Developing an ABM-CGE coupled model for researching climate-induced migration behaviour within the European Union

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MSc. Thesis

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Abstract

Climate-induced migration modelling is a popular way of assessing changes in population flows due to climate shocks. Although many models prove that modelling gives compelling insights into migration systems, there is a lack of models that capture micro-behavioural aspects while maintaining holistic realism. This thesis fills this gap by combining Computable General Equilibrium (CGE) data with an Agent-Based Model (ABM) for micro-behaviour modelling. The migration decisions are bound by three migration theories: the New Economics of Labour Migration (NELM), push-pull theory and Foresight's main factors of migration. Results show that the model can capture behavioural micro-decision making. Holistically, the model can capture migration flows, although accuracy is limited, mainly due to a lack of longitudinal household-survey data and datasets on intertwined social connections. Finally, the model shows that micro-macro coupled climate-induced migration methodologies can provide new and valuable insights within academics, policy design and policy validation.

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2 Summary

Climate change is rapidly changing our world. This also affects migration. Migration as a direct or indirect effect of climate change is referred to as climate-induced migration. This displacement of people can affect economies, cultures, and livelihoods within cities, states, countries, continents and ultimately the world. But predicting the impact of climate-induced migration is challenging due to the complexity of the system. To steer this system properly, policies are being developed within the global political systems. Without proper knowledge, it is, however, difficult to create appropriate policies. Therefore, this thesis aims to improve the field of climate-induced migration models. Improvements in complex climate-migration modelling help policymakers gain insights into the system of climate-induced migration, advancing the development of policies. Current gaps in knowledge involve a lack of micro-macro coupled models for climate-induced migration research. To bridge this gap, the following research question was formalised: "Given the case of climate-induced migration, can a macro-micro coupled simulation model give more accurate behavioural insights while maintaining and utilising holistic realism?"

To answer this question, literature was utilised to develop a CGE-ABM coupled model to research intra-European Union (EU) displacement. As migration is a central debate in the politics of the EU, numerous resources are available to support this research across the 27 countries. Literature identified three migration theories to bound the model in: New Economics of Labour Migration (NELM), push-pull theory and the Foresight main factors of migration. A scenario analysis was set up to include flooding of the Rhine and Danube as part of a climate shock. These rivers showed a grouping of wealthy and poorer EU countries, while also being rivers affected by climate change.

Results showed four key effects. Firstly, high-wage countries within the EU show resilience to flooding and even a long-term consumption increase. Secondly, lower-wage countries experienced a higher number of people leaving for higher-wage countries due to small increases in migration, even if higher-wage countries were experiencing a simultaneous flood event. Thirdly, the model demonstrated that incorporating micro-effects can still yield interpretable holistic results, despite correlations with real-world data indicating underfitting. Finally, the model showed better explainability due to the nature of agent-based models, highlighting differences in importance across certain factors.

This thesis was helpful for scenario analysis in the EU. Future research can utilise the model for policy assessments. The thesis furthermore contributed a Reusable Building Block (RBB), making the migration logic readily available for other models. The inclusion of a CGE model enabled the creation of a realistic, holistic economic environment while maintaining micro-based migration decisions. This allows one to scale the model to the EU-level, making it possible to get a better insight into how micro-level interactions influence intra-EU migration flows. This model, therefore, gives a more white-box approach to assessing policies.

Current limitations reside in the lack of large-scale longitudinal survey data, high computational requirements, and remaining difficulties of accurate holistic prediction when utilising methodologies that lean heavily on behavioural modelling. These limitations were most evident when examining predicted migration flows, which showed a correlation of 0.53 with actual data. This underfitting showed that many social ties were not captured, leaving variance unexplained. Finally, future research could focus on several key areas: gathering qualitative data, conducting expert interviews, tighter coupling of ABM with CGE, translating models from Python to a more computationally efficient language, and designing or verifying policies utilising this type of model.

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Abbreviations

ABM	Agent Based Model
ARIMA	Autoregressive Integrated Moving Average
CGE	Computable General Equilibrium
CRAB	Climate-economy Regional Agent-Based
EU27	The 27 countries of the European Union
NELM	New Economics of Labour migration
RBB	Reusable Building Block
XAI	Explainable Artificial Intelligence

EU27 Country ISO Codes

AT	Austria
BE	Belgium
BG	Bulgaria
HR	Croatia
CY	Cyprus
CZ	Czechia
DK	Denmark
EE	Estonia
FI	Finland
FR	France
DE	Germany
GR	Greece
HU	Hungary
IE	Ireland
IT	Italy
LV	Latvia
LT	Lithuania
LU	Luxembourg
MT	Malta
NL	Netherlands
PL	Poland
PT	Portugal
RO	Romania
SK	Slovakia
SI	Slovenia
ES	Spain
SE	Sweden

Roman Symbols

I	Net normalised income
L	Cost of living index
M	Portion of network in region
N	Social score region
P	Normalised population of network in region
S	Migration score
T	Taxes in region
U	Unemployment ratio
V	Income volatility in region
W	Normalised wage
X	Economic utility in region
c	Intercept of unemployment time series
d	Distance between two region nodes
p	Migration probability

Greek Symbols

α	Economic push pull weight
β	Distance push pull weight
γ	Cultural push pull weight
δ	Wage multiplication factor in region
ϵ	Social push pull weight
ϕ	AR coefficient for the unemployment time series
ξ	Standard error for unemployment time series
μ	Emigration percentage of region
ω	Distance weight of the edge between two country nodes

3 Introduction

Migration is one of the many factors influenced by global, long-term climate change [9]. Even though migration is often not directly caused by climate change, recent literature states that migration due to severe weather effects rose to 21.5 million people a year worldwide [86]. Due to the difficulty of collecting real-time migration data, the impact of climate change on migration is often studied by modelling. Consequently, migration models, rather than in field testing, have proven to be more useful [54]. Complex behaviours, such as migration, are often challenging to predict, but it is incorrect to consider these behaviours as random. By modelling, one can attempt to reconstruct emergent behaviours by including simple low-level interactions that are easily measured or observed.

In recent years, the field of climate-induced migration has gained significant interest from various organisations, leading to funds and investments such as the € 9.88 billion Asylum, Migration and Integration Fund (AMIF) [24]. Furthermore, the European Union alone has dedicated 100 million Euros for climate migration research [17]. This legislative focus on migration underscores the societal importance of understanding complex migration streams worldwide; this understanding often leads to the development of effective policies. Now that complex modelling has proven to be a valuable tool for (future) migrational behavioural analysis, refining and upscaling models is gaining traction in academia [68].

In most academic literature, climate-induced migration models are socioeconomic. Here, severe weather effects are combined not only with the social attributes of people but also with the economic environments of regions [78] [61] [46]. Socioeconomic factors and climate effects do not react linearly with each other but show emergent patterns [10]; these patterns emerge non-linearly from micro-level behaviours. Combining the macro elements of economics and climate with the micro aspects of migration decisions proves difficult to model, as there are limited publications that have attempted this. This difficulty mainly resides in the data availability and interdisciplinary collaboration required to couple different modelling techniques [68].

To ensure models can capture the clearest picture of climate-induced migration, a combination of micro real-world behavioural data is ideally combined with macro data, such as economic and environmental data. To capture this, theory and methodology should be carefully considered. Although many theories are helpful, it is essential to recognise that climate-induced migration is complex and requires a more comprehensive analysis than a single theory can often provide [21]. Older theories frequently assumed rational behaviour of migrants, as rightfully criticised by De Haas (2021) [20]. To ensure inclusion of non-rational behaviour in modelling analysis, many models include behavioural theories or extend existing theories. Examples of non-rational behaviour in humans, particularly in relation to climate change, are frequently observed in surveys. One survey found that 15% of humans did not believe climate change existed [83]. Accounting for this 15% is essential for high accuracy in climate-induced models, highlighting the importance of non-rationality.

This thesis aims to enhance the current state of climate-induced migration models by incorporating realistic behavioural data in conjunction with established and well-recognised migrational theories. Firstly, the knowledge gap will be formulated. Secondly, the research question and its sub-questions will be stated. Thirdly, the methodology and implementation are described. Finally, the results, conclusion, and discussion will be given.

3.1 Knowledge gap

The current stage of climate-induced migration models is rapidly advancing as increasing computing power (Moore's law), data availability [25], and funding [17] create opportunities. Utilising three literature research papers [68], [43], [10], this chapter will examine the knowledge gaps previously identified that are hindering the development of climate-induced migration models.

The first review by Schewel et al. [68] highlights the consensus among academics that climate-induced migration is often not a direct cause of climate-induced events, especially slow-onset events like temperature change: "For this reason, slow-onset climate changes contribute to migration but are often not the proximate cause of migration". Other socioeconomic dynamics often carry a bigger weight in the decision to migrate. These socioeconomic effects are frequently, however, influenced by climate shocks and therefore act as proxies. Hoffmann et al. [43] demonstrate that in a meta-analysis, this effect is highlighted, as most papers on climate-induced migration have a first author with an economic background. The review by Beyer et al. [10] confirms and cites these findings, while also expanding on them by further highlighting the significant discrepancies in academic models and their conclusions. The leading causes of these discrepancies are the data used, the migration theory employed, the migration factors considered, and the modelling techniques utilised.

