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Exploring the distribution of risk factors for drop-out from Ponseti treatment for clubfoot across Bangladesh using geospatial cluster analysis

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Abstract

Clubfoot is a congenital anomaly affecting 1/1,000 live births. Ponseti casting is an effective and affordable treatment. About 75% of affected children have access to Ponseti treatment in Bangladesh, but 20% are at risk of drop-out. We aimed to identify the areas in Bangladesh where patients are at high or low risk for drop-out. This study used a cross-sectional design based on publicly available data. The nationwide clubfoot program: 'Walk for Life' identified five risk factors for drop-out from the Ponseti treatment, specific to the Bangladeshi setting: household poverty, household size, population working in agriculture, educational attainment and travel time to the clinic. We explored the spatial distribution and clustering of these five risk factors. The spatial distribution of children <5 years with clubfoot and the population density differ widely across the different sub-districts of Bangladesh. Analysis of risk factor distribution and cluster analysis showed areas at high risk for dropout in the Northeast and the Southwest, with poverty, educational attainment and working in agriculture as the most prevalent driving risk factor. Across the entire country, twenty-one multivariate high-risk clusters were identified. As the risk factors for drop-out from clubfoot care are not equally distributed across Bangladesh, there is a need in regional prioritization and diversification of treatment and enrolment policies. Local stakeholders and policy makers can identify high-risk areas and allocate resources effectively.

Introduction

Clubfoot is a congenital anomaly affecting 1:1,000 live births of whom 80% are born in low- and middle-income countries (LMICs) (Owen *et al.*, 2018). When left untreated, clubfoot leads to pain, decreased mobility, increased risk of wounds, infections and potential social exclusion potentially leading to a perpetual cycle of poverty (Penny, 2005; Pirani *et al.*, 2009). The Ponseti method provides effective and affordable treatment, especially when implemented in early childhood (Ganesan *et al.*, 2017; Morcuende *et al.*, 2004; Ponseti, 1996). The foot is moulded into the right position using casts and maintained with a brace. The

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treatment course is lengthy, requiring regular follow-up visits until the age of 4 to 5 years (Ponseti, 1996).

The Ponseti treatment has been utilised in Bangladesh for children less than the age of three years through a national network of 42 clinics, run by the non-governmental organization (NGO) 'Walk for Life' (WFL) and the NGO 'Zero Clubfoot' (Evans *et al*., 2020). WFL was founded in 2009 (Evans *et al.*, 2020) with an average enrolment of 2,684 children per annum between 2011 and 2019. WFL reaches 60% of the estimated 3,900 children born with clubfoot annually in Bangladesh (Global Clubfoot Initiative, 2022). Government hospitals and other NGOs provide Ponseti treatment as well, however, their numbers remain negligible compared to WFL (Alam *et al.*, 2015). In addition to the 40% of children who remain unreached by WFL, approximately 20% fail to complete the treatment (Evans *et al.*, 2020). Access to care goes beyond mere geographic accessibility and must be understood as a multifaceted construct encompassing, among others, availability, geographic accessibility, affordability and acceptability. If any one of these components of access is not met, populations are excluded from safe, timely, and affordable healthcare (Levesque *et al.*, 2013). Previous research assessing the spatial distribution of risk factors of non-retention-in-care or drop-out used descriptive statistics and cluster analysis to identify areas in which care was less accessible due to geographic inaccessibility or socio-economic obstacles (Ridgway *et al.*, 2018; Terzian *et al.*, 2018; Zeng *et al.*, 2021). Cluster analysis allows the assessment of significant differences in the distribution of risk factors across the country and identifying areas that require specific attention and comparison of the distribution between different socio-economic factors (Terzian *et al.*, 2018).

WFL's clubfoot clinics allow geographic access within 60 km across Bangladesh aiming to improve admission (Evans *et al.*, 2020, 2021). Various barriers precipitating Ponseti treatment drop-out have been identified, including: parent income, travel time to the clinic and family problems (Evans *et al.,* 2021; Pigeolet *et al.*, 2022). In the Bangladeshi population these is also parental distress due to poor quality housing, longer travel time, lower educational attainment, unemployment of the father, absence of a mobile phone in the household and household size, all factors that are heavily intertwined with poverty (Evans *et al.*, 2021). The reasons for drop-out from treatment go beyond the individual level and are equally influenced by the health system and the wider social context of the patient that can influence the acceptability of the care offered (Sabaté, 2003). Drop-out from clubfoot care should be understood as a lack of access to care for the individual or for certain areas of the country as a whole.

Georeferenced census data is a powerful tool to identify vulnerable populations at a sub-national level (Jones *et al.*, 2021). However, without data providing information on vulnerabilities of the population, and using small enough census units for analysis, people risk being overlooked in aggregated datasets and miss out on targeted programs and interventions (Jones *et al.*, 2021). In Bangladesh data show an East-West divide in neonatal, maternal and under-5 mortality (Robin *et al.*, 2019), confirming the need to consider geographic factors in addition to population and biological factors when planning the distribution of health services (Juran *et al.*, 2018; Kumar Gupta *et al.*, 2010). In this study we aim to identify the upazilas (the third-level administrative sub-unit of a district) in which patients are at higher or lower risk for dropout from Ponseti treatment, based on the clustering of one or more risk factors. Secondly, we assess the potential of using geospatial analysis to inform the implementation of national clubfoot programmes.

Materials and Methods

Study design

This study used a cross-sectional study design where upazila-level data were used to identify the population-level risk of drop-out for children less than 5 years of age, based on the aforementioned risk factors.

Setting

Bangladesh is a country with a young population, a low educational attainment and an agriculture-focused economy (Table 1).

Table 1. Basic descriptive statistics for Bangladesh.

