

Gender-Based Vulnerability: Combining Pareto ranking and geostatistics to model gender-based vulnerability in Rohingya refugee settlements in Bangladesh

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Title: Gender-Based Vulnerability: Combining Pareto ranking and geostatistics to model gender-based vulnerability in Rohingya refugee settlements in Bangladesh

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ABSTRACT

27 Background: The Rohingya refugee crisis in Bangladesh continues to outstrip humanitarian resources and
28 undermine the health and security of over 900,000 people. Spatial, sector-specific information is required
29 to better understand the needs of vulnerable populations, such as women and girls, and to target
30 interventions with improved efficiency and effectiveness. This study aimed to create a gender-based
31 vulnerability index and explore the geospatial and thematic variations in gender-based vulnerability of
32 Rohingya refugees residing in Bangladesh by utilizing pre-existing, open source data.

33
34 Methods: Data sources included remotely-sensed REACH data on humanitarian infrastructure, United
35 Nations Population Fund resource availability data, and the Needs and Population Monitoring Survey
36 conducted by the International Organization for Migration in October 2017. Data gaps were addressed
37 through probabilistic interpolation. A vulnerability index was designed through a process of literature
38 review, variable selection and thematic grouping, normalization, and scorecard creation, and Pareto
39 ranking was employed to rank sites based on vulnerability scoring. Spatial autocorrelation of vulnerability
40 was analyzed with the Global and Anselin Local Moran's I applied to both combined vulnerability index
41 rank and disaggregated thematic ranking.

42
43 Results: Of the Rohingya settlements, 24.1% were ranked as 'most vulnerable,' with 30 highly vulnerable
44 clusters identified predominantly in the *upazila* of Sadar. Five settlements in Dhokkin, Somitapara, and
45 Pahartoli were categorized as less vulnerable outliers amongst highly vulnerable neighboring sites.
46 Security- and health-related variables appear to be the most significant drivers of gender-specific
47 vulnerability in Cox's Bazar. Clusters of low security and education vulnerability measures are shown
48 near Kutupalong.

49
50 Conclusion: The humanitarian sector produces tremendous amounts of data that can be analyzed with
51 spatial statistics to improve research targeting and programmatic intervention. The critical utilization of
52 these data and the validation of vulnerability indexes are required to improve the international response to
53 the global refugee crisis. This study presents a novel methodology that can be utilized to not only
54 spatially characterize gender-based vulnerability in refugee populations, but can also be calibrated to
55 identify and serve other vulnerable populations during crises.

56 57 **Key Words**

58 Rohingya, refugees, gender, open-source data, vulnerability index, spatial analysis, GIS, Pareto ranking,
59 spatial autocorrelation

60 **BACKGROUND**

61 The Rohingya refugee crisis is a result of decades of systematic discrimination, statelessness, and
62 violence exacerbated by the denaturalization of the Rohingya people by the then-Burmese state in 1977
63 [1]. Since that time, waves of Rohingya, now considered ‘illegal’ in their birth country, have fled into
64 Bangladesh in a complex cycle of forced displacement and repatriation efforts [2]. In August of 2017,
65 violent attacks perpetrated against the Rohingya triggered the largest and fastest mass displacement of
66 refugees from Myanmar’s Rakhine State to Bangladesh. As of March of 2019, there were over 909,000
67 Rohingya refugees in Ukhiya and Teknaf upazilas, representing an influx of over 745,000 people in less
68 than two years [3].

69
70 Women and girls comprise over 52% of the population in Rohingya settlements in Bangladesh, with
71 approximately one-sixth of families headed by a single mother [4]. Almost every woman and girl in the
72 Rohingya refugee community in Cox’s Bazar has either experienced or witnessed incidences of gender-
73 based violence [5], and the crisis disproportionately affects women, girls, and other marginalized
74 populations due to the perpetuation of pre-existing inequalities, violence, and discrimination. As of
75 February 2018, the Inter-Agency Working Group on Reproductive Health in Crisis [6] identified women
76 and girls as ‘critically underserved’ in the Rohingya Humanitarian Response, emphasizing a lack of
77 access to sexual and reproductive services and gender-based violence care. According to the World Food
78 Program, Rohingya refugee households in Bangladesh headed by women are disparately more vulnerable
79 to food insecurity, with 45% defined as vulnerable or highly vulnerable [7]. Over one-third of Rohingya
80 women report insecurity when collecting water or toileting [8], and over half of the female population
81 lack appropriate menstrual supplies. Many women remain within their shelters due to a lack of clothing,
82 insecurity, and concerns regarding cultural norms and dignity. Despite the humanitarian community’s
83 commitment to gender mainstreaming and women-targeted strategies [9] in response efforts, qualitative
84 data from a 2018 Oxfam report demonstrated that the humanitarian response has yet to adequately meet
85 the needs of women and girls in this community, failing to provide them with access to services and/or
86 addressing gender-specific issues critical to preventing further harm [4].

87
88 As of October 2019, there were nearly 272 million United States Dollars (USD) in unmet funding
89 requirements for the Rohingya Refugee Crisis Joint Response Plan for the year [10], making 2019 the
90 year with the biggest relative deficit in funding, with over one-third of requirements being unmet. This
91 funding-needs gap within humanitarian response is a global and protracted phenomenon, with nearly
92 twenty-seven billion USD needed for funding humanitarian programming as of 2019. As climate change,
93 protracted conflicts and social inequality continues to grow the need for humanitarian assistance, the

94 funding gap continues to hover around 40% [11], leaving nearly one-third of affected populations without
95 essential aid.

96
97 As is the case in many humanitarian and disaster response environments, the sheer magnitude of the
98 Rohingya crisis juxtaposed with inherent resource limitations compels donors and humanitarian actors to
99 create mechanisms to more precisely characterize need and design targeted, cost-effective services. One
100 such method of need assessment is through the lens of ‘vulnerability’ analysis, which articulates the
101 reality that hazards and subsequent assistance impact various population groups in grossly heterogeneous
102 ways [12]. Enumerable vulnerability indices have emerged in fields including infectious diseases [13, 14],
103 environmental health [15, 16], disaster preparedness [17-19], refugee services [7, 20], and climate change
104 [21-23] which incorporate diverse, cross-sectoral indicators such as socio-economic status, education,
105 information access, mobility, health and morbidity, security, and geographic location.

106
107 Such vulnerability indices require significant data, which is often incomplete, untimely, and ambiguous in
108 the humanitarian context. Designing and implementing primary data collection studies in humanitarian
109 settings requires substantial resources that can be otherwise utilized for response activities and is further
110 complicated by insecure or inaccessible environments. However, there exist tremendous data being
111 produced by agencies already operating in these contexts, and a recent impetus to share these invaluable
112 data has led to open source dissemination platforms. The Humanitarian Data Exchange (HDX) [24],
113 managed by United Nations Office for the Coordination of Humanitarian Affairs’ (OCHA) Center for
114 Humanitarian Data, was launched just over five years ago and is an online, open source data platform
115 aimed at making humanitarian data available for analysis and use by non-governmental organizations,
116 governments, and United Nation agencies. As of April 2018, it houses over 6,000 data sets from nearly
117 1,000 sources in 245 locations [25].

