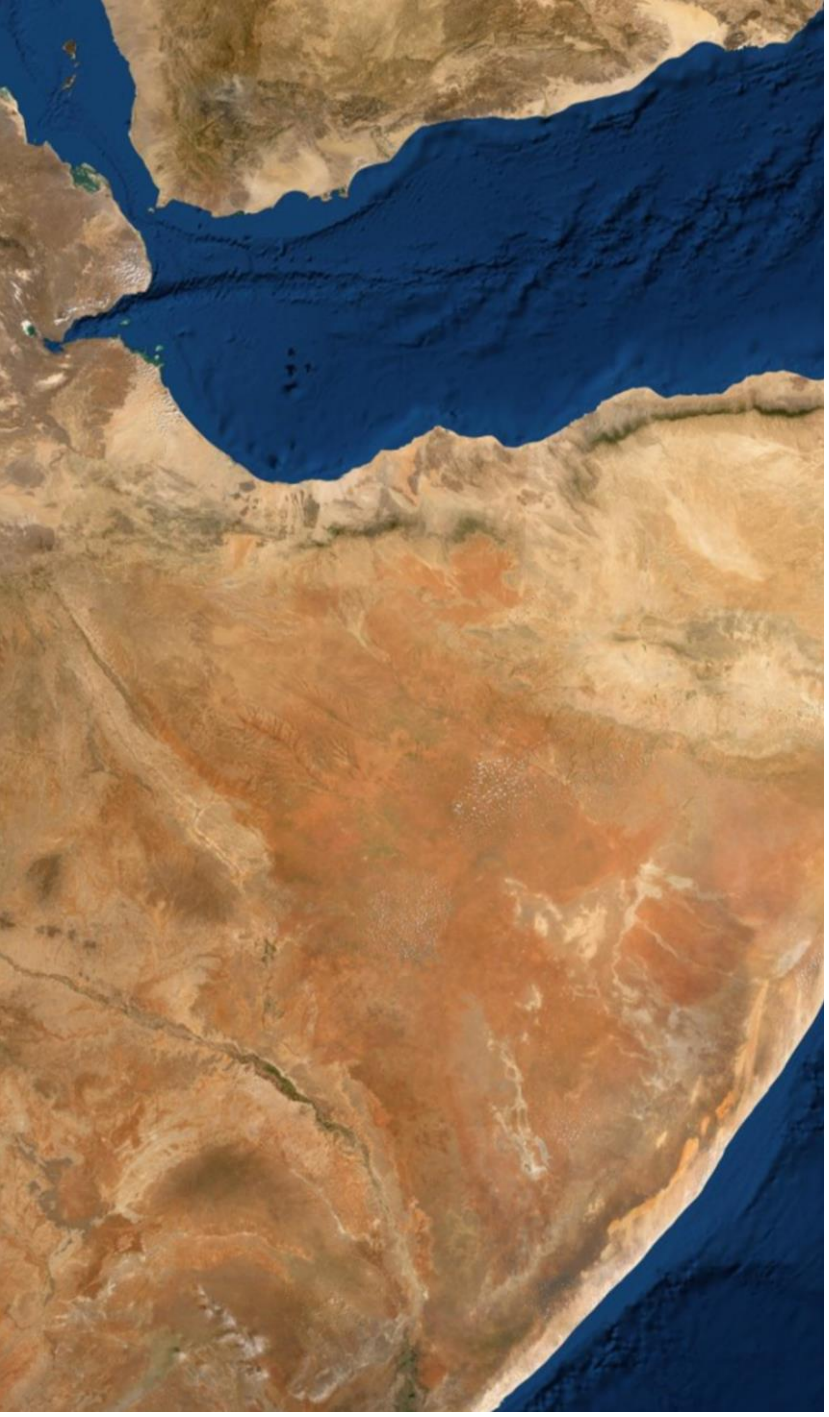


Marion Borderon, *University of Vienna*

CONCEPTUAL AND METHODOLOGICAL CHALLENGES IN UNDERSTANDING PATTERNS OF (IM)MOBILITIES IN A CHANGING CLIMATE. INSIGHTS FROM ETHIOPIA

06.07.2022

MIGRATION & ENVIRONMENTAL CHANGE

- **Migration as a normal aspect of life, multi-causal & complex**
- **Migration can be used as a coping strategy and the feedback effects of migration can & are studied (e.g. remittances)**
- **Immobility, left behind & trapped populations need to be studied**

challenging from a **theoretical perspective**: In the realm of migration theory, **a systematic neglect of the causes and consequences of immobility** hinders attempts to explain why, when, and how people migrate (Schewel, 2020).

challenging from a **methodological perspective**: Some populations affected by environmental degradation and disasters may not be able to move due to a lack of financial resources or social networks. They are highly vulnerable populations, but **data are scarce** (Vinke and Hoffmann, 2020).

Schewel, K. (2020). Understanding immobility: Moving beyond the mobility bias in migration studies. *International Migration Review*, *54*(2), 328-355.
Vinke, K., & Hoffmann, R. (2020). Data for a difficult subject: Climate change and human migration. Migration, Policy, Practice 10 (1), 16-21.

RESEARCH GAPS

REVIEW OF THE EMPIRICAL EVIDENCE ON MIGRATION INFLUENCED BY ENVIRONMENTAL CHANGE

The **current research field is generally divided** between detailed empirical case studies on the **micro level** that often draw on self-reported environmental information and with limited scope for generalization, and global and national assessments on the **macro level** that do not sufficiently represent the local situation.

(Cattaneo et al. 2020; Borderon et al. 2019)

Map of distribution of case studies by African country

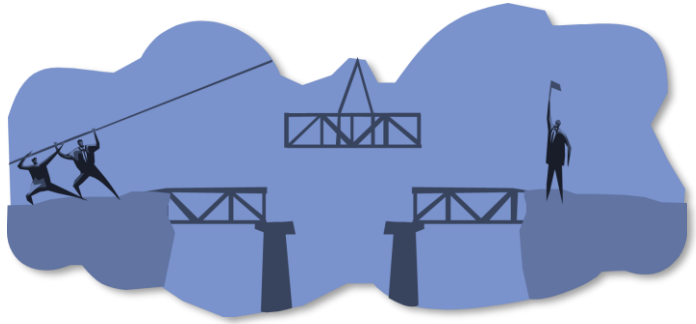
Borderon, M., Sakdapolrak, P., Muttarak, R., Kebede, E., Pagogna, R., & Sporer, E. (2019). Migration influenced by environmental change in Africa. *Demographic Research*, *41*, 491-544.

Cattaneo, C., Beine, M., Fröhlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., ... & Schraven, B. (2020). Human migration in the era of climate change. *Review of Environmental Economics and Policy*.

