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Resettlement capacity assessments for climate induced displacements: Evidence from Ethiopia

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A R T I C L E I N F O

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A B S T R A C T

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 often 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 the 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, with and without normalizing the relevant indicators for population size. The results show significant spatial variation in resettlement capacity, and a clear difference between using the population size normalized and non-normalized indicators, particularly regarding places with very low population density. High resettlement capacity sites are scattered in central, southcentral, and northern Ethiopia, and they also occur in small clusters along southern and northwestern borders. Moderate resettlement capacity sites occur more generally all over Ethiopia. Sites with low resettlement capacity cluster in southeastern and western parts of the country. 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 capacity groups, assets contribute significantly less to resettlement capacity than conditions. Sites that are prone to natural hazards, both currently and in the future, are concentrated in the western and northern tips of the country. The calculated resettlement capacity indices are robust to potential missing indicators and change in the unit of analysis. The findings of the study can be used to identify areas for more comprehensive, localized analyses to determine their suitability for resettlement.

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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 (Gemenne and Blocher, 2017; Mueller et al., 2014; Black et al., 2011; McLeman, 2011). In 2018, for example, weather-related events such as storms, floods, and droughts displaced more than 16 million people (IDMC and NRC, 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 (Rigaud et al., 2018; Barnett and Webber, 2010). Many of the displaced cannot or do not want to return to their former home places and often end up in another, but 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 adaptation 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 (Bukvic, 2018; Adugna, 2011; Findlay, 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 spans 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 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 given availability good quality data, good understanding of the study context, and appropriate selection of indicator processing and index creation approaches. It thus provides a more 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 areas can be targeted for site visits and more comprehensive, localized assessments to determine their potential as resettlement places. These results can hence 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.

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; Sina et al., 2019b; Arnall et al., 2013). Second, the engagement of the affected communities and respect for basic human rights, during the planning and implementation of resettlement programs, are necessary for successful resettlement (UNHCR, 2018; Brookings et al., 2015; Sipe and Vella, 2014; Correa et al., 2011). 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 are 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, regardless of the nature of resettlement – e.g., whether resettlement is forced or voluntary.

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

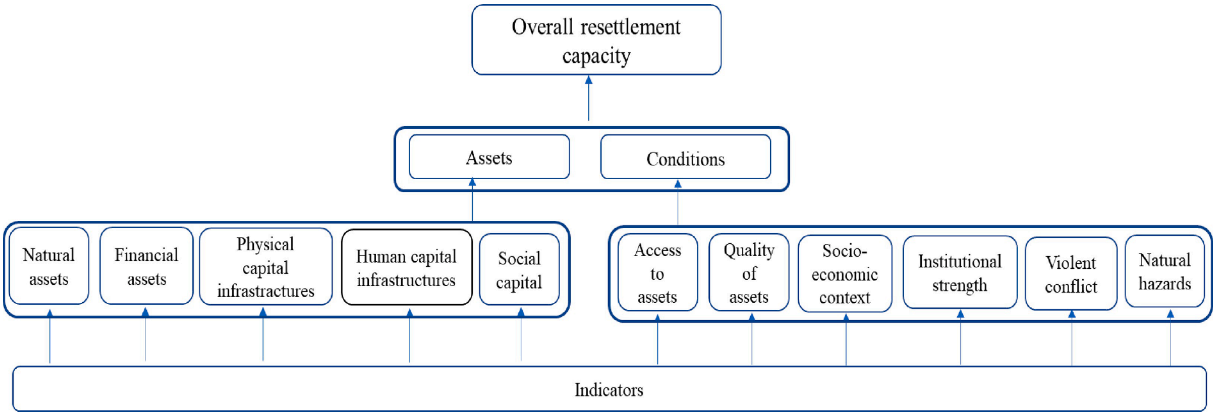

Fig. 1. Analytical framework to construct a resettlement capacity index for Ethiopia.

resettlement policy making. Even worse, the resulting assessments may lead to resettling people in places with low capacity as a result of the 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 a 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 (Fig. 1). For each sub-dimension, the framework presents a comprehensive list of generic indicators, 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 et al., 2011).

The empirical methodology and the accompanying assessment presented in this article follow 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 combine into the overall resettlement capacity index.

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 occurred 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 rain-fed agriculture characterized by low productivity, and are hence highly sensitive to climate change (Shumetie and Alemayehu, 2017; Gebrehiwot and van der Veen, 2014; Bezu et al., 2012; UNDP, 2012). 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 (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, negative impact on the livelihoods of tens of millions of smallholders in Ethiopia (Megersa et al., 2014; Di Falco et al., 2011; Deressa and Hassan, 2009). 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., 2011; 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 as these decisions 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-related events, and support in-situ adaptation strategies and rehabilitation programs to increase livelihood resilience, particularly in drought-prone areas (Woolf et al., 2018; Cochrane and Singh, 2016; Singh et al., 2016; 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 (Hermans-Neumann et al., 2017; Morrissey, 2013; Gray and Mueller, 2012; Ezra and Kiros, 2001).

Since the 1970s, the Ethiopian government has implemented several resettlement programs to resettle people from areas most exposed to adverse climate impacts (Rahmato, 2003). The first large-scale resettlement program, which came into effect in response to

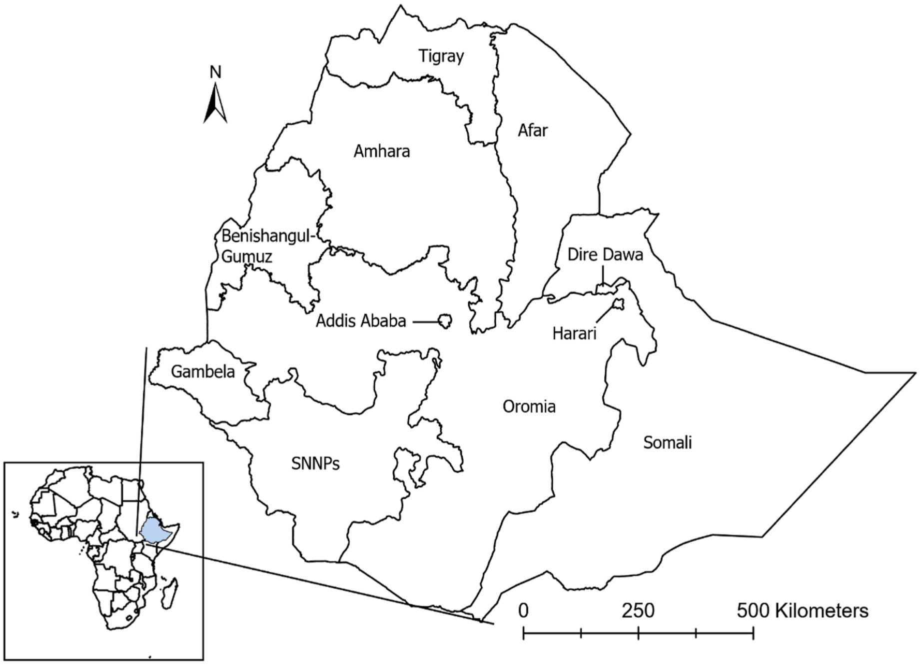

Fig. 2. Regions in Ethiopia. Note: SNNPs stands for Southern Nations, Nationalities, and Peoples'.

the 1972–73 famine, resettled over 110,000 people from the northern parts of the country to the western and southwestern parts (Fig. 2; Mengistu, 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[1], particularly in northern Ethiopia, and claimed the lives of about one million people[2] (Ezra, 2001; Kloos, 1990; Porter, 1986). As part of the program's long-distance resettlement component, 800,000 people relocated from the northern to southwestern parts of Ethiopia. In addition, 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).

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.[3] 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 resettlement. This need will most likely increase further in the coming decades due to climate change. Anticipating the increase in

[1] This resettlement programs were partly motivated by the political aim of depressing the military resistance in the north on the then government.

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

[3] 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; Mengistu, 1995).

displacement and need for future resettlement, 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.

