Supplemental material for

"Climate, Agriculture, and Migration: Exploring the Vulnerability and Outmigration Nexus in the Indian Himalayan Region", by Riccardo Biella, Roman Hoffmann, and Himani Upadhyay, published in *Mountain Research and Development* 42(2), 2022. (See https://bioone.org/toc/mred/42/2)

Contents

APPENDIX S1 Data sources 1
APPENDIX S2 Construction of the vulnerability index 7
APPENDIX S3 Quantitative estimation approach 9
APPENDIX S4 Mixed methods approach and qualitative insights 10
APPENDIX S5 Further descriptive statistics 12
APPENDIX S6 Illustrating the vulnerability-migration relationship 13
References 15

APPENDIX S1 Data sources

To study the role of climate vulnerability for migration, a vulnerability index was constructed, which reflects the socioeconomic and environmental conditions in an area. The index is based on prior work by Shukla et al (2016) who have developed the index for the local context in Uttarakhand. As main data source, we rely on information from the *Census of India* (2011), which was collected between 2008 and 2010. In addition, we retrieved district-level information on income per capita from the *Human Development Report of Uttarakhand* (GU 2018). The socioeconomic and demographic indicators obtained were combined with other sources of information on local vegetation, water balance, and topography, which are based on remote sensing data.

To derive information on local vegetation, we use the Landsat-7 Global Annual Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) for the period 2016 to 2018. ASTER GDEM data, based on a global digital elevation model, are used to describe the local topography and altitude (METI and NASA 2021). Both datasets have a resolution of 30 m. Additionally, pre-elaborated remote sensing data was obtained to measure the local forest cover through the portal of the Copernicus Program and soil erodibility through the European Soil Data Center (ESA 2021; European Commission 2021). Shapefiles and maps were obtained from the *Technical Report on District Level Vulnerability* (INRM 2016). The data were aggregated at the community development block level.

Data on some indicators used for the original index were not available and were substituted with equivalent alternative data. First, income and expenditures used in Shukla et al. (2016) were discarded as the authors used the data from the 2001 census. This was deemed too old to be used in this study and was instead replaced with the data on income at the district from the *Human Development Report of Uttarakhand* (GU 2018). As no data on expenditures was available, the income data was used as the sole indicator for financial capacity in this study. The indicator for dense forest used by Shukla et al. (2016) could not be accessed and was instead substituted with information from the Global Land Cover dataset from ESA's Copernicus Program (ESA 2021). Finally, the data for soil erodibility used by Shukla et al. (2016) was unavailable and instead replaced with the Soil Loss Index provided by the ESDAC (European Commission 2021). The list of the indicators used, and their description are presented in Table S1.

TABLE S1 List of indicators for constructing the vulnerability index (based on Shukla et al., 2016)

Sub-dimension	Indicator	Code	Description	Data Source
Sensitivity – Ecological dimension				
Agro-constraint (AgC)	Median elevation	Ele	Higher elevations limit agricultural land utilization and is correlated with remoteness and marginalization.	ASTER GDEM
	Mean slope	Slo	Steep slopes are more prone to soil erosion, negatively affecting the cultivation.	ASTER GDEM
	Mean aspect	Asp	Aspect determines the amount of sunlight in an area which is important for crop production.	ASTER GDEM
	Soil erosivity	Ero	High soil erosion is generally associated with yield reductions and degradation of soil structure.	ESDAC
	Barren land (% of total area)	BaL	Barren land is not suitable for agriculture owing to its soil characteristics. It is also more exposed to landslides.	Census 2011
Area exposed (ArE)	Net sown area (% of total area)	NSA	The proportion of agricultural land in a region represents the area that would be exposed to environmental risks. Hence, the greater the area under cultivation, the more sensitive is the region to climate impacts.	Census 2011
	Current fallow (% of total area)	CuF	Represents agricultural area not under cultivation. Land with reduced fertility is often left fallow. Linkages exist between fallow land and higher dependence on unreliable monsoon for irrigation.	Census 2011