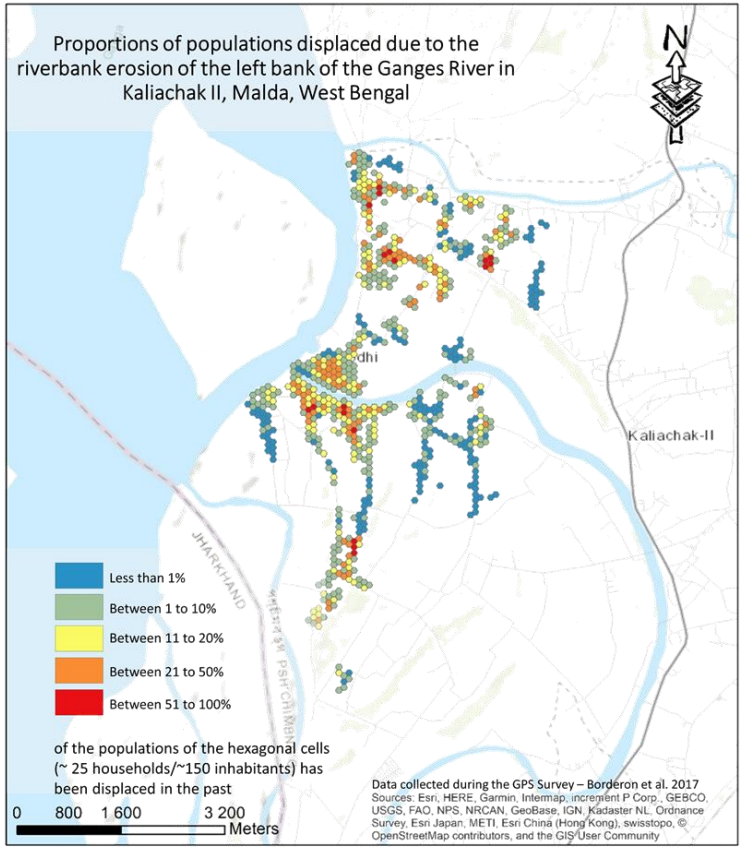
OVERARCHING CONTRIBUTION

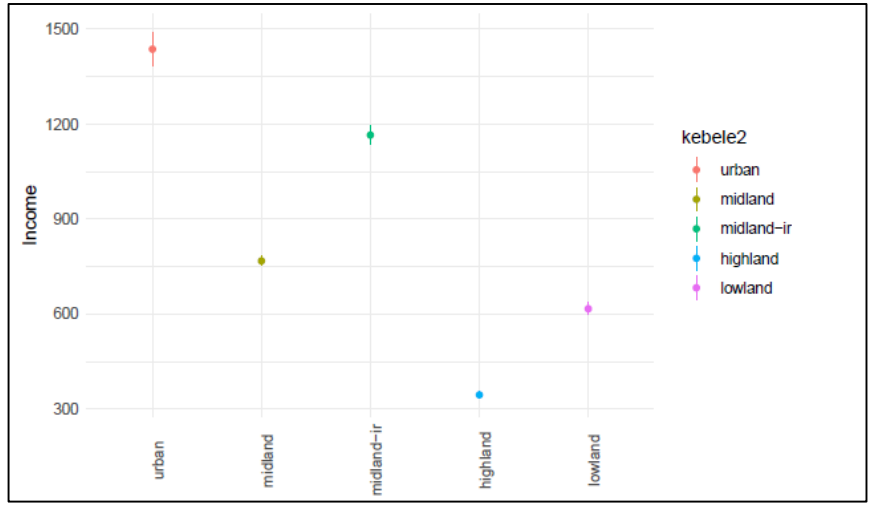
In our projects, we aim to chart a **middle path** between generalized, global-level analysis of migration drivers and impacts, and the specificities of individuals and households focused on in-depth ethnographic study research, and to “locate” the epistemology at the scale of deprived rural areas.

Use of subnational/meso scale & data to respond to some of the challenges



POTENTIAL OF MICRO/MESO-SCALE DATA

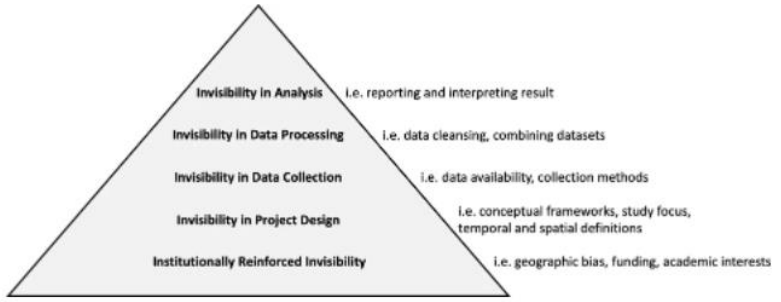




nature > humanities and social sciences communications > articles > article > figure

Fig. 1: The scales of invisibility in the research process.

From: The risks of invisibilization of populations and places in environment-migration research



Conceptual framework highlighting five scales at which invisibility may be introduced or reinforced in research that depends on the use of secondary data.

Empirical investigation

HOUSEHOLD CAPABILITIES AND SATISFACTION WITH LIVING CONDITIONS SHAPE (IM)MOBILITIES

A GENDERED ANALYSIS OF MIGRATION DYNAMICS OF A DROUGHT-PRONE AREA OF ETHIOPIA

With Laurence Reboul, Nega Assefa, Merga Deresa, Yoann Doignon, Patrick Sakdapolrak, Harald Sterly, Coline Garcia

BACKGROUND| DROUGHT

In Ethiopia, droughts are frequent and their effects are exacerbated by deep rural poverty, limited government capacity and exposure to additional political, economic and health crises (Gray and Mueller 2012).

Climate and Development Knowledge Network and World Weather Attribution Initiative
Raising Risk Awareness

The drought in Ethiopia, 2015

Science summary

Key messages

- North and central Ethiopia suffered their worst drought in decades in 2015, a year marked by a strong El Niño.
- The drought affected nearly 10 million Ethiopians.
- Scientists with World Weather Attribution used multiple methods of attribution science to look at the possible roles that climate change and El Niño played in the drought.
- They found that El Niño made this rare drought even drier in the *kiremt* season.

*"The observed 2015 drought was **an extremely rare event** that is expected to happen in the central to north-eastern parts of Ethiopia only about once every few hundred years "*

