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Abstract

Climate change migration is increasing and necessitates a re-examination of resettlement planning and processes. Although evidence-based selection of host places would improve climate change resettlement outcomes, few methods for the selection of host communities exist. Consequently, the information base on which most resettlement programs select a host place is inadequate. This article proposes an empirical methodology to assess resettlement capacity. The methodology uses a hierarchical aggregation approach, where resettlement capacity indicator values are aggregated first into sub-dimension resettlement capacity scores, then further into dimension resettlement capacity scores, and finally into an overall resettlement capacity index. The aggregation allows for calculation of the relative importance of the different sub-dimensions and the two primary dimensions – assets and conditions. Using 75 indicators and a hierarchical min-max additive approach based on a five-kilometer grid, we create an overall resettlement capacity index for Ethiopia. The results show significant spatial variation in resettlement capacity. Low resettlement capacity sites tend to cluster in southeastern and western Ethiopia, while high resettlement capacity sites are scattered in central, southern, and northern Ethiopia. Moderate resettlement capacity sites occur more generally all over Ethiopia. Compared to the low and moderate resettlement capacity sites, those with high resettlement capacity are endowed with human, physical, and financial capital infrastructures. In all three groups, assets contribute significantly less to resettlement capacity than conditions. Places in the western and northern tips of the country are prone to natural hazards both currently and in the future, making part of the moderate resettlement capacity cluster in the northern tip unsuitable for resettlement. The calculated resettlement capacity indices are robust to potential missing indicators and change in units of analysis. Enhancing resettlement capacity in the future to accommodate predictable climate change displacements should target sub-dimensions that are weak in the high-capacity areas, promoting places with moderate-to-high resettlement capacity through enhancing the asset base especially, and avoiding resettlement in conflict- and disaster-prone places.

Key words: displacement, resettlement, migration, climate change, livelihood, Ethiopia, subnational

JEL classification: Q48

1 Introduction

Population displacements – temporary or permanent – will increasingly become an ex-ante response or ex-post coping strategy for mitigating hazards and stressors related to climate change (Black et al. 2011; Gemenne and Blocher 2017; Mueller et al. 2014; McLeman 2011). In 2018, for example, weather-related events such as storms, floods, and droughts displaced more than 16 million people (IDMC 2019) while predictions show that as many as hundreds of millions of people may be displaced from their homes either temporarily or permanently over the coming decades (Barnett and Webber 2010; Rigaud et al. 2018). Many of the displaced cannot or do not want to return to their former locations and often end up in another at least equally vulnerable place (Black et al. 2011; Foresight 2011).

To avoid ad hoc resettlement and poor outcomes for the migrants, planned resettlement of populations exposed to climate-related hazards is increasingly recognized as an important adaptation strategy and the global community has advised highly vulnerable countries to incorporate internal resettlement in their climate change options (Arnall 2019; López-Carr and Marter-Kenyon 2015). For such resettlement plans, subnational assessments of the resettlement capacity of potential destination places are crucial (Bukvic 2018; Wilmsen and Webber 2015; Sipe and Vella 2014). Few studies, however, have thus far attempted to provide comprehensive subnational assessments of potential destination places (Findlay et al. 2011; Bukvic 2018; Adugna 2011). Consequently, resettlement programs often increase vulnerability among the resettled and expose them to increased risk of impoverishment (Arnall 2019; Connell and Lutkehaus 2017; Rogers and Xue 2015).

To promote research on and use of subnational resettlement capacity assessments, this article proposes an empirical methodology that operationalizes the climate change resettlement capacity (CCRC) framework developed by Walelign and Lujala (2020). The approach is applied to assess resettlement capacity in Ethiopia – a country highly vulnerable to climate change and with several unsuccessful resettlement programs. Using 75 indicators and a five-kilometer grid that span the whole of Ethiopia, we employ a hierarchical min-max additive approach to create a resettlement capacity index and assign a resettlement capacity score for each grid cell. Based on the scores, we identify cells with low, medium, and high resettlement capacity, and map these to study their spatial patterns. We then characterize – in terms of sub-dimension resettlement capacity scores – three categories: high, medium, and low resettlement capacities. We consider separately two sub-dimensions – conflicts or natural hazards – to identify places that are not suitable for resettlement even if they scored high on the other sub-dimensions.

This study makes four key contributions. First, it proposes an empirical methodology that can be applied to different contexts and spatial scales, allowing for identification and understanding of places with different resettlement capacities. In this way, the article guides further research on how to assess resettlement capacity and how to identify potential destination places for climate migrants. Second, the approach allows the accumulation of data to speak for itself as a resettlement capacity assessment, providing an objective selection of destination places. Third, the proposed approach allows for screening of the relative weaknesses of the high resettlement capacity places identified, so that these can be strengthened further through resource allocation and infrastructural investment to enhance resettlement capacity. Fourth, the study provides the first comprehensive subnational resettlement capacity assessment of potential destination places for a climate-exposed developing country. The article identifies places in Ethiopia with high resettlement capacity and their characteristics. These results can help the Ethiopian national and local government agencies as well as national and international organizations in planning for future internal migration in anticipation of climate-related hazards or when the hazards occur. It can even be used by vulnerable communities seeking to choose destination places with higher resettlement potential. The article also identifies places in which moderate can be transformed into high resettlement capacity.

2 Assessing resettlement capacity

Four findings stand out when we review previous studies of resettlement. First, several factors are crucial in successful resettlement: these include household assets, skills and expertise, and livelihood sources (Sina et al. 2019a; 2019b; Arnall et al. 2013). Second, the engagement of the affected communities and respect for basic human rights bring a vital social energy to the planning and implementation of resettlement programs (Sipe and Vella 2014; Correa et al. 2011; Brookings et al. 2015; UNHCR 2018). Third, most resettlement programs have failed to restore or improve the livelihoods of resettled people and communities (Arnall 2019; Connell and Lutkehaus 2017; Rogers and Xue 2015). Fourth, good and diverse livelihood opportunities in the resettlement location thus become key to the success of resettlement programs (Bukvic 2018, Vlaeminck et al. 2016). The last point underscores the need to conduct assessments that identify places with a high capacity for resettlement.

Few empirical studies have assessed subnational resettlement capacity in order to identify potential destination places in developing countries, and most of these base the assessment on a limited number of factors. Adugna (2011), who examined the suitability of Ethiopian districts for irrigation-based resettlement, mainly emphasized the availability of river water, terrain characteristics, and the relative density of population and roads. An assessment by Xiao et al. (2018), of the livelihood reconstruction potential of a county in China after people had been resettled there, was based on a few sets of indicators focused on financial and physical assets. In a more comprehensive study, Rigaud et al. (2018) modelled the hotspots for internal in- and out-migration in East Africa (with a focus on Ethiopia), South Asia (with a focus on Bangladesh), and Central America (with a focus on Mexico), using demographic, socio-economic, and climate data. Similarly, Hermans-Neumann et al. (2017), in a study on hotspots for in- and out-migration in Ethiopian districts, emphasized natural resources, rainfall trends, and a few other indicators.

The fact that these studies overlook many relevant indicators (e.g., conflicts and violence, availability of natural resources, disease outbreak, physical and human capital infrastructures, soil quality) in their assessments greatly diminishes their policy relevance for resettlement policy making. Even worse, the resulting assessments may lead to the resettling of people in places with low capacity as a result of overlooked indicators (for instance, high incidence of conflict or natural hazards).

To ensure that the most relevant factors influencing resettlement capacity are identified, this article proposes an empirical methodology based on the climate change resettlement capacity (CCRC) framework developed by Walelign and Lujala (2020). The CCRC framework includes two broad dimensions: *assets* include the available inputs for a viable livelihood; while *conditions* include factors that promote or constrain the successful translation of assets into livelihood outcomes such as food or income (see Walelign and Lujala 2020 for detailed explanation of assets, conditions, and their components). Both asset and condition dimensions are further divided into sub-dimensions to cover the different components more precisely (Figure 1). For each sub-dimension, the framework presents as exhaustive a list of generic indicators as possible, and proposes a set of specific measurable indicators for each of these, identified from the literature on sustainable livelihoods (e.g., Scoones 2015) and resettlement impoverishment risks and reconstruction (e.g., Cernea 2000), and from protocols and guidelines on planning and implementing resettlement programs (e.g., Brookings et al. 2015;

Correa 2011). The empirical methodology and the accompanying assessment presented in this article follows the hierarchical nature of the CCRC framework to construct resettlement capacity indices for Ethiopia. We first create sub-dimension resettlement capacity scores based on the indicators for each sub-dimension. Then we aggregate the sub-dimension indices into asset and conditions dimension indices, which in turn are aggregated into the overall resettlement capacity index.

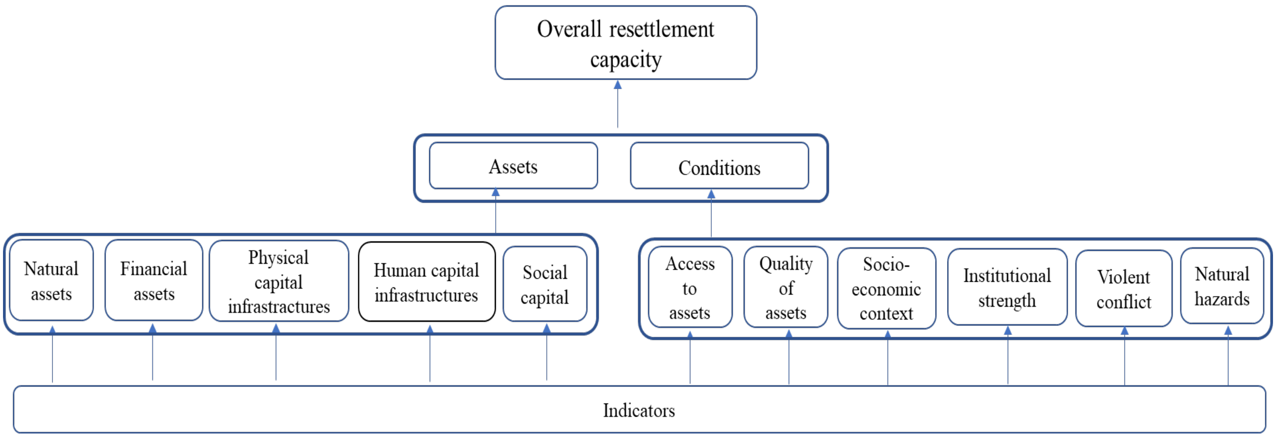

Figure 1: Analytical framework to construct a resettlement capacity index for Ethiopia

3 Climate change vulnerability and resettlement in Ethiopia

Ethiopia is among the countries most vulnerable to the adverse impacts of climate change (Cochrane and Singh 2016; Gashaw et al. 2014; Conway and Schipper 2011). Drought has become an annual event in Ethiopia, with the worst drought in 60 years occurring in 2011 (Nicholson 2016). Seventy percent of the country is covered by drylands with a 40% annual probability of moderate to severe drought (Singh et al. 2016). Smallholder farmers living on drylands often rely on rainfed agriculture characterized by low productivity, and are hence highly sensitive to climate change (Shumetie and Alemayehu 2017; UNDP 2012; Bezu et al. 2012; Gebrehiwot and van der Veen 2014). Rivers provide more favorable conditions for crop- and livestock-based livelihoods, but expose the adjacent areas to recurrent floods due to intense precipitation during extreme weather events (Haile et al. 2013; USAID 2012). Climate predictions show an increase in mean annual temperature and frequency of hot days and nights, and indicate that the proportion of total rainfall that falls during extreme events may increase by 18 percent annually (USAID, 2016). These changes in temperature and rainfall will increase the frequency of droughts and floods in Ethiopia (Teshome and Zhang 2019).

Recurrent droughts and floods have had a continuing impact on the livelihoods of tens of millions of smallholders in Ethiopia (Deressa and Hassan, 2009; Di Falco et al., 2011; Megersa et al., 2014). The affected people attempt to adapt to weather-related hazards, but poverty and the incidence of multiple stressors have reduced their ability to adapt to changing conditions and recover from weather shocks (Deressa et al., 2009; Di Falco et al., 2011). Some of the short-term adaptation strategies to such shocks, such as cutting household meals and pulling children out of school, can entail a huge cost through compromising household futures as these decision often have long-term negative consequences for income, education levels, health, and adaptive capacity to withstand future shocks.

The Ethiopian government and the international community provide social safety nets (such as cash transfers) and food assistance to the victims of weather, and support in-situ adaptation strategies and rehabilitation programs to increase livelihood resilience, particularly in drought-prone areas (Cochrane and Singh, 2017; Singh et al. 2016; Woolf et al. 2018; IDA, 1974). These in-situ efforts, however, have in some places been inadequate due to the increase in the frequency and intensity of droughts and floods that result in substantial losses in agricultural production, human lives, and infrastructure (Teshome and Zhang 2019). As a result, migration of whole households or individual household members is increasingly becoming an important adaptation strategy as an ex-ante risk management or an ex-post coping strategy (Ezra and Kiros 2001; Gray and Mueller 2012; Morrisey 2013, Hermans-Neumann et al. 2017).