The three reviews conclude with recommendations and future directions that highlight important weaknesses and knowledge gaps. The following points are mentioned [68], [43], [10]:

- Models should not be linear and capture more complexity, while treating decisions in a heterogeneous way.
- Rather than a focus on testing the significance of large sets of drivers, the selection of meaningful driver variables should be a priority.
- Consider climate variables with immediate relevance, such as floods and crop failure.
- Increasing data quality by looking at well-aggregated temporal data.
- Combining modelling techniques that capture both the macro and micro-level interactions of climate-induced migration.
- Qualitative data, such as expert inputs and more trans-disciplinary collaboration, can significantly improve realism in models

One aspect that is not explicitly mentioned, but utilised frequently in models, is the inclusion of bounded theory. Sherbinin et al. [21] demonstrate the importance of bounding migration models within theory, arguing that "letting the data speak for themselves" introduces vagueness. In contrast, conceptualising models helps increase interpretability and reusability. Therefore, migration models should be bound by theory:

- Migrational models should be bounded by theory, and the theory choice should be well argued.

To conclude this section, it is evident that the methodology and data aspects offer opportunities for improvement towards more realistic climate-induced migration modelling. Due to advancements in this field regarding both available tools and data, the environment presents opportunities. To the best of our current knowledge, no non-linear behavioural climate-induced migration simulation models have successfully combined micro- and macro-scales while accounting for heterogeneous socioeconomic weights. As Table 2 within the paper of Schewel et al. [68] shows, post-national models include exclusively gravity-based or econometric models that struggle to capture heterogeneity and behavioural explainability.

3.1.1 Research questions

Given the knowledge gap described in 3.1, one can formulate the following main research question:

RQ: "Given the case of climate-induced migration, can a macro-micro coupled simulation model give more accurate behavioural insights while maintaining and utilising holistic realism?"

This research question aims to push the boundaries of climate-induced migration simulation research and seeks to test the latest theoretical enhancements found in the literature. Due to the overarching subjects contained in a single question, multiple sub-questions are considered. Together, these subquestions address the complexity of the main research question, encompassing the requirements of both theory, methodology, development, and reporting. The following subquestions are composed:

SQ 1: "Given the macro and behavioural-micro requirements of the model, what modelling methodologies are most fit?"

SQ 2: "What migration theories are best grounded in a micro-macro coupled model and for what reason?"

SQ 3: "How can the macro-micro coupled model be developed, including bounded migrational theories?"

SQ 4: "Given climate scenarios, are the model results in line with expectations and how do they contribute to the current field?"

Sub-questions one and two are answered utilising literature on both migration theories and migration modelling methodologies. Sub-question three is addressed in the methods section of this thesis. The final subquestion is answered in both the results and the conclusion of this thesis. Finally, the answers to all subquestions will be merged to answer the final thesis question in the conclusion.

3.1.2 Research scope

As the research questions depend on the definitions of micro and macro scales, it is essential to define these scales precisely first. By examining current migration simulation research, we can identify the current scope of models. The literature analysis by Hoffman et al. [43] identifies 127 migration simulation models. In this meta-analysis, interactive scopes ranged from the individual-level to the country-level. The geographic focus ranged from the province/state level to the global level.

While many behavioural micro-models analyse one country, this thesis aims to scale this scope up. The main challenges arise from the increasing demands for data, particularly in micro-analytical methodologies (e.g., survey data) [43], [10]. In terms of data availability, the European Union (EU) shows an increasing positive attitude towards open data [30]. This leads to a more feasible implementation of simulated EU27 member states, as many economic and demographic datasets are freely available.

The EU also shows a fascinating migration simulation research field: "The past decade has confirmed the importance of human mobility for countries and societies across the globe. Even more so, it became central in political debates across the EU." [17]. This combination of investments in open data and the need for policy tools makes the EU27 member states an ideal starting point for more advanced simulation migration research.

3.2 Literature

3.2.1 Literature on climate-induced migration models

The first subquestion of this thesis aims to determine the best-fitting methodology (3.1.1). Therefore, this section examines popular choices for modelling climate-induced migration. Here, the literature review of Schewel et al. is used [68]. Five different categories of models have been identified and have proven to be well-suited for simulating migration. This section will further expand on the characteristics of these methodologies to facilitate comparison.

Gravity models The first type of model commonly used for climate-induced migration is the Gravity model. This model is often referred to as a spatial interaction model [60]. These models describe the movement of people, goods, or information across space as a result of a decision-making process. These models assume that certain aspects can increase flows, such as population size and wealth, while other elements decrease flows, including distance and unemployment. The models are tightly connected to Newton's law of gravitation, hence the name of the methodology. The first implementations of the gravity model show this similarity with the following equation [60]:

$$M_{ij} = \frac{k\,V_i W_j}{db_i} \tag{1}$$

Here V_i and W_j can be seen as "masses" and are often represented as population or flows. In the denominator, the distance is used as a factor, just like Newton's gravitational formula. This simple example illustrates the larger data scale of these models. The required data are at a high level of aggregation (GDP, population numbers, labour data). For this reason, the most popular use case for this model is at a macro-level. This reduces the reliance on micro-level data and can prove efficient at modelling large flows. This, however, minimises the explainability of the underlying interactions that can generate emergent flows. This makes the gravity model a black-box as it predicts aggregate flows without capturing individual decision-making.

Radiation models Radiation models are similar to gravity models. To explain the differences, the paper by Simini et al. [71] is used, as it presents the development of a radiation model and explains why it was preferred over using a Gravity model. Simini et al. [71] show six limitations of gravity models that they aim to overcome by developing a Radiation model.

The limitations include critiques of the theoretical foundation, its deterministic nature, unrealistic edge cases, and data requirements. The radiation model addresses these limitations by showing that it can be derived, does not require tunable parameters, and does not require flow data for calibration, utilising just population-based data. Additionally, flows cannot outgrow source populations and can include stochastic fluctuations. The radiation models expand upon the Gravity model by enhancing micro-realism with stochasticity and mathematical regularity. The Radiation model accounts for micro-interactions by taking stochasticity into account. This approach can therefore be more realistic on the macro-level. The model remains deterministic, as it lacks bounded rationality and does not model individual decisions; however, it incorporates idealised, simple decision rules.

Systems dynamics models System dynamics models (SDMs) model migration as a stock-flow relationship, where feedback loops and delays can simulate complex, non-linear behaviour [39]. All system dynamics models consist of both stocks and flows, where stocks show the level of a variable (e.g., the number of people in region i), and flows show how these variables increase and decrease over time.

Due to the feedback loops between stocks, interactions can be modelled nonlinearly. The inclusion of time-steps enables the addition of delays, thereby further enhancing model complexity. SDMs are often used for designing systems that can be easily modified to introduce policies, laws, or process changes. SDMs are theory-driven, as relations between stocks need to be proven or defended. Furthermore, it is challenging to introduce heterogeneity, as elements within stocks are often treated uniformly.

Agent Based Models Agent-based models (ABMs) are models that attempt to capture individual (micro) levels of behaviour through interactions between "agents". One of the first papers to theorise agent-based models is by Thomas C. Schelling [67], introduced as "Dynamic Models of Segregation." Schelling explains how individual decisions that seem mild at the micro-level can segregate into complex and emergent behaviour. By building an environment with individual interactions at its core, models become more explainable, as emergent effects can be directly linked to individual interactions combined with stochasticity. Individual decisions often include bounded rationality, which is usually at the core of ABM stochasticity, although stochasticity can be introduced in multiple ways. The introduction of stochasticity, however, presents challenges, as model outcomes must be interpreted with stochasticity in mind.

ABMs are unique in that they can model individual decision-making, demonstrating the potential to generate macro-level behaviour through micro-level interactions. Due to the modelling of individual agents, ABMs struggle to scale upwards. Parallelisation of large-scale ABMS is becoming more popular but requires high-performance compute clusters. ABMs are also reliant on micro-level (survey) data. This is often difficult to obtain, and quality can vary broadly [4].

Other statistical models Another popular choice is the use of more general statistical or econometric models that use historical data to fit models [68]. These methods, however, often do not provide a great deal of insight into the system's behaviours and complexities. It is also more challenging to account for heterogeneity within the population. More recent articles, however, found promise in the use of Explainable Artificial Intelligence (XAI). One paper by Ronco et al. [64] attempts to explore migration on a global scale, utilising XAI (with a high emphasis on Shapley values). These models can process highly dimensional input without the risk of overfitting, enabling the inclusion of heterogeneity. This approach aims to bridge the gap to true micro-based models, but it still lacks accurate behavioural modelling due to the indirect nature of modelling decisions. Introducing climate shocks can also be significantly more challenging with (X)AI-based systems, as there is no training data available for hypothetical climate events.

More recently, statistical models are more often coupled with theory-driven methodologies. By coupling models, weaknesses are addressed through the processing of data, making it more usable and interpretable. Often, coupling addresses scaling issues, making it easier to assess both the micro and macro elements of reality, thus increasing realism (e.g., ABM tele-coupled methodologies [4]

3.2.2 Literature on migration theory

The second subquestion of this thesis seeks to determine which theories should be incorporated into a micro-macro coupled migration model (3.1.1). To help aid in answering this question, an existing literature review by Sherbinin et al. [21] is utilised. It discusses multiple migration theories used for climate-induced migration models. The different theories are further explained in this section so they can be compared within the context of the desired model.

Neoclassical migration theory For neoclassical migration theory, the paper by Sjaastad [73] is often regarded as the canonical formulation; hence, this thesis will use this paper as the basis for its explanation. The neoclassical theory of migration is a classical theory that focuses primarily on wages and unemployment. In its most basic form, the theory posits that wage differences between countries or regions are the primary driving force behind migration. As the wage differential decreases, migration is expected to slow down and eventually cease. This idea aligns with the supply and demand economy that was prevalent in the 1960s.

This theory has since received considerable critique but still forms the basis of many spin-offs. Derivations of neoclassical migration theory were necessary because neoclassical migration theory often overlooked information asymmetry, overestimated the importance of economic factors, and disregarded social, cultural, and political influences. As mentioned earlier in the literature on methodologies, it is often better to include heterogeneity among agents, which this theory also overlooks.

