Scenario Development and Analysis of an Agent-based Model for environmentally-induced Human Migration in Ethiopia

Vanelli Caterina

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Faculty of Physics, Technical University of Dresden

MigSoKo Junior Research Group,
Computational Landscape Ecology Department, Helmholtz Centre for Environmental Research

Max Planck Institute for the Physics of Complex Systems

Supervisors:

Prof. Dr. Holger Kantz

Dr. Kathleen Hermans

Abstract

The scope of this thesis is the development and analysis of scenarios for the agent-based model named ABMig simulating the interactions between environmental change and human migration in the highland district of South Wollo, Ethiopia. ABMig includes fully coupled environmental linkages and extensive implementation of human-decision making for subsistence farmers, who decide on natural resource use and migration. Migration is a possible adaptation strategy to environmental stress with enabling factors being the major drivers in the case-study area, i.e. individuals from better-off, less vulnerable households are more probable to migrate. ABMig indirectly enhances this socio-ecological feedback loop feeding inequalities between migrants and non-migrants.

We analyze the 50-years time series of socio-ecological outputs and migration. The ecological submodel is sensitive to the different land-use parametrizations, with poor land-use management resulting in increased resource depletion. A climate-resilient green economy is correlated to better and diversified livelihoods, with less individuals impacted by food insecurity and resource scarcity. On the contrary, we found that the number of migrants is not sensitive to the different land-use approaches. Nevertheless, simulated policies addressing soil erosion decrease the resource gap between migrants and non-migrants, while population stress and environmental degradation increase it.

This work contributes to demonstrate that combining modeling tools from complexity science with social-science theories allows better understanding of the interactions between migration and global change to support policy-makers in the achievement of sustainable development.

Aknowledgements

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Statement of Authorship

I hereby declare that I have written this final thesis independently and have listed all used sources and aids. I am submitting this thesis for the first time as a piece of assessed academic work. I understand that attempted deceit will result in the failing grade “not sufficient” (5.0).

Dresden, 30th August 2021 Caterina Vanelli

Contents

List of Abbreviations

ABM	Agent-based Model
CRGE	Climate-resilient Green Economy (Scenario)
EE	Elementary Effect
EET	Elementary Effect Test
GIS	Geographical Information System
GSA	Global Sensitivity Analysis
HH	Household
IPBES	Intergovernmental Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
LHS	Latin Hypercube Sampling
LSA	Local Sensitivity Analysis
NCP	Nature Contribution to People
SA	Sensitivity Analysis
SSPs	Shared Socioeconomic Pathways
STEEP	Social, Technological, Economic, Environmental and Political
TF	Tech Future (Scenario)
TLU	Tropical Livestock Units

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1 Introduction

Complex systems are concerned with properties of sets of entities, whose behavior arises through interactions between their single parts at different space and time scales. From microscopic components and their connection, interaction, and/or competition macroscopic complex properties might arise, such as, among others, nonlinearity, self-organization, pattern formation, emergence, adaptation, and feedback loops. The resulting systemic behavior differs quantitatively and qualitatively from the behavior of the single entities and is often a product of multilevel interactions.
Complex system science includes heterogeneous theories, between others cybernetics, computational sciences, chaos, information and network theory. Technical advance has allowed the wide-ranged application of these concepts in different field of studies, involving complex systems such as the Earth's climate, neural networks, stock markets, power grids and condensed matter systems. In fact, applied sciences have been increasingly interested in understanding the mechanisms of collective behavior of these structures, and developed descriptive models with different levels of abstraction. [**2**, **14**, **22**]
The study of complex systems has adopted two polar approaches towards the development of models:

1. Focus on elegant and simplified rules in order to quantify the minimum of complexity needed for the emergence of macroscopic phenomena;
2. Focus rather on the detailed holistic simulation of real world processes, extensively taking advantage of fast-advancing computational tools.

Still, these two perspectives often mix up in state-of-the-art papers and result in hybrid models. [**14**]
A computational model is a representation of a system of interest, with some mathematical formulation as a starting point for the implementation in a computer program. It may be viewed as a set of functions $f_j : \Omega_j \mapsto \Gamma_j$, being $(x_1, \ldots, x_{n_j}) \in \Omega_j$ the input factors with $\Omega_j = \bigcup_i^{n_j} x_i$ that, when evaluated, produces outputs $g_j = f_j(x_1, \ldots, x_{n_j}) \in \Gamma_j$. When models involve some kind of stochaticity the relevant output is then the average over a given number of simulations $\langle g_j \rangle$. The explicit forms of f_j are often unknown, in particular when the model is not equation-based. [**37**]

In contrast to pure physical systems such as condensed matter models, complex systems involving social agents have to deal with the unexpected effects of social space, in particular they might be shaped by (human) decision-making and unpredictable or adaptive behaviors. Moreover, no unified theory has been developed to describe all the uncertainties of decision processes or captures the possible feedback loops between agents and a modelled environment. These systems are therefore difficult to represent through equation-based models. [**2**, **12**] While game theory considers mostly rational agents and has limits in dealing with a big number of agents interacting with an environment, Agent-based Models (ABMs) offer a powerful computational tool to analyze the actions of multiple agents in coupled social and physical space [**12**].

ABMs, sometimes also referred as individual-based models, are a collection of autonomous entities capable of interacting with each other and the environment based on some presupposed rule of behavior, which can be for example deterministic or stochastic, fixed or adaptive. ABMs are able to portrait both changing environment and adapting agents, through the implementation of learning processes and agents' memory. Agents can act without a goal or based on rational choices, implicitly or explicitly optimizing some state variables. Rational agents are generally optimizer, while agents with limited (or bounded) rationality can be, for example, satisficers. The individuals' perception of the environment can be limited or total, memory-less or path-dependant. They could be organized and exchanging information through networks, or within physical neighborhoods (for example Moore or Von Neumann neighborhoods). Agent-based modelling allows a bottom-up description of phenomena, where the macroscopic dynamic is not being superimposed by top-down systemic equations. In physical terms it can be referred to as multi-body system, where tools and theories of statistical physics can be applied. [**12**, **13**, **14**, **15**] In the following some relevant examples of ABMs will be presented. In Chapter 3.1 we will describe the model we work with, which represents the main experimental tool of this work.

Fireflies

By sending and perceiving signals, self synchronizing individuals influence each other, causing minor local adjustments that result in global synchrony to emerge in a decentralized manner. Certain species of (male) fireflies (e.g., luciola pupilla) are known to synchronize their flashes despite sparse connectivity network (each firefly has a small number of "neighbors"), the non-instantaneous visual communication and random initial signal periods. In the cardiac muscle, pacemaker cells create these rhythmic impulses and consequently the pace for blood pumping. Similarly, for a long time, it was believed that the fireflies' populations could synchronize their signals only thanks to leading individuals. ABMs where able to explain this phenomenon in absence of leaders, and were particularly effective in replicating the emergence of the pulse-coupled synchronization through a minimalistic set of rules [**9**]. In fact self-synchronization can be modelled at the microscopic scale through "coupled oscillators" where each agent is an independent oscillator. The oscillator model for fireflies is called light-controlled oscillator and has found a wide-spread application in electronic circuits.

The Schelling model of segregation

One of the earliest applications of agent-based modelling within social sciences is the Schelling model of segregation. The model was created to show how individual incentives and perception of differences can lead to the emergence of collective segregation [**10**]. The model's simplest form resembles a cellular automaton with a $N \times N$ grid, where most of the cells are occupied by agents from (at least) two different populations. The satisficer-agents relocate according to the fraction of friends (i.e., agents of their own group) within a neighborhood around their location. Hence, agents have an aim, that is living in a neighborhood with a higher share of friends B than their satisfaction threshold B_a, the main model parameter. Increasing B_a would mean rising the agents' intolerance towards individuals of the other population. The model showed that even populations with high level of tolerance, that is low values of B_a, were leading to clustering and segregation patterns. These patterns correspond to the emergence phenomena of self-organization, and are able to partly explain ethnic segregation and neighborhood tipping. One of the multiple empirical application of the Schelling's model consisted in comparing the residential dynamics of Jews and Arabs in Israeli cities. Even though it ignores many relevant factors of the residential market, the historical residential dynamics were partly congruent with the model's simulations and the Arab minorities where showed to be behaving with patterns corresponding to relative high level of tolerance [**11**].

Traffic models

One of the most famous application of agent-based simulations at the intersection with physics is traffic flow modelling. Here, (road) transport is reproduced microscopically, with autonomous car drivers being the agents, whose behavior is based on decisional activities and the environment. Traffic and congestion result from the interaction of each agent with the regulations, road infrastructure and other road users, which are simulated at different degrees of realism. Pioneers in this field created the Nagel-Schreckenberg model, a cellular automaton simulation for freeway traffic which incorporates concepts from hydrodynamics in agent-based modelling [**4**]. Each vehicle, localized in a single lane, has a random velocity $v_i \in [0, v_{max}]$, and at each iteration agents accelerate or slow down depending on the position of the next vehicle. Despite the simplicity of the behavior's rules, this model was able to explain start-stop traffic waves, a consequence of the fluctuation in the motion of

vehicles.
In the past years research efforts focused on further increasing the complexity of these models, incorporating for example anticipation effects, reduced acceleration capabilities and an enhanced interaction horizon for braking [**16**] or different agents driving styles [**17**]. For instance, it was found that an aggressive driving style was correlated with the formation of spontaneous traffic jams [**17**].

Models for environment-migration linkages

The environmental and climate crises put a massive pressure on socio-ecological systems. In particular environmental change can lead to human migration by affecting societies not only directly through climatic extreme events such as floods and droughts, but also indirectly due to the exacerbation of demographic and economic dynamics. Moreover, migration can further nourish environmental change by locally altering the resource pressure on vulnerable ecosystems. ABMs are valuable tools to study these linkages because they can represent individual migration decisions of human actors, while exploring their interaction and adaptation to a changing environment. [**1**, **3**, **8**, **28**]

2 Research Question, Aim and Purpose

The Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) has identified the combination of ecological modelling and scenario development as key for the investigation of the relationships and feedbacks between drivers of change, ecosystem services and, consequently, human society [**30**]. As defined by the Intergovernmental Panel on Climate Change (IPCC), a scenario is a coherent, internally consistent, and plausible description of a possible future state of the world. It is built upon scientific understanding of past and current observed relationships between drivers and environmental trends, drawing upon narratives of plausible socio-economic developments or particularly desirable future pathways under specific policy implementations. [**18**]
J. Thober et al. (2018) [**8**] reviewed existing ABMs for environmentally-induced migration in rural contexts of natural resource use and found:

1. General scarcity of models for environment-migration linkages;
2. Deficient analysis of non-migration;
3. ABMs focus either on human decision-making or on fully-integrated social-ecological feedbacks;
4. Migration flows such as migration into and out of the system as well as temporary migration processes were given little attention.