Variable (at the upazila level)	Data (various)	Range	Data source and time stamp
Population density (people/km^2), mean (SD)	8880.10 (36088.57)	34.80-410728.90	Bangladesh Bureau of Statistics 2011
Population 0-4 years (% of population), mean (SD)	10.46 (1.97)	3.41-16.67	Bangladesh Bureau of Statistics 2011
Number of children 0-4 years living with clubfoot (N), mean (SD)	27.70 (16.90)	0.48-153.28	Bangladesh Bureau of Statistics 2011
Poverty rate (% of population), mean (SD)	30.57 (14.43)	0.01-68.82	Bangladesh Bureau of Statistics 2010
Employment level (% of population)			Bangladesh Bureau of Statistics 2011
Working in agriculture, median (IQR)	61.16 (41.92-72.59)	0.11-91.74	
Working in industry, median (IQR)	8.10 (4.94-13.04)	0.63-62.22	
Working in services, median (IQR)	29.70 (21.39-44.73)	5.78-89.78	
Education level (% of population)			Bangladesh Bureau of Statistics 2011
Completed primary education or below, median (IQR)	87.40 (83.10-90.00)	28.26-96.34	
Completed secondary school, median (IQR)	10.46 (8.39-13.83)	2.98-37.63	
Completed university, median (IQR)	2.20 (1.57-3.10)	0-39.00	
Average household size, mean (SD)	4.56 (0.77)	2.40-16.85	Bangladesh Bureau of Statistics 2011
<4 members		11.97%	
4-6 members		86.74%	
>6 members		1.29%	
Travel time from centroid to health centre (minutes), median (IQR)	61.75 (33.65-101.21)	31.91-435.00	Google Maps, ArcGIS 2022

N, number; SD, standard deviation; IQR, inter-quartile range.

It is a LMIC in South Asia with an estimated 168 million inhabitants in 2022 (United Nations Department of Population, 2019). It borders India in the West and the North, Myanmar in the East and the Indian Ocean in the South where the confluence of the Ganges and the Brahmaputra Rivers creates a large river delta (Figure 1). The geographic level of analysis in this study was the upazila, 544 of which exist in Bangladesh as of May 2021 (Central Intelligence Agency, 2021). The upazila is the main level of non-centralized decision-making in Bangladesh and it is responsible for the implementation of development programmes and policies and the management of primary care provision (Sattar, 2021). The 34 WFL clinics and 8 associated clinics in the Chittagong Division (the south-easternmost areas of the country) were considered as the point of care for our patients.

Variables

For every upazila, we compiled and calculated the population density, the percentage of the population less than 5 years of age and the number of children with clubfoot. A prevalence rate of 1:1,000 live births for clubfoot was used to estimate the total number of children living with clubfoot in each upazila. Access to care is a combination of geographic accessibility, affordability, availability and acceptability. Clubfoot care is available free-of-charge throughout the country, making geographic accessibility and acceptability of care the factors of interest in this context. We identified five risk factors for drop-out with data available at the upazila-level: poverty rate, average household size, percentage of the population working in agriculture, percentage of adults with only primary education or less and travel time to the nearest clinic.

We used geographical information systems (GIS) available from ArcGIS (ESRI, Redlands, CA, USA). As starting point for measuring the travel distance between an upazila and the nearest clinic, a geographic centroid was produced and calculated in R Studio (https://www.r-studio.com). This distance was used for everyone living in this upazila. Where the centroid was located too far from a road for ArcGIS or Google Maps to calculate the travel distance, it was manually moved towards the nearest road, to enable distance calculation. The travel time from the centroid of each upazila to the nearest clinic was calculated using the available travel speed data for cars in ArcGIS, however as this is not fixed but based on a variety of open-source GIS travel speed data and real-life traffic information online such Open Street Map, its calculated travel times are probably the most accurate available at this moment (Mandloi & Zeng, 2019) and therefore used. Travel time within the upazila to reach the centroid was not taken into consideration. However, a sensitivity analysis was done for the travel time variable to understand the extent to which travel time is influenced by adding walking time or waiting times to the calculated drive times. These walking and waiting times were added to adjust for the fact that most patients in Bangladesh use public transport to attend the clinic instead of a personal vehicle (Evans *et al.*, 2020) and also to account for the usage of travel time from a centroid per

Figure 1. Geography of Bangladesh (On the world map, 2023).

upazila instead of every possible household in the upazila. The sensitivity analysis assessed the impact of adding walking time to the total travel time. Walking times ranging from zero minutes to 2 hours, with 30-minute increments, were assessed.

The geographic accessibility of clinics was assessed both by distance and drive time. Both were assessed separately. Therefore, the relationship between distance and drive-time is neither linear nor easy to calculate manually. Most of the country is covered within a 60-km radius (Euclidian distance) from one of the 42 clinics, according to the approach used by WFL at its inception to determine the best location of its clinics. However, when considering the available road network instead of using Euclidian distance, the surface area covered within 60 km driving distance from the clinics shrinks significantly. Unfortunately, ArcGIS is unable to take ferry data into consideration at this moment, and given the poor state of the road network and the large river delta in which travel is only possible by ferry, there are entire areas without access-to-care data. Total travel time includes combinations of public transportation, walking or other modes of transport and it includes waiting at bus stops. Currently, no software package offers to calculate travel times using multiple modes of transportation, therefore this had to be taken into consideration indirectly. A sensitivity analysis (not shown) informed us that the impact of walking as a mode of transportation on geographic access is minimal. Geographic access is thus almost entirely driven by motorized vehicle access.

The determination of the nearest clinic used actual travel distances over land. For centroids located on islands, or surrounded by a river with no direct road connection to the nearest clinic, the travel trajectory was mapped using Google Maps to allow for the use of ferries in the travel time calculation. For upazilas that contain no roads on their territory, and where no travel time can be calculated, it was manually adjusted to match the longest travel time calculated in the dataset. Google Maps and ArcGIS were made to calculate a travel time without leaving the country, even if travelling on a nearby road through India was technically faster.

