Validation of an Online Mapping Methodology to Locate Village of Residence of Tuberculosis Patients in Mombasa

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Abstract

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BACKGROUND

In Kenya, the dual TB-HIV epidemic has led to increasing morbidity and mortality especially in urban areas. National TB programs need to identify communities with the highest TB burden and to employ aggressive prevention measures such as intensive case finding and contact tracing in order to interrupt ongoing disease transmission. We evaluated the accuracy of an online mapping method to locate TB patientsôvillage of residence using addresses provided in TB registers in Mombasa, Kenya.

METHODS

To validate the spatial accuracy of a health-worker-based online mapping procedure, we compared whether latitude and longitude point locations of TB patients matched those collected using a Global Positioning System (GPS) device during a home visit. Patient, clinic, and village-level characteristics associated with correct location in village of residence were evaluated using logistic regression.

RESULTS

Between July 2012 and July 2013, 246 participants who met study inclusion criteria were mapped using both methods. The online method located 140 cases (56.9%) in the correct village of residence, 80 (32.5%) and 26 (10.5%) were incorrectly allocated to a neighboring and non-neighboring village, respectively. The mean error distance between the two methods was 225.2m (±296.2) for all cases, 106.5m (±92.5) and 382m (±386.9) for those correctly located and incorrectly located, respectively. Type of clinic, clinic caseload, village status, and density were significantly associated with being correctly mapped to the village of residence in bivariate analysis. In multivariate analyses, medium caseloads (201 ï 400 cases versus 0 ï 200 cases per year; adjusted OR 2.75 95% CI 1.37 ï 5.53; p 0.004); moderate number of households per village (1,001 ï 2000 versus 0 ï 1000 households; aOR 0.42 95% CI 0.21 ï 0.85; p 0.016); high village density (>30,000 versus 0-15,000 per km^2; aOR 0.43 95% CI 0.19 ï 0.94; p 0.035) and attending municipal clinics (aOR 0.45 95% CI 0.20 ï 0.99; p 0.048) were significantly associated with correct village location.

DISCUSSION

This online mapping tool correctly allocated almost 60% of TB cases in their village of residence while majority of misclassifications were cases located in neighboring villages. New mapping tools such as online Google Maps could be improved and employed in surveillance of TB cases for timely diagnosis, follow-up and treatment completion. Tuberculosis programs in dense urban areas with high caseload clinics may benefit from improving the quality of addresses obtained in their TB registers in order effectively implement intensive case finding and contact tracing activities.

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Dedication

To my loving family, Maurice and Lwanda Deya

INTRODUCTION

Tuberculosis (TB) is caused by *Mycobacterium tuberculosis,* which is transmitted by aerosolized droplet nuclei during close contact with an infectious person. The World Health Organization (WHO) estimated an incidence of 8.7 million cases globally in 2011 [1]. Although the global incidence of tuberculosis has been falling since 2002, eighty percent of cases occur in 22 countries in Southeast Asia and Africa that still bear the greatest part of the global burden of TB [2]. Kenya, a high-burden country, reported 103,981 new TB in 2011, with a incidence of 288 (276-300) per 100,000 population per year [1]. This rate is more than five-fold higher compared to 1990 [3]. The dramatic increase in TB incidence has been largely driven by the HIV epidemic, and affects mainly young adults in their reproductive years [4].

Due to the high prevalence of HIV in Kenya there exists a dual TB-HIV epidemic with both diseases being a major cause of morbidity and mortality in Kenya. Approximately 39% of TB patients tested positive for HIV in 2011 [5]. A person's risk of TB increases two-fold within a year of HIV acquisition [6, 7], and rises progressively with advancing immunosuppression. As a result, people living with HIV in TB-endemic regions are 20 times more likely to develop active TB compared to those who are HIV-negative [7]. In addition to HIV, urban communities in Kenya face congestion, poor living conditions, economic deprivation, and limited access to health care, further increasing their susceptibility to TB [8].

