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Fabíola Negreiros de Oliveira

Prioritization and equity in decision-making models for vulnerability driven public policies

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Engenharia de Produção of PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Engenharia de Produção.

Advisor : Prof. Adriana Leiras
Co-advisor: Prof. Douglas José Alem Júnior

Rio de Janeiro
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Abstract

Oliveira, Fabíola Negreiros de; Leiras, Adriana (Advisor); Alem, Douglas José Júnior (Co-Advisor). **Prioritization and equity in decision-making models for vulnerability driven public policies** . Rio de Janeiro, 2024. 137p. Tese de Doutorado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

Poverty, hunger and food insecurity, illiteracy and low education, poor housing conditions, and inadequate health care describe the living conditions of thousands of families worldwide. In a scenario of limited resources, a prerequisite for decision-making is to understand the vulnerabilities of the affected population so that it is possible to target and prioritize the most in-need areas/households/people. Among the numerous prioritization criteria, equity has emerged as a key criterion conceptualized in terms of fairness in allocating and distributing benefits and burdens in society. This thesis proposes to incorporate prioritization and equity issues into decision-making models for orientated vulnerable populations' public policies. We structure an approach that integrates means of measuring vulnerability as a way of prioritization (through developing prioritization indexes) and incorporating them into a decision-making model to optimize resource allocation and distribution effectively and especially equitably. To shed light on this problem, we study two real and complex cases applied in the malaria intervention context and hunger and food insecurity scenario in Brazil.

Keywords

Prioritization; Equity; Vulnerability; Malaria; Food insecurity.

Resumo

Oliveira, Fabíola Negreiros de; Leiras, Adriana; Alem, Douglas José Júnior. **Priorização e equidade nos modelos de tomada de decisão para políticas públicas de populações vulneráveis** . Rio de Janeiro, 2024. 137p. Tese de Doutorado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

Pobreza, fome e insegurança alimentar, analfabetismo e baixa escolaridade, condições precárias de moradia e assistência médica inadequada caracterizam as condições de vida de milhares de famílias em todo o mundo. Em um cenário de recursos limitados, um pré-requisito para a tomada de decisão é entender as vulnerabilidades da população afetada para que seja possível priorizar as áreas/famílias/pessoas mais carentes. Entre os vários critérios de priorização, a equidade emergiu como um critério-chave, conceituada em termos de justiça na alocação e distribuição de benefícios. A presente tese propõe incorporar questões de priorização e equidade em modelos de tomada de decisão para políticas públicas voltadas para populações vulneráveis. Estruturamos uma abordagem que integra meios de medir a vulnerabilidade como forma de priorização (através do desenvolvimento de índices de priorização) e incorporando-os a um modelo de tomada de decisão para otimizar a alocação e distribuição de recursos de forma eficaz, e principalmente, equitativa. Para lançar luz sobre esse problema, estudamos dois casos reais e complexos, aplicados no cenário de doenças endêmicas e no contexto de fome e insegurança alimentar no Brasil.

Palavras-chave

Priorização; Equidade; Vulnerabilidade; Malária; Insegurança alimentar.

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"Que é muito difícil você vencer a injustiça secular, que dilacera o Brasil em dois países distintos: o país dos privilegiados e o país dos despossuídos"

Ariano Suassuna, *em entrevista ao Jornal da Globo.*

1
Introduction

Poverty, hunger and food insecurity, illiteracy and low education, poor housing, and precarious health care services describe the living conditions of thousands of families worldwide, especially in low-income countries, rural and isolated areas or irregular urban agglomerations (DRACHLER et al., 2003). Such inadequate conditions – which these populations have been exposed to for decades – restrict their life options and influence their health, workforce, and learning ability, exposing them to physical and mental issues, activity limitations, and restrictions on social participation (ÜSTÜN et al., 2003), what makes them *socially vulnerable*.

Controversially, these populations are the most in need of health, economic, and social resources, and those who have the least access to these services (DRACHLER et al., 2014). This imbalance significantly contributes to the vicious cycle of poverty, often referred to as *poverty trap*[1], which is composed of self-reinforcing mechanisms that ensure poverty remains unless external interventions are taken to disrupt this cycle (AZARIADIS; STACHURSKI, 2005).

Such interventions are commonly performed through *public policies* – comprehensive strategies comprising actions, programs, measures, and initiatives created by governments. Their purpose is to secure rights, provide assistance, or deliver essential services to those in need. The overarching goal is to facilitate access to legally guaranteed rights for the population, mitigating social inequalities and vulnerabilities. Ultimately, these efforts contribute to breaking the vicious cycle of poverty that disproportionately affects the most vulnerable, as outlined by Pauly & Willett (1972).

The concept of vulnerability emerged from social sciences, but its meaning significantly differs across the literature (JANSSEN; OSTROM, 2006; FORDHAM et al., 2013). According to the *Lexico Dictionaries* powered by *Oxford*, vulnerability refers to *"the quality or state of being exposed to the possibility of being attacked or harmed, either physically or emotionally"*. For Adger (2006), the concept of vulnerability has been important in identifying susceptibilities to harm, incapacity, and marginality within both physical and social systems. Despite the variety of perspectives and concepts on vulnerability, it

[1]A poverty trap is a situation in which poverty forces people to remain poor. It is a vicious cycle that causes individuals, societies, regions, or economies to get stuck in extreme poverty, where they are unable to break out of it for considerably long periods (AZARIADIS; STACHURSKI, 2005).

seems there is a mutual consensus within the social science community on the main factors that escalate vulnerability levels (ALEM, 2021). These include age, gender, disability, poverty, race, ethnicity, life expectancy, occupation, political system and education (SMITH, 2013). In the human rights context, the term *'vulnerable'* refers to the plight faced by marginalized groups subjected to discrimination, cruelty, or inhumane treatment. This concept emphasizes the need for special attention, care, and protection for these individuals, aiming to improve their chances of survival and quality of life. The categorization of vulnerable groups is dynamic and depends on the research context. Examples of such groups include, but are not limited to, individuals with disabilities, ethnic minorities, those who are impoverished, the illiterate, the elderly, and the homeless (RAHMAN; YASIN, 2022).

A prerequisite for decision-making in any context of limited resources (e.g., budgetary ceilings, physical access, and existing capacities) – frequently common in low-income countries – is to consider the vulnerabilities of the individuals, communities, and regions so that it is possible to target the efforts to the most in-need. This approach allows the identification and prioritization of vulnerable groups/areas to enable the provision of timely and relevant support – in response to a crisis or as part of a safety net for vulnerable populations (WFP, 2020).

Researchers have long acknowledged the importance of prioritization policies for vulnerable and disadvantaged groups (ALEM et al., 2021). Jaspers & Shoham (1999) argue that prioritizing impoverished people based on geography means that all households living in a given area are assigned to have the same poverty level, which is a valid strategy for prioritization when resources are limited. Barnett et al. (2009) suggest that the allocation of limited public health resources during crises should primarily be guided by the needs of vulnerable populations through their socioeconomic status. More recently, Jiang & Yuan (2019) avowed the importance of prioritizing demand fulfillment for those that need resources the most, especially given the scarcity of resources. The authors, however, recognize the challenges associated with applying allocation rules in real-world cases.

From a conceptual point of view, a recognized way of using prioritization in optimizing humanitarian operations is the prioritization by groups of people or by location (GRALLA; GOENTZEL; FINE, 2014). This approach emphasizes the focus on groups/areas with varying characteristics or socioeconomic status. Many studies that focus on location-based prioritization rely on functions or scores mainly determined by the area's infrastructure or its hazard features (KILCI; KARA; BOZKAYA, 2015; TOFIGHI;

TORABI; MANSOURI, 2016; BASKAYA; ERTEM; DURAN, 2017; MOLLAH et al., 2018; REZAEI-MALEK; TORABI; TAVAKKOLI-MOGHADDAM, 2019), or the socioeconomic or demographic profiles of the population of the area under analysis (NOYAN; BALCIK; ATAKAN, 2016; MOLLAH et al., 2018; NOYAN; KAHVECIOĞLU, 2018; REZAEI-MALEK; TORABI; TAVAKKOLI-MOGHADDAM, 2019; ARNETTE; ZOBEL, 2019; ALEM et al., 2021; ALEM, 2021; ABDIN et al., 2023).

Prioritization helps better target resources to the most in need. Discussing such a prioritization-driven approach inherently addresses the issue of equity, primarily the *vertical equity*, in which different entities have different needs and circumstances and, therefore, might require different levels and types of support to achieve similar outcomes (SEN, 1995). The concept of equity substantially varies across disciplines, and it is found in many different contexts. While both the philosophy literature and political sciences state equity in terms of *[social] justice* and fairness (RAWLS, 1991; DANIELS, 2000; LANDWEHR; KLINNERT, 2015; KAPIRIRI; RAZAVI, 2022), the economics sciences tend to frame equity in terms of inequity (DEVAUX, 2013; ASADA et al., 2014) and frequently discusses it with the concept of efficiency (REINHARDT, 1992). While efficiency aims to reduce wastefulness, equity evaluates the outcomes of economic policies to ensure that they do not disproportionately benefit or disadvantage specific groups or areas (KAPIRIRI; RAZAVI, 2022). Sen (1973) states that economic inequality can be quantified in two ways: objectively, through statistical metrics, or normatively, positing that greater inequality is inversely related to social welfare at any given total income level. Lastly, the health literature commonly describes equity as the lack of systematic disparities in health and its determinants (BRAVEMAN; GRUSKIN, 2003; PRATT; MERRITT; HYDER, 2016).

The principles of equity and fairness often guide public and humanitarian institutions and not-for-profit organizations that mainly operate under social goals. In contrast to many for-profit entities, which primarily aim to maximize profits or minimize costs to meet demand, such public and humanitarian organizations are not solely cost-driven (ORGUT et al., 2018). This commitment to equity is especially crucial when allocation rules need to take place in a resource-constrained scenario. In this sense, it is important to include equity considerations to fairly address systemic inequalities.

Such a social approach of equity paves the way for the implementation of based priority-setting policies, which aim to assess needs across different entities in a *fair* manner (KAPIRIRI; NORHEIM; MARTIN, 2009; MALUKA, 2011; ZULU et al., 2014; ORGANIZATION et al., 2014b). In this sense, Orgut

& Lodree (2023) highlight that equity has the aim of ensuring fair treatment for all beneficiaries in a way that each one receives a share of resources proportionally aligned with their specific needs. Jain & Lorgelly (2022) declare that equity goes beyond mere equality, embodying the idea that resources should be distributed based on need.

Despite the variety of equity measures addressed in the literature, a universally accepted equity measure for all types of problems does not exist, making it necessary to select it tailored to the characteristics of the problem (SEN, 1973; MARSH; SCHILLING, 1994; BALCIK; IRAVANI; SMILOWITZ, 2010; LECLERC; MCLAY; MAYORGA, 2011). Leclerc, McLay & Mayorga (2011) argue that the type of resource being distributed, the beneficiaries and the allocation timeframe are important factors in choosing the most appropriate equity measure. According to Kapiriri & Razavi (2022), equity can be operationalized as a measure that guides the decision-making process, whereby different vulnerabilities (such as socioeconomic profiles, gender, ethnicity, geographic conditions etc) are identified and considered in prioritization. Another comprehensive approach to incorporate equity is through the criterion of *fair-share*, which, as the name suggests, seeks to distribute/allocate resources fairly. Such a concept can be associated with *horizontal equity*, which considers that individuals or groups should be treated *equally* (JOSEPH; RICE; LI, 2016).

Equity is often balanced with other conflicting objectives, such as effectiveness and efficiency. Such *trade-off* has been widely studied in the humanitarian and optimization context (BALCIK; IRAVANI; SMILOWITZ, 2014; SOLAK; SCHERRER; GHONIEM, 2014; ORGUT et al., 2016; ORGUT et al., 2018; ORGUT; LODREE, 2023), shedding light on the challenges between achieving equitable outcomes, while maintaining effectiveness and efficiency.

All the aforementioned contexts have inspired this thesis, which aims to develop a *prioritization-driven and equitable approach to resource distribution/allocation in public policies for vulnerable populations.* For this purpose, we develop mathematical models that optimize the distribution and allocation of resources, incorporating vulnerability indexes – primarily based on specific characteristics of each case addressed in this thesis, along with socioeconomic/ environmental features – as prioritization criterion, combined with equity measures, enabling policymakers to make oriented decisions that directly impact the *social welfare* of vulnerable locations/populations.

Therefore, we seek to respond to the following research question: *How to design prioritization-driven and equitable resource distribution/allocation in public policies for the vulnerable?*. To shed light on this problem, the thesis studies two real cases. The first one addresses the long-lasting insecticidal nets

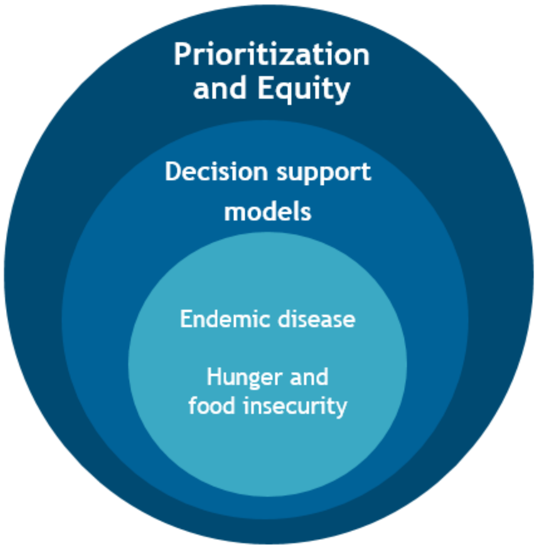

Figure 1.1: Overall context and application.

(LLINs) distribution campaigns for malaria prevention in Northern Brazil, and the second study addresses the allocation of food baskets as part of food aid programs targeted at traditional peoples and communities within Brazil. The significant socioeconomic disparities of the country, the diverse and vulnerable populations, and pressing public health and food security challenges make the country a "fertile ground" for such studies with a social approach. Figure 1.1 outlines the overall context of the thesis and its application.

1.1 Research topics and objectives

The present thesis is based on a set of academic papers developed during the doctoral period, constituting a *paper-based thesis* (KUBOTA et al., 2021). The main research question and its objective, previously outlined, motivated the development of the two papers further presented here. Paper 1 is under review at the *Production and Operations Management* (POM), and Paper 2 will be submitted after the exam members' consideration. Table 1.1 illustrates the thesis structure, considering the primary and secondary objectives, research questions, methodology, and deliverables of each paper.

Table 1.1: Research questions, objectives, methodology and deliverables.

Main research question	*How to design prioritization-driven and equitable resource distribution/allocation in public policies for the vulnerable?*	
Main objective	Support public policy decision-making for the distribution and allocation of resources to vulnerable populations by integrating principles of prioritization and equity.	
	PAPER 1	**PAPER 2**
Secondary Research Questions	1) How to evaluate the vulnerability to malaria in our current endemic areas?	1) How can public policies for allocating food baskets to traditional populations be more effective and equitable?
	2) How to incorporate the *Malaria Vulnerability Index (MVI)* into the design and optimization of LLINs distribution while ensuring equity across the malaria-endemic region?	2) Is there a way to guarantee that food baskets will be delivered to those who need them most, ensuring a fairer distribution both in terms of geographic area and populations that exhibit different socioeconomic and food insecurity profiles?
	3) What insights can be learned about the impact of introducing prioritization through MVI and equity concerns on key decisions of the LLIN campaigns' problem?	
Secondary Objectives	Presents practical data-driven mechanism to rank municipalities in the endemic area regarding malaria vulnerability	Develop policies that assist the Brazilian government in mitigating the subjectivity of food basket allocation decisions to traditional populations
	Presents a bi-objective location-allocation model that includes key challenging logistic decisions involved in LLINs distribution	Provide equitable and effective public policies on food basket allocation while targeting the most in-need traditional populations
Methodology	Decision models applied into real-world case	Decision models applied into real-world case
Deliverable	Malaria Vulnerability Index; Location-allocation model	Resource allocation model

1.2 Contribution, originality, relevance, non-triviality, and limitations

When resources are limited, and not all interventions can be pursued, finding a multifaceted solution that is not only effective and efficient but also equitable can be very challenging. Thus, finding equitable solutions always requires combined efforts to achieve improvements among the most vulnerable in an overall strategy to improve people's health and quality of life (ALEM et al., 2021).

This thesis contributes to both academic discourse and practical application by introducing a novel emerging topic of study, which we call *prioritization-driven and equitable optimization*. This concept entails the development of decision-support tools via optimization techniques underpinned by a vulnerability-based criterion while addressing equity concerns. It steers decision-making to distribute/allocate resources according to the needs of the areas/populations, exploring the *trade-off* mainly between two important objectives: equity and effectiveness.

From a theoretical perspective, the studies and insights of this thesis enable us to correlate important concepts addressed here, as shown in Figure 1.2. As previously described, prioritization approaches play a crucial role in directing resources towards those who are most in need. It concept directly tackles the idea of *vertical equity*, defined as *"the unequal but fair treatment of unequal"* (JOSEPH; RICE; LI, 2016) or a situation where individuals have varying needs and circumstances, necessitating differing levels and kinds of support, as highlighted by (SEN, 1995). A wide-ranging way of using prioritization in optimizing humanitarian is the one used in this thesis, which is based on the prioritization by groups of people or by location (GRALLA; GOENTZEL; FINE, 2014). We address it by incorporating the vulnerability index, represented by the Malaria Vulnerability Index (Paper 1) and the Food Insecurity Index (Paper 2), into the mathematical models. By integrating these scores into the objective function, we aim *to be "fair" by directing resources toward the most in need.* Also, our effectiveness measure is analyzed through the lens of the objective function, which is weighted by such a prioritization index. On the other hand, *horizontal equity* focuses on the idea that individuals or groups ought to receive equal treatment (JOSEPH; RICE; LI, 2016). This type of equity is addressed, as we include the concept of *fair-share*, aiming to fairly/equally distribute resources between entities (ORGUT et al., 2016). We achieve this (i) elevating the overall level of equity by bettering the levels for the most underserved areas (Paper 1) and (ii) allocating food proportional to the relative demands (Paper 2).

Governments often lack tools to improve the decision-making process of public policies, which ends up often being subjective or biased. From a practical standpoint, this thesis allows us to implement into practice such concepts studied here, offering policymakers optimized tools that focus on crucial aspects of the public context, such as prioritization and equity. Such issues became even more pronounced with the distribution of COVID-19 vaccines, underscoring the critical need for the development of well-designed-out and, therefore, optimized public policies in order to achieve fairness in resource allocation.

Considering this thesis comprises two papers, it's important to underscore the contributions of each. It is also important to mention that the *paper-based thesis* approach allows us to conduct a deeper exploration of individual aspects of the research topic through separate, focused studies, each raising insights

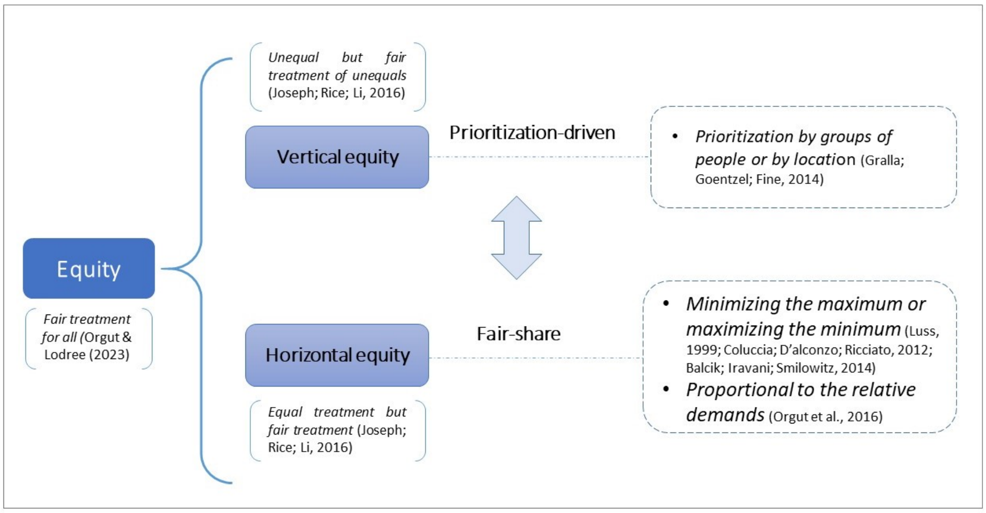

Figure 1.2: Framework of studied concepts.

and findings to the overarching narrative of the thesis. We will now explore each paper's contributions separately.

Paper 1 addresses an often neglected topic in the Operation Management (OM) literature, which is how to improve malaria mitigation strategies in malaria-endemic areas of developing countries. Differently from existing research in malaria intervention and optimization, we develop a location-allocation prioritization-based model to factor a prioritization indicator, the *Malaria Vulnerability Index* (MVI), into a decision support tool to help the Brazilian Ministry of Health (and other healthcare organizations) be more effective, equitable and accountable toward providing LLINs access to vulnerable populations in malaria-endemic areas. Through a rich and real case in the Brazilian Amazon, we discuss several aspects of LLIN distribution that could be implemented to support effective-equitable malaria intervention campaigns. The MVI aims to identify areas prone to malaria transmission that potentially need preventive supplies (LLINs) to contain the disease. To the best of our knowledge, we systematize for the first time in the literature epidemiological, socioeconomic, and environmental data to build a composite index that reflects the malaria vulnerability of the municipalities in malaria-endemic areas of Brazil. For this purpose, we use a non-statistical weighting scheme whose value-added relies on the fact that it is reasonably simple and easily understandable. The advantage of its simplicity is interpretability, which means the decisions on weighting can easily be recognized and discussed by practitioners (WONG, 2006) and applied to similar contexts where malaria transmission is reported. The MVI's development is based on the *Brazilian Social Vulnerability Index* (*Portuguese*: IVS) from the *Institute of Applied Economic Research* (*Portuguese*: IPEA), a federal public foundation associated with the

Brazilian Ministry of Economy. Different government entities have successfully adopted the IVS to understand the population's living conditions, identify those economically and socially vulnerable, and promote specific public policies for those populations. In addition, the ranking provided by our composite index can be used to identify areas that urge for more health-led improvements and resources, facilitating targeted healthcare interventions. There has been a great effort among academics to measure or quantify vulnerability through indexes, such that policymakers and stakeholders can use those indicators in a predictive manner to help in the identification, proposal, and evaluation of effective policies and actions, as well as the most useful coping responses (SMITH, 2013). We also translate our MVI into a prioritization map, making this weighted approach more practical, visual and practitioner-friendly. The MVI was comprehensively tested against its single indicators' correlation and robustness to make sure it is a reliable prioritization score to be adopted. Another innovative aspect of our location-allocation model is the inclusion of the so-called *discrete coverage levels* that allows policymakers to establish intervals to be possible parsimoniously cover LLINs requirements. Different from most papers in the literature, our approach for partial demand coverage is not based on critical distances or response times. Instead, it is based on given demand proportions (coverage levels) set beforehand to avoid covering an arbitrary proportion of LLINs that may turn out to be ineffective. Indeed, effective LLIN campaigns must reach out to a high proportion of those living in malaria-endemic counties. Nowadays, this proportion is as high as 80%, according to the World Health Organization (2022), meaning that any demand coverage less than 80% is highly ineffective and thus should be avoided. Our formulation, based on discrete coverage levels have two main advantages over existing ones: it is more flexible than *all-or-nothing strategies* ("maximal covering"), and it produces less arbitrary covering solutions than partial maximal coverage models since the demand level to be met is defined by the user based on the specificities of the application.

Paper 1, like any academic work, has limitations. Brazil is a huge country encompassing different decentralized states and municipalities. These states and municipalities have distinct policies, state-level regulations, tariffs, and autonomous policies that may reduce the application of our results to inter-state LLIN distribution. Indeed, this may be a potential barrier to our study's practical applicability. Furthermore, the distribution of an already scarce resource like LLINs from one state to another can cause some social disagreement, as happened in the case of the vaccine distribution. As an attempt to mitigate political issues, our distribution model for LLINs posits that, although distribution occurs at the municipal level, the Brazilian Ministry of Health holds the authority to resolve any inter-state disagreement, ensuring a more centralized decision-making process.

Paper 2 focuses on addressing the challenges of food insecurity among traditional peoples and communities, designing equitable and effective food aid allocation strategies. The first significant contribution highlighted in the paper is the development of an optimization tool designed to undermine subjectivity in government decisions on food basket allocation in food aid programs. Traditionally, the Brazilian government's allocation decisions have been reactive, relying on each national entity – that represents these communities, such as the *National Indigenous Foundation (Portuguese: FUNAI)* and the *Palmares Foundation*, to inform the government, their requirements for food baskets. The decentralized nature of such national bodies makes it difficult for governments to make synchronized decisions about the allocation of food baskets, leading to disparities in the timing and adequacy of responses to food insecurity. And, even if such food basket reports were synchronously submitted to the government, we would still have an issue, as the government lacks the necessary tools to, in an overall strategy, look simultaneously at all traditional populations and determine equitable and effective allocations. Additionally, such a timing mismatch might lead to the government distributing all available food baskets to certain traditional populations without foreseeing that other communities might require food assistance in the future. Such a scenario has motivated the development of paper 2. The paper's contribution is, then, substantial, as we provide the government with an optimization tool that incorporates two key equity considerations: geographical and population equity, ensuring food baskets will be fairly shared amongst different areas and traditional populations. Furthermore, we also assess the model's effectiveness, which is its ability to maximize the number of baskets allocated to areas and populations, weighted by a prioritization index that directs the baskets to the most needy populations. By testing the model across various levels of equity through adjustable deviation limits, the paper facilitates an examination of the trade-off between effectiveness and equity, guiding the government toward selecting solutions that align with its overarching goals (be more or less equitable/effective).

Paper 2 also has a social approach. We are committed to focusing on such specific populations, frequently neglected by the government and societal efforts, emphasizing that they deserve special attention not only in public food aid initiatives but across all social policies. In addition to the practical contributions, this study also discusses the importance of food aid to tackle hunger and food insecurity, focusing on the importance of food distribution programs. We emphasize its vital function in supporting vulnerable individuals to overcome crises and sustain their livelihoods, playing a vital role in alleviating hunger and food insecurity. Although food distribution programs will not alone end hunger, they can mitigate it when combined with other long-term food aid programs to enhance community development.

Owing to constraints in available data, our analysis was limited to just three populations. However, within a landscape comprising numerous populations, the application of such an index might yield more valuable comparisons among the populations. The constraints encountered in our research could pave the way for future investigations. Enhancements to this research might include incorporating cost factors to strike a balance between efficiency, effectiveness, and equity; introducing varied coverage levels to provide different service standards for prioritized groups; and focusing on a municipal-level analysis for greater granularity.

The originality and non-triviality of the thesis, composed of two papers, are also observed through the fact that we interestingly develop a framework on how we proceed to develop the models, enabling us to escalate the applicability of the model. Firstly, we assess areas/households/population vulnerabilities through the indexes based on variables aligned with the literature review. Then, we design decision-making models that incorporate the prioritization criteria, considering equity (fairness) in the problem formulation. After, we deliver to governments optimized outcomes that enable policymakers to mainly evaluate both effectiveness and equity. Finally, it is essential to monitor the outcomes and update them accordingly to potential changes. In this sense, the last module of the framework is crosshatched once we are not developing a decision support system (DSS). This would comprise one of the future research avenues of this thesis. For this purpose, it would be necessary to take further steps, including practitioner's validation, training, and managerial involvement, to build, therefore, a robust decision support system to help the government in the public policy decision-making process. Figure 1.3 illustrates the framework just described.

This thesis also has a social appeal, as it is well-aligned with the *United Nations' Sustainable Development Goals* 2 and 3, in particular with the targets to *'end hunger, achieve food security and improved nutrition and promote sustainable agriculture'* (Paper 2) and to *'end the epidemics of AIDS, tuberculosis, malaria, and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases'* (Paper 1).

Figure 1.3: Thesis' framework.

1.3 Methods

This thesis employs mathematical models as its main methodological approach to explore optimal solutions in public policy decision-making, particularly for vulnerable populations. The application of mathematical optimization models in real-world contexts represents a significant advancement in the ability to solve complex problems, especially in scenarios characterized by resource scarcity (as observed in Brazil) and the need to make decisions that directly affect people's lives.

Mathematical models are fundamental for understanding the complexity inherent in real-world challenges faced by society. By modeling such situations, these models serve as approximations that allow the analysis and simulation of different scenarios and strategies. According to Winston (2004), mathematical modeling provides a framework for structuring problems, helping to identify key variables and constraints, and predicting the impacts of different decisions. However, it is crucial to recognize that every model is a simplification of reality, whose accuracy depends on the quality and relevance of the data used, as well as the assumptions made during the modeling process (HILLIER; LIEBERMAN, 2015).

Data gathering and analysis play a central role in mathematical optimization, allowing patterns to be identified and hypotheses to be tested. The thesis data collection process was anchored in developing a questionnaire and conducting structured and semi-structured interviews. For *Paper 1*, we developed a questionnaire designed and available on the *Survey Monkey* platform.

This questionnaire[2] was mainly formulated to validate the factors associated with malaria transmission so that we could develop the Malaria Vulnerability Index (MVI) used in the mathematical formulation of the first paper. Questions associated with malaria transmission drivers were based on the literature review described in Section 2.2.1 of Chapter 2. The remaining questions were formulated in the process of brainstorming with the advisors of this thesis in order to understand the problem context of LLIN allocation and distribution in Northern Brazil and also to capture other model parameters. The questionnaire was fully reviewed by them. For a pilot test, we requested a practitioner specializing in parasitic diseases and working on malaria prevention actions in Northern Brazil to validate and respond to the questionnaire. Following this procedure, the questionnaire was made available to other respondents in December 2019 for a period of five months. Seven practitioners who possess hands-on experience in malaria interventions, specifically in the distribution of LLINs, responded to the questionnaire. These professionals work (or have worked) for international organizations such as *Médecins Sans Frontières* (MSF) and *United Nations High Commissioner for Refugees* (UNHCR) in Roraima state, and national health institutions such as *Fundação Oswaldo Cruz* (Portuguese: FIOCRUZ) and the *Department of Epidemiological Surveillance* from the Municipal Health Department (Portuguese: SESMA) in Amapá state. Data gathered from the questionnaire was spreadsheeted, organized and analyzed to be further used in the mathematical model. Finally, malaria epidemiological data and municipalities' socioeconomic and environmental data were collected from public sources. This is detailed in Section 2.4 of Chapter 2. The full questionnaire is presented in Appendix A.

Regarding *Paper 2*, a total of five interviews were conducted – being the initial one a structured interview (see full questions in Appendix B) with the manager of the Institutional Partnerships Department of the *National Supply Company (Portuguese: CONAB)*, who coordinates the distribution of food baskets through the *Food Distribution Action (Portuguese: ADA)* to traditional peoples and communities in Brazil. The primary aim of the interviews was to understand the problem context and the main challenges faced by this Action. The first structured interview took place in September 2022. The subsequent meetings, held in November 2022, February 2023, April 2023, and May 2023, aimed to clarify doubts and validate the qualitative

[2] The questionnaire included the Free and Informed Consent Form, which ensured that participants were fully informed about the study's purpose, procedures, potential risks, and benefits. This process aimed to obtain their voluntary agreement to participate, ensuring ethical standards were upheld in accordance with institutional and legal guidelines. Additionally, it guaranteed that participants' privacy and data confidentiality were rigorously maintained throughout the research.

model idea. This comprehensive series of interviews raised several challenges and issues faced by the Brazilian government in allocating food baskets to traditional peoples, thereby enabling the problem to be effectively modeled. All interviews were carried out via Zoom, recorded, and, in most instances, involved the participation of this thesis's co-advisor. On average, the interviews lasted about 40 minutes. Firstly, the interviews were transcribed in Portuguese and subsequently translated into English. The data used in the model were gathered from the Ministry of Social Development's website, organized into spreadsheets, compiled and analyzed.

Finally, to enhance the data visualization in both papers, we developed maps using the free and open-source *QGIS v.3.20.1* software, which provides a multi-platform geographic information system capable of visualizing, editing, and analyzing geo-referenced data.

The use of mathematical models facilitates a deeper understanding of the dynamics and constraints inherent in the distribution/allocation of limited resources (a cornerstone of this thesis). Through formulation, analysis, and interpretation, this thesis highlights the potential of mathematical models to inform and guide policy-makers toward more optimized decisions, underscoring their importance in the field of applied research.

1.4 Thesis structure

This thesis is structured as follows. Chapter 2 presents Paper 1, *"Long-lasting insecticidal nets campaigns for malaria control considering prioritization and equity"*, which is under review at POM. Chapter 3 presents Paper 2, *"From effectiveness to fairness: designing food allocation in food aid programs for traditional peoples and communities"*. Finally, Chapter 4 provides the final considerations and suggestions for future research.

2
Long-lasting insecticidal nets campaigns for malaria control considering prioritization and equity

This chapter presents Paper 1, which was submitted and is under review at POM.

2.1
Introduction

Malaria is an infectious and life-threatening disease caused by parasites and transmitted to people through the bites of infected mosquitoes. Malaria is endemic in over 100 tropical and subtropical countries (SMITH, 2013). It is widely reported in impoverished nations (WORRALL; BASU; HANSON, 2005; AYELE; ZEWOTIR; MWAMBI, 2012; AMEGAH et al., 2013; ORGANIZATION et al., 2022b), where people have low socioeconomic conditions and poor access to preventive measures and medical treatment (HUNT, 2008; YADAV et al., 2014). Despite being preventable and treatable, malaria remains to have a devastating impact on people's health worldwide. Globally, malaria accounted for 619,000 deaths and 247 million cases in 2021, an increase from 245 million in 2020 (ORGANIZATION et al., 2022b). Besides imposing a vast burden on health and welfare, malaria is a major hindrance to the economic development of low-and middle-income countries (PARVIN et al., 2018), as it significantly impacts the quality of life, livelihoods, and workforce (SACHS; MALANEY, 2002).

Over the years, malaria elimination, defined as the interruption of local transmission in a specific geographical area, has been a preference for health ministries, international and national health entities, and nongovernmental organizations (NGOs) (PARVIN et al., 2018). The global decrease in malaria cases since 2000 has primarily been attributed to vector control interventions, such as the use of insecticide-treated nets (ITNs), particularly LLINs, and indoor residual spraying (IRS) (NG'ANG'A; ADUOGO; MUTERO, 2021). An insecticide-treated net (ITN) is a net that repels, weakens, and/or kills mosquitoes in contact with impregnated insecticide on the net. A long-lasting insecticide-treated net (LLIN) is a type of ITN designed to maintain effectiveness for three years under World Health Organization (WHO) standard recommendations (ORGANIZATION et al., 2013). LLINs have played an essential role in reducing the malaria burden over the years. The rapid scale-up of LLINs distribution provided remarkable advances toward malaria elimination, which makes insecticide-treated nets the most effective malaria control tool available in endemic countries and widely used in public health interventions (LINDBLADE et al., 2015; KHANAM et al., 2018; PRYCE; RICHARDSON; LENGELER, 2018; MUSA et al., 2020; NGUFOR et al., 2020).

Because major diseases and epidemics have disproportionately affected the poorest and more disadvantaged communities, global malaria control and elimination strategy initiatives, such as the *Global Technical Strategy for Malaria 2016–2030*, have emphasized the importance of embedding actions to prioritize vulnerable areas at risk of malaria. This set of targeted interventions significantly improves the health of the most in need, enabling the poorest communities to interrupt the vicious cycle of malaria and poverty (ORGANIZATION et al., 2019b), as malaria is a cause and consequence of poverty (HUNT, 2008). Targeting the most in-need population enhances the sense of social justice, a core principle in public health that aims to improve people's health by equalizing access and opportunity to resources for achieving good health, especially among people in vulnerable circumstances. This vulnerability to poor health is known as *health disparities* when differences in health outcomes or health determinants are observed among populations due to economic, social, or environmental disadvantage (JOSEPH; RICE; LI, 2016).

2.1.1 Problem motivation and context

The fight against malaria in Brazil has lasted for more than half a century, undergoing several strategies and programs. Interventions to control the disease succeeded in the first years of the 1940s, when malaria was a nationwide problem with approximately six million people, 20% of the country's population, infected each year (OLIVEIRA-FERREIRA et al., 2010). Although many campaigns succeeded in freeing the majority of the country from malaria infection by the late 1960s/beginning of the 1970s, they could not contain the rapid spread of the disease in Northern Brazil. From the mid-1960s onward, this region witnessed a rapid and disorderly settlement process, driven by urbanization programs sponsored by the government that resulted in a massive and disorganized migratory movement, which led to an increase in malaria cases from 52,000 in 1970 to 578,000 in 1989 (MARQUES; GUTIERREZ, 1994). The highest rates were recorded in 1999 with 637,470 cases (OLIVEIRA-FERREIRA et al., 2010). This encouraged the government to launch the Plan to Intensify Malaria Control Actions (*Portuguese*: PIACM) in the following year. Despite government efforts, malaria rates in Northern Brazil remained high for the following years.

