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METHODS OF PRIORITIZING TARGET AREAS FOR VACCINATION CAMPAIGNS IN THE CONTEXT OF THE 2010 MEASLES EPIDEMIC IN MALAWI

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ABSTRACT

Background: Despite progress towards increasing global vaccination coverage, measles continues to be one of the leading, preventable causes of death among children worldwide. How to prioritize target areas for vaccination campaigns continues to remain a question. We analyzed three methods of prioritizing target areas: vaccination coverage, susceptible recruitment, and the effective reproductive ratio (R_E) in the context of the 2010 measles epidemic in Malawi.

Methods: Using surveillance data from the 2010 measles outbreak in Malawi, we estimated vaccination coverage and annual susceptible recruitment at the district scale and healthcare facility polygon scale to identify high priority target areas. We also estimated R_E at the healthcare facility polygon scale.

Results: Estimates of vaccination coverage and susceptible recruitment resulted in relatively similar prioritization of target areas, in particular, the districts of Mangochi and Kasungu had low vaccination coverage and large populations of unvaccinated children. Notably, the urban area of Blantyre, where the epidemic began, was identified as having the highest R_E. A few areas within the districts of Lilongwe, Kasungu, and Mangochi were prioritized by all three methods. Additionally, we found that district scale measurements masked significant heterogeneity at the healthcare facility polygon scale.

Conclusion: Each method of prioritization may result in discrete target areas for vaccination campaigns; thus, there are tradeoffs to choosing one method over another. However, in some cases, certain areas may be prioritized by all three methods. These areas should be treated with particular concern. Furthermore, the scale at which each method is conducted impacts the resulting prioritization and should also be considered when prioritizing areas for vaccination campaigns.

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Chapter 1

INTRODUCTION

Before the availability of the measles vaccine, 90% of children worldwide were infected with measles before the age of 15 (WHO, 2012), resulting in 2.6 million deaths annually (WHO, 2015). Since the effective, safe, and inexpensive vaccine became available, the WHO has made substantial progress towards the eradication of measles. Between 2000 and 2010, global vaccination coverage rose from 72% to 85% and measles mortality decreased by 74% (Simmons, 2012).

Despite this progress, measles continues to be one of the leading, preventable causes of death among young children worldwide (WHO, 2015). Approximately 145,700 people – primarily children under the age of 5 – died from measles in 2013 (WHO, 2015). Large measles outbreaks still occur in five of the six WHO regions (Minetti, 2013 B; Najjar, 2012; Muscat, 2013; Parker, 2010; Zhang, 2010; WHO, 2014). Elimination of measles requires strategies for increasing routine vaccination as well strategies for reacting to outbreaks (WHO, 2012). These strategies need to be tailored to each countries' specific needs – some countries rely on routine immunization services to deliver the first and second measles vaccine dose while other countries still require supplementary immunization activities that target low coverage areas (WHO, 2012). How to most effectively prioritize locations for vaccination campaigns before and/or during an epidemic continues to remain a question.

Vaccination coverage serves as one of the primary indicators of progress towards controlling and eliminating measles (Ferrari, 2013). The World Health Organization's goals and recommendations for the elimination of measles are outlined in the Global Measles and Rubella Strategic Plan 2012-2020 (WHO, 2012). By the end of 2015, the WHO's goal is to achieve 90% vaccination coverage with the first routine dose of a measles-containing vaccine for every nation and to exceed 80% vaccination coverage in every district or equivalent (WHO, 2012). The recommendations suggest two separate objectives: (1) obtaining equitable vaccination coverage and (2) minimizing the recruitment of non-immune children (WHO, 2012).

Obtaining country-wide equitable vaccination coverage can be done by targeting low coverage areas with supplemental immunization activities. According to the International Society for Equity in Health, equitability is defined as "the absence of systematic and potentially remediable differences in one or more aspects of health across population sub-groups defined socially, economically, demographically, or geographically" (Vijayaraghavan, 2007). Values for national vaccination coverage mask discrepancies in vaccination coverage typically found in impoverished or isolated populations (Vijayaraghavan, 2007; Metcalf, 2014) Vaccination coverage values at the local scale better reflect the susceptibility of populations to disease and can be used to prioritize vaccination targets before and/or during an outbreak (Vijayaraghavan, 2007; Metcalf, 2014).

Local scale measures of vaccination program performance are scarce. Those that do exist tend to be measures of vaccination rather than immunization. Vaccination coverage is typically calculated by administrative methods – comparing the number of vaccine doses to the target population. This method does not account for vaccine wastage (discarded doses, vaccination of individuals outside of the targeted area, and revaccination of individuals already vaccinated) and the inaccessibility of some sub-populations (Lessler, 2011). In addition, population estimates are often not up to date and produce inflated administrative estimates in comparison to population-based surveys (Ferrari, 2013). Not all distributed vaccine doses lead to an immunized individual; therefore, vaccination coverage values do not directly describe the susceptibility of a population (Lessler, 2011). Here, we will use an alternative method of calculating vaccination coverage at a local scale.