Push-pull theory Four years after Sjaastad's paper [73], Lee published his paper on migration theory [48]. This theory resembles one of the first push-pull-oriented frameworks (in the paper, push- and pull factors are mentioned as negative and positive factors). This theory examines migration, considering both negative factors that push people away from their country/region and positive aspects that attract them to that country or region. Lee did, however, also introduce "obstacles", which are barriers that slow people down (e.g., migration costs). Secondly, Lee argues that personal factors assign individual weights to the push-pull factors and barriers. This way, heterogeneity is introduced to the theory. The theory is also based on the decisions of individuals. Given these aspects, it is not surprising that push-pull theory is one of the most popular migration theories for ABMs.

For implementations, one can sum over positive factors, such as higher wages, social networks, and political stability, among many other factors. Factors can be weighted afterwards, and survey data can be used to extract these weights. Although this theory is old, there are many modern implementations, such as coupling with a gravity model [80]. Current criticisms of the theory stem from the inability to quantify factors such as political stability, necessitating workarounds. The individualistic nature of the theory also makes it challenging to capture group-based migration.

Mobility transition theory In 1972, Zelinsky developed the Mobility Transition Theory (MTT) [85]. This theory focuses on how the modernisation of societies dynamically changes migrational patterns. Each country/region is in a different stage of migration, characterised by specific migration patterns. The following items are mentioned (reduced to core points):

- The premodern traditional society: Mobility is limited, and circulation is only due to customary practices.
- The early transitional society: Mobility is more facilitated. Rural-to-urban migration is gaining traction, and there is a limited immigration of skilled workers from more advanced parts of the world.
- The late transitional society: Rural-to-urban migration is still growing, but at slower rates. Emigration declines. More increases in circulation.
- The advanced society: Migration now mainly comes from underdeveloped countries. Further reduced growth in Rural-to-urban migration. There is a further increase in circulation (also pleasure-oriented).
- A future super advanced society: Residential migration may be limited to interurban and intraurban migration. Further immigration from less-skilled workers from less developed areas. Strict political control of internal as well as international movements.

This theory is descriptive and quite macro-level and thus does not form the best basis for behavioural modelling. Further critiques of this theory primarily focus on the linear assumptions of stages and determinism, as migration patterns can often not be attributed to a direct result of one of these stages easily.

There are more macro-level theories described by Sherbinin et al. [21] in their historical structure. These, however, are not further discussed as they do not align with the thesis's use case.

New economics of labour migration (NELM) One decade later, Stark and Bloom published a revision of neoclassical migration theory called the New Economics of Labour Migration (NELM) [75]. NELM differentiates itself firstly by looking at households instead of individual migrants. The households aim to maximise their combined economic utility while minimising risk. The household decides to migrate when the expected utility is higher. This theory aligns more closely with the economics of the 1970s and 1980s, which shifted away from perfect markets and frequently assumed information asymmetry.

While NELM provides more economic realism, it is a flexible framework that makes it difficult to quantify. Many described elements of NELM do not apply to high-income parts of the world (e.g., remittances). Market failures are also often complex to quantify, which makes migration models typically NELM-inspired, as neoclassical migration theory is too restrictive. Still, true NELM is too vaguely formulated to be quantified accurately.

Forced migration theory Forced migration theory often refers to a migration framework that only includes involuntary migration. It can be seen as a collective work that does not necessarily include pull or voluntary push factors. In Forced Migration Theory, push factors include high amounts of risk. Forced migration is, therefore, often referred to as displacement [21]. This theory more closely aligns with a scenario involving high-risk environments than it is a standalone theory. In this thesis, forced migration will not be researched. It is, however, essential to note that forced migration is a relevant and significant consideration, as it may have considerable importance. When the researched system includes high probabilities of forced migration, regular migration theories are often insufficient.

Theories Addressing Sustained Migration Sherbinin et al. [21] also discuss theories that focus more on the sustaining of migration. These theories focus on aspects such as social network effects that lower barriers to migration. In modelling, however, these theories are not explicitly incorporated. It is, however, expected in models that, due to the feedback loops and modelling rules, the sustained migration arises naturally. Therefore, the theory can serve as validation.

Many of these more modern theories also incorporate the theories above and expand upon them. Network effects can often be incorporated as a push-pull factor with heterogeneous weight, making sustained migration theories reliant on existing formulations of migration.

Aspirations and Capabilities More recently, theory focuses on examining migrants more realistically, incorporating aspirations, desires, and life goals into shaping the migrant's personality [20]. This way, the decision maker can be heterogeneous not only in characteristics but also in their aspirations. The downside of combining these aspects is the requirement for high-quality and substantial quantities of data. Due to data availability, these elements are challenging to integrate and are difficult to include "all at once". This framework alone oversimplifies factors by reducing complex ones into just two dimensions (aspiration and capability). However, simplifying factors as economy, demographics, politics, and social ties into aspirations and abilities can be challenging.

Livelihood framework The livelihood framework looks at five livelihood assets in regions or countries (social, human, natural, physical, and financial capital) [12]. The assets are household-based, and therefore, the framework is often related to NELM. Environmental effects can influence all forms of capital, but have a primary impact on natural capital. Sherbinin et al. [21] also describe different migrational frameworks, one of which has a similar idea to the livelihood framework, but looks at aspects that are most important for migration [44]. Here, economic, social, environmental, political, and demographic factors are identified as the primary drivers of migration. The reasons these frameworks are helpful for models reside in the fact that they provide factors that ought to have significance or reasons not to be significant. This way, the model has a solid foundation of factors to consider. These frameworks often lack quantification of the decision-making processes and therefore rely on coupling with theories that share insights into the decision-making processes.

4 The Model

This chapter will focus on the development of the model. Firstly, the modelling methodologies will be selected by answering subquestion one. Secondly, the migration theories will be chosen that bind the model, answering subquestion two. Lastly, the model design, input data, and weights will be discussed, answering subquestion three.

4.1 Choice of methodology

In chapter 3.2.1, different options for climate-induced migration modelling have been mentioned. To provide an answer to subquestion one, this chapter will analyse the various methodologies and select the most effective methods for the model. Firstly, the methodologies should be compared on the macro and micro-behavioural requirements. The following table presents the methods available and their respective advantages, as described in 3.2.1. The methodology aims to cover behavioural insights at the micro level while maintaining holistic (macro) realism.

Table 5: Migration modelling methodologies [68], and on what scale they can be assigned to. The scale refers to the interactions within the model, which can originate from high-level (macro) data or low-level (micro) interactions.

Methodology	**Macro/Micro level**	**Behavioural focus**
Gravity models	Macro	Possible at macro scales
Radiation models	Macro	No
System Dynamics models	Macro	Possible at macro scales
Agent Based Models	Micro	Yes
Other statistical models	Often macro	Often included

From Table 10 in Appendix B, it becomes clear that no clear-cut methodology can capture micro-level behavioural data while maintaining macro-level realism. Therefore, it highlights the importance of coupling methodologies, as also suggested by previous literature reviews [43], [10]. Current approaches, which lack methodological coupling, such as the use of XAI by Ronco et al. [64], show promise but often fall short in capturing the micro-level decision-making processes, particularly those involving causal reasoning or individual-level behavioural mechanisms. Table 5 shows that only one popular simulation-based methodology is used in migration research to capture micro-level behaviours and decision-making. This methodology is ABM. ABMs are a popular and logical tool for the analysis of household-level decisions and interactions.

In recent academic studies, ABMs are coupled with other macro-level methodologies to obtain a broader, more realistic model. Although there are only a handful of articles with successful implementations, they provide valuable insights into the coupling of macro-level models with ABMs and the reasons behind it. Using the PRISMA method [1], a literature review on ABMs for migration was conducted. 13 Papers from 2020 onward were selected and analysed. These 13 papers are shown in Table 11 in Appendix B. From these studies, two attempted to couple the ABM with a gravity model [80],[79]. These articles, however, utilise the same model. This model is therefore the only model known to couple an ABM with a macro-scale model for migration.

DYNAMO-M; ABM-Gravity coupled model This coupled model utilises the strength of an integrated flood damage ABM to incorporate heterogeneity and behavioural theory with the macro strengths of a gravity model [80], [79]. This coupling was applied to coastal France, although the authors state that a global model is feasible, given that there is data to support the upscaling. The model's calibration utilised a survey on the implementation of dry flood-proofing measures. Although model-upscaling to global levels was possible, no such effort was undertaken, and the reliance on survey-level data raises questions about the feasibility of scaling up to a worldwide level.

ABM-CGE coupled models When looking at other fields similar to migration, another approach can be identified. One example combines micro and macro models for climate mitigation [55]. Here, the central question is how household decisions, related to energy use, lead to EU-level carbon emission reductions. By coupling with a computable general equilibrium (CGE), the model can examine the economic impacts at the macro level, while maintaining bounded rationality and heterogeneity from the ABM. This macro-element allowed the model to be upscaled to research economic variables (e.g., GDP) for EU member states. As variables such as wages, imports, and export demands are challenging to generate from micro-level interactions, generating this at a macro scale can give a more realistic economic environment to base decisions on. Currently, there is already interest among academics in using CGE models for migration [68]. As economic environments are among the most critical factors in a migration decision [44], it is logical to seek ways to make economic environments more realistic.

