study to assess the evolution of performance constitutes a relevant diagnostic and prognosis tool for WSS, contributing to a better understanding and proposition of assertive measures for the sector to comply with legal and regulatory requirements and provide the population with high-quality services.

APPENDIX: COMPOSITE INDICATOR AND GMI RESULTS FOR ALL YEARS ANALYZED

(continues)

Municipality	BoD				2009/2021	EC	BPC	Rank	GMI		
	2009	2013	2017	2021					2009/2013	2013/2017	2017/2021
Abdon Batista	–	0.843	0.895	0.912	–	–	–	–	–	1.077	1.077
Abelardo Luz	0.688	0.779	0.871	0.813	1.052	1.181	0.891	73	1.123	0.946	0.991
Agrolândia	0.938	0.809	0.810	0.893	0.862	0.952	0.905	219	0.835	0.964	1.071
Agronômica	0.997	0.815	0.841	1.082	1.018	1.085	0.939	93	0.773	0.860	1.533
Água Doce	0.720	0.718	0.814	0.816	0.938	1.133	0.828	164	1.037	0.922	0.981
Águas de Chapecó	0.602	1.085	1.048	1.018	1.469	1.689	0.870	10	1.721	0.906	0.942
Águas Frias	0.715	0.805	0.918	1.021	1.237	1.429	0.865	27	1.162	1.022	1.041
Águas Mornas	1.003	1.022	0.999	1.015	0.898	1.011	0.888	191	0.947	0.877	1.081
Alfredo Wagner	0.990	0.707	1.012	0.768	0.626	0.776	0.807	265	0.696	1.413	0.636
Alto Bela Vista	–	–	0.605	0.970	–	–	–	–	–	–	1.589
Anchieta	0.746	0.718	0.876	0.812	1.014	1.089	0.931	101	1.035	0.963	1.018
Angelina	1.141	0.723	0.656	0.630	0.654	0.552	1.184	262	0.815	0.802	1.000
Anita Garibaldi	0.714	0.778	0.767	0.845	1.005	1.184	0.849	111	0.969	0.898	1.155
Anitápolis	0.568	0.701	1.022	1.075	1.876	1.895	0.990	2	1.304	1.269	1.134
Antônio Carlos	1.042	0.739	0.759	0.839	0.744	0.806	0.923	246	0.712	0.920	1.135
Apiúna	1.035	0.868	0.871	0.874	0.777	0.844	0.921	239	0.830	0.888	1.055
Arabutã	–	1.123	0.924	0.787	–	–	–	–	–	0.732	0.845
Araquari	0.801	0.686	0.737	0.853	0.966	1.064	0.908	142	0.774	0.995	1.255
Araranguá	0.906	1.046	1.003	1.074	1.051	1.185	0.887	75	1.137	0.850	1.088
Armazém	0.806	0.727	0.790	0.817	0.758	1.014	0.747	242	0.824	0.943	0.976
Arroio Trinta	1.050	1.063	0.875	0.958	0.916	0.912	1.004	178	1.050	0.767	1.137
Arvoredo	–	–	0.570	–	–	–	–	–	–	–	–
Ascurra	0.938	0.957	0.979	1.035	0.964	1.104	0.873	143	0.995	0.974	0.995

Appendix: Composite Indicator and GMI results for all years analyzed

(continuation)

Municipality	BoD				2009/2021	EC	BPC	Rank	GMI		
	2009	2013	2017	2021					2009/2013	2013/2017	2017/2021
Atalanta	0.686	0.749	0.860	0.809	1.052	1.180	0.891	74	1.145	0.978	0.939
Aurora	1.084	0.898	0.950	0.994	0.815	0.917	0.889	227	0.816	0.886	1.128
Balneário Arroio do Silva	–	0.964	1.001	1.052	–	–	–	–	–	0.984	1.085
Balneário Barra do Sul	0.857	0.900	0.950	0.948	1.012	1.107	0.914	104	0.980	1.019	1.014
Balneário Camboriú	1.151	1.122	1.185	1.056	0.873	0.917	0.952	211	0.924	1.063	0.889
Balneário Gaivota	0.796	0.929	0.709	0.752	0.798	0.946	0.844	234	1.015	0.693	1.135
Balneário Piçarras	0.742	0.904	0.952	0.974	1.267	1.313	0.965	25	1.193	1.017	1.045
Balneário Rincão	–	0.880	0.984	1.049	–	–	–	–	–	1.125	1.059
Bandeirante	0.569	1.235	1.017	0.810	1.191	1.423	0.837	31	2.085	0.675	0.846
Barra Bonita	0.732	0.682	0.744	0.711	0.712	0.970	0.733	253	0.841	0.879	0.962
Barra Velha	–	0.977	1.000	0.972	–	–	–	–	–	0.998	0.982
Bela Vista do Toldo	0.818	0.766	0.779	0.919	0.801	1.123	0.713	233	0.793	0.885	1.142
Belmonte	0.960	1.003	0.855	0.632	0.587	0.658	0.892	267	1.005	0.690	0.847
Benedito Novo	0.910	0.659	0.780	0.931	0.786	1.023	0.768	236	0.715	0.987	1.115
Biguaçu	1.017	0.956	0.949	0.957	0.901	0.941	0.957	190	0.893	0.997	1.012
Blumenau	0.915	0.958	0.939	0.897	0.992	0.980	1.011	123	1.018	0.974	1.000
Bocaina do Sul	0.706	0.675	0.768	0.779	0.929	1.105	0.841	169	0.980	0.950	0.998
Bom Jardim da Serra	0.648	0.661	1.170	0.756	0.954	1.167	0.817	153	1.027	1.576	0.589
Bom Jesus do Oeste	0.691	0.630	0.850	0.870	1.021	1.260	0.810	91	0.914	1.155	0.967
Bom Jesus	–	1.012	0.896	1.003	–	–	–	–	–	0.738	1.085
Bom Retiro	0.804	0.817	0.824	0.802	0.875	0.997	0.878	210	0.956	0.896	1.021
Bombinhas	0.890	0.964	1.011	0.956	1.051	1.073	0.979	76	1.056	1.024	0.973

Appendix: Composite Indicator and GMI results for all years analyzed

(continuation)

Municipality	BoD				2009/2021	EC	BPC	Rank	GMI		
	2009	2013	2017	2021					2009/2013	2013/2017	2017/2021
Botuverá	1.030	0.633	0.678	0.780	0.537	0.757	0.709	270	0.596	0.893	1.009
Braço do Norte	0.772	0.776	0.845	0.921	0.986	1.194	0.826	126	0.957	0.896	1.150
Braço do Trombudo	0.650	0.981	1.040	0.875	1.299	1.346	0.965	20	1.312	1.133	0.874
Brunópolis	0.918	0.932	0.901	0.932	0.961	1.015	0.946	148	0.964	0.977	1.020
Brusque	0.763	0.939	0.946	0.959	1.152	1.257	0.916	43	1.167	0.976	1.011
Caçador	0.822	0.848	0.908	0.855	0.957	1.040	0.920	150	0.957	1.027	0.973
Caibi	0.638	0.692	0.775	1.037	1.370	1.625	0.843	16	1.119	0.955	1.282
Calmon	0.830	0.931	0.955	0.768	0.809	0.926	0.874	230	1.053	0.892	0.862
Camboriú	1.101	0.899	0.929	0.906	0.760	0.823	0.923	241	0.762	1.029	0.969
Campo Alegre	–	0.942	0.992	0.900	–	–	–	–	–	1.035	0.956
Campo Belo do Sul	0.782	0.771	0.809	0.834	0.936	1.067	0.877	165	0.884	0.995	1.064
Campo Erê	0.869	0.894	0.984	0.953	1.033	1.096	0.942	83	1.029	1.013	0.991
Campos Novos	1.036	1.003	1.016	1.012	0.974	0.976	0.998	136	0.979	0.988	1.007
Canelinha	0.595	0.778	0.777	0.747	1.131	1.254	0.902	47	1.230	0.970	0.948
Canoinhas	1.010	0.862	0.915	0.938	0.897	0.928	0.967	193	0.842	1.001	1.064
Capão Alto	0.726	0.853	1.017	1.139	1.404	1.567	0.896	11	1.143	1.161	1.058
Capinzal	0.856	0.873	0.982	0.980	0.967	1.145	0.845	141	0.934	1.076	0.962
Capivari de Baixo	0.959	–	0.959	0.856	0.868	0.892	0.972	215	–	–	0.939
Catanduvas	1.014	0.984	1.009	1.016	0.987	1.002	0.986	125	0.997	0.980	1.011
Caxambu do Sul	0.792	0.723	0.771	0.794	0.887	1.002	0.885	203	0.850	0.941	1.109
Celso Ramos	0.624	0.661	0.760	0.925	1.257	1.483	0.848	26	1.090	0.959	1.203
Cerro Negro	0.664	0.914	1.011	0.841	1.183	1.267	0.934	34	1.573	0.861	0.873

Appendix: Composite Indicator and GMI results for all years analyzed
(continuation)

Municipality	BoD				GMI						
	2009	2013	2017	2021	2009/2021	EC	BPC	Rank	2009/2013	2013/2017	2017/2021
Chapadão do Lageado	0.817	0.698	0.834	0.794	0.657	0.972	0.676	260	0.728	0.951	0.949
Chapecó	1.084	0.948	1.005	0.959	0.858	0.884	0.971	220	0.811	1.053	1.005
Cocal do Sul	0.954	1.034	1.039	0.996	0.913	1.044	0.874	182	1.000	0.955	0.955
Concórdia	0.831	0.893	0.935	0.929	1.014	1.119	0.906	100	0.954	1.031	1.031
Cordilheira Alta	0.815	0.762	0.856	0.859	1.035	1.054	0.982	79	0.957	1.109	0.975
Coronel Freitas	0.718	0.939	0.799	0.769	1.011	1.070	0.945	106	1.263	0.757	1.057
Coronel Martins	0.801	0.730	0.861	0.970	1.034	1.211	0.854	82	0.960	0.976	1.104
Correia Pinto	0.839	0.931	0.979	0.931	1.015	1.109	0.915	99	1.041	1.028	0.948
Corupá	0.757	0.845	0.816	0.931	1.159	1.231	0.942	40	1.049	0.945	1.169
Criciúma	0.904	0.985	0.987	0.981	1.013	1.084	0.934	103	1.026	0.982	1.005
Cunha Porã	0.682	0.717	0.763	0.725	0.968	1.063	0.911	140	1.039	0.920	1.013
Cunhataí	0.738	0.849	0.855	0.872	1.076	1.181	0.911	64	1.345	0.794	1.008
Curitibanos	0.833	0.823	0.899	0.985	1.068	1.183	0.903	68	0.913	1.070	1.093
Descanso	0.672	0.621	0.717	0.727	1.000	1.081	0.925	115	0.981	0.934	1.091
Dionísio Cerqueira	0.747	0.773	0.954	1.063	1.386	1.424	0.973	15	1.029	1.063	1.266
Dona Emma	0.897	0.669	0.833	0.868	0.699	0.968	0.722	254	0.665	1.070	0.983
Doutor Pedrinho	0.796	0.741	0.764	0.779	0.793	0.979	0.810	235	0.883	0.909	0.988
Entre Rios	0.974	–	0.709	0.695	0.551	0.714	0.771	268	–	–	0.903
Ermo	1.015	0.801	0.728	0.650	0.547	0.641	0.854	269	0.733	0.759	0.983
Erval Velho	0.822	0.848	0.855	1.014	1.185	1.234	0.960	33	1.016	0.935	1.248
Faxinal dos Guedes	0.708	1.085	0.848	1.080	1.528	1.525	1.002	6	1.542	0.738	1.343
Flor do Sertão	–	0.885	0.834	1.062	–	–	–	–	–	0.803	1.155
Florianópolis	1.033	1.003	1.003	0.978	0.923	0.947	0.975	174	0.937	0.979	1.007
Formosa do Sul	0.714	0.662	0.814	0.733	0.896	1.027	0.872	196	0.938	1.035	0.923
Forquilha	0.924	0.989	1.001	1.047	1.034	1.133	0.913	81	0.995	0.995	1.045
Fraiburgo	0.774	0.790	0.942	0.803	1.004	1.037	0.968	112	1.003	1.030	0.972

Appendix: Composite Indicator and GMI results for all years analyzed
(continuation)

Municipality	BoD				2009/2021	EC	BPC	Rank	GMI		
	2009	2013	2017	2021					2009/2013	2013/2017	2017/2021
Frei Rogério	–	0.614	–	0.909	–	–	–	–	–	–	–
Galvão	0.709	0.707	0.776	0.925	1.195	1.304	0.916	30	0.967	1.034	1.195
Garopaba	1.063	0.908	0.925	0.942	0.865	0.887	0.976	218	0.841	1.000	1.028
Garuva	0.599	–	0.990	0.905	1.321	1.511	0.874	18	–	–	0.889
Gaspar	0.895	0.912	0.892	0.818	0.893	0.913	0.978	198	0.967	0.954	0.968
Governador Celso Ramos	0.817	0.820	0.868	0.919	1.134	1.125	1.008	45	1.024	1.036	1.069
Grão Pará	0.705	0.907	0.881	1.094	1.072	1.552	0.691	66	1.083	0.922	1.073
Gravatal	0.777	0.860	–	0.980	1.208	1.261	0.958	29	1.063	–	–
Guabiruba	0.819	0.723	0.780	0.779	0.836	0.951	0.879	226	0.909	0.894	1.028
Guaraciaba	0.799	0.832	0.895	0.831	0.866	1.040	0.832	217	1.054	0.904	0.908
Guaramirim	0.898	0.839	1.012	0.893	0.869	0.994	0.874	214	0.827	1.204	0.873
Guarujá do Sul	0.769	0.801	0.830	0.848	0.982	1.103	0.891	129	1.052	0.917	1.019
Guatambú	1.033	1.017	1.058	1.131	1.010	1.094	0.923	108	0.932	1.003	1.081
Herval D Oeste	0.958	0.984	1.004	1.008	1.014	1.052	0.964	102	0.988	1.017	1.009
Ibiam	0.570	1.229	0.921	1.012	1.775	1.777	0.999	3	2.064	0.572	1.504
Ibicaré	0.774	0.922	0.773	0.761	0.928	0.983	0.944	171	1.210	0.742	1.034
Ibirama	0.805	0.892	0.980	0.974	1.110	1.209	0.918	51	1.032	1.091	0.985
Içara	0.830	0.927	1.045	0.984	1.162	1.185	0.981	39	1.043	1.165	0.957
Ilhota	0.841	0.710	0.984	0.943	1.173	1.121	1.046	36	0.880	1.275	1.046
Imaruí	1.091	0.938	0.707	0.549	0.458	0.503	0.909	272	0.763	0.738	0.813
Imbituba	0.900	0.989	0.911	0.931	0.968	1.034	0.936	138	1.039	0.921	1.012
Imbuia	0.725	0.694	0.786	0.740	0.850	1.021	0.832	224	0.944	0.955	0.943
Indaial	0.970	0.956	1.004	0.984	0.949	1.014	0.935	155	0.908	1.052	0.993
Iomerê	0.752	0.841	0.867	0.803	0.951	1.068	0.890	154	1.175	0.876	0.923

Appendix: Composite Indicator and GMI results for all years analyzed
(continuation)

Municipality	BoD				GMI						
	2009	2013	2017	2021	2009/2021	EC	BPC	Rank	2009/2013	2013/2017	2017/2021
Ipira	0.676	1.030	0.889	1.012	1.292	1.497	0.863	22	1.560	0.758	1.093
Iporã do Oeste	0.738	0.842	0.869	0.790	0.964	1.071	0.900	144	1.234	0.864	0.904
Ipuacu	0.646	1.012	0.941	0.776	0.981	1.200	0.818	132	1.506	0.782	0.833
Ipumirim	0.700	0.662	0.746	0.749	0.892	1.070	0.833	200	0.897	0.991	1.003
Iraceminha	0.892	0.758	0.779	0.764	0.740	0.856	0.865	249	0.904	0.814	1.005
Irani	0.886	0.905	0.960	0.977	0.921	1.104	0.835	175	0.927	0.989	1.006
Irati	0.858	1.088	–	0.592	0.656	0.690	0.951	261	1.297	–	–
Irineópolis	0.812	0.723	0.817	0.919	0.883	1.132	0.780	205	0.849	0.934	1.114
Itá	0.752	0.805	1.043	1.014	1.233	1.348	0.915	28	0.996	1.232	1.005
Itaiópolis	0.782	0.767	0.816	0.836	0.921	1.068	0.862	176	0.987	0.921	1.013
Itajaí	0.889	0.939	1.023	0.962	0.974	1.081	0.901	135	0.984	1.061	0.933
Itapema	0.996	1.008	1.003	0.979	0.939	0.983	0.955	163	0.950	0.995	0.994
Itapiranga	0.910	1.023	1.001	1.015	1.021	1.116	0.915	90	1.046	0.990	0.985
Itapoá	1.025	0.914	0.961	0.985	0.893	0.960	0.930	199	0.833	1.044	1.026
Ituporanga	0.761	0.776	0.807	0.875	1.035	1.150	0.900	80	0.968	0.981	1.089
Jaborá	0.693	0.743	0.800	0.713	0.968	1.028	0.942	139	1.108	0.907	0.963
Jacinto Machado	0.663	0.863	0.981	1.091	1.470	1.646	0.893	9	1.256	1.149	1.019
Jaguaruna	0.784	0.998	0.972	0.921	1.002	1.175	0.853	114	1.170	0.980	0.875
Jaraguá do Sul	0.917	1.003	0.999	0.891	0.991	0.972	1.020	124	1.036	0.997	0.959
Jardinópolis	0.713	0.799	0.773	0.981	1.298	1.375	0.943	21	1.078	0.975	1.234
Joaçaba	1.000	1.033	1.026	1.012	0.961	1.012	0.949	147	1.020	0.948	0.993
Joinville	0.932	0.954	0.999	0.983	0.996	1.055	0.944	116	0.985	1.000	1.011

Appendix: Composite Indicator and GMI results for all years analyzed

(continuation)

Municipality	BoD				2009/2021	EC	BPC	Rank	GMI		
	2009	2013	2017	2021					2009/2013	2013/2017	2017/2021
José Boiteux	1.032	1.007	0.868	0.847	0.644	0.821	0.785	263	0.952	0.745	0.908
Jupia	0.754	0.777	0.912	0.834	1.031	1.107	0.931	85	1.045	1.051	0.938
Lacerdópolis	0.790	0.755	0.766	0.749	0.890	0.948	0.939	202	0.963	0.899	1.028
Lages	0.889	0.944	0.934	0.949	1.015	1.068	0.950	98	1.029	0.966	1.021
Laguna	0.922	0.974	0.966	0.981	1.015	1.064	0.955	97	1.003	0.986	1.026
Lajeado Grande	0.656	0.691	0.894	0.761	1.049	1.161	0.903	77	0.981	1.324	0.807
Laurentino	0.850	0.933	1.007	0.972	1.067	1.143	0.934	69	0.978	1.095	0.996
Lauro Muller	0.794	0.768	0.781	0.825	0.897	1.038	0.864	192	0.910	0.880	1.121
Lebon Régis	0.810	0.768	0.822	0.801	0.896	0.990	0.905	195	0.949	0.909	1.039
Leoberto Leal	0.695	0.658	0.691	0.712	0.857	1.024	0.837	221	0.963	0.890	1.000
Lindóia do Sul	0.642	0.672	0.687	0.728	0.995	1.135	0.877	117	1.034	0.887	1.085
Lontras	1.046	0.870	0.922	0.908	0.810	0.868	0.934	229	0.778	1.022	1.019
Luiz Alves	0.697	0.757	0.777	0.700	0.866	1.004	0.863	216	1.010	0.893	0.961
Luzerna	1.012	1.051	1.032	1.043	1.004	1.031	0.974	113	1.011	0.961	1.033
Macieira	0.733	0.670	0.848	0.882	1.017	1.204	0.844	95	0.991	1.046	0.980
Mafra	0.903	0.899	0.935	0.970	0.946	1.073	0.882	156	0.883	1.026	1.044
Major Gercino	0.565	0.699	0.664	0.582	0.962	1.031	0.933	146	1.195	0.825	0.976
Major Vieira	0.681	0.660	0.754	0.768	0.877	1.128	0.778	207	0.927	0.941	1.006
Maracajá	0.589	0.740	0.962	0.993	1.390	1.685	0.825	13	1.248	1.054	1.057
Maravilha	0.763	0.837	0.908	0.970	1.178	1.271	0.927	35	1.062	1.031	1.075
Marema	0.683	0.793	0.848	0.877	1.032	1.285	0.803	84	1.145	0.905	0.996
Massaranduba	0.807	0.720	0.708	0.729	0.758	0.904	0.839	243	0.835	0.910	0.998
Matos Costa	0.766	0.718	0.814	0.790	0.895	1.030	0.869	197	0.912	0.952	1.031
Meleiro	–	0.747	0.849	0.997	–	–	–	–	–	0.914	1.151
Mirim Doce	1.010	0.791	0.850	0.686	0.602	0.679	0.887	266	0.735	1.074	0.764
Modelo	0.831	0.857	0.804	0.876	0.876	1.054	0.831	208	0.925	0.907	1.044