J. Thober et al. (2018) also provided the classification of socio-environmental linkages. For one-way linkages, agents are influenced by the environment but do not influence the ecosystem. In the case of partly integrated linkages, agents can alter for example land-use and are in turn influenced by harvest success. Finally, for fully integrated linkages also environmental consequences of natural resource use and migration decisions are considered within the model (e.g. resource depletion or soil degradation). In addition to these technical research recommendations, recent research [**8**, **22**] also calls for an interdisciplinary approach between social and natural scientists, modelers and empiricists on socio-ecological ABMs.

Hence, the purpose of this work is to advance scientific research on agent-based simulations for migration and environment interaction in rural context. Specifically, our research question aims at contributing to filling the above-mentioned gaps, through the development and analysis of scenarios for the ABM called ABMig, consistently with the research recommendations provided by IPCC and IPBES. The characteristics of the scenarios to be developed involve the following aspects:

1. be exploratory and based on trends, i.e. consistent with future possible geopolitical and ecological trajectories;
2. focusing on selected direct and indirect drivers of change;
3. be comparable to the baseline Scenario and produce different qualitative output one from the other, in particular for the migration-related model's outputs.

3 Methods

3.1 The Model

Developed by the research group MigSoKo from the Computational Landscape Department of UFZ, the model ABMig aims to represent subsistence farmers who decide on natural resource use and migration in Ethiopia. For synthesis reasons we will describe the model loosely following the ODD+D standard protocol [**25**] and the protocol proposed in [**8**] for environment-migration ABMs.

3.1.1 General Aspects

The model's concept builds upon previous scientific papers [**1**, **3**, **6**, **7**, **8**, **19**], stylised data and workshops of MigSoKo, in particular those referring to the case study area in the Ethiopian highlands. ABMig is written in NetLogo, one of the

Figure 3.1: The highland region of South Wollo, Ethiopia. Source: Heinz Sielmann Stiftung

most widespread programming languages for socio-ecological ABMs. Another fundamental characteristic of the model is the inclusion of stochaticity in form of random number generators applied to initialization and other dynamical processes, such as the simulation of precipitation. As a consequence, when running experiments with ABMig, it is necessary to perform an adequate number of repetitions to achieve robust results. The theoretical background of the implementation of human decision-making grounds on the theory of bounded rationality and heuristics. The considered migration flow is out-migration, with both permanent and (direct) return migration. Socio-environmental linkages are fully coupled, as they include the influence of resource depletion and land degradation on the rural livelihoods.

Model's purpose

ABMig is designed for system understanding, communication and hypothesis testing with the key audience being scientists and local stakeholders, including farmers and the local governance structures. ABMig ought to be a tool to support decision-making concerning policies in rural Ethiopia, but does not aim at any quantitative prediction of future migration flows or environmental conditions.
Nevertheless, the modelled socio-ecological processes root in the above-mentioned literature and in other validated socio-ecological ABMs, listen in the review paper by Thober et al. (2018) [**8**], and are therefore able to provide a solid base for qualitative comparison of the outputs.

Case study and spacial scale

The region of South Wollo in Northern Ethiopia has been chosen as case-study area since it has been identified as hotspot of socio-ecological pressure in Ethiopia by Hermans-Neumann et al. (2017) [**3**], which comprises high population densities, migration, land degradation, and rainfall variability. Rainfall in South Wollo has a bimodal pattern with a smaller spring season (Belg) and a larger summer season (Kiremt). The region is affected by changing rainfall patterns with increasing variability between the years. The local population highly depends on rain-fed agriculture, leading to reduced adaptive capability to the environmental and climate stress. Moreover, food insecurity affects the majority of the rural households. Due to the declining Nature Contribution to People (NCP) and increasing population densities, the rural kebeles (the smallest administrative units in Ethiopia) of South Wollo have been identified by previous studies as a possible hotspot for human out-migration [**7**]. The NCP approach, presented in the IPBES Framework, recognizes the central and pervasive role that culture plays in defining all links between people and nature, going beyond the concept of ecosystem services [**29**, **30**]. The computational repre-

Figure 3.2: Gully erosion in South Wollo, Ethiopia. Source: MigSoKo

sentation of the Ethiopian region constitutes the modelled environment where the agents, both individuals and the households (HH), are located. The modelled socio-environmental processes in ABMig were equipped with a baseline parametrization, aiming to mirror the present environmental and demographic conditions in South Wollo. Specifically, all the existing robust empirical data and literature was used for calibration of climate-environmental parameters and their distributions to depict local socio-ecological dynamics. Hence, an empirical validation, for example through the common procedures applied to climate models using historical and present data [**55**], is unfeasible. ABMig's validation and verification rely rather on conceptual and operational reasonability. This kind of validation approach, common to ABMs, tests whether the model is able to robustly generate and regenerate a behavior to be observed in reality. [**45**, **46**]

The scenarios developed in this work seek to investigate how different land-use management priorities or demographic evolution have an impact on the model's dynamics and outputs. These simulated processes give insights on the real world's possible migration and environmental outcomes, extrapolating trends which can be observed today or in the near future, and basing upon a solid knowledge of the present situation in the region of South Wollo.

3.1.2 Relevant Processes

In Figure 3.3 the conceptual structure of the model is represented. All the processes are run once for each iteration, which corresponds to the time scale of one year. In the following, one simulation refers to a model's run over many years. Depending on the soil quality of the patches (pasture productivity) the HHs take specific farming decisions. Agricultural processes are modulated by soil quality and annual precipitation. Afterwards, if applicable, other livelihood sources (livestock and non-farm activities) are simulated. Food production and savings directly impact the food security of the HHs. Migration and demographic processes are the last run procedures.

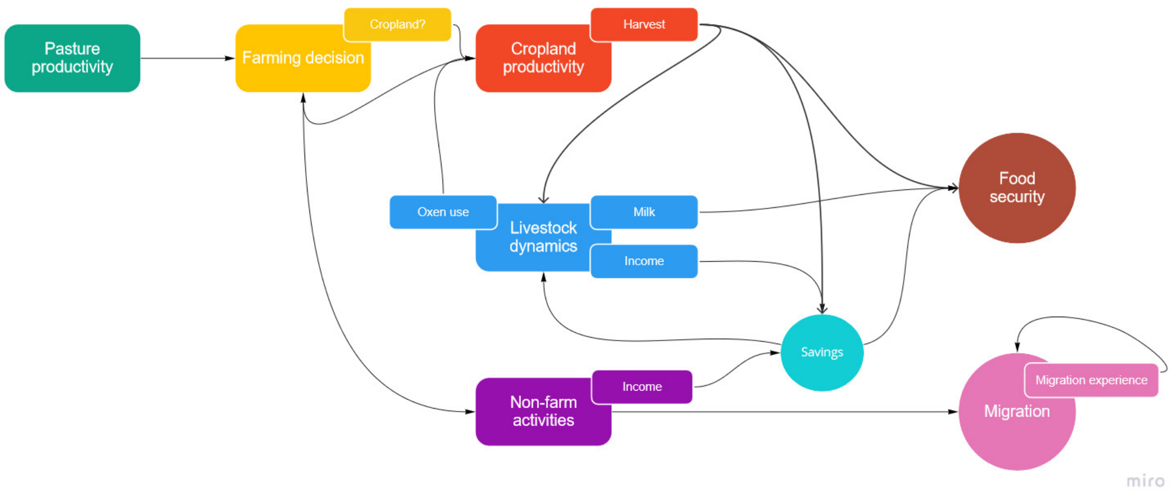

Figure 3.3: Conceptual flowchart for ABMig's processes.

Landscape and Climate

In ABMig climate is represented by the precipitation variable, which has been derived by the CHIRPS dataset, an established data set providing rainfall estimates from rain gauge and satellite observations for trend analysis and seasonal drought monitoring [**27**, **28**]. Considering that South Wollo has been defined as a hotspot for rain variability [**3**], the use of CHIRPS for the simulation of monthly precipitation in ABMig already includes regional droughts [**27**] and the fact that for this region climate emergency is a present issue rather than a future scenario. With this bitter reflection in mind, the idea of developing climate scenarios was dropped, and we focused mostly on different land-use management and demographic scenarios. Space has been modelled explicitly, but is not based on Geographic Information System (GIS) data. The landscape is divided into two altitude classes corresponding to the two agroecological belts of Ethiopia, called Dega (above 2400 m) and Weyna Dega (1,500-2,400 m), respectively in darker and lighter color shades in Figure 3.4. Depending on the altitude class, either Belg or both Belg and Kiremt are used for cropping, i.e. HHs in the higher elevated areas of Dega refrain from cropping during Kiremt. Slope and initial soil quality are set – randomly and spatially heterogeneously – based on assumed distributions from empirical data. Soil quality is influenced by agricultural management (that is whether the HH owns a oxen or not) and slope-dependent natural degeneration. A predefined share of the landscape is assigned as communal grazing land by randomly selecting the respective number of patches.

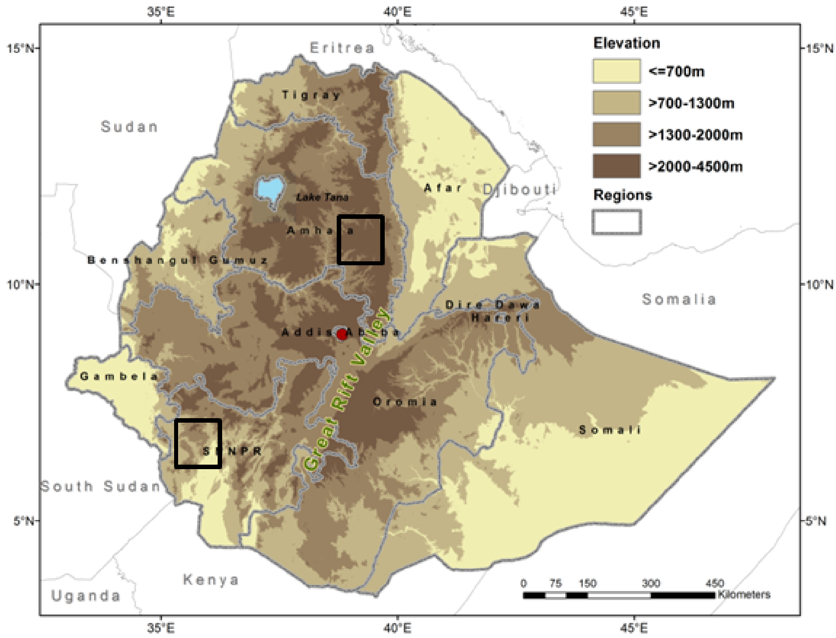

Figure 3.4: Map of Ethiopia with two case study areas of MigSoKo (indicated with rectangles). South Wollo is the northernmost rectangle.Source: [**1**]

Households and individuals

First, a number of individual agents is calculated depending on the population size:

$$N_{ind} = \sum_{x} A_x \cdot D_x \tag{3.1}$$

where A_x is the area of the respective altitude class x and D_x is the population density of the respective altitude class. To sum up, the regions at different elevations are dissimilar for population density (higher regions are less populated) and precipitation distribution/cropping season.

