POMS

Original Article

Production and Operations Management
2025, Vol. 34(1) 120–141
© The Author(s) 2024
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/10591478241279247
journals.sagepub.com/home/pao
Sage

Long-Lasting Insecticidal Net Campaigns for Malaria Control Considering Prioritization and Equity

Fabíola Negreiros de Oliveira[1], Douglas Alem[2], Fabricio Oliveira[3] and Adriana Leiras[1]

Abstract

Malaria remains a significant public health concern in several developing countries. Tropical weather, coupled with poor environmental and socioeconomic conditions, increases mosquito activity and disease transmission in impoverished nations. The most effective strategy to prevent and control malaria is the use of long-lasting insecticidal nets, or LLINs. Ensuring that LLINs are effectively and equitably distributed to those who need them most is crucial yet challenging, especially since financial and health resources are scarce in endemic countries. Through a real-world case study conducted in the Brazilian Amazon, which accounts for 99% of malaria cases in Brazil, we propose a Malaria Vulnerability Index (MVI). This composite index encompasses epidemiological, socioeconomic, and environmental factors. Using the MVI, we developed a prioritization-based location-allocation model to maximize the benefits of targeting the most vulnerable municipalities for malaria interventions. Our mathematical model relies on discrete coverage levels, which makes the allocation of LLINs more flexible while ensuring community-wide protection. We also explore the theoretical relationship between our proposed model and classical demand covering problems. Finally, we discuss some approaches to delivering more equitable solutions by minimizing the number of underserved areas. Our results include comparisons between various malaria interventions and provide practical insights. In particular, we show that we can drastically reduce the number of underserved areas without compromising the effectiveness of the LLINs allocation through lexicographic optimization. The results also reveal that with investment levels up to 50% of the ideal, we can fully protect the endemic area after 2 years of successive interventions.

Keywords

Malaria, Location-Allocation With Discrete Coverage Levels, Prioritization, Vulnerability, Equity

Date received 3 February 2023; accepted 10 August 2024 after three revisions

Handling Editor: Sushil Gupta

1 Introduction

Malaria is an infectious and life-threatening disease caused by parasites, transmitted to people through the bites of infected mosquitoes. It is endemic in several tropical and subtropical countries and is predominantly reported in impoverished nations, where people often face low socioeconomic conditions and poor access to preventive measures and medical treatment (WHO, 2022). Despite being preventable and treatable, malaria continues to have a devastating impact on global health. Over the years, malaria elimination, defined as the interruption of local transmission within a specific geographical area, has been a priority for health ministries, international and national health entities, and non-governmental organizations.

The global decrease in malaria cases is primarily attributed to vector control interventions such as the use of insecticide-treated nets (ITNs), especially long-lasting insecticidal nets (LLINs), and indoor residual spraying (IRS). An insecticide-treated net is designed to repel, weaken, and/or kill mosquitoes that come into contact with the insecticide impregnated into

[1]Industrial Engineering Department, Pontifical Catholic University of Rio de Janeiro, Rio de Janeiro, Brazil
[2]Business School, The University of Edinburgh, Edinburgh, UK
[3]Department of Mathematics and Systems Analysis, Aalto University, Espoo, Finland

Corresponding author:
Adriana Leiras, Pontifical Catholic University of Rio de Janeiro, Gávea, Rio de Janeiro, Brazil.
Email: adrianaleiras@puc-rio.br

the net. A long-lasting insecticidal net is a type of ITN engineered to maintain its effectiveness for three years, according to World Health Organization (WHO) recommendations. LLINs have played a crucial role in reducing the malaria burden over the years. The rapid scale-up in the distribution of LLINs has provided remarkable progress toward malaria elimination, establishing insecticide-treated nets as the most effective malaria control tool available in endemic countries and widely used in public health interventions (Ngufor et al., 2020).

Because major diseases and epidemics disproportionately affect the poorest and most disadvantaged communities, global initiatives like the Global Technical Strategy for Malaria 2016–2030 have emphasized the importance of actions that prioritize vulnerable areas at risk of malaria. These targeted interventions significantly improve the health of those most in need, enabling the poorest communities to break the vicious cycle of malaria and poverty (WHO, 2019). Targeting the populations most in need enhances the sense of social justice, a core principle in public health aimed at improving health by equalizing access to and opportunity for resources needed to achieve good health, particularly among those in vulnerable circumstances. These vulnerabilities to poor health, known as health disparities, refer to differences in health outcomes or determinants observed among populations due to economic, social, or environmental disadvantages (Joseph et al., 2016).

1.1 Problem Motivation and Context

Brazil's battle with malaria has persisted for over fifty years, with various strategies and programs implemented. In the 1940s, with six million infections annually (20% of the Brazilian population), initial interventions had some early success. However, despite reducing malaria significantly across most of the country by the early 1970s, outbreaks were uncontrollable in Northern Brazil. This region experienced a boom in migration and urbanization from the mid-1960s, significantly impacting malaria cases over the next decades, which culminate in the 2000 launch of the Plan to Intensify Malaria Control Actions (PIACM), yet high infection rates persisted in the north.

In 2006, the Brazilian Ministry of Health began introducing LLINs as a vector control strategy alongside IRS to contain the spread of malaria in the North. LLINs were initially distributed in three endemic municipalities in the state of Acre, which recorded the highest number of malaria cases in Brazil in 2005: Cruzeiro do Sul, Mâncio Lima, and Rodrigues Alves. After LLINs demonstrated a positive impact on reducing disease transmission, the Ministry of Health officially adopted their use in 2010 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, selected based on epidemiological variables.

After 7 years of declining malaria cases, Brazil saw a resurgence in 2016. Experts from the Oswaldo Cruz Foundation (Fiocruz) link this to two main factors. Firstly, the decrease in cases made malaria a lower priority for the government, leading to reduced funding and weaker vector control efforts, which in turn caused a swift comeback of the disease. Research confirms that withdrawing vector control in endemic areas can lead to a resurgence of malaria, as seen in Africa due to inconsistent LLIN coverage (WHO, 2019). Secondly, the increase is also tied to deteriorating socioeconomic conditions and environmental changes affecting the population of the North of Brazil.

1.2 Research Questions and Outline

Over the past decade, most countries, including Brazil, have struggled to establish effective national-scale mechanisms for LLIN distribution, primarily due to challenges in mobilizing resources for procurement, storage, allocation, and distribution. Proper storage of LLINs is particularly crucial because exposure to direct sunlight and high temperatures can degrade their impregnated insecticides, reducing bio-efficacy (Musa et al., 2020). Furthermore, in addition to addressing logistical challenges, it is also essential to ensure that resources are effectively and equitably allocated to those who need them most. Prioritization, for instance, is a possible approach to improve resource targeting and to mitigate health disparities in budget-constrained situations. However, it is not clear how to properly identify and prioritize populations most vulnerable to malaria transmission, a crucial issue given the current scenario of limited investment in malaria interventions and in alignment with global malaria eradication initiatives. Moreover, designing an equitable LLIN distribution strategy under these prioritization guidelines remains an open question in the literature. Therefore, our specific research questions in this paper are threefold.

(1) *How to evaluate the vulnerability to malaria in the current endemic areas?* To address this research question, we present 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 variables, which is well-aligned with the malaria healthcare literature. This MVI is validated by malaria practitioners 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. 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).

(2) *How to incorporate the MVI into the design and optimization of LLIN distribution while ensuring community-wide protection and equity across the malaria-endemic region?* To address this research question, we develop a novel location-allocation model that tackles key logistical challenges involved in LLIN distribution. These challenges include determining the optimal location and density of hubs for storing LLINs procured from suppliers, deciding the number of LLINs to be distributed, and selecting which hubs should store them, as well as making transportation decisions. The model's objective function aims to maximize the number of LLINs allocated to the municipalities in the endemic area. These allocations are weighted by each municipality's prioritization score, provided by the MVI, to ensure increased coverage in the most vulnerable areas. The novelty of the mathematical approach relies on "discrete coverage levels," which allows policymakers to flexibilize the allocation of LLINs while ensuring community-wide protection. We also present some special cases of our approach that have practical considerations and discuss different ways to generate equitable location-allocation plans based on discrete coverage levels, also shedding some light into the trade-off between effectiveness and equity.

(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 several 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 several important health and development goals in the global efforts to reduce the burden of malaria. These goals are outlined in the Sustainable Development Goals (SDGs) framework, the World Health Organization (WHO) Global technical strategy for malaria 2016–2030 (GTS) and the RBM Partnership to End Malaria Action and investment to defeat malaria 2016–2030 (AIM) (WHO, 2022).

The remainder of this article is organized as follows: Section 2 reviews the literature and summarizes our main contributions. Section 3 presents the LLIN location-allocation with discrete coverage-levels and derives some analytical results. In this section, we also propose equity-based approached to LLIN allocation, and a lexicographic solution method to deal with the trade-off between effectiveness and equity is presented. Section 4 presents our case study based on the malaria-endemic region in the Brazilian Amazon and discusses several malaria intervention policies. Finally, Section 5 summarizes the main takeaways and presents a framework to help policymakers choose the most suitable malaria intervention based on priority and equity. Promising opportunities for future research are also discussed.

2 Literature Review

Optimization of malaria interventions is an overlooked topic in Operations Research (OR)/Operations Management (OM). Due to the lack of papers that explicitly address key-decisions related to LLIN location/allocation, this literature review positions our work from the perspective of four streams: (1) the role of LLINs in malaria intervention and optimization; (2) application of location-allocation models to humanitarian operations; (3) prioritization-driven and equitable resource allocation in humanitarian operations; (4) drivers of malaria transmission. We then summarize this article's major contributions in the last subsection.

2.1 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. 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). 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 et al., 1999). Although the public health benefit of LLINs is widely known and discussed, the use of analytical approaches to support this type of malaria intervention is a relatively new study area. So far, only a handful of papers have offered analytical modeling to support operations fighting malaria worldwide. Rottkemper et al. (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. De Mattos et al. (2019) developed a robust optimization model that minimizes mosquito net distribution costs, considering protection against market, financial, and logistical uncertainties. Our aim in this article is to explore location-allocation decisions to optimize LLIN allocation and distribution to the malaria-endemic region in Brazil.

2.2 Application of Location-Allocation Models to Humanitarian Operations

Roughly speaking, location-allocation decisions concern the location of critical facilities (e.g., warehouses/hubs to stock emergency goods, relief/healthcare centers, and temporary shelters), as well as the allocation/deployment of goods and services to affected or vulnerable people, which often considers different "demand coverage" strategies to fulfill people's needs. Recent examples include De Vries et al. (2020), who studied a problem of where to locate additional healthcare clinics and the type of health service provided at each facility to maximize the population served and the effectiveness of the service. Also, Zhai et al. (2023) developed location-allocation approaches to improve water access in developing countries amidst conflicts in which the goal is related to minimizing travel distance and costs. In this article, we are particularly interested in location-allocation problems with *partial demand coverage*, which is a very popular subject not only in humanitarian operations, but also more broadly in facility location. Indeed, the idea of satisfying demands or requirements gradually or partially was first discussed by Church and Roberts (1983) to overcome the crisp all-or-nothing demand satisfaction assumption of the typical maximal covering location problem. Years later, Karasakal and Karasakal (2004) extended the concept of coverage to take into account full coverage, partial coverage within a threshold, and no coverage outside the threshold. Problems that involve partial coverage assume that demands can be covered within a critical or coverage distance/radius. This is often the case of humanitarian problem whose demand coverage depends on a given response distance or time requirement between established facilities and demand zones. This is the case of the seminal paper Balcik and Beamon (2008) in which the authors assumed that demands could be satisfied at different coverage levels in terms of response time limit.

2.3 Prioritization-Driven and Equitable Resource Allocation in Humanitarian Operations

There are two main ways to address prioritization issues in the optimization of humanitarian operations: the prioritization of needs or by item type, or the prioritization by groups of people or by location (Gralla et al., 2014). The prioritization of needs or by item type intends to reflect the importance or criticality of relief aid goods (Rodríguez-Espíndola et al., 2020). In most cases, this prioritization is modeled as a penalty factor to avoid relief aid shortage. The prioritization by groups of people or by location focuses on groups of people that exhibit different characteristics or socioeconomic profiles. Most papers that prioritize by location type use prioritization functions or scores based on the infrastructure of the area or hazard characteristics (Baskaya et al., 2017), or the socioeconomic or demographic characteristics of the population of the area under analysis (Abdin et al., 2023; Alem et al., 2021; Caunhye and Alem, 2023). This is a research perspective particularly aligned with our paper. Popular equity approaches include welfare-based functions and spread-based functions. In the first case, the most used perspective is the so-called Rawlsian, whose main idea is to improve the equity of the worst-off entities. This is usually done by means of min-max formulations or in the form of a hard constraint to ensure that allocation is above a given threshold (Arnette and Zobel, 2019). Similarly, spread-based functions are usually minimized or enforced via hard constraints, such as absolute deviations (Sengul Orgut and Lodree, 2023) and Gini index (Alem et al., 2022; Park and Berenguer, 2020). Ultimately, the design of proper equity formulations is problem and context-dependent, since the concept of equity itself is subject to various interpretations depending on the situation or problem, and there is no universal consensus on how to mathematically represent equity nor an unrestrictedly recommended approach in mathematical optimization and/or in humanitarian operations. In this article, to make LLIN allocation more equitable, we develop an approach based on minimizing the number of underserved areas, which is a type of welfare function, and compare to some state-of-the-art equity constraints based on perfect equity.