Appendix: Composite Indicator and GMI results for all years analyzed
(continuation)

Municipality	BoD				GMI						
	2009	2013	2017	2021	2009/2021	EC	BPC	Rank	2009/2013	2013/2017	2017/2021
Mondai	0.782	0.761	0.830	0.864	0.934	1.104	0.845	166	0.980	0.900	1.058
Monte Carlo	0.766	1.038	0.967	1.010	1.305	1.319	0.989	19	1.379	0.873	1.084
Monte Castelo	0.710	0.709	0.756	0.774	1.020	1.091	0.935	92	1.012	0.930	1.084
Morro da Fumaça	0.876	0.898	0.921	1.023	1.061	1.168	0.908	71	0.979	0.998	1.086
Morro Grande	–	–	–	–	–	–	–	–	–	–	–
Navegantes	0.872	0.927	–	0.858	0.942	0.984	0.958	160	0.990	–	–
Nova Erechim	0.684	0.706	0.744	0.760	1.038	1.111	0.934	78	1.012	0.993	1.032
Nova Itaberaba	0.524	0.844	0.780	0.940	1.363	1.796	0.759	17	1.520	0.853	1.052
Nova Trento	0.951	0.898	0.875	0.758	0.668	0.797	0.839	255	0.818	0.904	0.905
Nova Veneza	0.756	0.868	0.933	0.817	0.993	1.081	0.919	122	1.054	0.958	0.983
Novo Horizonte	0.581	0.728	0.885	0.780	1.154	1.343	0.859	42	1.246	1.011	0.917
Orleans	0.986	1.075	1.050	1.023	1.018	1.038	0.981	94	1.084	0.966	0.973
Otacílio Costa	0.906	0.884	0.906	0.912	0.928	1.007	0.922	170	0.919	1.000	1.010
Ouro Verde	0.595	0.610	0.803	0.727	1.139	1.222	0.931	44	1.076	1.111	0.953
Ouro	0.643	0.793	0.806	1.043	1.400	1.621	0.863	12	1.081	0.959	1.350
Paial	–	–	0.760	–	–	–	–	–	–	–	–
Painel	0.961	0.617	0.720	0.707	0.665	0.736	0.903	257	0.694	0.989	0.968
Palhoça	0.861	0.927	1.029	1.034	1.091	1.200	0.909	61	1.022	1.035	1.032
Palma Sola	0.744	0.880	0.834	0.919	1.109	1.236	0.897	52	1.212	0.832	1.099
Palmeira	0.673	0.633	0.704	0.732	0.976	1.088	0.898	133	0.988	0.924	1.069
Palmitos	0.913	0.778	0.849	0.701	0.742	0.767	0.966	247	0.833	0.927	0.960
Papanduva	0.545	0.640	–	0.624	1.075	1.145	0.938	65	1.175	–	–
Paraíso	0.648	0.667	0.730	1.162	1.521	1.792	0.849	8	1.093	0.886	1.571
Passo de Torres	0.742	0.639	0.954	0.868	1.157	1.170	0.989	41	0.883	1.175	1.115
Passos Maia	0.737	0.747	0.962	0.812	0.877	1.102	0.796	206	0.960	1.108	0.825
Paulo Lopes	0.684	0.686	0.720	0.782	0.981	1.142	0.859	131	0.934	0.921	1.140

Appendix: Composite Indicator and GMI results for all years analyzed

(continuation)

Municipality	BoD			2021	2009/2021	EC	BPC	Rank	GMI		
	2009	2013	2017						2009/2013	2013/2017	2017/2021
Pedras Grandes	0.723	–	1.122	–	–	–	–	–	–	–	–
Penha	0.981	0.970	0.867	0.891	0.855	0.908	0.942	222	0.956	0.885	1.011
Peritiba	0.640	0.737	0.789	0.763	1.106	1.193	0.926	54	1.140	0.949	1.021
Pescaria Brava	–	–	0.714	0.719	–	–	–	–	–	–	0.929
Petrolândia	0.738	0.770	0.820	0.730	0.839	0.989	0.848	225	0.998	0.896	0.938
Pinhalzinho	0.846	0.893	1.005	0.930	0.976	1.100	0.887	134	0.949	1.027	1.001
Pinheiro Preto	0.755	0.691	0.754	0.867	1.092	1.148	0.952	60	0.903	0.993	1.219
Piratuba	0.747	0.824	0.964	0.918	1.172	1.229	0.954	37	1.087	1.136	0.949
Planalto Alegre	1.013	–	–	0.802	0.667	0.791	0.843	256	–	–	–
Pomerode	–	0.824	0.785	0.786	–	–	–	–	–	0.958	1.021
Ponte Alta do Norte	0.952	0.872	0.897	0.923	0.909	0.969	0.939	185	0.840	1.034	1.046
Ponte Alta	0.814	0.787	0.861	0.889	1.011	1.092	0.926	105	0.932	1.041	1.043
Ponte Serrada	0.696	0.722	0.747	0.770	0.983	1.107	0.888	128	1.031	0.913	1.044
Porto Belo	0.823	0.977	0.914	0.980	1.095	1.190	0.920	57	1.123	0.930	1.048
Porto União	1.148	1.126	1.027	1.006	0.744	0.877	0.849	245	0.988	0.760	0.991
Pouso Redondo	0.694	0.744	0.768	0.788	0.963	1.135	0.849	145	1.046	0.902	1.021
Praia Grande	0.750	0.710	0.836	0.972	1.099	1.296	0.848	56	0.875	1.028	1.222
Presidente Castello Branco	0.678	0.597	0.762	0.670	0.902	0.988	0.913	188	0.908	1.067	0.931
Presidente Getúlio	0.808	0.755	0.790	0.786	0.923	0.973	0.949	173	0.928	1.003	0.992
Presidente Nereu	0.728	0.641	0.614	0.590	0.754	0.811	0.931	244	0.894	0.869	0.971
Princesa	0.761	0.762	0.850	0.613	0.664	0.804	0.825	258	0.899	0.960	0.770
Quilombo	0.730	0.731	0.789	0.775	0.994	1.061	0.937	119	0.982	0.944	1.071
Rancho Queimado	0.691	1.044	1.077	1.012	1.536	1.465	1.049	5	1.598	1.063	0.904
Rio das Antas	0.896	0.718	0.749	0.716	0.641	0.799	0.802	264	0.760	0.869	0.971
Rio do Campo	0.789	0.806	0.852	0.897	0.993	1.136	0.874	121	1.046	0.922	1.029
Rio do Oeste	0.742	0.697	0.820	0.816	0.945	1.100	0.859	157	0.924	1.008	1.015

Appendix: Composite Indicator and GMI results for all years analyzed

(continuation)

Municipality	BoD					GMI					
	2009	2013	2017	2021	2009/2021	EC	BPC	Rank	2009/2013	2013/2017	2017/2021
Rio do Sul	0.988	0.915	0.945	0.945	0.901	0.956	0.943	189	0.890	1.016	0.997
Rio dos Cedros	1.043	0.870	0.883	0.854	0.720	0.818	0.880	252	0.860	0.875	0.956
Rio Fortuna	0.586	0.714	0.854	0.860	1.167	1.468	0.795	38	1.162	0.926	1.085
Rio Negrinho	0.904	0.989	0.998	1.047	1.102	1.158	0.952	55	1.046	0.981	1.075
Rio Rufino	0.531	–	0.743	1.213	2.093	2.287	0.915	1	–	–	1.603
Riqueza	0.697	0.683	0.778	0.731	0.956	1.049	0.911	152	0.993	0.953	1.010
Rodeio	0.784	1.068	1.011	1.010	1.134	1.289	0.880	46	1.309	0.851	1.017
Romelândia	0.890	0.727	0.799	0.706	0.658	0.793	0.829	259	0.826	0.847	0.940
Salete	0.791	0.756	0.737	0.748	0.891	0.945	0.943	201	0.926	0.926	1.040
Saltinho	0.825	0.889	0.932	1.044	1.091	1.264	0.863	62	1.020	0.899	1.190
Salto Veloso	0.844	0.836	0.792	0.836	0.944	0.991	0.952	158	0.958	0.942	1.046
Sangão	0.704	1.053	0.704	0.956	1.130	1.358	0.832	48	1.397	0.674	1.200
Santa Cecília	0.855	0.860	0.864	0.969	1.009	1.134	0.890	109	0.912	0.997	1.110
Santa Helena	0.816	0.765	1.013	1.150	1.281	1.409	0.909	23	0.911	1.347	1.044
Santa Rosa de Lima	0.659	0.622	0.636	0.719	0.915	1.091	0.839	181	0.898	0.919	1.109
Santa Rosa do Sul	0.815	0.870	0.978	0.843	0.869	1.035	0.840	213	1.034	1.093	0.769
Santa Terezinha do Progresso	0.581	0.811	0.614	0.936	1.277	1.611	0.792	24	1.215	0.780	1.347
Santa Terezinha	0.693	0.681	0.851	0.839	0.903	1.209	0.747	187	0.916	1.062	0.929
Santiago do Sul	1.053	0.904	0.953	0.973	0.875	0.924	0.947	209	0.802	1.065	1.024
Santo Amaro da Imperatriz	0.896	0.913	1.005	0.980	1.082	1.094	0.989	63	0.983	1.115	0.987
São Bento do Sul	0.930	0.957	0.982	0.999	1.024	1.075	0.953	88	0.997	1.004	1.024
São Bernardino	0.748	0.738	0.883	0.849	0.885	1.136	0.779	204	0.906	1.031	0.947
São Bonifácio	0.594	0.639	0.653	0.633	0.915	1.064	0.860	180	1.046	0.927	0.943
São Carlos	0.830	0.795	0.877	0.863	0.811	1.039	0.781	228	0.876	0.985	0.941
São Cristovão do Sul	1.058	0.910	0.926	0.860	0.731	0.813	0.899	251	0.813	0.968	0.929
São Domingos	0.745	0.814	0.817	0.855	1.106	1.146	0.965	53	1.076	0.929	1.107

Appendix: Composite Indicator and GMI results for all years analyzed

(continuation)

Municipality	BoD				GMI						
	2009	2013	2017	2021	2009/2021	EC	BPC	Rank	2009/2013	2013/2017	2017/2021
São Francisco do Sul	0.874	0.962	0.781	1.006	1.022	1.151	0.888	89	1.022	0.812	1.231
São João Batista	1.007	0.968	0.914	0.903	0.807	0.896	0.900	232	0.869	0.945	0.982
São João do Itaperiú	0.702	0.887	0.909	0.762	0.958	1.085	0.882	149	1.203	0.909	0.876
São João do Oeste	0.849	0.748	–	0.682	0.741	0.803	0.922	248	0.840	–	–
São João do Sul	0.593	0.659	0.736	0.711	0.939	1.198	0.784	162	1.075	0.925	0.944
São Joaquim	0.813	0.809	0.915	0.857	0.933	1.054	0.885	167	0.946	0.988	0.998
São José do Cedro	0.800	0.797	1.041	0.986	1.093	1.233	0.887	59	1.049	1.176	0.886
São José do Cerrito	0.637	0.605	0.680	0.669	0.872	1.050	0.830	212	0.922	0.931	1.016
São José	1.022	1.006	1.001	1.039	0.956	1.016	0.942	151	0.941	0.987	1.030
São Lourenço do Oeste	0.755	0.842	0.896	0.915	1.118	1.212	0.922	50	1.037	1.036	1.041
São Ludgero	1.093	1.064	1.024	1.031	0.911	0.943	0.966	184	0.965	0.939	1.006
São Martinho	0.999	0.650	0.802	0.992	0.808	0.993	0.814	231	0.626	1.115	1.157
São Miguel da Boa Vista	0.832	0.771	–	1.021	1.190	1.227	0.970	32	0.961	–	–
São Miguel do Oeste	0.795	0.757	0.805	0.826	0.920	1.040	0.885	177	0.872	0.993	1.062
São Pedro de Alcântara	–	0.725	0.867	0.765	–	–	–	–	–	1.189	0.949
Saudades	–	0.792	0.766	0.958	–	–	–	–	–	0.924	1.247
Schroeder	0.882	0.980	0.899	0.952	0.942	1.080	0.873	159	1.001	0.939	1.003
Seara	0.692	0.704	0.793	0.717	0.912	1.036	0.880	183	0.960	0.971	0.979
Serra Alta	1.066	1.085	0.942	0.573	0.505	0.538	0.940	271	0.993	0.832	0.612
Siderópolis	0.785	0.889	1.012	0.875	1.016	1.114	0.912	96	1.029	1.049	0.941
Sombrio	–	0.974	0.922	0.868	–	–	–	–	–	1.017	0.892
Sul Brasil	–	1.109	0.945	1.257	–	–	–	–	–	0.956	1.143
Taió	0.668	0.705	0.778	0.768	1.064	1.150	0.925	70	1.083	0.951	1.033
Tangará	0.688	0.706	0.754	0.764	1.007	1.111	0.906	110	1.068	0.949	0.993
Tigrinhos	–	0.954	0.949	0.997	–	–	–	–	–	0.993	0.837
Tijucas	0.771	0.969	1.041	1.163	1.526	1.509	1.011	7	1.311	1.049	1.110

Appendix: Composite Indicator and GMI results for all years analyzed (conclusion)

	BoD				2009/2021	EC	BPC	GMI			
	2009	2013	2017	2021				Rank	2009/2013	2013/2017	2017/2021
Timbé do Sul	0.820	0.928	0.930	0.938	0.994	1.144	0.869	120	1.032	0.991	0.972
Timbó Grande	0.968	0.836	0.809	0.857	0.770	0.886	0.869	240	0.844	0.841	1.084
Timbó	0.944	0.953	0.950	0.963	0.916	1.020	0.898	179	0.944	0.974	0.995
Três Barras	0.817	0.806	0.845	0.936	0.994	1.146	0.868	118	0.871	1.033	1.105
Treviso	0.617	0.683	–	0.721	0.942	1.168	0.806	161	1.042	–	–
Treze de Maio	0.605	0.667	0.765	0.771	1.010	1.275	0.792	107	0.988	0.982	1.041
Treze Tílias	0.852	0.910	1.006	0.999	1.125	1.172	0.959	49	1.044	1.055	1.021
Trombudo Central	0.732	0.817	0.859	0.859	1.061	1.175	0.903	72	1.100	0.981	0.982
Tubarão	0.895	0.928	0.998	0.978	1.029	1.093	0.942	87	1.015	1.023	0.991
Tunápolis	0.811	0.863	–	0.745	0.926	0.918	1.009	172	1.038	–	–
Turvo	0.682	0.714	0.944	1.012	1.387	1.484	0.935	14	1.019	0.978	1.392
União do Oeste	0.562	1.151	1.000	1.009	1.577	1.796	0.878	4	2.065	0.700	1.091
Urubici	0.702	0.654	0.740	0.780	0.982	1.112	0.883	130	0.940	0.962	1.085
Urupema	0.646	0.798	0.722	0.816	1.094	1.262	0.867	58	1.179	0.769	1.206
Urussanga	0.912	1.127	0.962	1.064	1.030	1.166	0.884	86	1.097	0.860	1.093
Vargeão	0.912	0.762	0.740	0.811	0.732	0.889	0.824	250	0.795	0.864	1.066
Vargem Bonita	0.841	0.756	0.783	0.806	0.897	0.958	0.936	194	0.870	0.981	1.051
Vargem	–	0.876	1.094	0.843	–	–	–	–	–	1.017	0.922
Vidal Ramos	0.674	0.674	0.712	0.722	0.905	1.072	0.844	186	1.022	0.897	0.986
Videira	0.949	0.897	0.936	0.874	0.852	0.921	0.926	223	0.905	1.021	0.923
Vitor Meireles	0.795	0.817	0.865	0.812	0.784	1.021	0.768	237	0.919	0.980	0.872
Witmarsum	0.888	1.042	1.039	1.029	0.985	1.159	0.850	127	1.170	0.940	0.895
Xanxerê	0.743	0.767	0.843	0.817	0.930	1.099	0.846	168	1.012	0.884	1.039
Xavantina	0.687	0.760	0.705	0.724	0.778	1.054	0.738	238	0.988	0.786	1.001
Xaxim	0.796	0.833	0.897	0.915	1.072	1.150	0.932	67	0.981	1.021	1.071
Zortéa	0.858	–	1.158	0.835	0.968	0.974	0.995	137	–	–	0.741
Average	0.801	0.830	0.869	0.872	0.967	1.083	0.893		0.996	0.957	1.017
Std Dev.	0.111	0.111	0.094	0.105	0.146	0.155	0.053		0.126	0.083	0.085

4 FROM DATA TO DECISION: A ROBUST RANKING OF WATER AND SANITATION SERVICES IN BRAZIL

This chapter presents the final version of the article that was submitted to a high-impact journal and is under review.

Abstract

Benchmarking techniques play a crucial role in the Water Supply and Sewage (WSS) sector by enabling performance comparisons, identifying best practices, and driving sectoral improvements. Accurate assessment methods are essential to provide a reliable picture of the sector status and to guide strategic enhancements. This study introduces a methodological framework for performance assessment based on a robust Benefit-of-the-Doubt (BoD) model. The BoD approach facilitates the construction of performance rankings and serves as a strategic management tool to support data-driven decision-making. Currently, the most widely used ranking in Brazil is provided by Instituto Trata Brasil (ITB). It aggregates sub-indicators from the Brazilian National System for Water and Sanitation Data (SNIS) using expert-assigned weights, giving the process a high degree of subjectivity. The robust BoD approach addresses this limitation by determining weights endogenously through optimization techniques, reducing the influence of extreme values and enhancing the fairness and accuracy of performance evaluation. A case study is conducted on Brazil's 100 most populous municipalities in 2021, representing approximately 86 million inhabitants. Additionally, this study incorporates contextual variables to identify the key characteristics of Brazilian municipalities that influence WSS performance.

Keywords: Data Envelopment Analysis; Benchmarking; Water supply and sewage sector; Composite indicator; Benefit-of-the-Doubt.

4.1 INTRODUCTION

Benchmarking techniques are used in various sectors to improve entities performance by comparing their achievements. The benchmarking process enables the identification of best practices and draws attention to areas that require improvement. However, performance assessments will only bring real benefits if applied appropriately, with a sensitive interpretation of the results obtained. Otherwise, these studies can lead to biased conclusions about the sector under analysis.

In Water Supply and Sewage (WSS) services, attention is especially important

given the growing market competition in areas with relevant commercial and financial interests. In this sector, comparative performance studies are becoming more prevalent, mainly driven by the scarcity of resources available and the need for greater efficiency, which is mandatory in the context of stricter legal and regulatory requirements.

Another concern regarding the use of benchmarking is the dissemination of technical results to the press or the general public, without providing a descriptive contextualization to guarantee a proper interpretation of results. This can lead to biased conclusions tailored to specific interest groups. Therefore, benchmarking rankings must be analyzed sparingly, from a technical point of view and away from considerations about its infallibility or immutability.

Data Envelopment Analysis (DEA) is a technique that has been used for carrying out benchmarking studies for several decades. This nonparametric method compares the entities under analysis, called Decision Making Units (DMUs), and identifies the best and worst practices of the sample, identifying areas for improvement. DEA focuses on the production process transforming resources (inputs) into products (outputs), providing the estimation of an efficiency score for each DMU.

The Benefit-of-the-Doubt (BoD) approach (Cherchye *et al.*, 2007) is a technique derived from DEA, where the inputs are replaced by a dummy variable equal to one and the outputs correspond to the sub-indicators that are aggregated to form the Composite Indicator (CI). A composite indicator consolidates multiple dimensions measured in different scales to summarize the performance of the units under assessment. The use of sub-indicators in an aggregate form through the CI offers a holistic view of the sector, since individual assessment of sub-indicators may not fully capture the performance of each unit under assessment.