Climate & Development Knowledge network

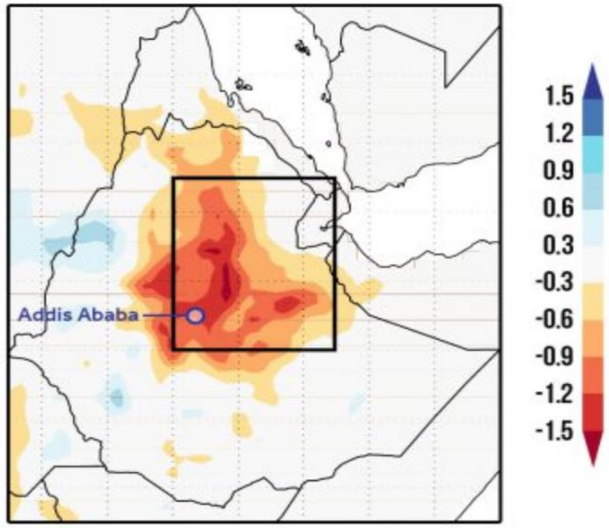
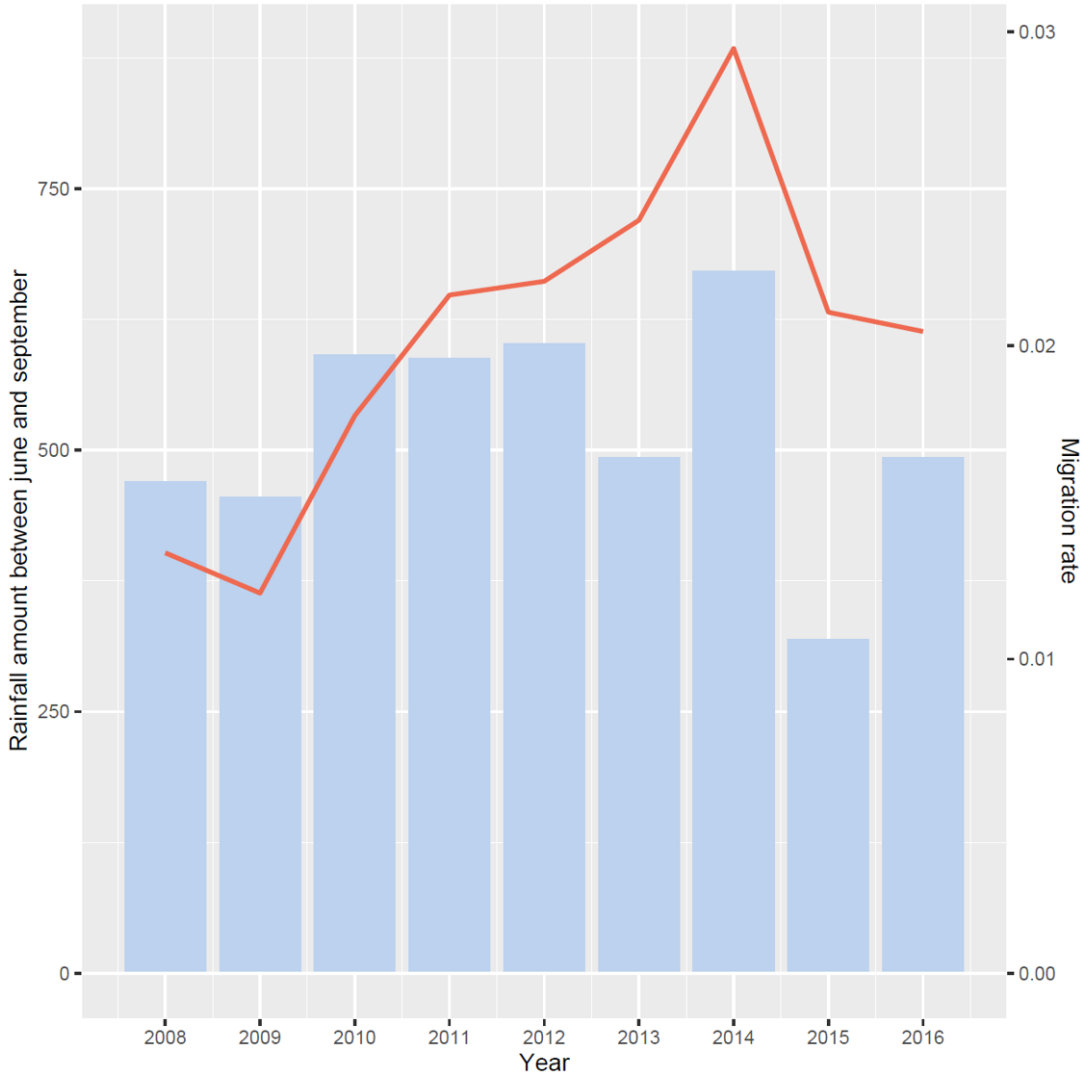


Figure 1: Map showing area of analysis, northeastern Ethiopia, 8°-13°N, 38° – 43°E. Anomaly in precipitation (CHIRPS, over 1981-2010 climatology) averaged over February — September 2015. Source: CHIRPS, available from the Climate Explorer (climexp.knmi.nl)

YEARLY OUTMIGRATION RATES & KIREMT RAINS



Most agricultural activities depend on this seasonal rainfall between mid June to mid September where farming takes place.