	Tree crop (% of total area)	TrC	Tree crop area is a proxy for area under horticulture. Environmental changes threaten horticulture production due to its high sensitivity. These areas are highly exposed to climate stress and more susceptible to damages.	Census 2011
	Culturable waste land (% of total area)	CWL	Culturable waste land areas are suitable for cultivation but have not been cultivated in the last 5 years. Presence of such land-use types reflects that cultivation in these areas is economically redundant owing to adverse site conditions and propensity to degradation.	Census 2011
Sensitivity – Social dimension				
Agricultural-density (AgD)	Total population (per unit agricultural land)	ToP	The number of people per unit of agricultural land indicates the severity of demographic pressure	Census 2011
	Agricultural population (per unit agricultural land)	APD	Higher density of agricultural population results in intensification of agriculture and fragmentation leading to land degradation	Census 2011
Livelihood dependency (LiD)	Main cultivators (% of total population)	MaCL	Main cultivators are involved for more than 6 months in agriculture on their own land. Most of the farmers in Uttarakhand are owners of the land they cultivate. Cultivators have more access to resources, but they face enhanced risks of income losses owing to their complete dependence on agriculture-based activities	Census 2011
	Main agricultural workers (% of total population)	MaAW	Main agriculture workers work on the land of other cultivators for a period of more than 6 months a year.	Census 2011
	Marginal cultivators (% of total population)	MgCL	Marginal cultivators are involved for less than 6 months in agriculture on their own land.	Census 2011

	Marginal agricultural workers(% of total population)	MgAW	Marginal agricultural workers do not own agriculture lands and work as wage labor for less than 6 months a year.	Census 2011
Marginalized population (MaP)	Schedule caste (% of total population)	SCP	Schedule castes and tribes represent the socially marginalized communities. The construct of caste and its hierarchy creates barriers and limits the capacities to generate livelihoods. These communities are noted to have higher dependence on natural resources thus making then more vulnerable.	Census 2011
	Schedule tribe (% of total population)	STP		Census 2011
Adaptive capacity – Ecological dimension				
Environmental capacity (EnC)	High density forest (% of total forest area)	HDF	Forest is an important resource for agriculture. It prevents soil erosion, maintains soil moisture and water level. Also, dense forest cover plays a major role in maintaining the hydrological regime.	Copernicus Program
	NDVI	NDVI	NDVI is generally used as a proxy for productivity. Higher NDVI values are an indicator of good vegetation health.	Landsat-7 Global Coverage
	NDWI	NDWI	NDWI, a wetness index, identifies water and irrigated areas. Higher availability of water resources enhance agricultural production	Landsat-7 Global Coverage
Agro-ecological capacity (AEC)	Net irrigated area (% of agricultural area)	NIA	Agricultural production is higher on irrigated lands. Higher agricultural productivity further enhances the livelihoods of the agricultural communities.	Census 2011
	Forest availability (Per unit of agricultural area)	FAD	Approximately 10-15 ha of forest land is needed for every hectare of cultivated land to maintain agricultural stability. Therefore, locations with higher forest availability per unit of agricultural area typically have higher agricultural yields.	Census 2011

Adaptive capacity – Social dimension				
Human capacity (Hum)	Literacy rate (% of population)	Lit	Literacy is considered to be an important factor in determining access to information. Moreover, literacy reduces poverty and provides wider social benefit. The skills required to organize and manage natural resources in mountains is enhanced through higher literacy, along with higher capacity for adaptive learning.	Census 2011
	Sex- ratio (female per 1000 male)	SeR	Symmetric sex-ratio indicates gender equality. Role of females have been extensively highlighted in maintaining agriculture in mountains.	Census 2011
	Non-agriculture dependent workers (% of total population)	OTW	Income generated from non-agricultural sources supports the livelihoods of agricultural communities and helps build resilience. It is also indicative of presence of non-farm skills within the communities.	Census 2011
Infrastructure capacity (Inf)	Availability of roads	RoN	Availability of roads is crucial for connectivity with markets and for access to basic necessities. Presence of roads increases the opportunities for non-farm economic activities.	Census 2011
	Availability of irrigation facilities	IrF	Agricultural production and its economic gains increase with the presence of irrigation facilities.	Census 2011
	Availability of education facilities	EdF	Education facilities are required for the empowerment and skill development of communities. Higher access to education enhances human potential and provides wider social benefits.	Census 2011
	Availability of communication facilities	CoF	Availability of communication facilities provides several benefits for agricultural communities living in isolated mountain regions. Improved communication of agrometeorological information has synergies for agricultural	Census 2011

