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QUANTIFYING THE IMPACT OF PROACTIVE COMMUNITY CASE MANAGEMENT ON SEVERE MALARIA CASES USING AGENT-BASED SIMULATION

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ABSTRACT

Malaria remains a major global health threat, especially for children under five, causing hundreds of thousands of deaths annually. Proactive Community Case Management (ProCCM) is an intervention designed to enhance early malaria detection and treatment through routine household visits (sweeps), complementing existing control measures. ProCCM is crucial in areas with limited healthcare access and low treatment-seeking rates, but its effectiveness depends on transmission intensity and the coverage of existing interventions. To quantify the impact of ProCCM, we calibrated an agent-based simulation model for settings with seasonal transmission and existing interventions. We evaluated how different ProCCM scheduling strategies perform under varying treatment-seeking rates in reducing severe malaria cases. Our proposed heuristics—greedy and weighted—consistently outperformed a standardized, uniformly spaced approach, offering practical guidance for designing more effective and adaptive malaria control strategies.

1 INTRODUCTION

Malaria remains one of the most pressing public health challenges worldwide, particularly in sub-Saharan Africa. In 2023 alone, the World Health Organization estimated 263 million cases and 597,000 malaria-related deaths, with the majority occurring in children under five in Africa (WHO 2024). Despite decades of progress driven by preventive tools like insecticide-treated nets, indoor residual spraying, and intermittent preventive treatment in pregnancy, malaria control has plateaued in recent years (Paaijmans and Lobo 2023). This stagnation is compounded by persistent gaps in access to timely diagnosis and treatment, especially in rural and remote regions. Early detection and prompt malaria treatment are essential to reduce both severity of disease and mortality (Mousa et al. 2020). However, barriers such as geographic distance, transportation costs and lack of health system trust often prevent individuals from seeking care quickly.

To address these barriers, Senegal introduced Prise en Charge à Domicile (PECADOM) in 2008, a form of malaria community case management (mCCM) where trained community health workers (CHWs) residing in villages diagnose and treat malaria cases locally (Programme National de Lutte contre le Paludisme 2010). While this approach significantly expanded access to care, the utilization of CHWs remained suboptimal, and preventable malaria morbidity and mortality persisted (Linn et al. 2015).

To improve upon PECADOM's passive structure, a proactive variant—Proactive Community Case Management (ProCCM), or PECADOM Plus—was piloted in Senegal beginning in 2012. Under ProCCM, CHWs perform regular household sweeps during the transmission season, visiting every household in the village to screen for symptomatic individuals. CHWs use rapid diagnostic tests (RDTs) to confirm malaria infection and administer artemisinin-based combination therapy (ACT) to positive cases. Those showing signs of severe disease are referred to a health facility for urgent care. By bringing care directly to patients, ProCCM aims to increase access to care by shortening time to treatment, reducing transmission by lowering the infectious reservoir, and ultimately reduce the number of severe malaria cases. A 2013 pilot study in the Saraya Health District in Senegal demonstrated that weekly ProCCM sweeps throughout the transmission season led to a substantial drop in symptomatic prevalence compared to villages with limited or no household visits (Linn et al. 2015). These findings led to the national adoption and gradual scale-up of the ProCCM strategy across Senegal.

Despite the demonstrated effectiveness of ProCCM in improving malaria case detection and treatment, there is little evidence on its impact on severe malaria cases — a critical outcome for malaria control. The interaction between ProCCM and contextual factors like treatment-seeking rates have not been systematically evaluated. Moreover, few empirical or modeling studies have explored how to optimize the frequency, timing, and distribution of ProCCM sweeps based on local conditions, including weather patterns and epidemiological trends. This lack of evidence leaves program implementers without clear strategies for maximizing the impact of ProCCM in different transmission settings.

In this study, we develop and apply a simulation-based framework to investigate the effectiveness of ProCCM in reducing severe malaria cases given various treatment seeking behaviors and we assess the potential for improving the impact of ProCCM through adaptive sweep scheduling. Using the Saraya Health District in Senegal as a case study, we extend a validated agent-based malaria transmission model that incorporates individual-level disease progression, mosquito dynamics, immunity development, and treatment-seeking behavior. We propose and compare three heuristics for sweep scheduling: (1) an evenly spaced approach, (2) a greedy algorithm that targets days of highest symptomatic burden, and (3) a weighted method that balances prevalence distribution with temporal spacing. These strategies are evaluated across a range of treatment-seeking rates to understand their impact on severe malaria cases.