4.1.1 Model choice

Since the choice for the behavioural micro-based modelling part has fallen to ABMs, it remains to be seen which model is the best fit for the macro-environment. In the literature, it is prominent that there have been two macro-models coupled with an ABM for climate-migration and -mitigation research: one economic macro model (CGE) and one more general macro model (gravity model). The CGE model has not yet been applied to migration, and the gravity-coupled model has not yet been scaled up to the post-regional level. Both models are viable options for researching climate-induced migration. To determine which model is the best fit, the conceptual framework of Foresight (The Government Office for Science, London) is utilised, as visualised by the International Organisation for Migration (IOM) [44]. This framework is the same as the Foresight framework described in section 3.2.2. Here, the five primary drivers for migration are described; one can test these five drivers against the two methodologies considered.

Table 6: Primary drivers for migration [6], [40], [44].

Driver	**Methodology**	**Reasoning**
Economic	CGE	It can generate realistic labour characteristics and how they could change, which is very difficult to capture with a gravity approach
Social	ABM	The ABM can handle heterogeneity and social ties from the ground up much more consistently than macro-based models.
Environmental	CGE, Gravity, ABM	CGE can include economic effects of environmental constraints, Gravity models can capture effects like distance with less data dependence, the ABM can capture individual responses to shocks
Political	CGE, ABM, Gravity	CGE have the option to simulate macroeconomic effects of political drivers. Gravity models can include political proxies.
Demographic	ABM, Gravity	The ABM will account for demographic attributes (often from survey data). Gravity models can look at population flows on a macro-level

From Table 6, it becomes clear that for economically driven decisions, a CGE model is a better fit. It is, however, a more complicated solution and requires much more data [6]. Utilising a gravity model removes many of the micro-interactions in an ABM, as spatial interactions are handled from a macro perspective. It is thus more useful as a complementary benchmark than as an integrated tool. A CGE, on the other hand, supports the ABM in making decisions, keeping micro-level decisions fully intact. For this thesis, utilising the CGE for the economic side of the simulation environment gives more room for the ABM to capture other socio-economic factors. It enables a more nuanced integration of micro- and macro-environments. This coupling creates a higher reliance on the ABM and underlying demographical data, but should allow scaling up the understanding of complex migrational decisions to post-regional levels.

The lack of detailed macroeconomic models in recent literature can result in less accurate behavioural micro predictions, as gravity models apply to more generalised use cases than CGE models, which specialise in macroeconomic use cases [6]. Because economic drivers heavily influence migration decisions [44], the need for accurate financial data in household migration decisions is highlighted. Combining these economic macro-environments with ABM would further support the goal of not modelling existing migration flows and statistical expectations of their trajectories. Conversely, it would model human-based decisions regarding migration, making shock-based research possible. CGE models will therefore keep the micro-based decision-making intact, which is something Gravity models based on actual migration data do not.

4.2 Included migration theory

In section 3.2.2, different migration theories bound in climate-induced migration models were discussed. To address subquestion two, this section aims to test the theories against the needs of this research, thereby providing an overview of the theories relevant to the final model. Since the previous section provided an ideal coupling of ABM-CGE for the EU27 countries, this can be taken into account when addressing the theory.

For migration, modelling methodologies must be grounded in a theoretical framework [21]. Although the use of behavioural theories has a rich history in ABMs, it is essential to highlight that migration theory is not the same as behavioural theory. Often, behavioural theory focuses on the decision-making process of individuals or households. This element is essential and finds its way into migration theory; however, it overlooks the primary factors that influence the decision-maker's decision to migrate. Migration theories, furthermore, have different scopes (e.g., meso, micro); therefore, the included theories should be carefully considered based on providing migration factors, reasoning behind the decision and an appropriate scope.

To aid in choosing fitting theories for a CGE-ABM coupled migration model, they are further compared. In Table 10 (Appendix B), the scopes of the different theories are summarised based on their characteristics. If the theory works on all scopes, all are included; otherwise, the main scope is noted. Because ABM is a simulation modelling framework that works with micro-level decisions, it should be grounded in a theory that operates at the micro-level. ABMs often use households as the decision-making unit; these households are assigned household-survey extracted attributes. Looking at the migration theory described in 3.2.2, it becomes apparent that this modelling approach aligns with the philosophy of New Economics of Labour Migration (NELM) [75]. Here, the households are the primary decision-making unit and attempt to minimise risk and maximise economic utility by considering a migration decision. This theory provides a more comprehensive representation of the economic factors involved in deciding to migrate than more neo-classical theories. NELM, by definition, assumes heterogeneity of households. For these reasons, this theory will be fundamental to the economic factors influencing the migration decisions in the ABM.

NELM provides considerable flexibility in determining which economic aspects can be considered. While there is a significant focus on wages, the main point is that all factors with the ability to reduce economic risk for households should be regarded in an economic utility function. As described by the Foresight report, economic factors such as income volatility and income are influential: "Whether at the individual or the household level, and whether concerning expected income or income volatility, economic drivers influence migration in diverse and non-deterministic ways" [44]. When examining the framework, it becomes apparent that the decision to migrate in most models is primarily driven by unemployment and potential wages, while minimising uncertainty by measuring income volatility. To capture these factors accurately, it is crucial to see expected economic utility accounting not only for raw wages and unemployment but also for costs of living, taxes, and income volatility.

Although NELM covers many essential aspects of household decision-making, it does not incorporate bounded rationality into its theory. Bounded rationality acknowledges that decision-makers rarely have perfect information [72]. Humans do not assign scores to countries they might want to move to; instead, they pick the country they feel the best towards over a set period of time. Humans often consider just a few options and figure one of them is "good enough." [47]. Therefore, bounded rationality should be taken into account. One way of achieving this is by coupling NELM with push-pull theory. The push-pull theory is widely used in migration-based research, demonstrating the theory's flexibility. It can be used to define factors that deter people or attract them to a particular country. These factors are extracted from household survey data, literature, or other datasets. This introduces the ability to scale the economic score from NELM with other factors that are important for migration, such as culture, distance, and climate. This scaling of factors for individual households introduces bounded rationality into the model.

Finally, this raises the question of what push-pull factors should be included in the migration decision. The framework of Foresight shows a good starting point [44]. This framework was also used to pick the modelling methodology. It gives five main driving factors of migration that are most important for humans. The actual distribution of the migration factor's importance should ideally be extracted from empirical household data. The following figure gives an overview of the used theories and how they are connected:

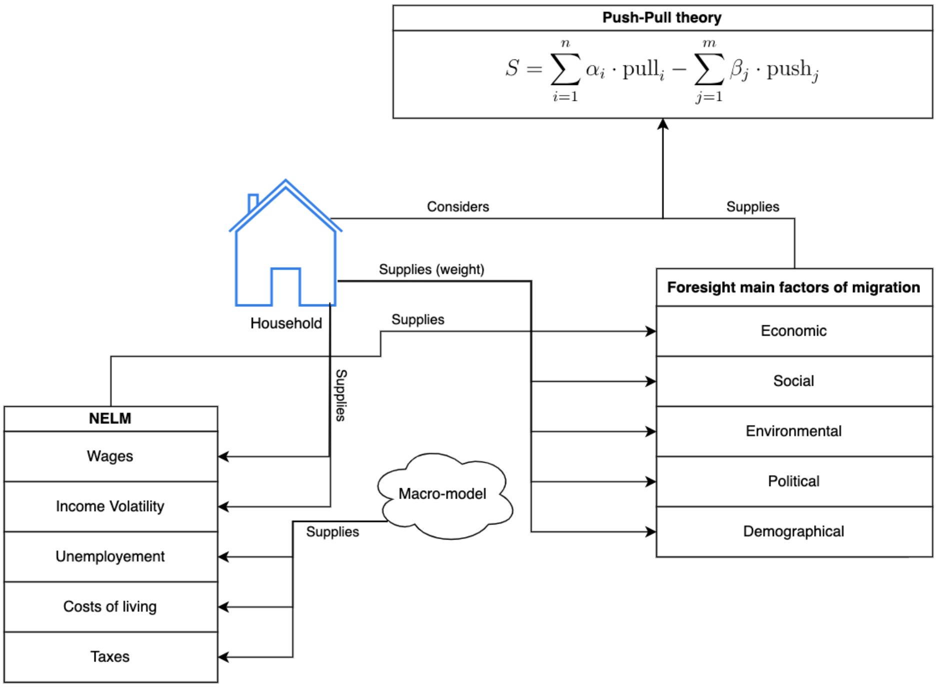


Figure 1: Household decision-making logic bounded in New Economics of Labour Migration theory [75] coupled with push-pull theory [48]. The main factors of migration are extracted from the framework of Foresight [44].

4.3 Model design

Previous sections have answered subquestion one (utilising an ABM-CGE coupled model) and subquestion two (the model is bounded in NELM, push-pull theory, and the foresight framework for migration). This section aims to answer question three and provide a clear plan for developing such an ABM-CGE coupled model for climate-induced migration. Given the rich academic history in both ABM and CGE modelling, it is not necessary to build a model from scratch. Within academics, there are ready-made models available. Building upon other works enables greater potential in models, as one should not reinvent the wheel.

For the CGE models, this choice is more limited, as these models are complex and challenging to understand and develop. Luckily, the model used by Niamir et al. [55] is available for use and has already proven helpful in coupling with an ABM. The model used is the EU-EMS model [59]. This CGE is capable of generating financial data for all EU27 member states, making it ideal for the model's macroeconomic environment and the selected scope.

For the ABM, the CRAB model was chosen as a starting point. This model, developed by Taberna et al. [78], already incorporates a comprehensive economic system including households, firms, and governments. The model is the only known ABM from the literature (3.2.1) grounded in general equilibrium and is therefore a perfect fit for coupling with the CGE output data. This model already succeeds in coupling macro with micro insights but has yet to be implemented on the EU scale. Therefore, the model should be modified to work with multiple countries. The biggest challenge, however, is that the model is not developed for migration. The model should therefore be expanded with rich migration behaviour stemming from the theory earlier examined.

