FEDERAL UNIVERSITY OF SÃO CARLOS

CENTER FOR SCIENCE AND TECHNOLOGY FOR SUSTAINABILITY

POSTGRADUATE PROGRAM IN PLANNING AND USE OF RENEWABLE RESOURCES

Gabriela Giusti

Development of Characterization Factors for Health Effects of Particulate Matter in Brazil

Sorocaba

2025

FEDERAL UNIVERSITY OF SÃO CARLOS

CENTER FOR SCIENCE AND TECHNOLOGY FOR SUSTAINABILITY

POSTGRADUATE PROGRAM IN PLANNING AND USE OF RENEWABLE RESOURCES

Gabriela Giusti

Development of Characterization Factors for Health Effects of Particulate Matter in Brazil

Thesis presented to the Graduate Program in Planning and Use of Renewable Resources in fulfillment of the requirements for the degree of Doctor in Planning and Use of Renewable Resources at the Federal University of São Carlos. Area of concentration: Environmental Sciences.

Advisor: Dr. Diogo Aparecido Lopes Silva
Co-advisor: Dra. Yara de Souza Tadano
Funding: Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP) process n° 2021/06685-1, Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) Finance Code 001, and Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) process n°201121/2022-0 (sandwich Ph.D period)

Sorocaba

2025

Giusti, Gabriela

Development of characterization factors for health hffects of particulate matter in Brazil / Gabriela Giusti -- 2025.
142f.

Tese de Doutorado - Universidade Federal de São Carlos, campus Sorocaba, Sorocaba
Orientador (a): Diogo Aparecido Lopes Silva
Banca Examinadora: Bhavik Bakshi, Lourdes Conceição Martins, Marcell Mariano Correa Maceno, Maria Cléa Brito de Figueirêdo
Bibliografia

1. Air pollution. 2. Regionalization . 3. Human health. I. Giusti, Gabriela. II. Título.

Ficha catalográfica desenvolvida pela Secretaria Geral de Informática (SIn)

DADOS FORNECIDOS PELO AUTOR

Bibliotecário responsável: Maria Aparecida de Lourdes Mariano - CRB/8 6979

UNIVERSIDADE FEDERAL DE SÃO CARLOS

Centro de Ciências e Tecnologias Para a Sustentabilidade
Programa de Pós-Graduação em Planejamento e Uso de Recursos Renováveis

Folha de Aprovação

Defesa de Tese de Doutorado da candidata Gabriela Giusti, realizada em 29/04/2025.

Comissão Julgadora:

Prof. Dr. Diogo Aparecido Lopes Silva (UFSCar)

Prof. Dr. Bhavik Bakshi (ASU)

Profa. Dra. Maria Cléa Brito de Figueirêdo (EMBRAPA)

Prof. Dr. Marcell Mariano Corrêa Maceno (UFPR)

Profa. Dra. Lourdes Conceição Martins (UNISANTOS)

O Relatório de Defesa assinado pelos membros da Comissão Julgadora encontra-se arquivado junto ao Programa de Pós-Graduação em Planejamento e Uso de Recursos Renováveis.

I dedicate this work to my family

ACKNOWLEDGMENTS

Firstly, I express my gratitude to God for guiding my steps and providing physical and mental health to achieve my goals. I am immensely thankful to my family, who have been my safe haven, an endless source of strength and love throughout these years of academic journey. To my mother, Maria Aparecida, my brother, João Marcos, my grandmothers, Maria Aparecida and Dirce (in memory), and to my boyfriend, Igor, I express my deep gratitude. Especially, I thank my father, Marcos (in memory), who has always been and will be my inspiration. Thank you all for the encouragement, collaboration, and understanding during moments of absence. I dedicate this work to you.

I extend my thanks to my advisor, Prof. Dr. Diogo Aparecido Lopes Silva, and to my co-advisor, Prof. Dra. Yara de Souza Tadano, for their dedication and valuable teachings throughout the master and doctoral period. I also thank Prof. Dr. Peter Fantke from the Technical University of Denmark (DTU) for his valuable supervision during the sandwich Ph.D. period, and for his collaboration during the research development. I am also grateful to all members of the Sustainability Engineering Research Group, the Sustainable Production Laboratory, and the Life Cycle Impact Assessment Research Network (RAICV, Portuguese acronym).

I express my sincere gratitude to the Graduate Program in Planning and Use of Renewable Resources (PPGPUR, Portuguese acronym), as well as to my fellow students in the program, for the valuable conversations and friendships cultivated. And I cannot fail to mention my gratitude to the staff and technicians of UFSCar, whose support was fundamental at various times, especially to the coordination and secretariat of PPGPUR.

Finally, I am immensely grateful to the funding agencies for their support of this research. This work was financed by the Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP), process n° 2021/06685-1 and the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq), process n° 201121/2022-0 (sandwich Ph.D. period at DTU). Also, this study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

This work is the result of a collective effort, and each expression of gratitude mentioned above significantly contributed to the realization of this thesis and made the years of doctoral studies an enriching journey. I thank everyone for their support.

ABSTRACT

GIUSTI, Gabriela. Development of Characterization Factors for Health Effects of Particulate Matter in Brazil. 2025. Doctoral Thesis (Ph.D. in Planning and Use of Renewable Resources) – Federal University of São Carlos, Sorocaba, 2025.

Particulate matter (PM) is an atmospheric pollutant that cause adverse health effects and Life Cycle Assessment (LCA) can support the management of PM emissions from production systems. However, there are currently no highly spatialized characterization factors (CFs) available to Brazil. Then, this study aimed to calculate CFs for PM and precursor gas emissions (NH_3, SO_x, NO_x, VOC) for Brazil. For this, the first step was a critical review of existing models, which showed that the models with global coverage and availability of CFs for Brazil, are the most appropriate: Van Zelm *et al*. (2016), Fantke *et al*. (2017, 2019), and Oberschelp *et al*. (2020). However, limitations have been observed. Then, CFs for $PM_{2.5}$ and precursor gases were calculated per state, mesoregion and nationally, using death results calculated using the InMAP (Intervention model for air pollution) and national emission inventories. At the state level, the highest CFs were observed for SO_x (ranging from 1.18×10^{-1} to 4.09×10^{-4} deaths/ton), followed by $PM_{2.5}$ (9.49×10^{-2} to 2.09×10^{-4}), NH_3 (6.38×10^{-2} to 1.41×10^{-4}), NO_x (1.35×10^{-2} to 5.42×10^{-4}), and VOCs (2.61×10^{-3} to 1.32×10^{-5}). The highest CFs were observed in the Southeast region, particularly in São Paulo and Rio de Janeiro. Finally, a sensitivity analysis verified the variation in results of an LCA case study concerning the choice of the characterization model, including the recommended models for Brazil and the CFs calculated in this research. The analysis used four milk production systems as a case study. Spearman's correlation was calculated to verify the consistency of the milk systems' ranking. Correlation analysis showed that regionalized CFs presented higher variation in the milk systems' ranking. The CFs calculated by this research presents high correlation (> 0.9) with global CFs from other models. However, the CFs at state level resulted in low correlation (< 0.5) with all models, except with the state CFs from Oberschelp *et al*. (2020), the only model with CFs for Brazilian states, which presented correlation indicator equal to 0.9. The consistency between the CFs obtained in this study and those found in the literature reinforces the validity of the results and highlights the importance of using regionalized factors in LCA studies. The main limitations of the CFs are the effects equation based on data from the United States, incorporated into the global InMAP model, and the unavailability of these factors in LCA software. However, the results obtained contribute to advancing knowledge and refining the calculation of health impacts resulting from atmospheric pollutant emissions in Brazil. These contributions can benefit both academia and the business sector by providing data more aligned with national realities for impact management.

Key-words: life cycle impact assessment; air pollution; regionalization; human health.

RESUMO

GIUSTI, Gabriela. Desenvolvimento de Fatores de Caracterização para Efeitos na Saúde Devido ao Material Particulado no Brasil. 2025. Tese (Doutorado em Planejamento e Uso de Recursos Renováveis) – Universidade Federal de São Carlos, Sorocaba, 2025.

O material particulado (MP) é um poluente atmosférico que causa efeitos adversos à saúde humana, e a Avaliação do Ciclo de Vida (ACV) pode auxiliar na gestão das emissões de MP provenientes de sistemas produtivos. No entanto, atualmente, não há fatores de caracterização (FCs) altamente espacializados disponíveis para o Brasil. Assim, este estudo teve como objetivo calcular FCs para as emissões de MP e gases precursores (NH_3, SO_x, NO_x, VOC) no contexto brasileiro. Para isso, a primeira etapa consistiu em uma revisão crítica dos modelos existentes, a qual indicou que os modelos com cobertura global e disponibilidade de FCs para o Brasil são os mais apropriados: Van Zelm *et al*. (2016), Fantke *et al*. (2017, 2019) e Oberschelp *et al*. (2020). No entanto, foram observadas limitações nesses modelos. Em seguida, foram calculados FCs para $MP_{2.5}$ e gases precursores por estado, mesorregião e em nível nacional, utilizando resultados de número de mortes estimados pelo InMAP (Intervention Model for Air Pollution) e inventários nacionais de emissões. Em nível estadual, os maiores FCs foram observados para SO_x (variando de $1{,}18\times10^{-1}$ a $4{,}09\times10^{-4}$ mortes/tonelada), seguidos por $MP_{2.5}$ ($9{,}49\times10^{-2}$ a $2{,}09\times10^{-4}$), NH_3 ($6{,}38\times10^{-2}$ a $1{,}41\times10^{-4}$), NO_x ($1{,}35\times10^{-2}$ a $5{,}42\times10^{-4}$) e VOCs ($2{,}61\times10^{-3}$ a $1{,}32\times10^{-5}$). Os maiores FCs foram identificados na região Sudeste, especialmente em São Paulo e Rio de Janeiro. Por fim, uma análise de sensibilidade avaliou a variação nos resultados de um estudo de caso de ACV em relação à escolha do modelo de caracterização, incluindo os modelos recomendados para o Brasil e os FCs calculados nesta pesquisa. A análise utilizou quatro sistemas de produção de leite como estudo de caso. Foi calculada a correlação de Spearman para verificar a consistência na classificação dos sistemas de produção de leite. A análise de correlação mostrou que os FCs regionalizados apresentaram maior variação na classificação dos sistemas de produção de leite. Os FCs calculados por esta pesquisa apresentaram alta correlação (> 0,9) com os FCs globais de outros modelos. No entanto, os FCs em nível estadual resultaram em baixa correlação (< 0,5) com todos os modelos, exceto com os FCs estaduais de Oberschelp *et al*. (2020), o único modelo com FCs para estados brasileiros, para o qual apresentou um indicador de correlação igual a 0,9. A consistência entre os FCs obtidos neste estudo e aqueles encontrados na literatura reforça a validade dos resultados e destaca a importância do uso de fatores regionalizados em estudos de ACV. As principais limitações dos FCs são a equação de efeitos baseada em dados dos Estados Unidos, incorporada ao modelo global InMAP, e a indisponibilidade dos FCs calculados em softwares de ACV. No entanto, os resultados obtidos contribuem para o avanço do conhecimento e o aprimoramento do cálculo dos impactos à saúde decorrentes das emissões de poluentes atmosféricos no Brasil. Essas contribuições podem beneficiar tanto o meio acadêmico quanto o setor empresarial, fornecendo dados mais alinhados com as realidades nacionais para a gestão de impactos.

Palavras-chave: Avaliação de Impacto do Ciclo de Vida; poluição do ar; regionalização; saúde humana.

FIGURES

TABLES

SUMARY

1 INTRODUCTION

This section provides a general introduction to the research conducted and is structured into three sections: contextualization and justification of the research (1.1), general and specific goals (1.2), and the overall structure of the complete work (1.3).

1.1 CONTEXTUALIZATION AND JUSTIFICATION

Life Cycle Assessment (LCA) is a robust and scientifically recognized technique for calculating environmental impacts, internationally standardized by ISO 14040 and 14044 (ISO 2006 a,b). LCA considers all stages of a production system's life cycle to calculate potential environmental impacts, from raw material extraction to final waste disposal, thus offering a holistic view of the environmental impacts of the production chain. This provides decision-makers with better insights into the entire production chain of interest (ISO, 2006a, b).

The development of an LCA consists of defining the goal and scope of the study (stage 1), conducting a Life Cycle Inventory (LCI), which involves quantifying all inputs and outputs of material, energy, and elementary flows (stage 2), converting the flows into environmental impact indicators (stage 3), and interpreting the results (stage 4) (ISO 2006a, b). Thus, the potential environmental impact is estimated in the third stage of the methodological development, called Life Cycle Impact Assessment (LCIA), through the multiplication of elementary flows by their respective characterization factors (CFs) for each impact category. CFs are responsible for assigning an environmental weight to an elementary flow and are determined through characterization models, which consider the environmental pathway of the pollutant from its emission to its arrival in a receiving region, where it will cause environmental effects (RAICV, 2019). Through this procedure, an LCA study can assess various environmental impact categories that affect three protection areas: resources, health, and ecosystems (Bulle *et al*., 2019). Studies can be conducted at the endpoint level, estimating the final damage impact in a protection area, or at the midpoint level, estimating the impact that occurs in the middle of the cause-and-effect chain (Verones *et al*., 2017).

Modeling CFs for certain impact categories requires parameters dependent on the geographical context of the emission location of the elementary flow. One of these categories is health effects due to Particulate Matter (PM), which affects the human health protection area (Mutel *et al*., 2019). Human health encompasses both mortality and morbidity, and impact categories affecting this protection area are usually measured in Disability-Adjusted Life Years (DALYs) (Verones *et al*., 2017). Thus, health effects due to PM is the category responsible for estimating the potential impact on human health caused by atmospheric emissions of primary

PM and precursor gases, including ammonia, nitrogen oxides, and sulfur dioxide (Van Zelm *et al*., 2016).

The health effects associated with PM have global proportions, with an estimated 6.45 million deaths attributed to the pollutant annually, of which approximately 33% occur in countries with medium Human Development Index (GBD, 2019). The main health effects associated with global exposure to the pollutant include: ischemic heart disease, chronic obstructive pulmonary disease, stroke, lower respiratory infections, and ischemic stroke, which together cause about 5.3 million deaths annually (GBD, 2019). In Brazil, deaths surpass 57,000 people per year, with the most affected states being São Paulo, Minas Gerais, Rio de Janeiro, Bahia, and Rio Grande do Sul, where 55.7% of deaths occur (GBD, 2019).

In Brazil, in 2018, approximately 1668.67 kt of $PM_{2.5}$ (particles with less than 2.5 micrometers in aerodynamic diameter) were emitted. Biomass burning emissions contributed 44% of these emissions, being the main emitting activity in the country, followed by manufacturing and construction industries, and residential activities (EC, JRC, PBL, 2022). To manage the impacts associated with these production systems, LCA can be used. Thus, LCA studies of production systems that contribute to emissions of these gases in the Brazilian context often access this impact category (Du *et al*., 2019; Silva *et al*., 2018). However, the datasets of CFs currently available in the literature were developed for different geographical contexts than Brazil, mainly for North America (Humbert *et al*., 2011, Gronlund *et al*., 2015) and Europe (Van Zelm *et al*., 2008). More recently, models covering the global context have proposed regionalized CFs in different geographical scopes, some of them specifying factors for Brazil (Van Zelm *et al*., 2016) and for regions of the country, such as states (Oberschelp *et al*., 2020) and cities (Fantke *et al*., 2017, 2019). Despite the availability of data, there are still uncertainties about which existing model is most suitable for application in case studies in Brazil and about the real adequacy of the data for the country's context, especially considering the reality of data lag in the country (Giusti, 2021). Therefore, the regionalization of models for Brazil, using Brazilian data, can assist LCA researchers in generating results with fewer uncertainties for the country, allowing for targeted mitigating actions to be proposed for life cycle stages that have the greatest potential impact on human health due to PM and precursor gas emissions.

1.2 GOALS

This research aims to calculate CFs for the impact category of human health damage due to PM formation considering the Brazilian geographical context. In light of this, the following specific goals have been outlined:

1. Understand the state-of-the-art in air quality research focusing on PM, air quality policies within the life cycle management context, and LCIA models for health effect of PM formation;
2. Identify the strengths and weaknesses of the characterization models available in the literature to define the best practices for application and use in the Brazilian context;
3. Calculate CFs for health effects of PM formation impact category specific to the Brazilian context and analyze the uncertainties associated with these factors;
4. Provide a list of CFs for the impact category under study to support future applications in LCA studies and/or LCA software and databases.
5. Analyze the sensitivity of LCA study results and conclusions regarding the choice of characterization model for health effects of PM.

1.3 RESEARCH STRUCTURE

In this research, the term characterization model refers to the mathematical model for calculating the CFs for a specific LCIA category. On the other hand, the term method refers to LCIA methods that cover characterization models for several impact categories, usually available in LCA software.

This work is structured in the classic format of academic texts, divided into seven main sections: (1) introduction, (2) literature review, (3) methodology, (4) results and discussion, (5) conclusions, (6) references, and (7) appendices. Figure 1 presents the work structure focusing on content presented in sections 1 to 5.

Figure 1 - Work structure

Section	Content
Introduction	• Introduces general information about: LCA, air pollution, LCIA for health effects due to PM; • Presents the goals of the thesis
Bibliographic review	• Raises, presents and discusses the current literature on two main topics: (1) Air quality focused on PM pollution; (2) LCIA for health effects due to PM.
Methodology	• Described the thesis methodology divided into three main analyses: (1) Critical assessment of characterization models; (2) Calculation of Brazilian CFs for health effects of PM; (3) Regionalized sensitivity analysis
Results and discussion	• Presents the results also divided according to the three main analyses: (1) Critical assessment of characterization models; (2) Calculation of Brazilian CFs for health effects of PM; (3) Regionalized sensitivity analysis
Conclusion	• Concludes the main findings of the research

Source: author

2 LITERATURE REVIEW

Atmospheric pollution is the contamination of indoor or outdoor environments by chemical, physical, or biological agents, altering the natural characteristics of the atmosphere (WHO, 2024). In 2019, air pollution was responsible for approximately 6.67 million deaths globally (GBD, 2019). Among the main pollutants, PM stands out for its high association with human health effects, leading to environmental risks in 2019 and contributing to 53.52 deaths per 100,000 inhabitants (GBD, 2019). This pollutant is defined as a complex mixture of solid and liquid particles, both organic and inorganic, suspended in the atmosphere. Health effects are especially associated with the toxicity and size of the particles, as those with smaller dimensions (PM_{10} and $PM_{2.5}$, with aerodynamic diameters less than 10 and 2.5 micrometers, respectively) have the potential to penetrate more deeply into the human body after inhalation (EPA, 2023). The main causes of death related to PM pollution include ischemic heart disease, lower respiratory infections, chronic obstructive pulmonary disease, hemorrhagic stroke, and ischemic stroke (GBD, 2019).

PM emissions, both direct and from precursors such as ammonia (NH_3), nitrogen oxides (NO_x), and sulfur dioxide (SO_2), are intensified by human activities (United Nations, 2018), with developing countries significantly contributing and experiencing the effects of this environmental issue (Sicard *et al*., 2023). In this context, Brazil recorded 1.41 million deaths due to PM exposure in 2019 and was identified as one of the most populous countries with a high risk of exposure (Zhao *et al*., 2021).

One way to monitor and assess the impacts associated with the emission of PM and its precursors by production systems of goods or services is through the Life Cycle Assessment (LCA) of products (ISO 2006 a,b), accessing the impact category of health effects due to PM (Fantke *et al*., 2015). LCA is a technique for estimating the potential environmental impact of a functional unit of a production system, converting inventory information (flows of inputs and outputs of materials, energy, waste, and pollutants) into environmental impact indicators (Oliveira *et al*., 2021). This conversion occurs through the multiplication of PM, or precursor gases, emission flows by their respective characterization factors (CFs). CFs are defined through characterization models, which in PM category case, consider the environmental pathway from the emission of the pollutant to its arrival in a receiving area, where it will cause health effects on the population (Van Zelm *et al*., 2016).

The calculation of CFs for health effects due to PM is highly dependent on the characteristics of the emission and reception sites of the pollutant, and there are several models available in LCA databases, offering different CF values for the same emission flow (Owsianiak *et al*., 2018). LCA standards do not specify which model should be used, leaving this decision to LCA practitioners (Dekker *et al*., 2020). However, the choice of one model over another can influence the results and conclusions of a case study, hindering decision-making guidance (RAICV, 2019). The topic of "Regionalized LCA" is emerging. Although the perception of the importance of regionalization occurred in the 1990s (Potting e Hauschild, 2005), current research still highlights the limitations and uncertainties behind this perspective (Dekker *et al*., 2020).

Over the years, with advances in the scientific community, various studies have been conducted to characterize air quality with an emphasis for PM health effects on a global and national scale, to evaluate the effectiveness of air quality policies, to quantify the impacts of PM on Brazilian production systems through LCA, to develop characterization models for health damages related to PM, and to emphasize the importance of regionalized LCAs. In light of this, this literature review analyzes these advancements and assesses the state of the art in the mentioned topics. The review is structured in two main sections: the first addresses air quality focused on PM, examining emission standards, exposure, and health effects globally and nationally, as well as mitigation opportunities. This section is important to understand the patterns that influence Life Cycle Impact Assessment (LCIA) studies related to PM health damages, the central focus of the second section. In the second section, methods and characterization models were analyzed concerning their applications in national case studies and their mathematical structures. Finally, the implications of the literature review were discussed.

2.1 AIR QUALITY WITH A FOCUS ON PARTICULATE MATTER

The health impacts associated with exposure to PM are a global issue but highly dependent on local climate and health conditions. Governments in partnership with civil society should take responsibility for the development and implementation of effective public policies to ensure the right to clean air for all. Considering that PM and its precursor emissions are directly related to production systems, Life Cycle Management can serve as an effective tool for assessing and directing air quality policies. Therefore, the following sections present discussions related to global air quality focusing on PM (section 2.1.1), PM in the Brazilian context (section 2.1.2), and air quality policies focusing on PM and Life Cycle Management of products (section 2.1.3). Sections 2.1.1 and 2.1.2 are organized according to the environmental pathway of air pollutants, beginning with information related to emissions and pollutant characteristics, followed by transport and increased pollutant concentrations, and concluding with information on health impacts resulting from exposure to these pollutants.

2.1.1 Global air quality with a focus on particulate matter

PM can be emitted into the atmosphere by natural sources (volcanic eruptions, marine salt aerosols, biological particles, forest fires, and sandstorms) or anthropogenic sources (for example, transport activities, industries, and agriculture). However, air quality has deteriorated since the emergence of the manufacturing industry (Singh *et al*., 2022). Among the most polluting sectors, six stand out, accounting for about 80% of health effects associated with air pollution between 2013 and 2018: electricity, gas, and water (26.6% contribution); agriculture (16.87%); transportation (9.31%); metal manufacturing (8.25%); chemicals (6.92%); construction (6.28%); and food (5.43%) (United Nations, 2018).

In the electricity sector, Amster (2019) demonstrates that PM emissions from coal-fired power plants, responsible for approximately 38% of global electricity generation from 1990-2020 (IEA, 2023), have a significant impact on public health, causing respiratory problems, cancer, and birth defects. Additionally, miners working in these plants are highly susceptible to respiratory issues. In the agricultural sector, PM emissions can occur in various activities, including livestock and animal production, handling and storage of animal waste, fertilizer application, and use of agricultural machinery (diesel combustion). Wyer *et al*. (2022) highlight that agriculture contributes to over 81% of global ammonia emissions, a precursor of PM. In the transportation sector, which encompasses land, maritime, and air transport (Xiong *et al*., 2022), global land transport contributes to about 25% of urban PM air pollution (Karagulian *et al*., 2015), with heavy-duty vehicles, passenger cars, buses, and light commercial vehicles being the main emitters of $PM_{2.5}$ (Bai *et al*., 2022). Maritime transport contributes up to 15% of countries' $PM_{2.5}$ emissions around the world, particularly affecting the health of riverside populations living near major shipping routes and ports worldwide (Mueller *et al*., 2023). Air transport, on the other hand, is the sole source of anthropogenic PM emissions at high altitudes, but the effects of aviation emissions can be felt at ground level, especially near airports (Ge *et al*., 2022).

Forest fires (natural or intentional) and sandstorms are also critical events for air quality. According to Roberts and Wooster (2021), fires expose about 44 million people to unhealthy air quality, with $PM_{2.5}$ concentrations above 55 μg/m³, especially in regions of Africa and Asia. Li *et al*. (2023) emphasize that particles emitted by fires can cause up to five times more acute respiratory infections than particles from other sources, being responsible for approximately 678,000 premature deaths annually. Regarding sandstorms, Zhang *et al*. (2016) reviewed the literature and highlighted that they occur mainly in Asia, the Sahara Desert, Australia, North America, and South America. The authors also found positive associations between respiratory and circulatory mortality and particles from the desert. Considering these emission sources as inevitable natural events, efforts should be directed towards preparedness for critical episodes, including containment of emissions, prevention of exposure, and identification of vulnerable populations (Kelly and Fussell, 2020). Additionally, it is important to control and prevent deliberate and controlled fires (e.g., for land clearing for agricultural activities), which are anthropogenic sources of PM emissions.

In addition to outdoor sources, there are various sources of PM emissions in indoor buildings (Vardoulakis *et al*., 2020), such as the use of cleaning products, household activities, pets, and human movement, which can emit or resuspend PM_{10}. Smoking, kitchen activities, use of incense, candles, insecticides, and heating methods can be significant sources of $PM_{2.5}$ (Vardoulakis *et al*., 2020). Emissions during cooking processes tend to be especially relevant in underdeveloped and developing countries. According to Kumar *et al*. (2022), four factors affect the level of exposure to PM in the kitchen: (1) choice of fuel, as the use of coal can increase $PM_{2.5}$ emissions by 1.3 times compared to natural gas, and 3.1 times compared to liquefied petroleum gas; (2) kitchen volume, with smaller kitchens resulting in higher exposure; (3) food preparation, with excessive frying habits generating more PM emissions; and (4) ventilation, where the use of double ventilation (mechanical and natural) can reduce exposure by up to two times compared to using only natural ventilation. In addition to domestic exposures, humans can be exposed to PM in occupational environments. Driscoll *et al*. (2020) estimated approximately 519,000 deaths in 2016 from chronic respiratory diseases due to occupational exposures to atmospheric pollutants globally.

Thus, it is evident that PM emissions result from various sources, and this diversity of sources leads to different pollutant compositions (Ali *et al*., 2019). Shao *et al*. (2022) classified PM into three categories: carbonaceous particles, non-carbonaceous particles, and mixed particles (which consist of more than one phase of chemical composition). Table 1 presents the characterization of carbonaceous and non-carbonaceous particles in terms of composition and main emission sources.

Table 1 - Characterization of carbonaceous and non-carbonaceous particles

Type:	Main source:	Main elements:
Carbonaceous particles		
Soot	Combustion of fossil fuels and biomass	Mainly C, with small amounts of O, Si, and K
Organic	Combustion of fossil fuels and biomass	Mainly C and O, and small amounts of S, Na, Mg, K and other trace elements
Biologic	Spores, bacteria, plant debris	C, O, P, K, and Si
Non-carbonaceous particles		
Minerals	Construction dust, road dust, crustal dust, sandstorms	Si, Al, Ca, and Fe
Metals	Industry, fuel combustion, vehicle wear, and train rail wear	Fe, Zn, and Pb
Fly ash	Coal combustion	Aluminosilicates, and small amounts of Ca, Ti, Mn, and Fe
Sulfur-rich	Urban and marine emissions	S
Potassium-rich	Biomass combustion	K, N, Cl, and S
Sea salt	Evaporated oceans and lakes	Na, Cl, and S

Legend: Al = Aluminum; C = Carbon; Ca = Calcium; Cl = Chlorine; Fe = Iron; K = Potassium; Mg = Magnesium; Mn = Manganese; N = Nitrogen; Na = Sodium; O = Oxygen; P = Phosphorus; Pb = Lead; S = Sulfur; Si = Silicon; Ti = Titanium; Zn = Zinc

Source: Data based on Shao *et al*. (2022)

Also concerning the emissions, it is important to note that carbonaceous soot particles are the main ones containing organic or elemental carbon (Ali *et al*., 2019), and they have the smallest aerodynamic diameter among all (10-100 nm). In addition to the components highlighted in Table 1, Ali *et al*. (2019) discuss that PM can contain chemically organic substances (olefins, ketones, quinones), as well as other toxic elements (arsenic, nickel, antimony).

After emission, pollutants are transported and dispersed by the atmosphere, forming a plume (Braga *et al*., 2005). The transport of pollutants is influenced by environmental and anthropogenic factors such as precipitation, humidity, temperature, vegetation cover, urban obstacles (such as buildings), wind speed, pressure, and solar radiation (Fu and Li, 2020; Lu *et al*., 2021; Xu *et al*., 2023; Yu *et al*., 2023). From a physical view, Braga *et al*. (2005) emphasize that the movement of air by advection and turbulent diffusion is essential for pollutant transport and dispersion.

Regarding transport, $PM_{2.5}$ has a long residence time in the atmosphere, allowing it to be transported over long distances (Xu *et al*., 2023). Anenberg *et al*. (2014) identified that regional concentrations of $PM_{2.5}$ are predominantly influenced by local emissions but emphasized that significant effects can also occur outside the originating region. Transboundary transport of $PM_{2.5}$ contributes to about 14.5% of global premature deaths associated with the pollutant, with middle to high-income countries being the main emitters (Chen *et al*., 2022).

Then, international cooperation is essential to mitigate transboundary pollution and complement national emission control policies (Anenberg *et al*., 2014; Chen *et al*., 2022).

In addition to meteorological and physical parameters, levels of exposure to PM are also affected by social and economic factors, such as the urbanization rate, social vulnerability, and countries' level of development (Lu *et al*., 2021; Xu *et al*., 2023). The urbanization rate can lead to an increase in $PM_{2.5}$ concentration due to increased emissions and reduced pollutant dispersion caused by buildings and lower wind speed (Fu and Li, 2020; Lu *et al*., 2021). Social vulnerability is related to $PM_{2.5}$ pollution levels, especially by dimensions of population rate, educational inequality, biocapacity (ecosystem's capacity to produce resources for humans and absorb pollution), and social governance (Yang *et al*., 2021). The relationship between PM pollution and economic development follows the Kuznets environmental curve, characterized by an inverted "U" shape pattern, indicating an initial increase in emissions and concentrations during economic development, followed by a reduction with air quality management at higher levels of development (Guillerm and Cesari, 2015; Sang *et al*., 2022).

This pattern occurs due to the lack of effective pollution control during economic development (Xu *et al*., 2023), when pollution becomes seen as an acceptable consequence of growth (Johnson *et al*., 2021). Global air quality research presents results that converge with this theory. For example, Sicard *et al*. (2023) observed that East and South Asia have the highest average annual concentrations of $PM_{2.5}$ (> 45 μg/m³) due to biomass burning, manufacturing industries, and vehicle emissions, while North America and Europe were the regions with lower concentrations, especially due to regional emission control policies. Xu *et al*. (2023) identified that from 2000 to 2019, developed countries showed a trend of reducing $PM_{2.5}$ concentration, while other regions showed an increasing trend, especially in the Middle East and India. According to Hammer *et al*. (2020), the trend of reducing $PM_{2.5}$ concentration in North America is, on average, -0.28 μg/m³/year and in Europe -0.15 μg/m³/year, while in India there is and increasing trend of 1.13 μg/m³/year.

Disassociating economic growth from increased degradation of air quality is a priority action for current society to achieve sustainable development. Developing countries represent 80.4% of those characterized by an energy-intensive development pattern. Such countries have not reached the inflection point of the Kuznets curve, and their growth is associated with industries with high energy consumption and high potential for PM emissions (Fu and Li, 2020). Research assumes that more developed regions have optimized and modernized secondary industries (Fu and Li, 2020), completed urbanization (Xu *et al*., 2023), and have better air quality management (Sang *et al*., 2022). However, it is important to emphasize that developed countries invested in environmental protection after polluting and transferring polluting sources to developing countries (Johnson *et al*., 2021; Xu *et al*., 2023).

Monitoring emissions and concentrations of PM is essential for a better understanding of the problem, as the emission leads to increased PM concentrations and raises the potential for population exposure to pollutants, resulting in health effects. Although the number of monitoring stations and databases has increased, there are still inequalities in distribution and gaps in temporal data series (Sicard *et al*., 2023), which may occur due to electrical failures, communication breakdowns, equipment failures, and cyberattacks (Tan *et al*., 2022). It is estimated that more than half of the global urban population lacks adequate $PM_{2.5}$ measurements (Apte *et al*., 2021).

Regarding human effects, air pollution caused by PM represents a significant health risk to the population, rising to the 7th position of risk in 2019 compared to the 13th position in 1990 (Sang *et al*., 2022). In terms of environmental risks, PM pollution is the leading risk factor for mortality, responsible for 6.67 million deaths in 2019 (GBD, 2019), of which about 90% occur in middle- and low-income countries (Wolf *et al*., 2022). Chen *et al*. (2022) calculated that of the total accumulated premature deaths attributed to PM between 1950 and 2014 (185.7 million deaths), 29% occurred in high-income countries, 44% in high-middle-income countries, 25% in lower-middle-income countries, and 2% in low-income countries, following a similar trend to the Kuznets environmental curve. Although PM concentrations are reducing in developed countries (Xu *et al*., 2023), there are no safe levels for $PM_{2.5}$ pollution (Yu *et al*., 2023).

There is evidence of a causal relationship between $PM_{2.5}$ and 13 groups of diseases (GBD, 2019): ischemic heart disease (1.84 million global deaths attributed to PM in 2019, for both sexes and all ages); stroke (1.7 million deaths); chronic obstructive pulmonary disease (1.09 million deaths); lower respiratory infections (749.18 thousand deaths); tracheal, bronchus, and lung cancer (387.44 thousand deaths); neonatal disorders (372.58 thousand deaths); diabetes mellitus (292.53 thousand deaths); diarrheal diseases (10.39 thousand deaths); meningitis (3.36 thousand deaths); sudden infant death syndrome (499.02 deaths); encephalitis (286 deaths); otitis media (53.48 deaths), and; upper respiratory infections (21.23 deaths). Men are more susceptible to experience about 1.5 times more health effects than women; two most vulnerable age groups are babies (0-4 years), due to the immaturity of the immune system, and the elderly (70-74 years for men, and 80-84 years for women) due to the presence of chronic diseases (Sang *et al*., 2022).

The composition and aerodynamic size of PM influence the type and severity of health effects. Smaller particles have a higher capacity to penetrate the respiratory system and can travel from the lungs to the pulmonary alveoli, cross the blood-brain barrier, reach the central nervous system, and affect multiple organs and tissues through the circulatory system (Zhang *et al*., 2024). The composition of the particles also affects their toxicity, which can cause genetic mutations, deformities, and cancer, as well as induce oxidative stress (Zhang *et al*., 2024).

In addition to health impacts, PM pollution also has significant economic consequences, resulting in global losses of over $5 trillion annually (Johnson *et al*., 2021). Low-income countries may lose up to 7.5% of their annual nominal GDP due to the effects of pollution (Johnson *et al*., 2021). The costs of mitigating PM pollution are about 30 times lower than the costs of associated effects (Singh *et al*., 2022).

Improving air quality and reducing health effects related to PM are essential goals for achieving sustainable development (UN, 2023a). In light of this, various mitigation strategies are highlighted in research. Government actions, such as laws and air quality improvement policies, are essential. Successful examples include the Clean Air Act in the United States and the Ambient Air Quality Directive in the European Union. In addition to legislation, governments can implement emission reduction plans (such as establishing Low Emission Zones for road transport), apply higher taxes on polluting fuels, enforce bans (on burning or on the use of more polluting fuels), improve urban infrastructure (increasing green areas and improving public transportation), and promote environmental education (Singh *et al*., 2022). The private sector can contribute by reducing emissions from production chains, prioritizing the use of renewable fuels and energy sources (Bai *et al*., 2022), using post-treatment technologies like particle filters (Wu *et al*., 2022), and adopting efficient agricultural practices (Gu *et al*., 2021). Individuals can also take actions to reduce exposure to pollution, such as avoiding wood burning indoors (Avenbuam and Zelikoff, 2020), using air filtration systems, and avoiding outdoor activities during extreme pollution episodes (Rajagopalan *et al*., 2020).

The issue of PM pollution is global and requires joint actions from various stakeholders. Understanding PM emissions, concentrations, and effects is essential to inform pollution control and mitigation actions, aiming at improving health and achieving sustainable development. Although the effects of pollution are of global concern, local characteristics influence the extent of health problems, so mitigation strategies should also be studied in local and regional contexts.

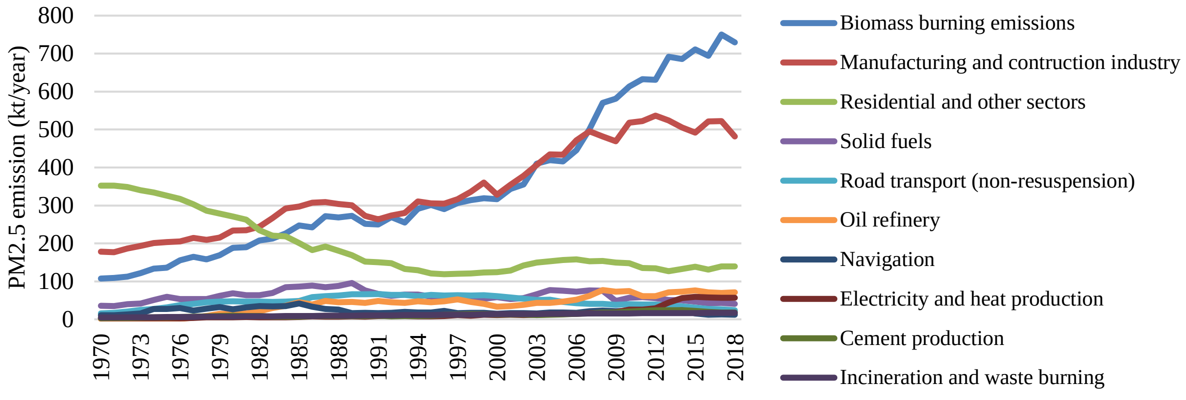
2.1.2 Particulate matter in Brazilian context

Brazil, with its continental dimensions, is the fifth largest country in terms of territorial extension, covering 8.5 million square kilometers (IBGE, 2022). In 2023, it reached the seventh position in terms of population, totaling 216.4 million inhabitants (UN, 2023b). In 2021, its Human Development Index (HDI) reached 0.754, placing the country in the class of highly developed countries according to the classification of UN (2021). In the context of air quality, the country faces several challenges, including: (1) the diversity of biomes, such as the Atlantic Forest, Cerrado, Amazon Rainforest, Caatinga, Pampa, and Pantanal, each with its own geomorphological, social, and specific emission sources; (2) in some biomes, the propensity for fires is higher, resulting in significant emissions of atmospheric pollutants that can disperse over long distances; (3) land use, particularly deforestation, negatively affects air quality; (4) there is a gap in adequate monitoring and implementation of effective air pollution control policies; and (5) the quality and accessibility of healthcare services vary among populations, directly influencing social justice and the degree of pollution's impact on health (Réquia and Castelhano, 2023; Réquia *et al*., 2023).

Especially regarding air quality monitoring, Brazil has 371 active monitoring stations, located in only ten states plus the Federal District, with 80% of them located in the Southeast Region and only 26% monitoring $PM_{2.5}$ (Vormittag *et al*., 2021). Consequently, other forms of monitoring and concentration estimates are explored by air quality studies in Brazil, such as transport modeling (Guo *et al*., 2023), low-cost sensors (Silva *et al*., 2023), biomonitoring (Andrade *et al*., 2022), and satellite data (Gardin and Requia, 2023).

According to the international emissions inventory EDGAR v.6.1, Brazil recorded a 127% increase in total $PM_{2.5}$ emissions between 1970 (733.65 kt) and 2018 (1668.67 kt), elevating its position from the sixth to the fourth largest emitting country in the same period (EC, JRC, PBL, 2022). Analysis of the most emitting sectors reveals a change in the profile of $PM_{2.5}$ emissions over the 49 years of available data. From 1970 to 1981, residential emissions accounted for an average of 39% of $PM_{2.5}$ emissions. In the following 26 years, emissions from manufacturing industries and construction surpassed residential emissions, contributing to approximately 31% of the country's emissions. From 2008 to 2018, emissions from biomass burning stood out, representing an average of 40% of national emissions, while residential emissions decreased their contribution to about 9% (EC, JRC, PBL, 2022). Figure 2 illustrates the evolution of emissions from the top ten emitting sectors from 1970 to 2018 (EC, JRC, PBL, 2022).

Figure 2 - $PM_{2.5}$ emissions from the top ten emitting sectors from 1970 to 2018



Source: EC, JRC, PBL (2022)

In the context of residential activities, cooking emissions are particularly relevant, and the type of fuel used can influence pollutant emission rates (Kumar *et al*., 2022). Until 1968, before the widespread use of liquefied petroleum gas in the country, Brazilian families mainly used wood stoves (Gioda *et al*., 2019). This may explain the high contribution of residential emissions in the 1970s and the decreasing trend in the analyzed period. The change in emission profile reflects the country's industrialization trajectory, which faced contradictions between economic development and environmental quality. An example of these contradictions was the Brazilian government's stance at the 1972 Stockholm Conference, where economic development was advocated as necessary action to reduce poverty, while environmental protection measures were challenged as obstacles to progress (Duarte, 2015). With evidence of health effects associated with air pollution, mitigating measures were subsequently implemented in the industrial sector (Duarte, 2015).

From 2008 onwards, biomass burning emissions - associated with forest fires, agricultural processes, and industrial activities - have become prominent in Brazil. According to Cobelo *et al*. (2023), Brazilian forest fires vary in space and time, so that in 2003 the fires occurred mainly on the borders of the Amazon and Cerrado biomes, and by 2018 they had expanded to the border between the Cerrado and the Caatinga, many of which were associated with the opening of areas for the expansion of agricultural and mining activities, a common practice in Brazil. The transport of pollutants from biomass burning can be long-range and increase pollutant concentrations by about 80% in regions with low $PM_{2.5}$ concentrations (Martins *et al*., 2018). A severe fire event occurred in Brazil in September 2020, destroying about 4 million hectares in the Pantanal. The smoke plumes combined with fires in the Amazon and pre-harvest sugarcane burning in the state of São Paulo caused 99% of monitoring stations in the São Paulo Metropolitan Region to have $PM_{2.5}$ concentrations above World Health Organization standards (considered 25 μg/m³ for 24 hours in the cited study) on the event days (Souto-Oliveira *et al*., 2023).

A chemical composition analysis of PM in the country also highlights the significance of biomass burning. Comparing the composition of PM_{10} in the cities of Lima (Peru), Medellín (Colombia), and São Paulo in June 2010, Pereira *et al*. (2019) observed high concentrations of levoglucosan, a biomass burning marker, for the city of São Paulo, which was particularly related to sugarcane burning. Silva *et al*. (2019) analyzed the physicochemical properties of PM_{10} in a ceramics industry complex in Northeast Brazil and found particles typical of biomass burning (soot carbon, organic carbon, and inorganic ash), which occurs through the consumption of wood as fuel for clay firing. Maia *et al*. (2022) characterized PM_{10} in the Federal District, and the results indicated that air pollution in the city is influenced by the burning of plants and vegetation of Cerrado.

In air quality studies, the use of locally developed inventories is more recommended than international inventories (Huneeus *et al*., 2020). However, despite efforts to construct local inventories, their availability is still in the early stages in Brazil (Kawashima *et al*., 2020). In this regard, the research of Kawashima *et al*. (2020) and Hoinaski *et al*. (2022) can be highlighted. Kawashima *et al*. (2020) developed a national inventory for industrial emissions of NO_x, SO_x, CO, PM_{10}, Total Organic Compounds, and CO_2 for 2011, covering 1906 emission sources: 16 refineries, 1730 thermoelectric plants, 96 cement industries, and 64 pulp and paper industries. For PM_{10}, the authors estimated an annual emission of 10.4 ± 10.1 Tg/year, which is 360 times higher than vehicular emissions. Hoinaski *et al*. (2022) provided emissions of 41 different chemical species with spatial resolution of 0.05°×0.05° and annual temporal resolution, with data from 2013 to 2019. Both studies found the highest emissions for the Southeast region of Brazil and assert that the developed inventories provide differences in emission values and more spatial details compared to international inventories.