Data sources

Baseline demographic data and drop-out indicators were obtained from the Bangladesh Bureau of Statistics, the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) and the World Bank (Bangladesh Bureau of Statistics, 2011; UNOCHA, 2022; World Bank, 2014). Due to the ongoing COVID-19 pandemic, the 2021 census in Bangladesh was postponed (United Nations Fund for Population Activities- UNFPA, 2020; United Nations Statistics Division, 2020). Therefore, the most recently available data at the upazila-level stem from the 2011 census. The location of the 34 WFL clinics and the 8 NGO-associated Zero Clubfoot clinics were obtained from their websites (WFL, 2021; Zero Clubfoot, 2012). Each clinic was manually searched with Google Maps to obtain specific latitudes and longitudes.

Statistical methods

Basic descriptive statistics of all variables were conducted, including range, mean and standard deviation (SD) for normally distributed data and the median and inter-quartile range for non-normally distributed data. The descriptive spatial analysis of the data included mapping the distribution of the overall population density, the distribution of children less than 5 years of age and the estimated distribution of children living with clubfoot. The distribution of all five risk factors for drop-out was mapped as well, to allow the identification of single upazilas that are different from their neighbours and would not show up in the cluster analysis. The maps were made to visualize the distribution using quantiles, 11 of which were used for basic demographic data to adequately capture the large range of the data. Quintiles were also used for the distribution of the risk factors.

Poverty is known to be a cross-cutting, socio-economic factor underlying many of the risk factors analyzed in this article and one of the main drivers of drop-out (Evans *et al.*, 2021; Pigeolet *et al.*, 2022). We therefore studied the relationship between travel time (geographic access) and poverty hotspots (acceptability of care) in depth to better understand which areas in Bangladesh would most likely to be at increased risk of drop-out.

Social phenomena tend to cluster in certain areas across a territory. Areas with a higher than average prevalence of a certain disease or risk factor (hotspots) as opposed to areas with a lower than average prevalence (cold spots) were of specific interest (Kumar Gupta *et al.*, 2010). Such areas can be identified by the local Moran's *I* statistic (Moran, 1950) or the local Geary's C test (Geary, 1954). Both tests use the same null hypothesis of spatial randomness, which means that a certain phenomenon has the same chance of happening anywhere in the described geographic space.

Local Moran's *I* test seeks a linear association between similar Low-Low (LL) and High-High (HH) and dissimilar Low-High (LH) and High-Low (HL) observations with regard to areas and their immediate surroundings and thus provides information about both location and significance of potential clusters. Local Moran's *I* analysis considers a first-order queen's contiguity matrix, which defines neighbourhoods based on a shared boundary or vertex. Significance was assessed based on 1,000 permutations, and correction for multiple comparisons was done using the false discovery rate (FDR) test (Benjamini & Hochberg, 1995). We chose local Moran's *I* instead of ordinary least squares (OLS) regression for the spatial data analysis because of its easy and intuitive interpretation. The generation of easily and intuitively interpretable results were of great importance to our team as we wished to include an audience beyond readers experienced in geospatial analysis.

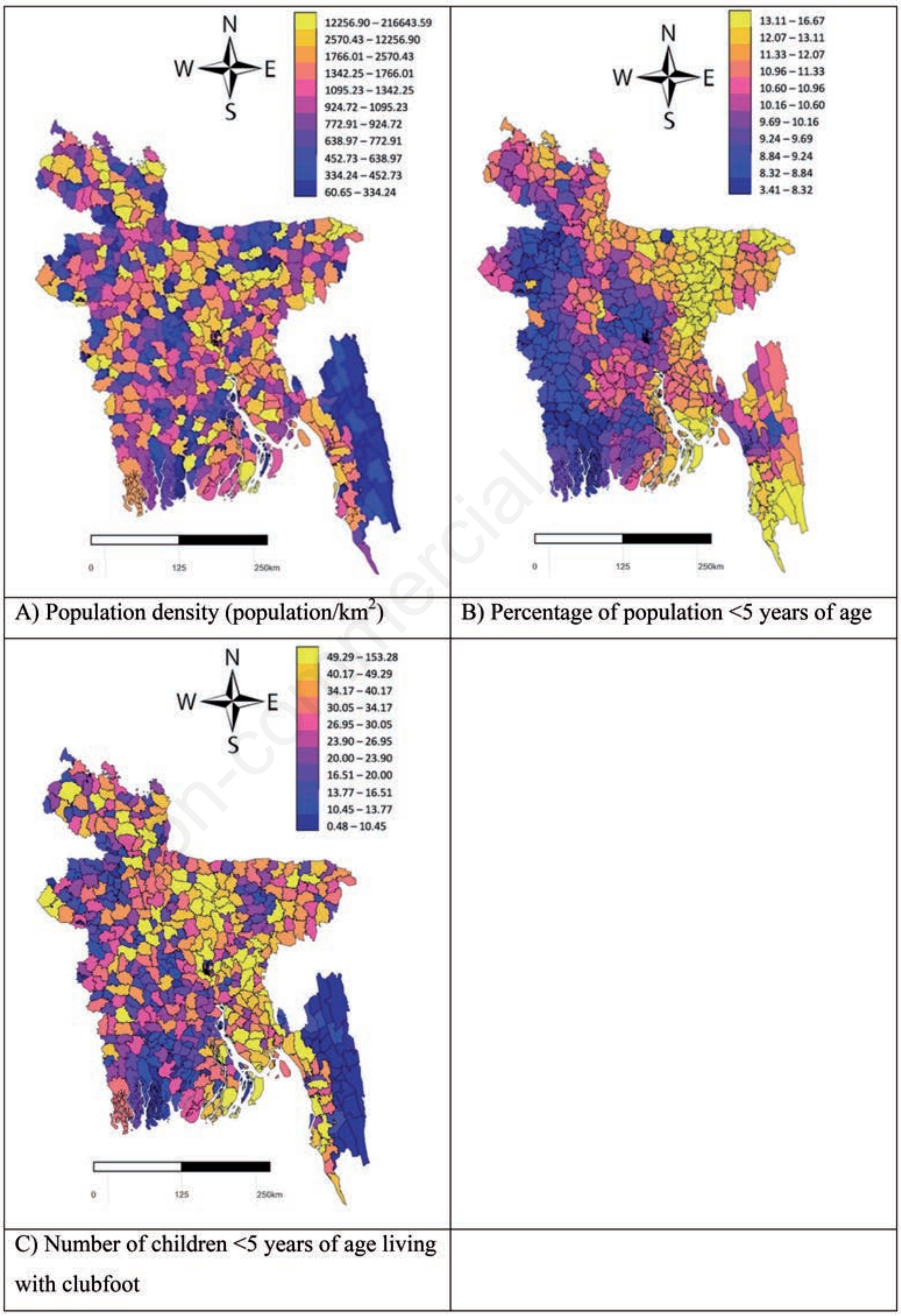
The Geary's C test is currently the only geospatial statistic that allows for multivariate analysis using more than two variables. The multivariate local Geary's C is an extension of the univariate local Geary's C and requires the calculation to be visually interpreted. The local Geary's C test uses the squared differences between observations and therefore allows both linear and non-linear relationships to be described. However, because of the use of squared values, the multivariate local Geary's C cannot itself differentiate between HH or LL clusters. This interpretation had to be done manually, so we calculated a univariate local Geary's C for every risk factor. The five univariate local Geary's C cluster maps were used to separate the hotspots from the coldspots in the multivariate analysis and identify the main driver(s) of each multivariate cluster. Like the local Moran's *I*, the local Geary's C statistic considers a first-order queen's contiguity matrix as the neighbourhood definition. All five risk factors identified above were included in the analysis and a higher rate for each corresponded to a higher risk of drop-out. Significance was assessed based on 99,999 permutations and correction for multiple comparisons was done at the $p<0.01$ significance level without using the FDR adjustment as recommended by Anselin (2019).