2.4 Drivers of Malaria Transmission

Several studies have associated socioeconomic inequalities and low environmental conditions with malaria incidence, suggesting that these aspects should be considered when developing and implementing malaria control interventions (Carrasco-Escobar et al., 2021). Human-made transformations of the natural environment can also interfere with the malaria transmission cycle, for example, some studies associate malaria incidence with gold mining operations since mining workers are highly exposed to mosquitoes, and often lack malaria preventive measures and medical treatment (Recht et al., 2017). Areas that also report high levels of malaria transmission are locations with great forest coverage. Climate conditions pose risks to malaria prevalence. Indeed, the frequency, intensity, and duration of precipitation contribute to developing suitable water habitats for mosquito breeding (Castro, 2017). 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. We consolidate the socioeconomic and environmental drivers to malaria transmission in Appendix EC.2 in the E-Companion along with the supporting literature.

2.5 Summary of Contributions

To the best of our knowledge, we are the first to systematize epidemiological, socioeconomic, and environmental data to build a composite index that reflects the malaria vulnerability of municipalities in the endemic areas of the Brazilian Amazon. For this purpose, we employ a non-statistical weighting scheme, valued for its simplicity and ease of comprehension. The advantage of this simplicity is its high interpretability, allowing practitioners to easily understand and discuss the decisions on weighting, and to apply these concepts to similar contexts where malaria transmission occurs. In addition, our composite index helps identify areas that urgently require enhanced health-driven interventions and resources, facilitating targeted healthcare strategies. We also translate our MVI into a prioritization map, making our approach more practical, visual, and user-friendly. The MVI has been thoroughly tested against its individual indicators' correlation and robustness to ensure it provides a reliable prioritization score. *This is our research contribution to the literature streams 2.3 and 2.4*. An innovative aspect of our location-allocation model is the inclusion of discrete coverage levels, which enable policymakers to establish intervals that efficiently meet LLIN requirements. Unlike most papers, our model for partial demand coverage does not depend on critical distances or response times; instead, it utilizes predefined demand proportions (coverage levels) to avoid covering an arbitrary proportion of LLIN needs. Effective LLIN campaigns must cover a significant proportion of residents in malaria-endemic areas. Our model, based on these discrete coverage levels, offers three main advantages over existing models: it is more flexible than all-or-nothing strategies; it produces less arbitrary coverage solutions than partial maximal coverage models, as the demand level to be met is user-defined based on the specifics of the application; and it avoids trivially infeasible solutions, which would result from enforcing minimum coverage with hard constraints. Moreover, we provide a theoretical analysis of the proposed mathematical model and establish its relationship with popular demand covering formulations. Finally, we propose methods for fairly allocating LLINs by minimizing the number of underserved municipalities through a prioritization-based variable and discuss their implications to policymaking. *This is our main contribution related to the literature streams 2.1 and 2.2*.

3 LLIN Location-Allocation With Discrete Coverage-Levels

We start by giving some context around the LLIN supply chain in Brazil and describe the specific problem to be tackled (Section 3.1). Afterwards we define the mathematical model based on prioritization (Section 3.2). Next, we discuss some special cases of the model that end up defining alternative strategies to allocate LLINs (Section 3.3). Finally, we discuss some approaches to make LLIN allocation more equitable (Section 3.4) and a lexicographic method to solve the effectiveness-equity problem (Section 3.5).

3.1 Problem Description

The Ministry of Health plays a crucial role in managing the supply chain of LLINs by overseeing their procurement, typically from international suppliers, and handling their storage, allocation, and distribution. LLINs are usually shipped from suppliers to major northern ports in Brazil, such as Manaus or Belém, which then distribute the nets to existing Municipal Health Departments (MHDs). These MHDs are tasked with providing LLINs to the final beneficiaries in malaria-endemic areas (municipalities). However, the MHDs often lack the necessary infrastructure to maintain large stockpiles required for mass distribution campaigns. Additionally, optimal storage conditions to prevent LLIN damage, such as maintaining dry and cool environments away from sunlight, are not consistently met. As an alternative, we propose establishing strategic hubs that can adequately store large quantities of LLINs from the ports until needed by the municipalities. This solution raises challenges, including determining the geographical location of these hubs, their operational capacity in terms of LLIN quantity, and how best to prioritize and distribute LLINs to the municipalities, especially when the investment is insufficient to cover all the needs of malaria-endemic areas.

Therefore, we develop a single-period location-allocation model to assist the Brazilian Ministry of Health in making the aforementioned logistical decisions. Unlike other location-allocation problems involving a specified commodity, the allocation of LLINs to municipalities cannot be arbitrary due to epidemiological considerations. Indeed, "*there is robust evidence from trials that LLINs at relatively high population coverage levels provide community-wide protection, whereby unprotected individuals within or in proximity to high ITN coverage areas are conferred protection from infectious bites*" (Yukich et al., 2013). Currently, this proportion is as high as 80% according to WHO (2022). The proposed model aims to satisfy as much as possible the requirement of covering at least 80% of the municipalities also taking into account the municipalities' epidemiological, socioeconomic, and environmental profile, which is reflected by means of the MVI, tailored to our case-study. 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 1 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 3 years, MVI is updated, a new campaign (LLIN replacement) is initiated, and so on.

Our location-allocation approach operates under the following assumptions: (i) the Ministry of Health operate with

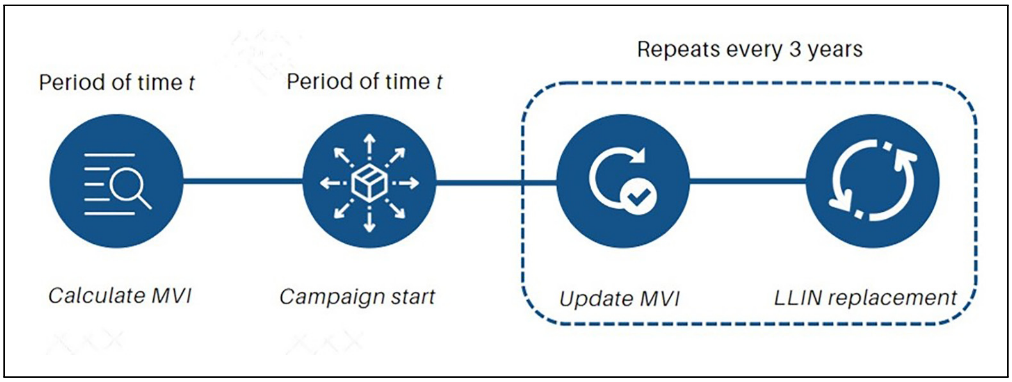

Figure 1. Overview of the proposed long-lasting insecticidal net (LLIN) distribution campaign.

a limited budget (investment level) to establish the hubs, and carry out LLIN procurement, storage and transportation from hubs to municipalities; (ii) decisions must regard a predefined maximum and minimum number of LLINs per hub; (iii) hubs have different capacity categories in terms of LLIN storage; (iv) there is a vehicle fleet capacity per hub and a transportation capacity per vehicle; (v) only one type of LLIN is considered—a rectangular medium LLIN with dimensions of 180 × 160 × 150 cm—as it is the most commonly type; (vi) the capitals of the states are potential candidates for hub locations since they typically serve as the state's business, cultural, and population centers, offering more advantages and better infrastructure compared to other cities; (vii) only road transport is considered because we disregard the last-mile delivery to families that eventually live in areas that are difficult to reach by road; (viii) transshipments between hubs or municipalities are not allowed.

3.2 Model Formulation

The mathematical model uses the following notation. Let $h = 1, \ldots, H$ be the potential hub locations. Hubs have $k = 1, \ldots, K$ different capacity categories. Hub at location h and size k has an associated opening cost c^{o}_{hk} ($) and a capacity given by κ^{max}_{hk} (m^3). A minimum quantity κ^{min}_{hk} of LLINs (unit) in each hub type k located at h is also required. The unit procurement and storage cost of LLIN in hub h is given by c^{inv}_{h} ($) regardless of the hub. Each municipality $m = 1, \ldots, M$ is associated with an estimated demand for LLINs d_m (units of LLINs), which is evaluated as its estimated population divided by 2 (WHO recommendation). The transportation cost of LLINs between hub h and municipality 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 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 $\ell = 1, \ldots, L$ are the levels, such that $\alpha_1 > \alpha_2 > \cdots > \alpha_\ell > \cdots > \alpha_L$. In our modeling approach, we assume that the first level corresponds to the fully (universal) coverage, that is, $\alpha_1 = 1$, whereas the last level L represents no coverage at all, that is, $\alpha_L = 0$. The financial budget (investment) available to establish the hubs, manage the inventory of LLINs and transport the LLINs from hubs to municipalities is given by η ($). Finally, the MVI associated with municipality 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 to be discussed in the next subsection). For this reason, we create a decision variable $W_{m\ell}$ that indicates whether municipality 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 municipality that is supposed to be covered. This variable is aligned with the current practice of providing a community-wide protection (above 80%) to maximize the effectiveness of the LLIN campaign in a given area when universal coverage is hard to achieve. The location variable Y_{hk} indicates whether hub h is established at capacity category k ($Y_{hk} = 1$) or not ($Y_{hk} = 0$); and P_h defines the number of LLINs that should be set to hub h. The allocation variable X_{hm} determines the flow of LLINs from hub h to municipality m. Finally, N_{hm} gives the corresponding number of trips between hub h and municipality m. Table 1 summarizes the model's notation.

The problem, hereafter called LLINs with discrete coverage levels (LLINs-DCL), can be formulated as follows:

(LLINs-DCL)

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

subject to:

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

Table 1. Mathematical notation.

$\ell = 1, \ldots, L$	Coverage levels
$k = 1, \ldots, K$	Capacity categories
$h = 1, \ldots, H$	Hubs
$m = 1, \ldots, M$	Municipalities
c^{o}_{hk}	Opening cost for hub h at capacity category k (\$)
c^{inv}_{h}	Procurement and storage cost of LLINs in hub h (\$/unit)
c^{transp}_{hm}	Transportation cost of LLINs between hub h and municipality m (\$/unit of trip)
d_m	Needs for LLINs in municipality m (unit)
κ^{max}_{hk}	Maximum capacity of hub h at capacity category k (vol in m^3)
κ^{min}_{hk}	Minimum quantity of LLINs in hub h at capacity category k (unit)
κ^{fleet}_{h}	Fleet capacity of hub h (in number of vehicles)
ρ	Volume of LLIN (vol in m^3)
ρ'	Transportation mode capacity (vol in m^3)
η	Financial budget or investment level (\$)
α_ℓ	Coverage level ℓ (%) such that $\alpha_1 > \alpha_2 > \cdots > \alpha_\ell > \cdots > \alpha_L$
MVI_m	Malaria vulnerability index of municipality m such that $0 \leq \text{MVI}_m \leq 1$
Θ	Sufficiently large number
Y_{hk}	Binary variable that indicates whether hub h is established at capacity category k ($Y_{hk} = 1$) or not ($Y_{hk} = 0$)
$W_{m\ell}$	Binary variable that indicates whether municipality m is prioritized at coverage level ℓ ($W_{m\ell} = 1$) or not ($W_{m\ell} = 0$)
P_h	Quantity of LLINs set to hub h
N_{hm}	Number of trips between hub h and municipality m
X_{hm}	Flow of LLINs between hub h and municipality m

Abbreviation: LLINs = long-lasting insecticidal nets.