			development and adaptation processes.	
	Availability of power supply for agriculture	PoS	Energy is an important input for agricultural production. In mountain areas, access to electricity enables the usage of water pumps required for irrigation substantially reducing manual labor.	Census 2011
	Nearness to nearest town (km)	NNT	Accessibility to markets is critical for remunerative agricultural development. Proximity to markets provides easier access to agricultural inputs. Better networks develop for selling and marketing of agricultural products. On the contrary, communities living in isolated areas face difficulties in accessing markets.	Census 2011
Financial capacity (Fin)	Income (per capita)	Inc	High income and expenditure, a measure of wealth, provide better access to markets, technology, and other agricultural inputs increasing the capacity of agricultural communities to cope with any stress.	Human Development Report of Uttarakhand 208.2019
Institutional capacity (Ins)	Availability of self-help groups	SHG	Self-help groups (generally women groups) are established to meet the local credit needs in a village. These collective institutions not only empower agricultural communities but also provide financial and social benefits. Presence of SHGs also indicate active involvement of women.	Census 2011
	Availability of agricultural credit societies	ACS	Agricultural credit societies provide microcredits to meet funding requirements for agricultural development.	Census 2011
	Availability of agricultural marketing societies	AMS	Agricultural marketing societies are formed to cater to the agricultural marketing needs of the communities. These societies provide efficient market linkages, help in distribution as well as storage of agricultural commodities.	Census 2011

APPENDIX S2 Construction of the vulnerability index

From the different data sources, indicators were derived for the construction of the vulnerability index, following the methodology developed by Shukla et al (2016). The index consists of a range of indicators of relevance to the local context reflecting both the sensitivity and the adaptive capacity of the area (Table S1). In turns, these are compiled into a of multiple sub-components reflecting specific aspects of vulnerability.

Based on 35 different indicators, the vulnerability index was constructed using a weighted sum of the individual indicators and sub-components. The indicators were normalized to a scale from 0 to 1. For simplicity, all sensitivity components are indicated with 0 as least sensitive and 1 as most sensitive, while the adaptive capacity is inverted with 0 indicating highest adaptive capacity, and 1 indicating the lowest possible value. The same weights used by Shukla et al. (2016) were applied to each indicator when constructing the index. The weights were derived using the Analytic Hierarchy Process (AHP) method which utilizes a ranking system based on literature review and expert consultation (Zahedi 1986; Shukla et al. 2016). The hierarchical composition of the index and the weights used are presented in Figure S1.