In 2006, the Brazilian Ministry of Health started introducing LLINs as a vector control strategy, besides the IRS, to contain the spread of the disease in the North. LLINs began to be distributed in three endemic municipalities in the state of Acre, accounting for the largest number of malaria cases in Brazil in 2005: Cruzeiro do Sul, Mâncio Lima, and Rodrigues Alves. After showing a positive impact on reducing disease transmission levels, since 2010, the Ministry of Health has officially adopted the use of LLINs through the *'Project on Expansion of Access to Malaria Prevention and Control Measures'*, sponsored by the *Global Fund to Fight AIDS, Tuberculosis, and Malaria*. As part of this program, 1.1 million LLINs were distributed and installed in the households of 47 priority municipalities in Northern Brazil (LIMA et al., 2016). The prioritization of municipalities was primarily based on epidemiological factors, like the incidence of malaria cases, which is a reasonable approach as the number of cases is one of the main indicators of municipality priority. However, such prioritization overlooked socioeconomic and environmental factors that can also influence malaria incidence. Several studies highlight the association between low socioeconomic conditions and environmental changes with malaria prevalence and resurgence, especially in Northern Brazil (MACIEL; SILVA; SOUTO, 2011; GOMES et al., 2020). As a result, resources might not have been allocated to the areas of greatest need and where they could yield the most sustained impact. Thus, after seven years of witnessing a decrease in malaria cases, Brazil started to experience a new increase in malaria incidence in 2016.

2.1.2 Research questions and contributions

Universal coverage (UC) concerns 100% access to and use of vector control measures by populations at risk of malaria (ORGANIZATION et al., 2017). To pursue UC targets, malaria-endemic countries usually implement combined channels of LLIN distribution (WORRALL et al., 2020), such as mass free distribution - through campaigns being conducted every 3 years - and continuous distribution (ORGANIZATION et al., 2014a; YUKICH et al., 2020). According to the WHO, mass campaigns are the only proven cost-effective alternative to reach high and equitable fast coverage (ORGANIZATION et al., 2017).

Most countries, including Brazil, have struggled to establish effective national-scale mechanisms for LLIN distribution over the past decade, mostly because of the challenging mobilization of resources to procure, store, allocate, and distribute it. Proper storage of LLINs is especially important in this challenging scenario. LLINs' exposure to direct sunlight and high temperatures degrade its impregnated insecticides. Therefore, adequate storage is essential to retain the bio-efficacy of the product (MUSA et al., 2020). In addition to logistical issues, knowing whether resources are efficiently allocated to those needing them most is also relevant. Prioritization is an approach that helps target resources better and mitigates health disparities. According to the *WHO World Malaria Report 2022*, to minimize the impact of the limited resources, there will be an even greater need to maximize the efficient, effective, and equitable use of malaria resources. *The focus of this research is to develop effective and equitable mass LLIN distribution campaigns for malaria control that target the most vulnerable populations to malaria transmission, which is a crucial issue in the current scenario of limited investments in malaria interventions and is aligned with global malaria eradication initiatives.* Our specific research questions are threefold.

(1) *How to evaluate the vulnerability to malaria in our current endemic areas?* To address this research question, we develop a practical data-driven mechanism to rank municipalities in the endemic area regarding malaria vulnerability. For this purpose, we develop the Malaria Vulnerability Index (MVI), a composite index that encompasses epidemiological, socioeconomic, and environmental drivers, which is well-aligned with the malaria healthcare literature. Malaria practitioners validated the MVI via a questionnaire designed, applied, and analyzed by the authors. It is worth mentioning that the MVI is inspired by an epidemiological index to prioritize municipalities to receive LLINs, adopted by the Brazilian Ministry of Health during the 2010 LLIN campaign sponsored by the *Global Fund to Fight AIDS, Tuberculosis, and Malaria.* Our MVI is then translated into a prioritization map, ranking the endemic area from lower to higher malaria vulnerability. The methodology applied for the MVI's development is based on the *Brazilian Social Vulnerability Index* (*Portuguese*: IVS[1]) from the *Institute of Applied Economic Research* (*Portuguese*: IPEA), a federal public foundation associated with the Brazilian Ministry of Economy. Different government entities have successfully adopted the IVS to understand the population's living conditions, identify those economically and socially vulnerable, and promote specific public policies for those populations. Similarly,

[1]The IVS comprises 16 variables organized into three dimensions: Urban Infrastructure; Human Capital; and Income and Work, representing different living conditions. The index is estimated through the arithmetic mean of these dimensions and ranges between 0 and 1, where 0 corresponds to lower social vulnerability, and values closer to 1 represent higher social vulnerability.

we believe that the proposed MVI can also be successfully understood and used by other national entities and practitioners.

(2) *How to incorporate the MVI into the design and optimization of LLINs distribution while ensuring equity across the malaria-endemic region?* To address this research question, we develop a bi-objective location-allocation model that includes key challenging logistic decisions involved in LLINs distribution, such as the location and density of hubs that will store the LLINs procured from suppliers, the number of LLINs to be distributed and in which hub they should be stored, as well as transportation decisions. The first objective function maximizes the LLIN coverage according to three levels, ranging from 100% to 80%, which is in line with LLIN coverage principles introduced by WHO 2015 (ORGANIZATION, 2015) and weighted by our MVI to encourage better coverage in more vulnerable areas (higher MVIs). The second objective function minimizes the number of underserved areas, which is accomplished without considerably sacrificing the LLIN coverage of priority areas, which represents a way to equitable access to LLINs.

(3) *What insights can be learned about the impact of introducing prioritization through MVI and equity concerns on key decisions of the LLIN campaigns' problem?* To further explore this research question, we compare and contrast four approaches, combining prioritization and non-prioritization models (with and without MVI, respectively) and with and without equity considerations. We use a real-world case study conducted on the world's largest tropical rainforest biome, the Amazon Rainforest, more specifically in the Brazilian Amazon Region, which accounts for 99% of malaria cases in Brazil. We believe that the insights from this research will improve the performance of malaria public health programs and strengthen the responsibility of how public resources have been deployed. Last but not least, this research's overarching goal is well-aligned with the scope of the *2030 Agenda for Sustainable Development*, particularly with SDG 3 ("*ensure healthy lives and promote well-being*") and its Target 3.3, which is committed to eradicating several diseases, including malaria (ORGANIZATION et al., 2019a).

The remaining of this paper is organized as follows: Section 2.2 brings our theoretical foundation. Section 2.3 formally describes the problem and the mathematical model. Section 2.4 presents our case study based on the malaria-endemic case in the Brazilian Amazon, as well as the MVI development. Section 2.5 shows the results and managerial implications. Finally, Section 2.6 discusses the models' value and opportunities for future research.

2.2 Background and Literature Review

This study is mostly related to two streams of research, which we review in the following subsections: (1) *Drivers of malaria transmission*; (2) *The role of LLINs in malaria intervention and optimization.*

2.2.1 Drivers of malaria transmission

Spatial heterogeneity has been observed in most diseases, including malaria, whereby some locations experience more intense transmission than others. Malaria transmission is a dynamic process involving several interconnected features, from natural environmental conditions to human-made disturbances to nature (KAR et al., 2014). In this sense, the risk of malaria infection is not homogeneous, even in endemic areas. The causes and consequences of malaria spatial heterogeneity have been a subject of interest for understanding and monitoring transmission and providing opportunities for more effective control mechanisms (PAULL et al., 2012; JR et al., 2015).

Several studies have associated low socioeconomic and environmental conditions with malaria incidence, suggesting that these aspects should be considered when developing and implementing malaria control interventions (TUSTING et al., 2013; YADAV et al., 2014; CASTRO, 2017; EBHUOMA; GEBRESLASIE; MAGUBANE, 2017; MUTEGEKI; CHIMBARI; MUKARATIRWA, 2017; DEGAREGE et al., 2019; LANERI et al., 2019; TUSTING et al., 2020; CARRASCO-ESCOBAR; FORNACE; BENMARHNIA, 2021).

Malaria is commonly referred to as a disease of poverty. As in other infectious diseases, socioeconomic inequalities are frequently reported to impact malaria cases and deaths (WORRALL; BASU; HANSON, 2005; ONWUJEKWE; UZOCHUKWU; EZEOKE, 2010; TUSTING et al., 2016; WERE et al., 2018). Several studies have reported relevant evidence about the role of socioeconomic inequalities in malaria transmission in Sub-Saharan African and South American countries (VALLE; CLARK, 2013; TUSTING et al., 2016; WERE et al., 2018; ILINCA et al., 2019). These studies highlight the significant heterogeneity between socioeconomic conditions at sub-national and local levels and the importance of socioeconomic assessment to better target malaria control interventions. Socioeconomic development has been highlighted as one of the most effective interventions for malaria control in the long term (TUSTING et al., 2013). Dahesh et al. (2009) showed that malaria infection has increased with the decrease of the socioeconomic level of families, educational level of individuals, and unemployment. Yadav et al. (2014) observed significantly more malaria cases among poor people with low monthly incomes living in bamboo houses in India. Sonko et al. (2014) found that malaria prevalence was expressively higher among poor children living in poor households. Degarege et al. (2019) highlighted the lack of education, low wealth and income, and poor housing conditions as the main drivers of malaria infection in Sub-Saharan African countries. Canelas et al. (2019) concluded that the Gini Index[2] and illiteracy rate are the most important socioeconomic risk factors for high malaria incidence in the Brazilian Amazon region. Yang et al. (2020) proposed a logistic regression to demonstrate that malaria is mainly associated with poor drinking water, sanitation, and hygiene (WASH) conditions among children in Sub-Saharan African countries.

Human-made transformations of the natural environment can also interfere with the malaria transmission cycle. Implementing development projects such as railways, roads, dams, irrigation, mining, oil extraction, and population resettlement often comes with social and environmental impacts that can negatively affect people's health (CASTRO, 2017). Such impacts are associated with, for example, the migration of native populations to malaria-endemic areas or migration of infected people to areas where malaria vector is present; a great concentration of workers living in poor housing and thus highly exposed to vectors; and the emergence of ideal water habitats for mosquito breeding, such as artificial lakes associated with mining and dam construction (CASTRO, 2017). Examples of studies associating malaria incidence with gold mining operations include (BARBIERI; SOARES-FILHO et al., 2005; OLIVEIRA et al., 2011; VALLE; LIMA, 2014; RECHT et al., 2017). Besides the high exposure to mosquitoes, mining workers often lack malaria preventive measures and medical treatment, contributing even more to malaria transmission (RECHT et al., 2017). Similarly, indigenous reserves also present a high incidence of malaria (VALLE; CLARK, 2013; FERREIRA; CASTRO, 2016; RECHT et al., 2017). In South America, malaria cases in indigenous people are frequently reported in countries such as Venezuela, Brazil, Colombia, and Ecuador (RECHT et al., 2017; FLETCHER et al., 2020). The difficulty in reaching isolated populations (i.e., Indigenous, miners, riverine people) for whom conventional health system practices are scarce remains a substantial challenge for malaria control and elimination (FLETCHER et al., 2020). Areas that also report high levels of malaria transmission are locations with great forest coverage (MANH

[2]Also known as the Gini coefficient. It is a measure of statistical dispersion intended to represent the income or wealth inequality within a nation or a social group. It ranges from 0 to 1, where 0 signifies perfect equality (everyone has the same income) and 1 indicates maximum inequality (one person has all the income) (COWELL; EBERT, 2004).

et al., 2011; VALLE; CLARK, 2013; VALLE; LIMA, 2014; CANELAS et al., 2019), suggesting that increased human presence in forested areas, for (e.g.) hunting, fishing, or timber logging, can increase malaria risk, once people in these areas are exposed to a higher abundance of vectors (CONFALONIERI; MARGONARI; QUINTÃO, 2014; VALLE; LIMA, 2014; CANELAS et al., 2019).

Climate conditions also pose critical risks to malaria prevalence. Meteorological changes can modify the biological cycle of the disease vector, increasing malaria transmission (CARRASCO-ESCOBAR; FORNACE; BENMARHNIA, 2021). The frequency, intensity, and duration of precipitation contribute to developing suitable water habitats for mosquito breeding (CASTRO, 2017). The positive relationship between the rainy season and malaria transmission has been studied over the years by several researchers (LOEVINSOHN, 1994; KILIAN et al., 1999; LINDBLADE et al., 1999; GIL et al., 2007; GALARDO et al., 2009; CASTRO, 2017; CANELAS et al., 2019; DABARO et al., 2021). Table 2.1 summarizes the major socioeconomic and environmental drivers related to malaria transmission and shows the proportional/ inversely proportional relationship of these drivers with malaria incidence.

The use of data-driven analysis in malaria control efforts has been increasingly encouraged by national malaria control programs (YOUNG et al., 2022) to incorporate factors that are no longer restricted to epidemiological variables such as reported malaria cases (HEMINGWAY et al., 2016; STRESMAN; BOUSEMA; COOK, 2019). To the best of our knowledge, we systematize epidemiological, socioeconomic, and environmental data to build a composite index that reflects the malaria vulnerability of the municipalities in malaria-endemic areas of Brazil for the first time in the literature. For this purpose, we use a non-statistical weighting scheme whose value-added relies on the fact that it is reasonably simple and easily understandable. The advantage of its simplicity is interpretability, which means the decisions on weighting can easily be recognized and discussed by practitioners (WONG, 2006) and applied to similar contexts where malaria transmission is reported. In addition, the ranking provided by our composite index can be used to identify areas that urge for more health-led improvements and resources, facilitating targeted healthcare interventions. We also translate our MVI into a prioritization map, making our weighted approach more practical, visual, and practitioner-friendly.

Table 2.1: Major socioeconomic and environmental drivers of malaria transmission based on the existing literature.

Dimension	Risk factors	Proportional (↑) or Inversely proportional(↓) to malaria transmission	References
Socioeconomic	Poor and inadequate housing and Water, Sanitation and Hygiene (WASH) conditions	(↑)	(NKUO-AKENJI et al., 2006); (CASTRO, 2017); (EBHUOMA; GEBRESLASIE; MAGUBANE, 2017); (MUTEGEKI; CHIMBARI; MUKARATIRWA, 2017); (TUSTING et al., 2016); (DEGAREGE et al., 2019); (YANG et al., 2020)
	Unemployment	(↑)	(DAHESH et al., 2009); (ACHCAR et al., 2011); (EBHUOMA; GEBRESLASIE; MAGUBANE, 2017)
	Human Development Index (HDI)	(↓)	(ACHCAR et al., 2011)
	Illiteracy and low levels of education	(↑)	(BARAGATTI et al., 2009); (DAHESH et al., 2009); (EBHUOMA; GEBRESLASIE; MAGUBANE, 2017); (MUTEGEKI; CHIMBARI; MUKARATIRWA, 2017); (CANELAS et al., 2019); (DEGAREGE et al., 2019); (TSELIOS; TOMPKINS, 2020); (SINGH et al., 2020); (CARRASCO-ESCOBAR; FORNACE; BENMARHNIA, 2021)
	Poor income	(↑)	(BARAGATTI et al., 2009); (DAHESH et al., 2009); (TUSTING et al., 2013); (SONKO et al., 2014)(YADAV et al., 2014); (MUTEGEKI; CHIMBARI; MUKARATIRWA, 2017); (DEGAREGE et al., 2019); (SINGH et al., 2020)
	Gini Index	(↑)	(CANELAS et al., 2019); (DEGAREGE et al., 2019); (TSELIOS; TOMPKINS, 2020)
Environmental	Presence of indigenous land	(↑)	(VALLE; CLARK, 2013); (FERREIRA; CASTRO, 2016); (ANGELO et al., 2017)
	Forest coverage	(↑)	(MANH et al., 2011); (DURNEZ et al., 2013); (VALLE; CLARK, 2013); (KAR et al., 2014); (VALLE; LIMA, 2014); (CANELAS et al., 2019)
	Rainy season	(↑)	(LOEVINSOHN, 1994); (KILIAN et al., 1999); (LINDBLADE et al., 1999); (GIL et al., 2007); (GRAVES et al., 2008); (GALARDO et al., 2009); (KIMBI et al., 2013); (CASTRO, 2017); (CANELAS et al., 2019); (PADILHA et al., 2019); (ROUAMBA et al., 2019); (DABARO et al., 2021)
	Presence of mines	(↑)	(VALLE; LIMA, 2014); (RECHT et al., 2017)

2.2.2 The role of LLINs in malaria intervention and optimization

The use of long-lasting insecticide nets, or simply LLINs, is a highly effective strategy for malaria control that significantly reduces disease morbidity and mortality in endemic countries. Of 663 million malaria cases averted in sub-Saharan Africa since 2001, 68% were due to the use of insecticide-treated nets (BHATT et al., 2015). A five-year study undertaken by the WHO in the African and Asian continents showed that people who used insecticide-treated nets to sleep had significantly lower malaria infection rates than those who did not sleep under the nets (LINDBLADE et al., 2015). Yadav et al. (2014) also showed that individuals who did not use insecticide-treated nets regularly reported a high occurrence of malaria infection compared to those who used the nets daily. The WHO recommends that LLINs should be available to all people at malaria risk in endemic areas seeking universal coverage, recognized as the availability of one mosquito net for every two individuals (ORGANIZATION et al., 2014a). In Brazil, the Ministry of Health distributes and installs the LLINs for free in households. The initial study using insecticide-treated nets in Brazil was conducted in the state of Rondônia (Northern Brazil), where a significant decrease in vector density was observed during high-transmission periods (SANTOS; SANTOS; MACÊDO, 1999). Another study in Rondônia showed a reduction in malaria cases in locations where 39.5% to 55.3% of individuals have been reported to sleep under the LLINs (LIMA et al., 2016).

Although the public health benefit of LLINs is widely known and discussed, the use of analytical approaches to support these malaria interventions is a relatively new study area. So far, only a handful of papers have offered analytical modeling to support operations fighting malaria worldwide. Rottkemper, Fischer & Blecken (2012) developed a multi-objective and multi-period model for stock relocation and distribution of Artemisinin Combination Therapy (ACT) used in malaria treatment in Burundi, Africa. Parvin et al. (2018) developed an optimization model that integrates strategic and tactical-level models to better manage malaria pharmaceutical distribution through a three-tier centralized health system. To validate the model, the authors conducted a case study in 290 districts in Malawi. Mattos et al. (2019) developed a robust optimization model that minimizes mosquito net distribution costs, considering protection against market, financial, and logistical uncertainties. Brito et al. (2020) proposed a deterministic transshipment model to define the optimal procurement and distribution plan of more than 12 million mosquito nets in the Ivory Coast during a mass distribution campaign held by the United Nations Children's Fund (UNICEF).

Differently from existing research in malaria intervention and optimization, we develop a prioritization-based model to factor the MVI into a decision support tool to help the Brazilian Ministry of Health (and other healthcare organizations) be more effective and accountable toward providing LLIN access to vulnerable populations in malaria-endemic areas. An attractive aspect of our mathematical model is the inclusion of two objective functions that represent possible ways to perceive healthcare equity. Equity is often critical in allocation contexts, where goods or resources must be allocated to a set of entities in a “fair” manner (KARSU; MORTON, 2015). The application of equity revolves around two principles: horizontal and vertical equity. Whereas horizontal equity is defined as the equal treatment of equals, or the sameness, and is contextualized by fair outcomes, vertical equity is often defined as the unequal but fair treatment of unequal and is contextualized by a fair process (JOSEPH; RICE; LI, 2016). We address the issue of vertical equity by using the MVI index, which helps identify the most malaria-prone areas and encourages better LLIN coverage. The horizontal equity is tackled by the second objective that minimizes the number of underserved areas, therefore making LLINs allocation more equitable across different areas irrespective of their vulnerability to malaria.

2.3 Research Context and Problem Description

Malaria vector control is primarily achieved using LLINs by as many people as possible. According to health officials from the Brazilian Ministry of Health, LLINs protect not only people who use them at night but also the entire community. That is because the fewer people infected, the lower the parasite risk. In Brazil, the Ministry of Health plays a crucial role in ensuring the availability of LLINs to malaria-endemic communities. This is done by coordinating the acquisition, storage, allocation, and last-mile distribution of LLINs. LLINs are mainly procured from international suppliers, which end up responsible for shipping the LLIN cargo to the discharge ports located in either Manaus (Amazonas State) or Belém (Pará State). These cities are the two largest in the Northern region and thus hold the best port infrastructure. From the ports, LLINs are then transported to the warehouses of the State Health Secretary to be further distributed to the final beneficiaries. The bid-winning supplier must deliver LLINs at the warehouse of the State Health Secretary within 120 days counted from the purchase order issuance and following the Incoterms DDP (Delivered Duty Paid), which means that the supplier is responsible for all costs and risks associated with transporting the

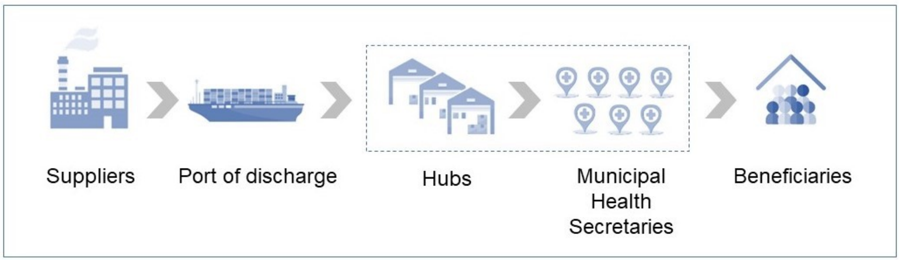

Figure 2.1: Summarized LLIN network structure.

goods to the specified location, including import duties and taxes.

As the Health Secretaries' warehouses temporarily store multiple types of items, they do not necessarily have the required infrastructure to store large amounts of LLINs to be strategically pre-positioned when mass campaigns take place. In addition, LLINs must be stored in safe and dry places away from direct sunlight and high temperatures to avoid damage; such storage conditions are not necessarily observed in the existing warehouses. In this context, we propose the establishment of strategic hubs that can properly stock large amounts of LLINs coming from the ports until they must be allocated to the existing Municipal Health Secretaries (MHS) located in each and every municipality. The last-mile distribution then gradually starts as soon as the MHS receives and consolidates the LLINs. This logistic process is illustrated in Figure 2.1. We focus only on the hub-MHS tier as the discharge ports are already defined, and it is beyond the scope of this paper to model the complexities of the last-mile distribution problem.

Therefore, we develop a single-period and capacitated location-allocation model to help the Brazilian Ministry of Health carry out some of the aforementioned logistics decisions, including where the hubs should be geographically positioned, at which capacity the hubs should operate (in terms of LLINs quantity), and how many LLINs should be sent away to the MHS (considering prioritization). The proposed model aims to satisfy as much as possible the demand for LLINs taking into account the municipalities' epidemiological, socioeconomic, and environmental profile, which is reflected using the proposed MVI. We focus on LLIN mass distribution campaigns that occur in cycles of three years, which is the ideal average LLIN replacement time (WHO, 2022). Figure 2.2 presents the overview of our proposed solution methodology. At the start of the campaign, let us say period t, the MVI is calculated to assess the vulnerability to malaria of the municipalities under scrutiny. The campaign starts, and LLINs are allocated to the MHS according to the municipalities' priority list. After three years, MVI is updated, a new campaign (LLINs replacement) is initiated, and so on.

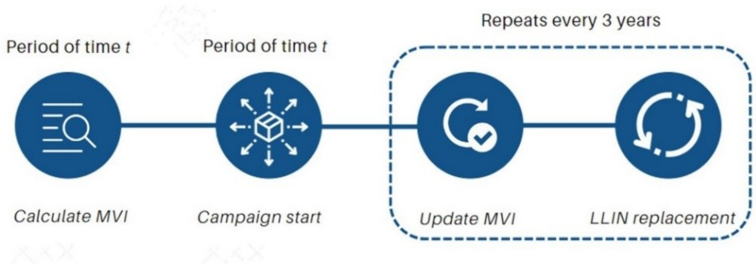

Figure 2.2: Dynamics of LLIN distribution campaign.

Our location-allocation approach operates under the following assumptions: (i) The capitals of the states are potential candidates for hub locations as capitals are commonly the state's business, cultural, and population center, presenting more advantages and infrastructure when compared to other cities; (ii) Decisions must consider a limited number of hubs to be established per capital with pre-defined maximum and minimum capacities; (iii) Only one type of LLIN is considered (rectangular medium LLIN with dimensions: 180x160x150cm) as it is the most common type adopted by the countries; (iv) Only the road transport mode is considered because we focus on allocation and distribution decisions limited to hubs and MHS. If the objective was focused on the last-mile distribution, it would be crucial to include other sorts of transportation modes, such as boats, since the majority of beneficiaries in the North region live in precarious locations that are difficult to reach out by means of road transportation. Also, the goal here is not to scale the fleet but only to obtain an approximate number of trips from the hubs to the MHS to account for the logistics costs; (v) Transshipments between the hubs or Municipal Health Municipalities are not allowed; (vi) Deterministic data are considered to simplify the model and make it as applicable as possible to the practitioners. Table 2.2 presents the model's mathematical notation.

To define the mathematical model, let $h = 1, \cdots, H$ be the potential hub locations. Hubs can be of $k = 1, \cdots, K$ different types or sizes. Hub at location h and size k has an associated opening cost c^{o}_{hk} (\$) and a capacity given by $k^{\max}_{hk}$ (m^3). A minimum quantity $k^{\min}_{hk}$ of LLINs (unit) in each hub type k located at h is also required. The unit inventory cost of LLIN in hub h is given by c^{inv}_{h} (\$) regardless of the hub size. Each Municipal Health Secretary $m = 1, \cdots, M$ is associated with an estimated demand for LLINs d_m (units of LLINs), which is evaluated as the estimated population in the malaria-endemic region covered by m divided by 2, as recommended by the World Health Organization world2017achieving. The transportation cost of LLINs between hub h and MHS m is represented by c^{transp}_{hm} (\$/trip). There is a maximum number of trips $\kappa^{\text{fleet}}_{h}$ that can be used to reflect the transportation capacity

Table 2.2: Mathematical notation.

$\mathrm{T} = \{1, ..., L\}$	Set of time periods
$\mathrm{C} = \{1, ..., K\}$	Set of counties
$\mathrm{V} = \{1, ..., H\}$	Set of all traditional groups
$\mathrm{C} = \{1, ..., N\}$	Set of counties
c_h^{inv}	Inventory cost of LLINs in hub h (\$/unit)
c_{hm}^{transp}	Transportation cost of LLINs between hub h and district m (\$/unit of trip)
c_{hk}^{o}	Opening cost for hub h at level k (\$)
d_m	Absolute needs for LLINs in municipality m (unit)
$k_{hk}^{\max}$	Maximum capacity of hub h at level k (vol in m^3)
$k_h^{\min}$	Minimum quantity of LLINs in hub h (unit)
κ_h^{fleet}	Number of vehicles available in the hub h
ρ	Volume of a LLIN unit (in m^3)
ρ'	Truck capacity (vol in m^3)
η	Available budget (\$)
α_ℓ	Coverage level ℓ (%) such that $\alpha_1 > \alpha_2 > \cdots > \alpha_\ell > \cdots > \alpha_L$
MVI_m	Malaria vulnerability index such that $0 \leq \mathrm{MVI}_m \leq 1$
M	Sufficiently large number
Y_{hk}	Binary variable that indicates whether hub h is established at level ℓ ($Y_{hk} = 1$) or not ($Y_{hk} = 0$)
$W_{m\ell}$	Binary variable that indicates whether municipality n is prioritised at coverage level ℓ ($W_{m\ell} = 1$) or not ($W_{m\ell} = 0$)
P_h	Quantity of LLINs required by hub h
N_{hm}	Number of trips between hub h and the municipality n
X_{hm}	Flow of LLINs between hub h and municipality m

of hub h (if it is the case for a given economic scenario), considering the unit LLIN volume ρ (m^3) and a transportation mode capacity ρ' (m^3). The demand for LLINs are satisfied at different coverage levels α_ℓ (%), where $\ell = 1, \cdots, L$ are the levels, such that $\alpha_1 > \alpha_2 > \cdots > \alpha_\ell > \cdots > \alpha_L$. In our modeling approach, the last level L represents zero coverage, i.e., $\alpha_L = 0$. The financial budget (investment) available to establish the hubs, manage the inventory of LLINs and transport the LLINs from hubs to MHS is given by η (\$). Finally, the Malaria Vulnerability Index associated with municipality/MHS m is MVI_m.

The decision variables of the location-allocation model for LLIN campaigns aim to support the Ministry of Health with a tool that can be useful in designing an effective and equitable distribution network to guarantee that LLINs are allocated to the most in-need malaria-endemic municipalities (model's effectiveness) while mitigating as much as possible underserved areas (model's equity). For this reason, we create a decision variable $W_{m\ell}$ that indicates whether MHS m is prioritized at level ℓ ($W_{m\ell} = 1$) or not ($W_{m\ell} = 0$), in which ℓ is related to the percentage of demand of a given MHS or municipality that is supposed to be covered. This variable is aligned with the current practice of ensuring a given coverage level (around 80%) to maximize the effectiveness of the coverage in a given area when universal coverage is hard to achieve. For the hubs, Y_{hk} is used to indicate whether hub h is established at size k ($Y_{hk} = 1$) or not ($Y_{hk} = 0$); and P_h defines the number of LLINs that should be allocated to hub h. The distribution variables are represented by X_{hm} that determines the number of LLINs sent to MHS m from hub h and N_{hm} that estimates the corresponding number of trips between hub h and MHS m. The problem can be formulated as follows.

$$\text{Maximize} \sum_{m=1}^{M}\sum_{\ell=1}^{L-1} \text{MVI}_m \alpha_\ell d_m W_{m\ell} \tag{2-1}$$

$$\text{Minimize} \sum_{m=1}^{M} W_{mL} \tag{2-2}$$

subject to:

$$\rho P_h \leq \sum_{k=1}^{K} \kappa_{hk}^{\max} Y_{hk}, \ \forall h = 1, \cdots, H \tag{2-3}$$

$$P_h \geq \sum_{k=1}^{K} \kappa_{hk}^{\min} Y_{hk}, \ \forall h = 1, \cdots, H \tag{2-4}$$

$$\sum_{k=1}^{K} Y_{hk} \leq 1, \ \forall h = 1, \cdots, H \tag{2-5}$$

$$\sum_{m=1}^{M} X_{hm} \leq P_h, \ \forall h = 1, \cdots, H \tag{2-6}$$

$$\sum_{h=1}^{H} X_{hm} \geq d_m \sum_{\ell=1}^{L-1} \alpha_\ell W_{m\ell}, \ \forall m = 1, \cdots, M \tag{2-7}$$

$$\sum_{h=1}^{H} X_{hm} \leq d_m(1 - W_{mL}), \ \forall m = 1, \cdots, M \tag{2-8}$$

$$\sum_{\ell=1}^{L} W_{m\ell} = 1, \ \forall m = 1, \cdots, M \tag{2-9}$$

$$N_{hm} \geq \frac{\rho}{\rho'} X_{hm}, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-10}$$

$$N_{hm} \leq 1 + \frac{\rho}{\rho'} X_{hm}, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-11}$$

$$N_{hm} \leq M \sum_{k=1}^{K} Y_{hk}, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-12}$$

$$\sum_{m=1}^{M} N_{hm} \leq \kappa_h^{\text{fleet}}, \ \forall h = 1, \cdots, H \tag{2-13}$$

$$\eta \geq \sum_{k=1}^{K}\sum_{h=1}^{H} c_{hk}^{\text{o}} Y_{hk} + \sum_{h=1}^{H} c_h^{\text{inv}} P_h + \sum_{h=1}^{H}\sum_{m=1}^{M} c_{hm}^{\text{transp}} N_{hm} \tag{2-14}$$

$$W_{m\ell} \in \{0,1\}, \ \forall m = 1, \cdots, M; \ell = 1, \cdots, L \tag{2-15}$$

$$Y_{hk} \in \{0,1\}, \ \forall h = 1, \cdots, H; \ k = 1, \cdots, K \tag{2-16}$$

$$N_{hm} \geq 0 \text{ and integer}, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-17}$$

$$P_h \geq 0, \ \forall h = 1, \cdots, H \tag{2-18}$$

$$X_{hm} \geq 0, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M. \tag{2-19}$$

The objective function (2-1) maximizes the effectiveness of the LLIN campaign, the extent to which it manages to cover as many demands as possible, which is mathematically a function of the prioritization variable $W_{m\ell}$ and the parameters MVI_m, coverage level α_ℓ, and demands d_m. Therefore, considering that $\alpha_1 > \alpha_2 > \cdots > \alpha_L$ and $\alpha_L = 0$, the maximization will be in favor of covering demands of more vulnerable municipalities (higher MVIs) with greater demands at better coverage levels (greater α's). Because the maximization of effectiveness will eventually prefer to cover fewer areas at better coverage levels than covering more areas at worse coverage levels, there is no guarantee that the solution will be *as equitable as possible* in this specific context. Therefore, the objective (2-2) function minimizes the number of underserved municipalities, i.e., the number of municipalities for which $W_{mL} = 1$, in an attempt to make coverage more equitable across different municipalities. To solve this two-objective model, we adopt the ϵ-constraint method. Notice that our initial ϵ is simply the total number of underserved municipalities (thus, an integer value) that we obtain when we solve the problem solely assuming the objective function (2-1), which is the maximum effectiveness. This way, by gradually reducing ϵ in steps of 1 we can generate all possible solutions for the bi-objective problem.

Constraints (2-3) ensure that LLINs can only be stored at the established hubs. Whether inventory of LLINs takes place, there is a corresponding minimum quantity that must be kept in stock according to constraints (2-4). Constraints (2-5) ensure that each hub is established at a given capacity level. Constraints (2-6) state that the inventory of LLINs in these hubs limits the number of LLINs transported from the hubs to the municipalities. Constraints (2-7) evaluate the flow of LLINs for each coverage level but not for the last one. In fact, for a given α_ℓ, $\ell = 1, \cdots, L-1$, the flow of LLINs to the municipality m must supply a given percentage of its needs. Even with extra supplies, it is sometimes impossible to cover all needs. Thus, we propose a coverage level approach rather than forcing the model to cover all demands or not cover any. If 100% of demand cannot be fully met, it is at least met by another coverage level such as 90% (α_ℓ, $\ell = 2$) or 80% (α_ℓ, $\ell = 3$). This constraint comes from the fact that WHO recommends a minimum threshold of 80% of the target population to be covered with LLINs. Constraints (2-8) state that the flow of LLINs at the last coverage level (not covering any demand) must be zero. Constraints (2-9) ensure that only one coverage level is selected for each municipality. Constraints (2-10) and (2-11) define the number of trips between hubs and municipalities. Constraints (2-12) ensure that travels from the hubs to the municipalities only exist if the hub is established. Constraints (2-13) guarantee that the number of trips from each hub to all the municipalities is upper-bounded. Constraints (2-14) refer to the financial budget to perform malaria interventions. Finally, constraints (2-15)-(2-19) state the domain of the decision variables.

2.4 Empirical Setting and Evaluation of the Malaria Vulnerability Index

Brazil is officially divided into North, Northeast, Central-West, Southeast, and South regions. The North region is the largest in Brazil, accounting for 45.27% of the country's total area. It includes seven states: Acre (AC), Amazonas (AM), Amapá (AP), Pará (PA), Rondônia (RO), Roraima (RR), and Tocantins (TO). Such region accounts for a limited proportion of the nation's economic output, ranking fourth in terms of gross domestic product per capita and human development index. The North region has most of the Amazon Rainforest, comprising about 40% of Brazil's total area. High temperatures, humidity, and rainfall are highly prevalent in this region, and mineral extraction and forestry are the main economic activities. Indigenous people are typical inhabitants, occupying all North states. The tropical weather, combined with the poor environmental and socioeconomic aspects of the region, creates favorable conditions for the cycle of malaria transmission in the North region (GOMES et al., 2020). This region is considered the endemic area for malaria in Brazil, accounting for 99% of malaria cases in the country.

The proposed Malaria Vulnerability Index (MVI) is evaluated for 310 municipalities in six of the seven states of the North Region: Acre, (AC), Amazonas (AM), Amapá (AP), Pará (PA), Rondônia (RO), and Roraima (RR), as shown in Figure 2.3. We excluded the state of Tocantins as no malaria cases were registered in 2020, and fewer than 5 cases were reported in the previous years. We also excluded the municipality of Mojuí dos Campos (PA), as it was officially emancipated from Santarém (PA) in 2013, and most of the data is unavailable for this municipality. The State of Pará is the most populated state, with the largest number of municipalities in the North, followed by Amazonas State. Table 2.10 presents some demographic data of the studied states.

As aforementioned, the MVI is a composite index comprising several malaria risk factors associated with malaria incidence and discussed in diverse academic papers. Based on the current epidemiological variables used by the Brazilian Ministry of Health to prioritize municipalities in the 2010 LLIN campaign (the number of malaria cases; the percentage of malaria cases caused by *P. Falciparum*; malaria cases registered within 7 days and malaria cases that started treatment within 48 hours) and on our literature investigation regarding socioeconomic and environmental malaria transmission drivers (see

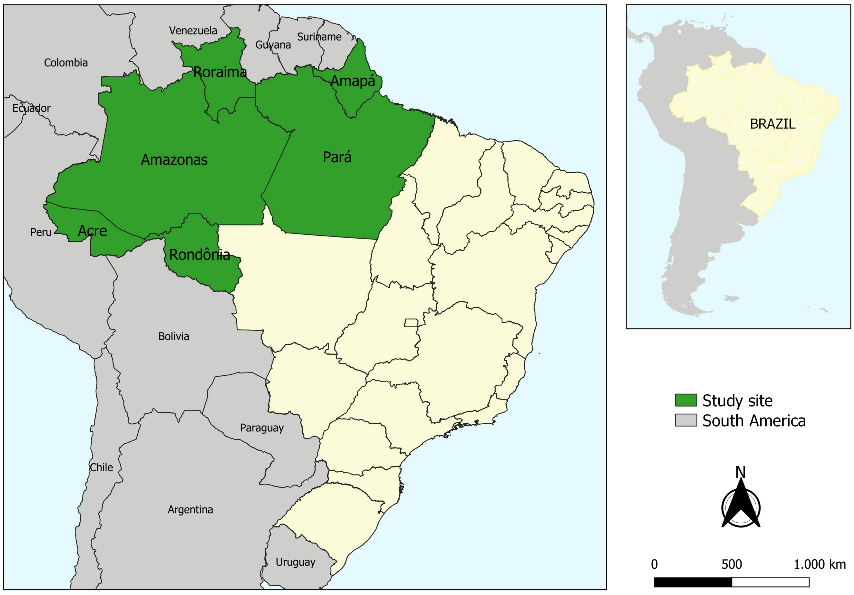

Figure 2.3: Map of Brazil showing the states within the Northern that are the focus of this study.