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 most indicators, we use the latest data available to gauge the current conditions (e.g. data on latest election to measure political participation). For indicators that measure prevalence (of flood, for example, or conflict), we used longitudinal data starting from the year 2000. For these, we used an appropriate summary statistic (e.g., number of events over the period, mean number of fatalities). 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. While this procedure is relevant, it posed a problem by identifying places that are not suitable for resettlement as a high resettlement capacity places due to their low population density. Hence, we do a separate analysis (constructed an overall, asset, and condition resettlement capacity indices) using non-normalized indicators (see section 4.2 and 5).

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., Falchetta et al., 2019; GloBio; Malaria Atlas) (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 5 km grid cell (resulting in 46,006 cells, about three times the number of villages – the lowest administrative unit – in Ethiopia) using the Adindan 37 N 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 5 km resolution or higher (see SM2, Supplementary Materials, for details).

4.2. Indicator screening and selection

The preliminary 107 indicators had a standardized Cronbach alpha of about 0.93, exhibiting a high degree of information redundancy (Tavakol and Dennick, 2011; Streiner, 2003). 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 (≥ 0.8), 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 but limits information redundancy in data (Tavakol and Dennick, 2011; Streiner, 2003). The final list of indicators was grouped into 10 sub-dimensions (compared to 11 sub-dimensions in the CCRC framework) as we merged the indicators for institutional strength and contexts dimensions.[4] 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).

4.3. Index construction

To accommodate the hierarchical nature of the analytical framework, and following Cutter and Derakhshan (2020), Scherzer et al. (2019), and Cutter et al. (2014), 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 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 contribution 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:

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

Table 1
Inter-item correlation and Cronbach alpha by dimensions 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.

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

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), and 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 constructed normalized and non-normalized versions of dimension (asset and condition) and overall resettlement capacity indices. In the normalized indices, relevant indicators[5] are devided by population size , i.e., expressed in per capita terms, while in the non-normlized indices no indicator is devided by population size, but population size is included as an additional indicator.

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 that construct 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 and Derakhshan, 2020; Scherzer et al., 2019; Cutter et al. 2014). In addition, as the current paper aims at identifying destination places for upcoming resettlement programs, we do not have data on resettlement success, which potentially could be used as the dependent variable to drive different weights for the different components of the index. Even though sub-dimensions like violent conflicts and natural hazards can be more important to resettlement capacity, both have the same weight as the other sub-dimensions when we calculate the index.

However, following the suggestion of Waleligan 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. More specifically, we identify three categories of places based on conflict and natural hazard sub-dimension indices (see below on how we define the categories), and places that falls in the high conflict and/or natural hazard category are deemed to be unsuitable for resettlement regardless of their overall resettlement capacity. Further, 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 high temperatures and low precipitation levels that are not necessarily singled out as natural hazard prone areas by our indicators for drought and flood.[6]

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 and Derakhshan, 2020; Scherzer et al., 2019; Cutter et al., 2014), we used a cut-off value of *1.5 standard deviation from the mean* to distinguish grids with high and low resettlement capacity. The use of *1.5 standard deviation* as a cut-off value ensures that only the extremes of the distributions (about 13% of our grid cells) are identified either as to be in the low or high resettlement capacity place. 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] A total of 26 inicators (25 and 1 in asset and condition dimensions, respectively) are normalized for population size.
[6] We observe similar patterns using SSP585 and low emission scenario (SSP126) (results can be provided on request).

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 (Fig. 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 (Fig. 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 (Fig. 3, Panel C).

5.2. Geographies of resettlement capacity

We observe clear spatial variation in asset and condition capacity scores (Fig. 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 (Fig. 4, Panel Ai). The clusters in the northeast and east disappear and the clusters in the southeast become sparser and smaller when the indicators are not normalized for population size (Fig. 4, Panel Aii).[7] 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 (Fig. 4, Panels Ai and Aii). 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 (Fig. 4, Panel Ai). When the indicators are not normalized for population size, the cluster in the west becomes sparser while new scattered low resettlement spots appeared in the southern part of Ethiopia (Fig. 4, Panel Aii). Places with low scores for conditions cluster in southeastern and western parts of Ethiopia, while the cells with high scores cluster in south-central and southwestern parts (Fig. 4, Panels Bi and Bii). As expected, the patterns for population normalized and non-normalized condition scores are strikingly similar which is mainly because only one indicator is normianlized in condition dimension.

To examine the pattern of high and low resettlement capacity in both assets and conditions simultaneously, Fig. 4 (Panel Ci and Cii) displays the bivariate distribution of asset and condition index scores. Very few grids have a high resettlement capacity in terms of both asset and condition (1% and 1.5% of the cells for the population normalized and non-normalized resettlement cell scores, respectively). 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 0.0002% of cells when population normalized indicators are used, and 0.005% of the cells when non-normalized ones are used). Most of these cells are located in the western tip of the country (Fig. 4, Panel Ci). When the indicators are normalized for population size, the low resettlement grids – in both asset and condition dimension scores – extend to southeastern and southern Ethiopia (Fig. 4, Panel Cii).

Regarding overall resettlement capacity (normalization of the relevant indicators for population size), 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 (Fig. 5, Panel A). 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.

What is notable in these results, is they indicate as highly potential resettlement places areas that, in reality, have very harsh natural environmental conditions. These include the high resettlement capacity clusters in northeast and southeast (Fig. 5, panel A). Both places are characterized by high temperature and low rainfall and the northeast cluster is home for active volcanoes. These places, thus, do not have favorable conditions for settlement and viable livelihoods. It turns out that these places came out to have a high resettlement capacity due to their very low population density (see Appendix G) as one of third of our indicators are normalized by population size (see SM2 in supplementary materials, for the list), inflating the normalized values. This is evident from Fig. 5 (Panel B) that shows the results for the population non-normalized overall resettlement capacity index. It shows that (i) the high capacity places along the southeastern and northeastern no longer are in the high resettlement capacity category and (ii) the high resettlement capacity clusters along the southern and the northwestern borders have become sparser.[8] The population normalized and non-

[7] We have investigated what asset indicators constituent the high asset clusters (spots) in the southeast, northeast, and south (south Oromia) (Fig. 4Aii) as the clusters are counterintuitive. Compared to an average cell (grid), all the clusters (spots) have larger values (1.5 time or more, min-maxed, non-normalized) in the length of rivers with medium discharge, likelihood of presence of bank agents, likelihood of presence of saving and credit cooperative organizations (SACCO), likelihood of presence of public secondary schools, mobile phone use, likelihood of presence of public information notice board, and likelihood of presence of productive safety net programs. In addition, the spots in the northeast have higher value in lake area; the southeast cluster has higher value in area of shrubland, density of other roads (secondary, tertiary and local), mineral and oil deposits (mainly oil), and number of airports; and the south (south Oromia) cluster has higher value in area of grassland and shrubland (see SM4 in Supplementary Materials).

[8] There are also still spots with high resettlement overall resettlement capacity scores in the northeast (Afar) and south (south Oromia) (Figure B and C). As these clusters were counterintuitive, investigation of the indicators for these spots shows, the spots in both places, compared to the average cell, have larger (1.5 times or more, non-normalized, min-maxed) values in length of river density with medium discharge, bank agent, likelihood of presence of saving and credit cooperative organization (SACCO), likelihood of presence of public secondary schools, likelihood of presence of public information notice board, mobile phone use, and availability of productive safety net programs. In addition, the northeast spots have larger values in area of lake while the south spots have a larger value in grass and shrub land area (SM5 in Supplementary Materials). Regarding condition dimension indicators, both spots have larger value in ethnic diversity, immigrants for work, and lower rainfall erosion. In addition, spots in the northeast have higher soil carbon density and higher surface water seasonality (measured in the number of months, per year, water is available) (SM6 in Supplementary Materials).