$$P_h \geq \sum_{k=1}^{K} \kappa^{min}_{hk} Y_{hk}, \ \forall h = 1, \ldots, H \tag{3}$$

$$\sum_{k=1}^{K} Y_{hk} \leq 1, \ \forall h = 1, \ldots, H \tag{4}$$

$$\sum_{m=1}^{M} X_{hm} \leq P_h, \ \forall h = 1, \ldots, H \tag{5}$$

$$\sum_{h=1}^{H} X_{hm} \geq d_m \sum_{\ell=1}^{L-1} \alpha_\ell W_{m\ell}, \ \forall m = 1, \ldots, M \tag{6}$$

$$\sum_{h=1}^{H} X_{hm} \leq d_m (1 - W_{mL}), \ \forall m = 1, \ldots, M \tag{7}$$

$$\sum_{\ell=1}^{L} W_{m\ell} = 1, \ \forall m = 1, \ldots, M \tag{8}$$

$$N_{hm} \geq \frac{\rho}{\rho'} X_{hm}, \ \forall h = 1, \ldots, H; \ m = 1, \ldots, M \tag{9}$$

$$N_{hm} \leq 1 + \frac{\rho}{\rho'} X_{hm}, \ \forall h = 1, \ldots, H; \ m = 1, \ldots, M \tag{10}$$

$$N_{hm} \leq \Theta \sum_{k=1}^{K} Y_{hk}, \ \forall h = 1, \ldots, H; \ m = 1, \ldots, M \tag{11}$$

$$\sum_{m=1}^{M} N_{hm} \leq \kappa^{fleet}_{h}, \ \forall h = 1, \ldots, H \tag{12}$$

$$\eta \geq \sum_{k=1}^{K} \sum_{h=1}^{H} c^{o}_{hk} Y_{hk} + \sum_{h=1}^{H} c^{inv}_{h} P_h + \sum_{h=1}^{H} \sum_{m=1}^{M} c^{transp}_{hm} N_{hm} \tag{13}$$

$$W_{m\ell} \in \{0, 1\}, \ \forall m = 1, \ldots, M; \ell = 1, \ldots, L \tag{14}$$

$$Y_{hk} \in \{0, 1\}, \ \forall h = 1, \ldots, H; \ k = 1, \ldots, K \tag{15}$$

$$N_{hm} \geq 0 \text{ and integer}, \ \forall h = 1, \ldots, H; \ m = 1, \ldots, M \tag{16}$$

$$P_h \geq 0, \ \forall h = 1, \ldots, H \tag{17}$$

$$X_{hm} \geq 0, \ \forall h = 1, \ldots, H; \ m = 1, \ldots, M. \tag{18}$$

The objective function (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 $\alpha_1 > \alpha_2 > \cdots > \alpha_L$, with $\alpha_1 = 1$ 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), and will avoid as much as possible the last coverage level that leads to no benefit. This way, we address the issue of vertical equity in the sense that the allocation favors the municipalities most in need because of the MVI weight. However, the maximum effectiveness solution is not necessarily horizontally equitable since it will eventually prefer to cover fewer areas at better coverage levels than covering more areas at worse coverage levels. Subsection 3.4 discusses alternative approaches to explicitly address horizontal equity. Constraint (2) ensures that LLINs can only be stored at the established hubs. Whether storage of LLINs takes place, there is a corresponding minimum quantity that must be kept in stock according to constraint (3). Constraint (4) ensures that each hub is established at a given capacity category. Constraint (5) states that the overall number of LLINs allocated to municipalities must be less than or equal to its availability. Constraints (6)–(8) define the allocation of LLINs for each municipality. By constraint (6), this allocation must satisfy one of the coverage levels α_ℓ, for $\ell = 1, \ldots, L-1$. Otherwise, by constraint (7), this municipality is simply underserved. Constraint (8) ensures that the allocation satisfies exactly one coverage level. Constraints (9) and (10) define the number of trips between hubs and municipalities. Constraint (11) ensures that travels from a given hub to any municipality can only exist if this hub is established. Constraint (12) guarantees that the total number of trips cannot exceed a given capacity. Constraint (13) refers to the financial budget or investment to perform malaria interventions. Finally, constraints (14)–(18) state the domain of the decision variables.

3.3 Special Cases and Analytical Results

In our application, if municipalities cannot be fully covered, we expect to cover them within another coverage level such as 90% (α_2) or 80% (α_3) to guarantee a recommended community-wide protection, as aforementioned. However, our modeling paradigm is general enough to represent situations with different number of coverage levels and intervals. We now show two special cases of the formulation LLINs-DCL when the number of coverage levels is said to be minimum or maximum, as well as discuss some theoretical properties whose proofs are given in Appendix EC.1 in the E-Companion.

DEFINITION 1. *Following our modeling assumptions, $L = 2$ is said to be the minimum number of coverage levels needed in the mathematical formulation LLINs-DCL. In this case, $\alpha_1 = 1$ and $\alpha_2 = 0$ correspond to the trivial coverage levels, and we have the so-called "all-or-nothing" LLIN allocation strategy.*

The LLINs-All-or-Nothing model can be stated as follows:

(LLINs-All-or-Nothing)

$$\text{Maximize} \sum_{m=1}^{M} \text{MVI}_m d_m W_m \quad (19)$$

$$\text{Subject to: constraints (2)–(5), (9)–(13), (15)–(18)}$$

$$\sum_{h=1}^{H} X_{hm} = d_m W_m, \ \forall m = 1, \ldots, M \quad (20)$$

$$W_m \in \{0, 1\}, \forall m = 1, \ldots, M. \quad (21)$$

In this case, each municipality is either fully covered, $W_m = 1$, or not covered at all (underserved), $W_m = 0$.

PROPOSITION 1. *The optimal solution value obtained from the LLINs-All-or-Nothing formulation is a lower bound to the LLINs-DCL formulation with an arbitrary number of coverage levels $L > 2$.*

The second special case refers to the situation where the number of coverage levels is said to be at its *maximum*. For this purpose, let us assume that LLIN requirements are discrete values, which is a reasonable assumption in practical applications as the one at hand. The LLINs-DCL formulation with the maximum number of coverage levels is such that any integer allocation can be properly identified, that is, $\sum_h X_{hm} \in \{0, 1, 2, \ldots, d_m\}$ $(m = 1, \ldots, M)$. This case is of theoretical importance since we will show that under the maximum number of coverage levels, the LLINs-DCL formulation simply becomes the so-called *partial maximal covering location problem*.

DEFINITION 2. *$L^{\max}$ is defined as the maximum number of non-trivial coverage levels such that any LLIN requirement from 1 to $d_m - 1$ can be identified (and eventually covered) using the mathematical formulation LLINs-DCL. In this case, the total number of coverage levels $L = L^{\max} + 2$ takes also into account the two trivial coverage levels, that is, 0 and 1.*

DEFINITION 3. *The set containing both the trivial and non-trivial coverage levels, $\mathcal{L}$, can be represented as $\mathcal{L} = \{\alpha_1, \alpha_2, \ldots, \alpha_{L^{\max}}, \alpha_{L^{\max}+1}, \alpha_L\}$, in which $\alpha_1 = 1$ and $\alpha_L = 0$ are the trivial coverage levels and $\alpha_2, \ldots, \alpha_{L^{\max}+1}$ are the non-trivial ones. In this case, $\alpha_{L^{\max}+1}$ refers to the last non-trivial coverage level.*

Next, we formalize how to calculate $L^{\max}$ and the non-trivial coverage levels. For notational convenience, we assume that $\alpha_l^{(m)}$ is the coverage level l associate with d_m and $\mathcal{L}^{(m)}$ is the set of non-trivial coverage levels for d_m.

LEMMA 1. *Given a finite sequence of non-zero integer LLIN requirements $(d_m)_{m=1,\ldots,M}$, the total number of non-trivial coverage levels is given by $L^{max} = |\mathcal{L}^*|$, in which*

- $\mathcal{L}^* = \bigcup_{m=1,\ldots,M} \mathcal{L}^{(m)}$;
- $\mathcal{L}^{(m)} = \{\alpha_l^{(m)}\}_{l=1,\ldots,d_m-1}$;
- $\alpha_l^{(m)} = 1 - \frac{l}{d_m}$, *for* $l = 1, \ldots, d_m - 1$ *and* $m = 1, \ldots, M$.

EXAMPLE 1. *Assume $M = 3$, $d_1 = 10$, $d_2 = 11$, and $d_3 = 5$. The coverage levels for $m = 1$ are then $\alpha_l^{(1)} = 1 - \dfrac{l}{d_1} = 1 - \dfrac{l}{10}$ for $l = 1, \ldots, 9$, which gives $\alpha_1^{(1)} = 9/10$, $\alpha_2^{(1)} = 8/10$, …, $\alpha_9^{(1)} = 1/10$. The set $\mathcal{L}^{(1)} = \{\alpha_l^{(1)}\}_{l=1,\ldots,9}$ then contains all the non-trivial coverage levels for $m = 1$. For $m = 2$, we have $\alpha_l^{(2)} = 1 - \dfrac{l}{d_2} = 1 - \dfrac{l}{11}$ for $l = 1, \ldots, 10$, which gives $\alpha_1^{(2)} = 10/11$, $\alpha_2^{(2)} = 9/11$, …, $\alpha_{10}^{(2)} = 1/11$. The set $\mathcal{L}^{(2)} = \{\alpha_l^{(2)}\}_{l=1,\ldots,10}$ contains all the non-trivial coverage levels for $m = 2$. Finally, for $m = 3$, we have $\alpha_l^{(3)} = 1 - \dfrac{l}{d_3} = 1 - \dfrac{l}{5}$ for $l = 1, \ldots, 4$, which gives $\alpha_1^{(3)} = 4/5$, $\alpha_2^{(3)} = 3/5$, …, $\alpha_4^{(3)} = 1/5$. The set $\mathcal{L}^{(3)} = \{\alpha_l^{(3)}\}_{l=1,\ldots,4}$ contains all the non-trivial coverage levels for $m = 3$.*

Therefore, $\mathcal{L}^* = \mathcal{L}^{(1)} \bigcup \mathcal{L}^{(2)} \bigcup \mathcal{L}^{(3)}$ is the set of all coverage levels. Notice that as d_3 is multiple of d_1, then the union of the three subsets gives $\mathcal{L}^* = \{\alpha_1^{(1)}, \alpha_2^{(1)}, \ldots, \alpha_9^{(1)}, \alpha_1^{(2)}, \alpha_2^{(2)}, \ldots, \alpha_{10}^{(2)}\}$, therefore, $L^{\max} = |\mathcal{L}| = 19$. In this case, note that the set $\mathcal{L}$ can be represented as $\mathcal{L} = \{\alpha_1, \alpha_2, \ldots, \alpha_{20}, \alpha_{21}\}$ in which $\alpha_1 = 1$, $\alpha_{21} = 0$, and $\alpha_2, \ldots, \alpha_{20}$ are the 19 non-trivial coverage levels given by $\mathcal{L}^*$ assumed to have been sorted in descending order.

PROPOSITION 2. *If $L = L^{\max}+2$, in which $\alpha_1 = 1$, $\alpha_L = 0$, and the $L^{\max}$ number of non-trivial coverage levels are determined according to Lemma 1, then the formulation LLINs-DCL is equivalent to the following partial maximal covering location problem (LLINs-PMC)*

(LLINs-PMC)

$$\text{Maximize } \sum_{m=1}^{M} \sum_{h=1}^{H} MVI_m X_{hm} \tag{22}$$

$$\text{Subject to: constraints } (2)-(5), (9)-(13), (15)-(18)$$

$$\sum_{h=1}^{H} X_{hm} \leq d_m, \ \forall m = 1, \ldots, M. \tag{23}$$

The formulation LLINs-PMC is based on the well-known maximal covering location problem in the presence of partial coverage (Karasakal and Karasakal, 2004) under the main assumption that the demands for LLINs can be fulfilled *at any level*, implying that defining the coverage levels is no longer necessary. Therefore, the decision variable $W_{m\ell}$ is dropped and the effectiveness is simply written in terms of the allocation decision X_{hm}. Interestingly, LLINs-PMC is an upper bound to LLINs-DCL, which is formalized next.

PROPOSITION 3. *The LLINs-PMC formulation provides an upper bound to the original LLINs-DCL formulation for an arbitrary number of coverage levels $L < L^{\max} + 2$.*

From the theoretical point of view, notice that both the lower and upper bounds help position our approach with regard existing and popular "demand covering" problems, the all-or-nothing and the partial maximal covering, respectively. From the practical point of view, the identification and analysis of the lower bound is grounded on the LLIN distribution campaign carried out by the Brazilian Ministry of Health in 2010 whose strategy relied on universally covering the demand for LLINs of a few priority municipalities, whereas all the other municipalities of the endemic region were underserved. Therefore, the lower bound model is actually of a valid practical interest. Moreover, the identification and analysis of the upper bound is also relevant because it shows that allocating resources following the partial maximal covering principle ends up improving effectiveness, that is, more resources can be allocated in comparison to LLINs-DCL. The partial maximal covering strategy is indeed quite appealing when allocating "generic commodities" (e.g., mattress and cleaning kits in disaster aftermath situations) for which minimum requirements are not necessarily relevant. However, it fails to capture some of the realities when dealing with LLINs or vaccines' allocation whose minimum coverage must be sufficiently high to be effective. In the next section, we show how these two approaches perceive an equitable allocation of LLINs; and in Sections 4 and 5, we give a number of managerial insights into their performance along with pros and cons of each strategy.

3.4 Addressing Equity Concerns

As previously stated, the incorporation of the MVI weight favors or 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 et al., 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 vulnerability to malaria transmission. It is easy to see that by maximizing the effectiveness of the LLIN 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, it may happen that the best-case effectiveness solution is myopic in the sense of identifying solutions more aligned with the general principle of *horizontal equity*, which is perceived here as avoiding as much as possible underserving areas, as we can see in the following illustrative example.

EXAMPLE 2. *Consider a case where $M = 3$ and $L = 3$, in which $\alpha_1 = 1$, $\alpha_2 = 0.8$, and $\alpha_3 = 0$, and $MVI_1 = 0.8$, $MVI_2 = 0.8$, and $MVI_3 = 0.4$. Let us assume that the overall resources are sufficient to allocate 240 LLINs out of 300, assuming that each municipality requires 100 LLINs. It is easy to see that the best-case effectiveness solution is 160, which is achieved when the first two municipalities with the highest MVIs are covered in the first level and the third municipality is underserved, that is, $W_{11}^{\star} = 1$, $W_{21}^{\star} = 1$, and $W_{33}^{\star} = 1$, while the other variables $W_{m\ell}^{\star}$ are zero. On the other hand, a more equitable solution would be to cover 80% of the LLIN requirements for each municipality, that is, the optimal variable values being $W_{12}^{\star} = 1$, $W_{22}^{\star} = 1$, and $W_{32}^{\star} = 1$, while the other variables $W_{m\ell}^{\star}$ would be zero, which gives the same effectiveness value of 160. If $MVI_3 = 0.3$, other parameters remaining the same, the best-case effectiveness does not change, but a more equitable solution would be to cover the three areas in the second coverage level, which would give a worsened effectiveness of 152.*

The above discussion clarifies the trade-off between effectiveness and equity: the best-case effectiveness does not imply the *best-case equity* and vice-versa. Before properly defining what best-case equity represents, the previous example shows that while improving equity, the area that has been not served ($m = 3$) is now served in the second coverage level (the last non-trivial level), which means that its LLIN allocation has changed from 0 to 80 units, which can be seen as the minimum LLIN requirement. This minimum percentage of LLINs allocated per municipality m could be simply enforced by $\sum_{h=1}^{H} X_{hm} \geq \alpha_{L-1} d_m$, which is exactly constraint (6) for $W_{m\ell} = 1$ for $\ell = L-1$, and $W_{m\ell} = 0$, otherwise. In this case, $L-1$ represents the last non-trivial coverage level (i.e., immediately before the null coverage level L) and, therefore, α_{L-1} represents the minimum LLIN requirement. Equity formulations based on a minimum percentage or requirement are often classified as the type *social welfare* and are amongst the most popular fairness metrics in humanitarian logistics problems. However, the minimum requirement (equity) constraints are often infeasible as they make the model severely constrained. That is when decision variable $W_{m\ell}$ comes into place to guarantee that if $\alpha_{L-1} d_m$ cannot be met for a given m, then $W_{mL} = 1$. Therefore, instead of enforcing the minimum requirement constraint to have a typical allocation-based equity metric, we build a coverage-level-based equity metric that relies on minimizing the number of underserved areas as much as possible.

