Determinants of Malaria Spending Efficiency in Sub-Saharan Africa: Double Bootstrap Data Envelopment Analytics

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Research Article

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Abstract

Background: Malaria is a major cause of morbidity and mortality in many countries in sub-Saharan Africa (SSA). The main objective of this study was to examine malaria spending efficiency and its associated factors between 2013 and 2019.

Methods: This study employed the two-stage double bootstrap data envelopment analysis (DEA) proposed by Simar and Wilson. In the first stage, technical efficiency scores are estimated using the output-oriented variable returns to the scale (VRS) DEA framework. In the second stage, the double bootstrap DEA model was used to identify the environmental variables that affect malaria spending efficiency.

Results: The overall malaria spending efficiency score was estimated to be 82.9% (95% CI: 81.4% to 84.4%) over the study period. This estimate suggests that malaria treatment and prevention outcomes can potentially be improved by at least 17% by using existing resources. We found a significant association between efficiency and education, temperature levels, nurses and midwives' density, and the proportion of children of age five who slept in insecticide-treated bed nets.

Conclusion: To achieve the targets spelt out in the *Global Technical Strategy for malaria* by 2030, policymakers must not only be concerned with improving educational outcomes but also consider ways to mitigate the effects of climate change and improve access to healthcare services.

Keywords: Malaria spending efficiency, Environmental factors, Data envelopment analysis, Double bootstrap, SSA countries

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1.1 Introduction

Malaria remains a major cause of morbidity and mortality in many countries in Sub-Saharan Africa (SSA) [1]. Approximately 93 percent of all malaria cases and 94 percent of malaria-related deaths occur in the region [2] with more than 55 percent of the estimated 241 million cases globally in 2020 being accounted for by six countries: Nigeria (27%), Democratic Republic of Congo (12%), Uganda (5%), Mozambique (4%), Angola (3.4%), and Burkina Faso (3.4%) [3]. Children below the age of five years accounted for 77% of the total estimated 627,868 (95% uncertainty range: 583,000 – 765,000) malaria deaths globally in 2020 alone [3].

More than two decades ago, the World Health Organization (WHO) in partnership with the United Nations Children's Fund (UNICEF), the United Nations Development Programme (UNDP), and the World Bank (WB) launched the Roll Back Malaria (RBM) program in 1998. The target of the RBM program was to help halve the enormous malaria burden on the health of people and economies from 2000 to 2010 and a further half reduction from 2010 to 2015 [4]. In the era of Millennium Development Goals (MDGs), a target was set to reduce the incidence of malaria by 2015 [5]. In line with the current Sustainable Development Goals (SDGs), the targets are to reduce malaria incidence and mortality by 90% and eliminate malaria in at least 35 malaria-endemic countries by 2030 from the 2015 baseline [6, 7]. Despite a reduction in the malaria incidence rate from 368 to 222 cases per 1000 populations at risk in the WHO African Region between 2000 and 2019, the progress falls short of the improvements needed to meet the targets set by the WHO in the *Global Technical Strategy for malaria 2016-2030* (GTS) and Sustainable Development Goals target 3.3 [3, 7, 8].

Globally, increasing amounts of resources are being expended on malaria control and elimination. In 2020 alone, US$3.3 billion was invested in combating this plague of which 79 percent went to countries in the WHO African Region. A third of this amount was contributions from the governments of the malaria-endemic countries [9]. Though the US$3.3 billion invested in 2020 represents a 10 percent increase over the 2019 figure, it fell short of the annual investment of US$6.8 billion (or US$3.90 per person at risk of malaria) estimated to be required globally to achieve the targets set out in the *Global Technical Strategy for malaria 2016-2030* (GTS) [7, 9, 10]. Again, the SSA region faces the risk of declining external financing due to its economic growth and the resulting donor requirements for increased contributions from domestic governments. This would further widen the financial gap. This gap in resources must be met by mobilizing additional funding domestically [11] and maximizing the efficiency of health systems in the allocation and use of available resources for malaria control and elimination [3, 12].

There is extensive literature on the efficiency of health systems in SSA [13, 14, 15, 16] and African countries [17], OECD countries [18, 19, 20], and World Health Organization countries [21, 22, 23, 24, 25]. These studies assess the efficiency of health systems in transforming health inputs such as healthcare labor force and hospital beds in 'producing' health outcomes in form of health-adjusted life expectancy (HALE), disability-adjusted life expectancy (DALE), and mortality outcomes. Few studies have focused on the efficiency of health systems in providing public health and medical healthcare services to control or eliminate specific diseases including the works of Abou Jaoude et al. [26], Novignon et al. [27], and Scot et al. [11].