Vaccination coverage alone is limited because it does not account for the absolute number of susceptible individuals or the recruitment of new susceptible individuals. The persistence of measles may be due to differences in the annual recruitment of non-immune children resulting from variation in local birth rates (Ferrari, 2013). Large, highly populated places with high vaccination coverage may lead to recruitment of large numbers of non-immunized children while small, lowly populated places with low vaccination coverage may have a minor impact on the recruitment of non-immunized children. Considering both local vaccination coverage and local susceptible recruitment may be more effective in prioritizing vaccination campaign targets than considering vaccination coverage alone (Ferrari, 2013).

The reproductive ratio (R_0), defined as the average number of secondary cases that result from a single infectious individual in a completely susceptible population, is another epidemiological measure used to determine the length and duration of an outbreak (Anderson and May, 1991). However, populations affected by measles, as discussed in this paper, have partial immunity due to prior vaccination or previous infection. Therefore, the effective reproductive ratio (R_E), the average number of secondary cases that result from a single infectious individual in a partially immunized population (Anderson and May, 1991), is a more appropriate measure than $R_{0.}$

R_E varies within populations. Large-scale population estimates which do not account for the heterogeneity of R_E conceal clusters of susceptible individuals that may increase the susceptibility of the larger population to an outbreak (Lloyd-Smith, 2005; Hickson, 2014; Smilkov, 2014). The heterogeneity within a population arises because of variable baseline levels of immunity (Grais, 2006), birth rates (Anderson and May, 1991), mixing between age classes (Van Effelterre, 2008), and population densities. Because of this heterogeneity, estimates of R_E may be used as another method of prioritizing vaccination targets within a population. In fact, Lloyd-Smith et al. found that individual-specific control measures – like those that would be based on fine-scale estimates of R_E – are more effective than population-wide control measures (Lloyd-Smith, 2005).

Here, we quantify the local variation in estimated vaccination coverage, recruitment of non-immunized children, and R_E at the district scale and the individual healthcare facility catchments scale in Malawi using measles case records from an outbreak in 2010. Based on these analyses, we make recommendations for prioritizing regions with respect to separate goals of (1) achieving equitable vaccination coverage and (2) minimizing the recruitment of non-immune children as well as reducing R_E. These measures may or may not result in the same prioritization of target areas; however, here, we highlight the overlapping target areas that were prioritized regardless of measure.

Chapter 2

METHODS

Data:

Through retrospective review of health registers and weekly communication to the district level, a line list of all measles cases presented at healthcare facilities was created (Minetti, 2013 B). A positive measles case was recorded if the patient was exhibiting a generalized maculopapular rash, a fever of $\geq 38°C$, and at least one of the following: cough, runny nose, or conjunctivitis or if the patient was diagnosed with measles by a health professional (Minetti, 2013 B). For each suspected measles case, the date of onset, date of clinic visit, epidemic week of clinic visit, location and name of healthcare facility, age, and vaccine history (recorded as positive if the patient had a vaccine card or if the patients mother reported positive vaccination status) (Minetti, 2013 B). The line list contained 129,037 entries.

We obtained fertility information at a regional scale (North, Central, South) from the 2008 Malawi Census. The northern region contains the districts of Chitipa, Karonga, Nkhata Bay, Rumphi, Mzimba, Likoma, and Mzuzu City. The central region contains the districts of Kasungu, Nkhotakota, Ntchisi, Dowa, Salima, Lilongwe, Mchinji, Dedza, and Ntcheu. The southern region contains the districts of Mangochi, Machinga, Zomba, Chiradzulu, Blantyre, Mwanza, Thyolo, Mulanje, Phalombe, Chikwawa, Nsanje, Balaka, and Neno.

Data Cleaning:

We cleaned the data specifically focusing on the dates of consultation and healthcare facility names. Dates in the line list were given in several different formats (MDY, DMY, YMD) and contained possible typos. We put all dates in a common format (YYYY-MM-DD) by shifting dates through their possible formats until they matched their corresponding epidemic week. If a date could not be placed into its correct epidemic week, the entry was discarded. 5,676 entries were discarded after this process.

Healthcare facility names were recorded into the line list with variations in spelling and typos. We merged variant spellings of healthcare facility names together to generate a list of unique healthcare facilities from the line list. We obtained two lists of known healthcare facilities with their corresponding geolocations from reference maps from the Malawi Ministry of Health and the National Statistical Office of Malawi. We combined the two lists from the reference maps, removing any duplicates. This list was then matched to our unique healthcare facility from the line list. To verify that healthcare facilities had been properly to their corresponding geolocations, we checked that each healthcare facility was in the correct district. 22,925 entries were discarded because they could not be matched to a known healthcare facility or placed in their correct location.

After correction, the line list included approximately 100,436 entries of the original 129,037. Of the 1092 healthcare facility polygons, 390 had reported cases and 338 had reported vaccination history.