For the climate hazard, the original authors chose flooding because it is seen "as the costliest, most widespread climate-induced hazard and the first to hit urbanised regions worldwide today." [78]. The European Commission confirms this observation [16]. Literature furthermore shows that extremely rapid but heavy shocks are most common in climate migration models [43]. In the CRAB model, flooding is handled using flood maps. In the CRAB model, flood maps have return periods of 30,000, 3,000, 300, 30, and 10 years, respectively, for the Netherlands. This would need to be changed to a flood map that includes all EU27 countries. The floodmap should furthermore have a return period significant enough for scenario analysis. Given a flood return period of 100 years, it gives a 1% chance of occurrence every year [15]. Due to climate change, it is, however, difficult to state if a return period of 100 years today will be the same in 10 years. Therefore, this thesis aims to utilise a flood map with a return period as high as possible. For measuring impact and changes in states, higher return periods will produce bigger differences; therefore, high return periods are more useful for comparison of states.

To couple the EU-CMS CGE model and the CRAB-ABM model, four main changes need to be made:

- The model must include the EU27 countries.
- The model must be able to initialise with the EU-EMS generated CGE data.
- The model must incorporate a migration module based on NELM, push-pull theory, and the main factors of migration from Foresight.
- The model flood depths must be changed due to the increased scale of the model.

To achieve these changes, a conceptual model is given in Figure 2. Here, it is highlighted how the model should be modified regarding the four main characteristics that should be included.

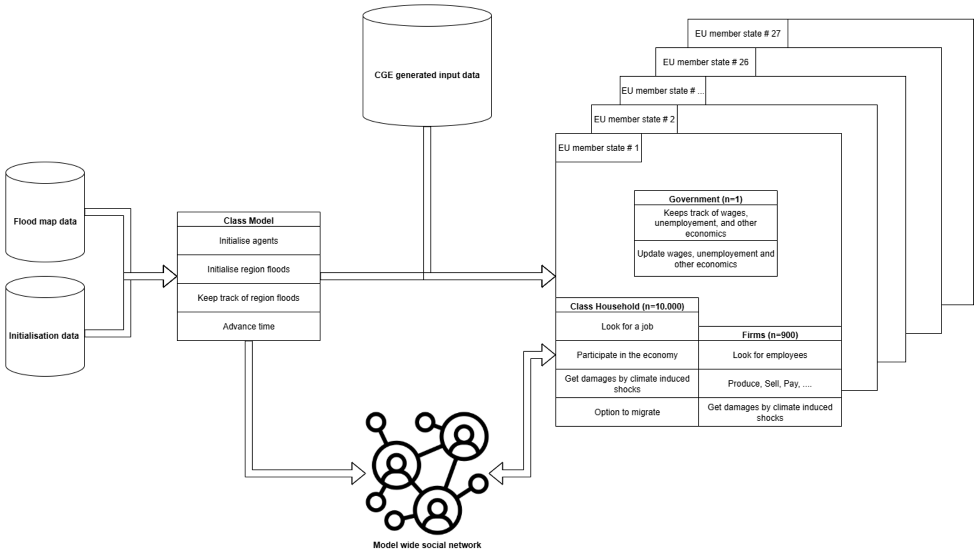


Figure 2: A conceptual approach to the CRAB-ABM CGE coupled model including isolated EU27 countries. The social network is model-wide, enabling international connections. The model class initialises the different EU27 countries together with the CGE-generated economic data.

This approach creates multiple instances of households, firms, and governments that operate in isolation from one another, separated by "borders". CGE economic data are shared model-wide, as firms should have access to the entire European market. The social network of people should also be shared, as there is a possibility of inter-regional relationships. This approach creates a comparable environment for regions, which is essential for enabling migration possibilities. Migration itself can be handled as shown in Figure 1, where agents compare regions and calculate scores for each country. This can lead to agents relocating from their country of origin to one they prefer.

Additionally, flood map data is provided to the model in the initialisation phase alongside other initialisation data. This initialisation data primarily comprises economic variables that highlight initial differences between EU27 countries (e.g. wages, taxes and costs of living), which can be updated using the CGE functionality in the model. Initialisation data also consists of some demographic data, such as education and perception towards push-pull factor weights, introducing forms of heterogeneity.

4.3.1 Model initialization

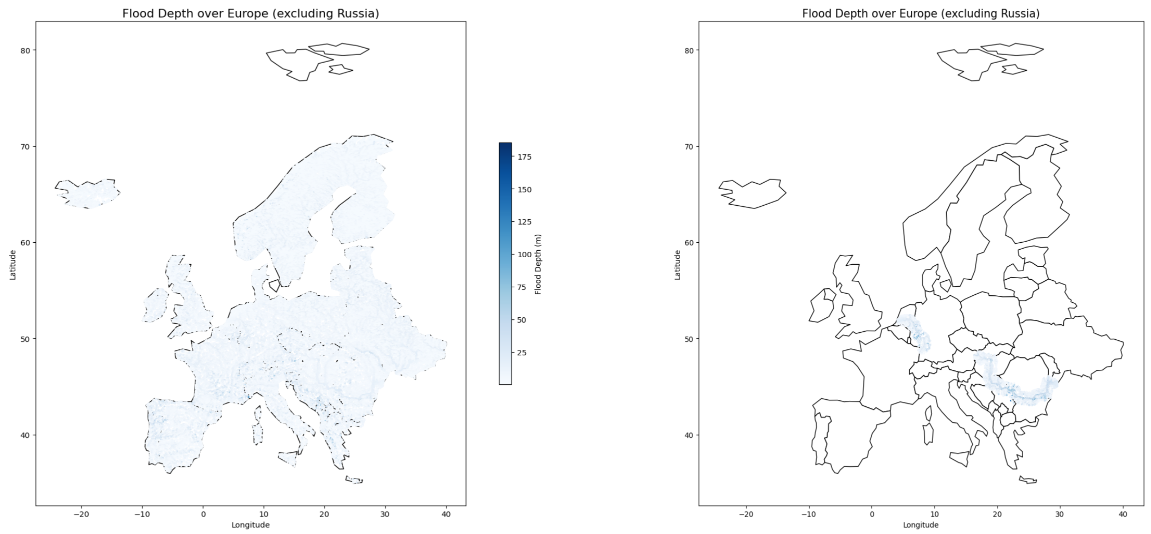
The model will be initialised with 10.000 households in each of the EU27 regions, totalling 270.000 households. 900 firms per EU27 country are initialised (100 firms per category, as is the default for the CRAB model Taberna et al. [78]), totalling 24.300 firms. The sample is uniform across all of the EU27 countries, as results should be kept comparable. If the population were included in the sampling distribution, comparing differences would be much more challenging. The model will run for 124 quarters starting in 2020, with the first 20 quarters used to generate data. This leaves 104 quarters from the start of 2025, meaning the model will run until 2050. This limit is a direct cause of the CGE-generated data being available until 2050. To help visualise how the model runs during a single time step, Figure 21 in Appendix D.2 provides a sequence diagram.

To generate a large volume of data, the Delft Blue supercomputer [22] was utilised after the model was parallelised correctly. The model was run on 48 CPU cores, enabling the execution of 48 parallel models. Because 100 Monte Carlo simulations were planned for each scenario, batches of 34 models were chosen twice, and 32 models were chosen once. This enabled the generation of 100 Monte Carlo simulations in 8 to 9 hours.

4.3.2 Scenarios

A significant use case of a micro-based model is the ability to understand behaviours in various scenarios. In the case of this model, these scenarios are climate-related. Therefore, questions related to different climate-based scenarios must be analysed using the ABM-CGE coupled model. To ensure the model can handle such questions, a scenario analysis is proposed. As discussed before, the model is built with the ability to analyse flood-based climate shocks. These flood-based shocks are generated using a flood map. The flood map for this research has a return period of 500 years [7]. To further extract differences from the model, the flood depth values were multiplied by a factor of two.

Two scenarios are proposed for researching migration differences due to extreme flooding events. The first "base" scenario includes no flooding in the EU27 countries. This scenario will be compared to the second scenario, where the Rhine and Danube are flooded. These are two major rivers that traverse vastly different countries in Europe. The Rhine travels through an economically well-developed area, whereas the Danube travels through a less economically developed area by comparison. Case studies also show that these two rivers are being affected by temperature changes and increasing ice-water flows, reaching peak flow as much as two months earlier in some scenarios [69]. When flooding both these rivers, this simple exemplary scenario analysis can give insights into the emergent and complex behaviour that is to be expected from such vastly different areas being flooded. To aid in researching these scenarios, a 100Km band along the two rivers has been extracted from the total flood map (see Figure 3b). This value was chosen because flood travel times are approximately 1.3 to 3 m/s, equivalent to about 4.6 to 10.8km/hour [3]. Although discharge times vary, for rivers it is common to see a 12 to 48 hour period of discharges [82]. Taking a conservative estimate using a 4.6km/h travel time with a day to discharge fully, a band of 100Km shows to be a realistic estimate.



(a) Flood map showing full unfiltered flood depths for Europe, excluding parts of Russia and Turkey.

(b) Reduced (extreme scenario) flood map taking a 100km band along the Rhine and Danube

Figure 3: Flood map with the Rhine and Danube filtered (3b), coming from a European flood depth map (3a) [7] with a return period of 500 years multiplied by a factor of two to ensure extreme flooding. The original map (3a) consists of 11 million depth points.

The flood map shown in Figure 3b cannot be directly used for sampling, as the populations do not follow a uniform distribution across the EU27 countries. Therefore, a density filter has been applied to the flood map, creating more sampling points in heavily populated areas. The density filter was created using a population grid projection from the European Commission for 2025 [11].

