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Abstract

Extreme climate events have been on the rise in both their frequency and intensity, displacing millions of people in vulnerable countries worldwide in recent years. This calls for prioritizing resettlement plans in adaptation frameworks and strategies in these countries. Toward this end, this article provides a methodological and empirical contribution in resettlement capacity assessment for climate change adaptation. It examines the effect of using weights while constructing composite resettlement capacity indices and empirically assesses the resettlement capacity of locations in Bangladesh using one hundred indicators from thirty-one data sources. We categorize the indicators into two main dimensions: assets, being inputs available for a viable livelihood; and conditions, or factors that constrain or promote the use of these assets. These are further divided into five asset and six condition subdimensions. We create both weighted and unweighted overall-, dimension-, and subdimension-specific resettlement capacity indices using an additive hierarchical index construction approach, whereby the weights are derived from expert assessment of the relevance of the dimensions and subdimensions. We then employ latent cluster analysis to identify clusters with similar capacity profiles. We find that although the distribution and mean values of the weighted and the unweighted resettlement capacity indices differ, they tend to highly correlate and have similar distributional patterns, leading to comparable conclusions. We identify four unique resettlement capacity clusters that are distinct in asset, condition, and subdimension resettlement capacity scores. These clusters exhibit a clear spatial pattern throughout Bangladesh, with the northern, western, and central (southern and eastern) areas characterized by higher (lower) resettlement capacity clusters. These findings provide important policy implications with respect to climate change-related displacement.

Keywords: resettlement capacity, Bangladesh, climate change, livelihood, migration, displacement.

JEL classification: Q48, Q54

1. Introduction

Every year, extreme climate events claim many lives, cause substantial destruction of infrastructure, and displace millions of people worldwide (Bukvic 2018; Mathur 2015; Rigaud et al. 2018). The global average temperature is also expected to reach the 1.5-degree centigrade limit sooner than expected (between 2030–2050), which will intensify the frequency and severity of climate events (IPCC 2019; IPCC 2021). Consequently, many places will become more environmentally hostile, resulting in large-scale and permanent human displacement (Bukvic 2018; Mathur 2015; Rigaud et al. 2018). Available forecasts suggest that by the year 2050, extreme climate change events may displace hundreds of millions of people worldwide (Barnett and Webber 2010; Clement et al. 2021; Rigaud et al. 2018). In such a context, planned resettlement will be crucial, something that has only recently been recognized as an effective adaptation strategy (Arnall 2019).

Nevertheless, many countries vulnerable to climate change have failed to manage existing climate change-induced population displacement (Islam and Khan 2018). Hence, people in these countries migrate—either temporarily or permanently—as either an ex ante response or ex post coping strategy to extreme climate events (Black et al. 2011; Gemenne and Blocher 2017; McLeman 2011; Mueller et al. 2014). However, not everyone is able to migrate. For example, the poor and the most vulnerable people, who often lack the necessary resources or face logistical barriers, tend to remain in unsafe places or end up in urban slums with poor public infrastructure and services (McNamara et al. 2015; Rahaman et al. 2018). This highlights the importance of planned resettlement in minimizing the socioeconomic losses of those forced to relocate, but also avoiding any social tensions and conflicts arising from displacement. Hence it is crucial to assess the resettlement capacity of potential destinations to allow resettlement of climate migrants in places with better capacities and prospects with positive outcomes (Bukvic 2018; Sipe and Vella 2014; Vlaeminck et al. 2016; Wilmsen and Webber 2015).

While previous studies (mostly focusing on not climate change-related resettlement) have highlighted the importance of resettlement location and its attributes in (re)building the livelihood of resettled people, they have not considered *assessing* the resettlement capacity of the potential destinations. This could be one reason most resettlement programs have failed to restore or at least improve the livelihoods of resettled people. Instead, these programs have led to increased vulnerability (e.g., Rogers and Xue 2015; Sarrafi and Moahamadi 2018) and entailed substantial risk of impoverishment (e.g., Arnall 2019; Brookings et al. 2015; Connell and Lutkehaus 2017; Correa et al. 2011). Therefore, assessing resettlement capacities using a rigorous empirical approach is critical for informing policies on climate change adaptation in vulnerable countries.

While some studies address resettlement capacity (Adugna 2011; Bukvic 2018; Walelign et al. 2021; Xiao et al. 2020) and the identification of hotspots for outward and inward migration (Hermans-Neumann et al. 2017; Rigaud et al. 2018) that provide insights for empirical assessment of resettlement capacity of potential destination places and the resettlement of displaced people, they suffer from the following three limitations.

First, all these studies, except for Bukvic (2018), have used equal weights[1] in the construction of the composite indices. This assumes all components of the overall resettlement capacity indices are equally important, which may not be realistic as some components (e.g., conflict) can be more critical for resettlement capacity than others (e.g., the availability of certain resources such as forests). However, the implications of the assumption of equal weights are yet unknown and call for further investigation.

Second, the studies, apart from Walelign et al. (2021), do not consider many relevant indicators (e.g., violent conflicts, the availability of different types of natural resources, soil quality, physical and human capital infrastructure). Hence, the resulting assessments may suggest resettling people in places with low capacity in terms of the overlooked indicators (e.g., people may end up in places with, say, a high incidence of conflict) (Walelign et al. 2021). Finally, the spatial coverage of these studies has been mostly small (e.g., at the district level), and are then not representative of a larger population of interest, and geographically limited to a single country. These empirical shortcomings limit our understanding of resettlement capacity, which then hinders the development of coherent national resettlement policies.

Our study bridges these gaps in the literature by providing robust and policy-relevant empirical assessment of local resettlement capacities in Bangladesh, a country extremely vulnerable to climate change. Using data from thirty-one sources and a hierarchical min-max additive index construction approach, we construct two versions—weighted and unweighted—of fourteen indices at a lower administrative level (union). The fourteen indices include an overall, two main dimensions (assets and conditions), and eleven subdimension resettlement index scores. Assets comprise the available inputs for a viable livelihood, while conditions include factors that promote or constrain the successful translation of these assets into livelihood outcomes.

The weights for generating the weighted resettlement capacity scores are based on expert evaluation of the components of the overall resettlement capacity scores at the subdimension and dimension levels in Walelign and Lujala (2022). We evaluate the differences between the weighted and unweighted indices using significance tests and compare whether the results differ spatially to determine whether the different weighting strategies result in different conclusions. Finally, we identify and characterize four resettlement capacity clusters using latent class cluster analysis and assess the characteristics and the geographic distribution of these clusters.

This study makes three major contributions to the literature, all with substantial policy implications. First, it provides novel evidence of the validity of using an equal weight assumption in resettlement capacity assessments, a common approach used in the construction of indices for resettlement capacity, including the related literature on resilience and vulnerability (Cutter et al. 2014; Cutter and Derakhshan 2020; Scherzer et al. 2019). The results reveal that the choice of weights can indeed result in different resettlement capacity index calculations, but still lead to similar conclusions. Second, the study develops a methodology to identify clusters with similar resettlement capacity profiles. This allows us to assess the common relative weaknesses

[1] Most studies that construct composite indices in other related areas (e.g., vulnerability, resilience) also use equal weights (see e.g., Cutter et al. 2014; Cutter and Derakhshan 2020; Scherzer et al. 2019)

of places with high resettlement capacity so that they can be strengthened through resource allocation and infrastructure investment. This can help policymakers target clusters of places judged to be more optimal for resettlement, but with similar weaknesses, and tailor investment to increase their absorptive capacity. Third, the study provides the first comprehensive subnational level resettlement capacity assessment of potential resettlement destinations in Bangladesh. It does this by identifying unions and clusters of unions with high and low resettlement capacity. These results can then be used to build on existing work by national and local government agencies and NGOs, along with international organizations, in planning for resettlement and internal migration in anticipation of climate-related hazards, and during emergencies when a hazard occurs. As the study also identifies places with low resettlement capacity, it provides valuable information on what areas to avoid when choosing places for shelter and/or resettlement.

2. Climate change, migration, displacement, and planned relocation in Bangladesh

Given its topography and socioeconomic characteristics, Bangladesh is extremely vulnerable to the adverse impacts of climate change. For instance, the country contains the second-largest river basin in the world and is mostly comprised of low and flat land (USAID 2012). Consequently, Bangladesh is regarded as the seventh-most climate change-exposed country in the world (Eckstein et al. 2021). As shown in Figure 1, Bangladesh's coastal regions are increasingly affected by salinity intrusions and recurrent tropical cyclones and tidal surges (Brown, 2008; Dastagir 2015; Dewan 2015; Paul and Rahman, 2006). Places along the river deltas repeatedly experience destructive floods (Dastagir 2015; Dewan 2015), and heavy monsoons can cause floods that can cover up to 70 percent of the country (Brown, 2008; Paul and Routray 2010a; USAID 2012).

At the same time, the northern, northwestern, western, southwestern, and central parts of Bangladesh experience recurrent droughts (Rahman and Lateh 2016). These events, which have become increasingly recurrent and often more intense, have claimed many lives, caused substantial damage to private properties and public infrastructure, interrupted public service provision (e.g., health, education), and severely disrupted the livelihoods of people (Begum, 2017; Dastagir 2015; Dewan 2015; Paul and Routray 2010a). In turn, the disruption of livelihoods has forced Bangladeshis to adopt unsustainable livelihood activities (e.g., logging) that serve to reinforce the vulnerability to climate and other environmental changes. They can also create social and economic repercussions, for example, in the form of punishment or even imprisonment, if people are caught engaging in illegal activities (Ahmed et al. 2019).

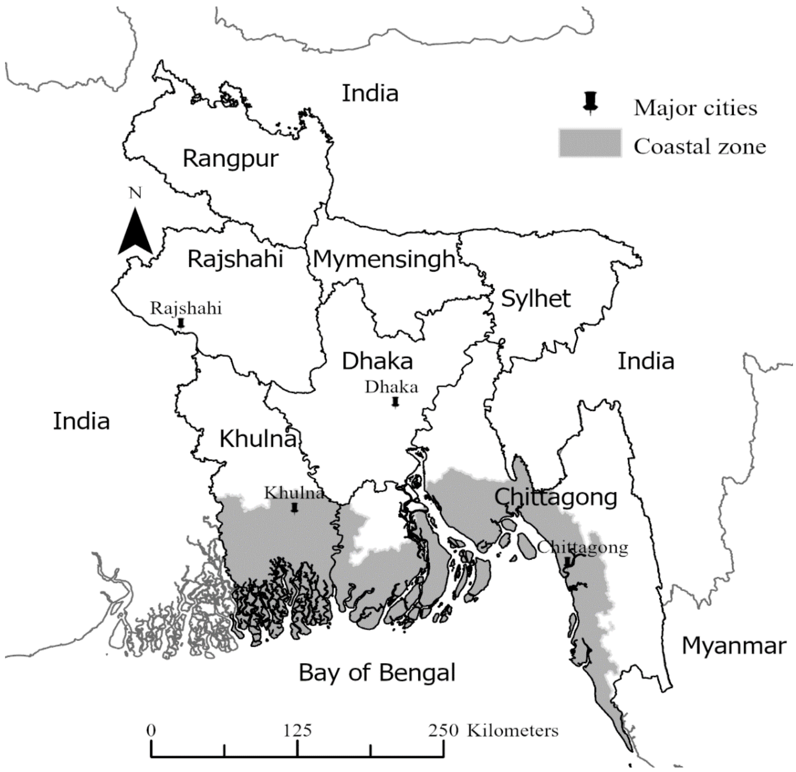

Figure 1: Divisions, major cities, and coastal zone of Bangladesh

Households facing climate and other environmental changes seek to adapt to them (Paul and Routray 2010a, Paul and Routray 2010b), but are often constrained by low adaptive capacity. Local communities also face other socioeconomic challenges due to high population growth, small land holdings, and unemployment (Kartiki 2011). In the main, government support for local adaptation has focused on building new and maintaining existing embankments to protect from flooding and sea incursion, providing cyclone shelters, and establishing early warning systems (Begum 2017).

