

Freedom From Infection in Cabo Verde: Supporting Evidence-Based Decision-Making for Malaria Elimination

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Abstract

Background

Cabo Verde was certified malaria-free in January 2024, yet remains at risk given continued importation and ecological receptivity across multiple islands. Quantifying how robust health systems are in preventing malaria reintroduction, and how sensitive elimination conclusions are to key definitional assumptions, can support programmatic decision-making to maintain absence of transmission. We aimed to estimate facility-level evidence for freedom from infection using the Freedom From Infection (FFI) framework, stress-test conclusions under different operational definitions of elimination, and compare classifications before versus after certification.

Methods

We extended and applied the FFI framework to jointly model latent malaria infections and the surveillance detection cascade. We combined 14 years of passive surveillance data from 25 facilities with health-facility capacity surveys and active surveillance to estimate the probability of freedom from infection (P^{FREE}). Robustness to critical elimination thresholds was assessed by varying both the population denominator (people per infection) and the P^{FREE} evidence cut-off, and by comparing classifications before versus after certification.

Results

Using a reference operational definition of elimination as fewer than one infection per 10,000 people and requiring at least 95% posterior confidence of being below that threshold, 18/25 facilities (72%) met the criterion in December 2024. Fewer facilities met elimination criteria under more stringent thresholds. Classifications were largely stable between pre- and post-certification periods, with no facilities improving and only a small number decreasing.

Conclusions

Maintaining strong surveillance system capacity is essential to sustain malaria elimination, particularly in settings with continued importation risk. The FFI framework provides a tool to quantify evidence for freedom from infection, stress-test elimination assumptions, and inform the likelihood of achieving and sustaining interruption of malaria transmission.

INTRODUCTION

Malaria surveillance is critical for achieving malaria elimination (Reithinger, 2025; Stresman et al., 2025). Effective surveillance not only aids in the timely detection and treatment of cases but also supports

efforts to confirm elimination and prevent reintroduction (Schapira & Kondrashin, 2021; World Health Organization, 2025). Traditional surveillance mechanisms, such as routine health facility data and active case detection, have played significant roles in monitoring malaria trends and guiding control strategies (World Health Organization, 2017) but have limitations when the aim is to prove absence of transmission (Nelli et al., 2024).

The World Health Organization (WHO) provides comprehensive guidelines for malaria surveillance, monitoring, and evaluation, emphasizing the importance of robust surveillance systems to confirm the absence of malaria transmission and to prevent its re-establishment (Marsh et al., 2024; World Health Organization, 2021). Countries can apply for malaria-free certification after demonstrating zero indigenous cases for three consecutive years. They must also submit evidence that their surveillance system is sufficient to detect, investigate and prevent re-establishment of transmission; however, no formal quantitative protocol exists, and the submitted evidence is qualitatively appraised by an expert committee to recommend certification to the WHO.

The Freedom From Infection (FFI) method that we previously developed (Nelli et al. 2024) provides a robust framework for assessing malaria elimination. This novel statistical approach combines routinely collected health system data with state-space modeling to probabilistically demonstrate the absence of malaria. By simultaneously modeling transmission dynamics within the population and the probability of detection, the FFI method estimates the sensitivity of the surveillance system (S_{Se}) and the probability of elimination (P^{FREE}) per health facility catchment area. This approach addresses the limitations of traditional criteria by explicitly accounting for both transmission dynamics and the end-to-end surveillance detection process (from care-seeking and testing to reporting), thereby improving the design and implementation of surveillance systems, ultimately informing more effective control strategies (Nelli et al., 2024; Reithinger, 2025; Stresman et al., 2025). However, it is unknown how sensitive the results of the FFI model are to assumptions for which detection thresholds are consistent with confidence in elimination nor any implications for stability of the classification of elimination status.

Malaria has long been a formidable public health challenge in Cabo Verde, an archipelago off the coast of West Africa with between 5,000 and 15,000 cases annually, with over 200 malaria-related deaths reported in the late 1950s. Control measures led to the temporary elimination of malaria twice, but the disease was reintroduced, highlighting the need for sustained and comprehensive strategies (DePina et al., 2018; Kokori et al., 2024). Key strategies in Cabo Verde's malaria elimination efforts included effective vector control, robust surveillance systems, and community participation (DePina et al., 2020). Cabo Verde's relentless efforts culminated in the significant achievement of WHO certification as malaria-free in January 2024, granted after four consecutive years of zero indigenous malaria cases and no malaria deaths (Nakweya, 2024; DePina et al., 2018, 2025; Kokori et al., 2024).

Despite achieving WHO malaria-free certification in January 2024, Cabo Verde has remained vulnerable, consistent with broader evidence that malaria re-introduction risk can persist after certification where importation, receptivity, mobility, and surveillance-response factors interact (Lu et al., 2023). Sporadic

cases have continued to occur in Cabo Verde even after certification, including likely imported and introduced cases post certification (DePina, Lima, et al., 2025). This combination of recent certification, ongoing importation, including possible recent focal outbreaks makes Cabo Verde an ideal test case for applying and extending the FFI framework, to provide a more rigorous and transparent assessment of elimination sustainability and implications of model assumptions.

In this study we apply and extend the Freedom From Infection framework in Cabo Verde to determine the potential of the FFI framework to support elimination decision-making and how quantitative evidence can guide post-certification vigilance. Our objectives were (i) to generate facility-level time series of P^{FREE} ; (ii) to examine the implications of key model assumptions regarding how “elimination” is defined in the FFI framework, specifically, in terms of the power to detect infections if they exist and the probability cut-off for what constitutes elimination; and (iii) to compare conclusions drawn from model results in the period prior to and after the 2024 WHO elimination certification.

METHODS

Study Site

Cabo Verde is a volcanic archipelago of ten islands (nine inhabited) about 450–500 km off the West African coast. Malaria transmission has been highly focal: over 1988–2022, indigenous cases were restricted to Santiago (2,360 cases) and Boa Vista (21 cases), while the other islands reported imported cases only. The last local cases occurred on Boa Vista in 2015 and Santiago, the highest burden area in the country, in 2017; since 2018 only introduced/imported infections have been detected (DePina et al., 2025; DePina et al., 2018; World Health Organization, 2012). The malaria parasite in Cabo Verde is predominantly *Plasmodium falciparum*, and *Anopheles arabiensis* is the only known malaria vector identified in the country. Recent entomological surveillance (2016–2023) confirmed *An. arabiensis* on six inhabited islands—Santiago, Boa Vista, Santo Antão, São Vicente, São Nicolau, and Maio—highlighting heterogeneity in ecological receptivity across the archipelago (Leal et al., 2024; DePina et al., 2018)

Data Collection

We collated data from both routine malaria surveillance and targeted surveys to evaluate the sensitivity of Cabo Verde’s surveillance system and estimate P^{FREE} .