Since the 1970s, the Ethiopian government has implemented several resettlement programs to resettle people from areas most exposed to adverse climate (Rahmato 2003). The first large-scale resettlement program, which came into effect in response to the 1972-73 famine, resettled over 110,000 people from the northern parts of the country to the western and southwestern parts (Figure 2) (Woube 1995). The largest resettlement program in Ethiopian history took place between 1984 and 1991 as a response to the 1984 drought that caused widespread famine, particularly in northern Ethiopia, and claimed the lives of about one million people[1] (Ezra 2001; Porter 1986; Kloos 1990). As part of the program's long-distance resettlement component, 800,000 people were relocated from the northern to southwestern parts of Ethiopia. In addition,

[1] The number of deaths reported varies, but most documents estimate about one million deaths.

the program relocated 5.7 million people to 11,000 newly established villages within a short distance of their former homes as part of its villagization component (Steingraber 1987).

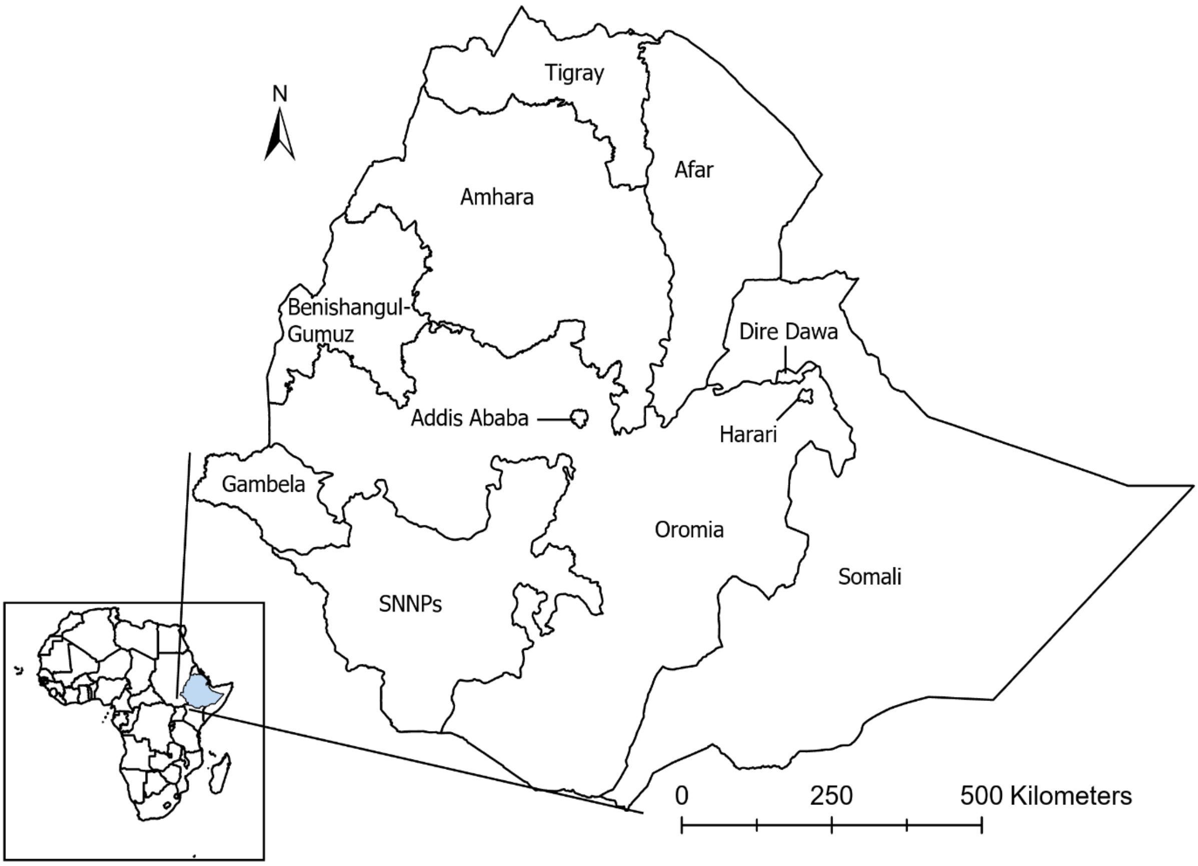

Figure 2: Regions in Ethiopia. Note: SNNPs stands for Southern Nations, Nationalities, and Peoples'.

The need for resettlement was acknowledged in the 1995 constitution, which explains that the "state shall ensure that human settlement patterns correspond to the distribution of natural resources to create favorable conditions for development" (Article 10(2)) and the "state shall encourage the scattered rural population to form consolidated communities in order to free rural life from backwardness and enable the people to attain a better social life" (Article 10(3)) (FDRE, 1995, p. 19). Consequently, the government developed a new resettlement plan in 2002, as part of the food security strategy that was a quick response to a drought that had affected the lowlands in the Southern Nations, Nationalities, and Peoples' (SNNPs'), Tigray, Oromia, and Amhara regions (Wayessa and Nygren 2016; Hammond 2008). The plan envisioned resettling about 2.2 million of the affected people to places with fertile soil and abundant rainfall within each region. The program was implemented in 2003 and about half of the targeted people had been resettled by 2007 (Hammond 2008). Resettlement within each region (intraregional resettlement) was included as one principle to avoid potential conflicts arising from interregional resettlement due to ethnic and linguistic differences between regions (FSP 2003).

Most of the resettlement programs implemented in Ethiopia have been characterized by a poor selection of resettlement sites.[2] Often selection has been based on very short reconnaissance visits by a government official, without conducting detailed feasibility assessments on the suitability of the selected sites or learning from resettlement experiences in Ethiopia and other countries (Kloos 1990, Rahmato 2003). Other shortcomings – such as a shortage of logistic resources for implementing the resettlement plans and improving public services at scheduled destinations, security concerns due to ongoing armed conflicts, a top-down approach in planning and implementation, and inadequate incentives and compensations for the resettled people – have characterized these programs (Kloos 1990; Porter 1986). Consequently, they have generally failed to rebuild or improve the livelihoods of the resettled people, introduced new social and economic tensions at destination arising from conflicts over land, caused environmental degradation, and affected adversely the welfare of resettled people (Kloos 1990; Hammond 2008; HRW 2012; Abbink 2012).

Currently, Ethiopia has about three million internally displaced persons, primarily victims of violent conflicts and weather-related disasters (IDMC and NRC, 2019; IOM 2019). Some cannot (or do not want to) return to their former homes (IOM 2019) and thus need to be resettled. This need will most likely increase further in the coming decades due to climate change and development projects. Anticipating this, the 2017 national resettlement policy framework (FDRE, 2017) has been developed. The framework seeks to create relocation sites similar to original sites with respect to opportunities to support pervious livelihood activities, although the relocation sites should also allow for new livelihood opportunities. Selection of suitable places for resettlement thus requires rigorous assessments that account for a spectrum of livelihood elements – a major objective of the current paper.

[2]In addition to the three large-scale resettlement programs outlined above, several smaller ones have resettled a substantial number of people in Ethiopia (Abbink 2012, HRW 2012; Woube 1995).

4 Data and methods

4.1 Data

We used the CCRC framework (Walelign and Lujala 2020) as the basis on which to select the resettlement indicators, while ensuring that the selected indicators were relevant to the Ethiopian context. Although data availability and coverage were an issue, we were able to collect data for all 11 sub-dimensions. In total, the dataset has 107 preliminary indicators (see SM1, Supplementary Materials, for a list). For indicators that measure prevalence (of flood, for example, or conflict), we used longitudinal data starting from the year 2000. Some indicators (e.g., number of universities, number of conflicts) include values from the neighboring cells as the availability of infrastructures or occurrence of the events has implications for the neighboring cells as well. Most indicators are normalized using population size to maintain comparability.

In total, we used 24 different data sources, including (i) surveys from the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA), Afrobarometer, and Demographic and Health Surveys (DHS); (ii) datasets from national institutions in Ethiopia and other countries (NASA, British Geological Survey (BGS), European Space Agency (ESA)), and (iii) datasets produced by individual projects and studies (e.g., GloBio; Malaria Atlas, Falchetta et al. 2019) (see SM2, Supplementary Materials for a list of data sources and summary statistics for the 75 indicators included in the final assessment). As the data came in different formats and resolutions, comprehensive data processing was required prior to analysis (see Appendix A for details).

The unit of analysis is a 5km grid cell (resulting in 46,006 cells, about three times the number of villages – the lowest administrative unit – in Ethiopia) using the Adindan 37N projection system (Adugna 2011), to which all datasets were (re)projected. Most of the gridded input datasets for the final indicators were available at a 5km resolution or higher (SM2, Supplementary Materials, for details).

4.2 Indicator screening and selection

The preliminary indicators had a standardized Cronbach alpha of about 0.93, exhibiting a high degree of information redundancy (Streiner 2003; Tavakol and Dennick 2011). This was because some of the indicators measure similar aspects of resettlement capacity (e.g., prevalence of giving bribes vs. corruption) and result in high correlations. Using pairwise correlations and considering conceptual relationships among the indicators, we identified indicators that were highly correlated, and either excluded or aggregated them to reduce the redundant information. This lowered the number of indicators to 75 with a standardized Cronbach alpha of about 0.87 (Table 1; see SM2, Supplementary Materials for more information on these indicators). This ensures a good internal consistency for creating the index while not compromising information redundancy (Streiner 2003; Tavakol and Dennick 2011). The final list of indicators was grouped into 10 sub-dimensions (compared to 11 sub-dimensions in the analytical framework, and in the case of preliminary indicators) as we merged the indicators for institutional strength and contexts dimensions.[3] The Cronbach alphas for the asset and condition dimensions are 0.75 and 0.87, respectively, and for each sub-dimension they range from 0.26 (human capital infrastructure) to 0.80 (access to assets).

Table 1: Inter-item correlation and Cronbach alpha by dimension and sub-dimensions

Dimension	Sub-dimension	# of indicators	Inter-item correlation	Cronbach alpha
Assets	Natural assets	10	0.07	0.42
	Financial capital	5	0.18	0.53
	Human capital infrastructure	7	0.05	0.26
	Physical capital infrastructure	9	0.13	0.54
	Social capital	5	0.18	0.53
	Overall	36	0.08	0.75
Conditions	Access to assets	9	0.30	0.80
	Quality of assets	7	0.13	0.51
	Contexts (social, economic, natural and institutional)	14	0.14	0.69
	Violent conflicts*	4	0.42	0.72
	Natural disasters*	5	0.09	0.33
	Overall	39	0.12	0.84
Overall index		75	0.08	0.87

Note: *Sub-dimensions that are reversed in constructing the dimension indices. The reversed violent conflicts and natural disasters are labelled as peaceful conditions and stable natural conditions, respectively.

4.3 Index construction

To accommodate the hierarchical nature of the analytical framework, and following Cutter et al. (2014), Cutter and Derakhshan (2020), and Scherzer et al. (2019), we use a hierarchical minimax additive index construction approach, which we implement in three steps. First, we min-max scale the indicators, sum them within each sub-dimension, and divide each sub-dimension by the number of indicators to get its average score. Second, the sub-dimension

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[3] After removal of redundant indicators, only three indicators were left for the institutional sub-dimension. All these were available only at the regional level (separately for urban and rural areas).

scores are min-max transformed and summed to get the dimension indices. Third, we sum the dimension (or all the min-max scaled sub-dimension) indices to get the overall resettlement index. Thus, the theoretical scores for the asset and condition resettlement capacity sub-indices range from 0 to 5 as we have five sub-dimensions (each ranging from 0 to 1), and for the overall resettlement capacity index ranges from 0 to 10.

The min-max scaling has two advantages. First, it allows the indicators to be comparable by suppressing the measurement unit differences across indicators through scaling the original values to be between zero and one. Second, it allows easy inference of the importance of each component through calculating the share of sub-dimension index scores to the dimension index scores and both the sub-dimension and dimension index scores to the overall index score. In the scaling, we use the following formula:

$$X_t = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X_t is the min-max transformed value of the indicator (sub-dimension index scores in step 2), X is the original value of the indicator (sub-dimension index score), X_{max} and X_{min} are the maximum and minimum values of the indicator (sub-dimension index scores), respectively. Min-max transformed values of the indicators and sub-dimensions that are hypothesized to be negatively associated with resettlement capacity were reversed (using the formula $1 - X_t$) so that all the indicators have a positive influence on the constructed resettlement capacity score (see SM2, Supplementary Materials for a list for the reversed indicators and Table 1 for the reversed sub-dimensions). The reversed violent conflicts and natural hazards sub-dimensions are, hereafter, labeled as peaceful conditions and stable natural conditions, respectively.

We use equal weights in calculating the sub-dimension, dimension, and overall resettlement capacity index scores. Equal weights have been adopted in many previous studies on resilience and vulnerability indices as there rarely is theoretical justification for weighting one component of a composite index as more important that the others (Cutter et al. 2014, Cutter and Derakhshan 2020, Scherzer et al. 2019). In addition, as the current paper aims at identifying destination places for upcoming resettlement programs, we do not have data on resettlement success, which can be used as the dependent variable to drive different weights for the different components of the index. In consequence, even though sub-dimensions like violent conflicts and natural hazards can be more important to resettlement capacity, both have equal weights as other sub-dimensions in calculating overall resettlement capacity index in the current paper. However, following the suggestion of Walelign and Lujala (2020), as a further analysis, we identify places that are currently hostile for resettlement due to violent conflict or exposure to natural hazards. Using WorldClim data with Model for Interdisciplinary Research on Climate 6 (MIROC6) and the high emission scenario (SSP585) (WorldClim 2020), we also identify places that are hostile for resettlement in the future due to changes in temperature and precipitation. We observe similar patterns using SSP585 and low emission scenario (SSP126) (results can be provided on request).