2 METHODS

2.1 Malaria Transmission Model

We adapted the agent-based simulation model for malaria transmission originally developed by (Griffin et al. 2016), extending the mosquito dynamics and incorporating ProCCM sweeps based on the frameworks proposed by (White et al. 2011) and (Wang et al. 2024). The simulation explicitly tracks individual human agents through daily transitions across infection states, and updates their age and immunity level, while modeling mosquito populations as a compartmental system. Figure 1 illustrates the full transmission flow between and within the human and mosquito systems.

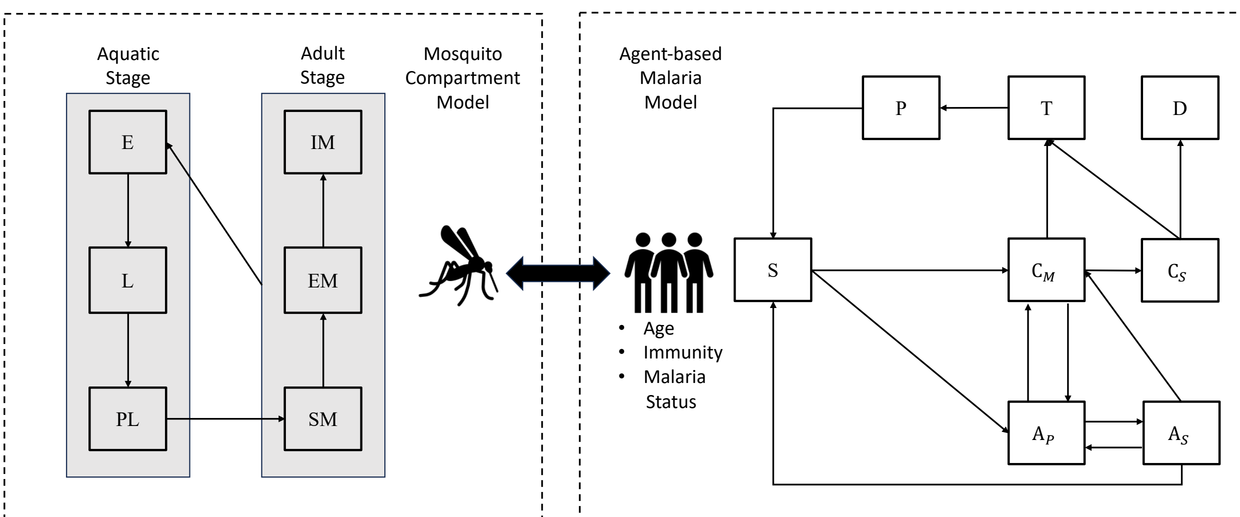

Figure 1: Simulation model transmission flow diagram which incorporates interactions between a mosquito compartmental model and an agent-based model of human capturing age, immunity, and malaria status (infection state) in each day.

2.1.1 Human Infection States

Table 1 outlines the human infection stages captured in the model. A human infection begins in the susceptible (S) stage, following a successful bite by an infectious mosquito. After infection, the malaria parasite first passes through a pre-erythrocytic liver stage, which typically lasts 1–2 weeks, before progressing to the blood stage. During this stage, as the parasite density increases, the infected individual may begin to exhibit mild clinical symptoms (C_M), with the probability of symptom onset determined by their immunity level. If no symptoms appear, the individual progresses to an asymptomatic patent infection (A_P), where the parasite is still detectable by RDT. Some of these parasites may develop into gametocytes, making the human infectious to mosquitoes. Individuals in the mild clinical stage (C_M), may seek treatment (T), after which they receive a temporary period of protection (P) before returning to the susceptible stage (S). If not treated, they may self-recover and transition to (A_P) and then to asymptomatic subpatent stage (A_S), where the parasite becomes undetectable by RDT but still present. Alternatively, some untreated individuals may deteriorate into the severe clinical stage (C_S), where there is a defined probability of death (D). In contrast to the original model where the C_M stage was fixed at 5 days (Griffin et al. 2016), we allow its duration to vary uniformly between 1 and 9 days, which better captures the clinical variability of malaria progression, known to worsen rapidly—sometimes within 24 hours. This model also allows for superinfection (the infection of a host already carrying a malaria parasite with a genetically distinct strain of the parasite) during both the A_S and A_P stages. The full state transition diagram is shown in Figure 1.