Abou-Joude et al. [26] employed data envelopment analysis (DEA) and stochastic frontier analysis (SFA) to examine the tuberculosis spending efficiency of 121 low-income and middle-income countries between 2010 and 2019. Tuberculosis spending was used as an input variable, whereas treatment coverage of tuberculosis was defined as the output measure. Several variables including health expenditure as a proportion of gross domestic product (GDP), population density, HIV prevalence, diabetes prevalence, universal health coverage indicator, out-of-pocket health spending, and tuberculosis spending accounted for by external sources were included as explanatory variables in the second-stage analysis. The findings indicate that global TB treatment coverage could be increased by 12.3 percent and 26.2 percent for the same amount of spending. They also found that out-of-pocket spending on health, UHC coverage, and health expenditure as a share of GDP had a significant association with tuberculosis spending efficiency.

Novignon et al. [27] and Scot et al. [11] examined the efficiency of malaria resource use in Ghana and Nigeria, respectively, using data from individual countries. However, such studies may not be appropriate when there are inadequate number of comparable health service providers available within the country, especially in developing countries [25]. To evaluate the overall health system performance, with respect to malaria spending efficiency, and make comparisons across countries, an international health system benchmarking study is very important. To date, no study has specifically examined malaria spending efficiency at the international level.

It is very important that the resources earmarked for malaria control in SSA countries are used efficiently. Malaria remains the most commonly reported case in outpatient departments of health facilities in many SSA countries [28]. Malaria treatment imposes and will continue to impose a heavy financial burden on households and public health budgets in highly malaria-endemic countries [29]. In many SSA countries, out-of-pocket payments or personal health expenses are the major cause of poverty because of the absence of health insurance coverage for majority of the population [30, 31. The heaviest burden of malaria is borne by the majority of people in the poorest countries of the region [3]. In light of this, it is important that the health systems of these countries maximize the efficiency of malaria spending.

A study on the efficiency of malaria spending and its determinants in this region will provide valuable lessons including comparisons across countries. The main objective of this study was to assess the performance of health systems in SSA in transforming resources earmarked for malaria control and elimination into improved malaria-related health outcomes using the double bootstrap data envelopment analysis (DEA) approach. Health system efficiency scores are estimated for each country using the DEA model based on germane input and output variables. The efficiency scores are then be regressed on a set of relevant explanatory/environmental variables that include quality of governance, access to healthcare, the proportion of children under-5 years who sleep under insecticide-treated bed nets, and educational level.

The remainder of this paper is organized as follows. Section II describes the double bootstrap DEA methodology and the data used in this study. In Section III, we discuss the results obtained from the estimations. Finally, Section IV concludes the study with relevant policy implications.

2.1 Methods and Materials

2.1.1 Double Bootstrap DEA Model

The two main approaches to examining the relative efficiency of comparable multiple decision-making units (DMUs) with similar goals are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The SFA approach is an econometric model that requires specification of the functional form of the model for efficiency estimation. On the other hand, the DEA is a non-parametric method that uses linear programming techniques to estimate the efficiency of each DMU within a group of homogenous DMUs. In estimating efficiency using the DEA approach, the theoretical production frontier is constructed using the best practice DMUs in the sample in a piece-wise linear method. The DMUs situated below the frontier have inefficient health systems. The DEA method is particularly useful in assessing the efficiency of public organizations such as healthcare institutions which are non-profit-oriented entities and employ multiple inputs and outputs in their production functions [25].

In light of the foregoing, this study adopts the output-oriented variable returns to scale (VRS) DEA method to estimate malaria spending efficiency scores for malaria-endemic SSA countries. Since the standard DEA efficiency scores might be biased, and the explanatory variables might correlate with the input and output variables, the use of bootstrapping techniques is recommended [32]. Bootstrap DEA improves the estimation because it uses sampling variations to analyze the sensitivity of the estimated efficiency scores. The linear programming problem assuming an output-oriented VRS is estimated in Equation 1 for the i^{th} country:

$$
\begin{aligned}
& Max_{\theta,\lambda}\theta_i \\
& Subject\ to\ \theta_i y_i \leq Y\lambda \\
& x_i \geq X\lambda \\
& n1'\lambda = 1 \\
& \lambda \geq 0
\end{aligned}
\qquad [1]
$$

Where y_i and x_i are vectors of the output and input variables, respectively. Assuming that there are p output variables and q input variables for n countries, then Y is the $(p \times n)$ output matrix and X is the $(q \times n)$ input matrix. The value θ_i ranges between zero and infinity. It represents the efficiency score which measures the technical efficiency of the i^{th} country as the distance to the production frontier (i.e. the linear combination of the best practice countries). Lambda λ is the

$(n \times 1)$ vector of weights used to measure the location of an inefficient country if it as to become efficient.