The exposure of the Brazilian population to PM emitted by various sources positioned the country among the most populous (over 100 million inhabitants) at high risk of exposure to $PM_{2.5}$ (Zhao *et al*., 2021). The main effects observed in Brazil in 2019 were cardiovascular diseases (2.22% of total deaths in Brazil - 1,411,785), chronic respiratory diseases (0.72%), diabetes (0.52%), respiratory infections and tuberculosis (0.47%), neoplasms (0.26%), and maternal and neonatal problems (0.13%) (GBD, 2019). Six Brazilian states had a death rate (number of cases per 100,000 inhabitants) above 30: Maranhão (36.1), Paraíba (35.0), Piauí (34.7), Alagoas (34.7), Rio de Janeiro (33.8), and Rio Grande do Sul (32.1). On the other hand, four states had a death rate below 15: Roraima (12.9), Amazonas (11.5), Amapá (11.5), and Distrito Federal (11.3). In addition to differences in sources and emission rates among Brazilian regions, cultural, social, and behavioral differences also explain the variation in health effects, such as the decision-making process to seek medical care and the variation in the availability of health facilities in Brazil (Réquia *et al*., 2023).

Both short-term and long-term exposure to $PM_{2.5}$ is associated with negative health effects on the population. For short-term exposures, studies covering all regions of Brazil estimated that a 10 µg/m³ increase can raise the risk of hospital admissions by 1.06% for all causes (Guo *et al*., 2023), 3.28% for respiratory diseases, and 1.86% for cardiorespiratory diseases (Réquia *et al*., 2023). The associations tend to be stronger in children aged 0-4 years and in elderly individuals aged 80 years or older (Guo *et al*., 2023). For long-term exposures to $PM_{2.5}$, national research found that a 1 µg/m³ increase over two years can increase cancer admissions by 4.4% (Yu *et al*., 2021), and a 10 µg/m³ increase over three years can increase cancer mortality risk by 15.8% (Yu *et al*., 2022a). The relationship occurs because finer particles can accelerate cancer progression in already diagnosed patients and weaken the immune system of these patients. According to Yu *et al*. (2022b), if concentrations in the country were reduced to the WHO-recommended level (5 µg/m³ for annual average) or to the minimum observed concentration in the country (2.9 µg/m³), there would be an increase of 0.78 or 1.09 years in the life expectancy of the population, respectively. However, even when PM is in compliance with air quality standards, there are health risks for the population (Galvão *et al*., 2023).

National research has also investigated the relationship between pollution specifically associated with forest fires and its health effects. According to Ye *et al*. (2021), a 10 µg/m³ increase in $PM_{2.5}$ related to forest fires can increase hospitalizations for respiratory problems (5.09%) and cardiovascular issues (1.10%). Wu *et al*. (2023) identified that from 2000 to 2016, costs due to mortality from cardiovascular and respiratory effects related to $PM_{2.5}$ from forest fires represent approximately 0.14% of Brazil's Gross Domestic Product. Congenital defects were also observed, according to Réquia *et al*. (2022), exposure to pollution from fires in the first, second, and third trimesters of gestation is respectively associated with anomalies in the nervous system, cleft lip/palate, and respiratory system. All three studies identified that the Central-West, North, and South regions of Brazil were the most affected.

Similarly to the global scenario, personal exposure levels to PM are also affected by social conditions, as evidenced by Singer *et al*. (2023). According to the authors, socioeconomically disadvantaged individuals living in São Paulo - SP are more exposed to air pollution, justified especially by the longer commuting time of the population living in peripheral areas. Additionally, socioeconomic level is a decisive factor in increasing the use of solid fuels for cooking, which is associated with fluctuations in the price of liquefied petroleum gas (Gioda *et al*., 2019). According to Gioda *et al*. (2019), estimates from 2016 indicate that wood was used for cooking in about three million Brazilian households, being the second most used fuel, and exposing about nine million individuals to indoor pollution. The states that consumed the most wood were Rio Grande do Sul, Bahia, Minas Gerais, Santa Catarina, Piauí, Ceará, Paraíba, Pará, Paraná, and Tocantins. Highlights from the Southern region of Brazil may be associated with cold weather and cultural issues, while in the North and Northeast, it may be more related to the population's purchasing power (Gioda *et al*., 2019). However, disparities in exposure according to socioeconomic characteristics may vary between different regions. Réquia *et al*. (2023) observed that the most exposed racial groups varied by region in Brazil, so that in the North, brown-skinned individuals were the most exposed, in the South, it was blacks, and in the Northeast, Midwest, and Southeast, it was Asians. The authors also identified higher exposure for high-income groups in Brazil, and suggest that this occurred mainly in regions with high agricultural activity.

Managing and reducing $PM_{2.5}$ emissions, and consequently exposure levels, in Brazil is essential to decrease the burden of non-communicable diseases (Stein *et al*., 2022) and to help the country achieve the goals of the 2030 Agenda. National research has explored potential solutions to air quality issues in the transportation sector, industry, and urban areas. In the transportation sector, Santana *et al*. (2021) advocate for replacing fossil fuels with renewable fuels, such as biodiesel, to help reduce pollutant emissions and, consequently, hospitalizations due to respiratory diseases. For the industrial sector, Costa *et al.* (2023a) analyzed the use of a regular Venturi scrubber to control PM emissions from biomass burning and observed an efficiency of 96.6% for $PM_{2.5}$, 85.5% for $PM_{1.0–2.5}$, and 66.9% for $PM_{<1.0}$. In urban areas, research focuses on nature-based solutions, especially urban greening. Trees can reduce PM levels by acting as natural barriers (Ramon *et al*., 2023) and generating an exponential decay in concentrations towards the interior of urban parks (Moreira Junior *et al*., 2022; Martins *et al*., 2021).

It is important to highlight that national research also highlighted the significance of public policies for effective control of air pollution and its impacts on public health. Silva *et al.*

(2023) argue that air quality plans should effectively control local emissions while also considering improvements in air quality in neighboring cities, changes in land use, population growth, green areas, and transportation matrices and infrastructure. Souza *et al*. (2022a) emphasize the importance of public policies to enhance communication between healthcare professionals and the population.

2.1.3 Air quality policies in the context of Life Cycle Management in Brazil

This section of the literature review is based on the research "Air Quality Policies in Brazil and Life Cycle Management: Analysis of Scientific Production", which was published in the 8th Brazilian Congress on Life Cycle Management.

The first Brazilian legislation related to air pollution was the Law of Misdemeanors (Brazil, 1941), which penalized abusive emissions capable of causing adverse effects. At the federal level, the National Environmental Policy (Brazil, 1981) is the main legislation providing guidelines for air quality management. Resolutions of the National Environment Council (CONAMA – Brazilian acronym) also influence air quality management, with the main one being the National Program for Air Quality Control (PRONAR – Brazilian acronym) (Brazil, 1989).

Despite the existing policies, there was an increase in air pollution in the country between 1990 and 2018 (United Nations, 2018), making it relevant to assess the effectiveness of these interventions. In this regard, Nogueira *et al*. (2021) observed a reduction in CO and NO_x emission factors in the city of São Paulo over time, influenced by the Vehicle Air Pollution Control Program (PROCONVE – Brazilian acronym). Additionally, Fernandes *et al*. (2020) estimated 4,148 avoidable hospitalizations and a public health economic gain of US$1.1 million if the final pollutant standards of CONAMA Resolution No. 491/2018 were met in the cities of São Paulo - SP, Rio de Janeiro - RJ, Belo Horizonte - MG, and Vitória - ES.

An approach that can assist in the evaluation of these interventions, as well as in the creation of new interventions, is the Life Cycle Management (LCM). An example of using LCM to aid in policy decision-making is presented in Gabriel *et al*. (2021), where the authors compare, through Life Cycle Assessment (LCA), the air quality impacts caused by diesel, electric, and natural gas-powered buses in the city of Bangkok, Thailand.

The studies by Nogueira *et al*. (2021) and Fernandes *et al*. (2020) indicate a potential effectiveness of the evaluated interventions, but there is a scarcity of works integrating the context of LCM with public air quality management in Brazil. To understand this integration, documentary research covering 10 years of publication (2013 - May 2022) was conducted in the Scopus database using the string "*public policy*" OR "*policy instrument*" AND "*air quality*" AND "*Brazil*". The search returned 176 articles, of which 21 analyzed the effectiveness of air quality policies in Brazil, including policies in the transportation sector, air quality standards, social distancing policies during the COVID-19 pandemic, and urbanization policies.

The most addressed policies were developed for the transportation sector, with emphasis on PROCONVE, which has shown potential to reduce vehicle emissions in the long term as the program phases progress (Cezarino *et al*., 2022; Jafari *et al*., 2021; Nogueira *et al*., 2021; Rocha *et al*., 2020). As a limitation of PROCONVE, Cezarino *et al*. (2022) highlight the lack of emissions monitoring by carriers. Several recommendations were generated for decision-makers, such as increasing fees for vehicles using more polluting fuels; offering incentives for companies and individuals to replace vehicles manufactured before 2012 (Cezarino *et al*., 2022); considering secondary organic aerosols and black carbon in policies (Jafari *et al*., 2021); involving different stakeholders in policy agreements (Xavier *et al*., 2017); considering spatial differences in vehicle emissions (Réquia *et al*., 2016); generating incentives for electric vehicles in Brazil (Santos *et al*., 2016); and increasing air quality monitoring (Pérez-Martínez *et al*., 2014).

In addition to PROCONVE, other policy instruments in the transportation sector have been studied, such as the implementation of a ring road in São Paulo – SP (He *et al.,* 2018) and the use of flex-fuel vehicles powered by ethanol at the national level (Quarmby *et al*., 2019). He *et al*. (2018) observed a reduction in NO_x levels with the implementation of the ring road in São Paulo – SP, and recommended investment in ring roads in other megacities. Quarmby *et al*. (2019) observed improved air quality with the use of ethanol in flex-fuel vehicles, and recommended other policy instruments to further reduce vehicle emissions, such as: creating low emission zones, investing in public transportation and cycling areas, and managing vehicle speed.

Regarding the ambient air quality standards set by CONAMA, resolution 491/2018, studies have shown that air quality characteristics vary over space and time and have identified the inadequate monitoring of air quality in the country as the main limitation of the standard (Gidhagen *et al*., 2021; Fernandes *et al*., 2020; Santana *et al*., 2020; Tischer *et al*., 2019; Zeri *et al*., 2016). As for social distancing policies during COVID-19, they were discussed by Sthel *et al*. (2021) and Connerton *et al*. (2020) for the city of São Paulo – SP. The studies observed reductions in atmospheric pollutant concentrations, except for ozone (O_3). Sthel *et al*. (2021) recommended maintaining remote work in the industrial sector and using renewable and clean energy sources in the transportation sector, while Connerton *et al*. (2020) recommended prioritizing active transportation and promoting public transportation to reduce private vehicles.

Policy instruments related to urbanization were evaluated by Stevenson *et al*. (2016), including urban design and transportation modal choice for a city. The study was conducted in six cities around the world, one of which was São Paulo – SP. The authors recommended government policies focused on compact cities that support a transition to active transportation, such as biking or walking commutes.

In terms of the relationship between LCM and air quality policies in Brazil, three examples of implementation based on LCA can be cited: the National Solid Waste Policy (Law No. 12,305/2010) (Brazil, 2010), Type 1 Labeling (Maia de Souza *et al*., 2017), and the National Biofuels Policy (RenovaBio) (Law No. 13,576/2017) (Brazil, 2017). Of these, only the latter can be considered an air quality policy with direct application of LCA, focusing on decarbonization but indirectly affecting particulate pollution. Globally, LCA has been timidly used in public policies, as there are various methodological and implementation challenges for this integration (Rajagopal *et al*., 2017), such as lack of decision-makers' experience, resource needs, and methodology accuracy (Seidel, 2016).

Despite the challenges, there are a variety of options for using LCA in public policies, as it can help identify opportunities to reduce environmental impacts associated with production processes (Seidel, 2016; Rampasso *et al*., 2021). The ability to compare different options (products or processes) in terms of environmental efficiency can be highlighted as a potential benefit of LCA to meet decision-makers' recommendations. Examples of recommendations/limitations of air policies that could benefit from comparative analyses include: increasing fees for vehicles using more polluting fuels; incentivizing the replacement of old vehicle fleets (Cezarino *et al*., 2022); promoting the use of electric vehicles (Santos *et al*., 2016); maintaining remote work post-COVID-19 (Sthel *et al*., 2021); using clean energy sources (Sthel *et al*., 2021), and; encouraging the use of active and public transportation (Connerton *et al*., 2020). LCA, for instance, could be applied in these different contexts to compare the recommended options, allowing the quantification of the expected improvement potential with the proposed changes. Rampasso *et al*. (2021) proposed a framework with short, medium, and long-term environmental policy actions based on LCA in the context of public policies for the national bioeconomy. The proposed step-by-step process could be adapted to the context of air quality policies in the country.

Researchers from PROCONVE discussed the policy's inefficiency in reducing O_3 emissions (Jafari *et al*., 2021) and the lack of regulation for CO_2 (Réquia *et al*., 2016), secondary aerosols, and black carbon (Jafari *et al*., 2021). Bringing a life cycle perspective to PROCONVE could assist these recommendations, avoiding environmental trade-offs in the life cycle of transportation activities. There are examples of such applications in the United States, where based on LCA, a 10% reduction in carbon intensity in transportation fuels was requested (Seidel, 2016).

For PROCONVE, Cezarino *et al*. (2022) discuss the lack of monitoring of emissions by carriers, which could be overcome through tools to model vehicle emissions, accessible to non-experts, such as the proposal of the GHG Protocol (GHG Protocol, 2023) for greenhouse gases. Réquia *et al*. (2016) recommend considering spatial differences in vehicle emissions, and assessments of emissions and environmental impacts at the regional level are accessible through LCA. In Brazil, there are initiatives for the development of life cycle inventories of national processes (Maia de Souza *et al*., 2017), and the Life Cycle Impact Assessment Research Network (RAICV) has been working on regionalization of Characterization Factors (CFs) for different impact categories, including those related to air pollution, such as photochemical smog and PM formation (RAICV, 2023).

Although there are benefits generated by LCA for air quality policies, the barriers to this application need to be considered. Paes *et al*. (2018) emphasize that the quality of the diagnosis generated by LCA approaches in policy formulation processes depends on how the process is conducted. Thus, following the PDCA (Plan-Do-Check-Act) cycle as proposed by Lehmann *et al*. (2015) is essential to ensure that relevant policy issues are appropriately matched with LCA steps. In the "Check" stage, it is essential to create adequate means for policy effectiveness analysis (Rampasso *et al*., 2021), which is the main recommendation of this research in terms of priority needed when integrating LCA with Brazilian air quality policies. It is important to note that to achieve this, methodologies considering Brazil's geographical context are necessary, and in this sense, the development of recommendations, emission factors for inventories, and CFs for LCA stages are essential. Thus, studies for the impact category of PM formation in Brazil become essential.

2.2 LIFE CYCLE IMPACT ASSESSMENT FOR HUMAN HEALTH DUE TO PM EXPOSURE

LCA is an impact assessment technique that characterizes the exchanges that occur between human activities and the environment (Esnouf *et al*., 2018). Its application is focused on production systems of goods or the execution of services, allowing for the analysis of the entire product life cycle (ISO 2006a, b). Its methodological development is standardized by ISO 14040 (ISO, 2006a) and ISO 14044 (ISO, 2006b) and occurs in four stages:

1. Goal and scope definition: consist in delineating the study to be developed, defining, for example, the production system, system boundaries, impact categories to be assessed, the function, and the functional unit of the system (Oliveira *et al*., 2021);
2. Life Cycle Inventory (LCI) analysis: quantifies input and output flows within the defined boundaries, including material, energy, waste, and pollutant flows (to soil, air, and water) (Oliveira *et al*., 2021);
3. Life Cycle Impact Assessment (LCIA): responsible for converting inventory flows into environmental impact indicators by multiplying elementary flows (which have a direct interface with the environment) by CFs, defined through characterization models (further details in sections 3.2, 3.3, and 3.4) (Oliveira *et al*., 2021);
4. Interpretation: aggregates all results from the previous stages to interpret and conclude on findings, which may include hotspot, sensitivity, and uncertainties analysis (Oliveira *et al*., 2021).

According to ISO (2006 b), LCA can be directly applied in product development and improvement, strategic planning, public policy development (as discussed in section 2.3), marketing, among others. Through LCA, potential impacts of various impact categories can be estimated, including impacts on human health associated with emissions of PM and precursor gases (NO_x, SO_2, and NH_3) (Bulle *et al*., 2019). In light of this, this section presents the current status of research in LCIA and the category of health damage due to PM in the Brazilian context. Thus, it discusses Brazilian case studies analyzing impacts in national production chains (section 3.1), presents the cause-and-effect chain (section 3.2), and the characterization models available in the literature for the category (section 3.3).

2.2.1 Brazilian case studies of LCA covering PM impacts

Since the main emissions of PM and precursor gases come from anthropogenic systems (industries, transportation, agriculture) (Singh *et al*., 2022), LCA can assist in monitoring emissions and quantifying the potential impact on human health associated with PM emitted by production chains. From this, the tool enables comparisons of different production systems with the same function (Rosado *et al*., 2017), identification of key hotspots (Santos *et al*., 2017a), and directing mitigating actions at target points in the life cycle of production systems. Therefore, several LCA studies have been developed in the Brazilian context, covering the PM impact category within the scope, for various sectors of the economy, including energy, construction, agriculture and livestock, industry, mining, health, and safety (Table 2).

Most of the LCA studies presented in Table 2 work with comparisons of systems, considering different product options (Maceno *et al*., 2023; Muneron *et al*., 2021; Capaz *et al*., 2020), processes (Bueno *et al*., 2023; Du *et al*., 2019; Santos *et al*., 2017a), or producing regions (Sadhukhan, 2022; Dick *et al*., 2021; Rosado *et al*., 2019). Overall, these studies conclude which system presents the lowest environmental impacts and propose mitigating measures aimed at the identified hotspots. It is also interesting to note that the papers were conducted throughout the entire Brazilian territory, with analyses of systems located in the southern (Kohlbeck *et al*., 2023; Restrepo *et al*., 2015; Zappe *et al*., 2020), southeastern (Haddad *et al*., 2023; Rosado *et al*., 2019; Ferreira *et al*., 2020), midwestern (Dick *et al*., 2021; Menezes *et al*., 2022), northern (Bueno *et al*., 2023; Costa *et al*., 2023b), and northeastern (Monteiro *et al*., 2021; Santos *et al*., 2017b) regions

Table 2 - Brazilian case studies of Life Cycle Assessment that included the impact category associated with exposure to Particulate Matter

Sector	Paper	System	Geographic scope	LCIA method*	Impact category name	Impact indicator
Agriculture and livestock	Dick *et al*. (2021)	Beef cattle ranching	Amazon, Cerrado, Pampa, and Pantanal biomes	ReCiPe mid v.1.13	*PM formation*	kg PM_{10} eq.
	Zappe *et al*. (2020)	Three tobacco cultivars	Rio Grande do Sul, Santa Catarina and Paraná states	ReciPe mid v.1.0 (2016)	*Fine PM formation*	kg $PM_{2.5}$ eq.
	Du *et al*. (2019)	Harvesting of sugarcane (manual vs. mechanical)	Brazil	ReCiPe mid (2013)	*PM formation*	kg PM_{10} eq.
	Santos *et al*. (2017b)	Cheese	Itapetinga - Bahia	ReCiPe mid H v.1.12	*PM formation*	kg PM_{10} eq.
Construction	Muneron *et al*. (2021)	Bricks (ceramic vs. concrete)	Brazil	Ecoindicator 99	*Respiratory effects*	Points
	Antunes *et al*. (2020)	Pavement (permeable vs. impermeable)	Florianópolis - Santa Catarina	ReCiPe mid (2016)	*Fine PM formation*	kg $PM_{2.5}$ eq.
	Silva *et al*. (2020)	Construction inputs for a 66 m² house	Brazil	ReCiPe mid H v.1.01 (2016)	*Fine PM formation*	kg $PM_{2.5}$ eq.
	Rosado *et al*. (2017)	Road construction aggregates (recycled vs. natural vs. mixed)	Southeastern Brazil	Impact 2002+	*Respiratory inorganics*	kg $PM_{2.5}$ eq.
	Stafford *et al*. (2016)	Bricks	Brazil	ReCiPe mid H v.1.06	*Fine PM formation*	kg PM_{10} eq.
	Lassio *et al*. (2016)	Residential building	São Gonçalo - Rio de Janeiro	Impact 2002+ v.2.05	*Respiratory organics*	Relative results only
	Souza *et al*. (2016)	External wall (ceramic brick vs. concrete brick vs. reinforced concrete)	Brazil	Impact 2002+ v.Q.2.2	*Respiratory organics and inorganics*	Relative results only
	Bueno *et al*. (2016)	Structural external wall (clay masonry vs. concrete masonry vs. concrete panels vs. steel frame)	São Paulo state	EDIP97 (2003); CML (2001); Impact 2002+; ReCiPe (2008); ILCD	*PM formation*	Relative results only
	Souza *et al*. (2015)	Roof tiles (ceramic vs. concrete)	Brazil	Impact 2002+ v.Q.2.2	*Human health; Respiratory inorganics and organics*	DALY
Energy	Costa *et al*. (2023)b	Electricity (photovoltaic panel vs. batteries)	Indigenous community of Catual - Roraima	ReCiPe mid H (2016)	*PM formation*	t PM_{10} eq.
	Haddad *et al*. (2023)	Water heating (natural gas vs. solar heating)	Rio de Janeiro - Rio de Janeiro	ReCiPe end (2016)	*Fine PM formation*	DALY
	Menezes *et al*. (2022)	BioLPG from soybean oil (comparing three technologies)	Goiás, Mato Grosso, Mato Grosso do Sul, Paraná, Rio Grande do Sul and São Paulo states	ReCiPe mid H (2016)	*Fine PM formation*	g $PM_{2.5}$
	Souza *et al*. (2022b)	Sugarcane biomass (bagasse vs. bagasse and straw)	Brazil	ReCiPe mid H v.1.13	*PM formation*	kg PM_{10} eq.
	Sadhukhan (2022)	Electricity systems (national mixes)	15 countries, including Brazil	ReCiPe mid H; Impact 2002+; Environmental Prices	*Fine PM formation*	kg $PM_{2.5}$ eq.

Table 3 - Brazilian case studies of Life Cycle Assessment that included the impact category associated with exposure to Particulate Matter (continuation)

Sector	Paper	System	Geographic scope	LCIA method*	Impact category name	Impact indicator
Energy	Capaz *et al*. (2020)	Aviation fuel (sugarcane vs. soy vs. four types of residues)	Brazil	ReCiPe mid H v.1.13	*PM formation*	g PM eq.
	Karkour *et al*. (2020)	Electricity systems (national mix)	20 countries, including Brazil	LIME 3	*Air pollution*	monetary (US$/kWh)
	Azevedo *et al*. (2017)	Bioethanol from cattle manure	South of Brazil	ReCiPe mid e end v.1.06	*PM formation*	kg PM_{10} eq.
	Santos *et al*. (2017a)	Vegetable charcoal (compares three technologies)	Brazil	ReCiPe end H/A v.1.12	*PM formation*	Relative results only
	Restrepo *et al*. (2015)	Energy charcoal	Paraná River Basin (including Santa Catarina and Rio Grande do Sul)	Ecoindicator 99	*Respiratory inorganics*	Relative results only
	Cavalett *et al*. (2013)	Fuel (ethanol vs. gasoline)	Brazil	CML (2001); Impact 2002+; EDIP (2003); Eco-indicador99; TRACI 2; ReCiPe; Ecological Scarcity (2006)	*PM formation* (ReCiPe); *Respiratory effects* (TRACI 2); *Human toxicity air* (EDIP 2003); *Respiratory inorganics and organics* (IMPACT2002+)	kg PM_{10} eq. (ReCiPe mid); kg $PM_{2.5}$ eq (TRACI2; IMPACT2002+ mid); m³ (EDIP2003); DALY (ReCiPe end; Eco-indicator99; IMPACT2002+ end); UBP (Ecological Scarcity)
End-of-life	Rosado *et al*. (2019)	Construction and demolition waste management	13 cities in São Paulo state	CML baseline v3.03; Impact 2002+ v.2.12	*Respiratory inorganics* (CML)	kg $PM_{2.5}$ eq. (CML)
	Bueno *et al*. (2023)	*Sargassum* algae (four end-of-life destinations)	Salinópolis - Pará	ReCiPe mid H (2016)	*Fine PM formation*	Relative results only
	Talang and Sirivithayapakorn (2021)	Urban solid waste disposal (24 schemes)	Global, including Brazil	Stepwise (2006)	*Respiratory organics and inorganics*	monetary (US$/ton)
	Miranda *et al*. (2023)	Gas capture (compares metal-organic frameworks)	Laboratory level	ReCipe mid v.1.03 (2016)	*PM formation*	kg PM_{10} eq.
	Rocha and Penteado (2021)	Reverse logistics of electronic waste	Campinas - São Paulo	EF v.1.00 (adaptaed)	*Respiratory inorganic*	Disease incidence
Industrial	Camargo *et al*. (2019)	Cosmetics from Natura company	Brazil	ReCiPe mid e end H v.1.06	*PM formation*	kg PM_{10} eq.
	Kohlbeck *et al*. (2023)	Recycled polypropylene for refrigerators	Joiville - Santa Catarina	ReCiPe mid H (2016)	*Fine PM formation*	Relative results only
	Monteiro *et al*. (2021)	Concrete industry	Teresina - Piauí	CML (baseline) e ReCiPe mid H	*Fine PM formation*	kg $PM_{2.5}$ eq.
	Ferreira *et al*. (2020)	Heavy-duty vehicles (traditional vs. differential axle modification)	Southwestern Brazil	ILCD mid 1.0.8 (2016)	*Human health; Respiratory inorganics and organics*	kg $PM_{2.5}$ eq.
Mining	Ferreira and Leite (2015)	Iron ore	Germano, Iron Quadrangle	Ecoindicator 99	*Inhalable organic and inorganic material*	DALY
Health	Maceno *et al*. (2023)	Face masks (reusable vs. disposable)	Brazil	ReCiPe mid (2016); Impact World+	*Fine PM formation* (ReCiPe); *PM formation* (Impact World+)	kg SO_2 eq. (ReCiPe); kg $PM_{2.5}$ eq. (Impact World+)
Security	Passon *et al*. (2023)	Demilitarization of ammunition	Brazil	CML baseline v.4.4; USETox v.1.01; TRACI v.2.1	*Respiratory effects* (TRACI)	kg $PM_{2.5}$ eq.

*mid = midpoint; end = endpoint

Source: Author

The studies also considered different LCIA methods. The ReCiPe method was selected by 21 case studies, being the most used. In addition to it, 12 other methods were used: Impact 2002+, eight times; CML, five times; Ecoindicator, four times; EDIP97, ILCD, and TRACI, twice each; Lime, Ecological Scarcity, Stepwise, Environmental Footprint, Impact World+, and Environmental Prices once each. The high adherence to ReCiPe can be explained by the method's robustness, which was initially published in 2008, based on a harmonization of the CML and Eco-indicator99 methods (Goedkoop *et al*., 2009). Furthermore, its most recent version (ReCiPe 2016) covers 17 midpoint impact categories with factors that are representative for the globe and nationally for certain categories (Huijbregts *et al*., 2017; Dekker *et al*., 2020), instead of having European representativeness, like the previous version (ReCiPe 2008). Of the methods observed in Brazilian case studies, ReCiPe (2016) (Huijbregts *et al*., 2017), Impact World+ (Bulle *et al*., 2019), and Lime 3 (Tang *et al*., 2018) have global scope. The TRACI method, on the other hand, was developed for the North American context, and all others consider the European context (Mendes *et al*., 2016).

The choice of LCIA method is a methodological decision to be made during the goal and scope definition stage (Dekker *et al*., 2020). LCA practitioners make this decision based on existing guidelines, the outlined goal and scope, the context of method modeling, and also based on their habits and professional experiences (Esnouf *et al*., 2018). However, the choice of method can influence the results and conclusions of a case study (Cavalett *et al*., 2013; Bueno *et al*., 2016; Dekker *et al*., 2020). Result discrepancies occur because different methods consider different characterization models, differences in the list of substances considered as elementary flows, or due to differences in geographic and spatial coverage in CF modeling (Dekker *et al*., 2020; Li *et al*., 2024). In fact, Table 2 shows that the different methods use different names and indicators for PM-related impacts.

For LCIA studies developed in Brazil, the geographical scope of characterization methods is a relevant factor, considering that there is no specific LCIA method for the country, or even for Latin America (Bueno *et al*., 2016). Thus, the use of global methods, which consequently include Brazil, is preferable compared to methods developed for North America or Europe, which are the majority in LCIA literature. This is because there is a consensus among the LCA community that certain impact categories, including the PM formation category, are dependent on regionalized factors, meaning factors specific to the location of elementary flows occurrence (RAICV 2019; Mutel *et al*., 2019).

LCIA methods access various impact categories through different sets of CFs, which will connect the emissions of elementary flows to the impact indicators of the categories (ISO, 2006 a,b), through Equation 1.

$$I_k = \sum_k (CF_{i,c,k} \times E_{i,c}) \tag{1}$$

Where: I_k is the impact factor for category k; $CF_{i,c,k}$ is the characterization factor for substance i, emitted to compartment c (air, water, soil), impacting category k; and $E_{i,c}$ is the emission of substance i to compartment c (elementary flow, recorded in the life cycle inventory stage). The CFs are calculated through characterization models, which are developed considering the cause-and-effect chain of elementary flows, connecting the emission (cause) to the associated impacts (effect) (RAICV, 2019).

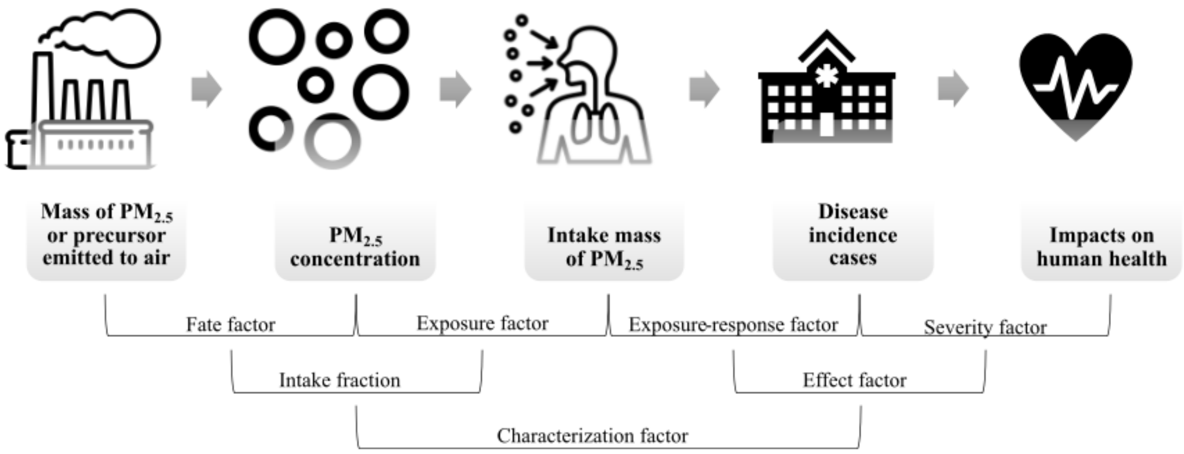
Table 2 also indicates that the studies vary between calculating midpoint and endpoint impacts. Endpoint impacts are those that occur at the end of the cause-and-effect chain, while midpoint impacts are located in the middle of it (Goedkoop *et al*., 2009) and are represented by characteristic pollutant equivalents (Li *et al*., 2024). For PM formation, at the endpoint level, the DALY (Disability-Adjusted Life Years) indicator is widely adopted, composed of the YLL (Years of Life Lost) and YLD (Years Lived with Disability) indicators. The DALY is well-established and widely adopted for impact categories affecting human health (Verones *et al*., 2017). For midpoint, the commonly used impact indicator is kg of PM (10 or 2.5). The decision between assessing impacts at the midpoint or endpoint level can lead to different conclusions, as more information is added to the mathematical modeling of CFs at the endpoint level (Verones *et al*., 2017). Thus, joint analysis can be a good alternative for generating more information for decision-making (Yi *et al*., 2011).

Currently, there is an agreement regarding the cause-and-effect chain for this impact category (section 3.2), but the various existing models vary in terms of calculation approaches (section 3.4). The following sections detail the functioning and differences between characterization models for the PM formation category.

2.2.2 Cause-and-effect chain for PM health effects and the importance of regionalization models

Until 2013, there was no broad consensus and harmonization among LCA researchers on how to include health effects associated with PM exposure in LCIA, leading to inconsistent results when using different models (Fantke *et al*., 2015). In response to this demand, the Life Cycle Initiative of the United Nations Environment Programme (UNEP) and the Society of Environmental Toxicology and Chemistry (SETAC) established a working group to develop a framework and recommend CFs for health impacts caused by $PM_{2.5}$ emissions. The starting point of this global effort was the organization of an Initial Guidance Workshop held in Switzerland in 2013, which involved 16 experts in the field of research (Fantke *et al*., 2015). During this workshop, there was consensus among the experts on the cause-and-effect chain to be adopted for the impact category, as presented in Figure 3.

Figure 3 - Cause-and-effect chain for health damage due to $PM_{2.5}$ exposure



Source: Based on Fantke *et al*. (2015)

The cause-and-effect chain begins with emissions of primary $PM_{2.5}$ or PM precursors, which occur during anthropogenic activities. Once released, pollutants are carried by the wind and undergo dilution through atmospheric turbulence until they experience dry or wet deposition (precipitation). PM precursors chemically react with atmospheric compounds to form secondary PM (Sarigiannis and Triacchini, 2000). The phenomena involved in the transport and transformation of precursors into PM are well-known but complex, nonlinear, and dependent on local parameters (Gilmore *et al*., 2019). From these phenomena, the pollutant mass emitted alters the ambient concentration of $PM_{2.5}$ in the receiving environment, which can occur even in locations distant from the emission source (Xu *et al*., 2023). Atmospheric dispersion models can assist in estimating the concentration increase from emissions, and they have long been applied in PM research in LCA (Nigge *et al*., 2001; Tin and Bilec, 2018; Oberschelp *et al*., 2020).

The increase in $PM_{2.5}$ concentration at the pollutant's destination area implies greater exposure of the population to particles with a diameter of less than 2.5 micrometers. Population exposure is influenced by the type of pollutant emitted (primary or secondary PM), emission height, residence time, and atmospheric conditions. For primary PM, emissions at high altitudes lead to lower population exposure near the source, while ground-level emissions result in higher exposure for the local population (Nishioka *et al.*, 2005). Regarding secondary PM, the chemical reactions responsible for its generation are less influential near the emission source, especially for emissions at high altitudes, and the exposure of the local population becomes highly dependent on the atmospheric vertical exchange rate (Sarigiannis and Triacchini, 2000). Lastly, the relationship between exposure and residence time indicates that substances with longer residence times may increase exposure in locations farther from the emission source, while substances with shorter atmospheric lifetimes have more influence on local exposure (Nigge *et al.*, 2001).

Exposure to higher pollutant concentrations increases the potential for particle inhalation. The intake fraction depends on population density and the existing pollutant concentration at the receiving site (Moriguchi and Terazono, 2000; Nishioka *et al.*, 2005). The intake fraction can be converted into population risk using exposure-response functions, which mathematically analyze the relationship between concentration change and health effects, usually based on epidemiological studies (Krewitt *et al.*, 2001; Nishioka *et al.*, 2005; Fantke *et al.*, 2019). The quantification of DALY represents the final health damage indicator from PM emissions. Thus, the impacts associated with PM emissions affect the area of human health protection in LCA, which assesses the intrinsic health damage, including cases of mortality and morbidity (Verones *et al.*, 2017).

To translate the environmental pathway of PM, from emission to final damage, and calculate the CFs to be used in LCA, model developers have determined a series of intermediate factors. Equation 2 (Fantke *et al.*, 2015) represents the generic calculation of the CF through the intermediate factors presented in Figure 3.

$$CF_{PM} = IF \times ERF \times SF \qquad (2)$$

Where CF_{PM} is the CF for human health damage due to $PM_{2.5}$ exposure (DALY/kg emitted); IF is the intake fraction, which involves the fate of pollutants and exposure of the population (kg intake/kg emitted); ERF is the exposure-response factor, responsible for quantifying cases of health effects due to the increased pollutant concentration (cases/kg intake); and SF is the severity factor, which estimates DALY per health effect (DALY/cases). For SF, it is recommended to use data provided by the Global Burden of Disease studies and document the indicator separately for YLL and YLD components (Verones *et al*., 2017). It is common for characterization models to unify the ERF and SF factors into the effect factor (EF), representing the CF by multiplying IF and EF.

It is interesting to note that the workshop developed by experts in the field focused on emissions, concentrations, and health effects associated with PM in its fraction below 2.5 micrometers in aerodynamic diameter. This is because the finer fractions of PM reach deeper levels of the respiratory system, having a greater potential to cause health effects in the population (EPA, 2024).

Figure 3 and Equation 2 indicate the calculation of CFs at the endpoint level, considering the complete cause-and-effect chain of PM impact. To access CFs at the midpoint level, different methods employ different approaches, with no established consensus base. For example, the ReCiPe 2016 method, the most used by LCA case studies in Brazil presented in Table 2, estimates midpoint CFs using the $PM_{2.5}$ intake fraction as an indicator (Huijbregts *et al*., 2017). In the ILCD method (EC, JRC, IES, 2011), midpoint CFs are calculated considering the intake fraction (obtained from the fate factor and the exposure factor) and the exposure-response factor; in other words, only the severity factor of the endpoint CF is disregarded. Another approach is used in the Impact 2002+ method (Jolliet *et al*., 2003), which obtains midpoint CFs based on the CFs from the Eco-Indicator 99 method (which presents endpoint CFs), normalizing the CFs of PM precursors based on the CF of the reference substance for the category (in this case, $PM_{2.5}$). These three examples indicate that different methods access different levels of the cause-and-effect chain to calculate midpoint CFs, considering only the intake fraction, as ReCiPe 2016, or going to the end of the chain and normalizing the obtained results, as in Impact 2002+.

For the category of impacts associated with PM, the importance of regionalization is observed both for the intake fraction and for the effect factor (Krewitt *et al*., 2001), since the impacts are sensitive to the characteristics of the emitting sources, geographical location, type of $PM_{2.5}$ precursor, meteorology, topography, background pollutant concentration, population density, age distribution, individual health status, mortality, and concentration-response functions (Sarigiannis and Triacchini, 2000; Thind *et al*., 2022). Krewitt *et al*. (2001) compared damage factors for atmospheric pollutants between South America, Asia, and Europe and identified that the variation among continents is smaller than the variation among individual countries. The high level of variation in air pollution-associated impacts by region led

Finnveden and Nilsson (2005) to conclude that even country-level factors may be inappropriate, especially for countries with large territorial dimensions. The authors calculated impacts with variations of up to an order of magnitude between regions of Switzerland, due to differences in population densities.

Indeed, several studies have observed variability in the results of LCA studies when comparing the generic and regionalized CFs for atmospheric pollutant emissions. Nigge *et al*. (1998) were among the first to study this variation and observed a difference by a factor of five between the highest and lowest impact results from traffic emissions in Germany. The authors attributed this variation mainly to population density and incremental pollutant concentration. Owsianiak *et al*. (2018) assessed the life cycle of biochar produced in Indonesia and identified minor health impacts when considering $PM_{2.5}$ emissions at specific locations, with statistically significant differences between specific and generic locations. Canaj *et al*. (2020) studied tomato production in Albania, and the use of regionalized CFs generated 21% more impact associated with particle emissions. These studies highlighted the importance of regionalization.

However, despite the perception arising in the 1990s that the results of a case study using generic CFs may exhibit significant deviations from the actual impact pattern (Potting and Block, 1995), the operationalization of regionalized LCA studies is emerging. Potting and Hauschild (2005) discussed that a decade after the observation of the importance of regionalization, regional LCA methodologies had not yet been fully integrated into LCA tools and were primarily applied in sensitivity analyses. In recent years, the number of regionalized LCA methods has intensified in the literature (Owsianiak *et al*., 2018), but although region-specific CFs are now available and regionalized inventory flows are often accessible, software tools are still not sufficiently developed for implementing these factors and for the development of regionalized LCAs (Dekker *et al*., 2020). However, the use of global generic factors can lead to under or overestimation of impacts (Verones *et al*., 2017), and the use of foreign models cannot accurately reflect the impact of the system (Li *et al*., 2024). Thus, the introduction of regionalization, despite increasing the complexity of LCA development, has come to be accepted as a way to reduce uncertainties, improve result accuracy (Mutel *et al*., 2012; Verones *et al*., 2017), and enable the applicability of LCA in public policies (Sarigiannis and Triacchini, 2000) and decision-making based on comparative studies (Owsianiak *et al*., 2018).

2.2.3 Characterization models for PM impacts

Given the importance of using regionalized characterization factors and the advancements in LCA research, several characterization models have emerged in the literature. Currently, there are at least 16 models for the impact category of PM formation, which vary in terms of calculation approaches, elementary flows, geographical scopes, among other methodological modeling decisions and calculation parameters. Table 4 presents the models identified in the literature and their main characteristics.

Models developed for specific geographical contexts have mostly covered the European (Wenzel *et al*., 1997; Hofstetter, 1998; Potting and Hauschild, 2005; van Zelm *et al*., 2008; Notter *et al*., 2015) and North American (Bare, 2011; Humbert *et al*., 2011; Gronlund *et al*., 2015) contexts. Seven other models were developed with a global approach. It is interesting to note that the two oldest ones (Steen, 1999; Huijbregts *et al*., 2000) presented average factors for the globe or large regions (climatic zones), in line with the LCA development at that time, which considered generic factors (Potting and Hauschild, 2005). On the other hand, the more recent ones (van Zelm *et al*., 2016; Tang *et al*., 2018; Fantke *et al*., 2017, 2019; Oberschelp *et al*., 2020) calculated both global and regionalized factors at different spatial levels, ranging from factors for archetypes (indoor, urban, and rural environments) with differentiation between cities (Fantke *et al*., 2017, 2019) to factors for continental regions (Tang *et al*., 2018). These recent regionalized models even provide factors for the Brazilian geographical context as follows: Tang *et al*. (2018) present a factor for Latin America; van Zelm *et al*. (2016) provide a factor for Brazil; Oberschelp *et al*. (2020) calculate an average factor for Brazil and regionalized factors by states of the country, and; Fantke *et al*. (2017, 2019) worked with the lowest spatial resolution, presenting average factors for Brazil and regionalized for 127 cities in Brazil with over one hundred thousand inhabitants, divided into archetypes.

Table 4 - Characterization models for health damage due to particulate matter

Model	LCIA method	Factor(s)	Geographic scope	Spatial differentiation	Mathematical approach	Elementary flows	Factor for Brazil?
Wenzel *et al*. (1997)	EDIP 1998	Effect	Europe	Average factor for Europe	Geographic	NO_x; SO_2	No
Hofstetter (1998)	Eco-Indicator 99; Impact 2002+	Intake and effect	Europe	Factor for Europe in grid-cells of 100×100 km	Geographic	PM_{10}; $PM_{2.5}$; NH_3; NO_x; SO_x	No
Steen (1999)	EPS 2000	Intake and effect	Global	Average factor for the world	Geographic	PM_{10}; $PM_{2.5}$; NH_3; NO_x; SO_2; COV	Yes
Huijbregts *et al*. (2000)	CML 2002	Intake and effect	Global	Factor for three climatic zones: Artic, moderate and tropical	Geographic	PM_{10}; NH_3; SO_2	Yes
Potting and Hauschild (2005)	EDIP 2003	Intake	Europe	Factor for Europe in grid-cells of 150×150 km	Geographic	PM_{10}; NO_x; SO_2	No
van Zelm *et al*. (2008)	ReCiPe 2008	Intake and effect	Europe	Average factor for Europe and European countries	Geographic	PM_{10}; NH_3; NO_x; SO_2	No
Bare (2011)	TRACI 2.0	Intake and effect	United States	Factor for United States in grid-cells of 100×100 km	Geographic	$PM_{2.5}$; NO_x; SO_2	No
Humbert *et al*. (2011)	Impact World +	Intake	North America	Indoor, urban, rural and remote archetypes	Archetypes	PM_{10}; $PM_{10-2.5}$; $PM_{2.5}$; NH_3; NO_x; SO_2	No
Wenger *et al*. (2012)	-	Intake	Regional	Factor for indoor archetype in temperate climate	Archetypes	Total Suspended Particles	No
Gronlund *et al*. (2015)	Impact World +	Effect	North America	Average factor for United States	Archetypes	$PM_{2.5}$	No
Notter (2015)	-	Intake and effect	Europe	Urban and rural archetype	Archetypes	PM_{10}; $PM_{2.5}$; NH_3; NO_x; SO_x	No
van Zelm *et al*. (2016)	ReCiPe 2016; LC-Impact	Intake and effect	Global	Average factor for world and for countries	Geographic	$PM_{2.5}$; NH_3; NO_x; SO_2	Yes
Tang *et al*. (2018)	Lime 3	Intake and effect	Global	Average factor for the world and for 10 continental regions	Geographic	Black carbon; Organic carbon; $PM_{2.5}$; NO_x, SO_2	Yes
Fantke *et al*. (2017)	-	Intake	Global	Average factor for the world, for countries and cities	Archetypes	$PM_{2.5}$	Yes
Fantke *et al*. (2019)	-	Effect	Global	Average factor for the world, countries and cities	Archetypes	$PM_{2.5}$	Yes
Oberschelp *et al*. (2020)	-	Intake and effect	Global	Average factor for the world, countries and regions/states	Geographic	$PM_{2.5}$; NH_3; NO_x; SO_2	Yes

Source: Author

Although science has advanced in the regionalization process of CFs for the health damage impact category due to PM formation, the calculation of factors can significantly differ among available models, potentially leading to different conclusions for the same case study (Dekker *et al*., 2020). Besides the different spatial scales considered by model developers, another relevant difference is observed in the substances (elementary flows) that affect the category. Van Zelm *et al*. (2016) and Oberschelp *et al*. (2020) calculated CFs for the traditional substances of this impact category, namely: primary $PM_{2.5}$, ammonia, nitrogen oxides, and sulfur dioxide. Tang *et al*. (2018) consider, in addition to some traditional substances, black carbon and organic carbon, which are specified $PM_{2.5}$ species. On the other hand, Fantke *et al*. (2017, 2019) presented factors only for primary $PM_{2.5}$. Depending on the variation of covered elementary flows, the selected characterization model for a case study may consider more or fewer inventory elementary flows throughout the life cycle of the production system under analysis, altering the achieved results.