The estimated resettlement capacity scores are unitless and cannot be interpreted in absolute terms; rather they must be interpreted in comparative (relative) terms across grid cells. For interpretive reasons, we identify three resettlement capacity groups based on the distribution of the scores. Following previous literature (Cutter et al. 2014, Cutter and Derakhshan 2020, Scherzer et al. 2019), we used a cut-off value of *1.5 standard deviation from the mean* to distinguish grids with high and low resettlement capacity. Accordingly, grids with a resettlement capacity score below *-1.5 standard deviations of the mean* are in the low resettlement category, grids with a resettlement capacity score of above *+1.5 standard deviations of the mean* are in the high resettlement category, and the remaining grids fall in the medium resettlement category. The same cut-off rule was used for the overall resettlement capacity index, and for the dimension and sub-dimension indices.

5 Results

5.1 Descriptive results

Places, on average, have a resettlement capacity asset score of 1.3 and a condition score of 3.6. The distribution of the asset scores is positively skewed, with 59% of grid cells scoring below the average (Figure 3, Panel A). The distribution of the condition scores has a slight negative skew, with 52% of the grids having a score above the average (Figure 3, Panel B). On average, places in Ethiopia have an overall resettlement capacity score of 4.6 and the distribution of the scores follows normal distribution more closely (Figure 3, Panel C).

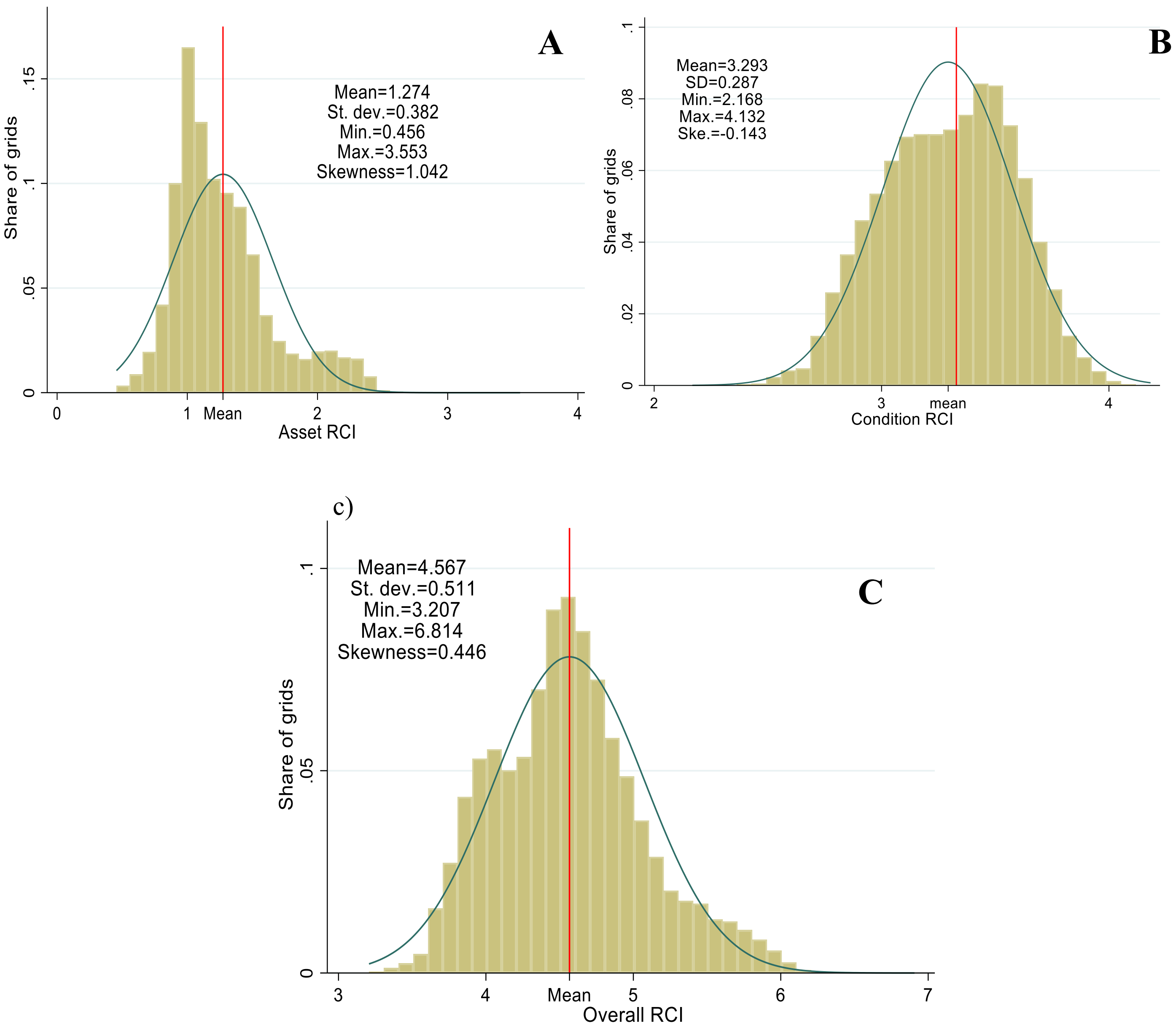

Figure 3: Distribution of asset (A), condition (B), and overall (C) resettlement capacity index scores.

5.2 Geographies of resettlement capacity

We observe clear spatial variation in asset and condition capacity scores (Figure 4, Panels A and B). Places that have a high asset index score (i.e., 1.5 standard deviation above the mean score) occur in small clusters along the international borders, particularly in northeastern, eastern and southeastern parts of Ethiopia. Northern and central parts are dominated by places with a moderate asset resettlement score, with a scattering of places having a high resettlement capacity score. Places with low asset index scores (i.e., 1.5 standard deviation below the mean score) tend to cluster in the western part of Ethiopia. Places with high scores for conditions cluster in southeastern parts of Ethiopia, while the cells with high scores cluster in south-central and southwestern parts.

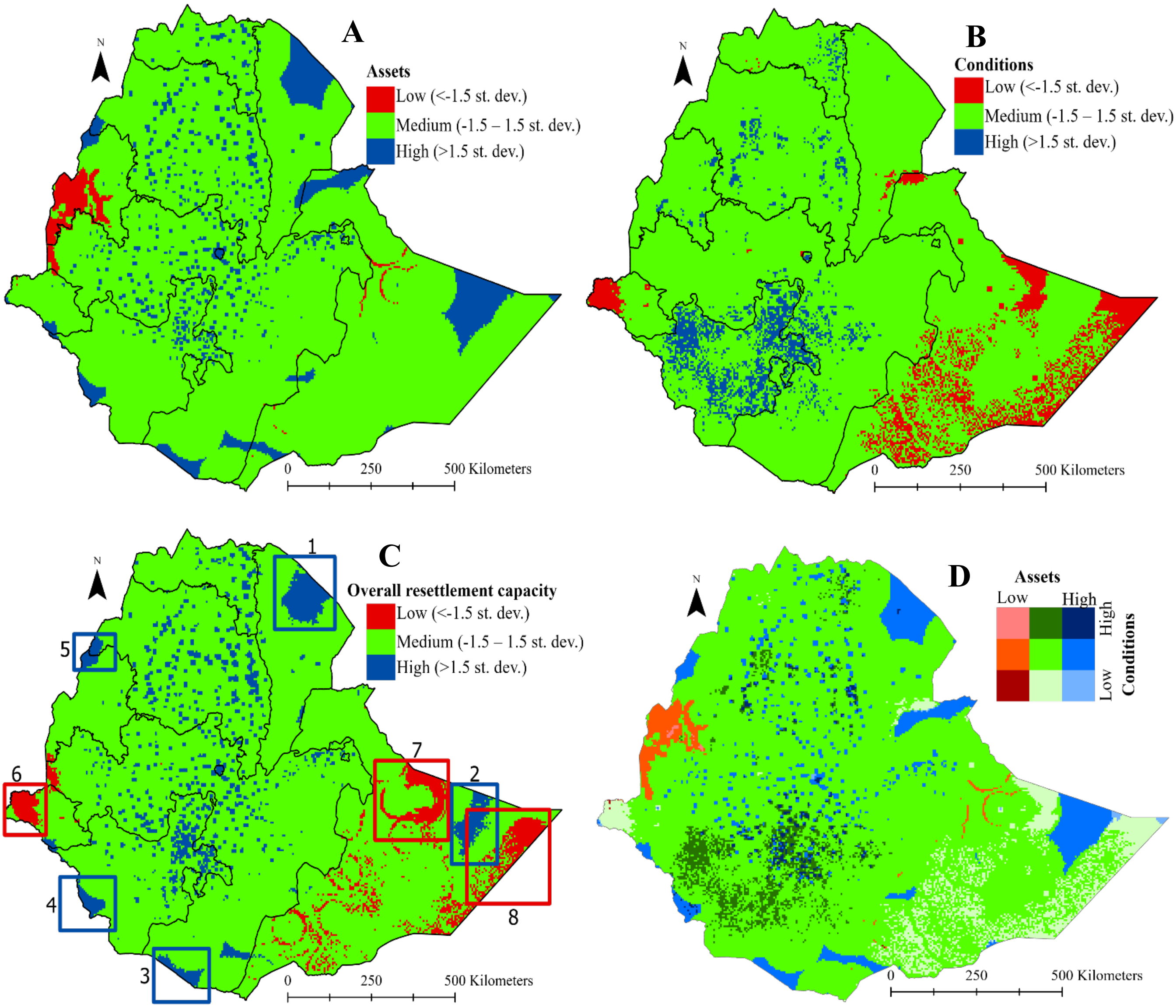

Figure 4: Resettlement capacity index for assets (A), conditions (B) and overall resettlement capacity (C), and bivariate combination of asset and condition indices (D). The blue and red boxes in Panel C correspond to the high and low resettlement capacity clusters included in Table 2.

Regarding overall resettlement capacity, grid cells with a low overall index score account for 8.5% of all grids and are mainly located in the southeast and the west (Figure 4, Panel C). Grids with high overall resettlement capacity account for 5% of the grids and are scattered throughout central and northern Ethiopia, clustering along the international borders.

To examine the pattern of high and low resettlement capacity in both assets and condition simultaneously, we display a bivariate distribution of asset and condition index scores (Figure

4, Panel D). Very few grids (only 475, i.e. 1% of all cells) have a high resettlement capacity in terms of both asset and condition. These occur in the north, central, and south-central parts of the country. Places that have a low resettlement capacity in both assets and conditions are very rare (only 9 grids). Most of these grids are in the western tip.

5.3 Drivers of overall resettlement capacity scores

To examine the drivers of overall resettlement capacity, we calculate: (i) the mean of dimension and sub-dimension indices by overall resettlement categories (Figure 5, Panel A) and (ii) the share of dimension and sub-dimension indices in the overall resettlement index by overall resettlement capacity categories (Figure 5, Panel B). The results demonstrate that the high resettlement category has the highest mean scores in both asset and condition scores. The high resettlement category also had the highest mean score in all sub-dimension scores except the natural capital sub-dimension, for which low resettlement capacity had the highest mean score, and the peaceful conditions sub-dimension, for which the medium resettlement category had a slightly higher mean score. These differences are significantly different (SM3, Supplementary Materials). This suggests that low resettlement capacity places are rich in natural capital and poor in most other sub-dimensions of resettlement capacity.

The results also reveal that the conditions dimension (72.5%), and particularly the peaceful conditions sub-dimension (22%), make the largest contribution to the overall resettlement capacity score (Figure 5, Panel B). Three points stand out when examining resettlement capacity scores by groups with high or low scores. First, assets make the largest contribution to high resettlement capacity grids as compared with medium and low resettlement capacity grids; and so, do most asset sub-dimensions, particularly financial, human, and physical capital infrastructures (Figure 5, Panel A). These differences are significantly different (SM3, Supplementary Materials). Second, the conditions dimension makes the highest contribution to the low overall resettlement category (76%). Peaceful conditions and stable natural conditions account for about 48% of the overall resettlement capacity score for this group. All the differences between the categories, except the share of peaceful conditions between low and medium resettlement categories, are significantly different (SM3, Supplementary Materials). Third, conditions – compared with the asset dimensions and its sub-dimensions, particularly peaceful and stable natural conditions – compared with all the sub-dimensions, make the largest contribution to all the three resettlement capacity categories.