Bangladesh has long witnessed episodes of large (mostly temporary) displacement from affected areas through rapid onset extreme events to nearby areas. According to IDMC (2015), more than 4.7 million people in Bangladesh were displaced because of natural disasters between 2008 and 2014. The more permanent migration is to urban areas, particularly the main cities of Dhaka and Chittagong, where people join the ever-growing slums with limited access to health, education, infrastructure, transportation, and housing (Begum 2017). Using district-level data over the period 1974–2000, Iqbal and Roy (2015) show that uncertainty about changes in temperature and rainfall impacts migration through agricultural productivity and predict that an increase in rainfall uncertainty could increase net outmigration rates by up to 20% in 2030 relative to 1990.

By 2100, the sea level along the Bangladesh coast is expected to rise between 9 and 100 centimeters and may submerge up to 20% of the country (Habiba et al. 2013; USAID 2012). Further, according to USAID (2012), from the 1960 baseline, temperature will rise by 1.4° C and 2.4° C by 2050 and 2100, respectively.

Some parts of Bangladesh will receive more precipitation, while others will receive less than normal. By 2100, tropical storms will be stronger in the North Indian Ocean (USAID 2012). These changes will increase the frequency and intensity of extreme climate events—with their first impacts already felt in many places—and subsequently induce substantial displacement and migration (Begum 2017; Habiba et al. 2013; Riguad et al. 2018). For instance, Davis et al. (2018) has projected that about 0.9 and 2.1 million people will be displaced by 2030 and 2050, respectively, due to direct inundation alone. Potential destination places should then anticipate a substantial rise in the demand for jobs, housing, and food (Davis et al. 2018). To minimize social and economic repercussions, Bangladesh needs to be prepared to cope with the inevitable population displacement and migration and incorporate planned relocation and resettlement in its national climate adaptation plans (Naser et al. 2019).

While most Bangladesh national climate change-related regulations and plans acknowledge the implications of climate change-induced displacement, they sometimes portray migration as an adaptation failure at the place of origin (Naser et al. 2019). However, planned resettlement has recently been acknowledged as part of the future adaptation strategies in the National Strategy on the Management of Disaster and Climate Induced Internal Displacement (NSMDCIID) (Siddiqui et al. 2020). Planning relocation (resettlement) requires identification of places that have a greater potential to accommodate vulnerable people and communities. Resettlement capacity assessment is therefore crucial for Bangladesh, especially given the limited experience of large-scale climate and development-induced resettlement, to minimize the economic and social costs from major displacement.

3. Data and methods

Analytical framework

This article adopts the empirical framework for climate change resettlement capacity assessment used by Walelign et al. (2021) for Ethiopia. Drawing on the climate change resettlement capacity (CCRC) framework developed by Walelign and Lujala (2022), the assessment here is based on two key dimensions: assets and conditions. Assets include the available inputs for a viable livelihood, while conditions consist of factors that promote or constrain the successful translation of these assets into livelihood outcomes such as food security or income.

As shown in Figure 2, both dimensions are further divided into several subdimensions to cover their different components. Assets are categorized into five subdimensions: natural assets, financial assets, human capital infrastructures, physical capital infrastructures, and social capital. Likewise, the condition dimension is categorized into six subdimensions: access to assets, quality of assets, socioeconomic context, institutional quality and strength, violent conflict, and natural hazards. For each subdimension, the CCRC framework presents a comprehensive list of generic indicators and proposes a set of specific, measurable indicators identified in the literature on sustainable livelihoods (e.g., Scoones 2015) and the literature on resettlement impoverishment risks and reconstruction (e.g., Cernea 2000), and from the various protocols and guidelines for planning and implementing resettlement programs (e.g., Brookings et al. 2015; Correa 2011).

The adopted empirical framework and the accompanying assessment presented are hierarchical. To start, individual subdimension resettlement capacity indices are constructed based on the indicators. The subdimension indices are then aggregated into asset and condition dimension indices, which in turn are aggregated into the overall resettlement capacity index (RCI).

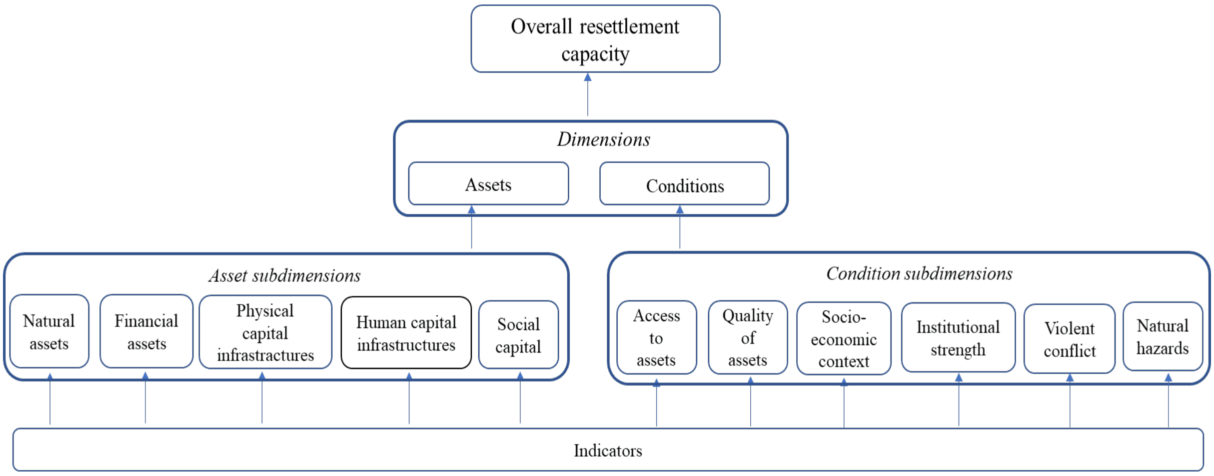

Figure 2: Analytical framework used to construct resettlement capacity index (RCI) for Bangladesh (Source: Adapted from Walelign et al. 2021)

Data sources and processing

The CCRC framework used to identify the resettlement capacity indicators ensures that the selected indicators are relevant to the Bangladesh context by selecting those indicators best reflecting the country specific reality. These indicators, in different formats and resolutions, are sourced from 31 data sets. The data sources include geocoded survey datasets (e.g., Demographic and Health Survey (DHS), the World Value Survey (WVS)); spatial datasets from the national institutions of various countries (e.g., NASA, ESA); and individual projects (e.g., GloBio, the Malaria Atlas).

As the data come in different coordinate systems, forms, and resolutions, four data processing techniques were used prior to index construction (see Appendix B for details). All the data sets were converted to the Gulshan 303 (Bangladesh Transverse Mercator) projection system. We use union, the lowest level administrative unit, as the unit of analysis. Most of the unions in Bangladesh are small (with a median area of about 23 square kilometers, corresponding closely to the size of a 5-kilometer grid cell). This small size means that resettlement capacity is unlikely to vary significantly within unions. In total, there are 5,158 unions in the 2019 Global Administrative Areas (GADM) database, which was used for identifying unions and other administrative units.

The resulting data set contains 106 preliminary indicators, which are organized across the 11 subdimensions. See Appendix A for the list of indicators and their categories and SM1 in the Supplementary Materials for additional details). Most indicators are recent (2015–2019), although for some only data after 2010 were available (e.g., livestock density). Some of the indicators, such as prevalence of drought and conflict, are longitudinal (covering the period 2000–2019). Most indicators were normalized using union size (population) to ensure comparability across unions.

Indicator screening and selection

The preliminary indicators within each of the subdimensions were first checked for correlation. To reduce information redundancy, we excluded indicators that had a high correlation (>0.8) with other indicators. The correlation with the remaining indicators was also considered when excluding the highly correlated indicators. For instance, if two indicators were highly correlated, the one that had the highest correlation with the remaining indicators was excluded. In total, we removed four indicators using this approach. In addition, we merged four indicators to generate two composite indicators (see Appendix D for details). Consequently, we developed a final list of 100 indicators with a standardized Cronbach's alpha of about 0.85, which ensures low information redundancy while not compromising internal consistency (Streiner 2003; Tavakol and Dennick 2011). As shown in Table 1, the Cronbach's alphas for the asset and condition dimensions are 0.67 and 0.80, respectively, and for each subdimension, ranges from 0.29 (for the natural assets and human capital infrastructures subdimensions) to 0.77 (for the access to assets subdimension).

Table 1: Inter-item correlation and Cronbach's alpha by dimension and subdimension

Dimension	Subdimension	# of indicators	Inter-item correlation	Cronbach's alpha
Assets	Natural assets	8	0.05	0.29
	Financial capital	5	0.16	0.48
	Human capital infrastructure	6	0.07	0.29
	Physical capital infrastructure	11	0.20	0.73
	Social capital	6	0.12	0.45
	Overall	36	0.05	0.67
Conditions	Access to assets	22	0.13	0.77
	Quality of assets	7	0.25	0.70
	Contexts (social, economic, and natural)	8	0.14	0.56
	Institutional strength	8	0.08	0.40
	Violent conflicts*	7	0.28	0.73
	Natural disasters*	12	0.19	0.77
	Overall	64	0.06	0.80
Overall index		100	0.05	0.85

*Reversed subdimensions

Index construction

To accommodate the hierarchical nature of the empirical framework and conceptual framework adopted, we use a hierarchical minimax additive index construction approach like Cutter et al. (2014), Cutter and Derakhshan (2020), and Scherzer et al. (2019). The construction of the unweighted indices is implemented in three steps. First, we min-max scale the indicators within each subdimension and sum the min-max indicator values to obtain the subdimension indices. Second, we take the average of each subdimension score (i.e., divide each by the number of indicators used in its construction) before min-max scaling and summing the subdimension scores into dimension indices. Third, we sum the dimension index scores to get the overall resettlement index.

The min-max scaling allows the indicators to be comparable by suppressing the measurement unit differences through scaling the original values to be between zero and one using the following formula:[2]

$$X_t = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

where X_t is the min-max transformed value of the indicator (or the subdimension index score in the second step), X is the original value of the indicator (subdimension index score), and X_{max} and X_{min} are the maximum and minimum values of the indicator (subdimension or dimension index scores), respectively. Min-max transformed values of the indicators that are hypothesized to be negatively associated with resettlement capacity were reversed (using the formula, $1 - X_t$) so that all the indicators can be interpreted as having a positive influence on the constructed resettlement capacity score (indicated with a star in Table 1). For reasons of comparability and presentation, we divided the assets and conditions score by the number of subdimensions (i.e., by 5 and 6, respectively) as well as the overall score by the number of dimensions (i.e., by 2). This means that all the subdimension, asset, condition, and RCI scores range between 0 and 1. The estimated resettlement capacity scores are unitless and cannot be interpreted in absolute terms; instead, they should be interpreted in relative terms when comparing scores across unions. The weighted indices are constructed in the same way as the unweighted ones, the only difference being that each subdimension index was weighted by its unique weight in calculating the weighted dimension indices, and each dimension index was further weighted by its unique weight in calculating the weighted overall resettlement capacity index.