Differences among models can also be observed in the calculation approaches of intake fractions and effect factors. Regarding the intake fraction, one of the most significant differences lies in calculating the factors using archetype (classes of scenarios or similar situations that can explain part of the variability of CFs, such as urban area, rural area, indoor environment, outdoor environment) or geographical (calculation of factors at the grid-cell or geographically delimited region level, e.g., cities, states, countries) approaches (Mutel *et al*., 2019). Both approaches have characteristics that justify their use and contribute to understanding the spatialization of impacts associated with PM exposure. The use of the geographical approach is advocated by van Zelm *et al*. (2016), who state that using local climatic and demographic data contributes to more accurate results than using generic archetypes. In agreement, Thind *et al*. (2022) argue that the use of archetypes can introduce significant uncertainties in CF results due to the inability to capture differences in pollutant dispersion and effects depending on the specific emission location. On the other hand, Humbert *et al*. (2011) claim that life cycle inventories often do not provide specific emission location information, making it challenging to connect inventories with CFs, and Mutel *et al*. (2019) argue that even the use of refined spatial scales makes the factors less precise than differentiation between urban and rural areas, as population density variation is more relevant than knowing whether the emission occurs in one country or another. Despite advocating for the archetype approach, Mutel *et al*. (2019) acknowledge that even archetypes may not be sufficient to reflect all CF variability since an urban archetype may include large variations in population densities (big city vs. small city) and different atmospheric pollution realities.

Therefore, the authors suggest that a hybrid approach may be a way forward, calculating factors by archetypes for different geographical regions, as applied in the Fantke *et al*. (2017, 2019) characterization model.

In addition to this difference, other decisions may influence the intake fraction results, such as the choice of weighting form to scale native CFs to national, continental, and/or global CFs (Mutel *et al*., 2019); the selection of databases used to obtain input data for characterization models, as well as the temporal scope of these data (RAICV, 2019); and the choice of the transportation model applied to calculate concentration variation since each model developer uses a preferred transportation model.

The variations among models regarding the effect factor can be identified in several aspects, such as the choice of health effects to be considered, the use of average or marginal approach, the selection of the final indicator to be used, and the origin and temporal scope of implemented data. Taking the global models that provide factors for the Brazilian context as an example, van Zelm *et al*. (2016) calculate effect factors based on cardiopulmonary and lung cancer effects using data from a study developed in the United States and extrapolating the results globally. Tang *et al*. (2018), on the other hand, consider chronic mortality cases in adults for all causes, as well as chronic bronchitis, use of asthma medication, indoor respiratory symptoms, restricted activity days, and hospital admissions due to respiratory effects, using data from a global study including Brazilian cities. Fantke *et al*. (2017, 2019) and Oberschelp *et al*. (2020) use a very similar effect factor calculation approach, considering cases of ischemic heart disease, stroke, chronic obstructive pulmonary disease, and lung cancer in adults, as well as lower respiratory tract infections in children. Both models use the Global Burden of Disease database, which provides global data on health effects, including data for Brazil with differentiation between Brazilian states. Of these four CF models, only van Zelm *et al*. (2016) did not use DALY as the final damage indicator; instead, the authors work with YLL, a DALY component, but state that the results can be compared with DALY since YLL contributes most to the final indicator.

In terms of calculation approach, model developers may consider working with a marginal, average, or linear approach. This decision is necessary because modeling the factors takes into account the variation in health effects as emissions and pollutant concentrations in the atmosphere change, requiring a reference state to be defined. In the marginal approach, the current state is considered the reference state, and from this consideration, marginal effect factors represent a change in impact caused by an infinitesimal change in emissions, being particularly relevant for calculating the effects of small emission changes. In the average and linear approaches, the reference state is determined based on a desired target condition. In the linear model, this target situation is defined as zero concentration of pollutants in the atmosphere, and in the average model, it is often defined as the background concentration of the pollutant, below which no health effects on the population are observed. These approaches may be more useful for calculating the effects of larger emission changes. It is recommended that both approaches be provided by model developers (Mutel *et al*., 2019; Oberschelp *et al*., 2020). Among the models with data for Brazil, only Fantke *et al*. (2017, 2019) and Oberschelp *et al*. (2020) work with different approaches for calculating effect factors, considering at least average and marginal factors. Van Zelm *et al*. (2016) and Tang *et al*. (2018) consider the average approach.

According to Mutel *et al*. (2012), it is not always clear when native scale CFs should be used, and it is recommended that developers promote guidelines to assist LCA practitioners in properly using regionalized factors. Other recommendations are provided by specialists to characterization model developers. Verones *et al*. (2017) recommend more research on how to integrate temporally and spatially differentiated LCIA models into LCA studies, as well as suggesting more investigations and transparency regarding the quantitative uncertainties of CFs. Young *et al*. (2021) recommend international standardization of elementary flows to facilitate the connection of CFs with elementary flows. Indeed, the connection between CFs and elementary flows is a concern of other LCIA researchers, as indicated by Mutel *et al*. (2019), who suggest that the archetype approach is favored by LCIA specialists as it facilitates communication with inventories, since it may be easier to know if an emission occurs in an urban or rural area than to know the exact geographical location of the emission. Finally, Thind *et al*. (2022) recommend distinguishing CFs by source type or emission sector to reduce estimation uncertainty.

Still regarding the literature recommendations for selecting LCIA methods to be applied in LCA case studies, the United Nations Life Cycle Initiative launched, in 2013, the “Global Guidance for Life Cycle Impact Assessment Indicators and Methods” (GLAM). The work involved the participation of various scientists from around the world, specialists in LCA impact categories, and has been led by the University of Michigan, the Norwegian University of Science and Technology, and the Technical University of Denmark (GLAM, 2024). The initiative’s first report was published in 2016 (UNEP and SETAC, 2016), suggesting average CFs on a global scale. More recently, the GLAM initiative published new recommendations, suggesting: (1) the use of the characterization model by Oberschelp et al. (2020) as a spatialized model for outdoor emissions using a geographic approach; (2) the models by Fantke et al.

(2017, 2019) as a model based on archetype approaches; and the models by Hodas et al. (2015) and Bhoonah et al. (2023) for indoor emissions, the former focused on an exposure model and the latter on analyzing different types of activities occurring in indoor environments.

Thus, it is observed that the GLAM initiative recommends the use of models with regionalized data. Specifically for the context of Brazil, Fantke et al. (2017, 2019) provide factors for 126 Brazilian cities, while Oberschelp et al. (2020) provides data for the states of Brazil.

In addition to model recommendations, the GLAM (2024) initiative provided spreadsheets with the elementary flows and the registered CFs. The factors are provided varying emission height (ground level, low stack, high stack, very high stack, unspecified), calculation approach (marginal, average, linear), and compartment (urban, rural, and indoor with different scenario configurations). However, it is worth noting that, despite recommending models with regionalized factors, the spreadsheets provide CFs only at the country level for the Brazilian context, varying only the aforementioned parameters, but not the emission region.

In light of these recommendations, it is evident that research in LCIA is ongoing, and improvements in CFs, regionalization procedures, and the operationalization of regionalized LCA studies are still current demands in this research area. Specifically for the Brazilian context, despite the existence of models with CFs available for the country, all methodological decisions that need to be made by model developers result in variations in CF results, which can reflect in the findings and conclusions of an LCA case study. Although there are models that provide factors for Brazil, there are still uncertainties about which model to select in a case study and whether these models are suitable for the country's context.

2.3 CRITICAL REVIEW IMPLICATIONS

The study of air quality is relevant to meet emerging societal demands, such as achieving the Sustainable Development Goals (SDGs) by 2030 and operating within planetary boundaries. Concerning the SDGs, PM pollution is directly related to SDG 3 (good health and well-being) and SDG 11 (sustainable cities and communities), especially in targets 3.9 (reduce deaths and illnesses from air pollution) and 11.6 (reduce the negative environmental impact per capita of cities, including paying special attention to air quality) (UN, 2023a). Regarding planetary boundaries, the concept is based on the "acceptable environmental burden" of PM-related diseases, estimated at 1.6×10^{-3} DALY/person/year (Vargas-Gonzales *et al.*, 2019). Thus, it is expected that anthropogenic activities do not generate annual emissions capable of exceeding this limit, which is weighted based on a concentration of up to 10 $\mu g/m^3$. Using LCA to manage air quality impacts caused by production systems allows using the results to analyze the contribution of systems to the SDGs (Weidema *et al*., 2018) and to verify the absolute sustainability rate in terms of air quality, checking if systems operate within planetary boundaries (Sala *et al*., 2020).

Understanding the state of the art in air quality and LCIA research focusing on health impacts from PM exposure in Brazil allows identifying important opportunities for regionalization of CFs for the Brazilian context. Questions such as "which characterization model is most recommended for application in Brazil?" and "how sensitive are the results of a case study to the choice of characterization model?" still remain unanswered in the current literature. Additionally, characterization models specific to the Brazilian context have not been identified.

Literature review suggests that model recommendations, sensitivity analysis to existing models, and regionalization of CFs are research areas that can promote benefits for the academic, business, and governmental sectors in Brazil. In the academic sector, LCA research conducted throughout Brazilian territory (such as the examples presented in Table 2) can use regionalized CFs to obtain more uniform and precise results. Companies can use less uncertain LCA results to direct mitigating measures to the most impactful production stages and communicate their potential impacts and mitigation actions to stakeholders (Almeida *et al*., 2019). Finally, regionalization can incentivize governments to integrate LCA into national policies, as one of the main challenges for this is the high uncertainty associated with the results (Seidel, 2016). With the union of these three important sectors, strategic decisions can provide better environmental conditions for civil society and ensure that human operations occur sustainably.

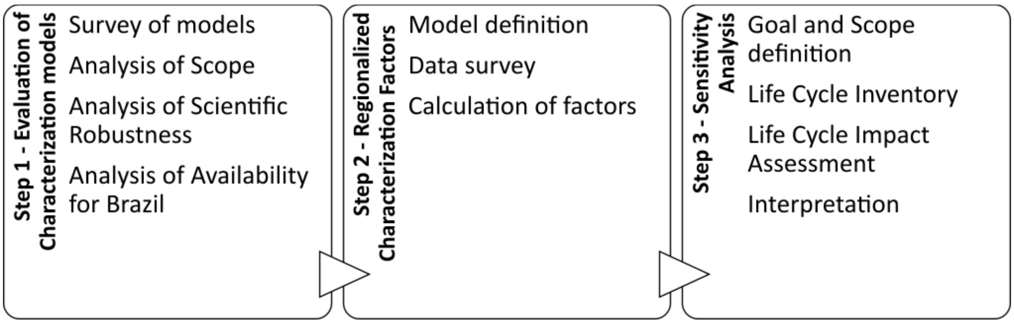
Analyzing global air quality standards and comparing them with estimates of increased PM emissions and health effects in Brazil, it is concluded that the country may not have reached the inflection point in the Kuznets environmental curve for this pollution category. However, research assessing the effectiveness of air quality policy instruments in the country has shown local improvements with policy compliance and an increase in such improvements over time. Nevertheless, focusing on emission control, population exposure, health effects, and mitigating actions is necessary to ensure the right to clean air for all, especially considering that there are no safe limits for PM concentration in the atmosphere.

Research highlights the current demand for regionalized characterization models to reduce the calculation uncertainties of health damage impacts due to PM exposure. Global models with regionalized factors for Brazil, states, and cities are available in the literature, but there is still no certainty about which one is the best to be selected, nor if they are suitable for Brazil's reality. Improving measurement techniques for LCA impacts can expand the use of the technique and reduce uncertainties in case study conclusions, enabling fair comparisons between production systems, more precise mitigation proposals, and strategic decision-making regarding emerging sustainability issues such as the SDGs and planetary boundaries. Thus, studying air quality from a product life cycle perspective has the potential to generate benefits for different economic actors, such as academia, companies, governments, and civil society.

3 METHODOLOGY

The methodology of this research was designed in three main stages: (1) evaluation of the characterization models available in the literature; (2) calculation of regionalized CFs for Brazil; and (3) regionalized sensitivity analysis. Figure 4 outlines the methodological procedure.

Figure 4 - Methodological procedure



Source: Author

The following sections detail the methodological procedure for each stage, and it is interesting to note that they are complementary to each other.

3.1 EVALUATION OF CHARACTERIZATION MODELS

The review and evaluation of the characterization models available in the literature aimed to understand the strengths and weaknesses of each identified model, providing guidance for the regionalization of factors for Brazil. This first stage was also important for identifying the most suitable models for application in case studies in the country, aiming for a better representation of the social, environmental, and economic conditions in the LCIA stage.

An evaluation of characterization models was previously presented in Giusti (2021). This analysis provides an update of the evaluation criteria, as well as the inclusion of the Oberschelp *et al*. (2020) model and the update of the Itsubo and Inaba (2012) model to the Tang *et al*. (2018) model, which features the model considered in the most recent update of the Lime 3 method. It is worth noting that this stage of the thesis is also available in the II Recommendation Report of LCIA Models prepared by the LCIA Research Network of Brazil, which is open access. It is also important to highlight that an approach to this evaluation of characterization models was published in Giusti *et al*. (2022) using a Multi-Criteria Decision Analysis based on the Simple Multi-Attribute Rating Technique (SMART), and the approach presented here complements and is based on the aforementioned publication.

The evaluation of the characterization models was developed in 3 methodological stages, following the procedure of Giusti *et al*. (2022), as described in the sections: (3.1.1) survey of characterization models; (3.1.2) evaluation of intake fractions (iF) and effect factors (EF); (3.1.3) critical analysis for recommendation.

3.1.1 Survey of characterization models

The characterization models evaluated were identified in Giusti *et al*. (2022). Initially, the search was conducted in Humbert *et al*. (2015), where 10 distinct models for the category were identified. Subsequently, the list was updated based on the systematic literature review by Giusti *et al*. (2020), from which the models by Notter *et al*. (2015), Van Zelm *et al*. (2016), and Wenger *et al*. (2012) were included. In addition to these, three other models were mapped and included in the evaluation: Fantke *et al*. (2017, 2019) and Oberschelp *et al*. (2020). Table 5 presents the complete list of the identified models and their availability in LCIA methods.

Table 5 - Characterization models and their availability in methods

Model	**Life Cycle Impact Assessment Method**
Wenzel *et al*. (1997)	EDIP 1998
Hofstetter (1998)	Eco-Indicator 99 and Impact 2002+
Steen (1999)	EPS 2000
Huijbregts *et al*. (2000)	CML 2002
Potting e Hauschild (2005)	EDIP 2003
Van Zelm *et al*. (2008)	ReCiPe 2008
Bare (2011)	TRACI 2.0
Humbert *et al*. (2011)	Impact World+
Tang *et al*. (2018)	Lime 3
Wenger *et al*. (2012)	-
Gronlund *et al*. (2015)	Impact World+
Notter (2015)	-
Van Zelm *et al*. (2016)	ReCiPe 2016 and LC-Impact
Fantke *et al*. (2017)	-
Fantke *et al*. (2019)	-
Oberschelp *et al*. (2020)	-

Source: Author

These identified characterization models were evaluated regarding their iF and EF, as described in section 3.1.2. It is worth noting that 11 of the 16 models are already available in LCIA methods commonly used in LCA studies, as indicated in Table 5.

3.1.2 Intake Fraction (iF) and Effect Factors (EF) assessment

The evaluation of the characterization models was conducted individually for the iF and EF, as model developers commonly treat these two main factors of the cause-effect chain separately. The analysis of the models was based on the criteria of scope, scientific robustness, and the presence of a factor for Brazil, as outlined in the method presented in Ugaya *et al.* (2016) and RAICV (2019).

The evaluation subcriteria were defined in Giusti *et al.* (2022), specifically for the reality of the health damage impact category due to PM formation, following EC, JRC, IES (2011), Hauschild *et al.* (2013), and Mutel *et al.* (2019). Table 6 and Table 7 present the evaluation subcriteria for the scope criterion for the iF and EF, respectively.

Table 6 - Template scores assigned to the Scope Criterion for Intake Fraction evaluation

Sub criteria	**Low (1)**	**Moderate - Low (2)**	**Moderate (3)**	**Moderate - High (4)**	**High (5)**
Geographic coverage	Regional or national (except for Brazil)	Continental (except for Latin America)	National or regional (for Brazil); Global or Latin America (average)	Latin America model including factor for Brazil	Global model including factor for Brazil
Spatial differentiation (geographic)	>150 × 150 km	>100×100 to ≤150×150 km	>50×50 km to ≤100×100 km	>10×10 km to ≤50×50 km	≤10×10 km
Spatial differentiation (archetype)	1 compartment	-	Urban and rural; OR indoor and outdoor	Indoor, outdoor, urban and rural	Indoor with and without combustion and outdoor urban and rural
Temporal resolution	Before 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 or later
Coverage of elementary flows	$PM_{2.5}$ or PM_{10}	$PM_{2.5}$ and PM_{10}	$PM_{2.5}$ and/or PM_{10}, and secondary PM (1 substance)	$PM_{2.5}$ and/or PM_{10}, and secondary PM (2 substance)	$PM_{2.5}$ and/or PM_{10}, and secondary PM (≥3 substance)

Source: Author, based on Giusti *et al.* (2022)

Since it is an atmospheric pollutant, part of the PM can be transported outside the territorial boundaries of the emitting country/continent, causing effects on the population in other parts of the world (Tessum *et al.*, 2017). Therefore, a global model with an available factor for Brazil covers better the impact of PM in the country and thus receives the highest score.

Regarding spatial differentiation, the models use two approaches for calculating the iF: the geographical approach, in which the region is divided into grid-cells; and the archetype approach, in which factors are grouped into environmental compartments, such as urban vs. rural areas or indoor vs. outdoor environments. Regardless of the approach used, it is important that the territorial division of the model is capable of capturing the existing variability. According to Mutel *et al*. (2019), the variation between urban and rural areas is more significant than the division into high-resolution grid-cells, because within the same grid, there can be different population densities, which affect the intensity of the impact that can be generated by PM. To capture this variability, Mutel *et al*. (2019) recommend that geographical models use a grid-cell resolution of 10×10 km or smaller, and thus, this was the highest resolution score for the subcriterion in question. For the archetype approach, it was considered that both the indoor vs. outdoor and urban vs. rural divisions are relevant for the category (Hauschild *et al*., 2013; Hodas *et al*., 2016), scoring equally as moderate. The highest score in this case was assigned to models that consider all four archetypes, as well as considering indoor environments with and without solid fuel combustion.

For the temporal resolution subcriterion, it was considered that the more recent the input data of the model, the closer to the current reality the factors would be. For elementary flows, the highest score was given to models that cover a larger number of flows, including both primary and secondary PM, since the ISO (2006a) standard recommends that the model be capable of covering all impacts generated by a life cycle inventory, and PM precursors also have the potential to affect human health (Lee *et al*., 2015).

In the evaluation of the EF scope, the application coverage considered the relationship between these factors and the healthcare infrastructure of the study area. Thus, the evaluation assigned the highest score to models that provide specific factors for countries with the same Human Development Index (HDI) as Brazil, that is, a high HDI (ranging from 0.7 to 0.8) according to the UN (2021).

Table 7 - Template scores assigned to the Scope Criterion for Effect Factor evaluation

Sub criteria	**Low (1)**	**Moderate - Low (2)**	**Moderate (3)**	**Moderate - High (4)**	**High (5)**
Demographic representativeness	Countries with low HDI	average EF covering countries with medium and very high HDI	average EF covering countries with medium-high and very-high HDI; or global average	Specific EF for countries with high HDI	Specific EF for Brazil
Exposure-response coverage	Consider cohort studies only for countries outside Latin America with a background MRRI associated with PM <1.7 or >4.9	Consider cohort studies for Latin America country with a background MRRI associated with PM <1.7 or > 4.9	Consider cohort studies only for countries outside Latin America with a background MRRI associated with PM between 1.7 and 4.9	Consider cohort studies for Latin America country with a background MRRI associated with PM between 1.7 and 4.9	Consider cohort studies for Brazil
Temporal resolution	Before 1999	2000 - 2004	2005 - 2009	2010 - 2014	2015 or later
Included health effects	Capture <10% of the total PM-related disease burden	Capture ≥10% but <40% of the total PM-related disease burden	Capture ≥40% but <70% of the total PM-related disease burden	Capture ≥70% of the total PM-related disease burden	100% of the total PM-related disease burden
Considered substances	PM_{10}	$PM_{2.5}$	$PM_{2.5}$ and PM_{10}	$PM_{2.5}$, PM_{10}, and single PM precursor	$PM_{2.5}$, PM_{10} and all relevant PM precursors

HDI = Human Development Index

MRRI = Mortality rate from respiratory infections

Source: Author, based on Giusti *et al*. (2022)

The calculation of the EF considers a variable called relative risk, which estimates the risk to a population based on the concentration of ambient air to which it is exposed. The relative risk is obtained from epidemiological studies. In this regard, this subcriterion was defined based on the location for which the studies were developed. Those covering regions with a mortality rate from respiratory infections associated with PM similar to Brazil's received the highest score, which, according to GBD (2019), is 3.1 deaths per 100,000 inhabitants, with a minimum of 1.7 and a maximum of 4.9 deaths. Temporal resolution was assessed similarly to the evaluation of the IF scope.

Regarding the subcriterion of health effects considered, the score was given based on the percentage of YLL (Years of Life Lost) covered by the model. This indicator was obtained from GBD (2019), considering the proportion of YLL from the effects covered by the model in relation to the YLL attributed to all health effects related to PM, based on data from the Brazilian reality. Finally, in the last subcriterion, the highest score was given to models that considered more substances for calculating the relative risk.

For the scientific robustness criterion, the iF and EF were evaluated based on the same subcriteria, described in Table 8.

Table 8 - Template scores assigned to the Scientific Robustness Criterion for intake Fraction and Effect Factor evaluations

Subcriteria	**Low (1)**	**Moderate - Low (2)**	**Moderate (3)**	**Moderate - High (4)**	**High (5)**
Considered by a LCIA method?	No	-	No (recent model)	-	Yes
Cause-and-effect chain	-	-	No	-	Yes
Model transparency and accessibility (calculation procedure and input data)	Low description and accessibility (no reproducible model)	Not complete description or accessibility (no reproducible model)	Not complete description or accessibility (reproduction possible but hampered by lack of clarity)	Not complete description or accessibility (reproducible model)	High description and accessible (reproducible model)
Clarity of variables and mathematical model's description	Part of the variables described, low clarity in unit AND input data	Part of the variables described, low clarity in units OR input data	Part of the variables described, moderate clarity in units or input data	All variables described, moderate clarity in units or input data	All variables and units described and easy identification of the input data
Clarity of equations and parameters used for modelling	No description of procedure and without equations. Not reproducible	Description of part of the procedure without equations. Not reproducible	Description of the procedure without equations. Partly reproducible	Description of the procedure without equations. Largely reproducible	All equations are presented and described. Fully reproducible

Source: Author, based on Giusti *et al*. (2022)

The evaluation of scientific robustness considered the availability of the model in LCIA methods, as integration into methods facilitates the use of the model in LCA studies. Recent models received a moderate classification, as they have not yet had sufficient time to be incorporated into a LCIA method. It was also assessed whether the model presented a cause-and-effect chain, as well as the level of transparency, clarity of equations, and variables. The highest score was given to those models that provide clear information regarding the calculation procedure, allowing reproducibility.

Finally, the evaluations of the criteria for the availability of iF and EF for Brazil were conducted based on the subcriteria described in Table 8 and Table 9, respectively. The subcriteria considered are: whether there is a factor for Brazil; spatial differentiation for Brazil (geographical); spatial differentiation for Brazil (archetypes); and whether the factor is suitable for Brazil.

Table 9 - Template scores assigned to the Intake Fraction for Brazil

Sub criteria	**Low (1)**	**Moderate - Low (2)**	**Moderate (3)**	**Moderate - High (4)**	**High (5)**
Is there IF for Brazil?	No	-	-	-	Yes
Brazilian spatial differentiation (geographic)	>150 × 150 km	>100×100 to ≤150×150 km	>50×50 km to ≤100×100 km	>10×10 km to ≤50×50 km	≤10×10 km
Brazilian spatial differentiation (archetypes)	1 compartment	-	Urban and rural; OR indoor and outdoor	Indoor, outdoor, urban and rural	Indoor with and without combustion and outdoor urban and rural
Is the available iF for Brazil appropriate for its singularity?	No	-	Partly	-	Yes

Source: Author, based on Giusti *et al*. (2022)

Table 10 - Template scores assigned to the Effect Factor for Brazil

Sub criteria	**Low (1)**	**Moderate - Low (2)**	**Moderate (3)**	**Moderate - High (4)**	**High (5)**
is there EF for Brazil?	No	-	-	-	Yes
Brazilian spatial differentiation (geographic)	One global EF (covering Brazil)	-	At least 1 specific EF for Brazil	-	More than one specific EF for Brazil
Brazilian spatial differentiation (archetypes)	1 compartment	-	Urban and rural; OR indoor and outdoor	Indoor, outdoor, urban and rural	Indoor with and without combustion and outdoor urban and rural
Is the available EF for Brazil appropriate for its singularity?	No	-	Partly	-	Yes

Source: Author, based on Giusti *et al*. (2022)

In both the criteria presented in Table 8 and Table 9, a high score was given to models that provided iF and EF for Brazil, as these would be the most suitable for application in the country. For models with the availability of Brazilian factors, the level of spatial differentiation was reassessed considering the values assigned to Brazil, as it is common to group factors, for example, from grid-cells to geo-administrative regions (countries, states, cities), changing the spatial differentiation of the final factors provided. Finally, it was evaluated whether the factors provided to the country were appropriate for its geographical context or not.

The score for the evaluation criteria of each factor (scope, scientific robustness, and factor for Brazil) was calculated by averaging the scores of the subcriteria. The final score of the models for iF and EF was obtained by calculating the average of the three evaluation criteria corresponding to the factor, as equation 3.

$$P_f = \left(\underline{SC_{esc_f}} + \underline{SC_{RC_f}} + \underline{SC_{FB_f}}\right)/3 \tag{2}$$

In equation 3: P_f is the final score of the model for factor f; $\underline{SC_{esc}}$ is the average of the subcriteria for the scope criterion (Table 6 and Table 7, for iF and EF, respectively), and indicates the score of the respective criterion; $\underline{SC_{RC}}$ is the average of the subcriteria for the scientific robustness criterion (Table 8), and; $\underline{SC_{FB}}$ is the average of the subcriteria for the factor availability for Brazil criterion (Table 8 and Table 9, for iF and EF, respectively). The division by three indicates that the final score is given by the arithmetic mean of the criterion scores.

3.1.3 Critical evaluation for recommendation

The choice of the characterization model should be consistent with the goal and scope of the LCA (Berger *et al*., 2020; Giusti *et al*., 2022; ISO 2006a). In this regard, twelve questions were developed by Giusti *et al*. (2022) to identify which characterization models are most appropriately connected to different scopes, inventoried pollutants (elementary flows), and the level of knowledge about emission locations:

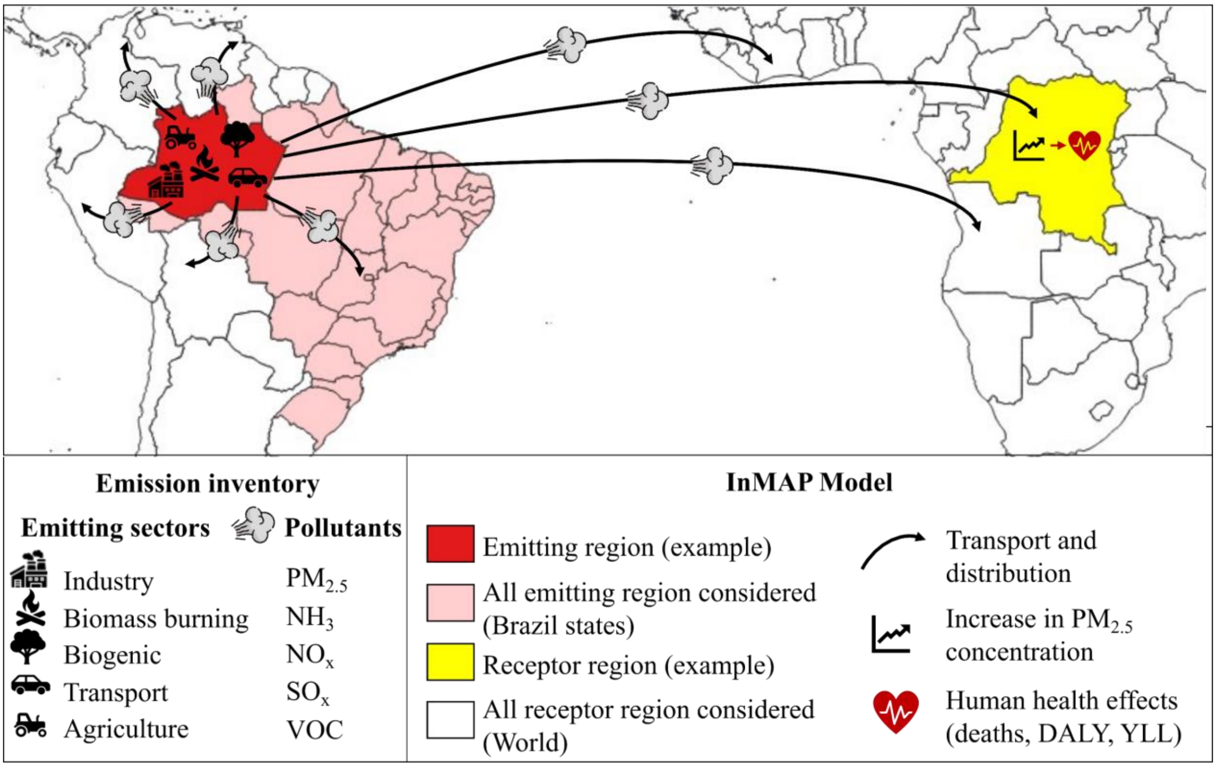
- Does the inventory present particulate matter (PM) emissions at a global level?
- Does the inventory present PM emissions at the country level?
- Does the inventory present PM emissions in Brazil with specified city/state levels?
- Does the inventory present PM emissions in indoor environments?
- Does the inventory present PM emissions specified for urban or rural environments?
- Does the inventory present PM emissions with specified emission height?
- Does the inventory present PM emissions with unspecified emission height?
- Does the inventory present emissions of PM precursors?
- Does the inventory present primary PM emissions?
- Does the study require a marginal curve for EF?
- Does the study require an average or linear curve for EF?
- Does the inventory have monthly and/or daily period variations in PM emissions?

Based on these 12 questions, a recommendation description for the use of the highest-rated models was made, according to the criteria and subcriteria in section 4.1 and the average score of the criteria.

3.2 REGIONALIZATION OF CHARACTERIZATION FACTORS

Despite the existence of several characterization models for particulate matter formation available in the literature, all of them have limitations for the Brazilian territory. In most cases, the models were not able to use specific data from Brazil for the calculation (Giusti *et al*., 2022). In this context, obtaining regionalized CFs for the country was the main goal of this research. This section aims to describe the calculation of the CFs as well as the generation and collection of national data used as variables for the proposed characterization model. The CFs were provided for outdoor emissions considering the average approach (Oberschelp et al. 2020) for health effects based on the background concentration as baseline, Figure 5 summarizes the methodological procedure.

Figure 5 - Methodological approach for characterization factors calculation



Source: Author

The calculation of the regionalized CFs for Brazil assumed the environmental pathway that the pollutant travels from emission regions to reach the human population and cause health effects. Thus, the model considers that from an emission E of a pollutant k, in an emitting region i, there will be atmospheric transport of the emitted mass to a receptor region j. Five pollutants (k) were included in the evaluation: primary $PM_{2.5}$ and the precursor pollutants of $PM_{2.5}$, including ammonia (NH_3), sulfur oxides (SO_x), nitrogen oxides (NO_x), and volatile organic compounds (VOC), which, during the transport process, undergo chemical reactions with atmospheric particles and transform into $PM_{2.5}$. In the receptor region, there will be a variation in the concentration of $PM_{2.5}$, and consequently, a potential increase in mortality cases ($M_{k,i\rightarrow j}$) due to higher exposure to the pollutant. The 26 federal units (states) of Brazil, plus the Federal District site, were established as emitting regions (i), and the entire global territory with a resident population was targeted as the receiving area (j). Both emitting and receiving regions were worked at the grid-cell level with varying resolution, as described in section 3.2.1.

Based on this, the ratio between the total number of deaths associated with the marginal variation in the PM concentration due to pollutant k in the receiving regions j and the emitted mass of pollutant k in the emitting region i results in the CF for the emitted pollutant. Equation 4, adapted from Thind *et al*. (2022), presents the mathematical equation that describes the calculation of the CFs. The authors apply a similar approach to calculate the CF for a single economic sector in the United States, and here the equation has been modified to be applied to different regions of Brazil (states) and different emission sources.

$$CF_{k,i} = \frac{\sum_j M_{k,i\rightarrow j}}{\sum_i E_{k,i}} \tag{4}$$

In equation 4, $CF_{k,i}$ represents the characterization factor for pollutant k, emitted in region i (in deaths/ton emitted); $M_{k,i\rightarrow j}$ represents the total number of deaths associated with pollutant k, emitted in region i, transformed in $PM_{2.5}$ and reaching the receiving region j; and, $E_{k,i}$ represents the emission of pollutant k in the emitting region i (in ton). To convert the results to deaths per kilogram, it is just necessary to convert emissions from ton to kilogram.

To better understand which parameters, between emissions and mortality, most affect the CF results, a Pearson correlation analysis was conducted using Excel. Additionally, CFs for the five pollutants were also calculated for the mesoregions of Brazil (North, Northeast, South, Southeast, and Midwest), as well as representative CFs for the entire country. For these cases of extrapolating state-level CFs into mesoregional or national CFs, the aggregation was done by applying the weighted average of the state-level CFs from each mesoregion or the entire country, using annual emissions as weights for the averaging, as recommended by Mutel *et al*. (2019).

The methodological procedure for the calculation of the CFs was assisted by InMAP (Intervention Model for Air Pollution) (detailed in section 3.2.1) with input from Brazilian pollutant emission inventories (section 3.2.2) and mortality rates (section 3.2.3). The main output of the methodological procedure was the total number of deaths due to changes in atmospheric pollutant emissions (section 3.2.3) and the attribution of the number of deaths to each atmospheric pollutant of interest (section 3.2.4).

3.2.1 InMAP Model

InMAP is a global air quality model with high resolution and reduced complexity, capable of estimating the average annual change in concentrations of both primary and secondary $PM_{2.5}$ attributed to a marginal change in the emission of primary $PM_{2.5}$ and four precursor pollutants: NH_3, SO_x, NO_x, and VOC (Thakrar *et al.*, 2022). One advantage of InMAP is that, despite being a low-complexity model, it achieves efficient temporal coverage by considering a parametrization based on an annual simulation of the GEOS-Chem model (Goddard Earth Observing System - Chemical), being able to incorporate temporally explicit information whenever possible to calculate annual averages of the calculation parameters (Tessum *et al.*, 2017; Wu *et al.*, 2021). Also, the results provided by the InMAP model allow for the easy identification of each secondary pollutant's contribution to the increase in PM2.5 concentrations, which is important for calculating the characterization factors (CFs) of these pollutants without the need to introduce additional considerations or uncertainties beyond those already inherent to the use of the InMAP model itself.

Moreover, the model efficiently handles the spatial resolution of the output, varying the size of grid-cells according to population density, so that resolutions are higher in urban areas and lower in remote or rural areas. This property of InMAP is relevant in the context of characterization models for LCIA in the health damage category due to PM formation, as population density is a variable with a high influence on CFs (Mutel *et al.*, 2019). It is interesting to note that Thind *et al*. (2022) also used the InMAP model to calculate CFs for the health damage category due to PM formation for specific emissions in the United States.

Considering the advantages presented in relation to the InMAP model, in this research, the global InMAP was used to simulate the dispersion of pollutants emitted by each Brazilian federal unit, plus the Federal District. Thus, 27 InMAP simulations were performed, each containing data input for the emissions of a specific Brazilian state. Each model run took an average of 41 hours to complete, ranging from 30 to 55 hours depending on the Brazilian state. The high computational demand was a decisive factor in determining the level of regionalization of the CFs in this study.

Subsequently, the results for the concentrations of primary and secondary $PM_{2.5}$, by InMAP grid-cell, were associated with the mortality rate for each grid to estimate the number of deaths globally associated with the emissions from Brazilian states.

3.2.2 Emissions of atmospheric pollutants in Brazilian territory

To use the InMAP Global model, the main input is a shapefile (or a set of shapefiles) containing locations of annual emissions of VOCs, SO_x, NO_x, NH_3, and $PM_{2.5}$ primary, in ton per year. The locations can be polygon, line, or point entities and can include stack attributes to represent elevated sources (Thakrar *et al.*, 2022). Considering the focus on the Brazilian geographical context, the following inventory sources were used: Brazilian Atmospheric Inventories (BRAIN) (Hoinaski, Will, Ribeiro, 2024), which compiles emissions inventories for Brazilian territory, and EDGAR v.431 (EC, JRC, 2018). Table 11 presents details about the inventory sources, the sectors and pollutants used to run InMAP.

Table 11 - Details of Brazilian inventories used to run InMAP

Sector	Temporal resolution	Geographical resolution	Pollutants	Source
Transport	2019	20×20 km	$PM_{2.5}$, SO_x, NO_x, VOC	Hoinaski, Will, Ribeiro, (2024) – BRAVES[1]
Biogenic emissions	2019	20×20 km	NO_x, VOC	Hoinaski, Will, Ribeiro, (2024) – MEGAN[2]
Biomass burning	2019	20×20 km	$PM_{2.5}$, SO_x, NO_x, VOC, NH_3	Hoinaski, Will, Ribeiro, (2024) – FINN[3]
Industry	2022	0.1°×0.1°	$PM_{2.5}$, SO_x, NO_x, VOC, NH_3	EDGAR v. 431
Agriculture	2022	0.1°×0.1°	$PM_{2.5}$, SO_x, NO_x, VOC, NH_3	EDGAR v.431

[1]BRAVES (Brazilian Vehicular Emission Inventory)
[2]MEGAN (Model of Emissions of Gases and Aerosols from Nature)
[3]FINN (Fire Inventory from National Center for Atmospheric Research)
Source: Author

Hoinaski, Will, Ribeiro (2024) presented inventories from biogenic emissions, transport, and biomass burning in Brazil, considering 2019 as temporal scope. The files are available in netCDF format, hourly temporal resolution, and 20×20 km spatial resolution. Dataset presents one netCDF file per day, totaling 365 files for each sector. To adapt the inventory for application in the InMAP model, the annual emissions were estimated multiplying the hourly emissions per 24 hours, and summing the emissions of 365 days of the year. Then, the pollutants of interest were isolated, and the netCDF files were converted to a shapefile. Entire manipulation of the netCDF files was performed using Python language in a Jupyter Notebook version 6.5.4 with the assistance of libraries xarray, geopandas, pandas, and netCDF4. The estimation of NO_x considered that this pollutant usually includes two gases: nitric oxide (NO) and nitrogen dioxide (NO_2) (EEA, 2023), both available in the transport inventory. The SO_x emission was estimated considering that SO_2 is the most common sulphur oxide, thus it was considered that $SO_x \approx SO_2$ (EEA, 2023). As a final result of the adaptation of the inventories, a shapefile was obtained for each pollutant of interest available in the transportation inventory in the WGS84 projection.

To complement the emissions of industrial and agricultural sectors in Brazil, the international inventory EDGAR v.431 (EC, JRC, 2018) was used. EDGAR v.431 provides global emissions for all the pollutants of interest in shapefile format, covering 2022 as temporal scope and spatial resolution of 0.1°×0.1°. The industrial inventory used did not provide data regarding emission heights, like other national inventories, such as Hoinaski, Will, Ribeiro (2024), Kawashima *et al*. (2020), and Rey (2023). However, not adding emission height in the InMAP model implies that emissions occur at ground level. Therefore, to avoid overestimated concentration results, chimney characteristic data were added for industrial emissions, considering a height of 20.5 meters, a diameter of 2.5 meters, an ambient temperature of 302.9 Kelvin, and a fluid velocity of 12.1 meters per second, considering the average data from Almeida Filho (2008), who obtained these characteristics by monitoring PM emissions from chimneys in ferroalloy and alcohol production industries in Brazil.

The inventories were adjusted to cover only the Brazilian territory, following the same geographical scope as the other inventories used. To standardize the spatial resolutions of the shapefile files from EDGAR v.431 (EC, JRC, 2018) with the netCDF files provided by Hoinaski, Will, Ribeiro (2024), all of them were adjusted to a spatial resolution of 20×20 km using the EPA ANTHR O_EMIS tool (NCAR, 2024; Pfister, 2014) by Albino (2024).

This inventory set used to run InMAP was recommended by Albino (2024) for use in pollutant distribution models, after analyzing six different inventory sets available for Brazil. Among those sets of inventories, the group used in this research showed the best accuracy after simulations compared to the real monitoring data of pollutant concentrations. Then, the recommendation by Albino (2024) assisted the inventory choice for use in models for characterizing LCIA in the category of health damage due to PM formation.

The inventory set was stratified by state, allowing InMAP to be run separately for each one. This way, it was possible to identify the variation in concentration in the model's grid cells caused by emissions from each state. This variation was used to calculate the number of deaths attributed to air pollution (section 3.2.3).

The inventory data were also used to obtain the emission variable ($E_{k,i}$) in tons. Since the inventories provided state-level emission data with a 20×20 km resolution, the emission points of the same pollutant k, located within the same state, were summed to calculate the total annual emission of each pollutant, resulting in the $E_{k,i}$ corresponding to each state.

3.2.3 Number of deaths and health impact due to atmospheric pollutant emissions

The number of deaths due to atmospheric pollutant emissions from Brazilian states was calculated for each grid-cell of the globe based on the variation in $PM_{2.5}$ concentration, using Equation 5, as proposed by the InMAP model (Krewski *et al*., 2009).

$$M_{i\to j} = (exp\ (log\ (1.078)/10\ \times\ \Delta C_{PM2.5_{i\to j}})\ - 1)\ \times TotalPop_j \times MR_j/100{,}000 \quad (5)$$

Where: $M_{i\to j}$ is the number of deaths attributed to pollutant emissions in region i that cause variation in $PM_{2.5}$ concentration in the receiving region j; $\Delta C_{PM2.5_{i\to j}}$ is the variation in total $PM_{2.5}$ concentration in region j due to emission changes in i, including contributions from both primary and secondary $PM_{2.5}$ (in µg/m³); $TotalPop_j$ is the population size in j, and; MR_j is the mortality rate in j for all health effects (in number of deaths per 100,000 inhabitants). The equation was applied to all grid-cells where the concentration increase occurred.