118
119 The aim of this study was to harness the potential of pre-existing, open source data provided by the
120 Humanitarian Data Exchange to create a gender-based vulnerability index and explore the geospatial and
121 thematic variations in the gender-based vulnerability of Rohingya refugees residing in Bangladesh.

122 123 **METHODS**

124 This study designed a gender-based vulnerability analysis grounded in constructs derived from a literature
125 review and modified secondary to data availability, executed a Pareto ranking as a method to avoid
126 artificial weighting in aggregated index scores, and subsequently employed geostatistical methods of
127 spatial autocorrelation and cluster/outlier analysis. This methodological framework (Figure 1) was applied

128 to open-source humanitarian data collected at Rohingya refugee settlements in Bangladesh directly after
129 the 2017 refugee influx. Briefly, this methodology intends to capitalize on pre-existing spatial
130 humanitarian data to identify those refugee settlements wherein women and girls are the most vulnerable,
131 and create a statistically-grounded, spatial understanding of gender-based vulnerability that can lead to
132 more relevant and better targeted programmatic design and resource allocation.

133

134 Figure 1. Methodological process for creating a gender-based vulnerability index and subsequent
135 geostatistical analysis

136

137 *Data collection*

138 Three data streams were utilized for this study, including the International Organization for Migration
139 (IOM) Needs and Population Monitoring Data from October 2017, in Bangladesh; REACH remotely
140 sensed infrastructure location data, and United Nations resource availability data. These data were
141 obtained from the open source, online Humanitarian Data Exchange between October 2017 and January
142 2018. A description of these data and data collection methodologies follow.

143

144 The International Organization for Migration conducted a Needs and Population Monitoring site
145 assessment of Rohingya refugee communities at 28 collective sites and 99 locations within dispersed
146 settings in host communities in Cox's Bazar, Bangladesh between the 30th of September and 9 October
147 2017 [26] with a final sample size of 157 sub-site assessments. The site assessment covers all locations
148 where Rohingya refugees have been identified, notwithstanding the type of location or proximity to
149 Bangladeshi host communities. Information regarding the demographics, distribution, and needs of the
150 Rohingya refugee population spanned 12 areas of inquiry and 184 unique questions that were both
151 quantitative and qualitative in nature. Information was collected by locally-recruited enumerators through
152 key informant interviews using closed-ended questionnaires, and findings were triangulated at the field
153 level through direct observation and spontaneous group discussions.

154

155 Distance to distribution centers, health care, nutritional facilities, and child- and women-friendly spaces
156 were gleaned from remotely-sensed and ground-based, global positioning system (GPS)-enabled surveys
157 conducted by REACH and the United Nations Population Fund (UNFPA) in cooperation with the Inter
158 Sector Coordination Group in Bangladesh (ISCG), with datasets collected between November 2017 and
159 February 2018. These data were retrieved from the Humanitarian Data Exchange as either geodatabases
160 containing point data, shapefiles, and/or spreadsheets containing each facility's spatial coordinates.

161

162 *Gender-Based Vulnerability Index*

163 This study followed a multi-step process for developing a gender-based vulnerability score, founded on
164 principles articulated in the Handbook on Constructing Composite Indicators [27]. After reviewing
165 existing literature, a theoretical framework was developed to serve as a basis for selecting indicators into
166 a composite score. By reviewing pre-existing data available through the HDX database, component
167 themes and indicators were identified to include in the gender-based vulnerability index (Table 1).

168

169 Table 1. Component themes and indicators selected to contribute to the gender-based vulnerability index.

170 All distances are in kilometers.

Component theme	Indicators
Demographics	Percentage of pregnant women, percentage of women lactating
Education	Presence of barriers to education for adolescent girls
Health	Access to antenatal care, access to psychiatric support services, access to vaccinations, distance to the nearest healthcare facility
Water, Sanitation, and Hygiene (WASH)	Perception of ‘enough water for household needs,’ recent outbreaks of diarrhea, and where women defecate at night (categorized as private facilities, communal, and open defecation, with open defecation being the most ‘vulnerable’).
Resource Availability	Access to food supplementation for pregnant and lactating women, distance to the nearest distribution center
Security	Access to gender-based violence services, access to incident reporting mechanism, access to police and courts, distance to the nearest women-friendly space, distance to the nearest child-friendly space.

171

172 Vulnerability, commonly defined in the humanitarian community as the diminished capacity of an
173 individual or group to anticipate, cope with, and resist and recover from the impact of a hazard [12], is a
174 relative and dynamic concept. It is multi-dimensional and differential, scale-dependent, and spatially
175 heterogeneous. The definition of vulnerability suggests that it is referential to specific hazards. In the
176 setting of Rohingya refugees, hazards are abundant, including vulnerability to food insecurity,
177 interpersonal violence, diseases, and natural hazards such as cyclones, landslides, and flooding. In light of
178 such reality, this study defines vulnerability in alignment with the Vulnerability Assessment Framework
179 established by the United Nations High Commissioner for Refugees as the ‘risk of exposure of ... refugee
180 households to harm, primarily in relation to protection threats, inability to meet basic needs, limited
181 access to basic services, and food insecurity, and the ability of the population to cope with the
182 consequences of this harm” [20].

183

184 Despite the fact that gender is a social construct, vulnerability is undoubtedly gender-differentiated.
185 Variables, such as lack of access to and/or control over essential resources and lack of entitlements,
186 compound women's vulnerability and undermine agency and adaptive and recovery capacities from
187 hazards [28]. Many gender indices exist to examine the role of gender discrimination as it influences
188 human development and wellbeing at the national level. These indices, including the Social Institutions
189 Gender Index [29], the Gender Inequality Index [30], the Global Gender Gap Index [31], identify several
190 dimensions that influence gender inequality. These range from health and protection parameters such as
191 access to prenatal care and laws regarding gender-based violence, attainment of education, economic
192 indicators, and freedom of movement, to discriminatory family codes, restricted civil liberties,
193 representation in government, and empowerment within socio-economic realms.

194

195 However, previous gender-based vulnerability indices are limited in their utilization and reporting in
196 academic literature. One such gender vulnerability index, conceived and implemented by Plan India,
197 attempted to develop collective perspectives and generate a normative consensus on the status of girls and
198 women in India. This index identified nine thematic indicators of gender-based vulnerability, including 1)
199 safety and protection, 2) health and survival, 3) illiteracy, 4) poverty, 5) policy framework and
200 implementation, 6) climate change and migration, 7) digitalization vulnerabilities, 8) cultural and social
201 practices, and 9) urban/rural vulnerability [32]. Given the lack of data available to speak to each of these
202 themes, they identified four dimensions that captured the predominant variables contributing to gender-
203 based vulnerability: protection, health, education, and poverty. Similarly, while we acknowledge that
204 many variables influence gender-based vulnerability in refugee populations, these data were not available
205 in open-source, secondary data, and thus were not included in the analysis.