In the second stage DEA analytics, we examine the non-discretionary (or environmental) factors that affect the output variables but over which the managers of the health systems have no control. In the DEA literature, econometric models such as probit, logit, and truncated (Tobit) regressions are employed to account for the effects of these variables on the estimated technical efficiency scores [33, 34] as in Equation 2:

$$\theta_i = z_i\beta + \varepsilon_i \qquad [2]$$

Where θ_i is the technical efficiency score estimated by solving Equation 1; z_i is the vector of the non-discretionary factors; β is the vector of parameters to be estimated; and ε_i is a truncated normal random variable distributed $N(0, \sigma_\varepsilon^2)$. However, Simar and Wilson [32] criticized this approach and argued that conventional statistical inferences are inappropriate as they violate the basic assumptions of regression models. Simar and Wilson [32] recommended a two-stage double bootstrap DEA approach and demonstrated that it was statistically superior.

In the first stage of the double bootstrap DEA procedure, a parametric bootstrap to solve the linear programming problem in Equation 1 to obtain a bias-corrected efficiency score $\hat{\theta}_i$ as an estimate for θ_i. After that, the second stage evaluates the effect of non-discretionary (or environmental) factors on the efficiency and estimates Equation 2. In the second stage, a large number of bootstrap estimates for β and σ_ε is computed, and estimate the truncated regression $\hat{\hat{\theta}}_i^* = z_i\hat{\beta} + \varepsilon_i$ by maximum likelihood yielding a bootstrap estimates $\left(\hat{\beta}^*,\ \hat{\sigma}_\varepsilon^*\right)$. Given 2000 bootstrap estimates, as suggested by Simar and Wilson [32], it becomes possible to conduct hypothesis tests and construct confidence intervals for β and σ_ε. Thus, this study adopts Algorithm #2 of the two-stage double bootstrap approach as recommended by Simar and Wilson [32] to examine the determinants of malaria spending efficiency.

2.1.2 Data and Variables

2.1.2.1 Input and Output Variables

In the first stage of this study, the major assumption with the use of the DEA model is that the selected malaria outcomes (outputs) are dependent on inputs of malaria resources that a country devotes to the control and elimination of the disease. Malaria output in this study is measured in two ways: (i) malaria incidence and (ii) malaria mortality. In line with the World Health Organization's definitions [35], malaria incidence is measured as the number of new confirmed malaria cases per 1000 population at risk per year, whereas the malaria mortality is measured as the number of new confirmed malaria-related deaths per 100,000 population at risk per year. The data on malaria incidence and mortality were extracted from World Malaria Reports 2021 [3]. In the DEA framework, outputs must be measured in such a way that more is preferable. Therefore, we used the reciprocals of malaria incidence and malaria mortality as the output variables in the estimations.

Malaria spending per capita, measured in purchasing power parity (PPP) rate, was used as the input variable in this study. This data was obtained from the WHO's Global Health Expenditure Database (GHED) 2021. This database presents comprehensive and internationally comparable health expenditures (by sources and healthcare functions) for all WHO member countries from 2000 to 2019. The health expenditure values in the database are computed using the new System of Health Accounts (SHA 2011) framework which was rigorously developed by the Organization of Economic Cooperation and Development (OECD) to track health expenditures.

2.1.2.2 Environmental (Explanatory) Variables

In the second-stage bootstrapping regression, the study used variables representing access to healthcare for malaria treatment and prevention, socio-economic variables, governance quality variables, and other environmental variables that have the potential to influence the efficiency of malaria spending. The selection of these variables was guided by the literature and data availability. In this study, hospital beds density (per 1000 population), nurses and midwives density (per 1000 population), the proportion of children under-5 years who sleep under insecticide-treated bed nets, and access to basic sanitation services were used as proxies for access to healthcare services for malaria treatment and prevention. The evidence of the effect of improved access to healthcare and preventive services on health outcomes and health system efficiency is provided in previous studies [36, 37, 38].

The socio-economic factors were represented by the level of education in each country. It was measured as the arithmetic mean of two education indices: mean years of schooling and expected years of schooling [39]. It is strongly believed that the level of education is a major determinant of health status and health system efficiency [40, 41]. Higher educational attainment is found to be positively correlated with higher income which, in turn, secures a healthy living environment and access to healthcare [42].

In addition, governance effectiveness was used as a proxy for the quality of governance of the health system. It captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies [43]. A higher level of government effectiveness promotes a transparent system of accountability that ensures effective and efficient use of public resources in health [13].