4.4 Novelty and Contribution

The purpose of this section is to support the model design academically and practically. There are many climate-induced migration models, as a recent meta-analysis shows a magnitude of 127 models [43]. It is therefore essential to highlight the contribution of this model and why it is so vital that innovations in climate-induced migration models are being made.

Firstly, and most importantly, the CGE-ABM coupled model proposes that individual migration decision-making processes can be modelled for larger areas. To the best of our knowledge, no climate-induced migration models predict migration flows from individual household decisions at the scale of the EU27 countries. If successful, this model can incorporate behaviour at the household level, measuring the effect of emergence at the scale of the EU27 countries. This is useful for policy analysis and would be valuable not only for European policy makers but also for the policy analysis of any of the EU27 countries. Different flooding policies could be tested to measure not only economic impact, but also international population displacement differences. For example, countries could analyse the shift in inter-EU population flows based on the proposed plans of dikes that reduce expected flood depths. Moreover, it would be easier to examine changes between climate events for EU27 countries and the EU as a whole, allowing for faster identification of potential economic and demographic changes due to climate hazards.

Secondly, current models that measure climate-induced migration on larger scales do not use heterogeneous and behavioural data that lead to complex and unpredictable relationships; therefore, they often miss the complete picture of cause and effect. Simplifying this can yield good holistic results, but the underlying causes are difficult to explain. The EU-CGE coupled model has no compromises on the micro-scale migration decision-making, as the CGE data is merely there to support the economic decision-making process of households, building the complex interactions from the ground up. This is, however, a difficult approach as capturing decisions while accounting for bounded-rationality shows the need for large quantities of heterogeneous data [4].

Although it is well known in academics that coupling methodologies holds benefits (see section 3.1), there have only been a few contributions that couple and scale micro-macro methodologies. The reason for this mainly resides in data dependency and performance barriers that come from micro-based models such as ABMs [4]. This is logical as many micro elements make up a macro element; therefore, modelling all micro elements will require both more data and more performance. But modelling micro-processes brings realism. In an ideal model, every modelled element would be a perfect micro-level element, as this would ensure the most realism. This is, however, not possible, so replacing highly complicated macro systems such as the economy with macro-models gives more room for other, deemed more essential micro-aspects. This model demonstrates that it is possible to retain many micro-level elements, enabling the scaling of climate-induced migration models to the EU27 countries and potentially beyond.

Finally, this thesis is a small contribution to the accessibility of evidence-based policy-making. As evidence-based policy making is gaining attraction worldwide, it remains challenging to enforce collaboration between policy and academics [76]. By creating a model that is comparable across states and flexible in adaptation, it aims to provide inspiration and a first step towards more behaviourally focused and adaptable climate-induced migration models. In the end, this aids in more accessible evidence-based policy-making.

4.5 Input data

In previous sections, it was shown how the ABM-CGE coupled model should function; in this section, the data requirements will be filled in. Data requirements will need to help inform migration decisions and analyse the effects of climate shocks on the system. Macrodata sources are often utilised to initialise differences for the EU27 countries; all data is pre-processed before being used as input for the model. Microdata will consist of survey data or processed data that was extracted from survey data.

4.5.1 Economic data

To accurately reflect economics in the model, multiple data sources are selected. Firstly, the EU-EMS CGE model [45] addresses consumption, import, and export demands. This model utilises different large European datasets as inputs. The main ones being: "the 2013 OECD database, BACI trade data, Eurostat regional statistics, and national Supply and Use tables, as well as the detailed regional level transport database of DG MOVE called ETIS-Plus" [55].

Secondly, unemployment in the model is handled by households seeking jobs at firms, and the firms, in turn, can hire or fire. It is, however, not always the case that a household is unemployed because there is no employer. Therefore, a minimum unemployment band is set for each region. This is done utilising the Eurostat unemployment dataset [36]. To track the unemployment, the data was detrended, and an ARIMA(1,0,0) model was fit:

$$U_t = c + \phi_1 U_{t-1} + \xi_t \tag{2}$$

U_t The value of employment at time t.

c Intercept.

ϕ_1 The auto-regressive coefficient of lag 1.

U_{t-1} The value of unemployment at time $t-1$.

ξ_t A white noise error term at time t.

This ARIMA model provides a straightforward threshold for unemployment across the EU27 countries, based on historical trends. Table 12 in Appendix B gives an overview of the coefficients gathered. When firms in the model are unable to supply enough jobs for households, the ARIMA model baseline will be exceeded, and unemployment can rise above these thresholds.

Thirdly, the current average [28] and minimum [29] wages for the EU27 countries are used to establish a base wage level for each country. These data are extracted from Eurostat's continuous wage tracking. Average wages are normalised by assigning a value of one to the highest average wage (Luxembourg) and dividing all other wages by this value. Values are taken from 2020 as the model takes the first 5 years to initialise migration fully (see Figure 23 in Appendix D.3). The initial differences in average wages between the highest and lowest wage country is a factor of 7.5. Minimum wages are furthermore calculated by taking a fraction of the average wage. Afterwards, the CGE input is used indirectly to update wages (see Appendix C.1 for the CGE input data).

Fourthly, the costs of living in different European countries are considered. This is done by considering the Numbeo cost of living index [57]. This index takes costs such as groceries, transportation, dinners, and utilities into account. This way, high wages can be offset by high costs of living.

Fifthly, property values for households and firms are extracted from a longitudinal household survey [38], and open data for the Netherlands. These data were used for the original development of the CRAB model and did not include European property values. Due to a lack of European property value data, the Dutch property values were scaled with the cost-of-living index. Although this approach overlooks the differences in value distributions, it effectively shifts the value proposition in a semi-realistic manner. The property value is used to calculate the extent of flood damage for households.

Lastly, taxes are extracted from the OECD's publication [58] on wage taxation (Table 1.3, p. 24 in the OECD report). For the model, average labour taxes and employee social security contributions are considered and subtracted from the household income, resulting in a realistic net income.

4.5.2 Social data

Firstly, household education levels are determined with Eurostat education data [35]. Initially, these values were only applicable to the Netherlands, but with this dataset, they were expanded to the European level. Each household is assigned a value corresponding to its country's education distribution, which mimics the country's population education levels. This will be used to ensure households with higher education are more likely to be hired by firms.

Secondly, it is essential to consider the cultural differences between EU27 countries. One way cultural differences can be differentiated is by utilising Ronen and Shenkar's world clustering paper [65]. Although the paper is not recent, this should not be a concern, given the long lifespan of cultural aspects within regions and countries. Figure 4 shows the clusters. For the model, two clusters (one specific at p = 0.25 and one general at p = 0.5) are chosen. Cultural aspects can be considered both social and demographic, given the nature of the clustering methodology and the high importance of demographic elements such as religion, language, and historical commonalities. These cultural clusters can be weighted as demographic factors (see Figure 1).

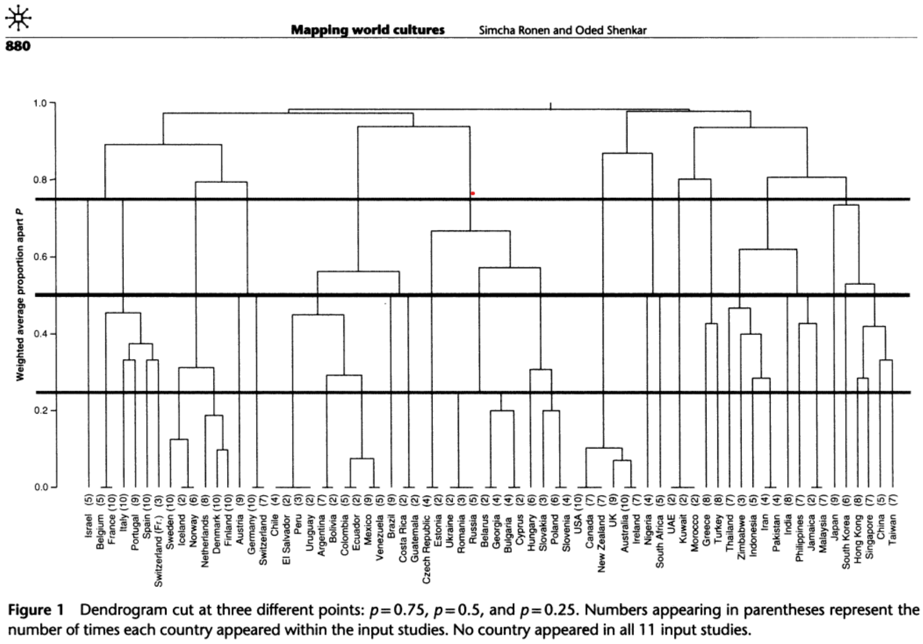


Figure 4: Dendrogram of cultural clusters of select countries, taken from Ronen and Shenkar. [65]

Lastly, European emigration data ensures control of the migration flows. These data from Eurostat describe migration for the EU27 countries by country of origin [33]. For each of the EU27 countries, links with other EU26 countries are taken, and numbers are normalised with population [32]. The primary use cases for this data are to control stochasticity and migration probabilities, ensuring reasonable flows. Migration data are further enhanced with survey data [38]. This survey data was used to identify the proportion of the population willing to move to another country in the absence of flooding events, and the proportion willing to move when there are flooding events. To gather probabilities for these events, survey data were utilised to research the effects that worry levels regarding climate have on the willingness to move. Still, no significance was found (using a mixed logit), indicating that households in the population do not perceive potential climate issues as the primary drivers of migration. Figure 19 in Appendix D shows this relationship. Due to this effect not being found, the percentage of households expressing a willingness to migrate is taken into account to determine the percentage of the population that can make a migration decision (24% without flooding events in the country, 35% with flooding events in the country). These values and the process of initialisation can also be retrieved from literature sources: "while more than 20% of the population expresses the desire to make an international journey, less than 1% actually does migrate." [50]

4.6 Methods

This section utilises the design from section 4.3, and the data from 4.5 to implement the full methodology, providing an answer on how the CGE-ABM coupled model can be developed.