Passive case detection (PCD)

Monthly routine surveillance data were obtained from the National Malaria Programme (NMP) for 25 health facilities across Cabo Verde between January 2014 and December 2024. These data consist of all hospitals and health delegations in the country where the data encompass those captured by all health delegations and their associated health posts. Collected data included the number of patients attending,

the number suspected of malaria, the number tested, and the number confirmed positive. For confirmed cases, information was also available on the *Plasmodium* species and whether infections were classified as imported or locally acquired.

Health system surveys

To characterise health system factors influencing surveillance sensitivity, structured surveys were conducted with lead clinicians at 25 health facilities using an online Open Data Kit (ODK) based survey (Hartung et al., 2010). The surveys captured information on malaria diagnostic and treatment availability, history of commodity stock-outs, training, and estimated catchment population size. Surveys were administered in April and November 2021.

Active case detection (ACD)

Active case detection was conducted from October to November 2021 in Praia (Santiago) and Boa Vista. A reactive, risk-targeted respondent-driven sampling (RDS) strategy was used, focusing on adults with recent travel histories to the African continent, the group most likely to import malaria into Cabo Verde. Initial participants (“seeds”) self-reported recent travel to Africa and were asked to refer up to three additional travellers. This referral process continued for up to six waves. To assess the potential for onward transmission, household follow-ups were conducted for all RDT-positive individuals and for a random 30% of RDT-negative individuals. Household members older than one year residing in the index case households and the five nearest neighbours were included.

Finger-prick blood samples were collected from all participants. Rapid diagnostic tests (RDTs) were performed in the field, while dried blood spots were analysed by pooled RT-PCR for malaria infection and by Luminex assay to assess antibody responses to *Plasmodium falciparum* antigens. Antibody markers were classified as recent or historical exposure using supervised machine learning following Stresman et al. (2025), with methodological details described in Byrne et al. (2022) and Wu et al. (2020). The use of serological markers as complementary endpoints in low-transmission settings is further supported by Wu et al. (Wu et al., 2022). All RDT-positive participants were referred to the nearest health facility for treatment according to national guidelines.

Statistical Analyses

We applied the FFI framework to assess malaria transmission and elimination sustainability in Cabo Verde. The core model is a Bayesian hierarchical state-space formulation that jointly represents the latent infection process (state process) and the surveillance pathway through which infections are detected and reported (observation process) (Nelli et al., 2024). We used the previously published multi-component extension that allows integration of passive case detection (PCD) with active case detection (ACD) metrics, including molecular and serological endpoints (Stresman et al., 2025). Here, we adapted

this framework to the Cabo Verde context and extended it by incorporating (i) risk stratification across islands and (ii) facility-specific capacity to detect imported infections. A brief overview of the model structure is provided below; full mathematical specifications, parameterisation, and priors are provided in Supplementary material.

State process

The state process models the true (but unobserved, i.e., latent) number of malaria infections across facility catchments over time. Infections are represented as two components: (i) *Endemic infections* – locally acquired cases within each catchment, capturing persistence of malaria transmission; and (ii) *Incoming infections* – infections originating outside a given catchment (from other facilities or from external sources), estimated through a spatial kernel that models the rate of case incursions as a function of distance between source and receiver sites. Endemic transmission is modelled statistically with a temporal autoregressive model, with two monthly lags, such that infection levels in any given month depend partly on infections observed in the preceding two months. This permits flexibility in the reconstructions of endemic dynamics, without the need for a detailed SIR-type model with multiple hosts (Nelli et al., 2024; Viana et al., 2015). Incoming infections are layered onto this, reflecting spatial spillover and connectivity between catchments. Together, these processes allowed us to approximate the total pool of true infections underlying the surveillance data.

Observation process

The observation process describes how latent infections generate reported cases through routine surveillance, represented as a detection cascade with four stages: (1) whether infected individuals develop symptoms; (2) whether symptomatic individuals seek care; (3) whether febrile attendees are tested for malaria; and (4) whether infections are correctly diagnosed and reported. Each stage is parameterised using available empirical data and literature-informed priors, allowing detection to vary across facilities and through time. This structure captures heterogeneity in surveillance performance and explicitly represents bottlenecks that reduce the probability that infections are observed.

Integration of additional malaria metrics

To strengthen inference in a low-transmission setting, we incorporated two supplementary ACD-derived data streams—PCR and serology—using the previously published multi-component FFI formulation (Stresman et al., 2025). PCR results provided sensitive estimates of parasite carriage, while serological endpoints captured evidence of recent (approximately within the preceding ~ 12 months) and cumulative historical exposure. These data were treated as additional observation components alongside routine surveillance indicators, with full likelihood specifications provided in Supplementary Appendix 2.

Model Extensions: Risk stratification and facility capacity

Building on the core FFI frameworks (Nelli et al., 2024, Stresman et al., 2025), we further extended the model to account for heterogeneity across the archipelago. Facilities were grouped into high-, mid-, and low-risk strata based on the historical burden of malaria transmission at island level. Risk strata were incorporated by allowing key parameters governing endemic transmission intensity in the state process and testing probability in the observation process to vary by stratum. Justification for this classification, including historical and entomological evidence for each island, is provided in the Supplementary Appendix 2, alongside full model specifications. In addition, facilities with demonstrated capacity to detect internationally imported infections were modelled as having higher testing probabilities. Together, these additions allow the model to reflect both variation in transmission potential and differences in health system performance.