About 2 billion people globally are latently infected with TB and about 10% of these will progress to become active TB cases. This high prevalence of latent TB along with the presence of undiagnosed active TB cases and the dual TB-HIV epidemic in Sub Saharan Africa [9] result in sustained transmission in communities. In such populations, aggressive prevention strategies such as intensified case finding which includes active case finding (ACF) and contact tracing are requisite to ensure early diagnosis and treatment of TB [10-12]. However, due to the increased burden on the health system in Kenya, the TB control program focuses on diagnosis and treatment of active cases reporting to health facilities leaving scant resources for ACF. The Kenyan strategy for TB control includes expansion of directly observed treatment (DOTS), improvement in DOTS quality, expansion of TB/HIV collaborative activities, addressing the challenge of multiple-drug resistant TB (MDRTB), and empowering communities with knowledge about TB.

Active case finding is defined as a strategy for actively searching for TB disease in a defined population. These are usually contacts of a TB patient, high risk groups, or the general community. The aim of ACF is to reduce transmission by early detection and treatment of TB cases. Contact tracing in addition to ACF will include interventions to test and treat for latent TB among contacts after excluding active disease. These interventions are cost effective in high prevalence areas where DOTS coverage and treatment success rates are high [10], as is the case in Kenya, where treatment success in 2010 was 87% [3]. Recent recommendations encourage national TB programs to include intensified case finding for TB control in addition to DOTS, antiretroviral therapy (if HIV-infected), isoniazid prophylaxis, and infection control in order to reduce delays in TB diagnosis, TB mortality and also decrease transmission [13-15].

In the context of ACF, it is important to identify and evaluate the most susceptible household contacts of TB patients. Correct identification of the geographical locations of all TB cases identified through passive case finding in health facilities could help to inform TB programs of the key locations in which to focus their intensive case finding resources. Information on best practices to implement TB control interventions is sparse [15], and no research has been undertaken to evaluate the spatial distribution of TB cases in Kenya. In this study, we sought to evaluate the accuracy of an online mapping method to locate TB patientsôvillage of residence using addresses provided in TB registers in Mombasa, Kenya.

METHODOLOGY

Study Setting and Participants

The study was conducted between July 2012 and July 2013 in Mombasa District (currently part of Mombasa County) which is further subdivided into 291 villages. Located on the Indian Ocean coast of Kenya, the county has an area of 295 km^2, with an estimated population of 939,370. This includes the urban population of Mombasa city, which is 554,425 based on the 2009 census.

Study participants were drawn from TB cases registered with the Ministry of Health's National TB program registers between January 1st and December 31st 2012. We included all patients diagnosed with TB according to the National guidelines [16] and registered at TB clinics in Mombasa during 2012, regardless of primary site of involvement (e.g., pulmonary or extra-pulmonary). We excluded those who indicated that they initiated treatment outside the study area.

Clinical TB data were abstracted from the TB registers at the facility by trained study staff familiar with the TB program records. Home addresses are routinely provided by each TB patient at the time of treatment initiation and recorded in facility registers. Study staff were assisted by volunteer community health workers (CHW) who were knowledgeable about the geographic catchment area for each clinic. Using the physical address and guidance from the community health worker, a geographical location was mapped for each case. We utilized a customized Google-maps application to obtain a latitude and longitude coordinate pair identifying their home location. These point locations were then used to identify the village of residence using village boundaries from the Kenya National Bureau of Statistics 2009 census maps and ArcGIS version 10.1 (Environmental Systems Research Institute, Inc. Redlands California USA).