Definition 4. *The best-case equity occurs when the number of underserved municipalities is at its minimum, which is equivalent to solving problem (24):*

(LLINs-equity)

$$\textit{Minimize} \sum_{m=1}^{M} W_{mL}$$

$$\textit{Subject to: constraints } (2)-(5), (9)-(13), (15)-(18). \tag{24}$$

Clearly, our equity perspective here is *Rawlsian* (a type of social welfare function) since the idea is to mitigate the inequity of the worst-off municipalities, which turn to be the underserved municipalities.

Note that the best-case equity is specially tailored for the LLINs-DCL formulation when the number of coverage levels $2 < L < L^{\max} + 2$. For $L = 2$, the best-case equity is equivalent to the best-case effectiveness, which is simply min $\sum_{m=1}^{M}(1 - W_{ml}) \Leftrightarrow \sum_{m=1}^{M} W_m$. Finally, when $L = L^{\max} + 2$, the best equity could be equivalently stated as min $\sum_{m=1}^{M}(1 - \sum_{h=1}^{H} X_{hm}/d_m)$, which is in turn equivalent to max $\sum_{m=1}^{M} \sum_{h=1}^{H} X_{hm}$.

Definition 5. *Perfect equity occurs when all the municipalities receive at least their minimum LLIN requirement, that is,* $\sum_{h=1}^{H} X_{hm} \geq \alpha_{L-1} d_m$, *for all* $m = 1, \ldots, M$.

For the All-or-Nothing strategy, this perfect equity perspective implies $\sum_{h=1}^{H} X_{hm} \geq d_m$, for all $m = 1, \ldots, M$. For the LLINs-PMC, this perfect equity perspective is straightforward.

Proposition 4. *Let Z^B be the optimal solution of problem (24). Then, perfect equity exists if and only if $Z^B = 0$.*

From Proposition 4, we can infer that a necessary and sufficient condition to ensure perfect equity is to have a feasible solution for LLINs-DCL when constraint (8) is replaced by $\sum_{\ell=1}^{L-1} W_{m\ell} = 1$, $m = 1, \ldots, M$. Furthermore, from Definitions 4 and 5, one can notice that, whereas perfect equity can be defined in terms of *perfect equality*, that is, ensuring that the ratio of outcomes to inputs is equal for each entity (municipality), our perspective for perfect equity allows for solutions that may deviate from each other. Therefore, our approach is more flexible and aligned with the modeling paradigm based on coverage levels. The next proposition shows how to trivially determine the worst-case deviation of LLINs allocations. It is also worth highlighting that the idea of perfect equity not necessarily coinciding with equality comes from Harry's proportionality model (Harris et al., 1981) and some extensions (Wagstaff and Perfect, 1992).

Proposition 5. *The worst-case deviation ratio of LLINs allocation is at most $1 - \alpha_{L-1}$ under perfect equity.*

3.4.1 Benchmark Equity Formulations. We propose to compare our Rawlsian equity approach against a benchmark equity based on absolute deviations from *what they consider perfect equity*, which is the case of several aforementioned papers. Based on the equity idea of Orgut et al. (2016), our benchmark formulation assuming that $d_m > 0$ for all $m = 1, \ldots, M$ can be cast as follows:

$$\left| \frac{\sum_{h=1}^{H} X_{hm}}{\sum_{m'=1}^{M} \sum_{h=1}^{H} X_{hm'}} - \frac{d_m}{\sum_{m'=1}^{M} d_{m'}} \right| \leq \delta, \ \forall m = 1, \ldots, M, \tag{25}$$

in which $\delta \in [0, 1]$ is an input parameter to reflect the equity/inequity level related to the proportion of LLINs allocated to the municipalities; $\delta = 1$ is equivalent to the default case in which equity is not enforced, whereas the so-called perfect equitable solution is when $\delta = 0$, which implies

$$\frac{\sum_{h=1}^{H} X_{hm}}{d_m} = \frac{\sum_{h=1}^{H} X_{hm'}}{d'_m}, \quad \forall m, m' = 1, \ldots, M, \text{ such that } m \neq m'. \tag{26}$$

Notice that this perfect equity perspective is unlikely to yield non-trivial solutions to the All-or-Nothing and LLINs-DCL formulations, as we show in the next proposition.

Proposition 6. *The All-or-Nothing optimal solution under the perfect equity perspective given by (26) is either (a)* $W_m^\star =$

1 or (b) $W^{\star}_{m} = 0$, for all $m = 1, \dots, M$. Analogously, the LLINs-DCL optimal solution with $L < L^{\max}$ in this case will be either (a) $W^{\star}_{m\bar{\ell}} = 1$ for a given $\bar{\ell} \in [1, L-1]$ and $W^{\star}_{m\ell} = 0$ for $\ell \neq \bar{\ell}$, or (b) $W^{\star}_{m,L} = 1$, for all $m = 1, \dots, M$.

3.5 Solving the Effectiveness-Equity Problem

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. Here, our primary goal is to maximize the effectiveness of the LLIN campaign, which is given by the objective function (1), whereas the secondary goal is to guarantee that this effective campaign is as equitable as possible, which is represented by the objective function (24). To deal with this trade-off, we adopt a lexicographic approach or preemptive optimization aligned with Zhai et al. (2023) such that equity is optimized as far as it does not interfere with effectiveness maximization. Mathematically, the lexicographic model is cast as

$$(\mathbf{LLINs\text{-}Lexo_1})$$
$$\text{Lex max } (Z_1, -Z_2)$$
$$\text{Subject to: constraints } (2)-(5), (9)-(13), (15)-(18), \quad (27)$$

in which $Z_1 = \sum_{m=1}^{M}\sum_{\ell=1}^{L-1} \mathrm{MVI}_m \alpha_\ell d_m W_{m\ell}$ and $Z_2 = \sum_{m=1}^{M} W_{mL}$.

The resolution of LLINs-Lexo$_1$ involves two main steps: (1) find the optimal solution $Z_1^\star$ of the problem LLINs-DCL (1)–(18); and (2) solve the problem LLINs-equity (24) with the additional constraint $\sum_{m=1}^{M}\sum_{\ell=1}^{L-1} \mathrm{MVI}_m \alpha_\ell d_m W_{m\ell} \geq Z_1^\star$. For the sake of numerical comparison, let us also define the *counterpart lexicographic problem* when minimizing Z_2 is the primary goal LLINs-Lexo$_2$, which is given by Lex max $(-Z_2, Z_1)$, whose resolution entails finding the optimal solution $Z^\star 2$ of the problem LLINs-equity (24), and then solving the problem LLINs-DCL (7)–(18) with the additional constraint $\sum^{M} m = 1 W_{m,L} \leq Z_2^\star$. Note that by solving LLINs-Lexo$_1$ and LLINs-Lexo$_2$, we can determine the range in which the efficient solutions for both effectiveness and equity fall within, respectively.

One of the main advantages of lexicographic/preemptive optimization over weighted sum and epsilon constraint is to avoid defining the weights and the epsilon-constraint steps and, in addition, an efficient solution is always returned. Indeed, arg max (LLINs-DCL) and arg min (LLINs-Equity) are both non-empty since the trivial solution $W_{m\ell} = 0$ ($\forall m$, $\ell = 1, \dots, L-1$), and $W_{m\ell} = 1$ ($\forall m$, $\ell = L$) is always feasible for both problems. Therefore, we can assume that there exists $x_1^\star \in$ arg max (LLINs-Lexo)$_1$ and $x_2^\star \in$ arg max (LLINs-Lexo)$_2$, that is, the corresponding lexicographic models are also always feasible. However, this does not mean that LLINs-Lexo$_1$ (resp. LLINs-Lexo$_2$) will improve the solution of LLINs-DCL (resp. LLINs-Equity). Here, the concept of improvement depends on whether or not the lexicographic approach can return a solution in which the secondary goal is "better" considering that the primary goal does not change, as defined below.

Definition 6. *For LLINs-Lexo$_1$, we say that a given effectiveness-equity solution $\mathcal{X}$ dominates another solution $\mathcal{Y}$ if and only if the number of underserved municipalities of $\mathcal{X}$ is strictly smaller than the number of underserved municipalities of $\mathcal{Y}$ for the same effectiveness value. Conversely, for LLINs-Lexo$_2$, we say that a given effectiveness-equity solution $\mathcal{X}'$ dominates another solution $\mathcal{Y}'$ if and only if the effectiveness solution of $\mathcal{X}'$ is strictly greater than the effectiveness solution of $\mathcal{Y}'$ for the same number of underserved areas.*

Although LLINs-DCL and LLINs-Lexo$_1$ have the same effectiveness solution, LLINs-Equity and LLINs-Lexo$_2$ are supposed to produce more equitable solutions but with a rather deteriorated effectiveness, due to their primary goal of minimizing the number of underserved municipalities. This deterioration is defined as the *Price of Equity* (PoE), as shown below.

Definition 7. *The price of equity is defined as the system effectiveness loss when equity is enforced via the approaches in which minimizing the number of underserved areas is the primary goal, that is, LLINs-Equity or LLINs-Lexo$_2$. Mathematically, PoE $= \frac{Z_1^\star - Z_1^{eq}}{Z_1^\star}$, in which $Z_1^\star$ is the best effectiveness solution given by LLINs-DCL, whereas Z_1^{eq} is the effectiveness solution calculated a posteriori after solving LLINs-Equity or LLINs-Lexo$_2$.*

4 Numerical Analysis and Implications

In this section, we investigate the added-value of our proposed approach and discuss the implications of prioritization and equity on LLIN campaigns. For this purpose, we start discussing our empirical setting and evaluation of the MVI in Section 4.1. Section 4.2 compares the different so-called interventions given by LLINs-DCL and its special cases LLINs-All-or-Nothing and LLINs-PMC for different investment levels. Section 4.3 highlights the main differences amongst these interventions with and without MVI-based prioritization. The impact of equity is discussed in Section 4.4, which points out the equity improvement given by the lexicographic models, and in Section 4.5, which shows the benchmark equity results. Finally, Section 4.6 aims to assess the benefit of the interventions throughout a three-year cycle in terms of potentially averted malaria infections and deaths.

The mathematical approaches were implemented in GAMS 43 and solved with Cplex (default settings) on a Xeon® Silver 4110 desktop with 64 GB of RAM. The stopping criteria are either elapsed times exceeding 1,000 s or optimality gaps relative to the best lower bound smaller than 0.1%. It is worth noting that the different investment levels were estimated based on solving an auxiliary cost-minimization problem in which LLIN requirements must be fully met. This mathematical model is presented in Appendix EC.6.1 in the E-Companion. The optimal objective function of this formulation is assumed to be the ideal investment level. All the approaches were then tested for investment levels ranging from 90% to 10% of this ideal value.

4.1 Empirical Setting and Evaluation of the MVI

The proposed MVI is a composite index comprising several malaria risk factors associated with malaria incidence and discussed in diverse academic papers. Based on the epidemiological variables used by the Ministry of Health in Brazil to prioritize municipalities during 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 hr) and on our literature investigation regarding socioeconomic and environmental malaria transmission drivers, we build a questionnaire to understand how practitioners perceive the importance of each variable in determining the most priority municipalities for malaria (Appendix EC.5 in the E-Companion). Other methodological details of the empirical setting and its validation are discussed in Appendix EC.3 in the E-Companion.

After the validation, the proposed MVI end up comprising *two variables of epidemiological dimension*: (1) the number of malaria cases, and (2) the percentage of malaria cases caused by *P. falciparum*; *six variables of socioeconomic dimension*: (3) per capita income, (4) the 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; and finally, *four variables of environmental dimension*: (9) indigenous land, (10) forest coverage, (11) length of the rainy season, and (12) presence of mines. These epidemiological, socioeconomic, and environmental data were gathered from several secondary sources, which are also detailed in Appendix EC.3 in the E-Companion.