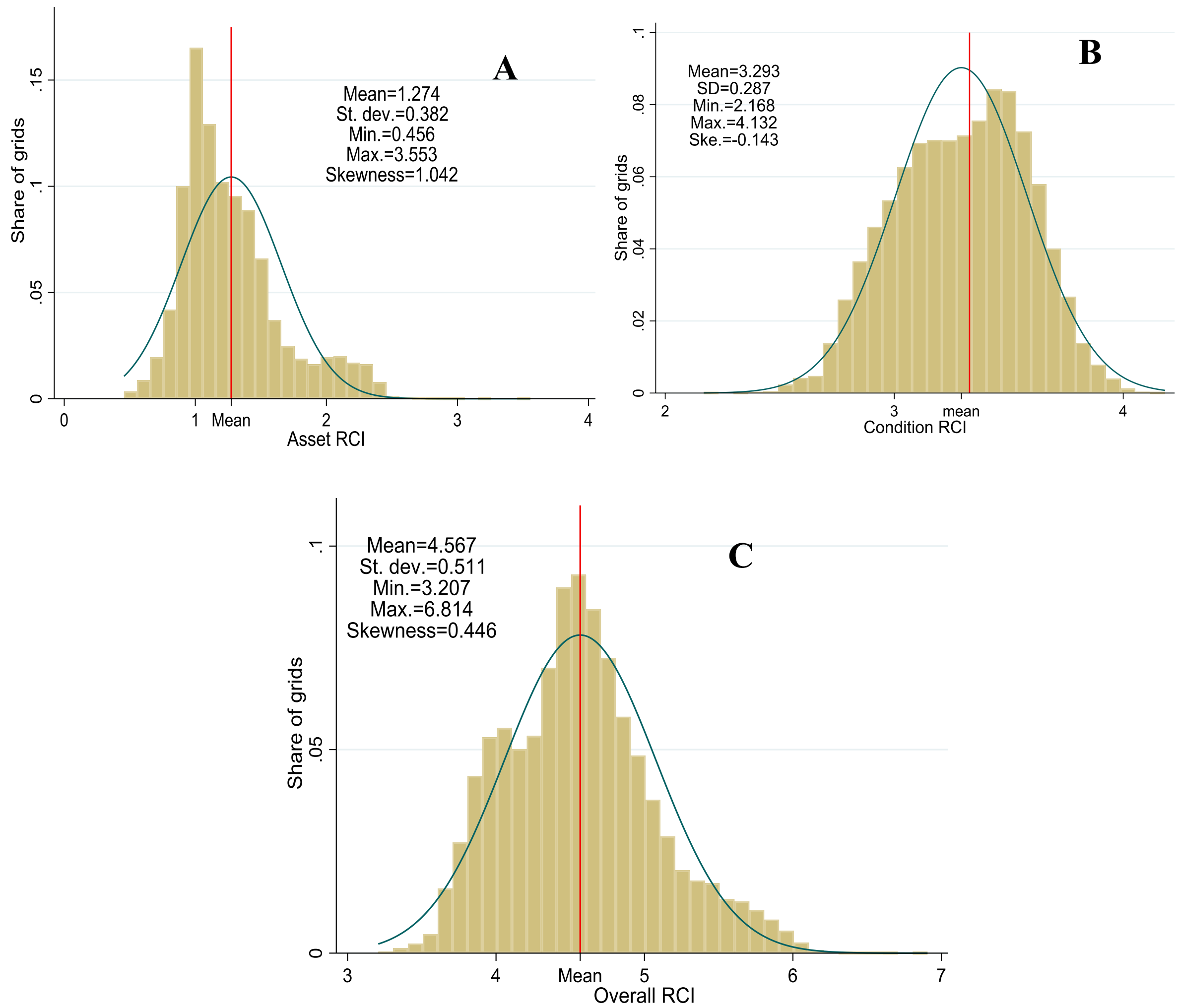

Fig. 3. Distribution of asset (A), condition (B), and overall (C) resettlement capacity index scores using the population non-normalized indicator values.

normalized resettlement capacity indices are highly correlated (0.92), and most of the grid cells (92.4%) fall in the same resettlement capacity category. There thus is a high degree of similarity between the adjusted and unadjusted overall resettlement capacity score. However, there is a striking difference when it comes to cells with very low population density, and for these cells, the per capita adjusted index can lead to wrong conclusions.

Hereafter, we will focus on high and low resettlement capacity grids that are robust to population size adjustment, i.e., grids that fall in the same category using the population size normalized and non-normalized overall resettlement capacity scores. Hence, low resettlement capacity category refers to low in both normalized and non-normalized overall resettlement capacity scores; the same applies for the high and moderate resettlement capacity categories. The remaining grids (about 8%), that are not robust for population adjustment are categorized as others.[9] We use the population size normalized resettlement capacity scores for the analysis below as the normalized scores ensure better comparability across grids as argued above.

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 (Fig. 6, Panel A) and (ii) the share of dimension and sub-dimension indices in the overall resettlement index by overall resettlement capacity categories (Fig. 6, Panel B). Most high resettlement grids tend to concentrate in and around cities and towns while most of the low resettlement categories are far away from cities and towns (see, Appendix J for the location of cities and

[9] This category contains the six combination of population normalized vs non-normalized categories (low-medium, low–high, medium–low, medium–high, high-low, and high-medium)

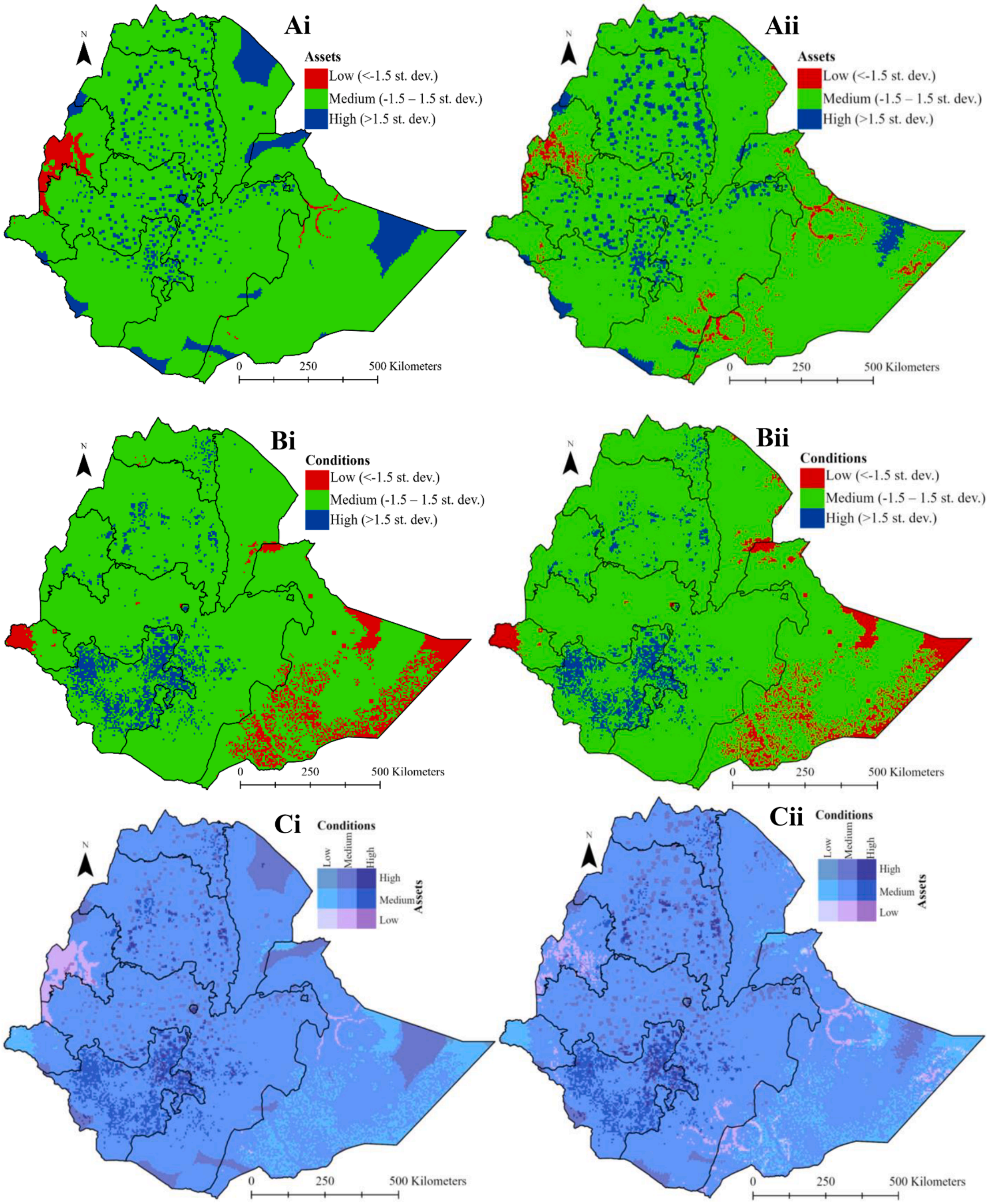

Fig. 4. Resettlement capacity index for assets normalized (Ai) and non-normalized (Aii) for population size; conditions – normalized (Bi) and non-normalized (Bii) for population size; and bivariate combination of asset and condition indices – normalized (Ci) and non-normalized (Cii) – for population size.