Table 1: Human infection stages.

Stage	Description
S	Susceptible
A_P	Asymptomatic patent infection
A_S	Asymptomatic subpatent infection
C_M	Clinical mild stage
C_S	Clinical severe stage
T	Treatment
D	Death
P	Protection after treatment

2.1.2 Mosquito Dynamics

The mosquito life cycle is modeled using a compartmental approach. The aquatic stages include eggs (E), larvae (L), and pupae (PL), which progress sequentially in water. Upon emergence as adults, mosquitoes enter the susceptible adult (SM) compartment. After biting infectious humans (in C_M, C_S, A_P or A_S stages), susceptible mosquitoes become exposed (EM) and eventually progress to the infectious (IM) stage after an extrinsic incubation period. These infectious mosquitoes can then transmit malaria to susceptible humans (S), or create superinfection for asymptomatic patent or subpatent (A_P or A_S) patients creating a bidirectional infection loop between humans and mosquitoes. The mosquitos in the adult stage (SM, EM or IM) will produce eggs, and subsequently evolve into the next generation.

2.1.3 Treatment Seeking and Sweep Modeling

Th agent-based simulation model explicitly tracks treatment-seeking behavior at the individual level. For individuals in either the mild clinical (C_M) or severe clinical (C_S) stages, there is a daily probability, defined as the treatment-seeking rate (TSR), that they will access formal healthcare services. Empirical studies have shown no significant difference in TSR between children and adults across several malaria-endemic countries; therefore, we assume a uniform TSR for all individuals in the population (Battle et al. 2016).

In addition to routine treatment-seeking, this model incorporates ProCCM sweeps, where community health workers actively visit households and screen for symptomatic individuals. In the model, each sweep is assumed to perfectly identify and treat all symptomatic individuals (those in C_M and C_S) present on the sweep day. As a result, all such individuals immediately transition to the treatment stage (T), bypassing the usual probabilistic TSR-based care access.

2.2 Study Site and Model Calibration

The ProCCM pilot study was conducted in 2013 in the Saraya Health District, Senegal, where malaria transmission is highly seasonal, with the peak transmission season typically lasting from June to November. Weekly household sweeps conducted from July 8 to November 25—a period that largely overlapped with the peak transmission season. In total, 20 sweeps were implemented in the intervention group/villages, while 3 sweeps were conducted in the comparison group (control villages) to collect data on symptomatic malaria prevalence. In addition to the sweeps, two other malaria control interventions took place in both groups during this period: a Long-Lasting Insecticide-treated Net distribution campaign from July 15 to July 25, and a Seasonal Malaria Chemoprevention campaign conducted from November 1 to November 4.

A key metric from this study is the symptomatic malaria prevalence, defined as the proportion of individuals who had experienced fever within the previous 48 hours, tested positive via RDT, and had not yet received treatment, relative to the total population. In our model, once symptomatic individuals seek treatment or are identified during a sweep, they are transitioned to the treatment stage (T) (Figure 1) and are no longer considered symptomatic, even though clinical symptoms could persist for several days given treatment. We used this symptomatic prevalence measure, along with data on the number of symptomatic individuals who sought treatment, to calibrate the model. Specifically, the calibration was based on multiple metrics from the pilot study, including symptomatic prevalence in both control and intervention villages, the number of self-reported malaria cases in both groups, and the total number of systematically detected cases in the intervention village. We also incorporated contextual transmission information using real rainfall data from the National Centers for Environmental Information, as well as estimates of the entomological inoculation rate (EIR) and Plasmodium falciparum parasite prevalence among children aged 2–10 years (PfPR 2–10) from Malaria Atlas Project (MAP) (MAP 2025). More details can be found in (Griffin et al. 2016), (White et al. 2011) and (Wang et al. 2024).