We then evaluated the MVI by using the weighted-mean method according to the equation $\text{MVI}_m = \sum_i \text{weight}_i \cdot v_{im},\ m = 1, \ldots, 310$, in which v_{im} is the value of driver i for municipality m and weight_i is the weight of driver i, which is based on the importance of each variable according to the practitioner's response. 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. Figure 2 shows the case-study area and the corresponding MVI from lower to higher vulnerability values. The municipalities with the lowest MVI 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 10 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 4 years. On the other hand, the municipalities with the highest malaria vulnerability 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 and hold the highest percentages of Amazon Rainforest coverage in South America. The municipalities of Atalaia do Norte, Itamarati, and São Gabriel da Cachoeira have the highest MVIs. 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 10 municipalities with the highest rates of indigenous peoples and precipitation. We also analyzed the robustness of the MVI and show how the list of priority municipalities may change for alternate ways to evaluate it based on removing variables and changing the weighting scheme (Appendix EC.4 in the E-Companion).

4.2 A Discussion on Different Interventions: All-or-Nothing, PMC, and DCL

We now present some insights into the different LLIN interventions, namely, (a) LLINs-All-or-Nothing, (b) LLINs-PMC, and (c) LLINs-DCL. Table EC.9 (Appendix EC.7 in the E-Companion) summarizes the main results in terms of effectiveness and the number of underserved areas for each approach, assuming investment levels varying from 90% to 10% in steps of 10%. The results confirm the theoretical discussion presented in Section 3.3: LLINs-All-or-Nothing $\leq$ LLINs-DCL $\leq$ LLINs-PMC in terms of the bounds of the LLINs-DCL optimal value (model's effectiveness). Interestingly, these bounds are very tight, showing that the flexibility of meeting demands through different coverage levels does not significantly impact the model's effectiveness. However, from the perspective of the number of underserved areas, the all-or-nothing strategy almost always yields a worse solution compared to LLINs-DCL. This confirms that varying coverage levels indeed provide flexibility that results in more municipalities being covered. For instance, LLINs-DCL covers 13 more municipalities than the all-or-nothing strategy at a 60% investment level. Although LLINs-PMC almost always covers at least 80%, there are instances where the coverage drops below the minimum LLIN requirement of 80%. Indeed, the last column of Table EC.9 shows that at investment levels of 90%, 70%, 60%, 50%, and 30%, this occurs in at least one municipality. Since the 80% threshold is crucial for providing widespread community protection from infectious bites, any coverage solution that fails to meet this target is ineffective. The coefficient of variation also reveals that the All-or-Nothing strategy is slightly less equitable, followed by LLINs-DCL and LLINs-PMC, as expected. This is

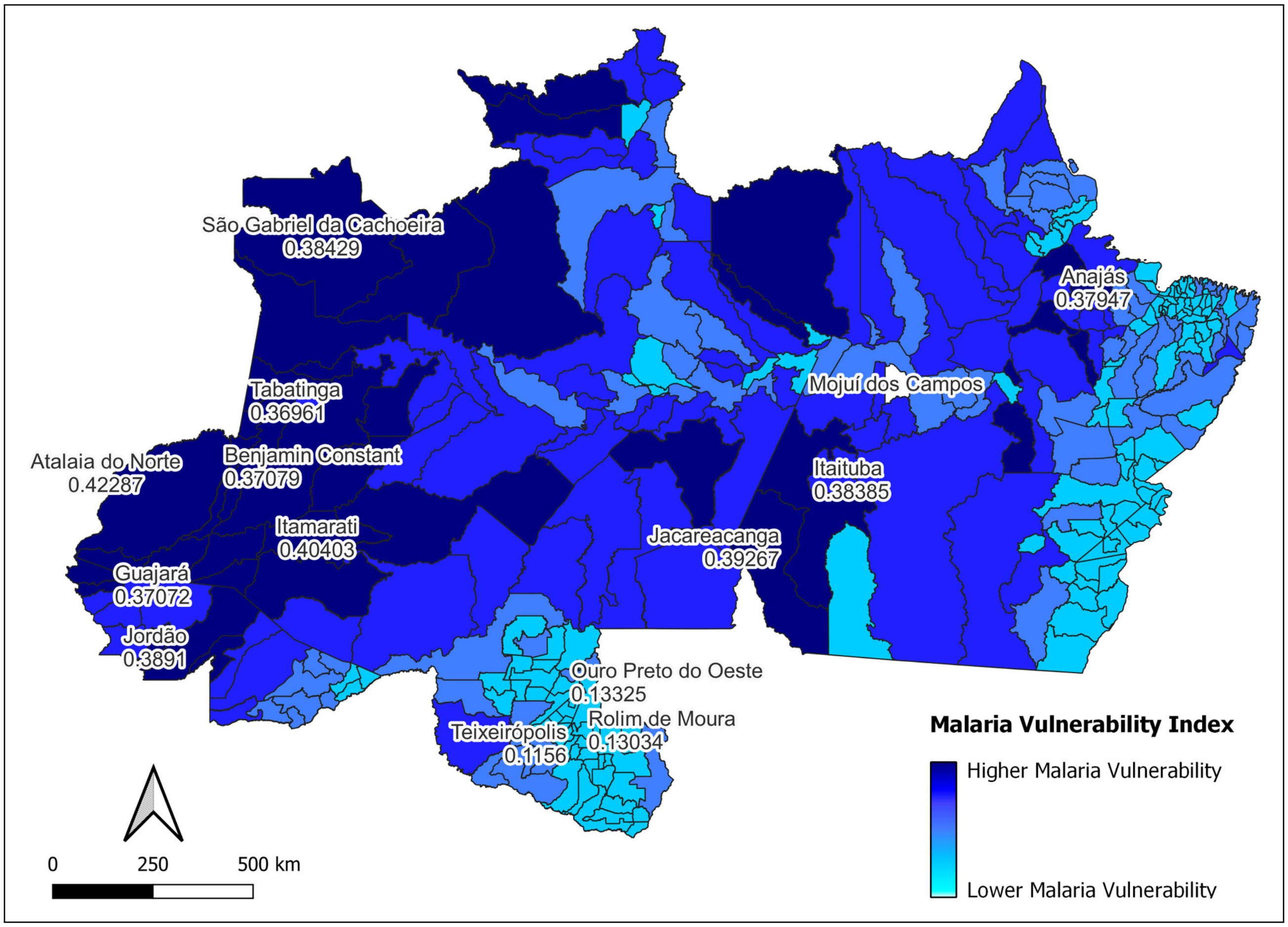

Figure 2. Malaria Vulnerability Index (MVI) per municipality. The top ten most vulnerable municipalities as well as the top three least vulnerable ones are highlighted along with their MVIs.

because higher coverage levels are supposed to make the allocation differences among municipalities less pronounced. For investment levels below 30%, the solutions are practically the same.

4.3 The Benefit of Prioritization in Different Interventions: All-or-Nothing, PMC, and DCL

The benefit of prioritization in the three interventions is discussed in light of three main aspects: (i) the total quantity of LLINs allocated; (ii) the number of underserved areas; and (iii) the average coverage of the 41 most vulnerable municipalities according to the MVI. These results are depicted for both non-prioritization and MVI-based prioritization approaches in Figure 3 (see Tables EC.10 to EC.12 for details in the E-Companion). We highlight that the solutions without MVI-based prioritization end up allocating a greater overall number of LLINs compared to the solutions weighted by MVI, but this allocation is substantially more unequal in terms of the number of underserved areas. As an illustration,[1] the non-prioritization strategy manages to allocate 1% more LLINs to the malaria-endemic area at the expense of underserving 35% more municipalities, which is a trade-off that clearly favors the MVI-based approach. Moreover, the most vulnerable municipalities are often neglected when MVI is not factored into the problem, as can be seen in Figure 3: even for optimistic investment levels around 90%–70%, the most vulnerable populations have a negligible coverage on average, and for lower investment levels, these populations are barely covered. In contrast, MVI-based coverage consistently achieves 100% for these populations, which is expected by design. Figure 4 evidences how the coverage solutions switch from allocating slightly fewer LLINs to more municipalities with lower demands but with higher MVIs (with MVI) to allocating slightly more LLINs to fewer municipalities with higher demands but lower MVIs (without MVI).

4.4 The Price of Equity and Implications Via Lexicographic Optimization

We now analyze the solutions of the lexicographic models LLINs-Lexo$_1$ and LLINs-Lexo$_2$, and compare them against their corresponding single-objective models, LLINs-DCL and LLINs-Equity, respectively. The main observations, based on

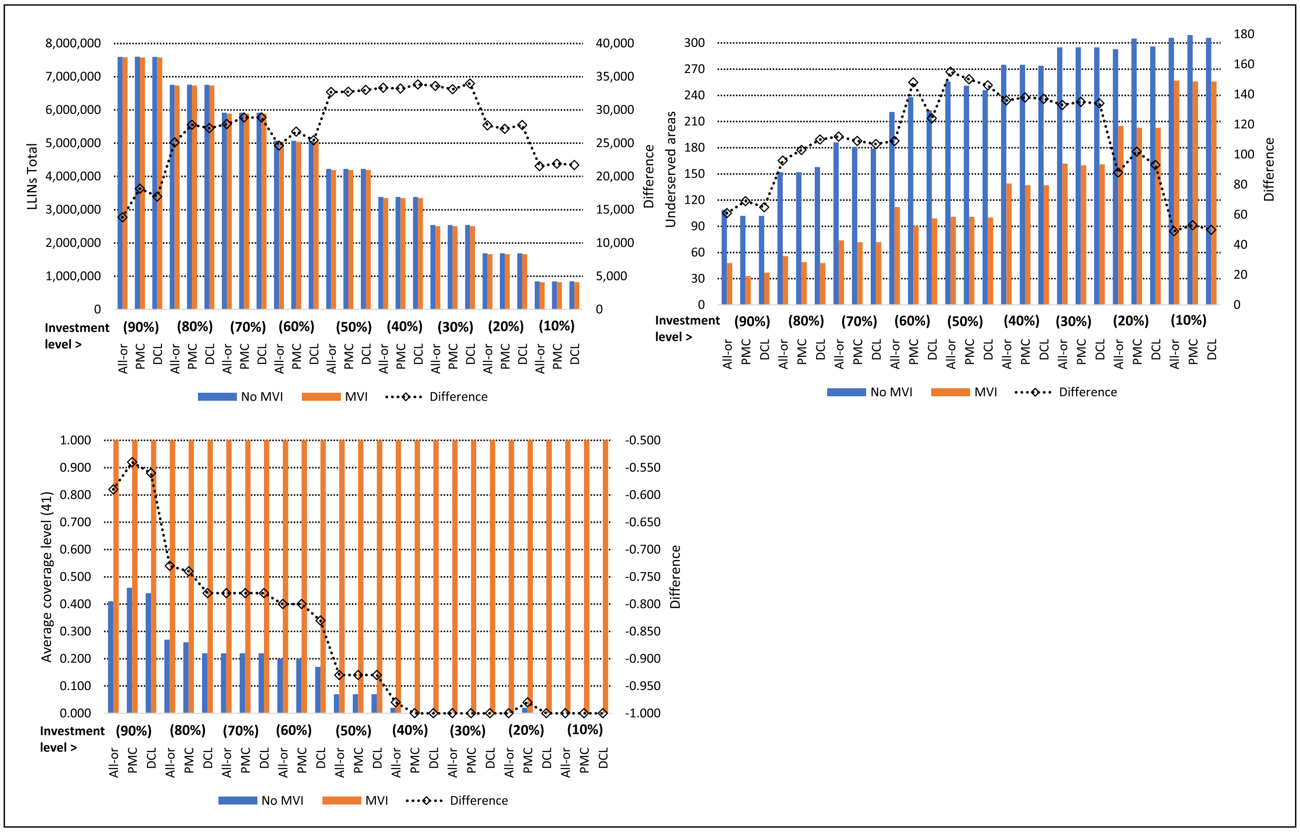

Figure 3. Performance of the interventions with and without MVI-based prioritization, considering three aspects: (i) the total quantity of LLINs allocated (top-left); (ii) the number of underserved areas (top-right); and (iii) the average coverage of the 41 most vulnerable municipalities according to the MVI (bottom-right). MVI = Malaria Vulnerability Index; LLINs = long-lasting insecticidal nets.

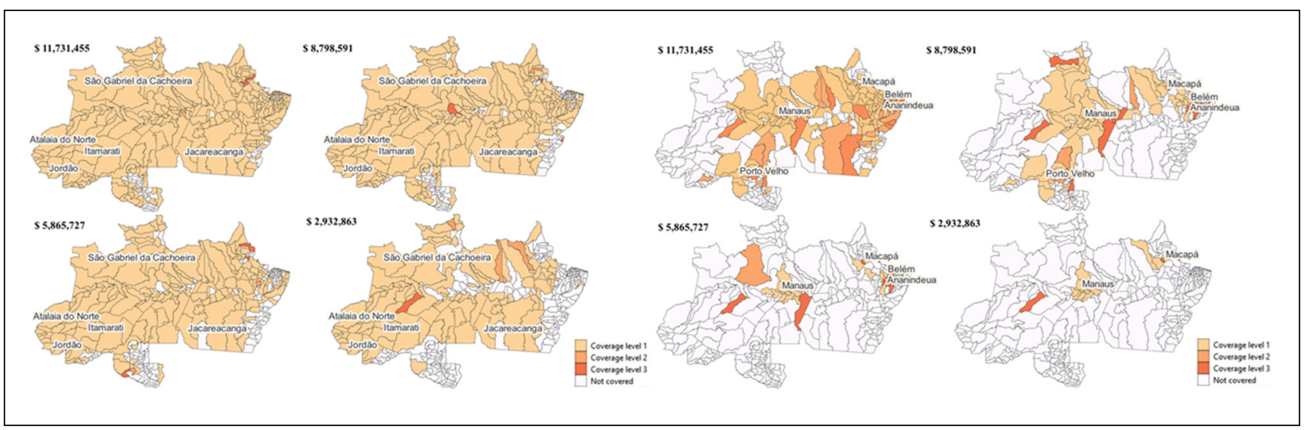

Figure 4. A spatial example of coverage levels given by LLINs-DCL with (right-hand-side map) and without (left-hand-side map) MVI-based prioritization under four investment levels. MVI = Malaria Vulnerability Index; LLINs-DCL = long-lasting insecticidal nets with discrete coverage levels.