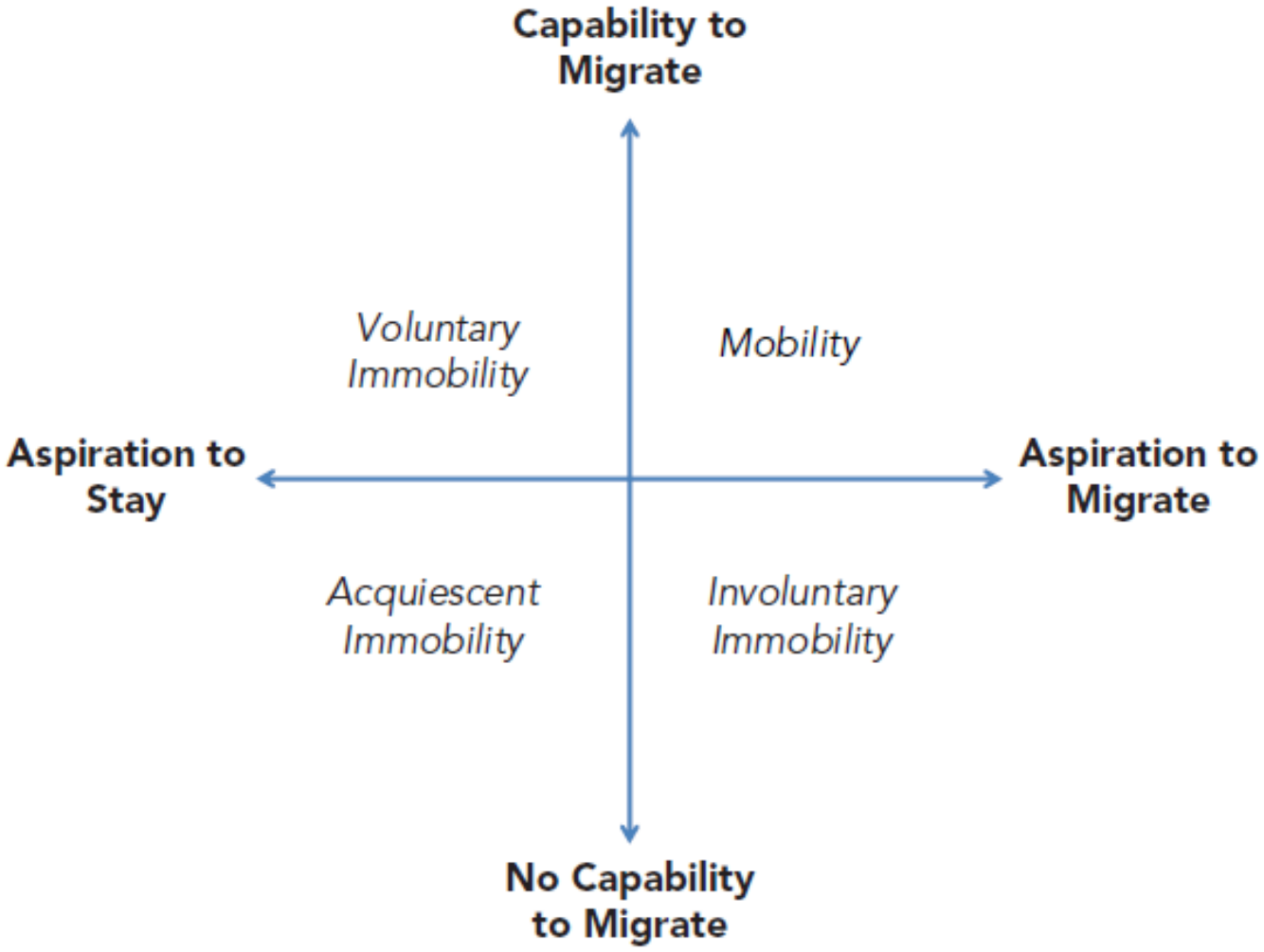
MIGRATION & ENVIRONMENTAL CHANGE

RESEARCH QUESTIONS

What are the determinants of individual (im)mobility in Kersa, a drought-prone area of Ethiopia?

Do we observe a risk of involuntary immobility among some segments of the population?

MIGRATION & ENVIRONMENTAL CHANGE



De Haas, H. (2021). A theory of migration: the aspirations-capabilities framework. *Comparative Migration Studies*, *9*(1), 1-35.
Schewel, K. (2020). Understanding immobility: Moving beyond the mobility bias in migration studies. *International Migration Review*, *54*(2), 328-355.

DATA FROM HDSS KERSA

We have investigated the population of 44,720 individuals, 12,494 households which gives a longitudinal dataset of 574,266 person-semesters between 2007 and 2016.

Overall, 8,992 persons experienced at least one event of outmigration, that is to say 9,622 events overall (from 3,157 men and 5,835 women).

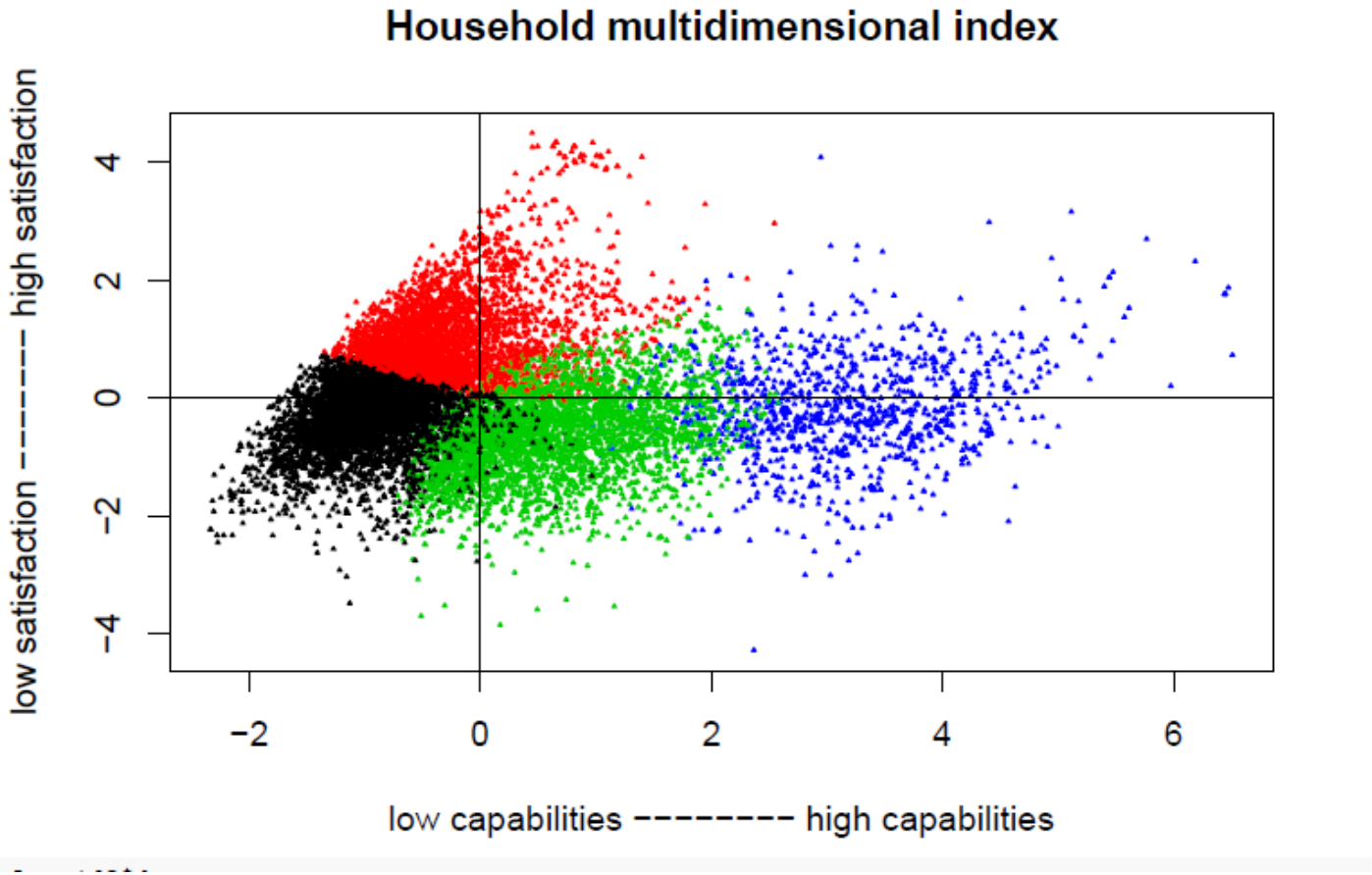
DATA DESCRIPTION

In the database, **a migrant** is a person who has established **for more than 6 months**, a new place of usual residence (e.g. locality, district) other than the one in which they habitually lived.

we study the determinants of experimenting at least one migration during the observation period (2007-2016) for **men and women** older than 13 years old.

Characteristics of explanatory variables	Individual-level	Household-level	Community level
Time varying	Age (continuous) Occupation (Agricultural related activities, Secondary &Tertiary Sector, Dependent Pop) Literacy (Illiterate, Literate)	Household size (continuous)	Drought (2007-2014, 2015, 2016)
fixed	Ethnicity (Oromo, Others) Relation to the head (Spouses, Children, Others)	Capabilities* (continuous) Satisfaction* (continuous) Land owner (Yes, No)	Geographical feature (Lowland, Highland, Midland, Midland with irrigation, Urban setting)

ZOOM IN | HH CAPABILITY & SATISFACTION



Multiple factor analysis (MFA) and Clustering Analysis (CA) at the HH level

Variables used : Assets & housing conditions (17 variables) , Literacy (2 variables) & Perceived satisfaction on living conditions (3 variables)

MODEL

A MULTILEVEL DISCRETE TIME EVENT HISTORY MODEL BY GENDER

Let Y_{ijt}=1 if individual i in household j experiences a migration at semester t, otherwise 0.
Let p_{ijt}= probability that individual I in household j moves on semester t (Y_{ijt}=1) given that he didn't move before and given all covariate measurements.