Defining threshold assumptions

We follow the FFI formulation (Nelli et al., 2024), where the probability of freedom from infection, P^{FREE} , is defined as the posterior probability that a facility's true infection prevalence lies below a pre-specified elimination threshold, which is defined as "fewer than one infection per d people," with d defined a priori (e.g., 10,000) relative to the estimated population size. In this study, we evaluate the implications of the set elimination thresholds on P^{FREE} in three ways. First, rather than fixing the denominator d , we assess robustness across a grid of denominators from 100 to 30,000 (step 100), to determine the sensitivity of the assumed d on defining "elimination." To evaluate the second critical threshold for defining elimination, we pair denominators with a grid of probability cut-offs for P^{FREE} from 0.50 to 1.00 (step 0.005) and declare a facility to "meet" the criterion within a window if P^{FREE} exceeds the chosen cut-off.

Finally, we compare the corresponding interpretation based on the threshold combinations to the last 36 months up to December 2023 (PRE-elimination) and January–December 2024 (POST-elimination). Model results from the last 36 months up to December 2024 were examined as a sensitivity check. For every denominator, cut-off pair we summarise both the proportion of facilities that meet the rule and how facility status changes between windows: Improved (not meeting in PRE, meeting in POST), Decreased (meeting in PRE, not meeting in POST), Sustained met, and Sustained not met.

RESULTS

In the following sections, we present outputs from passive case detection (attendances, suspected, tested, confirmed), followed by facility maps of the posterior mean probability of care-seeking (P^{SEEK}), and probability of testing among febrile attendees (P^{TEST}) to December 2024. We then report facility probability of freedom from infection (P^{FREE}) at the Nelli et al. (2024) reference definition (denominator $d = 10,000$; probability cut-off 0.95) using three complementary summaries: the end-of-period value (December 2024), the mean over time, and the longest run above the cut-off (defined as the maximum number of consecutive months within the evaluation window in which P^{FREE} exceeds the cut-off). Next, we illustrate sensitivity to threshold assumptions with three alternative denominators,

show a 2024 robustness heatmap over the denominator–cut-off grid, and compare the last 36 months to December 2023 with 2024, reporting for each denominator and cut-off how many facilities meet the rule in both periods, only in 2024, only before 2024, or in neither period.

Passive Case Detection

Across 132 months (January 2014 to December 2024) and 25 facilities, we recorded 4,410,045 attendances. 116,138 met the suspected malaria case definition (2.63% of attendees), and 104,555 were tested (90.0% of suspected; 2.37% of all attendees). Among those tested, 806 infections were confirmed (0.77% positivity; 7.7 per 1,000), comprising 534 classified as locally acquired and 272 as imported (66.3% vs 33.7% of confirmed, respectively).

Active Case Detection

In total, 461 contacts were screened between October and November 2021. All screened individuals were tested by PCR and none were positive. Serology identified evidence of exposure in a subset of contacts: 5 with markers consistent with recent exposure and 15 with markers consistent with historical exposure; these findings should be interpreted cautiously given the small numbers.

Surveillance capacity across facilities

Posterior means of the surveillance cascade varied widely across facility catchments (Fig. 1). The probability of care-seeking (P^{SEEK} ; panel A) ranged from 0.394 to 0.999 (median 0.998; IQR 0.723–0.999; mean 0.864): however, most (17/25) catchments exceeded 0.8, indicating generally high likelihood of individuals seeking care. The probability of testing among febrile attendees (P^{TEST} ; panel B) showed a dichotomy: results spanned 0.00045 to 1.000 (median 1.000; IQR 0.063–1.000; mean 0.654) with the majority of facilities (18/25) being at or near 1.00, while a small subset remained very low (< 0.10). Spatial clustering is evident, with pockets of higher and lower values across islands, providing essential context for interpreting facility-level P^{FREE} in subsequent sections.

Risk stratification and imported infection detection capacity

The model extensions designed to capture heterogeneity in transmission context and surveillance performance were broadly consistent with expectations. In the state process, endemic force of infection tended to increase with transmission-risk stratum. Relative to low-risk islands, the effect for mid-risk strata was small and uncertain, with credible intervals overlapping zero, indicating limited evidence for systematic differences in endemic transmission. In contrast, high-risk strata showed a clearer positive effect, corresponding to an estimated 1.36-fold increase in endemic force of infection relative to low-risk settings. By contrast, the influence of risk stratum on the probability of malaria testing was highly uncertain, with posterior distributions centred near zero and broad credible intervals for both mid- and high-risk effects, suggesting little evidence that transmission history alone explained variation in testing

probability after accounting for other model components. Imported infection detection capacity, however, showed a strong positive association with testing probability, indicating that facilities able to identify imported infections had substantially higher inferred surveillance sensitivity

Facility-level probability of freedom

At the Nelli et al. (2024) reference definition (denominator $d = 10,000$; probability cut-off 0.95), three complementary summaries show substantial between-facility heterogeneity (Fig. 2). P^{FREE} in December 2024 (end of the time series) ranged from 0.00 to 1.00 (quartiles 0.86, 1.00; median 1.00; mean 0.861). Eighteen of 25 facilities (72%) had $P^{FREE} > 0.95$ in December 2024, while a small subset remained well below the cut-off, including two at 0.00. Averaged over the full 132-month period to December 2024, mean P^{FREE} ranged from 0.366 to 1.000 (quartiles 0.532, 0.994; median 0.931; mean 0.817), with 12 of 25 facilities (48%) above 0.95. Persistence of high confidence was also uneven: the longest consecutive run of months with $P^{FREE} > 0.95$ spanned 0 to 132 months (quartiles 43, 130; median 119; mean 94), with 19 facilities sustaining at least 36 months and 18 sustaining at least 60 months. Together, these views indicate that while most facilities now exhibit very high or sustained confidence in freedom from infection, a small group continues to lag.

Sensitivity of facility

$\backslash \text{varvec}P \backslash \text{varvec}F \backslash \text{varvec}R \backslash \text{varvec}E \backslash \text{varvec}E$ to the
elimination denominator (endpoint, Dec 2024)

To illustrate how conclusions depend on the elimination definition, we show P^{FREE} in December 2024 (end of the time series under three illustrative denominators spanning looser to stricter thresholds ($d = 100, 30,000$, and $100,000$ people per infection; Fig. 3). These values are presented as narrative examples to aid visual interpretation; the full sensitivity analysis across denominators in steps of 100 is summarised in the denominator–cut-off grid below. At $d = 100$, P^{FREE} was near-saturated for most facilities (range 0.00–1.00; quartiles 1.00–1.00; median 1.00; mean 0.920), with 23 of 25 facilities (92%) above 0.95. Assuming $d = 30,000$ shifted the distribution downward (range 0.00–1.00; quartiles 0.77–1.00; median 0.98; mean 0.834), with 15 of 25 (60%) above 0.95. At the strictest setting tested, $d = 100,000$, the contraction continued (range 0.00–1.00; quartiles 0.77–1.00; median 0.96; mean 0.801), with 13 of 25 (52%) above 0.95.