Table 2.3: Municipality and population data per state.

State	Capital city	Number of municipalities	Estimated population per state (2020)
Pará (PA)	Belém	144	8,690,745
Amazonas (AM)	Manaus	62	4,207,714
Rondônia (RO)	Porto Velho	52	1,796,460
Acre (AC)	Rio Branco	22	894,470
Amapá (AP)	Macapá	16	861,773
Roraima (RR)	Boa Vista	15	631,181

Table 2.1), we build a questionnaire to understand how practitioners perceive the importance of each driver in determining the most priority municipalities for malaria.

In this way, malaria drivers were validated by seven practitioners and specialists who have gathered practical experience in malaria interventions focused on the distribution of LLINs in Northern Brazil. These professionals work (or have worked) for international organizations such as *Médecins Sans Frontières* (MSF) and *United Nations High Commissioner for Refugees* (UNHCR) in Roraima state, and national health institutions such as FIOCRUZ and the *Department of Epidemiological Surveillance from the Municipal Health Department* (*Portuguese*: SESMA) in Amapá state. We designed a questionnaire composed of 32 questions and sent it to practitioners through the *Survey Monkey platform* (see full questionnaire in A). In addition to validating the

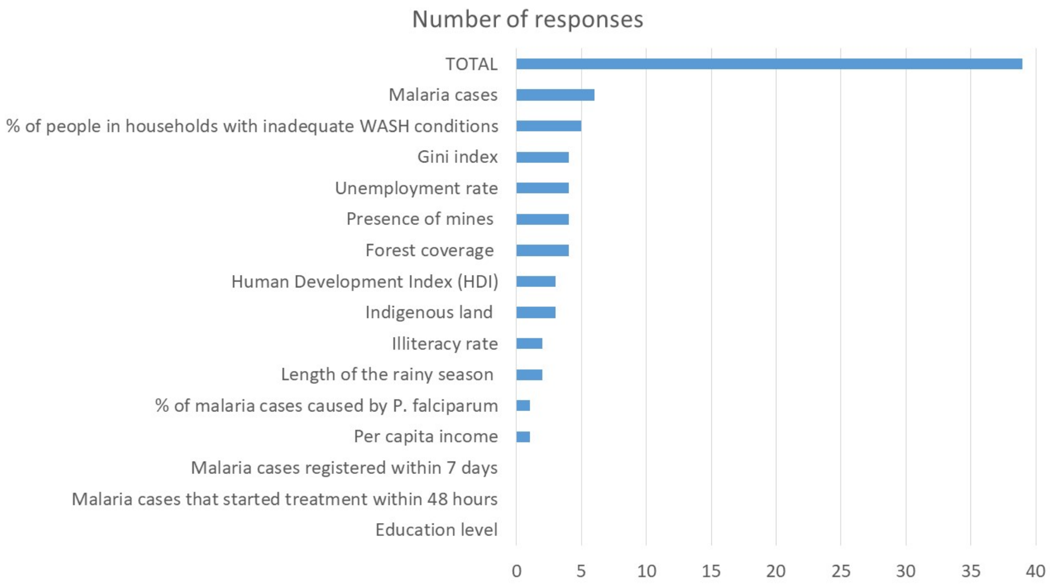

Figure 2.4: Number of responses for each driver according to specialists.

variables used to develop the MVI, questions were also designed to understand the problem of LLIN allocation and distribution in Northern Brazil and to capture other model parameters. Regarding malaria risk drivers validation, respondents were asked to choose the variables they considered important when selecting priority municipalities. Figure 2.4 shows the number of responses; the weight of each variable is then its number of responses divided by the total number of responses (39).

Respondents could choose as many variables (drivers) as they considered important. According to the practitioners, and not surprisingly, the number of malaria cases was the first variable to be considered when determining malaria priority municipalities, followed by some socioeconomic variables such as the percentage of people in households with inadequate WASH conditions, Gini index, unemployment rate, and environmental variables such as the presence of mines, and forest coverage. Together, these six variables represent 69% of the total answers. The responses validate the literature findings, as most of the socioeconomic and environmental drivers were considered important by at least one of the respondents. Notice that the last three variables (the number of malaria cases registered within seven days, the number of malaria cases that started treatment within 48 hours, and education level) were not considered to be part of our MVI formulation since none of the respondents chose them, so their relative weight was set to be zero. Thus, MVI drivers are composed of two variables of epidemiological dimension: (a) the number of malaria cases, and (b) the percentage of malaria cases caused by *P. Falciparum*; six variables of socioeconomic dimension: (a) the percentage of people in households with inadequate water, sanitation, and hygiene (WASH) conditions, (b) unemployment rate, (c) Human Development Index (HDI), (d) illiteracy rate, (e) per capita income, (f) Gini index; and finally, four variables of environmental dimension: (a) indigenous land, (b) forest coverage, (c) length of the rainy season, and (d) presence of mines. These epidemiological, socioeconomic, and environmental data were gathered from several secondary sources.

An important disclaimer when using the Gini index is that it measures inequality. This means that in scenarios of extreme poverty, such as in Sub-Saharan African countries, the index may appear low since poverty is widespread. Thus, it is important to consider a nuanced understanding of its implications. In contrast, Brazil experiences poverty but not to the extent observed in African nations, highlighting the importance of contextualizing the Gini index within each country's specific socio-economic landscape.

Epidemiological data were obtained through the *Epidemiological Surveillance System for Malaria* (*Portuguese*: SIVEP/Malária), a Brazilian governmental program that registers all quantitative information regarding malaria. We collected the number of confirmed malaria cases and the percentage of malaria cases by *Plasmodium falciparum* from 2017 to 2020 for every municipality. Then, we calculated the average of the cases in the last four years and divided it by the population average during these years for each municipality. Yearly population data were gathered from the *Brazilian Institute of Geography and Statistics* (*Portuguese*: IBGE). All socioeconomic data were obtained from the last IBGE Census (*Demographic Census and Population Count*) carried out in 2010. Regarding environmental drivers, indigenous land information was collected from the *Instituto Socioambiental* (*Portuguese*: ISA), a Brazilian non-profit organization. We calculated the percentage of indigenous areas dividing the indigenous land area of the municipality by the total area of that municipality. Territorial data information of each municipality was obtained from IBGE. Precipitation data were collected monthly from 2015 to 2019 through *NASA POWER Data Access Viewer* and used to calculate the length of the wet season (number of months with more than 100 mm of rainfall), following the methodology presented by (VALLE; LIMA, 2014). Thus, we calculated the percentage of the wet season for each municipality by dividing the number of months with more than 100 mm of rainfall by the total number of months from 2015 to 2019 (a total of 60 months). Forest coverage was gathered for each municipality from *Amazon Deforestation Estimation Project* (*Portuguese*: PRODES), which surveys the Amazon forest and provides yearly estimates. Finally, regarding the presence of mines, we selected the number of operative mines for each municipality, gathered from *Brazil's National Department of Mineral Production* (*Portuguese*: DNPM). Table 2.4 summarizes the proxy drivers used as indicators of epidemiological, socioeconomic, and environmental conditions.

From the number of responses presented in Figure 2.4 we calculate the relative frequency of each variable to be included in our MVI. We then evaluated the MVI for each of the 310 municipalities by using the weighted-mean method according to the equation $\text{MVI}_m = \sum_i \text{weight}_i \cdot v_{im},\ m = 1, \cdots, 310$, in which v_{im} is the value of driver i for municipality m and weight_i is the weight of driver i. The MVI resulted in an index varying from 0 to 1, where 0 and values close to 0 correspond to lower malaria vulnerability, whereas values closer to 1 represent higher malaria vulnerability. It is important to emphasize that we calculated the MVI based on the methodology typically adopted to estimate the IVS. We believe that our index is understandable, replicable, and can be easily adopted by practitioners and applied to other diseases and contexts.

Table 2.4: Summary of the drivers and data of the proposed Malaria Vulnerability Index.

Dimension	**Driver**	**Description**	**Year**	**Source**	**Temporal measure**	**Units**
Epidemiological	Number of malaria cases	Arithmetic mean of malaria cases in the last 4 years	2017-2020	Sivep-Malária	Yearly	Number of cases
	Percentage of malaria cases caused by P. *falciparum*	Percentage of the number of P. *falciparum* cases in the last 4 years	2017-2020	Sivep-Malária	Yearly	%
Socioeconomic	Percentage of people in households with inadequate water, sanitation and hygiene (WASH) conditions	Ratio between the number of people living in households whose water supply does not come from a clean source and whose sanitization is not carried out by a sewage collection or septic tank and the total population living in permanent private households	2010	IBGE Census	Yearly	%
	Unemployment rate	Percentage of economically active population that is unemployed	2010	IBGE Census	Yearly	%
	Human Development Index (HDI)	Municipal Human Development Index	2010	IBGE Census	Yearly	–
	Illiteracy rate	Ratio between the population who cannot read or write and the total population	2010	IBGE Census	Yearly	%
	Per capita income	Ratio between the sum of the income of all household individuals and the total number of these individuals. Values in Brazilian Reais (BRL)	2010	IBGE Census	Yearly	%
	Gini index	Income inequality	2010	IBGE Census	Yearly	–
Environmental	Indigenous land	Ratio between the area of indigenous land and the total area of the municipality	2021	Indigenous Lands in Brazil	Yearly	%
	Forest coverage	Ratio between forest cover area and the total area of the municipality	2019	PRODES	Yearly	%
	Length of rainy season	Ratio between the number of months with more than 100 mm of rain and the total number of months from 2015 to 2019 (total of 60 months)	2015-2019	NASA POWER	Yearly	%
	Presence of mines	Number of operating mines in each municipality	2021	DNPM	Yearly	Number of operating mines

Figure 2.5 shows the case-study area and the corresponding MVI from

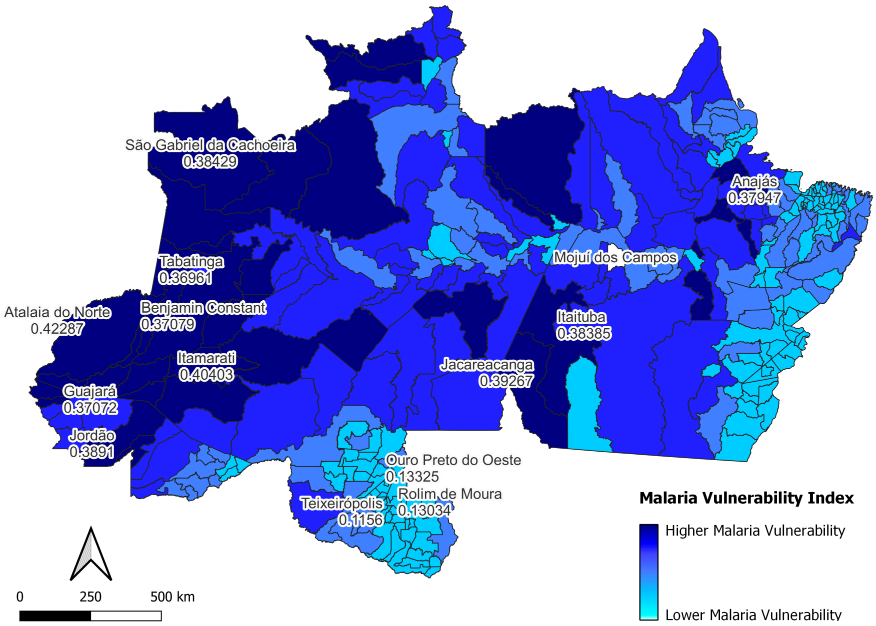

Figure 2.5: Malaria Vulnerability Index per municipality.

lower to higher vulnerability values. We present ten municipalities with the highest MVIs on the map. These are respectively: Atalaia do Norte (AM), Itamarati (AM), Jacareacanga (PA), Jordão (AC), São Gabriel da Cachoeira (AM), Itaituba (PA), Anajás (PA), Benjamin Constant (AM), Guajará (AM), and Tabatinga (AM). We also show municipalities with the lowest MVIs: Teixeirópolis (RO), Ouro Preto do Oeste (RO), and Rolim de Moura (RO).

Municipalities with the lowest MVI represent the least vulnerable to malaria. They are mainly located along the eastern state of Pará and in almost the entire state of Rondônia, which concentrates the 11 municipalities with the lowest MVIs. Out of the six studied states, Rondônia is the third most populous. The state encompasses eight of the ten municipalities with the lowest rates of the Gini Index and the percentage of people living with inadequate WASH conditions. It holds the lowest average of malaria cases in the last four years. On the other hand, municipalities with the highest malaria vulnerability indexes represent the most vulnerable to malaria. They are thoroughly condensed in the northwest of Amazonas state, especially in municipalities bordering Peru, Colombia, and Venezuela, countries that, together with Brazil, are responsible for the largest number of malaria cases (ORGANIZATION et al., 2022b) and hold the highest percentages of Amazon Rainforest coverage in South America. The municipality of Atalaia do Norte has the highest MVI, with approximately 0.422, followed by the municipality of Itamarati, with 0.404. Along with São Gabriel da Cachoeira, Itamarati presents the highest Gini Index and the second-lowest illiteracy rate, while

Atalaia do Norte holds the ninth-worst illiteracy rate. Regarding environmental aspects, Atalaia do Norte and Itamarati concentrate the highest percentages of forest coverage, and São Gabriel da Cachoeira and Benjamin Constant are among the ten municipalities with the highest rates of indigenous peoples and precipitation. Table 2.5 presents the overall mean of all 310 MVIs and the mean of MVIs per state in descending order. Only the states of Pará and Rondônia are below the average; that is, the mean of the MVIs of their municipalities is lower than the general average of the MVIs, indicating they are the states with municipalities holding the lowest MVIs, or that is, less vulnerable to malaria.

Table 2.5: MVI's mean per state.

State	MVI's mean
Overall mean	**0.24**
Amazonas (AM)	0.30
Acre (AC)	0.28
Roraima (RR)	0.27
Amapá (AP)	0.25
Pará (PA)	0.23
Rondônia (RO)	0.18

As previously mentioned, the Brazilian government relies only on epidemiological drivers to assess priority municipalities for malaria transmission, as observed in the 2010 LLIN campaign, and more recently in 2019, where the Health Surveillance Department of the Ministry of Health listed 41 cities (9% of the total number of municipalities in the North) as priority municipalities to receive malaria interventions. The *National Malaria Control Program* (*Portuguese*: PNCM) considers a "priority municipality" the municipalities that together are responsible for 80% of malaria cases in the country and hold high transmission levels. Comparing the 41 priority municipalities ranked by the Ministry of Health in 2019 (that considers only epidemiological data), to our 41 priority municipalities ranked according to the proposed MVI, we observe that only 16 municipalities remain ranked in both lists, as illustrated in Figure 2.6. *The incorporation of socioeconomic and environmental drivers modifies the list of priority municipalities for malaria and, therefore, the scenario of interventions and campaigns to combat the disease. As the role of socioeconomic and environmental factors in reducing malaria risks can highly vary between municipalities, it is essential to assess the real impact of these drivers to set up targeted campaigns against malaria at an accurate scale.*

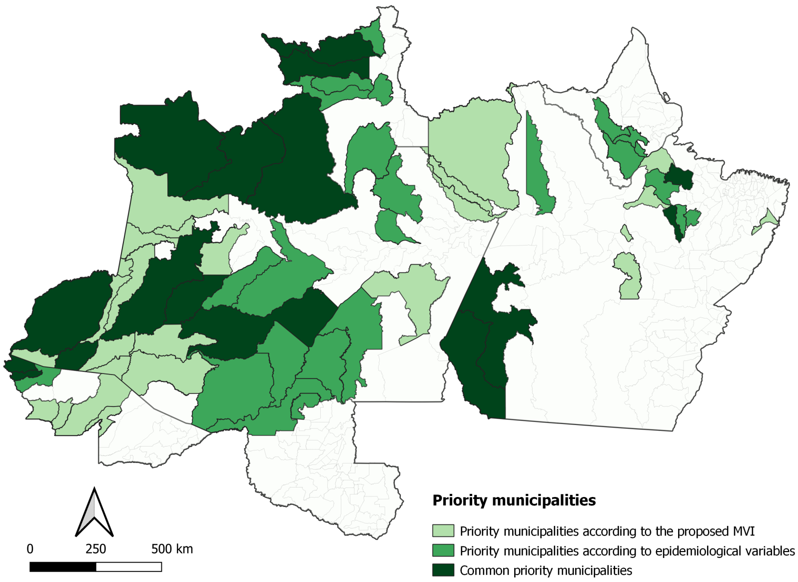

Figure 2.6: Priority municipalities according to different prioritization measures.

2.4.1 The Malaria Vulnerability Index: correlation analysis and robustness check

In dealing with composite indicators, which is the case of this paper, the selection of variables is usually based on the subjective judgment of the importance of a given aspect/dimension and/or based on a quantitative measurement, such as correlation analysis, to identify whether different indicators appear to be measuring the same aspect (WONG, 2003). As previously explained, the selected indicators have been chosen based on the current practice of the government and on a vast literature review about the main drivers of malaria vulnerability. Afterwards, the variables were validated based on the practitioner's judgment, and a correlation analysis was finally performed to ensure the suitability of the selected variables. The twelve variables, shown in Table 2.4, were then used to evaluate the MVI.

Here, we adopted the widely accepted *Pearson's correlation coefficient*(r) to analyze the correlation between the variables that compose our MVI. Pearson's coefficient measures the strength and direction of the linear relationship between two quantitative variables.

We can use the Pearson correlation coefficient in our dataset because it consists of numerical variables that allow for the measurement of linear relationships between pairs of variables. The Pearson correlation coefficient is appropriate for identifying how one variable changes in response to another in a linear manner, and our dataset has sufficient data points to produce reliable and meaningful correlation coefficients.

Interestingly, despite the fact correlation analysis is mainstream in most academic sciences, there is no unanimous agreement on how to interpret the numerical values. Ultimately, the interpretation of the relationship strength between variables is heavily context-dependent (PALLANT; MANUAL, 2013). Indeed, whereas classical statistical textbooks point out that a correlation coefficient larger than 0.5 may indicate a strong correlation, several academic papers defend that $r > 0.7$ indicates a strong linear relationship, $r < 0.3$ a weak one, and the remaining is moderate (RUSAKOV, 2023). Moreover, several papers that develop composite indicators assume that a strong correlation is solely when $r \geq 0.9$ (GRIFFITH; MARTINKO; PRICE, 2000; SU et al., 2014; XIAO; WANG; WANG, 2018) with the main rationale of making sure that variables are not simply replaced by a *"dummy"* one that not necessarily reflects the important aspects under investigation (FIGUEIRA et al., 2023), thus maintaining the indicator interpretability.

Table 2.6 shows the correlation matrix (*Pearson's correlation coefficient*) for all the twelve variables that compose the MVI. Notice that most correlation coefficient values are weak or moderate. There are a few cases where they can be seen as strong based on the *classical approach* to interpret the coefficient values:

- HDI (6) x Per capita income (3), with $r = 0.848$;
- Illiteracy rate (7) x HDI (6), with $r = 0.776$;
- Percentage of people in households with inadequate water, sanitation and hygiene (WASH) conditions (4) x Per capita income (3), with $r = 0.653$;
- HDI (6) x Percentage of people in households with inadequate water, sanitation and hygiene (WASH) conditions (4), with $r = 0.647$;
- Illiteracy rate (7) x Per capita income (3), with $r = 0.574$.

The apparent strong correlation values of some of these variables, especially between HDI and per capita income, indicates that there is a statistical dependence between them. However, this does not mean that there is a *subjective dependence* between them since they are of a different nature (FIGUEIRA et al., 2023) and measure different aspects of socioeconomic vulnerability. In fact, "per capita income" is a single *economic* variable, whereas "HDI" is itself a composite indicator built upon several factors that measure *human well-being* according to societal variables. That is why in several popular composite indicators/indexes, such as the *United Nations Development Programme* (UNDP) Disaster Risk Index (SMITH, 2013), it is quite common to account for these two variables simultaneously. On top of that, and as aforementioned, there is no

Table 2.6: Pearson correlation coefficient values.

	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000											
2	0.294	1.000										
3	0.191	0.053	1.000									
4	0.066	−0.009	**0.653**	1.000								
5	0.044	−0.061	0.063	0.050	1.000							
6	0.226	0.064	**0.848**	**0.647**	-0.058	1.000						
7	0.376	0.211	**0.574**	0.437	−0.070	**0.776**	1.000					
8	0.407	0.201	0.335	0.272	0.109	0.374	0.410	1.000				
9	0.291	0.113	0.129	−0.054	−0.029	0.124	0.177	0.420	1.000			
10	0.385	0.240	0.275	0.267	−0.013	0.287	0.327	0.419	0.388	1.000		
11	0.154	0.138	0.312	0.209	0.064	0.245	0.153	0.100	−0.019	0.357	1.000	
12	0.023	0.065	−0.113	−0.002	0.021	−0.096	−0.070	−0.006	0.019	0.104	−0.053	1.000
Max	0.407	0.240	0.848	0.647	0.109	0.776	0.410	0.420	0.388	0.357	−0.053	1.000
Min	0.023	−0.061	−0.113	−0.054	−0.070	−0.096	−0.070	−0.006	−0.019	0.104	−0.053	1.000

1: Number of malaria cases. 2: Percentage of malaria cases caused by *P. Falciparum*. 3: Per capita income. 4: Percentage of people in households with inadequate water, sanitation and hygiene (WASH) conditions. 5: Unemployment rate. 6: Human Development Index (HDI). 7: Illiteracy rate. 8: Gini index. 9: Indigenous land. 10: Forest coverage. 11: Length of rainy season. 12: Presence of mines

unambiguous view on the correlation in the case of composite indicators (HUDRLIKOVÁ et al., 2013); high correlations may be a feature of the measured comprehensive phenomenon (NARDO et al., 2005); therefore, not necessarily they need to be corrected by removing some of them. It is noteworthy that we would have no strong correlations whatsoever from the point of view of more recent composite indicators' development, as none of our coefficient values is greater than 0.9. All of those aforementioned reasons made us believe our MVI does not double count variables, as well as it is consistent and aligned with existing (similar) indicators; therefore, we maintained the twelve variables in the final analysis.

To further showcase the consistency and robustness of our composite indicator, we conducted a sensitivity analysis on the MVI by removing one at a time the three most correlated variables (per capita income, HDI, and illiteracy rate, which account for the two highest correlations $r = 0.848$ and 0.776; see Table 2.6), recalculating the weights or relative frequencies (since the removal of one variable changes the relative frequency of all of them), and finally reevaluating MVI. We also proposed two different methods to assign the weights of the variables not dependent on the responses of the practitioners. The first method assigns the weights to all the twelve variables in an equiprobable manner (i.e, $w_i = 1/12$ for all $i = 1, \cdots, 12$), assuming that all the variables are equally important. The second method is based on assigning the same weight to the three considered dimensions of the MVI, epidemiological, socioeconomic, and environmental. Afterward, the 1/3 weight is equally distributed among the number of variables within each dimension.

For example, as the epidemiological dimension has two variables, then their weight is 1/6. The summary of all the evaluated MVIs is given below:

- MVI benchmark: MVI originally calculated based on the twelve variables and weights given by the practitioners' responses;
- MVI 1: without the socioeconomic variable *Per capita income*;
- MVI 2: without the socioeconomic variable *Illiteracy rate*;
- MVI 3: without the socioeconomic variable *HDI*;
- MVI 4: equiprobable weights for all the twelve variables (1/12);
- MVI 5: equiprobable weights for all three dimensions with the twelve variables.

The reevaluated MVIs were plotted in Figure 2.7 and their key statistics are summarized in Table 2.7. The main takeaways from this analysis are as follows. The novel MVIs exhibit a similar qualitative behavior in comparison to the original MVI, which is further attested by the summary statistics; this is particularly true for MVIs 1 and 2. The exception is perhaps MVI 5, which presents overall "underestimated" statistics in comparison to the remaining MVIs and more pronounced peaks and valleys, suggesting that the ranking of the municipalities (most/least vulnerable) presents variations against the benchmark MVI. We further investigated how much the ranking changes based on each MVI. For this purpose, we proposed a cut-off of the k most vulnerable municipalities according to the benchmark MVI and analyzed their reevaluated MVIs. The main rationale here is to figure out whether the original k most vulnerable municipalities would remain amongst the most vulnerable ones based on different ways to evaluate our indicator. Here, k was chosen to be either 41[3] or 100 (arbitrarily). Table 2.8 summarizes the number of municipalities that would remain on the list of the k-most most vulnerable municipalities for $k = 41$ and 100, confirming that the MVIs have a similar performance in terms of ranking the most/least vulnerable municipalities. On average, more than 90% of the municipalities ranked as the most vulnerable remain this way regardless of the way MVI is evaluated. The exception, as expected, is MVI 5 for a cut-off of 41 (75.6%), but even in this case, the vast majority of municipalities would be amongst the most vulnerable ones.

[3]This number is somehow aligned with the Ministry of Health strategy that prioritized only 41 municipalities in terms of LLINs allocation back in 2019.

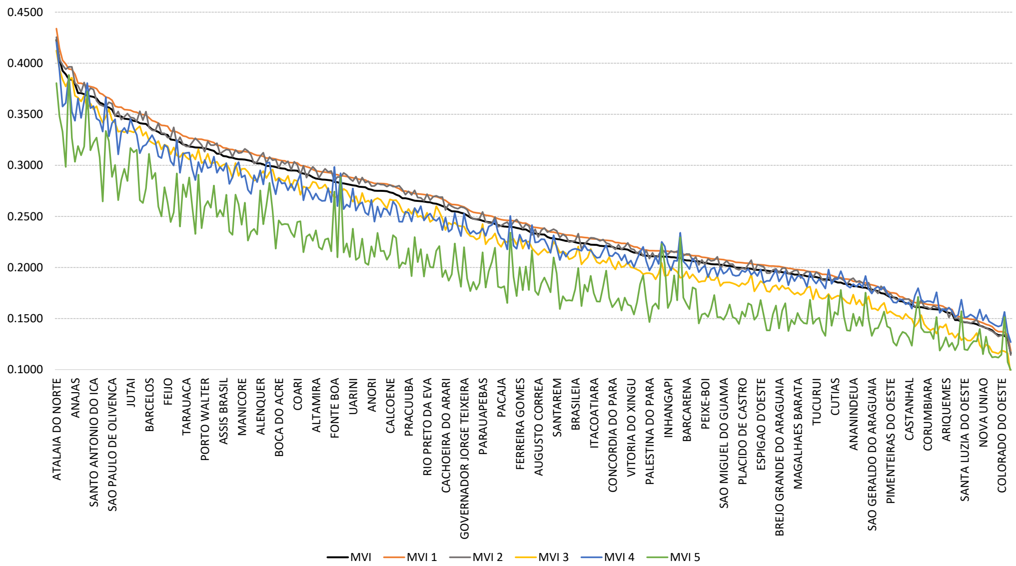

Figure 2.7: MVIs per municipality plotted against the original MVI in descending order of vulnerability (from the most to least vulnerable municipalities). Notice that "Atalaia do Norte" is the most vulnerable to malaria based on the original MVI.

Table 2.7: MVI summary statistics.

Statistic	**MVI Bench**[a]	**MVI 1**[b]	**MVI 2**[c]	**MVI 3**[d]	**MVI 4**[e]	**MVI 5**[f]
Max	**0.4229**	0.4338	0.4255	0.4123	0.4203	0.3885
Min	**0.1156**	0.1186	0.1143	0.0955	0.1269	0.0993
Mean	**0.2447**	0.2510	0.2480	0.2312	0.2368	0.1991
St. dev.	**0.0645**	0.0661	0.0656	0.0670	0.0581	0.0578

[a] Benchmark MVI.[b] Without Per capita income. [c] Without Illiteracy rate .[d] Without HDI. [e] Equiprobable weight for the 12 variables. [f] Equiprobable weight for the 3 dimensions.

2.5 Numerical Analysis and Insights

In this section, we use numerical results from our model to better understand the impact of prioritization and equity on LLIN campaigns. For this purpose, we first briefly discuss the ideal universal coverage solution in Section 2.5.1. Then, Section 2.5.2 analyzes the impact of the prioritization approach (with MVI) for different investment levels, and Section 2.5.3 compares the solutions with/without prioritization (with/without MVI). Finally, Section 2.5.4 shows how to make LLIN allocation more equitable. Further managerial implications are given in Section 2.5.5. The models were implemented in *Julia* 1.3 and solved with *GUROBI* on an *Intel core i5* processor with 8 GB RAM under *Windows 10* operating system with a 1-hour time limit for each run.

Table 2.8: Cut-off analysis.

	Cut-off 41	**Cut-off 100**
MVI 1	41 (100%)	100 (100%)
MVI 2	40 (97.5%)	99 (99%)
MVI 3	38 (92.6%)	98 (98%)
MVI 4	37 (90.2%)	96 (96%)
MVI 5	31 (75.6%)	90 (90%)

The optimality gap of all instances within this time limit was less than 0.01%.

2.5.1 Universal coverage solution

To obtain the universal coverage solution, we solved the corresponding cost-minimization problem, such that total demand is met at the first coverage level (100%). The problem is formulated as follows:

$$\text{Minimize } \sum_{h,k} c^{\text{o}}_{hk} Y_{hk} + \sum_{h} c^{\text{inv}}_{h} P_h + \sum_{h,m} c^{\text{transp}}_{hm} N_{hm} \tag{2-20}$$

subject to:

$$\rho P_h \leq \sum_{k=1}^{K} \kappa^{\max}_{hk} Y_{hk}, \ \forall h = 1, \cdots, H \tag{2-21}$$

$$P_h \geq \sum_{k=1}^{K} \kappa^{\min}_{hk} Y_{hk}, \ \forall h = 1, \cdots, H \tag{2-22}$$

$$\sum_{k=1}^{K} Y_{hk} \leq 1, \ \forall h = 1, \cdots, H \tag{2-23}$$

$$\sum_{m=1}^{M} X_{hm} \leq P_h, \ \forall h = 1, \cdots, H \tag{2-24}$$

$$\sum_{h=1}^{H} X_{hm} = d_m, \ \forall m = 1, \cdots, M \tag{2-25}$$

$$N_{hm} \geq \frac{\rho}{\rho'} X_{hm}, \quad \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-26}$$

$$N_{hm} \leq 1 + \frac{\rho}{\rho'} X_{hm}, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-27}$$

$$N_{hm} \leq M \sum_{k=1}^{K} Y_{hk}, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-28}$$

$$\sum_{m=1}^{M} N_{hm} \leq \kappa^{\text{fleet}}_{h}, \ \forall h = 1, \cdots, H \tag{2-29}$$

$$Y_{hk} \in \{0, 1\}, \ \forall h = 1, \cdots, H; \ k = 1, \cdots, K \tag{2-30}$$

$$N_{hm} \geq 0 \text{ and integer}, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M \tag{2-31}$$

$$P_h \geq 0, \ \forall h = 1, \cdots, H \tag{2-32}$$

$$X_{hm} \geq 0, \ \forall h = 1, \cdots, H; \ m = 1, \cdots, M. \tag{2-33}$$

This solution requires an investment of \$14,664,319.23, and establishes six hubs to store the LLINs, as shown in Table 2.9, which is ordered according to the greatest number of delivered LLINs by each hub. The states of Pará (PA) and Amazonas (AM) are, respectively, the largest in terms of population and number of municipalities in the North Region. Not surprisingly, the delivered quantities of LLINs from the hubs based in Belém (PA) and Amazonas (AM) are the largest. The hub located in Belém, the most populated state in Northern Brazil, is the only one that opens at a medium-sized capacity.

Consequently, besides the greatest delivered quantity of LLINs, this hub also covers the largest number of municipalities (110). All the other capitals establish small hubs. Although Manaus is the second state with the largest number of delivered LLINs, it is not the second state covering the largest

Table 2.9: Cost-minimization model results.

Hub	**Hub size**[a]	**Maximum capacity**[b] **(quantity)**	**LLINs**[c] **(quantity)**	**Municipalities**[d] **(quantity)**
Belém (PA)	Medium	4,117,647	3,770,662	110
Manaus (AM)	Small	1,647,058	1,647,058	48
Porto Velho (RO)	Small	823,529	823,529	59
Macapá (AP)	Small	823,529	823,529	52
Rio Branco (AC)	Small	823,529	723,570	36
Boa Vista (RR)	Small	823,529	632,438	25

[a]Size of established hubs. [b]Maximum capacity in terms of LLINs according to the hub size. [c] Number of required LLINs. [d]Number of covered municipalities. This last column adds up to more than 310 municipalities, as hubs can cover more than one municipality, as shown in Figure 2.8.

number of municipalities. Porto Velho is the hub that covers the second largest number of municipalities (59), followed by Macapá (52) and Manaus (48). This happens because the hub opened in Manaus covers more populous cities, reaching its maximum capacity. The hubs established in Porto Velho, Macapá, and Boa Vista also reach their maximum capacity. Figure 2.8 visually shows the municipalities covered by each hub. It is important to note that a municipality can be covered by more than one hub.

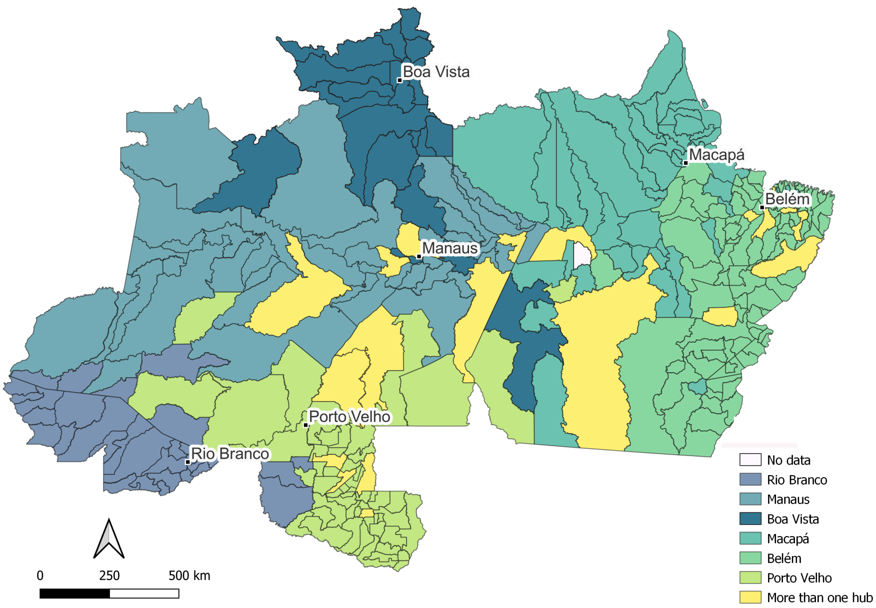

Figure 2.8: Spatial distribution of municipalities covered by each hub.

With this solution, we have 8,420,786 LLINs delivered for all 310 municipalities under study, which will further be distributed and impact almost 17 million people. Table 2.10 shows each hub's covered demand percentage. For example, the hub located in Rio Branco, the capital of Acre State, fully meets not only its own state's demand but also 11% of the demand in Amazonas State and 13% of the demand in Rondônia State. As shown in Figure 2.3, Acre state borders with both Amazonas and Rondônia states. Thus, the hub opened in Rio Branco also covers cities in these two states. The hub located in Manaus covers 73% of its own state's demand and also covers 2% of the demand in Pará. The hub in Boa Vista meets 100% of its state's demand, 15% of the demand in Amazonas, and 1% of the demand in Pará. The hub located in Macapá meets 100% of its state's demand and 25% of the demand in Pará. The hub located in Belém meets 76% of its own state's demand. Finally, Porto Velho meets nearly all its own state's demand (94%), plus 13% of the demand in Amazonas State, and 1% in Pará. *These results show that the strategic decision of which municipality will be covered by which hub is strongly driven by the distance between hubs and municipalities (as we could expect from a cost-minimization problem), as all hubs cover municipalities that are closest to it. When a municipality cannot be covered by its closest hub, because the hub has already reached its maximum capacity, it is covered by the second closest hub, indicating that the criterion for choosing the municipalities covered by a particular hub is simply their proximity to the hub.* Not surprisingly, the cost-minimization approach will fail to balance the allocation of LLINs according to the principle "more to those who need it most and less to those who require less" in a typical situation of scarce resources. In what follows, we discuss *alternative* results when prioritization and equity are also factored in the problem analysis.

Table 2.10: Percentage of the demand met by each hub in each state.

Hub	**Acre (AC)**	**Amazonas (AM)**	**Roraima (RR)**	**Amapá State (AP)**	**Pará State (PA)**	**Rondônia State (RO)**
Rio Branco (AC)	100%	11%	-	-	-	13%
Manaus (AM)	-	73%	-	-	2%	-
Boa Vista (RR)	-	15%	100%	-	1%	-
Macapá (AP)	-	-	-	100%	25%	-
Belém (PA)	-	-	-	-	76%	-
Porto Velho (RO)	-	13%	-	-	1%	94%

2.5.2 The role of prioritization for different investment levels

We now investigate the role of prioritization for different investment levels as resources for combating endemics are limited. For this purpose, we first evaluate the prioritization-based function (2-20) subject to constraints (2-21)-(2-33) for investment levels that represent 80% (\$11,731,455); 60% (\$8,798,591); 40% (\$5,865,727); and 20% (\$ 2,932,863) of the *ideal* investment. Figure 2.9 shows the opened hubs and capacity sizes, the number of delivered LLINs, and the number of covered municipalities by each hub under different investment levels. Figure 2.10 represents the covered municipalities by each hub as well as the not covered ones. Municipalities not covered by any hub are represented on the map in white, and municipalities covered by more than one hub are in yellow.