The total $PM_{2.5}$ concentration variations due to emissions from Brazilian states were obtained as output from the InMAP model, and the variable $TotalPop_j$ was obtained from the model's configuration data. The mortality rate data were obtained from the internationally recognized Global Burden of Disease (GBD, 2022) database.

The mortality rate data were collected as the number of deaths for all health effects, considering all ages and both sexes (male and female). To align with the temporal scope of the emission inventories (Table 10), the average mortality rate from 2019 to 2021 was used. Although 2022 is part of the scope of the emission inventories, it was not included in the analysis due to a lack of data in the GBD (2022) database at the time this research was conducted. Regarding the geographical scope, mortality data were collected for all regions of the world, as emissions from Brazil may impact different locations. Given the goal of regionalization for Brazil at the state level, mortality data for the country were collected at this same geographical scale. For other locations worldwide, mortality data were assigned at the country, continent, or global average level, depending on the availability of data in the GBD (2022) database. A total of 256 regions were considered, of which 211 had data available at the country level, 42 at the continent level, and 5 at the global level (all in Antarctica).

Years of Life Lost (YLL) and Disability-Adjusted Life Years (DALY) data were also collected for these 256 regions in GBD (2022) database, considering all health effects, all ages, and both sexes. From the YLL and DALY values, the number of YLL and DALY were divided by the total number of deaths for each region (YLL/death and DALY/death), obtaining a severity factor for the receiving region j (SF_j), and this information was used to determine the total health impact (I) in YLL and DALY attributed to PM by multiplying the severity factor with the number of deaths ($M_{i\rightarrow j}$) obtained from Equation 5, as demonstrated in Equation 6.

$$I(DALY\ or\ YLL)_j = M_{i\rightarrow j} \times SF_j \tag{6}$$

These data were then used to calculate the CFs into DALY/kg emitted and YLL/kg emitted, facilitating comparison with other characterization models available in the literature.

3.2.4 Attribution of the number of deaths to the pollutants of interest

The calculation of the number of deaths from equation 5 considers the entire variation in $PM_{2.5}$ concentration in the receiving region, regardless of whether it is a contribution from primary or secondary $PM_{2.5}$ emissions. However, the output of the InMAP model allows the identification of $PM_{2.5}$ concentration from each pollutant of interest, which makes it possible to calculate the number of deaths for each emitted pollutant based on their contributions to the total $PM_{2.5}$ concentration. As an example, Equation 7 presents the calculation of mortality for ammonia emissions.

$$M_{NH3,i\rightarrow j} = M_{i\rightarrow j} \times \frac{\Delta C_{pNH4_{i\rightarrow j}}}{\Delta C_{PM2.5_{i\rightarrow j}}} \tag{7}$$

Where: $M_{NH3,i\rightarrow j}$ is the number of deaths in region j associated with ammonia emissions in region i; $M_{i\rightarrow j}$ is the number of deaths associated with the total $PM_{2.5}$ concentration (calculated in equation 5); $\Delta C_{pNH4_{i\rightarrow j}}$ is the variation in secondary $PM_{2.5}$ (ammonium particulate) concentration in region j, resulting from ammonia emissions in region i; and, $\Delta C_{PM2.5_{i\rightarrow j}}$ is the variation in total $PM_{2.5}$ concentration in region j due to all pollutant emissions (primary and precursors of PM) in region i. The same procedure was followed for all the pollutants of interest for $PM_{2.5}$ formation, also for DALY and YLL calculation.

3.2.5 Uncertainty analysis

The calculation of CFs involves uncertainty models and data, making it essential to understand the magnitude of this uncertainty (Finnveden *et al.*, 2009). Uncertainty measurements of the parameters and models used would offer the best source for estimating uncertainty intervals and the distribution of CFs. However, the emission datasets and the modeling of health effects via InMAP did not provide uncertainty measurements.

Given this, and aiming to develop an uncertainty analysis, the Pedigree approach for CFs developed by Qin *et al*. (2020) was applied. This method is widely used in the life cycle assessment (LCA) field (Weidema *et al*., 2013), and estimates quantitative uncertainty based on qualitative characteristics of a dataset. The proposed pedigree matrix consists of five evaluation criteria:

1. Reliability of underlying science: assesses the scientific acceptance of the characterization model, particularly whether it has undergone peer review;
2. Model completeness: evaluates the coverage of elementary flows by the model;
3. Temporal specification: verifies whether the model is dynamic or static;
4. Geographical specification: analyzes the level of regionalization of the model;
5. Input data characteristics: assesses the quality of the model's input data, considering whether the parameters are measured or statistically representative.

Each criterion was rated from 1 (low uncertainty) to 5 (high uncertainty). After scoring the model using the pedigree matrix, the geometric standard deviation (GSD) of the CFs was calculated using the equation from Frischknecht *et al*. (2007) (Equation 8):

$$GSD = exp^{\sqrt{[\ln(U1)^2]+[\ln(U2)^2]+[\ln(U3)^2]+[\ln(U4)^2]+[\ln(U5)^2]+U6}} \quad (8)$$

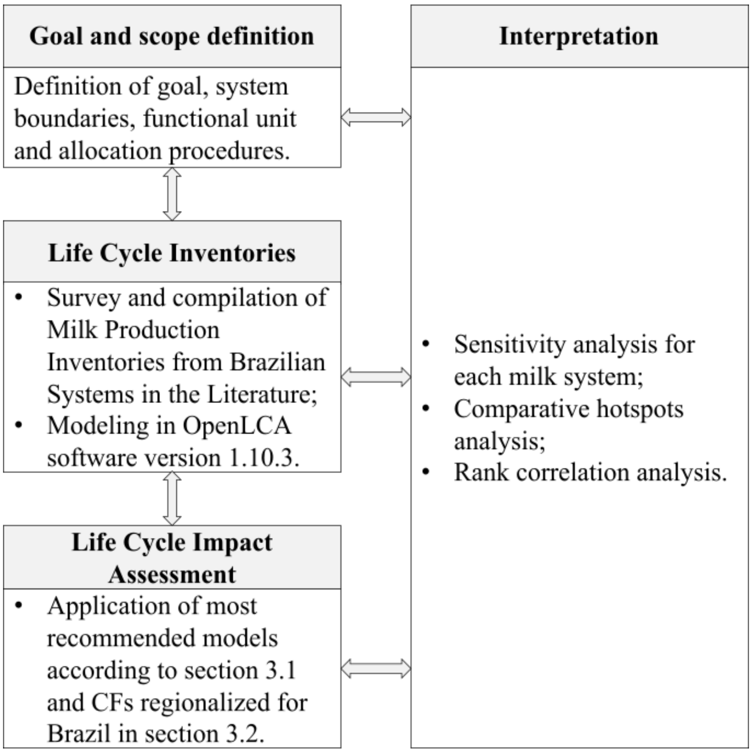
Where: GSD is the geometric standard deviation of the model; U1 is the uncertainty of reliability of underlying science; U2 is the uncertainty of model completeness; U3 is the uncertainty of temporal specification; U4 is the uncertainty of geographical specification; U5 is the uncertainty of input characteristics, and; U6 is the default basic uncertainty (variance of the log transformed data).

Due to the lack of specific data, the value for the model's basic uncertainty was taken as 0.3, corresponding to the basic uncertainty of $PM_{2.5}$ emissions as suggested by Weidema *et al*. (2013).

3.3 REGIONALIZED LCA SENSITIVITY ANALYSIS

The methodology of this step followed the four steps of LCA methodology defined by ISO (2006a, b): goal and scope definition, life cycle inventory analysis, LCIA, and LCA interpretation. The case study is based on Giusti *et al*. (2023), with the main difference being the inclusion of the CFs calculated in this work, according to the methodology presented in section 3.2. Figure 6 illustrates the study's methodological flowchart.

Figure 6 - Methodological flowchart of sensitivity analysis



Source: Author

For the sensitivity analysis, a case study was designed based on the production of milk in Brazil from different production systems. Milk production was selected as a case study due to the agricultural sector's significant potential to contribute to PM emissions (Wyer *et al*., 2022), which can occur through mechanical processes, engine emissions, and animal feeding operations (Mostafa *et al*., 2016). Also, in the Brazilian context, there was an increase of 107% in health effects due to PM and precursor gasses emitted in the management of ruminant animals between 1990 and 2018 (UN, 2018). The following sections detail the step-by-step methodology.

3.3.1 Goal and scope definition

Four milk production systems were used as LCA case studies (Table 12). All of them were taken from Barros *et al.* (2022) and Silva (2022).

Table 12 - Evaluated milk production systems

System	**1 - Confined**	**2 - Confined**	**3 - Semi-confined**	**4 - Semi-confined**
Geographical scope	Vale do Paraíba, São Paulo state	Campos Gerais, Paraná state	Campos Gerais, Paraná state	Zona da Mata, Minas Gerais state
Animals	Black and white Holsteins	Black and white Holsteins	Black and white Holsteins	Girolando
Manure Management	Compost barn type	Covered and uncovered lagoon	Covered and uncovered lagoon	Reused as biofertilizer (50%) or deposited in the pasture area (50%)
Milk protein	2.97%	3.26%	3.22%	3.40%
Milk fat	3.75%	3.61%	3.53%	3.48%
Reference	Silva (2022)	Barros *et al*. (2022)	Barros *et al*. (2022)	Barros *et al*. (2022)

Source: Author

It is interesting to highlight that in the System 1, the manure management consists of constant insertion of sawdust (residue from the wood industry) as bulking material for cows' beds. The sawdust was mixed daily with animal waste (manure and urine) to produce biofertilizer through aerobic composting. Also, the manure management of Systems 2 and 3 produced treated manure and biofertilizer. Then, all the four systems are multifunctional, producing milk, meat and biofertilizer, and two allocation approaches were applied to address multifunctionality: mass and economic, as detailed in the next sections.

The technological scope of the four systems was similar, using mechanical milking, manual and automatic cleaning, and breeding through artificial insemination. The four systems were evaluated in the cradle-to-farm gate approach, and the functional unit was 1 kg of fat and protein-corrected milk (FPCM).

3.3.2 Data collection for life cycle inventory

The research focus was the sensitivity analysis of the LCA results for damage to human health caused by PM, mainly to identify how the use of different datasets of CFs for this category can change the results and interpretation of a LCA case study, including the main models for Brazil and the CFs obtained in this research. The foreground inventory data was obtained from Barros *et al.* (2022) and Silva (2022).

The inventory of the confined compost barn system produced in the Vale do Paraíba (System 1) was obtained in Silva's (2022) master thesis, covering the 2020/2021 period, while the inventories of the other milk production systems (Systems 2, 3, and 4) were extracted in Barros *et al.* (2022). All the four inventories covered the animal feed production, herd management, and waste management stages. The semi-confined systems (3 and 4) included pasture production as a foreground process, accounting for direct emissions of ammonia and nitrogen oxides due to the mineral fertilizer application in the pasture crop. On the other hand, in the confined systems (1 and 2), the animal diet production was modeled as background processes, and there were no emissions of PM or precursor gases accounted for as direct emissions.

The four compared systems were modeled in OpenLCA software version 1.10.3, using ecoinvent 3.7 cut-off databases as the background data to complete the LCI. Modeling the systems in the software tool was necessary to obtain the atmospheric emissions of PM and the related precursor gasses (sulfur dioxide, nitrogen oxides, ammonia, and volatile organic compounds) in the foreground and background processes. The complete inventory of the systems is available on the Appendix A (Table A 1).

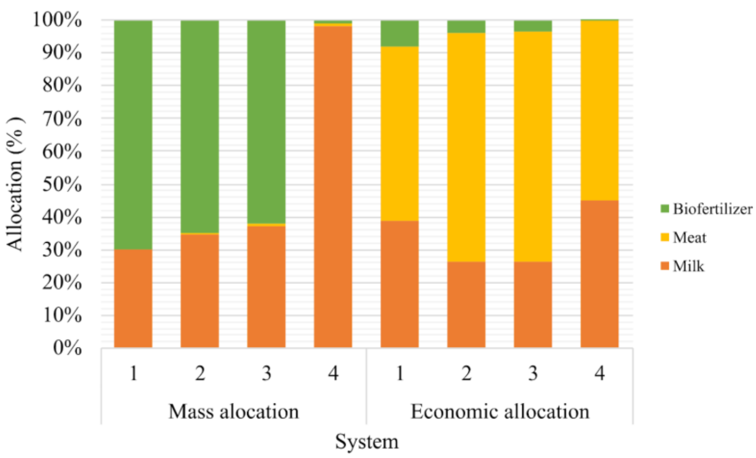
To address multifunctionality, the mass allocation uses the inventoried product and co-products weight quantities. For the economic allocation, product prices for the compost barn management system (system 1) were obtained by Silva (2022). For the Paraná and Minas Gerais' milk systems (systems 2, 3, and 4), the market prices of milk and meat were obtained from the CONAB (2022a) database, and the price of biofertilizer was obtained from the CONAB (2022b) database, all considering 2021 for the temporal scope. These inventories and allocation approaches were also used by Giusti et al. (2023), and the main goal here is to verify how the CFs calculated in this research affects the LCA sensitivity results. Figure 7 presents the allocation procedure.

Figure 7 - Data (A) and percentage (B) applied in the allocation procedure considering mass and economic approach

A)

		Weight (kg)	Market price (R$/kg)
1	Milk	1.00	2.25
	Meat	0.01	278.59
	Biofertilizer	2.33	0.20
2	Milk	1.00	2.12
	Meat	0.02	281.94
	Biofertilizer	1.88	0.16
3	Milk	1.00	2.12
	Meat	0.02	281.94
	Biofertilizer	1.67	0.16
4	Milk	1.00	2.27
	Meat	0.01	275.24
	Biofertilizer	0.01	0.16

B)



Source: Author

The choice of physical (mass) and economic allocation is in accordance with ISO 14040 and 14044 (ISO 2006a, b), and these approaches were also applied by Silva (2022) in the preparation of the life cycle inventory for system 1.

3.3.3 Comparative life cycle impact assessment

The LCIA step was developed in an Excel spreadsheet following the mandatory elements of ISO 14044 (ISO, 2006b), including selection of category indicators, impact classification, and characterization of PM formation. The assessment focused solely on human health impacts from PM at the endpoint level, using the DALY indicator.

At this stage, the characterization models with the highest scores in the recommendation analysis for application in Brazil were applied, along with the CFs calculated in this study, following the methodology described in Section 3.2. Additionally, CFs from the United Nations Life Cycle Initiative (Frischknecht and Jolliet, 2016) were used for comparison. The models covered different geographic scopes, and these scopes were explored in the sensitivity analysis, also, the models considered different calculation approaches, considering variations in environmental compartments and elementary flows.

The classification step consists of identifying the elementary flows inventoried correlating them to the impact category in question (ISO, 2006b). In this step, the complete inventories of the four milk production systems, obtained in the OpenLCA v. 1.10.3, were analyzed, and the elementary flows with the potential to impact human health by PM were identified: ammonia, nitrogen oxides, particulates < 2.5 µm, sulfur dioxide, and volatile organic compounds. The inventories considered the emission of the cited substances for five different environmental sub-compartments: high population density, low population density, long-term low population density, lower stratosphere + upper troposphere, and unspecified.

To ensure the best connection between CFs and elementary flows, the following considerations were made: (1) if the characterization model follow the geographic approach, we considered the same CF to emissions for different environmental archetypes, since this approach does not make such spatial differentiation; (2) identification of inventoried emissions location were respected, so for national-level analysis, if specific regional factors were available they were used; (3) emissions for countries in continents without specific CFs considered continent-average factors; (4) if the model does not provide global factor it was obtained by averaging the factors of all regions available; (5) for the models with archetype approach, we considered that emissions for high population density compartment represented the urban archetype, while emissions for low population density represented the rural archetype; (6)

emissions for “low population density long-term” compartment received the same CF attributed to the emissions for “low population density”; (7) we considered the highest outdoor CF of the substance for emissions to “lower stratosphere + upper troposphere” compartment and to “unspecified” compartment, usually using the CF of urban environments.

In the characterization step, the calculation of the impact indicator result occurred (ISO, 2006b). To this end, the elementary flows of PM and precursor gasses were multiplied by their respective CFs obtained by the different characterization models selected.

3.3.4 Results interpretation

The interpretation step focused on the sensitivity analysis of the LCA results. Initially, the results of human health impacts by PM were obtained for the different milk production systems and compared, verifying the percentage variation of the results followed by the analysis of hotspots.

Then, a rank correlation analysis was employed calculating Spearman's correlation coefficient to verify the consistency of the systems' ranking from the most to the least impactful. Heijungs and Dekker (2022) recommended Spearman's correlation for sensitivity analyses of LCIA methods in LCA studies, and has already been employed by Dekker *et al.* (2020). Spearman coefficient ranges from -1 to 1, when the classification of systems by the x-model agrees with the classification by the y-model, the spearman indicator (r_s) results in 1. Disagreement in priority classification in at least one pair of systems causes the indicator to result in values less than 1 (Heijungs and Dekker, 2022). Systems were ranked from least impactful (rank 1) to most impactful (rank 8) and evaluated at the elementary flow level (ammonia, nitrogen oxides, sulfur dioxide, volatile organic compounds, and $PM_{2.5}$) and in terms of the total impact.

The interpretation of the result of the indicator was based on Mukaka (2012), considering, for the positive and negative side: between 0 and 0.3 insignificant correlation; between 0.3 and 0.5 low correlation; between 0.5 and 0.7 moderate correlation; between 0.7 and 0.9 high correlation, and between 0.9 and 1 very high correlation.

We tested the null hypothesis that the population value of Spearman's coefficient is zero ($H_0: \rho = 0$) and the alternative hypothesis that the value is different from zero ($H_0: \rho \neq 0$), following the methodology described in Heijungs and Dekker (2022). Thus, a conversion of the correlation indicators to t-Student statistics was performed, considering $n - 2$ degrees of freedom. Then, the ρ values were calculated, and the significant values for α equal to 1% and 5% were highlighted.

4 RESULTS AND DISCUSSION

This section presents and discusses the main results of the research. Section 4.1 presents the analysis and recommendations of the characterization models available in the literature. Section 4.2 shows the results of the regionalization of the CFs. Finally, section 4.3 presents the results of the sensitivity analysis of a LCA case study regarding the use of different characterization models for PM formation, including the best models evaluated in section 4.1 and the regionalized factors presented in section 4.2.

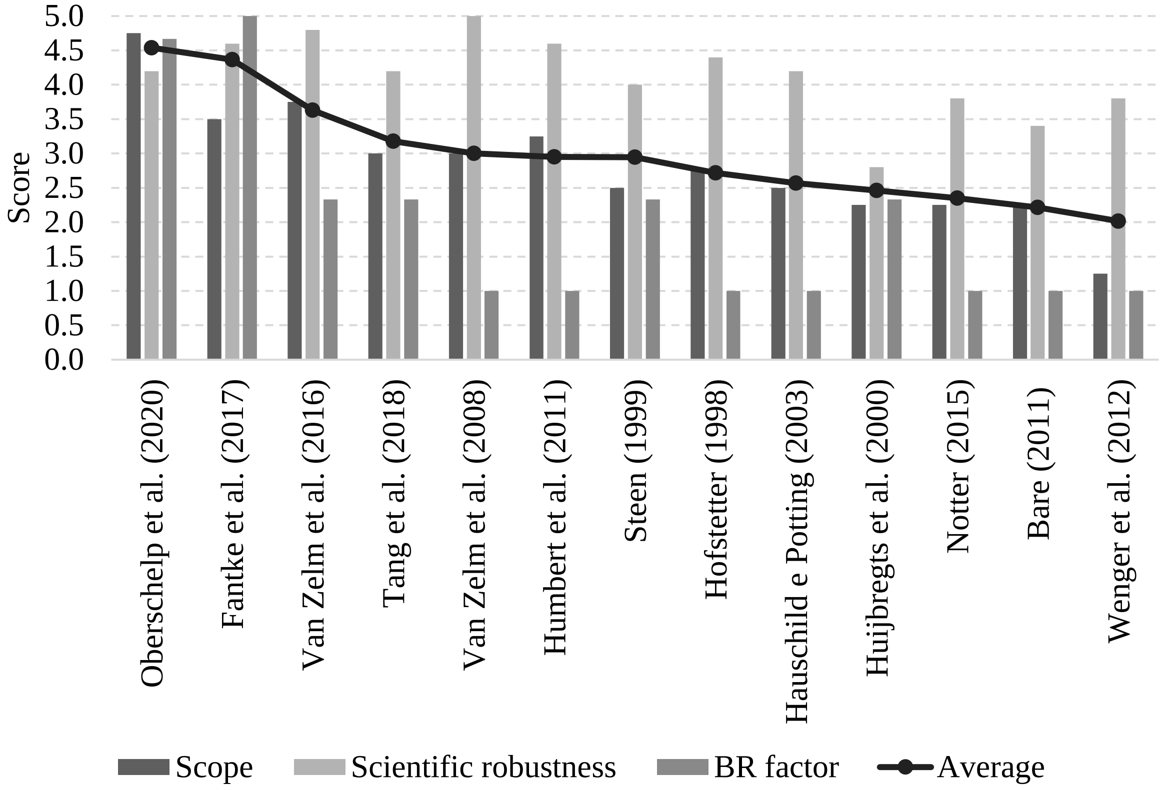
4.1 EVALUATION OF CHARACTERIZATION MODELS

The analysis of the characterization models was separated between the iF and EF as presented in section 4.1.1. However, the choice of the characterization model should consider the goal, scope, and inventory aspects of the LCA studies. Therefore, section 4.1.2 explores how the highest-rated models connect with different case studies.

4.1.1 Characterization model scoring

The evaluation of the iF (Figure 8) and EF (Figure 9) revealed that the global models with specific factors for Brazil stood out with higher scores, being identified as more suitable for the country’s context. The score of each model, analyzed by sub-criteria level, can be found in Appendix B (Table A 3 to Table A 8).

Figure 8 - Models' scoring based on the calculation of intake fraction



Source: Author

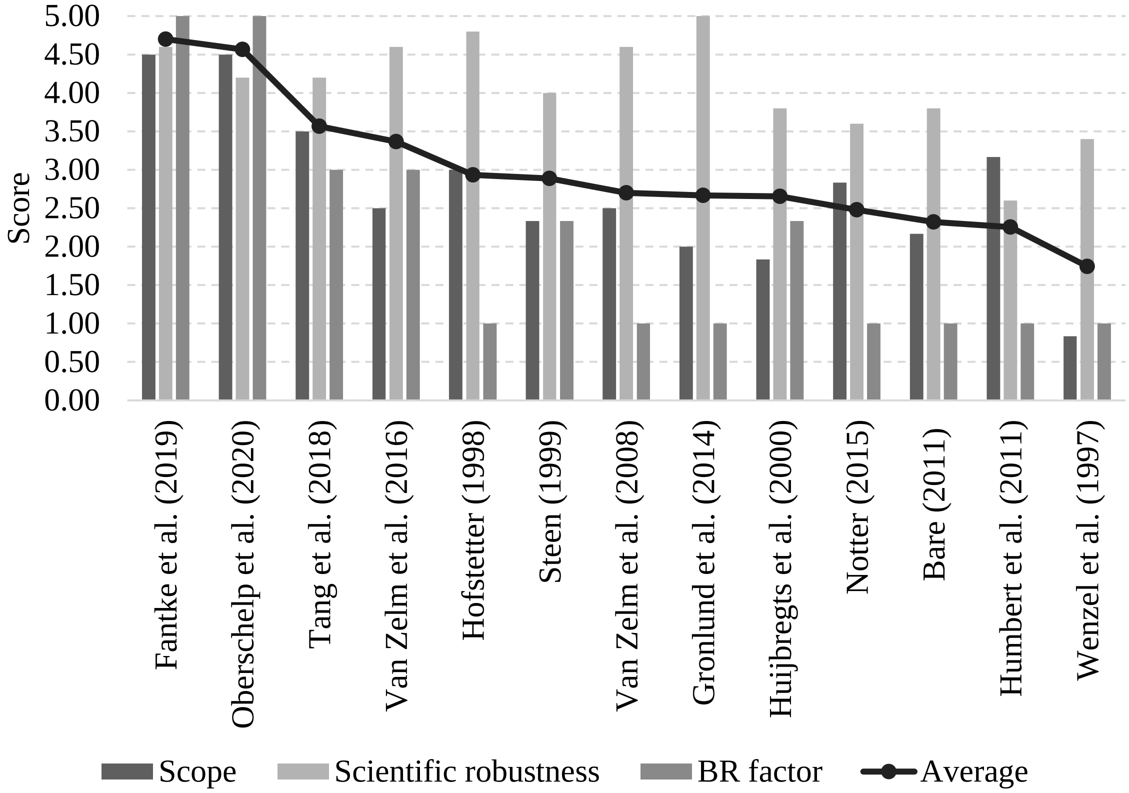
Regarding the iF (Figure 8), the highest-scoring model was that of Oberschelp *et al.* (2020). This model was developed using a geographic approach with a spatial scale of 0.25°×0.25° grid cells (approximately 25×25 km at the equator). The model provides factors for elementary flows of $PM_{2.5}$, SO_2, NO_x, and NH_3, including for Brazil, with data aggregated by state. The input parameters were obtained at different time scales, but mainly within the 2015-2019 range. With these characteristics, it was the highest-scoring model in the scope criterion (4.75), which significantly influenced its final score. In the evaluation of the scientific robustness criterion, it was observed that this model is not considered by an LCIA method at this time, but it is a newly published model in the literature. The authors clearly outline the cause-and-effect chain employed, the equations, and the calculation variables. However, the developed mathematical model is complex, and according to the authors, its reproducibility is affected by the large number of input parameters and the high computational demand required to run the modeling developed in the R statistical software. Based on this information, the score for the Scientific Robustness criterion was 4.2. Finally, the model also received a high score in the iF criterion for Brazil (4.67), as it provides factors for the country's states, obtained at a fine spatial scale, and is considered suitable for the Brazilian context.

The Fantke *et al*. (2017)'s model was the second highest-scoring in the analysis, with a final score of 4.37. Unlike Oberschelp *et al*. (2020), this model was developed using a hybrid approach, providing factors for the urban indoor, rural indoor, urban outdoor, and rural outdoor archetypes, different continents, countries, and cities around the world. However, the score for the scope criterion was lower than that of Oberschelp *et al*. (2020), due to the use of input data from the 2005-2009 and, mainly, because only factors for primary $PM_{2.5}$ were calculated. For the criteria of Scientific Robustness and iF for Brazil, the model by Fantke *et al*. (2019) scored higher than Oberschelp *et al*. (2020), as shown in Figure 8. Regarding Scientific Robustness, the higher score is mainly justified by the greater reproducibility of the model, as the authors provide Excel spreadsheets with automated factor calculations. For this criterion, only the sub-criterion of availability in LCIA methods did not receive a score of 5, but received 3 (moderate), as no method using it was identified. Finally, for the iF for Brazil criterion, the model by Fantke *et al*. (2017) was the only one in the analysis to receive a score of 5, which is justified by the authors providing factors for the country, as well as specific factors for states and 127 large Brazilian cities.

The third highest-scoring model regarding iFs, also identified as suitable for Brazil, is the one developed by Van Zelm *et al*. (2016). Like Oberschelp *et al*. (2020), this model was developed using a geographic approach, but its spatial differentiation has a higher resolution of 1°×1° (approximately 100×100 km at the equator). This higher resolution, along with the use of input data from the 2000-2004, resulted in a lower score for the scope criterion (3.75). The score for the Scientific Robustness criterion of Van Zelm *et al*. (2016) was 4.8, with only the sub-criterion of transparency and accessibility receiving a score of 4 instead of 5, as the grouping of the grid-cell factors for the 56 regions established in the model is not clearly described. The model provides a single iF for Brazil, which was considered inadequate for the Brazilian context, as a single factor for a country of continental dimensions cannot adequately describe the variability of this category and the heterogeneity of Brazil.

The models developed by Oberschelp *et al*. (2020), Fantke *et al*. (2019), and Van Zelm *et al*. (2016) also scored well in the evaluation of EFs, as shown in Figure 9.

Figure 9 - Models' scoring based on the calculation of effect factor



Source: Author

The model developed by Fantke *et al*. (2019) ranked first, with a final score of 4.7. The main difference in the final score between Fantke *et al*. (2019) and Oberschelp *et al*. (2020) occurred in the Scientific Robustness criterion, in the transparency and accessibility sub-criterion. As observed in the evaluation of iFs, the Oberschelp *et al*. (2020)'s had greater difficulty in reproducibility, with a higher number of input parameters and greater computational requirements for reproducing the calculations, compared to the Fantke *et al*. (2019)'s model, which had greater ease of reproduction and access to input data. It is important to note that Oberschelp *et al*. (2020) is based on the calculation of EFs from the modeling of Fantke *et al*. (2019), and because of this, all other sub-criteria received the same score. Thus, it is emphasized that both models provide suitable EFs for the Brazilian context; they use recent data (from 2015-2019); they work with the five health effects most associated with PM (ischemic heart disease, stroke, chronic obstructive pulmonary disease, lung cancer, and lower respiratory infections); and they include only $PM_{2.5}$ in the calculation of relative risk.

For the EF analysis, Tang *et al*. (2018) ranked third, with a score of 3.57, followed by Van Zelm *et al*. (2016), with an average score of 3.37. The main reason for Tang *et al*. (2018)'s higher score compared to Van Zelm *et al*. (2016) was the high performance in the scope criterion, due to the inclusion of epidemiological studies covering the Brazilian context, and the fact that they considered all causes of mortality. The model by Van Zelm *et al*. (2016), on the other hand, extrapolates relative risk data from the United States to the entire world, which is not considered representative for Brazil. The health effects included in the model were cardiopulmonary effects and lung cancer, which together cover about 60% of the years of life lost related to PM, according to GBD (2019).

For the other sub-criteria of the scope criterion, both models received the same score. The temporal resolution of the input data for both models is earlier than that of Fantke *et al*. (2019) and Oberschelp *et al*. (2020), in the range of 2000-2004. Both models are global and present data for Brazil, receiving the same score for the Brazil factor criterion. A significant difference between them is that Van Zelm *et al*. (2016) presents a specific factor for Brazil, while Tang *et al*. (2018) presents a factor for Latin America. Given this difference and the higher score of Van Zelm's model in the iF, it was considered moderately more recommended for application in Brazil.

The other models evaluated, both for iF and EF, received a final score of ≤ 3, making them less qualified for application in the Brazilian context. Among these, the models by Steen (1999) and Huijbregts *et al*. (2000) are of global scope and thus cover Brazilian territory in the modeling. However, both are models that present average factors for the globe, making it impossible to stratify local factors, which are relevant for the category of health damage from PM formation. The other models on the list were developed for geographic contexts different from Brazil's (such as Europe and North America), and are the least recommended for the country.

It is interesting to note that the methodological approach used in this stage of the research—namely, the criteria and subcriteria applied for recommending the characterization model—achieved a result aligned with the recommendations of the GLAM initiative for outdoor environments. The highest-scoring models in this evaluation were observed to Oberschelp et al. (2020) and Fantke et al. (2017, 2019), which are the same models recommended by GLAM (GLAM, 2024). This alignment reinforces that the approach used here yields meaningful results and is in line with international consensus in the field, suggesting that it may also be applied to assess the adequacy of new models that may emerge in the literature for the impact category associated with PM.

Giusti *et al*. (2022) ranked the models most recommended for Brazil using a Multi-Criteria Decision Analysis based on the Simple Multi-Attribute Rating Technique (SMART) method, which weighted the model scores based on the order of importance of the criteria and sub-criteria, assigning higher scores to the models more recommended for Brazil. Comparing the results of this analysis with the results of Giusti *et al*. (2022), it is noticeable that the difference in methodology resulted in changes in the classification of the models with intermediate scores. However, the models with the highest and lowest scores were analogous.

4.1.2 Critical analysis of the models and recommendations

The methodological recommendations in the field of LCA research converge on the fact that decision-making in the LCA stage should align with the study's goal and scope definitions (Berger *et al*., 2020; Giusti *et al*., 2022; ISO 2006a). Additionally, within the category of health damage from PM formation, the consensus recommendation in the literature is to use regional factors. However, in certain case studies, there may be no access to information about the exact location of pollutant emissions (Mutel *et al*., 2019). Therefore, the use of regional factors may not be ideal for all situations (Giusti *et al*., 2022).

Thus, Table 13 shows the connection of the highest-scoring LCA models from section 4.1.1 with different characteristics that may be observed in an LCA study with PM emissions.

Table 13 - Analysis of characterization models and recommendation for use in different scopes of LCA studies

Scope of case study:		**Recommended models to apply in Brazilian LCA studies:**
1	Does the inventory present PM emissions at a global level?	Fantke *et al*. (2019), Oberschelp *et al*. (2020), Van Zelm *et al*. (2016)
2	Does the inventory present PM emissions at the country level?	Fantke *et al*. (2019), Oberschelp *et al*. (2020), Van Zelm *et al*. (2016)
3	Does the inventory present PM emissions in Brazil with city/state level specified?	Fantke *et al*. (2019), Oberschelp *et al*. (2020)
4	Does the inventory present PM emissions in indoor environments?	Fantke *et al*. (2019)
5	Does the inventory present particulate matter PM emissions specified as urban or rural environments?	Fantke *et al*. (2019)
6	Does the inventory present PM emissions with emission height specified?	Fantke *et al*. (2019), Oberschelp *et al*. (2020)
7	Does the inventory present PM emissions with emission height unspecified?	Fantke *et al*. (2019), Oberschelp *et al*. (2020), Van Zelm *et al*. (2016)
8	Does the inventory present emissions of PM precursors?	Oberschelp *et al*. (2020), Van Zelm *et al*. (2016)
9	Does the inventory present primary PM emissions?	Fantke *et al*. (2019), Oberschelp *et al*. (2020), Van Zelm *et al*. (2016)
10	Does the study require a marginal curve for the effect factors?	Fantke *et al*. (2019), Oberschelp *et al*. (2020)
11	Does the study require an average or linear curve for the effect factors?	Fantke *et al*. (2019), Oberschelp *et al*. (2020), Van Zelm *et al*. (2016)
12	Does the inventory have monthly variations and/or variations throughout the day for PM emissions?	Oberschelp *et al*. (2020)

Source: Adapted from Giusti *et al*. (2022)

The models developed by Fantke *et al*. (2017, 2019), Oberschelp *et al*. (2020), and Van Zelm *et al*. (2016) provide global and country-specific average factors. Therefore, the three models can be applied in case studies that indicate PM emissions in unspecified locations or at global or country levels. However, Van Zelm *et al*. (2016) does not stratify countries into regional levels (such as states or cities). Since the recommendation for this impact category is to use regional factors (Mutel *et al*., 2019), if the emission region is known, it is ideal to prioritize the use of the models by Fantke *et al*. (2017, 2019) or Oberschelp *et al*. (2020).

For case studies indicating PM emissions in indoor environments, rural areas (with low population density), or urban areas (with high population density), the ideal model to use is that of Fantke *et al*. (2017, 2019), as it is the only one among the highest-scoring models that allows working with this variability in factors, which is associated with the use of the archetype approach.

The height of PM emissions is also a parameter that can affect the intensity of the pollutant's impact on human health. Emissions from high chimneys can disperse more easily, reducing the exposure level for the local population. On the other hand, emissions at ground level (such as vehicle emissions) can more easily affect the population, potentially causing a greater impact on health (Parvez *et al*., 2017). Thus, this level of detail is relevant for PM emission sources, and the models by Fantke *et al*. (2017, 2019) and Oberschelp *et al*. (2020) provide factors for different emission heights, allowing access to this level of detail in LCA.

It is important that the LCA model is capable of accounting for all significant impacts in a given category (ISO, 2006 a). For PM formation, both primary and secondary PM emissions can affect human health. Therefore, case studies with significant precursor PM emissions should prioritize the use of the models by Oberschelp *et al*. (2020) or Van Zelm *et al*. (2016), as Fantke *et al*. (2017, 2019) do not provide factors for secondary PM, which could lead to an underestimation in the final results for this category (Giusti *et al*., 2021).

In the calculation of EFs, the use of a marginal exposure-response curve is required to account for the impact of small changes in PM emissions, while linear curves are more useful for accounting for the impact of more significant changes in emissions (more details in Oberschelp *et al*., 2020). The models by Fantke *et al*. (2017, 2019) and Oberschelp *et al*. (2020) work with both approaches for EF calculation, while Van Zelm *et al*. (2016) works only with the linear approach.

Finally, it is important to highlight the model developed by Oberschelp *et al*. (2020) as the only one, among all the models evaluated, that allows access to the variability of the impact associated with PM emissions in different months of the year and day period. This is an innovative and significant contribution of this model to the LCA category, as the impacts of PM are dependent on meteorological conditions such as calm conditions, thermal inversions, and low air humidity—events common during winter periods (CETESB, 2021).

Thus, it is clear that the three highest-scoring models in section 4.1.1 can be used in LCA studies in Brazil. It is up to the LCA study developer to identify the points of greatest interest in the goal and scope of their system to connect the most suitable characterization model. It is worth noting that the three models highlighted in this recommendation are also widely accepted by the scientific community. The model by Van Zelm *et al*. (2016) is used in the ReCiPe 2016 LCA method (Huijbregts *et al*., 2017), a recent and globally applied method widely used in case studies across various sectors (Ferrara *et al*., 2021; Payen and Ledgard, 2017). Fantke *et al*. (2017, 2019) form the basis for the UNEP and SETAC (2016) characterization factor recommendation. Oberschelp *et al*. (2020) is the most recent model of all, but it brings a high level of robustness in modeling and the temporal differentiation of characterization factors as an innovation for this impact category. However, limitations were also identified in the highlighted models, such as the lack of factors for secondary PM (Fantke *et al*., 2019) or the lack of access to relevant archetypes, such as indoor environments (Oberschelp *et al*., 2020).

4.2 REGIONALIZATION OF CHARACTERIZATION FACTORS

The calculation of CFs for the Brazilian context considered the number of deaths caused by an increased emission of primary PM and precursor pollutants from five Brazilian sectors. These factors can be used to calculate the potential of deaths caused by production systems throughout the LCA approach. This section presents the analysis of pollutant emissions in the country (section 4.2.1), the health effects associated with these emissions (section 4.2.2), and finally, the CFs for health damages due to PM formation in the Brazilian context (section 4.2.3).

4.2.1 Analysis of national PM and precursor emissions

Considering the five sectors evaluated in this research, Brazil recorded a total emission of 203.12 thousand tons of primary $PM_{2.5}$, of which 77.4% were associated with the transportation sector and 22.6% with biomass burning. Regarding NH_3, the country emitted 18.38 thousand tons, with the main sources being the industrial sector (50.7%) and biomass burning (48.5%), while the agricultural sector had a minor contribution (0.7%).

In the case of NO_x, total emissions were 3,804.73 thousand tons, with the largest contributions coming from biogenic emissions (50.7%) and the transportation sector (45.7%), while the other sectors had contributions below 2%. Regarding SO_x, the country emitted 73.81 thousand tons, with similar values for the industrial sector (46.3%) and transportation (45.9%), along with small contributions from biomass burning (4.1%) and agriculture (3.8%).

VOC emissions totaled 44,245.06 thousand tons, dominated by biogenic emissions (81.1%). The industrial (9.0%) and agricultural (8.2%) sectors had secondary contributions, while emissions from transportation and biomass burning were negligible (0.9% each).

Figure 10 presents the spatial analysis of primary $PM_{2.5}$, NH_3, NO_x, SO_x, and VOC emissions by the evaluated sectors.

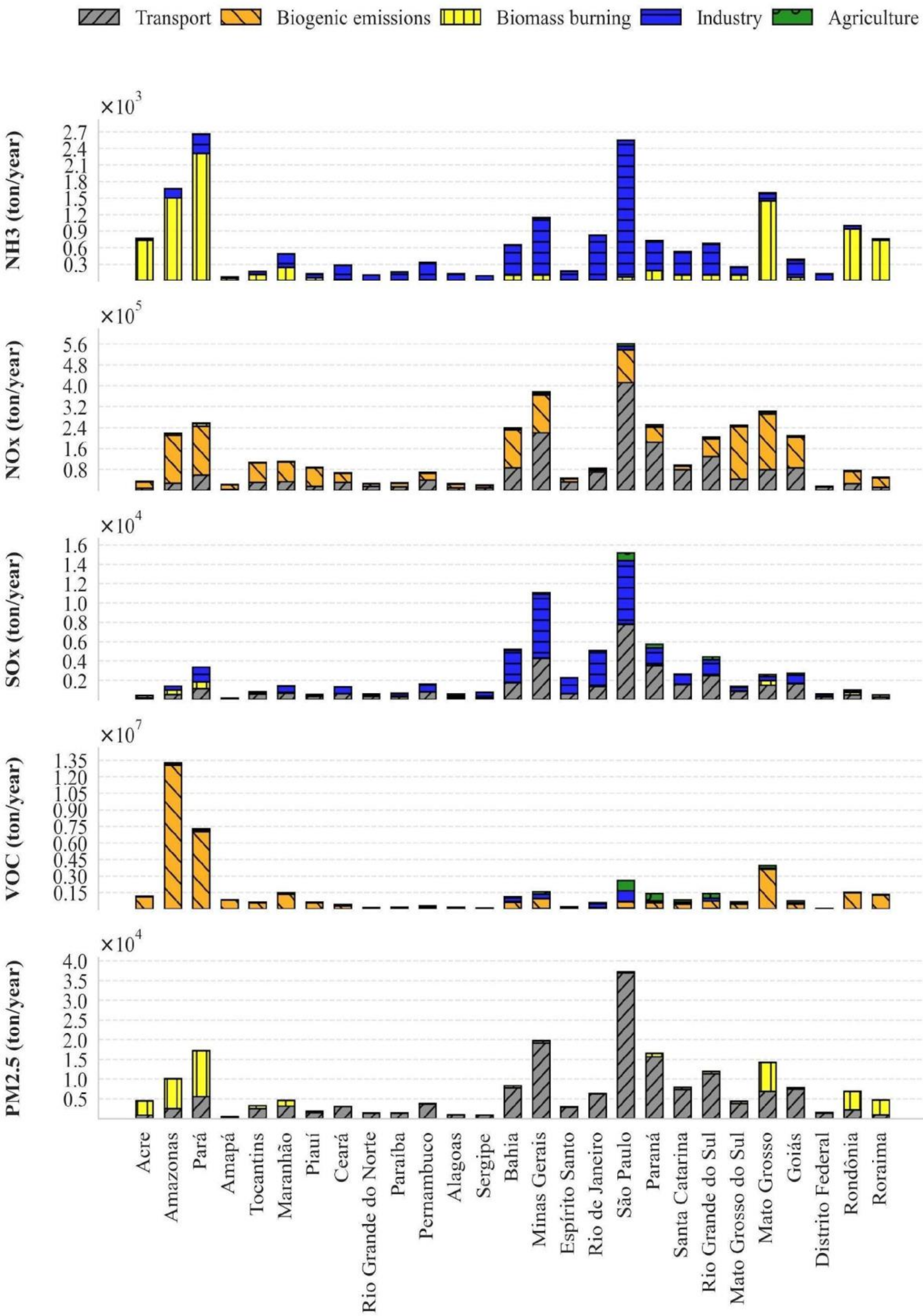
The spatial analysis showed that the states of the Legal Amazon, which include Acre, Amazonas, Pará, Amapá, Tocantins, Mato Grosso, Rondônia, Roraima, and part of Maranhão, stood out for their biogenic and biomass burning emissions. Biogenic emissions were the main contributors to VOC emissions, with Amazonas as the largest contributor (36.3%), followed by Pará (19.5%) and Mato Grosso (10.0%). In addition to VOC, biogenic emissions also made a significant contribution to NO_x, with the largest emitters being Mato Grosso (11.1%), Mato Grosso do Sul (10.4%), Pará (9.8%), and Amazonas (9.5%).

Biomass burning was the second most impactful sector in NH_3 and $PM_{2.5}$ emissions, with Pará, Amazonas, and Mato Grosso again standing out as the top three emitters. The high contributions of biomass burning can be explained by the impact of deforestation and wildfires in this region of Brazil (Cobelo *et al*., 2023).

On the other hand, the states of the Southeast region, particularly São Paulo and Minas Gerais, stood out for their industrial and transportation sectors emissions. São Paulo was responsible for 26.6% and 19.1% of NH_3 and SO_x emissions from the industrial sector, respectively, while Minas Gerais contributed 11.1% and 19.3% of these respective emissions. It is worth noting that the industrial sector was the main emitter of these two pollutants. However, it is important to highlight those agricultural emissions, particularly of NH_3, are likely underestimated in this study. This underestimation makes the results sensitive to updates in the emission inventories used by the InMAP model. Although the findings are consistent with those reported by Godoy et al. (2024), more recent versions of the EDGAR inventory indicate significant agricultural emissions of ammonia that were not captured by the data applied in this research.