Figure 5 and Table EC.13 in the E-Companion, are discussed as follows. Notice that LLINs-DCL and LLINs-Lexo$_1$ provide the same effectiveness solution, whereas LLINs-Equity and LLINs-Lexo$_2$ deliver the same solution in terms of the number of underserved areas, due to the lexicographic constraints. Perfect equity (see Definition 5 in Section 3.4) is achieved only at the 90% investment level when minimizing the number of underserved municipalities is the primary goal. In this case, the perfect equity solution results in zero underserved municipalities, aligning with Proposition 4. However, this solution does not lead to perfect equality, as LLIN coverage varies among municipalities. According to Proposition 5,

Table 2. The price of equity.

Investment level	90%	80%	70%	60%	50%	40%	30%	20%	10%	Average
LLINs-Equity	14.1	17.6	9.6	10.6	10.4	10.8	15.7	20.8	28.5	15.3
LLINs-Lexo$_2$	1.33	2.12	3.27	5.22	7.10	8.70	13.5	17.8	24.8	9.3

LLINs = long-lasting insecticidal nets.

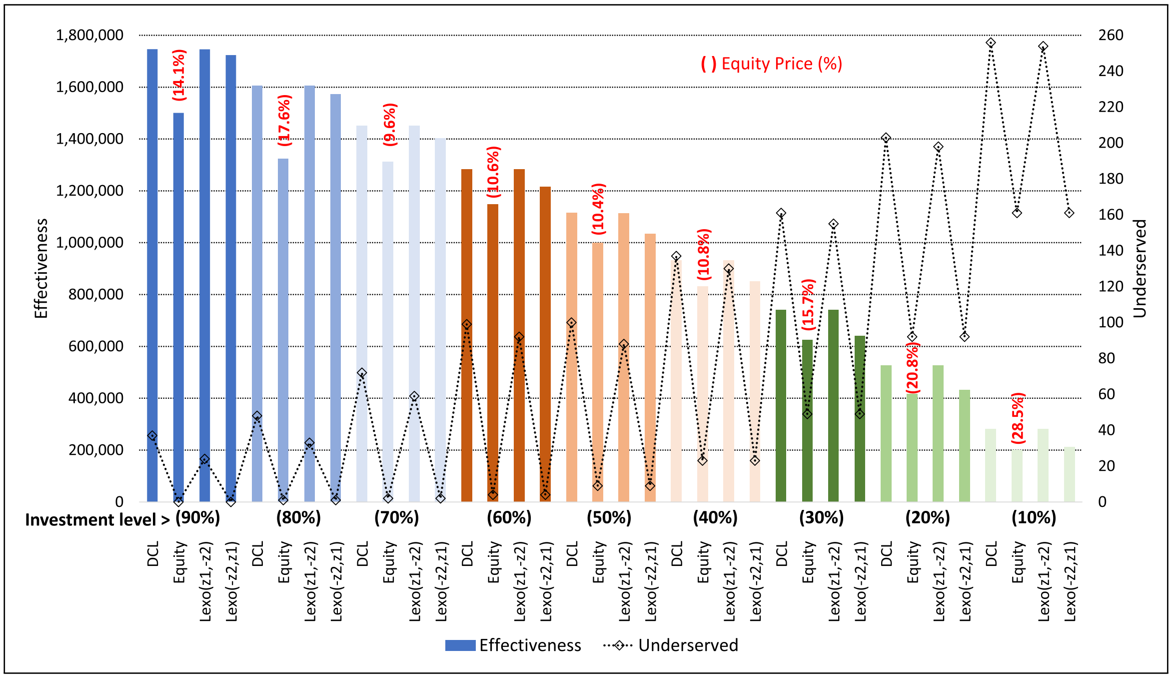

Figure 5. Performance of the lexicographic solution according to effectiveness and number of underserved areas. Here, Lexo(z1, −z2) means LLINs-Lexo$_1$ and Lexo(−z2, z1) means LLINs-Lexo$_2$. LLINs-DCL and LLINs-Equity solutions were plotted as per comparison. The equity price of LLINs-Equity is also shown.

the worst-case deviation ratio of LLIN allocation in this case is only 20%. Moreover, the perfect equity solution provided by LLINs-Lexo$_2$ clearly dominates the perfect equity solution given by LLINs-Equity, as the former exhibits a much better effectiveness value. Indeed, its PoE is only 1.33%, whereas LLINs-Equity yields a much higher price of 14.1%. As a general trend, we can see that obtaining the best-case equity via LLINs-Equity or LLINs-Lexo$_2$ is too costly for low investment levels; although LLINs-Lexo$_2$ manages to drastically reduce its price up to a 60% investment level, the price remains similar in more resource-constrained scenarios (see Table 2). The implication of this effectiveness loss is particularly pronounced among the most vulnerable municipalities, whose coverage is substantially reduced. Whereas LLINs-DCL provides full coverage to all the top 41 most vulnerable municipalities under a 10% investment level, the average coverage provided by LLINs-Equity/LLINs-Lexo$_2$ is 0.51 (see the column "Average (41)" in Table EC.13).

Interestingly, the solutions given by LLINs-Equity or LLINs-Lexo$_2$ share three main aspects compared to those from LLINs-DCL and LLINs-Lexo$_1$: fewer underserved municipalities (as per design); a significantly reduced coefficient of variation; and a higher number of municipalities covered at the last coverage level (80%). On the other hand, the effectiveness-driven approaches tend to cover the municipalities at the first coverage level, even at low investment levels, and prioritize the most vulnerable ones due to the MVI. The trade-off between effectiveness and equity is depicted in Figure 6, where it is evident that solutions from LLINs-DCL/LLINs-Lexo$_1$ are more scattered and concentrated above those from LLINs-Equity/LLINs-Lexo$_2$, indicating better effectiveness performance. Meanwhile, LLINs-Equity/LLINs-Lexo$_2$ solutions are mostly located in the left-hand quadrant, a region indicative of lower inequity.

4.5 Benchmark Equity Analysis

Table EC.14 in the E-Companion shows the performance of the models LLINs-All-or-Nothing, LLINs-PMC, and LLINs-DCL when the benchmark equity formulation is adopted. Although we ran tests for the equity parameter δ varying from 0 to 1 in steps of 0.1, we only show the results for $\delta = 0$, 0.5,

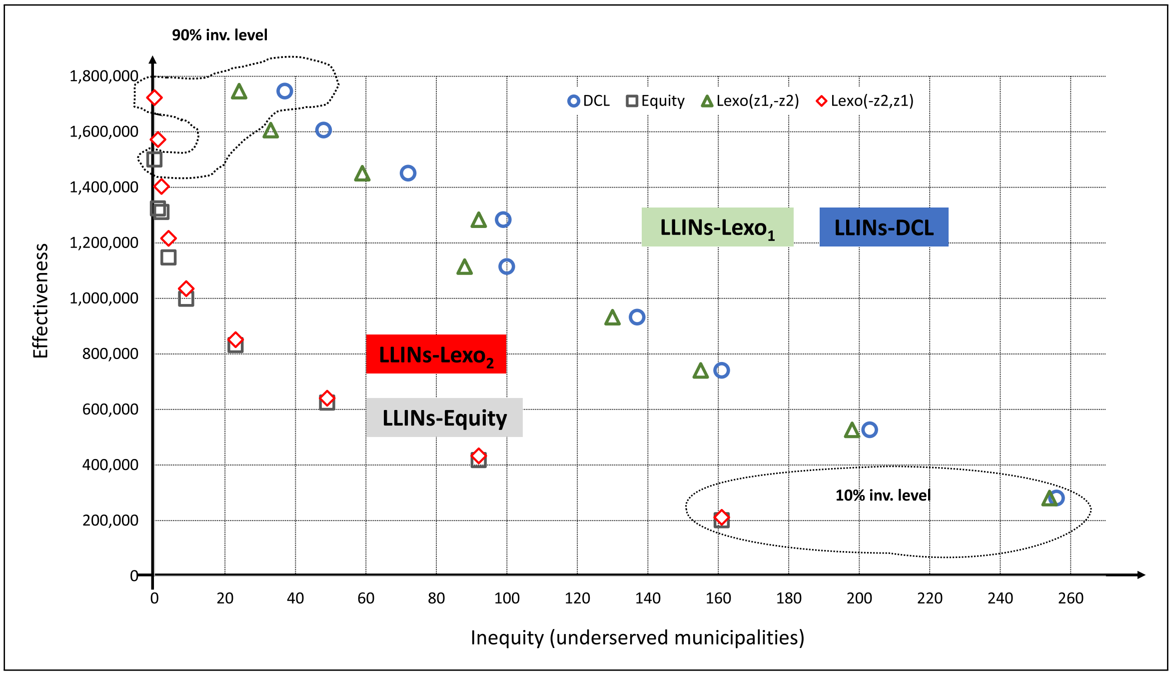

Figure 6. Trade-off between solution effectiveness and inequity (number of underserved areas).

and 1 (default case when equity is not enforced), considering that the results practically do not change for most values of δ. Under the perfect equity perspective given by expression (26), the All-or-Nothing model's optimal effectiveness is zero regardless of the investment level, since in this case, $W_m^\star = 0$ for all m is the only feasible solution. The LLINs-DCL model achieves a non-trivial optimal effectiveness solution only at a 90% investment level; in this case, we have the so-called perfect equity aligned with the concept of perfect equality. For the other investment levels, enforcing equity solely produces the trivial solution zero effectiveness. All these results are aligned with Proposition 6. Conversely, LLINs-PMC achieves perfect equity (equality) at all investment levels when $\delta = 0$; in this case, there is not a single underserved municipality. However, this solution violates the minimum LLIN coverage of 80% for investment levels from 70% downward and therefore would not effectively prevent mosquito bites. It is also worth noting that perfect equity (equality) is achieved at the expense of a drastic effectiveness loss ranging from 3.4% (at a 90% investment level) to 37% (at a 10% investment level), as illustrated in Figure 7. There is no convincing empirical evidence that the benchmark equity formulation improves the system's equity for any $\delta \neq 0$. In particular, $\delta = 0.5$ provides practically the same solution as the default case across all interventions types.

4.6 Validation of Interventions Via Simulation

The purpose of this validation is to simulate yearly interventions within a three-year malaria campaign cycle, as recommended by WHO, and estimate the benefits of the interventions in terms of the number of people protected against mosquito bites, as well as the number of unprotected people at the end of each intervention and at the end of the three-year cycle. For this purpose, we adapted data from existing literature and assume that the level of protection against malaria transmission is proportional to the LLIN coverage. Fully covered municipalities are also fully protected. Accordingly, people in underserved areas are considered not protected. For example, if a given municipality is 80% covered, we assume that 20% is not protected, and so on. The fraction of unprotected people then has a probability of getting infected, which was derived from the medical literature. The details of our simulation algorithm and data estimation for this experiment are in Appendix EC.8 in the E-Companion. We assume interventions based on the Lexo$(z_1, -z_2)$ strategy, which has been shown to deliver great effectiveness and reduce the number of underserved areas. We also assume that yearly interventions maintain the same investment level, varying from 90% to 10%, as previously mentioned. The results in Table EC.15 and corresponding Figure 8 reveal that for investment levels up to 50%, it is possible to fully protect the population of the endemic area after 2 years. For a 40% investment level, it is necessary to run the interventions for all the 3 years. Investment levels lower than 40% are considered ineffective, as after the three-year cycle there are still unprotected areas and high variation among the protected ones. In the worst-case scenarios, up to 66% of the population of the endemic area remains unprotected for a 10% investment level. These results highlight the importance of planning successive intervention cycles, as well as determining the investment levels for each intervention to provide

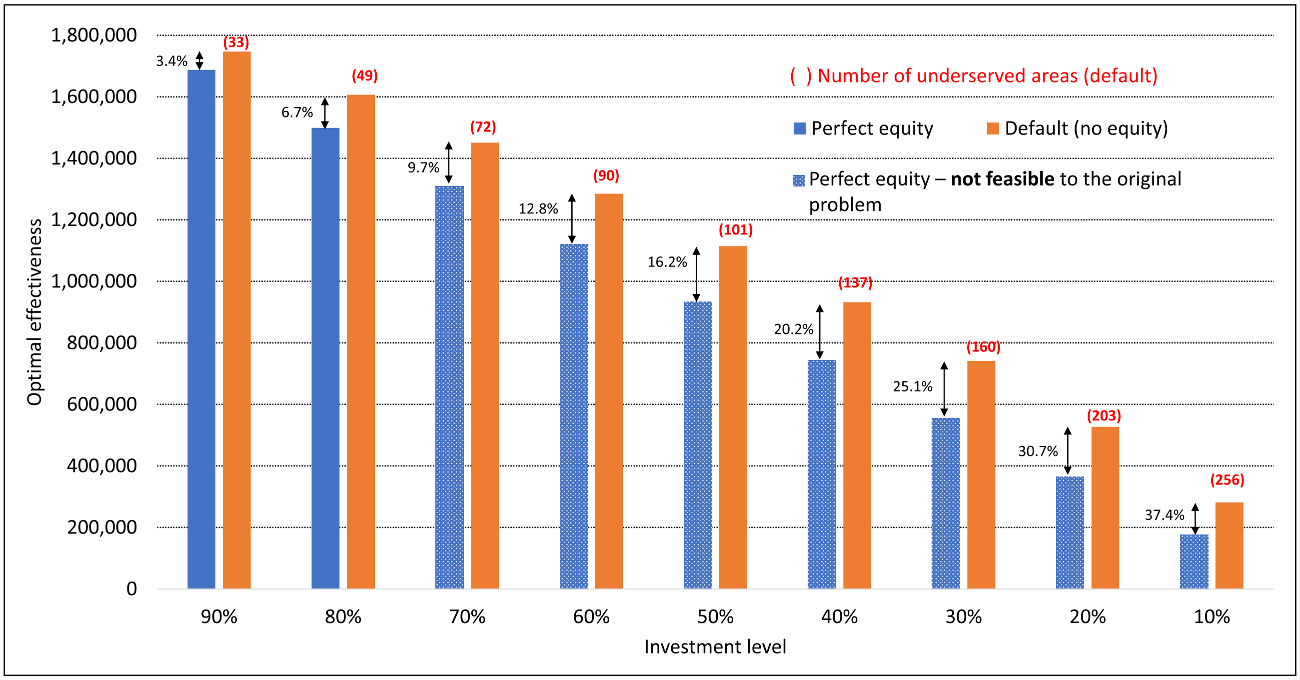

Figure 7. Perfect equity (equality) versus default solutions for long-lasting insecticidal nets with partial maximal covering location problem (LLINs-PMC).