One notable advantage of the BoD technique is not requiring a predefinition of the weights assigned to each sub-indicator in the aggregation process. These weights are determined through an optimization model, being generated endogenously from the dataset. The optimization model is designed to select the most favorable weights for each unit under assessment, addressing a common concern of decision support methods regarding the fairness of weight assignment.

In the standard BoD approach, the indicators must reflect desirable process outcomes, such that higher values indicate better performance. However, in some cases, undesirable indicators, where lower values indicate better performance, may

need to be considered. In this case, the use of a Directional Distance Function (DDF) model allows for considering both desirable and undesirable outputs in the estimation of the CI.

To address the limitations of score sensitivity to extreme values, a robust BoD approach can be utilized. This involves a bootstrapping sampling procedure, ensuring that the composite indicator score for each unit is derived from a large number of calculations, involving sub-samples of the set of entities under evaluation.

Brazil is one of the most populous countries in the world and has a high demand for water in urban centers, especially in the Southeast and Northeast regions. Meeting demands for water supply and sewage collection and treatment in densely populated areas is a challenge, requiring efficient resource management. Consequently, the legislation has been updated with a view to ensuring the sustainability of the systems. Monitoring of the sector's indicators is carried out continuously through the National System for Water and Sanitation Data (SNIS).

The Instituto Trata Brasil (ITB), a Brazilian institute for WSS, prepares a performance ranking of water and sanitation providers. It is released annually and attracts considerable attention in Brazil, especially after the country's recent and comprehensive normative and regulatory changes through the promulgation of the Basic Sanitation Guideline in 2020 (Brazil, 2020a). Several providers tend to use the disclosure of the ITB ranking as a marketing strategy. Moreover, the influence of the ranking has been increasingly beyond commercial use to encompass governmental entities. For instance, the Federal Senate, one of the chambers representing the Brazilian Legislative branch, has already used the ITB ranking as a source of diagnosis for the WSS situation in the country (Vasco, 2022). Similarly, the Public Ministry, a public institution that monitors compliance with laws, has also referenced the ITB ranking in legal processes (MPAC, 2021). The ITB results have also served as a reference for developing strategic water use plans in the industrial sector (FIESC, 2023).

Nonetheless, the ITB ranking has faced some criticisms. Service providers often question the methods adopted and the selection of criteria and indicators used for evaluating water and sewage coverage (CAGECE, 2023). Despite different points of view, the pioneering spirit of ITB in using SNIS data to carry out benchmarking between municipalities has increased general interest in information related to the WSS, adding

more transparency to the process. In addition, the ITB ranking instigates competitiveness among service providers in order to achieve the best positions.

The case study explored in this work applies the robust directional BoD approach to evaluate performance in the provision of water supply and sewage services, in 2021, for the 100 most populous municipalities in Brazil. These municipalities collectively represent approximately 40.5% of the total Brazilian population, accounting for around 86 million inhabitants.

The robust directional BoD technique offers an alternative to constructing the ranking presented by Instituto Trata Brasil (ITB). ITB is a civil society organization of public interest formed by companies that operate in the Brazilian WSS sector. The rank issued by ITB assigns the relative importance of each indicator through the selection of weights predetermined by experts in the sector. In this work, unlike ITB, no specific weights defined using stakeholder opinions are assigned to the sub-indicators, which helps mitigate the subjectivity surrounding the weight-setting process.

This paper aims to apply the BoD technique to 100 municipalities in Brazil to evaluate their performance in the water supply and sewage sector. The sub-indicators used in the composite indicator are the same as the ITB, allowing a comparison between the rankings. Given the considerable heterogeneity in WSS performance across Brazil – leading to extreme values in some sub-indicators – we advocate for a robust approach in developing the BoD composite indicator. This strategy not only mitigates the common criticism regarding the selection of aggregation weights but also attenuates the influence of outliers, offering a more reliable and nuanced assessment of WSS performance in Brazil. Furthermore, the ability to account for contextual effects in the performance assessment of the water sector represents a key advantage of the BoD approach over the current methodology used by ITB.

The exogenous variables originate from data of reliable sources such as the Agência Nacional de Águas e Saneamento Básico, ANA (National Water and Basic Sanitation Agency); Instituto Brasileiro de Geografia e Estatística, IBGE (Brazilian Institute of Geography and Statistics) and United Nations Development Program (UNDP). The application of the BoD technique at a national level in Brazil, encompassing all 26 states of the country (plus the Federal District, Brasília), is unprecedented, offering a fresh perspective to evaluate the sector development. Expanding on the ITB ranking methodology, this study introduces an enhanced approach to identify the dimensions that require improvement. In this way, the indices

can portray the reality of the sector in the best possible way. Additionally, the use of contextual data from ANA, IBGE, and UNDP to evaluate environmental effects in the performance assessment enhances the applicability and practical relevance of the proposed approach and represents an innovative contribution to the literature.

The remaining parts of this paper are structured as follows: Section 4.2 presents a brief literature review. An overview of the water supply and sewage sector in Brazil is presented in Section 4.3. The proposed methodology is explained in Section 4.4. The case study is introduced in Section 4.5. Section 4.6 discusses the results and their implications. Finally, the study conclusions are presented in Section 4.7.

4.2 LITERATURE REVIEW

Comparative methods for relative performance assessment, or benchmarking, aim to enhance performance by drawing attention to the best practices and areas with potential for improvement.

Marques and Witte (2010) discuss two alternative benchmarking approaches: metric and process. The first allows organisations to evaluate performance and compare it with competitors. The other focuses on the company's internal processes and looks for best practices to enable superior performance.

Despite the benefits arising from benchmarking, Bruijn *et al.* (2004) point out that its incorrect use can hold negative consequences, such as the phenomenon known as “gaming the numbers”. Gaming the numbers occurs when systems are manipulated with data that may meet the system's criteria, but lack social significance or, worse, convey a negative social impact. If a financial reward or an important external recognition is attached to an organization's performance, the incentives for engaging in this behavior tend to be stronger.

In the water supply and sewage sector (WSS), several studies use benchmarking to demonstrate advances or possible setbacks in the sector and, to support regulatory and normative practices. Data Envelopment Analysis (DEA), a non-parametric technique originally developed by Charnes *et al.* (1978), is often used for this purpose. DEA focuses on the production process transforming resources (inputs) into products (outputs), involving the estimation of an efficiency score for the entities under analysis, called Decision Making Units (DMUs).

Several benchmarking works applying DEA have dealt with the efficiency of WSS worldwide: Thanassoulis (2000a), Thanassoulis (2000b) and Walker *et al.* (2019) in United Kingdom, Byrnes *et al.* (2010) and Ananda (2019) in Australia, Wang *et al.* (2018) in Canada, Berg and Lin (2008) in Peru, Pereira *et al.* (2023) in Portugal, Alsharif *et al.* (2008) in Palestina, Dong *et al.* (2018) in China, Storto (2018), D’Inverno *et al.* (2021) and Romano and Guerrini (2011) in Italy, Maziotis *et al.* (2020) in Chile, De Witte and Marques (2010) in a comparative study between Netherlands, England and Wales, Australia, Portugal and Belgium, among others papers.

In Brazil, the DEA model was also used by various authors to benchmarking and performance assessment in the WSS sector (e.g. Tupper and Resende (2004), Da Motta and Moreira (2006), Carvalho and Sampaio (2015), Barbosa *et al.* (2016), Macedo (2018), Cetrulo *et al.* (2020) and Tourinho *et al.* (2023)). These studies reflected the regional inequalities that exist in Brazil and pointed to important improvements that could occur in the country’s WSS, such as cost savings (Tupper and Resende, 2004). The territorial area of coverage (local, state or micro-regional), and legal characteristic of the provision of the service (private or public) were addressed by Da Motta and Moreira (2006) and Barbosa *et al.* (2016). The results indicated that local entities are the most efficient and, no evidence of better performance by private entities compared to public ones was found.

Carvalho and Sampaio (2015), Barbosa *et al.* (2016), Macedo (2018) and Tourinho *et al.* (2023) evaluate the productivity change over time of Brazilian WSS sector. Productivity gains were revealed between the years 2006 and 2011 by Carvalho and Sampaio (2015) and in the period from 2004 to 2015 by Macedo (2018). The results were mainly influenced by the institutional changes implemented in Brazilian WSS sector.

On the other hand, Barbosa *et al.* (2016) showed that the deficit of universal access is the principal factor of the inefficiency in Brazilian WSS from 2005 to 2013. The study conducted by Tourinho *et al.* (2023) indicated a productivity loss of approximately 4% from 2012 to 2019.

The Benefit-of-the-Doubt (BoD) approach, a framework derived from DEA, was popularized by Cherchye *et al.* (2007). The composite indicator aggregates individual indicators of different dimensions to summarize the performance of the units under assessment. In the BoD assessment, a linear programming model needs to be constructed with the objective of maximizing the performance of the DMU under

assessment. The weights represent decision variables, being the outcomes of the model, and the results of model computation provide optimal weights. These optimal weights reflect the best feasible performance when comparing the DMU under assessment to all other DMUs in the dataset. Thus, these optimal weights represent the most favorable weights that could be assigned to that DMU, preventing potential concerns about fairness in the weight assignment process. Another clear advantage of the BoD techniques is that several indicators can be used in their original units of measurement without the need for unit conversion.

In the BoD technique, the indicators to be aggregated correspond to the outputs of the standard DEA model, while a dummy input with a value of one is also considered. Desirable outputs mean that higher values indicate better performance (e.g., number of consumers). However, in some cases, undesirable results are part of the production process (e.g., water losses), and need to be considered to avoid biased or inaccurate conclusions due to omitting important factors that characterise the production process. Cetrulo *et al.* (2020) showed that accounting for undesirable outputs can significantly change positions in benchmarking rankings. In the presence of desirable and undesirable outputs, the standard BoD approach needs to be replaced by the Directional BoD (Zanella *et al.*, 2015) model, which allows the simultaneous expansion of outputs and contraction of inputs according to a directional vector (Chambers *et al.*, 1996).

The number of studies that use desirable and undesirable outputs in parallel is still small, but Chile (Sala-Garrido *et al.*, 2021), Portugal (Henriques *et al.*, 2020; Vilarinho *et al.*, 2024, 2023b), and, Brazil (May *et al.*, 2024) are some examples of countries where those studies have been undertaken.

Sala-Garrido *et al.* (2021) used a set of seven variables, reflecting desirable and undesirable factors, in order to evaluate the quality of service of a sample of Chilean water companies. The results showed that Chilean water and sewerage services are provided with high homogeneity in terms of quality.

Henriques *et al.* (2020), Vilarinho *et al.* (2024) and Vilarinho *et al.* (2023b) applied a BoD model to support regulation in the WSS sector in Portugal. The first two studies assessed the quality of service provided to users, while the third one focused on evaluating operators' asset management performance. Henriques *et al.* (2020) applied a directional BoD to evaluate the quality of service provided to users in the year 2018. The results showed that six wholesale operators and thirteen retail operators

were found to be outstanding according to the quality of service. Vilarinho *et al.* (2024) used a directional BoD in conjunction with a Multi-criteria Decision Analysis technique to evaluate the service quality of wholesale water supply and wastewater utilities from 2016 to 2021. The finding highlighted areas for improvement that can support the enhancement of the services provided. Vilarinho *et al.* (2023b) applied directional BoD to evaluate the asset management performance of water supply utilities operating at the retail level in Portugal. The authors concluded that the direct management model was unfavorable concerning developing structured management systems, whilst urban environments favor managerial advancement.

May *et al.* (2024) was the first paper to use BoD in the Brazilian WWS sector. The authors applied a Directional BoD model to estimate the performance of the State of Santa Catarina municipalities from 2009 to 2021, considering financial, operational, and quality dimensions. The study findings revealed significant room for improvement in WSS services of Santa Catarina state. The significant difference in performance between the best and worst-ranked municipalities reflected the challenges of advancing in basic sanitation.

Previous studies have proven that the use of contextual (or exogenous) factors is relevant for a greater understanding of the performance of basic sanitation services (Tourinho *et al.*, 2022; Vilarinho *et al.*, 2023a). Tourinho *et al.* (2022) evaluated the performance of water supply and sanitation services in 448 large Brazilian municipalities (with more than 50,000 inhabitants) using Data Envelopment Analysis (DEA). The author identified that Brazilian municipalities that use surface water tend to have lower efficiency levels. The heterogeneity in productivity among Brazilian regions also is highlighted in the study. Vilarinho *et al.* (2023a) applied robust and conditional BoD approaches to assess asset management performance of Portuguese water supply companies operating in the bulk market between 2016 and 2020. The results show that the type of management systems and areas of intervention (urban, semi-urban or rural) are factors that present significant impact in asset management performance.

With the development of this study, we expect to extend the existing literature by considering a new approach to benchmarking and performance assessment in the Brazilian WSS sector. The application of the BoD at a national level, encompassing all 26 states of the country (plus the Federal District, Brasília), is unprecedented in Brazil. Using the robust directional BoD allows analyzing the indicators in an integrated way,

overcoming the limitations of current methods that deal with indicators considered as independent factors and ignoring their tradeoffs.

4.3 THE WATER AND SEWAGE SECTOR IN BRAZIL

In 2020 Brazil promulgated the Law No. 14,026/2020 (Brazil, 2020a), an update of the Law N° 11,445/2007, which established the Basic Sanitation Guideline of the country (Brazil, 2007). According to these laws, the municipalities are the entities responsible for basic sanitation services in Brazil. They can provide services themselves, hire companies providers, and enter municipal partnerships, among other options. The provision of these services must be planned by the municipalities through the preparation of the Municipal Basic Sanitation Plan (PMSB - Plano Municipal de Saneamento Básico).

The Law No. 14,026/2020 (Brazil, 2020a) established the goal of universalizing Brazilian WSS services. It means that 99% of the population should have access to potable water, and 90% should have proper sewage management by 2033. In 2021, the total population served with water supply in Brazil was approximately 177 million inhabitants, which represents 84.2% of coverage with the public network, considering urban and rural populations. The urban coverage is about 93.5%, serving 167 million inhabitants living in urban areas. The 2021 total and urban sewage coverage were 55.8% and 64.1%, respectively (Brazil, 2022b).

Regulatory agencies are responsible for overseeing adherence to these goals. WSS regulation was established in 2007, and since that, some states founded regulatory agencies while some municipalities have created their agencies or joined regional agencies. Brazil currently has 89 regulatory agencies. The Agência Nacional de Águas e Saneamento Básico, ANA (National Water and Basic Sanitation Agency) holds the responsibility of issuing reference standards for Brazilian WSS sector (ANA, 2023). ANA is the regulatory agency dedicated to ensuring compliance with the objectives and guidelines of the Brazilian Water Law, Law No. 9,433/1997 (Brazil, 1997), and the new legal framework for basic sanitation, Law No. 14,026/2020 (Brazil, 2020a). ANA is an agency linked to the Ministry of Integration and Regional Development of Brazil.

Brazilian WSS indicators are monitored through the National System for Water and Sanitation Data (SNIS), serving as the official repository of data on basic

sanitation. Created in 1996, the SNIS is a unit linked to the Ministry of Cities. With national coverage, it has institutional, administrative, operational, managerial, economic-financial, accounting and quality information of the provision of WSS services in urban areas. SNIS information is self-declaratory, being provided annually by the service provider (Brazil, 2022b).

The self-declaratory characteristics and exclusively urban scope are the main limitations of SNIS. Aiming to overcome the self-declaratory limitation, the Ordinance no. 719 (Brazil, 2018b), in 2018, established a methodology for data auditing and certification: the Program Acertar. The objective of Acertar is to ensure that SNIS information is reliable and allows for benchmarking between different municipalities and providers. Audits carried out by regulatory agencies aim to ensure the reliability and accuracy of all SNIS data by 2024.

Due to the urban characteristic of SNIS, the System does not consider the individual solutions in its indicators. Individual solutions consist of alternative means of access to water supply and final disposal of sewage in locations that are not directly served by the public network, especially in rural areas. This situation has caused some controversy in WSS management, since the National Basic Sanitation Plan (PLANSAB) and the National Rural Sanitation Plan (PNSR) consider individual solutions to be appropriate. According to PLANSAB (Brazil, 2023a), total water coverage is 94.5% instead of the 84.2% shown by SNIS. The total sewage coverage in PLANSAB is 74.3%, a difference of 18.5% from the SNIS data (55.8%). However, according to the Decree No. 11,599/2023 (Brazil, 2023c), the exclusion of individual systems from SNIS must be maintained until new guidance is provided. Therefore, water supply fountains or sewage treatment by septic tanks, for example, are ignored in Brazil's official data.

Reducing water losses is another goal to be achieved by service providers. Quantitative targets were established by Ordinance nº 490/2021 (Brazil, 2021b). The goals are more stringent as the years go by, reaching 216 l/connection/day in 2034. In case of non-compliance, resources and financing may be denied to service providers. In 2021 the water losses in Brazil totaled 325.4 l/connection/day (Brazil, 2022b).

After the promulgation of Law No. 14,026/2020, two issues have dominated the discussion of basic sanitation in Brazil: public versus private and, regionalized service provision. The Law Nº 14,026/2020 established that states must group their municipalities into regions, with their specific governance structures. The municipalities

and the state jointly exercise the management functions of basic sanitation policy. However, the lack of clarity and objectivity of some items on this agenda has significantly delayed the regionalization of services, prolonging the climate of uncertainty in the sector.

4.4 METHODOLOGY

This section presents the Benefit-of-the-Doubt (BoD) framework, which is the methodology proposed in this paper to evaluate the water and sewage systems performance of the most populous municipalities in Brazil.

The standard deterministic BoD formulation is equivalent to an original DEA model Charnes *et al.* (1978), with a dummy input equal to one and multiple desirable outputs. In the BoD approach, the individual indicators are aggregated as a Composite Indicator (CI) (Cherchye *et al.*, 2007). The composite indicator has the objective of summarizing the performance of DMUs considering the multi-dimensional nature of their activities.

However, in some cases, where undesirable outcomes of the production process need to be considered, the standard BoD approach needs to be replaced with a Directional Distance Function (DDF). The BoD model based on DDF was enhanced by Zanella *et al.* (2015). It allows the simultaneous adjustment of both desirable and undesirable outputs without requiring the adjustment of measurement scales. The multiplier formulation of the directional BoD model is shown in Model (1).

$$\text{Minimize } \beta_{j_0} = - \sum_{r=1}^s y_{rj_0} u_r + \sum_{k=1}^l b_{kj_0} p_k + v \quad (1)$$

$$\text{sujeito a: } \sum_{r=1}^s g_y u_r + \sum_{k=1}^l g_b p_k = 1$$

$$- \sum_{r=1}^s y_{rj} u_r + \sum_{k=1}^l b_{kj} p_k + v \geq 0, \quad j = 1, \dots, n$$

$$\begin{aligned}
v &\in \mathbb{R} \\
u_r &\geq 0, \text{ para } r = 1, \dots, s \\
p_k &\geq 0, \text{ para } k = 1, \dots, l
\end{aligned}$$

In this directional BoD model, y_{rj} represents the desirable sub-indicators and b_{kj} represents the undesirable sub-indicators for DMU j ($j = 1, \dots, n$), where n indicates the number of DMUs under assessment. The parameters y_{rj_0} and b_{kj_0} are the values of desirable and undesirable sub-indicators observed for the DMU j_0 under assessment.

The weights are the decision variables of the model, where u_r is associated to the desirable outcomes r , p_k is related to the undesirable outcomes k and, v is associated with the dummy input.

The directional distance vector $(g_y, -g_b)$ indicates the direction of expansion of desired outputs and reduction of undesired ones towards the optimal condition. The direction vector used in the model must be chosen carefully and in accordance with the objectives of the study. In this work the values of $(g_y, -g_b)$ were chosen as being equal to $(y_{rj_0}, -b_{kj_0})$, following Zanella *et al.* (2015) and Rogge *et al.* (2017). This way, each DMU can improve using the values of its output metrics, resulting in a proportional interpretation of the composite indicator value.

The model objective function aims to find the optimal value of β_{j_0} . β_{j_0} represents the proportional increase of the desirable outputs and the proportional decrease of the undesirable outputs toward the best-practice frontier.

The value of the composite indicator (CI) associated with DMU j_0 can be obtained as $1/(1 + \beta_{j_0})$. It ranges from 0 to 1, where 1 represents the best performance level and indicates that DMU under assessment is in the best-practice frontier.