To validate the spatial accuracy of this health-worker-based online mapping procedure, for a subset of the mapped TB patients, we conducted home visits collecting an accurate (5m) latitude and longitude pair using a Global Positioning System (GPS) device. Patients were recruited for home visits at the TB facilities during their routine visits to collect medication. From each of the four TB program zones in Mombasa District, a purposive sample of government, municipal, and private clinics with a range of high and low caseloads were selected. Consecutive patients were approached during TB clinic days from a total of 13 clinics in Mombasa District. Study staff obtained written informed consent from patients willing to participate in the study. At a predetermined date, the study staff visited the patientøs residence in the company of a community health worker. Two hundred and eighty six GPS home-visit records had corresponding online mapping home locations. Cases that were ineligible for the study (n=8) because they either started treatment outside the study area (Mombasa District) or study period (2012) were excluded. Also we excluded cases where the address provided in the TB register, which was used for online mapping, referred to a completely different location than the site visited during the home visit (n=32). Some of these addresses were either of poor quality or referred to distant landmarks, others referred to workplaces, alternative residences or to new home locations after registration.

We obtained data from the 2009 national census to determine the population demographics and administrative boundaries of each of the 291 villages in the study area [17]. All study procedures were approved by the University of Washingtonøs Human Subjects Review Committee and the Ethics and Research Committee at Kenyatta National Hospital.

Statistical Methods

The accuracy of the online mapping method was assessed in two ways. First, the straight-line distance between each patientøs online mapping and GPS point locations was calculated and summarized. Second, the longitude ï latitude coordinates obtained during online mapping and

GPS home visits were compared to the Mombasa village boundaries to determine whether the online approach was correct in locating the village of residence (Online and GPS matched) or incorrect (Online and GPS did not match).

We evaluated the following factors as predictors of correct village allocation: village size (km^2), number of individuals in the village, population density in each village, number of households per village, village location, and village status (predominantly formal versus informal settlements in the village). An informal settlement or a slum is defined as a contiguous settlement where the inhabitants are characterized as having inadequate housing and basic services [18]. Clinic and patient-level factors included TB clinic case load for 2012, TB clinic type (Ministry of health, municipal or private facility), TB patient type (new vs. relapse, retreatment, or failure), age, sex, TB smear positivity status, and HIV status. For continuous variables, medians and interquartile ranges were computed, and variables compared using the two sample t-test. For categorical variables, count and proportions were computed and variables compared using the chi-squared or Fisher's exact test.

We performed logistic regression to determine odds ratios (OR) and 95% confidence intervals (CIs) of the factors associated with correct identification of village of residence. Predictors with p-values <=0.10 in bivariate analysis were included in a multivariate model. Adjusted odds ratios (aORs) and their 95% confidence intervals (CIs) were computed. Analyses were performed using IBM SPSS Statistics 19.0 (PASW Inc., Chicago, USA) and STATA 12 (StataCorp, College Station, TX, USA).

RESULTS

Between July 2012 and July 2013, 2458 TB patients were mapped by our online method using addresses provided in TB records from 56 TB treatment facilities in Mombasa. Of these, 346 (14%) from 13 clinics were approached for participation in the GPS physical mapping phase of the study. Two-hundred and eighty six (83%) agreed to participate; were available for the home-visit GPS mapping and matched with their online home location. The 246 participants who met study inclusion criteria were distributed across 122 villages in Mombasa after excluding cases who did not meet study criteria (8) and those with discrepant physical addresses in the TB registers (32). Their baseline characteristics are presented in Table 1. The online method located 140 cases (56.9%) in the correct village of residence, 80 (32.5%) were incorrectly allocated to a neighboring village, and 26 (10.5%) in non-neighboring villages (Figure 1). When using a straight line to estimate the error distance between the actual GPS point location and the online location, there was a mean distance of 225.2m (±296.2) for all cases, 106.5m (±92.5) and 382m (±386.9) for those correctly located and incorrectly located respectively (Table 2).