Health facility polygons:

Using the combined reference map lists of healthcare facilities from the Malawi Ministry of Health and the National Statistical Office of Malawi (discussed above), we mapped all of the healthcare facilities using a Transverse Mercator Projection. We approximated catchment areas around each healthcare facility using a Voroni tessellation. Each catchment area is the set of all points nearest to it than to any other healthcare facility. We generated a GIS shapefile with all healthcare facility polygons. To get population sizes for each polygon, we overlaid a population density map on top of the GIS shapefile we created.

Vaccination coverage:

We estimated vaccination coverage using equation 1 (Orenstein, 1985),

$$VC = \frac{PCV}{(1 - VE + PCV \times VE)}$$

Equation 1: Estimation of proportion of people vaccinated (PPV)

which relates the proportion of people vaccinated (VC) within a population to the proportion of measles cases that had been vaccinated (PCV) and measles vaccine efficacy (VE). PCV is the proportion of measles cases with positive vaccination history out of all the cases with vaccination history in an area. We used a vaccine efficacy of 0.85 (Uzicanin, 2009). We estimated VC at both the district scale and healthcare facility polygon scale.

Due to vaccination history not always being recorded, variability in the number of individuals reported vaccination history, and variability in the size of each healthcare facility polygon, we created a more uniform spatial scale by smoothing PCV values. Smoothing allowed us to estimate PCV values for polygons with no recorded measles cases and it ensured that the number of cases per polygon and the size of each polygon did not affect our PCV estimates. We calculated smoothed PCV for each polygon by dividing the sum of all the cases with positive vaccination history reporting to healthcare facilities within a radius of 0.15 degrees of the reference polygon by the sum of all the cases with vaccination history within the same radius. We applied equation 1 to estimate smoothed VC values using the smoothed PCV values.

Annual Recruitment of Non-immune Individuals (Susceptible Recruitment):

We estimated the annual recruitment of unvaccinated individuals, Y, as:

$$Y = \text{female population size} \times \text{fertility} \times (1 - VC)$$

where the female population size is given for that spatial unit, fertility is the number of live births within a region (North, Central, South) divided by the number of females within that region, and VC is the estimated vaccination coverage for that spatial unit.

To estimate the annual recruitment of unvaccinated individuals at the district scale, we used female population sizes from the 2008 Census. To estimate the recruitment of non-immune individuals at the healthcare facility polygon scale, we assumed female population to be 50% of the population.

Effective Reproductive Ratio (R_E):

To estimate the effective reproductive ratio (R_E) for each healthcare facility polygon, we used equation 2 (Lipsitch, 2013),

$$R = 1 + IG + F(1 - F)(IG)^2$$

Equation 2: Estimation of the effective reproductive ratio

where I is the mean serial interval, G is the exponential growth rate of the cumulative number of cases during the first 33^{rd} percentile of cases recorded, and F is the ratio of the infectious period to the serial interval. I for measles is 14 days. G is given by

$$G(t) = \frac{\ln(S(t))}{t}$$

where S is the cumulative number of cases and t is the time it took for the first 33^{rd} percentile of cases to present to healthcare facilities within a polygon. F is 0.5.

Chapter 3

RESULTS

Vaccination coverage (VC):

On average, vaccination coverage across all districts was 84%, but there was a high degree of variability between districts (Figure 1a and 1b, see reference map for district locations). Six districts (Mangochi, Kasungu, Nkhata Bay, Mwanza, Nkhotakota, and Dedza) had vaccination coverage below 80%. Mangochi, which is found in central Malawi below the lake, had the lowest vaccination coverage (~60%).

Broadly speaking, vaccination coverage at the healthcare polygon level resembled coverage at the district level, but more variation in coverage was visible at the healthcare polygon level (Figure 1c and 1d). The healthcare polygons within the district of Mangochi had uniformly low coverage, which was consistent with the district level estimate. However, many other districts did not follow this pattern. For example, Kasungu had district level coverage of 66-70%, but the healthcare polygon level estimates ranged from 0-98%. District level estimates masked large heterogeneity in vaccination coverage. Interestingly, in the district of Lilongwe in central Malawi, this heterogeneity formed a pattern where vaccination coverage increased radially outward from the center of Lilongwe City.