Finally, temperature (measured in degree Celsius) was included to examine its effect on malaria spending efficiency. A plethora of studies have shown a robust relationship between temperature levels and malaria parasite transmission [44, 45, 46, 47]. This study seeks to assess the impact of temperature levels on malaria spending efficiency.

Based on these environmental (explanatory) variables, the bootstrap regression model was specified as in Equation 3:

$$\theta_{it} = \beta_0 + \beta_1 Educ_{it} + \beta_2 San_{it} + \beta_3 Geff_{it} + \beta_4 Temp_{it} + \beta_5 Beds_i + \beta_6 Nurs_i + \beta_7 ITN_i + \varepsilon_{it} \quad [3]$$

where θ_{it} is the bias-corrected technical efficiency score; $Educ_{it}$ is the educational level; San_{it} is access to basic sanitation services; $Geff_{it}$ is government effectiveness; $Temp_{it}$ is temperature level; $Beds_i$ is bed density (a categorical variable: 1=less than one bed, 2=one bed or more but less than two beds, and 3 = two or more beds); $Nurs_i$ is nurses and midwives density (a categorical variable: 1=less than one nurse, 2=one nurse or more but less than two nurses, and 3 = two or more nurses); ITN_i is the proportion of children under five years who sleep under insecticide-treated bed nets (a categorical variable: 1=less than 30%, 2=between 30% and 50%, 3 = between 50% and 70%, and 4=more than 70%). Lastly, ε_{it} is the error term.

2.2.1.3 Data Source

In this study, available data set covering 21 highly malaria-endemic SSA countries for the period of 2013 – 2019 was used. The data set was obtained from different sources including World Malaria Reports 2021 [3], Global Health Expenditure Database (GHED) [48], World Development Indicators (WDI) [49], and Worldwide Governance Indicators (WGI) [50]. According to the United Nations Development Programme (UNDP), 46 of the 54 countries in Africa are described as 'sub-Saharan'. Some countries in the SSA were excluded from the analysis for two main reasons: (i) if there is missing data of the selected output and input variables for more than three years of the study period (2013 – 2019), and (ii) if the country is not a malaria-endemic country. We defined a malaria-endemic country as a country with a malaria incidence rate of at least 100 (per 1000 population per year). This was necessary to exclude outlier observations from the analysis to achieve a more homogenous group of countries. In DEA applications, it is critical to achieve homogeneity of DMUs in terms of social and economic development indicators and policy objectives for robust analysis.

Again, it is recommended that the number of DMUs should be at least three times more than the sum of the output and input variables to ensure econometrically meaningful DEA results [51]. Given that this study employs two output and one input variable in its DEA estimations, this condition is not a binding constraint. Finally, the bootstrap DEA was applied to an unbalanced panel of 21 countries with 127 observations.

3.1 Results and Discussions

Malaria spending efficiency is estimated based on two outputs and one input model. A total of 21 SSA countries (representing nearly 82% and 87% of the total global malaria cases and malaria-related deaths, respectively, in 2019) are involved in this study. These countries were selected based on the availability of relevant data needed for the analysis and to achieve homogeneity in the observations.

A summary of statistics for the variables used in this study is presented in **Table 1**. As shown, the average malaria incidence per 1000 population at risk is 299 per year, and the malaria mortality rate per 100,000 people at risk is 70.37 per year with a standard deviation of 29.30 (see also

Appendix A). The malaria incidence per 1000 people at risk per year ranges from a minimum of 127 at Tanzania to a maximum of 406 in Burkina Faso. However, the malaria mortality rate per 100,000 people at risk is the smallest in Gabon (19) and highest in Burkina Faso (112). **Figure 1** and **Appendix B** present the spatial distribution of malaria incidence and mortality, respectively, for the year 2019. For the input variable, the average malaria spending per capita is $26.88. It ranges from an average minimum of $6.31 (DR Congo) to a maximum of $73.22 (Nigeria).

Table 1: Summary statistics of input, outcome, and environmental variables

Variable Description	Mean	SD	Min.	Max.	Source
Input variable					
Malaria spending per capita (Int. $PPP)	26.88	16.62	3.56	87.68	GHED
Outcome variables					
Malaria incidence (per 1000 people at risk)	298.99	80.75	111.84	487.20	WMR
Malaria mortality (per 100000 people at risk)	70.37	29.30	17.54	150.50	WMR
Environmental/explanatory variables					
Use of ITN (% of under-5 population)	55.14	16.70	16.6	95.5	WDI
Hospital beds (per 1000 people)	0.83	0.71	0.10	3.20	WDI
Nurses and midwives (per 1000 people)	0.82	0.65	0.12	2.95	WDI
Sanitation (% of the population with access)	24.65	9.85	11.68	49.78	WDI
Government effectiveness	-.929	.432	-2.48	-.11	WGI
Temperature (annual average in ºC)	25.99	2.13	21.94	29.14	WBG
Educational level	0.43	0.11	0.21	0.65	UNDP