206

207 *Incomplete Data: Probabilistic Interpolation*

208 Within the IOM's Needs and Population Monitoring dataset, there were settlement assessment points that
209 lacked data regarding specific indicators. For instance, gaps in gender specific food insecurity household
210 coping strategies such as preferentially feeding boys over girls were not included. Rather than include
211 these incomplete data points, access to food at distribution points was utilized as these were more
212 complete in the dataset. Gaps in binary and categorical data were determined to be random in the
213 geographic bounds of the data, and were imputed by assigning likelihoods of "0" or "1" or by category
214 using a probabilistic interpolation method of indicator formalism. This required transforming the missing
215 indicator binary or categorical variable to a probability for the category or binary value; the probability of

216 a category or binary value for a given indicator, I , at a location u , for a binary or categorical value z_k is the
217 transformation:

218

$$219 \quad I(u: z_k) = \{1, \text{if } Z(u) = z_k\} \text{ or } \{0, \text{if otherwise}\}$$

220

221 Several sites did not include enough data to be included in the vulnerability analysis, leading to a total
222 number of settlements evaluated being 145.

223

224 *Quantifying and Normalization:*

225 Quantification

226 Each variable was enumerated for incorporation into the vulnerability scoring, with higher scores
227 indicating a higher contribution to vulnerability. Non-enumerated variables, such as binary variables that
228 defined the presence or absence of service, were quantified as vulnerable=1 and not vulnerable=0. For
229 example, if prenatal care was available, the site would be scored a zero, and if prenatal care was not
230 available, the site was scored a one, given the assumption that a failure to provide prenatal care would
231 make women and girls more vulnerable. Similarly, the places in which women defecate at night were
232 reported as a generalized response of either 1) in private, 2) in communal latrines, or 3) open defecation.
233 These were scored as 1-3 responses, with open defecation defined as the most vulnerable.

234

235 Distance to facilities or resources were measured in kilometers (Km) utilizing Euclidean distance and
236 quantified within the scorecard with the equation:

$$237 \quad \text{Score} = \text{Distance (Km) to facility} / \text{Max Distance (Km)}$$

238

239 thereby creating a vulnerability score that is relative to other refugee sites. Variables that were reported as
240 percentiles (e.g., percent lactating women) were incorporated as decimals, normalizing the variable
241 between zero and one.

242

243 Normalization

244 Prior to total vulnerability score calculation, each thematic score was normalized to prevent arbitrary
245 weighting of individual thematic components utilizing the equation below, which has been employed by
246 many studies and is recommended by the Humanitarian Development Index as a standardized method
247 [33].

$$248 \quad \text{Normalized score} = \frac{(x - x_{min})}{(x_{max} - x_{min})}$$

249

250

251 After quantification and normalization were completed, scorecards that summed each of the six thematic
252 scores (i.e., education, health, sanitation, etc.) were utilized to create an aggregate ‘vulnerability score’ for
253 each refugee settlement site to provide a preliminary understanding of gender-based vulnerability.

254

255 *Aggregating thematic component scores and the role of Pareto ranking*

256 Composite vulnerability indices have long been criticized for employing arbitrary calculations to
257 aggregate indicator scores into a single metric [34]. Thematic component scores (e.g., health or security)
258 may be simply averaged or a weights-matrix may be applied, but both of these mathematical decisions are
259 foibled and more likely represent the researcher’s biases than the realities of vulnerability. Simple
260 averaging obscures extreme values when both high and low scores exist in different thematic components.
261 Weighting schema are equally problematic, requiring researchers to judge and quantify the relative
262 importance of different components either through Delphi procedures or qualitative or quantitative
263 methods. Even qualitatively derived weights matrices will likely fail the test of external validation, as the
264 importance of indicators is spatio-temporally heterogeneous.

265

266 Thus, this study utilized Pareto ranking, as implemented by Rygel et al. [35], to avoid the aforementioned
267 challenge of aggregation and the subjective weighting of thematic components, and yet still create a
268 composite vulnerability hierarchy that takes into account multiple variables. Pareto ranking is a method
269 by which non-domination is applied to ascribe vulnerability ranks to each refugee site. Non-domination is
270 achieved by a site when no other sites in the dataset are more vulnerable, i.e., if in each thematic
271 component, that site scores at least as high or higher than all other refugee sites. The non-dominated set of
272 sites includes all sites that are non-dominated in the dataset and represent the most vulnerable. These sites
273 are then removed from the dataset, and the algorithm iterated to identify the next most vulnerable set of
274 refugee sites. The process is repeated until all sites are ranked, thereby creating a hierarchical ranking of
275 gender-based vulnerability amongst these sites. An illustration of this process is provided in Figure 2.
276 Note that this illustration demonstrates each point as having only two thematic components that factor
277 into its vulnerability ranking. In this study, Pareto ranking utilized the six thematic components identified
278 above with identical logic and procedures applied to the higher-dimensional data.

279

280 Figure 2. A two-dimensional illustration of Pareto ranking in which each data point (in our study,
281 settlement site) has two thematic component scores. Those data points represented as circles are
282 considered the most vulnerable rank, in that each site is non-dominated. Those represented as ‘X’s are
283 second-most vulnerable, and those represented by squares are least vulnerable.

284

285 The Pareto ranking algorithm was executed in Python.

286

287 *Geospatial analysis*

288 Spatial analysis has been extensively adopted for exploring spatial heterogeneity and cluster detection in
289 public health research and environmental epidemiology [36-38] Ranging greatly in application and
290 methodology, spatial autocorrelation and local indicators of spatial association (LISA) have been utilized
291 to appreciate clusters of disease, morbidity, and mortality, and thereby contribute to a knowledge base
292 surrounding exposure pathways, social determinants of health, and the intersection between socio-
293 economic, environmental, and human wellbeing. Practically, cluster detection methods have provided a
294 means by which health policy officials and public health personnel can better target interventions and
295 further research. Through this lens of spatial epidemiology, this study undertook a geospatial analysis of
296 gender-based vulnerability ranking to characterize the spatial heterogeneity that would lead to a better
297 spatial understanding of gender-based vulnerability in this community and could potentiate better
298 targeting of programs for women and girls within the Rohingya refugee settlements. Spatial
299 autocorrelation analysis and LISA, utilizing the Global Moran's and Anselin Local Moran's I, were
300 employed to identify large-scale trends of autocorrelation and clusters and outliers of refugee settlement
301 sites that possessed high and low gender-based vulnerability scores.

302

303 Global Moran's I is an inferential, spatial statistical method that determines spatial autocorrelation based
304 on feature location and attributes value, e.g., vulnerability score utilizing the equation:

305

306

$$I = \frac{N \sum_i \sum_j w_{ij} (x_i - \bar{x}) (x_j - \bar{x})}{W \sum_i (x_i - \bar{x})^2}$$

307

308 Wherein N is the number of spatial units indexed by i and j , x and \bar{x} are the variables of interest and its
309 mean, w_{ij} is a matrix of spatial weights, and W is the sum of all w_{ij} . With the null hypothesis being no
310 spatial autocorrelation, the expected value of Moran's I is

311

312

$$E(I) = \frac{-1}{N - 1}$$

313

314 Wherein, as N approaches infinity, the expected value approaches zero [39]. Application of the Global
315 Moran's I statistic allows for the characterization of the pattern of features and associated attributes to be

316 identified as clustered, dispersed, or random. Positive values of Moran's I with significant p-values
317 suggest clustering of features more than expected given complete spatial randomness.

318

319 Anselin's Local Moran's I was then executed to characterize clusters of settlements that possessed high
320 and low gender-based vulnerability scores and to identify those communities that had scores statistically
321 higher or lower than neighboring settlements, i.e., outliers. The calculations below were applied to both
322 the Pareto ranks as an aggregate gender-based vulnerability score and subsequently to disaggregated
323 thematic scores to lend insight into which thematic variables, such as health or security, are potentiating
324 high/low levels of vulnerability in those communities.