Cases that were correctly located in their village of residence by the online mapping method were compared to those whose village was incorrectly located. The two groups had similar age and sex characteristics. Most participants in each group were males (63% vs. 68%) newly diagnosed TB cases (79% vs. 85%), HIV negative (78% vs. 84%), living urban villages (99% vs. 100%), and attended municipal clinics (72% vs. 83%). Relative to those who were incorrectly located, cases who were correctly located were significantly more likely to live in villages with formal settlements (81% vs. 68%). Other clinic and village level factors were that significantly associated with being correctly mapped to the village of residence in univariate analysis included type of clinic, clinic caseload, total households per village, and village population density (Table 1).

In multivariate analysis, the odds of correctly locating a case were 2.75 times higher in clinics with medium caseloads (adjusted OR 2.75 95% CI 1.37 ï 5.53) compared to low caseload clinics. Facilities with high caseloads did not differ significantly from low caseload clinics (aOR 0.66 95% CI 0.28 ï 1.58). Compared to patients from villages with the lowest numbers of households, patients living in villages with moderate and high numbers of households were less likely to be correctly located (aOR 0.42 95% CI 0.21 ï 0.85 and aOR 0.34 95% CI 0.09 ï 1.26, respectively), although the latter finding was not statistically significant. Similarly, relative to low density villages with less than 15,000 inhabitants per km^2, increasing population density was associated with lower odds of being correctly allocated to village of residence (15,001-30,000 per km^2; aOR 0.94 95% CI 0.48 ï 1.87 and >30,000 per km^2; aOR 0.43 95% CI 0.19 ï 0.94, Table 3).

DISCUSSION

To our knowledge, this validation study of an online mapping method using satellite images is the first study to use this technology to map locations of TB patients in Kenya. We found that compared to the actual GPS home location, about 90% of the cases were either correctly identified in their village of residence (56.9%) or allocated to a neighboring village (32.5%), by the online mapping method.

Living in areas with medium and high population density significantly reduced the odds of being found in the correct village. On the other hand, factors such as patient demographic and clinical characteristics did not influence the odds of correct allocation in this study. Mombasa district is mostly urban and is densely populated. We found a mean population density of 21,296 inhabitants per km^2 in villages represented in this study. Moreover, formal street addresses are not used, and it is challenging to precisely locate homes using the descriptive addresses and landmarks provided by most TB patients. This problem is compounded by the existence of informal housing. Additionally, the presence of cloudy satellite images in certain areas obscured landmarks and roads making it difficult to visualize the study area while mapping and may have contributed to some misclassification in those areas.

Clinic-level characteristics also influenced the accuracy of the online method with municipal and private clinics performing worse than government-run facilities. Compared to low caseload clinics, moderate clinic caseload was significantly associated with correct village allocation. In contrast, high clinic caseload was not associated with a significantly different likelihood of correct village assignment compared to low caseload clinics. The finding that clinics with intermediate caseloads performed better in mapping than either high or low caseload clinics is somewhat difficult to explain. This result may be related to a variety of factors including training, patient-staff ratios, and the fact that most of the smaller facilities did not have specific staff dedicated to the TB clinic.

Understanding and visualizing the spatial distribution of cases could play a key role in controlling transmission of TB in urban communities. Although we did not find literature on any studies using a similar online tool to map TB patients, local TB programs can utilize accurate data on patient's location to identify local community needs and inform the development of appropriate interventions [19]. A few African studies have been conducted to analyze factors associated with spatial distribution of TB in Gambia [20], Madagascar [21], and South Africa [19, 22]. These and other studies conducted in both high and low incidence areas demonstrated that geographical information systems (GIS) used for mapping and spatial analysis can be useful in identifying areas where clusters of TB occur and delineating environmental, socio-economic and demographic factors that are associated with TB transmission [22-24]. One study conducted in Nyanza Province of Kenya modeled the effects of local vs. global transmission on TB disease incidence using space-time cluster analysis from TB case notification data in about 240 villages [25]. The model showed pronounced local effects that depend on factors such as age and gender, and was found useful in designing an effective of community randomized trials in villages with geographical clusters of TB cases. Overall, these studies highlight the importance of understanding determinants of varied TB burden across geographical areas.