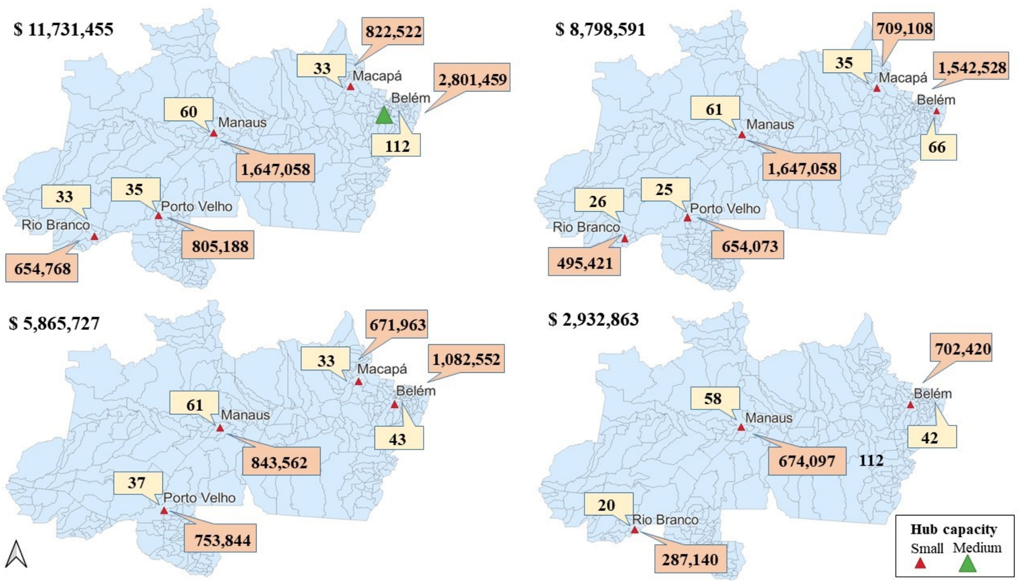

Figure 2.9: Main results under different investment levels (prioritization approach).

Five hubs are established when the investment level is limited to \$11,731,455 (80%): Rio Branco, Manaus, Macapá, Belém, and Porto Velho. All these hubs are opened at a small size except for the hub established in Belém (Pará State), the most populated state and with the largest number of municipalities in the North region. From Figure 2.10, we can see that opened hubs always cover municipalities of its state and municipalities from neighbor states when necessary at all investment levels. For example, considering the investment level of \$11,731,455 (80%), the hub established in Rio Branco, the capital of Acre State, covers 100% of its state's demand, plus 13% and 5,76% from neighbor municipalities of Amazonas and Porto Velho State, respectively. We observe that the hub in Rio Branco does not cover municipalities from Amapá or Pará at any investment levels. The same pattern appears in Porto Velho, the capital of Rondônia State, and other hubs. At the investment levels of \$11,731,455 (80%), \$8,798,591 (60%), and \$5,865,727 (40%), in which Porto Velho is chosen to have a hub, it covers municipalities of its state and also covers several municipalities of Amazonas and Acre, states that border Rondônia. *The distance between hubs and municipalities also plays an important role in the prioritization strategy due to the limited budget.*

When the investment level decreases to \$8,798,591.54 (60%), the same five hubs are opened, but at a small capacity for all. The opened hubs

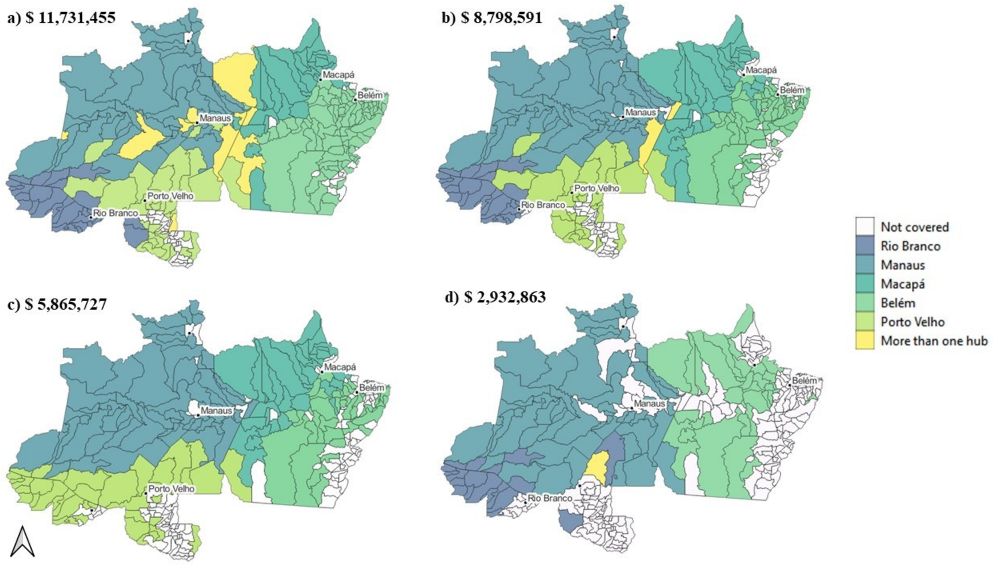

Figure 2.10: Spatial distribution of municipalities under different investment levels (prioritization approach).

configuration changes when the investment level reduces to $5,865,727 (40%). Rio Branco is no longer chosen as a hub location. Municipalities of Acre State, previously covered by Rio Branco, the closest city to any of the municipalities in Acre, are now covered by Porto Velho, the second closest city to municipalities in Acre (see Figure 2.10c). It is worth noting that even when Rio Branco is not chosen to have a hub, all municipalities of Acre, except for 6, are covered. The state of Acre has the second-highest average MVI, surpassing the overall average of 0.24 (see Table 2.5). Rio Branco, Senador Guiomard, Acrelândia, Plácido de Castro, Capixaba, and Epitaciolândia, which are the closest municipalities to Porto Velho, and the municipalities with the lowest MVIs of Acre are not covered, whereas further cities located at the extreme of Acre such as Mâncio Lima, Rodrigues Alves, and Cruzeiro do Sul, which, respectively, hold the highest MVIs of the state are covered.

When the investment drops to its lowest level $ 2,932,863 (20%) (Figure 2.9d), only 3 hubs are opened: Rio Branco, Manaus, and Belém. In this scenario, only one municipality in Rondônia, whose MVI is greater than the overall average, is covered. Municipalities of west Pará, whose MVIs are the lowest of the state (and lower than the overall average), are not covered except for Nova Esperança do Piriá (whose MVI is also greater than the overall average). Looking at the previous MVI map (Figure 2.5), we observe that the lighter blues are concentrated in Rondônia State and the west of Pará State. Municipalities from these areas concentrate the lowest MVIs and are shown in white on the map in Figure 2.10; they are not covered at all. Thus, Rondônia and Pará States concentrate the lowest percentage of covered municipalities at all investment levels (Table 2.11).

Table 2.11: % of covered municipalities per state (prioritization approach).

Investment level ($)	Acre	Amazonas	Roraima	Amapá	Pará	Rondônia
11,731,455.38 (80%)	100%	100%	93%	100%	88%	42%
8,798,591.54 (60%)	91%	95%	86%	81%	63%	30%
5,865,727.69 (40%)	72%	93%	80%	81%	46%	17%
2,932,863.85 (20%)	54%	79%	66%	31%	21%	2%

Despite being the most populous state in Northern Brazil, the state of Pará is not the one with the highest number of covered municipalities. Amazonas is the state with the largest number of covered municipalities at all investment levels because it is the state with the highest average MVI (0.3), as seen in Table 2.5. Thus, we observe the correlation between the MVI and the prioritization of municipalities. *Municipalities more vulnerable to malaria are covered because of their priority, even if they are further from their hubs.*

The capital Boa Vista, in Roraima State, which has an average MVI above the overall average, was not chosen to set up a hub at any investment level. However, its municipalities are covered by the hub located in Manaus at all investment-level scenarios. Its distance to the prioritized municipalities in Roraima is the second smallest (only greater than the distance from Boa Vista to the selected municipalities). Thus, the municipalities of Roraima are covered by Manaus, the hub with the shortest distance to these municipalities. Even though the capital of Boa Vista was not chosen to host a hub, the municipalities of Roraima are covered by Manaus, as they are municipalities with high MVIs, above the general MVI average. Manaus and Belém are the hubs with the highest capacities; they are the only hubs opened at all investment levels. It is important to highlight that within Pará, there is significant heterogeneity in terms of MVIs, which further reflects in the prioritization strategy. Municipalities from the west of Pará are less vulnerable to malaria than municipalities from the east, which are covered by the hub located in Macapá or Belém.

Interestingly, there are a few situations in which proximity to the chosen hub becomes more important than the MVI itself. When MVIs are similar, our prioritization approach prefers to cover the closest municipality rather than the one with the highest MVI. Consider, for example, the investment level of $11,731,455 (80%) and two municipalities: Bannach (PA) (MVI = 0.18737) and Cutias (AP) (MVI = 0.18638). The difference between the two MVIs is slightly small. Cutias is covered by the hub established in Macapá, whose distance to this municipality is 147 km, whereas Bannach is 865km away from its nearest potential hub in Belém and, therefore, it is not covered at all even though its

MVI is slightly higher than Cutias's MVI. Similar results are observed with two other municipalities: São João do Araguaia (PA) (MVI = 0.20603) and Itaubal (AP) (MVI = 0.20475). When the budget is \$8,798,591 (60%), Itaubal is covered by Macapá, whose distance to this municipality is 110 km, whereas São João do Araguaia, whose MVI is greater than Itaubal and its distance to the nearest potential hub is greater than the distance between Itaubal and Macapá, is not covered. Another similar case is observed when the investment level decreases to \$2,932,863 (20%) with the municipalities of Prainha (PA) (MVI = 0.27467), whose shortest distance to its potential hub in Belém is 1488 km; and Tefé (AM) (MVI = 0.27296) whose shortest distance to its hub is 631 km. Although Prainha holds a slightly higher MVI, this municipality is not covered.

2.5.3 Maximizing effectiveness with or without prioritization?

A natural question that may arise in our prioritization-based setting is what sort of solution we could obtain by maximizing effectiveness solely based on the LLINs' demand and coverage level. For this purpose, we exclude the MVI from the objective function (2-1) and rerun the experiments. Figure 2.11 shows the results of opened hubs and their respective quantity of delivered LLINs and covered municipalities, whereas Figure 2.12 gives the spatial distribution of the covered municipalities by each hub as well as the not covered ones under different investment levels for a non-prioritization approach.

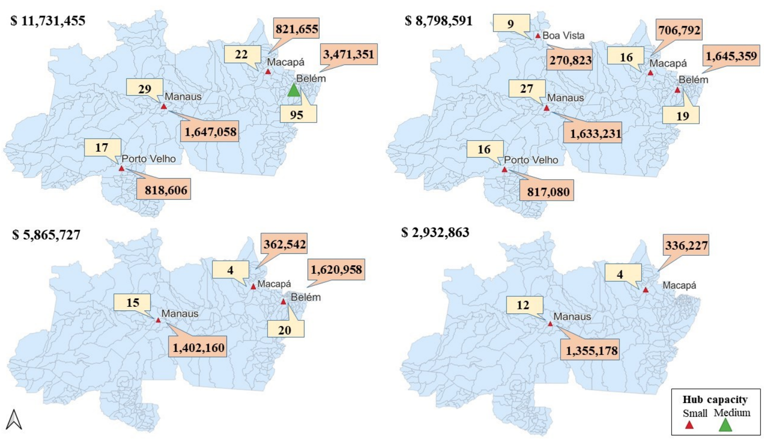

Figure 2.11: Main results under different investment levels (non-prioritization approach).

We now can see that the non-prioritization approach gives different solutions in terms of opened hubs and number of municipalities fully served (shown to be significantly reduced in some cases). The city of Boa Vista, in Roraima state, which had not been chosen at any investment level in

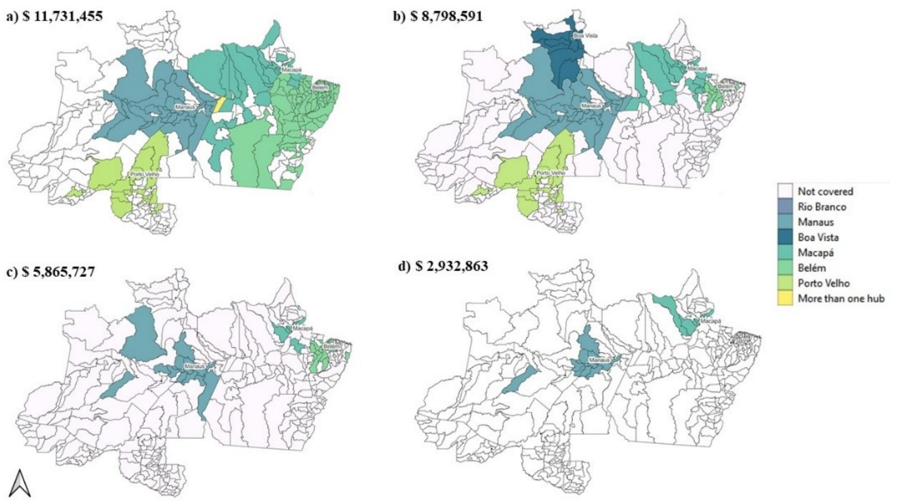

Figure 2.12: Spatial distribution of municipalities under different investment levels (non-prioritization approach).

the prioritization-based model, is now chosen to establish a hub when the investment is \$8,798,591 (60%). Boa Vista (the city with the seventh highest demand) is now covered. The hub located in Manaus, the capital of Amazonas State, is open in all scenarios. The city of Manaus, whose demand is the greatest of all, is covered at all investment levels. Although its demand is the highest, the MVI of Manaus is the second lowest among the remaining municipalities of Amazonas state and among the 80 municipalities with the lowest MVI. For this reason, the prioritization-based model fully covers Manaus when the investment level is relatively high (up to \$8,798,591 in our experimentation).

As per design, the non-prioritization approach favors municipalities with greater demands, which are not necessarily the places with high MVIs. Therefore, Manaus, Belém, Ananindeua, Porto Velho, and Macapá (the top 5 municipalities with the highest demands), are all fully covered when the investment level is \$11,731,45 (80%). When the investment level decreases, the coverage level decreases accordingly. In the last investment scenario, only Manaus and Macapá are fully covered. At the same time, the top 5 most vulnerable municipalities, Atalaia do Norte, Itamarati, Jacareaganga, Jordão, and São Gabriel da Cachoeira, are underserved at all investment levels. This sort of solution structure is rarely observed in the prioritization-based approach.

Tables 2.12 gives the results of prioritization and non-prioritization-based approaches in terms of total coverage (municipalities and people), number of underserved areas, amount of LLINs delivered, and quantity of opened hubs. Figure 2.13 compares the spatial coverage of both approaches. Although the total number of people covered (and/or LLINs delivered) is

Table 2.12: Comparison between prioritization and non-prioritization-based approaches.

Budget ($)	Coverage level 1[a]	Coverage level 2[b]	Coverage level 3[c]	Unserved[d] municipalities	Total Coverage [e] (municipalities)	Total Coverage [f] (people)	Hubs[g] (opened)	LLINs[h] (quantity)
Prioritization-based approach								
11,731,455.38	259	2	1	48	262	13,461,990 (79.9%)	5	6,730,995
8,798,591.54	207	1	3	99	211	10,096,376 (59.9%)	5	5,048,188
5,865,727.69	169	2	3	136	174	6,703,842 (39.8%)	4	3,351,921
2,932,863.85	103	3	1	203	107	3,327,314 (19.7%)	3	1,663,657
Non-prioritization approach								
11,731,455.38	131	17	11	151	159	13,517,340 (80.2%)	4	6,758,670
8,798,591.54	67	8	12	223	87	10,146,570 (60.2%)	5	5,073,285
5,865,727.69	27	3	9	271	39	6,771,320 (40.2%)	3	3,385,660
2,932,863.85	14	0	2	294	16	3,382,810 (20.0%)	2	1,691,405

[a] Number of municipalities covered at level 1 (100% coverage). [b] Number of municipalities covered at level 2 (90% coverage). [c] Number of municipalities covered at level 3 (80% coverage). [d] Number of municipalities not covered at all. [e] Total coverage at levels 1, 2, and 3 in number of municipalities. [f] Total coverage at levels 1, 2, and 3 in number of people. [g] Number of hubs opened. [h] Quantity of LLINs delivered to municipalities.

slightly higher in the non-prioritization approach, the prioritization-based approach manages to provide (by far) a better coverage policy in terms of the overall number of municipalities covered (and partially covered), which means *we end up achieving more effective protection against malaria when focusing on prioritization rather than simply allocating as many LLINs as possible*. The strategy of focusing on attending priority municipalities seems more reasonable since individuals in these areas are more vulnerable, requiring, therefore, priority protective measures against malaria given their higher risk of mortality and reduced basic health treatment access compared to people located in non-priority municipalities. Covering more people in the model without prioritization does not necessarily guarantee that these covered individuals are the most vulnerable, necessitating, therefore, ultimate help. In resource-constrained countries like Brazil, where health intervention in all malaria-endemic areas is desirable but infeasible, prioritization-based strategies are recommended to ensure that LLIN allocation is indeed effective, in the sense of optimizing the number of people covered but also guaranteeing that the most vulnerable areas are taking into account, which is a legitimate strategy to mitigate *health inequalities* and eradicate the disease (in long-term).

2.5.4 Equitable LLIN allocation

Here, we analyze the solution given by our bi-objective model in an attempt to *equitabilize coverage across different municipalities* so that more municipalities can have access to LLINs even at lower coverage levels (2 or 3). For each investment level, we take the number of underserved municipalities

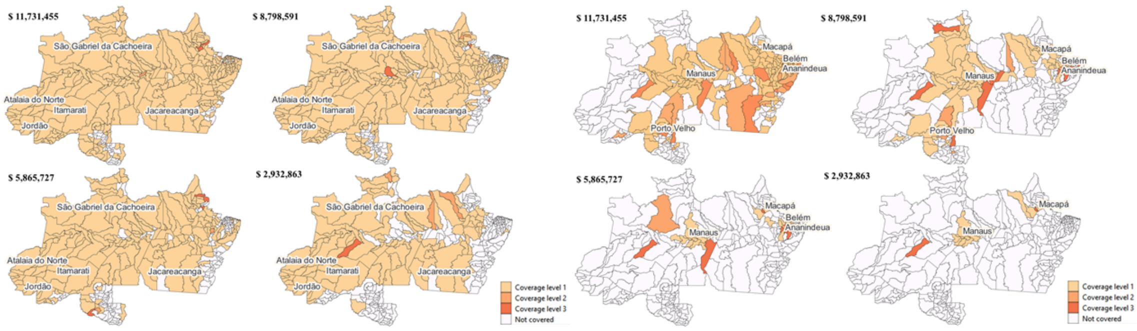

Figure 2.13: Prioritization and non-prioritization approach coverage levels for different investment levels.

as the initial ϵ value and reduce it accordingly until finding the first infeasible solution (which means we cannot further reduce the number of underserved areas given the financial budget) (Table 2.13). Notice that a given solution x is said to be more equitable than another y if and only if x has a number of underserved areas strictly less than y. In this case, it is expected that x also possesses fewer fully covered municipalities (and/or fewer overall covered people) than y, but the overall coverage level will still be within the recommended by WHO.

Table 2.13: ϵ - upper bound and feasible iterations.

	Prioritization-based approach	
Budget ($)	ϵ [a]	Feasible iterations [b]
11,731,455.38 (80%)	48	48
8,798,591.54 (60%)	99	96
5,865,727.69 (40%)	136	114
2,932,863.85 (20%)	203	112
	Non-prioritization approach	
11,731,455.38 (80%)	151	151
8,798,591.54 (60%)	223	220
5,865,727.69 (40%)	271	249
2,932,863.85 (20%)	294	203

[a] Number of municipalities not covered, which are our upper bound. [b] Number of feasible iterations (it represents the number of possible iterations starting from the upper bound ϵ. It is only possible to reduce the number of underserved municipalities up to the first unfeasible solution).

Table 2.14 presents the results of the last feasible iteration of the bi-objective model for prioritization and non-prioritization-based approaches. The bi-objective formulation makes it possible to reduce inequities of LLIN allocation in several cases. *Interestingly, this is achieved by swapping the coverage of some municipalities (eventually with slightly lower MVIs) from level 1 (100%) to level 3 (80%), which is sufficient to drastically mitigate the overall*

Table 2.14: Results of bi-objective prioritization and non-prioritization-based approach.

Budget ($)	ϵ [a]	Coverage level 1[b]	Coverage level 2 [c]	Coverage level 3 [d]	Underserved municipalities [e]	Total coverage (municipalities)[f]	Total coverage (people)[g]	LLINs (quantity) [h]
Prioritization-based approach								
11,731,455.38	0	170	3	137	0	310	13,455,256	6,727,628
8,798,591.54	3	49	2	256	3	307	10,061,410	5,030,705
5,865,727.69	22	3	2	283	22	288	6,684,352	3,342,176
2,932,863.85	91	0	1	218	91	219	3,305,284	1,652,642
Non-prioritization approach								
11,731,455.38	0	83	5	222	0	310	13,465,476	6,732,738
8,798,591.54	3	42	3	262	3	307	10,063,170	5,031,585
5,865,727.69	22	0	1	287	22	288	6,687,462	3,343,731
2,932,863.85	91	0	0	219	91	219	3,307,810	1,653,905

[a] ϵ of the last feasible iteration. [b] Number of municipalities covered at level 1 (100% coverage). [c] Number of municipalities covered at level 2 (90% coverage). [d] Number of municipalities covered at level 3 (80% coverage). [e] Number of municipalities not covered at all. [f] Total coverage at levels 1, 2, and 3 in number of municipalities. [g] Total coverage at levels 1, 2, and 3 in number of people. [h] Quantity of LLINs delivered to municipalities.

number of underserved areas at all investment levels for both prioritization and non-prioritization approaches. The number of underserved municipalities is substantially smaller when compared with the single-objective model for both approaches (prioritization and non-prioritization), whereas the number of delivered LLINs, and consequently the number of covered people, is slightly smaller in the bi-objective model. This result was expected given the inherent *trade-off* between overall effectiveness expressed by the objective function (2-1) and the total number of underserved areas measured by the objective function (2-2). *However, it is remarkable to see that inequity mitigation happens at such a small price in terms of absolute coverage.*

In particular, for the prioritization-based model, Figure 2.14 shows the *trade-off* curves between the number of underserved areas (*vertical axis*) and the number of fully served areas (*horizontal axis*). It is also worth noting that the bi-objective model with MVI starts by prioritizing the most vulnerable municipalities and then reduces the level of coverage to prioritize more municipalities at levels 2 and/or 3.

2.5.5 Managerial Implications

When allocating public resources, managers should consider equity, especially under limited resources. Our optimization model focuses on maximizing the benefit of prioritizing the most vulnerable municipalities to malaria transmission. Therefore, municipalities with the highest MVIs are selected to be covered. In this way, we can suggest that our prioritization-based model touches *vertical* equity, in the sense that LLINs are allocated based on the malaria vulnerability of each municipality, which is aligned with the idea of

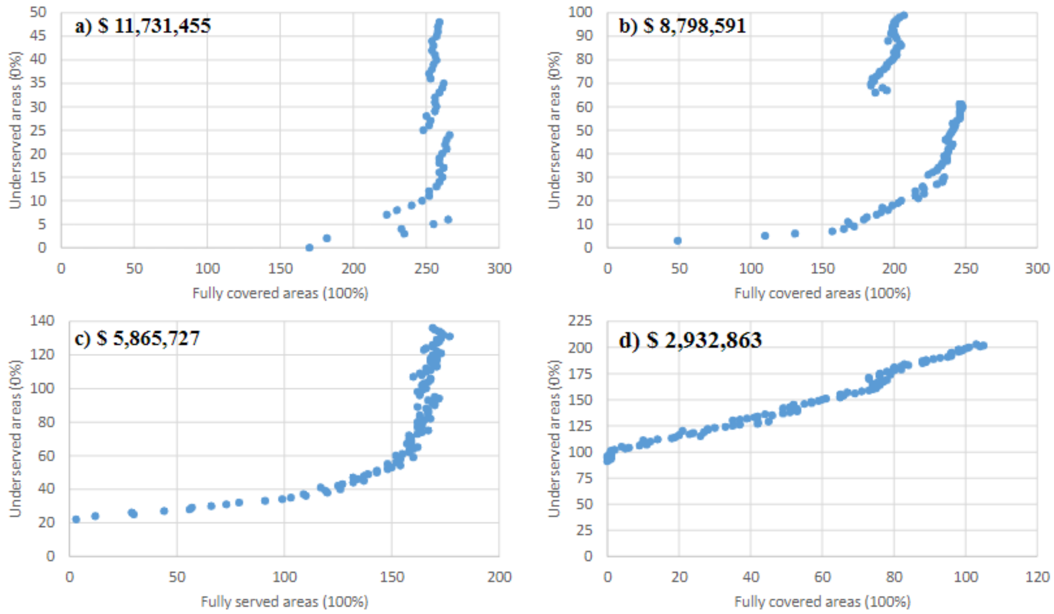

Figure 2.14: Prioritization-based coverage levels for varying investment levels: *tradeoff* between underserved and fully covered areas.

"the unequal, but fair treatment of unequals" (JOSEPH; RICE; LI, 2016).

The analysis of the prioritization-based model has shown that prioritization *is not greedily pursued because the objective function also contains the demand factor, and there is a limited financial budget to perform cost-dependent logistics decisions*. However, as it is more mathematically beneficial to fully cover as many municipalities as possible (rather than covering them within other levels), and again considering the limited budget, the prioritization-based solution eventually generates a relatively high number of underserved areas, i.e., whose coverage level is zero, which potentially aggravates *health disparities* and contributes to an unequal allocation of public resources.

To mitigate this inequitable situation, we also developed and analyzed a bi-objective optimization approach in which the second objective relies on minimizing the total number of underserved areas. Using the ϵ-constraint method, we managed to start with the maximum number of underserved areas for each investment level and gradually reduced it until finding the first infeasible solution. This approach is also said to touch *horizontal equity* in the sense of promoting a more effective and fairer allocation of LLINs, assuming that all entities *equally* deserve at least an 80% coverage level, which is aligned with the "the equal treatment of equals, or the sameness" (JOSEPH; RICE; LI, 2016). These two principles of equity can help Brazilian public health stakeholders to recognize that there are social determinants that inevitably impact *health inequalities* and vulnerability to malaria, such as living conditions, income, and access to education, and therefore make decisions more aligned with the idea of alleviating the impact of the vulnerabilities by offering "more to those who need it most". At the same time, because "nobody should be left behind", it makes sense to find alternative solutions that slightly worsen a situation of universal coverage in exchange for having a marginal number of underserved municipalities. Finding more equitable solutions always requires combined efforts to achieve improvements among the most vulnerable in an overall strategy to improve most people's health. In our case, this means to diversity coverage levels from mostly either 100% or 0% to include more and more 80% and 90% coverage levels.

2.6 Conclusions and Implications for Future Research

As the role of socioeconomic and environmental factors in reducing malaria risks highly varies amongst areas of the same endemic region, it is important to make decisions more aligned according to the vulnerability to malaria in each area. This study (i) evaluates the vulnerability to malaria in the current Brazilian Amazon endemic area by proposing a novel index named MVI and demonstrates its applicability; (ii) develops a decision support model to help locate hubs for LLIN allocation and distribution to Municipal Health Secretaries. The model is simple for decision-makers to help make logistics decisions and is aligned with the important concept of equity. The results of the proposed approach brought key insights that can be useful to re-think not only LLIN allocation and distribution but also other malaria interventions in Brazil. In particular, we showed that incorporating socioeconomic and environmental variables in developing MVI modifies the list of priority municipalities for malaria and, therefore, the intervention and campaigns to combat this disease. The present study reinforces that malaria eradication in the long term relies not only on health interventions but also on improving the population's socioeconomic and environmental living conditions. This implies coordination and sustained political leadership within and beyond the health sector.

Our study also illustrates that more equitable solutions are more diverse regarding coverage levels. This helps to significantly mitigate the number of underserved areas, especially in situations of scarce resources. Promising future research includes factoring in the model population awareness on how to use LLINs. Also, our questionnaire covers issues such as the reverse logistics of LLINs, which can be incorporated into our approach by understanding the LLINs cycle. Finally, the malaria vaccine is being tested in Africa, and its distribution can be based on models that use the same prioritization approach as in this study.

3
From effectiveness to fairness: designing food allocation in food aid programs for traditional peoples and communities

3.1
Introduction

Daily access to food is one of the most basic human needs. However, in 2022, about 3.2% of the world's population (roughly 258 million people) experienced acute food insecurity, which refers to restricted and/or uncertain access to an adequate supply of nutritious food (Food Security Information Network, 2023). It is estimated that almost 600 million people will be chronically undernourished in 2030. This is approximately 119 million more people than in a scenario where neither the pandemic nor the Ukrainian war had arisen (FAO et al., 2023). Such a situation poses unique challenges to achieving the *Sustainable Development Goal* (SDG) of a world free of hunger and food insecurity by 2030 (SDG2) as part of the 2030 Agenda for Sustainable Development (UN, 2015).

Hunger and food insecurity do not affect everyone equally. Their consequences mostly affect lower-middle-income countries, which bear the greatest burden of stunting, wasting low birth weight, and anemia cases (ORGANIZATION et al., 2022a). Moreover, some groups, including children, black people, indigenous communities, rural farmers, and other marginalized groups, face hunger at much higher rates (FEEDING AMERICA, 2003). They are the ones who suffer the most from precarious socioeconomic conditions, always being stuck in the 'hunger and poverty trap' [1]. Hunger is an expression of the world's social inequalities, having socioeconomic and political root causes. Undeniably, food insecurity and hunger have been linked to poor household conditions and inadequate sanitation, limited access to healthy foods, lack of education, low wages and economic instability (SOUZA et al., 2016; BROWN; MILLS; ALBANI, 2022; DREWNOWSKI, 2022).

Besides being connected to socioeconomic disparities, hunger and food insecurity inherently embody political issues, necessitating comprehensive policy interventions and government engagement to address food insecurity not only effectively but also equitably. One of the strategies employed by governments to tackle world hunger and food insecurity involves the provision

[1] A hunger and poverty trap or nutrition-based poverty trap is described to be when someone is too poor to afford to buy enough food, leading to them being less active and productive which again makes them poorer (AZARIADIS; STACHURSKI, 2005).

of food aid, a critical component of broader humanitarian efforts. It consists of providing food and food-related assistance either in emergencies or as an attempt to mitigate longer-term hunger and achieve food security − which can be defined as *a situation where people do not have to live in hunger or fear of starvation* (SHAH, 2007). Governments must always balance short-term interventions with longer-term resilience solutions as they respond to hunger and food insecurity crises. While short-term solutions are essential to meet immediate needs to avert severe and prolonged food crises, long-term projects build and support a more resilient and sustainable food system that directly improves health, economies, and the planet (WBG, 2023).

A common type of food aid is the distribution of food, typically used in emergency situations such as wars and conflicts, climate-related disasters, or when certain populations are so chronically undernourished and food insecure that makes them permanent recipients of this form of aid, having thereby, continuous dependence on such aid (SHAH, 2007). This approach not only aims to provide immediate relief from hunger but also seeks to mitigate the adverse effects of acute and enduring food shortages. Several food aid programs worldwide play a pivotal role in maintaining the nutritional status of vulnerable people through the provision of food, enabling them to sustain their lives. The United States Department of Agriculture (USDA)'s food distribution programs, for example, strengthen the nutrition safety net through the distribution of food and provide nutrition assistance to children, low-income families, emergency feeding programs, Indigenous reservations, and the elderly. In the Middle East, Syrian refugees in Lebanon receive electronic food cards from The World Food Program (WFP), while struggling farmers in drought-stricken Ethiopia get traditional food commodities like sorghum or wheat flour. In Brazil, the Ministry of Social Development (*Portuguese:* MDS) coordinates the free food basket distribution to specific traditional people and communities such as indigenous, quilombolas, rural communities, fishermen, and other specific populations in situations of food and nutritional insecurity.

As previously delineated, the escalating number of undernourished people underscores the urgency of designing immediate and targeted food aid for these individuals. Food distribution programs serve not only as a lifeline, providing essential sustenance to those in dire need, but they also embody an important step towards achieving the SDG of *zero hunger*. By bridging the gap between emergency aid and long-term sustainability, food distribution initiatives ensure that the most vulnerable groups receive the necessary support to maintain their livelihoods amidst the complexities of global food insecurity.

3.1.1
Problem motivation and context

Brazil is well-known as one of the most racially diverse countries. The early stages of the Portuguese colonies in Brazilian territory fostered a mixture of Portuguese colonizers, African enslaved people and indigenous tribes, who left a legacy of mixed race in Brazil. Such legacy made the Federal Government of Brazil recognize the massive existence and the rights of indigenous and quilombolas[2] in the 1988 Constitution. But it was only in 2007 that the government officially acknowledged the existence of the so-called *'Traditional Peoples and Communities'* (TPC) through Decree no. 6,040, on 7 February 2007[3], extending the recognition partially made in the 1988 Constitution to other communities such as extractivists, *ribeirinhos* (riverside communities), fishermen, and gypsies. The law also establishes the *National Policy on Sustainable Development for Traditional Peoples and Communities*, which aims to promote their sustainable development and strengthen their rights in areas including land, environment, culture, health, and economic practices (BRAZIL, 2007). It is estimated that 26 traditional communities are spread over the country, totaling approximately 4.5 million people (JÚNIOR; SOUZA, 2009).

Traditional peoples and communities experienced a historical process especially marked by geographical, socioeconomic, and environmental aspects that significantly impacted their living conditions (AFONSO; CORREA; SILVA, 2020). Historically, most of these people were excluded from society and pushed to places far from central areas, often with very limited access to basic infrastructure, healthcare, food, and other essential public services, which rendered them *systemically vulnerable*. Unsurprisingly, millions of undernourishment cases and food deprivation are frequently reported among these groups. Recently, Brazil has seen over a thousand indigenous being rescued from critical undernutrition and relocated from *Yanomami* lands in Brazil's Northern region (SCHERF; SILVA, 2023). Furthermore, nearly 86% of quilombola households in the Northeast present some form of food insecurity, with almost 56% facing moderate to severe levels (CHEROL; FERREIRA; SALLES-COSTA,

[2]A *quilombola* is an Afro-Brazilian inhabitant of quilombo settlements, first established by fugitive enslaved people in Brazil. These communities have deep historical roots in Brazil, dating back to the period of slave trafficking from West Central Africa. Most of the existing quilombolas live in poverty (COLITT, 2007; PYL, 2010).

[3]Decree no. 6,040, on 7 February 2007, defines *Traditional Peoples and Communities* as culturally distinct groups that self-identify as such, possessing unique social structures. They have their own forms of social organization, occupy and use territories and natural resources as a condition for their cultural, social, religious, ancestral and economic continuity, using knowledge, innovations and practices that are rooted in and passed down through generations (BRAZIL, 2007).

2021), highlighting the urgent need to foment public policies aimed at enhancing quilombola's food security. Santos, Azevedo-Ramos & Guedes (2021) present the vulnerability to food insecurity of extractive people in the Amazon, reporting that around 35% of the families struggle with severe levels of food insecurity in the region.

Hunger and malnutrition – which until by the late 1940s had been approached from a biological or physiological perspective – started to be addressed as a social phenomenon in Brazil (CASTRO, 1963). However, it was only in the 1990s that food and nutritional security began to be part of the Brazilian public agenda. Since then, Brazil has been endeavoring to eradicate hunger, food insecurity, and malnutrition through the implementation of food aid policies and programs for vulnerable populations (VASCONCELOS, 2005). One of these initiatives, started in 2003, is the Food Distribution Action (*Portuguese*: ADA), a national-level food aid initiative, that takes place in partnership with the *Ministry of Social Development (Portuguese: MDS)* and it is operationalized by the*National Supply Company (Portuguese: CONAB)*. The ADA operates through the provision of food baskets for traditional peoples and communities living in food insecurity. The *food basket needs* of each traditional population are reported to the CONAB by the national bodies of each population. These national bodies are decentralized and independent institutions that take care of the general interests of their respective traditional community. For example, the National Indigenous People Foundation (*Portuguese*: FUNAI) is the executing body of the Federal Government's indigenous policy; The Palmares Cultural Foundation is the body that executes policies to support quilombola communities; the Chico Mendes Institute of Conservation for Biodiversity (*Portuguese*: ICMBio) is the federal support organization for extractive population and other families residing in federal conservation units, and so on.

Given the decentralized and independent nature of these institutions, their food requirements are communicated to CONAB in a decentralized manner at different moments in time, usually triggered by an emergency and critical demand or even because of political interests. In this sense, government decisions on food basket allocation end up being typically subjective and reactive, apparently trying to attend to an already-in-place severe case of food insecurity in some region of Brazil. The decentralized nature of Brazil's national bodies, along with the fact that governments frequently lack comprehensive decision-support tools to make more thoughtful and tailored decisions, makes it difficult to make synchronized decisions about the allocation of food baskets, leading to disparities in the timing and adequacy of responses to food insecurity. Thus, the main criticism of this Action is that it is typically conceived in a one-off, myopic, reactive and subjective way, undermining any possibility of guaranteeing its effectiveness and, even less so, fairness and, consequently, equity in food allocation decisions. Thus, not only their short-term effectiveness is compromised, but also any attempt to consolidate long-term fair public policies in food distribution is jeopardized. In addition to this, considering the limited number of food baskets – that historically has been insufficient to serve the needs of all food-insecure traditional populations – there is always one or more populations or states unserved with food baskets, which compromises their food insecurity levels and worsens their social vulnerability and susceptibility to future food emergencies and crises.