325

326 Local Moran's I statistic [40] of spatial association is given as:

327

$$328 \quad I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j \neq i}^n w_{i,j} (x_j - \bar{X})$$

329

330 Where X_i is an attribute for feature i , \bar{X} is the mean of the corresponding attribute, $w_{i,j}$ is the spatial
331 weight between feature i and j , and

$$332 \quad S_i^2 = \frac{\sum_{j=1, j \neq i}^n (x_j - \bar{X})^2}{n - 1}$$

333

334 with n equal to the total number of features.

335

336 In this study, parameterization of the model included the adoption of inverse-weighted distance as the
337 spatial conceptual model, Euclidean distance as the measurement construct, and row standardization to
338 address any sampling bias present in the IOM settlement assessments. These parameters were applied
339 throughout both Global Moran's I and Anselin's Local Moran's I analyses.

340

341 All mapping and geostatistical analyses were done within ESRI ArcMap 10.6 software. The study was
342 reviewed by the Harvard T.H. Chan School of Public Health Institutional Review Board and determined
343 to be exempt from full review given that it involves open-source data and is not explicitly human subjects
344 research.

345

346 **RESULTS**

347 *Pareto Ranking of Gender-based Vulnerability*

348 Only 145 of the 174 settlements sampled by the IOM’s Needs and Population Monitoring Survey
 349 possessed enough data to be included in the vulnerability analysis. The Pareto rankings determined by
 350 this methodology ranged from 1-6, with one being the least vulnerable and six being the most vulnerable
 351 (Table 2). Approximately 24%, or 35 settlements, were deemed ‘most vulnerable’ based upon Pareto
 352 rankings of the thematic elements. Thirty-nine settlements were characterized as the second most
 353 vulnerable, comprising 26.9% of the refugee communities. Only one settlement was considered ‘least
 354 vulnerable,’ and 15 settlements were considered second to least vulnerable, comprising 10.3% of the
 355 analyzed encampments. The remaining 55 settlements have intermediate scores of relative gender-based
 356 vulnerability.

357
 358 Table 2.

	Least Vulnerable					Most Vulnerable
	1	2	3	4	5	6
Number of Settlements	1	15	29	26	39	35
Percentage	<1%	10.3%	20%	17.9%	26.9%	24.1%

359
 360 The spatial distribution of the relative gender-based vulnerability scores can be seen in Figure 3. Grossly,
 361 a large geographic spread of gender-based vulnerability is evidenced throughout the study area. Visuo-
 362 spatial patterns identify higher levels of vulnerability around Cox’s Bazar and the north of the region,
 363 along the Myanmar/Bangladesh border near Gundum, and in the south-east near Teknaf. Those
 364 settlements with the lowest gender-based vulnerability appear to be dispersed, but predominantly located
 365 in the south-east of the region, with intermediate scores predominating much of Ramu upazila.

366
 367 Figure 3: Total gender-based vulnerability index rankings of Rohingya refugee settlements in Bangladesh
 368 wherein 1=least vulnerable and 6=most vulnerable.

369
 370 This visuo-spatial intuition of the clustering of higher levels of gender-based vulnerability is ratified by
 371 the Global Moran’s I spatial autocorrelation analysis in which spatial clustering is significantly noted.
 372 With a Z-score of 4.5 and a P-value less than 0.001, the spatial distribution of high and low vulnerability
 373 scores demonstrate a spatial clustering more than would be expected given complete spatial randomness.

374

375 The Anselin Local Moran's I analysis demonstrated thirty settlements that occupy 'highly vulnerable'
 376 clusters, with only five settlements comprising 'less vulnerable' clusters (Table 3). Several communities
 377 in the northwest of the study area (Figure 4) around Cox's Bazar, delineated as statistically-significant,
 378 'highly vulnerable' clusters are, strictly speaking, the cores of each 'highly vulnerable' cluster. Two
 379 settlements in Idgar, along the northernmost part of the study region, are spatially disparate cores of two
 380 high-vulnerability clusters. Less vulnerable clusters are demonstrated in the south-east region near
 381 Kutupalong, its expansion and surrounding settlements, and near Dakshin Nhila.

382

383 Figure 4. Cluster analysis with Anselin Local Moran's I of gender-based vulnerability in Rohingya
 384 Refugee settlements in Bangladesh

385

386 Table 3.

Analysis Outcome	Number of Sites
Highly Vulnerable Clusters	30
Highly Vulnerable Outliers	8
Less Vulnerable Outliers	3
Less Vulnerable Clusters	5
Not Significant	115

387

388 Outlier communities that display statistically significant higher or lower vulnerability scores than their
 389 neighbors are demonstrated in Figure 5. Given the evidenced generalization that gender-based
 390 vulnerability is higher in the Cox's Bazar metropolitan region, the outcomes of the outlier analysis are
 391 justified, with all low-level vulnerability outliers, the settlements of Dhokkin, Somitapara, and Pahartoli,
 392 existing in that vicinity. Conversely, those settlements that are statistically more vulnerable than
 393 surrounding neighbors reside within the relatively less vulnerable regions along the Myanmar/Bangladesh
 394 border near Kutupalong.

395

396 Figure 5. Outlier analysis with Anselin Local Moran's I of gender-based vulnerability in Rohingya
 397 Refugee settlements in Bangladesh

398

399 When disaggregated into thematic components of education, WASH, security, and health, the spatial
 400 heterogeneity of hot- and cold-spots of gender-based vulnerability remains (Figure 6). Gender-based

401 health and security variables display significant spatial dependence. Those previously classified,
402 composite highly-vulnerable clusters in the northwestern regions near the metropolitan area of Cox's
403 Bazar are now defined as the most-vulnerable settlements when considering health and security
404 indicators. Conversely, security-dependent, gender-based vulnerability is lowest in refugee settlements
405 along the border with Myanmar. And refugee settlements identified as the centroids of low levels of
406 health-related vulnerability clusters are in the south-east, and specifically in Nhila and Sabrang Unions
407 along the Naf River. Education variables are demonstrated to have very few statistically significant
408 clusters, yet educational access appears to be best along ingress points near Gundum and problematic at
409 the Kutupalong 2E refugee site. Water, sanitation, and hygiene clusters are similarly sparse, but cold-
410 spots are identified in the most northern and southern refugee settlements, and in the Kutub Bazar
411 community near Cox's Bazar, where composite least vulnerable outliers were demonstrated previously.

412

413 Figure 6. Cluster analysis of gender-based vulnerability in Rohingya refugee settlements as disaggregated
414 by thematic components, including education, WASH, security, and health

415

416 **DISCUSSION**

417 Through the application of a vulnerability index and subsequent spatial analytics to open source
418 humanitarian data, this study demonstrated significant spatial heterogeneity of gender-based vulnerability
419 in Rohingya refugee settlements in the southwest of Bangladesh. Clusters of high levels of gender-based
420 vulnerability were identified in or around the town of Cox's Bazar, with clusters of low levels of gender-
421 based vulnerability residing predominantly near the Myanmar border in or near Kutupalong camp. This
422 finding may be attributable to many variables, including the formality of settlements, longevity of those
423 settlements, and/or relative urban/rural contexts.