The directional BoD model allows the incorporation of weight restrictions. The weight restrictions reflect the relative importance of the outputs and prevent assessments that could disregard certain indicators by assigning them a weight equal to zero. Wong and Beasley (1990), Allen *et al.* (1997), Sarrico and Dyson (2004), among others, discussed several kinds of weight restrictions for DEA models. In this study the assurance regions type I (AR-I) was applied Zanella *et al.* (2015). The AR-I weight restrictions are displayed in expressions (2).

$$\begin{aligned}
\frac{u_r \bar{y}_r}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_r, & r = 1, \dots, s \\
\frac{p_k \bar{b}_k}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_k, & k = 1, \dots, l
\end{aligned} \tag{2}$$

This method uses an “artificial” DMU that is composed of the average values of the outputs observed in the sample. The parameters ϕ_r and ϕ_k represent the lower bounds of the weights for desirable and undesirable indicators, respectively.

According to Zanella *et al.* (2015), the use of AR-I restrictions, using an average “artificial” DMU, presents the advantage of allowing the assessment of the performance of all DMUs against the same frontier. Another advantage is the interpretation of the magnitude of the weights bounds as the relative importance of a given output dimension in percentage terms. In this study, only the lower bounds of the output weights are considered in the Directional BoD model.

4.4.1 Robust and conditional approaches for CI calculation

To overcome sensitivity to outliers, which is one of the limitations of the BoD approach, Cazals *et al.* (2002) and Daraio and Simar (2007) proposed a robust composite indicator approach for frontier methods computations, the principles of which are applicable to BoD calculations.

In the robust composite indicator approach, a bootstrapping sampling procedure is applied, where each DMU is evaluated B times using a sample of size m randomly drawn with replacement from the original set of DMUs. By using a large B , the influence of extreme values is minimized in the average composite indicator CI calculation. The robust composite indicator is then derived as the average of the composite indicators generated across all B samples of size m .

The robust composite indicator $CI_{j_0}^m$ is shown in equation (3), where $CI_{j_0}^{b,m}$ is the composite indicator of the DMU j_0 under assessment calculated using sub-sample b .

$$CI_{j_0}^m = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m} \tag{3}$$

If the DMU j_0 is not included in sample b , the results may indicate that it outperforms all other DMUs in the sample. In such cases, the DMU is classified as “super-performing”, and its score β_{j_0} exceeds 1. Consequently, $\beta_{j_0}^{b,m}$ (see Model 1) becomes negative, and the resulting value of $CI_{j_0}^{b,m}$, calculated as $1/(1 + \beta_{j_0})$, fails to capture the expected performance improvement for a better-performing DMU. As noted by Mergoni *et al.* (2022), this issue can be addressed by modifying the calculation of $CI_{j_0}^{b,m}$, as shown in expressions (4).

$$CI_{j_0}^{b,m} = \frac{1}{1 + \beta_{j_0}^{b,m}}, \quad \text{if } \beta_{j_0}^{b,m} \geq 0; \quad (4)$$

$$CI_{j_0}^{b,m} = \log_{10}(1 - \beta_{j_0}^{b,m}) + 1, \quad \text{if } \beta_{j_0}^{b,m} < 0$$

As discussed by Vilarinho *et al.* (2023a), the proposed formulation for cases where $\beta_{j_0}^{b,m} < 0$ follows a similar pattern to the original formulation for positive $\beta_{j_0}^{b,m}$ values. This ensures that the value of $CI_{j_0}^{b,m}$ proportionally increases as the performance of the DMUs improves. Consequently, the robust composite indicators in this study are calculated using the expressions (4), as outlined by Mergoni *et al.* (2022).

To account for the influence of contextual variables, the robust conditional approach must be employed. This method adjusts the CI to enable fairer comparisons by ensuring that DMUs are assessed in relation to others with similar exogenous characteristics. The procedure is analogous to the robust CI strategy, however, the conditional approach uses a Kernel function to perform sampling based on a similarity function. Using a Monte Carlo simulation procedure, B sub-samples $\Gamma^{b,m,z}$ are generated for each DMU j . For each sub-sample, B values of $\beta^{b,m,z}$ are obtained by running model 1, considering only the DMUs within $\Gamma^{b,m,z}$. Subsequently, the mean of the B $\beta^{b,m,z}$ values is calculated. Finally, the corresponding Composite Indicator $CI^{m,z}$ is computed using expression (4). The conditional CI, referred to as $CI_{j_0}^{m,z}$, is computed as the average of the conditional $CI_{j_0}^{b,m,z}$ for B samples of as shown in equation 5.

$$CI_{j_0}^{m,z} = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m,z} \quad (5)$$

The conditional approach allows the analysis of the context through nonparametric significance tests. After the set of conditional composite indicators $CI_{j_0}^{m,z}$ is generated, both the significance and the direction of influence of the contextual variables can be assessed. The relationship between the robust CI and the conditional CI ($CI_{j_0}^m/CI_{j_0}^{m,z}$) is used to perform a nonparametric regression on the exogenous variables. By constructing partial plots, it is possible to visualize the confidence intervals of these variables at varying levels of exogenous factors. If these intervals do not overlap, it means that contextual effects are statistically significant.

A downward trend in the ratio as the conditional CI increases (i.e., a negative slope in the regression plot) indicates that the conditional score surpasses the robust score due to comparisons being made among units that are more alike concerning environmental characteristics. This implies that the environment negatively impacts the performance level. Conversely, when the regression plot exhibits a positive slope, it signifies a beneficial influence of the environmental variable on performance (Vilarinho *et al.*, 2023a; D’Inverno *et al.*, 2021).

4.5 CASE STUDY

This section details the case study explored in this research. Subsection 4.5.1 describes the data set containing the variables collected by Instituto Trata Brasil (ITB). Subsection 4.5.2 presents the main descriptive statistics of variables used in the study.

4.5.1 Data Collection

The data of water supply and sewerage services used in this study were obtained from the Instituto Trata Brasil (ITB). The ITB is a Civil Society Organization of Public Interest, formed by companies that operate in the Brazilian water supply and sewage system (ITB, 2023). Since 2009, ITB has published the Ranking do Saneamento (Sanitation Ranking, in English). The ranking analyzes annually the WSS services of the 100 most populous municipalities in Brazil. ITB carries out its study based on information made available by the National System for Water and Sanitation Data (SNIS), which is the official source of basic sanitation data in Brazil.

The ITB ranking analyzes indicators related to water and sewage coverage, the relationship between the volume of water consumed and sewage treated, investments made by different entities (i.e., provider, municipality, state), the relationship between the evolution of water and sewage connections and the goals envisaged, revenue losses and water losses. Each indicator has a specific score. ITB establishes the indicators and their respective weightings based on interviews with sector experts (Oliveira *et al.*, 2023).

This study employs the twelve metrics collected by Instituto Trata Brasil to 2021 for the most populous municipalities in Brazil (Oliveira *et al.*, 2023).

The annual samples correspond to 40.5% of the total Brazilian population, being 86,470,729 inhabitants. In the year analyzed, the municipality with the fewest inhabitants was Gravataí, in the state of Rio Grande do Sul, with a population of approximately 285 thousand inhabitants. The most populous municipality in the sample is São Paulo, in the state of São Paulo, with a population of over 11 million inhabitants. The state with the largest number of municipalities in the sample is São Paulo, with 28 municipalities analyzed. These municipalities correspond to around 30.8% of the population of the entire sample, that is, 26.6 million inhabitants. The Southeastern region of Brazil, where São Paulo is located, has 49 municipalities analyzed, corresponding to 53.7% of the sample, approximately 46.4 million inhabitants. The Center-west region has the smallest number of municipalities analyzed, that is, 7. The North region has the lowest concentration of population among the large Brazilian municipalities: 7.9%. The water and sewerage services are provided by local administrations, government-controlled companies, municipal companies, autarchies and private companies.

The detailed description of the indicators utilized in this study is presented in Table 9. It was decided to keep the variable code in their original form (the acronym originates from Portuguese terms), following the ITB standard, to facilitate the identification of variables in the original data source.

Table 9 - Description of the indicators used in the Composite Indicator

Variable Code	Variable Description (Scale)	Variable Definition	Type	Subsector	ITB Weight
ITA	Total Water Coverage Index (%)	Ratio of the total population served with water supply to the total resident	Desirable	WS	5.0%
IUA	Urban Water Coverage Index (%)	Ratio of the urban population served with water supply to the total resident	Desirable	WS	5.0%
ITE	Total Sewage Coverage Index (%)	Ratio of the total population served with sewage collection to the total resident	Desirable	WWD	12.5%
IUE	Urban Sewage Coverage Index (%)	Ratio of the urban population served with sewage collection to the total resident	Desirable	WWD	12.5%
ITR	Treated Sewage Referred Consumed Water Index (%)	Ratio between the volume of treated sewage in relation to the volume of water consumed	Desirable	WWD	25.0%
IIT	Total Investment by Receipt Index (%)	Ratio of total investments in water and sewage systems, made by provider, municipality and, state, to total receipt	Desirable	WS, WWD	7.5%
IIP	Investment by Provider per Receipt Index (%)	Ratio of the investments in water and sewage systems, made by the provider, to total receipt	Desirable	WS, WWD	7.5%
ILA	Water Connections Index (%)	Variation in the number of water connections in the analyzed period divided by the total number of connections that the provider should make to universalize the service	Desirable	WS	5.0%
ILE	Sewage Connections Index (%)	Variation in the number of sewage connections in the analyzed period divided by the total number of connections that the provider should make to universalize the service	Desirable	WWD	5.0%
IPF	Total Revenue Loss Index (%)	Ratio between the volume of non-revenue water in relation to the volume of water available for consumption	Undesirable	WS	5.0%
IPD	Distribution Water Loss Index (%)	Relation between the total volume of drinking water produced and the total volume of water consumed	Undesirable	WS	5.0%
IPV	Volumetric Water Loss Index (l/con./day)	Volume of water losses per connection	Undesirable	WS	5.0%

Source: the author

WS – Water Supply. WWD – Wastewater Drainage

Total Water Coverage Index (ITA) corresponds to the SNIS indicator IN055 - Total Water Service. It is aligned with the principle of universal access to drinking water. It corresponds to the proportion of the total population that is effectively served with public water networks, including those located in areas not considered urban. As exposed in Section 4.3, individual solutions are not considered in this indicator, such as wells, springs, cisterns and fountains.

The Urban Water Coverage Index (IUA) corresponds to the SNIS indicator IN023-Urban Water Service, representing the total urban population served with water supply in relation to the total population residing in the municipality. Individual solutions are also not considered in this indicator.

Total Sewage Coverage Index (ITE) corresponds to the SNIS indicator IN056 - Total sewage service referred to municipalities served with water. The ITE indicator represents the population that is effectively served with sewage access services, which is associated with the number of active residential sewage dwellings.

Urban Sewage Coverage Index (IUE) corresponds to the SNIS indicator IN024-Urban sewage service referred to municipalities served with water. The indicator shows what percentage of the municipality's urban population has its sewage collected.

Treated Sewage Referred Consumed Water Index (ITR) corresponds to the SNIS indicator IN046-Treated sewage referred to water consumed. This indicator shows, in relation to water consumed, what percentage of sewage is treated. The method considers a return coefficient (volume of sewage treated divided by the volume of water consumed) of 0.8, in accordance with the value recommended by Brazilian standard NBR 9649 - Sanitary sewage collection network design (ABNT, 1986). This means that a ratio between treated sewage and consumed water above 80% is considered adequate.

Total Investment by Receipt Index (IIT) does not have a corresponding indicator in SNIS. It is an indicator created by ITB using as a reference the information available in SNIS. The numerator of the equation is the total investments made by provider, municipality and state. The denominator is the total revenue. The higher the ratio between investment and revenue, the more investments the municipality is making in relation to how much it collects, so that it has a better position in the ranking.

Investment by Provider per Receipt Index (IIP) is similar to the IIT, but only takes into account investments made by the service provider.

Water Connections Index (ILA) measures the variation in the number of water connections between year t and year $t-1$ divided by the total number of connections that the provider should make to universalize the service. This indicator was also created by ITB and has no counterpart in SNIS. The higher the value of this parameter for a municipality, the more efforts are being made to universalize its services, so that the municipality deserves a better position in the ranking.

Sewage Connections Index (ILE) is an indicator very similar to the ILA, but it uses data corresponding to sanitary sewage.

Total Revenue Loss Index (IPF) measures the percentage of water produced that was not billed. It is similar to SNIS indicator IN013-Revenue Loss index, however ITB does not consider the volume of service (water used for operational procedures or special supplies, such as provision of water for shanty towns) in the calculations. The ITB believes that there is a very large discrepancy of the procedures for aggregating service volumes between service providers. IPF is an undesirable indicator, since the smaller the volume of unbilled water, the better the municipality's performance.

Distribution Water Loss Index (IPD) corresponds to the SNIS indicator IN049-Distribution loss index. Water losses correspond to the difference between the total volume of drinking water produced at the treatment plants (plus water imported from other systems, if applicable) and the sum of volumes measured by hydrometers installed at customers' properties (in addition to estimated consumption volume for connections without a hydrometer or with a non-functional hydrometer, if applicable). Water losses are directly related to operational and commercial performance since total water losses may result from issues in these two areas. These issues include leaks, reservoir overflows, measurement errors, consumer fraud and others (Brazil, 2022b). IPD is an undesirable indicator, since the smaller the volume of water lost, the better the municipality's performance.

Volumetric Water Loss Index (IPV) corresponds to the SNIS indicator IN051-Loss water per connection. IPV calculates water losses in terms of volume, depending on the number of active water connections. It was considered that the ideal loss level for a municipality is 216 l/connection/day, in accordance with Ordinance No. 490/2021. Just like IPD, IPV is also an undesirable indicator.

Using the BoD technique, the weights are generated endogenously from the data set using optimization, which gives more flexibility to selecting the weights without requiring previous specification of the relative importance of each indicator. As shown

in Table 9, three indicators of the ITB rank (ITE, IUE and ITR) correspond to 50% of the total weight assigned to the analysis. These indicators are related to sewerage, which demonstrates the concern with achieving the coverage targets and, above all, with the effective treatment of the collected sewage. However, for example, greater sewage coverage (ITE and IUE) will only be achieved if a minimum number of connections are made annually, making ILE a relevant indicator for achieving goals.

4.5.2 Descriptive Statistics

The individual analysis of descriptive statistics of the variables available in Table 10 allows a first panorama of WSS in the more populated municipalities of Brazil.

Table 10 - Descriptive statistics of the variables (2021)

Variable	Average	Std. Dev.	Minimum	Maximum
ITA – Total Water Coverage (%)	92.1	9.8	26.0	100.0
IUA – Urban Water Coverage (%)	93.2	9.2	28.6	100.0
ITE – Total Sewage Coverage (%)	71.9	24.2	0.7	100.0
IUE – Urban Sewage Coverage (%)	73.3	24.5	0.9	100.0
ITR – Treated Sewage Referred Consumed Water (%)	56.7	26.3	0.0	100.0
IIT – Total Investment by Receipt (%)	26.5	16.2	1.2	97.5
IIP – Investment by Provider per Receipt (%)	21.9	14.2	0.0	97.5
ILA – Water Connections (%)	61.8	39.6	0.0	100.0
ILE – Sewage Connections (%)	45.5	43.1	0.0	100.0
IPF – Total Revenue Loss (%)	39.2	15.3	3.7	81.5
IPD – Distribution Water Loss (%)	40.4	10.9	7.9	77.2
IPV – Volumetric Water Loss (l/connection/day)	486.7	257.0	98.1	2,185.7

Source: the author

Statistics show that water coverage, both total and urban (ITA and IUA, respectively), are in general the variables with the best performance. Urban coverage is slightly higher than total coverage, but both need to advance in order to meet the goal of Law No. 14,026/2020 that 99% of the Brazilian population has access to drinking water by 2033.

Compliance with Law No. 14,026/2020 is even more challenging in the case of sewage. According to the results of ITE and IUE, reaching the target of 90% sewage coverage in 2033 requires an average annual advance of 1.5%. The average value of 56.7% for Treated Sewage Referred to Consumed Water (ITR) still leaves the target of 80% far from being achieved.

Total Investment by Receipt (IIT) results shows that only 1/4 of the revenue has been invested in basic sanitation. A worrying situation, especially in municipalities that are still far from the universalization of services.

As expected, the results of Investments made by providers (IIP) are slightly worse than those of the IIT, as it only considers investments made by the service provider.

Water Connection Index (ILA) results shows that not all the water connections necessary to achieve the goals of universalization by 2033 are being made. Furthermore, 11 municipalities obtained a result of 0% in this indicator. This may have occurred due to problems in updating the municipality's water connection records, indicating a lower number of connections made than was actually carried out. The suppression of default connections, which increases the number of connections necessary to achieve universal services, can also be a reason for low performance in the ILA.

The result of the Sewage Connections (ILE) being lower than the ILA confirms that the challenges of universalizing sewage services are greater than those related to water supply, since the pace for the sewage connections is below the minimum number of connections necessary to achieve universalization goals. Furthermore, there is stability over the years, not growth, as should be expected. In 2021, 13 municipalities obtained a result of 0% in this indicator.

Total Revenue Loss Index (IPF) results indicate that around 39% of the water produced is not being billed. Reducing the IPF is essential to ensure the continuity of service provision and to guarantee the necessary fundings for maintenance and expansion of water and sewerage systems.

Water loss indicators are among the most significant in the management of water systems, since greater efficiency in controlling losses increases water availability, as less raw water needs to be captured from sources for treatment. Direct and indirect operational costs are also significantly impacted by the reduction in water losses, as the lower the losses, the lower the expenses for energy collection and labor for leak repairs, for example. If Distribution Water Loss (IPD) maintain their current performance, the target set by Ordinance No. 490/2021 (Brazil, 2021b) will not be reached until 2034. In 2021, only 14 municipalities reached the 25% target and, 46 municipalities had losses greater than the average of 40.2%. It is worth highlighting

that among these municipalities there are some with very high water losses, greater than 50%.

The Volumetric Water Loss index (IPV) result follows the same trend as the IPD. In the IPV case the average result is more than double that established by the Ordinance nº 490/2021, indicating the great efforts and investments that must be allocated to reducing losses in Brazil, especially by 2034.

As presented in Table 10, the variables considered as sub-indicators in the BoD CI construction exhibit considerable variation, suggesting the presence of extreme values or outliers. This fact justifies the need for a robust approach in developing the composite indicator to ensure a more reliable comparison with the current performance metric used by ITB.

4.5.3 Exogenous Contextual Variables

The use of contextual (or exogenous) factors has proven to be relevant for a greater understanding of the performance of basic sanitation services. According to Tourinho *et al.* (2022) the most frequent contextual variables used in the literature are: ownership, regional differences, scope of services, customer and population density, water source, water losses and peak factor (ratio between the highest and the average water consumption). The definition of contextual variables varies according to the objectives of each study, and other variables also identified in the literature review were the typology of the area of intervention (urban, semi-urban or rural), length of the network, percentage of leakage and proportion of water supplied to industrial customers in relation to domestic users, for example (Vilarinho *et al.*, 2023a; De Witte and Marques, 2011).

In this study, we will use four context variables, two of which are listed as the most commonly used: water source type (WST) and geographic region, the latter related to regional differences. Two other context variables were added to expand the study on external influences on performance: water source vulnerability (WSV) and Municipal Human Development Index (HDIM).

The contextual variables used in this study aim to expand the interpretation of the performance results of the municipalities, providing decision makers with more accurate information to support future action plans. The conditional approach will serve

to evaluate the influence of contextual variables on the municipalities' performance through non-parametric testing.

The four context variables are categorical and will be described in the following subsections.

4.5.3.1. Water Source Type (WST)

Surface water sources are associated with surface water runoff, whether from rain or from underground sources, and are represented by rivers, streams, dams or lakes. Due to their greater exposure, surface water can be more easily contaminated by improper sewage discharges, chemical spills, among others. Therefore, it is common for their potability to require a higher degree of treatment.

Underground sources are reservoirs of water that accumulate below the Earth's surface, filling the pores and fissures of rocks and soil. In general, the quality of groundwater is superior to that of surface water, and water treatment consists only of the disinfection stage. On the other hand, due to limited available flows, groundwater supply in large municipalities is not frequent and, when it occurs, it is usually done in combination with surface water supply (Brazil, 2020c).