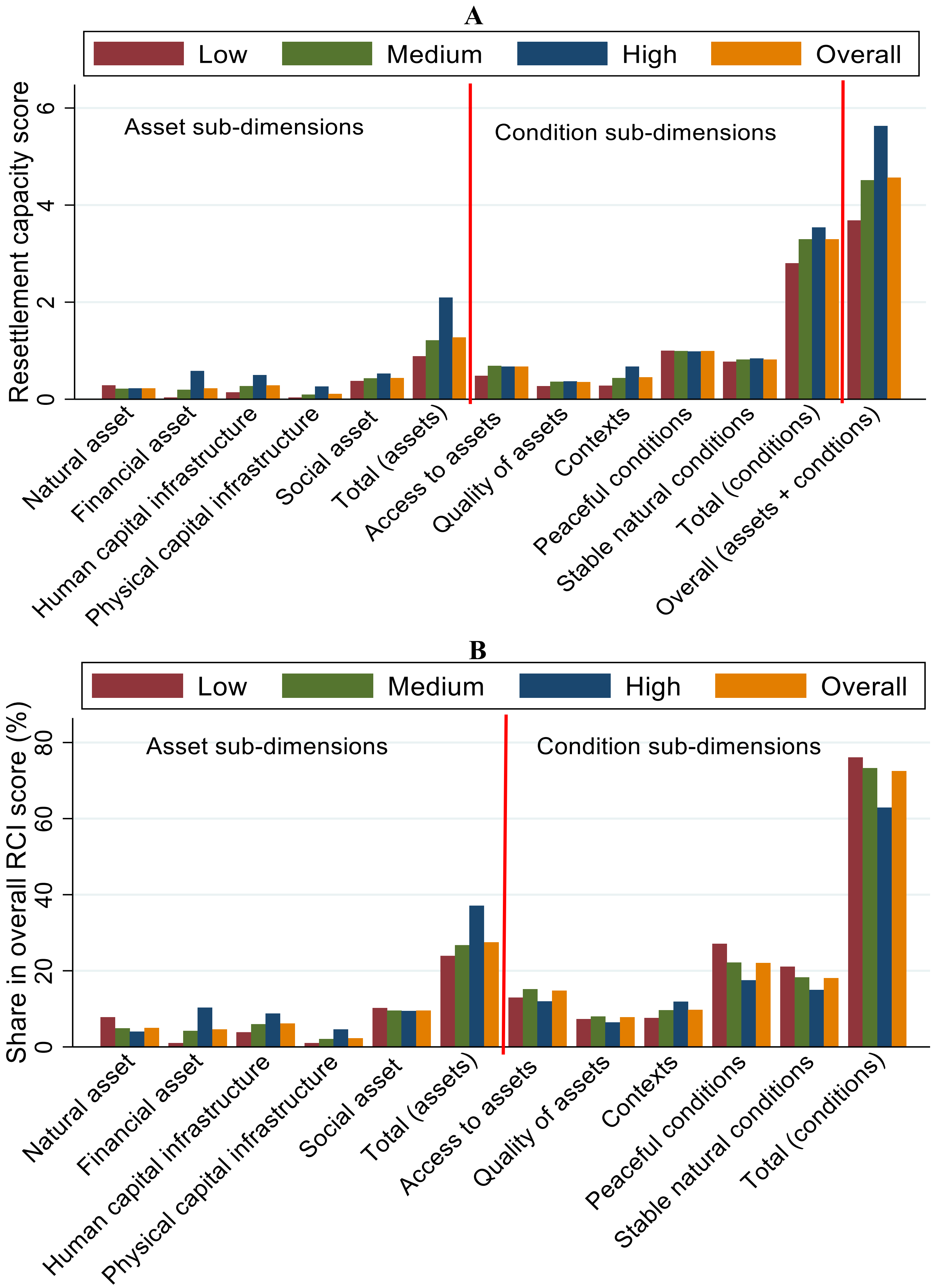

Figure 5: Mean values of overall, asset, condition and their sub-dimension scores (A) and share of asset, condition and their sub-dimensions score to the overall resettlement capacity score (B) by overall resettlement capacity score categories.

To further investigate the drivers of resettlement capacity, we selected relatively bigger clusters of high and low resettlement scores in Figure 4, Panel C (blue and red boxes, respectively). Then, we calculated the mean scores for each dimension and sub-dimension, and the ratio between these means and the overall means – the values for the average cell for the whole of Ethiopia (Table 2). The selected high resettlement capacity clusters are, on average, characterized by a very high resettlement scores (more than double that of the average cell – for the whole Ethiopia – in most of the cases) in financial assets, human, and physical capital infrastructure while the selected clusters with low resettlement capacity have low scores in these assets. The high resettlement capacity clusters also have a higher resettlement capacity in contexts. The clusters with low resettlement capacity are, on average, characterized by higher resettlement scores in natural capital, though the high resettlement cluster located in southeast Ethiopia has the highest score (0.459, twice that of the average cell). Both the high and the low resettlement clusters tend to have a similar score for peaceful conditions, but most of the low resettlement clusters have a lower score for stable natural conditions, meaning that most low resettlement clusters experience a higher incidence and intensity of natural hazards (i.e., floods and droughts).

Table 2: Mean values of overall resettlement capacity index (RCI) and mean and share of asset, condition and their sub-dimension indices for high and low resettlement clusters in Figure 4C (values in parenthesis are the ratio between the mean value and mean values of all the cells).

		High resettlement clusters					Low resettlement capacity cluster		
		North Eastern Ethiopia (1*)	South East Ethiopia (2*)	South Ethiopia (in Oromia region) (3*)	South Western Ethiopia (in SNNPs region) (4*)	North Western Ethiopia (border between Benishangul-Gumuz and Amhara) (5*)	West Ethiopia (6*)	South east Ethiopia (north of Somali region) (7*)	South east Ethiopia (South east Somali region) (8*)
Assets	Natural	0.221 (1.0)	0.449 (2.0)	0.273 (1.2)	0.249 (1.1)	0.224 (1.0)	0.357 (1.6)	0.293 (1.3)	0.325 (1.5)
	Financial	0.603 (2.7)	0.608 (2.7)	0.520 (2.3)	0.567 (2.6)	0.612 (2.8)	0.061 (0.3)	0.052 (0.2)	0.068 (0.3)
	Human capital infrastructure	0.559 (2.0)	0.535 (1.9)	0.583 (2.1)	0.564 (2.0)	0.556 (2.0)	0.115 (0.4)	0.044 (0.2)	0.063 (0.2)
	Physical capital infrastructure	0.324 (3.0)	0.292 (2.7)	0.214 (2.0)	0.236 (2.2)	0.316 (2.9)	0.050 (0.5)	0.028 (0.3)	0.030 (0.3)
	Social	0.581 (1.3)	0.424 (1.0)	0.657 (1.5)	0.625 (1.4)	0.511 (1.2)	0.261 (0.6)	0.462 (1.1)	0.410 (0.9)
	Overall	2.287 (1.8)	2.307 (1.8)	2.246 (1.8)	2.241 (1.8)	2.218 (1.7)	0.844 (0.7)	0.879 (0.7)	0.895 (0.7)
Conditions	Access to assets	0.505 (0.7)	0.490 (0.7)	0.562 (0.8)	0.543 (0.8)	0.519 (0.8)	0.542 (0.8)	0.336 (0.5)	0.473 (0.7)
	Quality of assets	0.183 (0.5)	0.265 (0.7)	0.335 (0.9)	0.395 (1.1)	0.352 (1.0)	0.458 (1.3)	0.182 (0.5)	0.258 (0.7)
	Contexts	0.675 (1.5)	0.580 (1.3)	0.595 (1.3)	0.710 (1.6)	0.771 (1.7)	0.199 (0.4)	0.323 (0.7)	0.255 (0.6)
	Peaceful conditions	1.000 (1.0)	0.992 (1.0)	1.000 (1.0)	1.000 (1.0)	1.000 (1.0)	1.000 (1.0)	1.000 (1.0)	1.000 (1.0)
	Stable natural conditions	0.932 (1.1)	0.851 (1.0)	0.899 (1.1)	0.931 (1.1)	0.800 (1.0)	0.515 (0.6)	0.880 (1.1)	0.811 (1.0)
	Overall	3.295 (1.0)	3.178 (1.0)	3.390 (1.0)	3.578 (1.1)	3.441 (1.0)	2.713 (0.8)	2.720 (0.8)	2.798 (0.8)
Overall RCI		5.583 (1.2)	5.485 (1.2)	5.636 (1.2)	5.819 (1.3)	5.659 (1.2)	3.557 (0.8)	3.599 (0.8)	3.693 (0.8)

*Location for the high and low resettlement capacity clusters in Figure 4C.

5.4 Geography of unsuitable places for resettlement

To identify places that are unsuitable for resettlement – currently or in the future – we mapped risk of violent conflicts and natural hazards, and projected (changes in) temperature and precipitation between 2061 and 2080. To measure risk of violent conflict, we used the violent conflict resettlement capacity score, which is constructed using four indicators: (i) prevalence of battles, violence against civilians, and remote violence; (ii) annual fatalities due to battles, violence against civilians or remote violence; (iii) prevalence of riots; and (iv) annual fatalities due to riots[4]. Places with a high risk of conflict for resettlement (i.e., a 1.5 standard deviation above the mean score) are few and scattered all over Ethiopia, but tend to have higher concentration in eastern, southeastern and central parts (Figure 6, Panel A). No places fall in low risk of conflict (i.e., 1.5 standard deviation below the mean score) because of the very high positively skewed distribution of the conflict score. Most of the grids (90%) have a score of 0 with a mean closer to 0 (the minimum value) and no grid falls 1.5 standard deviation below the conflict mean score of the distribution. Hence, the absence of low conflict risk category on the map does not mean the absence of places with low conflict in absolute terms given that the majority of the grids have not experienced conflict over the last two decades (see Appendix B). Places that experience at least one conflict of any type mentioned above from 2001 through 2018 are spatially concentrated in central and eastern parts of Ethiopia (Appendix C).

Natural hazard risk was measured using the natural hazard sub-dimension index score which is constructed from four indicators: (i) drought prevalence (from 2001 through 2015); (ii) flood prevalence; (iii) flood fatalities per event; and (iv) displacements per event (from 2001 through 2018). Places with high natural hazard risk (i.e., 1.5 standard deviation above the mean score) occur in bigger clusters in most northern and western Ethiopia and in small clusters in southeastern, eastern, and central Ethiopia, while places with low natural hazard risk (i.e., 1.5 standard deviation below the mean score) occur in bigger clusters in southern, southwestern, and northeastern Ethiopia (Figure 6, Panel B).

[4]All the indicators are measured from 2001 through 2018. See https://acleddata.com/acleddatanew/wp-content/uploads/dlm_uploads/2019/04/ACLED-Event-Definitions_Final.pdf for the definition of violent events.

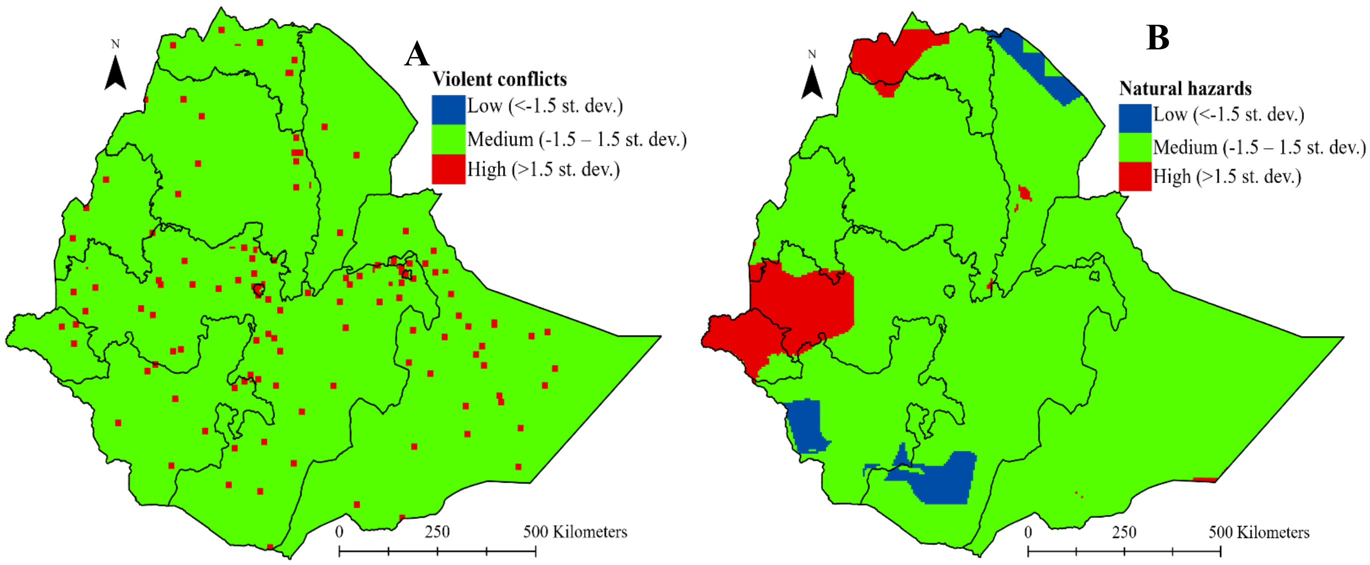

Figure 6: Geography of conflict (A) and hazard risk (B).

To identify places that are unsuitable for resettlement in the future, we map the distribution of projected temperature and rainfall between 2061 and 2080 (Figure 7, Panels A and B). We also map change in projected temperature and rainfall from historical (near current) climate change data (between 1970 and 2000) (Figure 7, Panel C and D). The results show that northeastern and southeastern, western, and the peripheries of southern, southwestern and western parts of Ethiopia will get warmer between 2061 and 2080 compared to other parts of Ethiopia, and could experience drought. Most parts of western, southern, and northwestern Ethiopia, meanwhile, will get wetter than the rest of Ethiopia, and could experience floods. Compared to the trend observed in 1970 to 2000, western, southern, and southeastern parts of Ethiopia will get warmer while the western and northwestern parts of Ethiopia will get wetter between 2061 and 2080. These are comparable with the high hazard risk clusters in western tip and northwestern part of Ethiopia (Figure 6, Panel B) and the low overall resettlement capacity cluster in the western tip of Ethiopia (Figure 4, Panel C).