424

425 Kutupalong and Nayapara in Teknaf are the two oldest official refugee camps in Bangladesh, having been
426 established in 1992 [2]. While population size within Kutupalong has swelled exponentially since 2017,
427 the formality and longevity of this vast settlement likely potentiate organizations to provide resources and
428 services by providing preexistent infrastructure when compared to more informal, less established
429 settlements. With over 600,000 refugees, Kutupalong and its surrounding expansion camps also possess
430 significant notoriety, given its label as the largest refugee camp in the world [41]. This status has likely
431 lead to larger degrees of funding and programming for Rohingya refugees, in general, but also for women
432 and girls, specifically.

433

434 Settlements in and around Cox's Bazar town are predominantly designated as 'informal,' with Rohingya
435 often living in and amongst the host community. With over 250,000 people in the metropolitan area,
436 Rohingya refugees in this urban environment likely face similar hardships as nearly half the world's
437 refugee population. Outside of formal, often rural, settlements, refugees confront unique challenges such
438 as difficulty accessing services, uncertain legal status and subsequent harassment, obstacles regarding
439 identifying and maintaining non-exploitive livelihoods, exclusion from social security systems and
440 community support mechanisms, and discrimination [42]. Given that these threats to wellbeing affect all
441 refugees, the finding of high levels of gender-based vulnerability surrounding Cox's Bazar town are
442 predictable.

443
444 Outliers of vulnerability are understandably identified within clusters of high- or low-gender-based
445 vulnerability. Sites identified as low vulnerability outliers, such as Dhokkin, Somitapara, and Pahartoli in
446 the Cox's Bazaar township region, and the alternately high vulnerability outliers found in the settlements
447 near Kutupalong and southwards, are in need of critical investigation. Identifying variables that influence
448 access to resources, humanitarian programmatic impact, and security will undoubtedly shed valuable light
449 on how these settlements have become outliers, and how best to improve gender-based vulnerability in
450 both present and future programming.

451
452 In this study, security and health variables appear to be the predominant drivers of gender-based
453 vulnerability in this region. Security was evidenced as a key component to both high and low gender-
454 based vulnerability clusters in Cox's Bazar township and near the border, respectively. While it is feasible
455 that the high level of security-based vulnerability in Cox's Bazar township is likely secondary to
456 settlements existing within a metropolitan area, there are also hot spots of security-based vulnerability
457 near Teknaf. And currently, Teknaf has the highest level of drug related violence within Bangladesh with
458 kidnapping and violence noted specifically in refugee camps [43]. Notwithstanding explanatory variables,
459 both gender-based vulnerability themes provide researchers and programmatic organizations with
460 valuable data to better understand and target specific gender-based programming.

461 462 **Limitations**

463 As with all vulnerability indices, this framework is subject to the critique of being too positivistic and
464 reductionist. It does not take into account the multitude of alternate variables such as societal norms and
465 preexistent systems of power and privilege that Rohingya women and girls face. Limitations on their
466 involvement in certain parts of civic and public life, 'purdah' or gender segregation, mobility constraints,
467 and decision-making inequalities [44] are likely to exacerbate vulnerability in the refugee context. Given

468 these societal norms, many Rohingya refugee women are considered to be living in ‘extremely vulnerable
469 conditions of insecurity’ as heads of households. Furthermore, Rohingya women are often subjected to
470 harassment, economic deprivations, and psychological, physical, and sexual violence. While clearly
471 important to understanding the vulnerability of Rohingya women and girls, disambiguated data were not
472 available for many of these variables. According to the Women’s Refugee Commission [9], gender
473 equality and women’s empowerment indicators are being monitored through the 2019 Rohingya refugee
474 Joint Response Plan, but these data have yet to be made open-source, and there is ‘currently no structured
475 process for analysis.’ The index and methodology utilized in this study have the capacity to include
476 additional parameters given the availability of future data if it is spatially codified.

477

478 **Upcycling data**

479 The utilization of open-source data is fraught with challenges that undermine scientific rigor, accuracy,
480 and external validation. Indicators used by organizations collecting data may be inappropriate,
481 incomplete, or adjacent to those critical to the research question at hand. Data collection methodologies
482 may not follow standardized or evidenced-based methods, be they sampling methodology, best practices
483 for survey or interview conduct, or precise geo-coding. Data collection methodologies may include
484 processes that lead to bias. Appreciating, accounting for, and being transparent about these challenges is
485 critical to the utilization of any research that uses secondary data. Humanitarian data is certainly rife with
486 these issues, and the imperfections of these data are recognized. However, upcycling pre-existent,
487 humanitarian data not only minimizes the resources required for situational awareness and critical
488 programmatic design, but also reduces the impact on the community and the potential for harm reduction
489 [45]. In an attempt to capitalize on these resources, this study chose to utilize secondary data in an effort
490 to demonstrate that actionable conclusions can be produced through a methodology that intentionally
491 combines pre-existent, freely available, open-source data.

492

493 **Validation**

494 The validation of such a methodology will prove difficult. As previously discussed, no specific construct
495 has been academically validated to quantify gender-based vulnerability. More prudent, however, is the
496 impact of such a method on funding, programming, and the improvement of the lives of refugee women
497 and girls. In alternative vulnerability indices, such as the Heat Vulnerability Index [15] and the Center for
498 Disease Control’s Social Vulnerability Index [17], success has been measured by including independent
499 variables such as morbidity and mortality, or the ability to recover from external hazards, respectively.
500 Unfortunately, there continues to be equipoise regarding indicators that should be utilized to gauge
501 success regarding gender-based vulnerability within refugee communities. Future research is required to

502 understand how vulnerability indices, and specifically gender-based vulnerability indices in refugee
503 populations, impact not only programming but the health and wellbeing of refugee women and girls.

504

505 **CONCLUSION**

506 In this study, we propose and implement a methodology for utilizing previously captured humanitarian
507 data to identify and spatially characterize populations in need. While specifically targeted at women and
508 girls in the Rohingya refugee community in Bangladesh, the application of a methodology that combines
509 vulnerability indices, Pareto ranking, and spatial analysis represents a novel technique to upcycle precious
510 humanitarian data that may be applied to many populations defined as 'vulnerable'. While validation is
511 critical and difficult, by leveraging such a methodology, researchers and humanitarian actors can harness
512 the potential of open-source data to bypass the resource-intensive process of primary data collection and
513 create actionable outcomes to target research and programming, monitor progress, and strengthen
514 coordination and resource-allocation in many humanitarian spheres.

515

516 **LIST OF ABBREVIATIONS**

517 GPS: Global positioning system

518 HDX: Humanitarian Data Exchange

519 IOM: International Organization for Migration

520 ISCG: Inter Sector Coordination Group in Bangladesh

521 Km: Kilometer

522 LISA: Local Indicators of Spatial Association

523 NPM: Needs and Population Monitoring

524 OCHA: United Nations Office for the Coordination of Humanitarian Affairs

525 UNFPA: United Nations Population Fund

526 USD: United States Dollar

527 WASH: Water, Sanitation, and Hygiene

528

529 **DECLARATIONS**

530 **Ethics approval and consent to participate**

531 This research (Protocol IRB19-2073) has been reviewed by the Harvard T. H. Chan School of Public
532 Health Institutional Review Board (FWA00002642) and was determined to be exempt from the IRB
533 process given that it involves open-source data and is not explicitly human subjects research.