towns; see, SM7, 8, and 9 – in Supplementary Materials – for the list of cities and towns that falls in the high resettlement places). The high resettlement category has the highest mean scores in both asset and condition dimensions. The high resettlement category also had the highest mean score in all sub-dimension scores with two notable exceptions. First, natural capital sub-dimension, for which low resettlement capacity had the highest mean score. Second, 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.

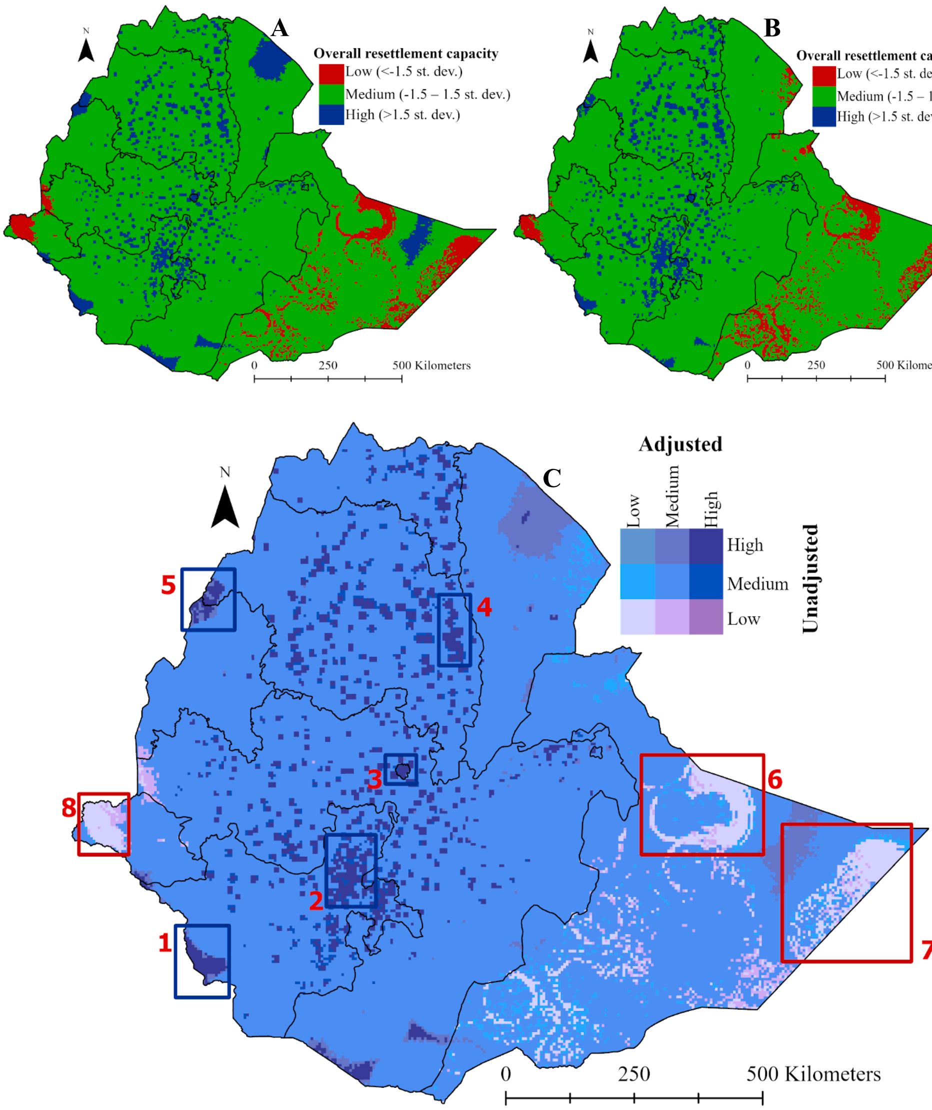

Fig. 5. Overall resettlement capacity index with population normalized (A) and population non-normalized indicators (B), and bivariate combination of the two (C). The blue and red boxes in Panel C correspond to the high and low resettlement capacity clusters included in Table 2. See Appendix H for a map highlighting cells that fall in the low or high category according to both indices.

The results also reveal that the conditions dimension (72.5%), and particularly the peaceful conditions sub-dimension (22%), make the largest contribution[10] to the overall resettlement capacity score (Fig. 6, 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 (Fig. 6, 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.

To further investigate the drivers of resettlement capacity, we selected relatively bigger clusters of high and low resettlement scores in Fig. 5, Panel C (blue and red boxes, respectively). For these, we calculated the mean scores (normalized for population size) for each

[10] This means that peaceful condition contributes more for the calculated resettlement capacity of places; it does not mean peaceful conditions matter more for resettlement than other sub-dimensions.

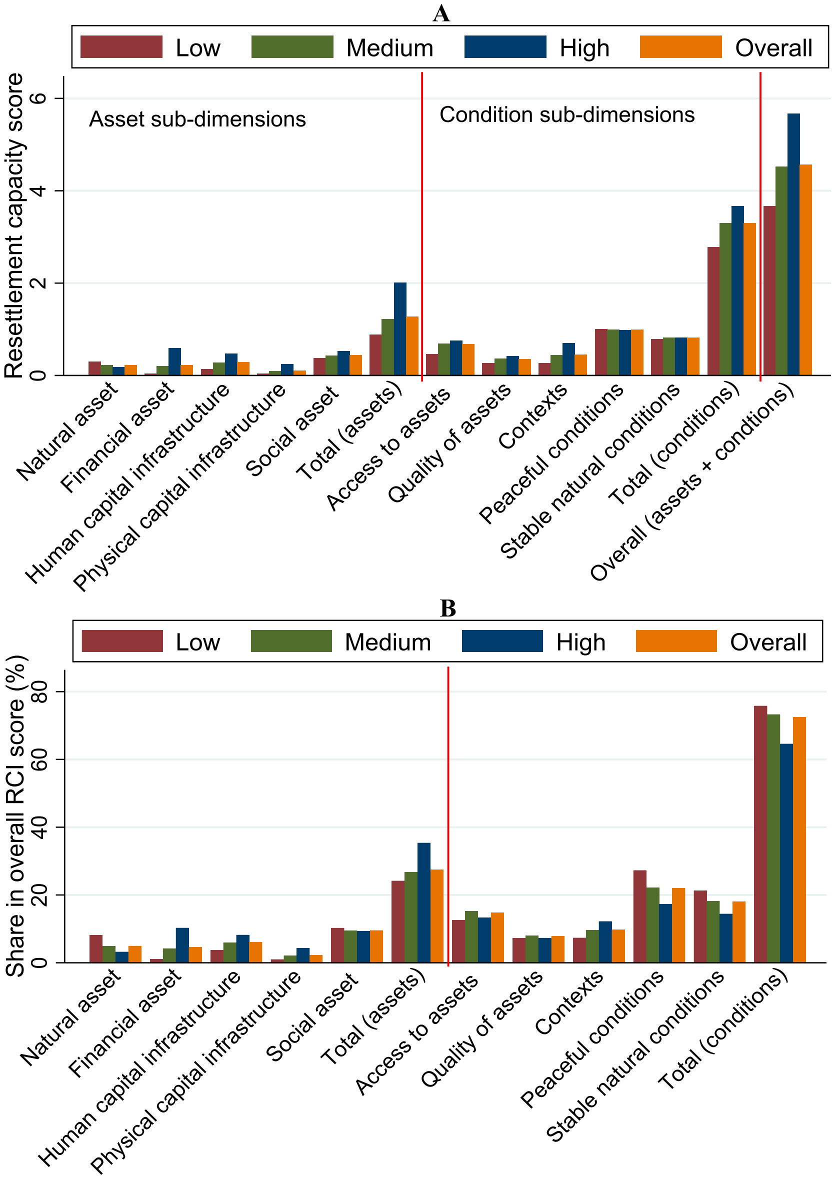

Fig. 6. Mean values (normalized for population size) of overall, asset, condition, and sub-dimension scores (A) and share of asset, condition, and sub-dimensions scores to the overall resettlement capacity score (B) by overall resettlement capacity score categories.