The number of HHs is calculated as:

$$N_{HH} = \frac{N_{ind}}{\overline{n}_{HH}} \tag{3.2}$$

where $\overline{n}_{HH} = 4.9$ is the mean HH size derived from ERHS data. The distribution functions for HH and individual characteristics have been fitted to the data using a Gaussian kernel density estimator. Each HH receives initial savings, based on interview data from South Wollo [**1**]. For reasons of simplicity, we made several assumptions with respect to the wealth of HHs (e. g. initial savings are assigned independently of further assets belonging to the HH such as livestock and farmland). A fixed share of HHs is randomly selected to engaged in non-farm activities. HHs are randomly allocated into the landscape and the owned patches are distributed according to the empirical data on farm size. Agents differ in agricultural intensity as the ownership of oxen increases productivity through the input parameter oxen-use and decreases yearly soil quality through the input parameter oxen-factor.

Food security

Each HH is defined by static land holdings and consumption requirements whilst income and wealth are modelled dynamically. HHs depend on cropping and livestock keeping for subsistence, sell crops and livestock, and might additionally engage in non-farm activities to secure their livelihood. To determine the level of a HH's food security, the calorie demand per HH is calculated and compared to the calorie supply. The calorie supply is provided by harvested crops and livestock products. HHs try to meet their demand based on crops and milk. If this is not sufficient, they first use any existing savings or they sell livestock to buy crops. Whether or not the demand can be met determines the food security of the HH and the respective individuals.

Migration

Once a year each HH member decides whether to migrate or not, this process is visually represented in Figure 3.5. Firstly, potential HHs are selected based on the conditions following Groth et al., 2020 [**1**]. 85% of the individuals with migration potential belong to HH with migration experience (that is, somebody of the HH already migrated) and either use both harvest seasons (and are therefore located in the Weyna Dega area) or engage in non-farm activities based on results from [**1**]. Non-farm activities and favorable environmental conditions during the Kiremt season increase economic resources and as such migration ability. However, only together with migrant networks, which can reduce the costs and risks of migration and influence migration aspirations, can these drivers explain why HHs engage in migration. Secondly, the other 15% of individuals being assigned the variable of migration potential belongs to the rest of population which does not full fill these conditions. Afterwards individuals from the potential HHs are appointed a specific migration probability based on age and sex. These probabilities are calculated from discrete frequency analysis derived from the ERHS data [**33**]. The initial migration experience of HHs and the transformation of the derived individual probability are calibrated so that the share of HHs and the share of individual migrants over a five year time interval in the baseline scenario follow the share of HHs and individual migrants found in [**19**]. The actual implementation of migration decision is modelled by a random number generator. A given share of migrants permanently stay in the destination and do not return, while the rest of migrants decide to temporary migrate; i.e. they stochastically return to their HH from outside the focus area to South Wollo.

To sum up, the technical representation of migration decision, following [**1**], is focusing more on the enabling factors, i.e. factors which are generally a sign of an HH being well-off [**19**, **28**], rather than on the push factors. In addition, these factors are structurally semi-static in iterations. This implementation of the migration decision poses some challenges in the development of our scenarios, as the number of migrants might not react sensitively to changes in parameters.

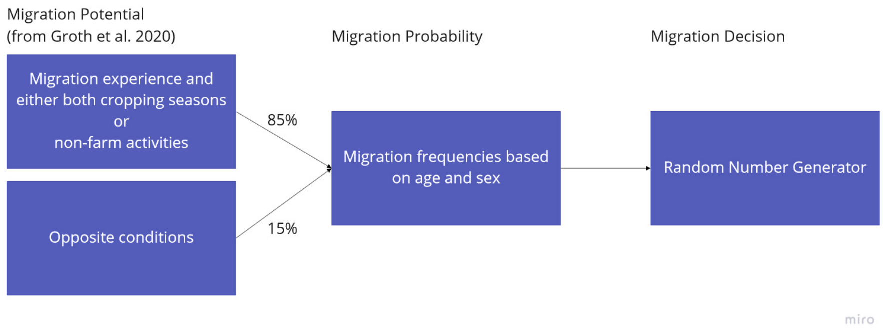

Figure 3.5: Migration decision in ABMig

3.2 Scenario Development

For the development of robust model scenarios, the following workflow has been developed [**44**]:

1. Parameter Ranking: Creation of a ranking list for all the variable input factors according to their relative contribution to the output uncertainty.
2. Scenario Storylines & Parameter Translation: Conceptualization of possible scenarios in form of abstract storylines and possible parameter translations.
3. Parameter Selection: Picking of a shortlisted number of relevant parameters for each scenario
4. Value Definition: Choice of parameter value for each scenario, to be changed with respect to their baseline value.

Parameter Ranking

ABMig includes $M = 67$ variable input parameters each with a different physical meaning. The entanglement of complex procedures in the different submodels and at the microscopic scale makes a pure analytical-mathematical approach for model evaluation time-intensive and unsuitable. In the early stages of the exploration of ABMig it is necessary to identify the most important parameters, that is, parameters with the most impact on the model‘s output. To investigate the relative effect of the variation of input factors on the output of a computational model the application of methods of Sensitivity Analysis (SA) is necessary. In fact, SA is increasingly being used in environmental modelling for a variety of purposes, including uncertainty assessment, model calibration and evaluation. [**39**, **45**]

Local sensitivity analysis (LSA) considers the output variability against variations of an parameter value around a specific parameter value, while global sensitivity analysis (or GSA) considers variations within the entire space of variability of the input factors. Consequently, the application of LSA requires the specification of a nominal value x_i^0 for the input factors. Although the limitation due to the choice of a specific parameter value is absent in GSA, the latter still requires the careful specification of the input variability space Ω. Another complication one must take into account when using GSA is the computational efficiency, which generally decreases with more precise and complex methods. [**39**, **48**] As we are interested in a general picture of the model's output with respect to different parameter combination choices, the implementation of GSA is justified.

Factor prioritization aims to create a ranking list of the input factors $x_1, x_2, \ldots, x_M$ according to their relative contribution to the output variability. For the purpose of parameter ranking the method of Morris has been chosen, as suggested by Pianosi et al. (2016) [**39**]. Morris developed a so-called One-At-Time method, meaning that in each model evaluation only one input parameter is given a new value. The main idea is to look at the output perturbations from multiple starting points $\tilde{x}_i^j$ for each i-th parameter within the input space, and to measure their aggregated effect on each output state variable through sensitivity indices [**36**, **37**]. The method of Morris, also called the Elementary Effect Test (EET) consists in particular in computing the mean of r finite differences (also called 'Elementary Effects' or EEs) as a measure of global sensitivity. The EEs are computed at fixed points $\tilde{x}^j$ in the feasible parameter space, being Δ_i the finite variation or perturbation length the i-th parameter space is divided into. For a given output g, the sensitivity index S_i is the averaged sum of the finite differences of g with respect to x_i at $\tilde{x}_i^j$ over r reference values $\tilde{x}_i^j$. The index S_i quantify those changes in g due solely to changes in the i-th input. The sensitivity measure for the i-th input factor thus takes the form:

$$S_i = \sum_{j=1}^{r} EE^j = \frac{1}{r} \sum_{j=1}^{r} \frac{g(\tilde{x}_1^j, \ldots, \tilde{x}_i^j + \Delta_i^j, \ldots, \tilde{x}_M^j) - g(\tilde{x}_1^j, \ldots, \tilde{x}_i^j, \ldots, \tilde{x}_M^j)}{\Delta_i^j} c_i \quad (3.3)$$

where c_i is a scaling factor.

For each input and output factor, both mean μ_i and standard deviation σ_i of the EEs are computed , where the latter provides information on the non-linear interactions between the i-th parameter and the other input factors. This way of computing indices produces robust results if the model's output has a characteristic length of the same scale of Δ_i. Thus, in practice, the so-called simulation design levels r and correlated perturbation length Δ_i have to be chosen carefully. [**36**, **37**]

Scenario Storylines, Parameter Translation and Parameter Selection

The development of scenarios is achieved through a step-by-step procedure, bearing in mind the Scenarios Frameworks proposed by the IPCC, such as GEO-4, and Shared Socioeconomic Pathways (SSPs) [**47**]. The conceptual storylines were built through a process of iterative revision and inclusion of relevant literature and local stakeholders positions, classified in the STEEP categories, that is Social, Technological, Economic, Environmental and Political drivers of change. Furthermore, the different stakeholders positions have been divided into expected, preferred and planned socio-environmental outcomes.

While in this first conceptual development ABMig's technicalities have not been considered, the next step was to take into account just the relevant storyline components which can have a mathematical parametric translation for the model. By matching both technical feasibility and conceptual content, this process led to a downscaling of the scenario storylines to a few different processes and to a list of relevant input parameters.

The next step is to select parameters which will be changed with respect to their baseline value. Since our goal is to compare scenarios between each other, the final elected parameters must have an impact on the model's output, i. e. the model must react sensitively to their perturbation. Thus, we cross-check the parameters with both a content-wise reasonable translation and a relative high ranking, using the results from the GSA.