The transportation sector, in turn, had a high contribution to $PM_{2.5}$, SO_x, and NO_x emissions, with São Paulo and Minas Gerais occupying the first and second positions in the ranking of the most emitting states, respectively. In both states, contributions to these three pollutants ranged from 12% to 23% of total emissions. These results reflect the high rate of industrialization and the high vehicle density in the Southeast region of Brazil (Kachba *et al*., 2020; Nogueira *et al*., 2021).

Figure 10 - Emissions of PM2.5 primary and precursor gases per sector and state of Brazil



Source: Author

Overall, these results reflect the country's economic and environmental diversity and suggest that while the northern and central-western regions face challenges related to biomass burning, possibly associated with land-use change from forest to agricultural areas (Cobelo *et al*., 2023), the more industrialized Southeast region faces challenges with industrial and transportation sector emissions (Nogueira *et al*., 2021). The results found here are in accordance with Albino (2024), who analyzed different datasets of pollutant emissions in Brazil and observed that the biogenic and industrial sectors are the most polluting in the country.

4.2.2 Mortality associated with Brazilian atmospheric pollutant emissions

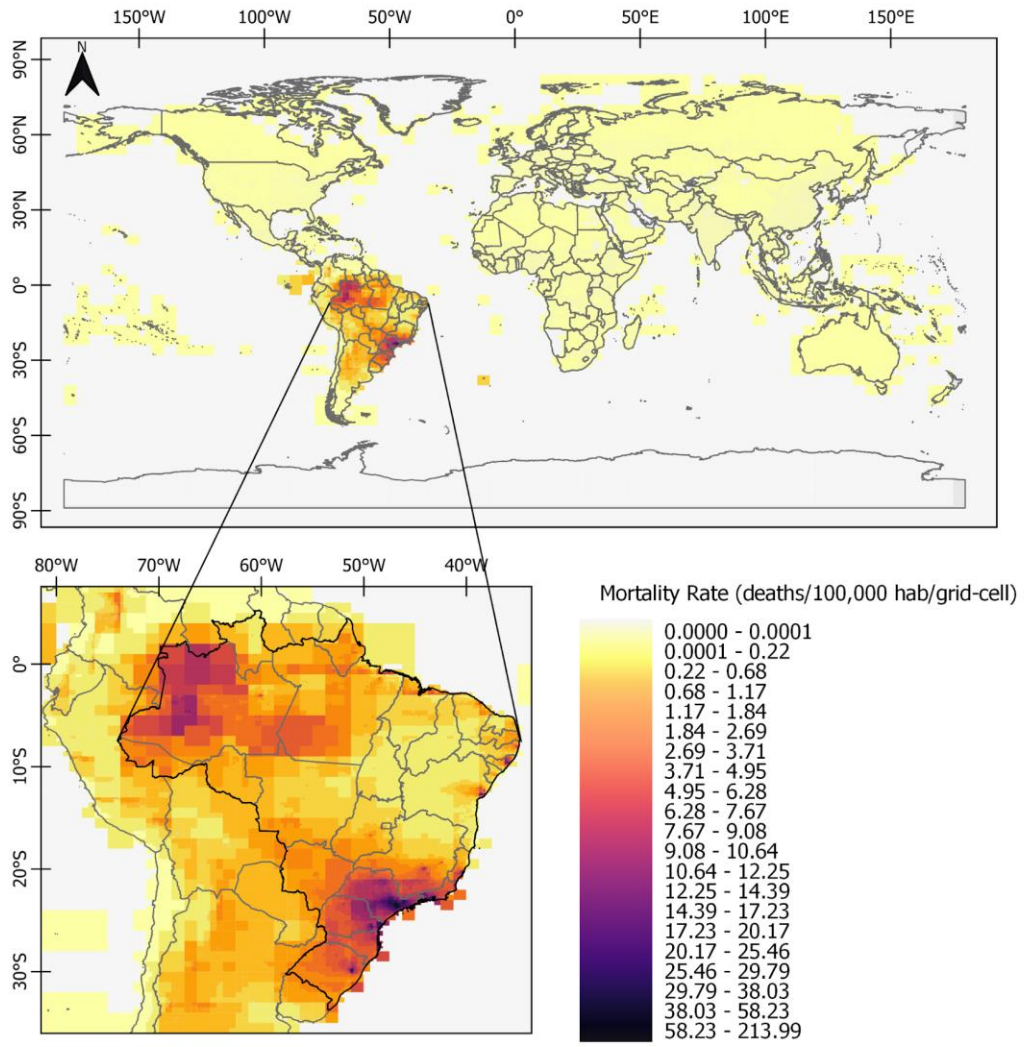
For all the five sectors, the results showed that the variation in PM concentration caused by Brazilian emissions of PM and precursor gases was associated with 31.46 thousand deaths globally. Of these, 94% occurred within Brazilian territory, while cross-border impacts accounted for 6% of the deaths, with 5% occurring in other Latin American countries and 1% in regions outside the continent. Figure 11 shows the spatial distribution of mortality associated with PM and precursor gases emitted in Brazil.

Figure 11 considers the sum of mortality in each grid cell due to emissions of the five pollutant sources from all Brazilian states, and the calculation of the mortality rate based on the population size per grid cell from the InMAP model. The analysis highlighted that the highest mortality rates occurred in the Southeast and South regions of Brazil, with particular attention to the states of São Paulo (35.23 deaths/100,000 inhabitants), Rio de Janeiro (20.6), Paraná (12.9), Rio Grande do Sul (12.26), Santa Catarina (11.95), and Minas Gerais (11.61). Additionally, intermediate mortality rates were observed in Northern Brazil, particularly in the state of Amazonas (6.79), and parts of the Northeastern region, especially in Alagoas (5.32) and Ceará (5.22).

The variation in mortality rates due to PM formation by state is explained by both pollutant emissions and distribution, as well as differences in population density. In the Southeast and South regions, the mortality rates can be especially associated with the high emissions from industrial and transport activities in the Southeast, most notably in the states of Minas Gerais and São Paulo. Emissions from Minas Gerais were associated with approximately 2,400 deaths, 40% of which occurred within the state. The most affected neighboring states were São Paulo (34% of the deaths), Rio de Janeiro (16.6%), Paraná (2.9%), and Santa Catarina (1.25%). Meanwhile, emissions from São Paulo were responsible for around 15.7 thousand deaths, 94.5% of which occurred in the state itself, followed by 2.4% in Paraná and 0.8% in

Santa Catarina. These numbers show that emissions from these two states primarily impacted the Southeast and Southern regions of Brazil.

Figure 11 - Spatial variation in the mortality rate associated with Brazilian emissions of primary PM2.5 and precursor gases



Source: Author

In addition to high emissions, the Southeast region also stands out for having the states with the highest population densities in the country: Rio de Janeiro, with an estimated 366.97 inhabitants per km², and São Paulo, with 178.92 inhabitants per km² (IBGE, 2025). Thus, besides the increase in $PM_{2.5}$ concentration in these regions, caused by industrial and transport emissions, there is a large population exposed to pollution, increasing the potential for health effects.

In Amazonas, the occurrence of mortality is explained by high biogenic emissions and biomass burning within the state and its neighboring states, Pará and Mato Grosso. However, the mortality rate was diluted due to the low population density of 2.53 inhabitants per km²

(IBGE, 2025). Emissions from these three states caused approximately 1,500 deaths, 39% of which occurred in other Latin American countries, mainly due to secondary pollutants such as NH_3, NO_x, and VOC, which tend to cause damage in regions far from the emission sources, because the secondary components are formed downwind and after chemical reactions (Anenberg *et al*., 2014). However, for $PM_{2.5}$ and SO_x emissions, the associated mortalities occurred primarily within the emitting state.

The mortality rate observed in parts of the Northeast region, despite standing out compared to other regions (particularly the Midwest), may be associated with the inflow of pollution from other Brazilian states, along with the high population density in the region. Alagoas, for instance, stands out with the third-highest population density in Brazil, with 112.4 inhabitants per km² (IBGE, 2025).

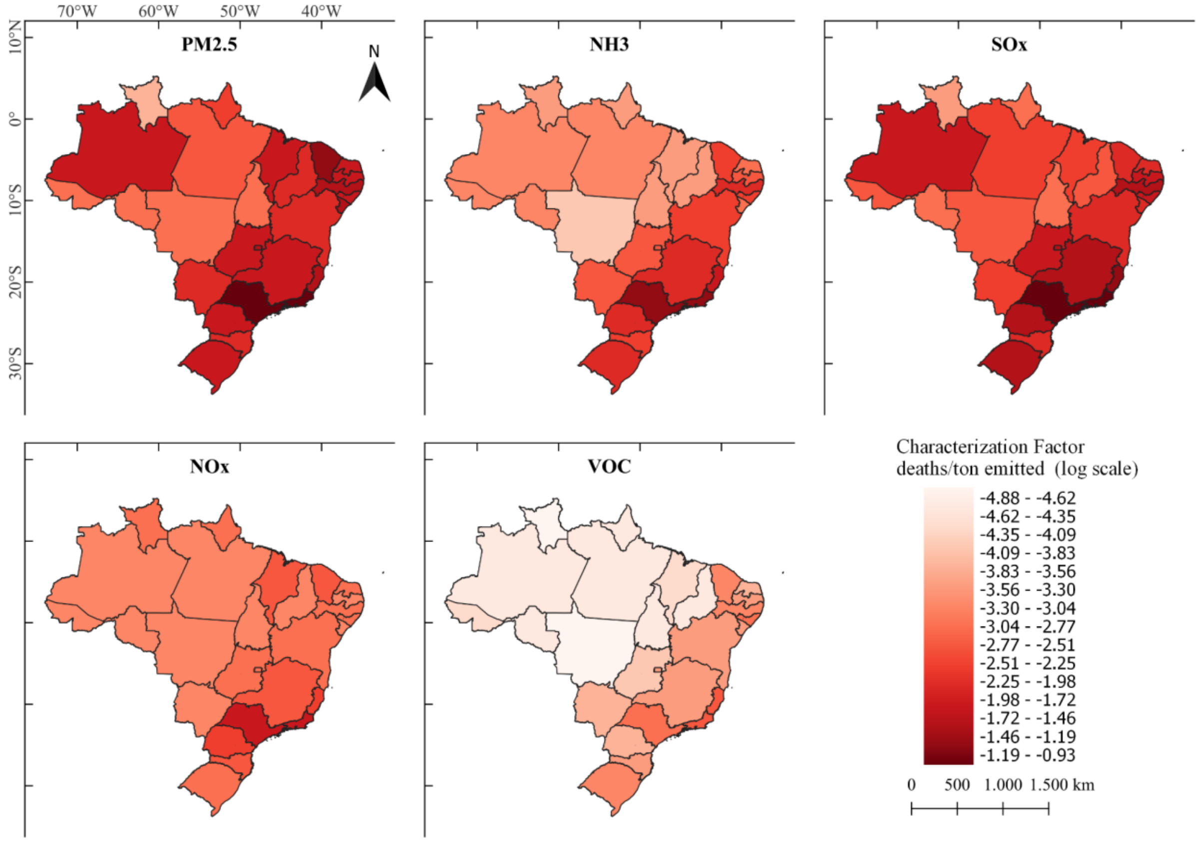
The Southeast region has already been highlighted in the literature due to health problems caused by air pollution in the area. The analysis of mortality estimates attributable to $PM_{2.5}$ by municipality, developed by the Vigiar Panel of the Brazilian Ministry of Health, also highlighted the Southeast region as having the highest estimated mortality, along with high estimates for the Northern region. This pattern is observed throughout the entire analysis period, starting with the 2010–2012 triennium and ending in 2021–2023 (Brazil, 2025).

The spatial distribution of mortality rates observed in this study is consistent with previous research in literature, reinforcing the Southeast and South regions of Brazil as critical areas of concern regarding pollutant emissions and associated health impacts. According to GBD (2019), states at South and Southeast regions had some of the highest death rates due to pollution-related diseases, aligning with the present analysis, which identified São Paulo and Rio de Janeiro as major contributors to mortality due to variation in $PM_{2.5}$ and precursor gases emissions. Similarly, Northeast states, highlighted here with intermediate mortality rates, also appear in national estimates with elevated death rates (GBD, 2019). This validates the relationship between high emissions, population density, and increased health risks, as discussed by Réquia *et al*. (2023), who emphasize the role of socioeconomic and infrastructural disparities in exacerbating exposure and outcomes. The importance of industrial and transport sectors in the Southeast, especially in São Paulo and Minas Gerais, aligns with prior research (Santana *et al*., 2021; Costa *et al*., 2023a), which identifies these sectors as relevant sources of $PM_{2.5}$. In the North, particularly in Amazonas, the health burden from biogenic and fire-related emissions is supported by studies such as Tadano *et al*. (2024), Ye *et al*. (2021) and Wu *et al*. (2023), which connect forest fire pollution to increased hospitalizations and mortality.

4.2.3 Characterization factors for health damage due to Brazilian emissions of PM and precursor pollutants

The division of the total number of deaths associated with air pollutants emitted per region of Brazil by the total pollutant emissions from the respective region, resulted in the CFs, in deaths per ton. The CFs obtained for each Brazilian state for the five pollutants of interest ($PM_{2.5}$, NH_3, SO_x, NO_x, VOC) are presented in Figure 12. The complete list of CFs in deaths, DALY and YLL per kg emitted is presented in Appendix C, as the emission and health effects per region (Table A 9 to Table A 11).

Figure 12 - Characterization factors for $PM_{2.5}$, NH_3, SO_x, NO_x, and VOC per Brazilian state in deaths per ton emitted. Maps are presented in log scale



Source: Author

The analysis of Figure 12 reveals that the CFs for $PM_{2.5}$ and SO_x were the highest among the five pollutants evaluated. The CFs for $PM_{2.5}$ ranged from 2.09×10^{-4} to 9.49×10^{-2} deaths/ton emitted, corresponding to results for Roraima and Rio de Janeiro, respectively. For SO_x, the values ranged from 4.09×10^{-4} to 1.18×10^{-1} deaths/ton emitted, associated with Roraima and São Paulo, respectively. In the sequence, the highest CFs were observed for NH_3, with values ranging from 1.41×10^{-4} deaths/ton emitted in Mato Grosso to 6.38×10^{-2} in São Paulo. For NO_x, the values varied from 5.42×10^{-4} deaths/ton emitted in Rondônia to 1.35×10^{-2} in São Paulo. Lastly, the smallest CFs were recorded for VOC emissions, ranging from 1.32×10^{-5} deaths/ton emitted in Mato Grosso to 2.61×10^{-3} in Rio de Janeiro. These results suggest that emitting one ton of $PM_{2.5}$ has a far greater potential to cause health impacts than emitting one ton of VOC, with up to a 580.73 times difference in Amazonas.

The regional analysis highlighted that the highest CFs were obtained for the states of São Paulo and Rio de Janeiro. Rio de Janeiro had the highest CFs across all states for primary $PM_{2.5}$ and VOC emissions. For NH_3, SO_x, and NO_x emissions, the state also stood out, with CFs only lower than those of São Paulo. The disparity between Rio de Janeiro's CFs and other states reached up to 453 times when comparing $PM_{2.5}$ CFs with Roraima. São Paulo displayed the highest CFs for NH_3, SO_x, and NO_x, ranked second for $PM_{2.5}$, and third for VOC, trailing Rio de Janeiro and Minas Gerais for VOC's CFs. In São Paulo, the CFs were up to 452 times higher than Mato Grosso's for NH_3 emissions. These high CFs for Rio de Janeiro and São Paulo can be attributed to the intense industrial emissions and transportation activities in these regions (section 4.2.1), combined with the large number of deaths associated with atmospheric pollutants in these states (section 4.2.2).

The number of deaths per state had a greater influence on CF results compared to the emission rate. A Pearson correlation analysis between these parameters and the CFs resulted in an average indicator (across the five pollutants) of 0.34 for emission rate and 0.77 for the number of deaths. This result can be associated to the fact that the pollution can have transboundary effects, impacting areas far from the original emission site (Anenberg *et al*., 2014), and also demonstrates that an increase in pollutant concentration in densely populated areas, where more people can be exposed and suffer health effects, tends to be more concerning than an increase in concentration in less populated areas. Population density has been identified as one of the most influential parameters in characterization models for PM formation (Moriguchi and Terazono, 2000; Nishioka *et al*., 2005).

Since linking regionalized CFs with life cycle inventory data in case studies remains a challenge for the LCA community (Mutel *et al*., 2019), and considering the difficulties in mapping the exact location of atmospheric emissions in life cycle inventories, representative CFs were calculated for Brazil's mesoregions (North, Northeast, Southeast, South, and Midwest), as well as national-level CFs. The results are presented in Table 14.

Comparing the state CFs with the CFs calculated for the country, it was observed that more than half of the 27 analyzed Brazilian regions had CFs lower than the national average for $PM_{2.5}$ (22 regions), NH_3 (25), SO_x (24), and NO_x (25). This analysis suggests that the country's result was mainly influenced by states with higher CFs, especially São Paulo, which had a CF up to 3.6 times higher than the national average for $PM_{2.5}$, and Rio de Janeiro, where the CF for NH_3 was 4.8 times greater. Regarding VOC, 13 regions presented CFs higher than the national average. The use of a weighted average can assist in analyzing these results, as it tends to bring the country's CF closer to the CFs of regions with higher emission rates.

Table 14 - Characterization factors for Brazil per geographical emitting region

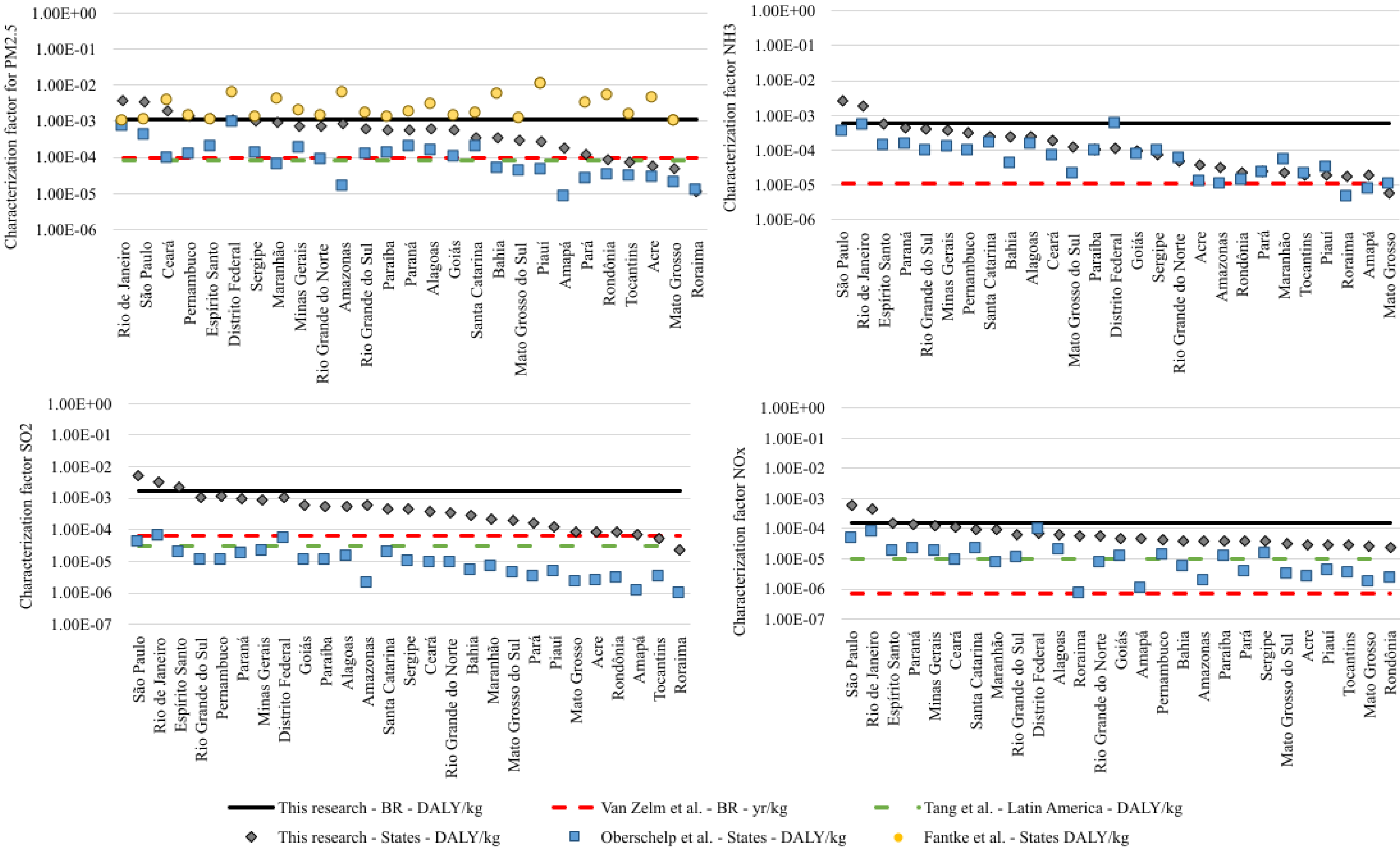
Characterization Factors (deaths/ ton emitted)					
Region	$PM_{2.5}$	NH_3	SO_x	NO_x	VOC
North	5.17×10^{-03}	6.27×10^{-04}	4.14×10^{-03}	8.08×10^{-04}	2.88×10^{-05}
Northeast	1.81×10^{-02}	3.68×10^{-03}	8.93×10^{-03}	1.24×10^{-03}	3.02×10^{-04}
Southeast	6.08×10^{-02}	4.55×10^{-02}	7.55×10^{-02}	9.16×10^{-03}	1.13×10^{-03}
South	1.27×10^{-02}	8.79×10^{-03}	2.06×10^{-02}	2.36×10^{-03}	3.68×10^{-04}
Midwest	5.90×10^{-03}	9.06×10^{-04}	7.86×10^{-03}	8.04×10^{-04}	5.41×10^{-05}
Brazil	2.63×10^{-02}	1.34×10^{-02}	4.05×10^{-02}	3.45×10^{-03}	2.09×10^{-04}

Source: Author

To compare the CF results obtained in this study to other characterization models with data for Brazil, Figure 13 presents a comparative analysis with the highest-rated models from section 4.1 (Fantke *et al*., 2017, 2019; Oberschelp *et al*., 2020; Tang *et al*., 2018; and van Zelm *et al*., 2016), considering a descending ranking of Brazilian states based on the CFs obtained. From those models in section 4.1, we are also consistent to the suggested models by GLAM (2024), which were Fantke et al. (2017, 2019) and Oberschelp et al. (2020). The Fantke *et al*. (2017, 2019) model was included only in the analysis of CFs for primary $PM_{2.5}$, as it did not provide CFs for secondary pollutants. The analysis did not include CFs for VOC emissions since the available characterization models do not currently consider this pollutant in their analyses. It is noteworthy that, to the best of our knowledge, this is the first publication of CFs for VOC emissions for the country.

For a better comparison of the CFs from this research with those from other models, the CFs converted to DALY/kg emitted were used (see section 3.2.3 for considerations on the DALY calculation). It is worth emphasizing that among the models included in the analysis, Van Zelm *et al*. (2016) presented the CFs in YLL/kg emitted, which differs from the indicator used in the other models. However, the authors state that YLL is the main contributor to DALY and that, despite the difference, the results can still be compared. It is also relevant to mention that all set of CFs are using the average factors, the same approach of the set of CFs developed by this research, except for Fantke et al. (2017, 2019), that is considering marginal CFs. However, Fantke et al. (2017, 2019) is the model recommended by GLAM (2024), as well as Oberschelp et al (2020), and because of this they were kept in the comparison.

Figure 13 - Comparison of CFs per Brazilian State and characterization model



Source: Author

Based on Figure 13, it can be inferred that the CFs calculated in this research using the InMAP model fall within the range of CFs calculated for Brazil by models currently available in the literature. However, it is worth noting that the national average value tended to be higher than the average factors calculated by literature.

The differences in CFs between this research and the compared models can be explained by several factors. Firstly, the InMAP model was used to calculate the concentration variation and the number of deaths attributed to this variation—a recent model that had not yet been applied in characterization models with CFs for Brazil. The only application of this model in the field of LCIA was developed by Thind *et al*. (2022) when calculating CFs and other air quality indicators for $PM_{2.5}$ emissions from corn stover harvesting in the United States and its processing for biofuel production. Additionally, this is the first application of national emission inventories in CF calculations. National inventories are recommended for air quality research (Huneeus *et al*., 2020; Albino, 2024), but they are still in the early stages of development in Brazil, making access difficult for model developers until now.

The variation in results can also be explained by differences in the diseases considered when calculating health effects. Van Zelm *et al*. (2016) calculated YLL associated with cardiopulmonary effects and lung cancer, while Fantke *et al*. (2017, 2019) and Oberschelp *et al*. (2020) considered ischemic heart disease, stroke, chronic obstructive pulmonary disease, and lung cancer in adults, as well as lower respiratory infections in children. In contrast, this research considered all health effects, following the calculation of deaths throughout InMAP running, which may have resulted in higher CF values. It is important to highlight that there are limitations in calculating health effects in this study, as a generalized equation (Equation 5) was used instead of more specific models for Brazil or its regions. It considers the total deaths due to increase of $PM_{2.5}$ concentration not specifying precursor pollutant, region, or specific health effects.

Given the differences in CFs, within the context of this research, it is relevant to analyze how the results and conclusions of a LCA case study can be influenced by the choice of the CF set applied. Therefore, section 4.3 presents the results of the regionalized sensitivity analysis developed.

4.2.4 Uncertainty of characterization factors

Following the Pedigree matrix developed by Qin et al. (2020), the uncertainty analysis for the set of CFs developed by this research was:

1. Reliability of underlying Science: Moderately low uncertainty (U=1.11), which means that the used model is based on peer-reviewed results. This score was selected because the calculation was based on Thind et al. (2020)'s approach, using the InMAP model (Thakrar et al., 2022) for pollutant distribution, and all input data were collected from published papers or recognized databases, such as Hoinaski, Will, Ribeiro (2024) and GBD (2022). This sub-criterion will be classified as having low uncertainty (U = 1) upon the publication of the characterization factors.
2. Model completeness: Moderately low uncertainty (U=1.08), because the results of the CFs dataset have relatively high coverage of the CFs for all elementary flows in an LCI. This score reflects the good coverage of pollutants but was penalized by the lack of differentiation between low and high population density (as recommended by Mutel et al., 2019 for this impact category) and the lack of a factor for indoor environments. To minimize the uncertainty of this sub-criterion, future research can focus on provide separate CFs using the same approach for rural and urban archetypes and for indoor environment.,
3. Temporal specification: Moderate uncertainty (U=1.12), because the model is a steady-state model that considers some dynamic components. This score can be justified by the InMAP model characteristics, as it is a steady model but with annual average parameters obtained by considering the annual variation of data (Thakrar et al., 2022). Better uncertainty scores can be achieved by including dynamic processes in the factor calculation.
4. Geographical specification: Low uncertainty (U=1.00), because the model is spatially explicit for Brazil, with a high level of spatial detail, especially in high-density population areas.
5. Input characteristics: Moderate uncertainty (U=1.14), considering that the CFs were calculated using proxy values based on some statistical representativeness as input parameters. This score reflects the equation used to calculate deaths in the InMAP model, as it was developed with representative proxies for the United States and was used here to calculate deaths under Brazilian emission conditions. However, it is important to highlight that all other parameters were statistically representative proxies for Brazil. Thus, to minimize the uncertainty associated with mortality data, it is recommended to conduct a more thorough investigation of the health effects related to PM exposure, using an effect equation based on Brazilian data rather than relying on the mortality equation provided in the InMAP model.

This analysis shows that the CFs present low to moderate uncertainty for Brazil, and the geometric standard deviation resulted in 1.8. This value is recommended for use in LCA studies interested in developing uncertainty analysis of impact results, including CF uncertainty.

4.3 REGIONALIZED LCA SENSITIVITY ANALYSIS

The regionalized sensitivity analysis was developed by evaluating four case studies of dairy cattle production in different regions of Brazil through LCA, including: (1) a confined system in the Paraíba Valley (São Paulo), with manure management through composting with sawdust; (2) a confined system in the Campos Gerais region (Paraná), with manure treatment in lagoons and biofertilizer production; (3) a semi-confined system in the Campos Gerais region (Paraná), with manure also treated in lagoons and biofertilizer production; (4) a semi-confined management system in the Zona da Mata region (Minas Gerais), with manure being reused as biofertilizer or deposited in grazing areas.

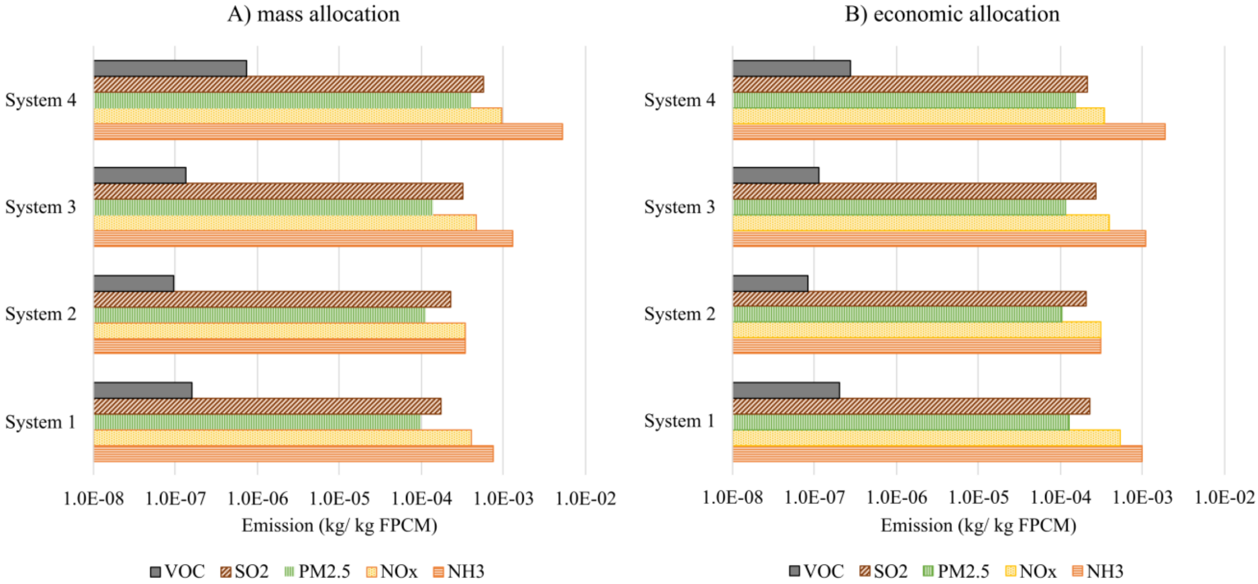
The results are presented following the stages of a traditional LCA. This section begins with the life cycle inventory analysis focused on primary PM emissions and precursor pollutants (section 4.3.1). Then, the LCIA stage is presented for the damage category of health impacts due to PM formation, including a sensitivity analysis of the results in relation to the different characterization models selected for use (section 4.3.2). The sensitivity analysis concludes with the results of the LCA interpretation stage, including a correlation analysis (section 4.3.3).

It is worth noting that the text presented here is based on the previous publication by Giusti *et al*. (2023), the methodology and results were partially presented here as permitted by Springer Nature publisher, with the main differences being the inclusion of VOC emissions from production systems and the application of the CFs calculated in this research and presented in section 4.2.2.

4.3.1 Life cycle inventory analysis

Figure 14 presents a comparison of $PM_{2.5}$, NO_x, NH_3, SO_x, and VOC emissions among the four dairy systems evaluated in the case study.

Figure 14 - Life cycle inventory of milk production systems considering the mass (A) and economic (B) allocation approach



Source: Author

Among the evaluated systems, System 4 (semi-confined in Zona da Mata) stood out as the highest emitter of all atmospheric pollutants included in the analysis. This result may be associated with the intensive use of nitrogen fertilizers in pasture management, which, in this system, is a key input for cattle feed. This factor led to high pollutant emissions, particularly the release of ammonia into the atmosphere.

On the other hand, System 3 (semi-confined in Campos Gerais), despite also incorporating pasture into the animal diet, demonstrated a fertilizer consumption 24% lower than that of System 4, reducing the associated emissions.

Conversely, Systems 1 and 2, which are confined production systems, showed the lowest pollutant emission rates, as they do not rely on pastures for animal feed. However, all analyzed systems exhibited relatively consistent variations in SO_2, NO_x, $PM_{2.5}$, and VOC emissions, a phenomenon attributed to the combustion of fossil fuels in heavy machinery, such as agricultural tractors, and electricity generation.

4.3.2 Life cycle impact assessment - sensitivity analysis

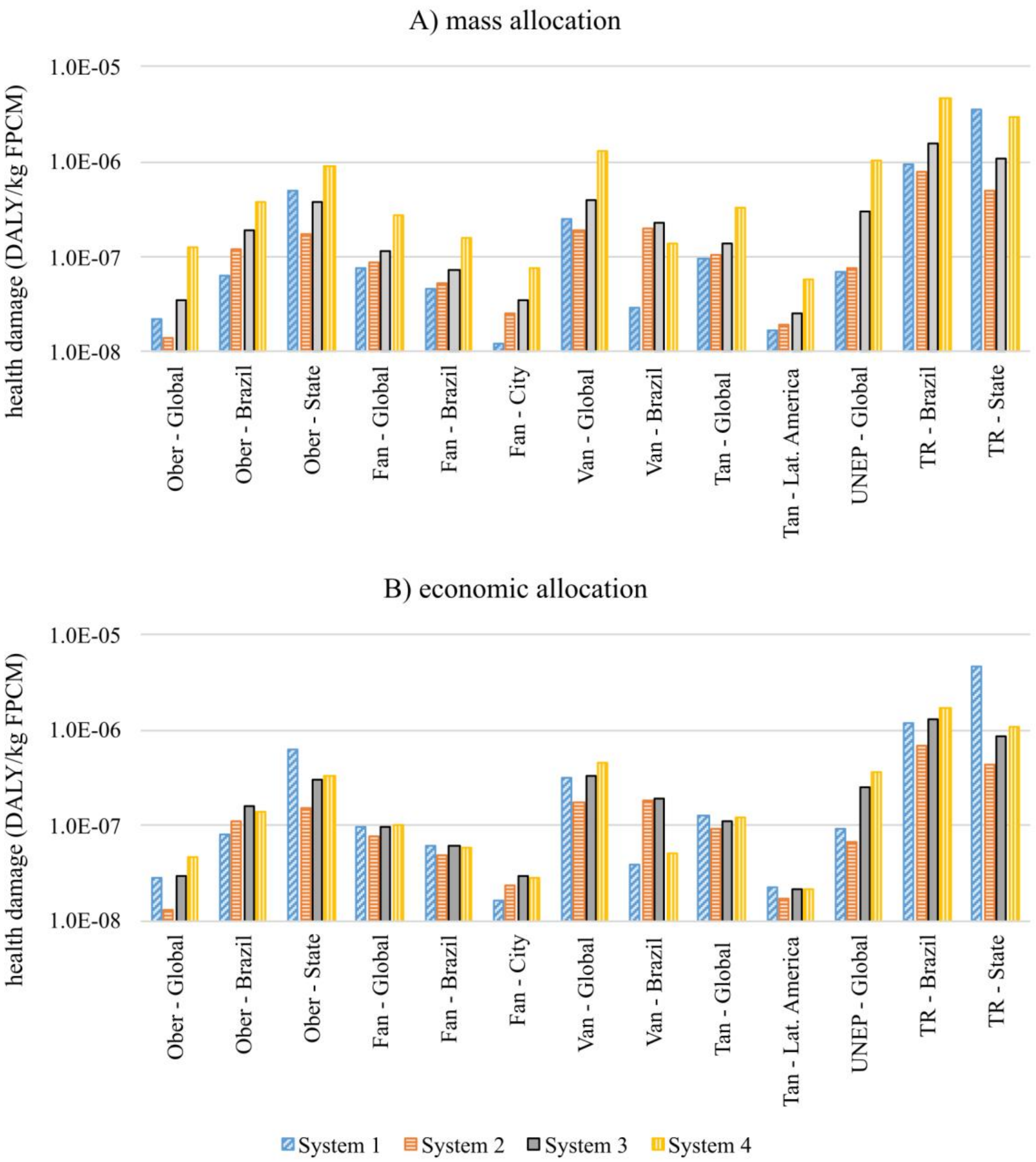
The LCIA stage was developed with the primary objective of assessing the sensitivity of the case study results and conclusions by using different sets of CFs. For this purpose, the characterization models with the highest scores in the recommendation assessment (section 4.1) were used, namely: Fantke *et al*. (2017, 2019), Oberschelp *et al*. (2020), and Van Zelm *et al*. (2016). Additionally, the analysis includes the model by Tang *et al*. (2018), which also received a high rating in the recommendation assessment and provides CFs for Latin America, as well as the global average characterization factors recommended by the Life Cycle Initiative (UNEP and SETAC, 2016).

Below is a brief characterization of the selected models, reflecting how the results were obtained:

- Van Zelm *et al*. (2016): Uses a geographical approach to calculate global CFs for 56 regions worldwide, including Brazil. This model provides CFs for primary $PM_{2.5}$, NH_3, NO_x, and SO_2 emissions and is available in LCA software within the ReCiPe 2016 method (Huijbregts *et al*., 2017).
- Fantke *et al*. (2017, 2019): Utilizes a hybrid approach for CF calculation, considering geographical and archetypes variation, providing factors for global average, for countries (including Brazil), and for 3,448 cities worldwide, of which 126 are in Brazil. For each geographic region, the model provides factors for urban, rural, indoor, and outdoor archetypes. Only $PM_{2.5}$ emissions were modeled, and this set of CFs is not yet available in any LCIA method.
- Oberschelp *et al*. (2020): Uses a geographical approach to calculate CFs for global average, for countries (including Brazil), and for regions (including Brazilian states). The model provides factors for $PM_{2.5}$, NH_3, NO_x, and SO_2 emissions. This model has not yet been implemented in LCIA methods.
- Tang *et al* (2018): Employs a geographical approach to provide CFs for primary $PM_{2.5}$, NO_x, and SO_x emissions at the global and continental levels (including Latin America). This set of factors can be accessed through the LCIA method LIME 3, available in LCA software.
- UNEP and SETAC (2016): Provides the recommendation of the Life Cycle Initiative for CF in LCA studies. The recommended values are global average factors divided into urban, rural, indoor, and outdoor archetypes, with variations based on chimneys' chimneys' emission height. The factors were recommended for $PM_{2.5}$, NH_3, NO_x, and SO_x emissions. The recommended factors have not yet been implemented in LCIA methods.

The implementation of these CF sets in the case study was conducted to compare them with the results obtained using the CFs calculated in this research (section 4.2.2). Figure 15 presents the impact results for the four dairy production systems using each selected characterization model for analysis, considering both mass-based and economic allocation.

Figure 15 - Comparison of LCIA results for the four dairy production systems considering mass (A) and economic (B) allocation against different sets of characterization factors



Legend: Ober - Oberschelp *et al*. (2020); Fan - Fantke *et al*. (2017, 2019); Van - Van Zelm *et al*. (2016); Tan - Tang *et al*. (2018); UNEP - UNEP and SETAC (2016); TR - This Research.

Source: Author

The analysis of Figure 15 highlights that the choice of characterization model can influence case study results in terms of total impact value, a finding also observed by Chen *et al*. (2021). This reinforces that comparisons between systems should not be made using different CF datasets.

Considering mass-based allocation, most of the CF sets applied in the case study identified System 4 as the most impactful, which is justified by the fact that System 4 exhibited the highest pollutant emissions compared to the other systems. Additionally, only 50% of the manure produced in System 4 was converted into biofertilizer, leading to a greater share of the system's impacts being allocated to milk production.

Exceptions to this trend were the results obtained using the Van Zelm *et al*. (2016) model with country-level CFs, which indicated Systems 3 and 2 as the most impactful, and the state-level CFs calculated in this research, which pointed to System 1 as the most impactful. In the case of Van Zelm *et al*. (2016), the main reason was the prominence of NH_3 emissions in Systems 2 and 3, coupled with the fact that this model assigns higher CFs to NH_3 compared to other pollutants. For the regional CFs developed in this research, the values were higher for São Paulo, where System 1 is located, than for Paraná and Minas Gerais, where the other systems are situated. This result underscores that the location of an emission is a key factor in determining the magnitude of the calculated environmental impact. The regionalization of CFs captures significant spatial variations, demonstrating that impact characterization can differ substantially depending on emission location, especially when CFs were calculated using national data.

With economic allocation, the results were more influenced by the choice of characterization model, as this procedure reduced the contribution of milk in all evaluated systems compared to meat—a byproduct with higher commercial value but lower mass contribution (see Figure 7). However, the reduction in contribution was not proportional across systems. For instance, in System 2, the milk impact contribution decreased from 34.5% to 26.3% when switching from mass-based to economic allocation, whereas in System 4, this contribution dropped from 98% under mass allocation to 45.2% under economic allocation.

This result contradicts the findings of Cherubini *et al*. (2018) that evaluated LCA sensitivity for allocation procedure selections in pork production including four approaches: case-by-case, economic, mass, and substitution method. The authors did not identify any variation in the ranking of the evaluated systems concerning the allocation approach selection per se. However, the authors did not include the human health category due to PM emissions, and this difference may also be related to the specific context of the system or sector under analysis, as well as the level of influence that the choice of allocation procedure has on the systems. The results of this research reinforce that the decision regarding the allocation method can significantly affect case study results and create substantial discrepancies in identifying the most impactful system, particularly when different CF sets are used for impact calculations.

Moreover, beyond the significant variations in the impact results of the dairy production systems, changes in the CF dataset also altered the hotspot analysis. Table 15 presents the substance with the highest attributed impact in each system for each considered CF dataset, considering the results obtained using mass allocation. The results obtained using economic allocation were equivalent to results of mass allocation, which means that the allocation procedure did not influence the hotspots analysis.

Table 15 - Main hotspot per analyzed system using different datasets of CFs

	System 1		**System 2**		**System 3**		**System 4**	
CFs dataset	**Hotspot**	**Contr (%)**	**Hotspot**	**Contr (%)**	**Hotspot**	**Contr (%)**	**Hotspot**	**Cont. (%)**
Ober. - Global	NH_3	69.7%	NH_3	47.7%	NH_3	73.3%	NH_3	80.9%
Ober. - Brazil	NH_3	78.2%	NH_3	87.8%	NH_3	90.1%	NH_3	87.5%
Ober. - State	NH_3	79.1%	NH_3	75.8%	NH_3	85.5%	NH_3	87.1%
Fan. - Global	$PM_{2.5}$	100%	$PM_{2.5}$	100%	$PM_{2.5}$	100%	$PM_{2.5}$	100%
Fan. - Brazil	$PM_{2.5}$	100%	$PM_{2.5}$	100%	$PM_{2.5}$	100%	$PM_{2.5}$	100%
Fan. - City	$PM_{2.5}$	100%	$PM_{2.5}$	100%	$PM_{2.5}$	100%	$PM_{2.5}$	100%
Van - Global	NH_3	49.4%	$PM_{2.5}$	21.5%	NH_3	53.2%	NH_3	65.9%
Van - Brazil	SO_2	37.7%	NH_3	87.1%	NH_3	85.0%	NH_3	43.9%
Tan - Global	$PM_{2.5}$	16.7%	$PM_{2.5}$	52.9%	$PM_{2.5}$	49.5%	$PM_{2.5}$	59.7%
Tan - Latin America	$PM_{2.5}$	30.1%	$PM_{2.5}$	35.2%	$PM_{2.5}$	37.9%	$PM_{2.5}$	54.6%
U&S - Global	$PM_{2.5}$	63.6%	$PM_{2.5}$	67.9%	NH_3	68.0%	NH_3	79.5%
TR - Brazil	NH_3	47.7%	SO_2	51.4%	NH_3	48.2%	NH_3	64.8%
TR - State	NH_3	58.8%	SO_2	45.3%	NH_3	56.2%	NH_3	67.9%

Legend: Ober – Oberschelp *et al*. (2020); Fan – Fantke *et al*. (2017, 2019); Van – Van Zelm *et al*. (2016); Tan – Tang *et al*. (2016); U&S – UNEP and SETAC (2016); TR – This Research

Source: Author

Table 15 shows that, using the models by Fantke *et al*. (2017, 2019) and Tang *et al*. (2018), $PM_{2.5}$ emissions were the most impactful across all four systems, whereas for Oberschelp *et al*. (2020), Van Zelm *et al*. (2016), and the CFs calculated in this study, ammonia emissions stood out in most systems.