The WST data used in this study come from the Atlas Águas (Water Atlas, in English), prepared by the Agência Nacional de Águas e Saneamento Básico, ANA (National Water and Basic Sanitation Agency) (ANA, 2021). According to the Atlas, 55% of the sample of the 100 most populous municipalities in Brazil are supplied exclusively by surface water sources, denominated by the acronym ES - Exclusively Surface. Another 41 municipalities have a mixed supply system, that is, they use both surface and groundwater simultaneously, with surface water sources predominating (PS - Predominantly Superficial). Only 4 municipalities are supplied exclusively by underground water sources (denominated by the acronym EU - Exclusively Underground).

4.5.3.2 Water Source Vulnerability (WSV)

The report of Intergovernmental Panel on Climate Change (IPCC, 2021) warns that climate change and continued global warming will further intensify the water cycle

in the coming decades, including its variability, global precipitation, and the severity of rain and drought events, making it urgent to implement adaptation strategies and actions.

Seeking to reflect these strategies, ANA classified Brazilian water sources according to their vulnerability, considering their degree of resilience (potential of natural and artificial water reserves to supply multiple users in situations of severe drought and drought), meeting demand (supply x demand ratio) and the size of the source.

The Water Atlas (Brazil, 2021c) indicated that 58 of the most populous municipalities in Brazil are classified as non-vulnerable water sources (NV - Non-vulnerable), 18 are low-vulnerable (LV) and 24 are moderately vulnerable (MV). The non-vulnerable group includes all municipalities in the Midwest and North regions, as well as 60% of municipalities in the Southeast region. The South and Southeast regions have the highest proportion of municipalities with low and moderate vulnerability, with 71% in the south and 60% in the Northeast, respectively.

The challenge of supplying water to large cities can only be overcome through the availability of raw water in sufficient quantity and quality to meet demands, which depends on the existence of minimally vulnerable water sources, whose exploration and treatment costs are viable.

4.5.3.3 *Municipal Human Development Index (HDI-M)*

The Human Development Index (HDI) is an indicator established by the United Nations that measures human development and social well-being based on criteria such as life expectancy at birth, education, and per capita income. The HDI ranges from 0 to 1, with the closer it is to 1, the greater the human development. In 2013, the global HDI methodology was adapted to the Brazilian context and the availability of national indicators, resulting in the Municipal Human Development Index (HDI-M). The HDI-M is composed of the same three dimensions as the HDI, accompanied by socioeconomic indicators that support the analysis and broaden the understanding of phenomena and dynamics related to municipal development (Macedo *et al.*, 2022). Table 11 summarizes the HDI-M parameterization ranges (Pinto *et al.*, 2022).

Table 11 - Parameterization of HDI-M ranges

Parameterization	Range
Very Low (VL)	0.000 - 0.499
Low (L)	0.500 - 0.599
Medium (M)	0.600 - 0.699
High (H)	0.700 - 0.799
Very High (VH)	0.800 - 1.000

Source: the author

The spectrum of HDI-M results is broad, ranging from 0.862 (São Caetano do Sul, state of São Paulo, southeast region) to 0.418 (Melgaço, state of Pará, North region), reflecting the regional inequalities of a territorially extensive and culturally diverse country like Brazil (Brazil, 2013c).

In this study, we intend to investigate whether poor performance in the HDI-M tends to hinder the adequate provision of sanitation services, since the qualification of the workforce and the available resources are more limited in relation to more developed municipalities. In this context, we can enhance our understanding of the potential existence of a vicious cycle between HDI-M and the inadequate basic sanitation infrastructure, where the former negatively impacts the population's quality of life and the latter exacerbates the issue.

Among the 100 largest municipalities in Brazil, 70 have a high HDI-M. Another 21 municipalities have a very high HDI-M and, only 9 have a medium HDI-M. Most municipalities with medium HDI-M are in the northeast region (55.5%), corresponding to the highest proportion of this indicator among all regions in Brazil. In turn, the Southeast region has the largest number of municipalities with a very high HDI-M (66.67%).

4.5.3.4 Geographic Region

The geographic location of municipalities is an important factor in performance analyses in a country of continental dimensions such as Brazil since each region has its own environmental, economic, social, and cultural characteristics.

Brazil currently has 5,570 municipalities, distributed among 26 states and 1 Federal District (Brasília, the Federal Capital). The states are organized into 5

geographic regions: Midwest (3 states and the Federal District), North (7 states); Northeast (9 states), Southeast (4 states) and South (3 states).

The Southeast region is the most populous in Brazil, with over 84 million inhabitants, representing approximately 41% of the country's total population (IBGE, 2022b).

In general, the South, Southeast and Midwest regions have the best quality of life in the country, both in social, infrastructural and economic terms (IBGE, 2021) (IBGE, 2022a) (Brazil, 2023b).

4.6 RESULTS AND DISCUSSION

This section presents the results of the study. In Subsection 4.6.1, the robust composite indicators' results are presented, as well as comparisons between the ITB ranks and BoD robust ranks. Subsection 4.6.2 shows the effect of exogenous contextual variables in municipalities' performance, using the conditional approach.

4.6.1 Robust Composite Indicator Results

This subsection discusses the findings associated with the estimation of the BoD composite indicator, using a robust approach.

As the composite indicator considered both desirable and undesirable outputs, a Directional BoD model was computed adopting the formulation presented in model (1). Regarding the weight restrictions shown in expressions (2), different values of ϕ_r and ϕ_k ranging from 1% to 5% were tested. After running this sensitivity analysis, the value of 5% was chosen for all the metrics. Using this value the occurrence of null weights is avoided. The value of 5% is also the minimum weight adopted by the ITB.

For the robust composite indicator, the values of the parameters m and B must be determined. B is often a high number, and for this study, the value of 2,000 was employed for B . Following Daraio and Simar (2007), a sensitivity analysis using several levels of m and evaluating the number of super-performing units was performed to decide the value of bootstrapping sample size m . These findings led to the choice of $m=60$. The CI calculation was performed using the packages Rglpk (Hornik *et al.*, 2012) and IpSolve (Berkelaar *et al.*, 2015) in R software.

Table 12 shows the descriptive statistics for the results covering all municipalities in the sample considering the unconditional robust approach applied to the sample in year 2021.

Table 12 - Composite Indicator ($CI_{j_0}^m$) average performance statistics - 2021

Average	Std. Dev.	Minimum	Maximum
0.818	0.130	0.487	1.071

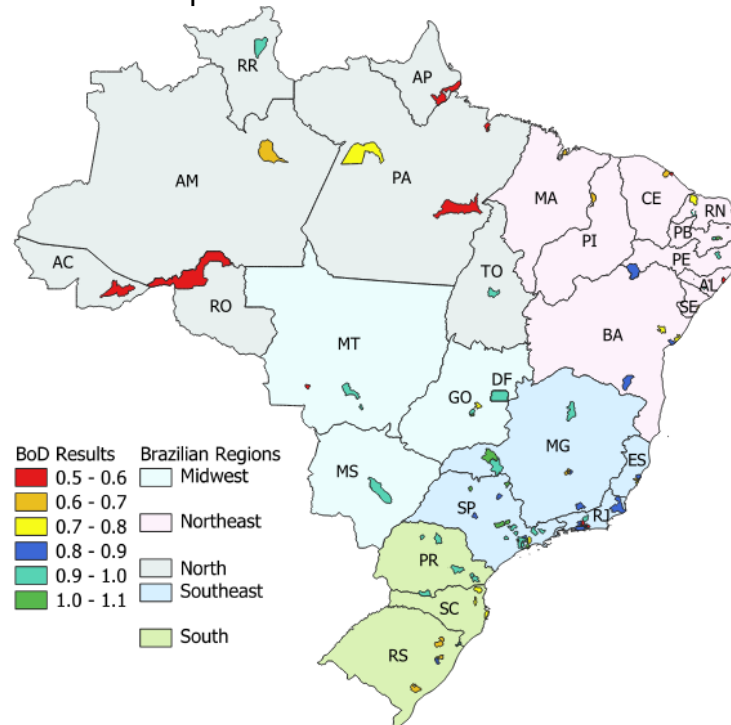
Source: the author

The average value of the composite indicator denote the existence of potential for improvement in the performance of water supply and sewage services in the municipalities studied. Furthermore, the frontier is only spanned by 11 municipalities.

Appendix A shows the robust composite indicator results for all DMUs and the comparison between the rankings of the Instituto Trata Brasil (ITB) and the robust BoD results.

Figure 13 graphically represents the robust BoD results in the year 2021. Only the municipality of Macapá had a CI result below 0.5. Most municipalities (30%) are in the range of 0.90 to 0.99.

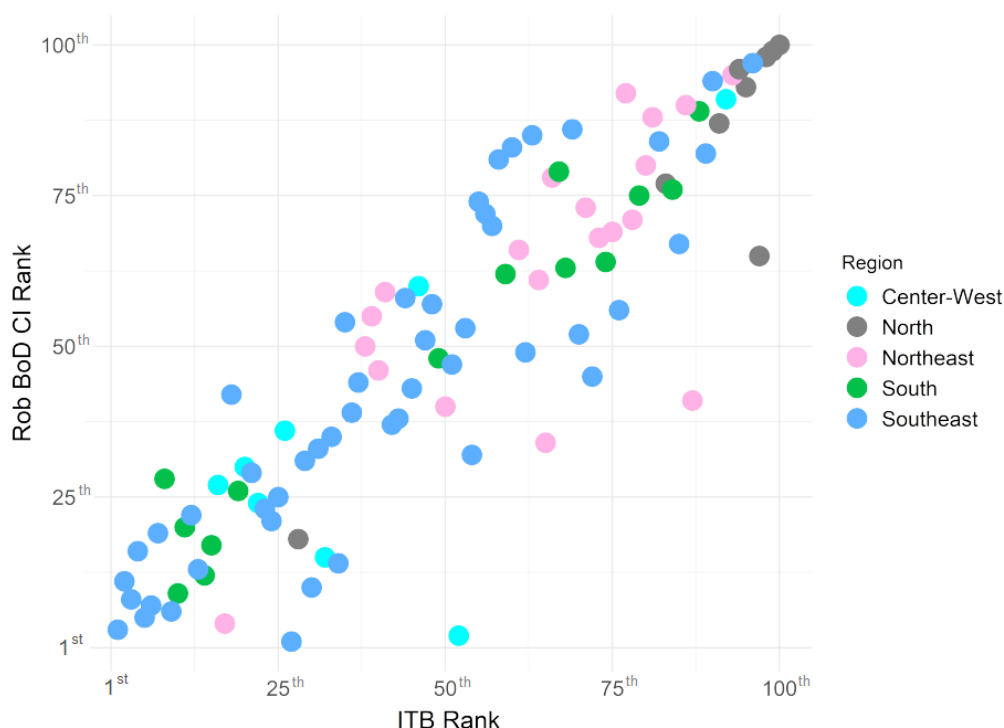
Figure 13 - Brazilian municipalities BoD robust unconditional results 2021



Source: the author

The Spearman's rank correlation between the ITB rank and BoD rank is 0.8882, corresponding to a p-value of 0.0000, indicating that the correlation is statistically significant. A scatter plot showing the correlation between the ITB rank and the BoD rank positions is presented in Figure 14.

Figure 14 - Scatter plot of BoD and ITB rank positions



Source: the author

Although the high correlation between the two rankings indicates that the BoD and ITB results are aligned, in general the individual analysis shows that there are significant differences between positions in both rankings for several municipalities. These differences in position can significantly impact various municipalities, guiding the data analysis and decision-making process in different ways. The ITB ranking places greater emphasis on sewage collection and treatment by assigning higher weights to the indicators in this area. In Brazil, sewage treatment coverage remains significantly lower than that of water supply, and if this scenario persists, achieving universal service coverage by 2033 may be at risk.

In contrast, the BoD ranking allows municipalities to highlight their best-performing areas while also offering advantages such as identifying their strengths and weaknesses and detecting peers municipalities for benchmarking. By avoiding

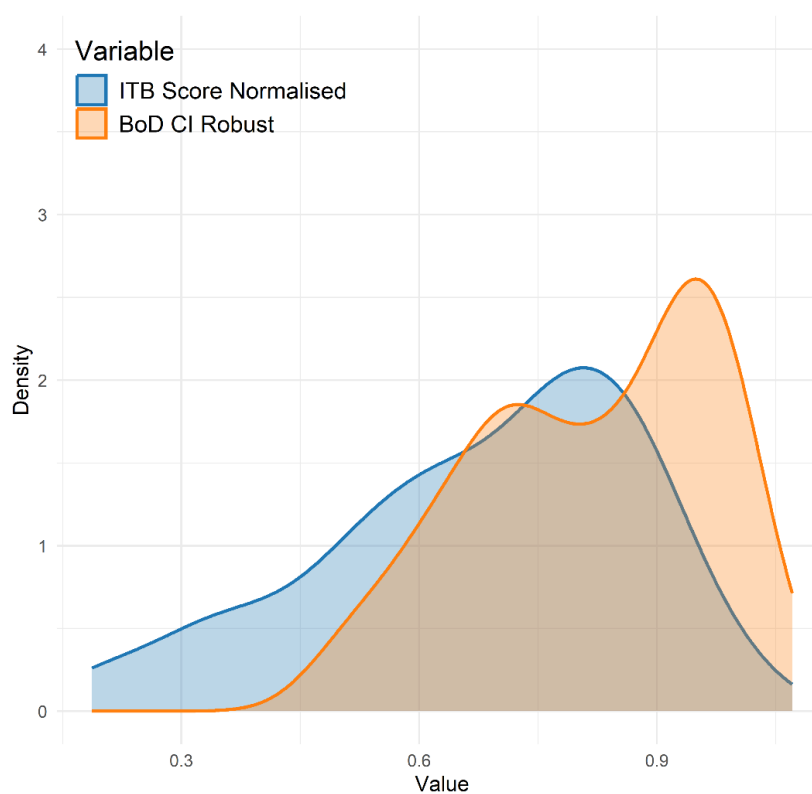
predefined focal areas in sector assessment, BoD provides a broader and fairer perspective on performance.

Given the ITB ranking's broad national reach, including among audiences unfamiliar with the intricacies of WSS sector evaluations, a rigid weighting structure can lead to oversimplified conclusions. Without a clear understanding of the underlying assumptions, municipalities may be unfairly judged based on predefined criteria rather than a more holistic assessment of their performance. The BoD approach mitigates this risk by adapting to the unique strengths of each municipality, offering a more nuanced and equitable evaluation framework.

Figure 15 graphically shows the distribution densities of both measurement scores. In this case, the original ITB score was normalised to the same scale as the BoD score. The ITB score ranges from 0 to 10, so in order to normalize the data, the values were divided by 10 to obtain a scale from 0 to 1, compatible with the BoD composite indicator. The kernel density graph shows that the most frequent values in the robust Benefit-of-the-Doubt distribution are concentrated near the best-performing frontier, where the composite indicator equals one. In contrast, the normalized score from Instituto Trata Brasil exhibits greater heterogeneity.

According to Appendix A, 91% of the DMUs experienced differences in the rank between the two methodological approaches. In total, 50 municipalities varied from 1 to 9 positions; 31 municipalities varied between 10 and 20 positions and, another 10 municipalities varied more than 20 positions. Among the 41 municipalities that varied at least 10 positions, either up or down, 18 improved their positions in the BoD ranking. The remaining 23 municipalities had better positions in the ITB ranking.

Figure 15 - Kernel Density Plot - ITB Score Normalised vs. BoD robust composite indicator



Source: the author

Aparecida de Goiânia (GO) was the municipality that evolved the most in the BoD ranking (2nd) compared to ITB ranking (52nd). The top position of Aparecida de Goiânia in the CI robust results is mainly a consequence of the municipality's performance in indicators related to water losses and investments, precisely the indicators with the lowest weights in the ITB. This suggests that the ITB criteria of fixed weighting methods may undervalue key factors where Aparecida de Goiânia excels. Given each location's unique characteristics and needs, it could be the most critical factor for effective WSS management in that city.

Vitória da Conquista (BA) was the municipality that regressed the most positions in the BoD ranking (42nd) compared to the ITB ranking (18th). This probably occurred because Vitória da Conquista has a good performance in the ITE, IUE and ITR indicators, precisely those that have the greatest weight in the ITB. In the IIT and IIP indicators, Vitória da Conquista performed below the average of other municipalities in the same geographic region. Since the weights that the ITB attributes to these

indicators are low, the municipality's position in the ITB ranking is not greatly affected, which does not happen in the BoD ranking due to the flexible weights.

Vitória da Conquista's result in the ITB ranking was celebrated by the company that provides sanitation services to the city (Embasa, 2025). The announcement made on the company's website states that Vitória da Conquista is the best sanitized city in the Northeast. However, according to the BoD results, the northeastern cities of Campina Grande, Caruaru, Jaboatão dos Guararapes and Olinda present a better performance than Vitória da Conquista.

The BoD approach offers several advantages. It determines weights without relying on subjective judgments about indicator importance, uses variables in their original form and mitigates the effect of extreme values. As a result, each municipality's assigned weights represent the optimal configuration for its evaluation, ensuring that no alternative set of weights could yield a better overall performance index.

However, it is important to note that the robust approach cannot directly pinpoint the contextual factors driving variation in the results. In such cases, possible approaches could be empirically assessing the likely causes of variation through descriptive statistics, DMU characteristics, and insights from previous studies. These explanations can be more challenging in large, heterogeneous samples or studies covering extensive territories. Under these circumstances, other approaches using contextual exogenous variables can offer valuable information for a more precise analysis, as suggested by May *et al.* (2024).

4.6.2 Effect of exogenous contextual variables

This subsection presents the calculation of robust conditional CIs, which reveals municipalities' performance, taking into account their own water, geographical and social characteristics. The np package (Hayfield and Racine, 2008) was employed in R software to obtain samples based on the similarity level among municipalities and to execute non-parametric significance tests.

In the initial stage, the calculation of the robust conditional CI and significance tests was performed individually for each exogenous variable. This step-by-step approach allowed the inclusion of one variable at a time and facilitated the identification of the contextual factors that influenced the outcomes. The p-value of the hypothesis test used to compare the groups (Kernel regression significance test) returned values

of 0.000 for all contextual variables. The low p-values indicate that the exogenous variables WST, WSV, HDI-M and geographic region have a significant effect on the performance of DMUs and can indeed influence the provision of services.

In the second stage, the four contextual variables were incorporated into the final calculation to generate the robust conditional CI, whose summary statistics are reported on Table 13. The results of each municipality are presented in Appendix A.

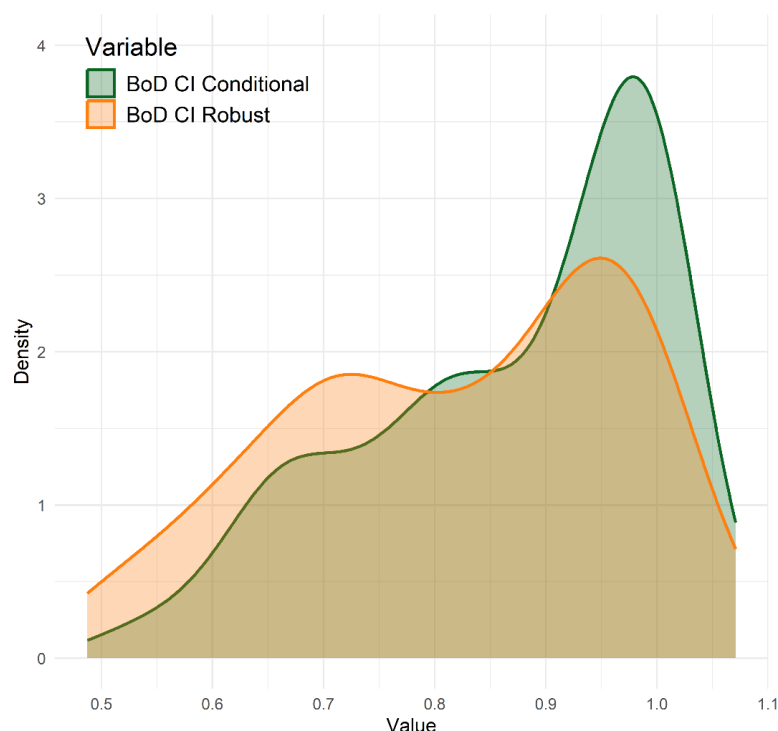
Table 13 - Composite Indicator ($CI_{j_0}^{m,z}$) average performance statistics – 2021

Average	Std. Dev.	Minimum	Maximum
0.869	0.114	0.522	1.001

Source: the author

Comparing the results of Table 13 and Table 12, it can be seen that the average performance advanced by approximately 5%, showing that exogenous variables tend to positively influence the result. As can be seen in the Figure 16, the Kernel density graph indicates the concentration of municipalities closest to the frontier in the BoD CI Conditional.