Robustness of elimination conclusions pre- and post-elimination certification over the denominator–cut-off

Figure 4 summarises how the proportion of facilities meeting an elimination criterion varies across a range of elimination denominators d (100 – $30,000$ people per infection) and probability cut-offs for P^{FREE} (0.50 – 1.00), using the rule that a facility meets a criterion if $P^{FREE}(d)$ is at least the chosen cut-off in every month of the last 36-month window to December 2024 (i.e., the minimum monthly

P^{FREE} in the window is $\geq$ the cut-off). As expected, the proportion meeting the criterion declined as definitions became more stringent, both with increasing d and higher probability cut-offs.

At a cut-off of 0.95, 52% of facilities met the criterion at $d = 1,000$, decreasing to 48% at $d = 10,000$ and 40% at $d = 30,000$. Holding the denominator fixed at $d = 10,000$, the proportion meeting the criterion was 48% at cut-offs of 0.90 and 0.95, falling to 40% at a cut-off of 0.99. Together, these results show that facility classification is moderately sensitive to model assumptions for what constitutes elimination: tightening the denominator from 10,000 to 30,000 or increasing the probability cut-off to 0.99 reduces the proportion of facilities that can be said to have sustained elimination over the window.

Transition patterns between the pre-certification and post-certification windows

Across the pre- versus post-certification comparison, facility classifications were largely stable and, where changes occurred, they were predominantly in the direction of reduced attainment rather than improvement (Fig. 5). At $d \approx 10,000$ and a cut-off of 0.95, no facilities transitioned from not meeting to meeting the criterion in 2024 (Improved = 0), while two facilities shifted from meeting in the pre-certification window to not meeting in 2024 (Decreased = 2). Most facilities retained their status across both periods, with 12 facilities sustaining attainment (Sustained met; 48%) and 11 sustaining non-attainment (Sustained not met; 44%). Under a stricter denominator ($d \approx 30,000$; cut-off 0.95), the same qualitative pattern held: no improvements, three decreases (12%), and stability dominated by Sustained met (10 facilities; 40%) and Sustained not met (12 facilities; 48%). Tightening the probability cut-off at $d \approx 10,000$ to 0.99 produced no improvements and only one decrease (4%), but shifted more facilities into sustained non-attainment (14 facilities; 56%), with 10 remaining sustained attainment (40%). These results indicate that, at these reference settings, differences between the pre- and post-certification windows were limited and were more consistent with isolated losses of sustained attainment under stricter criteria than with broad improvements.

DISCUSSION

Cabo Verde's malaria-free certification (January 2024) is a landmark achievement in the WHO African Region (Kokori et al., 2024; Nakweya, 2024). However, the central operational question after certification is not whether the country was free of endemic transmission during the certification window, but whether the health system can continuously detect, classify, and extinguish malaria introductions fast enough to prevent re-establishment—particularly in receptive foci and in the presence of persistent importation (Schapira & Kondrashin, 2021). This study demonstrates the utility of the Freedom From Infection (FFI) framework for identifying nuances in the likelihood of malaria elimination across Cabo Verde. By jointly modelling the latent infection process and the surveillance cascade, we quantified both the sensitivity of the health system to detect malaria (SSe) and the probability of freedom from infection (P^{FREE}). The results revealed a dichotomy in P^{FREE} across facility catchments: many facilities sustained high confidence under the reference definition, while a smaller subset showed persistently

weaker evidence even after national malaria-free certification in January 2024 (Nakweya, 2024). Variation in surveillance performance, particularly the probability of testing among febrile attendees (P^{TEST}) emerged as a key determinant of facility-level elimination confidence in this setting, alongside inferred infection pressure in receptive areas. The risk-stratification component supported this interpretation, with high-risk settings showing a modest but credible increase in endemic force of infection relative to low-risk islands, while risk stratum itself did not clearly explain variation in testing probability

A central decision-oriented output of this analysis is the explicit sensitivity of facility classification to the elimination definition and evidence standard. As expected, tightening either the elimination denominator (larger d) or the P^{FREE} cut-off reduces the proportion of facilities that meet the criterion, but the resulting robustness heatmap suggests moderate sensitivity rather than abrupt instability across plausible policy choices. For example, at a cut-off of 0.95, the proportion meeting the criterion declines as d increases, and at fixed d the proportion declines as the probability cut-off tightens, illustrating the trade-offs between stringency and sustained evidence. Comparing pre-certification (last 36 months to December 2023) with 2024 further indicates that facility classifications are largely stable; where changes occur, they are limited in number and tend to reflect loss of sustained attainment under stricter criteria rather than widespread improvement. Because our rule requires the criterion to be met in every month of the evaluation window, short-lived dips in P^{FREE} can drive reclassification, so decreases should be interpreted as weaker sustained evidence under the chosen definition rather than as confirmation of renewed endemic transmission.

Defining what ‘elimination’ means within the FFI framework is essential if outputs are to be actionable and comparable across settings, particularly as countries move through the final phase of elimination and into prevention of re-establishment (Marsh et al., 2024). In practice, this requires consensus on two policy choices: the elimination threshold (fewer than one infection per d people) and the evidentiary standard for declaring freedom (the P^{FREE} cut-off and the requirement to sustain it over time). Without standardisation, programmes can select definitions that differ in stringency, limiting comparability between countries and across years. In this study, we use $P^{FREE} \geq 0.95$ as a reference evidence standard and evaluate sensitivity across alternative denominators and cut-offs, but broader adoption of FFI for elimination decision-making will require agreement among stakeholders on harmonised definitions and reporting conventions.