We fit the model (Allison, 1982)

$$\log\left(\frac{p_{ijt}}{1 - p_{ijt}}\right) = a(t) + h_j + b' X_{ijt}$$

X_{ijt} = vector of covariates for individual i in household j at time t

b = vectors of fixed parameter

h_j = household-specific j random intercept such that $h_j \propto N(0, s_h^2)$

$a(t) = a_0 + a_1 t + a_2 t^2$ = baseline hazard function

	Men	Women
Fixed effects		
Constant	-6.200***(0.263)	-4.800***(0.209)
Time	0.061** (0.026)	0.079***(0.019)
Time²	0.002 (0.002)	-0.0003 (0.001)
Individual-level variables		
Age	-0.286***(0.034)	-0.510***(0.024)
Ethnicity (ref=Arama/Oromo)		
Other	-0.136 (0.084)	-0.260***(0.066)
Relation to the head (ref=spouses/head)		
Children	0.209***(0.068)	0.430***(0.049)
Others	1.340***(0.080)	0.937***(0.045)
Literacy (ref=illiterate)		
Literate	0.195***(0.052)	0.239***(0.032)
Occupation		
Agricultural activities	ref	0.703***(0.053)
Dependant population	0.059 (0.048)	0.510***(0.036)
Secondary/tertiary sectors	0.435***(0.068)	ref
Household-level variables		
Land owner (ref=no)		
Landyes	0.255 (0.173)	-0.121 (0.149)
Satisfaction	0.022 (0.049)	0.020 (0.038)
Capabilities	0.146** (0.057)	0.122***(0.046)
Household size	0.060***(0.023)	-0.002 (0.015)
Satisfaction*capability	-0.094***(0.018)	-0.076***(0.014)

Note: *p<0.1; **p<0.05; ***p<0.01

NB: The coefficients are the log-odds of migrate.

$$ICC = \frac{\sigma_v^2}{\pi^2/3 + \sigma_v^2}$$

	Men	Women
Community-level variables		
Geographic feature (ref=midland)		
highland	-0.063 (0.084)	0.010 (0.047)
lowland	-0.123 (0.096)	0.023 (0.054)
midland-ir	-0.372***(0.075)	-0.084* (0.045)
urban	0.588***(0.093)	0.279***(0.066)
Drought (ref= before drought)		
drought	-0.365 (0.238)	-0.459** (0.195)
drought+1	-0.353 (0.243)	-0.380** (0.193)
Precipitation	0.136***(0.038)	0.058** (0.027)
Temperature	0.079** (0.031)	0.008 (0.022)
Land owner/drought interaction		
landyes/drought	0.389** (0.184)	0.151 (0.162)
landyes:/drought+1	-0.506*** (0.179)	-0.286* (0.156)
Geographic feature/drought interaction		
highland/drought	0.142 (0.149)	0.081 (0.114)
Lowland/drought	-0.906***(0.236)	-0.032 (0.129)
midland-ir/drought	-0.416** (0.164)	-0.018 (0.111)
urban/drought	0.237 (0.177)	0.164 (0.157)
highland/drought+1	0.164 (0.175)	0.126 (0.112)
lowland/drought+1	0.509***(0.181)	0.289** (0.121)
midland-ir/drought+1	0.270* (0.164)	0.282***(0.105)
urban/drought+1	0.263 (0.198)	0.236 (0.158)
Satisfaction/drought interaction		
Satisfaction/drought	-0.122** (0.052)	-0.075* (0.040)
Satisfaction/drought+1	-0.129** (0.054)	-0.049 (0.039)
Capabilities/drought interaction		
Capabilities/drought	0.0001 (0.061)	0.088* (0.050)
Capabilities/drought+1	0.023 (0.060)	-0.007 (0.049)
Random effects		
menage intercept	7.53e-01	
ICC	0.186	
Groups observations		
Menage	11556	12034
Observations	285873	288387
Log Likelihood	-16,438.000	-27,722.000
Akaike Inf. Crit.	32,954.000	55,521.000
Bayesian Inf. Crit.	33,366.000	55,934.000

	Men (job)		Women (marriage)	
Fixed effects				
Constant	-8.330***	(0.284)	-6.620***	(0.158)
Time	0.114***	(0.013)	0.119***	(0.025)
Time^2	0.002	(0.002)	-0.005***	(0.001)
Individual-level variables				
Age	0.132**	(0.059)	-0.852***	(0.042)
Ethnicity (ref=Arama/Oromo)				
Other	-0.137	(0.161)	-0.429***	(0.123)
Relation to the head (ref=spouses/head)				
Children	1.500***	(0.132)	0.505***	(0.074)
Others	2.520***	(0.152)	1.090***	(0.071)
Literacy (ref=illiterate)				
Literate	0.308***	(0.094)	0.274***	(0.041)
Occupation				
Agricultural activities	ref		1.270***	(0.072)
Dependant population	0.003	(0.083)	1.070***	(0.053)
Secondary/tertiary sectors	0.802***	(0.123)	ref	
Household-level variables				
Land owner (ref=no)				
Landyes	-0.759***	(0.197)	-0.094	(0.120)
Satisfaction	0.139***	(0.052)	0.037	(0.023)
Capabilities	0.225***	(0.065)	-0.086**	(0.034)
Household size	0.023	(0.045)	0.033*	(0.019)
Satisfaction*capability	-0.152***	(0.036)	-0.061**	(0.024)

Note: *p<0.1; **p<0.05; ***p<0.01

NB: The coefficients are the log-odds of migration.

	Men (job)		Women (marriage)	
Community-level variables				
Geographic feature (ref=midland)				
highland	-0.899***	(0.165)	0.158***	(0.060)
lowland	-1.190***	(0.207)	0.132*	(0.068)
midland-ir	-1.010***	(0.148)	0.123**	(0.057)
urban	-0.419**	(0.186)	-0.279**	(0.109)
Drought (ref= before drought)				
drought	-0.084	(0.347)	-0.605*	(0.351)
drought+1	-0.896***	(0.324)	0.025	(0.357)
Precipitation	0.167***	(0.060)	-0.043	(0.038)
Temperature	0.032	(0.048)	-0.033	(0.029)
Land owner/drought interaction				
landyes/drought	0.389	(0.278)	0.237	(0.320)
landyes:/drought+1	-0.161	(0.268)	-0.178	(0.325)
Geographic feature/drought interaction				
highland/drought	-0.472	(0.287)	0.005	(0.161)
Lowland/drought	-1.160**	(0.521)	0.297*	(0.163)
midland-ir/drought	-0.686**	(0.279)	0.113	(0.150)
urban/drought	0.495*	(0.261)	0.272	(0.273)
highland/drought+1	0.628**	(0.279)	-0.038	(0.144)
lowland/drought+1	0.538	(0.376)	0.240	(0.153)
midland-ir/drought+1	0.560**	(0.268)	0.058	(0.136)
urban/drought+1	1.150***	(0.297)	-0.376	(0.303)
Satisfaction/drought interaction				
Satisfaction/drought	-0.054	(0.079)	0.018	(0.058)
Satisfaction/drought+1	-0.212**	(0.088)	0.080	(0.054)
Capabilities/drought interaction				
Capabilities/drought	-0.066	(0.094)	0.058	(0.083)
Capabilities/drought+1	0.034	(0.094)	-0.028	(0.081)
Random effects				
menage intercept variance	5.06			
ICC	0.606			
Groups observations				
Menage	11556		12034	
Observations	285873		288390	
Log Likelihood	-7675		-15702	
Akaike Inf. Crit.	15424		31478	
Bayesian Inf. Crit.	15815		31870	