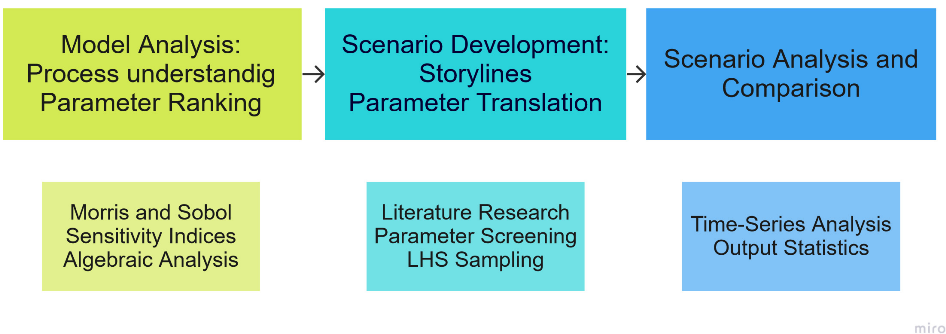

Figure 3.6: Schematic workflow for the development and analysis of scenarios.

Value Definition

Once potential varying parameters for each scenario have been selected, it is necessary to select a specific value for each input. For each parameter we have N_i =

$(\tilde{x}_i^0 - \tilde{x}_i^{extremal})/\Delta_i$ possible parameter values , assuming that the characteristic length of the model is Δ and being $\tilde{x}_i^{extremal}$ the minimum or maximum of the parameter range in the direction of change for the given scenario. So, for each scenario k the number of possible parameter combinations are:

$$P_k = \prod_{i=1}^{s} N_i \tag{3.4}$$

where s is the number of parameters to be changed for each scenario. Of course, a simulation which evaluates the model at all the possible input combinations, i.e. covers the whole selected parameter space, would be unfeasible due to its inaccessible time of computation. Hence, it is necessary to select a reasonable statistical sampling, which does not underestimate the model's complexity while keeping the runs efficient.

Latin Hypercube Sampling (LHS) can be viewed as a compromise procedure that incorporates many of the desirable features of random sampling and stratified sampling. LHS is a probabilistic procedure in the sense that a weight (i.e. $w_i = 1/n_S$) can be associated with each sample element that can be used in probabilistic calculations. Like random sampling, the implementation of LHS does not involve the complex determination of strata and strata probabilities. [**43**] LHS operates in the following manner to generate a sample of size n_S from $x = [x_1, x_2, \ldots, x_{n_k}]$. The range of each input variable is exhaustively divided into n_S disjoint intervals of equal probability and one value is selected at random from each interval. The n_S values thus obtained for x_1 are paired randomly without replacement with the n_S values obtained for x_2. These n_S pairs are combined in a random manner without replacement with the n_S values of x_3 to form n_S triples. This process is continued until a set of n_S n_k-tuples is formed. These n_k-tuples are of the form:

$$X_k = [x_{i_1}, x_{i_2}, \ldots, x_{i,n_X}], i = 1, 2, \ldots, n_S \tag{3.5}$$

and constitute the Latin hypercube sample. [**41**, **43**]

Bearing in mind that we want to focus on the migration-environmental change nexus and we want the scenarios to specifically differ in the migration output, we reduce the parameter value choice to a small maximization problem. We looked at the sum of the normalized distances of the migration output function for all the sampled combinations:

$$\sum_{t,i \neq j} \mid f_t^i(\tilde{x}_1, \ldots, \tilde{x}_{n_i}) - f_t^j(\tilde{y}_1, \ldots, \tilde{y}_{n_j}) \mid \tag{3.6}$$

where i, j refer to the given scenario, n_i to the number of parameters to be changed for each scenario, $f^i(\tilde{x}_1, \ldots, \tilde{x}_{n_i})$ is the output, i.e. migration events, for a specific set of parameter values $(\tilde{x}_1, \ldots, \tilde{x}_{n_i})$. We chose then the tuple of parameter combinations maximizing the quantity in Equation 3.6.

4 Main

4.1 Sensitivity Analysis

In the context of this thesis, SA were useful to shortlist parameters ABMig is responding sensitively to and leading to scenarios which actually differ from each other. During test runs we observed that the model‘s behavior was robust against parameter perturbations, so we made the assumption that $r = 50$ levels for the Morris simulation design where appropriate to explore the model’s global behavior [**37**]. This way, we are sure that all the finite differences Δ_i of the Morris Method (referring to the i-th parameter) are homogeneously covering the whole parameter space Ω , without missing important variations in the output space Γ for a given output g. The computation time for this GSA simulation phase approximately 8 hours.

In Figure 4.1 some exemplary results of the GSA are shown. This heat map gives an idea of the sensibility of each output variable to each input parameter, despite the direction of change of the parameter value. It is important to mention that the normalization is column-based, so that one can visually distinguish for each output which are the most important input factors, despite of how big the absolute impact of a factor is. A direct consequence of this consideration is that even though two slots in different columns of Figure 4.1 might have the same colour, they might not correspond to similar absolute index values. The SA of ABMig were heavily affected by the choice of range of each parameter. In addition, when looking at a reduced number of parameters the indices appeared to be generally increasing. Figure 4.1 shows for instance the relative importance of population density (factors density-weynadega-km2 and density-dega-km2) change on most of the model’s outputs except for the harvest quantity. Focusing on the migration output, we observe a higher sensitivity to calories content of crops (calories-crops) and to the share of HHs with migration experience (share-HH-mig-experience) than to other factors. A deeper analysis of the GSA’s results goes beyond the scope of this work.

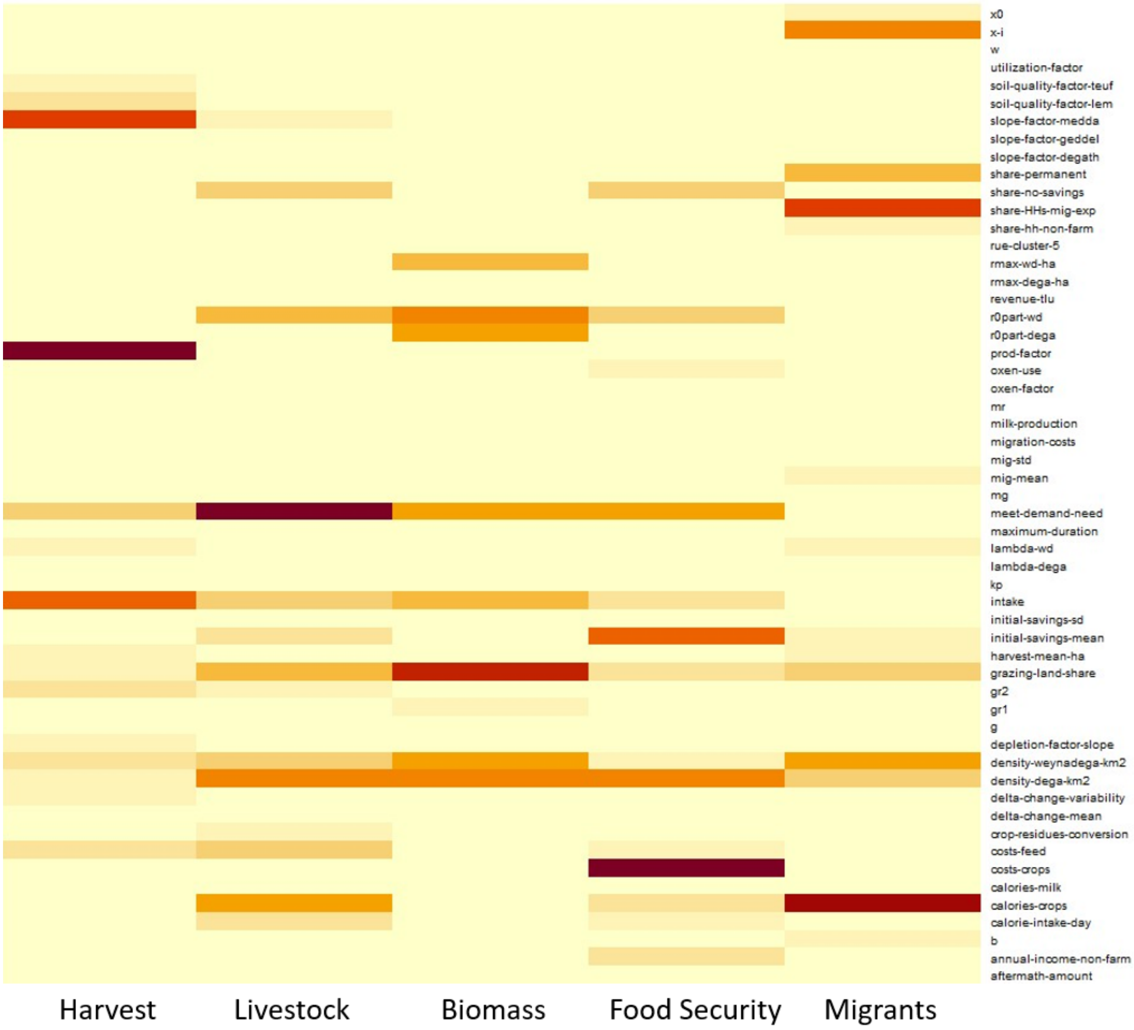

Figure 4.1: Exemplary results of Morris sensitivity indices for each relevant output (columns) and input parameter (rows), with column-wise normalization. A darker shade of color represents a higher index, that is a bigger absolute response of the output to the parameter's change.