We construct weights using information from the 24 expert assessments in Walelign and Lujala (2022). These experts assessed the relevance of the two dimensions and each of the subdimensions using a unipolar Likert scale from 0 (not relevant) to 4 (extremely relevant). The weights are calculated by multiplying the Likert scores by the number of experts choosing that score and dividing this by the maximum possible score (i.e., if all the experts chose a score of 4). This means that the weights range between 0 and 1. For the asset subdimensions, the calculated weights range from 0.78 (financial assets) to 0.84 (physical capital infrastructures), while for the condition subdimensions, they range from 0.82 (quality of assets) to 0.95 (violent conflicts). The calculated weight for the asset dimension (0.84) was slightly higher than for the condition dimension (0.83) (see Appendix E for the weights).

Identification of resettlement capacity clusters

The identification of the resettlement capacity clusters comprises two steps. First, we used principal component analysis (PCA) to create a new set of indicators, called principal component scores, using the

[2] Min-max scaling also facilitates inference of the importance of each component (see Walelign et al. 2021).

asset and condition dimensions.[3] The principal component scores contain information on the original dimension indices but reduce its dimensionality and the correlations in the data. Therefore, it minimizes the possible difficulties and distortions in our cluster analysis (Hair et al. 1998). In our case, the latent root criterion and visual interpretation of the scree plot indicated that retaining the first principal component scores was optimal as these explain 59.1% of the total variation in the original dimensions.

Second, to identify resettlement capacity clusters, we applied latent class cluster analysis (LCA) for the principal component score derived in the first step. Unlike the traditional and most common partitional (e.g., k-means algorithm) and hierarchical (e.g., single linkage clustering) clustering methods, LCA is a model-based approach. It is therefore less arbitrary when it comes to determining the number of clusters and allocating the study units to the clusters (Magidson and Vermunt 2002). LCA is also more objective as it provides significance tests for the determination of the optimal number of clusters and minimizes the within-cluster variation by assigning the probability of membership of a study unit to each cluster (Haughton et al. 2009; Magidson and Vermunt 2002).

Following Vermunt and Magidson (2005a), we estimated a general latent class cluster model under the assumption of local independence among the indicators and without covariates as:

$$f(y_i) = \sum_{x=1}^{k} p(x) \prod_{t=1}^{T} f(y_i|x) \text{ for } x = 1, 2, 3, \dots, K \text{ and } t = 1, 2, 3, \dots, T \qquad (2)$$

where y_i is a vector of indicators or response variables (the principal component score in our case), x is a latent class variable, k is the number of clusters, $f(y_i)$ is the probability density of a particular set of vector y_i, and $f(y_i|x)$ is the probability density of a particular set of vector y_i given x which is a univariate probability density (assumed to have a multivariate normal distribution). We chose the optimal number of clusters based on model comparison using the Bayesian information criterion (BIC) for the logarithm of the likelihood function ($logL$): $BIC_{logL} = -2logL + jlogN$; such that the model with the lowest BIC has the best fit for the data (Vermunt & Magidson, 2005b). The replication data and detailed replication instruction will be made available through Mendeley upon publication of this article.

4. Results

Comparison of the weighted and unweighted resettlement capacity scores

We compared the weighted and the unweighted assets, conditions, and overall RCI using four approaches: correlation analysis, analysis of distribution of scores, comparison of mean scores, and examination of whether the use of weights leads to changes when the unions are categorized into low, medium, and high resettlement categories. The correlation analysis in Figure 3 shows that the weighted and the unweighted RCI scores for the assets, conditions, and overall indices are near perfectly correlated (0.9997 or higher).

[3]Our preferred approach was to use the 11 subdimension indices instead of the dimension indices. However, it turned out that the use of the subdimensions did not result in a feasible number of distinct clusters: even with a 20-cluster model the BIC statistics kept decreasing.

This suggests that the weighted and unweighted scores contain similar information on the resettlement capacity of unions.

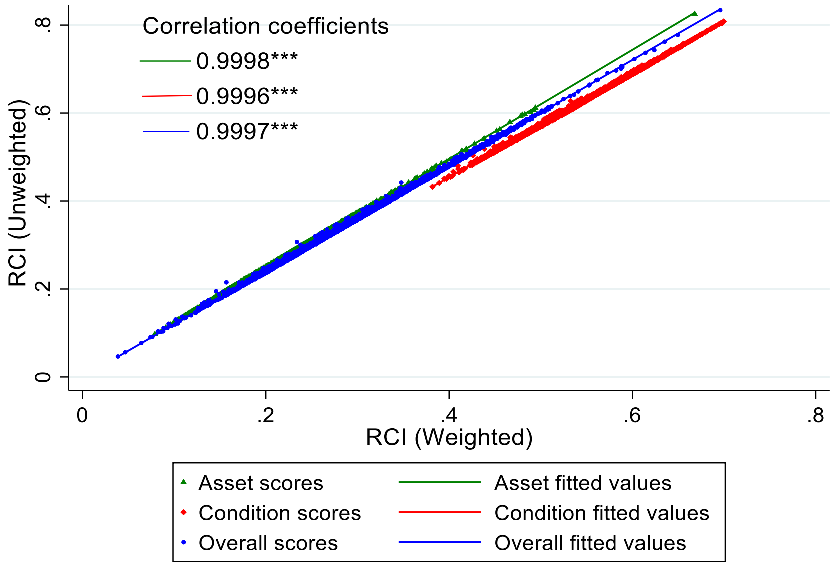

Figure 3: Scatter plots and fitted lines for weighted and unweighted resettlement capacity scores

Figure 4 displays the distribution of the weighted and unweighted asset, condition, and overall RCI scores using kernel density estimation. The distributions of weighted resettlement capacity scores are to the left of the unweighted scores, but the distributions follow very similar patterns. The Kolmogorov–Smirnov tests for the equality of distribution of the resettlement capacity scores reveal that the distributions of the weighted and unweighted asset, condition, and RCI scores are significantly different (D = 0.474, 0.554, and 0.310 with all p values <0.01, respectively).

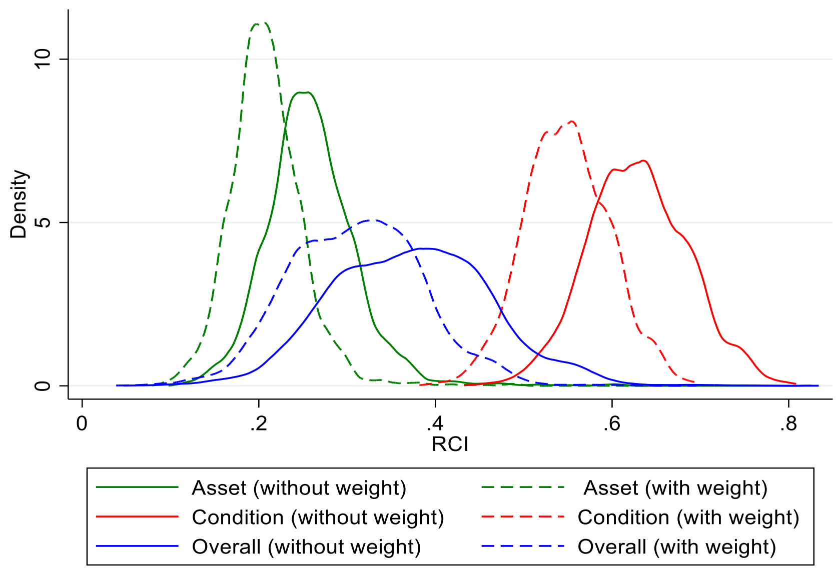

Figure 4: Distribution of resettlement capacity scores using kernel density estimates

The mean values of the weighted and unweighted asset resettlement capacity scores are 0.26 and 0.21, with standard deviations of 0.52 and 0.04, respectively. The mean values for the conditions are 0.63 (weighted) and 0.55 (unweighted), with standard deviations of 0.06 and 0.05, respectively. Mean values for the overall index are 0.37 (weighted) and 0.31 (unweighted), with standard deviations of 0.09 and 0.07, respectively. All these differences are statistically significantly different (p values <0.01) (see Appendix C for details). If these differences in distributions in Figure 4 lead to changes in the ordering of unions when ranked, the use of weighted contra unweighted indices can lead to different conclusions and policy implications. To assess whether this is the case, we next examine how the weighting impacts the ranking of the unions.

When composite indices are used, the units are ranked and then classified into 3–5 groups (e.g., Cutter et al. 2014; Cutter and Derakhshan 2020; Scherzer et al. 2019; Waleligh et al. 2021). We group the unions in three equal-size categories: low, medium, and high capacity. The question is whether the observed differences in mean values and the distributions (for the condition resettlement capacity scores) lead to a different categorization of the unions. The answer is no: most of the unions fall in the same tercile category (98.8%, 98.6%, and 99.2% for the asset, condition, and overall resettlement capacity scores, respectively). See Figure 5 and SM2 in Supplementary Materials. The unions that are categorized differently are scattered all over Bangladesh, except for the southwest for condition resettlement capacity and the northeast for the overall resettlement capacity, as shown in Figure 5.

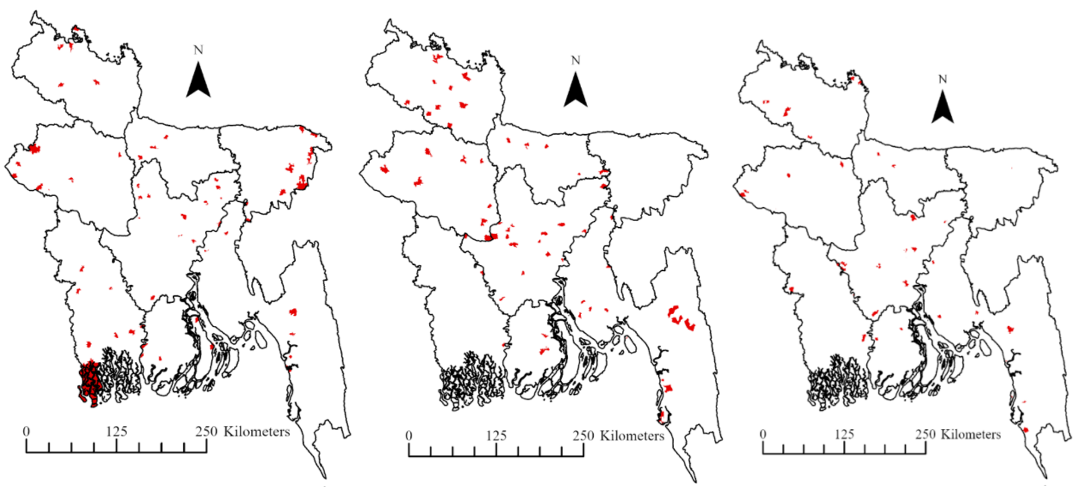

Figure 5: Unions falling into different tercile categories when ranked according to their weighted and unweighted scores for (from left to right) assets, condition, and overall resettlement capacity.