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 high resettlement capacity clusters are on average, characterized by a very high resettlement scores (more than double that of the average cell) 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 score in the contexts subdimension. The clusters with low resettlement capacity are, on average, characterized by higher resettlement scores in natural capital. 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).

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, 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;

Table 2
Mean values (normalized for population size) of overall resettlement capacity index (Overall RCI), asset, condition and their sub-dimension indices for high and low resettlement clusters in Fig. 5C (values in parenthesis are the ratio between the mean value and mean values of all the cells).

		High resettlement capacity clusters					Low resettlement capacity cluster		
		North Western Ethiopia (border between Benishangul-Gumuz and Amhara) (5*)	North central Ethiopia (East Amhara) (4*)	South Western Ethiopia (in SNNPs region) (1*)	South central Ethiopia (North SNNPs region) (2*)	Addis Ababa and its surroundings (3*)	West Ethiopia (Western Gambella) (8*)	South east Ethiopia (north of Somali region) (6*)	South east Ethiopia (South east Somali region) (7*)
Assets	Natural	0.226 (1.0)	0.165 (0.7)	0.237 (1.1)	0.161 (0.7)	0.164 (0.7)	0.357 (1.6)	0.292 (1.3)	0.303 (1.4)
	Financial	0.612 (2.8)	0.515 (2.3)	0.579 (2.6)	0.566 (2.5)	0.769 (3.5)	0.055 (0.2)	0.056 (0.3)	0.052 (0.2)
	Human capital infrastructure	0.557 (2.0)	0.384 (1.4)	0.567 (2.0)	0.373 (1.3)	0.667 (2.3)	0.112 (0.4)	0.044 (0.2)	0.067 (0.2)
	Physical capital infrastructure	0.311 (2.9)	0.273 (2.5)	0.240 (2.2)	0.218 (2.0)	0.275 (2.6)	0.053 (0.5)	0.027 (0.3)	0.033 (0.3)
	Social	0.523 (1.2)	0.628 (1.4)	0.646 (1.5)	0.526 (1.2)	0.450 (1.0)	0.257 (0.6)	0.462 (1.1)	0.414 (0.9)
	Overall	2.229 (1.7)	1.965 (1.5)	2.269 (1.8)	1.845 (1.4)	2.325 (1.8)	0.834 (0.7)	0.881 (0.7)	0.869 (0.7)
Conditions	Access to assets	0.525 (0.8)	0.832 (1.2)	0.545 (0.8)	0.863 (1.3)	0.731 (1.1)	0.522 (0.8)	0.328 (0.5)	0.488 (0.7)
	Quality of assets	0.353 (1.0)	0.369 (1.0)	0.397 (1.1)	0.436 (1.2)	0.462 (1.3)	0.452 (1.3)	0.181 (0.5)	0.262 (0.7)
	Contexts	0.774 (1.7)	0.705 (1.6)	0.724 (1.6)	0.788 (1.7)	0.724 (1.6)	0.196 (0.4)	0.316 (0.7)	0.264 (0.6)
	Peaceful conditions	1.000 (1.0)	0.951 (1.0)	1.000 (1.0)	0.999 (1.0)	0.912 (0.9)	1.000 (1.0)	1.000 (1.0)	0.999 (1.0)
	Stable natural conditions	0.800 (1.0)	0.843 (1.0)	0.936 (1.1)	0.754 (0.9)	0.783 (1.0)	0.516 (0.6)	0.879 (1.1)	0.808 (1.0)
	Overall	3.452 (1.0)	3.700 (1.1)	3.601 (1.1)	3.840 (1.2)	3.613 (1.1)	2.684 (0.8)	2.705 (0.8)	2.822 (0.9)
Overall RCI		5.681 (1.2)	5.665 (1.2)	5.869 (1.3)	5.685 (1.2)	5.938 (1.3)	3.518 (0.8)	3.586 (0.8)	3.691 (0.8)

*Location for the high and low resettlement capacity clusters in Fig. 5C; 1 covers parts of Surma and Maji districts in Benchi Maji zone in SNNPs; 2 parts of Hadya, Kembata Tembaro, Wolayita zones, and Alaba special district in SNNPs; 3 Addis Ababa city administration and surrounding districts (Mulona Sululta, Alem Gena, and Berlehna Alelitu); 4 parts of Kalu, Kutaber, Tehuledere, Werebabu, Guba Lafto, and Ambasel districts, Dessie city and its surroundings in Amhara region; 5 parts of Dangur and Guba districts in Benishangul-Gumuz region and Quara district in Amhara region; 6 parts of Misrak Gashamo, Degehabur, and Aware districts in Somali region; 7 parts of Boh, Geladin, and Warder districts in Somali region; 8 parts of Akobo, Jar, and Jikawa districts in Gambella region.

and (iv) annual fatalities due to riots.[11] 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 (Fig. 7, 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. Hence, the absence of low conflict risk category on the map does not mean the absence of places with low conflict in absolute terms as 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). This makes the high resettlement capacity cluster in Addis Ababa unsuitable for resettlement.

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 (Fig. 7, Panel B). This makes the high resettlement clusters scattered in northwestern tip of Ethiopia unsuitable for resettlement.

To identify places that are unsuitable for resettlement in the future, we map the distribution of projected temperature and rainfall between 2061 and 2080 (Fig. 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) (Fig. 8, 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 increasingly hotter and drier between

[11] 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.

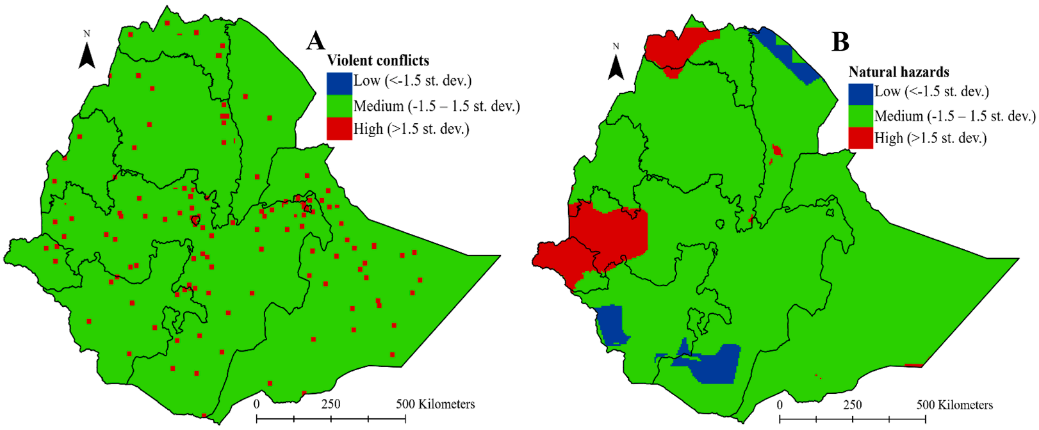

Fig. 7. Geography of conflict (A) and hazard risk (B).

2061 and 2080 and therefore should not be considered for resettlement. Most parts of western, southwestern, and northwestern Ethiopia, meanwhile, will get more precipitation, so they could experience more frequent floods. These are comparable with the high hazard risk clusters in western tip and northwestern part of Ethiopia (Fig. 7, Panel B) and the low overall resettlement capacity cluster in the western tip and southeastern part of Ethiopia (Fig. 5, Panel C), making these clusters unsuitable for resettlement.