Critically, our results show that the threshold of the population denominator is consequential when defining elimination. The larger the denominator, the more stringent and thus the stronger the surveillance system must be to provide a high confidence in freedom. There are also challenges with different sized catchment populations. For example, in large urban settings, using a threshold of 1/10,000 cases can still result in concluding elimination even if dozens of cases are reported in a given catchment area (e.g. in a population of 500,000, up to 50 reported locally acquired cases would still be consistent with elimination). Alternative approaches could include agreeing on a standard the threshold that balances the risk of missed infections or allowing the denominator to vary according to the

population (e.g, 1/catchment population size) and accept varying ‘stringency’ in different sized populations. Alternatively, a tiered approach could be used whereby different denominators are established as key milestones as programs progress towards elimination to increasingly identify priority areas to target interventions. Regardless, the approach taken is ideally standardized to ensure comparable results and that robust interpretation is possible. (Stresman et al., 2017; Nelli et al., 2024)

The Cabo Verde context illustrates why a probabilistic, facility-resolved evidence base is valuable even post-certification. Historically, locally acquired malaria was highly focal—restricted primarily to Santiago, with limited local transmission on Boa Vista—while the wider archipelago experienced importation without sustained endemic transmission (DePina, Lima, et al., 2025). This focality does not imply low consequence. The 2017 outbreak in Praia demonstrated how quickly transmission can re-emerge when importation pressure coincides with ecological receptivity and favourable conditions for human–vector contact (Stresman et al., 2022). Although local transmission was interrupted thereafter, Cabo Verde continues to face a persistent importation hazard, with evidence of increasing imported malaria in recent years and ongoing need for rapid detection and response to prevent onward transmission (DePina, Lopes Gomes, et al., 2025). Underpinning this vulnerability, entomological surveillance confirms the continued presence of *Anopheles arabiensis* on multiple inhabited islands, including Santiago and Boa Vista, indicating that receptivity is not uniformly absent across the archipelago (Leal et al., 2024). In this setting, prevention of reintroduction risk is not well summarised by a national, time-bound case criterion alone; it depends on where receptivity and importation intersect and on whether local surveillance reliably detects infections when they occur. This profile mirrors that of other island and near-island elimination settings, such as Zanzibar (Ali et al., 2023) d o Tomé and Príncipe (Lee et al., 2010), where importation risk remains structurally embedded through travel and trade despite substantial local control gains.

The strengths of this work lie in applying and extending the FFI framework in a recently certified, very low-incidence setting and in presenting outputs in forms that are directly interpretable for programme decisions. By integrating routine passive surveillance with a facility-resolved observation model—and incorporating archipelago heterogeneity through risk stratification—we reconstruct latent infection pressure and quantify uncertainty even when observed positives are sparse, while retaining facility-level variation in key surveillance parameters. The risk-stratification extension helped capture differences in underlying transmission potential, with high-risk settings showing higher endemic force of infection than low-risk islands. However, risk stratum did not clearly explain variation in testing probability, indicating that surveillance performance cannot be assumed to track historical transmission risk automatically. In contrast, facilities with demonstrated capacity to detect imported infections had higher inferred testing probability, supporting the inclusion of imported-case detection as an indicator of surveillance sensitivity. This provides a transparent bridge between “zero or few detected cases” and a formal statement about the strength of evidence for sustained elimination, and it enables identification of the steps in the detection cascade that most constrain confidence. Although developed here for malaria, the approach is generalisable to other infections in which decision-making depends on demonstrating freedom relative to an explicit threshold, and recent applications illustrate its value across different

epidemiological contexts (Stresman et al., 2025). In Cabo Verde, the results point to actionable opportunities: facilities with low probabilities of testing among febrile attendees represent clear candidates for targeted quality improvement, because strengthening testing practices is likely to yield disproportionate gains in end-to-end surveillance sensitivity and, in turn, in the robustness of P^{FREE} -based classifications.

Routine surveillance data have inherent limitations, including reporting gaps, delays in notification, and incomplete records, which may be more pronounced in remote or resource-limited settings. We mitigate these issues by explicitly modelling the observation process and propagating uncertainty through to SSe and P^{FREE} ; however, residual biases may remain if key steps in the detection cascade or reporting pathway change over time in ways not captured by the available data. These limitations should be borne in mind when interpreting fine-scale differences between facilities, particularly where estimates are driven by sparse observations.

As with any Bayesian state–space model, inference depends on structural assumptions and prior information for parameters that are only weakly identified by the observed data—an issue that is amplified in very low-incidence settings where positives are rare. We therefore used literature-informed priors and conducted sensitivity checks, but some posterior quantities may remain sensitive to plausible alternative parameterisations, particularly where facility-specific information is sparse. In addition, case classification into imported, introduced, and locally acquired categories is operationally complex and can vary with the quality and timeliness of investigations, completeness of travel histories, and supporting entomological evidence. Any misclassification can propagate through the model by affecting the balance between incoming and endemic infection components. To reduce inconsistency, we applied standardised definitions aligned with WHO guidance, while recognising that classification uncertainty cannot be eliminated entirely.

A further limitation relates to Cabo Verde’s island setting, where both importation pressure and receptivity can vary rapidly over space and time and such data were not available to incorporate into the modelling framework, despite their recognised importance in malaria re-introduction risk prediction (Lu et al., 2023). Human mobility—particularly international travel from malaria-endemic regions—is dynamic and only partially observed in routine health data, which limits how precisely changing importation hazard can be characterised and attributed. Likewise, while entomological surveillance is essential for interpreting receptivity, vector data remain sparse and unevenly distributed across islands, constraining inference about fine-scale variation in vector presence, density, and transmission potential. Environmental and climatic covariates can help contextualise receptivity, but available datasets may be too coarse to capture micro-ecological conditions that drive local human–vector contact and short-lived foci. These limitations mean that facility-level differences in inferred infection pressure should be interpreted alongside uncertainty about mobility and receptivity, and prioritised for follow-up where multiple lines of evidence align.

In conclusion, Cabo Verde's malaria-free certification is a major achievement, but continued vigilance is warranted in a setting where importation risk persists and ecological receptivity is not uniformly absent across the archipelago. The FFI framework provides a rigorous, probabilistic approach to quantify elimination confidence, make uncertainty explicit, and identify where surveillance performance most constrains that confidence. This reinforces the need to monitor surveillance performance directly, rather than assuming that historically higher-risk areas necessarily maintain stronger diagnostic vigilance. However, mapping results of the varying assumptions informing how the FFI model defines elimination across a range of plausible policy scenarios highlights the trade-offs between stringency and observed performance that must be weighed when establishing guidelines for use. More broadly, embedding probabilistic freedom metrics in routine surveillance can shift elimination from a milestone to a continuously evidenced status that programmes can monitor, audit, and protect.