When using the model developed by Fantke *et al*. (2017, 2019), $PM_{2.5}$ emissions accounted for 100% of the human health impact recorded in the four systems. However, this model only provides CFs for $PM_{2.5}$, meaning that the impacts of emissions from other pollutants could not be assessed. As a result, using Fantke *et al*. (2017, 2019) does not allow for a complete hotspot analysis, and the impacts tend to be underestimated due to not considering all necessary environmental aspects.

In the case of Tang *et al*. (2018), although the model includes CFs for PM precursors, it does not consider NH_3 as an elementary flow, which was the most impactful substance according to impact calculations using the other models. Compared to Oberschelp *et al*. (2020) and Van Zelm *et al*. (2016), these models identified $PM_{2.5}$ emissions as the second most significant impact driver in several systems. In Oberschelp *et al*. (2020), $PM_{2.5}$ contributed, on average, 15% of the impacts in all systems, while in Van Zelm *et al*. (2016), the average contribution of $PM_{2.5}$ was 25%.

For Oberschelp *et al*. (2020), NH_3 was the hotspot pollutant across all systems, regardless of the regionalization level of the CFs, contributing between 47.7% (System 2 with global CFs) and 90.1% (System 3 with CFs for Brazil). In this model, the CFs for $PM_{2.5}$ were the highest — about 53% higher than those for NH_3, which in turn were around 600% and 625% greater than those for SO_2 and NO_x, respectively. Furthermore, all systems showed higher NH_3 emissions compared to other pollutants, especially Systems 3 and 4, which also explains why this pollutant was the main hotspot in these two systems across all other CF sets that included NH_3 — namely Van Zelm *et al*. (2016), UNEP and SETAC (2016), and those developed in this research.

For Systems 1 and 2, there was higher variation in the hotspot depending on the characterization model used. This is possibly due to the fact that the difference in emission rates between pollutants was smaller than that observed in Systems 3 and 4, reducing the influence of the inventory and thus increasing the sensitivity of results to the choice of characterization model.

The use of CFs recommended by UNEP and SETAC (2016) indicated $PM_{2.5}$ emissions as the hotspot in Systems 1 and 2, due to the factors for this pollutant being significantly higher — at least 1000% greater than for other pollutants. In the case of Van Zelm *et al*. (2016), variation in hotspots was observed depending on the level of CF regionalization. At both levels, $PM_{2.5}$ had the highest assigned values, followed by factors for SO_2, NH_3, and NO_x; however, the difference between CFs for NH_3 and SO_2 was greater at the Brazil level.

Finally, the CFs developed in this study indicated NH_3 as the hotspot in System 1 and SO_2 as the hotspot in System 2. In System 1, higher emissions of NH_3 compared to other pollutants had a greater influence on the hotspot analysis. In System 2, emissions of NH_3, NO_x, and SO_2 showed less variation among them, and the CF for SO_x (used to account for SO_2 impacts) was three times higher than for NH_3 and 1.5 times higher than for $PM_{2.5}$.

Consistent with the findings of this sensitivity analysis, Chen *et al*. (2021) and Wang *et al*. (2020) also pointed to differences in substances covered by the models as a reason for variation in LCIA results when using different methods. Four main reasons can be identified for the variation in results: (1) differences in system inventories, (2) substances covered by the models, (3) variations in geographic context, and (4) variations in characterization factors, which was also observed in the studies by Chen *et al*. (2021) and Wang *et al*. (2020). Variations in the CFs, in turn, can be explained by the different structures of the characterization models (Wang *et al*., 2020).

4.3.4 Interpretation - correlation analysis

Given the differences observed in the results of the four milk production systems with respect to the choice of characterization model, both in terms of absolute human health impact values and the flows identified as hotspots, it becomes relevant to understand whether the choice between one model or another can affect the identification of which milk production system is the most impactful.

This is important because one of the main uses of LCA is to compare production systems in order to identify the one with the lowest impact, as shown in Table 2 (Section 2.2.1). Accordingly, Table 16 presents the Spearman correlation results, which indicate the ranking correlation of the systems under different sets of CFs.

Table 16 - Spearman correlation for system rankings by total human health impacts across characterization models

Model - Geographical scope	1 Global	1 Brazil	1 State	2 Global	2 Brazil	2 City	3 Global	3 Brazil	4 Global	4 Latin America	5 Global	6 Brazil	6 State
1 Global	1.00												
1 Brazil	0.74**	1.00											
1 State	0.62***	0.14ns	1.00										
2 Global	0.88*	0.81*	0.52ns	1.00									
2 Brazil	0.79*	0.86*	0.48ns	0.9*	1.00								
2 City	0.74**	1.00	0.14ns	0.81*	0.86*	1.00							
3 Global	1.00	0.74**	0.62***	0.88*	0.79*	0.74**	1.00						
3 Brazil	-0.02ns	0.60***	-0.50ns	0.24ns	0.38ns	0.60***	-0.02ns	1.00					
4 Global	0.86*	0.69**	0.71**	0.95*	0.9*	0.69**	0.86*	0.12ns	1.00				
4 Latin America	0.81*	0.74**	0.6***	0.98*	0.93*	0.74**	0.81*	0.21ns	0.98*	1.00			
5 Global	0.98*	0.81*	0.52ns	0.93*	0.83*	0.81*	0.98*	0.12ns	0.88*	0.86*	1.00		
6 Brazil	1.00	0.74**	0.62***	0.88*	0.79*	0.74**	1.00	-0.02ns	0.86*	0.81*	0.98*	1.00	
6 State	0.43ns	-0.21ns	0.90*	0.26ns	0.17ns	-0.21ns	0.43ns	-0.74**	0.33ns	0.33ns	0.31ns	0.43ns	1.00

* Significant at 1% probability
** Significant at 5% probability
*** Significant at 10% probability
ns: not significant

Legend: (1) Oberschelp *et al*. (2020); (2) Fantke *et al*. (2017, 2019); (3) Van Zelm *et al*. (2016); (4) Tang *et al*. (2018); (5) UNEP and SETAC (2016); (6) this research.

Source: Author

The highest correlation indicators (r_s) were observed for CF datasets with global geographical coverage. For example, Oberschelp *et al*. (2020) at the global level showed a perfect correlation ($r_s = 1$) with Van Zelm *et al*. (2016) global; Fantke *et al*. (2017, 2019) showed very high correlation indicators when compared with Van Zelm *et al*. (2016) global, Tang *et al*. (2018) global and for Latin America, and UNEP and SETAC (2016) ($r_s \geq 0.9$). The correlation indicator between Van Zelm *et al*. (2016) global and UNEP and SETAC (2016) was equal to 0.98. This indicates that at broader geographical levels, the models show good convergence and tend to provide similar rankings for the evaluated production systems.

On the other hand, increasing the spatial resolution led to higher variation in the ranking of systems, reducing the correlation indicators. For instance, the average correlation indicator for Oberschelp *et al*. (2020) at the global level was 0.73; at the country level, it dropped to 0.64; and at the Brazilian state level, the average dropped to 0.45. Interestingly, the lowest correlation indicators for Oberschelp *et al*. (2020) at the Brazilian level were observed when the correlation was calculated against Oberschelp *et al*. (2020) at the state level and the CF set from this study also at the state level. In other words, using the same characterization model significant changes were observed in system rankings varying the geographic scale.

Van Zelm *et al*. (2016) showed a similar pattern: at the global level, the average correlation with the other models was 0.73, while at the state level, the average dropped to 0.08, indicating high variability in rankings when compared both with global models and regionalized models.

The CF dataset developed in this study followed the same behavior observed in the other characterization models used in the sensitivity analysis. The average CFs for the country showed good correlation with the other models (average $r_s = 0.73$), with very high correlation ($r_s > 0.9$) with Oberschelp *et al*. (2020), Van Zelm *et al*. (2016), and Tang *et al*. (2018), all at the global level. A moderate correlation was observed with Oberschelp *et al*. (2020) at the state level ($r_s = 0.62$), and an insignificant correlation was found with Van Zelm *et al*. (2016) at the national (Brazil) level, which had the lowest correlation indicators in the entire analysis. All other correlation indicators were very high ($0.7 < r_s < 0.9$).

In the case of the CF dataset developed in this study at the level of Brazilian states, the correlation analysis revealed interesting results. Overall, the correlation indicators were either insignificant ($0 < r_s < 0.3$) or low ($0.3 < r_s < 0.5$) with almost all other CFs datasets in the analysis. The only exception was the correlation with the Oberschelp *et al*. (2020) model (recommended by GLAM (2024) as spatialized model) also at the Brazilian state level, which in turn, showed a high correlation ($r_s = 0.9$) only with the state-level CFs from this study.

This result highlights the consistency of the CFs developed in this research in relation to those available in the literature and reinforces the importance of using regionalized CFs in case studies of LCA that address the damage category of human health due to PM exposure. Using generic factors can distort the ranking of more and less impactful production systems, potentially leading to inaccurate conclusions. The use of regionalized factors for the states of the country yielded a ranking different from the other factor sets but aligned with the rankings obtained by different models using the same spatial scale.

Dekker *et al*. (2020) evaluated the ranking of more than 100 food production systems using global and regionalized (Netherlands-specific) factors from the ReCiPe 2016 method, which is based on the Van Zelm *et al*. (2016) model for human health impact from PM (Huijbregts *et al*., 2017). The authors did not observe any change in the ranking of systems with varying geographical contexts. However, in that study, all emissions were associated with CFs specific to the Netherlands, regardless of their actual origin—a methodological decision identified by the authors as a source of uncertainty.

In contrast, the present study associated elementary flows with defined national origins to CFs specific to the country of emission. When applying Brazilian CFs to all national emissions, ignoring the specific locations of some flows, the correlation coefficient between Van Zelm *et al*. (2016) national and global factors would be equal to one, indicating identical rankings among systems and aligning with Dekker *et al*.'s (2020) findings. This result further emphasizes the importance of regionalization and suggests that it should be applied throughout the entire life cycle of production systems.

4.4 RESEARCH IMPLICATIONS

Proper management of air pollution is essential for sustainable development and for achieving the United Nations Sustainable Development Goals (SDGs), being directly related to SDG 11: “Make cities and human settlements inclusive, safe, resilient and sustainable,” which includes as one of its targets “to reduce the adverse per capita environmental impact of cities, including paying special attention to air quality and municipal and other waste management” (UN, 2023a)

Since the main emissions of air pollutants are associated with anthropogenic activities, LCA can support the management of emissions and their associated impacts. In this context, this research becomes relevant as, for the first time (to the author’s knowledge), CFs for the health effects category due to PM concentration were calculated for Brazil using national pollutant emission inventories. Furthermore, Brazilian CFs for VOCs were obtained for the first time. Internationally, the only research calculating CFs for VOC was the study of Thind *et al*. (2022), but for a specific emission sector in the United States. It is important to emphasize that the results of this study are sensitive to the emission inventories used. In particular, emissions from the agricultural sector may be underestimated in the current datasets, which can affect the CFs, especially for ammonia.

The full list of CFs calculated in this study, in terms of DALYs, YLLs and deaths per kilogram of emission, is available in Appendix C, for the country, mesoregion and state level. The need to run the InMAP model for each desired geographic level limited the research to obtaining CFs at the state level. To reduce the geographic scale of the CFs, it would be necessary to significantly increase the number of models runs. For example, to obtain CFs at the city level in Brazil, the model would need to be run for each city, resulting in over 5,000 runs. Same procedure would be necessary to obtain CFs considering the emission height as a parameter. However, according to Bulle et al. (2019), the differences among regions are more relevant than the differences among emission heights.

The CFs obtained are suitable for application in Brazilian LCA studies conducted in Brazil, demonstrating consistency with results obtained from existing models. Although they present higher values than other Brazilian models—which underscores the importance of not combining them with CFs from different methodologies—the national average CFs maintained patterns similar to those of global models. Additionally, the state-level CFs were consistent with those from Oberschelp *et al*. (2020), highlighting the validity of the data. The case study also emphasized that the use of regionalized CFs is essential to ensure greater accuracy when comparing production systems across different regions of the country.

To understand the strengths and limitations of the set of CFs presented here, a recommendation assessment following the methodology outlined in Section 3.1 of this study was applied, considering the criteria and sub-criteria defined in RAICV (2019), as shown in Table 5 to Table 9. Table 17 and Table 18 present the scores referring to the inhalation and effect stages, respectively.

Based on the scores presented in Table 17 and Table 18, it can be observed that the set of CFs calculated in this study achieved the highest score for the inhalation stage (score = 4.6) compared to all other models evaluated in Section 4.1, even outperforming Oberschelp *et al*. (2020) and Fantke *et al*. (2017, 2019), which scored 4.54 and 4.37, respectively. Compared to Oberschelp *et al*. (2020), the CFs from this study received a lower score for the sub criterion “geographic coverage,” as they do not account for emissions outside Brazilian territory or calculate factors for locations beyond the country’s borders. On the other hand, these CFs received higher scores for "spatial differentiation," since the InMAP model can achieve fine-scale resolution in densely populated areas (below 10×10 km), and for "transparency and accessibility," as Oberschelp *et al*. (2020) was hindered by the difficulty of reproducing the model.

Concerning Fantke *et al*. (2017, 2019), their model was superior to the CFs from this study regarding the "geographic coverage" sub criterion, since it is a global model, and also in "transparency and accessibility", as Fantke *et al*. (2017, 2019) facilitates accessibility and reproducibility by providing CF calculations and all parameters in an Excel spreadsheet. On the other hand, the CFs presented here used more recent data and covered primary $PM_{2.5}$ and more than three precursor pollutants, resulting in higher scores for the subcriteria of "spatial resolution" and "elementary flows."

Table 17 - Score for intake step of CF dataset obtained in this research using the RAICV (2019) methodology

Criteria	Sub criteria	Score	Justification
	Geographic coverage	3	Presents CFs for national and regional regions in Brazil
	Spatial differentiation (geographic)	5	InMAP varies the grid-cell size according to population density, from 13 km² for urban density areas to 61,503 km² for low population regions.
	Temporal resolution	5	All data and tools used were published after 2015
	Coverage of elementary flows	5	FCs were calculated for PM2.5 and more than 3 precursor gases
Scope	**Scope score**	**4.5**	**-**
	Considered by a LCIA method?	3	CFs are not available in a LCIA, but it can be considered a recent dataset of CFs
	Cause-and-effect chain	5	The cause-and-effect chain was well described in the methodology
	Model transparency and accessibility (calculation procedure and input data)	4	The accessibility of inventories can be hampered by the adaptation of available inventories to be used in the InMAP model. However, all other data and also InMAP model are available for free
	Clarity of variables and mathematical model's description	5	All mathematical equations directly applied were described with their parameters and units
	Clarity of equations and parameters used for modelling	5	All mathematical equations directly applied were described with their parameters and units
Scientific robustness	**Scientific robustness score**	**4.4**	-
	Is there IF for Brazil?	5	CFs are specific for Brazil
	Brazilian spatial differentiation (geographic)	5	the factors were calculated considering the same grid-scall of InMAP model
	Is the available iF for Brazil appropriate for its singularity?	5	Yes, factors were calculated per state, meso-region and the country, using specific data for the country
Availability for Brazil	**Factors for Brazil score**	**5**	**-**
Final score		**4.6**	**-**

Source: Author

Table 18 - Score for effect step of CF dataset obtained in this research using the RAICV (2019) methodology

Criteria	Sub criteria	Score	Justification
	Demographic representativeness	5	The effects were calculated specific for Brazil
	Exposure-response coverage	1	The equation to calculate deaths is based on Krewski *et al*. (2009), a study that linked PM pollution and mortality in the United States.
	Temporal resolution	5	All data and tools used were published after 2015
	Included health effects	5	The CFs considered all mortality causes, then capture 100% of the total PM-related disease burden
	Considered substances	2	At least the effects were calculated for each elementary flow considered, the equation to calculate deaths consider the concentration of total PM2.5 concentration
Scope	**Scope score**	**3.6**	**-**
	Considered by a LCIA method?	3	CFs are not available in a LCIA, but it can be considered a recent dataset of CFs
	Cause-and-effect chain	5	The cause-and-effect chain was well described in the methodology
	Model transparency and accessibility (calculation procedure and input data0	4	The accessibility of inventories can be hampered by the adaptation of available inventories to be used in the InMAP model. However, all other data and also InMAP model are available for free
	Clarity of variables and mathematical model's description	5	All mathematical equations directly applied were described with their parameters and units
	Clarity of equations and parameters used for modelling	5	All mathematical equations directly applied were described with their parameters and units
Scientific robustness	**Scientific robustness score**	**4.4**	-
	Is there an EF for Brazil?	5	CFs are specific for Brazil
	Brazilian spatial differentiation (geographic)	5	More than one specific CF was calculated for Brazil
	Is the available EF for Brazil appropriate for its singularity?	5	Yes, factors were calculated per state, meso-region and the country
Availability for Brazil	**Factors for Brazil score**	**5**	**-**
	Final score	**4.3**	

Source: Author

For the stage of effect calculation, this study obtained a lower score (score = 4.3) compared to Fantke *et al*. (2017, 2019) and Oberschelp *et al*. (2020), which scored 4.70 and 4.57, respectively. This result is due to one of the main limitations of the CF calculation in this model: the use of a mortality calculation equation based on studies conducted in the geographical context of the United States, which lowered the score for the “Exposure-response coverage” sub criterion. The other scores were similar between those two models and the CFs from this study. All other models evaluated in Section 3.1 scored lower than the CFs presented in this research.

In terms of applicability, the CFs calculated in this study are especially recommended for LCA case studies developed in Brazil, whether at the national, meso-regional, or state level, as factors for other countries were not included in the calculations. Since mixing characterization models is not recommended for life cycle impact assessment (Section 4.3), the lack of factors for other geographical contexts may be seen as a limitation for use in international case studies. However, it is worth noting that the methodology applied in this research can be replicated for other locations and is therefore suggested for future studies.

Regarding the type of emission compartment, the CFs are mainly recommended for emissions in outdoor environments without specification of emission height, a similar application to that of Van Zelm *et al*. (2016). The distinction between CFs for urban (high population density) and rural (low population density) areas appears feasible with the use of the InMAP model, as the grid cells can be separated by population density. However, precise calculation of the factors depends on running the model for each state with varying population densities, which increases the computational demand. This is also an activity that could be developed in future research, especially since life cycle inventories tend to differentiate emissions based on the population density of the emission location (Mutel *et al*., 2019). The use of source-receptor matrix-based concentration calculation, as available in InMAP for the United States (Tessum, 2019), could speed up model processing time and facilitate its use in studies requiring multiple runs.

The set of CFs presented exhibits high completeness regarding elementary flows. In addition to the pollutants traditionally included in this impact category, VOCs were also incorporated. This inclusion was facilitated by InMAP's capability to account for VOC emissions in the calculation of $PM_{2.5}$ concentration increases, as it models the formation of secondary organic aerosols (SOA) from VOC precursors.

The CFs calculated in this study are feasible for use in LCA case studies, as demonstrated in the sensitivity analysis (Sections 3.3 and 3.4). However, their use is currently limited because they are not yet implemented in LCA software, meaning users interested in applying them to case studies must do so manually. Therefore, creating a dataset in a format compatible with LCA software is also recommended for future work.

In order to demonstrate the applicability of the CFs developed in this study, a case-specific calculation spreadsheet was created during the project CNPq 201121/2022-0 for the biomass pellet production sector. This sector was selected due to its high potential for fine particulate matter ($PM_{2.5}$) emissions during all biomass pellet’s life cycle, especially combustion, as highlighted in recent literature (Duong *et al*., 2022; Angulo-Mosquera *et al.*, 2021). Given the growing use of biomass pellets in renewable energy systems and the associated impacts on human health, such as increased risks of cardiovascular and respiratory diseases (Anenberg *et al*., 2019), this sector presents a relevant case to analyze the health effects due to $PM_{2.5}$ and precursor emissions.

The spreadsheet was designed to allow users calculating health-related impact (DALY) from pollutant emissions based on specific inventory data, using the CFs for Brazil calculated in this study and also the dataset of CFs provided by Van Zelm et al. (2016), Fantke et al. (2017, 2019), Obserchelp et al. (2020) and the recommended CFs of UNEP and SETAC (2016). Methodologically, the tool integrates emission data (from biomass production, transport, industrial activities to produce pellets, distribution and combustion) with Brazilian CFs, allowing users to assess the health burden associated with each stage of the production process. The spreadsheet is currently under review by project collaborators and will be made publicly available (https://www.grupoengs.com.br/produtos) upon completion and request by LCA users, aiming to support both academic studies and policy development related to the environmental performance of biomass-based energy production in Brazil.

5 CONCLUSIONS

The findings of this research enhance understanding of the health impacts of PM emissions from Brazilian production systems, contributing to improved environmental management and mitigation strategies. Including this impact category in LCA studies can support society's pursuit of sustainable development.

After the analysis of 16 characterization models, the models by Oberschelp *et al*. (2020), Fantke *et al*. (2017, 2019), and Van Zelm *et al*. (2016) were identified as the most recommended for use in the Brazilian context. The final choice among these three models should be made by the LCA practitioner based on the characteristics of the models and the scope of the case study in question. However, limitations were also identified in the highlighted models, such as the non-use of Brazilian data in the international models.

In light of this, this research presented a new set of CFs for the health effects of PM, expressed in deaths, YLLs and DALYs per kilogram emitted, calculated specifically for Brazil using national emission inventories. The set of CFs is coherent with the country's reality, presenting higher values for regions with higher emission rates and population density, and it allowed us to conclude that pollutant emissions in southeastern Brazil, such as in São Paulo and Rio de Janeiro, have a greater potential to affect human health than emissions in northern states, such as Roraima. This understanding can assist both the business sector and government in decision-making processes, such as prioritizing actions to improve air quality in areas where impacts are potentially greater, or in selecting locations for the establishment of new emission sources.

Furthermore, the LCA sensitivity analysis conducted in this study revealed that the use of regionalized CFs significantly influences the results of LCA case studies. In some scenarios, these changes were substantial enough to alter the identification of which production system performed best or worst. This demonstrates that relying on non-regionalized or global CFs may lead to misleading conclusions in LCAs. Therefore, the CFs developed in this research are recommended for use in national LCA studies, as they incorporate region-specific emission data and concentration levels that are consistent with local PM measurements.

Also, when the CFs were evaluated using the same set of criteria and sub-criteria applied during the model assessment phase — which successfully aligned with international consensus on the most recommended models for impact assessment — the CFs developed in this research ranked among the top approaches for use in the Brazilian context. This reinforces their relevance and applicability, offering a scientifically robust and context-sensitive tool to improve the assessment of health-related impacts in Brazilian LCAs.

The main limitations of this research include the use of a mortality equation for PM that was developed based on a United States study, which may not robustly represent the Brazilian context. Also, the generated list of CFs does not include distinct archetypes or emission height, and it is only available in spreadsheet format, making it more difficult for third parties to apply them in case studies. It is also worth noting that the results may be sensitive to the emission inventories adopted, particularly for sectors like agriculture, where emissions could be underestimated.

Given these limitations, the following recommendations are made for future work: (1) improve the calculation of health effects due to pollutant concentrations using national studies that correlate pollutant concentrations with mortality; (2) obtain CFs by state, separated by high and low population density, for better alignment and representation of inventories; (3) obtain CFs by state considering different emission height; (4) apply the calculation methodology to generate CFs globally, allowing the use of the CF set in LCA studies involving international supply chains; (5) implement the CF set in LCA software to facilitate its use by third parties.

6 REFERENCES

ALBINO, A. C. G. Avaliação de Modelos de Dispersão Atmosférica no Contexto de Avaliação de Impacto do Ciclo de Vida no Brasil. Dissertation (Master of Planning and Use of Renewable Resources) – Federal University of São Carlos, Sorocaba, 2024

ALI, M. U. *et al*. A systematic review on global pollution status of particulate matter-associated potential toxic elements and health perspectives in urban environment. **Environmental Geochemistry and Health**, [*s. l.*], v. 41, p. 1131-1162, 2019. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s10653-018-0203-z

ALMEIDA, A. R. *et al*. Mitigating environmental impacts using Life Cycle Assessment in Brazilian companies: A stakeholders' perspective. **Jornual of Environmental Management**, [*s. l.*], v. 15, n. 236, p. 291-300, 2019. Doi: 10.1016/j.jenvman.2019.01.094

ALMEIDA FILHO, F. Monitoramento e controle de emissão de material particulado em uma fonte estacionária. Dissertation (Master of Chemical Engineering) – Federal University of São Carlos, São Carlos, 2008.

AMSTER, E. Public health impact of coal-fired power plants: a critical systematic review of the epidemiological literature. **International Journal of Environmental Health Research**, Abingdon, v. 31, n. 5, p. 558-580, 2019. https://doi-org.ez31.periodicos.capes.gov.br/10.1080/09603123.2019.1674256

ANDRADE, G. C. *et al*. Leaf surface traits related to differential particle adsorption – A case study of two tropical legumes. **Science of the Total Environment**, Amsterdam, v. 823, p. 153681, 2022. https://doi.org/10.1016/j.scitotenv.2022.153681

ANDREÃO, W. L. *et al*. Quantifying the impact of particle matter on mortality and hospitalizations in four Brazilian metropolitan areas. **J. Environ. Manage**, [*s. l.*], 270, 110840, 2020. https://doi.org/10.1016/J.JENVMAN.2020.110840

ANENBERG, S.C., J. J. *et al*. Impacts of intercontinental transport of anthropogenic fine particulate matter on human mortality. **Air Qual. Atmos. Health**, [*s. l.*], v. 7, n. 3, p. 369-379, 2014. Doi:10.1007/s11869-014-0248-9.

ANENBERG, S. C. *et al*. Particulate matter-attributable mortality and relationships with carbon dioxide in 250 urban areas worldwide. **Scientific Reports**, v. 9, n. 11552, 2019. DOI: https://doi.org/10.1038/s41598-019-48057-9.

ANGULO-MOSQUERA, L. S. *et al*. Production of solid biofuels from organic waste in developing countries: A review from sustainability and economic feasibility perspectives. **Science of the total environment**, v. 795, n. 148816, 2021. DOI: https://doi.org/10.1016/j.scitotenv.2021.148816.

ANTUNES, L. N. *et al*. Environmental assessment of a permeable pavement system used to harvest stormwater for non-potable water uses in a Building. **Science of the Total Environment,** Amsterdam, v. 746, p. 141087, 2020. https://doi.org/10.1016/j.scitotenv.2020.141087

APTE J. *et al*. Air Inequality: Global Divergence in Urban Fine Particulate Matter Trends. **ChemRxiv**, [*s. l.*], 2021. doi:10.26434/chemrxiv.14671908.v1 (pre-print)

AVENBUAM, O. N.; ZELIKOFF, J. T. Review: Woodsmoke and emerging issues. **Current Opinion in Toxicology**, [*s. l.*], v. 22, p. 12-18, 2020. https://doi.org/10.1016/j.cotox.2020.02.008

AZEVEDO, A. *et al*. Life cycle assessment of bioethanol production from cattle manure. **Journal of Cleaner Production**, Amsterdam, v. 162, p. 1021-1030, 2017. https://doi.org/10.1016/j.jclepro.2017.06.141

BAI, X. *et al.* The health effects of traffic-related air pollution: A review focused the health effects of going green. **Chemosphere**, Oxford, v. 289, p. 133082, 2022. https://doi.org/10.1016/j.chemosphere.2021.133082

BARE, J. TRACI 2.0: The tool for the reduction and assessment of chemical and other environmental impacts 2.0. **Clean Technol. Environ. Policy**, [*s.l.*], v. 13, p. 687–696, 2011. https://doi.org/10.1007/s10098-010-0338-9

BARROS, M. V. *et al.* An analysis of Brazilian raw cow milk production systems and environmental product declarations of whole milk. **J. Clean. Prod.**, Amsterdam, v. 367, p. 133067, 2022. https://doi.org/10.1016/j.jclepro.2022.133067

BERGER, M., et al. Mineral resources in life cycle impact assessment: part II – recommendations on application-dependent use of existing methods and on future method development needs. **The international Journal of Life Cycle Assessment**, [*s.l.*], v. 25, p. 798–813, 2020. DOI: https://doi.org/10.1007/s11367-020-01737-5

BRAGA, B. *et al*. **Introdução a Engenharia Ambiental**. 2. ed. São Paulo: Pearson Prentice Hall, 2005. ISBN: 978-85-7605-041-4.

BRAZIL, **Decreto de Lei n° 3.688 de 3 de outubro de 1941**. Lei das contravenções penais. 1941. Available in: http://www.planalto.gov.br/ccivil_03/decreto-lei/del3688.htm.

BRAZIL, **Lei n° 6.938 de 31 de agosto de 1981**. Dispõe sobre a Política Nacional do Meio Ambiente. 1981. Available in: http://www.planalto.gov.br/ccivil_03/leis/l6938.htm.

BRAZIL, **Resolução Conama n° 05 de 1989**. Dispõe sobre Programa Nacional de Controle da Poluição do Ar – PRONAR. 1989. Available in: http://conama.mma.gov.br/?option=com_sisconama&task=arquivo.download&id=81

BRAZIL, **Lei n° 12.305 de 2 de agosto de 2010**. Institui a Política Nacional de Resíduos Sólidos. 2010. Available in: https://www.planalto.gov.br/ccivil_03/_ato2007-2010/2010/lei/l12305.htm

BRAZIL, **Lei n° 13.576 de 26 de dezembro de 2017**. Dispõem sobre a Política Nacional de Biocombustíveis (RenovaBio). 2017. Available in: https://www.planalto.gov.br/ccivil_03/_ato2015-2018/2017/lei/l13576.htm

BRAZIL, Vigilância em Saúde de Populações Expostas a Poluentes Atmosféricos. Painel da Poluição Atmosférica e Saúde Humana. 2025. Available in: https://app.powerbi.com/view?r=eyJrIjoiNmRhODQwNzItNThlOS00ZmQ4LWJjZmItZDYxOTNhOTRmYmFhIiwidCI6IjlhNTU0YWQzLWI1MmItNDg2Mi1hMzZmLTg0ZDg5MWU1YzcwNSJ9

BUENO, C. *et al*. Sensitivity analysis of the use of Life Cycle Impact Assessment methods: a case study on building materials. **Journal of Cleaner Production**, Amsterdam, v. 112, p. 2208-2220, 2016.

BUENO, C. *et al*. Life Cycle Assessment Applied to End-of-Life Scenarios of Sargassum spp. for Application in Civil Construction. **Sustainability**, [*s. l.*], v. 15, n. 7, 2023. https://doi.org/10.3390/su15076254

BULLE, C. *et al*. IMPACT World+: a globally regionalized life cycle impact assessment method. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 24, p. 1653-1674, 2019. https://doi.org/10.1007/s11367-019-01583-0

CAMARGO, A. M. *et al*. The implementation of organizational LCA to internally manage the environmental impacts of a broad product portfolio: an example for a cosmetics, fragrances, and toiletry provider. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 24, p. 104-116, 2019. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11367-018-1502-4

CANAJ, K. *et al*. LCA of tomato greenhouse production using spatially differentiated life cycle impact assessment indicators: an Albanian case study. **Environ Sci Pollut Res**, [*s. l.*], v. 27, p. 6960–6970, 2020. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11356-019-07191-7

CAPAZ, R. S. *et al*. Environmental trade-offs of renewable jet fuels in Brazil: Beyond the carbon footprint. **Science of the Total Environment**, Amsterdam, v. 714, p 136696, 2020. https://doi.org/10.1016/j.scitotenv.2020.136696

CAVALETT, O. *et al.* Comparative LCA of ethanol versus gasoline in Brazil using different LCIA methods. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 18, p. 674-658, 2013. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11367-012-0465-0

CETESB – Companhia Ambiental do Estado de São Paulo. Qualidade do ar: Poluentes. 2021. Disponível em: https://cetesb.sp.gov.br/ar/poluentes/. Acesso em novembro, 2021.

CEZARINO, L. O. *et al*. Every breath you take. Every freight you make: Environmental pollution index for road Transportation. **Brazilian Journal of Operations & Production Management**, Brazil, v. 19, n. 1, 2022. https://doi.org/10.14488/BJOPM.2021.038

CHEN, L. *et al*. Inequality in historical transboundary anthropogenic PM2.5 health impacts. **Science Bulletin**, Los Angeles, v. 67, n. 4, p. 437-44, 2022. https://doi.org/10.1016/j.scib.2021.11.007

CHEN, X. *et al*. Uncertainty caused by life cycle impact assessment methods: Case studies in process-based LCI databases. **Resour. Conserv. Recycl.**, Amsterdam, v. 172, p. 105678, 2021. https://doi.org/10.1016/j.resconrec.2021.105678

CHERUBINI, E. *et al*. Uncertainty in LCA case study due to allocation approaches and life cycle impact assessment methods. **Int. J. Life Cycle Assess.**, [*s. l.*], v. 23, p. 2055–2070, 2018. https://doi.org/10.1007/s11367-017-1432-6

COMPANHIA NACIONAL DE ABASTECIMENTO (CONAB). **Market prices - Milk and meat**, [*s. l.*], 2022a. Available in: https://sisdep.conab.gov.br/precosiagroweb/. Accessed on: September 2022.

COMPANHIA NACIONAL DE ABASTECIMENTO (CONAB). **Price of agricultural inputs: biofertilizer**, [*s. l.*], 2022b. Available in: https://consultaweb.conab.gov.br/consultas/consultaInsumo.do?method=acaoCarregarConsulta. Accessed on: September 2022.

COBELO, I. *et al*. The impact of wildfires on air pollution and health across land use categories in Brazil over a 16-year period. **Environmental research**, San Diego, v. 224, p. 115522, 2023. https://doi.org/10.1016/j.envres.2023.115522

CONNERTON, P. *et al*. Air Quality during COVID-19 in Four Megacities: Lessons and Challenges for Public Health. **International Journal of Environ. Res. Public Health,** [*s. l.*], v. 17, n. 14, 2020. https://doi.org/10.3390/ijerph17145067

COSTA, M.A.M. *et al*. Evaluation of the efficiency of a Venturi scrubber in particulate matter collection smaller than 2.5 μm emitted by biomass burning. **Environ Sci Pollut Res**, [*s. l.*], v. 30, p. 8835–8852, 2023a. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11356-022-22786-3

COSTA, V. B. F. *et al.* Small steps towards energy poverty mitigation: Life cycle assessment and economic feasibility analysis of a photovoltaic and battery system in a Brazilian indigenous community. **Renewable and Sustainable Energy Reviews**, [*s. l.*], v. 180, n. 113266, 2023b. https://doi.org/10.1016/j.rser.2023.113266

DEKKER, E., *et al*. A taste of the new ReCiPe for life cycle assessment: consequences of the updated impact assessment method on food product LCAs. **The International Journal of Life Cycle Assessment,** [*s. l.*], v. 25, p. 2315-2324, 2020. https://doi.org/10.1007/s11367-019-01653-3

DICK, M. *et al.* Environmental impacts of Brazilian beef cattle production in the Amazon, Cerrado, Pampa, and Pantanal biomes. **Journal of Cleaner Production**, Amsterdam, v. 311, p. 127750, 2021. https://doi.org/10.1016/j.jclepro.2021.127750

DRISCOLL, T. *et al*. Global and regional burden of chronic respiratory disease in 2016 arising from non-infectious airborne occupational exposures: a systematic analysis for the Global

Burden of Disease Study 2016. **Occupational and Environmental Medicine**, [*s. l.*], v. 77, n. 3, 2020. https://doi-org.ez31.periodicos.capes.gov.br/10.1136/oemed-2019-106013

DU, C. *et al*. Robust multi-criteria weighting in comparative LCA and S-LCA: A case study of sugarcane production in Brazil. **Journal of Cleaner Production**, Amsterdam, v. 218, p.708-717, 2019. https://doi.org/10.1016/j.jclepro.2019.02.035

DUARTE, R. H. "Turn to pollute": air pollution and development model during the Brazilian "miracle" (1967-1973). **Tempo**, Niterói, v. 21, n. 37, 2015. https://doi.org/10.1590/TEM-1980-542X2015v213710

DUONG V.M. et al. Emission characteristics from the combustion of *Acacia Mangium* in the automatic feeding pellet stove. **Renewable Energy**, v. 186, p. 183-194, 2022. DOI: https://doi.org/10.1016/j.renene.2021.12.152.

EUROPEAN ENVIRONMENTAL AGENCY (EEA). **Chemicals glossary**. Chemicals Glossary, 2023. Available in: Https://Www.Eea.Europa.Eu/Help/Glossary/Eper-Chemicals-Glossary. Access on: may, 2024

ENVIRONMENTAL PROTECTION AGENCY (EPA). **Particulate Matter (PM) pollution**, United States, 2023, Available in: https://www.epa.gov/pm-pollution. Access on: mar, 2023.

ENVIRONMENTAL PROTECTION AGENCY (EPA). **How does PM affect human health?**, United States, 2024. Available in: https://www3.epa.gov/region1/airquality/pm-human-health.html#:~:text=Fine%20particles%20(PM2.5)%20pose,eyes%2C%20nose%2C%20and%20throat. Accessed on: Jan, 2024.

ESNOUF, A. *et al.* Representativeness of environmental impact assessment methods regarding Life Cycle Inventories. **Science of the Total Environment**, Amsterdam, v. 621, p. 1264-1271, 2018. https://doi.org/10.1016/j.scitotenv.2017.10.102

EUROPEAN COMISSION (EC); JOINT RESEARCH CENTRE DATA CATALOGUE (JRC). Emissions Database for Global Atmospheric Research, version v4.3.2 part II Air Pollutants (gridmaps), Europe, 2018. Available in: https://data.jrc.ec.europa.eu/dataset/jrc-edgar-v432-ap-gridmaps. Accessed on: march, 2023.

EUROPEAN COMMISSION (EC), JOINT RESEARCH CENTRE (JRC), INSTITUTE FOR ENVIRONMENT AND SUSTAINABILITY (IES). International Reference Life Cycle Data System (ILCD) Handbook – Recommendations for Life Cycle Impact Assessment in the European context. 1. ed. Luxembourg: Publications Office of the European Union, 2011. https://doi.org/10.1017/CBO9781107415324.004

EUROPEAN COMMISSION, JOINT RESEARCH CENTRE (EC-JRC)/NETHERLANDS ENVIRONMENTAL ASSESSMENT AGENCY (PBL). **Emissions Database for Global Atmospheric Research (EDGAR)**, release EDGAR v6.1 (1970 - 2018) of May 2022, Netherands, 2022. Available in: https://edgar.jrc.ec.europa.eu/index.php/dataset_ap61. Access on: march 2024.

FANTKE, P. *et al*. Health effects of fine particulate matter in life cycle impact assessment: findings from the Basel Guidance Workshop. **Int. J. Life Cycle Assess.**, [*s.l.*], 20, 276–288, 2015. https://doi.org/10.1007/s11367-014-0822-2

FANTKE, P. *et al.* Characterizing Aggregated Exposure to Primary Particulate Matter: Recommended Intake Fractions for Indoor and Outdoor Sources. **Environ. Sci. Technol**., Easton, v. 51, p. 9089–9100, 2017. https://doi.org/10.1021/acs.est.7b02589

FANTKE, P. *et al.* Global Effect Factors for Exposure to Fine Particulate Matter. **Environ. Sci. Technol.**, Easton, v. 53, p. 6855–6868, 2019. https://doi.org/10.1021/acs.est.9b01800

FERNANDES, M. A. O. *et al*. Avoiding hospital admissions for respiratory system diseases by complying to the final Brazilian air quality standard: an estimate for Brazilian southeast capitals. **Environmental Science and Pollution Research**, [*s. l.*], v. 27, p. 35889-35907, 2020. Doi: 10.1007/s11356-020-07772-x.

FERRARA, C. *et al*. (2021). LCA of glass versus PET mineral water bottles: an Italian case study. **Recycling**, [*s.l.*], v. 6, n. 3, 2021. DOI: https://doi.org/10.3390/recycling6030050

FERREIRA, H.; LEITE, M. G. P. A Life Cycle Assessment study of iron ore mining. **Journal of Cleaner Production**, Amsterdam, v. 108, p. 1081-1091, 2015. https://doi.org/10.1016/j.jclepro.2015.05.140

FERREIRA, M. B. *et al*. Eco-efficiency of the differential ratio change in a heavy-duty vehicle and implications for the automotive industry. **Sustainable Production and Consumption**, [*s. l.*], v. 21, p. 145-155, 2020. https://doi.org/10.1016/j.spc.2019.12.005

FINNVEDEN, G., NILSSON, M. Site-dependent Life-Cycle Impact Assessment in Sweden. **Int J Life Cycle Assessment**, v. 10, p. 235–239, 2005. https://doi-org.ez31.periodicos.capes.gov.br/10.1065/lca2005.05.209

FINNVEDEN G. *et al*. Recent developments in life cycle assessment. **J Environ Manag**, v. 91, p.1–21, 2009. https://doi-org.ez31.periodicos.capes.gov.br/10.1016/j.jenvman.2009.06.018

FRISCHKNECHT *et al*. **Overview and methodology: data quality guideline for the ecoinvent database version 2**, 2007. Swiss Centre for Life Cycle Inventories, Swiss.

FRISCHKNECHT, R., JOLLIET, O. **Global Guidance for Life Cycle Impact Assessment Indicators**, Volume 1. ed. Paris, France, 2016.

FU, Z.; LI, R. The contributions of socioeconomic indicators to global PM2.5 based on the hybrid method of spatial econometric model and geographical and temporal weighted regression. **Science of the Total Environment**, Amsterdam, v. 703, p. 135481, 2020. https://doi.org/10.1016/j.scitotenv.2019.135481

GABRIEL, N. R. *et al*. A comparative life cycle assessment of electric, compressed natural gas, and diesel buses in Thailand. **Journal of Cleaner Production**, Amsterdam, v. 314, p. 128013, 2021. https://doi.org/10.1016/j.jclepro.2021.128013

GALVÃO, E. S. *et al*. Health risk assessment of inorganic and organic constituents of the coarse and fine PM in an industrialized region of Brazil. **Science of the Total Environment**, Amsterdam, v. 865, p. 161042, 2023. https://doi.org/10.1016/j.scitotenv.2022.161042

GARDIN, T. N.; REQUIA, W. J. Air quality and individual-level academic performance in Brazil: A nationwide study of more than 15 million students between 2000 and 2020. **Environmental research**, San Diego, v. 226, p. 115689, 2023. https://doi.org/10.1016/j.envres.2023.115689

GE, F., *et al*. Predicting aviation non-volatile particulate matter emissions at cruise via convolutional neural network. **Science of the Total Environment**, Amsterdam, v. 850, n. 1, p. 158089, 2022. https://doi.org/10.1016/j.scitotenv.2022.158089

GIDHAGEN, L. *et al*. An integrated assessment of the impacts of PM2.5 and black carbon particles on the air quality of a large Brazilian city. **Air Qual Atmos Health**, [*s. l.*], v. 14, p. 1455–1473, 2021. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11869-021-01033-7

GILMORE, E. A. *et al*. An inter-comparison of the social costs of air quality from reduced-complexity models. **Environmental Research Letters**, [*s. l.*], v. 14, n. 7, p. 074016, 2019. https://doi.org/10.1088/1748-9326/ab1ab5

GIODA, A. *et al*. Exposição ao uso da lenha para cocção no Brasil e sua relação com os agravos à saúde da população. **Ciência e saúde coletiva**, Rio de Janeiro, v. 24, n. 8, 2019. https://doi.org/10.1590/1413-81232018248.23492017

GIUSTI, G. et al. **Avaliação de Impacto do Ciclo de Vida para a categoria de formação de material particulado: Análise da produção científica e levantamento de modelos**. In: Congresso Brasileiro sobre Gestão do Ciclo de Vida, 7, Anais...Gramado: UFRGS, p. 603-608, 2020.

GIUSTI, G. et al. **Modelos de caracterização para a categoria de impacto de formação de material particulado no contexto brasileiro: uma análise de sensibilidade**. In: 9th International conference on Life Cycle Assessment in Latin America, Anais…Buenos Aires: edUTecNe, p. 65-69, 2021.

GIUSTI, G. Regionalização no contexto brasileiro de modelos de avaliação de impacto do ciclo de vida para a categoria de formação de material particulado. Dissertation (Master of Planning and Use of Renewable Resources) – Federal University of São Carlos, Sorocaba, 2021.

GIUSTI, G. *et al*. Health effects of particulate matter formation in Life Cycle Impact Assessment: critical review and recommendation of models for Brazil. **Int. J. Life Cycle Assess**, [*s. l.*], v. 27, p. 868-884, 2022.