The parameters we estimated during calibration included the environmental carrying capacity, the number of days of rainfall contributing to larval habitat availability, and the baseline treatment-seeking rate. The best-fitting baseline TSR was found to be 0.03 for both the control and intervention villages prior to the introduction of ProCCM sweeps. During the intervention period, we tested the effectiveness of ProCCM under various TSRs, driven by the additional treatment opportunities and the information about the availability of free treatment provided by the health workers. These sweeps significantly reduce the burden of untreated clinical infections and contribute to the overall reduction in severe cases and malaria transmission in the population.

2.3 Sweep Heuristics

We propose three different heuristics for determining the best timing for ProCCM sweeps: 1) uniform, 2) greedy, and 3) weighted. To enable a fair comparison across strategies, we define a fixed planning horizon from July 8 to November 25, matching the intervention period used in the 2013 pilot study. This corresponds to days 189 through 329 when expressed on a day-of-year scale. To evaluate the effectiveness of each heuristic, we analyze the relationship between the number of sweeps and the resulting reduction in severe malaria cases. Specifically, we vary the total number of sweeps from 5 to 20, the latter aligning with the weekly sweep schedule implemented during the original pilot.

The uniform heuristic considers evenly distributed sweeps. Sweeps are distributed across identical interval within the planning horizon, given a fixed number of total sweeps. This heuristic will result in predefined sweep dates, which will serve as the baseline for our comparison with the other more adaptive heuristics.

The greedy heuristic is designed to make the sweep schedule more adaptive to variations in malaria transmission. Due to the seasonal nature of weather and the influence of other malaria control interventions, the malaria burden can fluctuate significantly even within the peak season. To better align ProCCM sweeps with these dynamic patterns, the greedy heuristic selects sweep days iteratively based on the estimates of symptomatic prevalence, prioritizing the days with the highest transmission while ensuring adequate spacing between interventions. The pseudo code for the greedy heuristic can be found in Figure 2.

The greedy heuristic begins by initializing the set of potential sweep days as the full planning horizon and defining key parameters: the total number of sweeps to perform and a radius that enforces a minimum gap between sweep days. The *sweep_days* set, which contains the list of selected intervention days, is initialized to be empty. In each iteration of the algorithm, the current *sweep_days* are fixed in the simulation, which is run multiple times (e.g., 500 iterations) to estimate the average symptomatic malaria prevalence for each day. Days that fall within the exclusion *radius* of existing selected sweep day are removed from consideration to avoid overlap. From the set of remaining available days, the day with the highest average prevalence is selected and added to *sweep_days*. This process continues until all sweep slots are filled, resulting in a schedule that concentrates interventions on the most critical days while maintaining a practical distribution across the season. In this algorithm, various *radius* values (2,3,4 and 5) were tested and we chose the best performing value (i.e., *radius*=5) with respect to reducing the number of severe cases.

```
HEURISTIC 2: GREEDY
Define days = set of days in planning horizon
Define sweep_days = set of days to perform sweeps
Define radius = minimum number of days between sweeps
Define n_sweeps = number of sweeps to perform
Initialize sweep_days = ∅
For i = 1 to n_sweeps do
   Fix sweep_days in simulation
   Run simulation (500 iterations)
   Compute average prevalence for each day in days
   For all s in sweep_days do
      Define exclude_days_s = {d in days: d in s ± radius}
   End For
   Set valid_days = {d in days: d ∉ exclude_days_s for all s}
   Find max_day = day in valid_days with highest average prevalence
   Update sweep_days = union of (sweep_days, max_day)
End For
Return sweep_days
```

Figure 2: Pseudo code for the greedy heuristic.

Finally, the weighted heuristic is designed to incorporate prevalence data while maintaining temporal equity in the allocation of sweeps. Unlike the greedy heuristic, which may neglect lower transmission periods in favor of peak times, the weighted method ensures that no extended gaps occur between interventions, reducing the risk of untreated symptomatic cases over extended periods. The pseudo-code for the weighted heuristic is represented in Figure 3.