Figure 16 - Kernel Density Plot - BoD CI Conditional vs. BoD CI Robust



Source: the author

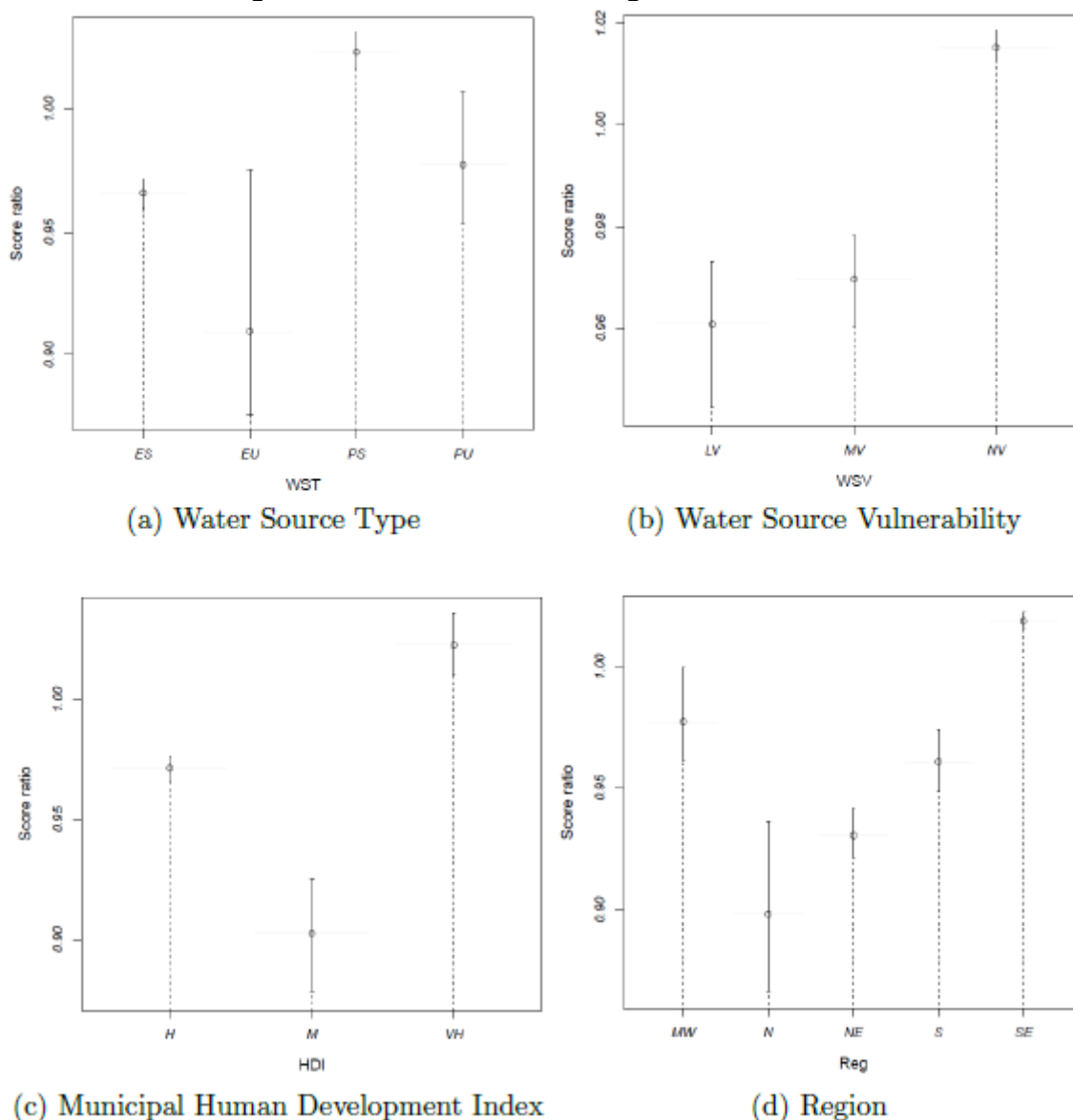
Figure 17 presents confidence intervals of score ratios between robust unconditional and conditional CIs for each context variable. In all plots shown in Figure 517 the confidence intervals do not overlap, confirming the findings of the Kernel regression significance test. This reinforces that all contextual variables studied significantly influence the performance of providers in the water sector.

The confidence interval shown in Figure 17a for municipalities supplied predominantly by surface water sources (PS – Predominantly Superficial) do not overlap with any of the other types of water resources, highlighting that this type of supply has a significant impact on the performance of municipalities. The remaining confidence intervals in the same figure overlap, so it is not possible to identify significant differences between them.

The score ratio between robust and robust conditional CIs for the PS systems is higher than the ones from other water source types, indicating that the mixed supply systems where superficial water is more used than surface water tend to perform better. This behavior may be related to the balance between demand and water quality.

In other words, although groundwater is of higher quality than surface water and, consequently, requires simpler purification processes, its volume is insufficient to meet the demand of highly populated municipalities. Furthermore, depending on the depth of the underground source, operational expenses, such as energy consumption, may make the cost-benefit ratio unviable for supply. Therefore, surface sources can meet the large demand for water in municipalities, being supplemented occasionally by underground sources. This evidence corroborates the conclusions of the study conducted by Ananda (2019), that identified that the source of raw water have a statistically significant influence on the environmental efficiency of drinking water and wastewater utilities.

Figure 17 - Effect of each exogenous variables



Source: the author

The balanced use of mixed supply systems can be better explored by Brazilian water supply service providers, given the better performance of municipalities supplied predominantly by surface sources, but with contributions from groundwater. However, it is important to reinforce the need to adopt appropriate techniques for the use of groundwater, avoiding its excessive exploitation, which could compromise water reserves and lead to the occurrence of saline intrusion.

Drinking water supply services rely entirely on water sources, whether surface or underground. The vulnerability of these water bodies poses a risk to their environmental balance and the continuity of these services. Protecting water sources

is a key responsibility of the sanitation sector, regulatory agencies, and water supply service providers. This effort is essential to ensure the economic sustainability of the sanitation sector and to promote comprehensive water security (Burgardta, 2021; Oliveira, 2021).

The results in Figure 17b reveal that municipalities with non-vulnerable water sources (NV) tend to present significantly better performances. According to Danelon *et al.* (2021) the quality of water resources impacts water treatment costs, highlighting the direct relationship between the quality of the water collected and the ideal treatment costs.

Measures to protect water sources must be improved, especially in the most populous cities strengthening the entities that govern the sector, such as ANA, ensuring water in adequate quantity and quality, with fair rates, resulting from adequate treatment costs and financial balance in the provision of services.

Regarding HDI-M (Figure 17c), studies on the impact of HDI on the efficiency of sanitation services are not frequent, but Macedo *et al.* (2022) found a direct relationship between the HDI and the deficient structure of basic sanitation, especially sewage. According to Macedo *et al.* (2022), the municipalities that did not have sewage collection, removal, and treatment facilities tended to have low life expectancies due to compromised hygiene and health conditions. The results of the exogenous variable HDI-M in Figure 17c show that municipalities with very high human development (VH) tend to have significantly better performances compared to the remaining levels, evidenced by the higher level and non-overlapping confidence interval in Figure 17c. As expected, the higher the HDI-M, the better the performance. According to the graph, municipalities with high HDI-M are expected to have significantly lower performance than VH municipalities. Municipalities with the lowest HDI-M, in this case, the medium HDI-M, are negatively impacted in performance.

The evolution of the Municipal Human Development Index must be expanded, with the adoption of effective actions in health, education, income generation, among others, maintaining the feedback of the quality of life - sanitation - quality of life cycle.

Concerning the impacts of geographic regions on the performance in the provision of sanitation services, Tourinho *et al.* (2022), Carvalho and Sampaio (2015), Ferro *et al.* (2014), and Da Silva e Souza *et al.* (2008) found heterogeneity in efficiency levels among Brazilian regions. By contrast, the results found by Barbosa *et al.* (2016) and, De Faria *et al.* (2005) reveal no statistical difference in the efficiency levels of

water services among regions. Studies conducted in Italy (Lombardi *et al.*, 2019) and Japan (Marques *et al.*, 2014) found that geographical differences within the country had a significant impact on water services' performance.

According to the results in Figure 17d, the geographic region has a significantly influence on the performance of municipalities. The Southeast region had the best performance. The South and Midwest regions are better than the North and Northeast. The differences between the North and Northeast are not significant for performance, as can be seen from the overlapping of the confidence intervals. These differences in performance between regions demonstrate the significant impact that regional differences have on Brazilian WSS.

In terms of Brazilian public policies, the results found in this study reinforce the need for specific actions for the North and Northeast regions, whose performance was significantly lower than that of the other regions.

Overall, this study demonstrates that the identification of exogenous variables that represent relevant local characteristics impacts performance results. In this way, for benchmarking purposes, it facilitates the identification of reference DMUs, resulting in greater efficiency in the dissemination of good practices. Regulatory agencies, service providers and other stakeholders can benefit from this technique to ensure the desired advancement of the WSS sector. This approach offers a notable advantage of the robust conditional BoD technique over the current methodology used by ITB.

4.7 CONCLUSIONS

This study assessed the performance of the 100 most populous municipalities in Brazil for the provision of water supply and sewage services. The Benefit-of-the Doubt (BoD) technique was used to synthesize twelve metrics that reflect the population served, water supply, sewage collection and treatment, investments, and water losses dimensions of WSS into a composite indicator.

The framework used a robust directional BoD model to aggregate desirable and undesirable aspects of the WSS and, determine the composite indicator results. The study findings show that the average performance is unsatisfactory in meeting efficiency goals and universal access to services imposed by Brazilian Law No. 14,026/2020. Furthermore, the robust unconditional BoD calculation allowed a detailed analysis of the ranking of Instituto Trata Brasil (ITB). Despite the Spearman's rank

correlation technique revealed a strong correlation between the two ranks, individual analysis of the municipalities' positions indicated profound differences, which can significantly affect each DMU, promoting distorted views about their performance and, rushing decision-making regarding points for improvement. In addition, there is the possible damage to public image due to misinterpretation of the data. BoD's feature of not defining weights for indicators added flexibility to the analysis and presented a more realistic view of the municipalities' performance. Additionally, the robust BoD approach mitigates the impact of extreme values, making it particularly well-suited for this study, given the significant heterogeneity in performance among the assessed municipalities.

Lastly, the conditional BoD approach demonstrated that the identification of exogenous variables that represent relevant local characteristics impacts performance results. Recognition of the impact that the type of source, the vulnerability of the source, the Municipal Human Development Index, and the geographic location have on performance assists decision makers in developing more assertive policies and disseminating good practices.

In summary, this study offers a more accurate, impartial, reliable, and nuanced assessment of water sector performance in Brazil's 100 most populous municipalities, outperforming the methodology currently used by Instituto Trata Brasil.

Subsequent studies could use a sample involving other municipalities in order to verify whether there are variations in performance depending on size. It is expected that the most populous municipalities will present larger amounts of human and financial resources to improve productivity in the sector, however, the great challenge of Brazilian sanitation may lie in small towns, which will require the adoption of different techniques for water supply and adequate treatment of effluents.

Acknowledgments

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

APPENDIX: BOD RESULTS AND RANKINGS

Appendix shows the BoD result for the three years analyzed and compares the positions of the municipalities in the BoD and ITB rankings. In the Rank BoD column, municipalities whose position in the BoD ranking worsened by 10 or more positions in relation to the ITB ranking are highlighted in red font. In the opposite direction, the classifications in blue font indicate the municipalities that improved 10 or more positions in the BoD ranking when compared to the ITB ranking.

Table A.6 - BoD results and comparison between BoD and ITB rankings for year 2021
(continues)

Municipality (State)	BoD Robust	BoD Conditional	Rank ITB	Rank BoD
Ananindeua (PA)	0.6261	0.8554	91	87
Anápolis (GO)	0.7806	0.8389	46	60 ↓
Aparecida de Goiânia (GO)	1.0268	1.0000	52	2 ↑
Aracaju (SE)	0.6954	0.7809	66	78 ↓
Bauru (SP)	0.8124	0.8389	76	56 ↑
Belém (PA)	0.5920	0.7953	95	93
Belford Roxo (RJ)	0.7317	0.8196	85	67 ↑
Belo Horizonte (MG)	0.8343	0.8185	47	51
Betim (MG)	0.6537	0.6557	63	85 ↓
Blumenau (SC)	0.7643	0.9092	68	63
Boa Vista (RR)	0.9673	0.9999	28	18 ↑
Brasília (DF)	0.9332	0.9795	20	30 ↓
Camaçari (BA)	0.7251	0.9409	75	69
Campina Grande (PB)	1.0138	1.0000	17	4 ↑
Campinas (SP)	0.9388	0.9590	21	29
Campo Grande (MS)	0.9197	0.9889	26	36
Campos dos Goytacazes (RJ)	0.8174	0.8320	35	54 ↓
Canoas (RS)	0.7041	0.7492	79	75
Carapicuíba (SP)	0.7993	0.8323	44	58 ↓
Cariacica (ES)	0.6539	0.6743	82	84
Caruaru (PE)	0.9066	0.9998	50	40 ↑
Cascavel (PR)	1.0049	1.0000	10	9
Caucaia (CE)	0.6231	0.7331	81	88
Caxias do Sul (RS)	0.6891	0.7503	67	79 ↓
Contagem (MG)	0.6567	0.6590	60	83 ↓
Cuiabá (MT)	0.9855	1.0000	32	15 ↑
Curitiba (PR)	0.9752	0.9998	15	17
Diadema (SP)	0.9069	0.9364	36	39
Duque de Caxias (RJ)	0.5828	0.6086	90	94
Feira de Santana (BA)	0.7408	0.7851	61	66
Florianópolis (SC)	0.7658	0.8104	59	62

Table A.6 - BoD results and comparison between BoD and ITB rankings for year 2021

(continuation)

Municipality (State)	BoD Robust	BoD Conditional	Rank ITB	Rank BoD
Fortaleza (CE)	0.5953	0.6598	77	92 ↓
Franca (SP)	1.0101	1.0000	9	6
Goiânia (GO)	0.9565	0.9992	22	24
Gravataí (RS)	0.6129	0.6749	88	89
Guarujá (SP)	0.7093	0.7165	55	74 ↓
Guarulhos (SP)	0.8524	0.8701	62	49 ↑
Itaquaquecetuba (SP)	0.9274	1.0001	54	32 ↑
Jaboatão dos Guararapes (PE)	0.9015	0.9993	87	41 ↑
João Pessoa (PB)	0.8362	0.9629	38	50 ↓
Joinville (SC)	0.7529	0.9656	74	64 ↑
Juiz de Fora (MG)	0.8263	0.8644	70	52 ↑
Jundiaí (SP)	0.9629	0.9845	24	21
Limeira (SP)	1.0132	1.0010	5	5
Londrina (PR)	0.9504	0.9769	19	26
Macapá (AP)	0.4873	0.5222	100	100
Maceió (AL)	0.5517	0.6525	93	95
Manaus (AM)	0.6969	0.9228	83	77
Marabá (PA)	0.5000	0.6549	99	99
Maringá (PR)	0.9963	1.0000	14	12
Mauá (SP)	0.8190	0.8251	53	53
Mogi das Cruzes (SP)	0.7151	0.7570	56	72 ↓
Montes Claros (MG)	0.9316	0.9551	29	31
Mossoró (RN)	0.7117	0.8279	71	73
Natal (RN)	0.7262	0.8356	73	68
Niterói (RJ)	0.9757	0.9957	4	16 ↓
Nova Iguaçu (RJ)	0.8650	0.9385	72	45 ↑
Olinda (PE)	0.9226	0.9998	65	34 ↑
Osasco (SP)	0.8870	0.9273	45	43
Palmas (TO)	0.9484	0.9995	16	27 ↓
Paulista (PE)	0.7674	0.8902	64	61
Pelotas (RS)	0.6990	0.7593	84	76
Petrolina (PE)	0.8139	0.9160	39	55 ↓
Petrópolis (RJ)	0.9200	0.9158	33	35
Piracicaba (SP)	1.0095	1.0010	6	7
Ponta Grossa (PR)	0.9637	0.9890	11	20
Porto Alegre (RS)	0.8527	0.9272	49	48
Porto Velho (RO)	0.5145	0.6267	98	98
Praia Grande (SP)	0.9904	1.0004	34	14 ↑
Recife (PE)	0.7162	0.7719	78	71
Ribeirão das Neves (MG)	0.6313	0.6928	69	86 ↓
Ribeirão Preto (SP)	0.8867	0.9172	37	44
Rio Branco (AC)	0.5355	0.5922	94	96
Rio de Janeiro (RJ)	0.8096	0.8316	48	57
Salvador (BA)	0.8531	0.9443	40	46

Table A.6 - BoD results and comparison between BoD and ITB rankings for year 2021

(conclusion)

Municipality (State)	BoD Robust	BoD Conditional	Rank ITB	Rank BoD
Santarém (PA)	0.7506	0.9988	97	65 ↑
Santo André (SP)	1.0709	1.0000	27	1 ↑
Santos (SP)	1.0003	0.9997	2	11
São Bernardo do Campo (SP)	0.9115	0.8496	43	38
São Gonçalo (RJ)	0.5224	0.5449	96	97
São João de Meriti (RJ)	0.6607	0.6937	89	82
São José do Rio Preto (SP)	1.0164	1.0000	1	3
São José dos Campos (SP)	0.9253	0.9403	31	33
São José dos Pinhais (PR)	0.9422	0.9996	8	28 ↓
São Luís (MA)	0.6046	0.6747	86	90
São Paulo (SP)	0.9670	0.9501	7	19 ↓
São Vicente (SP)	0.6830	0.6910	58	81 ↓
Serra (ES)	0.8530	0.9040	51	47
Sorocaba (SP)	0.9571	0.9656	12	22 ↓
Sumaré (SP)	0.9152	0.9546	42	37
Suzano (SP)	0.9927	1.0004	13	13
Taboão da Serra (SP)	1.0011	1.0005	30	10 ↑
Taubaté (SP)	0.9569	0.9782	23	23
Teresina (PI)	0.6888	0.7934	80	80
Uberaba (MG)	0.9559	0.9485	25	25
Uberlândia (MG)	1.0079	1.0010	3	8
Várzea Grande (MT)	0.6005	0.6404	92	91
Vila Velha (ES)	0.7229	0.7322	57	70 ↓
Vitória (ES)	0.7853	0.7990	41	59 ↓
Vitória da Conquista (BA)	0.8999	0.9997	18	42 ↓
Spearman's rank correlation			$p=$ 0.8882	

5 AN ANALYSIS OF WATER SUPPLY SYSTEM LOSSES: A CASE STUDY OF SANTA CATARINA STATE, BRAZIL

This chapter presents the article presented at the *International Conference on Industrial Engineering and Operations Management* promoted by the Industrial Engineering and Operations Management Society, in Orlando, United States, in June 2025. The article will be published in the book with the conference proceedings, in Oct./2025.

Abstract

Water losses are critical indicators of operational and commercial efficiency in water supply systems. This study investigates the determinants of water distribution losses in the state of Santa Catarina, Brazil, using official data from the National Sanitation Information System (SNIS) for the year 2022, encompassing 293 municipalities and a population of approximately 7.6 million. A three-phase analytical approach was adopted: exploratory analysis and dimensionality reduction through Principal Component Analysis (PCA); classification of municipalities using the CHAID decision tree algorithm; and interpretation of the resulting predictive model. The results identified 28 key variables explaining 75% of the variance in the dataset. Water consumption index, revenue loss, macro-metering, and water export volumes emerged as significant predictors of loss rates. The study found an inverse correlation between water consumption and loss rates - municipalities with consumption indices below 55.8% exhibited average losses of 52.5%, while those above 68.6% had losses reduced to 21.4%. The findings emphasize the need for integrated metering, infrastructure optimization, and tailored strategies based on municipal cluster profiles to reduce water loss and improve system performance. This methodology provides a replicable framework for data-driven decision-making in public water management.

Keywords: Water Loss; Water Supply System; Decision Tree Classification.