Software used

Basic descriptive statistics of the variables and the spatial analysis were done using R Studio 2022.02.3 according to the Integrated Development for R (R Studio, PBC, Boston, MA, USA) using the following packages: sf, sp, spData, spdep, ggplot2 and rgeos. Travel times and geographic coverage within certain time-frames were calculated in ArcGIS Pro 10.6.1., while Google Maps 10.66.1 was used to calculate travel times for routes including ferry data as well as to retrieve the coordinates of the clinics.

Results

We observed high overall population densities in the cities and a random mosaic pattern for the rural areas (Figure 2A). For the percentage of the population less than 5 years old (Figure 2B), there was a clear East-West divide. Upazilas in the East have a



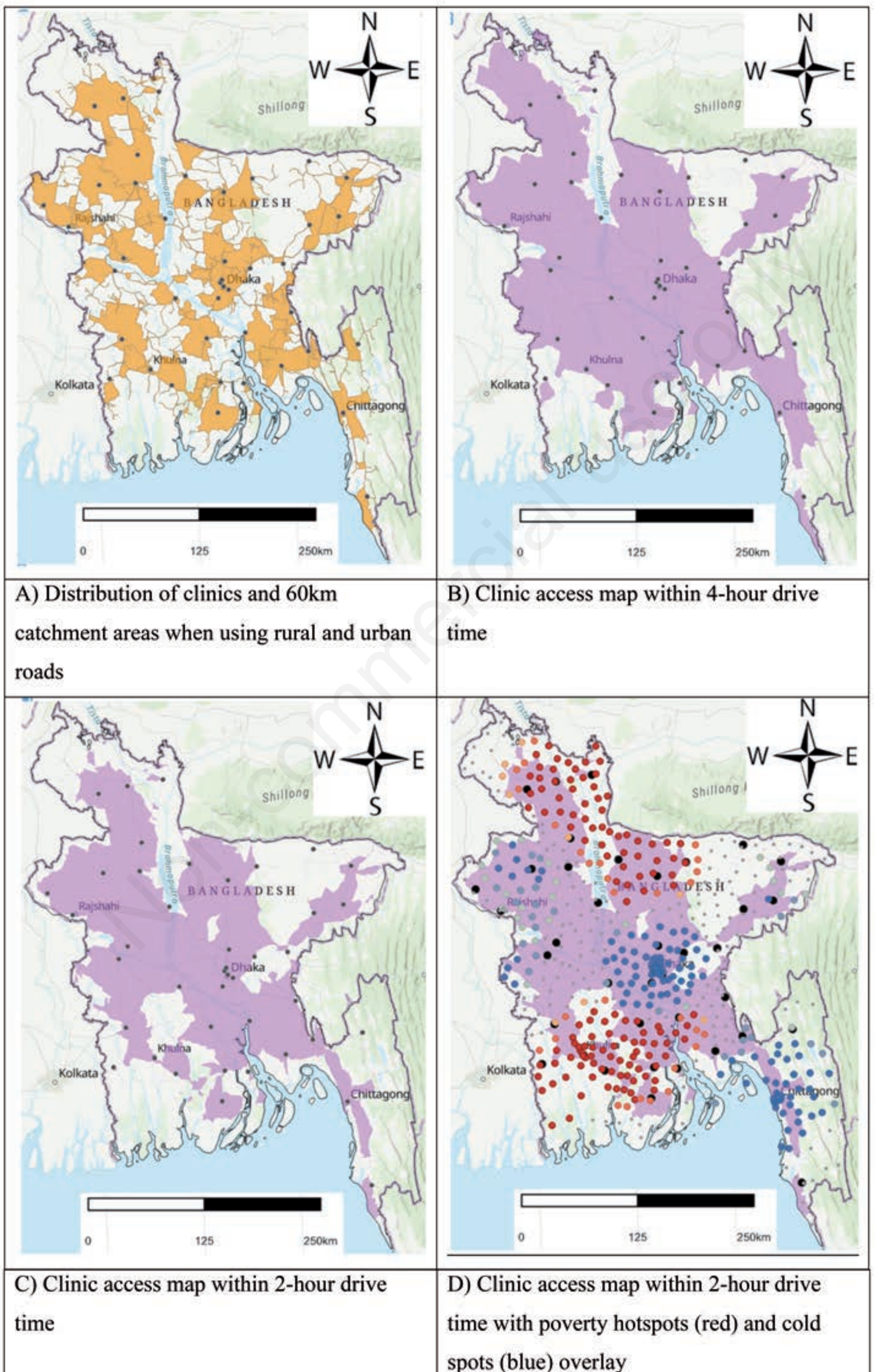
A) Population density (population/km^2)