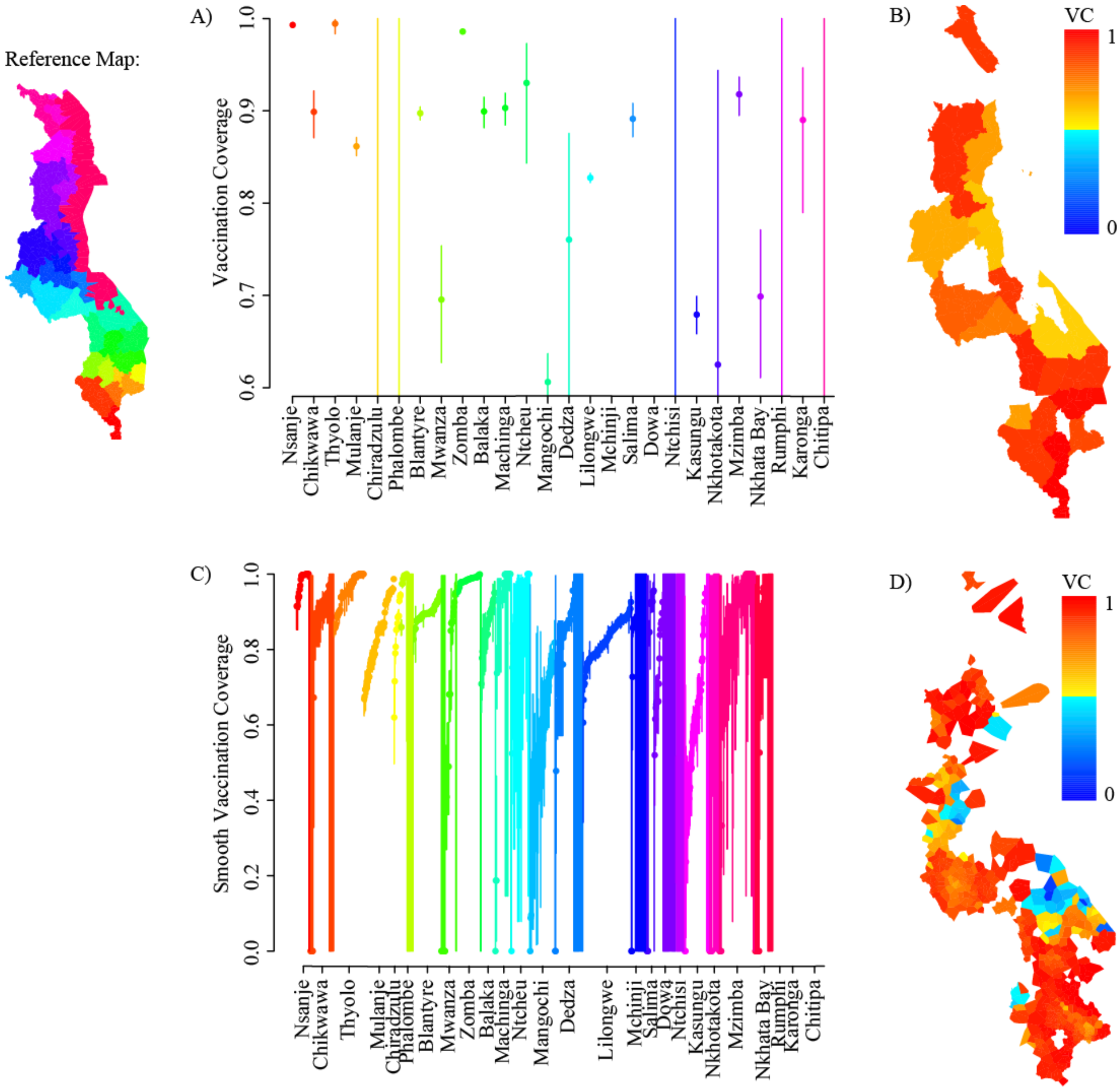

Figure 1: Estimated vaccination coverage at the district scale and healthcare facility polygon scale. A) Estimated VC for each district is indicated with a solid circle and vertical lines indicate 95% confidence intervals. Districts were ordered from south to north and colors correspond to the reference map. B) Estimated VC at the district scale plotted on a scale from blue (VC = 0) to red (VC = 1.0). Areas with no information are indicated in white. C) Estimated smoothed VC for each health facility polygon is indicated with a solid circle and vertical lines indicate 95% confidence intervals. Polygons were grouped by the district they fell within and then arranged by increasing VC. Districts were ordered from south to north and colors correspond to the reference map. D) Estimated smoothed VC at the healthcare facility polygon scale plotted on a scale from blue (VC = 0) to red (VC = 1.0). Areas with no information are indicated in white.

Annual recruitment of unvaccinated individuals (susceptible recruitment):

On average, the annual susceptible recruitment per district was 3510, but the value varied greatly from district to district (Figure 2A and 2B). The district of Mangochi, which had the lowest vaccination coverage, unsurprisingly had a large susceptible recruitment (11,240 - 13,199). Lilongwe, which had relatively high vaccination coverage (~83%), had the highest susceptible recruitment (12,792 - 13,582). These results demonstrate that places with high vaccination coverage and large populations can have larger susceptible recruitment than places with low vaccination coverage.

The district scale estimates for the annual recruitment of unvaccinated individuals (Figure 2B) were somewhat different than the healthcare facility polygon scale estimates of the density of susceptible recruitment within the population (Figure 2C). At the district scale, the districts of Lilongwe, Mangochi, and Kasungu had the largest susceptible recruitments. At the healthcare facility polygon scale, the largest susceptible recruitments were more dispersed throughout the country. In the districts of Mangochi and Kasungu, there were clusters of healthcare facility polygons with somewhat larger susceptible recruitments than the rest of the country. In the district of Lilongwe, the same pattern of heterogeneity as seen with VC arose with susceptible recruitment as well. Larger susceptible recruitments were found in the center of Lilongwe City and the size of the susceptible recruitment decreased radially outward from the center of the city.