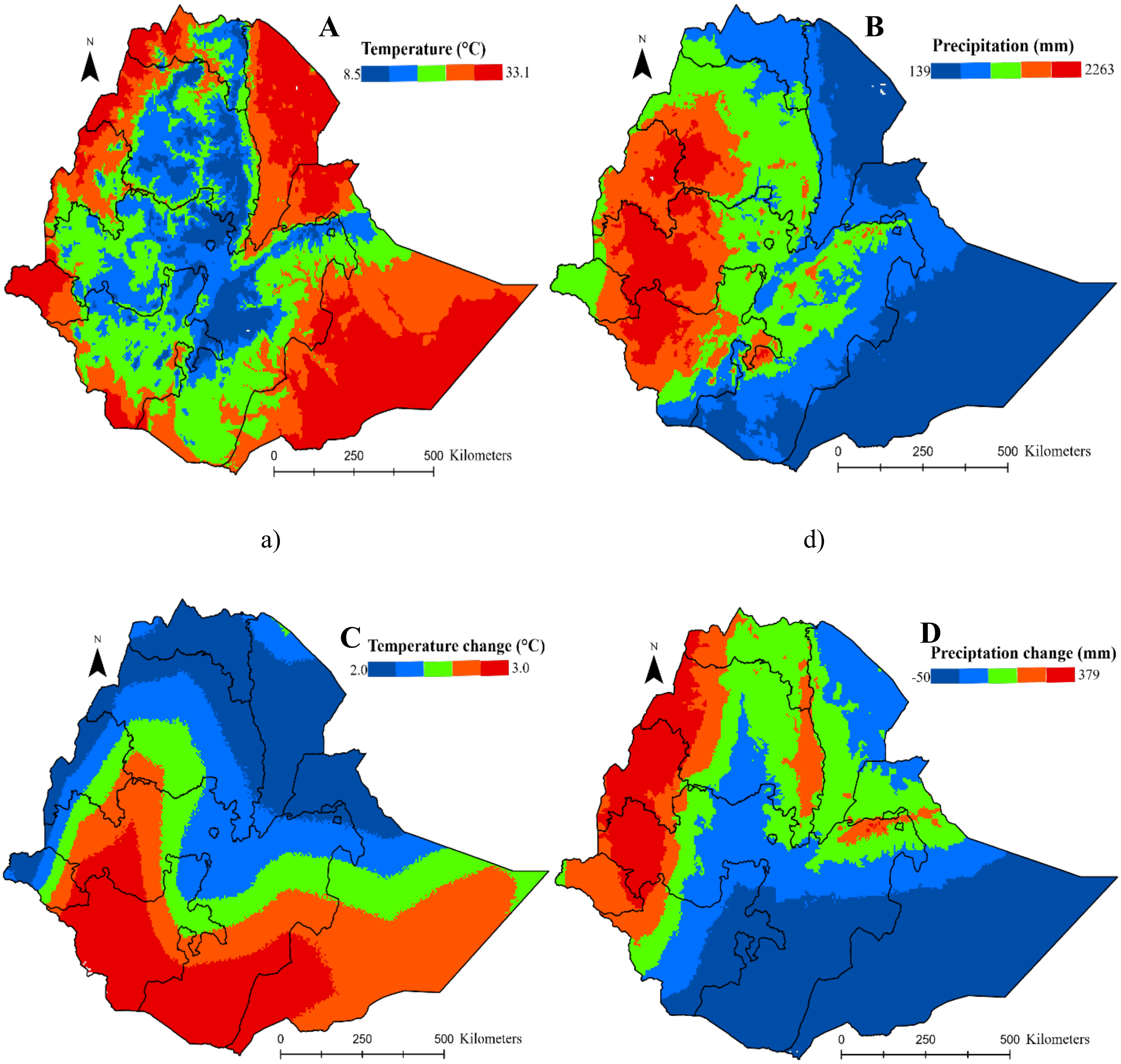

Figure 7: Projected temperature and annual precipitation (between 2061 and 2080) (A and B) and projected change in temperature and precipitation (C and D) (Source: WorldClim, 2020).

6 Robustness checks

We used three assessment criteria to check the robustness of the constructed index: its sensitivity to potential missing indicators, neighborhood effects, and change in the size of the unit of analysis. To check the sensitivity of the index to neighborhood effects and change in the size of the unit of analysis, we generated a new dataset that contains information from the grid cell plus the eight neighboring grids for all the indicators, and constructed a new overall resettlement capacity index using the resulting 15km grid cells. The correlation between the two indices is 0.99, suggesting our resettlement capacity index is robust to neighborhood effects and to change of the unit of analysis (Appendix D, Panel A). Global Moran's I autocorrelation statistics suggests that neighbors up to 20 km from the grid center are very similar (Appendix D, Panel B); accordingly, our resettlement capacity index is likely to be robust if the size of the grid cell is increased from 5km to 20km.

To check the sensitivity of the index to missing indicators, we excluded one sub-dimension at a time, estimated the reduced overall index (a total of 10), and compared it with the overall index using correlation coefficients and spatial autocorrelation (Global Moran's I). The results show that (i) the overall resettlement capacity index has positive and high correlation with the reduced indices (Appendix E, Panel A) and (ii) the spatial correlations of the reduced overall resettlement capacity scores are strikingly similar to the spatial correlation of the overall resettlement capacity scores (Appendix E, Panel B). These suggest that the constructed overall resettlement capacity index is robust to modifying or missing sub-dimensions and indicators.

To check the sensitivity of the geographic distribution of the overall resettlement capacity categories to the cutoff values (*the 1.5 standard deviation from the mean*), we used two alternative cutoff values: *1.25 and 1.75 standard deviation from the mean*. The geographic distribution based on the *1.25 and 1.75 standard deviation* cutoff values (Appendix F) follows a similar geographic pattern to the *1.5 standard deviation* cutoff value (Figure 4C).

7 Discussion

This article proposed an empirical methodology for resettlement capacity assessment in the context of climate migration and applied it to Ethiopia, which is expected to experience significant climate-related migration in the future. The approach is based on the climate change resettlement capacity (CCRC) framework (Walelign and Lujala 2020) that represents resettlement capacity by a set of indicators that are aggregated to generate 11 sub-dimension resettlement capacity scores and that are further aggregated into asset and condition dimensions, and finally into an overall resettlement capacity index. The generated sub-dimension, dimension, and overall indices can easily be constructed using a minmax hierarchical additive index construction approach, where the inputs for producing the indices at different levels are minmax-transformed and added together (Cutter et al. 2014). This approach to constructing resettlement capacity is more suited to the framework than other approaches (e.g., principal components analysis, or structural equation modelling) as it allows (i) a more intuitive comparison of the resettlement capacity scores among indicators, sub-dimensions, or dimensions and (ii) easy calculation of the importance/contribution of each component of the index to the overall resettlement capacity score. It is also an approach that various stakeholders (e.g., policy makers) will find suitable to apply and understand (Cutter et al. 2014).

Data collection and processing are the most challenging and time-consuming parts of resettlement capacity assessment. As resettlement capacity is multidimensional, its assessment requires use of an extensive number of indicators. Further, as the indicators encompass a wide variety of different aspects of resettlement capacity from natural environment to social conflicts, it is not possible to get all the indicators from a few available datasets; instead, researchers need to collect data from different sources, including various governmental and non-governmental organizations, individual projects, and studies (Walelign and Lujala 2020). This is particularly true for developing countries, where most governmental censuses and surveys are less comprehensive in terms of thematic coverage and are often outdated[5]. A further complication is that the data comes in different formats (e.g., gridded, spreadsheets) and at different spatial resolutions and units from individual cases (like a conflict event or the occurrence of a specific natural resource) and raster datasets to data for administrative units such as districts or regions. Hence, data processing requires converting the different data formats to the required format, aggregating or disaggregating the data to the relevant unit of analysis, and interpolating data when values are missing or available only as point data (e.g., geocoded surveys).

The empirical findings for Ethiopia show considerable spatial variation in overall resettlement capacity. The spatial distribution of overall resettlement capacity revealed that the high resettlement capacity scores occur in clusters along the north and southeastern, southern, southwestern, and northwestern international borders of Ethiopia, and as scattered cells in central and northern Ethiopia. The occurrence of high resettlement capacity clusters along the international border can be attributed to the combined effect of three factors: presence of refugee camps along the international border and the associated investment in public

[5] If the study area is small, primary data on relevant indicators can be collected, for example, through surveys or satellite images.

infrastructures; low population density; and the presence of major towns that conduct cross-border trade with neighboring countries. These places are endowed with financial capital (e.g., availability of banks) and human (e.g., schools) and physical capital infrastructures (e.g., roads). Places with low resettlement capacity are concentrated in southeastern and western (tip) parts of Ethiopia. These places lack financial capital and human and physical capital infrastructures, while they often are endowed with natural capital (e.g., natural resources). Places with high natural hazard risks are clustered in the northern and western tips of Ethiopia, while places with low hazard risk are clustered in the northeastern and southwestern parts of the country. The high conflict risk areas are scattered throughout the country, but with more concentration in the southeastern and central parts. These high-risk and hazardous places should be avoided when planning for resettlement.

We find that the conditions dimension makes a higher contribution than the assets dimension to the overall resettlement capacity scores, suggesting that places in Ethiopia relatively lack assets to accommodate climate migrants. Hence, while the potential to increase overall resettlement capacity lies in improving both the assets and conditions sub-dimensions, the assets have a larger potential for enhancement. On average, places record the lowest resettlement capacity score in human capital infrastructures, an asset sub-dimension. Compared to places (clusters) with high resettlement capacity, places (clusters) with medium or low resettlement capacities tend to have significantly lower scores in financial, human, and physical capital infrastructures (Table 2). These assets form the basis of people's livelihoods and provide the resources or services (e.g., land, water, education, loans, information) necessary to maintain and improve their livelihoods (DFID 1999, Ellis 2000, Scoones 2015, Winters et al. 2009). Our results thus suggest that investments in financial, human, and physical capital infrastructures should be emphasized to improve resettlement capacity in Ethiopia. This finding is in line with previous studies that have shown that investments in assets improve resettlement potential and resettlement outcomes in other contexts (Sina et al. 2019a, b; Xiao et al. 2018).

The findings also reveal the relative importance of social capital and peaceful and stable natural conditions for resettlement capacity in all places in Ethiopia, challenging the focus of most resettlement programs on building assets and physical and human capital infrastructure within assets to improve the livelihoods of resettled people and communities (Wilmsen and Webber 2015; Arnall 2019). The contribution of social capital, peaceful and stable natural conditions to the overall resettlement capacity index diminishes when one moves from low resettlement capacity to high resettlement capacity sites, suggesting that the three sub-dimensions (social capital, peaceful and stable natural conditions) is more important (in a relative sense) to the lower resettlement capacity sites. This result – the higher contribution of social capital and peaceful natural conditions to low resettlement capacity sites – for Ethiopia is in line with empirical and theoretical studies that highlight the relevance of promoting social capital and avoiding conflicts and natural hazards for maintaining or improving the livelihoods of people, particularly the poor (e.g., Scoones 2015; Fang et al. 2018; Kulatunga and Lakshman 2013).

Four points stand out when we compare our findings with past large-scale resettlement programs that mostly relocated people from northern Ethiopia to western, southwestern, and southern parts, and past famine hotspots that mostly affect the northern part of Ethiopia (Rahmato 2003; Kloos 1987). First, the resettlement programs mostly avoided low resettlement areas in the southeast. Second, most of the origin and relocation places had similar resettlement capacity in terms of both asset and condition sub-dimensions. This suggests that the livelihood of the resettled people would not improve at destination; they might perhaps fare worse when confronted by social, economic, and environmental challenges at the new sites (Rahmato 2003; Kloos 1987). Third, most destinations are in the major natural hazard risk zones (both present and future), suggesting that these sites should not have been used for resettlement. Fourth, most of the famine hotspots have moderate natural hazard risk and resettlement capacity index scores, suggesting that people could have been supported to improve through in-situ adaptation capacity instead of being forced to relocate. These points highlight how the selection of places has been based on poor assessment of destination places and too few reconnaissance visits by the government officials. Consequently, most resettlement programs in Ethiopia failed to maintain or improve the livelihood of the resettled people. In consequence, many resettled people migrate back to their original home areas (Rahmato 2003; Kloos 1987).

When we compare the distribution of overall resettlement capacity and natural hazard risks with WFP's monthly food insecurity status for Ethiopia (WPF 2019a, 2019b, 2020), we notice some degree of overlap between the food security assessments for 2019 and 2020 and our resettlement capacity indices. For instance, in October 2019, a large part of southeastern Ethiopia was classified under the 'crises' category;[6] in our analysis the same area was

[6] The five categories, in increasing order of food insecurity status, are minimal, stressed, crises, emergency, and famine (see IPC 2019 for the definition of the food insecurity categories).

characterized as having low resettlement capacity. A large part of southeastern Ethiopia was under the 'stressed' category of food insecurity in June 2019 and February 2020. For the same months, a large part of northern Ethiopia, including a part of the high resettlement cluster in Afar Region, was under 'crises' or in the stressed category of food insecurity. The two high hazard risk clusters identified in our analysis were in the minimal food insecurity category. Most of the central, north, and south-central parts were in the minimal food security category, and these places are identified as high or moderate resettlement capacity areas in our study. The absence of a high degree of overlap between the food security assessments and our resettlement capacity scores could be due to the prevalence of transitory food insecurity in most parts of Ethiopia. This suggests the need for complementing resettlement with other adaptation strategies at destination.