Approaches such as training CHWs to be familiar with satellite maps of their clinic catchment area and increasing the number of CHWs in high-volume clinics may improve the accuracy of locating TB cases using this online tool. Since these tools are user friendly, patients may be able to locate their own homes on a satellite image in addition to providing a description of their physical address, if a computer with internet access is available. In the most dense villages with slum dwellings, collection of actual GPS points using easily available GPS-enabled devices or phones may be necessary to obtain correct location data, possibly targeting sputum-positive cases, who present the greatest public health risk. Regardless, issues of stigma should be addressed by careful patient counseling, as efforts to locate cases during contact tracing may be frustrated by patients deliberately giving incorrect information.

Our study strengths include the ability to delineate between patient-level factors that did not influence location to village of residence from clinic and village-level factors that were associated with being correctly located. We validated a reasonably large sample of 246 cases (14%) from TB registers who were distributed across a wide range of villages 122 (42%) in Mombasa District.

However, we were limited because we did not collect information from patients on where they spend most of their time, including workplaces, sites for leisure activities, and other community locations where TB transmission may be occurring. In addition to patientsôresidence, settings outside the home where people tend to congregate, such as drinking places, churches, hospitals, and clinics have emerged as potentially high risk for transmission of TB in the setting of poverty [19]. Ascertainment of TB disease was also dependent on TB program definition and procedures which we did not evaluate. National TB program data however, is used for disease surveillance and is the most accurate source of TB data in the country.

Findings from this study show that using our online mapping tool resulted in correct allocation of almost 60% of TB cases in a densely populated urban area. The majority of misclassifications were located in neighboring villages, suggesting that despite the discrepant distances, mapping patients using this method may still be useful. As correct village allocation was influenced by clinic management and annual clinic caseloads our results indicate that TB programs interested in intensive case finding and contact tracing may benefit from improving the quality of addresses obtained in TB registers. In conclusion, new tools such as online Google Maps and GPS mapping could be improved and employed in surveillance of TB cases in the community for timely diagnosis, follow-up and treatment completion.

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Table 1. Baseline Characteristics of 246 participants

Characteristic	Cases correctly located*	Cases incorrectly located*	p
	Median (IQR) or Number (%)		
Patient characteristics	**(n = 140)**	**(n = 106)**	
Age Median (IQR)	30 (25 - 41)	31 (25 - 38)	0.416
Sex			
Male (n = 160)	88 (55.0)	72 (45.0)	0.409
Females (n = 86)	52 (60.5)	34 (39.5)	
TB Type			0.259
New case (n = 201)	111 (55.2)	90 (44.8)	
Relapse, Retreatment or Failure (n = 45)	29 (64.4)	16 (35.6)	
TB sputum smear			0.378
Negative (n = 59)	36 (61.0)	23 (39.0)	
Positive (n = 151)	82 (54.3)	69 (45.7)	
Not performed (n = 36)	22 (61.1)	14 (38.8)	
HIV positive			0.564
Positive (n = 47)	30 (63.8)	17 (36.2)	
Negative (n = 192)	106 (55.2)	86 (44.8)	
Not performed (n = 7)	4 (57.1)	3 (42.9)	
Clinic Characteristics			
Clinic type			**0.071**
Government (n = 3)	35 (71.4)	14 (28.6)	
Municipal (n = 8)	101 (53.4)	88 (46.6)	
Private (n = 2)	4 (50)	4 (50)	
Annual clinic case-load			**<0.001**
0 ï 200 cases (n = 9)	38 (51.4)	36 (48.7)	
201 ï 400 cases (n = 3)	86 (69.9)	37 (30.1)	
>400 cases (n = 1)	16 (32.7)	33 (67.3)	
Village Characteristics			
Village size (km^2)	0.184 (0.09 ï 0.281)	0.168 (0.096 ï 0.284)	0.198
Village density (per km^2)			**0.003**
0 ï 15,000 (n = 60)	62 (66.7)	31 (33.3)	
15,001 ï 30,000 (n = 38)	52 (59.1)	36 (40.9)	
>30,000 (n = 25)	26 (40)	39 (60)	
Total households per village			**0.002**
0 ï 1,000 (n =87)	93 (66.4)	47 (33.6)	
1,001 ï 2,000 (n = 31)	38 (46.9)	43 (53.1)	
>2,000 (n = 5)	9 (36.0)	16 (64.0)	
Village location			0.217
Urban (n = 120)	138 (56.6)	106 (43.4)	
Periurban (n = 2)	2 (100)	0 (0)	
Village status			**0.015**
Formal (n = 101)	114 (61.3)	72 (38.7)	
Informal (n = 21)	26 (43.3)	34 (56.7)	