KEY MESSAGES

- While the 2015 large-scale drought had negative effects on the mobility of women in Kersa, no significant impacts were recorded for men. However, the year following the drought, fewer men engaged in labour migration.

- Very limited capabilities combined with low satisfaction in living conditions are frequent and associated with low(er) levels of migration, suggesting **a high risk of involuntary immobility within the population and insufficient options to sustain livelihoods.**

- The inhabitants of the irrigated midlands are generally more satisfied with their living conditions and tend to be less mobile (especially men) whatever the period (drought or not) compared to their neighbours who do not benefit from irrigated agriculture.

- HDSS data are suitable to study the interactions between the social, demographic and environmental drivers of migration at a local scale.

KEY MESSAGES

While the 2015 large-scale droug
impacts were recorded for men.
migration.

Very limited capabilities combin
with low(er) levels of migration, s
insufficient options to sustain liv

The inhabitants of the irrigated r
to be less mobile (especially men
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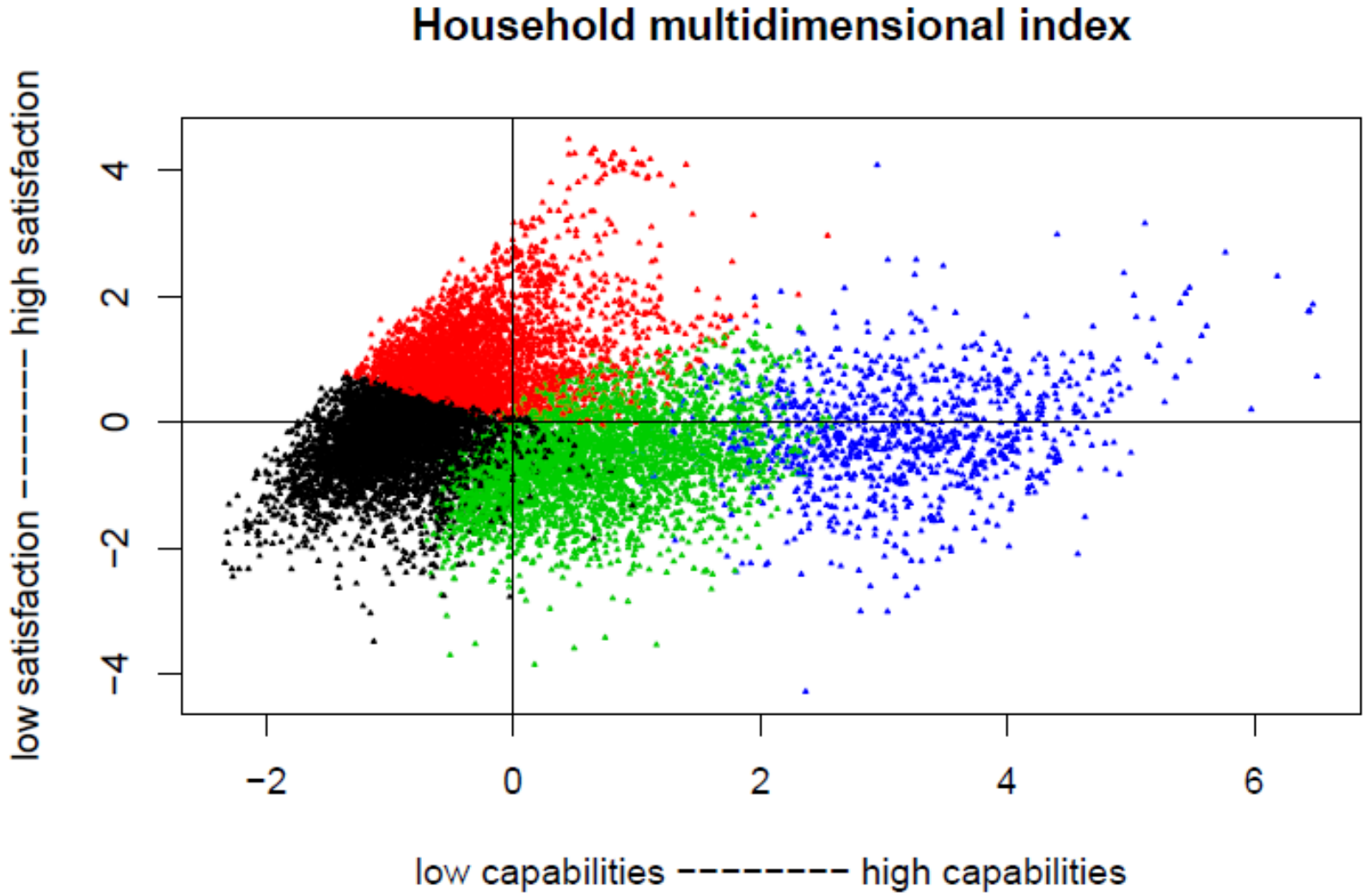
HDSS data are suitable to stud
drivers of migration at a local scal