As the fifth-largest country in the world, Brazil spans continental dimensions and exhibits huge diversity, both in terms of the peoples and communities that compose it and in relation to regional differences. The diversity of the states that compose it, together with the varied food needs and the different socioeconomic profiles of each traditional population, require a tailored approach to ensure that food distribution actions are fair and prioritize those who need it most within a broader analytical context. In this work, we formulate and analyze a mathematical model to design effective and equitable strategies by which the Brazilian government can allocate food baskets to food-insecure traditional populations who live in different geographic areas (states/counties).

In the context of food aid supply chain and optimization models, a comprehensive approach to incorporate equity in food allocation problems is the concept of *fair-share*, which, as the name suggests, seeks to allocate resources fairly. Orgut & Lodree (2023) studied the equitable distribution of perishable food donations within a food bank supply chain, where each recipient's share of food donations is proportional to the size of the food-insecure population they serve, relative to the total food-insecure population covered by the food bank. In this work, we also use the *fair share* concept to ensure an equitable allocation of food baskets *proportional to the relative demand*, modeling two types of equity: (i) geographic area and (ii) traditional population. The first type of equity ensures that food baskets will be fairly shared amongst different areas (states) of Brazil *(geo-fair share)*, regardless of the traditional population residing there. The second equity ensures that these populations will receive a fair share of food *(pop-fair share)* regardless of the area they are based in. When modeled together, these two types of equity ensure a fair share allocation of food baskets simultaneously to the counties and traditional peoples. The fair-share concept can be associated with *horizontal equity*, which considers that individuals or groups should be treated *equally*.

(JOSEPH; RICE; LI, 2016). Our model also goes beyond ensuring horizontal equity through the fair-share criterion. We also incorporated a prioritization factor into the model as an attempt to capture the different socioeconomic vulnerabilities related to each traditional population and, thus, prioritize those populations that most need resources (in our case, food baskets). Such a prioritization-driven approach is linked to the *vertical equity*, in which different entities have different needs and circumstances and, therefore, might require different levels and types of support to achieve similar outcomes (SEN, 1995).

We focus on the strategic problem of food basket allocation to traditional peoples and communities, which are spread over counties, aiming at *maximizing the amount of allocated food, weighted by a prioritization criterion, while satisfying equity constraints.*

3.1.2 Research questions and contributions

Previous studies show that marginalized populations exhibit different profiles regarding socioeconomic and availability of high-quality and nutritious food. In the case of the traditional peoples and communities, this scenario of vulnerability is even more pronounced (LOPES et al., 2022). This paper has two primary aims. The first one is to design and test policies that help benchmark and improve government decisions, mitigating any subjectivity in the decision-making process of food basket allocation. We address this aim by developing a mathematical model that explores the *trade-off* between equity and effectiveness of the total allocated food baskets to both geographic areas and populations. Our second aim is to drive managerial insights on *how to target the most in-need populations while being fair when allocating food baskets.* To address these goals, we propose then two research questions:

(1) How can public policies for allocating food baskets to traditional populations be more effective and equitable?

(2) Is there a way to guarantee that food baskets will be delivered to those who need them most, ensuring a fairer distribution both in terms of geographic area and populations that exhibit different socioeconomic and food insecurity profiles?

This research's overarching goal aligns with the current government objective, which aims to fight hunger and food insecurity in Brazil. Also, it is well-aligned with the *2030 Agenda for Sustainable Development* scope, particularly with SDGs 1 and 2 (UN, 2015). We use a real-world case carried out in Brazil. This Latin American country has a huge representation of traditional peoples and communities that have struggled with poverty, hunger, and food insecurity for decades. We believe the insights raised by this research can awaken public policymakers' reflections on how public resources (in this case, the delivery of food baskets) are being deployed. We are deeply aware that tackling hunger and food insecurity goes far beyond distributing food baskets. However, providing such food aid is undeniably crucial and ultimately required to alleviate hunger and malnutrition among those who have been historically vulnerable and excluded from society.

The remainder of this paper is organized as follows: Section 3.2 presents the theoretical background. Section 3.3 describes the problem and the mathematical model, while Section 3.4 shows the results and discusses the main insights. Finally, Section 3.5 brings conclusions and opportunities for future research.

3.2 Theoretical Background

This literature review positions our work from the perspective of two streams: (i) *Tackling food insecurity through food aid*; and (ii) *Effectiveness and Equity in food aid*.

3.2.1 Tackling food insecurity through food aid

The nature of food insecurity and its magnitude significantly differ in developed countries from that in underdeveloped countries as the latter include severe or chronic undernutrition (LEIRAS et al., 2021). Household food insecurity has been associated with several socio-economic indicators, such as income, basic sanitation, education, and per capita income (MARIN-LEON et al., 2011; LOOPSTRA; TARASUK, 2013; CHINNAKALI et al., 2014; FERREIRA et al., 2014). Many works have studied the links between such socioeconomic conditions and food insecurity, revealing a strong association between them (SALLES-COSTA et al., 2008).

Asghar & Muhammad (2013) find that household conditions, level of education and annual income are some of the most important factors influencing the household's food insecurity in Pakistan. The authors shed light on the need for targeted policies that improve such socio-economic determinants to combat food insecurity. In the United States, a developed country, Rose, Gundersen & Oliveira (1998) identify key factors contributing to food insecurity, concluding that households with higher incomes, those owning homes headed by high school graduates, have a lower likelihood of experiencing food insecurity. Interestingly, those households living in poverty are more than 3.5 times likely to face food insecurity, although not all food-insecure households are necessarily poor. Drysdale, Bob & Moshabela (2021) investigated the socio-economic determinants of increasing food insecurity during and after a drought in South Africa, showing that the most impoverished households faced the worst levels of food insecurity. In Brazil, Salles-Costa et al. (2008) explored the relationship between socio-economic determinants and food insecurity in the metropolitan area of Rio de Janeiro. The authors concluded that monthly income per family member, educational level of the family head, socioeconomic status, family size, and the presence of a water filter in the home were inversely and significantly associated with food insecurity. Palmeira et al. (2019) also conducted a study in Rio de Janeiro, concluding that social conditions are strongly associated with food insecurity, highlighting the urgent need for social policies to minimize the consequences of food insecurity in populations exposed to poverty. Their results strengthened the evidence that participation in the Brazilian conditional cash transfer program reduced household food insecurity.

Beyond changes in socioeconomic conditions, researchers have suggested that reductions in household food insecurity rates can result from income and education improvement and access to social programs such as cash transfers and food aid programs (LOOPSTRA; TARASUK, 2013; CABRAL et al., 2014; LOOPSTRA; DACHNER; TARASUK, 2015; PALMEIRA et al., 2019). Although food aid has often been criticized (LAVY et al., 1990; BARRETT, 2006; MARGOLIES; HODDINOTT, 2012), it remains an essential solution to alleviate hunger and food insecurity worldwide. Food aid is a universally acknowledged and commonly used instrument to the food insecurity problem (RANCOURT et al., 2015) as food aid could make the difference between life and death in several developing countries (GENTILINI, 2013).

Food aid is broad and multifaceted. While providing food and assistance to combat immediate hunger in emergencies or crises, it also encompasses non-emergency programs, which include food banks, educational nutrition programs, and broader long-term community development initiatives (USAID, 2023) to achieve food security. Additionally, in the realm of food aid, certain interventions are tailored to focus on specific groups, such as indigenous, pregnant women, children, the elderly, and refugees (GGI, 2024), chronically food-insecure and requiring permanent food aid.

A notable form of food aid is the distribution of food baskets or items (KENT et al., 2020; NECHIFOR et al., 2021). In our study, we consider the provision of food baskets, which refers to a collection of diverse food items intended to meet the nutritional needs of an individual or family, emphasizing its importance in ensuring food security and balanced dietary intake (WFP, 2024). Although it is not a type of food aid that directly enhances community development to end hunger and food insecurity once and for all, the distribution of food is vital to maintaining the nutritional status of such vulnerable people, mitigating their health and economic crises (SAMBUICHI et al., 2020), especially when they are fully dependent on food aid (WFP, 2024). This form of aid is, then, critical for enabling people to continue their lives. When combined with socioeconomic programs, alongside other long-term food aid development and resilience strategies, food distribution paves the way toward mitigating hunger and food insecurity.

Food aid distribution often encounters ethical and political challenges. Achieving equitable and fair distribution among vulnerable populations can be complex, requiring well-thought-out strategies and advance planning. Factors such as socioeconomic vulnerability and nutritional metrics should be taken into account during the targeting processes of food allocation (GGI, 2024) to prioritize the most in need. For many years, scholars have recognized the critical role of prioritization policies for vulnerable and marginalized groups (ALEM et al., 2021). In their work, Jiang & Yuan (2019) emphasized the importance of prioritizing the fulfillment of demands for those in dire need, especially in the context of resource scarcity. A well-acknowledged method of using prioritization in optimizing humanitarian operations involves the prioritization *by groups of people or by location* (GRALLA; GOENTZEL; FINE, 2014). Such an approach concentrates on identifying groups or areas distinguished by attributes or socioeconomic status.

The problem we consider is related to non-emergency food distribution programs for vulnerable people. In our case, we deal with specific groups of vulnerable populations known as *Traditional Peoples and Communities* (TPC). It includes indigenous, quilombolas, extractive peoples, riverside, and other peoples – groups historically excluded from society and chronically affected by food insecurity. We address the prioritization approach by groups of populations, assessing their socioeconomic characteristics and food insecurity metrics regardless of the area they are based in. Such an approach is well-aligned with the current practices of the Brazilian government, which are focused on devising policies for the population groups independently of the location they are based. For this purpose, we assess TPC's vulnerabilities through the *Food Vulnerability Index*, which reflects their socioeconomic and food insecure characteristics. We not only take prioritization into account in this paper, but we also consider two important criteria in the food aid context: effectiveness and equity, which will be explored in the following Section 3.2.2.

3.2.2 Effectiveness and Equity in food aid

Mathematical programming models have been widely applied to tackling issues related to resource allocation, distribution, location, and routing problems in the context of food aid (DAVIS et al., 2014; ORGUT et al., 2016; GRACE; WEI; MURRAY, 2017; ORTUÑO; PADILLA, 2017; ORGUT et al., 2018; REIHANEH; GHONIEM, 2018; GÓMEZ-PANTOJA; SALAZAR-AGUILAR; GONZÁLEZ-VELARDE, 2021; HASNAIN; ORGUT; IVY, 2021; STAUFFER et al., 2022). In many of these models, decision-makers frequently face conflicting criteria to identify the best solutions. Unlike most profit-oriented organizations – which are often set to maximize profit or minimize costs while meeting the demand – public institutions, humanitarian and not-for-profit organizations are not solely cost-driven. Social interests often drive such organizations, which are ruled by fairness and equity principles, beyond effectiveness and efficiency (NAIR; REY; DIXIT, 2017). Moreover, most of these organizations commonly operate under limited resources, where the amount of supply is often much lower than the number of beneficiaries. Therefore, satisfying the whole demand is not always a feasible option (ORGUT et al., 2018).

Equity, effectiveness, and efficiency are objectives widely explored in diverse contexts. The exact definitions of these terms are very subjective and context-dependent (STONE, 1997). For this paper's purposes, we will use the term *equity* to mean "the condition of being equal in quantity, amount, value, intensity etc." (SIMPSON; WEINER et al., 1989). Meanwhile, *effectiveness* corresponds to the extent to which a particular entity is "capable of being used to a purpose" (GOVE, 1981), and although we do not take *efficiency* into account, the term is referred to mean "achieving an objective for the lowest cost" (STONE, 1997). Cost efficiency is not addressed in this paper due to the limited available data regarding the problem. We focus, then, on the objectives of equity and effectiveness.

There is no equity measure universally advised for all optimization problems, as equity is usually problem and/or context-dependent (SEN, 1973; MARSH; SCHILLING, 1994; BALCIK; IRAVANI; SMILOWITZ, 2010; LECLERC; MCLAY; MAYORGA, 2011). Nonetheless, many papers (MARSH; SCHILLING, 1994; ORGUT et al., 2016; ORGUT et al., 2018; ORGUT; LODREE, 2023) have explored the notion of equity in terms of *fair share*. Such an approach is similar to that used in this study, where we consider equity to be the case in which areas (states) and populations receive their fair share of the total allocated food baskets. We address equity by allocating to the populations and states a number of food baskets that is proportional to their relative demands. On the other hand, effectiveness refers to maximizing the total amount of allocated food baskets, that is, meeting the states' and populations' needs, without necessarily considering the fairness of the allocation. In this sense, decision-makers often face trade-offs between these objectives. For example, prioritizing equity might mean fewer people overall receive food baskets (if some receive more than others due to greater need), whereas prioritizing the total amount distributed might mean a less fair distribution (some may get more than needed while others get less). Finding a balance between these conflicting objectives is a common challenge, which we are exploring in this paper. Our work contributes to the existing literature on food aid by (i) simultaneously considering the objectives of equity and effectiveness in the food allocation public context, (ii) providing governments with tools to undermine subjectiveness in food allocation decisions by offering effective and equitable solutions, (iii) using data from a real case to illustrate our results.

We will now explore how the objectives of equity, effectiveness, and efficiency are addressed in the literature. We found that many papers address equity in the objective function, while others incorporate it into the constraints. Marsh & Schilling (1994) explore twenty equity measures found in literature, examining diverse contexts where equity is used as an objective. Orgut, Ivy & Uzsoy (2017) cite some studies that consider the equity objective: Mazumdar, Mason & Douligeris (1991), Marsh & Schilling (1994), Meng & Yang (2002), Vossen et al. (2003), Wang, Fang & Hipel (2007), Chanta et al. (2011).

A main challenge often discussed in the literature is the inherent *trade-offs* between equity, effectiveness, and efficiency (GRALLA; GOENTZEL; FINE, 2014; MCCOY; LEE, 2014; BURKART; BESIOU; WAKOLBINGER, 2016; PARK; BERENGUER, 2020; HASNAIN; ORGUT; IVY, 2021; MAHMOUDI; SHIRZAD; VERTER, 2022; ORGUT; LODREE, 2023). Such *trade-offs* may be, for example, a food bank that might opt to distribute all available food with a focus on minimizing distribution costs, leading to counties closer to its warehouses receiving more food. Although this approach is effective and efficient, it results in an inequitable solution, with counties farther away getting less than their fair share (HASNAIN; ORGUT; IVY, 2021).

Lien, Iravani & Smilowitz (2014) consider equity and effectiveness service in a sequential resource allocation problem. They characterize service in terms of fill rate (the proportion of the allocated amount relative to the demand observed) and formulate an objective function to maximize the expected minimum fill rate between customers, which balances equity in fill rates with effectiveness in the use of resources. Fianu & Davis (2018) also address the balance between equity and effectiveness in food bank operations. Their model assists food banks in equitably allocating uncertain donated supplies while evaluating the performance of their distribution efforts.

Orgut et al. (2016) consider the objectives of equity and effectiveness in the distribution of donated food under capacity constraints. Their models are designed to minimize the amount of undistributed food while enforcing a specified upper limit on the deviation from a perfectly equitable distribution across counties, considering each county's demand proportional to its poverty population. Our equity measure is inspired by their approach. Later, Orgut et al. (2018) extended the work of Orgut et al. (2016) to support the equitable and effective distribution of donated food across the food bank's service area. Mandell (1991) also studies the trade-off between equity and effectiveness in the delivery systems of public services like libraries and formulates mathematical models to tackle this trade-off while using the Gini index as a metric for equity. Similar to Orgut et al. (2016) and to our work, Islam & Ivy (2022) define equity as the equal food distribution proportional to demand within the service region, while effectiveness is measured akin Eisenhandler & Tzur (2019) by maximizing the amount of distributed donations, which turns to minimizing unused donations/waste as addressed in Orgut et al. (2016).

A recent research developed by Zoha, Hasnain & Ivy (2022) introduces a multi-criteria optimization model for food banks, aiming for optimal distribution policies that account for both geographic and demographic equity alongside effectiveness (minimizing undistributed food) and efficiency (reducing distribution costs) goals. Their model addresses not only geographic equity − ensuring food is allocated across the service region proportional to its demand − but also demographic equity, recognizing existing disparities such as race, age, and religion among different demographic groups. Our study shares similarities, as we consider the fair share concept to model two types of equity: geographic and population equity. Zoha, Hasnain & Ivy (2022) focus on specific demographic groups like Latino, White, and African-American, while we also include specific groups of peoples such as Indigenous and Quilombolas. Unlike the authors, we consider socioeconomic characteristics to create an index within the objective function that prioritizes the most in-need populations.

Balcik, Iravani & Smilowitz (2014) address the challenge of distributing food donations equitably and efficiently. They aimed to reduce waste by planning the routes and distribution between donors and receiving agencies of a food bank. Their goal is to ensure equity by maximizing the minimum fill rate across all agencies while simultaneously maximizing the volume of distributed donations. Islam & Ivy (2022) consider efficiency similar to Hasnain, Orgut & Ivy (2021), by minimizing operational costs. Solak, Scherrer

& Ghoniem (2014), simultaneously optimize the locations for food delivery, agency allocation to these delivery sites and routing of delivery vehicles to minimize overall transportation costs in order to seek efficiency. In a vehicle routing problem, Reihaneh & Ghoniem (2018) also address efficiency by minimizing a weighted average of the vehicle routing and charitable agencies to food delivery points. None of the mentioned studies considers the *trade-off* between geographic area and population equity while considering prioritization criteria as a function of effectiveness. Table 3.1 summarizes the literature of existing optimization problems in the food aid literature, detailing the criteria addressed.

Table 3.1: The three criteria addressed in optimization models in the food aid literature.

Paper	Efficiency	Effectiveness	Equity	Problem type
Balcik, Iravani & Smilowitz (2014)	✓		✓	VR/RA
Davis et al. (2014)	✓			VR
Lien, Iravani & Smilowitz (2014)		✓	✓	RA/D
Nair et al. (2016b)			✓	D
Nair et al. (2016a)	✓		✓	RRA
Orgut et al. (2016)		✓	✓	RA/D
Grace, Wei & Murray (2017)	✓	✓		AL
Nair, Rey & Dixit (2017)	✓	✓	✓	RRA
Fianu & Davis (2018)		✓	✓	D
Orgut et al. (2018)		✓	✓	RA/D
Reihaneh & Ghoniem (2018)	✓	✓	✓	RRA
Eisenhandler & Tzur (2019)		✓	✓	RRA
Sucharitha & Lee (2019)				RA
Alhindi et al. (2020)	✓			VR
Alkaabneh, Diabat & Gao (2021)	✓	✓	✓	RA
Hasnain, Orgut & Ivy (2021)	✓	✓	✓	RRA
Islam & Ivy (2022)	✓	✓	✓	A/D
Liang & Lyu (2022)	✓	✓	✓	RA
Stauffer et al. (2022)		✓	✓	D
Zoha, Hasnain & Ivy (2022)		✓	✓	D
Firouz et al. (2023)	✓		✓	RA
Ma, Wang & Zheng (2023)				RA
Reusken, Cruijssen & Fleuren (2023)	✓		✓	RA
Orgut & Lodree (2023)				RA
Our work		✓	✓	RA

VR = Vehicle Routing; RA = Resource Allocation; RRA = Routing Resource Allocation; D = Distribution; AL = Allocation/Location

3.3 Problem Description and Mathematical Model

Our model considers a hypothetical situation where all demands are reported simultaneously, suggesting an operating policy for CONAB. Initially, the national bodies raise the demand for basic food baskets from their

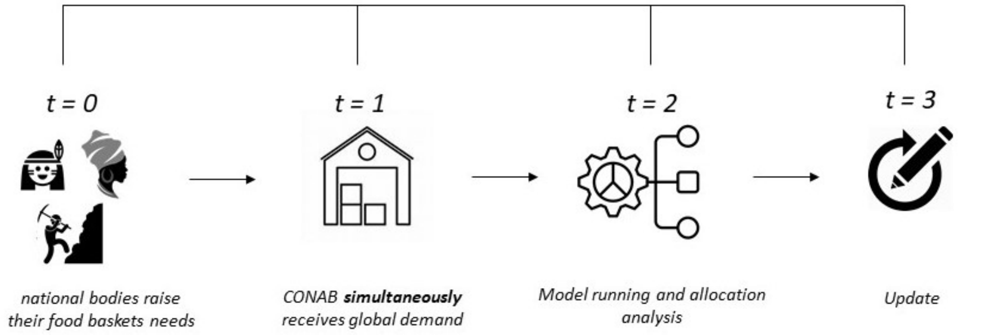

Figure 3.1: Suggested operating policy.

respective groups, which requires prior planning and synchronization. These bodies then report their demands to CONAB, which has a limited number of food baskets. With all demands by group and state gathered, CONAB can obtain a holistic view of the overall needs and, through the proposed optimization model, develop effective and equitable strategies. Figure 3.1 shows the hypothetical flow of how the suggested policy could operate.

The problem takes into account a finite number of traditional populations $\mathcal{P} = \{1, \cdots, P\}$ (such as indigenous, quilombolas etc.) who immediately before any food aid intervention is living under a known food insecurity level in a given geographical area $\mathcal{A} = \{1, \cdots, A\}$, such as counties. Our main aim is to devise a food basket allocation strategy to serve the needs of food-insecure traditional population p in area a, d_{pa}, achieving an optimal allocation of food baskets considering both objectives of *equity* and *effectiveness*. In this work, we model two types of equity: (i) geographic equity *(geo-fair share)*, ensuring food baskets will be fairly shared amongst different counties, regardless of the traditional population residing there (Constraints 3-4); (ii) population equity *(pop-fair share)*, which ensures that traditional populations will receive a fair share of food regardless of the geographic area they are located (Constraints 3-5). When modeled together, these two types of equity ensure a fair share allocation of food baskets simultaneously to the areas and traditional peoples, achieving overall equity in allocation decisions. Conversely, the allocation is effective if the amount of food baskets is maximized, which turns to minimize undistributed food baskets. Such effectiveness is weighted by an index, which reflects the vulnerability of each population. Table 3.2 presents the model's mathematical notation.

As previously explained, equity is usually problem and/or context-dependent. Many formulations are based on absolute deviations from what is deemed *perfect equity*, which is the case of several papers (ORGUT et al., 2016; ORGUT et al., 2018). Therefore, based on the equity idea of Orgut et

Table 3.2: Mathematical notation.

$\mathrm{P} = \{1, ..., P\}$	Set of all traditional populations
$\mathrm{A} = \{1, ..., A\}$	Set of geographic areas
d_{pa}	Needs of food-insecure traditional population p in area a (unit)
FVI_p	Food Vulnerability Index such that $0 \leq \mathrm{FVI}_p \leq 1$
B	Number of food baskets available (unit)
δ_p	*Equity deviation limit* for geographic equity, such that $0 \leq \delta_p \leq 1$
$\hat{\delta}$	*Equity deviation limit* for population equity, such that $0 \leq \hat{\delta} \leq 1$
X_{pa}	Number of food baskets to be allocated to a traditional population p in area a

al. (2016), our food-allocation model is formulated as follows:

$$\text{Maximize} \sum_{p \in \mathcal{P}} \sum_{a \in \mathcal{A}} \mathrm{FVI}_p X_{pa} \tag{3-1}$$

subject to:

$$X_{pa} \leq d_{pa}, \ \forall p \in \mathcal{P}, \ a \in \mathcal{A} \tag{3-2}$$

$$\sum_{p \in \mathcal{P}} \sum_{a \in \mathcal{A}} X_{pa} \leq B \tag{3-3}$$

$$\left| \frac{X_{pa}}{\sum_{a' \in \mathcal{A}} X_{pa'}} - \frac{d_{pa}}{\sum_{a' \in \mathcal{A}} d_{pa'}} \right| \leq \delta_p, \ \forall p \in \mathcal{P}, \ a \in \mathcal{A} \tag{3-4}$$

$$\left| \frac{\sum_{a \in \mathcal{A}} X_{pa}}{\sum_{a \in \mathcal{A}} \sum_{p' \in \mathcal{P}} X_{p'a}} - \frac{\sum_{a \in \mathcal{A}} d_{pa}}{\sum_{a \in \mathcal{A}} \sum_{p' \in \mathcal{P}} d_{p'a}} \right| \leq \hat{\delta}, \ \forall p \in \mathcal{P} \tag{3-5}$$

$$X_{pa} \geq 0 \text{ and integer}, \forall p \in \mathcal{P}, \ a \in \mathcal{A}. \tag{3-6}$$

The objective function (3-1) maximizes the effectiveness of the food basket allocation, the extent to which it manages to deliver as many food baskets as possible, which is mathematically a function of the prioritization score associated with a traditional population p given by FVI_p. Our main decision variable is the number of food baskets to be allocated to a traditional population p in area a, which is represented by X_{pa}. Constraints (3-2) state that the quantity of food baskets to be allocated should not exceed the demand. There is a known maximum number of available food baskets given by B. Thus, constraint (3-3) ensures that this available quantity limits the total amount of allocated food baskets. Constraints (3-4) and (3-5), respectively, represent geographic and population equity. Constraints (3-4) establish that the absolute difference between the proportion of allocated food baskets to population p in area a over the total allocated food baskets for such population across all areas and the proportion of demand for population p in area a over the total demand for this population across all areas must be less than or equal to a deviation limit δ_p. In simpler terms, these constraints ensure that the allocation of food baskets relative to the demand across different areas does not deviate beyond a specified limit for any population p in area a. It aims to ensure fairness in the allocation of food baskets *among various areas* (geographic equity or simply *geo-fair share*). In the same way, Constraints (3-5) specify that for each population p, the absolute difference between the ratio of the total allocated food baskets for population p across all areas to the total allocated food baskets for all populations across all areas, and the ratio of the total demand for population p across all areas to the total demand for all populations across all areas, must not exceed a certain threshold $\hat{\delta}$. Essentially, it ensures fairness in the allocation of food baskets *among different populations* (population equity or simply *pop-fair share*) independently of the area. Finally, constraints (3-6) state the domain of the decision variables.

The parameter δ, and $\hat{\delta}$, our *equity deviation limit* denotes the maximum tolerable deviation from equity, with values ranging from one to zero, allowing us to explore the *trade-off* between equity and effectiveness. When δ and $\hat{\delta} = 0$, it signifies a state of *perfect equity*, where, generally explaining, the fraction of the total allocated food baskets is exactly equal to the fraction of the total demand (both in terms of area and populations). On the other hand, the case of δ and $\hat{\delta} = 1$ simply means that equity is not enforced by means of constraints (3-4) or/and (3-5). Constraints (3-4) are equivalent to:

$$-\delta_p \leq \frac{X_{pa}}{\sum_{a' \in \mathcal{A}} X_{pa'}} - \frac{d_{pa}}{\sum_{a' \in \mathcal{A}} d_{pa'}} \leq \delta_p, \ \forall p \in \mathcal{P}, \ a \in \mathcal{A} \tag{3-7}$$

Therefore, the second $\leq$ inequality is written as:

$$X_{pa} \sum_{a' \in \mathcal{A}} d_{pa'} - d_{pa} \sum_{a' \in \mathcal{A}} X_{pa'} \leq \delta_p \sum_{a' \in \mathcal{A}} X_{pa'} \sum_{a' \in \mathcal{A}} d_{pa'}, \forall p \in \mathcal{P}, \ a \in \mathcal{A} \tag{3-8}$$

Then, the first inequality can be written as follows:

$$X_{pa} \sum_{a' \in \mathcal{A}} d_{pa'} - d_{pa} \sum_{a' \in \mathcal{A}} X_{pa'} \geq -\delta_p \sum_{a' \in \mathcal{A}} X_{pa'} \sum_{a' \in \mathcal{A}} d_{pa'}, \ \forall p \in \mathcal{P}, \ a \in \mathcal{A} \tag{3-9}$$

Similarly, constraints (3-5) can be written as:

$$\left|\frac{\sum_{a\in\mathcal{A}} X_{pa}}{\sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a}} - \frac{\sum_{a\in\mathcal{A}} d_{pa}}{\sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} d_{p'a}}\right| \leq \hat{\delta},\ \forall p \in \mathcal{P} \tag{3-10}$$

Now, let us eliminate the absolute value:

$$-\hat{\delta} \leq \frac{\sum_{a\in\mathcal{A}} X_{pa}}{\sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a}} - \frac{\sum_{a\in\mathcal{A}} d_{pa}}{\sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} d_{p'a}} \leq \hat{\delta},\ \forall p \in \mathcal{P} \tag{3-11}$$

By applying the same procedure, constraints (3-11) can be written as follows:

$$\sum_{a\in\mathcal{A}} X_{pa} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} d_{p'a} - \sum_{a\in\mathcal{A}} d_{pa} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a} \leq \hat{\delta} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} d_{p'a},\ \forall p \in \mathcal{P} \tag{3-12}$$

$$\sum_{a\in\mathcal{A}} X_{pa} \sum_{a\in\mathcal{A}}\sum_{p'} d_{p'a} - \sum_{a\in\mathcal{A}} d_{pa} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a} \geq -\hat{\delta} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a} \sum_{a\in\mathcal{A}}\sum_{p'} d_{p'a},\ \forall p \in \mathcal{P} \tag{3-13}$$

Therefore, the complete model is as follows:

(**Food-Allocation Model**)

$$\text{Maximize } \sum_{p\in\mathcal{P}}\sum_{a\in\mathcal{A}} \mathrm{FVI}_p X_{pa} \tag{3-14}$$

subject to:

$$X_{pa} \leq d_{pa},\ \forall p \in \mathcal{P},\ a \in \mathcal{A} \tag{3-15}$$

$$\sum_{p\in\mathcal{P}}\sum_{a\in\mathcal{A}} X_{pa} \leq B \tag{3-16}$$

$$X_{pa} \sum_{a'\in\mathcal{A}} d_{pa'} - d_{pa} \sum_{a'\in\mathcal{A}} X_{pa'} \leq \delta_p \sum_{a'\in\mathcal{A}} X_{pa'} \sum_{a'\in\mathcal{A}} d_{pa'},\ \forall p \in \mathcal{P},\ a \in \mathcal{A} \tag{3-17}$$

$$X_{pa} \sum_{a'\in\mathcal{A}} d_{pa'} - d_{pa} \sum_{a'\in\mathcal{A}} X_{pa'} \geq -\delta_p \sum_{a'\in\mathcal{A}} X_{pa'} \sum_{a'\in\mathcal{A}} d_{pa'},\ \forall p \in \mathcal{P},\ a \in \mathcal{A} \tag{3-18}$$

$$\sum_{a\in\mathcal{A}} X_{pa} \sum_{a\in\mathcal{A}}\sum_{p'} d_{p'a} - \sum_{a\in\mathcal{A}} d_{pa} \sum_{a\in\mathcal{A}}\sum_{p'} X_{p'a} \leq \hat{\delta} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} d_{p'a},\ \forall p \in \mathcal{P} \tag{3-19}$$

$$\sum_{a\in\mathcal{A}} X_{pa} \sum_{a\in\mathcal{A}}\sum_{p'} d_{p'a} - \sum_{a\in\mathcal{A}} d_{pa} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a} \geq -\hat{\delta} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} X_{p'a} \sum_{a\in\mathcal{A}}\sum_{p'\in\mathcal{P}} d_{p'a},\ \forall p \in \mathcal{P} \tag{3-20}$$

$$X_{pa} \geq 0 \text{ and integer}, \forall p \in \mathcal{P},\ a \in \mathcal{A}. \quad (3\text{-}21)$$

3.3.1 Empirical Setting

This study embodies a practical case in Brazil, a country officially divided into five regions: North, Northeast, Central-West, Southeast, and South. Figure 3.2 illustrates the geopolitical boundaries of the 26 Brazilian states considered in this study and the Federal District.

Figure 3.2: Map of Brazil (shadowed in brown) showing the study site.

We also consider three types of traditional populations: extractivist, indigenous and quilombolas, distributed across the 26 Brazilian states, holding specific demands. Such demands represent the total amount of families (rural and urban) − indexed in the so-called *CADÚnico*[4] − who are socially vulnerable and food-insecure, requiring then food assistance. Data regarding demand

[4] A Brazilian data and information collection instrument that aims to identify all low-income families in the country for the purpose of inclusion in social assistance and income redistribution programs.

was collected from the federal government website of the Ministry of Citizenship's Food and Nutrition Security Portal (NUTRICIONAL, 2017). Table B.1 presents such demand, which reflects the need for food baskets by population group and state. Figure 3.3 also depicts the demand distribution of the three populations across the Brazilian states.

The first map, shaded in green, shows the number of extractivist families, which represent a total of 35,333. Such people are likely involved in natural resource extraction, such as mining or forestry. The distribution of these families varies significantly, with the darkest green area indicating the highest demand, concentrated in Para (PA) (Northern region), with 10,932 families, Maranhão (MA) (Northeast region), with 10,782 and Amazonas (AM) (Northern region), with 9,557. Together, these three counties represent 88.5% of the total extractive demand. The second map, shaded in blue, represents the distribution of the indigenous families. It shows that the state of Amazonas has the darkest blue shade (38,723 indigenous families), indicating it as the state with the highest number of indigenous families, which correlates with the vast indigenous territories and preserved areas in the Amazon rainforest. The states of Mato Grosso do Sul (MS) and Roraima (RR) represent, respectively, the second and third states with the highest demands: 13,885 and 13,480. Together, the states of AM, MS and RR represent 55.6% of the total indigenous demand. Finally, the third map in red indicates the number of quilombola families. As previously explained, quilombolas are residents of quilombo settlements, communities founded by Afro-Brazilian people who resisted slavery. This map shows a greater distribution of quilombola families across the country, particularly concentrated in the northeastern states, as depicted by the darkest red shades. The state with the most pronounced quilombola concentration is Maranhão (with 35,834 families), where the darkest red hue is visible, highlighting a substantial quilombola population. The state of Bahia (BA), also in the Northeast (with 25,377 families), represents the second one with the largest demand. Finally, the third with the highest demand is Pará, with 13,484 quilombola families. Together, these three states represent 74.0% of the total quilombola demand.

The figure also shows states in white to indicate areas where each of these populations does not have any demand. Concerning the total demand across all states and populations, amounting to 255,077 families, it is noted that 46.6% of this demand comes from the indigenous population, with quilombola communities contributing to 39.6% of the overall demand. The demand from extractive communities makes up 13.9% of the total. Additionally, an analysis of demand distribution across states shows that extractivist communities present demand in 14 states, whereas both indigenous and quilombola

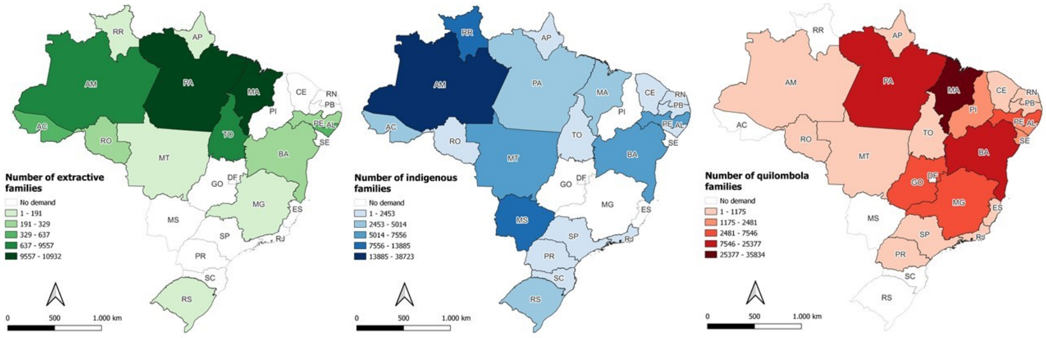

Figure 3.3: Geographical distribution of the extractive, indigenous and quilombola families in Brazilian states.

populations are found in 21 states.

3.3.1.1 Assessing social vulnerability of TPC

Different traditional populations have different socioeconomic conditions and needs. It is crucial to look at these different groups due to their distinct identities and cultures. These communities have unique dietary needs, traditional foods, and cultural practices that must be respected to ensure effective and appropriate aid. Additionally, each group has different historical backgrounds and social structures, which means that actions tailored to their specific circumstances are essential. By recognizing and honouring these differences, we can provide aid that truly supports and empowers each community rather than imposing a one-size-fits-all solution. In this work, we explore these differences by proposing a *Food Insecurity Index* (FVI) tailored to each group based on their unique socioeconomic conditions and levels of food insecurity. Thus, we assess traditional populations' vulnerability through the FVI, which considers socioeconomic characteristics alongside food insecurity-related metrics. This index ranges from 0 to 1, where 0 represents the lowest level of vulnerability, and 1 indicates the highest. The FVI is attributed to populations, meaning that each group has its own FVI, regardless of its geographical area. This approach is well-aligned with the current practices of the government, where food distribution actions are made focusing on the populations, regardless of the area they are based.