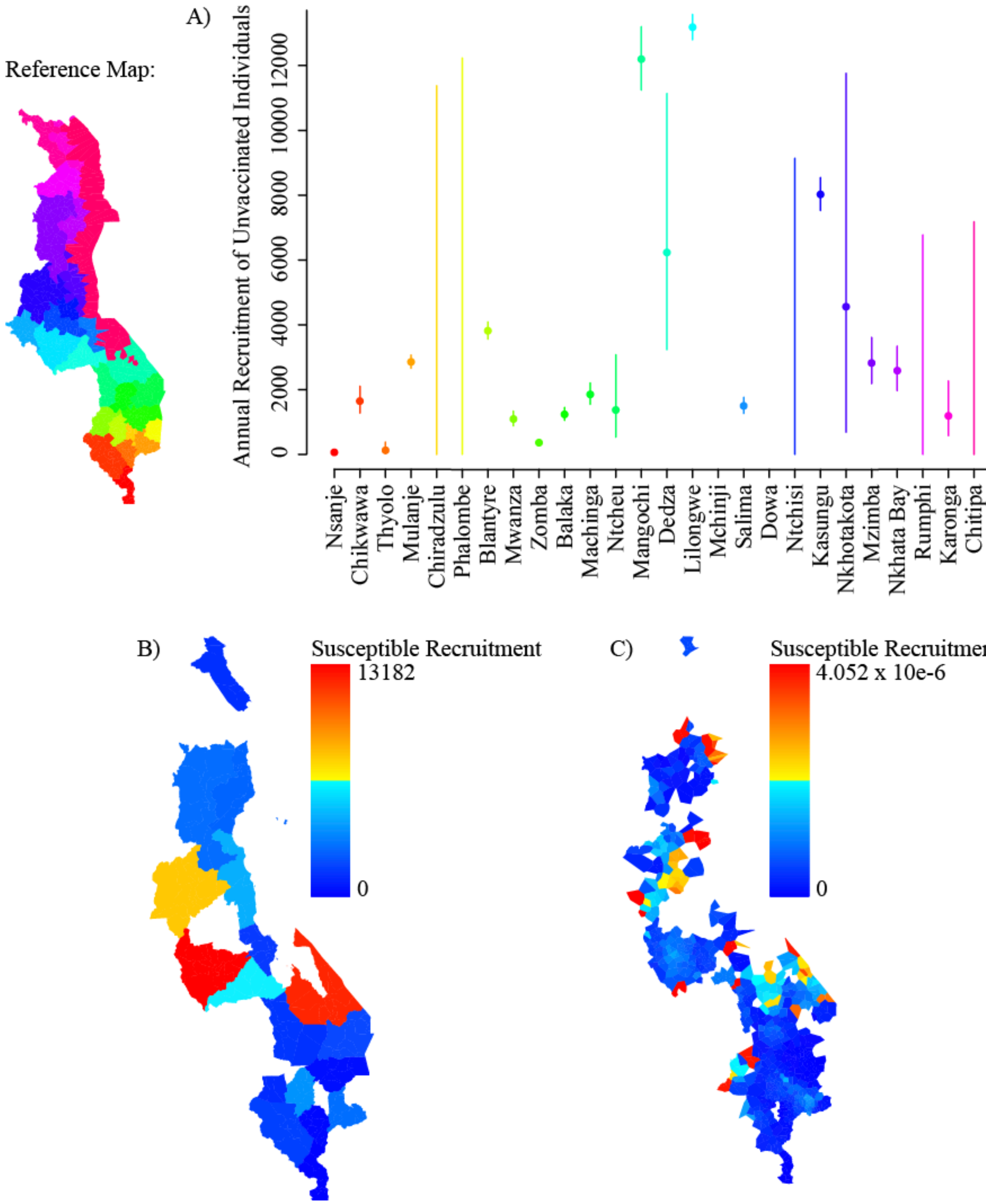

Figure 2: Estimated annual recruitment of unvaccinated individuals at the district scale and healthcare facility polygon scale. A) The absolute value of susceptible recruitment at the district scale is indicated with a solid circle and vertical lines represent a 95% confidence interval. Districts were organized from south to north with colors corresponding to the reference map. B) The absolute value of susceptible recruitment plotted on a scale from blue (Y = 0) to red (Y = 13,182). Areas with no information are indicated in white. C) The susceptible recruitment per healthcare facility polygon area plotted on a scale from blue (Y = 0) to red (Y = 4.05 x 10^{-6}). Areas with no information are indicated in white.

Effective reproductive ratio (R_E):

The effective reproductive ratio (R_E) at the polygon scale was the highest in southern Malawi and lowest in northern Malawi with the exception of two clusters of healthcare facility polygons with high R_E values in Mzimba and Lilongwe (Figure 3). Healthcare facility polygons within the district of Blantyre had the highest R_E values.