6. Robustness checks

We used three assessment criteria to check the robustness of the constructed index (with indicators normalized for population size): 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 (resulting in 15 km grid cell) for all the indicators, and constructed a new overall resettlement capacity index using the 15 km 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 suggest 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 5 km to 20 km.

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 missing sub-dimensions and indicators. Modifying the indicators (e.g., normalizing for population size) could lead identification of few unsuitable places for resettlement as a high resettlement capacity places due to their low population density. However, population normalized and non-normalized overall resettlement capacity scores have a very high correlation (0.92) and lead to similar categorization for most of the cells (92.4%).

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 (Fig. 5A).

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 min–max hierarchical additive index construction approach, where the inputs for producing the indices at different levels are min-max-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) usually find easily understandable and applicable

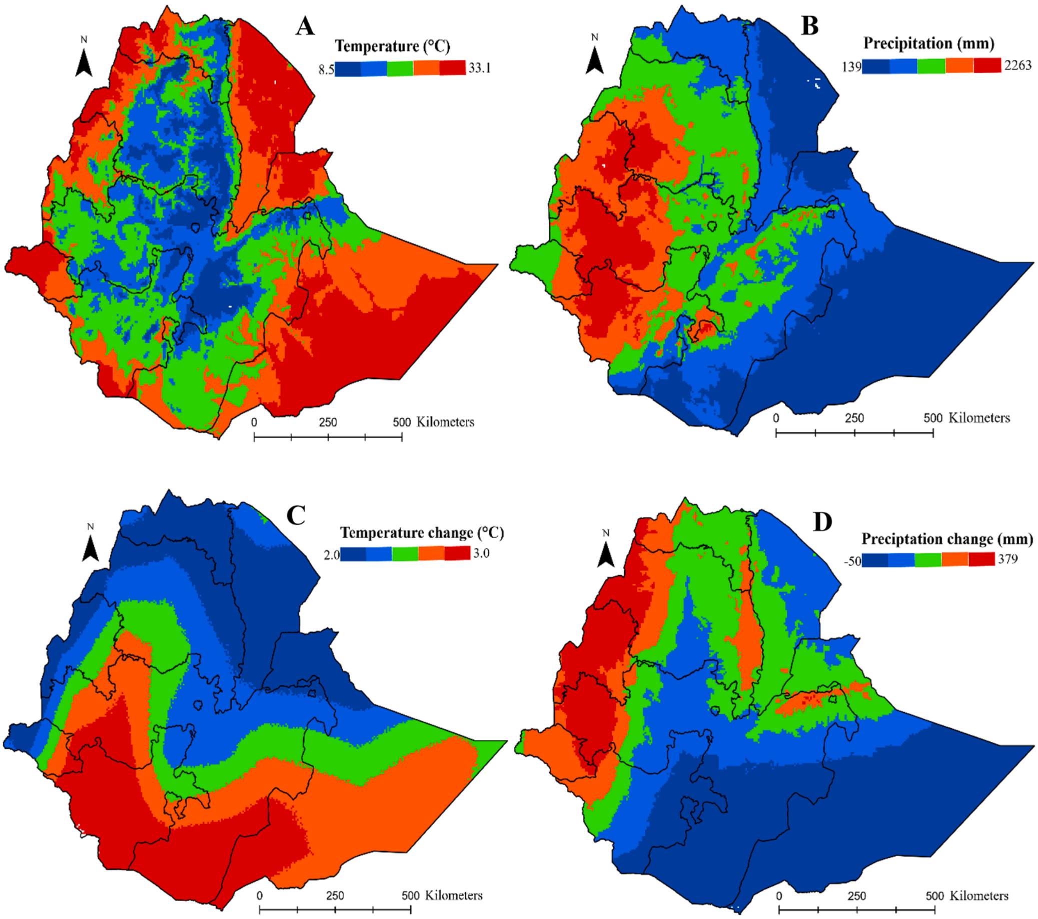

Fig. 8. Projected mean annual temperature and annual precipitation (between 2061 and 2080) (A and B) and projected change in temperature and precipitation (C and D) (Source: WorldClim, 2020).

(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.[12] 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).

Our findings revealed that normalizing indicators using population size, as suggested by Walelign and Lujala (2020), may lead to places with very small populations to appear having a high resettlement capacity score. To minimize identification of unsuitable places as high resettlement capacity places due to their low population density, we suggest that future studies construct the index using both population normalized and population non-normalized indicators, and select cells that both indices indicate has places with high potential. In our case, failing to do this would have led to the identification of areas with very harsh environmental conditions as potential resettlement areas.[13]

The empirical findings for Ethiopia show considerable spatial variation in overall resettlement capacity. The spatial distribution of

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

[13] We thank the reviewers to bring this point to our attention.

overall resettlement capacity revealed that the robust high resettlement capacity places – high in both population normalized and non-normalized overall resettlement capacity scores – are concentrated in central, south, and northcentral parts of Ethiopia, with smaller scattered clusters along the southern, southeastern, and northwestern international borders. The low resettlement capacity places – low in both population normalized and non-normalized overall resettlement capacity scores – are concentrated in southeastern and western (tip) parts of Ethiopia. The high resettlement capacity places are endowed with financial capital (e.g., availability of banks) and human (e.g., schools) and physical capital infrastructures (e.g., roads) while the low resettlement capacity places lack financial capital and human and physical capital infrastructures, while they often are endowed with natural capital (e.g., natural resources). Further, additional analyses revealed that 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 (Scoones, 2015; Winters et al., 2009; Ellis, 2000; DFID, 1998). 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; Sina et al., 2019b; 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 (Arnall 2019; Wilmsen and Webber, 2015). 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., Fang et al., 2018; Scoones, 2015; 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[14] that mostly affected the northern part of Ethiopia (Rahmato, 2003; Kloos, 1990). 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 was unlikely to improve at destination (as has been the case, see e.g. Rahmato, 2003; Kloos, 1990). 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. In addition, most of the resettlement programs were partly motivated by other motives (e.g., the political, making the poor less visible by moving to distant places). 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, 1990).

When we compare the distribution of overall resettlement capacity (Fig. 5C) with WFP's monthly food insecurity status for Ethiopia (WFP, 2020; WFP, 2019a; WFP, 2019b), we notice a high degree of overlap between the food security assessments for 2019 and 2020 and our overall resettlement capacity index. For instance, in October 2019, a large part of southeastern Ethiopia was classified under the 'crises' category;[15] in our analysis the same area was 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. 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. In contrast, a comparison of the distribution of natural hazard risks (Fig. 7B) with the WFP's food insecurity status reveals a low degree of overlap. For instance, the two high hazard risk clusters (in western and northern tip of Ethiopia) were in the minimal food insecurity category. The presence of a high degree of overlap between the food security assessments and our resettlement capacity scores as well as low degree of overlap between food security assessment and our natural hazard risk suggests that our resettlement capacity

[14] The military resistance in the north during the 1980′s contributed to the 1984 famine as the resistance hindered transportation.

[15] 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).

assessment could complement efforts to ensure food security.

Using a few sets of indicators, mainly on population, production, and climate trends, Rigaud et al. (2018) and Hermans-Neumann et al. (2017) 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 from our analysis. However, the overlap between most suitable destination places in Hermans-Neumann et al. (2017), Rigaud et al. (2018), and our study occur in southern Ethiopia, particularly the northern SNNPs region, and in and around the Harari 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); our resettlement hotspots, meanwhile, occur in a scattered pattern throughout central and northern Ethiopia, and in small clusters along the northwestern and southwestern 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 (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 5 km 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, but not to the indicator normalization by population size, which can lead to misleading results for areas with very low population size. 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 social capital, 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, its main contribution is the identification of potential areas to which more comprehensive, localized assessments can be targeted. Our advice for resettlement experts and decision makers is 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 assessments need to 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 assessed to avoid potential conflicts (Lujala et al., 2020; Kolstad et al., 2019). However, the findings of the current study and further assessments should not be used to justify resettlement. Resettlement should be used once all feasible *in-situ* adaptation strategies are exausted and be implemented on voluntary basis.