B) Percentage of population <5 years of age

C) Number of children <5 years of age living with clubfoot

Figure 2. Demographics of Bangladesh.

higher percentage of children less than 5 compared to upazilas in the West. When considering the absolute number of children living with clubfoot (Figure 2C), we noted a very low number of children living with clubfoot (demarcated in blue) in the eastern part of the Chittagong division. The demographic and socio-economic data of Bangladesh showed a wide variety across upazilas, with very wide ranges for most of the variables included. When considering the available road network instead of using Euclidian distance, the surface area (orange area in Figure 3A) covered within 60 km driving distance from the clinics shrinks significantly. As ArcGIS was unable to take ferry data into consideration, large areas lack access-to-care data and therefore left white in map 3A. When con-



A) Distribution of clinics and 60km catchment areas when using rural and urban roads

B) Clinic access map within 4-hour drive time

C) Clinic access map within 2-hour drive time

D) Clinic access map within 2-hour drive time with poverty hotspots (red) and cold spots (blue) overlay

Figure 3. Geographic accessibility of clinics using drive time and drive distance.

sidering travel time, we understood that a large part of the country has access to care within 4-hours' drive time, but this shrinks to about half when we consider a 2-hour access drive time (Figure 3B, 3C). Total travel time includes combinations of public transportation, walking or other modes of transport and it includes waiting at bus stops. We considered, the 2-hour access map, a more realistic representation of areas that can be accessed within 4-5 hours of travel time - 2 hours driving time plus the additional time necessary to access public transportation and reach the clinic from the bus station. The maps in Figure 3 only show a rough estimate of 4-hour access and not an exact calculation. When superposing the 2-hour geographic access map with the poverty hotspots (red) and coldspots (blue), we noticed that the Northwest and the Southwest have a combination of poor geographic access and high poverty (Figure 3D) and therefore require additional attention during initial programmatic planning to assure adequate access-to-care. Chittagong in the Southeast and the Northeast of the country are both areas where poor geographic access, which is also combined with high poverty rates. However, these areas also have low population densities as seen in Figure 2A and thus are areas with only a very small number of children living with clubfoot.

Table 2 shows a numerical overview of the distribution of risk factors at the upazila level. The covariates household size and travel time were reformatted from a continuous variable to a categorical variable based on known risk categories (obtained from WFL's prior research). Households with more than 4 children (a total household size of 6) were found to be most at risk for drop-out, while households with 2-3 children were found to be at moderate risk. A travel time of more than 4 hours was considered an increased risk for drop-out because it makes making a return trip on the same day impossible, imposing additional costs and logistical issues (Evans *et al.*, 2021).

All risk factors' basic spatial distribution (Figure 4) including hotspots and coldspots were plotted on individual thematic maps to explore spatial variations and trends. All demonstrated evidence of a spatial pattern of some kind. The percentage of people working in agriculture was the highest in the North and the Southeast (Figure 4). Agriculture hotspots on the other hand were scattered around the northern part of the country where rice farming takes place during the dry season (Northeast) and both the dry and the wet season (Northwest) using advanced techniques like polders and irrigation systems (More & Manjunath, 2013) (Figure 5A). Given the extremely low population density in the Southeast, the high level of agriculture would have little practical implications for programmatic planning. The distribution of household size followed a similar distribution pattern to that of children less than 5 years of age in the country (Figures 2B and 4B). A large coldspot was found in the East and a similar one in the West (Figure 5B), which follows the pattern of the overall distribution. Poverty hotspot and coldspots were scattered around the country, and overlapped almost perfectly with the 1st and 5th quintile on the distribution map with coldspots being particularly common in the Dhaka and Chittagong areas. Poverty hotspots were also seen around the river deltas (Figures 4C and 5C). Primary education as the highest educational attainment showed a clear band of yellow (5th quintile) in the eastern part of the country, while only a small coldspot was situated in the Dhaka region, and a small hotspot in the north-eastern part of the country unlinked to a clear geographical landmark (Figures 4D and 5D). The distribution of travel times followed a mosaic pattern across the country, apart from the regions in the far Northwest and the far Southeast. Travel distance coldspots were seen in their part-cluster in the Dhaka region, while there were two hotspots cluster in two border regions in the south-eastern and north-western part of the country (Figure 3E).

The multivariate local Geary's C renders multiple significant clusters of one or more risk factors for drop-out spread across the

Table 2. Risk factor distribution across upazilas.

Risk factor	Number of upazilas (%)	Estimated number of children <5years living with clubfoot in affected upazilas
Travel time >4 hours	17 (3.12)	465
Families working in agriculture (%)		
0-20	78 (14.34)	2178
20-40	50 (9.19)	1820
40-60	135 (24.82)	4000
60-80	234 (43.01)	6220
80-100	47 (8.64)	851
Household size>6 members	7 (1.29)	217
Education (primary school or less) (%)		
0-20	0 (0)	0
20-40	7 (1.29)	41
40-60	24 (4.41)	448
60-80	57 (10.48)	1870
80-100	456 (83.82)	12710
Living under the poverty line (%)		
0-20	133 (24.45)	3333
20-40	270 (49.63)	7665
40-60	130 (23.90)	3782
60-80	11 (2.02)	290
80-100	0 (0)	0