Using a few sets of indicators, mainly on population, production, and climate trends, Hermans-Neumann et al. (2017) and Rigaud et al. (2018) identified hotspots for in-migration, and, using river water availability and terrain slope, Adugna (2011) identified hotspots for irrigation-based resettlement in Ethiopia. The potential migration destination places identified by these studies are mostly located outside of the high hazard and conflict risk places identified in our analysis. However, the overlap between most suitable destination places in Hermans-Neumann et al. (2017), Rigaud et al. (2018), and our study is limited to southern Ethiopia, particularly the northern SNNPs region. In other parts of Ethiopia, Hermans-Neumann et al. (2017) found an in-migration hotspot in Southern Afar, and Rigaud et al. (2018) point to hotspots in eastern Ethiopia (northeastern Somalia region) as well as in and around the Harari regions and Dire Dawa city administration; our resettlement hotspots, meanwhile, occur in a scattered pattern throughout central and northern Ethiopia, and in small clusters along the southeastern, northwestern, and northeastern international borders. Further, there are no overlaps between high resettlement capacity places identified in our analysis and the ones identified in Adugna (2011).

8 Conclusions

This study proposes an empirical methodology to assess resettlement capacity for climate migration and applies it to Ethiopia. The approach operationalizes Walelign and Lujala's (2020) climate change resettlement capacity (CCRC) framework and facilitates research on resettlement capacity assessment. The empirical framework is hierarchical, allowing aggregation of resettlement capacity indicator values into sub-dimension resettlement capacity scores, then further into dimension (i.e., asset and condition) resettlement capacity scores, and, finally, the overall resettlement capacity index.

The study compiled a total of 75 indicators with different resolution and scale from several spatial data sources. Resettlement capacity indices were constructed using a 5km grid covering the entire country and a hierarchical minimax additive index construction approach. Sensitivity analyses showed that the index is robust for missing indicators, neighborhood effects, and size of unit of analysis. We find substantial geographic variation in resettlement capacity in Ethiopia, and that the resettlement capacity can be augmented through targeted investments, especially in assets. Some places (mostly from the low and moderate resettlement capacity categories) fall into the high conflict and hazard risk categories, suggesting (i) that these places should be avoided for resettlement, and (ii) that there is a need for climate change adaptation and conflict resolution mechanisms to augment the adaptive capacity of local communities in those places. The relative contribution to current resettlement capacity is higher for socially capitalized, peaceful, and stable natural conditions, while the relative contribution of financial, human, and physical capital infrastructure is lower. Both the moderate and low resettlement capacity places have lower scores in financial, human, and physical capital infrastructure, compared to high resettlement capacity places. These findings suggest that potential for improving resettlement capacity lies in investment in financial, human, and physical infrastructures.

The empirical methodology proposed in this article can be used to undertake further research on resettlement capacity in Ethiopia and elsewhere. Also, while findings of our study can be useful for resettlement policies in Ethiopia, we advise resettlement experts and decision makers to undertake further investigations when it comes both to identifying areas with high potential for resettling climate migrants and how to improve resettlement outcomes in those areas. These further researches should include personal visits and the generation of relevant primary information. The attitude of host communities towards resettlement and cultural and ethnic differences (between host communities and communities to be resettled) should also be further assessed to avoid potential conflicts (Lujala et al. 2020; Kolstad et al. 2019).

This study has two potential limitations. First, although we compiled data on 104 preliminary indicators from several data sources, the indicator selection is not exhaustive and may have omitted some relevant indicators. In addition, some indicators (e.g., poverty incidence) are interpolated from surveys and thus do not represent the actual values for the interpolated grids and, for some other indicators (e.g. safety), information was available only at the regional scale (although separately for urban and rural areas). These shortcomings can have an impact on the overall resettlement capacity scores. However, our robustness analysis showed that the index is robust to changes in the included indicators. Second, it is also possible that not all indicators or sub-dimensions are equally important for resettlement capacity, something that would entail using weights in the index construction. However, as there are few theoretical justifications that could help in assigning weights to the different indicators, sub-dimensions, and dimensions, we adopted equal weights following previous studies in vulnerability and resilience (Cutter et al. 2014, Cutter and Derakhshan 2020, Scherzer et al. 2019).

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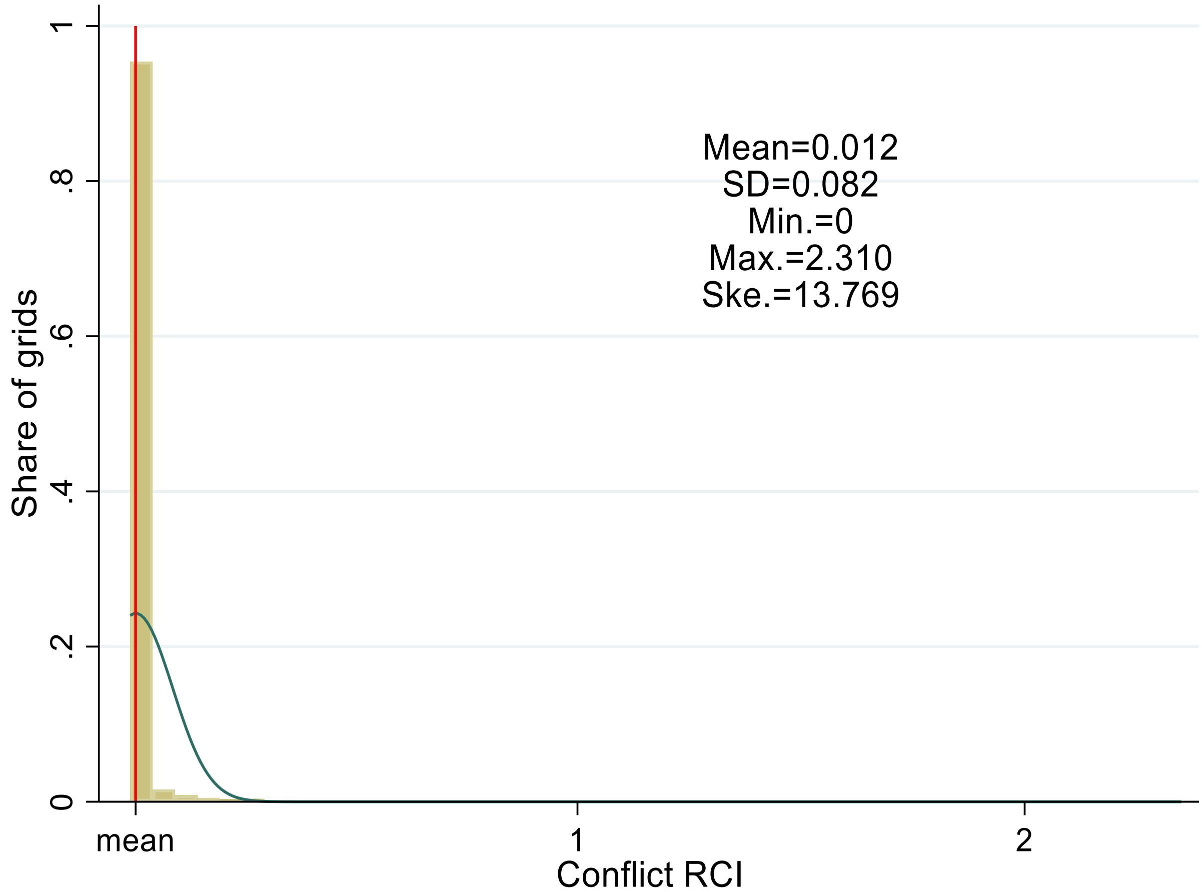
Appendices

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

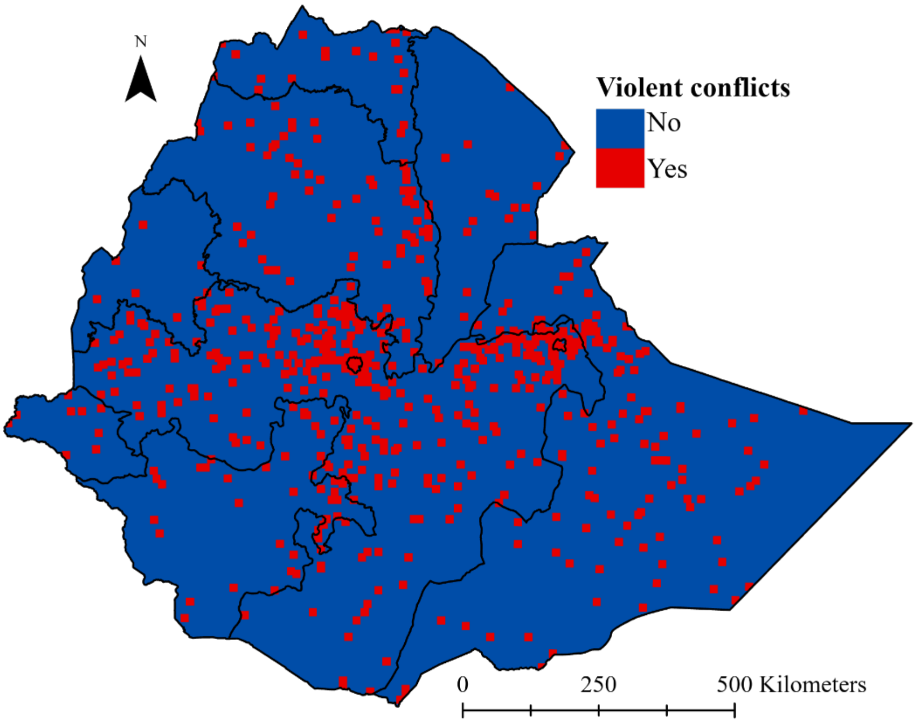
Dataset type	Spatial unit	Data processing
Raster (spatial)	Five-kilometer grid	Converted to polygon and joined with the five-kilometer vector grid
	Grids larger than five-kilometer	Resampled to five-kilometer resolution, converted to polygon and joined with the five-kilometer vector grid
	Smaller than five-kilometer grid	Aggregated to five-kilometer vector grid 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 using the five-kilometer vector grid 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).
LSMS-ISA (survey)	Geocoded enumeration area	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	
Afro-barometer (survey)	Region, separately for rural and urban areas	Calculate the values using the relevant summary statistics (mainly proportions) for the urban and rural areas of each region and join with the five-kilometer vector grid meaning that all the five-kilometer grids located in urban areas of one region will have the same value (i.e. the value of urban areas in that region) while the five-kilometer grids located in rural areas in one region will have the same value (i.e. the value of rural areas in that region).

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

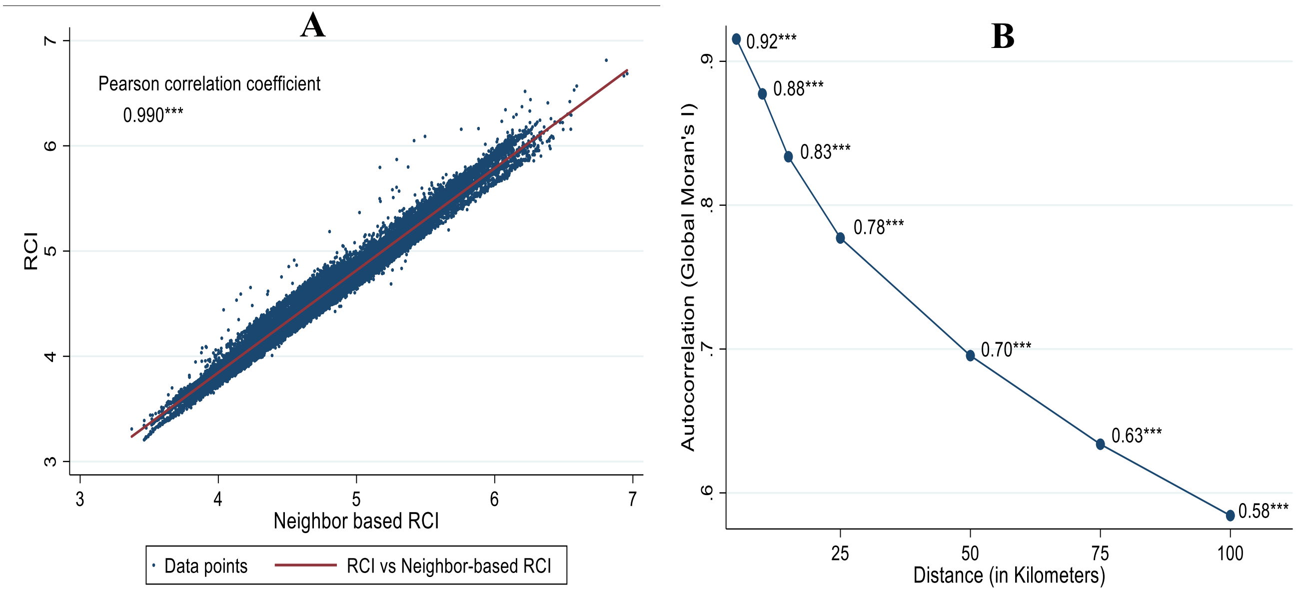
Appendix B: Distribution of conflict resettlement capacity score



Appendix C: Spatial distribution of places that have experienced one or more conflicts during the period 2001-2019