The above analyses suggest that the weighted and unweighted resettlement capacity scores yield remarkably similar results in our case. As the weighted resettlement capacity scores potentially provide additional information on the relevance of the different dimensions of resettlement capacity, we employ the weighted resettlement capacity scores in further analysis.

Resettlement capacity

Figure 6 displays the geographic distribution of union level resettlement capacity in Bangladesh. As shown, northern, southeastern, and southern Bangladesh are dominated by unions with low asset resettlement capacity scores while those in southwestern, central, eastern, and northwestern Bangladesh tend to have medium or high asset resettlement capacity scores. Unions with low asset resettlement capacity terciles also occur in small clusters in central, southwest, and northwestern Bangladesh. Similarly, unions with high asset resettlement capacity scores are scattered across southeastern, southern, and western Bangladesh, while the medium asset resettlement capacity tercile are scattered and occur in small clusters in south and southeastern Bangladesh.

However, we observe a different pattern for the condition resettlement capacity scores: unions with high scores are mostly in northwestern and central Bangladesh and those with low scores in southern, eastern, and central Bangladesh. In central Bangladesh, all three types of unions are present. Regarding the overall RCI scores, unions with high overall resettlement capacity tend to be in western Bangladesh. Smaller clusters with higher capacity also occur in the central and southeastern parts of the country. Unions in the low overall resettlement capacity tercile tend to be in the south, north, northeast, and southeast. The central and northeastern parts of the country are dominated by medium overall resettlement capacity terciles.

In sum, the southern, southeastern, and northeastern parts of Bangladesh are mainly characterized by low resettlement capacity, whereas the western, northwestern and central parts of Bangladesh are characterized by high resettlement capacity (Figure 6, Overall RCI).

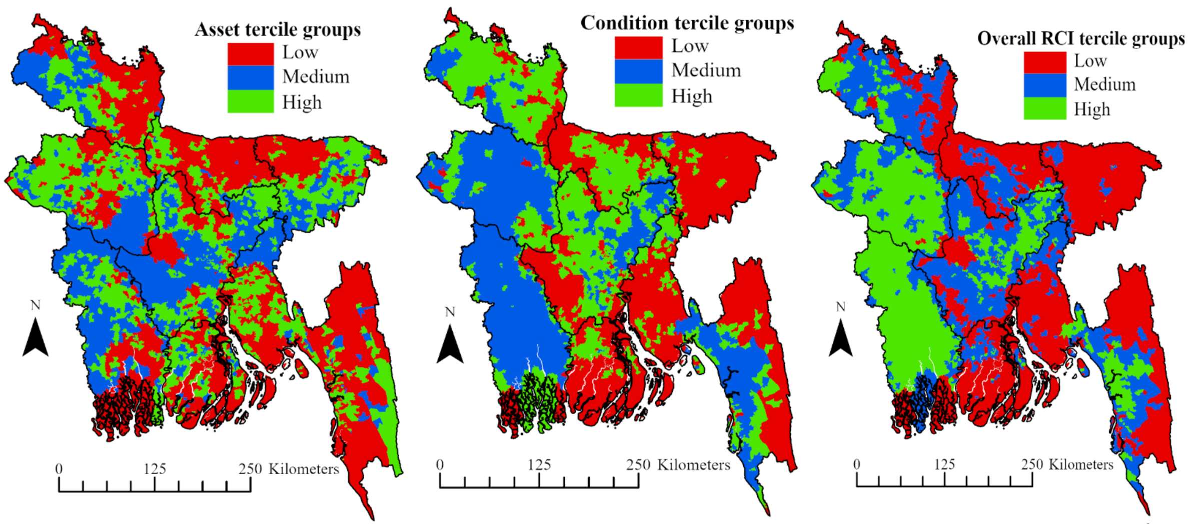

Figure 6: Assets, Conditions, and overall RCI tercile groups for all unions in Bangladesh.

Characteristics and geographic distribution of resettlement capacity clusters

The latent class cluster analysis resulted in four resettlement capacity clusters as the optimal number of clusters.[4] The one-way analysis of variance (ANOVA) significance test for the mean difference of subdimension, dimension, and RCI scores among the four clusters is statistically significant. This suggests that the identified clusters are distinct from each other and hence the clustering solution is optimal (see SM5 in Supplementary Materials).

Figure 7 characterizes these four clusters using the subdimension and dimension index scores (see SM6 in Supplementary Materials for detailed summary statistics). Cluster 4 has the highest average RCI score (0.48).[5] It also has the highest asset and condition dimension scores, and the highest asset and condition subdimension scores, except for the quality of assets and stable natural conditions subdimensions. Cluster 1 has the second-highest RCI score (0.35), the second-highest asset and condition dimension scores, and the highest scores for quality of assets and stable natural condition subdimensions. However, it also has the lowest score for the natural asset subdimension. Cluster 2 has the third-highest average RCI score (0.27) and the third-highest average scores for the asset and condition dimensions. Cluster 3 also has the lowest average RCI score (0.20) and the lowest scores for the asset and condition dimensions.

[4] We tested models with 1–15 clusters, with the four-cluster specification having the lowest BIC score (see SM4 in Supplementary Materials).
[5] The maximum possible score is one.

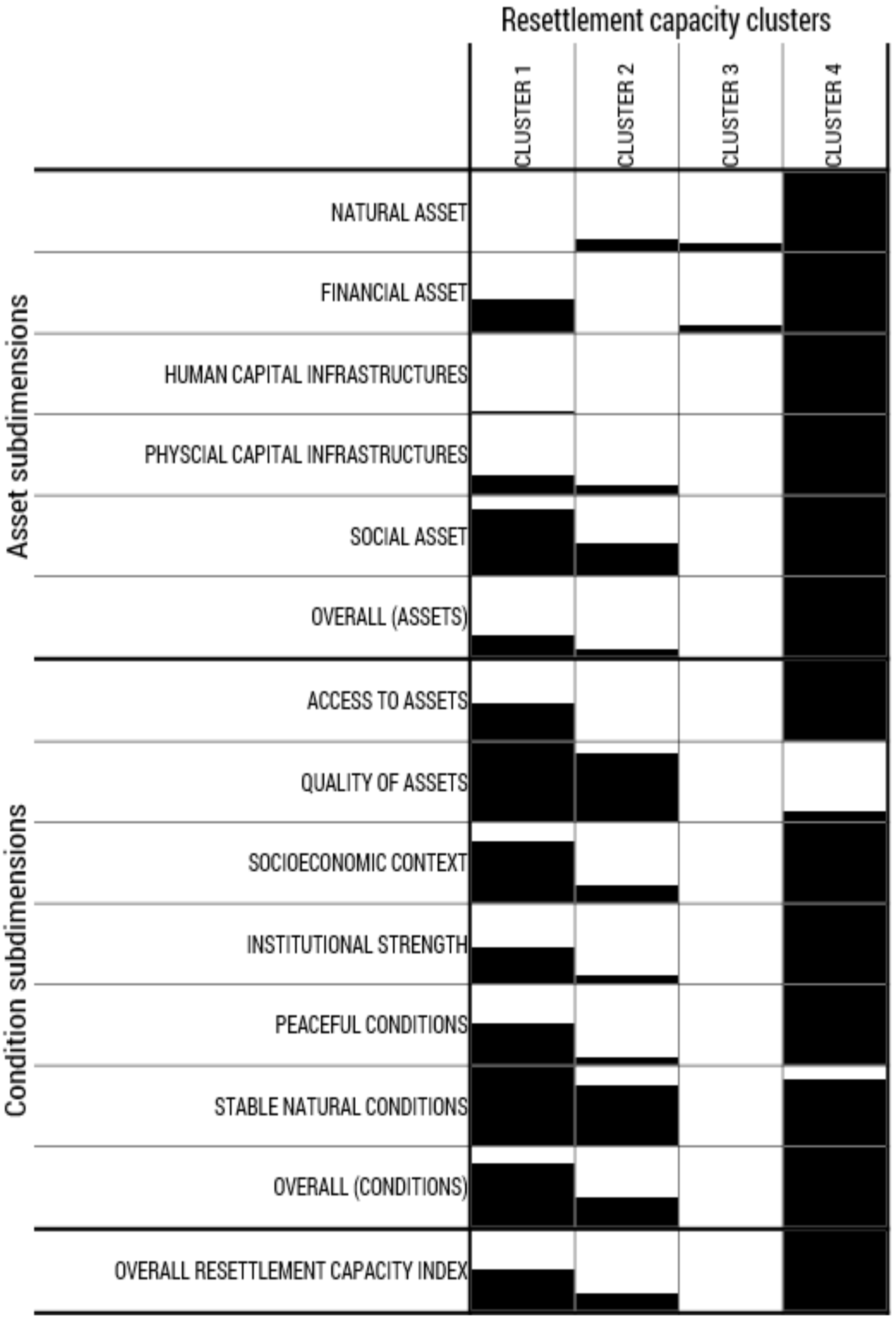

Figure 7: Multivariate comparison of four resettlement capacity clusters. Note: The height of the bars indicates the resettlement capacity scores of the cluster relative to the other three clusters.

Figure 8 illustrates the geographic distribution of the four clusters. Cluster 4, including those unions with the highest resettlement capacity, is the smallest in cluster size (72 unions, or just 1.4% of all unions). The unions in this cluster are spatially scattered all over Bangladesh. The cluster with the unions with lowest resettlement capacity, Cluster 3, includes unions from southern, central, and eastern Bangladesh. The dominant cluster, Cluster 1 (including 57% of unions), is in large clusters in western and central Bangladesh, while Cluster 2 is in northern, northeastern, and parts of southern Bangladesh. Dhaka, along with the other three major cities of Bangladesh and their surroundings, tend to fall in this cluster.

This spatial distribution of clusters corresponds with the spatial distribution of the resettlement capacity scores presented in Figure 6. The cluster analysis helped us to identify distinct groups of unions that have similar characteristics in both asset and condition dimensions, but different from unions in other groups, which is less arbitrary than creating equal sized bivariate category asset and condition terciles.