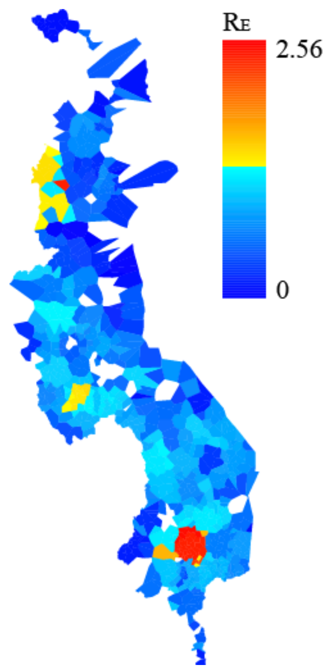

Figure 3: Estimates of RE at the healthcare facility polygon scale. RE values were plotted on a scale from blue (RE = 0) to red (RE = 2.56). Areas with no information are indicated in white.

Comparing target areas resulting from alternate measurements (VC, susceptible recruitment, and R_E):

Each of the measures (VC, susceptible population, and R_E) describe different characteristics of the epidemiology of the outbreak and define different areas of concern. To identify areas of particular concern, we looked at locations that were prioritized by multiple measures.

At the district level, we found six districts (Mangochi, Kasungu, Nkhata Bay, Mwanza, Nkhotakota, and Dedza) with vaccination coverage less than 80% (Figure 4A). To make a similar comparison, we mapped the six districts (Mangochi, Dedza, Lilongwe, and, Kasungu, Nkhotakota, and Blantyre) with the largest susceptible recruitment (Figure 4B). At the district scale, measurments of VC and annual recruitment of new susceptibles resulted in four district targets (Mangochi, Dedza, Kasungu, and Nkhotakota) that were the same and two district targets (Nkata Bay and Mwanza vs Lilongwe and Blantyre, respectively) that were different. Therefore, Mangochi, Dedza, Kasungu, and Nkhotakota were targets at the district scale based on both VC and susceptible recruitment (Figure 4C).

At the polygon scale, we found 254 polygons with VC values less than 80% (Figure 4D). To make parallel comparisons, we mapped the 254 polygons with the highest annual recruitment of new susceptibles per polygon area (Figure 4E) and the 258 (8 polygons had equal values) polygons with the highest values for R_E (Figure 4F). Interestingly, the measurements of VC and susceptible recruitment density had similar results, varying only slightly in the areas of Lilongwe and Mangochi. Mangochi had more target polygons when using VC to prioritize targets and Lilongwe had more target polygons when susceptible recruitment was used to prioritize targets. Conversely, the results for R_E differed greatly from the results for VC and susceptible recruitment density. The highest R_E values were in the areas of Blantyre, Ntcheu, Lilongwe, and Mzimba whereas the highest values for VC and susceptible recruitment were in the areas of Mangochi, Lilongwe, and Kasungu. The districts of Mangochi, Lilongwe, and Kasungu were prioritized by all three measurements at the healthcare facility polygon scale (Figure 4G).