GIUSTI, G. *et al.* Human health impacts of particulate matter emitted from different milk production systems in Brazil: a regionalized LCA sensitivity analysis. **Int. J. Life Cycle Assess**, [*s. l.*], v. 28, p. 1466-1480, 2023.

GLOBAL BURDEN OF DISEASE (GBD). **GBD Result Toll**, Seattle, 2019. Available in: https://vizhub.healthdata.org/gbd-results/. Access on: may, 2024.

GLOBAL BURDEN OF DISEASE STUDY 2021 (GBD). Results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2022. Available from https://vizhub.healthdata.org/gbd-results/.

GLOBAL GUIDANC FOR LIFE CYCLE IMPACT ASSESSMENT INDICATORS AND METHODS (GLAM). United Nations Environment Programme – Global Guidance for Life Cycle Impact Assessment Indicator and Methods (GLAM), 2024. Life Cycle Initiative. Acessed on May, 2025

GOEDKOOP, M. *et al*. **ReCiPe 2008 – A life cycle impact assessment method which comprises harmonized category indicators at the midpoint and endpoint level.** First ed. Report I: characterization, 2019. Available in: https://web.universiteitleiden.nl/cml/ssp/publications/recipe_characterisation.pdf. Accessed on: Jan, 2024.

GREENHOUSE GAS (GHG) PROTOCOL. **Programa Brasileiro GHG Protocol** – Ferramenta de Cálculo de Emissões de GEE, Rio de Janeiro, 2023. https://eaesp.fgv.br/centros/centro-estudos-sustentabilidade/projetos/programa-brasileiro-ghg-protocol

GRONLUND C. J. *et al.* Characterizing the burden of disease of particulate matter for life cycle impact assessment. **Air Qual. Atmos. Heal.**, [*s. l.*], v. 8, p. 29–46, 2015. https://doi.org/10.1007/s11869-014-0283-6

GU, B. *et al*. Abating ammonia is more cost-effective than nitrogen oxides for mitigating PM2.5 air pollution. **Science**, [*s. l.*], v. 374, n. 6568, p. 758-762, 2021. DOI: 10.1126/science.abf8623

GUO, Y. *et al*. A causal modelling framework for short-term effects of PM2.5 on hospitalisations: A nationwide time series study in Brazil. **Environment international**, New York, v. 171, p. 107688, 2023. https://doi.org/10.1016/j.envint.2022.107688

GUILLERM, N.; CESARI, G. Fighting ambient air pollution and its impact on health: from human rights to the right to a clean environment. **The international journal of tuberculosis and lung disease**, Paris, v. 19, n. 8, p. 887-897, 2015. https://doi-org.ez31.periodicos.capes.gov.br/10.5588/ijtld.14.0660

HADDAD, A. N. *et al*. An integrated approach of building information modelling and life cycle assessment (BIM-LCA) for gas and solar water heating systems. **International Journal of Construction Management**, [*s. l.*], v. 23, n. 14, 2023. https://doi-org.ez31.periodicos.capes.gov.br/10.1080/15623599.2022.2068179

HAMMER, M. S., *et al*. Global Estimates and Long-Term Trends of Fine Particulate Matter Concentrations (1998–2018). **Environmental Science and Technology**, Easton, v. 54, n. 13, p. 7879-7890, 2020. https://doi-org.ez31.periodicos.capes.gov.br/10.1021/acs.est.0c01764

HAUSCHILD, M. Z. *et al.* Identifying best existing practice for characterization modeling in life cycle impact assessment. **Int. J. Life Cycle Assess.**, [*s. l.*], v. 18, p. 683–697, 2013. https://doi.org/10.1007/s11367-012-0489-5

HE, J. *et al*. External Effects of Diesel Trucks Circulating Inside the São Paulo Megacity. **Journal of European Economic Association**, [*s. l.*], v. 17, n. 3, p. 947-989, 2018. https://doi.org/10.1093/jeea/jvy015

HEIJUNGS, R., DEKKER, E., 2022. Meta-comparisons: how to compare methods for LCA? **Int. J. Life Cycle Assess.**, [*s. l.*], v. 27, p. 993–1015. https://doi.org/10.1007/s11367-022-02075-4

HODAS, N. *et al.* Indoor inhalation intake fractions of fine particulate matter: review of influencing factors. **Indoor Air**, [*s. l.*] v. 26, p. 836–856, 2016. https://doi.org/10.1111/ina.12268

HOFSTETTER, P. **Perspectives in life cycle impact assessment a structured approach to combine models of the technosphere ecosphere valuesphere**. Dissertation (Doctor of Natural Sciences) – Swiss Federal Institute of Technology Zurich, Zurich, 1998.

HOINASKI, L. *et al*. Multispecies and high-spatiotemporal-resolution database of vehicular emissions in Brazil. **Earth System Science Data**, [*s. l.*], v. 14, n. 6, p. 2939–2949, 2022. https://doi.org/10.5194/essd-14-2939-2022

HOINASKI, WILL, RIBEIRO. **Brazilian Atmospheric Inventories– BRAIN: a comprehensive database of air quality in Brazil**. Earth System Science Data, v.16, p. 2385-2405, 2024. https://doi.org/10.5194/essd-16-2385-2024.

HUIJBREGTS, M. J. A. *et al.* Priority assessment of toxic substances in life cycle assessment. Part I: calculation of toxicity potentials for 181 substances with the nested multi-media fate, exposure and effects model USES LCA. **Chemosphere**, Oxford, v. 41, p. 541-573, 2000. https://doi.org/10.1016/S0045-6535(00)00030-8

HUIJBREGTS, M. A. J. *et al*. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 22, n. 2, p. 138-147, 2017.

HUMBERT, S. *et al*. Intake fraction for particulate matter: recommendations for Life Cycle Impact Assessment. **Environ. Sci. Technol**, Easton, v. 42, p. 4808-4816, 2011. https://libwvu.on.worldcat.org/oclc/5300120733

HUMBERT, S. *et al*. Particulate Matter Formation. *In*: HAUSCHILD, M. Z.; HUIJBREGTS, M. A. J. **Life Cycle Assessment:** LCA Compendium – The Complete World of Life Cycle Assessment. 1. ed. New York: Springer, 2015. p. 97 – 114.

HUNEEUS, N. *et al*. Evaluation of anthropogenic air pollutant emission inventories for South America at national and city scale. **Atmospheric environment**, Oxford, v. 235, p. 117606, 2020. https://doi.org/10.1016/j.atmosenv.2020.117606

INSTUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA (IBGE). **Áreas territoriais**, Brazil, 2022, Available in: https://www.ibge.gov.br/geociencias/organizacao-do-territorio/estrutura-territorial/15761-areas-dos-municipios.html#:~:text=Para%20a%20superf%C3%ADcie%20do%20Brasil,21%20de%20mar%C3%A7o%20de%202023. Acessed on: Jan, 2024.

INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA (IBGE). Cidades e Estados, Brazil, 2025, Available in: https://www.ibge.gov.br/cidades-e-estados. Acessed on: February, 2025.

INTERNATIONAL ENERGY AGENCY (IEA). **Energy Statistics Data Browser**, IEA, Paris, 2023. Available in: https://www.iea.org/data-and-statistics/data-tools/energy-statistics-data-browser. Accessed on: Sep 2023

INTERNATIONAL ORGANIZATION FOR STANDARDIZATION. ISO 14040: Environmental management — Life cycle assessment — Principles and framework. ISO, 2006a.

INTERNATIONAL ORGANIZATION FOR STANDARDIZATION. ISO 14044: Environmental management – Life cycle assessment – Requirements and guidelines. ISO, 2006b.

ITSUBO, N.; INABA, A. **Life-cycle impact assessment method based on endpoint modeling (LIME 2).** n. 14, [*s. l.*]: JLCA, 2012. Available in: https://lca-forum.org/english/. Access on: jan 2022.

JAFARI, A. J, *et al.* Urban air pollution control policies and strategies: a systematic review. **Journal of Environmental Health Science and Engineering**, [*s. l.*], v. 19, p. 1911-1940, 2021. Doi: 10.1007/s40201-021-00744-4

JOHNSON, R. *et al.* How does a country's developmental status affect ambient air quality with respect to particulate matter? **International Journal of Environmental Science and Technology**, [*s. l.*], v. 18, p. 3395-3406, 2021. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s13762-020-03072-6

JOLLIET, O. *et al.* IMPACT 2002+: A new life cycle impact assessment methodology. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 8, n. 6, p. 324-330, 2003.

KACHBA, Y. *et al*. Artificial Neural Networks to Estimate the Influence of Vehicular Emission Variables on Morbidity and Mortality in the Largest Metropolis in South America. **Sustainability**, [*s.l.*], 12, 2621, 2020. https://doi.org/10.3390/su12072621

KARAGULIAN, F. *et al*. Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. **Atmospheric Environment**, Oxford, v. 120, p. 475-483, 2015. https://doi.org/10.1016/j.atmosenv.2015.08.087

KARKOUR, S. *et al*. External-Cost Estimation of Electricity Generation in G20 Countries: Case Study Using a Global Life-Cycle Impact-Assessment Method. **Sustainability,** [*s. l.*], v. 12, n. 5, 2002. https://doi.org/10.3390/su12052002

KAWASHIMA, A. B. *et al*. Development of a spatialized atmospheric emission inventory for the main industrial sources in Brazil. **Environmental Science and Pollution Research**, [*s. l.*], v. 27, n. 29, p. 35941–35951, 2020. https://doi.org/10.1007/s11356-020-08281-7

KELLY, F. J.; FUSSELL, J. C. Global nature of airborne particle toxicity and health effects: a focus on megacities, wildfires, dust storms and residential biomass burning. **Toxicology Research**, [*s. l.*], v. 9, n. 4, p. 331-345, 2020. https://doi.org/10.1093/toxres/tfaa044

KOHLBECK, E. *et al*. Analysis of the application of recycled polypropylene: a case study in the refrigeration segment in south of Brazil. **Brazilian Journal of Operations and Production Management**, Brazil, v. 20, n. 4, 2023. https://doi.org/10.14488/BJOPM.1560.2023

KREWITT, W. *et al*. Country-specific damage factors for air pollutants: A step towards site dependent Life Cycle Impact assessment. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 6, p. 199-210, 2001. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/BF02979375

KREWSKI, D. *et al.* Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality. Research Report, Health Effects Institute, Boston, Massachusetts, 2009. Available on: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.healtheffects.org/system/files/Krewski140.pdf

KUMAR, P., *et al*. In-kitchen aerosol exposure in twelve cities across the globe. **Environment International**, New York, v. 162, p. 107155, 2022. https://doi.org/10.1016/j.envint.2022.107155

LASSIO, J. *et al*. Case Study: LCA Methodology Applied to Materials Management in a Brazilian Residential Construction Site. **Journal of Engineering**, [*s. l.*], 2016. https://doi.org/10.1155/2016/8513293

LEE, C. J. *et al.* Response of global particulate-matter-related mortality to changes in local precursor emissions. **Environ. Sci. Technol.**, Easton, v. 49, p. 4335–4344, 2015. https://doi.org/10.1021/acs.est.5b00873

LEHMANN, A. *et al*. **Policy options for life cycle assessment deployment in legislation. In: Sonnemann G. MM** (eds) (ed) LCA Compendium — the complete world of life cycle assessment. Springer, Dordrecht, pp 213–224, 2015.

LI, P., *et al*. The association of birthweight with fine particle exposure is modifiable by source sector: Findings from a cross-sectional study of 17 low- and middle-income countries. **Ecotoxicology and Environmental Safety**, New York, v. 253, p. 114696, 2023. https://doi.org/10.1016/j.ecoenv.2023.114696

LI, X. *et al*. An endpoint model for life cycle impact assessment in China and preliminary normalization values: A case study of vehicles. **Journal of Cleaner Production**, Amsterdam, v. 434, p. 140326, 2024. https://doi.org/10.1016/j.jclepro.2023.140326

LU, X., *et al*. Impacts of urbanization and long-term meteorological variations on global PM2.5 and its associated health burden. **Environmental Pollution**, Barking, v. 270, p. 116003, 2021. https://doi.org/10.1016/j.envpol.2020.116003

MACENO, M. M. C. *et al*. Life cycle assessment and circularity evaluation of the non-medical masks in the Covid-19 pandemic: a Brazilian case. **Environment, Development and Sustainability**, [*s. l.*], v. 25, p. 8055-8082, 2023. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s10668-022-02388-2

MAIA DE SOUZA, D. *et al*. Life cycle thinking in Brazil: challenges and advances towards a more comprehensive practice. **The International Journal of Life Cycle Assessment,** [*s. l.*], v. 22, p. 462-465, 2017. https://doi.org/10.1007/s11367-016-1234-2

MAIA, P. D., *et al*. Assessment of atmospheric particulate matter (PM10) in Central Brazil: Chemical and morphological aspects. **Atmospheric Pollution Research**, [*s. l.*], v. 13, n. 4, p. 101362, 2022. https://doi.org/10.1016/j.apr.2022.101362

MARTINS, A. P. G. *et al*. Infraestrutura verde para monitorar e minimizar os impactos da poluição atmosférica. **Energia e Ambiente**, Brazil, v. 35, n. 102, 2021. https://doi.org/10.1590/s0103-4014.2021.35102.003

MARTINS, L. D. *et al*. Long-range Transport of Aerosols from Biomass Burning over Southeastern South America and their Implications on Air Quality. **Aerosol and Air Quality Research**, [*s. l.*], v. 18, n. 7, 2018. https://doi.org/10.4209/aaqr.2017.11.0545

MENDES, N. C. *et al*. Avaliação de Impacto do Ciclo de Vida: revisão dos principais métodos. **Production**, São Paulo, v. 26, n. 1, p. 160-175, 2016, https://doi.org/10.1590/0103-6513.153213

MENEZES, N. A. *et al*. Obtaining bioLPG via the HVO Route in Brazil: A Prospect Study Based on Life Cycle Assessment Approach. **Sustainability**, [*s. l.*], v. 14, n. 23, p. 15734, 2022. https://doi.org/10.3390/su142315734

MIRANDA, J. L. *et al*. A case study for an eco-design of aluminum terephthalate metal-organic framework- MIL-53(Al) for CO2 and methane adsorption. **Sustainable Materials and Technologies**, [*s. l.*], v. 37, p. e00689, 2023. https://doi.org/10.1016/j.susmat.2023.e00689

MONTEIRO, N. B. R. *et al*. Environmental assessment in concrete industries. **Journal of Cleaner Production**, Amsterdam, v. 327, p. 129519, 2021. https://doi.org/10.1016/j.jclepro.2021.129516

MOREIRA JUNIOR, D. P. *et al*. The Effect of Urban Green Spaces on Reduction of Particulate Matter Concentration. **Bulletin of Environmental Contamination and Toxicology**, New York, v. 108, p. 1104-1110, 2022. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s00128-022-03460-3

MORIGUCHI, Y.; TERAZONO, A. A simplified model for spatially differentiated impact assessment of air emissions. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 5, p. 281-286, 2000. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/BF02977580

MOSTAFA, E. *et al*. Physical properties of particulate matter from animal houses—empirical studies to improve emission modelling. **Environ. Sci. Pollut. Res.**, [*s. l.*], v. 23, p. 12253–12263, 2016. https://doi.org/10.1007/s11356-016-6424-8

MUELLER, N. *et al.* Health impact assessments of shipping and port-sourced air pollution on a global scale: A scoping literature review. **Environmental Research**, San Diego, v. 216, n. 1, p. 114460, 2023. https://doi.org/10.1016/j.envres.2022.114460

MUKAKA, M. M., Statistics corner: A guide to appropriate use of correlation coefficient in medical research. **Malawi Med. J.**, Africa, v. 24, p. 69–71, 2012.

MUNERON, L. M. *et al*. Comparison of the environmental performance of ceramic brick and concrete blocks in the vertical seals' subsystem in residential buildings using life cycle assessment. **Cleaner Engineering and Technology**, [*s. l.*], v. 5, p. 100243, 2021. https://doi.org/10.1016/j.clet.2021.100243

MUTEL, C. *et al*. GIS-Based Regionalized Life Cycle Assessment: How Big Is Small Enough? Methodology and Case Study of Electricity Generation. **Environmental Science and Technology**, Easton, v. 46, n. 2, p. 1096-1103, 2012. https://doi.org/10.1021/es203117z

MUTEL, C. *et al.* Overview and recommendations for regionalized life cycle impact assessment. **Int. J. Life Cycle Assess.**, [*s. l.*], v. 24, p. 856-865, 2019. https://doi.org/10.1007/s11367-018-1539-4

NCAR, Atmospheric Chemistry Observations & Modeling. **WRF-Chem Tools for the Community**. [*S. l.*], 2024. Disponível em: https://www2.acom.ucar.edu/wrf-chem/wrf-chem-tools-community. Acesso em: 29 jul. 2024.

NIGGE, K. M. A Method for the Site-Dependent Life Cycle Impact Assessment of Toxic Air Pollutants from Traffic Emissions. **SAE Technical Paper** 982181, 1998, https://doi.org/10.4271/982181.

NIGGE, K. M. Generic spatial classes for human health impacts, Part I: Methodology. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 6, p. 257-264, 2001. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/BF02978786

NISHIOKA, Y. *et al*. A Risk-Based Approach to Health Impact Assessment for Input-Output Analysis, Part 1: Methodology. **Int J Life Cycle Assessment,** v. 10, p. 193–199, 2005. https://doi-org.ez31.periodicos.capes.gov.br/10.1065/lca2004.10.186.1

NOGUEIRA, T. *et al.* Evolution of Vehicle Emission Factors in a Megacity Affected by Extensive Biofuel Use: Results of Tunnel Measurements in São Paulo, Brazil. **Environmental Science and Technology**, Easton, v. 55, n. 10, p. 6677-6687, 2021. https://doi.org/10.1021/acs.est.1c01006

NOTTER, D. A. Life cycle impact assessment modeling for particulate matter: A new approach based on physico-chemical particle properties. **Environ. Int.**, New York, v. 82, p. 10-20, 2015. https://doi.org/10.1016/j.envint.2015.05.002

OBERSCHELP, C. *et al.* Globally Regionalized Monthly Life Cycle Impact Assessment of Particulate Matter. **Environ. Sci. Technol.**, Easton, v. 54, p. 16028–16038, 2020. https://doi.org/10.1021/acs.est.0c05691

OLIVEIRA, J.A. *et al*. **Life Cycle Engineering and Management of Products**. 1. Ed. Brazil: Springer, Cham, 2021. https://doi.org/10.1007/978-3-030-78044-9_1

OWSIANIAK, M. *et al*. Influence of spatial differentiation in impact assessment for LCA-based decision support: Implementation of biochar technology in Indonesia. **Journal of**

Cleaner Production, Amsterdam, v. 200, p. 259-268, 2018. https://doi.org/10.1016/j.jclepro.2018.07.256

PAES, M. X. *et al*. Life Cycle Assessment as a diagnostic and planning tool for waste management: a case study in a brazilian municipality (2018). **Journal of Solid Waste Technology and Management,** [*s. l.*], v. 44, n. 3, 259-269, 2018. Doi: 10.5276/JSWTM.2018.259

PARVEZ, F. *et al*. Primary and secondary particulate matter intake fraction from different height emission sources. **Atmospheric Environment**, [*s.l.*], v. 165, p. 1-11, 2017. DOI: https://doi.org/10.1016/j.atmosenv.2017.06.011

PASSON, B.C. *et al*. A systematic approach to assist in life-cycle assessment of ammunition demilitarization process: a case study with the 105-mm HE M1 ammunition. **Int J Life Cycle Assess**, [*s. l.*], v. 28, p. 398–428, 2023. https://doi.org/10.1007/s11367-023-02149-x

PAYEN, S.; LEDGARD, S. (2017). Aquatic eutrophication indicators in LCA: Methodological challenges illustrated using a case study in New Zealand. **Journal of Cleaner Production**, Amsterdam, v. 168, p. 1463-1472. DOI: https://doi.org/10.1016/j.jclepro.2017.09.064

PEREIRA, G. M. *et al*. A comparative chemical study of PM10 in three Latin American cities: Lima, Medellín, and São Paulo. **Air quality, Atmosphere and Health**, [*s. l.*], v. 12, p. 1141-1152, 2019.

PÉREZ-MARTÍNEZ, P. J. *et al*. Emission factors of air pollutants from vehicles measured inside road tunnels in São Paulo: case study comparison. **International Journal of Environmental Science and Technology**, [*s. l.*], v. 11, p. 2155-2168, 2014. https://doi.org/10.1007/s13762-014-0562-7

PFISTER, G. **EPA_ANTHRO_EMIS User Guide**. [*S. l.: s. n.*], 2014. Disponível em: https://www.acom.ucar.edu/wrf-chem/EPA_ANTHRO_EMIS_UserGuide.pdf. Acesso em: 29 jul. 2024.

POTTING, J., BLOK. K. Life cycle assessment of four types of floor covering. **Journal of Cleaner Production**, Amsterdam, v. 3, n. 4, p. 201–213, 1995

POTTING, J. HAUSCHILD, M. Z. Spatial differentiation in life cycle impact assessment: a decade of method development to increase the environmental realism of LCIA. **Int. J. Life Cycle Assess.**, [*s. l.*], v. 11, special issue 1, p. 11-13, 2005.

QIN, Y. *et al*. Perceived uncertainties of characterization in LCA: a survey. **Int J Life Cycle Assess**, [*s.l.*], v. 25, p. 1846–1858, 2020. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11367-020-01787-9

QUARMBY, S. *et al*. Air Quality Strategies and Technologies: A Rapid Review of the International Evidence. **Sustainability**, v. 11, n. 10, 2019. https://doi.org/10.3390/su11102757

RAJAGOPAL, D. *et al*. Life Cycle Assessment for Economists. **Annual Review of Resource Economics**, [*s. l.*], v. 9, p. 361-381, 2017. Doi: 10.1146/annurevresource-100815-095513

RAJAGOPALAN, S. *et al*. Personal-Level Protective Actions Against Particulate Matter Air Pollution Exposure: A Scientific Statement From the American Heart Association. **Circulation**, Baltimore. 2020. https://doi.org/10.1161/CIR.0000000000000931

RAMON, M. *et al*. Assessment of four urban forest as environmental indicator of air quality: a study in a brazilian megacity. **Urban ecosystems**, [*s. l.*], v. 26, p. 197-207, 2023. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11252-022-01296-7

RAMPASSO, I. *et al*. The Bioeconomy in emerging economies: a study of the critical success factors based on Life Cycle Assessment and Delphi and Fuzzy-Delphi methods. **International Journal of Life Cycle Assessment**, [*s. l.*], v. 26, p. 1254-1266 (2021). https://doi.org/10.1007/s11367-021-01913-1

REDE DE PESQUISA EM AVALIAÇÃO DE IMPACTO DO CICLO DE VIDA (RAICV). **Recomendação de modelos de Avaliação de Impacto do Ciclo de Vida para o Contexto Brasileiro**. 1. ed. Brasília: IBICT, 2019.

REDE DE PESQUISA EM AVALIAÇÃO DE IMPACTO DO CICLO DE VIDA (RAIV). **Temas de trabalho**. 2023. Available in: https://raicvbrasil.wixsite.com/raicv. Accessed on: sep, 2023.

RESTREPO, A. *et al*. A life cycle assessment of the Brazilian coal used for electric power generation. **Journal of Cleaner Production**, Amsterdam, v. 92, p. 179-189, 2015. https://doi.org/10.1016/j.jclepro.2014.12.065.

RÉQUIA, W. J.; CASTELHANO, F. J. Economic and racial disparities of the weather impact on air quality in Brazil. **Scientific reports**, [*s. l.*], n. 13, n. 6374, 2023. https://doi-org.ez31.periodicos.capes.gov.br/10.1038/s41598-023-33478-4

RÉQUIA, W. J. *et al*. Spatiotemporal analysis of traffic emissions in over 5000 municipal districts in Brazil. **Journal of the Air & Waste Management Association**, Pittsburg, v. 66, n. 12, 2016. https://doi.org/10.1080/10962247.2016.1221367

RÉQUIA, W. J. *et al*. Prenatal exposure to wildfire-related air pollution and birth defects in Brazil. **Journal of exposure science and environmental epidemiology**, [*s. l.*], v. 32, p. 596-603, 2022. https://doi-org.ez31.periodicos.capes.gov.br/10.1038/s41370-021-00380-y

RÉQUIA, W. J. *et al*. Short-term air pollution exposure and hospital admissions for cardiorespiratory diseases in Brazil: A nationwide time-series study be.tween 2008 and 2018. **Environmental research**, San Diego, v. 217, p. 114794, 2023. https://doi.org/10.1016/j.envres.2022.114794

REY, C. A. I. **Desenvolvimento de Inventário de Emissões Atmosféricas para Quatro Setores Industriais do Brasil com Abordagem Bottom-Up**. 2023. Dissertation (Master) - Federal University of Technology, Londrina, 2023.

ROBERTS, G.; WOOSTER, M. J. Global impact of landscape fire emissions on surface level PM2.5 concentrations, air quality exposure and population mortality. **Atmospheric environment**, v. 252, p. 118210, 2021. https://doi.org/10.1016/j.atmosenv.2021.118210

ROCHA, C. A. *et al*. Health impact assessment of air pollution in the metropolitan region of Fortaleza, Ceará, Brazil. **Atmospheric Environment**, Oxford, v. 241, p. 117751, 2020. https://doi.org/10.1016/j.atmosenv.2020.117751

ROCHA, T. B.; PENTEADO, C. S. G. Life cycle assessment of a small WEEE reverse logistics system: Case study in the Campinas Area, Brazil. **Journal of Cleaner Production**, Amsterdam, v. 314, p. 128092, 2021. https://doi.org/10.1016/j.jclepro.2021.128092

ROSADO, L. P. *et al*. Life cycle assessment of natural and mixed recycled aggregate production in Brazil. **Journal of Cleaner Production**, Amsterdam, v. 151, p. 634-642, 2017. https://doi.org/10.1016/j.jclepro.2017.03.068

ROSADO, L. P. *et al*. Life cycle assessment of construction and demolition waste management in a large area of São Paulo State, Brazil. **Waste Management**, Oxford, v. 85, p. 477-489, 2019. https://doi.org/10.1016/j.wasman.2019.01.011

SADHUKHAN, J. Net zero electricity systems in global economies by life cycle assessment (LCA) considering ecosystem, health, monetization, and soil CO2 sequestration impacts. **Renewable Energy**, Oxford, v. 184, p. 960-974, 2022. https://doi.org/10.1016/j.renene.2021.12.024

SALA, S. *et al*. Environmental sustainability of European production and consumption assessed against planetary boundaries, **Journal of Environmental Management**, v. 269, 2020, p. 110686, 10.1016/j.jenvman.2020.110686 (online)

SANG, S., *et al*. The global burden of disease attributable to ambient fine particulate matter in 204 countries and territories, 1990–2019: A systematic analysis of the Global Burden of Disease Study 2019. **Ecotoxicology and Environmental Safety**, New Tork, v. 238, p. 113588, 2022. https://doi.org/10.1016/j.ecoenv.2022.113588

SANTANA, J. C. C. *et al*. Effects of Air Pollution on Human Health and Costs: Current Situation in São Paulo, Brazil. **Sustainability**, v. 12, n. 12, 2020. https://doi.org/10.3390/su12124875

SANTANA, J. C. C. *et al*. Clean Production of Biofuel from Waste Cooking Oil to Reduce Emissions, Fuel Cost, and Respiratory Disease Hospitalizations. **Sustainability**, [*s. l.*], v. 13, n. 16, p.9185, 2021. https://doi.org/10.3390/su13169185

SANTOS, N. C. *et al*. The Brazilian automotive market: challenges for the growth of electric and hybrid vehicles. International Conference on Renewable Energies and Power Quality, 2016. https://doi.org/10.24084/repqj14.390

SANTOS, S. F. O. M., *et al*. Life Cycle Analysis of Charcoal Production in Masonry Kilns with and without Carbonization Process Generated Gas Combustion. **Sustainability**, [*s. l.*], v. 9, n. 9, 2017a. Doi: 10.3390/su9091558

SANTOS, H. C. M. S. *et al*. Life cycle assessment of cheese production process in a small-sized dairy industry in Brazil. **Environmental Science and Pollution Research**, [*s. l.*], v. 24, p. 3470-3482, 2017b. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11356-016-8084-0

SARIGIANNIS, D.; TRIACCHINI, G. Meso-scale life-cycle impact assessment of novel technology policies: The case of renewable energy. **Journal of Hazardous Materials**, Amsterdam, v. 78, n. 1-3, p. 145-171, 2000. https://doi.org/10.1016/S0304-3894(00)00221-1

SEIDEL, C. **The Application of Life-Cycle Assessment within a Public Policy Framework – Theory and Reality**. 2016. Dissertation, University of Alberta. https://era.library.ualberta.ca/items/598ce022-83b1-44eb-893ff1b45333bcc1/view/55929fe2-a055-4672-ad85-66dd510615c3/Seidel_Christina_V_201601_PhD.pdf

SHAO, L., *et al*. A review of atmospheric individual particle analyses: Methodologies and applications in environmental research. **Gondwana research**, Osaka, v. 110, p. 347-369, 2022. https://doi.org/10.1016/j.gr.2022.01.007

SICARD, P. *et al.* Trends in urban air pollution over the last two decades: A global perspective. **Science of the Total Environment**, Amsterdam, v. 858, p. 160064. https://doi.org/10.1016/j.scitotenv.2022.160064

SILVA, C. M. *et al*. Ares novos para a primeira infância: as crianças são o futuro do planeta. **Ambiente e Sociedade**, Campinas, v. 26, 2023. https://doi.org/10.1590/1809-4422asoc20220004r1vu2023L1AO

SILVA, D. A. L. *et al*. Life Cycle Assessment in automotive sector: A case study for engine valves towards cleaner production. **J. Clean. Prod.**, Amsterdam, v. 184, p. 286-300, 2018.

SILVA, D.V. **Avaliação do Ciclo de Vida e Avaliação dos Serviços Ecossistêmicos: um estudo de caso aplicado a diferentes sistemas de produção de leite**. Dissertation (Master in Production Engineering) - Federal University of São Carlos, 2022.

SILVA, F. B. *et al*. Primary data priorities for the life cycle inventory of construction products: focus on foreground processes. **The International Journal of Life Cycle Assessment**, [*s. l.*], v. 25, p. 980-997, 2020.

SILVA, K. K. *et al*. Physico-chemical properties and genotoxic effects of air particulate matter collected from a complex of ceramic industries. **Atmospheric Pollution Research**, v. 10, n. 2, p. 597-607, 2019. https://doi.org/10.1016/j.apr.2018.11.001

SINGER, J. M. *et al*. Assessing socioeconomic bias of exposure to urban air pollution: an autopsy-based study in São Paulo, Brazil. **The Lancet Regional Health – Americas**, London, v. 22, p. 100500, 2023. https://doi.org/10.1016/j.lana.2023.100500

SINGH, N. *et al*. Towards the World's Smallest Gravimetric Particulate Matter Sensor: A Miniaturized Virtual Impactor with a Folded Design. **Sensors**, [*s. l.*], v. 22, n. 5, p. 1727, 2022. https://doi.org/10.3390/s22051727

SOUTO-OLIVEIRA, C. E. *et al*. Impact of extreme wildfires from the Brazilian Forests and sugarcane burning on the air quality of the biggest megacity on South America. **Science of the Total Environment**, Amsterdam v. 888, p. 163439, 2023. https://doi.org/10.1016/j.scitotenv.2023.163439

SOUZA, D. M., *et al*. Comparative life cycle assessment of ceramic brick, concrete brick and cast-in-place reinforced concrete exterior walls. **Journal of Cleaner Production**, Amsterdam, v. 137, p. 70-82, 2016. https://doi.org/10.1016/j.jclepro.2016.07.069

SOUZA, D. M. D., *et al*. Comparative Life Cycle Assessment of ceramic versus concrete roof tiles in the Brazilian context. **Journal of Cleaner Production**, Amsterdam, v. 89, p. 165-173, 2015. https://doi.org/10.1016/j.jclepro.2014.11.029

SOUZA, I. D. *et al*. Metallic nanoparticle contamination from environmental atmospheric particulate matter in the last slab of the trophic chain: Nanocrystallography, subcellular localization and toxicity effects. **Science of the Total Environment**, Amsterdam, v. 814, n. 152685, 2022a. https://doi.org/10.1016/j.scitotenv.2021.152685

SOUZA, N. R. D. *et al*. Addressing the contributions of electricity from biomass in Brazil in the context of the Sustainable Development Goals using life cycle assessment methods. **Journal of Industrial Ecology**, [*s. l.*], v. 26, n. 3, p. 980-995, 2022b. https://doi-org.ez31.periodicos.capes.gov.br/10.1111/jiec.13242

STAFFORD, F. N. *et al*. Life cycle assessment of the production of cement: A Brazilian case study. **Journal of Cleaner Production**, Amsterdam, v. 137, p. 1293-1299, 2016. https://doi.org/10.1016/j.jclepro.2016.07.050

STEEN, B. A. systematic approach to environmental priority strategies in product development (EPS). Version 2000 – Models and data of the default method. Report 5. ed. [*s. l.*]: CPM, 1999.

STEIN, C. *et al*. Exposure to and Burden of Major Non-Communicable Disease Risk Factors in Brazil and its States, 1990-2019: The Global Burden of Disease Study. **Revista da Sociedade Brasileira de Medicina Tropical**, Oberaba, v. 55, 2022. https://doi.org/10.1590/0037-8682-0275-2021

STEVENSON, M. *et al*. Land use, transport, and population health: estimating the health benefits of compact cities. **The Lancet**, London, v. 388, n. 10062, p. 2925-2935, 2016. https://doi.org/10.1016/S0140-6736(16)30067-8

STHEL, M. S. *et al*. Dichotomous analysis of gaseous emissions as influenced by the impacts of COVID-19 in Brazil: São Paulo and Legal Amazon. **Environmental Monitoring and Assessment**, Dordrecht, v. 193, n. 834, 2021. https://doi.org/10.1007/s10661-021-09629-3

TADANO *et al*. Predicting health impacts of wildfire smoke in Amazonas basin, Brazil. **Chemosphere**, [s.l.], v. 367, n. 143688, 2024. https://doi.org/10.1016/j.chemosphere.2024.143688

TALANG, R. P.; SIRIVITHAYAPAKORN, S. Environmental and financial assessments of open burning, open dumping and integrated municipal solid waste disposal schemes among different income groups. **Journal of Cleaner Production,** Amsterdam, v. 312, p. 127761, 2021. https://doi.org/10.1016/j.jclepro.2021.127761

TAN, S. *et al*. Reconstructing global PM2.5monitoring dataset from OpenAQ using a two-step spatio-temporal model based on SES-IDW and LSTM. **Environmental Research Letters**, [*s. l.*], v. 17, p. 034014, 2022. 10.1088/1748-9326/ac52c9

TANG, L. *et al.* Development of human health damage factors for PM2.5 based on a global chemical transport model. **Int. J. Life Cycle Assess.**, [*s. l.*], 23, 2300–2310, 2018. https://doi.org/10.1007/s11367-014-0837-8

TESSUM, C. W. Working with source-receptor matrices using https://inmap.run and GeoPandas in Python. Available in: https://inmap.run/blog/2019/04/20/sr/. Acessed on march 2025.

TESSUM, C. W., HILL, J. D., MARSHALL, J. D., 2017. InMAP: A model for air pollution interventions. **PLoS One**, [*s. l.*], v. 12, e0176131. https://doi.org/10.1371/journal.pone.0176131

THAKRAR, S. K., *et al*. Global, high-resolution, reduced-complexity air quality modeling for PM2.5 using InMAP (Intervention Model for Air Pollution). **PLoS ONE**, [*s. l.*], v. 17, n. 5, 2022. https://doi.org/10.1371/journal.pone.0268714

THIND, M. P. S. *et al*. Characterization factors and other air quality impact metrics: Case study for PM2.5-emitting area sources from biofuel feedstock supply. **Science of The Total Environment**, Amsterdam, v. 822, p. 153418, 2022. https://doi.org/10.1016/j.scitotenv.2022.153418

TIN, S.; BILEC, M. Integrating site-specific dispersion modeling into life cycle assessment, with a focus on inhalation risks in chemical production. **Journal of the Air & Waste Management Association**, Pittsburg, v. 68, n. 11, p. 1224–1238, 2018. https://doi-org.ez31.periodicos.capes.gov.br/10.1080/10962247.2018.1496189

TISCHER, V. *et al*. Environmental and economic assessment of traffic-related air pollution using aggregate spatial information: A case study of Balneário Camboriú, Brazil. **Journal of Transport & Health**, [*s. l.*], v. 14, p. 100592, 2019. https://doi.org/10.1016/j.jth.2019.100592

UGAYA, C.M.L. *et al*. Rede de Pesquisa em Avaliação de Impacto do Ciclo de Vida: critérios para recomendação de métodos e modelos de caracterização para o Brasil. In: V Congresso Brasileiro em Gestão do Ciclo de Vida (V CBGCV), 5, 2016, Fortaleza/CE, Anais... Fortaleza/CE, 19 a 22 de setembro de 2016.

UNEP – United Nations Environmental Programme, SETAC – Society of Environmental Toxicology and Chemistry. Global Guidance for Life Cycle Impact Assessment Indicator. 1 ed. 164p, 2016.

UNITED NATIONS (UN). **Standard reports - Sector profiles**, [*s. l.*], 2018. Available in: http://scp-hat.lifecycleinitiative.org/sector-profiles/. Accessed on: September 2023

UNITED NATIONS (UN). **Human Development Index (HDI)**, [*s. l.*], 2021. Available in: https://hdr.undp.org/data-center/human-development-index?gad_source=1&gclid=CjwKCAiAs6-sBhBmEiwA1Nl8s_bVI5rEx-eRVMicnT8QNV0yoIakdSupGmlHpwrrv310J7-93l22JhoCKHIQAvD_BwE#/indicies/HDI. Accessed on: September, 2023.

UNITED NATIONS (UN). **The 17 goals**, [s. l.], 2023a. Available in: https://sdgs.un.org/goals. Accessed on Jan, 2024.

UNITED NATIONS (UN). **World Population Dashboard**, [*s. l.*], 2023b. Available in: https://www.unfpa.org/data/world-population-dashboard. Accessed on: Jan, 2024.

VAN ZELM, R. *et al.* European characterization factors for human health damage of PM10 and ozone in life cycle impact assessment. **Atmos. Environ.**, Oxford, v. 42, n. 3, p. 441-453, 2008. https://doi.org/10.1016/j.atmosenv.2007.09.072

VAN ZELM, R. *et al.* Regionalized life cycle impact assessment of air pollution on the global scale: Damage to human health and vegetation. **Atmos. Environ.**, Oxford, v. 134, p. 129-137, 2016. https://doi.org/10.1016/j.atmosenv.2016.03.044

VARDOULAKIS, S. *et al*. Indoor Exposure to Selected Air Pollutants in the Home Environment: A Systematic Review. **Int. J. Environ. Res. Public Health**, [*s. l.*], v. 17, n. 23, p. 8972, 2020. https://doi.org/10.3390/ijerph17238972

VARGAS-GONZALEZ, M. *et al*. Operational Life Cycle Impact Assessment weighting factors based on Planetary Boundaries: Applied to cosmetic products. **Ecological Indicators**, [*s. l.*], v. 107, p. 105498, 2019. https://doi.org/10.1016/j.ecolind.2019.105498

VERONES, F. *et al*. LCIA framework and cross-cutting issues guidance within the UNEP-SETAC Life Cycle Initiative. **J. Clean. Prod.**, Amsterdam, v. 161, p. 957-967, 2017. https://doi.org/10.1016/j.jclepro.2017.05.206.

VORMITTAG, E. M. P. A. A. *et al*. Análise do monitoramento da qualidade do ar no Brasil. **Energia e ambiente**, [*s. l.*], v. 35, n. 102, 2021. https://doi.org/10.1590/s0103-4014.2021.35102.002

WANG, Z. *et al*. Human Health Impacts of Aviation Biofuel Production: Exploring the Application of Different Life Cycle Impact Assessment (LCIA) Methods for Biofuel Supply Chains. **Processes**, [*s. l.*], 8, 158, 2020. https://doi.org/10.3390/pr8020158

WEIDEMA B. P., *et al.* **Overview and methodology: data quality guideline for the ecoinvent database version 3**, 2013. Swiss Centre for Life Cycle Inventories, Swiss.

WEIDEMA, B. *et al*. LCA-based assessment of the Sustainable Development Goals. August, 1–55. PRé Sustainability & 2.-0 LCA consultants, 2020

WENGER, Y. *et al.* Indoor intake fraction considering surface sorption of air organic compounds for life cycle assessment. **Int. J. Life Cycle Assess**., [*s. l.*], v. 17, p. 919–931, 2012. https://doi.org/10.1007/s11367-012-0420-0

WENZEL, H. *et al.* **Environmental Assessment of Products**. 1. ed. Norwell: Chapman & Hall, 1997.

WOLF, M. J. *et al.* New Insights for Tracking Global and Local Trends in Exposure to Air Pollutants. **Environmental Science & Technology**, Easton, v. 56, n. 7, p. 3984-3996, 2022. https://doi-org.ez31.periodicos.capes.gov.br/10.1021/acs.est.1c08080

WORLD HEALTH ORGANIZATION (WHO). **Ambient (outdoor) air pollution**, [*s. l.*], 2024. Available in: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health. Accessed on: mar, 2024.

WU, R. *et al.* Reduced-complexity air quality intervention modeling over China: the development of InMAPv1.6.1-China and a comparison with CMAQv5.2. **Geoscientific Model Development**, v. 14, n. 12, p. 7621–7638, 2021. https://doi.org/10.5194/gmd-14-7621-2021

WU, Y. *et al*. Wildfire-related PM2.5 and health economic loss of mortality in Brazil. **Environment international**, v. 174, p. 107906, 2023. https://doi.org/10.1016/j.envint.2023.107906

WU, W. *et al*. Polyelectrolyte aerogels with regeneration capacity for efficient removal of particulate matters. **Journal of colloid and interface science**, v. 625, p. 446-456, 2022. https://doi.org/10.1016/j.jcis.2022.06.046

WYER, K. E. *et al.* Ammonia emissions from agriculture and their contribution to fine particulate matter: A review of implications for human health. **Journal of Environmental Management**, London, v. 323, p. 116285, 2022. https://doi.org/10.1016/j.jenvman.2022.116285

XAVIER, J. C. M. *et al*. Air quality public policies and their implications for densely populated urban areas in Brazil. **Sustentabilidade em debate,** Brazil, v. 8, n. 1, 2017. Doi: 10.18472/SustDeb.v8n1.2017.18846

XIONG, Y., *et al.* Long-term trends of impacts of global gasoline and diesel emissions on ambient PM2.5 and O3 pollution and the related health burden for 2000–2015. **Environmental Research Letters**, [*s. l.*], v. 17, n. 10, p. 104042, 2022. 10.1088/1748-9326/ac9422

XU, X. *et al*. What Factors Dominate the Change of PM2.5 in the World from 2000 to 2019? A Study from Multi-Source Data. **Int. J. Environ. Res. Public Health**, [s. l.], v. 20, n. 3, p. 2282, 2023. https://doi.org/10.3390/ijerph20032282

YANG, X., *et al*. The construction and examination of social vulnerability and its effects on PM2.5 globally: combining spatial econometric modeling and geographically weighted regression. **Environmental Science and Pollution Research**, [*s. l.*], v. 28, p. 26732-26746, 2021. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11356-021-12508-6

YE, T. *et al.* Risk and burden of hospital admissions associated with wildfire-related PM2·5 in Brazil, 2000–15: a nationwide time-series study. **The Lancet**, London, v. 5, n. 9, p. 599-607, 2021. https://doi.org/10.1016/S2542-5196(21)00173-X

YI, S. *et al*. Life cycle impact assessment and interpretation of municipal solid waste management scenarios based on the midpoint and endpoint approaches. **Int J Life Cycle Assess**, [*s. l.*], v. 16, p. 652–668, 2011. https://doi-org.ez31.periodicos.capes.gov.br/10.1007/s11367-011-0297-3

YOUNG, B. *et al*. LCIA Formatter. **The Journal of Open Source Software**, [*s. l.*], v. 6, n. 66, p. 3392, 2021. https://doi.org/10.21105/joss.03392

YU, P. *et al*. The impacts of long-term exposure to PM2.5 on cancer hospitalizations in Brazil. **Environment international**, New York, v. 154, p. 106671, 2021. https://doi.org/10.1016/j.envint.2021.106671

YU, P. *et al*. Exposure to wildfire-related PM2.5 and site-specific cancer mortality in Brazil from 2010 to 2016: A retrospective study. **PLoS Medicine**, [*s. l.*], 2022a. https://doi.org/10.1371/journal.pmed.1004103

YU, P. *et al*. Loss of life expectancy from PM2.5 in Brazil: A national study from 2010 to 2018. **Environment international**, New York, v. 166, p. 107350, 2022b. https://doi.org/10.1016/j.envint.2022.107350

YU, W. *et al.* Global estimates of daily ambient fine particulate matter concentrations and unequal spatiotemporal distribution of population exposure: a machine learning modelling study. **The Lancet Planetary Health**, [s. l.], v. 7, n. 3, p. e209-e218, 2023. https://doi.org/10.1016/S2542-5196(23)00008-6

ZAPPE, A. L. *et al.* Human health risk and potential environmental damage of organic and conventional Nicotiana tobaccum production. **Environmental Pollution**, Barking, v. 266, p. 114820, 2020. https://doi.org/10.1016/j.envpol.2020.114820

ZERI, M. *et al*. Assessment of the variability of pollutants concentration over the metropolitan area of São Paulo, Brazil, using the wavelet transform. **Atmospheric Science Letters**, [*s. l.*], v. 17, n. 1, p. 87-95, 2016.