Notes: Int. $PPP = International dollar Purchasing Power Parity; ITN = Insecticide Treated bed-Nets; GHED = Global Health Expenditure Database; WMR = World Malaria Reports; WDI = World Development Indicators; WGI = World Governance Indicators; WBG = World Bank Group Climate Change Portal; UNDP = United Nations Development Programme; ºC = Degree Celsius; SD = Standard Deviation; Min. = Minimum; Max. = Maximum

Figure 2 shows a scatter plot relating malaria spending per capita and the malaria incidence per 1000 people at risk. A quick inspection of the plot reveals a negative correlation, that is, higher malaria spending per capita is generally associated with lower malaria incidence.

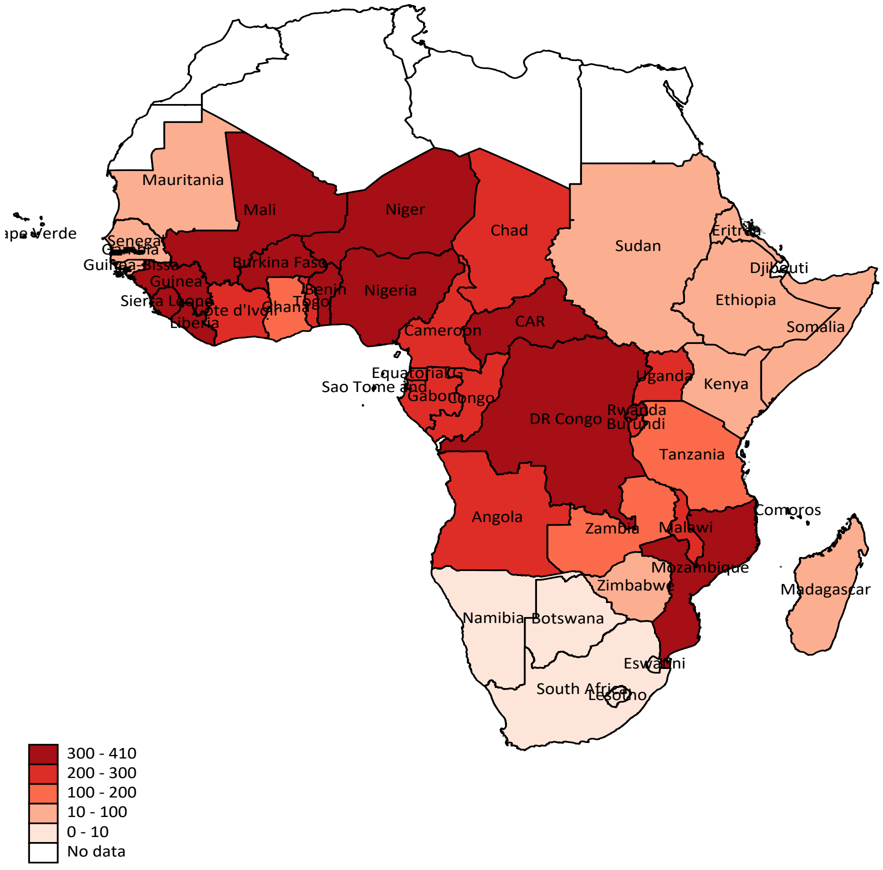

Figure 1: Spatial distribution of malaria incidence per 1000 population at risk, 2019.