*****Percentages shown are row % correctly vs. incorrectly identified

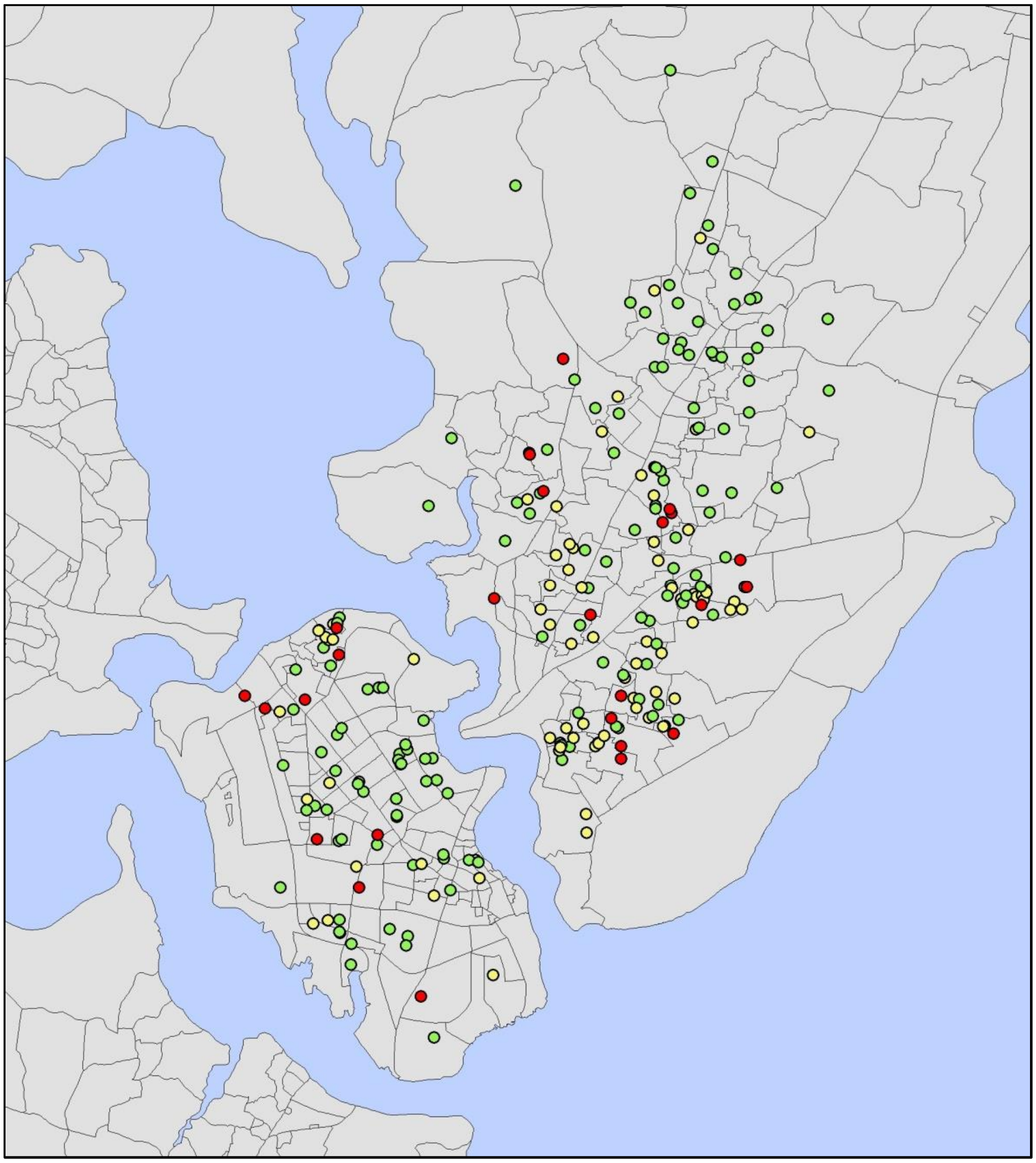
Table 2. Accuracy Assessment of the online mapping method