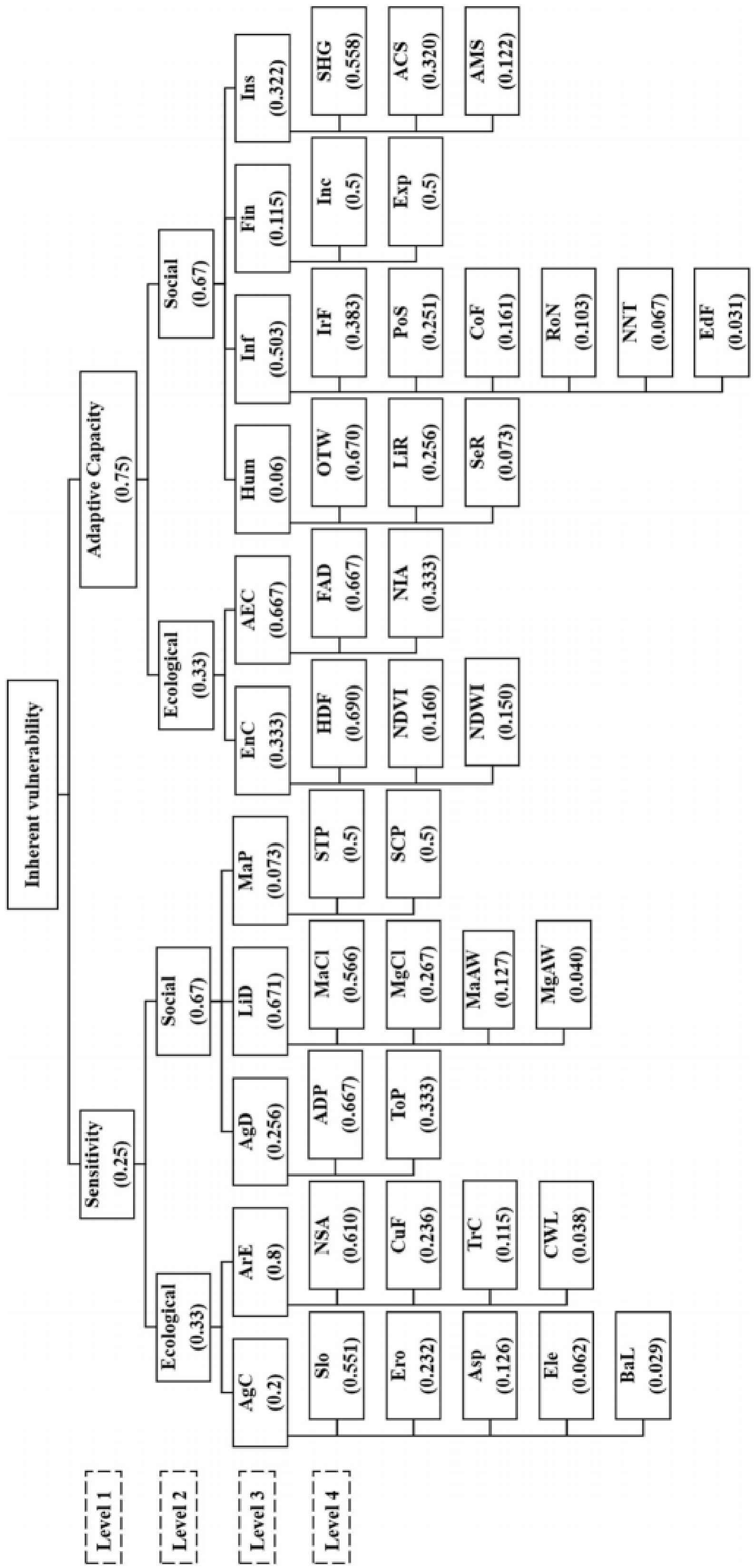

FIGURE S1 Hierarchical composition of the vulnerability index displaying every component and indicator with its relative weights (Taken from Shukla et al., 2016).

APPENDIX S3 Quantitative estimation approach

To estimate the role of vulnerability for migration, an Ordinary Least Square (OLS) linear regression model was used with vulnerability as predictor and migration as response variable. The OLS method allows us to evaluate the correlation between the variables and to explore differences in the effects in different contexts. We estimate the following cross-sectional baseline model

$$\ln(y_i) = b_0 + b_1 \ln(V_i) + \varepsilon_i \tag{1}$$

with y_i as the outmigration rate over the decade 2007-2017, V_i the vulnerability in development block *i* and b_1 as the relationship coefficient. To account for the right-skewedness in their distribution and to improve the fit of the model, both variables were log transformed. All estimated standard errors were clustered at the district level. We further varied the baseline model above to test for the impact of the different vulnerability subcomponents. For this, a series of independent bivariate and multivariate OLS models was estimated using the individual sub-components as predictors.

In additional models, we varied the migration outcome, considering different forms of migration or the mobility of different sub-groups in the population. Here, we distinguished between permanent and short-term migration (typically less than 12 months), migration of younger (below 25) and older people (above 25), and different reasons for migrating. For the latter, we consider differential impacts of vulnerability on migration due to "*lack of livelihood and employment opportunities*", "*lack of facilities and infrastructures*", and "*declining agricultural yields*". The different outcomes are expressed as the relative share of migrants falling into each category relative to the total share of migrants in the population.

The significance of the quantitative analysis is limited by the reduced population (96). While this is certainly preventing conclusive results to be drawn from the OLS models alone, it still allows to explore and discuss the observed trends. Additionally, the statistical significance of all quantitative results is presented.