4.2 Developed Scenarios

Applying the above described methodological research design, three scenarios have been developed using the baseline as a starting point. In the respective table the chosen parameter changes and values have been listed. Running LHS for ABMig, we get sets with sample size $n_S = 100$ of n_k-tuples, where n_k is the number of pre-selected parameters for the k-th scenario. [**56**, **41**]

Climate-Resilient Green Economy Scenario

The Climate-Resilient Green Economy Scenario (CRGE) corresponds to the implementation of more sustainable land-use management, including measures directly tackling the local increasing soil erosion and degradation [**42**]. The communities of South Wollo have access to green job positions, supported by the Ethiopian government. Subsistence farmers are earning more in non-farm activities, diversifying their income and livelihoods. As a consequence the population is expected to be less exposed to drought and more able to cope with harvest uncertainty. [**51**, **52**, **54**]

Parameter	Storyline	S0	CRGE
depletion-factor-slope	soil erosion prevented with smart land-management	2	1
grazing-land-share	more communal grazing land	0.05	0.1
gr1	more sustainable pasture management	0.5	0.33
gr2	more sustainable pasture management	0.1	0.03
share-non-farm-activities	income diversification through green jobs	0.7	0.8
prod-factor	farming practices addressing soil depletion	0.01	0.0067

Table 4.1: Input Parameters for CRGE Scenario

Tech Future Scenario

For the Tech Future Scenario we assume possible effects on South Wollo of financial investments into the agro-economy from foreign countries, leading to fast and less sustainable development. The main relevant narrative for our model is an intensified and industrialized agricultural production. Local crops are substituted with genetically modified crops with an higher calories content, or other cash crops. Also livestock production is optimized and leads to an increased amount of calories content in milk. [**42**, **51**, **52**]

Parameter	Storyline	S0	TF
calories-crops	diffusion of more efficient crops	3450	4483
calories-milk	new technology in livestock management	400	800
grazing-land-share	increased land privatization	0.05	0.033
gr1	intesified pressure on pasture vegetation	0.5	0.66
gr2	intesified pressure on pasture vegetation	0.1	0.2
oxen-factor	intensified farming practices	0.01	0.03
oxen-use	intensified farming practices	1.1	1.4

Table 4.2: Input Parameters for The Tech Future Scenario

Population Bomb Scenario

While the previous scenarios correspond to diametrically opposed approaches to land-use management and agricultural production, this last one aims at exploring the impact of demographic change on the available resources, livelihoods and economy. The Population Bomb scenario is characterized by an increased birth rate, while the initial population density is kept at set-up level. Due to the decreasing resources per capita and rural livelihoods at risk, migrants are also more likely to permanently stay in the regions of in-migration. Permanent migration is therefore increasing. [**42**, **52**, **52**]

Parameter	Storyline	S0	PB
birth-rate-change	demographic change	0	0.2
share-permanent	increased share of permanent migration	0.3125	0.45

Table 4.3: Input Parameters for Population Bomb Scenario

4.3 Scenario Analysis

For statistical robustness, in the following analysis we will always consider present the results for 100 model runs of 50 years each. The time horizon of 50 years has been chosen as it is a reasonable compromise between how much time the model's trajectories need to reach the steady state and the socio-ecological "forecastable" near-future. The computation time of 100 model runs was approximately one hour for each scenario.

To ease the comparison between scenarios we choose to leave untouched initial point values, in other words we keep a fixed "origin" for calibrated quantities. This work's focus lies rather on dynamical parameters, whose effect on the state variables spreads in the model for each iteration, while basing upon the baseline model calibration mimicing real-world dynamics.

ABMig is able to report a variety of outputs, but we focused on a small sample which we considered representative for different aspects of subsistence farmers' livelihoods, that is harvest, reserve biomass, livestock, food security and migration. Generally speaking, the model shows a typical behavior of complex systems: at the first simulation's tick the ABMig's outputs start from approximately the same point no matter which scenario is considered. Natural fluctuations and heterogeneity are simulated through the internal implementation of random number generators, (Gaussian and lognormal) distributions and seeds. In other words the initialization is on average similar for each parametrization, with small alterations caused by the above mentioned sources of stochasticity. After a transition phase ABMig's state variables find their steady state, which generally corresponds to a constant output value or constant slope. Since the ABM's aim is a qualitative analysis, absolute values of these "final" steady states are for this work not decisive per se, but their significance lies rather in the relative comparison between different scenarios.

Harvest

In Figure 4.2 the time development of harvest yields for the different scenarios is plotted in kg per year and household. The total harvest is calculated annually based on variable ecological factors and on annual precipitation.
In the baseline, considering the mathematical ecological processes, annual precipitation variability appears to be the main origin of the yearly agricultural production fluctuations, while ecological factors refer mostly to soil quality and might be driving the long term tendency. The 50-years trend is also influenced by the intrinsic precipitation trend itself, which for South Wollo is characterized by increasing droughts frequency and duration. The baseline and the Population Bomb Scenarios are characterized by a similar behavior. Harvest yields drop for the first 20 years, and

afterwards start to slowly increase, reaching a stable state with a constant slope. This finding is consistent with the SA, where harvest was not influenced by population density changes. Thanks to the increase in the production factor and the decrease in soil depletion due to slope , in CRGE harvest yields are higher than in the other parametrizations and strictly increasing. In contrast to the previous scenarios, agricultural yields in the Tech Future Scenario are dramatically dropping in the first two years. This is partly a consequence of the steep drop in soil quality because of the intensified farming practices (in particular the increase in the oxen-factor input). Afterwards, the curve presents a recovering behavior with a slow increase over time, but still not reaching the yields of the other scenarios. The increased use of oxen and new technologies (both represented by oxen-use) impacts positively on the quantity of harvest, partly balancing the effect of a land-use management not addressing the diminishing soil quality.

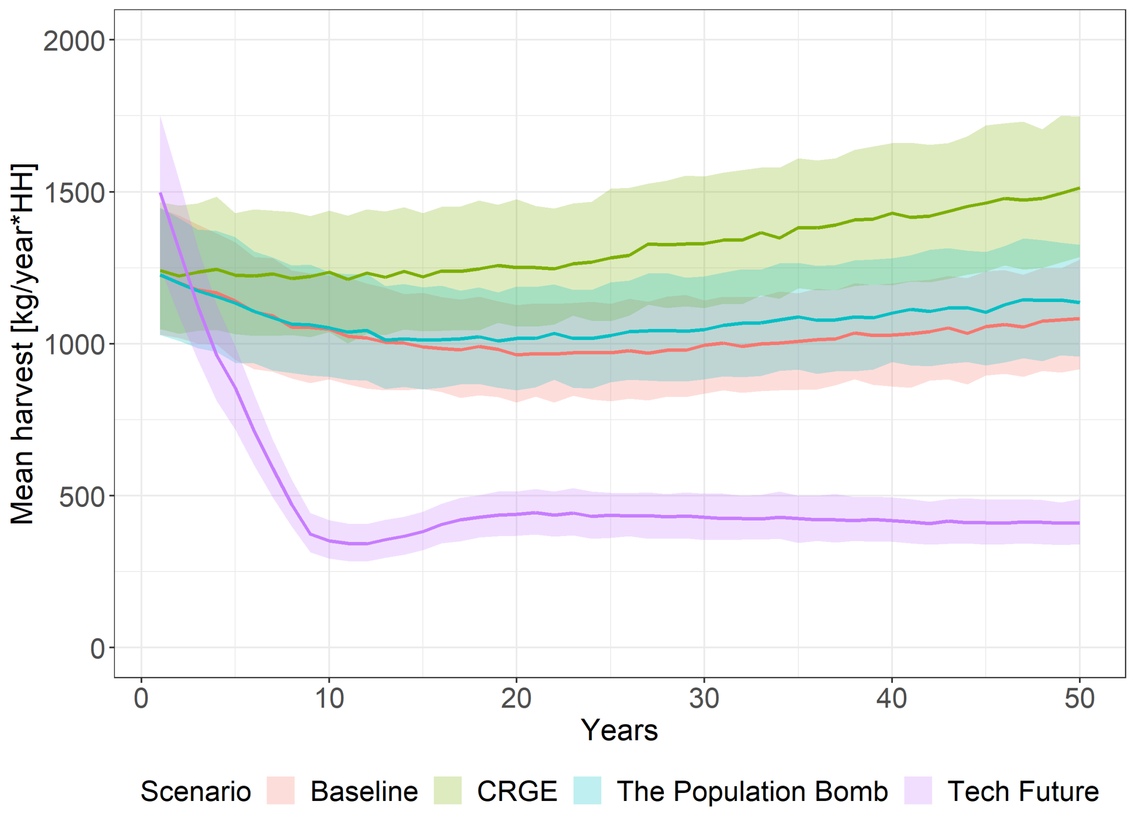

Figure 4.2: Time development of harvest yields in kg per year and household for the different scenarios. The line represents the mean, the shadowing represents downside and upside standard deviation.

Reserve Biomass

The time development of reserve biomass per area is plotted in Figure 4.3. Reserve biomass describes the non-photosynthetically active biomass which mainly serves as storage of the plants below and above ground, and includes for example roots or woody branches [**35**]. Here, the baseline and Population Bomb scenarios shows identical decreasing trajectories, TF resembles an exponential decrease and CRGE has again the largest values. In this plot, it is important to notice the asymmetry of downside and upside standard deviations, where the latter is smaller than the first. This kind of statistical approach allows to identify the asymmetries in the different simulations. In particular, the large downside standard deviation indicates that there are some outliers smaller than the mean. Moreover, the majority of the simulations produced outputs which accumulated around the average and were upper limited. In other words, some (few) simulations produced outputs with particularly low levels of reserve biomass, while there were less outliers with much higher value than the average biomass. Demographic change does not have an impact on reserve biomass. The dynamics of biomass are in fact determined mostly by the grazing pressure on reserve biomass (gr2), which was changed in opposite directions for CRGE and TF.

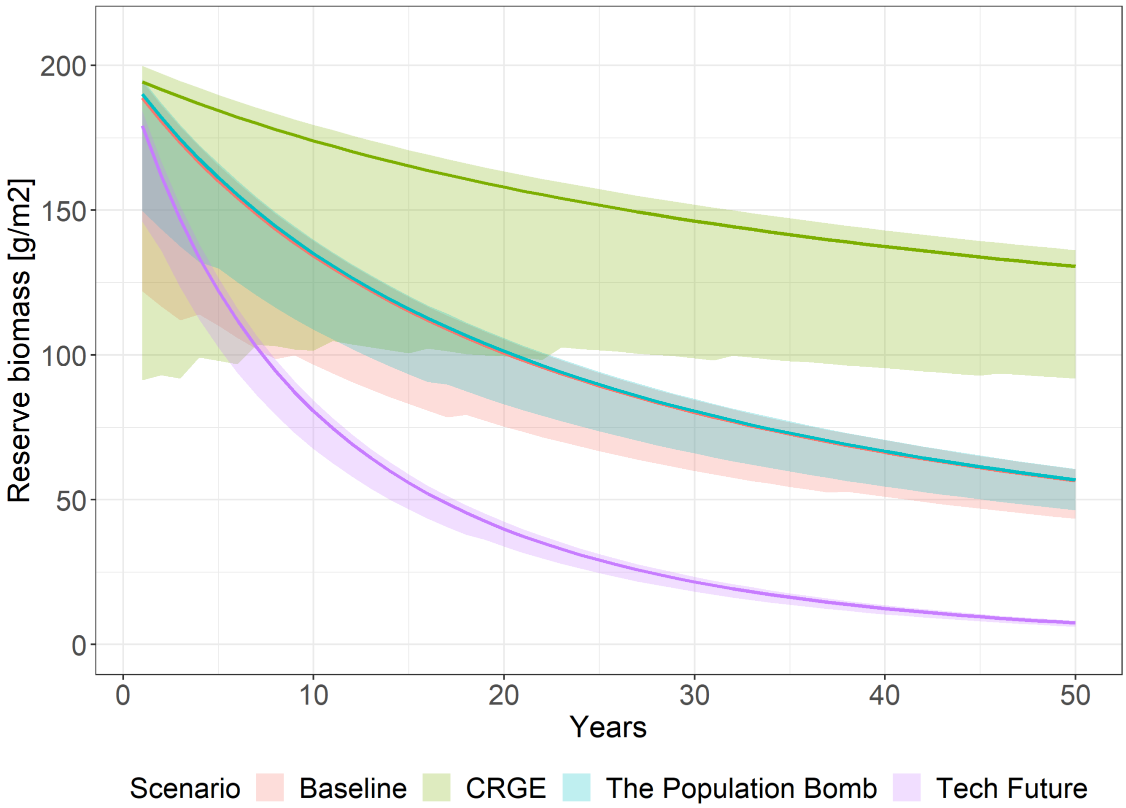

Figure 4.3: Time development of reserve biomass in g/m^2 for the different scenarios. The line represents the mean, the shadowing represents downside and upside standard deviation.