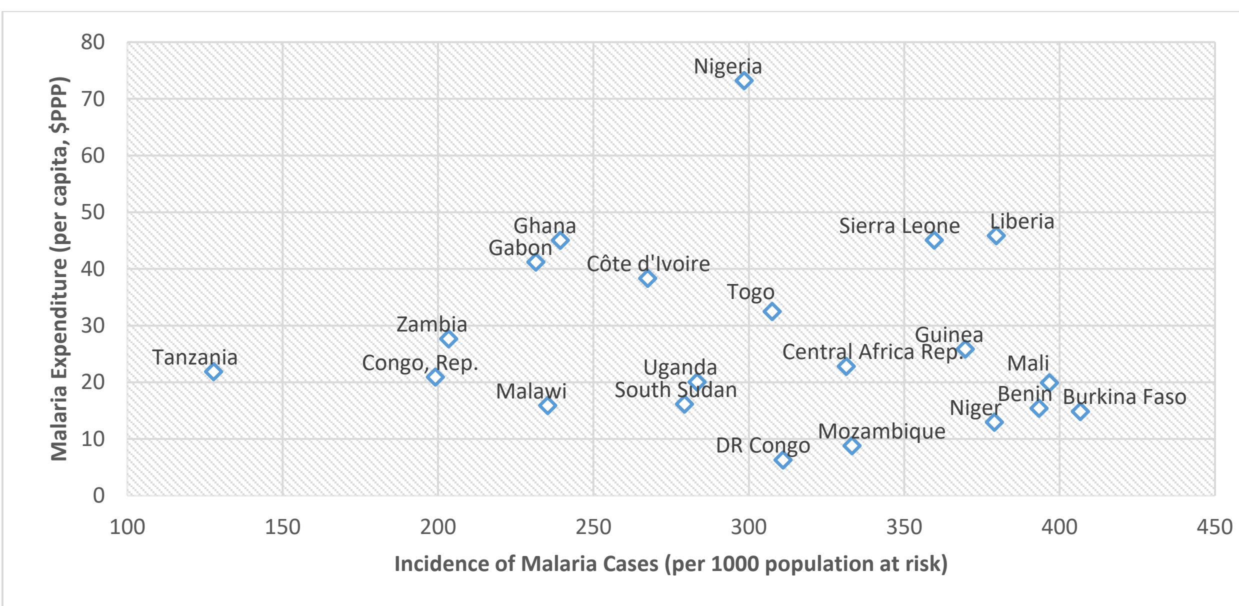

Figure 2: Malaria spending per capita and malaria incidence per 1000 people at risk

3.1.1 Results of First-Stage Bootstrap DEA

The efficiency scores for the selected SSA countries in this study were computed using STATA 15.1 package. The results of the original DEA scores, bias, bias-corrected efficiency scores, and the ranking for each country are presented in **Table 2**. The output-oriented Shephard VRS DEA model was adopted to compute the efficiency scores of the selected SSA countries. The efficiency scores range from zero to one, where one implies that the country is efficient in malaria spending and lies on the production frontier.

Table 2: Shephard VRS Output-Oriented DEA, Bias, and Bias-Corrected Efficiency Scores

Country	DEA Scores	Bias	Bias-Corrected	Rank
Gabon	0.979	0.007	0.972	1
Tanzania	0.992	0.035	0.957	2
Malawi	0.949	0.025	0.925	3
Congo	0.941	0.020	0.921	4
DR Congo	0.960	0.047	0.913	5
Zambia	0.899	0.014	0.886	6
Uganda	0.899	0.017	0.882	7
Ghana	0.886	0.010	0.876	8
Mozambique	0.899	0.030	0.868	9
South Sudan	0.852	0.029	0.823	10
Côte d'Ivoire	0.830	0.014	0.815	11
Togo	0.819	0.011	0.808	12
Niger	0.801	0.031	0.770	13
Nigeria	0.782	0.023	0.759	14
Central African Republic	0.784	0.028	0.755	15
Guinea	0.755	0.018	0.737	16
Burkina Faso	0.766	0.030	0.736	17
Benin	0.765	0.031	0.734	18
Liberia	0.743	0.014	0.729	19
Mali	0.750	0.025	0.726	20
Sierra Leone	0.742	0.020	0.722	21
Total Average	**0.851**	**0.023**	**0.829**	

The average original DEA score is 0.851, whereas the bias-corrected efficiency score is 0.829 with bias ranging from 0.007 to 0.047. The **Table 2** shows that Gabon, Tanzania, and Malawi had the most efficient health system among their peers. Thus the health systems of these countries are considered good benchmarks and offer useful information for the less efficient countries. On the other hand, we observe that Liberia, Mali, and Sierra Leone were least efficient countries and were ranked at the bottom of the **Table 2**. Other countries that performed below average malaria spending efficiency include Nigeria, Central African Republic, Guinea, Burkina Faso, and Benin. These results from the bootstrap VRS DEA model suggest that maximizing the efficient use of existing malaria resources could potentially improve output by at least 17% in terms of reduction in malaria incidence and mortality.