APPENDIX S4 Mixed methods approach and qualitative insights

We complement our findings with qualitative insights from semi-structured face-to-face interviews (n=70) which were conducted between September-November 2019, in four districts of Uttarakhand: Almora, Pauri Garhwal, Dehradun and Nainital. Of these, three are mainly mountainous and rural, while one (Dehradun) is mostly located in the plains and is urbanized. The site selection was based on consultations with local experts working on climate change and migration. In addition, secondary resources like data on climate change impacts, migration and depopulation were assessed before the sites were selected (GU 2014; GU 2018; RDMC 2018; RDMC 2019). The possibility to triangulate the quantitative results with the qualitative findings triangulates and strengthens the validity of the former. Thus, helping to circumvent limitations such as the limited population size and the relative age of some of the dataset.

In total 55 interviews were conducted with the affected population and 15 further interviews were done with key informants, such as policy experts, NGO representative and scientists (Table S2). An interview guide was used for interviewing the affected population, but the interview structure varied according to the interviewees, to make sure that their experiences and understandings were captured in an open and comprehensive way. Snowball sampling was used for the selection of interview partners among the affected population in the four districts (Parker et al. 2019) while purposeful sampling was used for the selection of key informants (Patton 2005).

All interviews were conducted in English and Hindi. Interviews focused on one key participant from a household, but often with other household members or villagers joining in, listening and at times contributing to the discussion. Interviews lasted between 20 to 90 minutes each and were either audio recorded, or text notes were taken. Interviewees gave an informed consent, and their data was anonymized and kept confidential. This is in line with the regulation of the European Parliament and of the Council 2016/679, known as the General Data Protection Regulation (GDPR). Qualitative data collected from the semi-structured interviews were translated and transcribed in English and later analyzed in MAXQDA, a software for the analysis of qualitative data (Kuckartz and Rädiker 2019: 1). The qualitative insights generated in the interviews allow us to in depth explore and interpret the quantitative results presented in this study.

TABLE S2 List of interview partners

Gender	Age	District	Reported livelihoods
Male	52	Almora	Climate scientist, contributes to family agriculture
Male	51	Almora	Government service, contributes to family agriculture
Male	61	Almora	Agriculture
Female	57	Almora	Agriculture
Female	38	Almora	Agriculture and animal husbandry
Female	64	Almora	Agriculture and animal husbandry
Female	in her 50s	Almora	Agriculture and animal husbandry
Female	in her 80s	Almora	Dependent on her son, who does agriculture
Male	42	Almora	Works in an agricultural cooperative
Male	33	Almora	Works in a local livelihood support project
Male	39	Almora	Works in a local livelihood support project

Male	42	Almora	Driver, also does agriculture
Male	37	Almora	Government service, also does agriculture
Male	51	Almora	Agriculture and also works in a BMC (biodiversity management committee)
Female	39	Almora	Agriculture, also an employee in a livelihoods support project
Male	48	Almora	Agriculture and floriculture
Male	in his 40s	Almora	International aid practitioner, contributes to family agriculture
Male	in his 50s	Almora	Scientist, contributes to family agriculture
Male	23	Almora	Agriculture , is also in charge of an automatic weather station
Male	in his 50s	Dehradun	Government service
Male	38	Dehradun	Scientist
Male	57	Dehradun	Environmentalist/ heads an NGO
Male	57	Dehradun	Government service
Female	41	Dehradun	Government service
Male	43	Dehradun	Government service
Female	29	Dehradun	Government service
Female	32	Dehradun	Government service
Male	in his 60s	Dehradun	NGO professional
Male	27	Dehradun	NGO professional
Male	52	Dehradun	University professor
Male	in his 40s	Dehradun	NGO professional, contributes to family agriculture
Male	in his 60s	Dehradun	NGO professional
Male	64	Dehradun	NGO professional
Male	48	Dehradun	NGO professional, contributes to family agriculture
Male	in his 60s	Dehradun	Government service
Male	52	Dehradun	Government service
Male	44	Haridwar	Research
Male	51	Nainital	University professor, contributes to family agriculture
Female	67	Nainital	Agriculture and animal husbandry
Female	66	Nainital	Agriculture and animal husbandry
Female	90	Nainital	Agriculture and animal husbandry
Female	in her 80s	Nainital	Agriculture and animal husbandry
Female	in her 70s	Nainital	Agriculture and animal husbandry
Female	47	Nainital	Agriculture and animal husbandry
Female	61	Nainital	Agriculture and animal husbandry
Male	41	Nainital	Agriculture and animal husbandry
Male	in his 50s	Nainital	Heads a NGO, contributes to family agriculture
Male	62	Nainital	Agriculture
Male	46	Nainital	Agriculture and animal husbandry
Male	74	Nainital	Agriculture
Male	33	Nainital	NGO professional, contributes to family agriculture
Female	76	Nainital	Agriculture
Female	37	Pauri Garhwal	Housewife, does agriculture
Female	40s	Pauri Garhwal	Housewife, does agriculture
Female	in her 80s	Pauri Garhwal	Agriculture
Female	in her 50s	Pauri Garhwal	Agriculture
Female	65	Pauri Garhwal	Agriculture
Male	54	Pauri Garhwal	Tailoring
Female	56	Pauri Garhwal	Agriculture
Female	32	Pauri Garhwal	Agriculture and animal husbandry
Male	69	Pauri Garhwal	Retired government servant, now doing agriculture