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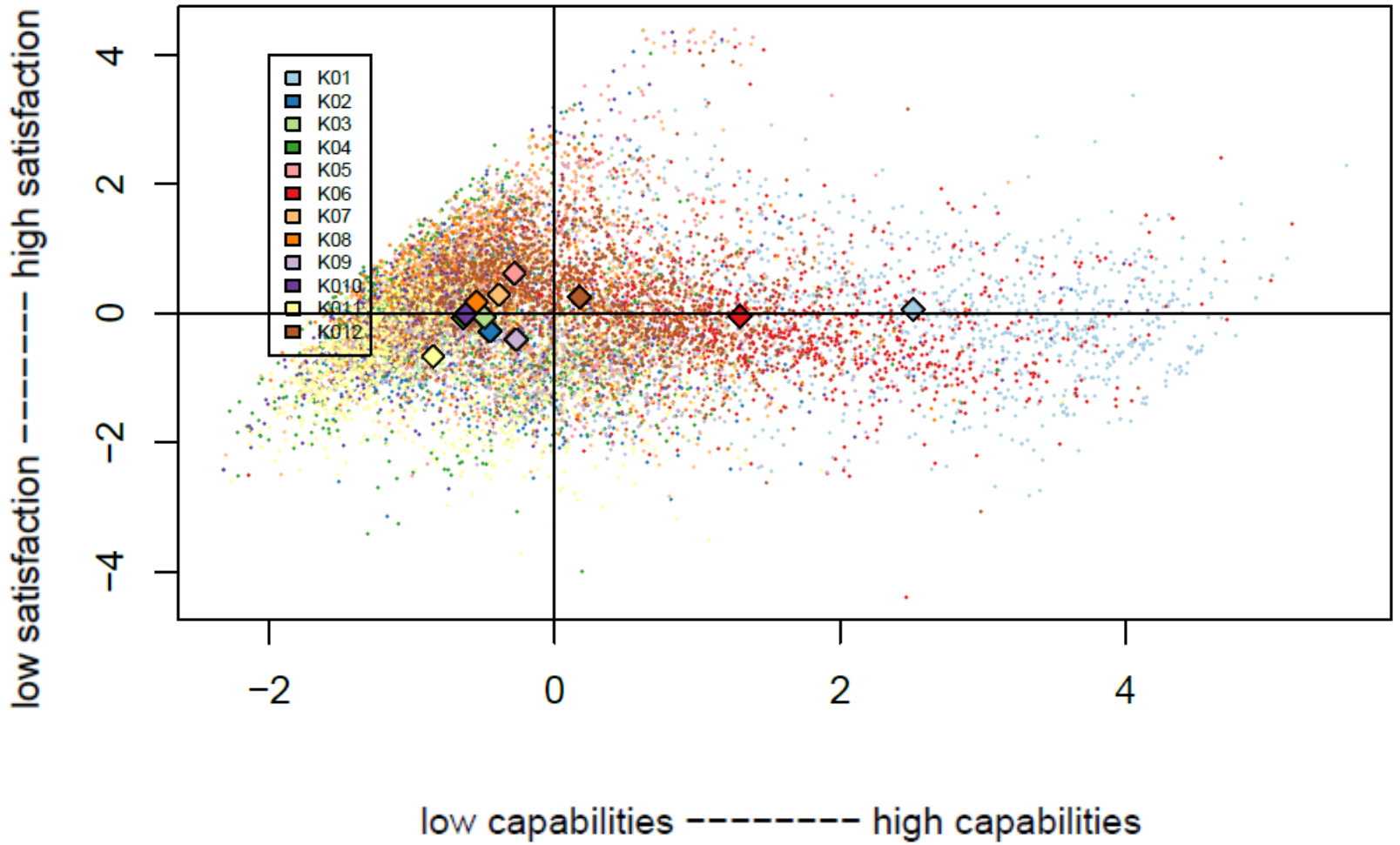
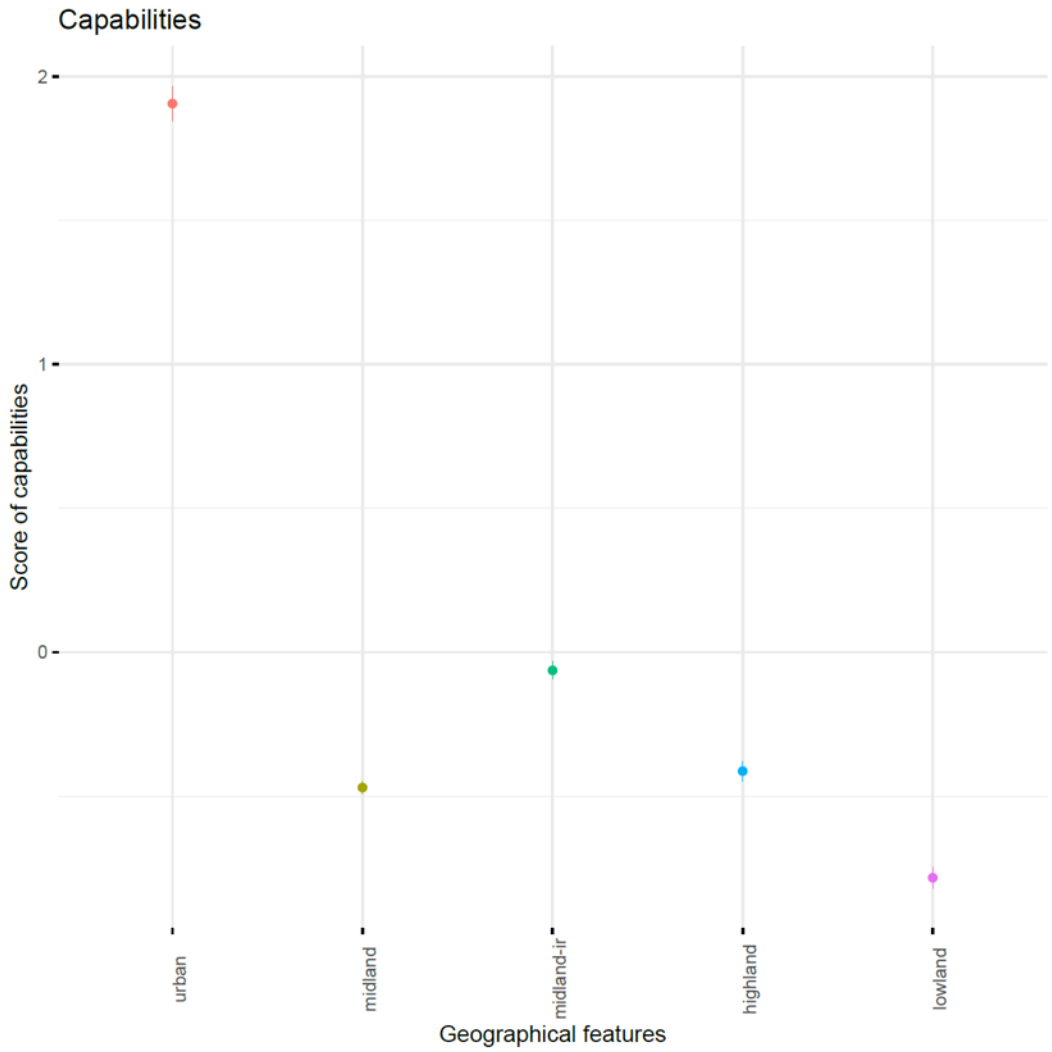
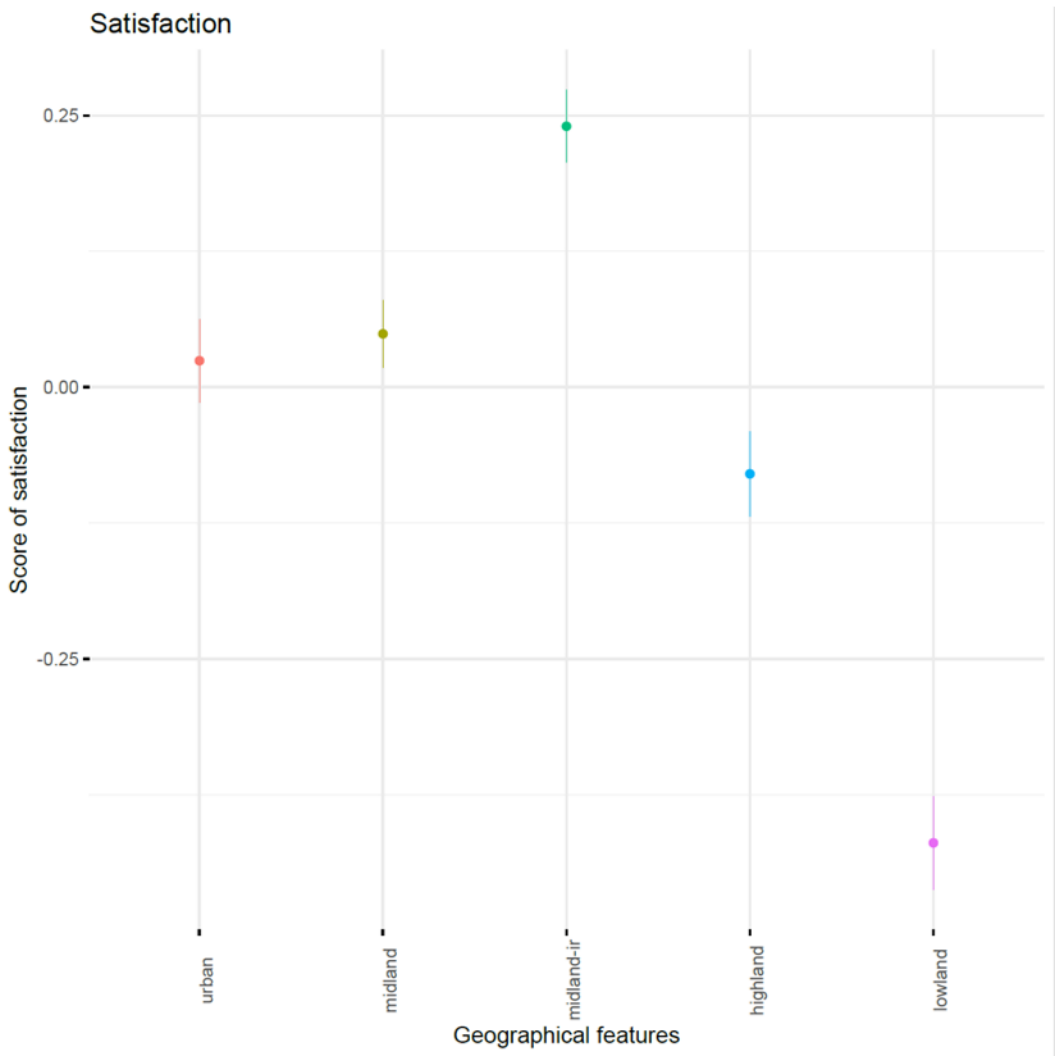