5.1 INTRODUCTION

Water loss in distribution systems is one of the most critical indicators of operational and commercial efficiency in the sanitation sector. In Brazil, the challenge of reducing these losses has gained national attention with the enactment of the Basic Sanitation Legal Framework (Law No. 14.026/2020), which aims to universalize access to potable water by 2033 and imposes performance targets on service providers. Among these, reducing distribution losses has become a central priority, given that, in 2022, the country recorded an average water loss rate of 37.8%, equivalent to 338 liters per connection per day (Brazil, 2023). These losses result from a combination of

real losses - such as physical leakage from networks and reservoirs - and apparent losses, often associated with metering inaccuracies or unauthorized consumption. Together, they reflect the capacity of water utilities to manage infrastructure, monitor consumption, and ensure financial sustainability. As potable water becomes increasingly scarce, tackling these inefficiencies is not only a technical imperative but also a matter of social and environmental urgency.

The state of Santa Catarina, located in southern Brazil, presents a diversified socioeconomic and geographical profile. Despite reporting above-average water supply coverage, exceeding 95% in urban areas, there are marked disparities in infrastructure and service efficiency across its 295 municipalities. Larger cities tend to benefit from consolidated management and technological investments, while smaller or rural municipalities frequently struggle with limited resources and outdated systems.

Institutionally, water services in Santa Catarina are provided through multiple arrangements, including a large mixed-capital public company, municipal utilities, private operators, and intermunicipal consortia. This fragmentation contributes to heterogeneity in service quality, data consistency, and infrastructure development, making it difficult to standardize strategies for water loss control. Understanding the underlying factors that influence water losses requires an integrative analytical approach. Loss rates are affected by a multitude of technical, operational, and management-related variables, which often interact in complex and nonlinear ways. Identifying the most influential among them is crucial for designing targeted policies and interventions.

In this context, this study investigates the drivers of water distribution losses in Santa Catarina using data from the National Sanitation Information System (SNIS) for the year 2022. It applies multivariate statistical techniques and decision tree modeling to classify municipalities according to their performance and to identify key variables associated with higher or lower loss rates. The analysis aims to contribute to evidence-based decision-making and to support the development of differentiated strategies adapted to the specific needs of small, medium, and large municipalities.

5.1.1 Objective

This study aims to examine the principal challenges related to water availability and service efficiency in the state of Santa Catarina, Brazil, with a particular emphasis

on the analysis of water distribution losses. Utilizing official secondary data from the National Sanitation Information System (SNIS) for the year 2022, the research seeks to identify the key determinants influencing the Water Distribution Loss Index, a fundamental performance metric for assessing the operational efficiency of water supply systems. To address these objectives, a structured three-phase analytical framework was employed: (i) Data Exploration and Dimensionality Reduction, to examine the dataset's structure and characteristics and to extract the most relevant variables for analysis; (ii) Classification via Decision Tree Algorithm, to model the relationships between selected independent variables and the dependent variable; and (iii) Interpretation of Classification Trees, to elucidate the structure and interpret the outcomes generated by the classification model.

5.2 LITERATURE REVIEW

Water loss in distribution systems remains one of the most pressing challenges in achieving universal access to quality water services and ensuring the financial and environmental sustainability of utilities. Losses are conventionally classified into two categories: real losses, stemming from physical issues such as pipe leakage and reservoir overflows, and apparent losses, caused primarily by metering errors and unauthorized consumption (Lambert and Hirner, 2001). Together, these losses comprise Non-Revenue Water (NRW), a widely recognized performance indicator in the sanitation sector (Alegre *et al.*, 2016). To address these inefficiencies, the International Water Association (IWA) has developed a standardized water balance framework and performance metrics that guide diagnosis and benchmarking in water utilities (Farley *et al.*, 2003). Such tools have become essential for informing investment decisions and guiding operational improvements, especially in contexts marked by aging infrastructure and limited institutional capacity.

In developing countries, studies consistently point to structural weaknesses as central drivers of elevated water loss rates. Silva *et al.* (2019) highlight the role of outdated or inadequate metering systems in increasing apparent losses, while Miranda (2006) underscores the limited financial and managerial capacity of providers to invest in preventive maintenance and technological upgrades. The situation is compounded by institutional fragmentation, which hinders standardized monitoring and consistent performance assessment.

At the regulatory level, Brazil has made significant advances by integrating water loss reduction targets into national policies. The Basic Sanitation Legal Framework (Law No. 14.026/2020) establishes progressive performance thresholds for service providers, with maximum allowable water loss rates capped at 25% by 2034. Complementary regulations, such as Ordinance No. 490/2021, link access to federal funding to compliance with these targets (Brazil, 2021), reinforcing the legal and financial incentives for loss mitigation.

Given the complexity and scale of data generated in water distribution systems, ranging from flow rates and pressures to spatial and consumer data, analytical techniques have become essential tools for diagnosing inefficiencies. In this regard, machine learning and multivariate analysis have proven especially useful.

Recent research has demonstrated the utility of decision tree models for identifying risk factors and predicting anomalies in distribution systems. For example, Yang *et al.* (2020) applied decision trees to evaluate pipe failure risks in Beijing, incorporating both technical and geographic variables. Sun *et al.* (2014) used similar models to classify aging infrastructure and guide replacement priorities, while Jalal and Ezzedine (2020) combined decision trees with Support Vector Machines for anomaly detection in water quality monitoring.

Complementary approaches based on clustering techniques have also contributed to the identification of spatial patterns in water loss. Di Nardo *et al.* (2017) used weighted spectral clustering to optimize district meter area (DMA) layouts, while Shuang *et al.* (2024) identified high-risk leakage clusters in Los Angeles using socioeconomic and engineering indicators. In Brazil, Sesso *et al.* (2020) employed spatial analysis to detect critical zones in the Paraná state distribution network, suggesting targeted interventions in areas with recurring billing losses and service interruptions. Heinz *et al.* (2021), focusing on Santa Catarina, applied cluster analysis to classify municipalities by service coverage, highlighting structural inequalities across regions.

Another widely used approach is Principal Component Analysis (PCA), which serves to reduce dimensionality in large datasets while retaining key patterns of variation. Jang *et al.* (2018) combined PCA with Artificial Neural Networks to improve leakage rate estimation, and Munhequete (2022) used PCA to identify dominant factors affecting per capita water availability in Mozambique. These techniques help distill complex information into actionable insights, enabling decision-makers to focus on the

most influential variables.

Collectively, these studies indicate an emerging consensus that reducing water losses necessitates not only technical enhancements, but also improved data governance, intersectoral coordination, and the implementation of context-specific strategies tailored to local conditions. While international methodologies offer a strong foundation, localized analyses – such as the one proposed in this study - are essential to adapt best practices to the unique geographic, institutional, and demographic conditions of each region.

5.3 METHODS

The methodological framework adopted in this study was designed to identify and classify the main variables associated with water distribution losses in municipalities of Santa Catarina, Brazil. The approach integrates multivariate statistical techniques with machine learning tools and is organized into three sequential phases: (1) data exploration and dimensionality reduction, (2) decision tree classification, and (3) interpretation of the resulting classification model.

5.3.1 Data Exploration and Dimensionality Reduction

The first phase involved a comprehensive exploratory analysis aimed at understanding the structure and characteristics of the dataset. This included descriptive statistics, correlation analysis, and clustering techniques. Initially, Pearson's correlation coefficients were calculated to detect multicollinearity among variables. Pairs of variables with correlation coefficients equal to or above 0.95 were considered redundant and excluded in accordance with the Principle of Parsimony (Hair *et al.*, 2018). After this filtering process, 93 variables were retained for further analysis.

To reduce the dimensionality of this dataset, Principal Component Analysis (PCA) was applied. PCA transforms a large set of potentially correlated variables into a smaller number of orthogonal components that explain most of the variance in the data (Jolliffe and Cadima, 2016). The analysis identified five principal components that accounted for approximately 75% of the total variance. The 28 most representative

variables - those with the highest loadings - were selected for use in the classification model.

Additionally, the k-means clustering algorithm was employed to group municipalities based on demographic and consumption patterns. This facilitated the identification of population-based trends in water use and infrastructure challenges, enabling subsequent analysis to consider cluster-specific characteristics.

5.3.2 Classification via Decision Tree Algorithm

In the second phase, a classification model was developed using a decision tree approach to relate the selected independent variables to the dependent variable: the Water Distribution Loss Index (expressed as a percentage).

Among various decision tree algorithms, the Chi-squared Automatic Interaction Detection (CHAID) method was selected due to its robustness in handling large datasets with multiple categorical and continuous variables. Unlike binary-splitting algorithms such as CART or C4.5, CHAID performs multi-level splits, which enhances the interpretability and granularity of the resulting tree (Kass, 1980; Breiman *et al.*, 2017).

The CHAID algorithm constructs the tree by recursively partitioning the data based on the statistical significance of the relationship between independent and dependent variables. Splits are determined using the chi-square test, and pruning is applied to avoid overfitting. The model was implemented using STATISTICA software, and the final tree structure was based on 265 municipalities with complete data records. The remaining 28 municipalities were excluded due to missing values in one or more of the selected variables.

5.3.3 Interpretation of Classification Trees

The final phase focused on interpreting the structure and results of the CHAID classification tree. Each node and branch represents a segment of municipalities grouped according to similar values of the independent variables, with terminal nodes (leaves) indicating the predicted average water loss index for that group.

This rule-based structure enables transparent and actionable insights: the path

from root to leaf can be interpreted as a sequence of conditional rules (e.g., “If water consumption index < 55.8% and revenue loss > 54.4%, then predicted loss = 61%”). This interpretability makes the model particularly useful for supporting public policy and infrastructure planning, as it highlights combinations of variables that lead to high or low performance outcomes (Molnar, 2025; Quinlan, 1993).

5.4 DATA COLLECTION AND PROCESSING

This study is based on secondary data obtained from the National Sanitation Information System (SNIS), the official database maintained by the Brazilian Federal Government for monitoring and evaluating basic sanitation services. The SNIS collects and consolidates data annually through self-reporting by water and sanitation service providers across all Brazilian municipalities, regardless of their legal or institutional status.

The analysis focuses on data from the year 2022, encompassing 293 of the 295 municipalities in the state of Santa Catarina, located in southern Brazil. Two municipalities were excluded due to the unavailability of complete data. As of that year, the average water supply coverage in Santa Catarina was approximately 90%, with individual municipal rates ranging from 73% to 98% (Narzetti *et al.*, 2023). Despite relatively high coverage, substantial disparities persist in service quality and efficiency, particularly in smaller or rural municipalities.

5.4.1 Preliminary Data Analysis and Clustering

To enhance the understanding of service patterns and consumption dynamics, the dataset was initially analyzed using descriptive statistics and clustering techniques. The *k*-means algorithm was applied to group municipalities based on two key variables: population size and volume of water consumed. This clustering yielded three distinct groups:

Cluster 1: Small municipalities with low consumption – typically rural or under-resourced regions.

Cluster 2: Medium-sized municipalities with moderate consumption – often experiencing urban development.

Cluster 3: Large municipalities with high consumption – generally urban centers with complex infrastructure and high service demand.

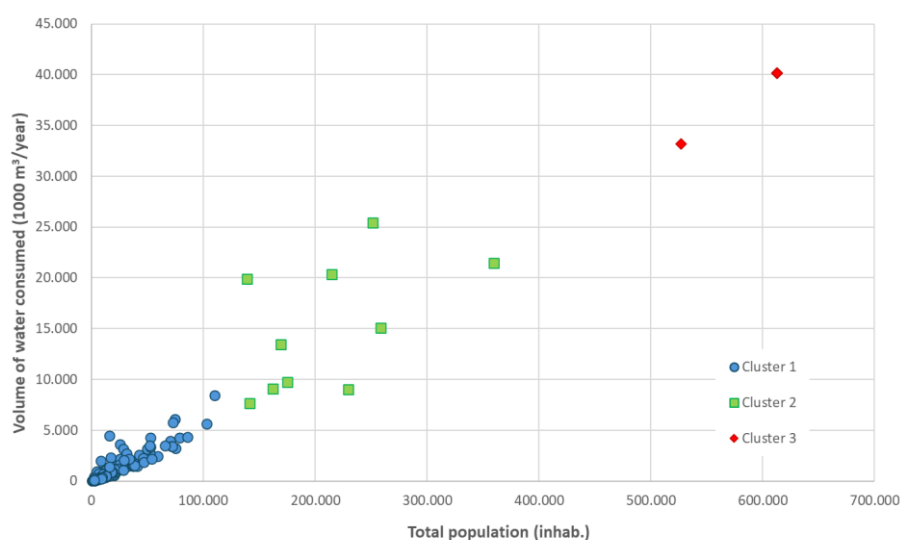
The clusters serve as a reference for comparing performance and tailoring recommendations, as summarized in Table 14 and visualized in Figures 18 and 19, which respectively show the relationships between municipal population, water consumption, and water distribution loss rates.

Table 14 - Cluster-based interpretation

Cluster	Profile	Observed Challenges	Recommended Focus
1	Small municipalities, rural profile	Limited technical capacity, high apparent losses	Shared services, low-cost leak detection, metering infrastructure
2	Mid-sized, transitional urbanization	Variability in performance, moderate data quality	Investment in real-time monitoring, performance benchmarking
3	Large, urban centers	High complexity, infrastructure aging	Pressure management, pipeline rehabilitation, contractual incentives

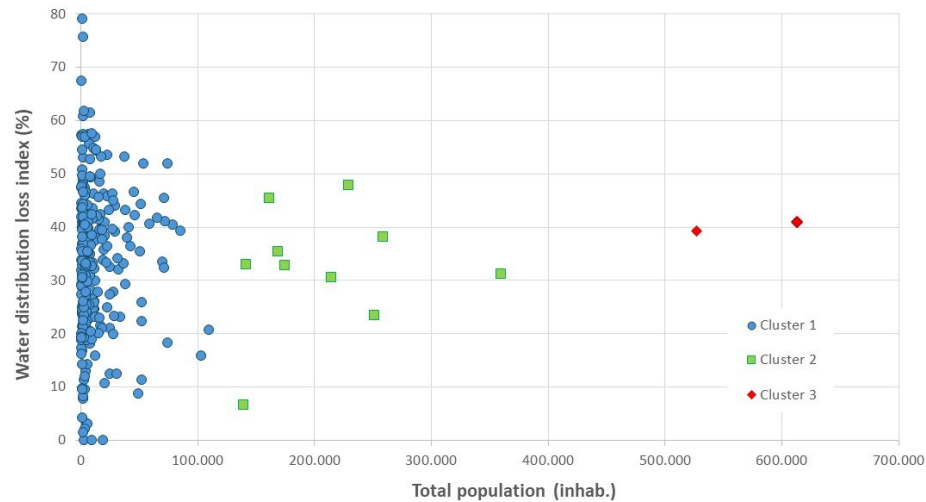
Source: the author

Figure 18 - Relationship between water consumption and municipal population



Source: the author

Figure 19 - Relationship between water distribution loss index and municipal population



Source: the author

5.4.2 Variable Selection and Dimensionality Reduction

Next, a correlation analysis was performed to assess redundancy among variables. Variables with Pearson correlation coefficients greater than or equal to 0.95 were considered duplicative and removed from further analysis. After this step, 93 variables remained.

To further streamline the analysis and focus on the most informative dimensions, Principal Component Analysis (PCA) was conducted. This technique reduces dimensionality by transforming the dataset into a smaller set of uncorrelated components that preserve most of the variance. The PCA identified five principal components, which together accounted for 75% of the variance in the original dataset. From these components, 28 variables with the highest loadings were selected for inclusion in the subsequent classification analysis. These variables listed in Table 15 represent the most influential features of the dataset and include indicators related to water consumption, metering, billing, macro-measurement, and inter-municipal water flows. The *Power* column in Table 15 represents the proportion of the total variance explained by each variable within the model. This metric, referred to as modeling power, is defined as the ratio of the explained standard deviation to the total standard deviation, indicating the relative contribution of each variable to the overall explanatory capacity of the model.

Table 15 - Key variables identified after PCA

Variable	Power	Importance
volume_water_consumed	0,9889	1
volume_water_metered	0,9828	2
volume_water_metered_active_economy	0,9795	3
volume_water_produced	0,9778	4
number_active_water_connections	0,9701	5
operational_revenue	0,9633	6
volume_water_macro_metered	0,9446	7
volume_treated_water_imported	0,8942	8
water_consumption_index	0,8775	9
water_distribution_loss_index	0,8775	10
macro_metering_available_volume_index	0,8705	11
water_network_length	0,8461	12
billing_loss_index	0,7925	13
water_billing_index	0,7925	14
relative_water_micro_metering_index	0,7895	15
metering_index	0,7329	16
connection_loss_index_water	0,7201	17
direct_operational_revenue_exported_water	0,6983	18
indirect_operational_revenue	0,6269	19
linear_loss_index_water	0,6164	20
volume_treated_water_exported	0,6154	21
per_capita_water_consumption_index	0,5276	22
water_per_connection_index	0,5060	23
debt_expense_variation	0,4802	24
imported_water_expense	0,4349	25
average_water_consumption_index	0,4293	26
water_fluoridation_index	0,3520	27
macro_metering_index	0,2468	28

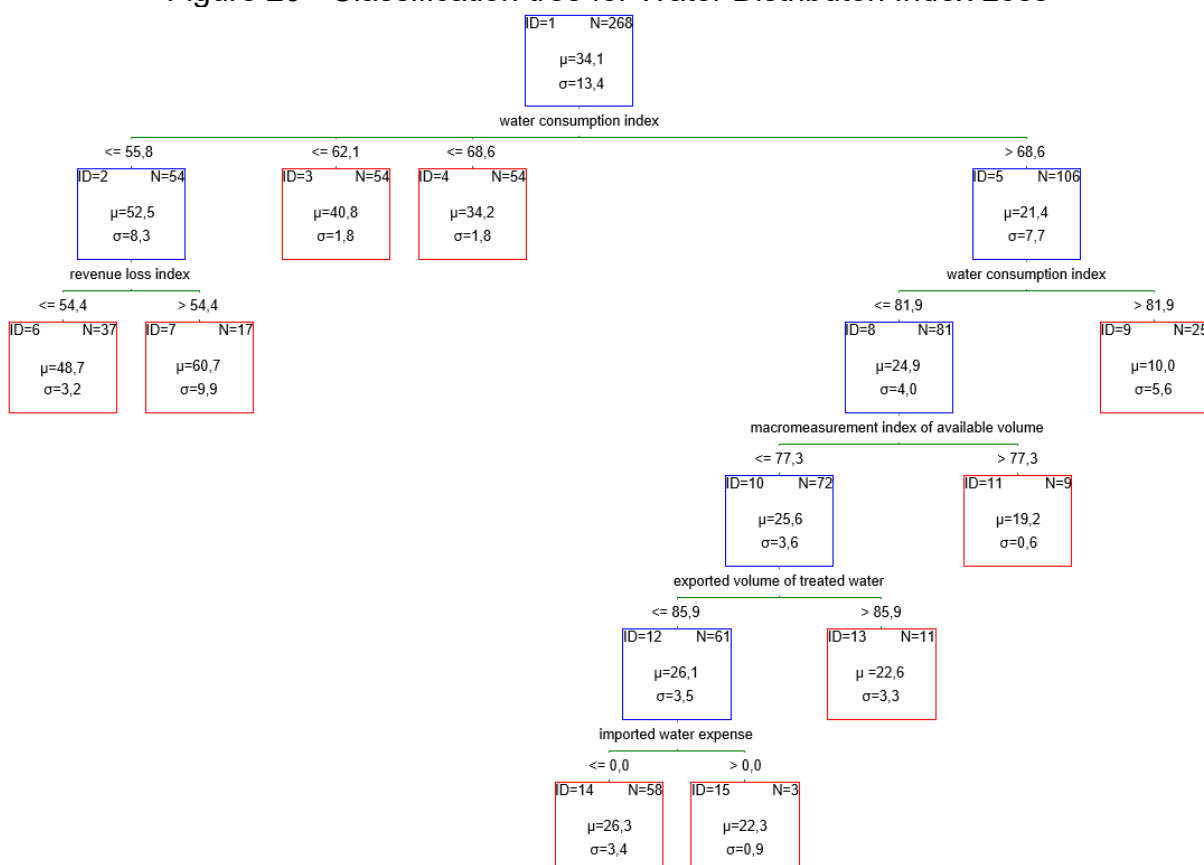
By combining statistical reduction and unsupervised clustering, this phase enabled a clearer segmentation of municipalities and provided a robust foundation for the decision tree modeling described in the next section.