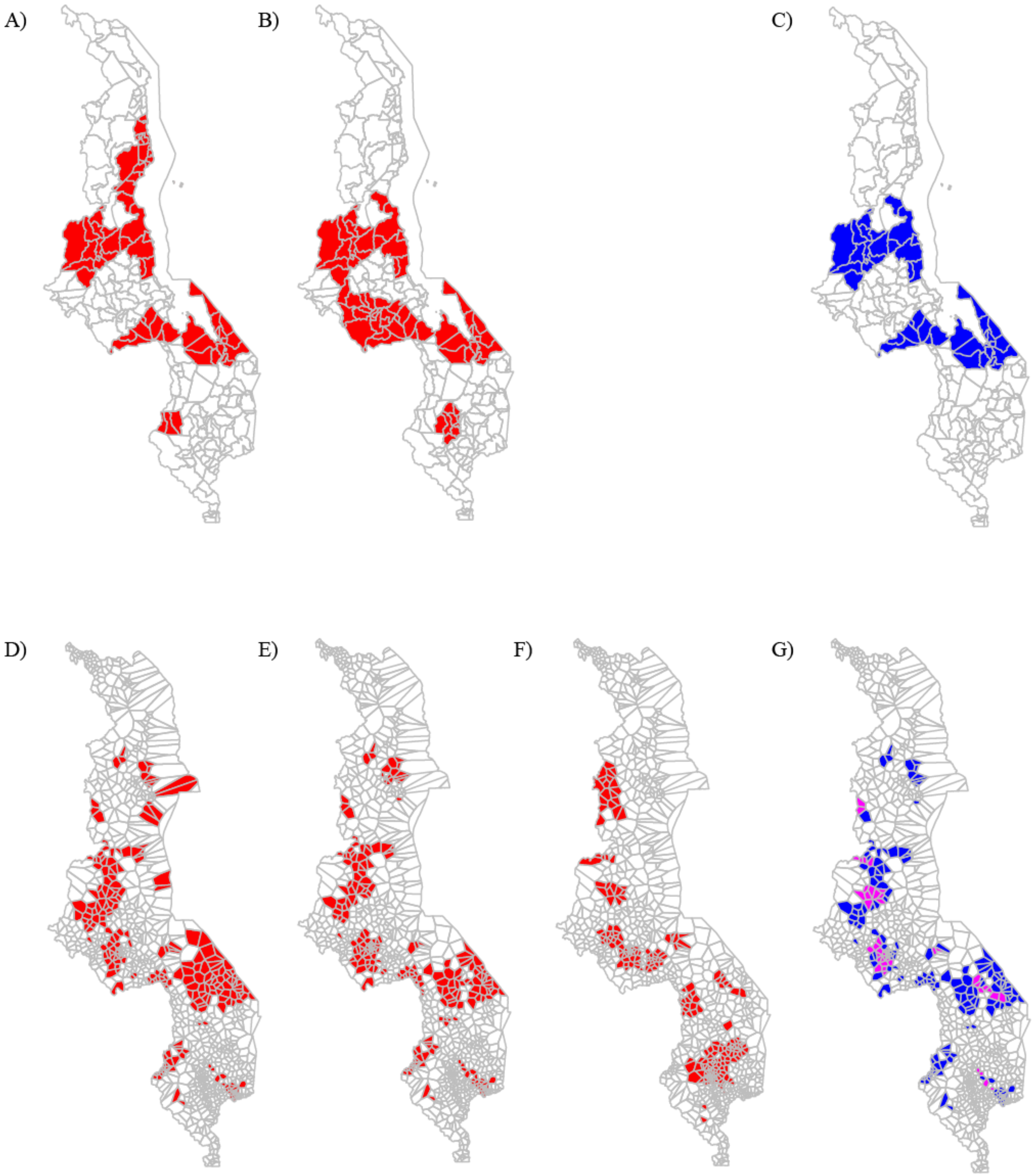

Figure 4: Highest priority targets based on VC, susceptible recruitment and RE at district (A, B, and C) and healthcare facility polygon scale (D, E, F, and G). A) Districts with vaccination coverage less than 80%. B) The four districts with the largest susceptible recruitment. C) Districts prioritized by both VC (A) and susceptible recruitment (B) at the district scale. D) Healthcare facility polygons with VC values less than 80%. E) The 254 polygons with the largest susceptible recruitment. F) The 258 polygons with the highest values for RE. G) Healthcare facility polygons prioritized by two methods (blue) or all three methods (purple) as seen in D, E, and F.

Chapter 4

DISCUSSION

Routine measles vaccination serves as an indicator of progress towards the United Nation's Millennium Development Goal 4 of reducing childhood mortality (WHO, 2012). Although routine measles vaccination limits the risk of potential epidemics occurring, additional supplementary immunization activities is necessary in many countries to achieve and maintain herd immunity (WHO, 2012) and outbreak response immunization is necessary to reduce cases and transmission for when measles outbreaks do occur (Cairns, 2015; Goodson, 2011; Grais, 2011). Because of limited resources, prioritization of target areas for vaccination campaigns is necessary.

We analyzed three methods for prioritizing areas for outbreak response immunization: vaccination coverage, susceptible recruitment, and R_E at the district and healthcare facility polygon scale in the context of the 2010 measles epidemic in Malawi. We found that vaccination coverage and susceptible recruitment estimates resulted in relatively similar prioritization of target areas, primarily in the regions of Mangochi and Kasungu, at both scales. However, R_E estimates resulted in prioritization of other areas, notably in the region of Blantyre which was not prioritized by vaccination coverage or susceptible recruitment estimates. We identified a few locations in the districts of Lilongwe, Kasungu, and Mangochi which were prioritized by all three methods. Additionally, we found that the scale at which each measurement was estimated had an impact on prioritization as well. District scale measurements masked significant heterogeneity at the healthcare facility polygon scale.

Each method – vaccination coverage, susceptible recruitment, and R_E – may result in discrete target areas for outbreak response immunization and may reflect different epidemiological characteristics. Vaccination coverage and susceptible recruitment measure the size of the population at risk, whereas R_E measures the rate of transmission and the proportion of at-risk individuals that will be affected by an outbreak (Anderson and May, 1991). Accordingly, in the context of the 2010 measles epidemic in Malawi, we found that vaccination coverage and susceptible recruitment estimates resulted in relatively similar prioritization of target areas, largely in the districts of Mangochi and Kasungu. Locations prioritized by these two estimates correspond to the areas affected later in the epidemic. Estimates of R_E resulted in the prioritization of other locations, predominantly within the district of Blantyre which is urban and densely populated. The areas where the outbreak originated correspond to the locations prioritized based on estimates of R_E.