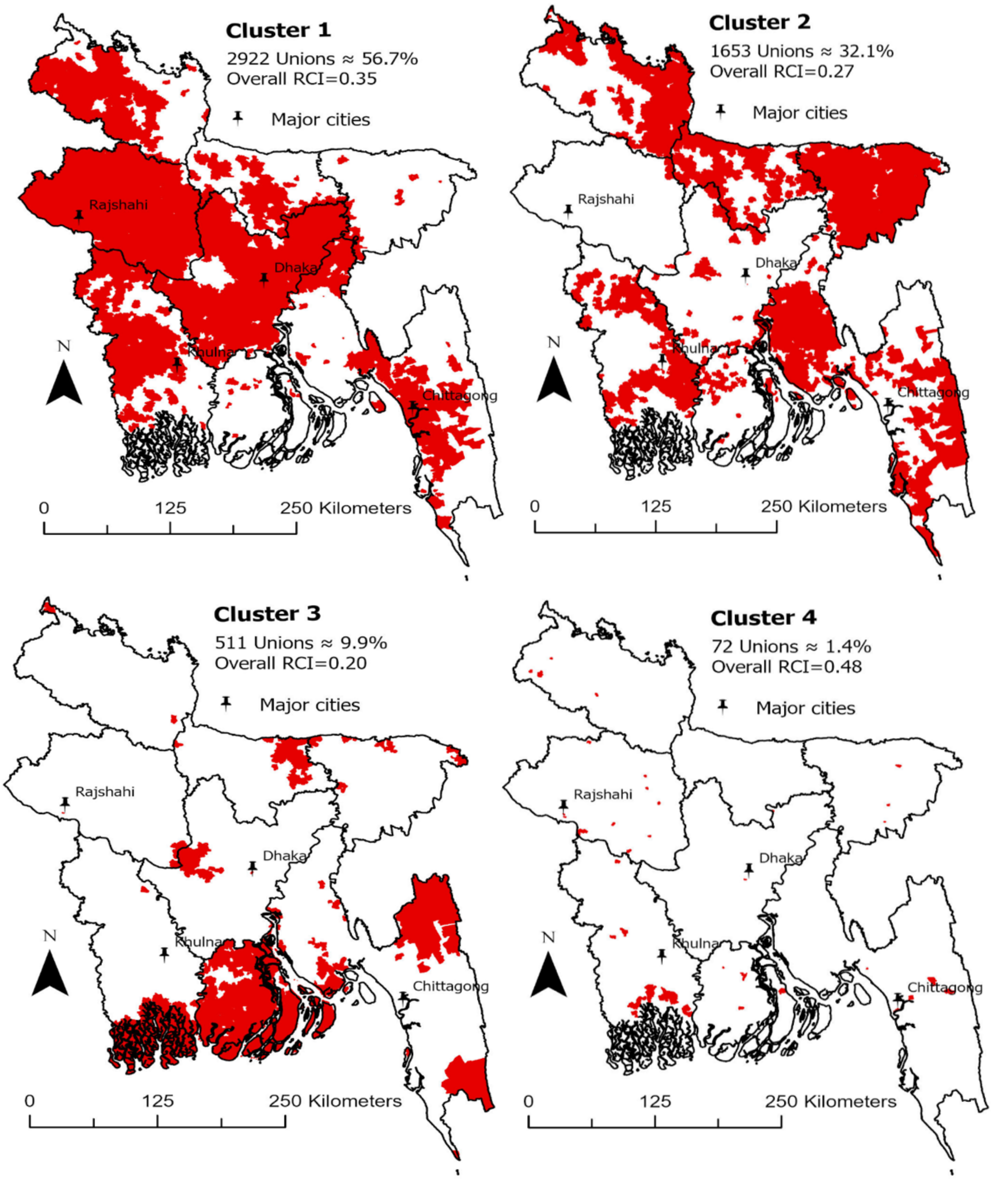

Figure 8: Geographic distribution of resettlement capacity clusters. Note: The total number of unions is 5,158.

Robustness checks

To check the robustness of the indices, we compared our results with the most common alternative index construction approaches, being principal component analysis (PCA) and the multiplicative method. With the former, we input the 11 subdimensions in the PCA analysis, extracted the five optimal number of principal scores (i.e., with eigen values greater than one) and summed them to drive the RCI scores.[6] With the latter, we used the geometric mean of the asset and condition dimension scores when the final RCI score was calculated.[7] Both alternative RCIs were constructed using the weights. When compared with our weighted RCI, indices constructed using PCA and the multiplicative method correlate highly (0.82 and 0.94, respectively, both with p values <0.01). This suggests that our index contains similar information as indices based on other index construction approaches.

Further, we checked the sensitivity of the index to missing indicators by excluding one subdimension at a time and constructing the corresponding reduced overall indices (in total eleven indices, one for each excluded subdimension). Correlation analysis shows that each of these reduced indices is highly correlated with the full index (see Appendix F for details). This suggests that the constructed overall resettlement capacity index is robust to missing subdimensions and indicators.

5. Discussion and conclusions

There is now a large literature that shows climate change is expected to cause substantial damage to people's livelihoods as well as major population displacement in vulnerable countries (Barnett and Webber 2010; Rigaud et al. 2018). However, the national and international efforts aimed at addressing this through climate change financing are limited to supporting in situ livelihood opportunities and resilience strategies for at risk or displaced populations in new locations (Burkett 2015) and that the planned resettlement of vulnerable people and communities is yet to take a central position in policymaking in countries highly vulnerable to climate change.

Assessment of the resettlement capacity within a country involves construction of a composite index using multiple livelihood indicators and dimensions (Waleign and Lujala 2022; Waleign et al. 2021). The resulting capacity indices can be affected by the weights applied. In this study, we provide (i) an empirical test for the use of weights in resettlement capacity assessments, and (ii) a comprehensive local-level assessment of resettlement capacity for Bangladesh. Using one hundred indicators from 31 data sources, we constructed RCI employing the hierarchical additive index construction approach for the 5,158 Bangladeshi unions. Our chosen index is robust to alternative construction approaches and missing indicators. Notably, weighting of the subindices does not affect the results. We identify four unique resettlement capacity clusters. The unions across clusters differ substantially when it comes to the average RCI scores as well as the asset and condition dimensions and subdimension resettlement capacity scores.

The conclusion based on the overall resettlement capacity index using either equal or different weighting for the subdimension components is strikingly the same. The findings clearly show a significant spatial disparity in terms of resettlement capacity in Bangladesh. Following the distribution of resettlement capacity scores,

[6] We were unable to apply the PCA at the indicator level as we do not have the weights at the indicator level, so we used PCA after deriving and weighting the subdimension indices.
[7] We apply the multiplicative approach at the dimension level as a high level of interaction is anticipated at this level according to the climate change resettlement capacity framework (Waleign and Lujala 2022).

the southern, eastern, and northern parts of Bangladesh are characterized by low resettlement capacity, implying that most unions in these regions look unsuitable for resettlement. In contrast, the western and parts of central and southeastern Bangladesh are characterized by unions with high resettlement capacity. The cluster analysis reveals four optimal resettlement capacity clusters, and their mapping indicates that of the four clusters, the lowest resettlement capacity cluster tend to occur in southern, central, and eastern Bangladesh. Combining these results, we observe a north–south and west–east divide in resettlement capacity: the northern and western parts of Bangladesh are well characterized by high resettlement capacity clusters whereas southern and eastern Bangladesh are well characterized by low resettlement capacity clusters.

The highest resettlement cluster of unions are characterized by high endowments of assets, particularly financial, human, and physical capital infrastructures, but lack good quality assets. While increasing the quality of assets of the unions in this cluster may help improve the resettlement capacity of the cluster, the unions in this cluster are very few (representing 72 unions or just 1.4% of all unions) and may not be large enough to accommodate the predicted number of displacements by 2050 (see e.g., Davis et al. 2018). Hence, it is also important to invest in the second-highest resettlement cluster of unions, which represent most of the unions (2,922 unions representing 56.7% of all unions), even though they lack natural conditions. Further, given the two major migrant destination cities, Dhaka and Chittagong, are located in these clusters, investment in increasing the resettlement capacity of the cluster could help to improve the precarity of migrant livelihoods in these cities and their surroundings.

We compared our findings with the World Bank internal displacement assessment (Riguad et al. 2018). That assessment identified small clusters in western Bangladesh as hotspots for in-migration and central, south-central, eastern, northeastern, and southeastern parts of Bangladesh as hotspots for outmigration. This aligns with our main finding of a west–east divide in resettlement capacity—eastern Bangladesh is characterized by a high resettlement capacity whereas western Bangladesh is characterized by a low resettlement capacity. Moreover, comparing the distribution of our resettlement capacity clusters with the district-level food insecurity information in Hossain et al. (2020), also suggests a high degree of overlap in the results. Most of the low resettlement capacity cluster unions in the south-central regions are characterized by high food insecurity prevalence, gap, and severity, while most of the high resettlement clusters in the western, northwestern, northeastern, and southeastern unions are characterized by lower food insecurity incidence, gap, and severity. This high degree of overlap between the distribution of resettlement capacity and the food security profiles suggests that our analysis can help support efforts in ensuring food security.

Although our results are robust to the use of weights, those used in this paper rely on experts' rating on the relevance of each of the dimensions and subdimensions considered in constructing the indices. Further validation of these results could be obtained by using the weights provided by entirely local-level experts in Bangladesh.[8] Moreover, as our weights were applied at the dimension and subdimension levels, the use of indicator-level weights could be applied for further robustness of our findings. It is also likely that a pair-wise rating of the subdimensions—assessing the importance of each subdimension relative to the other

[8] Four of the 24 experts interviewed in deriving the weights have research experience in Bangladesh.

subdimensions as opposed to our assessment of each subdimension individually, i.e., independently from the other subdimensions—could result in different weights for use in capacity assessments. It would also be useful to obtain weights using alternative approaches to ascertain their impact on the resettlement capacity assessment.

Our findings provide a comprehensive overview of resettlement capacity information from throughout Bangladesh. Nonetheless, further investigation, through field visits and microlevel data collection, would be needed to identify areas with high potential capacities for actual resettlement for climate migrants and directing investments to improve resettlement capacity of those areas. Such field-level assessments should also include ascertaining the attitude of host communities, as these would receive the climate migrants, toward resettlement and measure the proximity or similarity between the host communities and the climate migrants (Kolstad et al. 2022; Lujala et al. 2020). However, we caution policymakers and experts: (i) not to directly translate these findings into polices without further follow-up and justification for resettlement; (ii) to note that resettlement could be considered as a "last resort adaptation strategy" after all feasible alternatives are exhausted; and (iii) that resettlement, wherever possible, should consider individual preferences and be implemented on a voluntary basis.

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Disclaimer

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Appendix

Appendix A: List of preliminary indicators

Dimension	Subdimension	# of indicators	Indicators
Asset	Natural assets	9	Crop/agricultural land, grassland, urban land, forest land, groundwater, lake area, high discharge river length, low discharge river length, potential area with oil deposits
	Financial capital	6	Number of banks, number of ATM machines, proportion of people that have a bank account, proportion of people belonging to BRAC, proportion of people belonging to Grameen Bank and Asha, proportion of people belonging to BRDB and PROSHIKA
	Human capital infrastructure	6	Number of hospitals, number of health facilities other than hospitals, number of schools, number of kindergartens, number of colleges, number of universities
	Physical capital infrastructure	11	Number of airports, mobile phone use, number of post offices and boxes, number of transformers, highways, primary roads, secondary roads, tertiary roads, local roads, improved water, irrigated land
	Social capital	6	Number of community centers, number of social facilities and centers, number of sport places, number of places for worship, political participation, participation in voluntary organizations
Conditions	Access to assets	22	Distance to airports, distance to banks, distance to ATM, distance to community centers, distance to the nearest groundwater aquifer, distance to hospitals, distance to health facilities other than hospitals, distance to lakes, distance to low discharge river, distance to high discharge river, distance to post office and box, distance to transformer, distance to schools, distance to kindergartens, distance to social facilities and centers, distance to sport places, travel time to cities, distance to colleges, distance to universities, distance to number of places for worship, distance to mineral deposits, distance to petroleum deposits
	Quality of assets	8	Bare land, NDVI, soil carbon, soil depth, soil pH, terrain slope, terrain ruggedness index, surface water seasonality
	Social, economic and natural contexts	8	Nighttime luminosity, dependency ratio, HDI, livestock density, poverty incidence, rainfall erosion, attitude to immigrants, population density
	Institutional quality and strength	8	Number of police centers, number of prisons, distance to police centers, distance to prisons, trust of local council, feeling secured, proportion people participated in voting, bribe prevalence
	Violent conflict	8	Number of battles, battle fatalities, numbers of remote violence, number of remote violence fatalities, number of riots, number of riot fatalities, numbers of violence against civilians, violence against civilians' fatalities
	Natural disasters	14	Flood numbers, flood fatalities, flood displacements, flood severity, flood duration, drought incidence, number of cyclones, duration of the cyclone, cyclone speed, number of fires, fire size, fire duration, fire speed, perceptibility to sea-level rise
Overall	–	106	–

Appendix B: Data processing procedures for the different data sources and types

Data set type	Spatial unit	Data processing
Raster (spatial)	Grids larger than 1 km	Resampled to five-kilometer resolution, converted to polygons and joined with the five-kilometer vector grid
	Smaller than or equal to 1 km grid	Aggregated with zonal statistics tool in ArcGIS Pro using the relevant summary statistics (e.g., sum for irrigated land area, mean for road density)
Vector (spatial)	Point, line, or polygon	Summarized with the "summarize within" tool in ArcGIS Pro using the appropriate statistics (e.g., sum of area covered with buildings, count of number of conflicts)
WVS (survey)	Geocoded observation	Interpolated to the five-kilometer vector grid using generalized additive model (GAM) with enumeration area center coordinates (i.e., location in latitude and longitude) and distance to urban areas* as a covariate (independent variable)
DHS (survey)	Geocoded enumeration area	

*This was because the indicators that were interpolated (e.g., presence of schools) are influenced by the closeness to an urban area.