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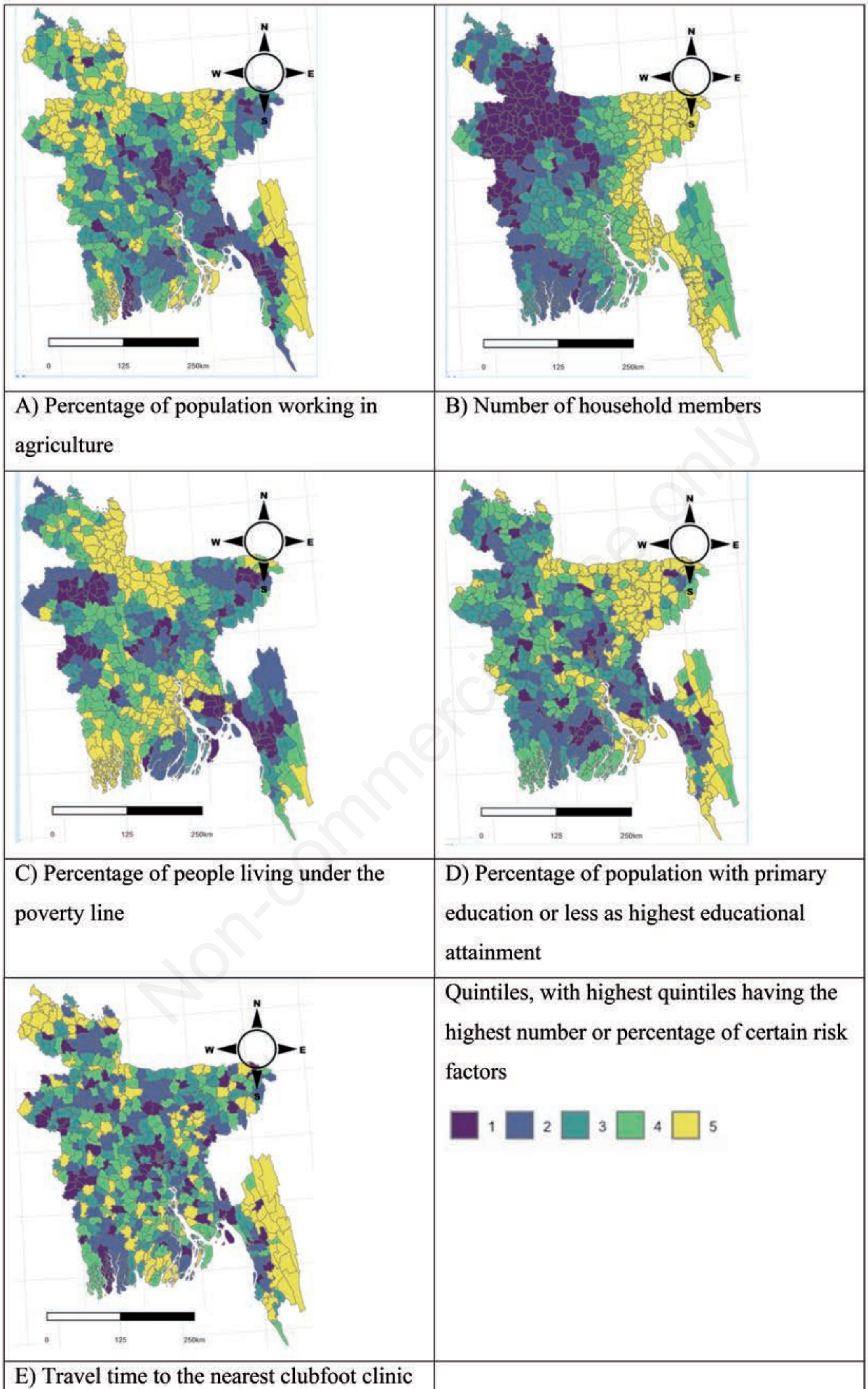


Figure 4. Distribution of risk factors for drop-out from the clubfoot programme across Bangladesh.