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 (e.g., volcanoes, water quality). 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).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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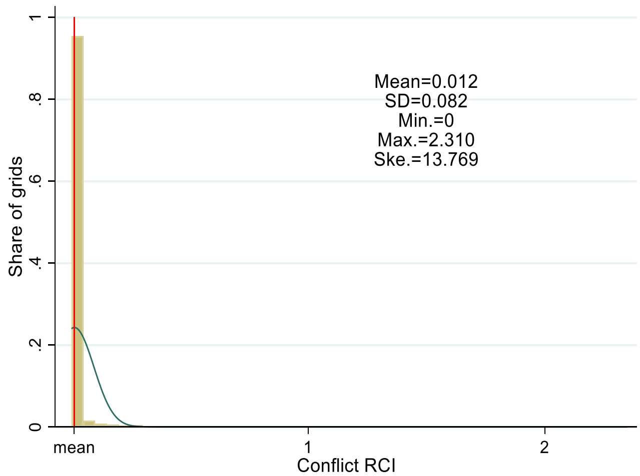
Appendices

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

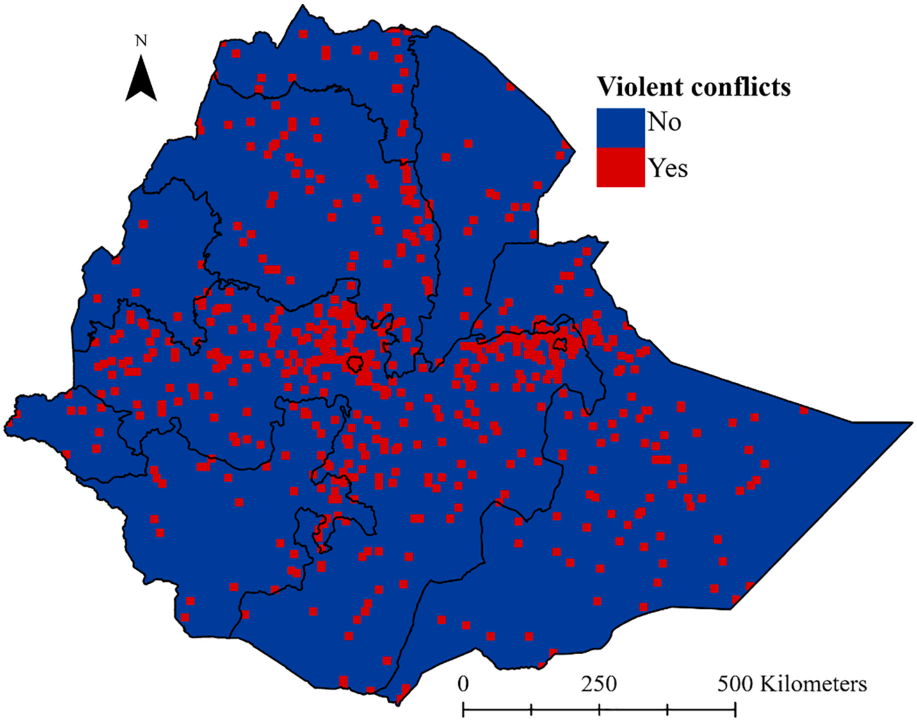
Dataset type	Spatial unit	Data processing
Raster (spatial)	Five-kilometer grid	Converted to polygon and joined with the five-kilometer vector grid
	Grids larger than five-kilometer	Resampled to five-kilometer resolution, converted to polygon and joined with the five-kilometer vector grid
	Smaller than 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) DHS (survey)	Geocoded enumeration area 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).
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.

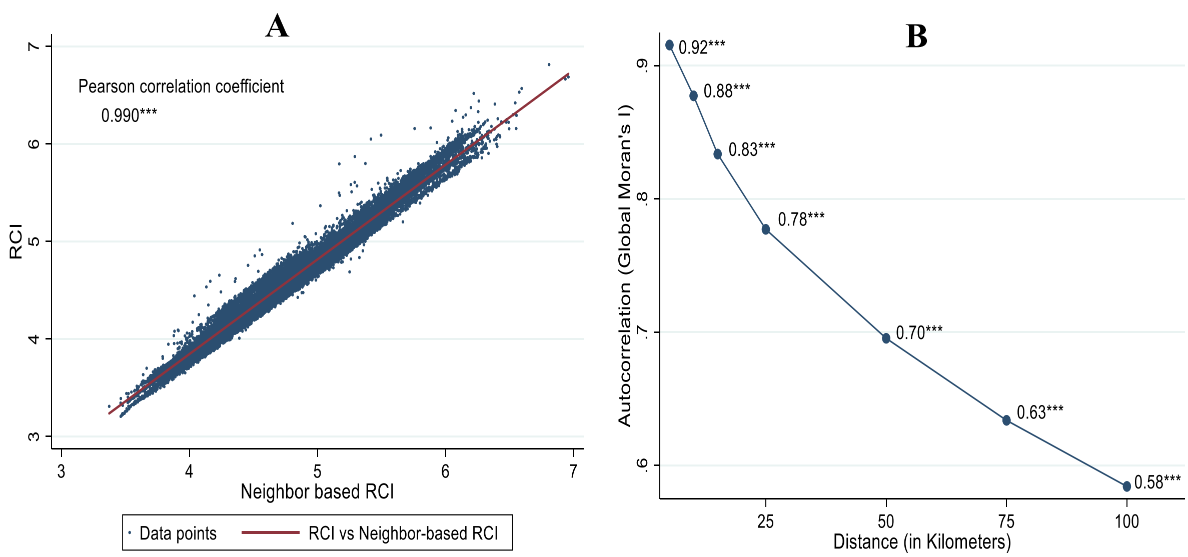
Appendix B: Distribution of conflict resettlement capacity score.



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, normalized for population size) 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%)

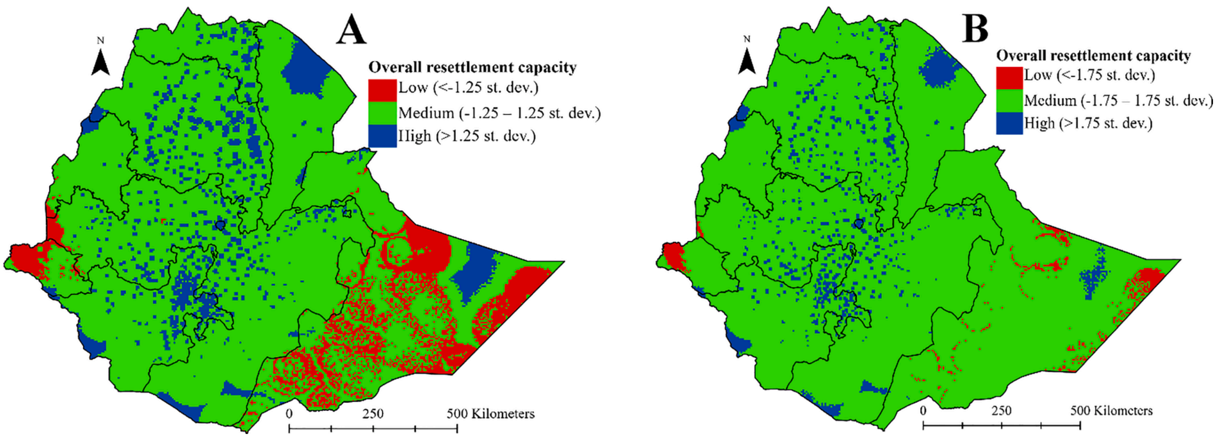


Appendix E: Correlation between resettlement capacity index (RCI) score and reduced RCI scores (Panel A) and Global Moran's I at 10, 25, and 50 kilometers distance (Panel B)