Appendix D: Relationship between overall resettlement capacity index (RCI) and neighbor-based resettlement capacity index (A) and global Moran's I statistic with different distance from the center of the grid (B) (Note: ***Signifcant at 1%)

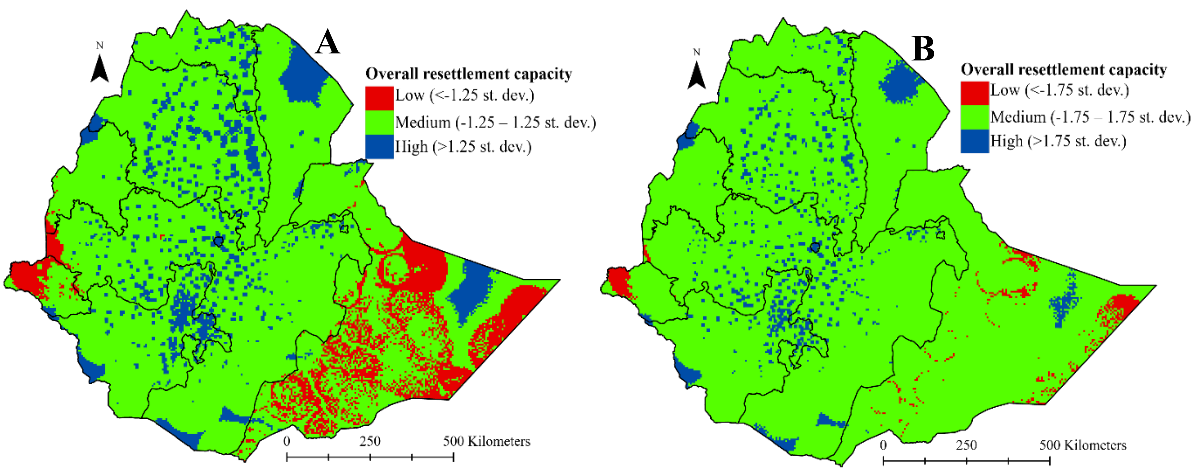


Appendix E: Correlation between resettlement capacity index (RCI) score and reduced RCI scores (Panel A) and Global Moran's I at 10, 25, and 50 kilometers distance (Panel B)

Panel A		Panel B			
	Correlation		Global Moran's I		
			10 kilometers	25 kilometers	50 kilometers
	-	RCI	0.8774***	0.7773***	0.6955***
RCI vs Reduced RCI by natural assets	0.987***	Reduced RCI by natural assets	0.8929*** (-0.0155)	0.8057*** (-0.0284)	0.7336*** (-0.0381)
RCI vs Reduced RCI by financial assets	0.951***	Reduced RCI by financial assets	0.8695*** (0.0079)	0.7770*** (0.0003)	0.7078*** (-0.0123)
RCI vs Reduced RCI by human capital infrastructure	0.981***	Reduced RCI by human capital infrastructure	0.8849*** (-0.0075)	0.7936*** (-0.0163)	0.7238*** (-0.0283)
RCI vs Reduced RCI by physical capital infrastructure	0.995***	Reduced RCI by physical capital infrastructure	0.8705*** (0.0069)	0.7755*** (0.0017)	0.6947*** (0.0007)
RCI vs Reduced RCI by social capital	0.952***	Reduced RCI by social capital	0.8775*** (-0.0001)	0.7798*** (-0.0026)	0.6934*** (0.0021)
RCI vs Reduced RCI by access to assets	0.956***	Reduced RCI by access to assets	0.8413*** (0.0361)	0.7151*** (0.0622)	0.6186*** (0.0768)
RCI vs Reduced RCI by quality of assets	0.975***	Reduced RCI by quality of assets	0.8817*** (-0.0042)	0.7803*** (-0.0030)	0.6966*** (-0.0011)
RCI vs Reduced RCI by contexts	0.973***	Reduced RCI by contexts	0.8832*** (-0.0058)	0.7887*** (-0.0114)	0.7015*** (-0.0060)
RCI vs Reduced RCI by conflicts	0.998***	Reduced RCI by conflicts	0.8761*** (0.0013)	0.7735*** (0.0038)	0.6904*** (0.0050)
RCI vs Reduced RCI by natural hazards	0.983***	Reduced RCI by natural hazards	0.8719*** (0.0055)	0.7684*** (0.0089)	0.6852*** (0.0103)

The difference in Global Moran's I value for the RCI and reduced RCI are in parentheses, ***significant at 1%.

Appendix F: Geographic distribution of overall resettlement capacity categories with alternative cutoff values: with 1.25 (A) and 1.75 (B) standard deviation from the mean.



Supplementary materials

SM1: List of preliminary indicators by dimensions and sub-dimensions

Dimmensions	Sub-dimensions	# of indicators	Indicators
Asstets	Natural assets	10	Percapita forest/tree area, percapita shrubland area, percapita cropland area, percapita grassland area, percapita residential area, per capita length of rivers with medium discharge, per capita length of rivers with low discharge, per capita lake area, ground water stock, per capita number of mineral and oil deposits
	Financial capital	7	Percapita number of banks, presence of micro-finance institutions, presence of authomatic teller machine(ATM), presence of saving and credit cooperative organization (SACCO), presence of bank agent, presence of agricultural agent, presence of cooperatives/micro-enterprises for emplyment promotion.
	Human capital infrastructure	8	Percapita number of public hopsitals, percapita number of other public health facilties, percapita number of university campuses, per capita number of college campuses, presence of public primary school, presence of public secondary school, presence of private primary school, presence of private secondary school
	Physical capital infrastructure	11	Percapita number of airports, Percapita irrigated land area, percapita highway density, percapita primary road density, percapita other road density, percapita high electricity consumption area, percapita building area, presence of public information notice board, mobile phone use, internet use, availability of improved water source
	Social capital	10	Poletical participation through campaign or rally, poletical participation through attending meetings, poletical participation through being part of campaigns, whether local council listen to the local community, presence of suggestion box, percapita number of churchs, percapita number of mosques, presence of institutions distributing malaria net, presence of institutions for help and support, presence of Productive SafetyNet program (PSNP)
Conditions	Access to assets	10	Distance to hospital, distance to other health facilities, distance to airport, distance to miniral and oil deposite site, distance to college campus, distance to university campus, distance bank, travel time to cities, price index, land right security
	Quality of assets	9	Percapita bareland area, soil absolute depth to bedrock, soil organic carbon density, soil pH index, terrain ruggedness index, terrain slope, surface water seasonality, ground water depth, Normalized difference vegetation index (NDVI).
	Social, economic and natural contexts	21	Night-time light radiance, Human development index (HDI), rainfall erosion, ethinic fractionalization, ethnic polarization, religious fractionalization, religious polarization, livestock density, safety, prevalence of theft and violence, freedom to talk; freedom to join any political party, immigration for work, emmigration for work, net immigration, net emigration, poverty incidence, measle vaccination coverage, DPT 1 vaccination coverage, DPT 2 vaccination coverage, DPT3 vaccination coverage, dependency ratio.
	Institutional quality and strength	5	Voting, freedom to vote, trust on local council, bribe prevalence, corruption prevalence
	Violent conflicts	8	Number of battles, number of violence againist civilians, number of remote violences, number of riots per year, number of battle fatalities, number of violence againist civilians fatalities, number of remote violence fatalities, number of riot fatalities
	Natural disasters	8	Drought prevalence; flood prevalence, flood fatalities, flood displacements, falcifarum incidence rate, falcifarum parasite rate, share of area with high land slide suspitibility, share of area with medium land slide suspitibility
Overall		107	-

SM2: Definition, summary statistics and source of data for final list of indicators; values in parentheses are standard deviations of the mean, values in closed brackets are the minimum and maximum values of the indicators.

#	Variable name	Brief description	Data source (link)	Spatial resolution of original dataset	Mean or mode**
1	Percapita forest area	Land area covered with forests/trees in square meter per person	European Space Agency (ESA) (http://2016africalandcover20m.esrin.esa.int/)	~ 20m	9190 (36829) [0,1126656.00]
2	Percapita shrub land area	Land area covered with shrubs in square meter per person			11661.41 (30491.64) [0,343918.10]
3	Percapita cropland area	Land area under use for crop production in square meter per person			3640.50 (6998.37) [0,146409.30]
4	Percapita grassland area	Land area covered with grass in square meter per person			19419.48 (37610.26) [0,782807.30]
5	Percapita residential area	Residential land area in square meter per person			9.49 (177.62) [0,29533.22]
6	Percapita length of rivers with medium discharge	Total length of rivers with medium discharge in square meter per person	HydroSHEDS (https://www.hydrosheds.org/page/hydrobasins)	Line feature	9.14 (19.22) [0,512.10]
7	Percapita length of rivers with low discharge	Total length of rivers with low discharge in square meter per person			3.90 (19.47) [0,1431.95]
8	Percapita lake area	Total area of land covered with lake water in square meter per person	HydroSHEDS (https://www.hydrosheds.org/page/hydrolakes)	Polygon feature	206.09 (6247.99) [0,865391.90]
9	Groundwater stock	Groundwater stock in water storage categories, where 0, 1, 2, 3, 4, and 5 represent groundwater storage of 0, 1-999, 1000-9999, 10000-24999, 25000-49999, and greater than 49999 mm, respectively)	British Geological survey (BGS) (https://www.bgs.ac.uk/africagroundwateratlas/)	~ 5000m	2 [0,4]
10	Percapita number of mineral and oil deposits	Number of metallic and non-metallic mineral and oil deposits in the cell (+in the neighboring cells) per person	United States Geological Survey (USGS) (https://mrdata.usgs.gov/major-deposits/) and Ethiopian Petroleum Licensing and Adiministration Directorate.	Point feature	$1.10X10^{-6}$ ($2.52X10^{-5}$) [0,0.001]
11	Percapita number of banks	The number of banks (all types) (+in the neighboring cells) per person	Open street map	Point feature	2.29X10-6 (2.47X10-5) [0,0.001]
12	Presence of automatic teller machine (ATM)	The probability of presence of one or more ATM(s) in the cell	World Bank Living Standard Measurement Survey – Integrated Survey on Agriculture (LSMS-ISA)	Point feature	0.150 (0.309) [0,0.994]

13	Presence of saving and credit cooperative organization (SACCO)	The probability of presence of one or more SACCO(s)			0.376 (0.273) [0.008,1.00]
14	Presence of bank agent	The probability of presence of one or more bank agent (s)			0.154 (0.309) [0,1.00]
15	Presence of cooperatives/micro-enterprises for employment promotion	The probability of presences of institutions, in the form of cooperatives/micro-enterprises, for employment promotion			0.149 (0.192) [0,0.931]
16	Percapita number of public hopsitals,	The number of public hospitals (+in the neighboring cells) per person	Maina et al. 2019	Point feature	1.12X10-6 ($2.04X10^{-5}$) [0,0.001]
17	Percapita number of other public health facilties	The number of public health facilities other than hospitals (+in the neighboring cells) per person			0.982 (4.39) [0,363.00]
18	Percapita number of university campuses	The number of university campuses (+in the neighboring cells) per person	Open street map	Point feature	$1.45X10^{-7}$ ($4.11X10^{-6}$) [0,$2.82X10^{-4}$]
19	Percapita number of college campuses	The number of college campuses (+in the neighboring cells) per person			$2.15X10^{-7}$ $5.41X10^{-6}$ [0,$3.67X10^{-4}$]
20	Presence of public primary school	The probability of presence of one or more public primary school (s)	LSMS-ISA	Point feature	0.739 (0.157) [0.136,0.984]
21	Presence of public secondary school	The probability of presence of one or more public secondary school(s)			0.260 (0.274) [0.014,1.00]
22	Presence of private primary and secondary schools	The probability of presence of one or more private primary or secondary school(s)			0.052 (0.088) [0,0.665]
23	Percapita number of airports	The number of airports (+in the neighboring cells) per person	Open flights Airport database (https://openflights.org/data.html#airport)	Point feature	$1.29X10^{-6}$ ($2.42X10^{-5}$) [0,0.001]
24	Percapita irrigated land area	Total land area in square meters equipped with irrigation per person	Global Irrigates areas: Meier et al. (2018) (https://doi.pangaea.de/10.1594/PANGAEA.884744)	Point feature	144.24 (1651.41) [0,128822]
25	Percapita highway density	Total length of highways in meters per square kilometer per person	The Global Roads Inventory Project (GRIP) dataset; Meijer et al. 2018 (https://www.globio.info/download-grip-dataset)	~ 8000m	$1.15X10^{-5}$ ($3.10X10^{-4}$) [0,0.026]
26	Percapita primary road density	Total length of primary roads in meters per square kilometer per person			0.027 (0.150) [0,9.02]
27	Percapita other road density	Total length of roads other than highways and primary roads in meters per square kilometer per person			0.140 (0.474) [0,29.84]