Appendix C: Descriptive statistics of asset, condition, and overall resettlement capacity scores

Asset			
	Unweighted	Weighted	t test
Mean	0.259	0.209	356***
SD	0.052	0.042	
Min.	0.098	0.079	
Max.	0.825	0.668	
Skewness	1.262	1.276	
Kurtosis	10.002	10.126	
Condition			
	Unweighted	Weighted	
Mean	0.629	0.549	666***
SD	0.057	0.048	
Min.	0.433	0.382	
Max.	0.808	0.670	
Skewness	0.094	0.075	
Kurtosis	2.919	2.925	
Overall			
	Unweighted	Weighted	
Mean	0.373	0.310	294***
SD	0.089	0.074	
Min.	0.047	0.039	
Max.	0.834	0.696	
Skewness	0.172	0.158	
Kurtosis	3.350	3.364	

Appendix D: Excluded or merged indicators

Variable name	Action	Subdimension	Reason
Ground water aquifer area	Removed	Natural assets	correlation with forest land (89%)
Proportion of people in Grameen membership	Merged with proportion of BRAC membership	Financial assets	Correlation with proportion of BRAC membership (84%)
Terrain ruggedness index	Removed	Quality of assets	High correlation with terrain slope (99.61%)
Number of riots	Merged with numbers of violence against civilians	Violent conflicts	High correlation with the numbers of violence against civilians
Cyclone duration	Removed	Natural disasters	High correlation with cyclone speed (99.46%)
Fire size	Removed	Natural hazards	Highly corrected with fire duration (83.08%)

Appendix E: Subdimension and dimension weights

		weights
Subdimensions	Natural assets	0.807
	Financial asset	0.783
	Human capital infrastructure	0.815
	Physical capital infrastructure	***0.826***
	Social capital	0.815
	Access to assets	***0.865***
	Quality of assets	0.823
	Socioeconomic conditions	0.859
	Institutional strength	0.826
	Violent conflict	***0.948***
	Natural hazards	0.844
Dimension	Asset	0.837
	Condition	0.830

Appendix F: Correlation between resettlement capacity index (RCI) score and reduced RCI scores

	Correlation
RCI vs Reduced RCI by natural assets	0.942***
RCI vs Reduced RCI by financial assets	0.883***
RCI vs Reduced RCI by human capital infrastructure	0.951***
RCI vs Reduced RCI by physical capital infrastructure	0.949***
RCI vs Reduced RCI by social capital	0.936***
RCI vs Reduced RCI by access to assets	0.967***
RCI vs Reduced RCI by quality of assets	0.961***
RCI vs Reduced RCI by contexts	0.875***
RCI vs Reduced RCI by institutional strength	0.937***
RCI vs Reduced RCI by conflicts	0.967***
RCI vs Reduced RCI by natural hazards	0.944***

Note: *** denotes level of significance at 1 percent level

Supplementary materials

SM1: Indicators and data source

#	Variable name	Brief description	Data source	Spatial resolution of original datasets (meters)	Mean or mode**
1	Percapita crop land	Land for crop production in square meter per person	European Space Agency https://www.esa-landcover-cci.org	300	609.498 (411.538) [0,825.551]
2	Percapita grassland	Grassland in square meter per person	European Space Agency https://www.esa-landcover-cci.org	300	7.356 (51.070) [0,1923.393]
3	Percapita residential land	Land for residence purposes in square meter per person	European Space Agency https://www.esa-landcover-cci.org	300	7.057 (34.059) [0,1126.107]
4	Percapita forest land	Forest land in square meter per person	European Space Agency https://www.esa-landcover-cci.org	300	121.692 (706.597) [0, 13277.160]
5	Percapita lake area	Lake area in square meters per person	Hydrosheds https://www.hydrosheds.org/	-	11.311 (112.934) [0, 3957.606]
6	High discharge river density	The total length of high discharge rivers in meters (with discharge larger than the median) per square kilometers	Hydrosheds https://www.hydrosheds.org/	-	231.741 (182.484) [0, 2312.346]
7	Low discharge river density	The total length of high discharge rivers in meters (with discharge larger than the median) per square kilometers	Hydrosheds https://www.hydrosheds.org/	-	169.623 (150.249) [0, 2706.263]
8	Percapita oil deposits	Land area of oil deposits in square meters per person	PRIO (https://www.prio.org/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset/Petroleum-Dataset-v-12/)	-	140.285 (343.631) [0, 6820.097]
9	Percapita banks	Number of banks per person	Open street map	-	$2.330X10^{-5}$ ($1.665X10^{-4}$) [0,.005]
10	Percapita Authomatic Taler Machine (ATM)	Number of ATM per person	Open street map	-	$7.740X10^{-6}$ ($8.010X10^{-5}$) [0,.003]
11	Bank account membership	Predicted proportion of people with bank account	Demographic and Health Survey (DHS)	-	0.309 (0.088) [0.131, 0.528]
12	Brac and Gramin membership	Predicted proportion of people who are Brac or Gramin members	Demographic and Health Survey (DHS)	-	0.260 (0.058) [0.145, 0.506]

13	Bangladesh Rural Development Board (BDRB) membership	Predicted proportion of people who are BDRB members			0.011 (0.004) [0.003, 0.027]
14	Percapita hopitals	The number of hospitals per person	HDX (https://data.humdata.org/dataset/bangladesh-health-facilities-by-lged)	-	4.150X10^{-6} (3.58X10^{-5}) [0, 0.002]
15	Percapita other health facilities	The number of health facilities other than hospital per person			1.56X10^{-5} (3.49X10^{-5}) [0, .001]
16	Per capita university	The number of universities per person	Open street map	-	1.22X10^{-6} (1.53X10^{-5}) [0, .001]
17	Pecapita college	The number if colleges per person			9.18X10^{-6} (6.93X10^{-5}) [0, 0.002]
18	Percapita kindergarten	The number of kindergartens per person			1.13X10^{-6} (2.06X10^{-5}) [0, .001]
19	Percapita school	The number of schools per person			3.400X10^{-5} (2.118X10^{-4}) [0, 0.005]
20	Airport	The number of airports with 50kms from the district per person	Open flights (https://openflights.org/data.html)	-	3.590X10^{-5} (5.96X10^{-5}) [0, 0.001]
21	Transformer	The number of electric transformers per person	Open street map	-	2.010X10^{-7} (6.300X10^{-6}) [0, 3.374X10^{-4}]
22	Tertiary road density	The total length of tertiary roads in meter per square kilometer per person	The Global Roads Inventory Project (GRIP) dataset; Meijer et al. 2018 (https://www.globio.info/download-grip-dataset)	~ 8000m	0.048 (.076) [0, 1.465]
23	Secondary road density	The total length of secondary roads in meter per square kilometer per person			0.007 (0.010) [0, 0.236]
24	Primary road density	The total length of primary roads in meter per square kilometer per person			0.004 (0.012) [0, 0.292]
25	Local road density	The total length of local roads in meter per square kilometer per person			0.005 (0.014) [0, 0.409]
26	Highway density	The total length of highway in meter per square kilometer per person			0.002 (0.006) [0, 0.182]
27	Irrigated land area	Total area of irrigated land in square meter per person	Global Irrigates areas: Meier et al. (2018) (https://doi.pangaea.de/10.1594/PANGAEA.884744)	-	290.913 (248.032) [0, 1421.488]
28	Post office and box	Number post office and boxes per person	Open street map	-	3.42X10^{-6} (2.93X10^{-5}) (0, 9.798X10^{-4})

29	Access to improved water	Predicted proportion of people who has access to improved water	Demographic and Health Survey (DHS)	-	0.977 (0.048) [0.436, 0.999]
30	Mobile phone access	Predicted proportion of people who has use mobile service			0.888 (0.035) [0.679, 0.950]
31	Community centers	Number of community centers (where people gather) per person	Openstreet map	-	2.77X10^{-6} (3.76X10^{-5}) [0, 0.002]
32	Social facility centers	Number pf social facility centers (where social service are delivered) per person			8.00X10^{-7} (2.27X10^{-5}) [0,0.002]
33	Sport places	Number of sport places (e.g. stadiums) per person			5.88X10^{-6} (5.15X10^{-5}) [0,0.002]
34	Worship places	Number of worship places (e.g., church, mosque) per person			6.54X10^{-5} (3.55X10^{-4}) [0, 0.009]
35	Political participation	Interpolated proportion of people participating in politics	World Value Survey	-	.3126 (.174) (0, 0.700)
36	Participation in voluntary organization	Interpolated proportion of people participating in voluntary organizations		-	.464 (.213) [0, 0.875]
37	Distance to airport	Distance to the nearest operational airport in meters	Openstreet map	-	39452.19 (22969.22) [0, 118659.6]
38	Distance to bank	Distance to the nearest bank in meters			6206.444 (6383.944) [0, 43841.54]
39	Distance to ATM	Distance to the nearest ATM in meters			11575.15 (9979.402) [0, 72550.79]
40	Distance to community center	Distance to the nearest community center in meters			14692.6 (11452.86) [0, 78500.04]
41	Distance to ground water	Distance to the nearest ground water aquifer	https://produktcenter.bgr.de/terraCatalog/OpenSearch.do?search=29949f35-6fe1-4775-bc97-62274a30c70b&type=/Query/OpenSearch.do	-	13.8304 (285.1079) [0, 14567.38]
42	Distance to hospitals	Distance to the nearest hospital in meters	HDX (https://data.humdata.org/dataset/bangladesh-health-facilities-by-lged)	-	5402.12 (4722.698) [0, 36424.99]
43	Distance to heath facilities	Distance to the nearest health centers other than hospitals		-	1694.157 (2562.79) [0, 22616.26]
44	Distance to lakes	Distance to the nearest lake in meters	Hydrosheds https://www.hydrosheds.org/	-	10575.04 (12373.84) [0, 107113.5]
45	Distance to small river	Distance to the nearest river with low discharge in meters		-	71.36789 (320.2422) [0, 11984.14]