4.6.1 Geological layout

To represent the geographical locations of the EU27 countries, a network layout is proposed. This network allows for straightforward calculations of distances between regions. Distances are essential factors for migration as they appear in multiple migration models and model reviews [68], [70]. Distances can be considered as an environmental factor in the Foresight framework (see Figure 1). The simplest and most computationally efficient way of including distances was found by computing all possible network distances before model initialisation, which was achieved by utilising Dijkstra's algorithm. One step of the algorithm is given below:

$$d(c_1) = \min\left(d(c_1),\ d(c_2) + w(c_2, c_1)\right) \tag{3}$$

$d(c_1)$ The current shortest known distance from the source country to the destination country c_1.

$d(c_2)$ The shortest known distance from the source to country c_2, a neighbouring country of c_1.

$w(c_2, c_1)$ The distance value of the network edge from c_2 to country c_1.

The figure below shows how this network looks for all 27 EU countries:

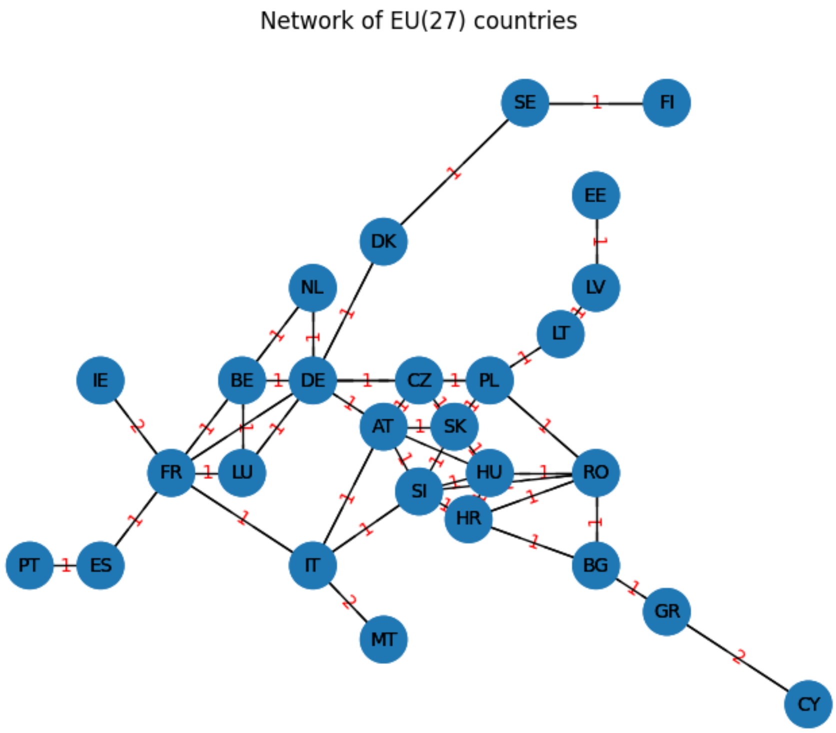


Figure 5: Initialization of the geographical layout of the EU(27) counties. Weights between countries are set to 1 for neighbouring countries and 2 for islands. Lines between nodes represent borders between countries, allowing for a simplified representation of the EU27 countries.

To simplify the distances, weights of 1 are given to edges between countries; for islands, weights of 2 are given with a connection to the nearest EU country, as travelling from an island proves to be more of a barrier [63]. The distances are normalised in the model to a value between $\frac{1}{9}$and 1, where 1 is the maximum distance (e.g., PT to CY) and $\frac{1}{9}$ is the shortest possible distance (e.g., NL to DE).

4.6.2 CGE generated input data

The CGE model is run first as described in section 4.5.1. The output of the CGE model is limited to consumption, production, imports, exports, and capital output ratios. Here, consumption is normalised across all countries and the countries' nine categories of firms [45]. This way, the market is shared between the EU27 countries, where each country has a consumption share of the total production. Capital-output ratios determine the relative expense or affordability of one unit of production, and import-export ratios influence the distribution of consumption shares across the entire market.

The CGE input dataset is updated annually and is re-read by the ABM model each year. This way, it is possible to have different scenarios or economic shocks. For the current model, no additional economic scenarios are considered, as the impact of a flood on current financial projections is being utilised as an example use case for this coupled approach. Therefore, there should be no differences in the CGE input for each year, apart from base projections.

4.6.3 Social networking within the model

To measure the impacts of social elements on migration, artificial social networks are initialised and maintained in the model. One important aspect of migration is social ties in potential destination countries [44], [50]. This observation also overlaps with economic theory, such as NELM theory [75], although social ties do not necessarily carry economic weight.

The social network is shared across all EU27 countries, forming a network with 270.000 nodes. The network is initialised to connect three households from the same country on average. This is combined with allowing a sub-sample of 10% per country to connect with one household from another region. Here, the chance is 10% to connect with a household in a country not culturally related, 50% for cultural ties at p=0.5, and 80% for cultural ties at p=0.25 (see Figure 4). These assumptions are made just so the initialisation of connections follows the cultural clustering described in section 4.5.2.

The final assumption made to create artificial social networking is to include the population. It is challenging to precisely initialise realistic social networks within a model without social survey data. Therefore, by including 50% of the social weight as synthetic social connections, and 50 % as the normalised population in the model, it is possible to initialise semi-realistic social ties synthetically. Social scores in the model are calculated as follows (example for region i):

$$\sum_{i=1}^{26} N_i = \sum_{i=1}^{26} \frac{M_i + P_i}{2} \tag{4}$$

M_i Portion of network in region i .

P_i Normalized population in region i.

By including the population with social ties, one balances the importance of personal stochastic connections with a more structural presence of migrants. The inclusion of population is not new in migration modelling and is at the core of many gravitational models [5] [18]. Although social networking relies on assumptions such as the average number of household connections and how the population is weighted against personal preferences, one can argue that these assumptions do not directly harm the model. The inclusion of the population regulates errors within the cultural clusters and personal weights, as captured by the stochasticity of including the population.

4.6.4 Modeling Migration

To handle migration, the model features an implementation of the theoretical framework as explained in section 4.2. A flow chart of the decision-making process is also given in Figure 20 (Appendix D.2). This section will utilise equations to explain the migration flow. For model code, please refer to Appendix E.

Migration logic Firstly, the migration decision begins by checking if the household belongs to the sample of the population that is willing to migrate, as described in section 4.5.2. When this is the case, the expected economic utility of the household gets calculated based on NELM. This is firstly done by calculating the net income in the current region and all other possible regions:

$$\sum_{i=1}^{26} \delta_i = \sum_{i=1}^{26} \frac{\bar{W}_{\mathrm{i}} - \bar{W}_0}{\bar{W}_0} \tag{5}$$

$$I_0 = L_0(W_0 \cdot (1 - T_0) \tag{6}$$

$$\sum_{i=1}^{26} I_i = \sum_{i=1}^{26} L_i \cdot \delta_i \cdot I_0 \cdot (1 - T_i) \tag{7}$$

δ_i Expected wage multiplication factor of the household in region i.

I Effective income adjusted for cost of living and taxes in region i or the agent's current region 0.

L Cost of living in region i or the agent's current region 0.

T Taxes in region i or the agent's current region 0.

W Wage in region i or the agent's current region 0.

$\bar{W}$ Average wage in region i or the agent's current region 0.

To achieve the full expected economic utility X, employment and income volatility V are also considered, as they add or reduce the financial risks faced by households. Both employment and income volatility can be seen as weights between 0 and 1; they will always increase the adequate income. The household will, however, always compare the home region (region 0) with all 26 other countries, so lower values for both employment and income volatility in a particular country decrease the probability of attracting agents to that country.

$$\sum_{i=0}^{26} X_i = \sum_{i=0}^{26} (1 + (V_i \cdot U_i))I_i \tag{8}$$

X Expected economic utility in region i or the agent's current region 0.

V Income volatility i or the agent's current region 0.

U Employment percentage i of the agent's current region 0.

In the model, a higher income volatility is viewed as a positive attribute because it combines volatility and trend. A value of 0 means a highly volatile **Negative** trend, a value of 1 means a highly volatile **Positive** trend, a value of $\frac{1}{2}$ means no volatility and a flat wage trend. The logical assumption here is that high volatility can be a positive phenomenon if the direction is upward. In simple terms, people consider migration less when their wages are rising steadily. To get this behaviour, income volatility for a single region is calculated like this:

$$\sum_{i=0}^{26} \mathrm{V}_i = \sum_{i=0}^{26} \begin{cases} \dfrac{1 + \frac{1}{n-1} \sum_{t=t-n}^{t} \left|\Delta \hat{W}_{i,t}\right|}{2} & \text{if } \overline{\Delta \hat{w}_r} < 0 \ for\ t >= n \\ \dfrac{1 - \frac{1}{n-1} \sum_{t=t-n}^{t} \left|\Delta \hat{W}_{i,t}\right|}{2} & \text{if } \overline{\Delta \hat{w}_r} >= 0 \ for\ t >= n \end{cases} \tag{9}$$

n Number of historical time steps considered.