534

535 **Consent for publication**

536 Not applicable

537

538 **Availability of data and materials**

539 The datasets analyzed during the current study are available in the Humanitarian Data Exchange
540 repository, <https://data.humdata.org/dataset>.

541

542 **Competing interests**

543 The authors declare that they have no competing interests.

544

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546 No funding was provided for this research.

547

548 **Authors' contributions**

549 EN designed this study, assisted in statistical analysis and interpretation of the data, and drafted and
550 revised the majority of the manuscript. DRS assisted in refining methodology, and contributed to data
551 acquisition, processing, and analysis. PGG assisted in refining methodological design, interpreting data
552 and results, and assisted in the revision of the manuscript. All authors read and approved the final
553 manuscript.

554

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556 Not applicable

557

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Figures

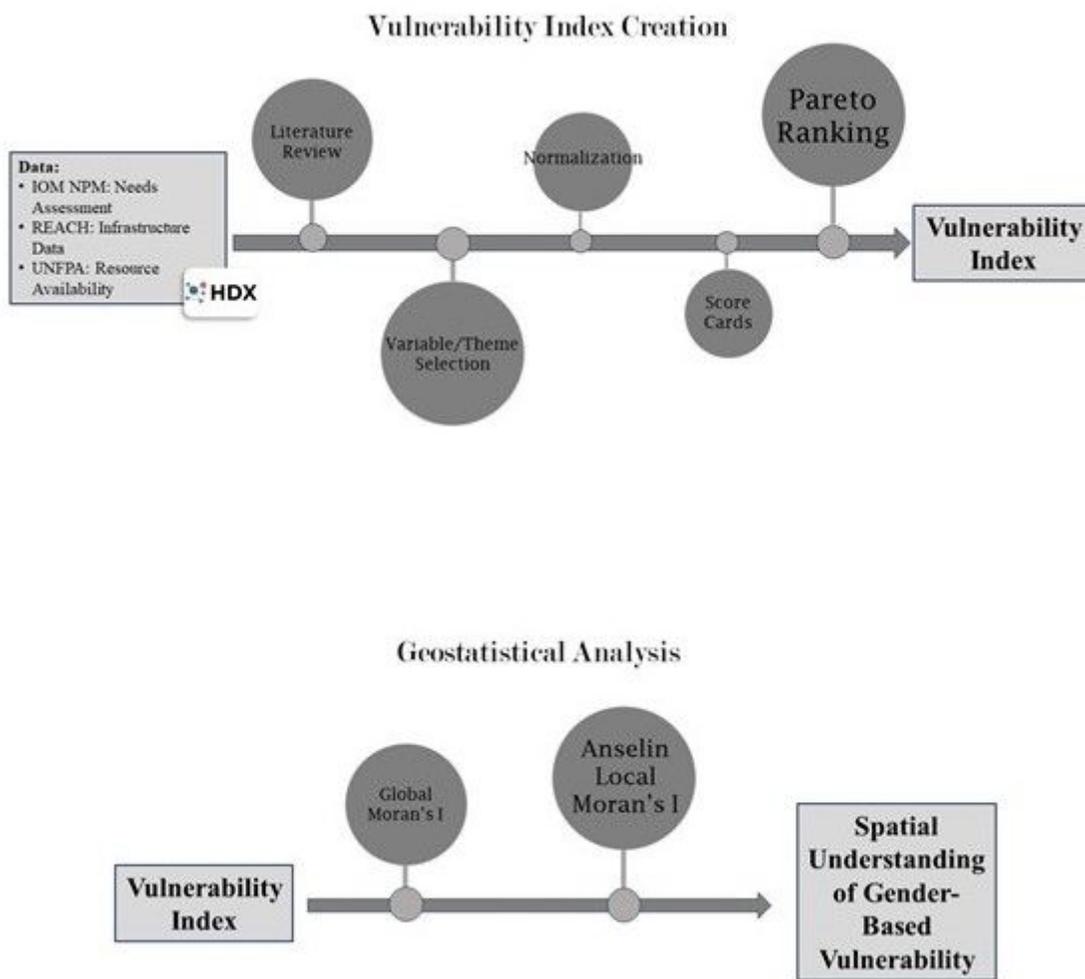


Figure 1

Methodological process for creating a gender-based vulnerability index and subsequent geostatistical analysis

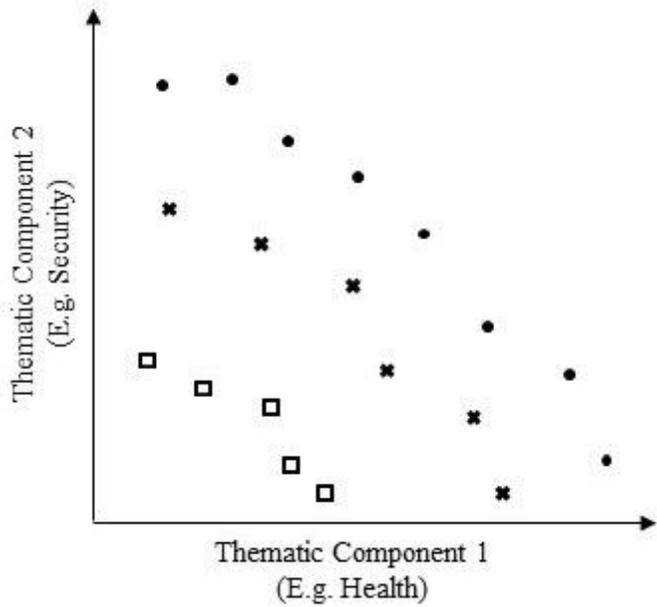


Figure 2

A two-dimensional illustration of Pareto ranking in which each data point (in our study, settlement site) has two thematic component scores. Those data points represented as circles are considered the most vulnerable rank, in that each site is non-dominated. Those represented as 'X's are second-most vulnerable, and those represented by squares are least vulnerable.