The index is comprised of six variables, whose values were also gathered from the federal government website of the Ministry of Citizenship's Food and Nutrition Security Portal (NUTRICIONAL, 2017). Two variables are directly related to food insecurity, and the other four are related to socioeconomic conditions (Table 3.3), which are well-aligned with the literature presented in

Section 3.2. This structured assessment enables a focused approach to mitigating food insecurity by identifying and addressing the specific vulnerabilities of each population group. To find the FVI for each population group, we used the values of the respective variables per municipality, as such variables are detailed at the municipal level. To mathematically formulate the calculation of the FVI for each population group, let us define the following:

- n: Number of municipalities;
- m: Number of variables considered (in this case, $m = 6$);
- X_{ij}: Value of the j-th variable for the i-th municipality;
- P_i: Population size of the i-th municipality;
- $\bar{X}_i$: Arithmetic mean of the six variables for the i-th municipality;
- FVI_i: FVI for the i-th municipality;
- $FVI_{weighted}$: Weighted FVI for the entire population

The steps are as follows:

1. Calculate the Arithmetic Mean of the variables for each municipality. This gives the average value of the six variables for the i-th municipality.

$$\bar{X}_i = \frac{1}{m} \sum_{j=1}^{m} X_{ij}$$

2. Determine the FVI for each municipality:

$$FVI_i = \bar{X}_i$$

3. Calculate the Weighted FVI for each municipality. This gives a weighted measure of vulnerability based on the population size of each municipality.

$$FVI_{weighted,i} = FVI_i \times P_i = \bar{X}_i \times P_i$$

4. Calculate the Overall FVI for the entire Population. This provides a comprehensive view of vulnerability across the entire population, taking into account the population size of each municipality.

$$FVI_{total} = \frac{\sum_{i=1}^{n} FVI_{weighted,i}}{\sum_{i=1}^{n} P_i} = \frac{\sum_{i=1}^{n} (\bar{X}_i \times P_i)}{\sum_{i=1}^{n} P_i}$$

Upon analyzing the FVI's, it was observed that extractivists exhibit a higher level of vulnerability (0.449) compared to indigenous communities (0.440), which in turn show to be more vulnerable than quilombolas (0.412). Table 3.3 presents all the variables considered to develop the FVI.

Table 3.3: Food insecurity and Socioeconomic indicators.

Dimension	Variable	Description	Reference
Food insecurity	Weight Deficit for Age children < 5 years	Proportion of children under five years of age presenting body weight below the acceptable normality limit for age, which is associated/sensitive to recent weight loss, height deficiency, or both	(TIWARI; AUSMAN; AGHO, 2014)
	Height Deficit for Age children < 5 years	Proportion of children under five years of age who present height below the acceptable normality limit for age, characterizing a chronic deficit	(TIWARI; AUSMAN; AGHO, 2014)
Socioeconomic	No access to water	Percentage of families without access to water, considering households that do not have access to the general network, well, spring, or cisterns	(SALLES-COSTA et al., 2008)
	Inadequate sewage conditions	Percentage of families with inadequate sewage, considering households that do not have access to sanitary sewage through a collective network or septic tank	(DRYSDALE; BOB; MOSHABELA, 2021)
	No education or incomplete primary education	Percentage of family Heads who have a low level of education, considering those who declare themselves without education or with incomplete primary education	(ROSE; GUNDERSEN; OLIVEIRA, 1998) (SALLES-COSTA et al., 2008); (ASGHAR; MUHAMMAD, 2013)
	Income up to $ 44 (conversion rate into Brazilian currency in 2018 = R$3.88)	Percentage of families with per capita income of up to R$ 170.00 (poverty line) calculated by the self-declared value in *CADÚnico*	(ROSE; GUNDERSEN; OLIVEIRA, 1998) (SALLES-COSTA et al., 2008); (ASGHAR; MUHAMMAD, 2013)

3.4 Results and discussions

The models were implemented with *Julia Programming Language* v1.10.2, using the *GLPK* solver on an Intel core i5 processor with 16 GB RAM under Windows 10 operating system with a *300-second time* limit for each scenario. A demonstrably optimal solution was found for each instance.

We first evaluate the basic model (3-1, 3-2, 3-3, 3-6), that we call *benchmark model*, to obtain our benchmark solution. Considering a limited number of food baskets, B = 250,000, the model gives an Objective Function of 141,283.50 (which is our effectiveness measure) covering 100% of the total demand of both extractive and indigenous populations (highest FVIs). The remaining quantity of food baskets is allocated for quilombolas, satisfying 94.9% of its total demand. Regarding the service level of quilombolas, the solution meets the needs of 100% of the quilombolas in 14 states, covers only 31.0% of the demand in Piauí, and completely fails to provide any food baskets to quilombola communities in the remaining six states (Rio de Janeiro, Rio Grande do Norte, Rondônia, São Paulo, Sergipe, and Tocantins) (see Figure

3.4).

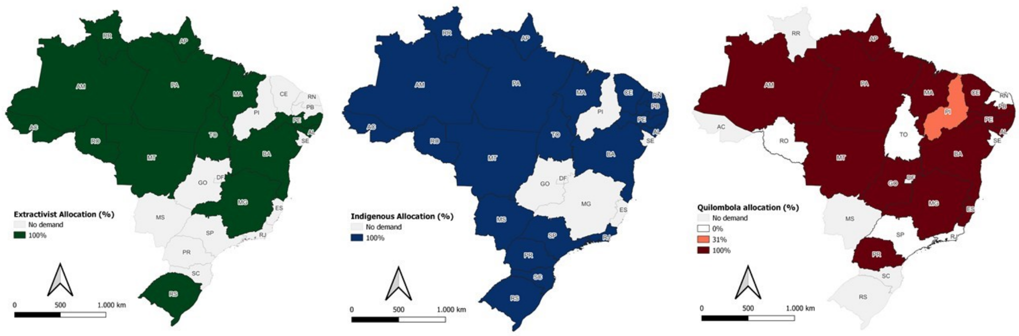

Figure 3.4: Benchmark model - allocation per population (B=250k).

Considering the service level of the states (regardless of their population), the average is around 86.0%, with Sergipe being the only state not covered at all, as its demand arises solely from quilombolas. *Without any equity criteria, our basic model is only FVI-driven, seeking to maximize the objective function and, therefore, the total amount of allocated food baskets to achieve maximum effectiveness.*

As mentioned earlier, this study explores two distinct types of equity: geographical and population. To assess the impact of these different forms of equity on the outcomes, we analyze each model separately. Let us refer to the model focusing on geographic equity as the *"Geo-Equity Model"* (3-14 to 3-18 and 3-21), the one focusing on population equity as the *"Pop-Equity Model"* (3-14 to 3-16, and 3-19, 3-20, 3-21), and the model that simultaneously integrates both equity measures as the *"Overall Equity Model"* (3-14 to 3-21). We assess the model's effectiveness through the lens of the objective function, which, as previously explained, aims to maximize the total number of allocated food baskets. On the other hand, equity is evaluated by examining the fair allocation among counties and populations. For practical purposes, we evaluate how "fair" the allocation is by comparing the *standard deviation* of the solutions, which shows the variation or dispersion from the average in a data set. The parameter δ_p and $\hat{\delta}$ are adjusted from 1 to 0, decreasing in increments of 0.1, which enables us to observe the model's adaptability to increasingly stringent equity requirements, assessing the trade-off between equity and effectiveness. In summary, our analysis is based on examining the effectiveness and equity trade-off, looking at the allocation between different areas and different populations for each of the models. Section, 3.4.1 presents the food basket allocation analysis among different areas. Section 3.4.2 explores the allocation based on population. In Section 3.4.3, we will also examine the implications of reducing the number of baskets, providing an in-depth look at the trade-off between effectiveness and fairness. Finally, in Section 3.4.4, we provide reasonable solution options for government implementation.

3.4.1 Assessing food basket allocation among different areas

We will now analyze the food basket allocation *among the areas* for all the models, considering $B = 250{,}000$. Let us first compare the *benchmark model* with the *geo-equity* model. To compare these models, we analyzed the level of service by state, calculating various metrics, including the mean, standard deviation, and objective function. Such values are found in the following Table 3.4. The complete tables are presented in the Appendix B.

Table 3.4: Benchmark x Geo-equity Model Results per areas for B = 250k.

Benchmark x Geo-equity Model Results per areas for B = 250k.

Metrics	**Benchmark model**	$\boldsymbol{\delta = 1}$	$\boldsymbol{\delta = 0.9}$	$\boldsymbol{\delta = 0.8}$	$\boldsymbol{\delta = 0.7}$	$\boldsymbol{\delta = 0.6}$	$\boldsymbol{\delta = 0.5}$	$\boldsymbol{\delta = 0.4}$	$\boldsymbol{\delta = 0.3}$	$\boldsymbol{\delta = 0.2}$	$\boldsymbol{\delta = 0.1}$	$\boldsymbol{\delta = 0.0}$
Solve Time	0.003	0.025	0.05	0.049	0.03	0.05	0.04	0.054	0.05	0.005	0.072	0.418
Std	0.2869	0.2664	0.2742	0.203	0.222	0.1709	0.1571	0.1376	0.0919	0.0486	0.0488	0.1034
Mean	85.91%	88.87%	88.15%	91.56%	88.67%	94.05%	93.41%	93.29%	95.89%	98.42%	96.96%	93.26%
Objective Function	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	123456.6
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	87.9%

When comparing the benchmark model objective function with the *geo-equity model* – varying δ_p from 1 to 0.1 – we notice that the objective function values remain the same: 141,283.50 as presented in Table 3.4, suggesting equal effectiveness across both models. However, when assessing the allocation service level of the models from an equity perspective, we observe certain differences. Notably, the benchmark model and the geo-equity model with $\delta_p = 1$ hold, besides the same effectiveness, similar inequity levels, both resulting in at least one area without any allocation. However, in the geo-equity model, from $\delta_p = 0.9$ to 0, the model ensures (at some service level) the allocation *for all counties*. This means that, in contrast to the benchmark model, the geo-equity model, when $\delta_p = 0.9$ to 0, does not leave any unserved area (see table B.2). Also, the geo-equity model's standard deviation of allocation service levels across the areas is lower at any δ_p scenario when compared to the benchmark model (see Table 3.4), indicating a lower data dispersion, also suggesting a more equitable and distributive allocation between the areas. When δ_p equals zero, the effectiveness of the model is compromised, as its objective function decreases to 123,456.61 (see Table 3.4). This implies that the model fails to optimize its objective function, leading to an ineffective allocation strategy. Out of the available 250,000 food baskets, the model allocates only 219,744, which is 87.9% of the total (see Table 3.4). When $\delta_p = 0$, it denotes a strict requirement that the ratio of food baskets allocated to a particular population in an area precisely matches the ratio of that population's demand within the total demand, ensuring no discrepancies in food basket allocation. Such strict criterion prevents any geographical area from receiving either more or less than its equitable share based on demand. *In the scenario of an integer solution, which is our case, achieving such precise equity is challenging due to the discrete nature of food baskets (they cannot be divided into fractions to perfectly match the demand ratios). Consequently, if the model cannot allocate resources in a manner that fully aligns with the zero-deviation equity requirement (perfect equity), it opts not to allocate the remaining food baskets*, in this case, 35,333, which coincides with the total demand of the extractivist. *This decision is made to avoid inequity: allocating these food baskets in a way that does not perfectly align with the demand proportions would violate the equity principle.* Thus, the model completely excludes the extractivist from allocation to adhere to the equity constraints. For a linear problem, where the model treats food baskets as continuous rather than discrete units, achieving equitable distribution becomes feasible. In this context, the food baskets can be allocated in fractional amounts, allowing the model to distribute resources in a manner that precisely aligns with the demand ratios across different populations and areas, adhering to the ideal of perfect equity (see Table B.7). Continuing the comparison between the geo-equity and benchmark model, a "good" solution *regarding the allocation between areas* emerges when $\delta_p = 0.2$, which exhibits the same effectiveness (141283.5) and manages to generate the fairest allocation when compared to other δ_p results and the benchmark model, as the $\delta_p = 0.2$ presents the smallest standard deviation (0.0486), indicating, therefore, a more uniform allocation among the areas, and a highest average coverage of 98.42% (see Table 3.4).

Even though the pop-equity model's central objective is to achieve equity among populations, it remains worthwhile to examine its performance in allocating food baskets *among the areas*. Therefore, it is expected that this model will not necessarily provide an equitable allocation between the areas. Table 3.5 presents the metric results we will now discuss.

Table 3.5: Benchmark x Pop, Geo, Overall-equity Model Results per areas for B = 250k

Benchmark x Pop-equity Model Results per areas for B = 250k.

Metrics	Benchmark model	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Solve Time	0.003	0.016	0	0	0	0	0	0	0	0.004	0	-
Std	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	-
Mean	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	-
Objective Function	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	-
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-

Benchmark x Geo-equity Model Results per areas for B = 250k.

Metrics	Benchmark model	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0.0$
Solve Time	0.003	0.025	0.05	0.049	0.03	0.05	0.04	0.054	0.05	0.005	0.072	0.418
Std	0.2869	0.2664	0.2742	0.203	0.222	0.1709	0.1571	0.1376	0.0919	0.0486	0.0488	0.1034
Mean	85.91%	88.87%	88.15%	91.56%	88.67%	94.05%	93.41%	93.29%	95.89%	98.42%	96.96%	93.26%
Objective Function	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	123456.6
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	87.9%

Benchmark x Overall-equity Model Results per areas for B = 250k.

Metrics	Benchmark model	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Solve Time	0.003	0.025	0.045	0.048	0.044	0.046	0.049	0.054	0.041	0.064	0.141	0.003
Std	0.2869	0.3142	0.2754	0.1331	0.1898	0.1353	0.1613	0.1371	0.0598	0.0462	0.0459	0.0
Mean	85.91%	84.26%	86.55%	95.29%	93.36%	95.17%	91.48%	93.18%	97.64%	97.95%	96.91%	0%
Objective Function	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	0
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%

In the pop-equity model, varying $\hat{\hat{\delta}} = 1$ to 0.1 yields a geographic allocation identical to that found in the benchmark model, indicating the same effectiveness and equal level of inequity among areas (see Table 3.5). Also, when compared to the geo-equity, the pop-equity model presents a less geographically equitable solution, as its standard deviations of the allocation service levels are higher than the geo-equity model at any δ (see Table 3.5). This is expected once the primary goal of the pop-equity model is to guarantee an equitable allocation between populations, not among areas. When the pop-equity model is configured with $\hat{\hat{\delta}} = 0$ and allowed to run for 300 seconds, it fails to solve the Integer problem, as shown in Table 3.5.

By integrating both equity types, we can finally examine the outcomes related to geographic and population equity simultaneously, resulting in the overall-equity model. When δ_p and $\hat{\hat{\delta}}$ are set from 1 to 0.1, the overall model exhibits the same objective function value, indicating that the effectiveness is maintained. At δ_p and $\hat{\hat{\delta}} = 0.1$, the overall model achieves the lowest standard deviation (0.045) in the allocation of service levels among areas, in comparison to both the benchmark model and the geo and pop-equity models with the same range of δ_p and $\hat{\hat{\delta}}$ (see Table 3.5), suggesting this solution (δ_p and $\hat{\hat{\delta}} = 0.1$) is also effective as the others, fairer and therefore, more equitable in terms of geographic allocation, as the allocation among areas is mostly uniform. When δ_p and $\hat{\hat{\delta}} = 0$, the model gives a trivial solution with perfect equity, where it allocates no food baskets to any areas, a consequence of striving for perfect equity, which requires equal distribution ratios. This occurs because the total demand of 255,077 exceeds the total available quantity of food baskets, 250,000, rendering the model unable to satisfy the equity constraints, thus leading to a situation where no allocations are made, and the objective function value is zero. *Although a zero-allocation solution is ineffective and unrealistic, it is an optimal solution if our sole objective is to achieve perfect equity.*

3.4.2 Assessing food basket allocation among different populations

In this section, we examine the allocation outcomes of the geographic and population equity models concerning their food basket allocations *among different populations*. Table B.2 presents the results we will discuss now. The allocation results across different populations are identical between all the models (benchmark, geo, pop, and overall-equity model) when δ_p and $\hat{\delta}$ vary from 1 to 0.1. In all these models, 100% of the extractivist and 100% of the indigenous populations are covered, and 94.97% of the quilombola population is covered.

Table 3.6: Benchmark, Geo, Pop and Overall equity Model Results per populations

Geo-equity Model Results for B = 250k

Population	Benchmark model	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
Indigenous	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Quilombola	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	100%
Std	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.4714
Mean	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	66.67%
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	87.9%

Population-equity Model Results for B = 250k

Population	Benchmark model	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
Indigenous	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
Quilombola	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	-
Std	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	-
Mean	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	-
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-

Overall-equity Model Results for B = 250k.

Population	Benchmark model	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
Indigenous	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
Quilombola	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	0%
Std	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0
Mean	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	0%
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%

In the case of the geographic equity model, when $\delta_p = 0$, the model allocates merely 87.9% of the available food baskets, resulting in an ineffective solution, as previously described. This leads to a situation where the extractive population receives no food baskets at all, rendering a solution that is not only ineffective but also significantly unfair from a population distribution perspective. Despite not focusing on ensuring equity among different populations, this solution provided by the geo-equity model is particularly concerning, as the extractive group, which holds the highest FVI and, therefore, should be prioritized, receives no allocation at all. For the pop-equity model, when $\hat{\delta}$ =0, the model can not find a solution in the running time of 300 seconds, as reported. Nonetheless, when the model was executed in its continuous version, a solution was identified that achieved perfect equity across populations, with each group being allocated resources to meet 98% of their needs, leading to a standard deviation of zero (see Table B.7 in Appendix B). Although this is not a practical solution, since food baskets cannot be divided into halves, the model delivered a perfect equity solution among populations when $\hat{\delta}$ =0.

3.4.3 Reducing the total amount of food baskets: deepening the trade-off between equity and effectiveness

This section examines the effects of decreasing the number of available food baskets to deepen our understanding of the trade-offs between effectiveness and equity in allocating food baskets. Results discussed in this section are provided in tables addressed in Appendix B.3. By lowering the number of available food baskets to 150,000 − a decrease of 40% from the initial number −, we observe significant changes in allocation both in terms of area and population. Such reduction means we are under a more restricted scenario, capable of satisfying *only 58% of the overall demand, highlighting, even more, the necessity to balance effectiveness and equity in food basket allocation.* The 150,000 benchmark model yields an objective function value of 85,916.68. Regarding its allocation between areas, we noticed that several states were left without any allocation. In the initial scenario with 250,000 baskets, Sergipe was the only state not receiving any baskets at all. However, with the reduced quantity of 150,000 baskets, more states, including Espírito Santo, Goiás, Piauí, and São Paulo, were left without any allocation. This led to a lower average service level between the areas (50%) when compared to the 250,000 benchmark model.

Regarding the allocation among population groups, the benchmark scenario with 150,000 baskets completely excludes the quilombola population from receiving any food basket while fully covering the extractivist's demands (who possess the highest FVI); it serves 97% of the indigenous population's food needs. Such a solution provided by the 150,000 benchmark model results in a scenario of total inequality, both geographically (with multiple areas left without food basket coverage) and in terms of population (entirely neglecting to provide food baskets to quilombolas). The pop-equity model then emerges to enhance, in terms of equity, the food basket allocation among populations. By modifying service levels − decreasing them for some populations while increasing them for others −, the model gives a more equitable and fairer distribution among different populations. For instance, when the value of $\hat{\delta}$ ranges from 1 to 0.4, the pop-equity model presents the same allocation service levels among populations of the 150,000 benchmark model, completely satisfying extractivist needs, serving 97% of indigenous demands, and leaving quilombolas with no allocation. The objective function value remains consistent with that of the benchmark model.

However, when $\hat{\delta}$ drops to 0.3, the pop-equity model's allocation strategy shifts towards greater inclusivity and fairness. This is achieved by reducing the service level for indigenous populations to 84%, while still fully meeting the demands of extractivists, who are deemed the highest priority, and starting to allocate 14% to the quilombolas. This approach, however, presents an objective function value of 85,681.94, which is slightly worse than both the benchmark model and the pop-equity model with $\hat{\delta}$ values varying from 1 to 0.4, suggesting that while the allocation becomes fairer, its effectiveness diminishes. As $\hat{\delta}$ is reduced to 0.2 and 0.1, the allocation among populations becomes even more equitable, but at the cost of reduced efficiency, with objective function values dropping to 85,437.14 and 85,192.34, respectively. At $\hat{\delta} = 0.2$, the model continues to fully satisfy extractivist demands, serves 72% of indigenous needs, and extends to cover 29% of quilombola demands. A further reduction to $\hat{\delta}$ $= 0.1$ ensures 100% fulfillment for extractivists, 59% for indigenous groups, and roughly 44% for quilombolas, with the lowest standard deviation (0.236), when compared to the allocation among the population of the benchmark and geo-equity model. By analyzing these solutions, we can clearly see the trade-off between effectiveness and equity. At $\hat{\delta} = 0$, similar to the scenario with the 250,000 baskets in the pop-equity model, the model is unable to generate an integer solution. Under a linear formulation, the allocation among populations achieves the perfect equity, with each group's demand being met at 58%, resulting in a standard deviation of zero.

In terms of allocation among populations within the geo-equity model, the outcomes for δ_p values ranging from 1 to 0.1 mirror those of the 150,000 benchmark model, achieving full coverage for extractivists and 97% for indigenous populations while completely excluding quilombolas. At $\delta_p = 0$, given that this model's primary aim is not focused on population equity, the allocation entirely fails to address the needs of the indigenous population (with no allocation at all for this population), rendering both inequitable and less efficient solutions. This is evidenced by a reduced objective function value of 76,478.071, reflecting a scenario where only 91% of the total is available.

In the overall model, setting $\hat{\delta}$ from 1 to 0.4 results in an allocation identical to the one where extractivist demands are fully met, 97% of indigenous are covered, and quilombolas receive no food basket at all, with the same objective function. However, adjusting $\hat{\delta}$ to fall between 0.3 and 0.1 shifts the model towards a more equitable allocation, reflecting the same allocation as those seen in the pop-equity model for equivalent $\hat{\delta}$ intervals.

In the overall model, regarding the *allocation among areas*, a worth recognition solution arises when $\delta_p = 0.1$, where the standard deviation reaches the lowest level (0.082) when compared to other models at any δ_p values, showing a stride towards equity across all δ_p values. Even though this solution does not provide a perfectly equitable solution, it emerges as the most balanced and fairest allocation both in terms of geographic and population allocation. Nevertheless, this approach results in a decrease in effectiveness, with an objective function value of 85,192.34. Finally, at $\delta_p = 0$, as previously reported, the model opts for a trivial solution of zero-allocation to the populations, failing in effectiveness.

3.4.4 Improving current policy: which model do we use?

As previously mentioned, public policies guiding the allocation of food baskets within food aid programs for traditional populations are frequently reported to be subjective and reactive. Without a comprehensive and well-planned strategy, such allocations compromise the possibility of guaranteeing, in food basket allocations, effectiveness and mainly equity, which is such an important objective in the public context when dealing with vulnerable populations that exhibit different socioeconomic profiles. Our models offer a way to reduce subjectivity in policymaking by providing optimization tools that help governments allocate food baskets in a fairer or more equitable way across different areas and populations (horizontal equity), while prioritizing the most in-need population (vertical equity). That makes a practical contribution stemming from our research. Models results offer a range of solutions for the government, but decisions are totally based on the government's final objectives to achieve more or less equity/effectiveness.

With 250,000 food baskets available, a reasonable solution when balancing effectiveness and equity is achievable with the overall model when $\delta_p/\hat{\delta} =$ to 0.2 or 0.1. At these values of $\delta_p/\hat{\delta}$, we achieve in both models, the same allocation service level among populations, which includes fulfilling 100% of the needs for extractivist and indigenous populations, and 94.97% for the quilombola communities. In terms of vertical equity, both solutions accomplish just that by prioritizing 100% coverage for extractive populations, who have the highest FVI. Looking at allocation among areas, when $\delta_p = 0.1$, we observe the smallest standard deviation (0.045) and an average service level of 96.91%. With $\delta_p = 0.2$, we have a slightly higher standard deviation (0.046), but the average service level is higher. Both solutions are deemed quite satisfactory as they maintain effectiveness compared to the benchmark model (and other models with variations of $\delta_p/\hat{\delta}$), holding a high level of equity both in terms of area (horizontal equity), and in terms of vertical equity, targeting food baskets to those most in need (extractivists and indigenous populations), without neglecting the quilombolas.

In implementing our strategies for a more distributive and equitable allocation, we use the concept of fair share and proportion, which is also connected to the notion of horizontal equity, where resources are evenly distributed. In our solutions, achieving a more distributive and equitable strategy implies slightly reducing, for example, the service level of some areas to enhance it for others. For example, in the geo-equity model with $\delta_p = 0.1$, while states like Ceará, Espírito Santo, Goiás, Maranhão, and Mato Grosso are fully covered in the benchmark model, their coverage level in the geo-equity model adjusts to 97%, 86%, 85%, 93%, and 98%, respectively. Similarly, Sergipe, which received no food baskets at all in the benchmark model, is now covered at 85% in the geo-equity model. *This aligns with equity literature practices (such as minimizing the maximum or maximizing the minimum equity measure), and although our equity measure is not addressed in the objective function, it also aims to elevate the overall level of equity by bettering the circumstances for the most underserved groups* (LUSS, 1999; COLUCCIA; D'ALCONZO; RICCIATO, 2012; BALCIK; IRAVANI; SMILOWITZ, 2014). In summary, there are alternative ways to optimize the effectiveness-equity trade-off. This is ultimately dependent on the policymaker's strategy of sacrificing or not effectiveness over equity, or vice-versa.

3.5
Conclusions and Implications for Future Research

This paper addresses the urgent need to design food distribution policies without a subjective or reactive bias in order to achieve a more well-planned allocation strategy, considering equity beyond effectiveness. The paper discusses, then, the development and application of a mathematical model for allocating food baskets in a food aid program aimed at traditional peoples and communities in Brazil, providing governments with solutions that can be analyzed and discussed in terms of effectiveness and fairness. In this way, we answer the first research question of this study.

To answer our second research question, differently from existing research in food aid and optimization, we develop a fairer and then equitable food basket allocation in terms of geographic areas and populations, incorporating a prioritization factor, the FVI, to ponder population vulnerabilities within a supportive decision-making tool. We analyze the models separately, both in terms of allocation by areas and populations. It is interesting to note that perfect equity can be accompanied by solutions that are unrealistic (as in the case of zero allocation, which is not practicable) or infeasible (in the case of entire problems like ours). We ran the integer model as we cherish its applicability. The effectiveness and equity trade-off will always exist, and it is up to the government to establish what levels of equity it intends to achieve.

Through a practical case inspired by the Food Distribution Action, which delivers food baskets to traditional peoples and communities, we are pleased to look at these peoples, who are often overlooked by governments and society, deserving special attention not only in public food aid policies but also in social policies as a whole.

In addition to the practical contributions, this study also makes methodological advancements by suggesting a prioritization-based alongside an equitable (fair-share) approach and discussing the importance of food aid to tackle hunger and food insecurity, focusing on the importance of food distribution programs. We emphasize its vital function in supporting vulnerable individuals to overcome crises and sustain their livelihoods, playing a vital role in alleviating hunger and food insecurity. Although food distribution programs will not end hunger, they can mitigate it, when combined with other long-term food aid programs to enhance community development.

Due to data limitations, our work analyzed only three populations. In the context of dozens of populations, such an index can be more insightful. Limitations of the work can potentially generate future work. Expanding this work could involve integrating cost considerations to balance efficiency with effectiveness and equity; adopting coverage levels to offer diverse service standards for prioritized groups; and focusing on a municipal-level analysis for greater granularity.

4
Conclusions and Future work

This thesis has explored the integration of prioritization and equity into decision-making models for public policies targeting vulnerable populations. By delving into two critical areas - malaria control interventions and food allocation in food aid programs - this research has not only proposed novel mathematical models approach but also provided practical solutions to humanitarian and social issues. The development of the Malaria Vulnerability Index (MVI), a robust prioritization index, and the application of equitable resource allocation principles stand out as pivotal contributions, offering a real data-driven approach to enhancing public health and food aid interventions in resource-limited settings. In this way, we answered the general research question of the thesis and achieved its main objective. Secondary research questions were answered as we developed Paper 1 and Paper 2.

The concept of equity is widely explored in this thesis. At the heart of this examination, two fundamental aspects of equity arise vertical equity and horizontal equity, each addressing different nuances of fairness in the distribution/allocation of scarce resources. We also highlight how such important concepts are associated with theoretical and practical perspectives.

In Paper 1, the incorporation of the MVI weight prioritizes the allocation of LLINs to the most vulnerable municipalities as per design of the objective function. The idea of prioritization is strongly related to the principle of vertical equity in the sense of conceptualizing the unequal but fair treatment of unequal individuals (JOSEPH; RICE; LI, 2016); in our context, the "unequal individuals" are the municipalities of the malaria-endemic region that often exhibit (very) different epidemiological, socioeconomic and environmental profiles, which usually translates into an unequal capacity to deal with malaria intervention campaigns. It is easy to see that by maximizing the effectiveness of the LLINs campaign, vertical equity is therefore maximized as well; this is what we call best-case effectiveness (or best-case vertical equity), which is our primary goal. However, the best-case effectiveness solution may be myopic in the sense of identifying solutions more aligned with the general principles of horizontal equity, which is perceived here as avoiding as much as possible underserving areas.

In paper 2, we also explored prioritization and equity, explicitly using the concept of fair share in a way to respectively address vertical and horizontal equity. As widely reported in this thesis, this paper's contribution is substantial, as we provide the Brazilian government with an optimization tool that incorporates two key equity considerations: geographical and population equity, ensuring food baskets will be fairly shared amongst different areas and populations. Furthermore, we also assess the model's effectiveness, which is its ability to maximize the number of food baskets allocated to areas and populations, weighted by a prioritization index that directs the food baskets to the most in need. By testing the model across various levels of equity through adjustable deviation limits, the paper facilitates an examination of the trade-off between effectiveness and equity, guiding the government toward selecting solutions that align with its overarching goals (be more or less equitable/effective).

The detailed real cases presented within this research not only underscore the practical feasibility of the proposed models but also spotlight their potential to significantly enhance public policy decision-making. By integrating considerations of equity and prioritization into the allocation of limited resources, these models offer a beacon for governments struggling to navigate the challenges of such a diverse and unequal society in Brazil. Such a thesis serves as a proof of concept for a novel tool design aimed at addressing specific challenges within public policy and resource allocation. By presenting the architectural framework and theoretical underpinnings, the thesis demonstrates how such a tool could resolve critical issues and contribute substantial benefits to the process. It is crucial to emphasize that the practical contribution is not properly the application itself but to propose a design that highlights the potential benefits and efficiencies of our prioritization-driven and equitable optimization tool could bring for the allocation of resources in public policies. This contribution focuses on the conceptual design, offering a blueprint for future software engineers, data collectors, and policymakers to consider and potentially implement. By envisioning a tool with this architecture, the thesis provides a practical perspective on how such a tool could improve decision-making processes regarding resource allocation and ultimately lead to more equitable and effective public policies.

This thesis fundamentally embraces a social approach well aligned with the Sustainable Development Goals (SDGs). We elucidate the intricate and direct connections between socioeconomic factors and the vulnerabilities experienced by specific populations and Municipalities in Brazil. It lays bare the reality that socioeconomic disparities − encompassing income levels, access to education, healthcare, and adequate housing − play a pivotal role in determining the susceptibility of communities to challenges such as health crises and food insecurity. Thus, our study also underscores the critical necessity for government interventions to not merely address the symptoms of vulnerability but to fundamentally enhance the underlying socioeconomic conditions of such vulnerable peoples. By advocating for policies that are both equitable and prioritized-driven based on the vulnerability level, this thesis contributes to a growing body of knowledge urging a shift in how public resources are allocated.

From our theoretical framework, illustrated in this thesis' Introduction, we can also draw other future research avenues of the thesis beyond each paper's proposition of future work. This would comprise the development of a decision support system (DSS) to build a tailored, practical and robust decision support to better help the governments in the public policy decision-making process. For this purpose, it would be necessary to take further steps, including practitioner's validation, training, and managerial involvement. Reflecting on the challenges of translating research results into practice, several limitations of this thesis become apparent, particularly in the practical implementation of the proposed tool design. One major limitation is the difficulty in obtaining comprehensive and high-quality data, which is essential for developing accurate and effective decision-making models. Data scarcity, inconsistencies, and the variability of data sources can hinder the tool's functionality and reliability. Additionally, influencing operational processes and integrating the tool within existing systems pose significant challenges. The practical application of the tool requires collaboration with various stakeholders, including policymakers, data collectors, and software engineers, which can be complex and time-consuming. Moreover, resistance to change and the inertia of established processes can impede the adoption of new technologies. Future work continuing from this thesis will need to address these challenges by establishing robust data collection frameworks, fostering interdisciplinary collaboration, and developing strategies to effectively integrate the tool into existing operational workflows. Overcoming these limitations will be crucial to realizing the full potential of the proposed tool and ensuring its impact on resource allocation in public policy for vulnerable populations.

5 Bibliography

ABDIN, A. F. et al. An optimization model for planning testing and control strategies to limit the spread of a pandemic–the case of covid-19. **European journal of operational research**, Elsevier, v. 304, n. 1, p. 308–324, 2023. Cited in page 15.

ACHCAR, J. A. et al. Use of poisson spatiotemporal regression models for the brazilian amazon forest: malaria count data. **Revista da Sociedade Brasileira de Medicina Tropical**, SciELO Brasil, v. 44, n. 6, p. 749–754, 2011. Cited in page 35.

ADGER, W. N. Vulnerability. **Global environmental change**, Elsevier, v. 16, n. 3, p. 268–281, 2006. Cited in page 13.

AFONSO, L. F. C.; CORREA, N. A. F.; SILVA, H. P. Segurança alimentar e nutricional em comunidades quilombolas no brasil: uma revisão da literatura indexada. **Segurança Alimentar e Nutricional**, v. 27, p. e020003–e020003, 2020. Cited in page 72.

ALEM, D. Insights from vulnerability-driven optimisation for humanitarian logistics. **Journal of the British Academy**, v. 9, n. s8, p. 23–53, 2021. Cited 2 times in pages 14 and 15.

ALEM, D. et al. Pro-poor'humanitarian logistics: prioritizing the vulnerable in allocating relief aid. **Optim. Online**, 2021. Cited 4 times in pages 14, 15, 18, and 78.

ALHINDI, A. et al. Vehicle routing optimization for surplus food in nonprofit organizations. **International Journal of Advanced Computer Science and Applications**, Science and Information (SAI) Organization Limited, v. 11, n. 3, 2020. Cited in page 82.

ALKAABNEH, F.; DIABAT, A.; GAO, H. O. A unified framework for efficient, effective, and fair resource allocation by food banks using an approximate dynamic programming approach. **Omega**, Elsevier, v. 100, p. 102300, 2021. Cited in page 82.

AMEGAH, A. K. et al. Malaria infection, poor nutrition and indoor air pollution mediate socioeconomic differences in adverse pregnancy outcomes in cape coast, ghana. **PloS one**, Public Library of Science, v. 8, n. 7, p. e69181, 2013. Cited in page 27.

ANGELO, J. R. et al. The role of spatial mobility in malaria transmission in the brazilian amazon: the case of porto velho municipality, rondônia, brazil (2010-2012). **PloS one**, Public Library of Science San Francisco, CA USA, v. 12, n. 2, p. e0172330, 2017. Cited in page 35.

ARNETTE, A. N.; ZOBEL, C. W. A risk-based approach to improving disaster relief asset pre-positioning. **Production and Operations Management**, SAGE Publications Sage CA: Los Angeles, CA, v. 28, n. 2, p. 457–478, 2019. Cited in page 15.

ASADA, Y. et al. A three-stage approach to measuring health inequalities and inequities. **International Journal for Equity in Health**, BioMed Central, v. 13, n. 1, p. 1–13, 2014. Cited in page 15.

ASGHAR, Z.; MUHAMMAD, A. Socio-economic determinants of household food insecurity in pakistan. 2013. Cited 2 times in pages 76 and 91.

AYELE, D. G.; ZEWOTIR, T. T.; MWAMBI, H. G. Prevalence and risk factors of malaria in ethiopia. **Malaria Journal**, Springer, v. 11, n. 1, p. 1–9, 2012. Cited in page 27.

AZARIADIS, C.; STACHURSKI, J. Poverty traps. **Handbook of economic growth**, Elsevier, v. 1, p. 295–384, 2005. Cited 2 times in pages 13 and 70.

BALCIK, B.; IRAVANI, S.; SMILOWITZ, K. Multi-vehicle sequential resource allocation for a nonprofit distribution system. **IIE Transactions**, Taylor & Francis, v. 46, n. 12, p. 1279–1297, 2014. Cited 4 times in pages 16, 81, 82, and 100.

BALCIK, B.; IRAVANI, S. M.; SMILOWITZ, K. A review of equity in non-profit and public sector: a vehicle routing perspective. **Wiley encyclopedia of operations research and management science**, Wiley Online Library, 2010. Cited 2 times in pages 16 and 79.

BARAGATTI, M. et al. Social and environmental malaria risk factors in urban areas of ouagadougou, burkina faso. **Malaria Journal**, Springer, v. 8, n. 1, p. 1–14, 2009. Cited in page 35.

BARBIERI, A. F.; SOARES-FILHO, B. S. et al. Population and land use effects on malaria prevalence in the southern brazilian amazon. **Human Ecology**, Springer, v. 33, n. 6, p. 847–874, 2005. Cited in page 33.

BARNETT, D. J. et al. Resource allocation on the frontlines of public health preparedness and response: report of a summit on legal and ethical issues. **Public Health Reports**, SAGE Publications Sage CA: Los Angeles, CA, v. 124, n. 2, p. 295–303, 2009. Cited in page 14.

BARRETT, C. B. Food aid's intended and unintended consequences. **Available at SSRN 1142286**, 2006. Cited in page 77.

BASKAYA, S.; ERTEM, M. A.; DURAN, S. Pre-positioning of relief items in humanitarian logistics considering lateral transhipment opportunities. **Socio-Economic Planning Sciences**, Elsevier, v. 57, p. 50–60, 2017. Cited 2 times in pages 14 and 15.