46	Distance large river	Distance to the nearest river with high discharge in meters	Hydrosheds https://www.hydrosheds.org/	-	113.4207 (535.6399) [0, 15190.34]
47	Distance to post office and postbox	Distance to the nearest post office and postbox in meters	Open street map	-	9853.148 (8789.162) [0, 60149.92]
48	Distance to transformer	Distance to the nearest transformer in meters		-	63170.79 (39926.64) [0, 213419]
49	Distance to school	Distance to the nearest school in meters		-	4331.116 (5093.979) [0, 57750.77]
50	Distance to kindergarten	Distance to the nearest kindergarten in meters		-	28848.34 (20462.2) [0, 121161.5]
51	Distance to social facility	Distance to the nearest social facility in meters		-	28074.37 (17695.41) [0, 90974.02]
52	Distance to sport places	Distance to the nearest sport places in meters		-	8718.337 (7108.359) [0, 55859.08]
53	Travel time to urban centers	Travel time urban centers in hours as a measure of accessibility to high density cities	The Malaria Atlas, Weiss et al. 2018 (https://malariaatlas.org/research-project/accessibility_to_cities/)	-	15.58735 (22.78326) [0, 586.3312]
54	Distance to university	Distance to the nearest university in meters	Open street map	-	25212.2 (20276.52) [0, 166988.2]
55	Distance to college	Distance to the nearest college in meters		-	6387.01 (6208.537) [0, 70153.4]
56	Distance to place of worship	Distance to the nearest place of worship in meters		-	3189.597 (4212.09) [0, 37224.57]
57	Distance to mineral deposit	Distance to the nearest mineral deposit in meters	USGS (https://mrdata.usgs.gov/pp1802/)		244304.1 (65344.16) [0, 354758.4]
58	Distance to petroleum deposit	Distance to the nearest petroleum deposit in meters	PRIO (https://www.prio.org/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset/Petroleum-Dataset-v-12/)	-	37996.13 (38105.49) [0, 164309.6]
59	Bare land area	Area of bare land in square meters per person	European Space Agency https://www.esa-landcover-cci.org	-	$5.58X10^{-6}$ ($6.84X10^{-5}$) [0, 0.002]
60	Normalized difference vegetation index (NDVI)	NDVI as a measure of the greenness of the vegetation (taking a value between 0 and 1)	Copernicus Global Land Service (https://land.copernicus.eu/global/products/ndvi)	~ 1000m	0.633 (0.095) [0.003, 0.936]
61	Soil organic carbon density	Soil organic carbon density in gram per cubic decimeter	International Soil Reference and Information Center	~ 250m	183.967 (67.843) [69.696, 540.031]

62	Soil absolute depth to bedrock	Soil absolute depth to bedrock in centimeter	(https://www.isric.org/explore/soilgrids)		6016.195 (2004.937) [2527.371, 14288.84]
63	Terrain slope*	Terrain slope in degrees	EathEnv (https://www.earthenv.org/topography)	-	0.859 (0.955) [0, 15.040]
65	Surface water seasonality	Average number of months water was present from 1984 to 2018	Global surface Water explorer: Pekel et al. (2016) (https://global-surface-water.appspot.com/)	-	0.647 (1.386) [0, 11.983]
66	Night-time light radiance	Average night-time light radiance data using nighttime data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB)	National Centers for Environmental Information (NCEI) (https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html)	-	0.979 (3.249) [0, 62.591]
67	Dependency ratio*	The ratio between the number of dependents (children younger than 14 and elder older than 64) and adults	WorldPop (https://www.worldpop.org/geodata/listing?id=23)	~ 1000m	69.852 (7.643) [49.614, 82.000]
68	Human development index (HDI)	An index based on a geometric mean of income, education and health variables	Kummu et al. 2018	-	0.580 (0.006) [0.557, 0.667]
69	Livestock density	Number of livestock (cattle, horse, sheep, goat, chicken, duck, and pick) in tropical livestock units per person	FAO (http://www.fao.org/livestock-systems/en/)	~ 10000m	14.813 (12.700) [0, 222.342]
70	Poverty incidence	The likelihood to be in poverty as defined by $2.50 a day poverty line	WorldPop (https://www.worldpop.org/geodata/listing?id=23)	~ 1000m	76.934 (4.977) [14.783, 169.192]
71	Rainfall erosion*	Soil loss due to rainfall in Universal soil loss equation R-factor	European Soil Data Center (https://esdac.jrc.ec.europa.eu/content/global-rainfall-erosivity)	-	9315.468 (1136.229) [4097.62, 12500.12]
72	Perception on immigrants	The interpolated mean opinion on the impact of immigrants on development of Bangladesh, measured with a five scale Likert (1=very bad, …, 5=very good)	World Value Survey (WVS)	-	3.182 (0.502) [2.316, 4.6]
73	Population density	Number of people per square kilometer	Gridded Population of the World (GPW), v4 (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11)	-	6247.114 (42050.91) [42.254, 1838741]

74	Police center	Number of policy centers percapita	Open street map	-	4.23X10^{-6} (3.72X10^{-5}) [0, 0.001]
75	Distance to police center	Distance to the nearest police center		-	8402.651 (7274.453) [0, 53702.62]
76	Prison	Number of prisons percapita		-	2.00X10^{-6} (5.74X10^{-5}) [0, 0.003]
77	Distance to prison	Distance to the nearest prison		-	23670.24 (15633.87) [0, 98965.42]
78	Trust	Interpolated proportion of people trusting local institutions	World Value Survey	-	0.125 (0.099) [0, 0.500]
79	Feeling secured	Interpolated average score for feeling secured (1=Not at all secure, 2=Not very secured, 3=Quite secured, 4=very secured		-	3.144 (0.267) [2, 3.7]
80	Voting	Predicted proportion of people participated in the last election		-	0.920 (0.136) [0, 1]
81	Bribe experience	Predicted average frequency of experiencing bribe with local officials (1=never, 2=rarely, 3=frequently, 4=always)		-	2.628 (0.478) [1.571, 3.8]
82	Battle	Number of battles	Armed Conflict Location and Event Data Project (ACLED) (https://www.acleddata.com/)	-	.261 (1.448) [0, 32]
83	Battle fatalities	Number of fatalities per battle		-	.063 (.504) [0, 28]
84	Remote violence	Number of remote violences		-	.034 (.339) [0,12]
85	Remote violence fatalities	Number of remote violence		-	.036 (.537) [0, 28]
86	Riot and violence against civilians (VAC)	Number of riot and VAC		-	1.479 (9.734) [0, 315]
87	Riot fatalities	Riot fatalities per riot		-	.068 (.314) [0, 8]
88	VAC fatalities	VAC fatalities per VAC		-	.079 (.264) [0, 2]
89	Flood	Number of flood events between 2001 and 2019	Dartmouth Flood Observatory (Global active archive of large flood events) (https://data.humdata.org/dataset/global-active-archive-of-large-flood-events)	-	13.726 (5.072) [0, 25]
90	Flood fatalities	Number of deaths per flood event			542.725 (302.125) [0, 3447]
91	Flood displacement	Number of displaced people per flood event			5755728 (1889503)

					[0, 2.01X10^{+7})
92	Flood severity	The average severity of flood events where severity class taking three values (1, 1.5. and 2)			1.363 (0.079) [0, 1.75]
93	Flood duration	Number of flood days per flood event			38.523 (7.889) [0, 60.571]
94	Drought prevalence*	Number of drought event based on Standardized Precipitation and Evapotranspiration Index per year from 2001 to 2015	Global drought monitor (https://spei.csic.es/map/maps.html#months=1#month=7#year=2019)	~ 55000m	.117 0.039 [0.061, 0.172]
95	Cyclone	Number of cyclones between 2001 and 2015	https://preview.grid.unep.ch/index.php?	-	.739 (1.430) [0, 16]
96	Cyclone category	Average number of cyclone category, where the category is defined in increasing intensity		-	0.031 (0.162) [0, 2]
97	Cyclone speed	Sum of average cyclone speed		-	963.797 1936.323 [0, 22491]
98	Fires	Number of fires	Artés et al. 2019. (https://www.nature.com/articles/s41597-019-0312-2)	-	.984 13.641 [0, 634]
99	Fire duration	Duration of fires in days per fire event		-	.256 (1.365) [0, 22]
100	Perceptibility to sea level rise	The product of elevation in meters and distance from coast.	EathEnv (https://www.earthenv.org/topography) and natural earth (https://www.naturalearthdata.com/downloads/110m-physical-vectors/110m-coastline/)	-	2383473 (4113870) [0, 3.94X10^{+7}]

SM2: Cross Tabulation of the number of unions by tercile categories of weighted and unweighted resettlement capacity indices (note: values in parenthesis and closed brackets are row and column percentage respectively)

		Weighted overall RCI				
		Tercile 1	Tercile 3	Tercile 3	Total	
Unweighted overall RCI	Tercile 1	1710 (99.42) [99.42]	10 (0.58) [0.58]	0 (0) [0]	1720 (100) [33.35]	Pearson Chi2=10000*** Cramer's V=0.9861
	Tercile 2	10 (0.58) [0.58]	1699 (98.84) [98.84]	10 (0.58) [0.58]	1719 (100) [33.33]	
	Tercile 3	0 (0) [0]	10 (0.58) [0.58]	1709 (99.42) [99.42]	1719 (100) [33.33]	
	Total	1720 (33.35) [100]	1719 (33.33) [100]	1719 (33.33) [100]	5158 (100) [100]	
	Unweighted asset RCI					
		Tercile 1	Tercile 2	Tercile 3	Total	
Unweighted asset RCI	Tercile 1	1705 (99.13) [99.13]	15 (0.87) [0.87]	0 (0) [0]	1720 (100) [33.35]	Pearson Chi2=9900*** Cramer's V=0.9814
	Tercile 2	15 (0.87) [0.87]	1687 (98.14) [98.14]	17 (0.99) [0.99]	1719 (100) [33.33]	
	Tercile 3	0 (0) [0]	17 (0.99) [0.99]	1702 (99.01) [99.01]	1719 (100) [33.33]	
	Total	1720 (33.35) [100]	1719 (33.33) [100]	1719 (33.33) [100]	5158 (100) [100]	
		Unweighted condition RCI				
		Tercile 1	Tercile 3	Tercile 3	Total	
Unweighted asset RCI	Tercile 1	1695 (98.55) [98.55]	25 (1.45) [1.45]	0 (0) [0]	1720 (100) [33.35]	Pearson Chi2=9900*** Cramer's V=0.9791
	Tercile 2	25 (1.45) [1.45]	1683 (97.91) [97.91]	11 (0.64) [0.64]	1719 (100) [33.33]	
	Tercile 3	0 (0) [0]	11 (0.64) [0.64]	1708 (99.36) [99.36]	1719 (100) [33.33]	
	Total	1720 (33.35) [100]	1719 (33.33) [100]	1719 (33.33) [100]	5158 (100) [100]	

Note: ***,**, and * denotes level of significance at 1, 5 and 10 percent level

SM3: Sub-dimension, Asset, Condition and Overall resettlement capacity scores of bottom and top 10 unions; values in parentheses in row 11 and 22 are standard deviation of the mean