The heuristic begins by running a baseline simulation without any ProCCM sweeps to estimate daily symptomatic prevalence across the planning horizon. Next, the algorithm computes a cumulative sum of the daily prevalence and normalizes it to span the interval [0,1], representing the temporal distribution of malaria burden. This normalized curve is then partitioned into equal-length intervals, corresponding to the number of sweeps to be scheduled. For each interval, the day with a cumulative prevalence closest to the interval's upper bound is selected as a sweep day. This heuristic ensures that sweep timing reflects the intensity of transmission while also providing even temporal coverage, resulting in a simple, data-driven strategy that balances responsiveness with fairness.

HEURISTIC 3: WEIGHTED

```
Define days = set of days in planning horizon
Define sweep_days = set of days to perform sweeps
Define n_sweeps = number of sweeps to perform
Initialize sweep_days = ∅
Initialize daily symptomatic prevalence based on simulation without sweep
Compute cumulative sum of daily symptomatic prevalence and normalize
    Define norm_d = normalized cumulative prevalence on day d in days
Divide [0,1] into i = n_sweeps + 1 intervals of equal length
    Define target_i = upper bound of interval i for i in (1 to n_sweeps)
For i = 1 to n_sweeps do
    Find target_day_i = day d with norm_d closest to target_i
    Update sweep_days = union of (sweep_days, target_day_i)
End For
Return sweep_days
```

Figure 3: Pseudo code for the weighted heuristics.

3 RESULTS

3.1 Symptomatic Malaria Prevalence and Sweep Plan

Figure 4 and Figure 5 report the average symptomatic malaria prevalence over time under the greedy heuristic (with radius 5 days) and weighted heuristic, respectively, for different treatment-seeking rates (TSRs). Each subplot corresponds to a different number of sweeps, for 5, 10, 15 and 20 sweeps. Since sweep days are selected by these heuristics based on the symptomatic prevalence curve, these prevalence plots indirectly reveal the timing of sweep implementation as indicated by the steep drops in prevalence when symptomatic individuals move immediately to the treatment state during a sweep. We present figures for the greedy and weighted heuristics and exclude the uniform heuristic as its sweep schedule is fixed and unresponsive to dynamic transmission patterns.

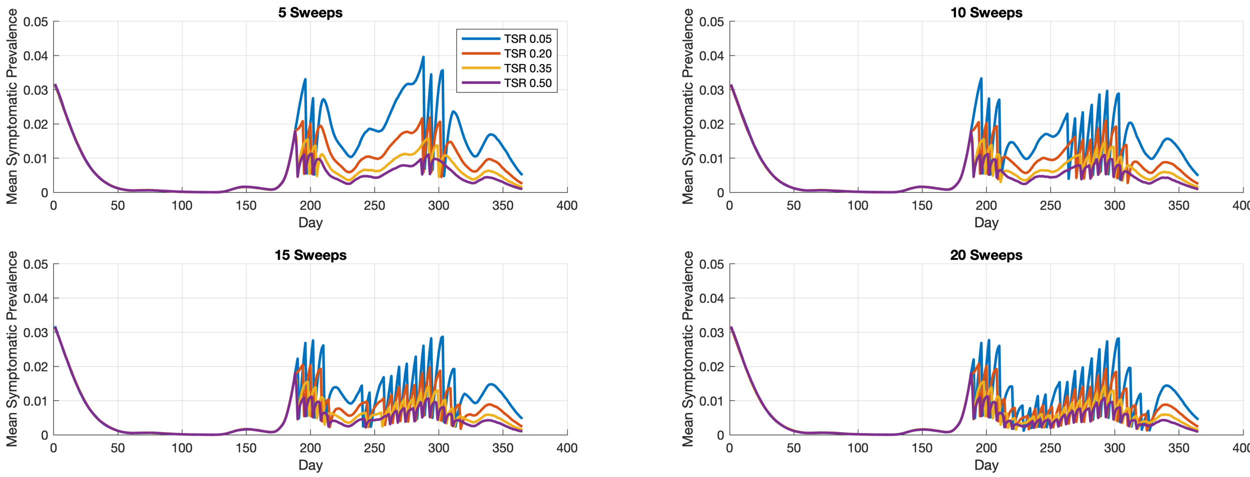

Figure 4: Symptomatic malaria prevalence with 5, 10, 15, and 20 sweeps using the greedy heuristic with radius 5 across four treatment seeking rates (TSR = 0.05, 0.20, 0.35, 0.50).