Declarations

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Author contributions

LN, GS and CD conceived and designed the study. AD, AALG, DDSM, ALM and SdVL contributed to data collection, data curation, interpretation of the Cabo Verde surveillance context, and liaison with the National Malaria Elimination Programme and Instituto Nacional de Saúde Pública. IB contributed to active case detection, study coordination, and interpretation of infection and exposure metrics. ED, MH, LG and KT contributed to molecular and serological assays and analysis, and interpretation of serological data. LN and JM developed and implemented the statistical modelling framework, analysed the data, and generated the outputs. LN drafted the manuscript. JM, GS and CD provided methodological supervision and contributed to interpretation of the model outputs. All authors contributed to interpretation of the findings, critical revision of the manuscript, and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Data availability

Data are available upon reasonable request. The anonymised data collected to support this analysis are available from the corresponding author upon reasonable request.

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Figures

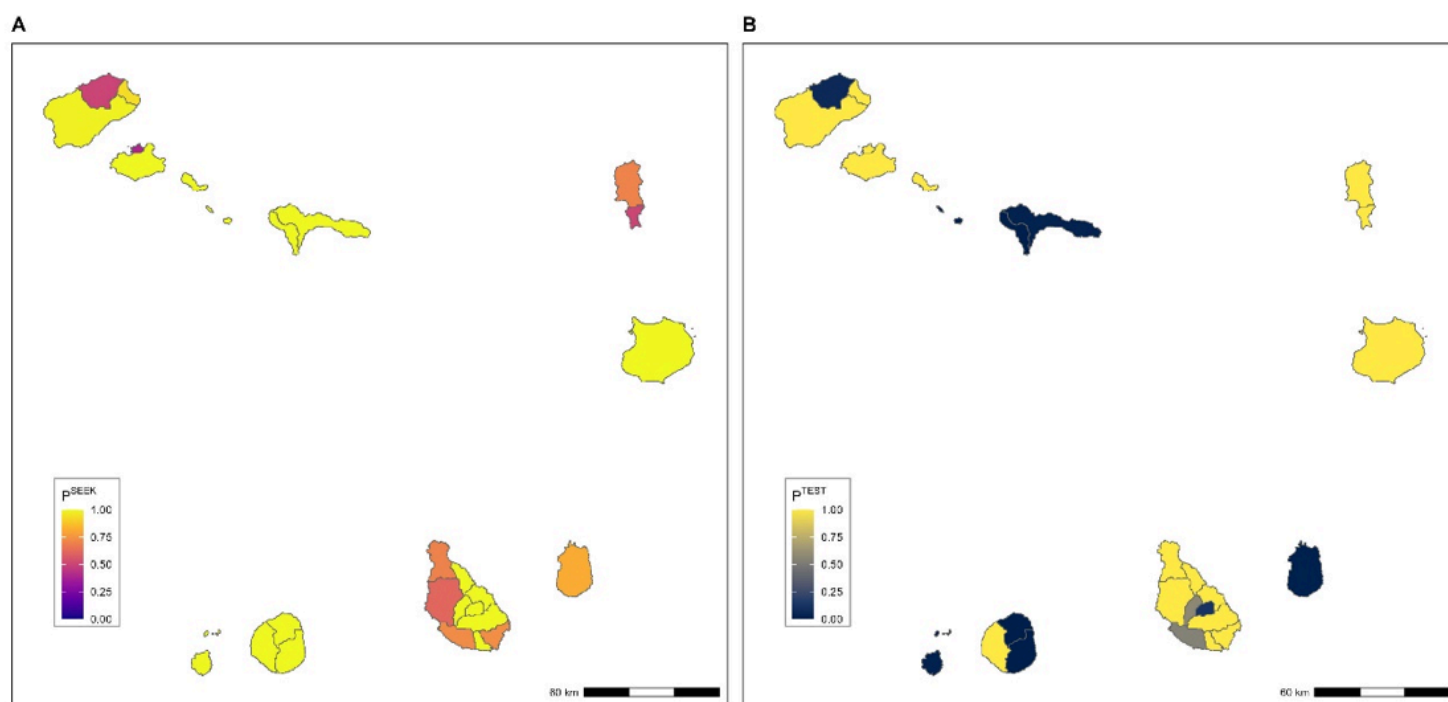


Figure 1

A: Posterior mean probability of care-seeking (); B: testing among febrile attendees () by facility catchment to December 2024. Both panels use a 0–1 scale (lighter = higher).

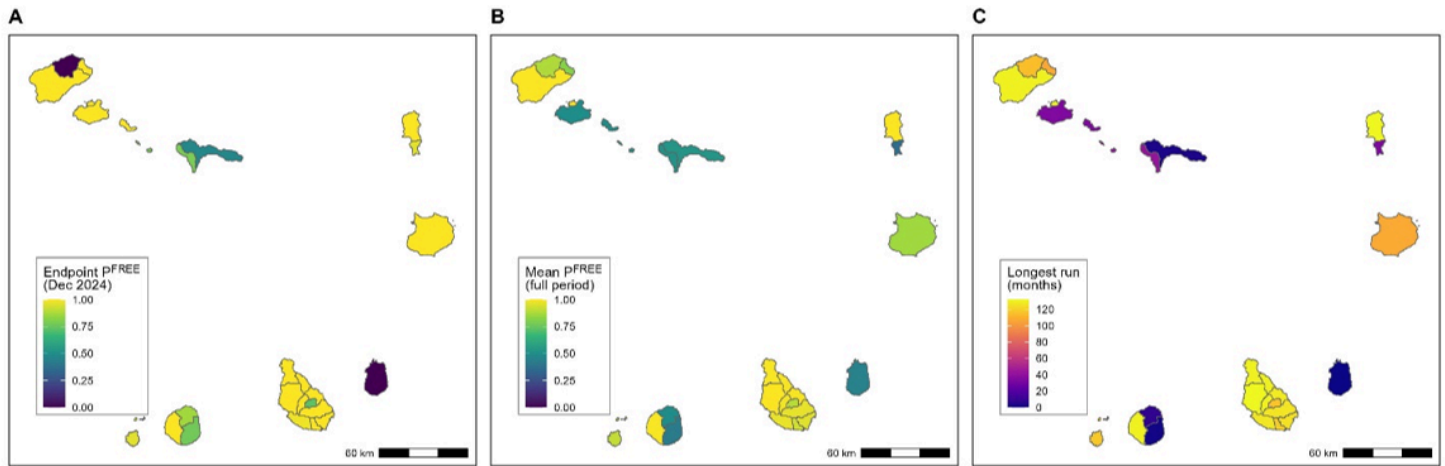


Figure 2

Facility-level probability of freedom at the reference definition ($d = 10,000$; cut-off 0.95). A: endpoint (December 2024); B: mean over the analysis period; C: longest consecutive run of months with