ZHANG, J. *et al*. Adverse effects of exposure to fine particles and ultrafine particles in the environment on different organs of organisms. **Journal of Environmental Sciences**, China, v. 135, p. 449-473, 2024.

ZHANG, X. *et al*. A Systematic Review of Global Desert Dust and Associated Human Health Effects. **Atmosphere**, Toronto, v. 7, n. 12, 2016. https://doi.org/10.3390/atmos7120158

ZHAO, C. *et al.* Spatio-Temporal Patterns of Global Population Exposure Risk of PM2.5 from 2000–2016. **Sustainability**, [*s. l.*], v. 13, n. 13, p. 7427, 2021. https://doi.org/10.3390/su1313

APPENDIX A – DETAILED INVENTORIES OF MILK PRODUCTION SYSTEMS

Table A 1 - Detailed inventory of milk production systems focused on particulate matter and precursor emissions. Based on Giusti et al. (2023) and including VOC emission

Elementary flow	Compar.*	System 1 - SP		System 2 - PR		System 3 - PR		System 4 - MG	
		Mass Emission (kg)	Economic Emission (kg)	Mass Emission (kg)	Economic Emission (kg)	Mass Emission (kg)	Economic Emission (kg)	Mass Emission (kg)	Economic Emission (kg)
Ammonia	HPD	8.46×10^{-6}	1.10×10^{-5}	2.83×10^{-6}	2.54×10^{-6}	8.76×10^{-6}	7.29×10^{-6}	4.56×10^{-5}	1.68×10^{-5}
Ammonia	LPD	7.46×10^{-4}	9.70×10^{-4}	1.90×10^{-4}	1.70×10^{-4}	2.30×10^{-4}	1.91×10^{-4}	1.67×10^{-3}	6.14×10^{-4}
Ammonia	U	2.14×10^{-6}	2.79×10^{-6}	1.38×10^{-6}	1.24×10^{-6}	9.03×10^{-4}	7.52×10^{-4}	3.48×10^{-3}	1.28×10^{-3}
Ammonia	***TOTAL***	$\boldsymbol{7.57\times10^{-4}}$	$\boldsymbol{9.84\times10^{-4}}$	$\boldsymbol{1.94\times10^{-4}}$	$\boldsymbol{1.74\times10^{-4}}$	$\boldsymbol{1.14\times10^{-3}}$	$\boldsymbol{9.51\times10^{-4}}$	$\boldsymbol{5.19\times10^{-3}}$	$\boldsymbol{1.91\times10^{-3}}$
Ammonia (Austria)	HPD	1.12×10^{-9}	1.46×10^{-9}	2.57×10^{-9}	2.30×10^{-9}	3.70×10^{-9}	3.08×10^{-9}	2.74×10^{-9}	1.01×10^{-9}
Ammonia (Bosnia and Herzegovina)	HPD	9.98×10^{-14}	1.30×10^{-13}	1.96×10^{-13}	1.76×10^{-13}	2.79×10^{-13}	2.32×10^{-13}	1.92×10^{-13}	7.08×10^{-14}
Ammonia (Belgium)	HPD	1.76×10^{-9}	2.29×10^{-9}	3.70×10^{-9}	3.32×10^{-9}	5.30×10^{-9}	4.41×10^{-9}	4.07×10^{-9}	1.50×10^{-9}
Ammonia (Belgium)	U	1.80×10^{-14}	2.34×10^{-14}	8.28×10^{-15}	7.43×10^{-15}	9.98×10^{-15}	8.31×10^{-15}	5.74×10^{-14}	2.11×10^{-14}
Ammonia (Bulgaria)	HPD	2.92×10^{-12}	3.79×10^{-12}	6.33×10^{-12}	5.69×10^{-12}	9.09×10^{-12}	7.57×10^{-12}	6.66×10^{-12}	2.45×10^{-12}
Ammonia (Switzerland)	HPD	3.75×10^{-8}	4.87×10^{-8}	2.27×10^{-7}	2.04×10^{-7}	3.30×10^{-7}	2.75×10^{-7}	2.11×10^{-6}	7.79×10^{-7}
Ammonia (Switzerland)	LPD	1.11×10^{-8}	1.45×10^{-8}	1.29×10^{-4}	1.16×10^{-4}	1.37×10^{-4}	1.14×10^{-4}	8.36×10^{-9}	3.08×10^{-9}
Ammonia (Switzerland)	U	1.17×10^{-9}	1.52×10^{-9}	1.05×10^{-9}	9.45×10^{-10}	1.37×10^{-9}	1.14×10^{-9}	4.57×10^{-9}	1.69×10^{-9}
Ammonia (Czechia)	HPD	7.66×10^{-10}	9.95×10^{-10}	1.68×10^{-9}	1.51×10^{-9}	2.42×10^{-9}	2.01×10^{-9}	1.75×10^{-9}	6.47×10^{-10}
Ammonia (Germany)	HPD	4.22×10^{-9}	5.48×10^{-9}	9.54×10^{-9}	8.56×10^{-9}	1.37×10^{-8}	1.14×10^{-8}	1.02×10^{-8}	3.74×10^{-9}
Ammonia (Germany)	LPD	2.85×10^{-11}	3.71×10^{-11}	1.21×10^{-8}	1.09×10^{-8}	1.29×10^{-8}	1.07×10^{-8}	8.75×10^{-11}	3.22×10^{-11}
Ammonia (Germany)	U	4.89×10^{-12}	6.35×10^{-12}	2.23×10^{-12}	2.00×10^{-12}	2.75×10^{-12}	2.29×10^{-12}	4.33×10^{-12}	1.60×10^{-12}
Ammonia (Denmark)	HPD	2.39×10^{-9}	3.10×10^{-9}	5.02×10^{-9}	4.50×10^{-9}	7.18×10^{-9}	5.98×10^{-9}	5.11×10^{-9}	1.88×10^{-9}
Ammonia (Estonia)	HPD	6.55×10^{-11}	8.52×10^{-11}	1.38×10^{-10}	1.23×10^{-10}	1.97×10^{-10}	1.64×10^{-10}	1.42×10^{-10}	5.23×10^{-11}
Ammonia (Spain)	HPD	2.14×10^{-9}	2.78×10^{-9}	3.67×10^{-9}	3.30×10^{-9}	5.31×10^{-9}	4.42×10^{-9}	4.64×10^{-9}	1.71×10^{-9}
Ammonia (Spain)	LPD	1.45×10^{-16}	1.89×10^{-16}	2.34×10^{-9}	2.10×10^{-9}	2.49×10^{-9}	2.07×10^{-9}	7.52×10^{-16}	2.77×10^{-16}
Ammonia (Spain)	U	9.83×10^{-11}	1.28×10^{-10}	5.35×10^{-12}	4.80×10^{-12}	7.66×10^{-12}	6.38×10^{-12}	7.72×10^{-14}	2.84×10^{-14}
Ammonia (Finland)	HPD	3.22×10^{-9}	4.19×10^{-9}	7.14×10^{-9}	6.41×10^{-9}	1.03×10^{-8}	8.56×10^{-9}	8.00×10^{-9}	2.95×10^{-9}
Ammonia (Finland)	LPD	7.54×10^{-12}	9.80×10^{-12}	1.65×10^{-5}	1.48×10^{-5}	1.75×10^{-5}	1.46×10^{-5}	3.90×10^{-11}	1.44×10^{-11}
Ammonia (France)	HPD	1.23×10^{-9}	1.60×10^{-9}	2.56×10^{-9}	2.30×10^{-9}	3.66×10^{-9}	3.05×10^{-9}	2.65×10^{-9}	9.78×10^{-10}
Ammonia (France)	LPD	1.95×10^{-13}	2.54×10^{-13}	9.47×10^{-8}	8.50×10^{-8}	1.01×10^{-7}	8.37×10^{-8}	8.30×10^{-13}	3.06×10^{-13}
Ammonia (France)	U	2.63×10^{-11}	3.42×10^{-11}	2.20×10^{-12}	1.97×10^{-12}	2.86×10^{-12}	2.38×10^{-12}	2.07×10^{-14}	7.62×10^{-15}
Ammonia (United Kingdom)	HPD	8.11×10^{-9}	1.05×10^{-8}	1.67×10^{-8}	1.50×10^{-8}	2.39×10^{-8}	$1.99E\times10^{-8}$	1.67×10^{-8}	6.17×10^{-9}
Ammonia (Greece)	HPD	1.17×10^{-11}	1.53×10^{-11}	2.33×10^{-11}	2.09×10^{-11}	3.32×10^{-11}	2.76×10^{-11}	2.29×10^{-11}	8.46×10^{-12}
Ammonia (Croatia)	HPD	1.01×10^{-11}	1.31×10^{-11}	2.03×10^{-11}	1.83×10^{-11}	2.90×10^{-11}	2.41×10^{-11}	2.02×10^{-11}	7.45×10^{-12}
Ammonia (Hungary)	HPD	8.52×10^{-10}	1.11×10^{-9}	1.80×10^{-9}	1.62×10^{-9}	2.58×10^{-9}	2.15×10^{-9}	1.84×10^{-9}	6.80×10^{-10}
Ammonia (Hungary)	LPD	4.08×10^{-42}	5.30×10^{-42}	1.47×10^{-41}	1.32×10^{-41}	2.14×10^{-41}	1.78×10^{-41}	5.78×10^{-42}	2.13×10^{-42}
Ammonia (Ireland)	HPD	1.91×10^{-10}	2.48×10^{-10}	3.85×10^{-10}	3.45×10^{-10}	5.49×10^{-10}	4.57×10^{-10}	4.05×10^{-10}	1.49×10^{-10}
Ammonia (Italy)	HPD	2.09×10^{-9}	2.71×10^{-9}	4.39×10^{-9}	3.94×10^{-9}	6.28×10^{-9}	5.23×10^{-9}	4.45×10^{-9}	1.64×10^{-9}
Ammonia (Lithuania)	HPD	1.57×10^{-11}	2.05×10^{-11}	3.29×10^{-11}	2.95×10^{-11}	4.70×10^{-11}	3.92×10^{-11}	3.34×10^{-11}	1.23×10^{-11}
Ammonia (Luxembourg)	HPD	2.19×10^{-11}	2.84×10^{-11}	4.34×10^{-11}	3.90×10^{-11}	6.18×10^{-11}	5.15×10^{-11}	4.27×10^{-11}	1.57×10^{-11}
Ammonia (Latvia)	HPD	2.13×10^{-11}	2.77×10^{-11}	4.25×10^{-11}	3.82×10^{-11}	6.06×10^{-11}	5.05×10^{-11}	4.21×10^{-11}	1.55×10^{-11}
Ammonia (Macedonia)	HPD	1.89×10^{-13}	2.46×10^{-13}	3.71×10^{-13}	3.33×10^{-13}	5.28×10^{-13}	4.40×10^{-13}	3.65×10^{-13}	1.34×10^{-13}
Ammonia (Netherlands)	HPD	1.07×10^{-9}	1.40×10^{-9}	2.48×10^{-9}	2.23×10^{-9}	3.58×10^{-9}	2.98×10^{-9}	2.69×10^{-9}	9.90×10^{-10}
Ammonia (Norway)	HPD	3.88×10^{-11}	5.05×10^{-11}	1.01×10^{-10}	9.03×10^{-11}	1.46×10^{-10}	1.22×10^{-10}	1.14×10^{-10}	4.18×10^{-11}
Ammonia (Poland)	HPD	2.78×10^{-9}	3.62×10^{-9}	6.36×10^{-9}	5.71×10^{-9}	9.15×10^{-9}	7.62×10^{-9}	6.79×10^{-9}	2.50×10^{-9}
Ammonia (Portugal)	HPD	6.87×10^{-10}	8.93×10^{-10}	1.55×10^{-9}	1.39×10^{-9}	2.23×10^{-9}	1.86×10^{-9}	1.70×10^{-9}	6.27×10^{-10}
Ammonia (Romania)	HPD	1.24×10^{-10}	1.62×10^{-10}	2.63×10^{-10}	2.36×10^{-10}	3.76×10^{-10}	3.13×10^{-10}	2.69×10^{-10}	9.91×10^{-11}
Ammonia (Russia)	HPD	2.89×10^{-10}	3.75×10^{-10}	1.65×10^{-10}	1.48×10^{-10}	2.71×10^{-10}	2.26×10^{-10}	1.51×10^{-9}	5.57×10^{-10}
Ammonia (Russia)	LPD	7.24×10^{-11}	9.41×10^{-11}	5.32×10^{-11}	4.78×10^{-11}	6.67×10^{-11}	5.55×10^{-11}	2.30×10^{-10}	8.47×10^{-11}
Ammonia (Sweden)	HPD	3.54×10^{-9}	4.59×10^{-9}	7.83×10^{-9}	7.03×10^{-9}	1.13×10^{-8}	9.38×10^{-9}	8.49×10^{-9}	3.13×10^{-9}
Ammonia (Slovenia)	HPD	4.43×10^{-11}	5.76×10^{-11}	9.80×10^{-11}	8.80×10^{-11}	1.41×10^{-10}	1.17×10^{-10}	1.03×10^{-10}	3.79×10^{-11}
Ammonia (Slovakia)	HPD	2.22×10^{-10}	2.89×10^{-10}	5.06×10^{-10}	4.54×10^{-10}	7.28×10^{-10}	6.06×10^{-10}	5.37×10^{-10}	1.98×10^{-10}
Ammonia (Ukraine)	HPD	4.89×10^{-12}	6.35×10^{-12}	1.10×10^{-11}	9.90×10^{-12}	1.59×10^{-11}	1.32×10^{-11}	1.13×10^{-11}	4.18×10^{-12}
Ammonia (Ukraine)	LPD	5.81×10^{-10}	7.56×10^{-10}	4.27×10^{-10}	3.83×10^{-10}	5.35×10^{-10}	4.46×10^{-10}	1.85×10^{-9}	6.80×10^{-10}
Ammonia - international	***TOTAL***	$\boldsymbol{8.76\times10^{-8}}$	$\boldsymbol{1.14\times10^{-7}}$	$\boldsymbol{1.46\times10^{-4}}$	$\boldsymbol{1.31\times10^{-4}}$	$\boldsymbol{1.55\times10^{-4}}$	$\boldsymbol{1.29\times10^{-4}}$	$\boldsymbol{2.21\times10^{-6}}$	$\boldsymbol{8.16\times10^{-7}}$
Nitrogen oxides	HPD	3.49×10^{-5}	4.54×10^{-5}	6.09×10^{-5}	5.47×10^{-5}	8.92×10^{-5}	7.43×10^{-5}	1.61×10^{-4}	5.93×10^{-5}
Nitrogen oxides	LPD	3.12×10^{-4}	4.05×10^{-4}	2.31×10^{-4}	2.07×10^{-4}	3.05×10^{-4}	2.54×10^{-4}	5.54×10^{-4}	2.04×10^{-4}
Nitrogen oxides	U	6.22×10^{-5}	8.09×10^{-5}	4.67×10^{-5}	4.20×10^{-5}	7.58×10^{-5}	6.32×10^{-5}	2.25×10^{-4}	8.31×10^{-5}
Nitrogen oxides	***TOTAL***	$\boldsymbol{4.09\times10^{-4}}$	$\boldsymbol{5.32\times10^{-4}}$	$\boldsymbol{3.38\times10^{-4}}$	$\boldsymbol{3.04\times10^{-4}}$	$\boldsymbol{4.70\times10^{-4}}$	$\boldsymbol{3.91\times10^{-4}}$	$\boldsymbol{9.41\times10^{-4}}$	$\boldsymbol{3.47\times10^{-4}}$

Table A 2 - Detailed inventory of milk production systems focused on particulate matter and precursor emissions. Based on Giusti et al. (2023) and including VOC emission (continuation)

Elementary flow	**Compar.***	**System 1 - SP**		**System 2 - PR**		**System 3 - PR**		**System 4 - MG**	
		Mass	**Economic**	**Mass**	**Economic**	**Mass**	**Economic**	**Mass**	**Economic**
Particulates, <2.5 um	HPD	6.94×10^{-6}	9.02×10^{-6}	9.08×10^{-6}	8.15×10^{-6}	1.30×10^{-5}	1.09×10^{-5}	2.15×10^{-5}	7.93×10^{-6}
Particulates, <2.5 um	LPD	8.76×10^{-5}	1.14×10^{-4}	1.02×10^{-4}	9.20×10^{-5}	1.23×10^{-4}	1.02×10^{-4}	3.67×10^{-4}	1.35×10^{-4}
Particulates, <2.5 um	U	3.84×10^{-6}	4.99×10^{-6}	3.06×10^{-6}	2.75×10^{-6}	4.04×10^{-6}	3.36×10^{-6}	1.43×10^{-5}	5.27×10^{-6}
Particulates, <2.5 um	***TOTAL***	$\boldsymbol{9.84\times10^{-5}}$	$\boldsymbol{1.28\times10^{-4}}$	$\boldsymbol{1.15\times10^{-4}}$	$\boldsymbol{1.03\times10^{-4}}$	$\boldsymbol{1.40\times10^{-4}}$	$\boldsymbol{1.17\times10^{-4}}$	$\boldsymbol{4.03\times10^{-4}}$	$\boldsymbol{1.48\times10^{-4}}$
Sulfur dioxide	HPD	5.34×10^{-5}	6.94×10^{-5}	9.84×10^{-5}	8.83×10^{-5}	1.41×10^{-4}	1.17×10^{-4}	1.93×10^{-4}	7.10×10^{-5}
Sulfur dioxide	LPD	9.82×10^{-5}	1.28×10^{-4}	1.14×10^{-4}	1.03×10^{-4}	1.62×10^{-4}	1.35×10^{-4}	3.06×10^{-4}	1.13×10^{-4}
Sulfur dioxide	U	2.04×10^{-5}	2.65×10^{-5}	1.51×10^{-5}	1.35×10^{-5}	2.07×10^{-5}	1.73×10^{-5}	8.12×10^{-5}	2.99×10^{-5}
Sulfur dioxide	***TOTAL***	$\boldsymbol{1.72\times10^{-4}}$	$\boldsymbol{2.24\times10^{-4}}$	$\boldsymbol{2.28\times10^{-4}}$	$\boldsymbol{2.04\times10^{-4}}$	$\boldsymbol{3.23\times10^{-4}}$	$\boldsymbol{2.69\times10^{-4}}$	$\boldsymbol{5.80\times10^{-4}}$	$\boldsymbol{2.14\times10^{-4}}$
Volatile Organic Compounds	***TOTAL***	$\boldsymbol{1.57}\times10^{-7}$	$\boldsymbol{2.04}\times10^{-7}$	$\boldsymbol{9.42}\times10^{-8}$	$\boldsymbol{8.46}\times10^{-8}$	$\boldsymbol{1.35}\times10^{-7}$	$\boldsymbol{1.12}\times10^{-7}$	$\boldsymbol{7.41}\times10^{-7}$	$\boldsymbol{2.73}\times10^{-7}$

*Compartment legend: HPD = High population density; LPD = Low population density; U = Unspecified

APPENDIX B – DETAILED SCORING OF THE PM IMPACT CHARACTERIZATION MODELS SELECTED FOR EVALUATION

Table A 3 - Scoring of sub-criteria for the Scope Criteria: Intake Fraction

Model	Geographic coverage	Spatial differentiation	Temporal resolution	Coverage of elementary flows	Criterion score
Geographic approach					
Hofstetter (1998)	2.00	3.00	1.00	5.00	2.75
Steen (1999)	3.00	1.00	1.00	5.00	2.50
Huijbregts *et al.* (2000)	3.00	1.00	0.00	5.00	2.25
Potting and Hauschild (2005)	2.00	2.00	1.00	5.00	2.50
Van Zelm *et al.* (2008)	2.00	4.00	1.00	5.00	3.00
Bare (2011)	1.00	3.00	1.00	4.00	2.25
Tang *et al.* (2018)	5.00	1.00	2.00	4.00	3.00
Van Zelm *et al.* (2016)	5.00	3.00	2.00	5.00	3.75
Oberschelp *et al.* (2020)	5.00	4.00	5.00	5.00	4.75
Archetype approach					
Humbert *et al.* (2011)	2.00	4.00	2.00	5.00	3.25
Wenger *et al.* (2012)	1.00	1.00	2.00	1.00	1.25
Notter (2015)	2.00	3.00	2.00	2.00	2.25
Hybrid approach					
Fantke *et al.* (2017)	5.00	5.00	3.00	1.00	3.50

Table A 4 - Scoring of sub-criteria for the Scientific Robustness: Intake Fraction

Model	Is the model considered by any LCIA method?	Cause-and-effect chain	Transparence accessibility	Equation's clarity	Variable's clarity	Criterion score
Geographic approach						
Hofstetter (1998)	5.00	5.00	4.00	4.00	4.00	4.40
Steen (1999)	5.00	3.00	2.00	5.00	5.00	4.00
Huijbregts *et al.* (2000)	5.00	3.00	1.00	2.00	3.00	2.80
Potting and Hauschild (2005)	5.00	5.00	4.00	4.00	3.00	4.20
Van Zelm *et al.* (2008)	5.00	5.00	5.00	5.00	5.00	5.00
Bare (2011)	5.00	3.00	3.00	1.00	5.00	3.40
Tang *et al.* (2018)	5.00	5.00	3.00	5.00	3.00	4.20
Van Zelm *et al.* (2016)	5.00	5.00	4.00	5.00	5.00	4.80
Oberschelp *et al.* (2020)	3.00	5.00	3.00	5.00	5.00	4.20
Archetype approach						
Humbert *et al.* (2011)	5.00	5.00	3.00	5.00	5.00	4.60
Wenger *et al.* (2012)	3.00	3.00	3.00	5.00	5.00	3.80
Notter (2015)	3.00	5.00	3.00	4.00	4.00	3.80
Hybrid approach						
Fantke *et al.* (2017)	3.00	5.00	5.00	5.00	5.00	4.60

Table A 5 – Scoring of sub-criteria for the Intake Fraction for Brazil

Model	iF for Brazil	Brazilian spatial differentiation	iF appropriate for Brazil	Criterion score
Geographic approach				
Hofstetter (1998)	1.00	-	-	1.0
Steen (1999)	5.00	1.00	1.00	2.30
Huijbregts *et al.* (2000)	5.00	1.00	1.00	2.30
Potting and Hauschild (2005)	1.00	-	-	1.00
Van Zelm *et al.* (2008)	1.00	-	-	1.00
Bare (2011)	1.00	-	-	1.00
Tang *et al.* (2018)	5.00	1.00	1.00	2.30
Van Zelm *et al.* (2016)	5.00	1.00	1.00	2.30
Oberschelp *et al.* (2020)	5.00	4.00	5.00	4.70
Archetype approach				
Humbert *et al.* (2011)	1.00	-	-	1.00
Wenger *et al.* (2012)	1.00	-	-	1.00
Notter (2015)	1.00	-	-	1.00
Hybrid approach				
Fantke *et al.* (2017)	5.00	5.00	5.00	5.00

Table A 6 - Scoring of sub-criteria for the Scope Criteria: Effect Factor

Model	Demographic coverage	Exposure-Response coverage	Temporal Resolution of exposure-response data	Health effects	Considered substances	Temporal resolution of concentration data	Criterion Scope
Geographic approach							
Wenzel *et al.* (1997)	3.00	0.00	0.00	1.00	1.00	0.00	0.83
Hofstetter (1998)	3.00	3.00	1.00	5.00	5.00	1.00	3.00
Steen (1999)	3.00	5.00	1.00	3.00	1.00	1.00	2.33
Huijbregts *et al.* (2000)	3.00	0.00	1.00	1.00	5.00	1.00	1.83
Van Zelm *et al.* (2008)	4.00	3.00	1.00	5.00	1.00	1.00	2.50
Bare (2011)	2.00	3.00	1.00	4.00	2.00	1.00	2.17
Tang *et al.* (2018)	5.00	5.00	2.00	5.00	2.00	2.00	3.50
Van Zelm *et al.* (2016)	5.00	1.00	2.00	3.00	2.00	2.00	2.50
Oberschelp *et al.* (2020)	5.00	5.00	5.00	5.00	2.00	5.00	4.50
Archetype approach							
Gronlund *et al.* (2015)	4.00	1.00	1.00	3.00	2.00	1.00	2.00
Notter (2015)	3.00	3.00	3.00	3.00	3.00	2.00	2.83
Fantke *et al.* (2019)	5.00	5.00	5.00	5.00	2.00	5.00	4.50

Table A 7 - Scoring of sub-criteria for the Scope Scientific Robustness: Effect Factor

Model	Is the model considered by any LCIA method?	Cause-and-effect chain	Transparence accessibility	Equation's clarity	Variable's clarity	Criterion score
Geographic approach						
Wenzel *et al.* (1997)	5.00	5.00	1.00	5.00	1.00	3.40
Hofstetter (1998)	5.00	5.00	4.00	5.00	5.00	4.80
Steen (1999)	5.00	3.00	2.00	5.00	5.00	4.00
Huijbregts *et al.* (2000)	5.00	3.00	1.00	5.00	5.00	3.80
Van Zelm *et al.* (2008)	5.00	5.00	3.00	5.00	5.00	4.60
Bare (2011)	5.00	3.00	1.00	5.00	5.00	3.80
Tang *et al.* (2018)	5.00	5.00	3.00	5.00	3.00	4.20
Van Zelm *et al.* (2016)	5.00	5.00	3.00	5.00	5.00	4.60
Oberschelp *et al.* (2020)	3.00	5.00	3.00	5.00	5.00	4.20
Archetype approach						
Gronlund *et al.* (2015)	5.00	5.00	5.00	5.00	5.00	5.00
Notter (2015)	3.00	5.00	4.00	3.00	3.00	3.60
Fantke *et al.* (2019)	3.00	5.00	5.00	5.00	5.00	4.60

Table A 8 - Scoring of sub-criteria for the Effect Factor for Brazil

Model	EF for Brazil	Brazilian spatial differentiation	EF appropriate for Brazil	Criterion Score
Geographic approach				
Wenzel *et al.* (1997)	1.00	-	-	1.00
Hofstetter (1998)	1.00	-	-	1.00
Steen (1999)	5.00	1.00	1.00	2.33
Huijbregts *et al.* (2000)	5.00	1.00	1.00	2.33
Van Zelm *et al.* (2008)	1.00	-	-	1.00
Bare (2011)	1.00	-	-	1.00
Tang *et al.* (2018)	5.00	3.00	1.00	3.00
Van Zelm *et al.* (2016)	5.00	3.00	1.00	3.00
Oberschelp *et al.* (2020)	5.00	5.00	5.00	5.00
Archetype approach				
Gronlund *et al.* (2015)	1.00	-	-	1.00
Notter (2015)	1.00	-	-	1.00
Fantke *et al.* (2019)	5.00	5.00	5.00	5.00

APPENDIX C – PARAMETERS AND RESULTS OF CHARACTERIZATION FACTORS

Table A 9 – Total emission (in kg) of $PM_{2.5}$ and precursor gases per Brazilian region

Region	**Meso-region**	**Emission (kg)**				
		$PM_{2.5}$	**NH_3**	**SO_x**	**NO_x**	**VOC**
Acre	North	4480219.6	758278.4	442232.9	33532613.9	1158271437.1
Amazonas	North	10053060.9	1663025.5	1382943.1	216776961.0	13280317162.1
Pará	North	17227994.6	2655342.8	3354030.1	256812035.3	7246773294.5
Amapá	North	496454.3	65018.4	143375.0	20904057.7	832601397.4
Tocantins	North	3190656.2	165846.3	812154.5	105375992.8	584306456.5
Maranhão	Northeast	4545746.1	487159.5	1413173.2	110070588.6	1459572135.8
Piauí	Northeast	1834002.3	125903.1	550663.1	87047134.5	586490826.4
Ceará	Northeast	3079017.7	279359.6	1310033.3	65811272.4	389046648.2
Rio Grande do Norte	Northeast	1354228.2	100911.7	559716.8	24219288.2	143275998.8
Paraíba	Northeast	1397098.2	155626.4	670334.7	27761630.5	171326281.0
Pernambuco	Northeast	3758831.8	333047.1	1614197.9	67354552.0	287319540.7
Alagoas	Northeast	991525.3	128449.4	582828.0	24438556.1	154509823.4
Sergipe	Northeast	860588.9	86673.8	758156.0	18901156.2	77573104.5
Bahia	Northeast	8267907.9	652391.3	5180737.5	237492916.3	1114582103.2
Minas Gerais	Southeast	19720687.2	1148332.4	11050842.9	376000800.8	1585510119.1
Espírito Santo	Southeast	2901382.3	171875.6	2231022.6	45403386.3	203141374.3
Rio de Janeiro	Southeast	6336832.1	824553.6	5065612.8	83521542.8	543880580.6
São Paulo	Southeast	37160153.4	2549908.8	15143335.2	560726896.0	2595112562.3
Paraná	South	16483893.3	725575.4	5723411.3	249974262.7	1377301469.8
Santa Catarina	South	7846260.6	524605.7	2647417.6	94748508.1	842224370.9
Rio Grande do Sul	South	11931012.9	674964.4	4437665.6	203581111.5	1396972660.2
Mato Grosso do Sul	Midwest	4346155.7	251828.0	1385120.4	247195796.6	626220930.9
Mato Grosso	Midwest	14210752.8	1592356.6	2597579.7	301356365.4	3931255972.2
Goiás	Midwest	7691753.3	382068.1	2707424.7	207259950.0	751409722.3
Distrito Federal	Midwest	1438058.6	129219.8	585963.7	13928243.6	62075369.6
Rondônia	North	6848208.8	997953.7	954751.5	75090433.9	1523981829.2
Roraima	North	4663975.1	749552.9	501903.2	49444210.8	1320008531.6
Brazil	-	203116458.2	18379828.3	73806627.5	3804730263.9	44245061702.6

Table A 10 - Global health effects from increased pollution concentrations caused by emissions from Brazilian regions

Region	**Meso-region**	**Deaths**					**Years of Life lost**					**Disability Adjusted life Years**				
		$PM_{2.5}$	**NH_3**	**SO_x**	**NO_x**	**VOC**	**$PM_{2.5}$**	**NH_3**	**SO_x**	**NO_x**	**VOC**	**$PM_{2.5}$**	**NH_3**	**SO_x**	**NO_x**	**VOC**
Acre	North	5.4	0.7	0.8	23.4	55.1	169.0	18.9	24.8	634.6	1580.0	269.6	29.1	39.5	1015.2	2466.3
Amazonas	North	155.7	1.2	15.5	193.9	354.3	5289.1	36.3	525.4	5260.2	10660.8	8515.2	57.5	845.8	8596.3	17012.2
Pará	North	39.7	1.4	10.4	224.0	200.0	1290.9	43.8	338.4	6298.5	6316.9	2112.8	71.0	553.8	10287.3	10255.6
Amapá	North	1.6	0.0	0.2	21.9	24.9	58.1	0.8	6.4	627.4	856.3	94.1	1.3	10.4	1030.4	1386.0
Tocantins	North	4.8	0.1	0.9	68.8	18.9	146.9	2.0	27.4	1847.8	536.9	243.7	3.3	45.4	3011.3	875.9
Maranhão	Northeast	82.4	0.2	5.9	207.3	86.1	2610.7	7.2	187.6	6231.7	2676.3	4180.9	11.6	301.7	10027.5	4303.0
Piauí	Northeast	10.5	0.1	1.4	58.8	24.9	306.8	1.5	43.1	1592.5	729.8	505.9	2.5	70.5	2596.0	1189.4
Ceará	Northeast	131.3	1.2	10.1	165.0	259.6	3682.8	33.4	289.3	4584.9	7298.0	6203.8	56.1	482.7	7652.6	12273.3
Rio Grande do Norte	Northeast	21.2	0.1	4.2	31.7	35.2	601.0	3.1	120.9	876.7	1000.2	1009.9	5.1	202.1	1448.9	1674.4
Paraíba	Northeast	18.1	0.4	8.3	24.6	50.4	479.6	10.6	223.8	662.3	1344.6	788.1	17.4	368.5	1082.0	2210.0
Pernambuco	Northeast	117.5	2.4	39.7	63.2	178.9	3343.5	68.7	1128.1	1736.8	5077.2	5477.0	112.4	1849.2	2836.1	8313.3
Alagoas	Northeast	12.8	0.7	6.6	34.9	181.5	381.7	19.4	196.1	1001.1	5439.3	628.0	31.9	322.6	1640.8	8945.0
Sergipe	Northeast	18.0	0.1	6.7	16.4	23.4	546.2	4.0	202.1	458.2	705.5	903.3	6.6	334.2	750.3	1165.2
Bahia	Northeast	59.5	3.4	29.9	219.4	484.7	1759.1	100.6	879.7	5924.6	14314.4	2916.2	166.4	1459.8	9732.2	23660.7
Minas Gerais	Southeast	326.1	10.0	224.6	1115.9	657.0	8517.0	261.6	5870.3	29235.4	17246.3	14406.9	436.6	9855.6	48642.2	28579.3
Espírito Santo	Southeast	76.7	2.3	109.4	154.0	397.3	2102.8	61.5	3010.1	4101.7	10920.1	3494.9	101.5	5010.7	6710.6	18147.9
Rio de Janeiro	Southeast	601.2	38.6	412.1	927.6	1418.2	15814.8	1016.1	10835.5	24388.7	37322.1	24669.9	1588.5	16955.6	38459.7	58380.9
São Paulo	Southeast	3017.3	162.6	1782.1	7568.5	3097.1	78061.1	4206.2	46105.8	196274.2	80276.4	131263.1	7072.5	77529.7	329589.4	134856.7
Paraná	South	213.4	7.4	124.9	774.8	203.7	5738.6	199.4	3359.6	20700.2	5432.3	9549.5	331.7	5589.6	34421.9	9058.1
Santa Catarina	South	63.8	2.8	25.8	191.1	417.9	1684.1	73.6	677.7	5029.9	11074.6	2916.7	127.3	1170.7	8573.3	19232.9
Rio Grande do Sul	South	183.3	6.7	113.0	327.6	709.4	4516.4	165.8	2782.8	8158.9	17507.7	7422.3	272.4	4572.6	13381.3	28752.6
Mato Grosso do Sul	Midwest	26.8	0.7	5.3	182.1	119.3	830.0	19.8	161.4	4869.1	3373.0	1356.2	31.7	263.3	7915.5	5410.3
Mato Grosso	Midwest	14.9	0.2	4.9	183.0	51.9	419.0	5.9	135.2	4861.1	1413.8	695.6	9.7	224.2	7980.0	2321.6
Goiás	Midwest	90.8	0.9	35.2	231.7	102.0	2641.3	23.5	1021.3	6202.1	2846.7	4355.2	38.9	1687.7	10226.4	4701.5
Distrito Federal	Midwest	30.9	0.3	11.8	22.2	17.6	904.8	8.9	344.9	604.3	504.5	1654.5	15.5	620.1	1026.8	892.6
Rondônia	North	11.6	0.6	1.6	40.7	57.3	358.0	15.5	49.3	1093.9	1679.0	600.7	24.1	81.4	1754.0	2662.8
Roraima	North	1.0	0.3	0.2	66.2	22.5	34.9	8.4	7.4	1772.1	647.2	54.6	13.7	11.6	2931.7	1040.0
Brazil	-	5336.1	245.5	2991.6	13138.4	9248.9	142288.3	6416.7	78554.2	345028.8	248780.0	236288.6	10636.3	130459.3	573319.9	409767.4

Table A 11 – Regionalized characterization factors for PM and precursor gases

Region	**Meso-region**	**CF - Deaths/kg**					**CF - YLL/kg**					**CF - DALY/kg**				
		$PM_{2.5}$	**NH_3**	**SO_x**	**NO_x**	**VOC**	**$PM_{2.5}$**	**NH_3**	**SO_x**	**NO_x**	**VOC**	**$PM_{2.5}$**	**NH_3**	**SO_x**	**NO_x**	**VOC**
Acre	North	1.19E-06	8.96E-07	1.77E-06	6.99E-07	4.75E-08	3.77E-05	2.49E-05	5.60E-05	1.89E-05	1.36E-06	6.02E-05	3.84E-05	8.92E-05	3.03E-05	2.13E-06
Amazonas	North	1.55E-05	7.15E-07	1.12E-05	8.95E-07	2.67E-08	5.26E-04	2.18E-05	3.80E-04	2.43E-05	8.03E-07	8.47E-04	3.46E-05	6.12E-04	3.97E-05	1.28E-06
Pará	North	2.30E-06	5.38E-07	3.10E-06	8.72E-07	2.76E-08	7.49E-05	1.65E-05	1.01E-04	2.45E-05	8.72E-07	1.23E-04	2.67E-05	1.65E-04	4.01E-05	1.42E-06
Amapá	North	3.16E-06	3.99E-07	1.24E-06	1.05E-06	2.99E-08	1.17E-04	1.26E-05	4.47E-05	3.00E-05	1.03E-06	1.90E-04	2.04E-05	7.25E-05	4.93E-05	1.66E-06
Tocantins	North	1.51E-06	4.54E-07	1.12E-06	6.53E-07	3.23E-08	4.60E-05	1.22E-05	3.37E-05	1.75E-05	9.19E-07	7.64E-05	1.99E-05	5.59E-05	2.86E-05	1.50E-06
Maranhão	Northeast	1.81E-05	4.99E-07	4.20E-06	1.88E-06	5.90E-08	5.74E-04	1.47E-05	1.33E-04	5.66E-05	1.83E-06	9.20E-04	2.37E-05	2.13E-04	9.11E-05	2.95E-06
Piauí	Northeast	5.70E-06	4.30E-07	2.59E-06	6.75E-07	4.25E-08	1.67E-04	1.21E-05	7.83E-05	1.83E-05	1.24E-06	2.76E-04	1.96E-05	1.28E-04	2.98E-05	2.03E-06
Ceará	Northeast	4.26E-05	4.27E-06	7.70E-06	2.51E-06	6.67E-07	1.20E-03	1.20E-04	2.21E-04	6.97E-05	1.88E-05	2.01E-03	2.01E-04	3.68E-04	1.16E-04	3.15E-05
Rio Grande do Norte	Northeast	1.57E-05	1.08E-06	7.56E-06	1.31E-06	2.46E-07	4.44E-04	3.04E-05	2.16E-04	3.62E-05	6.98E-06	7.46E-04	5.04E-05	3.61E-04	5.98E-05	1.17E-05
Paraíba	Northeast	1.30E-05	2.58E-06	1.24E-05	8.85E-07	2.94E-07	3.43E-04	6.84E-05	3.34E-04	2.39E-05	7.85E-06	5.64E-04	1.12E-04	5.50E-04	3.90E-05	1.29E-05
Pernambuco	Northeast	3.12E-05	7.26E-06	2.46E-05	9.38E-07	6.23E-07	8.90E-04	2.06E-04	6.99E-04	2.58E-05	1.77E-05	1.46E-03	3.37E-04	1.15E-03	4.21E-05	2.89E-05
Alagoas	Northeast	1.29E-05	5.08E-06	1.13E-05	1.43E-06	1.17E-06	3.85E-04	1.51E-04	3.36E-04	4.10E-05	3.52E-05	6.33E-04	2.49E-04	5.54E-04	6.71E-05	5.79E-05
Sergipe	Northeast	2.09E-05	1.57E-06	8.82E-06	8.69E-07	3.01E-07	6.35E-04	4.62E-05	2.67E-04	2.42E-05	9.10E-06	1.05E-03	7.62E-05	4.41E-04	3.97E-05	1.50E-05
Bahia	Northeast	7.19E-06	5.27E-06	5.77E-06	9.24E-07	4.35E-07	2.13E-04	1.54E-04	1.70E-04	2.49E-05	1.28E-05	3.53E-04	2.55E-04	2.82E-04	4.10E-05	2.12E-05
Minas Gerais	Southeast	1.65E-05	8.73E-06	2.03E-05	2.97E-06	4.14E-07	4.32E-04	2.28E-04	5.31E-04	7.78E-05	1.09E-05	7.31E-04	3.80E-04	8.92E-04	1.29E-04	1.80E-05
Espírito Santo	Southeast	2.64E-05	1.32E-05	4.91E-05	3.39E-06	1.96E-06	7.25E-04	3.58E-04	1.35E-03	9.03E-05	5.38E-05	1.20E-03	5.90E-04	2.25E-03	1.48E-04	8.93E-05
Rio de Janeiro	Southeast	9.49E-05	4.69E-05	8.14E-05	1.11E-05	2.61E-06	2.50E-03	1.23E-03	2.14E-03	2.92E-04	6.86E-05	3.89E-03	1.93E-03	3.35E-03	4.60E-04	1.07E-04
São Paulo	Southeast	8.12E-05	6.38E-05	1.18E-04	1.35E-05	1.19E-06	2.10E-03	1.65E-03	3.04E-03	3.50E-04	3.09E-05	3.53E-03	2.77E-03	5.12E-03	5.88E-04	5.20E-05
Paraná	South	1.29E-05	1.02E-05	2.18E-05	3.10E-06	1.48E-07	3.48E-04	2.75E-04	5.87E-04	8.28E-05	3.94E-06	5.79E-04	4.57E-04	9.77E-04	1.38E-04	6.58E-06
Santa Catarina	South	8.14E-06	5.31E-06	9.73E-06	2.02E-06	4.96E-07	2.15E-04	1.40E-04	2.56E-04	5.31E-05	1.31E-05	3.72E-04	2.43E-04	4.42E-04	9.05E-05	2.28E-05
Rio Grande do Sul	South	1.54E-05	9.96E-06	2.55E-05	1.61E-06	5.08E-07	3.79E-04	2.46E-04	6.27E-04	4.01E-05	1.25E-05	6.22E-04	4.04E-04	1.03E-03	6.57E-05	2.06E-05
Mato Grosso do Sul	Midwest	6.17E-06	2.92E-06	3.83E-06	7.37E-07	1.90E-07	1.91E-04	7.85E-05	1.17E-04	1.97E-05	5.39E-06	3.12E-04	1.26E-04	1.90E-04	3.20E-05	8.64E-06
Mato Grosso	Midwest	1.05E-06	1.41E-07	1.87E-06	6.07E-07	1.32E-08	2.95E-05	3.69E-06	5.20E-05	1.61E-05	3.60E-07	4.90E-05	6.09E-06	8.63E-05	2.65E-05	5.91E-07
Goiás	Midwest	1.18E-05	2.23E-06	1.30E-05	1.12E-06	1.36E-07	3.43E-04	6.15E-05	3.77E-04	2.99E-05	3.79E-06	5.66E-04	1.02E-04	6.23E-04	4.93E-05	6.26E-06
Distrito Federal	Midwest	2.15E-05	2.49E-06	2.02E-05	1.59E-06	2.84E-07	6.29E-04	6.91E-05	5.89E-04	4.34E-05	8.13E-06	1.15E-03	1.20E-04	1.06E-03	7.37E-05	1.44E-05
Rondônia	North	1.69E-06	5.53E-07	1.68E-06	5.42E-07	3.76E-08	5.23E-05	1.56E-05	5.16E-05	1.46E-05	1.10E-06	8.77E-05	2.41E-05	8.53E-05	2.34E-05	1.75E-06
Roraima	North	2.09E-07	4.08E-07	4.09E-07	1.34E-06	1.70E-08	7.49E-06	1.12E-05	1.48E-05	3.58E-05	4.90E-07	1.17E-05	1.83E-05	2.31E-05	5.93E-05	7.88E-07
Brazil	-	2.63E-05	1.34E-05	4.05E-05	3.45E-06	2.09E-07	7.01E-04	3.49E-04	1.06E-03	9.07E-05	5.62E-06	1.16E-03	5.79E-04	1.77E-03	1.51E-04	9.26E-06