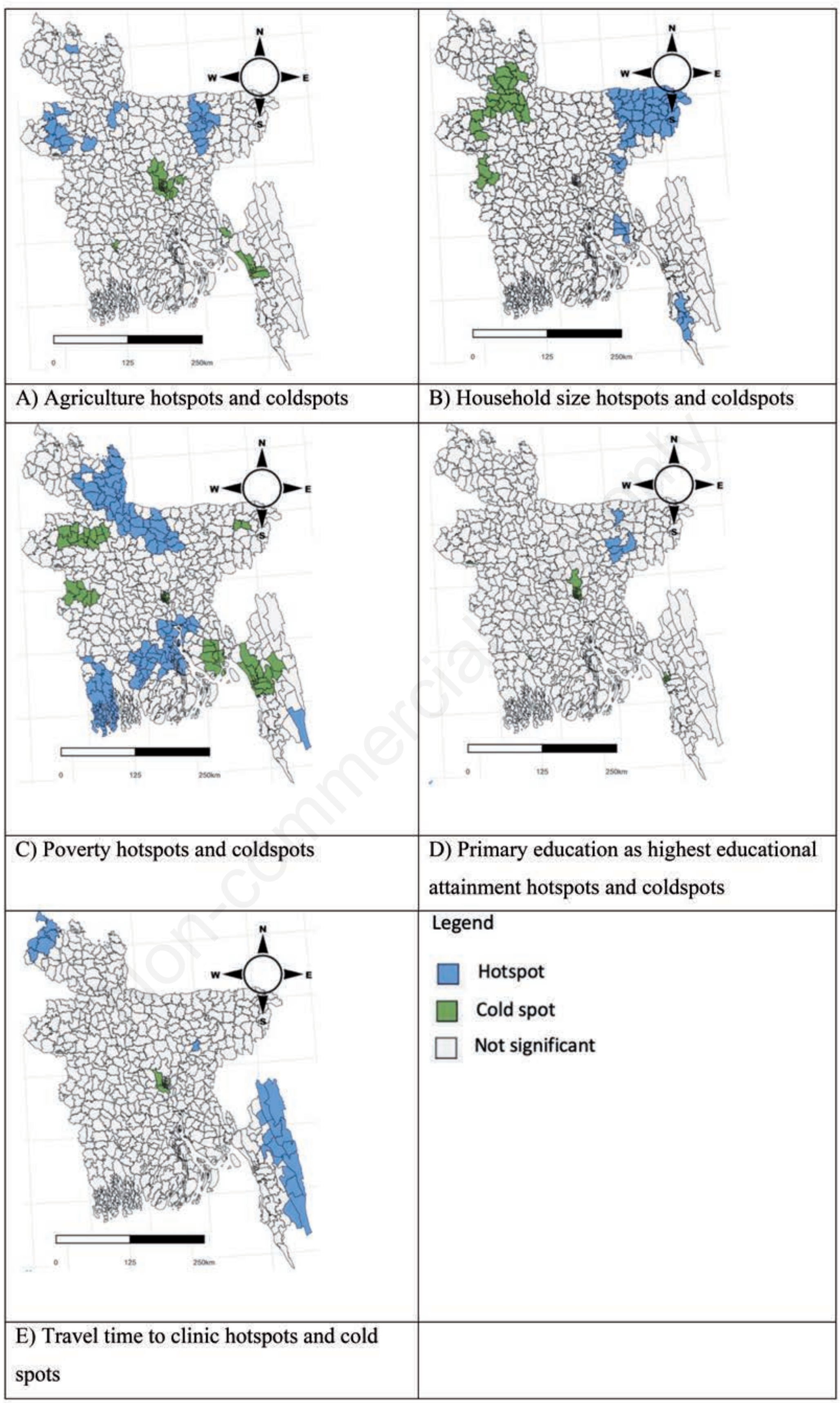


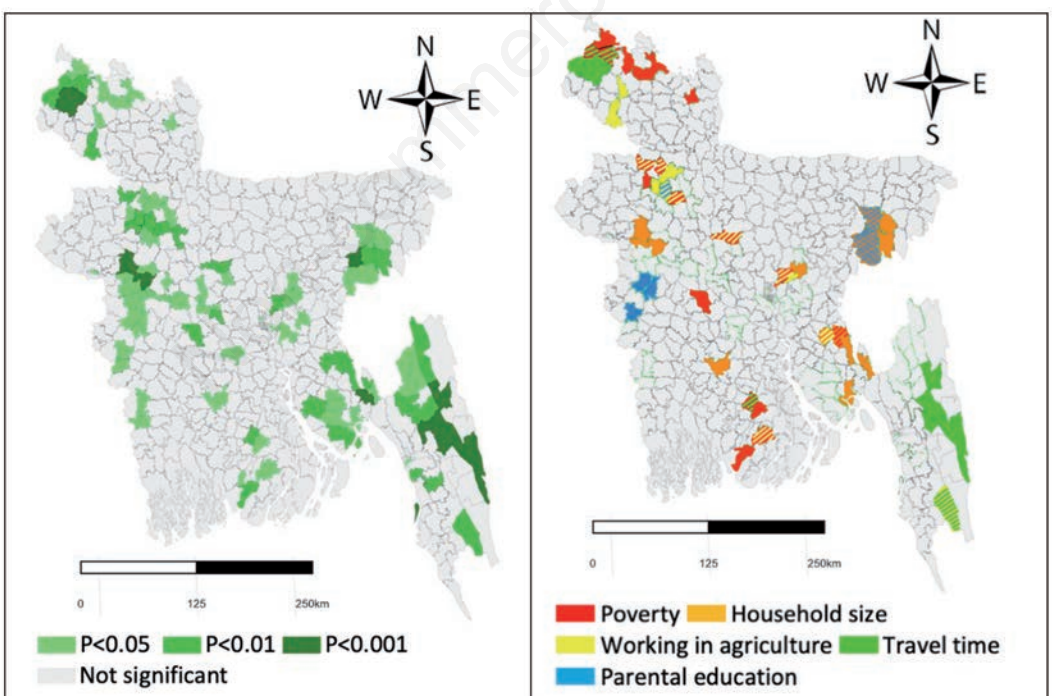
Figure 5. Univariate analysis of risk factors for drop-out from the clubfoot programme.

country (Figure 6A). Figure 6B shows which risk factors are the main drivers in making each multivariate hotspot cluster significant. Outliers and coldspots were deleted from Figure 6B to give a clearer overview of which risk factors most likely drive dropouts in certain regions. Twenty-one multivariate high-risk clusters were identified across the country, only five of which were partially or completely attributable to long travel time or decreased geographic access to clubfoot care. The remaining 16 multivariate clusters were found to be driven by socio-economic factors.

Discussion

The geospatial analysis of the distribution of the five selected risk factors showed a different spatial distribution for all five factors. Poverty, a cross-cutting socio-economic factor and travel time showed some distribution overlap, but not so strongly that both risk factors could be used interchangeably in a risk factor analysis. The multivariate cluster analysis showed that different risk factors varied with respect to pattern across the country.

Geospatial analysis can play a key role in optimizing both efficiency and equity when it comes to the distribution and placement of healthcare services. Iyer *et al.* (2020) used drive time as a proxy for equity, while population density was used to consider the effects of economies of scale to deliver more efficient care. Their studies from four African countries further showed that the geospatial distribution of healthcare centres favoured efficiency over equity leading to a high concentration of medical services available in urban areas and a lack of geographic access in rural areas (Iyer *et al.*, 2020). The World Health Organization (WHO) has stated that equity should be chosen over efficiency when trade-offs must be made (Ottersen *et al.* 2014). Therefore, a critical analysis of current or future treatment accessibility in Bangladeshis is essential. In the case of WFL, which already has established clinic locations across Bangladesh, the current distribution of clinics shows varying degrees of geographic access based on one variable - travel time. Particularly, the extreme north-western, south-western and the furthest eastern parts of the country have longer travel times. With increased travel time associated with drop-out, recognition of these at-risk communities should permit implementation of interventions that prevent patient drop-out, e.g., by adding new clinics. Because of its geographic nature with a large river cutting the country in two halves, large areas of Bangladesh have a limited transport infrastructure that hinders geographic access, irrespective of the method of analysis. In the western part of the country these areas of poor geographic access overlap strongly with areas with significantly higher poverty. The relationship between rural poverty and poor transport infrastructure is well-known (Chi *et al.*, 2019; Qin *et al.*, 2022). However, interventions focusing on maternal education (one of the risk factors studied in this article) show stronger correlations to better health outcomes and higher levels of poverty alleviation than improving the transport infrastructure.