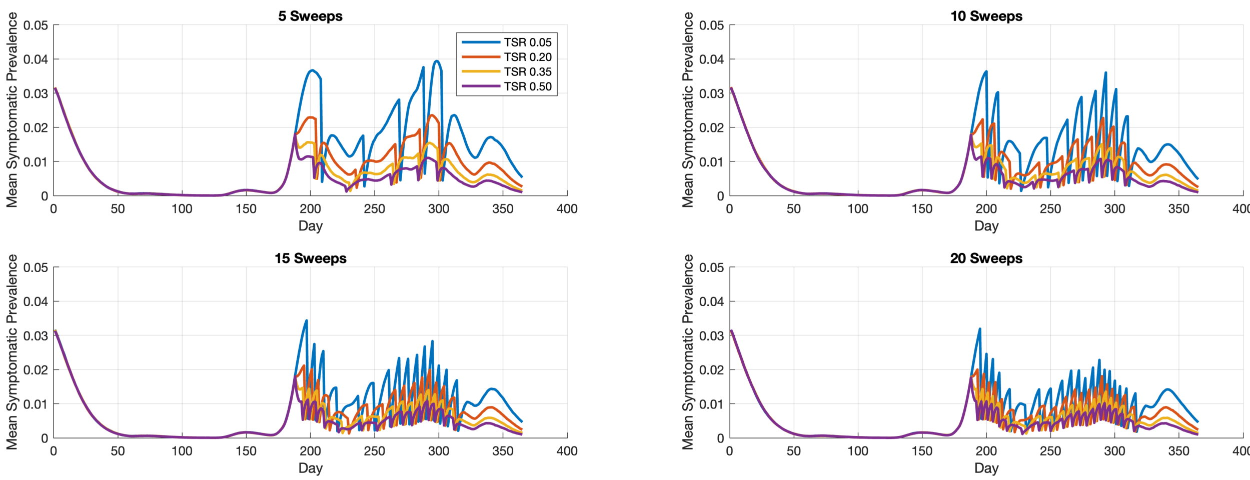

Figure 5: Symptomatic malaria prevalence with 5, 10, 15, and 20 sweeps using the weighted heuristic across four treatment seeking rates (TSR = 0.05, 0.20, 0.35, 0.50).

3.2 Severe Malaria Cases

Figure 6 presents the average number of severe malaria cases under the three sweep scheduling heuristics — uniform, greedy (with radius 5), and weighted — for TSR values of 0.05, 0.20, 0.35, and 0.50. Each subplot corresponds to a specific TSR level and plots the average severe case count as a function of the number of sweeps, which ranges from 5 to 20. The figure shows that as TSR increases, the number of severe cases decreases across all sweep strategies and sweep counts. At TSR = 0.05, the average number of severe cases starts above 20 with 5 sweeps and declines to around 7 by 20 sweeps. At TSR = 0.20, the curve begins near 10 and reaches approximately 3.5 at the maximum sweep count. At TSR = 0.35, the values range from about 4.5 to 2.5. The lowest range is observed at TSR = 0.50, where the average number of severe cases falls between just over 2 and around 1.5 across the sweep range. These trends demonstrate a consistent drop in severe malaria burden as the treatment-seeking rate increases, irrespective of the heuristic used or the number of sweeps applied.

When comparing the performance of the different heuristics, the greedy strategy yields the lowest severe case counts across nearly all sweep budgets, especially between 5 and 15 sweeps. In many cases, the greedy strategy results in noticeably sharper reductions in severe cases compared to the other two methods.

The weighted strategy tends to perform moderately, while the evenly spaced heuristic shows the highest average severe case counts across most settings. As the number of sweeps approaches 20, the difference in performance between the three heuristics narrows significantly, with all three strategies converging to similar levels of effectiveness across TSR levels.