5.5 RESULTS AND DISCUSSION

The results of the classification model, based on the CHAID decision tree algorithm, offer valuable insights into the main variables associated with water distribution losses across municipalities in Santa Catarina. From the 293 municipalities initially analyzed, 265 were included in the final model after excluding records with missing values. The decision tree model, presented in Figure 20, segments the municipalities into branches based on statistically significant splits in the independent variables. Each node in the tree displays the number of observations (N), the mean

(μ), and the variance (σ^2) of the Water Distribution Loss Index, which serves as the model's dependent variable.

Figure 20 - Classification tree for Water Distributon Index Loss



5.5.1 Key Findings

One of the most significant findings is the inverse relationship between the Water Consumption Index and the Water Distribution Loss Index. Municipalities with low consumption levels ($< 55.8\%$) exhibit an average loss rate of 52.5% , which is markedly higher than the sample mean of 34.1% . Conversely, when consumption exceeds 68.6% , the average loss falls to 21.4% , indicating that higher usage levels - likely associated with more accurate metering and billing practices - correlate with lower losses.

Another relevant variable is the Revenue Loss Index, which includes both physical losses and unbilled authorized consumption (e.g., firefighting, public fountains). The decision tree shows that municipalities with revenue loss below 54.4% tend to maintain lower water losses ($\sim 48.7\%$), while those exceeding this threshold

face losses close to 61%. These results suggest that financial efficiency and operational control are deeply interrelated.

The Macromasurement Index also emerged as a critical variable. This indicator measures the extent to which water flow is metered at key system points through high-capacity devices. The model confirms that higher macro-metering coverage is associated with lower loss rates, highlighting the importance of infrastructure for system monitoring and decision-making agility.

The tree identifies Exported Treated Water Volume as a protective factor against distribution losses. Municipalities involved in inter-municipal water transfers - typically within integrated systems - tend to present lower indices, potentially due to more complex, but better-managed, supply systems. However, the possibility of data quality issues in recording export/import volumes must be considered, given the complexity of hydraulic balancing.

Finally, Expense with Imported Water appears in one terminal node, but its interpretive power is limited due to the small number of municipalities reporting this indicator.

5.5.2 Cluster-Based Interpretation

To enhance the applicability of the findings, the classification results were analyzed in conjunction with the previously established three municipal clusters as shown in Table 15.

These distinctions support the implementation of targeted interventions, rather than one-size-fits-all strategies, allowing state and municipal agencies to allocate resources more effectively.

5.5.3 Strategic Implications

The CHAID model's results reinforce the importance of integrated management of metering, billing, and infrastructure. The significant variables identified - especially the Water Consumption Index, Revenue Loss, and Macromasurement - provide a technical foundation for prioritizing interventions. Moreover, the association between inter-municipal integration and better performance outcomes indicates that

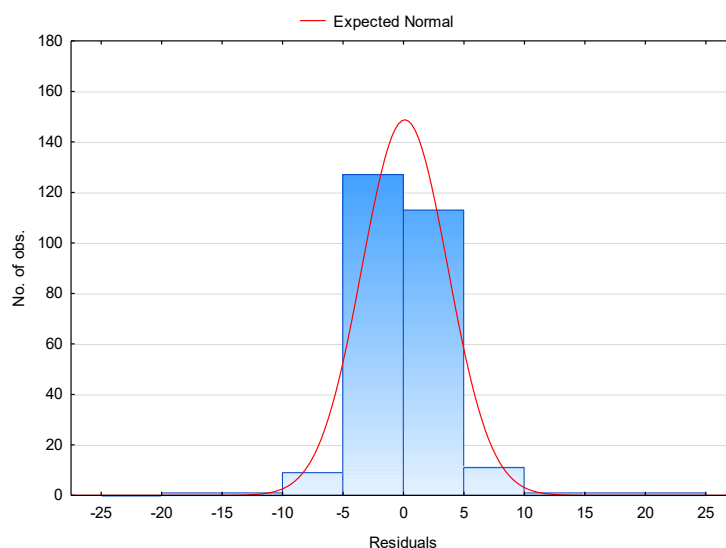
regionalized service provision may offer economies of scale and managerial improvements.

Given the interpretability of decision tree models, the insights can be readily translated into operational rules and technical standards for loss control programs, regulatory benchmarks, and public investment planning.

5.5.4 Validation

To assess the validity of the results obtained from the classification tree, an analysis of the residuals - calculated as the discrepancies between observed and predicted values of the Water Distribution Loss Index - was performed. Figure 21 presents the histogram of the residuals. The results of the Kolmogorov-Smirnov test ($d = 0.07694$, $p < 0.10$) indicate a moderate difference between the sample distribution and a normal distribution, providing marginal evidence against normality and thus supporting the acceptability of the results.

Figure 21 - Histogram of residuals



5.6 CONCLUSION

This study examined the determinants of water distribution losses in the state of Santa Catarina, Brazil, using a structured analytical framework that combined Principal Component Analysis (PCA) and CHAID decision tree modeling. Drawing on official data from the National Sanitation Information System (SNIS) for the year 2022, the

research covered 293 municipalities and aimed to identify the most influential variables associated with efficiency in water supply services.

The results indicate that variables such as the Water Consumption Index, Revenue Loss Index, Macromasurement Coverage, and Exported Treated Water Volume play a decisive role in shaping water distribution performance. Notably, municipalities with higher consumption and more robust metering systems exhibit significantly lower loss rates, while those with limited financial control or infrastructure monitoring face systemic inefficiencies.

By integrating multivariate statistical techniques with interpretable machine learning, this study provides an evidence-based methodology that enables the classification of municipalities according to performance patterns. The approach also allows for the formulation of tailored strategies based on municipal profiles, acknowledging the diverse operational realities of small, medium, and large cities.

The model's transparent rule-based structure facilitates its direct application by regulatory agencies, utilities, and policymakers, serving as a decision-support tool for investment prioritization and performance monitoring. In particular, the findings reinforce the need to strengthen integrated supply systems, expand macro-metering infrastructure, and reduce under-measurement at the consumer level.

Moreover, the proposed methodology has potential for replication in other Brazilian states or regions with similar data availability. As the SNIS provides nationwide coverage, the approach can be scaled to support national strategies for reducing water losses, contributing to the achievement of the legal targets set by Brazil's Basic Sanitation Framework.

Future studies may benefit from incorporating real-time sensor data, pressure management systems, or qualitative assessments of institutional practices, further enriching the diagnosis of loss drivers and enhancing predictive accuracy.

6 DISCUSSION/SUMMARY

This thesis aimed to propose and apply robust models for performance evaluation in the water and sewage sector, with a focus on Brazilian municipalities. By combining frontier efficiency methods with robust statistical tools and machine learning techniques, the thesis addresses multiple dimensions of performance and reflects the complexity of public service provision in diverse regional and institutional contexts.

The research was structured in three core articles, each contributing a distinct yet complementary perspective to the overarching research problem.

The article *Evolution of performance in the water and sewage sector in Brazil: a robust directional Benefit-of-the-Doubt assessment of municipalities from Santa Catarina state*, develops a composite indicator, based on the Benefit-of-the-Doubt approach, to estimate the performance of municipalities in the state of Santa Catarina, from 2009 to 2021. In addition, the Global Malmquist Index (GMI) is applied to assess the evolution of municipal performance over time. The results show an average loss of performance of 3.3% over the period studied and considerable variation in performance between municipalities, with scores ranging from 54.2% to 109.3%.

The most recent metrics from the journal *Annals of Operations Research*, dated April 2025, report that the article has been accessed almost 900 times since its publication on 5 October 2024, which demonstrates interest in the topic of maximising efficiency in basic sanitation services and the search for new methods that lead to a quantitative diagnosis of performance in the sector.

The composite indicator proposed in the article was created based on eight key indicators, which were defined after an extensive literature review and guided by legislation and sector standards. The application of the non-parametric method derived from DEA, the BoD, revealed the performance of the municipalities, allowing for the subsequent identification of their strengths and weaknesses, subsidising more assertive action for progress in the provision of services and the fulfilment of targets.

The second article, *From data to decision: a robust ranking of water and sanitation services in Brazil*, expands on the methodological approach of the previous publication, adding contextual variables to the performance assessment. The context variables make it possible to assess the impact of exogenous factors on the performance of water supply and sewage services in the 100 largest cities in Brazil in 2021. The relationship between the robust BoD and conditional BoD scores showed

that supply systems using predominantly surface sources tend to perform better than systems supplied exclusively by surface water or groundwater. The results of the exogenous variable Municipal Human Development Index (HDI-M) show that municipalities with very high human development tend to perform significantly better compared to the other HDI-M levels. Finally, the differences in performance between geographical regions demonstrate the significant impact that regional differences have on basic sanitation in Brazil.

As in the first article, the results of the second article highlight the points that need to be improved if the universalisation and quality targets set out in the Basic Sanitation Legal Framework, Law 14.026/2020, and other legal and regulatory provisions are to be achieved. In addition, the study provides a new perspective on the most widespread basic sanitation ranking in Brazil, the Instituto Trata Brasil (ITB) ranking. The individual comparison of the municipalities in the BoD ranking and the ITB's ranking shows profound differences in positions, indicating that decision-making in relation to action plans, for example, can be affected due to different interpretations and ways of evaluating the data.

The article *An Analysis of Water Supply System Losses: A Case Study of Santa Catarina State, Brazil*, sheds light on a key indicator discussed in the previous articles: water loss. The application of the Classification and Regression Trees technique made it possible to identify the variables directly related to water losses for the municipalities of Santa Catarina, considering data for 2021. This article complemented the results related to the specific objective of identifying key performance indicators, and its results highlighted the need for greater attention to be paid to integrated water supply systems and precision in measuring volumes, whether these result from the import/export of water between different municipalities or the volumes made available to customers, accounted for by means of water meters.

Together, these studies form an integrated framework for evaluating, understanding, and improving the performance of water and sewage services.

6.1 MAIN FINDINGS AND CROSS-CUTTING THEMES

Across the three articles, several cross-cutting findings emerge:

- a) **Persistent Inefficiencies:** Despite regulatory advancements and increased investments, many municipalities still operate with suboptimal efficiency, especially in sewage collection and treatment. These inefficiencies are often associated with regional disparities and limited institutional capacity;
- b) **Importance of Contextual Variables:** The inclusion of exogenous variables in the analysis allowed for a better understanding of the performance landscape. Factors such as vulnerability to water scarcity, and municipal human development levels influence both technical efficiency and operational results;
- c) **Robustness and Interpretability:** The adoption of robust and interpretable models (e.g., bootstrapped BoD and CART) proved essential to ensure the reliability of results and to make them accessible to decision-makers. This balance between methodological rigor and practical relevance strengthens the contribution of the thesis to applied public policy research;
- d) **Potential for Benchmarking:** The performance scores and classifications generated in the articles offer tools for benchmarking, enabling utilities and regulatory agencies to identify reference municipalities and good practices. Such benchmarking can guide investment decisions and foster continuous improvement.

6.2 POLICY AND PRACTICAL IMPLICATIONS

The findings of this thesis carry important implications for public policy, especially in light of the goals established by the new legal framework for sanitation in Brazil (Law No. 14,026/2020):

- a) **Evidence-Based Regulation:** Regulatory agencies can use robust composite indicators to monitor concessionaires and adjust targets based on fair and contextualized comparisons. This contributes to more efficient resource allocation and greater accountability in service provision;
- b) **Targeted Interventions:** The identification of key predictors of water losses allows managers to prioritize actions where they are most needed. For instance, municipalities with long and old networks, low macro

measurement coverage, and limited financial capacity should receive focused technical and financial support;

- c) Support for Universalization Goals: By highlighting bottlenecks and potential areas of improvement, the thesis supports the formulation of policies aimed at achieving universal access to water and sanitation services by 2033. It also reinforces the need for tailored strategies that consider local specificities.

6.3 CONTRIBUTION TO THE LITERATURE

From a theoretical and methodological standpoint, the thesis contributes to the literature on public service performance evaluation by:

- a) Applying the BoD model in a novel context (municipal sanitation performance in Brazil);
- b) Demonstrating the usefulness of dynamic efficiency analysis (Global Malmquist Index) for tracking progress over time;
- c) Incorporating classification models (CART) into the performance evaluation agenda, providing transparency and actionable insights;
- d) Proposing an analytical framework that is scalable, flexible, and adaptable to other countries and service sectors.

These contributions strengthen the methodological toolbox available to researchers and practitioners in public administration, production engineering, and infrastructure regulation.

Future studies could explore:

- a) The integration of spatial analysis to better capture regional spillovers and clustering of performance;
- b) The application of advanced machine learning techniques (e.g., random forests or gradient boosting) to compare predictive capacity and interpretability;

- c) Longitudinal studies assessing the impact of regulatory and investment changes following the 2020 legal framework;
- d) Qualitative research to complement the quantitative models with institutional and governance perspectives.

6.4 FINAL REMARKS

This thesis reinforces the importance of combining quantitative rigor with practical applicability in performance evaluation. In the Brazilian sanitation sector, where challenges are multifaceted and urgent, the use of robust, transparent, and context-sensitive tools is vital for guiding policies and improving services.

By providing methodological innovations and empirical evidence, this work contributes to more informed, equitable, and effective decision-making in the pursuit of sustainable development and social well-being.

7 CONCLUSIONS

In short, this thesis demonstrates that Brazil has endeavoured to make progress in the provision of water supply and sewage services, as evidenced by the various regulations governing the sector. Despite this, the overall results are unsatisfactory, exposing the need for immediate implementation of a truly articulated sector policy, based on continuous and accurate data analysis, coupled with a realistic action plan that takes into account the weaknesses of the process and local peculiarities.

In a country so vast and with such different regional characteristics, it will be difficult to achieve success if government plans are based on a single foundation and if the population is not an active part, present at all stages and aware of its responsibilities for the common good of this and future generations.

In addition, there is no investment without access to financial resources, which must be made available in an equitable manner, at viable rates, regardless of the legal nature of the service provider or the political leanings of the municipality or state. The implementation of the actions must be closely monitored by the competent bodies, ensuring that the resources are used efficiently and reflect improvements in the provision of services and the population's quality of life. Basic sanitation should be seen as a preventive and public health action and, as such, a priority.

Added to this scenario is climate change, which is having an increasingly critical effect on water supply services, either because of the scarcity of raw materials due to prolonged droughts, or because of flooding, which jeopardises structures and water quality.

As a result of this research, it is possible to conclude that the national universalisation and quality targets are unlikely to be achieved within the planned timeframe if the current scenario remains unchanged. However, change is possible, as long as actions are integrated and implemented quickly. The articles in this thesis show that there are various tools available to help with decision-making. The performance evaluation of the first two articles and the classification and regression tree of the third article prove that the challenges are great, proportional to the country's territorial extension and regional differences, but decision-making can be more assertive when diagnostic methods and performance evaluations are applied

continuously and free of economic or commercial interests.

Finally, given that Brazil's sanitation sector is still undergoing profound changes, combined with the fact that the goal of universalisation of services expires in 2033, it is recommended that the composite indicator and the key factors pointed out in this study be monitored continuously, so that it will be possible to verify the effectiveness of the sector's laws and regulations in the medium and long term. Change is possible, and benchmarks are available for consultation.

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APPENDIX A – ARTICLE INFORMATION

Article	Author	Publication/Submission	Date
<i>Evolution of performance in the water and sewage sector in Brazil: a robust directional Benefit-of-the-Doubt assessment of municipalities from Santa Catarina state</i>	Andreia May Carlos Ernani Fries Hermilio Vilarinho Ana S. Camanho	<i>Annals of Operations Research</i>	Published in Oct./2024
<i>From data to decision: a robust ranking of water and sanitation services in Brazil</i>	Andreia May Carlos Ernani Fries Hermilio Vilarinho Ana S. Camanho	<i>Socio-Economic Planning Sciences</i>	Submitted in April/2025
<i>An Analysis of Water Supply System Losses: A Case Study of Santa Catarina State, Brazil</i>	Andreia May Carlos Ernani Fries	<i>International Conference on Industrial Engineering and Operations Management</i> <i>Industrial Engineering and Operations Management</i>	Presented in June/2025 To be published in October/2025

APPENDIX B – EXTENDED ABSTRACT: DATA ENVELOPMENT ANALYSIS APPLIED TO INDICATORS OF SANITATION SERVICE IN BRAZIL

International Federation of Operational Research Societies (IFORS), Chile, 2023

This study applies the Data Envelopment Analysis (DEA) technique to evaluate the efficiency of the provision of water supply and sewage services in Santa Catarina state, Brazil, serving approximately seven million people. The data were collected from the database from official sources for the year 2021. Intensive exploratory research in the laws, norms, and technical documents from the main sources related to Brazilian basic sanitation allowed the identification of the most relevant variables for the analysis. These key indicators were framed in specific categories related to quality in the provision of services and financial sustainability. Contextual variables were also considered to assess their effect on Decision Making Units' performance. Finally, the categories and factors having a major impact on the efficiency and universalization of water supply and sanitation services in Santa Catarina were determined by the specification of Composite Indicators.

Several municipalities have not yet reached the desired efficiency levels; their performance can be improved by planning actions, focused on the categories with performance levels below expectations. In turn, the identification of efficient municipalities allows benchmarking of best practices. This allows for exploring the decisions made in pursuing enhanced service levels, alongside the reduction of water loss and optimization of resource usage. Applying the scientific method and unbiased research instruments sheds light on the recent discussions involving the update of the Brazilian legislation on basic sanitation, and it allows for the design of assertive public policies. Thus, this study can contribute to the definition of guidelines for a regulatory framework, foreseeing the universalization of sanitation services by 2033 for the entire Brazilian territory, with estimated investments of around \$70 billion.

APPENDIX C – EXTENDED ABSTRACT: DIRECTIONAL BENEFIT-OF-THE-DOUBT ASSESSMENT OF MUNICIPALITIES FROM SANTA CATARINA STATE

XVIII *European Workshop on Efficiency and Productivity Analysis* (EWEPA), Portugal, 2024

The water supply and sewage sector (WSS) is essential for promoting health and providing the population with drinking water and the adequate disposal of effluents. Assessing the evolution of performance in WSS allows for highlighting the best and worst results achieved, identifying benchmarks, and pinpointing sources of improvement for water services. Brazil has a large population and immense freshwater reserves that are unevenly distributed throughout the territory. This situation emanates a challenge that requires the efficient management of water resources.

This study develops a composite indicator framework based on the robust Benefit-of-the-Doubt (BoD) approach to estimate the performance of municipalities of the Brazilian State of Santa Catarina from 2009 to 2021, considering financial, operational, and quality dimensions associated with the provision of WSS services. Subsequently, the Global Malmquist Index (GMI) is applied to assess the performance evolution of the municipalities over time. The BoD results enable the quantification of the relative contribution of each sub-indicator to the performance score, allowing the assessment of the strengths and weaknesses of each municipality. The GMI results show an average performance loss of 3.3% in Santa Catarina state and considerable variability among municipalities, with scores ranging from losses of 54.2% to gains of 109.3% in the period analysed.

APPENDIX D – EXTENDED ABSTRACT: BENCHMARKING ANALYSIS IN THE BRAZILIAN WATER AND SEWAGE SECTOR: A DIRECTIONAL BENEFIT-OF-THE-DOUBT APPROACH

XVIII European Workshop on Efficiency and Productivity Analysis (EWEPA), Portugal, 2024

This study applies the Benefit-of-the-Doubt (BoD) approach, a framework derived from Data Envelopment Analysis (DEA), to estimate the performance of the Water Supply and Sewage (WSS) sector in the most populous municipalities in Brazil, from 2019 to 2021, serving approximately 86 million people.

The application of this technique offers an alternative solution to the benchmarking study presented annually by a civil organization formed by companies that operate in the Brazilian WSS sector, called Instituto Trata Brasil (ITB). ITB carries out its study based on information made available by the National System for Water and Sanitation Data (SNIS), which is the official source of WSS data in Brazil.

Following the BoD approach, the inputs were replaced by a dummy equal to one and, the twelve outputs were aggregated as a Composite Indicator (CI). A Directional Distance Function (DDF) was used to allow the simultaneous analysis of desirable and undesirable indicators.

The BoD results show an increasing average performance from 2019 to 2021, but still unsatisfactory in meeting efficiency goals and universal access to services imposed by Brazilian Basic Sanitation Guideline. The productivity frontier was only spanned by 11% of the municipalities in 2021 and, 7% in 2019 and 2020. The comparison of the municipalities' positions in the ITB ranking and in the BoD ranking had consistencies, but there were also cases of sixty position variation between the two classifications.