A) Significant multivariate clusters of all 5 risk factors after FDR-correction

B) Driving risk factor(s) per cluster (only hotspots) Areas with more than one driving risk factor are striped in multiple colours.

Figure 6. Multivariate analysis of risk factors for drop-out from the clubfoot programme.

This raises the question if geographic access is the best parameter to use when planning the location of clinics for a national programme in a country with a high rate of (rural) poverty and poor road infrastructure.

Prior research looking at the impact of increasing geographic access concluded that building more clinics would only alleviate a small part of the access problem (Quattrochi *et al.*, 2020). In addition, Buda *et al.* (2022) used geospatial analysis to understand the current and potential increase in surgical coverage rates by hospitals in Guatemala, which turned out to be minimal if only geographic access were to be increased. Therefore, with limited resources and competition for funding, expanding geographic access alone, may not appear as the most efficient option to assure access to care.

Lack of financial support for travel costs, increased travel time to the clinic and lack of parental understanding of the disease are the three most often raised reasons for drop-out from clubfoot care (Evans *et al.*, 2020, 2021). These reasons, combined with the five risk factors explored in this study, go well beyond geographic access as an issue and reflect on acceptability of care as well. However, risk factors associated with drop-out are not equally distributed across Bangladesh. Different risk factors tend to cluster in different parts of the country. Consequently, different policy approaches are needed to keep children enrolled in clubfoot treatment. The short-term policy implications could include adding an extra clinic in regions where patients currently must travel for more than 4 hours to access care and therefore potentially risk not being able to go back and forth on the same day. The estimated number of 465 children that now have to travel for more than 4 hours would probably justify creating an additional 2 clinics but, as stated above, previous research has shown that adding additional clinics tend to alleviate only part of the issue of access to care.

Multivariate cluster analysis offers the opportunity to assess multiple risk factors at the same time and identify areas in a country that require specific attention beyond the "one-size-fits-all" approach of many health programmes. Several open-source software packages are available online which allow for multivariate cluster analysis free of charge, creating opportunities for governments and NGOs in LMICs to utilize this technique for their health policy and planning. Cluster analysis also permits the identification of the leading risk factor(s) within each of these clusters, which plays a critical role in policy development and has implications that could improve access to care.

Agricultural communities have different needs compared to poorer communities with low educational attainment in terms of support to access care, and the same applies to mountainous areas without a functional road network. Each of these communities needs policies that address their specific barriers to care. Multivariate and univariate cluster analysis can help identify those at-risk communities and identify catchment areas of specific clinics that may benefit from a more targeted programmatic approach.

When assessing the distribution of the four socio-economic risk factors, we noted that the majority of the estimated number of children with clubfoot was particularly high in an upazila where the household size is smaller than 6 people for more than 80% of the population. In addition, most people there also have an educational attainment of primary education or less (Table 2). In Bangladesh, geospatial analysis does not assist differentiation between clinics since most of them lack specific policies to avert these risk factors. However, cluster analysis can help identify clinics in a catchment area that has a significantly higher rate of either risk factor and which could therefore serve as a pilot site for new policies. These could include distribution of informational documents adapted to illiterate or low-educated parents or outreach clinics for families with a newborn, who are unable to take the older child with clubfoot to the clinic. The distribution of poverty and the percentage of people working in agriculture vary considerably between the upazilas (Table 2). For these two factors cluster analysis can help information on which clinics should be prioritized to implement new policies, such as reimbursement of travel costs and outreach clinics during harvesting season, while the baseline analysis (Figure 4) can inform which clinics require implementation of these policies for the long term.

Analysis of individual risk factors at a population level always includes a risk of the ecological fallacy. However, Macintyre (2002) showed in her study that even though socio-economic factors are individual-level risk factors, there is equally a contextual impact and a certain risk generated by living in an area with a high number of people with a certain risk factor, even if a certain individual does not possess the risk factor in question. In the context of this study this means that the impact of having parents who work in agriculture or are illiterate has an impact both at the individual level as well as at the wider societal level. According to Macintyre's theory, children who grow up in an agricultural community, even though their parents do not work in agriculture, are still highly likely to be at a higher risk for drop-out than peers of them growing up in non-agricultural communities because their parents adopt some of the behavioural patterns that predominate in this community. Therefore, looking at risk factor distribution at the societal level can help identify at-risk communities, and decrease drop-out risk, if targeted policies are implemented.

This study has several limitations. The socio-economic data were not specifically collected for this study, and assumptions about their distribution among the population affected by clubfoot were applied. Additionally, the most recent upazila-level data available publicly were more than 10 years old when this work was carried out. It is unclear to what extent these data are still representative of the actual socio-economic situation in the country given the rapid demographic change and the pandemic that might have had an impact on internal mobility. The calculated travel times remain an approximation. In order to draw definitive conclusions on geographic access to care, a better understanding of travel modalities used, accessibility in different parts of the country and local speed limitations is necessary. Lastly, the current analysis of risk factors was done based on patients who had dropped out after accessing care. Little is known about the socio-economic level of the group of children that never attended care, however we do know that the risk factors for dropping out from clubfoot treatment are very similar to those for never seeking care for clubfoot in the first place (Pigeolet *et al.*, 2022).

Conclusions

The examples in this paper represent only the beginning of the contribution offered by geospatial analysis in how healthcare delivery can be designed, implemented and improved in the future. If WFL would have had access to geospatial planning at its inception back in 2009, this could have led to prioritized access for at-risk communities instead of creating equal access across the country (equity versus equality).

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