Consequently, there are tradeoffs to choosing one method of prioritization over another. Targeting areas with low vaccination coverage and high susceptible recruitment will decrease the size of the population at risk and prevent further spread of an outbreak, whereas targeting areas with high R_E will decrease the risk of an outbreak starting. Despite these differences, some areas within the districts of Lilongwe, Kasungu, and Mangochi were prioritized by all three methods. This overlap eliminates the tradeoffs between methods; thus, public health officials should treat these areas with particular concern. Our analyses demonstrate the need to consider multiple methods of prioritization when making public health decisions.

Prioritization of target areas is influenced by the scale at which each method of prioritization is conducted. We found that large scale district estimates masked substantial variation in the small scale healthcare facility polygon estimates. For example, the district scale estimate for vaccination coverage in the district of Kasungu was 66-70%, but the healthcare facility polygon scale estimates ranged between 0% and 90%. These results match previous findings and bolster the notion that small scale estimates of vaccination coverage, susceptible recruitment, and R_E may better reflect the probability of an epidemic emerging within a population (Vijayaraghavan, 2007; Metcalf, 2014; Lloyd-Smith, 2005).

A limitation of this study is that the analyses were completed retrospectively; therefore, it is difficult to be critical of the 2010 outbreak response. However, if the information presented in this study had been available, prioritization of outbreak response immunization may have been differently allocated. We found that areas within Lilongwe, Kasungu, and Mangochi were prioritized by all three methods. Out of the eight districts with vaccination campaigns, Lilongwe and Mangochi were fourth and fifth (week 24 of the epidemic) to receive campaigns and Kasungu received no vaccination campaigns (Minetti, 2013 B). The second and third districts to receive vaccination campaigns were Mzimba (week 19) and Chiradzulu (week 20) (Minetti, 2013 B); these districts were not prioritized by any of the three methods we used. Blantyre, which was prioritized based on R_E, was the first district to receive vaccination campaigns (week 18) (Minetti, 2013 B). Although our estimates were calculated retrospectively, estimating vaccination coverage and susceptible recruitment is possible before or during an outbreak (Orenstein, 1985; Grout, 2014; Lessler, 2011) and could be used to allocate resources during an outbreak. Estimating R_E before or during an outbreak tends to be more difficult, generally requiring the use of models (Grais, 2006). Classic methods of estimating R_E are completed retrospectively as we have done here; however, since we only used the first 33% of cases in our calculation, R_E could be estimated during the initial phase of an epidemic in a similar fashion (Lipsitch, 2003).

A further limitation of this study is that our estimates relied on convenience sampling surveillance data. Therefore, our estimates were dependent on the quality of the data recorded and on the areas the outbreak reached. If the outbreak did not reach a particular location, no information was recorded for that area for us to use in our analyses.

Eliminating measles requires effective outbreak response procedures in addition to increasing vaccination coverage to obtain ubiquitous herd immunity. Supplemental immunization activities and outbreak response immunization are strategies used to achieve this goal. However, because of limited resources, not all areas can be targeted immediately; thus, prioritization of target areas is necessary. Here, we have demonstrated that numerous methods of prioritization exist and result in discrete prioritizations, that some areas are prioritized by multiple methods, and that prioritizations vary based on estimate scale. When considering which method of prioritization to use, public health officials should consider multiple factors such as the country's measles control objectives, the local demographics, and the epidemiology of the initial phase of the epidemic (Minetti, 2013 A). Prioritization of target areas should be context-specific in order to achieve optimal allocation of vaccination campaigns (Minetti, 2013 A).

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McDowell High School, Erie, PA	June, 2011

HONORS:

Early Assurance Program: Penn State Hershey Medical School	2013-present
Kahkwa Club Scholarship	2014
Ray Finegan Agricultural Leadership Endowment Scholarship	2014
Rumbaugh Family Award	2014
Mario W. Alessio Scholarship Recipient (2)	2012, 2013
Schreyer's Honors College	2012- present
Burger King Scholarship Recipient	2011
McDowell High School Salutatorian	2011

ACTIVITIES/LEADERSHIP:

PSU Biomedical Sciences Club	
Membership Chair	2014-present
President	2013-2014
Biomedical Sciences Conference Chair	2012-2013
Conference Logistics Chair	2011

VOLUNTEER:

Fresh START Day of Service	
Group Leader	2012
Participant	2011
Saint Vincent Health Center auxiliary volunteer	
Immunology and Infectious Disease Unit	2012
Short Stay Unit	2010

EMPLOYMENT:

Physics 250 Guided Study Group Leader, Penn State Learning	2014-present
Math 141B (Biology-based Calculus 2) Tutor	2013
Server, Kahkwa Country Club of Erie, PA	2012-present

RESEARCH:

Research Assistant 2013
Smith, R.A., Greenberg, M., Wienke, S.E., Baker, M.K. (in progress). *Differences in wellbeing among persons diagnosed with alpha-1 antitrypsin deficiency: Using latent class analysis to better understand wellbeing and tailor support interventions.*

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