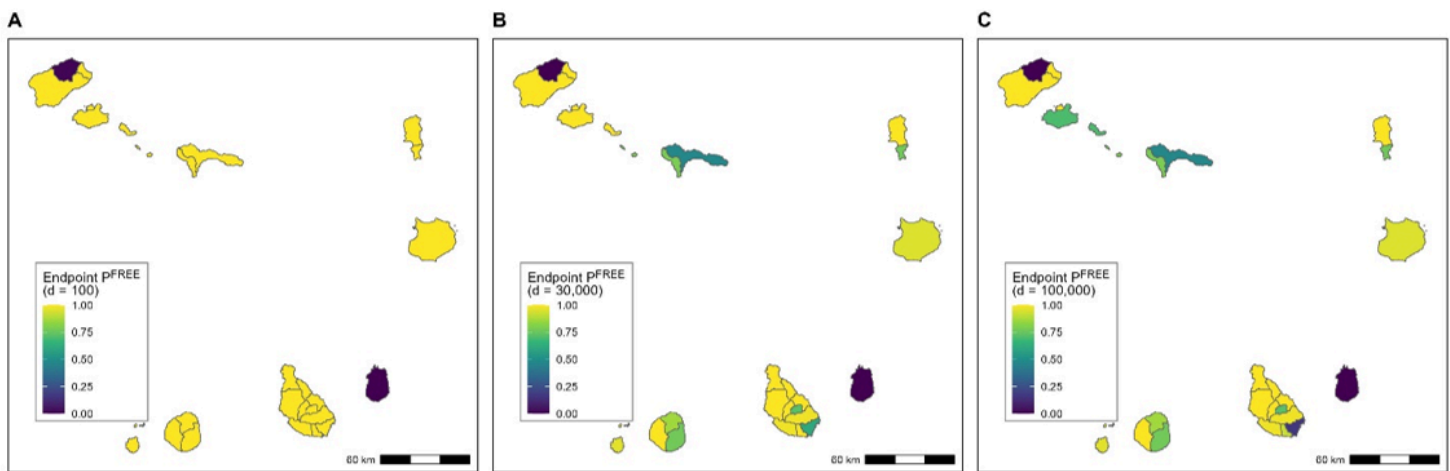


Figure 3

Endpoint probability of freedom () in December 2024 by facility catchment under three elimination denominators: A, $d = 100$; B, $d = 30,000$; C, $d = 100,000$ (larger d implies a stricter definition; “elimination” = fewer than one infection per d people)