Gender-Based Vulnerability in Rohingya Refugee Camps

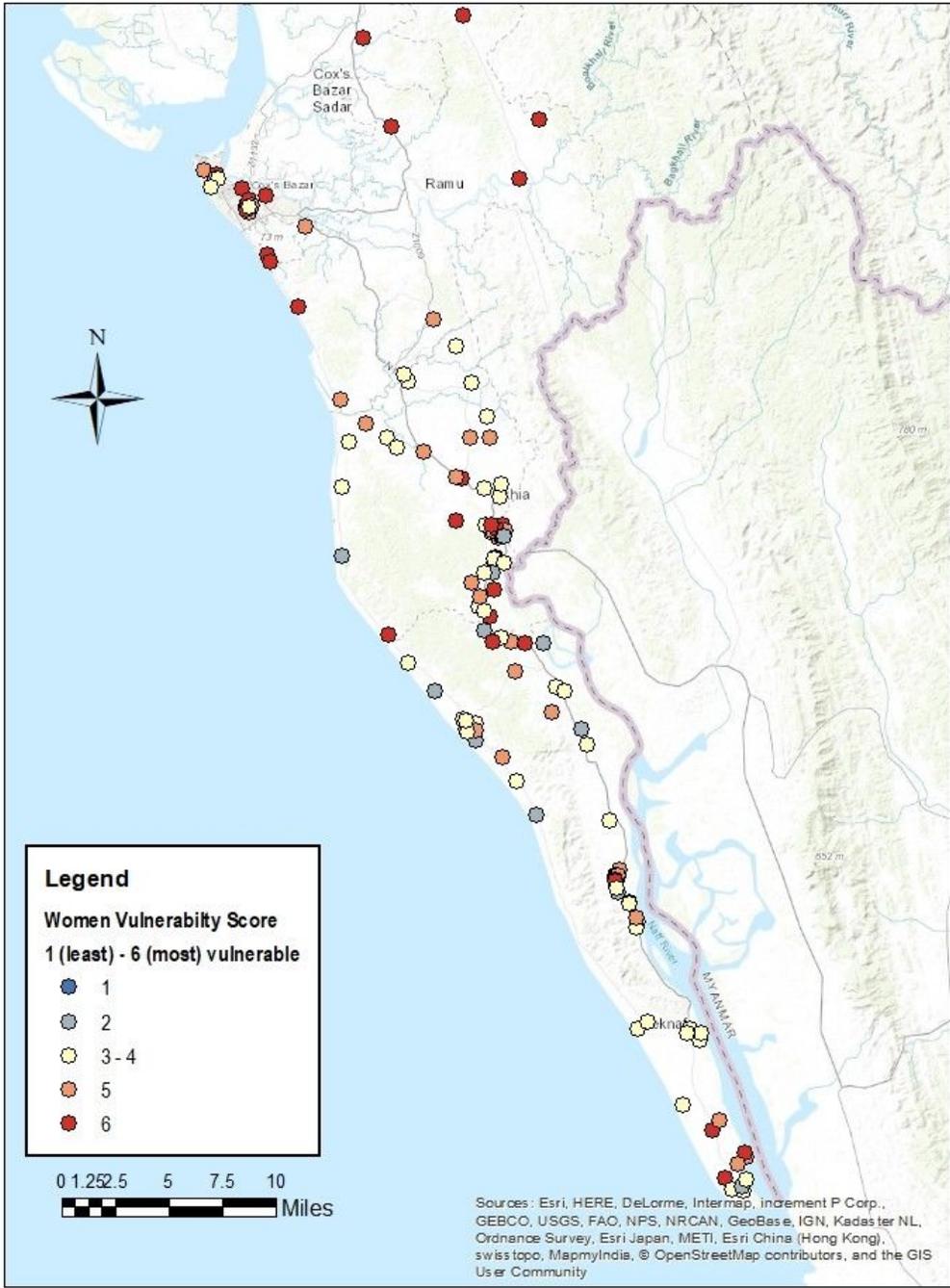


Figure 3

Total gender-based vulnerability index rankings of Rohingya refugee settlements in Bangladesh wherein 1=least vulnerable and 6=most vulnerable.

Gender-Based Vulnerability in Rohingya Refugee Settlements

Cluster Analysis with Anselin Local Moran's I

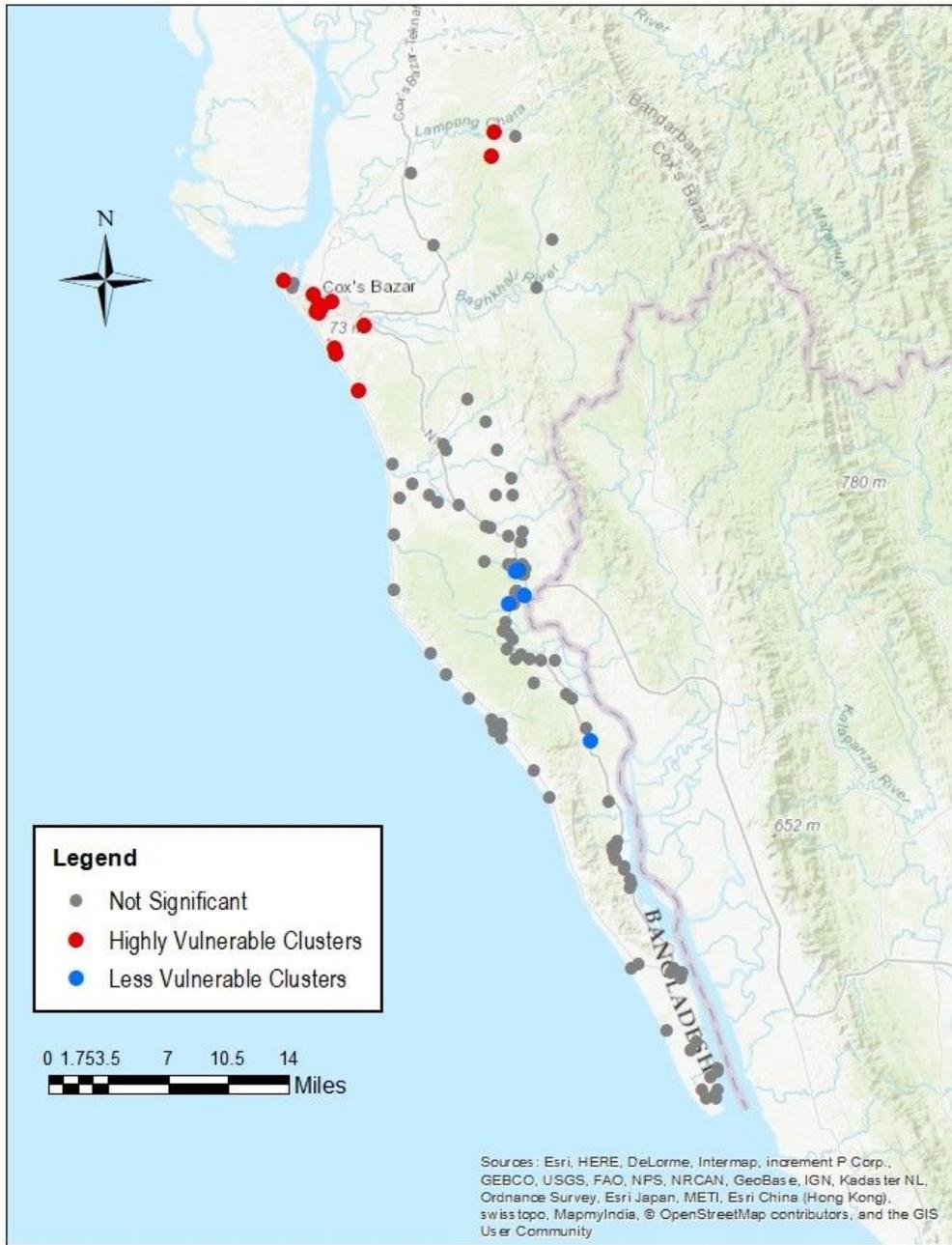


Figure 4

Cluster analysis with Anselin Local Moran's I of gender-based vulnerability in Rohingya Refugee settlements in Bangladesh