Rank	Union name	Region name	Asset						Condition							Overall RCI
			Natural	Financial	Human	Physical	Social	Oveall	Access	Quality	Context	Institutional strength	Peaceful condition	Stable natural condition	Overall	
1	Sonadia	Chittagong	0.136	0.235	0.000	0.154	0.141	0.133	0.285	0.278	0.302	0.129	0.905	0.394	0.382	0.039
2	Burir Char	Chittagong	0.135	0.224	0.000	0.154	0.141	0.131	0.279	0.286	0.327	0.121	0.905	0.417	0.389	0.047
3	Char Ishwar	Chittagong	0.111	0.255	0.000	0.200	0.141	0.141	0.306	0.285	0.323	0.169	0.905	0.393	0.397	0.064
4	Jahajmara	Chittagong	0.116	0.244	0.000	0.121	0.141	0.124	0.288	0.295	0.202	0.127	0.905	0.667	0.414	0.074
5	Char Montaz	Barisal	0.128	0.308	0.000	0.077	0.238	0.150	0.469	0.296	0.239	0.316	0.948	0.141	0.401	0.076
6	Hatiya Paurashava	Chittagong	0.118	0.385	0.000	0.211	0.141	0.171	0.376	0.295	0.320	0.184	0.759	0.435	0.395	0.082
7	Mujib Nagar	Barisal	0.105	0.297	0.000	0.148	0.244	0.159	0.562	0.284	0.236	0.393	0.948	0.000	0.404	0.085
8	Bara Thakuri	Sylhet	0.086	0.001	0.000	0.081	0.572	0.148	0.366	0.275	0.155	0.204	0.948	0.522	0.412	0.088
9	Nalchira	Chittagong	0.057	0.404	0.000	0.249	0.141	0.170	0.360	0.326	0.328	0.191	0.759	0.435	0.400	0.088
10	Tamaruddin	Chittagong	0.158	0.236	0.000	0.200	0.141	0.147	0.361	0.340	0.319	0.176	0.905	0.394	0.416	0.092
Mean for the bottom 10			0.115 (0.028)	0.259 (0.111)	0.000 (0.000)	0.159 (0.057)	0.204 (0.136)	0.148 (0.016)	0.365 (0.090)	0.296 (0.021)	0.275 (0.063)	0.201 (0.088)	0.889 (0.071)	0.380 (0.186)	0.401 (0.011)	0.074 (0.018)
5149	Chalna Paurashava	Khulna	0.349	0.420	0.000	0.488	0.807	0.413	0.698	0.258	0.711	0.629	0.948	0.633	0.646	0.582
5150	Ward No-30 (Part)	Chittagong	0.184	0.448	0.637	0.735	0.440	0.489	0.820	0.171	0.632	0.706	0.948	0.377	0.609	0.588
5151	Paurashava	Rangpur	0.383	0.772	0.043	0.405	0.729	0.466	0.701	0.291	0.612	0.672	0.948	0.505	0.621	0.588
5152	Sreemangal Paurashava	Sylhet	0.513	0.696	0.601	0.789	0.741	0.668	0.680	0.220	0.109	0.572	0.948	0.545	0.512	0.589
5153	Sundarban	Khulna	0.783	0.414	0.308	0.259	0.374	0.428	0.721	0.443	0.623	0.540	0.948	0.645	0.653	0.602
5154	Mongla Port Paurashava	Khulna	0.524	0.775	0.267	0.529	0.305	0.480	0.735	0.234	0.616	0.633	0.948	0.640	0.634	0.614
5155	Ward No-36 (Part)	Chittagong	0.355	0.408	0.588	0.826	0.285	0.492	0.820	0.195	0.859	0.608	0.948	0.379	0.635	0.624
5156	Mithakhali	Khulna	0.587	0.437	0.703	0.240	0.294	0.452	0.731	0.478	0.642	0.554	0.948	0.640	0.665	0.635
5157	Ward No-31	Chittagong	0.221	0.673	0.660	0.423	0.493	0.494	0.825	0.262	0.816	0.694	0.948	0.377	0.654	0.650
5158	Ward No-32	Chittagong	0.128	0.742	0.274	0.540	0.706	0.478	0.819	0.195	0.846	0.826	0.948	0.552	0.698	0.696
Mean for the top 10			0.403 (0.202)	0.579 (0.165)	0.408 (0.262)	0.523 (0.206)	0.517 (0.208)	0.486 (0.070)	0.755 (0.059)	0.275 (0.104)	0.646 (0.213)	0.643 (0.086)	0.948 (0.000)	0.529 (0.115)	0.633 (0.049)	0.617 (0.036)
Ratio of the top to bottom 10 mean			3.5	2.2		3.3	2.5	3.3	2.1	0.9	2.3	3.2	1.1	1.4	1.6	8.4

SM4: Determination of Optimal Cluster Model

		LL	*BIC(LL)*	*AIC(LL)*	*AIC3(LL)*	*Npar*	*Max. BVR*	*Class.Err.*	*Entropy R^2*
Model1	1-Cluster	-7748.453	15514.002	15500.906	15502.906	2.000	287.474	0.000	1.000
Model2	2-Cluster	-6409.091	12963.502	12852.181	12869.181	17.000	0.000	0.029	0.385
Model3	3-Cluster	-6287.601	12797.458	12627.202	12653.202	26.000	0.000	0.134	0.579
Model4	4-Cluster	-6231.486	12762.162	12532.972	12567.972	35.000	0.000	0.125	0.652
Model5	5-Cluster	-6200.500	12777.125	12489.000	12533.000	44.000	0.000	0.222	0.579
Model6	6-Cluster	-6187.315	12827.690	12480.630	12533.630	53.000	0.000	0.287	0.521
Model7	7-Cluster	-6189.825	12909.646	12503.651	12565.651	62.000	0.000	0.369	0.478
Model8	8-Cluster	-6175.273	12957.476	12492.546	12563.546	71.000	0.000	0.203	0.683
Model9	9-Cluster	-6164.339	13012.542	12488.678	12568.678	80.000	0.000	0.258	0.631
Model10	10-Cluster	-6160.903	13082.605	12499.806	12588.806	89.000	0.000	0.385	0.518
Model11	11-Cluster	-6145.498	13128.730	12486.996	12584.996	98.000	0.000	0.254	0.686
Model12	12-Cluster	-6155.355	13225.379	12524.710	12631.710	107.000	0.000	0.361	0.581
Model13	13-Cluster	-6153.804	13299.210	12539.607	12655.607	116.000	0.004	0.407	0.525
Model14	14-Cluster	-6147.312	13363.163	12544.625	12669.625	125.000	0.002	0.354	0.587
Model15	15-Cluster	-6157.916	13461.305	12583.832	12717.832	134.000	0.000	0.391	0.517

Notes: the optimal model is highlighted in green

SM5: Significance test for the mean difference between resettlement capacity clusters using ANOVA

		ANOVA (F(11,5157))
Asset subdimensions	Natural	166.53***
	Financial	314.82***
	Human	1108.74***
	Physical	597.90***
	Social	351.21***
	Oveall	1451.67 ***
Condition Subdimensions	Access	142.02***
	Quality	53.43***
	Context	331.61***
	Institutional strength	174.57***
	Peaceful condition	8.60***
	Stable natural condition	510.27***
	Overall	902.56***
Overall resettlement capacity index		2078.39***

Note: *** denotes level of significance at 1 percent level

SM6: Sub-dimension, dimension, and overall resettlement capacity scores by cluster (Values in parenthesis are standard deviations; values in closed brackets are the ratio between the cluster score to the average score)

		1	2	3	4	Total
Asset subdimensions	Natural asset	0.115 (0.059) [0.91]	0.139 (0.064) [1.10]	0.133 (0.057) [1.05]	0.265 (0.176) [2.09]	0.127 (0.067)
	Financial asset	0.359 (0.101) [1.10]	0.269 (0.117) [0.83]	0.289 (0.101) [0.89]	0.478 (0.143) [1.47]	0.325 (0.117)
	Human CI	0.021 (0.041) [0.93]	0.014 (0.025) [0.64]	0.015 (0.024) [0.66]	0.319 (0.232) [14.46]	0.022 (0.057)
	Physical CI	0.219 (0.031) [1.05]	0.195 (0.033) [0.93]	0.176 (0.049) [0.84]	0.346 (0.146) [1.66]	0.209 (0.044)
	Social asset	0.408 (0.134) [1.13]	0.318 (0.137) [0.88]	0.231 (0.112) [0.64]	0.443 (0.176) [1.22]	0.362 (0.146)
	Asset RCI	0.224 (0.031) [1.07]	0.187 (0.027) [0.90]	0.169 (0.032) [0.81]	0.370 (0.071) [1.77]	0.209 (0.042)
Condition Subdimensions	Access to assets	0.707 (0.070) [1.02]	0.666 (0.071) [0.96]	0.666 (0.108) [0.96]	0.752 (0.057)] [1.09]	0.690 (0.078)
	Quality of assets	0.327 (0.077) [1.02]	0.321 (0.075) [1.00]	0.282 (0.078) [0.88]	0.288 (0.074)] [0.90]	0.320 (0.078)
	Contexts	0.439 (0.124) [1.13]	0.325 (0.166) [0.84]	0.282 (0.152) [0.73]	0.485 (0.204) [1.25]	0.387 (0.156)
	Institutional strength	0.456 (0.098) [1.05]	0.401 (0.096) [0.93]	0.385 (0.126) [0.89]	0.542 (0.093) [1.25]	0.432 (0.105)
	Peaceful conditions	0.929 (0.064) [1.00]	0.920 (0.070) [0.99]	0.918 (0.094) [0.99]	0.939 (0.042) [1.01]	0.925 (0.070)
	Stable natural conditions	0.567 (0.069) [1.05]	0.529 (0.091) [0.98]	0.404 (0.150) [0.75]	0.540 (0.089) [1.00]	0.538 (0.100)
	Condition RCI	0.571 (0.039) [1.04]	0.527 (0.041) [0.96]	0.489 (0.033) [0.89]	0.591 (0.050) [1.08]	0.549 (0.048)
Overall RCI		0.350 (0.050) [1.13]	0.266 (0.050) [0.86]	0.204 (0.047) [0.66]	0.480 (0.078) [1.55]	0.310 (0.074)

Note: CI stands for capital infrastructure; RCI stands for resettlement capacity index

Extreme climate events have been on the rise in both their frequency and intensity, displacing millions of people in vulnerable countries worldwide in recent years. This calls for prioritizing resettlement plans in adaptation frameworks and strategies in these countries. Toward this end, this article provides a methodological and empirical contribution in resettlement capacity assessment for climate change adaptation. It examines the effect of using weights while constructing composite resettlement capacity indices and empirically assesses the resettlement capacity of locations in Bangladesh using one hundred indicators from thirty-one data sources. We categorize the indicators into two main dimensions: assets, being inputs available for a viable livelihood; and conditions, or factors that constrain or promote the use of these assets. These are further divided into five asset and six condition subdimensions. We create both weighted and unweighted overall-, dimension-, and subdimension-specific resettlement capacity indices using an additive hierarchical index construction approach, whereby the weights are derived from expert assessment of the relevance of the dimensions and subdimensions. We then employ latent cluster analysis to identify clusters with similar capacity profiles. We find that although the distribution and mean values of the weighted and the unweighted resettlement capacity indices differ, they tend to highly correlate and have similar distributional patterns, leading to comparable conclusions. We identify four unique resettlement capacity clusters that are distinct in asset, condition, and subdimension resettlement capacity scores. These clusters exhibit a clear spatial pattern throughout Bangladesh, with the northern, western, and central (southern and eastern) areas characterized by higher (lower) resettlement capacity clusters. These findings provide important policy implications with respect to climate change-related displacement.

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