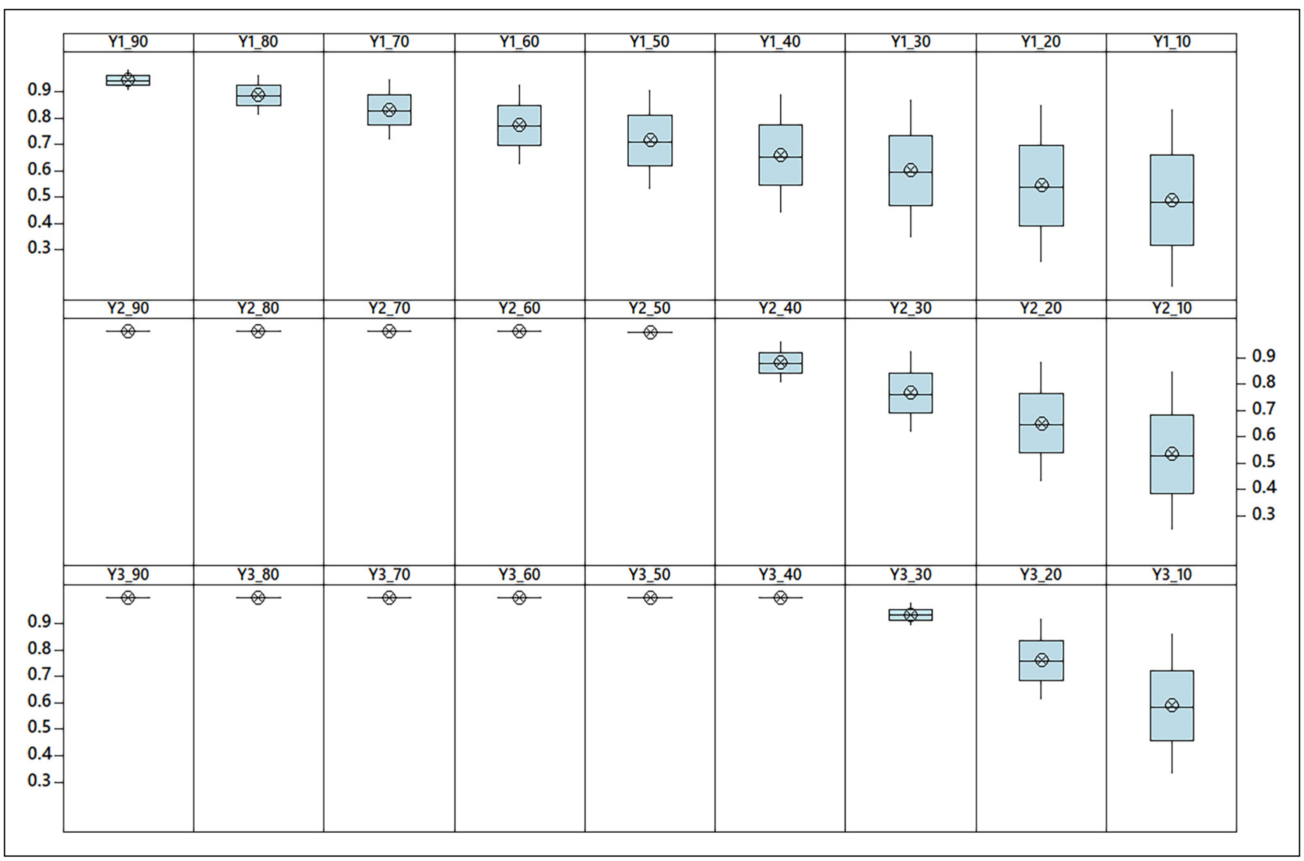

Figure 8. Fraction of people malaria-protected at the end of each year assuming a three-year cycle: first year (top), second year (middle), third year (bottom), considering investment levels from 90% (right-hand-side) to 10% (left-hand-side).

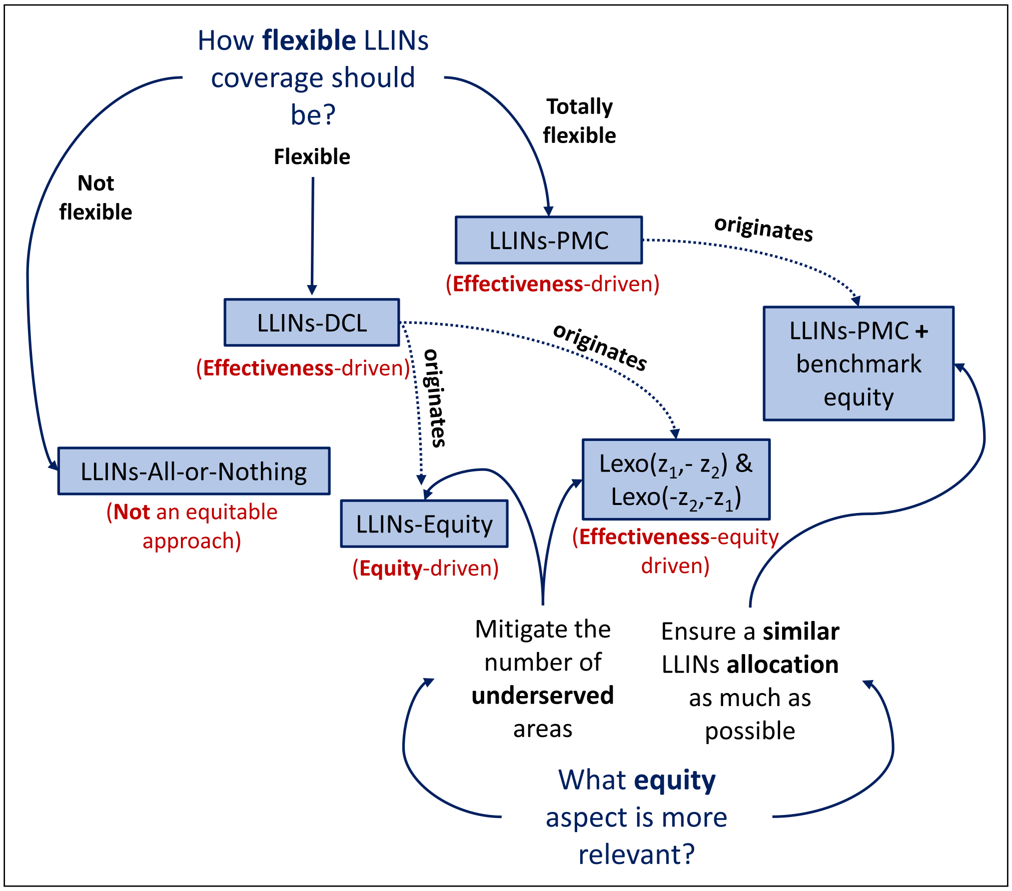

Figure 9. Framework of the proposed interventions.

decent coverage and derive significant benefits in terms of the total number of people protected at the end of each intervention. Particularly, for a 90% investment level, we can avert 7,941,641 infection cases and 1,588,328 deaths on average (20% of the total number of infection cases).

5 Conclusions and Managerial Implications

Asthe role of socioeconomic, environmental, and epidemiological factors in reducing malaria risks varies highly among areas of the same endemic region, this study evaluates the vulnerability to malaria in the Brazilian Amazon-endemic area by proposing a novel index named MVI and demonstrates its applicability. In particular, we show that the incorporation of socioeconomic and environmental variables can shed light on defining a list of municipalities that should be prioritized in malaria interventions when the available investment is insufficient to provide universal coverage. To optimize the allocation of LLINs, we present a novel location-allocation formulation based on the concept of discrete coverage levels (LLINs-DCL), which is particularly relevant in our context where a minimum-high coverage is essential to ensure effective protection against mosquito bites. We then analyze two special cases of the LLINs-DCL model when the number of coverage levels is considered to be minimum and maximum. These special cases lead to the LLINs-All-or-Nothing and LLINs-PMC interventions, respectively, which have been shown to be valid upper and lower bounds to LLINs-DCL. Although all these interventions ultimately encourage vertical equity in the sense of MVI-based prioritization, horizontal equity is not necessarily achieved. Therefore, we present a new perspective on best-case equity based on minimizing the number of underserved areas, which is specifically tailored for the LLINs-DCL case and results in a new intervention solely focusing on minimizing the number of underserved areas, named LLINs-Equity. A benchmark equity modeling based on the concept of perfect equality is also analyzed. From this theoretical discussion, we propose two additional interventions that better balance concerns of effectiveness and equity through lexicographic optimization, LLIns-Lexo$_1$ and LLIns-Lexo$_2$. Figure 9 depicts the overall framework in terms of interventions and serves as a guideline to policymakers. If coverage flexibility is not important and equity is not a tangible goal, we recommend using LLINs-All-or-Nothing, which will most likely provide universal coverage to the priority municipalities, but at the expense of slightly reduced effectiveness and a relatively high number of underserved areas. On the other extreme of coverage flexibility, we have LLINs-PMC,

Table 3. Summary of the main features of the proposed/tested interventions.

Intervention	Can it factor MVI?	Type of coverage & flexibility	Main equity aspect	Main pros	Main cons
LLINs-All-or	Yes	Not flexible—all or nothing only	Not equitable	Population is fully protected when municipality is covered; easier to implement	Overall inflexible, lower effectiveness and higher underservice; high CV
LLINs-PMC	Yes	Totally flexible	Not equitable	Higher effectiveness and lower underservice	It violates minimum requirement; population protection is not ensured
LLINs-PMC + benchark equity	Yes	Totally flexible	Quantity of LLINs allocated	As above; it can easily achieve perfect equity	As above; protection is even more fragmented
LLINs-DCL	Yes	Flexible given minimum requirement	Not equitable	Great effectiveness	The number of underserved areas can be high; high CV
Lexo(z1, −z2)	Yes	Flexible given minimum requirement	Number of underserved areas	Great effectiveness and reduced underservice	Relatively high CV
LLINs-Equity	No	Flexible given minimum requirement	Number of underserved areas	The number of underserved areas is the lowest; lowest CV	It overlooks vulnerability; poor/low overall effectiveness; high price of equity
Lexo(−z2, z1)	Yes	Flexible given minimum requirement	Number of underserved areas	The number of underserved areas is the lowest; good effectiveness; lowest CV	Effectiveness is compromised, especially among the most vulnerable

which is designed to yield the best possible effectiveness due to its full flexibility in allocating any quantity of LLINs to the municipalities. Although this intervention is the only one to achieve perfect equality when it is integrated with the benchmark equity (assuming $\delta = 0$), it is also likely to compromise the population's protection against mosquito bites due to the absence of minimum requirements. Therefore, we do not recommend adopting this intervention at all in our case study. If the equity concept is oriented toward mitigating the number of underserved areas, there are three possible approaches. LLINs-Equity is the most conservative approach, meaning that the minimum level of underservice is drastically reduced, but at the expense of substantial effectiveness deterioration (price of equity). This deterioration typically arises from allocating LLINs at lower coverage levels, which inevitably jeopardizes the coverage of more vulnerable areas. This intervention is clearly dominated by LLINs-Lexo$_2$ that always reduces the price of equity for the same level of underservice, but it rarely improves the effectiveness in the most vulnerable areas. For these reasons, we do not particularly recommend adopting either of these two interventions, assuming that it is paramount to provide extensive LLIN coverage to the areas with the highest MVIs. In this sense, LLINs-Lexo$_1$ proves to be the best intervention, as it yields great effectiveness, especially in more vulnerable areas, and the number of underserved areas is reasonably reduced. Table 3 summarizes the proposed interventions and some of their main features, including potential pros and cons. Although this table is not exhaustive, it provides a clear idea of the applicability of each approach and where it might fall short in general applications.