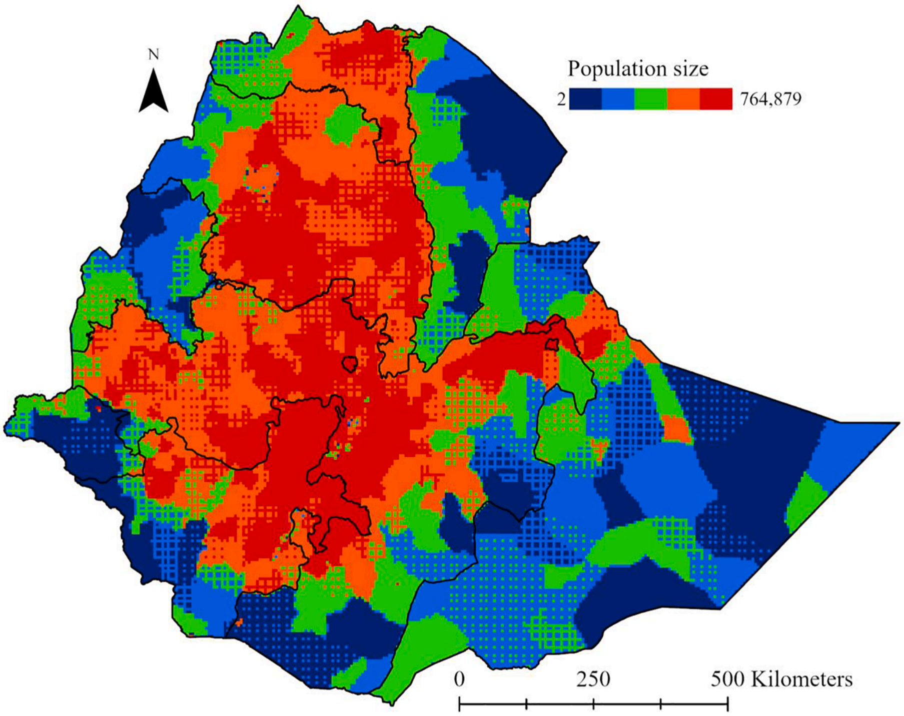
Panel A		Panel B			
	Correlation		Global Moran's I		
			10 kilometers	25 kilometers	50 kilometers
	-	RCI	0.8774***	0.7773***	0.6955***
RCI vs Reduced RCI by natural assets	0.987***	Reduced RCI by natural assets	0.8929*** (-0.0155)	0.8057*** (-0.0284)	0.7336*** (-0.0381)
RCI vs Reduced RCI by financial 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%.

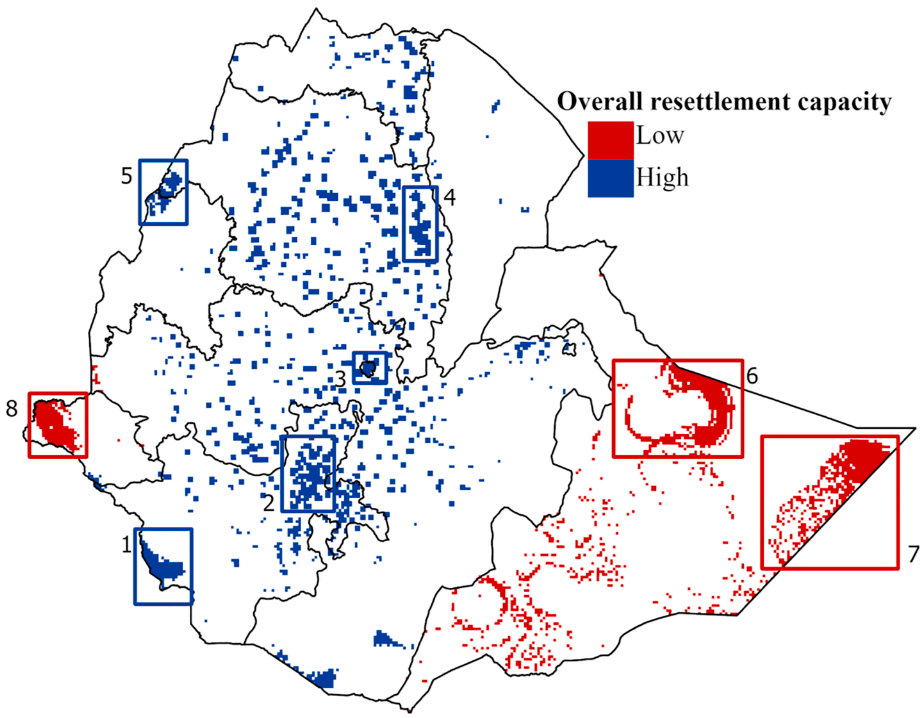
Appendix F: Geographic distribution of overall resettlement capacity categories (based index normalized for population size) with alternative cutoff values: with 1.25 (A) and 1.75 (B) standard deviation from the mean.



Appendix G: Geographic distribution of population size per 5-km grid (25 square km).



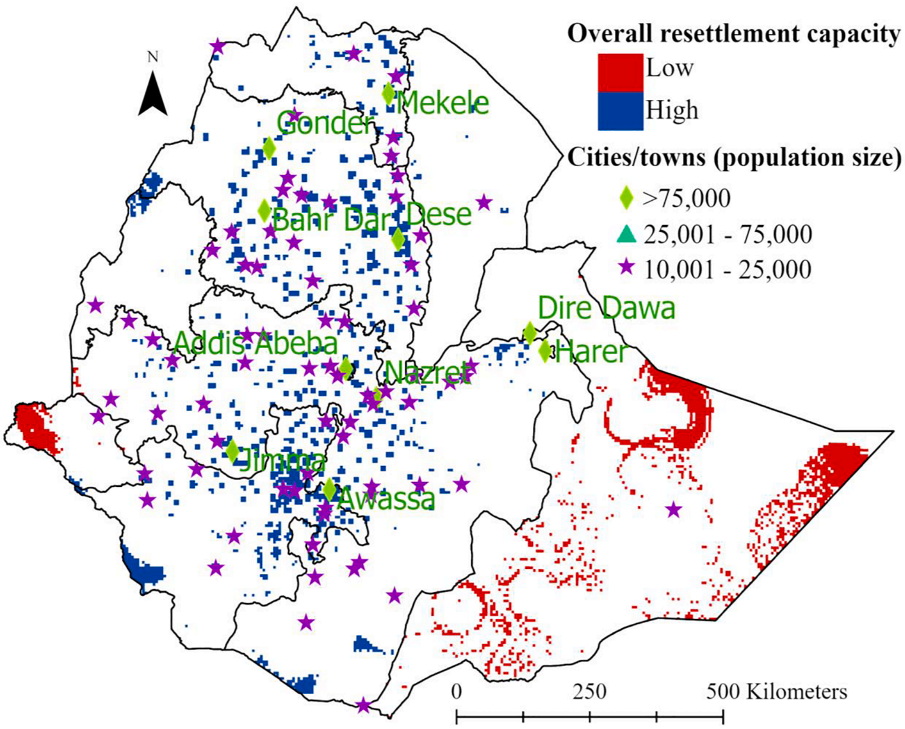
Appendix H: Geographic distribution of high and low overall resettlement capacity categories based on both indicators normalized and non-normalized for population size.



Appendix I: Crosstabulation of cells in each resettlement capacity category using the population normalized and non-normalized overall resettlement capacity indices (note: values in parenthesis is the proportion of grids, %).

		Adjusted overall RCI			
	Category	Low	Medium	High	Total
Unadjusted overall RCI	Low	1705(3.7)	972(2.1)	0(0)	2677(5.8)
	Medium	581(1.3)	38210(83.1)	1283(2.8)	40074(87.1)
	High	0(0%)	640(1.4)	2615(5.7)	3255(7.1)
	Total	2286(5.0)	39822(86.6)	3898(8.5)	46006(100)

Appendix J: Geographic distribution of overall resettlement capacity categories and cities and towns with different sizes (from IPAC GeoPortal 2021 – http://geoportal.icpac.net/layers/geonode%3Aeth_major_town, accessed April 19, 2021; correction to the data: Wolkite town is moved to the category of towns with a population between 25000 and 75000 from cities a population with above 75000 while Awassa town is moved to the category of cities with a population above 75000 from towns with a population between 25000 and 75000 categorized in cities with population greater than 75000; see SM7, 8, and 9 for the list of the cities and towns).



Appendix K. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2021.100347.

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