BHATT, S. et al. The effect of malaria control on plasmodium falciparum in africa between 2000 and 2015. **Nature**, Nature Publishing Group, v. 526, n. 7572, p. 207, 2015. Cited in page 36.

BRAVEMAN, P.; GRUSKIN, S. Defining equity in health. **Journal of epidemiology and community health**, BMJ Publishing Group, v. 57, n. 4, p. 254, 2003. Cited in page 15.

BRAZIL. **Decree no. 6,040, of 7 February 2007**. 2007. Official Gazette of the Federative Republic of Brazil. Establishes the National Policy for the Sustainable Development of Traditional Peoples and Communities. Cited in page 72.

BRITO, I. D. et al. Optimizing long-lasting insecticidal nets campaign in ivory coast. **Logistics**, Multidisciplinary Digital Publishing Institute, v. 4, n. 3, p. 18, 2020. Cited in page 36.

BROWN, H.; MILLS, S.; ALBANI, V. Socioeconomic risks of food insecurity during the covid-19 pandemic in the uk: findings from the understanding society covid survey. **BMC Public Health**, Springer, v. 22, n. 1, p. 590, 2022. Cited in page 70.

BURKART, C.; BESIOU, M.; WAKOLBINGER, T. The funding—humanitarian supply chain interface. **Surveys in Operations Research and Management Science**, Elsevier, v. 21, n. 2, p. 31–45, 2016. Cited in page 80.

CABRAL, C. S. et al. Food security, income, and the bolsa família program: a cohort study of municipalities in paraíba state, brazil, 2005-2011. **Cadernos de Saúde Pública**, SciELO Brasil, v. 30, p. 393–402, 2014. Cited in page 77.

CANELAS, T. et al. Environmental and socioeconomic analysis of malaria transmission in the brazilian amazon, 2010–2015. **Revista de saude publica**, SciELO Public Health, v. 53, p. 49, 2019. Cited 3 times in pages 33, 34, and 35.

CARRASCO-ESCOBAR, G.; FORNACE, K.; BENMARHNIA, T. Mapping socioeconomic inequalities in malaria in sub-sahara african countries. **Scientific reports**, Nature Publishing Group, v. 11, n. 1, p. 1–8, 2021. Cited 3 times in pages 32, 34, and 35.

CASTRO, J. de. **As Raízes da Fome**. Rio de Janeiro: Civilização Brasileira, 1963. Cited in page 73.

CASTRO, M. C. Malaria transmission and prospects for malaria eradication: the role of the environment. **Cold Spring Harbor perspectives in medicine**, Cold Spring Harbor Laboratory Press, v. 7, n. 10, p. a025601, 2017. Cited 4 times in pages 32, 33, 34, and 35.

CHANTA, S. et al. The minimum p-envy location problem: a new model for equitable distribution of emergency resources. **IIE Transactions on Healthcare Systems Engineering**, Taylor & Francis, v. 1, n. 2, p. 101–115, 2011. Cited in page 80.

CHEROL, C. C. d. S.; FERREIRA, A. A.; SALLES-COSTA, R. Social inequalities and household food insecurity in quilombola communities in brazil. **Revista de Nutrição**, SciELO Brasil, v. 34, 2021. Cited in page 73.

CHINNAKALI, P. et al. Prevalence of household-level food insecurity and its determinants in an urban resettlement colony in north india. **Journal of health, population, and nutrition**, BMC, v. 32, n. 2, p. 227, 2014. Cited in page 76.

COLITT, R. **Descendants of slaves still suffer in Brazil**. 2007. Accessed: 2023-07-23. Disponível em: <https://uk.reuters.com>. Cited in page 72.

COLUCCIA, A.; D'ALCONZO, A.; RICCIATO, F. On the optimality of max–min fairness in resource allocation. **annals of telecommunications-annales des télécommunications**, Springer, v. 67, p. 15–26, 2012. Cited in page 100.

CONFALONIERI, U. E.; MARGONARI, C.; QUINTÃO, A. F. Environmental change and the dynamics of parasitic diseases in the amazon. **Acta tropica**, Elsevier, v. 129, p. 33–41, 2014. Cited in page 34.

COWELL, F.; EBERT, U. Complaints and inequality. **Social Choice and Welfare**, Springer, v. 23, n. 1, p. 71–89, 2004. Cited in page 33.

DABARO, D. et al. Effects of rainfall, temperature and topography on malaria incidence in elimination targeted district of ethiopia. **Malaria Journal**, BioMed Central, v. 20, n. 1, p. 1–10, 2021. Cited 2 times in pages 34 and 35.

DAHESH, S. M. et al. Socioeconomic and environmental factors affecting malaria infection in fayoum governorate, egypt. **J Egypt Soc Parasitol**, v. 39, n. 2, p. 511–23, 2009. Cited 2 times in pages 32 and 35.

DANIELS, N. **Accountability for reasonableness: Establishing a fair process for priority setting is easier than agreeing on principles**. [S.l.]: British Medical Journal Publishing Group, 2000. 1300–1301 p. Cited in page 15.

DAVIS, L. B. et al. Scheduling food bank collections and deliveries to ensure food safety and improve access. **Socio-Economic Planning Sciences**, Elsevier, v. 48, n. 3, p. 175–188, 2014. Cited 2 times in pages 79 and 82.

DEGAREGE, A. et al. Improving socioeconomic status may reduce the burden of malaria in sub saharan africa: A systematic review and meta-analysis. **PloS one**, Public Library of Science San Francisco, CA USA, v. 14, n. 1, p. e0211205, 2019. Cited 3 times in pages 32, 33, and 35.

DEVAUX, M. Income-related inequalities and inequities in health care services utilisation in 18 selected oecd countries. **The European Journal of Health Economics**, Springer, v. 16, p. 21–33, 2013. Cited in page 15.

DRACHLER, M. d. L. et al. Proposta de metodologia para selecionar indicadores de desigualdade em saúde visando definir prioridades de políticas públicas no brasil. **Ciência & Saúde Coletiva**, SciELO Brasil, v. 8, p. 461–470, 2003. Cited in page 13.

DRACHLER, M. d. L. et al. Desenvolvimento e validação de um índice de vulnerabilidade social aplicado a políticas públicas do sus. **Ciência & Saúde**

Coletiva, SciELO Public Health, v. 19, p. 3849–3858, 2014. Cited in page 13.

DREWNOWSKI, A. Food insecurity has economic root causes. **Nat Food**, v. 3, n. 8, p. 555–556, 2022. Epub 2022 Aug 8. PMID: 35965676; PMCID: PMC9362113. Cited in page 70.

DRYSDALE, R.; BOB, U.; MOSHABELA, M. Socio-economic determinants of increasing household food insecurity during and after a drought in the district of ilembe, south africa. **Ecology of Food and Nutrition**, Taylor & Francis, v. 60, n. 1, p. 25–43, 2021. Cited 2 times in pages 77 and 91.

DURNEZ, L. et al. Outdoor malaria transmission in forested villages of cambodia. **Malaria journal**, Springer, v. 12, n. 1, p. 1–14, 2013. Cited in page 35.

EBHUOMA, O.; GEBRESLASIE, M.; MAGUBANE, L. Modeling malaria control intervention effect in kwazulu-natal, south africa using intervention time series analysis. **Journal of infection and public health**, Elsevier, v. 10, n. 3, p. 334–338, 2017. Cited 2 times in pages 32 and 35.

EISENHANDLER, O.; TZUR, M. The humanitarian pickup and distribution problem. **Operations Research**, INFORMS, v. 67, n. 1, p. 10–32, 2019. Cited 2 times in pages 81 and 82.

FAO et al. **The State of Food Security and Nutrition in the World 2023. Urbanization, Agrifood Systems Transformation and Healthy Diets across the Rural–Urban Continuum**. [S.l.]: FAO Rome, Italy, 2023. Cited in page 70.

FEEDING AMERICA. **Impact of Hunger on Marginalized Groups**. 2003. Discussion on the higher rates of hunger among children, Black people, indigenous communities, rural farmers, and other marginalized groups. Disponível em: <https://www.feedingamerica.org>. Cited in page 70.

FERREIRA, H. daSilva et al. Prevalence and factors associated with food and nutrition insecurity in families in municipalities of the north of the state of alagoas, brazil, 2010. **Ciência & Saúde Coletiva**, Associação Brasileira de Saúde Coletiva, v. 19, n. 5, p. 1533, 2014. Cited in page 76.

FERREIRA, M. U.; CASTRO, M. C. Challenges for malaria elimination in brazil. **Malaria journal**, BioMed Central, v. 15, n. 1, p. 284, 2016. Cited 2 times in pages 33 and 35.

FIANU, S.; DAVIS, L. B. A markov decision process model for equitable distribution of supplies under uncertainty. **European Journal of Operational Research**, Elsevier, v. 264, n. 3, p. 1101–1115, 2018. Cited 2 times in pages 80 and 82.

FIGUEIRA, J. R. et al. A multiple criteria approach for building a pandemic impact assessment composite indicator: The case of covid-19 in portugal. **European journal of operational research**, Elsevier, v. 309, n. 2, p. 795–818, 2023. Cited in page 52.

FIROUZ, M. et al. On the equity-efficiency trade-off in food-bank network operations. **Journal of the Operational Research Society**, Taylor & Francis, v. 74, n. 12, p. 2493–2514, 2023. Cited in page 82.

FLETCHER, I. K. et al. The relative role of climate variation and control interventions on malaria elimination efforts in el oro, ecuador: A modeling study. **Frontiers in Environmental Science**, Frontiers, v. 8, p. 135, 2020. Cited in page 33.

Food Security Information Network. **Global Report on Food Crises 2023**. 2023. <https://www.wfp.org/publications/global-report-food-crises-2023>. Cited in page 70.

FORDHAM, M. et al. Understanding social vulnerability. **Social vulnerability to disasters**, CRC Press Boca Raton, FL, v. 2, p. 1–29, 2013. Cited in page 13.

GALARDO, A. K. R. et al. Seasonal abundance of anopheline mosquitoes and their association with rainfall and malaria along the matapi river, amapi, brazil. **Medical and veterinary entomology**, Wiley Online Library, v. 23, n. 4, p. 335–349, 2009. Cited 2 times in pages 34 and 35.

GENTILINI, U. Banking on food: The state of food banks in high-income countries. **IDS Working Papers**, Wiley Online Library, v. 2013, n. 415, p. 1–18, 2013. Cited in page 77.

GGI. **Food Aid Programs: Sustaining Lives and Communities**. 2024. <https://www.graygroupintl.com/blog/food-aid-programs>. Accessed: 2024-01-27. Cited 2 times in pages 77 and 78.

GIL, L. H. S. et al. Urban and suburban malaria in Rondônia (Brazilian Western Amazon) ii: perennial transmissions with high anopheline densities are associated with human environmental changes. **Memórias do Instituto Oswaldo Cruz**, SciELO Brasil, v. 102, n. 3, p. 271–276, 2007. Cited 2 times in pages 34 and 35.

GOMES, M. d. S. M. et al. Malária na fronteira do brasil com a guiana francesa: a influência dos determinantes sociais e ambientais da saúde na permanência da doença. **Saúde e Sociedade**, SciELO Public Health, v. 29, p. e181046, 2020. Cited 2 times in pages 29 and 44.

GÓMEZ-PANTOJA, J. Á.; SALAZAR-AGUILAR, M. A.; GONZÁLEZ-VELARDE, J. L. The food bank resource allocation problem. **Top**, Springer, v. 29, p. 266–286, 2021. Cited in page 79.

GOVE, P. B. **Webster's third new international dictionary of the English language, unabridged**. [S.l.]: Merriam-Webster, 1981. v. 1. Cited in page 79.

GRACE, K.; WEI, R.; MURRAY, A. T. A spatial analytic framework for assessing and improving food aid distribution in developing countries. **Food Security**, Springer, v. 9, p. 867–880, 2017. Cited 2 times in pages 79 and 82.

GRALLA, E.; GOENTZEL, J.; FINE, C. Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. **Production and Operations Management**, Wiley Online Library, v. 23, n. 6, p. 978–989, 2014. Cited 4 times in pages 14, 19, 78, and 80.

GRAVES, P. M. et al. Effectiveness of malaria control during changing climate conditions in eritrea, 1998–2003. **Tropical Medicine & International Health**, Wiley Online Library, v. 13, n. 2, p. 218–228, 2008. Cited in page 35.

GRIFFITH, J. A.; MARTINKO, E. A.; PRICE, K. P. Landscape structure analysis of kansas at three scales. **Landscape and urban planning**, Elsevier, v. 52, n. 1, p. 45–61, 2000. Cited in page 52.

HASNAIN, T.; ORGUT, I. S.; IVY, J. S. Elicitation of preference among multiple criteria in food distribution by food banks. **Production and Operations Management**, Wiley Online Library, v. 30, n. 12, p. 4475–4500, 2021. Cited 4 times in pages 79, 80, 81, and 82.

HEMINGWAY, J. et al. Tools and strategies for malaria control and elimination: what do we need to achieve a grand convergence in malaria? **PLoS biology**, Public Library of Science San Francisco, CA USA, v. 14, n. 3, p. e1002380, 2016. Cited in page 34.

HILLIER, F. S.; LIEBERMAN, G. J. **Introduction to operations research**. [S.l.]: McGraw-Hill, 2015. Cited in page 24.

HUDRLIKOVÁ, L. et al. Composite indicators as a useful tool for international comparison: The europe 2020 example. **Prague economic papers**, Prague Economic Papers, v. 22, n. 4, p. 459–473, 2013. Cited in page 53.

HUNT, P. Poverty, malaria, and the right to health–exploring the connections. **Journal of Humanitarian Medicine**, International Association for Humanitarian Medicine-Brock Chisholm (IAHM), v. 8, n. 4, p. 46–48, 2008. Cited 2 times in pages 27 and 28.

ILINCA, S. et al. Socio-economic inequality and inequity in use of health care services in kenya: evidence from the fourth kenya household health expenditure and utilization survey. **International journal for equity in health**, Springer, v. 18, n. 1, p. 1–13, 2019. Cited in page 32.

ISLAM, M. H.; IVY, J. S. Modeling the role of efficiency for the equitable and effective distribution of donated food. **OR Spectrum**, Springer, v. 44, n. 2, p. 485–534, 2022. Cited 2 times in pages 81 and 82.

JAIN, V.; LORGELLY, P. A public health framework for the equitable global allocation of vaccines: Covid-needs. **Journal of Public Health Policy**, Springer, p. 1–13, 2022. Cited in page 16.

JANSSEN, M. A.; OSTROM, E. **Resilience, vulnerability, and adaptation: A cross-cutting theme of the International Human Dimensions Programme on Global Environmental Change**. [S.l.]: Pergamon, 2006. 237–239 p. Cited in page 13.

JASPERS, S.; SHOHAM, J. Targeting the vulnerable: a review of the necessity and feasibility of targeting vulnerable households. **Disasters**, Wiley Online Library, v. 23, n. 4, p. 359–372, 1999. Cited in page 14.

JIANG, Y.; YUAN, Y. Emergency logistics in a large-scale disaster context: Achievements and challenges. **International journal of environmental research and public health**, MDPI, v. 16, n. 5, p. 779, 2019. Cited 2 times in pages 14 and 78.

JOSEPH, K. T.; RICE, K.; LI, C. Integrating equity in a public health funding strategy. **Journal of public health management and practice: JPHMP**, NIH Public Access, v. 22, n. Suppl 1, p. S68, 2016. Cited 7 times in pages 16, 19, 28, 37, 68, 75, and 102.

JR, R. C. R. et al. Mapping residual transmission for malaria elimination. **Elife**, eLife Sciences Publications, Ltd, v. 4, 2015. Cited in page 32.

JÚNIOR, G. L. da S.; SOUZA, R. M. de. As comunidades tradicionais e a luta por direitos étnicos e coletivos no sul do brasil. **Revista da Faculdade de Direito da UFG**, v. 33, n. 2, p. 128–142, 2009. Cited in page 72.

KAPIRIRI, L.; NORHEIM, O. F.; MARTIN, D. K. Fairness and accountability for reasonableness. do the views of priority setting decision makers differ across health systems and levels of decision making? **Social science & medicine**, Elsevier, v. 68, n. 4, p. 766–773, 2009. Cited in page 15.

KAPIRIRI, L.; RAZAVI, S. D. Equity, justice, and social values in priority setting: a qualitative study of resource allocation criteria for global donor organizations working in low-income countries. **International Journal for Equity in Health**, BioMed Central, v. 21, n. 1, p. 1–13, 2022. Cited 2 times in pages 15 and 16.

KAR, N. P. et al. A review of malaria transmission dynamics in forest ecosystems. **Parasites & vectors**, Springer, v. 7, n. 1, p. 1–12, 2014. Cited 2 times in pages 32 and 35.

KARSU, Ö.; MORTON, A. Inequity averse optimization in operational research. **European journal of operational research**, Elsevier, v. 245, n. 2, p. 343–359, 2015. Cited in page 37.

KENT, K. et al. Prevalence and socio-demographic predictors of food insecurity in australia during the covid-19 pandemic. **Nutrients**, MDPI, v. 12, n. 9, p. 2682, 2020. Cited in page 77.

KHANAM, F. et al. Exploring the gap between coverage, access, and utilization of long-lasting insecticide-treated nets (llins) among the households of malaria endemic districts in bangladesh. **Malaria journal**, Springer, v. 17, n. 1, p. 1–12, 2018. Cited in page 28.

KILCI, F.; KARA, B. Y.; BOZKAYA, B. Locating temporary shelter areas after an earthquake: A case for turkey. **European Journal of Operational Research**, Elsevier, v. 243, n. 1, p. 323–332, 2015. Cited 2 times in pages 14 and 15.

KILIAN, A. et al. Rainfall pattern, el niño and malaria in uganda. **Transactions of the Royal Society of Tropical Medicine and Hygiene**, Royal Society of Tropical Medicine and Hygiene, v. 93, n. 1, p. 22–23, 1999. Cited 2 times in pages 34 and 35.

KIMBI, H. K. et al. Environmental factors and preventive methods against malaria parasite prevalence in rural bomaka and urban molyko, southwest cameroon. **J Bacteriol Parasitol**, v. 4, n. 162, p. 4172, 2013. Cited in page 35.

KUBOTA, F. I. et al. based thesis and dissertations: analysis of fundamental characteristics for achieving a robust structure. **Production**, SciELO Brasil, v. 31, p. e20200100, 2021. Cited in page 17.

LANDWEHR, C.; KLINNERT, D. Value congruence in health care priority setting: social values, institutions and decisions in three countries. **Health Economics, Policy and Law**, Cambridge University Press, v. 10, n. 2, p. 113–132, 2015. Cited in page 15.

LANERI, K. et al. Climate drivers of malaria at its southern fringe in the americas. **PloS one**, Public Library of Science San Francisco, CA USA, v. 14, n. 7, p. e0219249, 2019. Cited in page 32.

LAVY, V. et al. Does food aid depress food production? the disincentive dilemma in the african context. **Policy, Research and External Affairs World Bank (USA).**, n. 460, 1990. Cited in page 77.

LECLERC, P. D.; MCLAY, L. A.; MAYORGA, M. E. Modeling equity for allocating public resources. In: **Community-based operations research: Decision modeling for local impact and diverse populations**. [S.l.]: Springer, 2011. p. 97–118. Cited 2 times in pages 16 and 79.

LEIRAS, A. et al. Food aid supply and distribution in insecure regions: world food programme operation analysis in ethiopia. **Production**, SciELO Brasil, v. 31, 2021. Cited in page 76.

LIANG, J.; LYU, G. From efficiency to fairness: Design of allocation rules for food bank operations. In: IEEE. **2022 Winter Simulation Conference (WSC)**. [S.l.], 2022. p. 1557–1568. Cited in page 82.

LIEN, R. W.; IRAVANI, S. M.; SMILOWITZ, K. R. Sequential resource allocation for nonprofit operations. **Operations Research**, INFORMS, v. 62, n. 2, p. 301–317, 2014. Cited 2 times in pages 80 and 82.

LIMA, A. C. d. S. F. et al. **Avaliação de mosquiteiros impregnados com inseticidas de longa duração\2013 MILD em três regiões do município de Porto Velho, Estado de Rondônia, Brasil**. Tese (Doutorado), 2016. Cited 2 times in pages 29 and 36.

LINDBLADE, K. A. et al. A cohort study of the effectiveness of insecticide-treated bed nets to prevent malaria in an area of moderate pyrethroid resistance, malawi. **Malaria journal**, Springer, v. 14, n. 1, p. 1–15, 2015. Cited 2 times in pages 28 and 36.

LINDBLADE, K. A. et al. Highland malaria in uganda: prospective analysis of an epidemic associated with el nino. **Transactions of the Royal Society of Tropical Medicine and Hygiene**, Royal Society of Tropical Medicine and Hygiene, v. 93, n. 5, p. 480–487, 1999. Cited 2 times in pages 34 and 35.

LOEVINSOHN, M. E. Climatic warming and increased malaria incidence in rwanda. **The Lancet**, Elsevier, v. 343, n. 8899, p. 714–718, 1994. Cited 2 times in pages 34 and 35.

LOOPSTRA, R.; DACHNER, N.; TARASUK, V. An exploration of the unprecedented decline in the prevalence of household food insecurity in newfoundland and labrador, 2007–2012. **Canadian Public Policy**, University of Toronto Press, v. 41, n. 3, p. 191–206, 2015. Cited in page 77.

LOOPSTRA, R.; TARASUK, V. Severity of household food insecurity is sensitive to change in household income and employment status among low-income families1–3. **The Journal of nutrition**, Elsevier, v. 143, n. 8, p. 1316–1323, 2013. Cited 2 times in pages 76 and 77.

LOPES, A. F. et al. The brazilian food insecurity scale: a proposal adapted for traditional people and communities. **Demetra: Food, Nutrition & Health/Alimentação, Nutrição & Saúde**, v. 17, 2022. Cited in page 75.

LUSS, H. On equitable resource allocation problems: A lexicographic minimax approach. **Operations Research**, INFORMS, v. 47, n. 3, p. 361–378, 1999. Cited in page 100.

MA, Y.; WANG, T.; ZHENG, H. On fairness and efficiency in nonprofit operations: Dynamic resource allocations. **Production and Operations Management**, Wiley Online Library, v. 32, n. 6, p. 1778–1792, 2023. Cited in page 82.

MACIEL, F. O.; SILVA, R. B. L.; SOUTO, R. N. P. Fatores de riscos associados à transmissão de malária humana, em áreas de ressacas, nos bairros novo horizonte e zerão, macapá, amapá, brasil. **Biota Amazônia (Biote Amazonie, Biota Amazonia, Amazonian Biota)**, v. 1, n. 1, p. 49–57, 2011. Cited in page 29.

MAHMOUDI, M.; SHIRZAD, K.; VERTER, V. Decision support models for managing food aid supply chains: A systematic literature review. **Socio-Economic Planning Sciences**, Elsevier, v. 82, p. 101255, 2022. Cited in page 80.

MALUKA, S. O. Strengthening fairness, transparency and accountability in health care priority setting at district level in tanzania. **Global Health Action**, Taylor & Francis, v. 4, n. 1, p. 7829, 2011. Cited in page 15.

MANDELL, M. B. Modelling effectiveness-equity trade-offs in public service delivery systems. **Management Science**, INFORMS, v. 37, n. 4, p. 467–482, 1991. Cited in page 81.

MANH, B. H. et al. Social and environmental determinants of malaria in space and time in viet nam. **International journal for parasitology**, Elsevier, v. 41, n. 1, p. 109–116, 2011. Cited 2 times in pages 34 and 35.

MARGOLIES, A.; HODDINOTT, J. **Mapping the Impacts of Food Aid**. [S.l.], 2012. Cited in page 77.

MARIN-LEON, L. et al. Household appliances and food insecurity: gender, referred skin color and socioeconomic differences. **Revista Brasileira de Epidemiologia**, SciELO Public Health, v. 14, p. 398–410, 2011. Cited in page 76.

MARQUES, A.; GUTIERREZ, H. Combate à malária no brasil: evolução, situação atual e perspectivas. **Rev Soc Bras Med Trop**, v. 27, n. Supl III, p. 91–108, 1994. Cited in page 28.

MARSH, M. T.; SCHILLING, D. A. Equity measurement in facility location analysis: A review and framework. **European journal of operational research**, Elsevier, v. 74, n. 1, p. 1–17, 1994. Cited 3 times in pages 16, 79, and 80.

MATTOS, R. G. D. et al. Robust optimization of the insecticide-treated bed nets procurement and distribution planning under uncertainty for malaria prevention and control. **Annals of Operations Research**, Springer, v. 283, n. 1, p. 1045–1078, 2019. Cited in page 36.

MAZUMDAR, R.; MASON, L. G.; DOULIGERIS, C. Fairness in network optimal flow control: Optimality of product forms. **IEEE Transactions on communications**, IEEE, v. 39, n. 5, p. 775–782, 1991. Cited in page 80.

MCCOY, J. H.; LEE, H. L. Using fairness models to improve equity in health delivery fleet management. **Production and Operations Management**, Wiley Online Library, v. 23, n. 6, p. 965–977, 2014. Cited in page 80.

MENG, Q.; YANG, H. Benefit distribution and equity in road network design. **Transportation Research Part B: Methodological**, Elsevier, v. 36, n. 1, p. 19–35, 2002. Cited in page 80.

MOLLAH, A. K. et al. A cost optimization model and solutions for shelter allocation and relief distribution in flood scenario. **International Journal of Disaster Risk Reduction**, Elsevier, v. 31, p. 1187–1198, 2018. Cited 2 times in pages 14 and 15.

MUSA, J. J. et al. Long-lasting insecticidal nets retain bio-efficacy after 5 years of storage: implications for malaria control programmes. **Malaria journal**, BioMed Central, v. 19, n. 1, p. 1–12, 2020. Cited 2 times in pages 28 and 30.

MUTEGEKI, E.; CHIMBARI, M. J.; MUKARATIRWA, S. Assessment of individual and household malaria risk factors among women in a south african village. **Acta tropica**, Elsevier, v. 175, p. 71–77, 2017. Cited 2 times in pages 32 and 35.

NAIR, D. J. et al. Food rescue and delivery: Heuristic algorithm for periodic unpaired pickup and delivery vehicle routing problem. **Transportation Research Record**, SAGE Publications Sage CA: Los Angeles, CA, v. 2548, n. 1, p. 81–89, 2016. Cited in page 82.

NAIR, D. J. et al. **Models for food rescue and delivery: Routing and resource allocation problem**. [S.l.], 2016. Cited in page 82.

NAIR, D. J.; REY, D.; DIXIT, V. V. Fair allocation and cost-effective routing models for food rescue and redistribution. **IISE Transactions**, Taylor & Francis, v. 49, n. 12, p. 1172–1188, 2017. Cited 2 times in pages 79 and 82.

NARDO, M. et al. **Handbook on constructing composite indicators**. [S.l.]: OECD publishing, 2005. Cited in page 53.

NECHIFOR, V. et al. Food security and welfare changes under covid-19 in sub-saharan africa: Impacts and responses in kenya. **Global food security**, Elsevier, v. 28, p. 100514, 2021. Cited in page 77.

NGUFOR, C. et al. Efficacy of royal guard, a new alpha-cypermethrin and pyriproxyfen treated mosquito net, against pyrethroid-resistant malaria vectors. **Scientific reports**, Nature Publishing Group, v. 10, n. 1, p. 1–15, 2020. Cited in page 28.

NG'ANG'A, P. N.; ADUOGO, P.; MUTERO, C. M. Long lasting insecticidal mosquito nets (llins) ownership, use and coverage following mass distribution campaign in lake victoria basin, western kenya. **BMC public health**, Springer, v. 21, n. 1, p. 1–13, 2021. Cited in page 27.

NKUO-AKENJI, T. et al. Environmental factors affecting malaria parasite prevalence in rural bolifamba, south-west cameroon. **African journal of health sciences**, v. 13, n. 1, p. 40–46, 2006. Cited in page 35.

NOYAN, N.; BALCIK, B.; ATAKAN, S. A stochastic optimization model for designing last mile relief networks. **Transportation Science**, Informs, v. 50, n. 3, p. 1092–1113, 2016. Cited in page 15.

NOYAN, N.; KAHVECIOĞLU, G. Stochastic last mile relief network design with resource reallocation. **Or Spectrum**, Springer, v. 40, p. 187–231, 2018. Cited in page 15.

NUTRICIONAL, P. da Segurança Alimentar e. **Mapa InSAN**. 2017. Accessed: 2024-06-03. Disponível em: <https://aplicacoes.mds.gov.br/sagirmps/portal-san/artigo.php?link=15>. Cited 2 times in pages 88 and 89.

OLIVEIRA, E. C. de et al. Spatial patterns of malaria in a land reform colonization project, juruena municipality, mato grosso, brazil. **Malaria Journal**, Springer, v. 10, n. 1, p. 1–9, 2011. Cited in page 33.

OLIVEIRA-FERREIRA, J. et al. Malaria in brazil: an overview. **Malaria journal**, Springer, v. 9, n. 1, p. 1–15, 2010. Cited in page 28.

ONWUJEKWE, O.; UZOCHUKWU, B.; EZEOKE, O. Socio-economic inequalities in cost of seeking treatment for malaria in south-east nigeria. **International Journal of Medicine and Health Development**, v. 15, n. 2, p. 2–16, 2010. Cited in page 32.

ORGANIZATION, W. H. **Tracking universal health coverage: first global monitoring report**. [S.l.]: World Health Organization, 2015. Cited in page 31.

ORGANIZATION, W. H. et al. **Guidelines for laboratory and field-testing of long-lasting insecticidal nets**. [S.l.], 2013. Cited in page 27.

ORGANIZATION, W. H. et al. Achieving universal coverage with long-lasting insecticidal nets in malaria control. **Global Malaria Programme. Geneva: WHO**, 2014. Cited 2 times in pages 29 and 36.

ORGANIZATION, W. H. et al. Making fair choices on the path to universal health coverage: Final report of the who consultative group on equity and universal health coverage. World Health Organization, 2014. Cited in page 15.

ORGANIZATION, W. H. et al. **Achieving and maintaining universal coverage with long-lasting insecticidal nets for malaria control**. [S.l.], 2017. Cited in page 29.

ORGANIZATION, W. H. et al. **Guidelines for malaria vector control**. [S.l.]: World Health Organization, 2019. Cited in page 31.

ORGANIZATION, W. H. et al. World malaria report 2019. world health organization. 2019. Cited in page 28.

ORGANIZATION, W. H. et al. **The state of food security and nutrition in the world 2022: Repurposing food and agricultural policies to make healthy diets more affordable**. [S.l.]: Food & Agriculture Org., 2022. v. 2022. Cited in page 70.

ORGANIZATION, W. H. et al. **World malaria report 2022**. [S.l.]: World Health Organization, 2022. Cited 2 times in pages 27 and 49.

ORGUT, I. S.; IVY, J.; UZSOY, R. Modeling for the equitable and effective distribution of food donations under stochastic receiving capacities. **IISE Transactions**, Taylor & Francis, v. 49, n. 6, p. 567–578, 2017. Cited in page 80.

ORGUT, I. S. et al. Modeling for the equitable and effective distribution of donated food under capacity constraints. **IIE Transactions**, Taylor & Francis, v. 48, n. 3, p. 252–266, 2016. Cited 7 times in pages 16, 19, 79, 81, 82, 83, and 84.

ORGUT, I. S. et al. Robust optimization approaches for the equitable and effective distribution of donated food. **European Journal of Operational Research**, Elsevier, v. 269, n. 2, p. 516–531, 2018. Cited 6 times in pages 15, 16, 79, 81, 82, and 83.

ORGUT, I. S.; LODREE, E. J. Equitable distribution of perishable items in a food bank supply chain. **Production and Operations Management**, Wiley Online Library, v. 32, n. 10, p. 3002–3021, 2023. Cited 5 times in pages 16, 74, 79, 80, and 82.

ORTUÑO, J. C.; PADILLA, A. G. Assembly of customized food pantries in a food bank by fuzzy optimization. **Journal of Industrial Engineering and Management**, v. 10, n. 4, p. 663–686, 2017. Cited in page 79.

PADILHA, M. A. de O. et al. Comparison of malaria incidence rates and socioeconomic-environmental factors between the states of acre and rondônia: a spatio-temporal modelling study. **Malaria journal**, BioMed Central, v. 18, n. 1, p. 1–13, 2019. Cited in page 35.

PALLANT, J.; MANUAL, S. S. A step by step guide to data analysis using ibm spss. **Australia: Allen & Unwin. doi**, v. 10, n. 1, p. 1753–6405, 2013. Cited in page 52.

PALMEIRA, P. et al. Temporal changes in the association between food insecurity and socioeconomic status in two population-based surveys in rio de janeiro, brazil. **Social Indicators Research**, Springer, v. 144, p. 1349–1365, 2019. Cited in page 77.

PARK, C. H.; BERENGUER, G. Supply constrained location-distribution in not-for-profit settings. **Production and Operations Management**, Wiley Online Library, v. 29, n. 11, p. 2461–2483, 2020. Cited in page 80.

PARVIN, H. et al. Distribution of medication considering information, transshipment, and clustering: Malaria in malawi. **Production and Operations Management**, Wiley Online Library, v. 27, n. 4, p. 774–797, 2018. Cited 2 times in pages 27 and 36.

PAULL, S. H. et al. From superspreaders to disease hotspots: linking transmission across hosts and space. **Frontiers in Ecology and the Environment**, Wiley Online Library, v. 10, n. 2, p. 75–82, 2012. Cited in page 32.

PAULY, M. V.; WILLETT, T. D. Two concepts of equity and their implications for public policy. **Social Science Quarterly**, JSTOR, p. 8–19, 1972. Cited in page 13.

PRATT, B.; MERRITT, M.; HYDER, A. A. Towards deep inclusion for equity-oriented health research priority-setting: a working model. **Social Science & Medicine**, Elsevier, v. 151, p. 215–224, 2016. Cited in page 15.

PRYCE, J.; RICHARDSON, M.; LENGELER, C. Insecticide-treated nets for preventing malaria. **Cochrane Database of Systematic Reviews**, John Wiley & Sons, Ltd, n. 11, 2018. Cited in page 28.

PYL, B. **Incra não cumpre meta e titula 2 territórios quilombolas em 2009**. 2010. Accessed: 2023-07-23. Disponível em: <https://www.reporterbrasil.com.br>. Cited in page 72.

RAHMAN, N. H. binti A.; YASIN, R. bin. Children rights to 'zero hunger'and the execution challenges during the covid-19 crisis. **Hasanuddin Law Review**, v. 8, n. 2, p. 139–159, 2022. Cited in page 14.

RANCOURT, M.-È. et al. Tactical network planning for food aid distribution in kenya. **Computers & Operations Research**, Elsevier, v. 56, p. 68–83, 2015. Cited in page 77.

RAWLS, J. Justice as fairness: Political not metaphysical. In: **Equality and Liberty: Analyzing Rawls and Nozick**. [S.l.]: Springer, 1991. p. 145–173. Cited in page 15.

RECHT, J. et al. Malaria in brazil, colombia, peru and venezuela: current challenges in malaria control and elimination. **Malaria journal**, BioMed Central, v. 16, n. 1, p. 1–18, 2017. Cited 2 times in pages 33 and 35.

REIHANEH, M.; GHONIEM, A. A multi-start optimization-based heuristic for a food bank distribution problem. **Journal of the operational research society**, Taylor & Francis, v. 69, n. 5, p. 691–706, 2018. Cited 2 times in pages 79 and 82.

REINHARDT, U. E. Reflections on the meaning of efficiency: can efficiency be separated from equity. **Yale L. & Pol'y Rev.**, HeinOnline, v. 10, p. 302, 1992. Cited in page 15.

REUSKEN, M.; CRUIJSSEN, F.; FLEUREN, H. A food bank supply chain model: Optimizing investments to maximize food assistance. **International Journal of Production Economics**, Elsevier, v. 261, p. 108886, 2023. Cited in page 82.

REZAEI-MALEK, M.; TORABI, S. A.; TAVAKKOLI-MOGHADDAM, R. Prioritizing disaster-prone areas for large-scale earthquakes' preparedness: Methodology and application. **Socio-Economic Planning Sciences**, Elsevier, v. 67, p. 9–25, 2019. Cited 2 times in pages 14 and 15.

ROSE, D.; GUNDERSEN, C.; OLIVEIRA, V. Socio-economic determinants of food insecurity in the united states: Evidence from the sipp and csfii datasets. 1998. Cited 2 times in pages 76 and 91.

ROTTKEMPER, B.; FISCHER, K.; BLECKEN, A. A transshipment model for distribution and inventory relocation under uncertainty in humanitarian operations. **Socio-Economic Planning Sciences**, Elsevier, v. 46, n. 1, p. 98–109, 2012. Cited in page 36.

ROUAMBA, T. et al. Socioeconomic and environmental factors associated with malaria hotspots in the nanoro demographic surveillance area, burkina faso. **BMC public health**, Springer, v. 19, n. 1, p. 1–14, 2019. Cited in page 35.

RUSAKOV, D. A. A misadventure of the correlation coefficient. **Trends in Neurosciences**, Elsevier, v. 46, n. 2, p. 94–96, 2023. Cited in page 52.

SACHS, J.; MALANEY, P. The economic and social burden of malaria. **Nature**, Nature Publishing Group, v. 415, n. 6872, p. 680–685, 2002. Cited in page 27.

SALLES-COSTA, R. et al. Association between socioeconomic factors and food insecurity: a population-based study in the rio de janeiro metropolitan area, brazil. **Revista de Nutrição**, SciELO Brasil, v. 21, p. 99s–109s, 2008. Cited 3 times in pages 76, 77, and 91.