We also analyze all these interventions without considering MVI prioritization. In this situation, effectiveness is solely driven by the LLIN requirements of the different municipalities, and more vulnerable municipalities are often overlooked by the LLIN campaign. Interestingly, the solutions are clearly more inequitable in terms of underservice, as shown in Figure 4. However, if for some reason vulnerability is not a crucial issue, our suggestion would be to use LLINs-Equity or LLINs-Lexo$_2$, which provide very stable solutions in terms of LLIN allocation and simultaneously have the fewest underserved areas. Lastly, we briefly study a scenario-based LLIN location-allocation strategy in which LLIN requirements are modeled using a set of discrete realizations or scenarios. Considering the low population growth prediction in the malaria-endemic region, the benefit of the stochastic solution is not particularly pronounced. However, one interesting result is that more robust prioritization policies inevitably lead to lower effectiveness but a similar number of underserved areas. This discussion is presented only in Appendix EC.6.2 in the E-Companion.

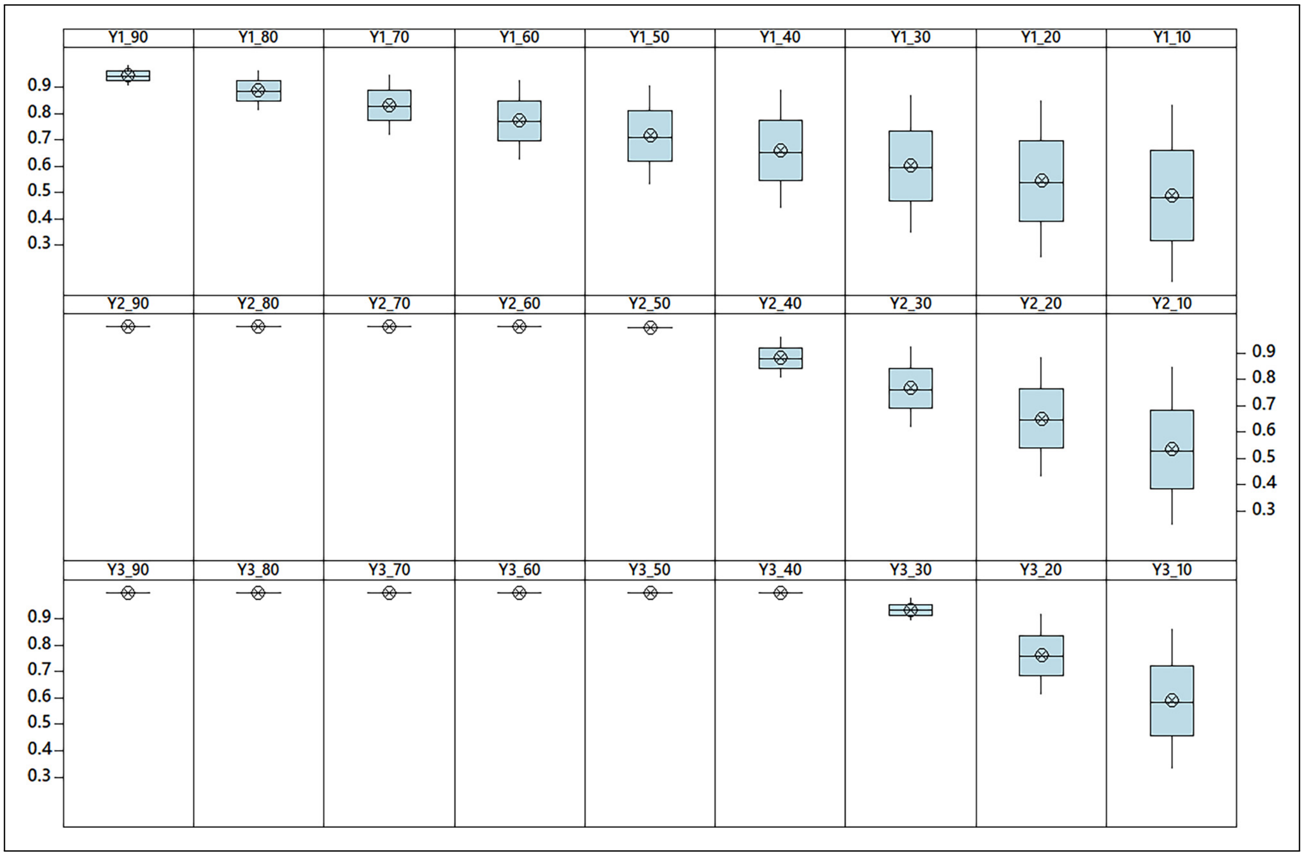

Figure 10. Fraction of people malaria-protected at the end of each year assuming a three-year cycle: first year (top), second year (middle), third year (bottom), considering investment levels from 90% (right-hand-side) to 10% (left-hand-side).

To understand the impact of a given intervention over a three-year cycle, we propose a simulation whose outputs provide the number of malaria cases and deaths that could potentially be averted. Assuming even a modest investment level of around 60%, there is the potential to save more than 8 million people in the malaria-endemic area after a two-year campaign. Moreover, we show that investment levels below 40% are negligible in mitigating the transmission of the disease. All in all, we believe that MVI-based interventions can help Brazilian public health stakeholders recognize that there are social determinants which inevitably impact health inequalities and vulnerability to malaria, and that long-term malaria eradication 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. Promising future research involves extending our approach to account for multiple malaria vector control measures, such as indoor residual spraying and malaria vaccines. This is not a trivial task, as it will entail multiple coverage levels associated with different measures, but there is also the cumulative effect when using all of them within the same household. In this case, the impact of demand uncertainty is likely to be more pronounced across the different interventions since the municipalities may not require all malaria mitigation measures within each campaign cycle. For this reason, the development of robust optimization models may be necessary to manage uncertainty and provide more robust LLIN allocations, as well as tailored solution methods that can enhance the model's solvability.

Acknowledgements

The authors express their gratitude to four anonymous reviewers and the editors for their constructive suggestions that enhanced the quality of this paper. The authors also thank Dr Aakil Caunhye for helpful discussions related to Lemma 1 and Proposition 4.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

This work was supported by Coordination for the Improvement of Higher Education Personnel (CAPES [88881.653896/2021-01; 88887.091739/2014-01 – Finance Code 001], the National Council for Scientific and Technological Development (CNPq) [309621/2022-4; 308084/2019-5] and the Foundation for Support of Research in the State of Rio de Janeiro (FAPERJ) [E-26/201.384/2021; E-26/210.025/2024]; and Aalto University.

ORCID iDs

Douglas Alem https://orcid.org/0000-0001-9490-0998
Adriana Leiras https://orcid.org/0000-0002-6305-9662

Supplemental Material

Supplemental material for this article is available online (doi: 10.1177/10591478241279247).

Note

1. Assuming average values over all investment levels and across all interventions.

References

Abdin AF, Fang Y-P, Caunhye A, Alem D, Barros A and Zio E (2023) 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* 304(1): 308–324.

Alem D, Bonilla-Londono HF, Barbosa-Povoa AP, Relvas S, Ferreira D and Moreno A (2021) Building disaster preparedness and response capacity in humanitarian supply chains using the social vulnerability index. *European Journal of Operational Research* 292(1): 250–275.

Alem D, Caunhye AM and Moreno A (2022) Revisiting gini for equitable humanitarian logistics. *Socio-Economic Planning Sciences* 82: 101312.

Arnette AN and Zobel CW (2019) A risk-based approach to improving disaster relief asset pre-positioning. *Production and Operations Management* 28(2): 457–478.

Balcik B and Beamon BM (2008) Facility location in humanitarian relief. *International Journal of Logistics* 11(2): 101–121.

Baskaya S, Ertem MA and Duran S (2017) Pre-positioning of relief items in humanitarian logistics considering lateral transhipment opportunities. *Socio-Economic Planning Sciences* 57: 50–60.

Carrasco-Escobar G, Fornace K and Benmarhnia T (2021) Mapping socioeconomic inequalities in malaria in sub-Sahara African countries. *Scientific Reports* 11(1): 1–8.

Castro MC (2017) Malaria transmission and prospects for malaria eradication: The role of the environment. *Cold Spring Harbor Perspectives in Medicine* 7(10): a025601.

Caunhye AM and Alem D (2023) Practicable robust stochastic optimization under divergence measures with an application to equitable humanitarian response planning. *Or Spectrum* 45(3): 759–806.

Church RL and Roberts KL (1983) Generalized coverage models and public facility location. *Papers of the Regional Science Association* 53: 117–135. Springer.

De Mattos RG, Oliveira F, Leiras A, de Paula Filho AB and Gonçalves P (2019) Robust optimization of the insecticide-treated bed nets procurement and distribution planning under uncertainty for malaria prevention and control. *Annals of Operations Research* 283(1): 1045–1078.

De Vries H, Van de Klundert J and Wagelmans APM (2020) The roadside healthcare facility location problem a managerial network design challenge. *Production and Operations Management* 29(5): 1165–1187.

Gralla E, Goentzel J and Fine C (2014) Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. *Production and Operations Management* 23(6): 978–989.

Harris RJ, Messick DM and Sentis KP (1981) Proportionality, linearity, and parameter constancy: Messick and Sentis reconsidered. *Journal of Experimental Social Psychology* 17(2): 210–225.

Joseph KT, Rice K and Li C (2016) Integrating equity in a public health funding strategy. *Journal of public health management and practice: JPHMP* 22(Suppl 1): S68.

Karasakal O and Karasakal EK (2004) A maximal covering location model in the presence of partial coverage. *Computers & Operations Research* 31(9): 1515–1526.

Lindblade KA, Mwandama D, Mzilahowa T, Steinhardt L, Gimnig J, Shah M, Bauleni A, Wong J, Wiegand R, Howell P, et al (2015) A cohort study of the effectiveness of insecticide-treated bed nets to prevent malaria in an area of moderate pyrethroid resistance, Malawi. *Malaria Journal* 14(1): 1–15.

Musa JJ, Moore SJ, Moore J, Mbuba E, Mbeyela E, Kobe D, Swai JK and Odufuwa OG (2020) Long-lasting insecticidal nets retain bio-efficacy after 5 years of storage: Implications for malaria control programmes. *Malaria Journal* 19(1): 1–12.

Ngufor C, Agbevo A, Fagbohoun J, Fongnikin A and Rowland M (2020) Efficacy of royal guard, a new alpha-cypermethrin and pyriproxyfen treated mosquito net, against pyrethroid-resistant malaria vectors. *Scientific Reports* 10(1): 1–15.

Orgut IS, Ivy J, Uzsoy R and Wilson JR (2016) Modeling for the equitable and effective distribution of donated food under capacity constraints. *IIE Transactions* 48(3): 252–266.

Park CH and Berenguer G (2020) Supply constrained location-distribution in not-for-profit settings. *Production and Operations Management* 29(11): 2461–2483.

Parvin H, Beygi S, Helm JE, Larson PS and Van Oyen MP (2018) Distribution of medication considering information, transshipment, and clustering: Malaria in Malawi. *Production and Operations Management* 27(4): 774–797.

Recht J, Siqueira AM, Monteiro WM, Herrera SM, Herrera S and Lacerda MVG (2017) Malaria in Brazil, Colombia, Peru and Venezuela: Current challenges in malaria control and elimination. *Malaria Journal* 16(1): 1–18.

Rodríguez-Espíndola O, Alem D and Da Silva LP (2020) A shortage risk mitigation model for multi-agency coordination in logistics planning. *Computers & Industrial Engineering* 148: 106676.

Rottkemper B, Fischer K and Blecken A (2012) A transshipment model for distribution and inventory relocation under uncertainty in humanitarian operations. *Socio-Economic Planning Sciences* 46(1): 98–109. DOI: 10.1016/j.seps.2011.09.003.

Santos J, Santos Fd and Macêdo V (1999) 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* 15: 281–292.

Sengul Orgut I and Lodree EJ (2023) Equitable distribution of perishable items in a food bank supply chain. *Production and Operations Management* 32(10): 3002–3021.

Wagstaff GF and Perfect T (1992) On the definition of perfect equity and the prediction of inequity. *British Journal of Social Psychology* 31(1): 69–77.

WHO (2019) *World Malaria Report 2019*. World Health Organization.

WHO (2022) *World Malaria Report 2022*. World Health Organization.

Young AJ, Eaton W, Worges M, Hiruy H, Maxwell K, Audu BM, Marasciulo M, Nelson C, Tibenderana J and Abeku TA (2022)

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* 21(1): 1–13.
Yukich J, Bennett A, Keating J, Yukich RK, Lynch M, Eisele TP and Kolaczinski K (2013) Planning long lasting insecticide treated net campaigns: Should households' existing nets be taken into account? *Parasites & Vectors* 6: 1–13.
Zhai C, Bretthauer K, Mejia J and Pedraza-Martinez A (2023) Improving drinking water access and equity in rural sub-Saharan Africa. *Production and Operations Management* 32(9): 2921–2939.

How to cite this article

de Oliveira FN, Alem D, Oliveira F and Leiras A (2025) Long-Lasting Insecticidal Net Campaigns for Malaria Control Considering Prioritization and Equity. *Production and Operations Management* 34(1): 120–141.