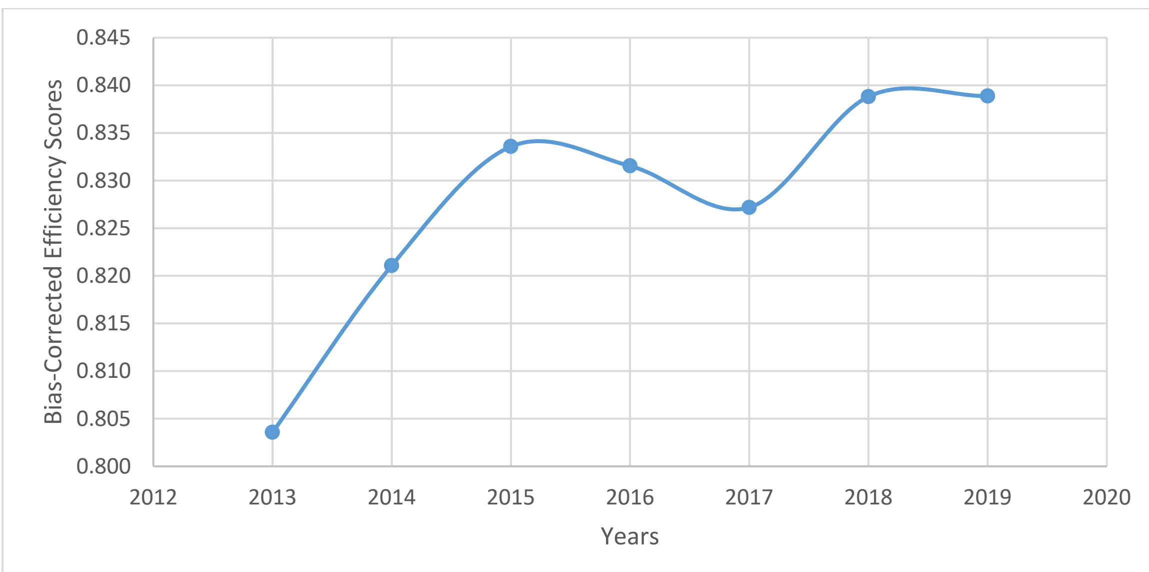

Figure 3: Average Technical Efficiency Scores over Years

Considering the average technical efficiency scores of the countries by years, it is observed from **Figure 3** that the increase in efficiency scores achieved began to decrease in 2016 and declined further in 2017 before rising substantially in 2018 and marginally in 2019. A basic reason for the decrease can be cuts in malaria spending across SSA countries between 2015 and 2017. A closer look at the data revealed a cut in malaria spending per capita by more than 30% which might be due to the busy political activities during those periods. Many countries in the region held presidential and parliamentary elections between 2015 and 2017.

Assessing the heterogeneity in efficiency scores based on the World Bank's income classification of countries, we observe from **Table 3** that the highest average VRS bias-corrected technical efficiency scores were obtained by upper-middle-income countries (0.972: 95% CI 0.961 to 0.982), followed by lower-middle-income countries (0.849: 95% CI 0.825 to 0.872), and low-income countries (0.804: 95% CI 0.785 to 0.822). These findings are consistent with other previous studies [24, 42] which also found developed countries to have more efficient health systems relative to less developed countries. This implies that if all countries were to operate at maximum efficiency, given their current capacity and malaria resources, low-income, lower-middle-income, and upper-middle-income countries could increase their malaria treatment and prevention outcomes (i.e. reduce malaria incidence and malaria mortality) by 19.6%, 15.1%, and 2.8%, respectively.

Table 3: Mean bias-corrected efficiency scores based on income level of SSA countries

Income Groups	Mean	Std. Err.	[95% Conf. Interval]		Malaria outcomes can be improved by (%)
Low-Income	0.804	0.009	0.785	0.822	19.6
Lower-Middle-Income	0.849	0.012	0.825	0.872	15.1
Upper-Middle-Income	0.972	0.005	0.961	0.982	2.8

3.1.2 The Results of Second-Stage Double Bootstrap DEA

In the first stage of bootstrap DEA, malaria spending per capita was used as the only discretionary input that affect malaria treatment and prevention outcomes. However, there are other factors that can account for the differences in the outcomes. Access to healthcare and preventive services, socio-economic factors, governance quality, and climatic conditions have been identified in previous studies to impact health outcomes and health system efficiency. Therefore, in this study, nurses and midwives' density, hospital bed density, the proportion of children under five years who sleep in insecticide-treated bed nets, access to basic sanitation services, education, temperature levels, and government effectiveness are included in the second stage of the double bootstrap DEA framework. **Table 4** presents the results of the bootstrap regression. Access to basic sanitation services, government effectiveness, and hospital beds density showed statistically insignificant association with malaria spending efficiency.