Male	in his 30s	Pauri Garhwal	Tea stall owner and does agriculture
Female	67	Pauri Garhwal	Pension from late husband, used to do agriculture
Female	64	Pauri Garhwal	Has stopped agriculture and dairy. Gets pension.
Female	20	Pauri Garhwal	University student, looking for a job
Male	59	Pauri Garhwal	Agriculture and animal husbandry
Male	57	Pauri Garhwal	Agriculture and animal husbandry
Female	32	Pauri Garhwal	Agriculture and animal husbandry
Male	22	Pauri Garhwal	Job at the Indian railways, contributes to family agriculture
Male	38	Pauri Garhwal	Tea Stall owner, also does agriculture

APPENDIX S5 Further descriptive statistics

Figure S2 displays the distribution of the two main variables, vulnerability and migration. Neither of the two variables is normally distributed. Instead, both variables show a bimodal distribution, having one main peak on the right hand and a smaller peak to the left of the distribution. By separately considering the distribution of the two variables for plains (<1200 m) and mountain districts (>1200 m), it can be noticed how the distribution differs for the different elevation classes, with the plains showing a uniform distribution, while vulnerability and migration are more normally distributed in the hills.

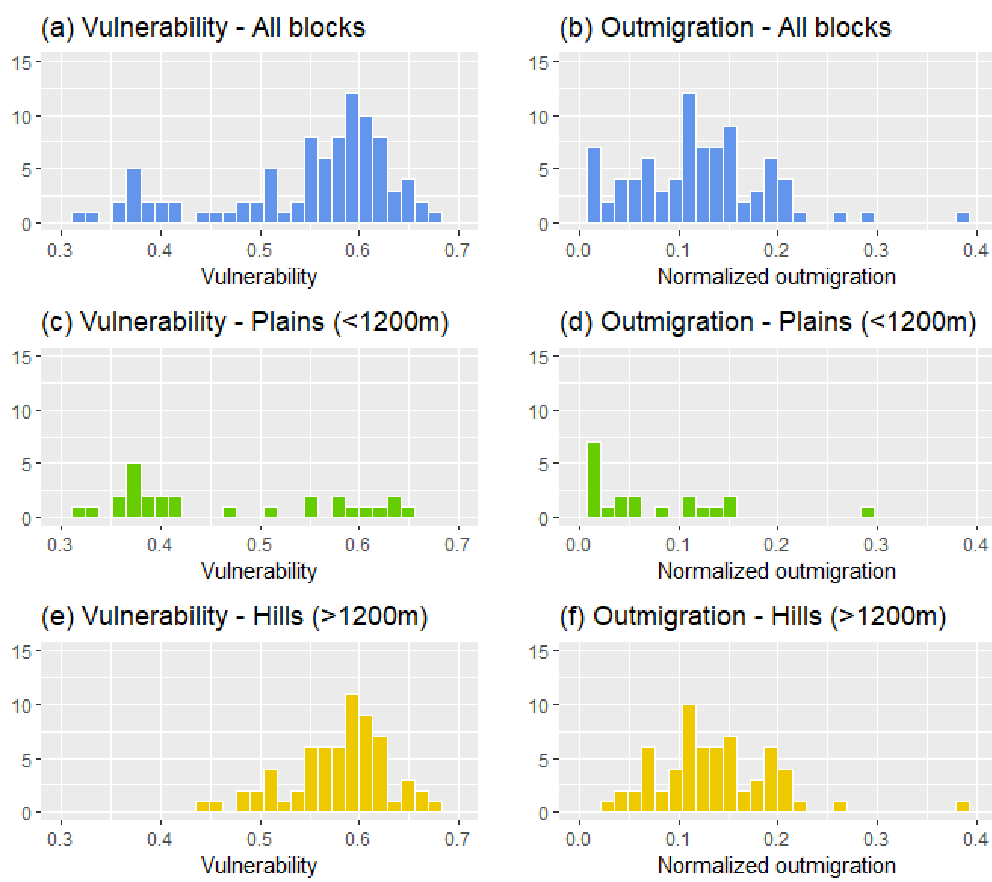

FIGURE S2 Vulnerability and outmigration distribution in different elevation classes.