28	Percapita high electricity consumption area	Total area in with high electricity consumption (greater than 0.48 and 0.45 light radiance level for urban and rural areas respectively) in square meters per person	Falchetta et al. (2019)	~ 1000m	41.37 (898.17) [0,69715.6]
29	Percapita building area	Total area covered with buildings in square meters adjusted per person	The Humanitarian data exchange (HDX) (https://data.humdata.org/dataset/hotosm_eth_buildings)	Polygon feature	0.280 (5.081) [0,410.65]
30	Presence of public information notice board	Probability of presence of public notice board, where important information is posted	LSMS-ISA	Point feature	0.362 (0.273) [$2.22X10^{-4}$, 0.999]
31	Mobile phone use	Proportion of people (older than 13 years) that have a mobile phone	Demographic and Health Survey (DHS)	Point feature	0.331 (0.167) [0.142,0.998]
32	Political participation	Proportion people who participates in the following political activities: campaign or rally, attending political meetings, being part of campaigns	Afrobarometer dataset	Region, separately for urban and rural areas	0.132 (0.047) [0,0.200]
33	Per capita number of churches	Predicted number of churches per person	LSMS-ISA	Point feature	0.010 (0.046) [$1.27X10^{-5}$,4.16]
34	Per capita number of mosques	Predicted number of mosques per person			0.027 (0.076) [$9.05X10^{-6}$,5.30]
35	presence of institutions for help and support	Probability of presence of institutions for help and support			0.153 (0.119) [$7.09X10^{-9}$,0.685]
36	presence of Productive SafetyNet program (PSNP)	Probability of presence of PSNP			0.520 (0.423) [0,1.00]
37	Distance to hospital*	Distance to the nearest hospital in meters	Maina et al. 2019	Point feature	66086.79 (46176.04) [0,314386.8]
38	Distance to other health facilities*	Distance to the nearest health facility other than hospital in meters			16893.26 (20003.2) [0,146404.3]
39	Distance to airport*	Distance to the nearest airport in meters	Open flights Airport database (https://openflights.org/data.html#airport)	Point feature	69973.27 (39184.19) [0, 205190.5]
40	Distance to mineral and oil deposit site*	Distance to the nearest metallic and non-metallic mineral or oil deposit in meters	United States Geological Survey (USGS) (https://mrdata.usgs.gov/major-deposits/) and Ethiopian Petroleum Licensing and Administration Directorate.	Point feature	155478.3 (98337.77) [0,435041.4]
41	Distance to university campus*	Distance to the nearest university campus	Open street map	Point feature	152634.8 (135421.8) [0, 663023.7]
42	Distance to bank*	Distance to the nearest bank			88154.35

					(80877.69) [0,540383.1]
43	Travel time to cities	Travel time in hours to cities as a measure of accessibility to high density cities	The Malaria Atlas, Weiss et al. 2018 (https://malariaatlas.org/research-project/accessibility_to_cities/)	~ 1000m	246.71 (177.13) [0,1282.49]
44	Price index*	Consumer price index as a measure of a cost of living.	LSMS-ISA	Point feature	1.02 (0.084) [0.762,1.35]
45	Land right security	Proportion of household with land certificates			0.279 (0.250) [5.44X10^{-7}, 0.820]
46	Percapita bare land area	Area of bare land per person	European Space Agency (ESA) (http://2016africalandcover20m.esrin.esa.int/)	~ 20m	6213.75 (30260.04) [0,863011.5]
47	Soil absolute depth to bedrock	Soil absolute depth to bedrock in centimeter	International Soil Reference and Information Center (https://www.isric.org/explore/soilgrids)	~ 250m	7662.58 (2428.80) [315.23,41360.15]
48	Soil organic carbon density	Soil organic carbon density in gram per cubic decimeter			142.82 (57.49) [25.20,537.85]
49	Terrain slope*	Terrain slope in degrees	EathEnv (https://www.earthenv.org/topography)	~ 1000m	5.90 (5.51) [0,31.23]
50	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/)	~ 30m	0.084 (0.851) [0,12]
51	Ground water depth*	The depth of ground water in six ordered categories, where 1, 2, 3, 4, 5, and 6 represents a depth of 0-7, 7-25, 25-50, 50-100, 100-250 and greater than 250 meters below ground level, respectively.	British Geological survey (BGS) (https://www.bgs.ac.uk/africagroundwateratlas/)	~ 5000m	1 [1,5]
52	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	0.424 (0.016) [0.398,0.475]
53	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)	~ 500m	0.012 (0.256) [0,24.49]
54	Human development index (HDI)	An index based on a geometric mean of income, education and health variables	Kummu et al. 2018	~ 5000m	0.448 (0.004) [0.370,0.555]
55	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)	~ 10000m	2809.88 (200.20) [2515.26,3020.24]
56	Ethinic fractionalization	Ethnic diversity measured using 1-Herfindahl index of diversification	DHS	Point feature	0.200 (0.205)

					[0.002,1.00]
57	Livestock density	Number of livestock (cattle, horse, sheep, goat, chicken, duck, and pick) in tropical livestock units per square kilometers	FAO (http://www.fao.org/livestock-systems/en/)	~ 10000m	131.98 (165.25) [0,2389.66]
58	Falcifarum parasite rate*	Proportion of children (2-10 ages) with falciparum parasite in 2017	Malaria Atlas (https://malariaatlas.org/)	~ 5000m	0.009 (0.007) [0,0.088]
59	Safety	Proportion of people feeling safe	Afrobarometer	Region, separately for urban and rural areas	0.963 (0.026) [0,1]
60	Freedom to talk	Proportion of people who perceives that they are free to talk			0.589 (0.070) [0,0.766]
61	Immigration for work	Probability that people come to the community for work	LSMS-ISA	Point feature	0.333 (0.247) [0.003,1.00]
62	Poverty incidence*	Proportion of people who are below 1.9 USD poverty line			0.681 (0.118) [0.217,0.957]
63	Vaccination coverage	Proportion of children under five coverage of measle and Diphtheria-tetanus-pertussis (DTP) dose 1, 2 and 3 vaccination coverage.	WorldPop (https://www.worldpop.org/geodata/listing?id=23)	~ 1000m	38.40 (20.78) [1.79,93.61]
64	Dependency ratio*	The ratio between the number of dependents (children younger than 14 and elder older than 64) and adults			95.18 (10.12) [37.85,133.04]
65	Voting	Proportion of people who participated in 2010 election	Afrobarometer	Region, separately for urban and rural areas	0.852 (0.041) [0,0.955]
66	Trust on local council	Proportion of people who trusts on local council			0.253 (0.104) [0,0.582]
67	Bribe prevalence*	Proportion of people who has paid bribe to get public services			0.072 (0.068) [0,0.476]
68	Prevalence of battles, violence against civilians, and remote violence*	Number of battles, violence against civilians, and remote violence per year from 2001 to 2018	Armed Conflict Location and Event Data Project (ACLED) (https://www.acleddata.com/)	Point feature (event)	0.029 (0.238) [0,11.12]
69	Prevalence of riots*	Number of riots per year from 2001 to 2018			0.004 (0.045) [0,2.42]
70	Battles, violence against civilians, and remote violence fatalities*	Number of people killed by battle, violence against civilians, and remote violence per event			2.18 (14.29) [0,348.13]
71	Riot fatalities *	Number of people killed by riots per event			0.107 (1.62)

					[0,56.21]
72	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	0.005 (0.006) [0,0.027]
73	Flood prevalence*	Number of flood events from 2001 to 2018	Dartmouth Flood Observatory (Global active archive of large flood events) (https://data.humdata.org/dataset/global-active-archive-of-large-flood-events)	Polygon feature	0.152 (0.078) [0,0.526]
74	Flood fatalities*	Number of people dead from 2001 to 2018 per event			0.0160 (0.334) [0,51.39]
75	Flood displacements*	Number of people displaced from 2001 to 2018 per event			26.03 (472.52) [0,45150.09]

*indicators reversed in constructing subdimension resettlement capacity index scores.
**we present the mode, instead of the mean, for ordinal variables.

SM3: Mean values of overall resettlement capacity and mean and share of asset, condition and their sub-dimensions by overall resettlement capacity score categories (values in parenthesis are standard deviations)

Dimensions	Sub-dimensions	Overall resettlement capacity categories						ANOVA F(2,46003)		Overall	
		Low		Medium		High					
		Score	Share	Score	Share	Score	Share	Score	Share	Score	Share
Assets	Natural	0.288[ab] (0.065)	7.83[ab] (1.82)	0.217[ac] (0.087)	4.89[ac] (2.10)	0.225[bc] (0.108)	4.00[bc] (1.92)	696.8***	2628.4 ***	0.222 (0.089)	4.96 (2.19)
	Financial	0.038[ab] (0.064)	1.02[ab] (1.72)	0.197[ac] (0.151)	4.23[ac] (3.09)	0.584[bc] (0.133)	10.34[bc] (2.20)	14335.2***	9265.3***	0.222 (0.186)	4.59 3.51)
	Human capital infrastructure	0.144[ab] (0.098)	3.87[ab] (2.62)	0.272[ac] (0.090)	5.99[ac] (1.82)	0.495[bc] (0.105)	8.79[bc] (1.79)	13371.4 ***	5735.8***	0.284 (0.115)	6.12 (2.09)
	Physical capital infrastructure	0.037[ab] (0.020)	1.00[ab] (0.54)	0.097[ac] (0.060)	2.09[ac] (1.19)	0.259[bc] (0.058)	4.60[bc] (1.01)	15389.1***	9887.1***	0.108 (0.075)	2.25 (1.37)
	Social	0.377[ab] (0.120)	10.23[ab] (3.25)	0.433[ac] (0.159)	9.56[ac] (3.35)	0.529[bc] (0.095)	9.41[bc] (1.71)	895.1***	52.2***	0.438 (0.156)	9.58 (3.24)
	Overall	0.882[ab] (0.113)	23.95[ab] (2.89)	1.216[ac] (0.290)	26.76[ac] (4.96)	2.092[bc] (0.252)	37.14[bc] (4.05)	19560.5***	8918.2***	1.274 (0.382)	27.50 (5.67)
Conditions	Access to assets	0.479[ab] (0.096)	12.99[ab] (2.55)	0.685[ac] (0.145)	15.15[ac] (2.88)	0.674[bc] (0.146)	11.98[bc] (2.62)	2221.4***	2659.4 ***	0.673 (0.150)	14.77 (3.01)
	Quality of assets	0.267[ab] (0.103)	7.28[ab] (2.88)	0.360[ac] (0.111)	7.98[ac] (2.41)	0.365[bc] (0.125)	6.47[bc] (2.18)	754.17***	758.7***	0.356 (0.113)	7.82 (2.46)
	Contexts	0.281[ab] (0.083)	7.63[ab] (2.21)	0.439[ac] (0.117)	9.67[ac] (2.28)	0.672[bc] (0.105)	11.92[bc] (1.72)	10048.9***	2893.3***	0.451 (0.137)	9.76 (2.38)
	Peaceful conditions	0.997[ab] (0.024)	27.10[b] (1.06)	0.995[c] (0.033)	22.20[bc] (2.00)	0.986[bc] (0.056)	17.54[bc] (1.20)	139.7***	18983.9***	0.995 (0.036)	22.05 (2.58)
	Stable natural conditions	0.775[ab] (0.113)	21.05[ab] (3.05)	0.819[ac] (0.092)	18.24[ac] (2.27)	0.840[bc] (0.081)	14.94[bc] (1.59)	354.7***	5792.1***	0.819 (0.093)	18.10 (2.54)
	Overall	2.800[ab] (0.127)	76.05[ab] (2.89)	3.298[ac] (0.263)	73.24[ac] (4.96)	3.536[bc] (0.238)	62.86[bc] (4.05)	6013.43***	8918.2***	3.293 (0.287)	72.50 (5.67)
Overall RCI		3.682[ab] (0.105)		4.514[ac] (0.372)	-	5.627[bc] (0.209)	-	25355.6***		4.567 (0.510)	-

[a]significance difference between low and medium resettlement capacity categories, [b]significance difference between low and high resettlement capacity categories, and [c]significance difference between medium and high resettlement capacity categories. The significance difference among group means is based on Bonferroni test. RCI stands for resettlement capacity index.

Climate change migration is increasing and necessitates a re-examination of resettlement planning and processes. Although evidence-based selection of host places would improve climate change resettlement outcomes, few methods for the selection of host communities exist. Consequently, the information base on which most resettlement programs select a host place is inadequate. This article proposes an empirical methodology to assess resettlement capacity. The methodology uses a hierarchical aggregation approach, where resettlement capacity indicator values are aggregated first into sub-dimension resettlement capacity scores, then further into dimension resettlement capacity scores, and finally into an overall resettlement capacity index. The aggregation allows for calculation of the relative importance of the different sub-dimensions and the two primary dimensions – assets and conditions. Using 75 indicators and a hierarchical min-max additive approach based on a five-kilometer grid, we create an overall resettlement capacity index for Ethiopia. The results show significant spatial variation in resettlement capacity. Low resettlement capacity sites tend to cluster in southeastern and western Ethiopia, while high resettlement capacity sites are scattered in central, southern, and northern Ethiopia. Moderate resettlement capacity sites occur more generally all over Ethiopia. Compared to the low and moderate resettlement capacity sites, those with high resettlement capacity are endowed with human, physical, and financial capital infrastructures. In all three groups, assets contribute significantly less to resettlement capacity than conditions. Places in the western and northern tips of the country are prone to natural hazards both currently and in the future, making part of the moderate resettlement capacity cluster in the northern tip unsuitable for resettlement. The calculated resettlement capacity indices are robust to potential missing indicators and change in units of analysis. Enhancing resettlement capacity in the future to accommodate predictable climate change displacements should target sub-dimensions that are weak in the high-capacity areas, promoting places with moderate-to-high resettlement capacity through enhancing the asset base especially, and avoiding resettlement in conflict- and disaster-prone places.

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