The relative reduction in severe cases from increasing the number of sweeps from 5 to 20 is more pronounced at lower TSRs. At TSR = 0.05, this reduction exceeds 60%, dropping from over 20 to around 8 severe cases. At TSR = 0.20, the drop is approximately 55%, from near 10 to just below 5. At TSR = 0.35, the reduction is about 40%, and at TSR = 0.50, the reduction is roughly 25%. While the absolute number of severe cases declines in all scenarios with more sweeps, the magnitude of that reduction decreases as TSR increases.

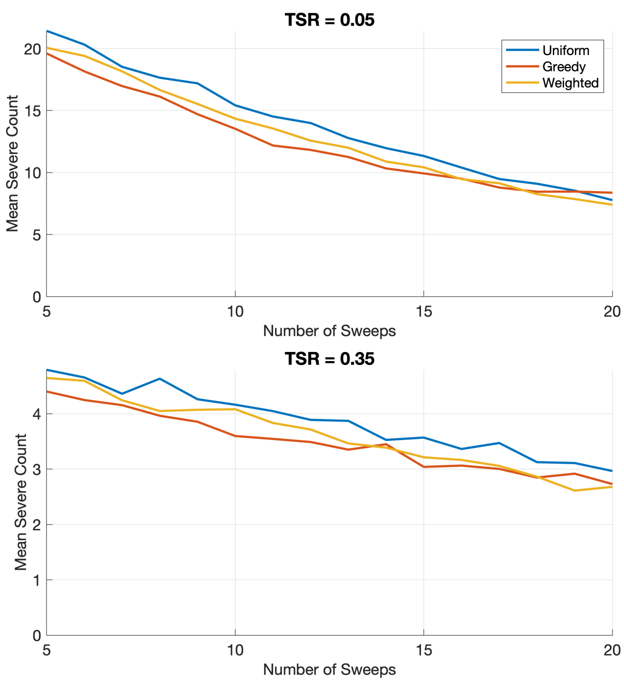

Figure 6: Predicted severe malaria cases given 5-20 sweeps using the three heuristics across four treatment seeking rates (TSR = 0.05, 0.20, 0.35, 0.50).

4 DISCUSSION

4.1 Operational Insights

This study highlights the value of ProCCM in reducing severe malaria cases, the critical role of treatment-seeking rates, and the operational improvements achievable through adaptive scheduling strategies. Across all tested scenarios, increasing the number of ProCCM sweeps consistently reduces the burden of severe malaria, underscoring the overall effectiveness of the intervention. TSR plays a dual role — it not only determines how quickly symptomatic individuals access treatment, but it also affects both the relative impact of ProCCM and the optimal timing of sweeps. Adaptive strategies, such as the greedy and weighted heuristics, deliver meaningful improvements over uniform scheduling, particularly in low-access settings. These enhancements can be substantial, with adaptive approaches reducing severe cases by an additional 20% under low TSR conditions.

The effectiveness of ProCCM in lowering severe malaria incidence is consistent and robust across all conditions. Regardless of the specific scheduling strategy or TSR level, increasing the frequency of community sweeps reliably decreases the average number of severe cases. This effect is especially important in regions like Senegal, where TSR is typically below 0.05 (Gaye et al. 2020). In such low-access environments, ProCCM plays a vital role in reaching symptomatic individuals who would otherwise remain untreated. For instance, with a TSR of 0.05, increasing sweep counts reduces severe cases from around 20 to just 8. However, as TSR rises, both the absolute burden of severe cases and the relative benefit of ProCCM decline, since more symptomatic individuals are treated through existing healthcare services. At a TSR of 0.5, increasing sweeps from 5 to 20 results in less than a 30% reduction in severe cases, indicating reduced dependence on ProCCM in high-access settings.