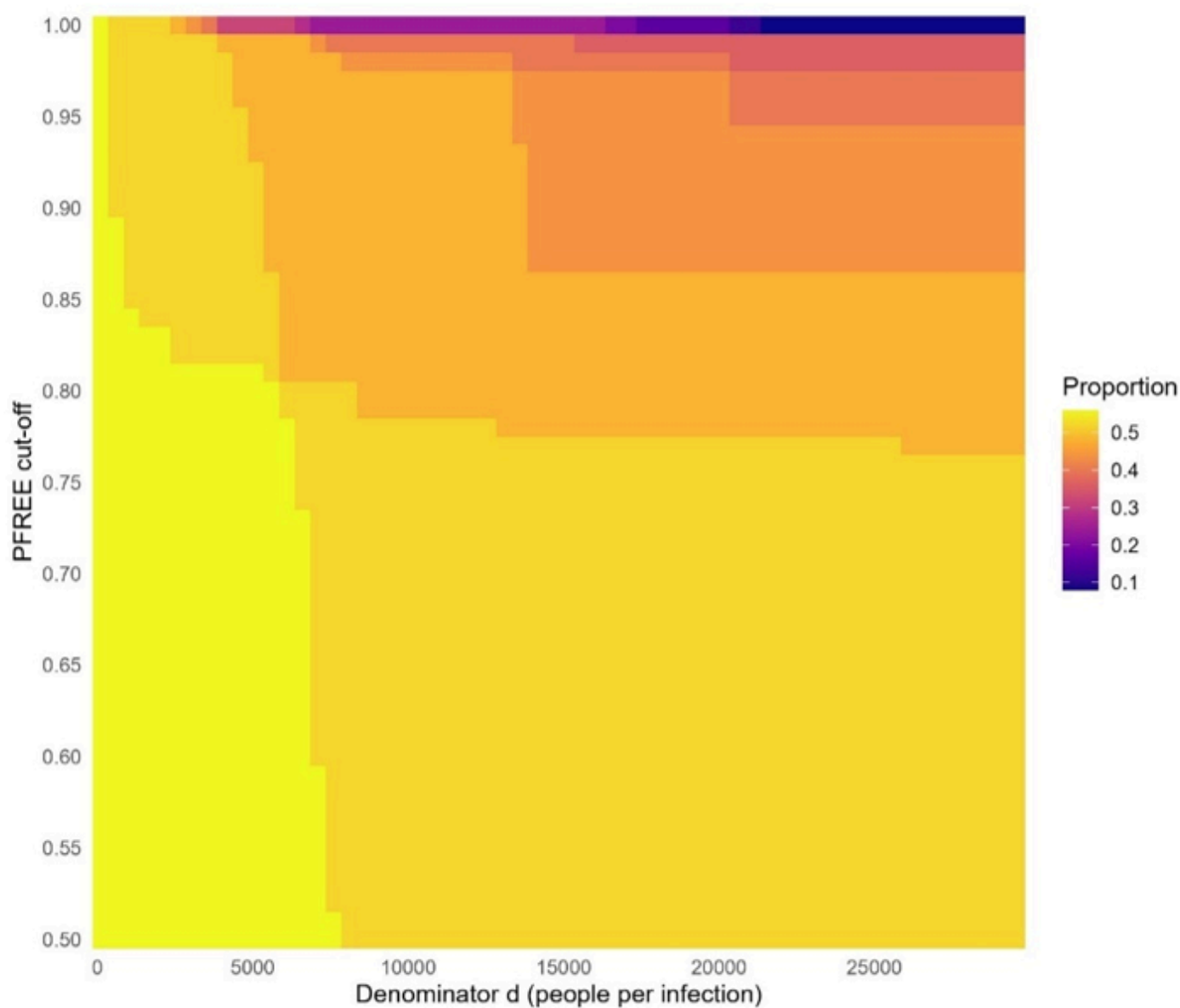


Figure 4

Robustness of facility-level elimination classification over the denominator–cut-off grid for the last 36 months to December 2024. Each pixel shows the proportion of health facilities that meet a given elimination criterion defined by (i) an elimination denominator d on the x-axis (fewer than one infection per d people) and (ii) a probability cut-off for PFREE on the y-axis. For each facility and month, PFREE is computed as the posterior probability that the latent number of infections (RC) is less than the threshold N/d , where N is the facility catchment population. A facility is classified as meeting the criterion for a given $(d, \text{cut-off})$ pair if PFREE is at least the cut-off in every month of the evaluation window (i.e., the minimum monthly PFREE across months 97–132 is $\geq$ the cut-off). Colour indicates the resulting proportion of facilities meeting the criterion.

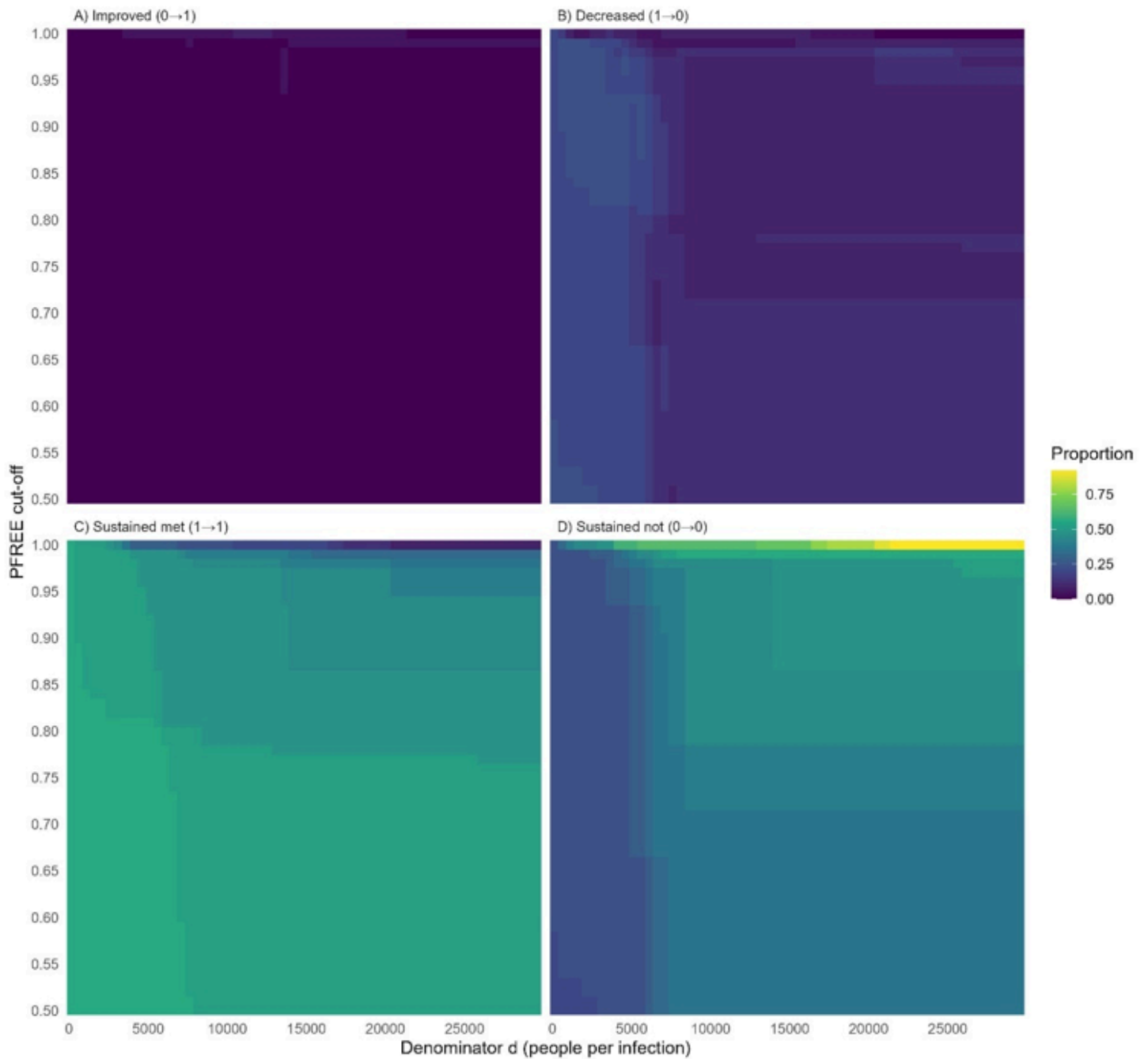


Figure 5

Disaggregation of facility elimination classifications between the pre-certification and post-certification windows over the denominator–cut-off grid. Each pixel reports the number of facilities in each transition category for a given elimination denominator d (x-axis; fewer than one infection per d people) and P^{FREE} cut-off (y-axis). Facilities are classified as meeting a criterion within a window if $P^{\text{FREE}}(d)$ is at least the cut-off in every month of that window (i.e., the minimum monthly P^{FREE} in the window is $\geq$ the cut-off). The PRE window is the last 36 months to December 2023 (months 85–120) and the POST window is calendar year 2024 (months 121–132). Panel A: Improved (not meeting in PRE, meeting in POST). Panel

B: Decreased (meeting in PRE, not meeting in POST). Panel C: Sustained met (meeting in both windows). Panel D: Sustained not (meeting in neither window).

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