Livestock

Figure 4.4 shows on the y-axis mean and standard deviation of the average livestock units per household and time on the x-axis. Livestock is measured in Tropical Livestock Units (TLU), a unit to compare livestock numbers for different animals based on the grazing equivalent of one "tropical cow" [**23**]. Again, livestock starts at the first time point at a similar value for all scenarios and then decreases until reaching a relatively constant value, which differs for each scenario. The fastest decrease is to be observed for TF, followed by The Population Bomb and the baseline. In the CRGE the decrease is the least sharp, and the final average TLUs per household is the highest. In the model more harvest generates more crop residues which can be used to feed the livestock. Also, the increases in communal grazing land and in the share of non-farm activities (which means also increased savings) positively affects the livestock dynamics by allowing HHs to diversify the feeding methods of their animals. On the contrary, an increase in birthrate negatively impacts the available resources and indirectly causes the HHs to sell their unfed livestock. Livestock dynamic is the result of complex socio-ecological interactions and other procedures - crop dynamics and the harvest output in the first place - compete to determine the different scenario trajectories.

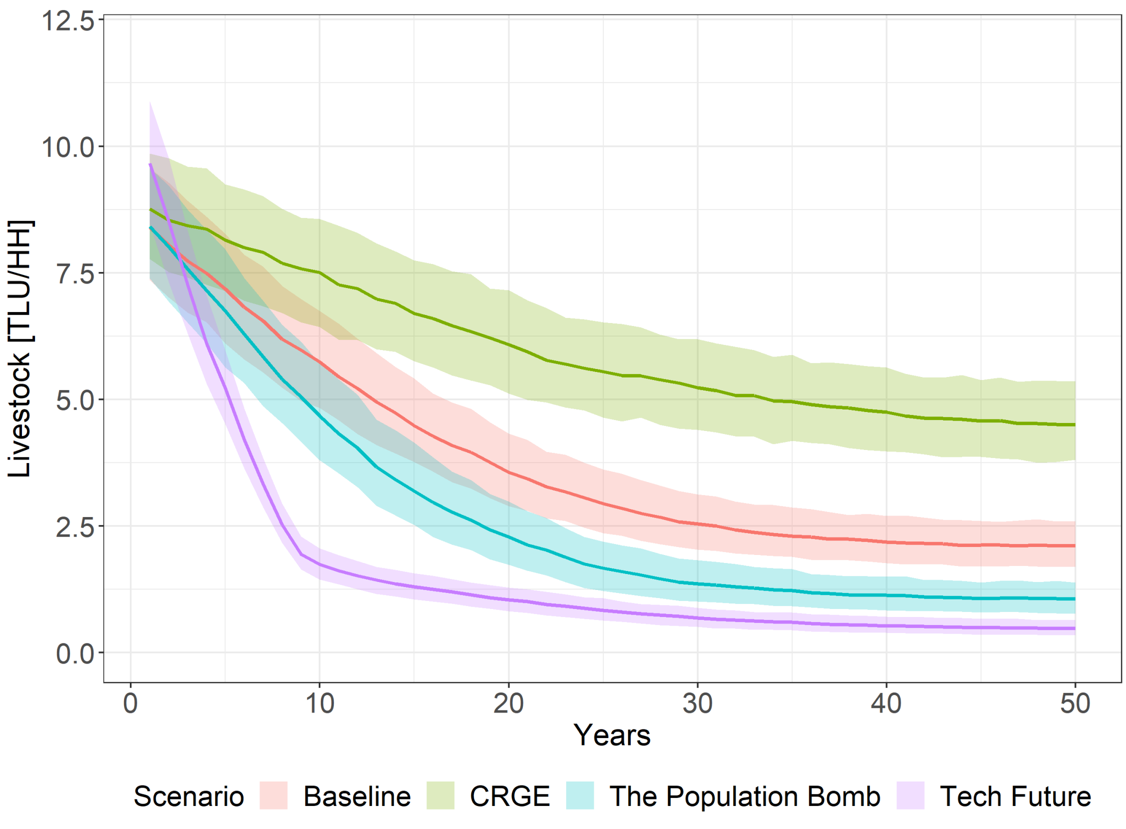

Figure 4.4: Time development of livestock units in tropical livestock units (TLU) per household for the different scenarios. The line represents the mean, the shadowing represents downside and upside standard deviation.

Food Security

Food Security is calculated as the percentage of population which is food secure, that is, whose yearly calories' demand is covered. Calories' intakes stem from milk and crops, and in case the available food is still not fulfilling the households need of 2100 calories per person, savings are used to buy food [**25**]. If there are no savings, then the households is considered food insecure. Initially all the agents in the system are set as food secure, but in time the share declines for all the scenarios, as seen in Figure 4.5. Food security in TF starts to decline later but faster than in the other parametrizations. After 50 years of simulation the share of food secure population for CRGE is around 47%, for the baseline 36%, for TF 25% and for the Population Bomb around 20%. The trajectories are influenced by livestock and harvest dynamics and by the savings available in the system and are therefore sensitive to the cumulative changes of parameters which control these processes. Thus, considered the above analysis of ABMig's outputs, it is clear how the different drops in food security emerge from complex submodels' interactions smoothing out its behavior.

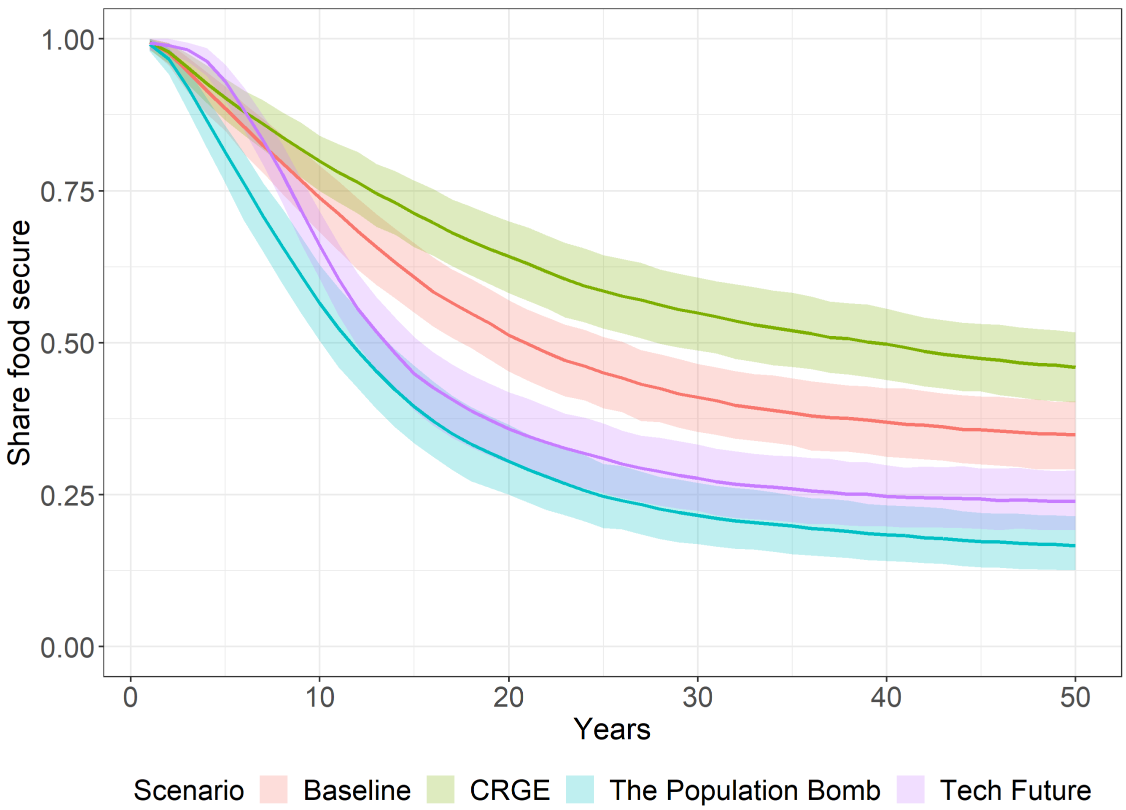

Figure 4.5: Time development of the share of food secure population for the different scenarios. The line represents the mean, the shadowing represents downside and upside standard deviation.