	Count	% of Total cases (95% CI)	Mean Error (sd) meters
All Cases	246	100%	225.2m (±296.2m)
Correct Village	140	56.9 (50.5 ï 63.2)	106.5m (±92.5m)
Incorrect Village	106	43.1 (36.8 ï 49.5)	382m (±386.9m)
Neighboring	80	32.5 (26.7 ï 38.8)	236.7m (±137.8m)
Non-Neighboring	26	10.57 (7.0 ï 15.1)	829m (±541.8m)

Table 3. Multivariate analysis of predictors associated with correct allocation of village of residence by online mapping method

	Crude Analysis		**Adjusted Analysis**	
	OR (95% CI)	**p**	**aOR (95% CI)**	**p**
Predictor	**n = 246**		**n = 246**	
TB Sputum smear				
Negative	1.0 (ref)		1.0 (ref)	
Positive	0.76 (0.41 ï 1.40)	0.379	0.70 (0.36 ï 1.40)	0.318
Not performed	1.00 (0.43 ï 2.35)	0.993	0.73 (0.28 ï 1.88)	0.509
Clinic type				
Government	1.0 (ref)		1.0 (ref)	
Municipal	0.46 (0.23 ï 0.91)	**0.025**	0.45 (0.20 ï 0.99)	**0.048**
Private	0.40 (0.08 ï 1.82)	0.237	0.57 (0.10 ï 3.20)	0.524
Annual clinic caseload				
0-200 cases	1.0 (ref)		1.0 (ref)	
201-400 cases	2.21 (1.21 ï 4.0)	**0.010**	2.75 (1.37 ï 5.53)	**0.004**
>400 cases	0.46 (0.22 ï 0.97)	**0.042**	0.66 (0.28 ï 1.58)	0.349
Village density				
0 ï 15,000	1.0 (ref)		1.0 (ref)	
15,001 ï 30,000	0.72 (0.39 ï 1.32)	0.292	0.94 (0.48 ï 1.87)	0.869
>30,000	0.33 (0.17 ï 0.64)	**0.001**	0.43 (0.19 ï 0.94)	**0.035**
Total households in village				
0 ï 1,000	1.0 (ref)		1.0 (ref)	
1,001 ï 2,000	0.45 (0.26 ï 0.78)	**0.005**	0.42 (0.21 ï 0.85)	**0.016**
>2,000	0.28 (0.12 ï 0.69)	**0.006**	0.34 (0.09 ï 1.26)	0.106
Village status				
Formal	1.0 (ref)		1.0 (ref)	
Informal	0.48 (0.27 ï 0.87)	**0.016**	1.14 (0.48 ï 2.68)	0.768

Figure 1. Point locations showing village boundaries and accuracy of the online mapping method in Mombasa District



Key: Green = Correct village, Yellow = Incorrect, but Neighboring village, Red = Incorrect, Non-Neighboring village