Gender-Based Vulnerability in Rohingya Refugee Settlements

Outlier Analysis with Anselin Local Moran's I

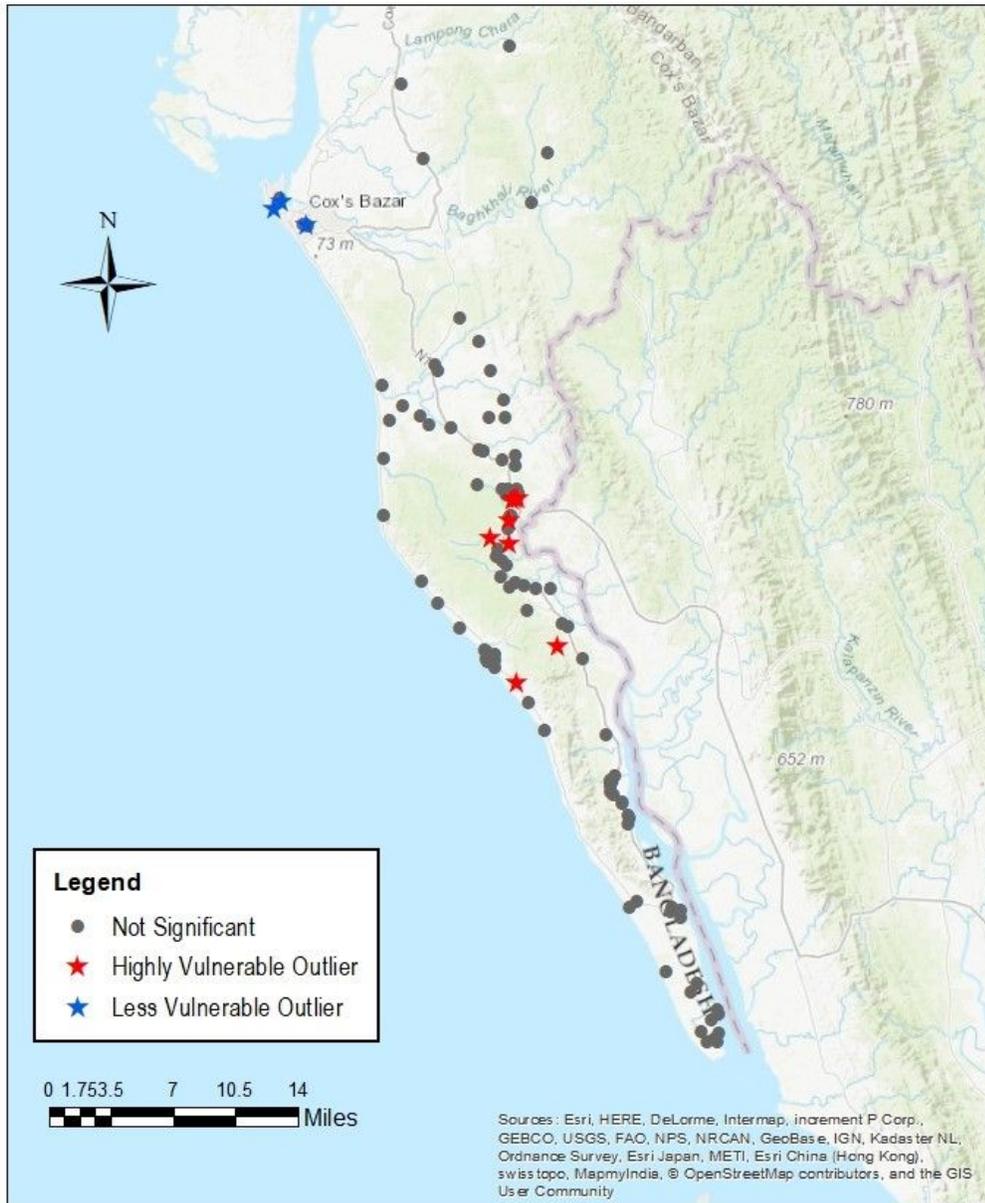


Figure 5

Outlier analysis with Anselin Local Moran's I of gender-based vulnerability in Rohingya Refugee settlements in Bangladesh

Gender-Based Vulnerability in Rohingya Refugee Settlements

Thematic Cluster Analysis

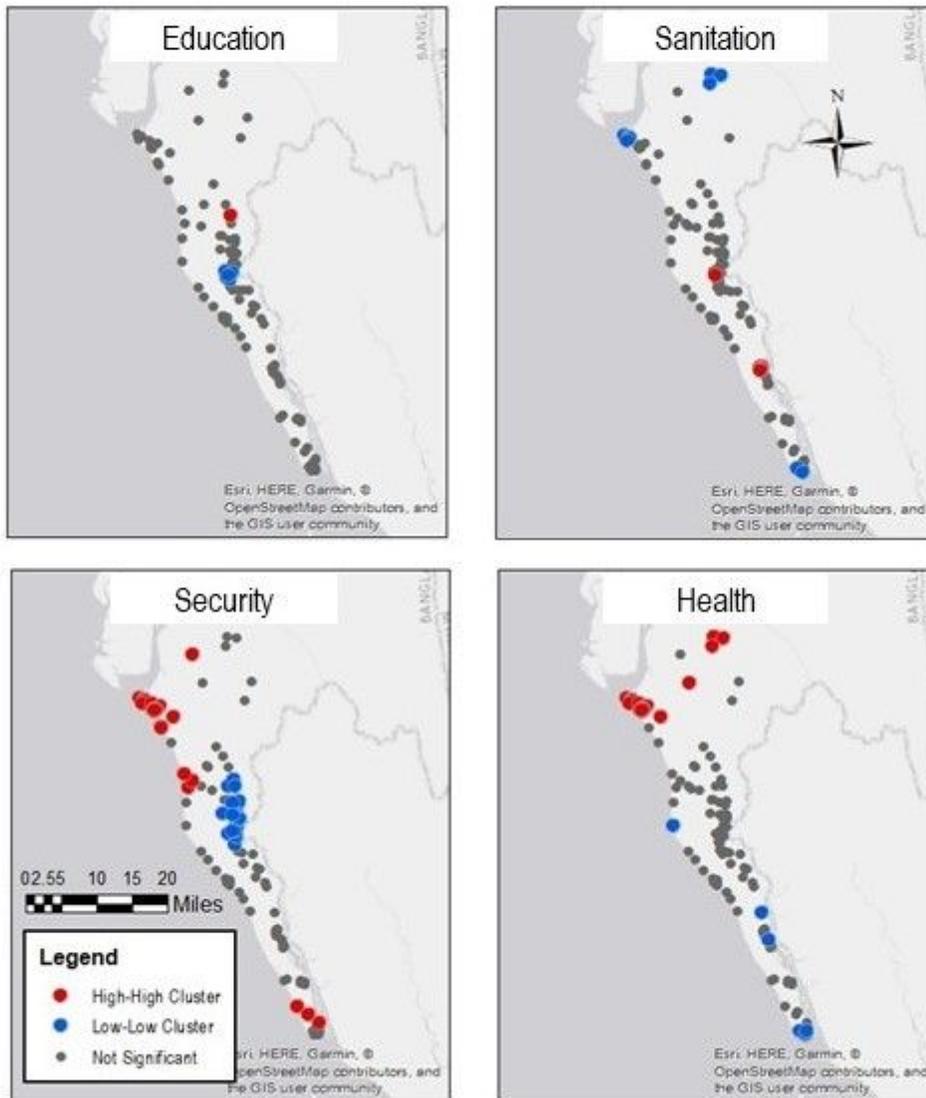


Figure 6

Cluster analysis of gender-based vulnerability in Rohingya refugee settlements as disaggregated by thematic components, including education, WASH, security, and health