Malaria transmission follows a pronounced seasonal pattern that shapes both the effectiveness and timing of ProCCM interventions. As illustrated in Figures 4 and 5, symptomatic prevalence is low during the early dry season, begins to increase around day 190, and peaks between July and November. This seasonal peak is not uniform — following an initial surge, prevalence temporarily drops before rising again toward a secondary peak, partly due to the impact of other interventions. The shape of this prevalence curve is influenced by both TSR and the number of sweeps. At low TSRs, the curve is more volatile due to accumulated untreated cases; at higher TSRs, prompt treatment flattens the curve. These dynamics affect sweep scheduling strategies. The greedy heuristic tends to cluster sweeps around peak periods and remains stable across different TSR levels due to its burden-driven design. In contrast, the weighted strategy adapts more flexibly to TSR changes by distributing sweeps proportionally to historical prevalence. Still, regardless of TSR or scheduling strategy, the overall transmission pattern remains largely unchanged, as asymptomatic carriers—who are not targeted by ProCCM—continue to drive transmission. This highlights an important finding: ProCCM cannot interrupt transmission on its own.

Among all scheduling strategies evaluated, the greedy heuristic with a five-day exclusion radius consistently produced the best results. Alternative exclusion radii of 2, 3, and 4 days were tested, but the five-day buffer yielded the greatest reduction in severe cases. This suggests that sweeps placed too close together provide diminishing returns. While the greedy strategy is highly effective at targeting peak burden periods, the weighted approach remains valuable for promoting temporal equity — an important consideration in public health service delivery. By contrast, the uniform strategy, which spaces sweeps at fixed intervals regardless of burden, performed the worst in all settings. Although this result aligns with expectations, our analysis quantifies the performance gap: in low-TSR environments, adaptive strategies can achieve up to 20% greater reduction in severe cases compared to uniform scheduling. These findings demonstrate the significant potential of optimizing ProCCM operations and underscore the importance of data-driven, context-specific planning in malaria control.

4.2 Limitations

This study has several limitations that should be acknowledged. First, while the model incorporates the development of immunity and successfully captures children as a high-risk population, it does not explicitly represent pregnant women, another group particularly vulnerable to severe malaria. During pregnancy, infected erythrocytes adhere to placental glycosaminoglycan receptors, reducing the protective effect of pre-existing immunity and increasing susceptibility (Rogerson et al. 2007). Given the high birth rate in many malaria-endemic regions, excluding this group may lead to an underestimation of the total number of severe cases. Nonetheless, since this omission does not alter the overall transmission dynamics captured by the model, we believe that the relative trends in case reduction and the comparative effectiveness of different sweep strategies remain valid.

Second, our ability to validate the simulation model is limited by the scarcity of high-quality field data. In many high-transmission settings, treatment-seeking rates are low, and healthcare infrastructure is limited, resulting in sparse and incomplete records of both symptomatic and severe malaria cases. This makes it challenging to directly compare model outputs with empirical observations. Moreover, predicting severe malaria is inherently difficult due to the high variability in individual immune responses and the fact that most infected individuals do not progress to severe disease. These constraints introduce uncertainty into absolute case count projections, but the model still offers valuable insights into the relative performance of different ProCCM strategies under varying operational conditions.

5 CONCLUSION AND FUTURE WORK

This study evaluates the effectiveness of different sweep scheduling heuristics for Proactive Community Case Management (ProCCM) in reducing severe malaria cases across a range of treatment-seeking behaviors. By integrating an agent-based malaria transmission model with adaptive intervention strategies, we demonstrate that data-informed, adaptive sweep plans—particularly the greedy and weighted heuristics—consistently outperform evenly spaced approach, achieving up to 20% greater reduction in severe cases. The greedy strategy, especially when paired with a five-day spacing radius, achieves the greatest reduction in severe cases by concentrating interventions on high-burden periods. Meanwhile, the weighted strategy offers an equitable alternative that remains sensitive to transmission dynamics. Our findings also highlight how TSR influences both the burden of disease and the relative benefit of ProCCM, with the largest impact observed in low-access settings.

A key direction for future work is the development of heuristics that utilize only historical and current information, enabling timely and adaptive decision-making without relying on full knowledge of future transmission patterns. Such strategies should be robust to uncertainty and grounded in data typically available in resource-constrained settings. We also aim to incorporate additional high-risk groups, such as pregnant women, into the model and improve empirical validation through expanded data collection efforts. By bridging simulation with field constraints, we hope to support the design of more effective, equitable, and operationally feasible malaria control policies.

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