Migration

The number of migration events is calculated yearly and plotted in Figure 4.6 . The time-dependent behavior of migration is unchanged for baseline, CRGE and TF Scenarios. The number of migrants is increasing linearly. In the PB Scenario the number of migrants is increasing faster over time, in other words the slope is not constant, it is instead increasing. The fact that the number of migration

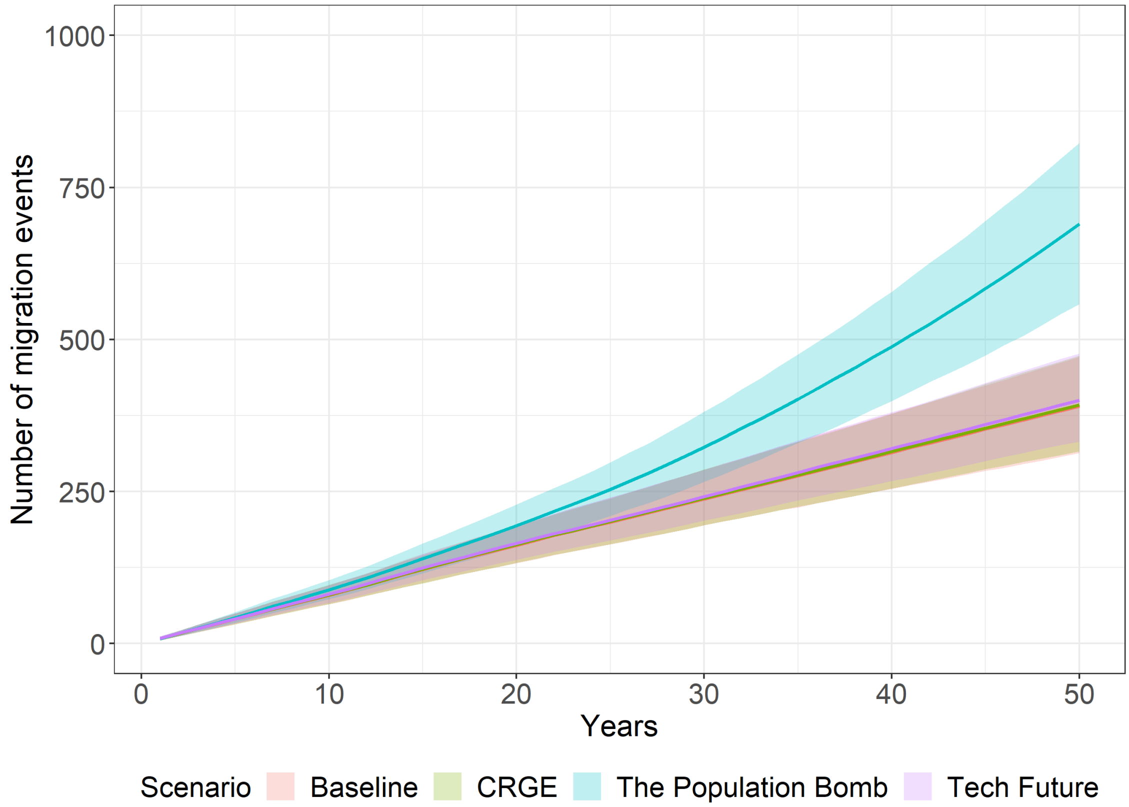

Figure 4.6: Time development of the migration events for the different scenarios. The line represents the mean, the shadowing represents downside and upside standard deviation.

events is scaling up with the number of agents in the system is not surprising. The behavior of the migration output is not responding sensitively to the different land-use management approaches parametrized in the different scenarios. To observe some differences in the simulated migration we will focus on a comparative analysis in the resources gap between migrants and non-migrants.

Migrants versus non-migrants

In the migration process we focus on the out-migration and its impact on their absence in South Wollo. Once that a person leaves the system (the so-called migration event), he or she is ignored by the model's future dynamics. The household divides its resources between the remaining family members in South Wollo, and does not send or receive money or resources from the migrant. Although remittances represent in the reality an important source of income for migrants' families, they are not part of the simulated processes as the model is limited for modelling exogenous factors. The agent, in case he or she is marked as non-permanent, is taken into account in the resources distribution in the model when he or she stochastically "decides" to come back to the household.

In Figure 4.7 we compare the financial resources of migrants in the year of the migration event to the resources of non-migrants in the same year the different elevation regions and scenarios. Considering the standard choice of 50 discrete time steps, the financial gap $g_{financial}$ for each scenario and altitude is calculated as:

$$g_{financial} = \sum_{t} \frac{\overline{f}_t^{migrant} - \overline{f}_t^{non-migrant}}{50 \cdot \overline{f}_t^{migrant}} \tag{4.1}$$

where $\overline{f}_t^{migrant}$ represents the mean over the respective savings over all migrants for a given year. It is known that the available resources in the system depend on the relative scenario and altitude. Moreover, in view of how the migration decision is technically implemented, generally migrants come from better-off households and have access to more resources. Consequently, it has been chosen to normalize the (mostly positive) gap to the average savings of migrants $\overline{f}_t^{migrant}$.

A gap of 200% means that the migrants have twice as much savings than non-migrants. A negative gap could occur when non-migrants have more savings than migrants, which is the case for outliers in CRGE and medium elevation, although the averaged gap is always positive. In all the scenarios the gap is broader for areas with high elevation. In general the biggest gaps are in the baseline and TF, while the smallest is in CRGE Scenario. The differences between high and medium elevation regions are flattened for the Population Bomb and the CRGE Scenarios. The TF Scenario causes an increase in the baseline gap, and still diverges for the different elevations. The altitude distribution and cropping seasons are correlated, in particular the households owning patches in the agricultural belt Weyna Dega (high elevation) only take advantage of the Belg rain season. As seen in Figure 3.5, individuals from Weyna Dega, thus harvesting just once per year, are assigned migration potential only for the cases:

1. there is migration experience in the household and they are engaging in non-farm activities
2. they are randomly selected from the rest of the population which does not full fill these conditions.

Households engaged in non-farm activities have more sources of income and there-

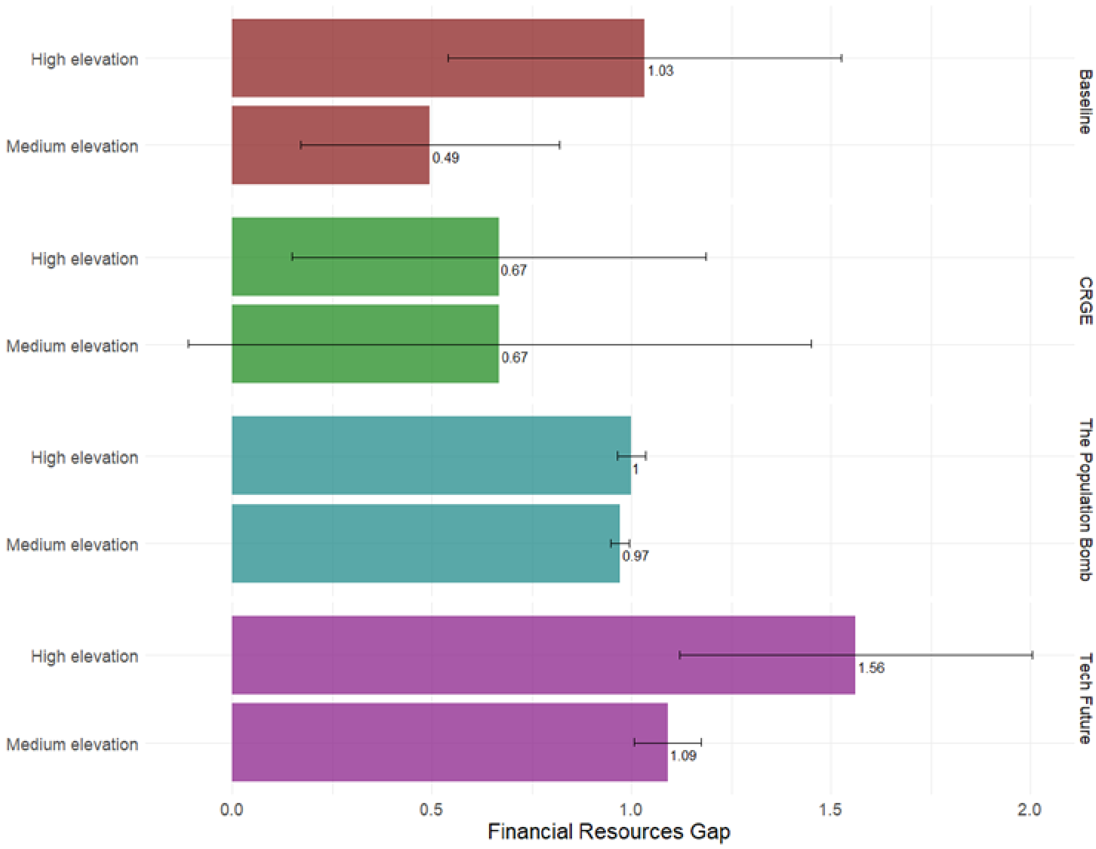

Figure 4.7: Mean and standard deviation of the financial gap between migrants and non-migrants at the year of the migration event for different scenarios and altitudes.

fore in ABMig more savings. As a consequence, migrants from Weyna Dega have a different income distribution than migrants from medium elevation areas, causing asymmetries in the financial resources gap. The inequalities between different altitudes are probably enhanced by the increasing land degradation in TF negatively affecting the whole economy. As for the Population Bomb Scenario, we suppose that the differences in resources gap for Dega and Weynadega are flattened out due to the increasing number of individuals in each household, no matter how their livelihoods are (in-)secured. In ABMig we find that sustainable land-use management addresses inequalities in income between migrants and non-migrants by diminishing the financial gap.

Similarly, we calculated the food security gap between migrants and non-migrants, and plotted it for different scenarios and altitudes in Figure 4.8. The gap is increasing for TF and Population Bomb, and narrows down for CRGE in comparison to the baseline. In baseline, TF and CRGE the food security difference between migrants and non-migrants is slightly bigger for medium elevation than for the high Weyna Dega regions.