Table 4: Results of Double Bootstrap Regression

Variable	Observed Coefficient	Bootstrap Std. Err.	[95% Bootstrap CI][a] Lower	Upper
Educational level	0.2006**	0.0842	0.0374	0.3674
Sanitation	0.0003	0.0007	-0.0011	0.0018
Government Effectiveness	-0.0146	0.0165	-0.0462	0.0171
Temperature level	-0.0341***	0.0038	-0.0416	-0.0264
Bed density [Ref.: fewer than 1 bed]				
Between 1 to 2 beds	-0.0189	0.0190	-0.0570	0.0179
More than 2 beds	0.1083	0.0787	-0.0214	0.2876
Nurses density [Ref.: fewer than 1 nurse]				
Between 1 to 2 nurses	-0.0044	0.0194	-0.0415	0.0334
More than 2 nurses	0.1339***	0.0370	0.0609	0.2073
Under-5 ITN (%) [Ref.: below 30%]				
Between 30% and 50%	0.0132	0.0242	-0.0332	0.0626
Between 50% and 70%	0.0496**	0.0230	0.0055	0.0952
More than 70%	0.0519**	0.0242	0.0042	0.0996
Constant	0.5427***	0.1224	0.3043	0.7898
Sigma	0.0610***	0.0042	0.0499	0.0661

Notes: Dependent Variable: first-stage bootstrap bias-corrected efficiency scores. CI: Confidence Interval. *** and ** represents statistical significance levels at 1% and 5%, respectively. Ref.: Reference category. [a] The values were computed by 2000 bootstrap iterations.

The estimated coefficient of the level of education is statistically significant and positively related to the efficiency scores. This means that an improvement in educational outcomes enhances malaria spending efficiency. This result coincides with those obtained in earlier empirical studies regarding health system efficiency, such as Afonso and St. Aubyn [19] and Ambapour [14]. However, higher temperature levels are found to have a statistically significant negative association with the efficiency scores, implying that countries with higher levels of temperature are less efficient and this further raises the critical issue of climate change. This result is consistent with many studies that found temperature as a major influence on transmission of malaria to human hosts [44, 45, 46, 47, 52].

Furthermore, nurses and midwives' density of more than two category has a statistically significant positive association with malaria spending efficiency as compared with the less than one nurse and midwife reference category. The results further show that countries that fall in more than one and less than or equal to two nurses and midwives category had no significant association with the efficiency scores. This indicates that the countries with less than two nurses and midwives density have lower technical efficiency. In the case of the proportion of children under five years who sleep in insecticide-treated bed net (ITN), we found that countries within 50% and more categories had higher technical efficiency scores as compared with countries with less than 30% coverage category. This implies that a country moves closer to the production possibility frontier as it crosses the 50% threshold of children under five years sleeping in ITN.

4.1 Conclusions

In this study, we employed the two-stage double bootstrap DEA framework to assess the malaria spending efficiency and its associated factors in 21 SSA countries for 2013-2019. In the first stage, we estimated the efficiency scores by output-oriented DEA under the VRS assumption using two outputs and one input. In the second stage, we utilized the double bootstrap DEA analysis to identify the environmental factors affecting the efficiency scores obtained in the first stage.

The main findings from the first stage analysis revealed that the overall average technical efficiency for malaria spending was estimated at 0.829. This implies that the sampled countries could potentially improve malaria treatment and prevention outcomes by 17% with the existing level of malaria spending. While Gabon, Tanzania, and Malawi were the most efficient countries during the 7-year period, Burkina Faso, Benin, Liberia, Mali, and Sierra Leone obtained efficiency scores below the average level. Again, we found that upper-middle-income countries were most efficient, followed by lower-middle-income countries, and the low-income countries were least efficient.

In the second stage analysis, while we found education to have a significantly positive association with malaria spending efficiency, statistically significant negative relationship existed between temperature levels and efficiency. Again, we found that higher nurses and midwives' density and sleeping in insecticide-treated bed nets were associated with improved malaria spending efficiency. The major policy recommendations that emerge from this study are that policy-makers should pay attention to education, climate change, and improved access to healthcare services if the targets spelt out in the *Global Technical Strategy for malaria 2016-2030* (GTS) are to be achieved by 2030.

Ethics approval and consent to participate (kindly mention the name of the Ethics Committee and the Ethical Approval Number)

Not Applicable

Consent for publication

All the authors have given their consents for the publication of this paper.

Availability of data and materials

The dataset used in this study was extracted from World Malaria Reports 2021, Global Health Expenditure Database (GHED), World Development Indicators (WDI), and Worldwide Governance Indicators (WGI). All are publicly available.

Competing interests

None of the authors of this paper has any competing interest. We, therefore, declare no competing interests.

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Authors' contributions

Kwadwo Arhin and Albert Opoku Frimpong conceived the presented idea. Kwadwo Arhin and Richard Boso developed the theory and performed the computations. Kwadwo Arhin wrote the manuscript with support from Kwame Acheampong and Albert Opoku Frimpong. Richard Boso and Kwame Acheampong verified the analytical methods and supervised the findings of the work. All authors discussed the results and contributed to the manuscript.

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