APPENDIX S6 Illustrating the vulnerability–migration relationship

Figure S3 shows a scatter plot highlighting the relationship between vulnerability and migration across all development blocks. The blocks in the more urbanized districts (Dehradun, Udham Singh Nagar, and Haridwar) are located almost entirely in the bottom left of the plot, while those at higher elevation and in more rural districts tend to be located almost entirely to the right-hand side of it. One can observe a small cluster of blocks in the bottom right of the graph, representing development blocks with low out-migration despite high levels of vulnerability.

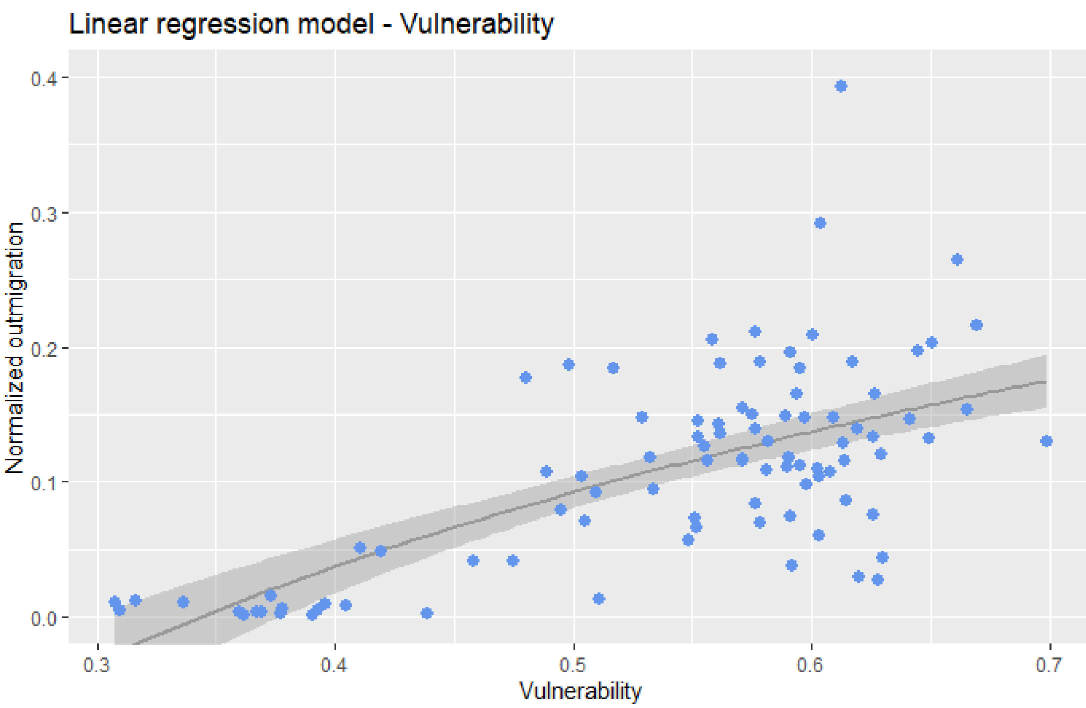

FIGURE S3 Scatterplot illustrating the relationship between vulnerability and migration. The lines show smoothed splines. Gray shading are the 95% confidence intervals.

Out-migration is later regressed on the two subcomponents of vulnerability: sensitivity and adaptive capacity. Figure S4 shows the relationships of both subcomponents with migration. Both variables are positively and significantly correlated with out-migration, yet adaptive capacity shows a much stronger correlation. The sensitivity model has a relatively low fit (r^2=0.093), and accounts for less variation than the one of adaptive capacity, further highlighting the more important role of adaptive capacities for the considered context.