Capabilities
2
1
0
Score of capabilities
urban
midland
midland-ir
highland
lowland
Geographical features


Satisfaction
0.25
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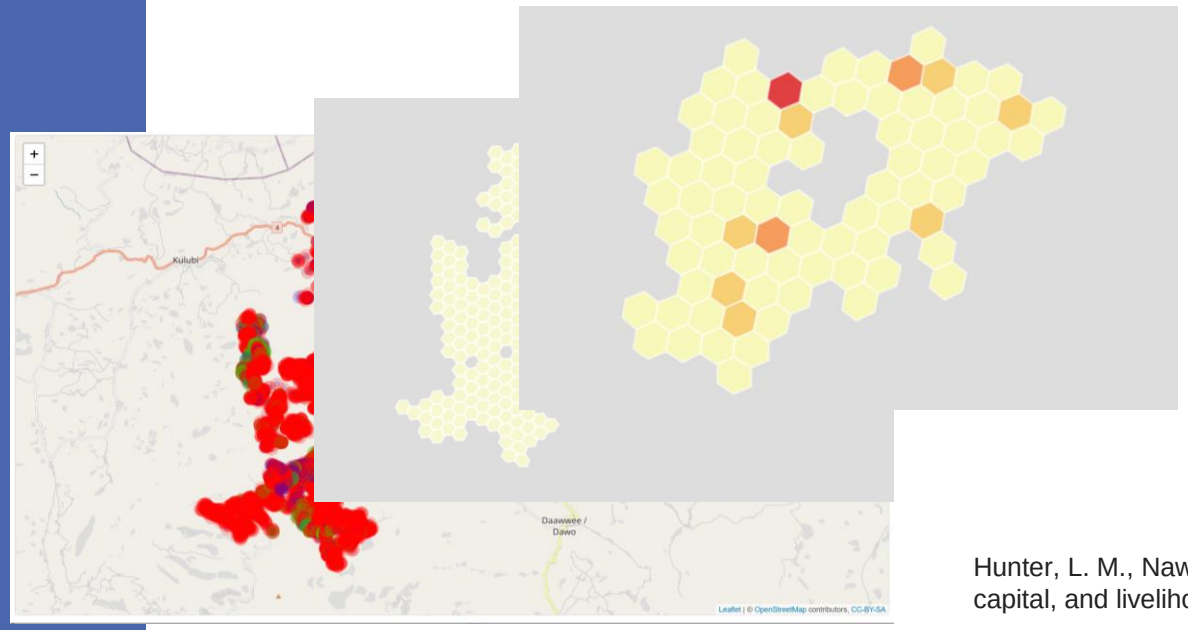
-0.25
Score of satisfaction
urban
midland
midland-ir
highland
lowland
Geographical features

PERSPECTIVES

Mapping **hotspots of risk & vulnerability to climatic change** at a fine scale

Mapping our data while **Protecting Personal Privacy & achieving geographic accuracy**

Analysing the role between the „capitals“ (especially the natural capital (Hunter et al. 2014 & 2015)) & the mobility dynamics, especially the use of migration-as-adaptation



Hunter, L. M., Nawrotzki, R., Leyk, S., Maclaurin, G. J., Twine, W., Collinson, M., & Erasmus, B. (2014). Rural outmigration, natural capital, and livelihoods in South Africa. *Population, space and place*, *20*(5), 402-420.

Hunter, L. M., Luna, J. K., & Norton, R. M. (2015). The environmental dimensions of migration. *Annual Review of Sociology*, *41*, 377.

PERSPECTIVES

Applying machine learning methods with this type of data :

(1) very large sample size impedes an application of regression models because the expressiveness of significance levels diminishes for samples larger than 10.000 observations (Lin et al. 2013)

(2) Machine learning as nonparametric technique allows to identify patterns and salient variables in large-scale and complex datasets without imposing any statistical assumptions (Zaveri et al. 2021). It would then cope with more **complex relationships** between variables.

We also planned to conduct fieldwork activities in Kersa for collecting primary data collection and test the assumptions drawn from the models.

THANK YOU !

marion.borderon@univie.ac.at