SAMBUICHI, R. H. R. et al. The food acquisition program (paa) as a strategy to face the challenges of covid-19. **Revista de Administração Pública**, SciELO Brasil, v. 54, p. 1079–1096, 2020. Cited in page 78.

SANTOS, E. S. dos; AZEVEDO-RAMOS, C.; GUEDES, M. C. Segurança alimentar de famílias extrativistas de açaí na amazônia oriental brasileira: o caso da ilha das cinzas. **Novos Cadernos NAEA**, v. 24, n. 2, 2021. Cited in page 73.

SANTOS, J. B.; SANTOS, F. d.; MACÊDO, V. Variação da densidade anofélica com o uso de mosquiteiros impregnados com deltametrina em uma área endêmica de malária na amazônia brasileira. **Cadernos de Saúde Pública**, SciELO Public Health, v. 15, p. 281–292, 1999. Cited in page 36.

SCHERF, E. D. L.; SILVA, M. V. Viana da. Brazil's yanomami health disaster: addressing the public health emergency requires advancing criminal accountability. **Frontiers in Public Health**, Frontiers, v. 11, p. 1166167, 2023. Cited in page 72.

SEN, A. **On economic inequality Clarendon Press**. [S.l.]: Oxford, 1973. Cited 3 times in pages 15, 16, and 79.

SEN, A. **Inequality reexamined**. [S.l.]: Harvard university press, 1995. Cited 3 times in pages 15, 19, and 75.

SHAH, A. **Food Aid**. 2007. <https://www.globalissues.org/article/748/food-aid>. Accessed: 2024-03-11. Cited in page 71.

SIMPSON, J. A.; WEINER, E. S. et al. The oxford english dictionary. **(No Title)**, 1989. Cited in page 79.

SINGH, M. P. et al. Socioeconomic determinants of community knowledge and practice in relation to malaria in high-and low-transmission areas of central india. **Journal of Biosocial Science**, Cambridge University Press, v. 52, n. 3, p. 317–329, 2020. Cited in page 35.

SMITH, K. **Environmental hazards: assessing risk and reducing disaster**. [S.l.]: Routledge, 2013. Cited 4 times in pages 14, 21, 27, and 52.

SOLAK, S.; SCHERRER, C.; GHONIEM, A. The stop-and-drop problem in nonprofit food distribution networks. **Annals of Operations Research**, Springer, v. 221, p. 407–426, 2014. Cited 2 times in pages 16 and 82.

SONKO, S. T. et al. Does socio-economic status explain the differentials in malaria parasite prevalence? evidence from the gambia. **Malaria Journal**, BioMed Central, v. 13, n. 1, p. 1–12, 2014. Cited 2 times in pages 33 and 35.

SOUZA, B. F. d. N. J. d. et al. Demographic and socioeconomic conditions associated with food insecurity in households in campinas, sp, brazil. **Revista de Nutrição**, SciELO Brasil, v. 29, p. 845–857, 2016. Cited in page 70.

STAUFFER, J. M. et al. Achieving equitable food security: How can food bank mobile pantries fill this humanitarian need. **Production and Operations Management**, Wiley Online Library, v. 31, n. 4, p. 1802–1821, 2022. Cited 2 times in pages 79 and 82.

STONE, D. A. **Policy Paradox: The Art of Political Decision Making**. New York, NY: W.W. Norton, 1997. Cited in page 79.

STRESMAN, G.; BOUSEMA, T.; COOK, J. Malaria hotspots: is there epidemiological evidence for fine-scale spatial targeting of interventions? **Trends in parasitology**, Elsevier, v. 35, n. 10, p. 822–834, 2019. Cited in page 34.

SU, S. et al. Peri-urban vegetated landscape pattern changes in relation to socioeconomic development. **Ecological Indicators**, Elsevier, v. 46, p. 477–486, 2014. Cited in page 52.

SUCHARITHA, R. S.; LEE, S. New policy design for food accessibility to the people in need. **arXiv preprint arXiv:1909.08648**, 2019. Cited in page 82.

TIWARI, R.; AUSMAN, L.; AGHO, K. Determinantes da baixa estatura e baixa estatura severa entre menores de cinco anos: evidências da pesquisa de demografia e saúde do nepal de 2011. **BMC Pediatrics**, BioMed Central, v. 14, p. 239, 2014. Disponível em: <https://doi.org/10.1186/1471-2431-14-239>. Cited in page 91.

TOFIGHI, S.; TORABI, S. A.; MANSOURI, S. A. Humanitarian logistics network design under mixed uncertainty. **European journal of operational research**, Elsevier, v. 250, n. 1, p. 239–250, 2016. Cited 2 times in pages 14 and 15.

TSELIOS, V.; TOMPKINS, E. L. Can we prevent disasters using socioeconomic and political policy tools? **International Journal of Disaster Risk Reduction**, Elsevier, v. 51, p. 101764, 2020. Cited in page 35.

TUSTING, L. S. et al. Housing and child health in sub-saharan africa: A cross-sectional analysis. **PLoS medicine**, Public Library of Science San Francisco, CA USA, v. 17, n. 3, p. e1003055, 2020. Cited in page 32.

TUSTING, L. S. et al. Measuring socioeconomic inequalities in relation to malaria risk: a comparison of metrics in rural uganda. **The American journal of tropical medicine and hygiene**, The American Society of Tropical Medicine and Hygiene, v. 94, n. 3, p. 650, 2016. Cited 2 times in pages 32 and 35.

TUSTING, L. S. et al. Socioeconomic development as an intervention against malaria: a systematic review and meta-analysis. **The Lancet**, Elsevier, v. 382, n. 9896, p. 963–972, 2013. Cited 2 times in pages 32 and 35.

UN. **Transforming our world: the 2030 Agenda for Sustainable Development**. New York, NY, USA: [s.n.], 2015. urlhttps://sustainabledevelopment.un.org/post2015/transformingourworld. Accessed: 2024-03-11. Cited 2 times in pages 70 and 75.

USAID. **USAID Food Assistance Programs Authorized by the Food for Peace Act**. 2023. <https://www.usaid.gov/>. U.S. Agency for International Development. Cited in page 77.

ÜSTÜN, T. B. et al. The international classification of functioning, disability and health: a new tool for understanding disability and health. **Disability and rehabilitation**, Taylor & Francis, v. 25, n. 11-12, p. 565–571, 2003. Cited in page 13.

VALLE, D.; CLARK, J. Conservation efforts may increase malaria burden in the brazilian amazon. **PLoS One**, Public Library of Science, v. 8, n. 3, p. e57519, 2013. Cited 4 times in pages 32, 33, 34, and 35.

VALLE, D.; LIMA, J. M. T. Large-scale drivers of malaria and priority areas for prevention and control in the brazilian amazon region using a novel multi-pathogen geospatial model. **Malaria journal**, BioMed Central, v. 13, n. 1, p. 1–13, 2014. Cited 4 times in pages 33, 34, 35, and 47.

VASCONCELOS, F. D. A. G. D. Combate à fome no brasil: uma análise histórica de vargas a lula. **Revista De Nutrição**, v. 18, n. 4, 2005. Cited in page 73.

VOSSEN, T. et al. A general approach to equity in traffic flow management and its application to mitigating exemption bias in ground delay programs. **Air Traffic Control Quarterly**, American Institute of Aeronautics and Astronautics, Inc., v. 11, n. 4, p. 277–292, 2003. Cited in page 80.

WANG, L.; FANG, L.; HIPEL, K. W. On achieving fairness in the allocation of scarce resources: Measurable principles and multiple objective optimization approaches. **IEEE Systems Journal**, IEEE, v. 1, n. 1, p. 17–28, 2007. Cited in page 80.

WBG. **Joint Statement by the Heads of the Food and Agriculture Organization, International Monetary Fund, World Bank Group, World Food Programme and World Trade Organization on the Global Food and Nutrition Security Crisis**. 2023. urlhttps://www.worldbank.org/en/news/statement/2023/02/08/joint-statement-by-the-heads-of-the-food-and-agriculture-organization-international-monetary-fund-world-bank-group-world-food-programme-and-world-trade-organization-on-the-global-food-and-nutrition-security-crisis. Cited in page 71.

WERE, V. et al. Socioeconomic health inequality in malaria indicators in rural western kenya: evidence from a household malaria survey on burden and care-seeking behaviour. **Malaria journal**, BioMed Central, v. 17, n. 1, p. 1–10, 2018. Cited in page 32.

WFP. **Annual Performance Report for 2020**. 2020. <https://www.wfp.org/publications/annual-performance-report-2020>. Available from: World Food Programme. Cited in page 14.

WFP. **WFP Management Plan 2024-2026**. 2024. <https://www.wfp.org/publications/wfp-management-plan-2024-2026>. Accessed: 2024-01-27. Cited in page 78.

WHO. **WHO Guidelines for malaria**. [S.l.]: World Health Organization, 2022. Geneva: World Health Organization. Available in: https://www.who.int/publications/i/item/guidelines-for-malaria. Cited in page 38.

WINSTON, W. L. **Operations research: applications and algorithm**. [S.l.]: Thomson Learning, Inc., 2004. Cited in page 24.

WONG, C. Indicators at the crossroads: ideas, methods and applications. **Town Planning Review**, Liverpool University Press, v. 74, n. 3, p. 253–279, 2003. Cited in page 51.

WONG, C. **Indicators for urban and regional planning: the interplay of policy and methods**. [S.l.]: Routledge, 2006. Cited 2 times in pages 20 and 34.

WORRALL, E.; BASU, S.; HANSON, K. Is malaria a disease of poverty? a review of the literature. **Tropical Medicine & International Health**, Wiley Online Library, v. 10, n. 10, p. 1047–1059, 2005. Cited 2 times in pages 27 and 32.

WORRALL, E. et al. Coverage outcomes (effects), costs, cost-effectiveness, and equity of two combinations of long-lasting insecticidal net (llin) distribution channels in kenya: a two-arm study under operational conditions. **BMC public health**, Springer, v. 20, n. 1, p. 1–16, 2020. Cited in page 29.

XIAO, R.; WANG, G.; WANG, M. Transportation disadvantage and neighborhood sociodemographics: A composite indicator approach to examining social inequalities. **Social Indicators Research**, Springer, v. 137, p. 29–43, 2018. Cited in page 52.

YADAV, K. et al. Socio-economic determinants for malaria transmission risk in an endemic primary health centre in assam, india. **Infectious diseases of poverty**, BioMed Central, v. 3, n. 1, p. 1–8, 2014. Cited 5 times in pages 27, 32, 33, 35, and 36.

YANG, D. et al. Drinking water and sanitation conditions are associated with the risk of malaria among children under five years old in sub-saharan africa: A logistic regression model analysis of national survey data. **Journal**

of advanced research, Elsevier, v. 21, p. 1–13, 2020. Cited 2 times in pages 33 and 35.

YOUNG, A. J. et al. A practical approach for geographic prioritization and targeting of insecticide-treated net distribution campaigns during public health emergencies and in resource-limited settings. **Malaria journal**, BioMed Central, v. 21, n. 1, p. 1–13, 2022. Cited in page 34.

YUKICH, J. et al. Sustaining llin coverage with continuous distribution: the school net programme in tanzania. **Malaria journal**, BioMed Central, v. 19, n. 1, p. 1–12, 2020. Cited in page 29.

ZOHA, N.; HASNAIN, T.; IVY, J. Tradeoff between geographic and demographic equity in food bank operations. In: **IIE Annual Conference Proceedings**. [S.l.: s.n.], 2022. Cited 2 times in pages 81 and 82.

ZULU, J. M. et al. Increased fairness in priority setting processes within the health sector: the case of kapiri-mposhi district, zambia. **BMC health services research**, Springer, v. 14, p. 1–12, 2014. Cited in page 15.

A
Questionnaire (Paper 1)

1. Initial information

   a) Organization
   b) Current position
   c) Country
   d) City/State

2. How long have you been working with malaria-related activities?

   a) 0-1 year
   b) 1-3 years
   c) 3-5 years
   d) 5+ years

3. What type of resource(s) does your organization adopt in malaria prevention and control?

   a) Insecticide-treated bed nets (ITN)
   b) Vaccine
   c) Indoor Residual Spraying (IRS)
   d) Medicines
   e) Others (specify)

4. Among the interventions to prevent and control malaria, how important do you think the distribution of bed nets is?

   a) Extremely important
   b) Very important
   c) Moderately important
   d) Not as important
   e) Not important at all

5. How do you estimate the number of bed nets to be distributed? That is, how is demand estimated?

6. How is demand estimated for specific types of bed nets (e.g., single or double net)?

7. Are there any criteria that prioritize some locations over others for receiving bed nets?

   a) Yes
   b) No

8. If the previous answer was 'yes', what are the criteria to prioritize the bed net distribution?

9. Which epidemiological factors are important to consider when selecting municipalities with the highest priority for malaria? You can choose more than one option.

   a) Number of malaria cases
   b) % of malaria cases caused by P. falciparum
   c) Malaria cases registered within 7 days
   d) Malaria cases that started treatment within 48 hours
   e) Other (specify)

10. As malaria is a disease generally associated with poverty, which socioeconomic factors are important to consider when selecting municipalities with the highest priority for malaria? You can choose more than one option.

    a) Gini index
    b) Human Development Index (HDI)
    c) % of people in households with inadequate WASH conditions
    d) Per capita income
    e) Education level
    f) Unemployment rate
    g) Illiteracy rate
    h) Other (specify)

11. Which environmental factors are important when selecting municipalities with the highest priority for malaria? You can choose more than one option.

a) Presence of mines
b) Indigenous land
c) Forest coverage
d) Length of the rainy season
e) Other (specify)

12. When a location is prioritized for receiving bed nets, is the demand in that location 100% met?

    a) Always
    b) Frequently
    c) Occasionally
    d) Rarely
    e) Never

13. If the demand is not 100% met, what is the minimum acceptable service level?

    a) Meet at least 90% of demand
    b) Meet at least 80% of demand
    c) Meet at least 70% of demand
    d) Meet at least 60% of demand

14. Does your organization have a warehouse to store the bed nets?

    a) Yes
    b) No

15. If the previous answer was positive, are these warehouses fixed or temporary?

    a) Fixed
    b) Temporary

16. What is the flow of the bed nets after being withdrawn from warehouses?

17. How many warehouses for storing bed nets exist in your region of operation?

18. What is the minimum and maximum capacity of each warehouse/depot?

19. What is the logistic modal used in the distribution of bed nets?

20. What is the capacity (in units of bed nets) of these logistical modes?

21. How many vehicles are available for bed net distribution?

22. Is there any training for the population about the correct use and disposal of the bed nets?

    a) Yes
    b) No

23. If the previous answer was 'yes', what is the training frequency?

24. If the answer to question 23 was 'no', do you consider it important to develop training on the correct use and disposal of bed nets?

    a) Yes
    b) No

25. What are the main costs incurred in bed net planning and distribution? You can choose more than one option.

    a) Acquisition cost
    b) Inventory cost
    c) Transport cost
    d) Opening cost

26. How are inventory and transport costs of bed nets estimated?

27. What are the main suppliers of bed nets?

28. What is the role of Municipal Health Departments in bed net planning and distribution?

29. Is there any planning and monitoring for replacing bed nets in households?

30. How often are bed nets replaced?

31. What are the challenges in the last mile distribution that is, distribution to households?

32. How do the reverse logistics of bed nets work?

B
Supplementary tables and semi-structured interview (Paper 2)

B.1
Food baskets demand by population group and state

Table B.1: Demand by population group and state.

State	Extractivist	Indigenous	Quilombola
Acre	637	3731	0
Alagoas	610	1941	2201
Amapá	101	1038	304
Amazonas	9557	38723	268
Bahia	290	6736	25377
Ceará	0	2384	756
Distrito Federal	0	0	0
Espírito Santo	0	0	92
Goiás	0	0	3095
Maranhão	10782	5014	35834
Mato Grosso	168	6523	1142
Mato Grosso do Sul	0	13885	0
Minas Gerais	132	0	3569
Pará	10932	4386	13484
Paraíba	0	1689	1175
Paraná	0	2346	298
Pernambuco	270	7556	7546
Piauí	0	0	2481
Rio de Janeiro	0	55	199
Rio Grande do Norte	0	317	588
Rio Grande do Sul	191	3383	0
Rondônia	329	1354	138
Roraima	92	13480	0
Santa Catarina	0	1648	0
São Paulo	0	119	65
Sergipe	0	0	1917
Tocantins	1242	2453	454
TOTAL	35.333	118.761	100.983
% of the total	13.9%	46.6%	39.6%

B.2
Supplementary tables for B =250k

B.2.1
Allocation results among areas

Table B.2: Benchmark x Geo-equity Model Results per areas

Benchmark x Geo-equity Model Results per areas												
Counties	**Benchmark model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0.0$
AC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	85.42%
AL	100%	100%	100%	100%	100%	71.3%	75.69%	80.09%	84.49%	100%	100%	87.16%
AP	100%	100%	100%	100%	84.96%	100%	100%	100%	93%	100%	96.95%	93%
AM	100%	100%	99.5%	99.55%	99.61%	100%	99.71%	100%	100%	99.87%	100%	80.31%
BA	100%	96.94%	100%	100%	100%	100%	100%	97.3%	100%	100%	100%	99.11%
CE	100%	100%	78.22%	100%	100%	100%	100%	89.65%	100%	100%	96.53%	100%
ES	100%	100%	9.78%	100%	100%	100%	100%	57.61%	67.39%	100%	85.87%	100%
GO	100%	0%	26.46%	100%	100%	100%	100%	57%	100%	100%	85.49%	100%
MA	100%	100%	100%	100%	100%	98.09%	100%	100%	100%	98.82%	92.81%	79.12%
MT	100%	100%	100%	100%	100%	100%	100%	100%	100%	96.5%	97.89%	97.86%
MS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
MG	100%	100%	100%	100%	100%	100%	62.12%	58.52%	100%	76.84%	100%	96.43%
PA	100%	100%	100%	92.94%	100%	100%	100%	100%	88.12%	88.75%	100%	62.04%
PB	100%	100%	100%	66.79%	70.67%	100%	100%	100%	100%	100%	94.06%	100%
PR	100%	100%	100%	100%	91.94%	100%	100%	100%	96.26%	100%	98.37%	100%
PE	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	98.24%
PI	30.83%	100%	100%	100%	32.12%	38.01%	47.52%	100%	100%	100%	100%	100%
RJ	21.65%	21.65%	100%	36.61%	44.09%	100%	100%	100%	100%	100%	88.98%	100%
RN	35.03%	35.03%	100%	100%	53.59%	100%	100%	100%	100%	100%	100%	100%
RS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	94.66%
RO	92.42%	92.42%	100%	93.9%	100%	100%	96.05%	100%	97.47%	98.19%	100%	81.93%
RR	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	99.32%
SC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SP	64.67%	64.67%	68.48%	71.74%	100%	100%	100%	85.33%	100%	100%	100%	100%
SE	0%	100%	9.55%	19.04%	28.53%	38.03%	47.52%	100%	66.51%	100%	85.5%	100%
TO	89.06%	100%	100%	100%	100%	100%	100%	100%	100%	100%	98.43%	70.07%
Solve Time	0.003	0.025	0.05	0.049	0.03	0.05	0.04	0.054	0.05	0.005	0.072	0.418
Std	0.2869	0.2664	0.2742	0.203	0.222	0.1709	0.1571	0.1376	0.0919	0.0486	0.0488	0.1034
Mean	85.91%	88.87%	88.15%	91.56%	88.67%	94.05%	93.41%	93.29%	95.89%	98.42%	96.96%	93.26%
Objective Function	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	123456.6
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	87.9%

Table B.3: Benchmark x Pop-equity Model Results per areas

Benchmark x Pop-equity Model Results per areas												
Counties	**Benchmark model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
AC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
AL	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
AP	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
AM	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
BA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
CE	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
ES	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
GO	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
MA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
MT	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
MS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
MG	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
PA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
PB	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
PR	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
PE	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
PI	30.83%	30.83%	30.83%	30.83%	30.83%	30.83%	30.83%	30.83%	30.83%	30.83%	30.83%	-
RJ	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	-
RN	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	-
RS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
RO	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	-
RR	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
SC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
SP	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	-
SE	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-
TO	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	-
Solve Time	0.003	0.016	0	0	0	0	0	0	0	0.004	0	-
Std	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	0.2869	-
Mean	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	85.91%	-
Objective Function	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	-
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-

Table B.4: Benchmark x Overall-equity Model Results per areas

Benchmark x Overall-equity Model Results per areas												
Counties	**Benchmark model**	$\boldsymbol{\delta = 1}$	$\boldsymbol{\delta = 0.9}$	$\boldsymbol{\delta = 0.8}$	$\boldsymbol{\delta = 0.7}$	$\boldsymbol{\delta = 0.6}$	$\boldsymbol{\delta = 0.5}$	$\boldsymbol{\delta = 0.4}$	$\boldsymbol{\delta = 0.3}$	$\boldsymbol{\delta = 0.2}$	$\boldsymbol{\delta = 0.1}$	$\boldsymbol{\delta = 0}$
AC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
AL	100%	100%	100%	100%	100%	71.3%	75.69%	80.09%	100%	100%	100%	0%
AP	100%	78.93%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
AM	100%	100%	99.5%	100%	100%	99.66%	99.71%	99.76%	100%	100%	100%	0%
BA	100%	98.16%	100%	100%	100%	100%	100%	97.84%	100%	100%	100%	0%
CE	100%	100%	78.22%	100%	82.8%	100%	100%	89.65%	100%	100%	100%	0%
ES	100%	0%	9.78%	100%	29.35%	100%	100%	57.61%	100%	100%	100%	0%
GO	100%	0%	43.65%	100%	28.5%	100%	100%	57%	100%	100%	100%	0%
MA	100%	100%	100%	100%	97.21%	97.88%	100%	100%	100%	100%	98.13%	0%
MT	100%	100%	100%	100%	89.58%	100%	92.35%	100%	100%	100%	100%	0%
MS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
MG	100%	100%	100%	100%	100%	100%	96.76%	58.52%	100%	100%	100%	0%
PA	100%	100%	100%	84.33%	100%	100%	100%	100%	84.31%	88.75%	93.2%	0%
PB	100%	100%	100%	100%	100%	74.58%	78.46%	100%	100%	100%	94.06%	0%
PR	100%	100%	100%	90.89%	100%	93.04%	100%	100%	96.26%	97.31%	98.37%	0%
PE	100%	100%	100%	100%	100%	100%	100%	100%	97.88%	89.12%	92.87%	0%
PI	30.83%	100%	100%	100%	100%	38.01%	47.52%	100%	100%	100%	85.49%	0%
RJ	21.65%	21.65%	100%	36.61%	100%	100%	59.06%	100%	74.02%	81.5%	88.98%	0%
RN	35.03%	35.03%	41.22%	100%	100%	100%	100%	100%	100%	100%	90.61%	0%
RS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
RO	92.42%	92.42%	100%	93.9%	100%	100%	100%	96.76%	97.47%	98.19%	98.9%	0%
RR	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
SC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
SP	64.67%	64.67%	68.48%	71.74%	100%	100%	81.52%	85.33%	88.59%	91.85%	95.11%	0%
SE	0%	100%	9.55%	100%	100%	100%	47.52%	100%	100%	100%	85.5%	0%
TO	89.06%	100%	100%	100%	100%	100%	100%	100%	100%	100%	98.43%	0%
Solve Time	0.003	0.025	0.045	0.048	0.044	0.046	0.049	0.054	0.041	0.064	0.141	0.003
Std	0.2869	0.3142	0.2754	0.1331	0.1898	0.1353	0.1613	0.1371	0.0598	0.0462	0.0459	0.0
Mean	85.91%	84.26%	86.55%	95.29%	93.36%	95.17%	91.48%	93.18%	97.64%	97.95%	96.91%	0%
Objective Function	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	141283.5	0
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%

Table B.5: Linear Pop-equity Model Results per areas

Linear Pop-equity Model Results	
Counties	$\boldsymbol{\delta = 0}$
AC	100%
AL	100%
AP	100%
AM	100%
BA	100%
CE	100%
ES	100%
GO	100%
MA	100%
MT	100%
MS	100%
MG	100%
PA	100%
PB	100%
PR	100%
PE	100%
PI	100%
RJ	100%
RN	100%
RS	100%
RO	100%
RR	100%
SC	100%
SP	100%
SE	18.83%
TO	15.13%
Std	0.221
Mean	84.26%
Objective Function	107714.3
Effectiveness	100%

B.2.2
Allocation results among populations

Table B.6: Benchmark, Geo, Pop and Overall equity Model Results per populations

Geo-equity Model Results for B = 250k												
Population	**Benchmark model**	$\boldsymbol{\delta = 1}$	$\boldsymbol{\delta = 0.9}$	$\boldsymbol{\delta = 0.8}$	$\boldsymbol{\delta = 0.7}$	$\boldsymbol{\delta = 0.6}$	$\boldsymbol{\delta = 0.5}$	$\boldsymbol{\delta = 0.4}$	$\boldsymbol{\delta = 0.3}$	$\boldsymbol{\delta = 0.2}$	$\boldsymbol{\delta = 0.1}$	$\boldsymbol{\delta = 0}$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
Indigenous	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Quilombola	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	100%
Std	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.4714
Mean	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	66.67%
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	87.9%
Population-equity Model Results for B = 250k												
Population	**Benchmark model**	$\boldsymbol{\delta = 1}$	$\boldsymbol{\delta = 0.9}$	$\boldsymbol{\delta = 0.8}$	$\boldsymbol{\delta = 0.7}$	$\boldsymbol{\delta = 0.6}$	$\boldsymbol{\delta = 0.5}$	$\boldsymbol{\delta = 0.4}$	$\boldsymbol{\delta = 0.3}$	$\boldsymbol{\delta = 0.2}$	$\boldsymbol{\delta = 0.1}$	$\boldsymbol{\delta = 0}$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
Indigenous	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
Quilombola	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	-
Std	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	-
Mean	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	-
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
Overall-equity Model Results for B = 250k												
Population	**Benchmark model**	$\boldsymbol{\delta = 1}$	$\boldsymbol{\delta = 0.9}$	$\boldsymbol{\delta = 0.8}$	$\boldsymbol{\delta = 0.7}$	$\boldsymbol{\delta = 0.6}$	$\boldsymbol{\delta = 0.5}$	$\boldsymbol{\delta = 0.4}$	$\boldsymbol{\delta = 0.3}$	$\boldsymbol{\delta = 0.2}$	$\boldsymbol{\delta = 0.1}$	$\boldsymbol{\delta = 0}$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
Indigenous	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
Quilombola	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	94.97%	0%
Std	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0
Mean	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	98.32%	0%
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%

Table B.7: Linear Pop-equity Model Results per areas

Linear Population Equity Model Results for B = 250k	
Population	$\boldsymbol{\delta = 0}$
Extractivist	98.01%
Indigenous	98.01%
Quilombola	98.01%
Std	0
Mean	98.01%
Effectiveness	100%

B.3
Supplementary tables for B =150k

B.3.1
Allocation results per areas

Table B.8: Benchmark x Geo-equity Model Results per areas

Benchmark x Geo-equity Model Results per areas												
Counties	**Benchmark Model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0.0$
AC	100%	100%	100%	100%	54.69%	100%	100%	100%	100%	80.56%	100%	14.58%
AL	53.68%	53.68%	16.79%	53.68%	24.68%	53.68%	32.58%	36.51%	40.45%	53.68%	53.68%	59.15%
AP	78.93%	78.93%	78.93%	20.93%	27.86%	78.93%	41.79%	78.93%	78.93%	78.93%	78.93%	28.07%
AM	99.45%	99.45%	94.63%	99.45%	99.45%	91.02%	99.45%	99.45%	99.45%	97.03%	97.06%	20.24%
BA	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	12.94%	21.68%	21.68%	21.68%	79.21%
CE	75.92%	75.92%	75.92%	14.68%	75.92%	75.92%	36.66%	75.92%	75.92%	58.66%	75.92%	24.08%
ES	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
GO	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
MA	30.59%	30.59%	30.59%	28.01%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	90.29%
MT	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	16.72%
MS	100%	100%	100%	100%	100%	100%	96.62%	100%	100%	100%	100%	0%
MG	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	100%
PA	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	49.72%	53.18%	84.77%
PB	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	41.03%
PR	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	68.57%	88.73%	11.27%
PE	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.85%
PI	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
RJ	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	78.35%
RN	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	64.97%
RS	100%	100%	100%	100%	100%	100%	100%	87.55%	100%	100%	87.6%	5.34%
RO	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	82.7%	25.65%
RR	100%	100%	100%	100%	100%	100%	100%	100%	74.47%	100%	86.99%	0.68%
SC	7.65%	7.65%	100%	100%	100%	100%	48.3%	100%	100%	100%	86.95%	0%
SP	0%	0%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	64.67%	56.52%	35.33%
SE	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
TO	29.93%	29.93%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	81.32%	40.88%
Solve Time	0	0	0.004	0.015	0.01	0.013	0.017	0.017	0.025	0.018	0.023	0.33
Std	0.3806	0.3806	0.3764	0.3805	0.3658	0.3668	0.358	0.3711	0.3634	0.3557	0.3479	0.3593
Mean	49.53%	49.53%	56.24%	53.16%	53.02%	57.52%	51.97%	56.37%	56.35%	55.43%	55.29%	48.9%
Objective Function	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	76478.071
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	91%

Table B.9: Benchmark x Pop-equity Model Results per areas

Benchmark x Pop-equity Model Results per areas												
Counties	**Benchmark model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
AC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
AL	53.68%	53.68%	53.68%	53.68%	53.68%	53.68%	53.68%	53.68%	100%	100%	100%	-
AP	78.93%	78.93%	78.93%	78.93%	78.93%	78.93%	78.93%	78.93%	100%	100%	100%	-
AM	99.45%	99.45%	99.45%	99.45%	99.45%	99.45%	99.45%	99.45%	100%	100%	100%	-
BA	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	57.52%	100%	100%	-
CE	75.92%	75.92%	75.92%	75.92%	75.92%	75.92%	75.92%	75.92%	75.92%	100%	100%	-
ES	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%	-
GO	0%	0%	0%	0%	0%	0%	0%	0%	0%	12.47%	100%	-
MA	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	54.4%	-
MT	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	-
MS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	30.2%	-
MG	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	-
PA	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	37.96%	-
PB	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	32.19%	0%	-
PR	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	0%	0%	-
PE	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	1.76%	1.76%	-
PI	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-
RJ	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	21.65%	0%	0%	-
RN	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	35.03%	0%	0%	-
RS	100%	100%	100%	100%	100%	100%	100%	100%	100%	5.34%	5.34%	-
RO	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	92.42%	49.7%	18.07%	18.07%	-
RR	100%	100%	100%	100%	100%	100%	100%	100%	0.68%	0.68%	0.68%	-
SC	7.65%	7.65%	7.65%	7.65%	7.65%	7.65%	7.65%	7.65%	0%	0%	0%	-
SP	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-
SE	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-
TO	29.93%	29.93%	29.93%	29.93%	29.93%	29.93%	29.93%	29.93%	29.93%	29.93%	29.93%	-
Solve Time	0	0	0	0	0	0.003	0	0.017	0	0	0.014	-
Std	0.3806	0.3806	0.3806	0.3806	0.3806	0.3806	0.3806	0.3806	0.3914	0.4351	0.4388	-
Objective Function	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85681.94	85437.14	85192.34	-
Mean	49.53%	49.53%	49.53%	49.53%	49.53%	49.53%	49.53%	49.53%	47.76%	41.28%	41.05%	-
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-

Table B.10: Benchmark x Overall-equity Model Results per areas

Benchmark x Overall-equity Model Results per areas												
Counties	**Benchmark model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
AC	100%	100%	100%	100%	100%	100%	100%	100%	65.09%	88.19%	70.17%	0%
AL	53.68%	53.68%	16.79%	53.68%	53.68%	53.68%	53.68%	53.68%	41.62%	64.18%	61.81%	0%
AP	78.93%	78.93%	14%	78.93%	78.93%	78.93%	78.93%	78.93%	53.43%	76.3%	63.89%	0%
AM	99.45%	99.45%	99.45%	99.45%	99.45%	99.45%	99.45%	99.45%	91.74%	71.44%	62.88%	0%
BA	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	21.68%	29.49%	46.15%	52.29%	0%
CE	75.92%	75.92%	31.21%	75.92%	75.92%	75.92%	75.92%	75.92%	47.32%	73.79%	61.02%	0%
ES	0%	0%	0%	0%	0%	0%	0%	0%	18.48%	34.78%	47.83%	0%
GO	0%	0%	0%	0%	0%	0%	0%	0%	9.98%	34.9%	48.34%	0%
MA	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	30.59%	43.45%	48.49%	56.99%	0%
MT	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	85.42%	86.88%	78.99%	63.4%	0%
MS	100%	100%	100%	81.22%	79.94%	78.66%	77.37%	76.1%	100%	86.17%	65.09%	0%
MG	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	3.57%	14.62%	37.23%	50.18%	0%
PA	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	53.18%	57.85%	61.97%	66.39%	0%
PB	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	58.97%	39%	60.37%	54.61%	0%
PR	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	88.73%	53.59%	79.08%	62.22%	0%
PE	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	50.91%	60%	41.43%	53.17%	0%
PI	0%	0%	0%	0%	0%	0%	0%	0%	18.5%	23.3%	39.58%	0%
RJ	21.65%	21.65%	21.65%	4.33%	6.3%	8.66%	10.63%	12.6%	27.17%	31.1%	44.88%	0%
RN	35.03%	35.03%	35.03%	6.85%	10.17%	13.59%	17.02%	20.33%	32.71%	35.36%	48.51%	0%
RS	100%	100%	100%	100%	100%	100%	100%	100%	61.3%	59.74%	55.76%	0%
RO	92.42%	92.42%	92.42%	32.45%	39.65%	46.79%	53.98%	61.18%	63.43%	62.6%	60.74%	0%
RR	100%	100%	100%	100%	100%	100%	100%	100%	59.39%	57.74%	53.58%	0%
SC	7.65%	7.65%	100%	100%	100%	100%	100%	100%	59.16%	57.46%	53.28%	0%
SP	0%	0%	64.67%	12.5%	19.02%	25%	31.52%	37.5%	45.11%	46.2%	48.91%	0%
SE	0%	0%	0%	0%	0%	0%	0%	0%	18.47%	23.32%	39.59%	0%
TO	29.93%	29.93%	89.06%	89.06%	89.06%	89.06%	89.06%	89.06%	66.91%	66.47%	65.77%	0%
Solve Time	0	0.014000177	0.023999929	0.023000002	0.019000053	0.019999981	0.018000126	0.023000002	0.180999994	0.085999966	0.095999956	0.078999996
Objective Function	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85916.688	85681.94	85437.14	85192.34	0
Std	0.3806	0.3806	0.3839	0.3837	0.3775	0.3722	0.3678	0.3645	0.2327	0.1877	0.0817	0.0
Mean	49.53%	49.53%	52.21%	51.06%	51.74%	52.42%	53.1%	53.76%	48.64%	55.64%	55.8%	0%
Effectiveness	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%

B.3.2 Allocation results per populations

Table B.11: Benchmark, Geo, Pop, Overall-equity Model Results per populations

Overall Equity Model Results for B = 150k												
Population	**Benchmark model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
Indigenous	97%	96.55%	96.55%	96.55%	96.55%	96.55%	96.55%	96.55%	84.44%	71.81%	59.18%	0%
Quilombola	0%	0%	0%	0%	0%	0%	0%	0%	14.24%	29.10%	43.95%	0%
Std	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.37303	0.29147	0.2366	0
Mean	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	66.23%	66.97%	67.71%	0%
Geo-equity Model Results for B = 150k												
Population	**Benchmark model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Indigenous	97%	97%	97%	97%	97%	97%	97%	97%	97%	97%	97%	0%
Quilombola	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
Std	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.47140
Mean	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	66.67%
Population-equity Model Results for B = 150k												
Population	**Benchmark model**	$\delta = 1$	$\delta = 0.9$	$\delta = 0.8$	$\delta = 0.7$	$\delta = 0.6$	$\delta = 0.5$	$\delta = 0.4$	$\delta = 0.3$	$\delta = 0.2$	$\delta = 0.1$	$\delta = 0$
Extractivist	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
Indigenous	97%	96.55%	96.55%	96.55%	96.55%	96.55%	96.55%	96.55%	84.44%	71.81%	59.18%	-
Quilombola	0%	0%	0%	0%	0%	0%	0%	0%	14.24%	29.10%	43.95%	-
Std	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.46349	0.37303	0.29147	0.2366	-
Mean	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	65.51%	66.23%	66.97%	67.71%	-

B.4 Structured Interview with the CONAB

B.4.1
Selection of Families and Locations

1. How are the families or locations selected to receive the basic food baskets? Are there specific criteria used to prioritize certain areas or families?

2. What is the estimated duration of supplies within these baskets, and for a family comprising how many members? Additionally, how many food baskets are allocated per family?

B.4.2
Storage and Distribution

3. Where do the purchased food baskets, or individual items within them, get stored prior to distribution? Is there an associated cost for storing or managing these food baskets?

4. How many warehouses are there per state, and what is their location? Would it be possible to obtain data on the storage capacity of the warehouses?

5. In cases where CONAB is responsible for the distribution of the food baskets, does it have its own vehicle fleet? What is the capacity and type of the fleet?

6. Is distribution exclusively carried out via road transportation, including in the North Region?

B.4.3
Allocation and Challenges

7. What locations are supposed to receive the baskets? Would it be possible to have detailed data on these locations, such as location and number of people/families served per area?

8. How is the process of allocation and distribution of these food baskets? Describe it, please.

9. What are the main challenges CONAB faces in the food basket distribution program to specific traditional peoples?