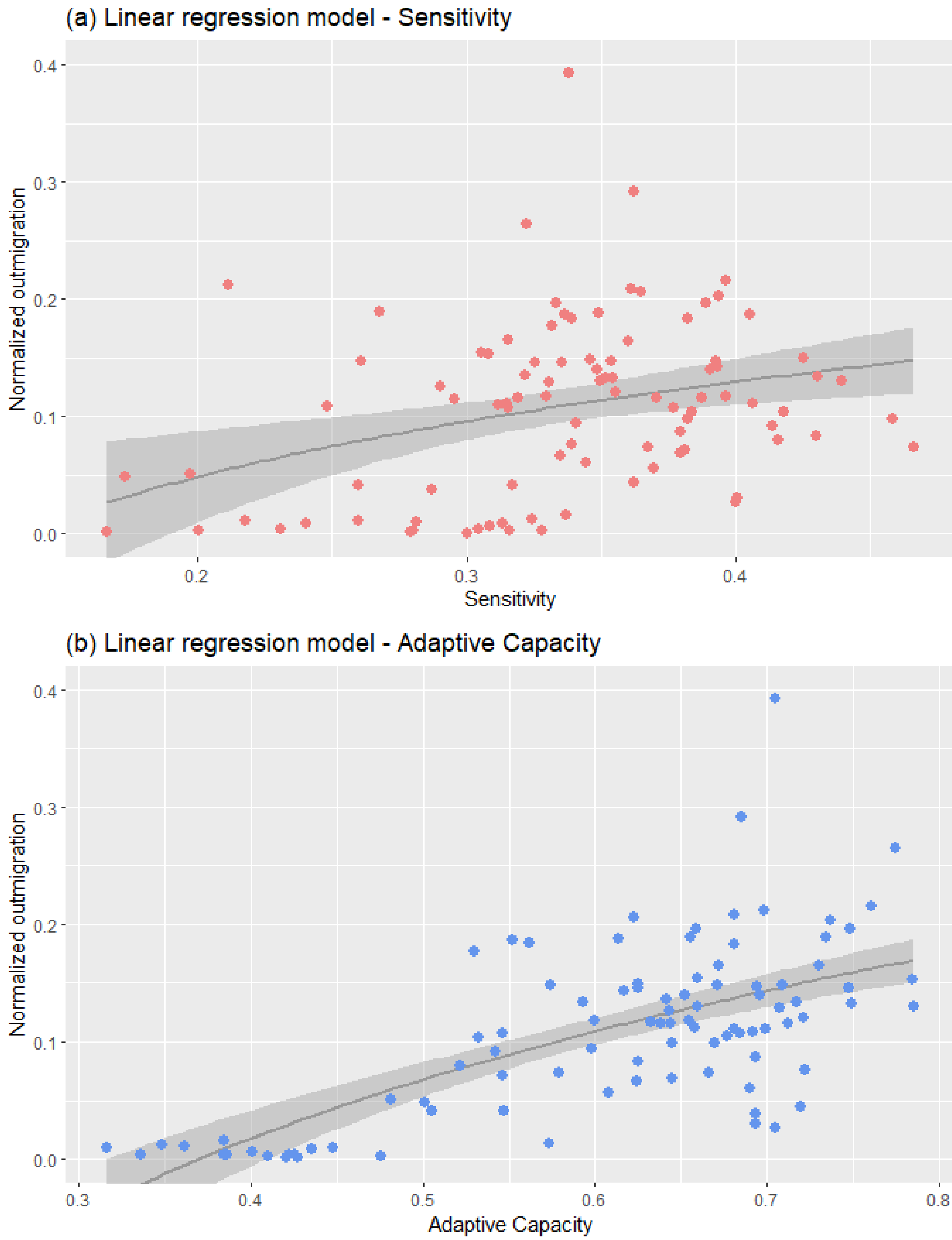

FIGURE S4 Scatterplots illustrating the relationship between migration and sensitivity (a), and migration and adaptive capacity (b). The lines show smoothed splines. Gray shading are the 95% confidence intervals.

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