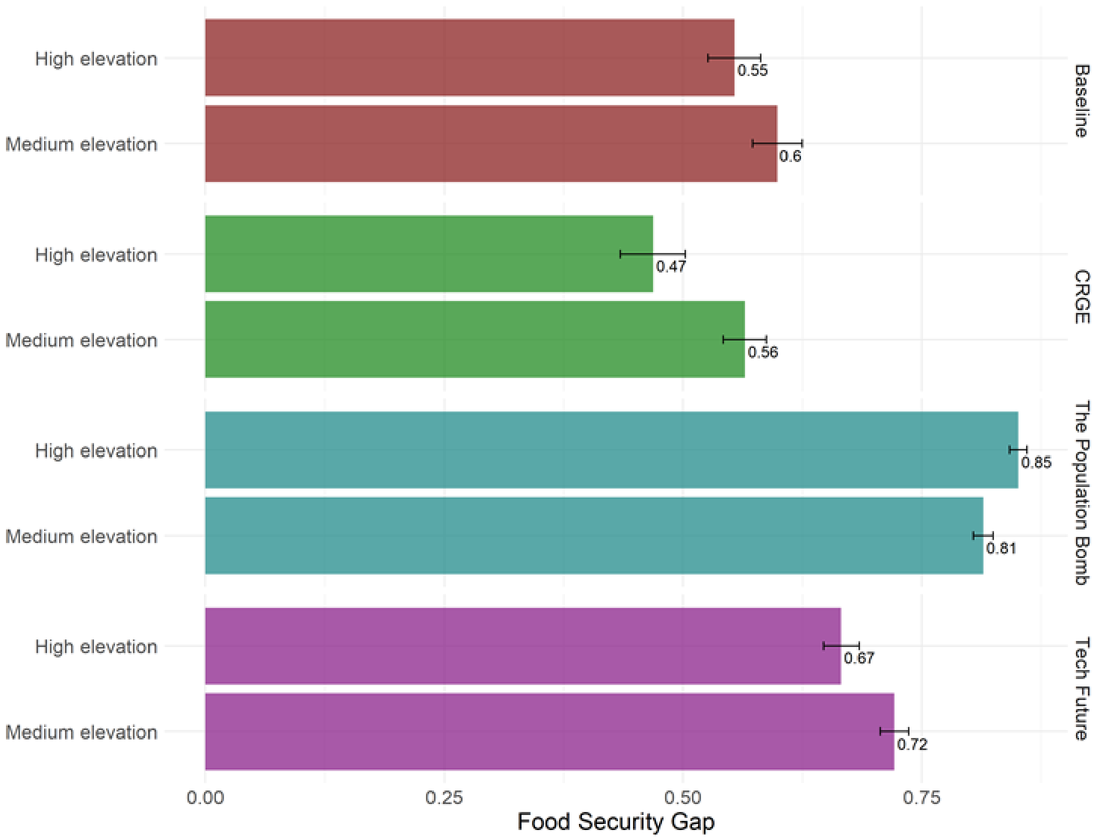

Figure 4.8: Mean and standard deviation of the food security gap between migrants and non-migrants at the year of the migration event for different scenarios and altitudes.

5 Discussion

Sensitivity analysis

To cope with the challenge of translating conceptual scenario narratives into quantitative model input variables, GSA have been run and produced a list of sensitivity indices coherent with ABMig's design. Although the computation of Morris Sensitivity Indices belongs to the most simple and efficient GSA methods [**36**, **39**], the process of parameter ranking was complex and time intensive, involving different model set-ups, specific packages (coupling NetLogo and R) [**38**] and high computational costs. Specifically, GSA showed that the different submodels in ABMig are reacting sensitively to parameter changes, and these reactions reflect the modeller's expectation and intention.

Scenarios and Livelihoods

The developed scenarios were 3+1: Climate-Resilient Green Economy, Population Bomb and Tech Future, plus a baseline. ABMig successfully represents some real-word processes for the different scenarios, for example the fact that harvest yields depend on the long term by the composition of precipitation and soil quality trends, and that harvest is responding to different simulated land-use management practices. [**31**, **32**] Moreover, the development in time of the model's state variables can be considered part of the ABMig's validation.

In comparison to other scenarios, CRGE portraits a society with less resource scarcity and diversified livelihoods. A technological future, with improved genetically modified crops but no policies directly addressing soil degradation, leads to a decrease in harvest yields, in livestock units and enhances inequalities between migrants and non-migrants. The available resources suffer from the unhampered environmental stress and damage the livelihoods of the farmers. As for the Population Bomb scenario, the iterativelly increasing population density places additional stress on the available natural resources, and the share of food insecure population increases sharply. In fact, food production per capita heavily drop as a result of the large demographic pressure on an unchanged (with respect to the baseline) and declining amount of natural resources, increasing the necessity of permanent migration rather than temporary drought-related mobility [**6**]. Consequently more adaptation strategies to deal with the declining NCPs are needed, with migration being one of the possible households coping approaches [**7**].

Migration Trajectories

Using a Bayesian Network, Groth et al. (2021) [**28**] suggested that environmental changes increase migration in South Wollo, as migration needs rise due to low agricultural production. This would be the case for the TF and Population Bomb scenarios, where, following this ratio, environmental degradation should drive an increment in the number of migration events.

In discordance with the conclusions from [**28**], the analyses from this thesis performed on different land-use management scenarios produced results where out-migration trajectories could not be altered. The reason is that ABMig lacks of sufficient strong feedback loops between migration and environmental change due to the technical implementation of migration decision.

As observable in Figures 3.5 and 3.3, a weak impact of parameter changes in the migration output was expected, due to the weak coupling between the modelled migration decision-making and the land-use environmental submodels. In fact, initial migration experience is parametrized based on empirical data, and it is re-linked with the migration progress itself, but has no direct connection with environmental processes. In particular, looking at the factors for migration potential in Figure 3.5, the used cropping season depends on the altitude of the owned patches, which is of course stable in time. Households engage in non-farm activities either because they belong to the selected household in the initialization process (which is 75% of the households) or because the mean soil quality of their patches is dropping below a certain threshold. Even though this might look like a dynamical condition, the soil quality in the system drops so fast in the first simulations years that most of the households engage in non-farm activities after the first simulation ticks. This trend is enhanced by the fact that the initial share of households engaged in non-farm activities is already high. The migration decision procedure depends mostly on the initial empirical parametrization, rather than on factors dynamically changing over time. Results from exploratory SAs were also supporting this hypothesis.

MigSoKo past research constitutes a solid theoretical base for the model's design, but limits the options for more complex non-linear behaviors. The theoretical background partly superimposes trends and stiff drivers, which might not be as relevant for the future as they are for the present. Considered these technicalities, it is unsurprising that the model migration output shows the same trajectories for different land-use scenarios, consequently disagreeing with the conclusions from [**28**].

Inequalities and Migration

While migration is an important adaptation strategy, it cannot be adopted equally among households and as a result often reinforces existing inequalities. From previous place-based researches [**1**, **28**], it is known that migration ability is correlated with the economic resources of HHs, which act as mobility-enabling factors. As visualized in Figure 3.5, this mechanism is indirectly depicted in ABMig through the migration decision-making process due to the non-farm activities, which represent an non-agricultural source of income.

In fact, the general gap in resource access and in vulnerability between mobile and immobile communities is both observed in the real world and simulated, where those not possessing the means or the network which facilitate migration are twofold disadvantaged [**1**, **49**]. Whilst considering this fact, we focused on analysing the differences in livelihoods between migrants and non-migrants in the year of migration and how they are influenced by the different altitudes and scenarios. Our results surprising suggest that this feedback loop feeding inequalities could be weakened by the adoption of more sustainable land-use practices, which hamper the increase in resources gaps between migrants and non-migrants. This effect is not intentionally modelled or intrinsic in the microscopic ABMig's design, hence it represents an emergent phenomenon in our model for the exploration of the migration-environment nexus and offers possible computational insights to the "mobility equity" framework [**49**].

6 Conclusion

Exploring the potential consequences of policy decisions as well as measuring progress towards sustainable development, holistic socio-ecological modelling and scenario development have been identified as keys for future research to assess effects of global change on ecosystems and society. By microscopically modelling sufficient real-world complexity, the scope of socio-ecological ABMs is twofold: firstly insights in the cause-effect relations of expected dynamics can be gained, and secondly unexpected dynamics from known processes can be qualitatively explored. The acquired knowledge adds to our understanding of the local system and can support policy makers and local stakeholder in decision-making. In this work we developed policy-oriented scenarios using the model ABMig for human migration-environment interactions in the Ethiopian highland region of South Wollo. This ABM incorporates not only complex human decision-making but also fully integrated socio-ecological feedbacks. It takes into account temporary migration while focusing on a out-migration and resource depletion hotspot. Hence, this thesis successfully contributes to filling the research gaps mentioned in the Research Question, Aim and Purpose.

After developing literature-based scenario narratives, GSA has been run to cope with the challenge of translating the conceptual storylines into a mathematical translation in quantitative model input variables. The new input values for the different scenarios have been chosen applying the LHS and output distance maximization methods as discussed in Chapter 2. The simulated results for the developed scenarios show that more sustainable land-use practices lead to improved livelihoods of the Ethiopian rural communities. In contrast, growing demographic pressure and policies not directly tackling soil erosion and resource depletion emphasize the local population's vulnerability to famine and result in a higher share of food insecurity in the rural community.

In general, this analysis was able to identify most of the responsible factors for the different model's behaviors, yet some dynamics remain unexplained, for example the role of soil quality as a possible global variable and the interaction between altitude and resource distributions. Following the example of Janssen, M. A. (2010) [**34**], a deeper inspection of the soil quality with respect to resource dynamics and demographic trends at the different altitudes could help to gain more insights on ABMig. Nevertheless, the model has been proven able to reliably represent selected processes and their cause-effect chains, and can be considered qualitatively validated. While the number of migration events where unchanged by land-use scenarios, interesting results have been found in how resources are distributed between mobile and immobile individuals for different altitudes and socio-ecological scenarios. ABMig replicates the feedback loop between resources inequalities and migration, where resources are unevenly distributed between mobile and immobile population, in favour of migrants. Unexpectedly, we found that the relative resources gap between migrants and non-migrants at different altitudes closes for the more sustainable scenario. On the contrary, the food security and financial resources gaps appear to worsen together with environmental degradation and demographic pressure.

For a deeper analysis of the human mobility and environment interlinkages, future research on ABMig could modify and/or extend the migration process to include more dynamical variables, different representations of human decision-making or a more complex social network between the agents [**40**]. A stronger coupling between the social and the physical submodels would be needed, together with a solid knowledge to justify it. The theoretical and empirical framework for model's extension and improvement must be provided by future place-based research, which takes into account the cultural and environmental heterogeneity of socio-ecological interactions. Environmentally-induced migration is increasingly being understood as a multi-causal phenomena and a solid scientific background should increasingly distinguish between migration desire, ability and willingness. [**1**, **6**, **7**, **49**]

Migration represents a risk diversification strategy for human beings to better cope with global change and can be interpreted in computational simulations as the agent's adaptation to a dynamic environment. Capable of the microscopic simulation of complex adaptive systems, agent-based models provide a powerful tool to analyze the nexus between global change and mobility, while considering the heterogeneity of the drivers of agents' decision-making. [**8**] Future research using ABMs should flexibly include different ecological mechanisms and agent rules of behavior for the further investigation of the feedback loops between migration and climate change, and provide a consistent tool for local governance and communities to achieve sustainable development in a changing word. Last but not least, ABMs serve as a fertile field for inter- and multi-disciplinarity, enriching and stimulating both natural and social sciences to solve together real world problems.

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