$\hat{W}_{i,t}$ Normalised wage in region i at time t, adjusted by the regional wage difference. If the current region is the home region, the wage does not need to be adjusted by wage ratios:

$$\sum_{i=0}^{26} \hat{W}_{i,t} = \sum_{i=0}^{26} \frac{\begin{cases} W_i - \min(W_i) & \text{if } i = 0 \\ (1 + \delta_i) \cdot W_{i,t} - \min(W_i) & \text{if } i \neq 0 \end{cases}}{\max(W_i) - \min(W_i)} \tag{10}$$

$\Delta \hat{W}_{i,t}$ Change in normalized wage at time t:

$$\sum_{i=0}^{26} \Delta \hat{W}_{i,t} = \sum_{i=0}^{26} \hat{W}_{r,t} - \hat{I}_{i,t-1} \tag{11}$$

$\overline{\Delta \hat{W}_i}$ Mean change in normalized wage across time.

$$\sum_{i=0}^{26} \overline{\Delta \hat{W}_i} = \sum_{i=0}^{26} \frac{1}{n-1} \sum_{t=0}^{n} \Delta \hat{W}_{i,t} \text{ if } t > 2 \tag{12}$$

To determine the final expected economic utility score for each of the 26 countries households can migrate to, the delta is calculated as the difference between the score for a possible destination country and the current country of residence. The delta is normalised by dividing by the score when migrating, while negative scores are set to zero.

$$\sum_{i=1}^{26} \Delta X_i = \sum_{i=1}^{26} \frac{(Xi - X_0)}{X_i} \tag{13}$$

$$\sum_{i=1}^{26} \Delta U_i \begin{cases} 0 \text{ if } \Delta X_i {<=} 0 \\ \Delta X_i \text{ if } \Delta X_i {>} 0 \end{cases} \tag{14}$$

Now that expected economic utility scores can be calculated for agents across all possible countries, other heterogeneous aspects can be introduced alongside the economic expected utility. This is done by utilising the following push-pull formula:

$$\sum_{i=1}^{26} S_i = \sum_{i=1}^{26} \alpha \Delta X_i + \beta D_i + \gamma G_i + \epsilon N_i \tag{15}$$

$\alpha, \beta, \gamma, \epsilon$ Heterogeneous weights for the different push pull factors. i.

D_i The distance from the origin country 0 to the destination country i as described in 4.6.1.

G_i The cluster score of the base country 0 with the destination country i. This score is 1 for tight cultural linkage (at p=0.25) and 0.5 for loser linkage (p=0.5), as shown in Figure 4

N_i Agents social score in region i, as described in section 4.6.3

One of the push-pull factors, as extracted from the foresight framework [44], is omitted because no significant weights were found for the political aspects. Therefore, these weights can be interpreted as zero and are excluded from Formula 15.

Finally, the agents examine all the different scores and assign a probability of migration to each. However, first, the highest score must be higher than the three previous scores to retain support (3 years). This aligns with NELM theory [75], which states that migration decisions occur when there is a continuous desire. If there is retained support for migration, the final probability will be calculated. The probability extracted from the scores follows a sigmoid distribution, commonly used in ABMs to model probability (e.g. [84], [49]). It does this for the four highest-scoring countries to mitigate the effect of compounding probabilities that influence total migration probabilities too heavily. This number stems from the portion of the population that can decide to migrate (24%), as discussed in section 4.5.2, which makes the probabilities more closely align with the likelihood of the full sample size.

$$\sum_{i=1}^{4} p_i = \sum_{i=1}^{4} \frac{\mu_0}{1 + \mu_0 \cdot e^{(10 \cdot (1 - S_i))}} \tag{16}$$

p_i Probability the household will migrate to one of the top 4 scoring countries i.

μ_i percentage of people who emigrate to other EU countries from the origin country 0.

The final step is to draw a binomial value for each of the four top probabilities. When this distribution returns 1, the agent decides to migrate to region i.

$$\sum_{i=1}^{4} X \sim \text{Bernoulli}(p_i) \tag{17}$$

4.6.5 Model weights

In the model, heterogeneity among agents is controlled by unique push-pull weights assigned to each household. To do this, ideally, household survey data are utilised. Unfortunately, such data is not yet openly available for the EU27 countries. To ensure the model can still generate realistic migration patterns, literature weights from the European Commission were utilised [50]. The report examines the factors that influence international migration globally. In particular, this thesis focuses on Table 1 (p. 99). This table is summarised and interpreted as shown below:

Table 7: General Migration – Regression Results (coefficient + standard error) by Income Level. Dependent variable used: migration flow by income level.

Variable	Low Income	Middle Income	High Income
(1) GDP per capita (origin)	Not sig	0.470* (0.132)	-0.383* (0.112)
(2) Expenditure in Education (origin)	0.0844* (0.0189)	0.0500* (0.0200)	Not sig
(3) Fertility (origin)	-0.403* (1.05e-08)	-0.194* (-1e-08)	Not sig
(4) Geographical distance (origin-destination)	-0.235* (0.0367)	-0.154* (0.0170)	-0.149* (0.0408)
(5) Networks (origin-destination)	0.565* (0.0272)	Not sig	0.433* (0.0173)
(6) Trade (origin-destination)	0.1192* (0.0105)	0.0105* (0.0114)	0.0660* (0.0181)
(7) GDP per capita growth (destination)	0.0637* (0.0222)	0.0386* (0.0180)	0.0360* (0.0112)
(8) Common language (origin-destination)	0.0773* (0.0394)	0.116* (0.0287)	0.0732* (0.0281)
(9) Colonial link (origin-destination)	Not sig	Not sig	0.111* (0.0429)

For the EU27 countries, the values for high-income countries were further analysed because the paper classifies a high-income country as follows: "High income countries have GDP per capita in 2015 higher than 15000 international dollars" [50]. For the EU27 countries, the lowest GDP per capita today belongs to Bulgaria, although the GDP is still above the 15.000 USD threshold [31] [37].

To extract the final literature weights utilised in the model, different weights were identified for economy, distance, culture, and social factors. The following approximation was used, utilising the weights from Table 7:

α Economic weight: $0.383(1) + 0.0360(7) + 0.00660(6) = 0.4256$

β Distance weight (Environmental): $0.149(4)$

γ Cultural cluster weight (Demographic): $0.0732(8) + 0.111(9) = 0.1842$

ϵ Social network weight (Social): $0.433(5)$

When looking back at the foresight framework [44] (Figure 1), economic weights can be summarised to a collection of: wages, income volatility, taxes, cost of living, and unemployment. Social weights involve: population and stochastic connections based on demographic and cultural clusters. Demographic weights refer to the degree of clustering among countries, as described by Ronen and Shenkar's cultural clustering [65]. Environmental weights apply to distance, but climate shocks can also increase the population that is willing to migrate.

Finally, these weights are made heterogeneous by assuming the distributions of these weights in the population are normal, and the standard errors correspond to the standard deviation of the distribution. This assumption is common in modelling when no direct empirical survey data are available [62]. The standard errors were estimated in the same way as the weights, giving: $\alpha_{std} = 0.1413$, $\beta_{std} = 0.0408$, $\gamma_{std} = 0.071$, $\epsilon_{std} = 0.0173$

5 Results

The previous sections showed why an ABM-CGE coupled model was chosen for simulating climate-induced migration for the EU27 countries, answering subquestion one. Further analysis of migration theory showed the coupling of NELM, push-pull theory and the Foresight main factors of migration as a logical answer to subquestion two. The methodology showed how the model was designed and why, answering subquestion three. Now, this section aims to answer the fourth and final subquestion, thus validating the results and determining their novelty and usefulness to the field. To further aid in answering the subquestions, the following results will be extracted from the model:

- Effect of flooding on the differences in the economic macro-environment for the EU27 countries.
- Effect of flooding on the different migration flows for the EU27 countries.
- Macro-based values regarding migration for the EU27 countries.
- Micro-based values regarding migration for the EU27 countries

The reason the following subjects have been chosen is to gain insight into the macro-micro coupled aspects of climate-induced (in this case, flood-induced) migration. The economic macro-environment is included, as this gives a nice overview of the results obtained from implementing the CGE model. Migration results furthermore encapsulate the migrational theory included, and by researching micro-migration values, these theories can be tested. One can, for example, extract migration probabilities that directly tie into how the push-pull factors have interacted to generate a probability for each of the households.

Before extracting the results, the model will be validated. However, the primary use case of ABMs does not reside in pure prediction, but in comparison between two states; it is, however, still essential that the model can capture macro-based effects that resemble the real world. If these results are significantly different or incorrect, it becomes challenging to describe the magnitude and direction of the differences accurately. To gain insight into the model's sensitivity to variable weight changes, a sensitivity analysis will also be conducted on the push-pull weights. This not only gives an idea of the model's resilience to errors in the weights but may also give an indication of what weights carry importance for macro-migration outcomes.

5.0.1 Validation of migration results

Firstly, the model results will be validated. To validate migration values, the model will be tested on real-world data from 2023. These data are the same as shown in section 4.5.2 [34]. From these data, it is possible to extract the number of households that moved to each EU27 country in 2023. This can be tested against the end-of-year model predictions for 2025. Due to the difference in years, slight deviations can not be validated, but general migration directions can be. The data must be normalised to samples of 10.000 households for each of the EU27 countries; therefore, all results are not scaled with population. It is important to note that population does, however, hold weight in migration decisions because of social interactions.

Figure 6 shows that the model is quite accurate, especially for an ABM. It is, however, still apparent that some behavioural aspects and factors are not adequately captured, causing the model to underfit for certain countries. This falls within the expectation due to the lack of actual survey data for the EU27 countries. Countries such as Spain are popular migration destinations due to factors like the weather. Without household survey data, these preferences could not be included. Importantly, social ties are modelled as a relation between population and cultural similarity (as described by Ronen and Shenkar [65]). It is expected, however, that accuracy will increase when social ties reflect actual data on where the international relations of households primarily reside. This can eliminate the need to include rough estimation data, such as population.

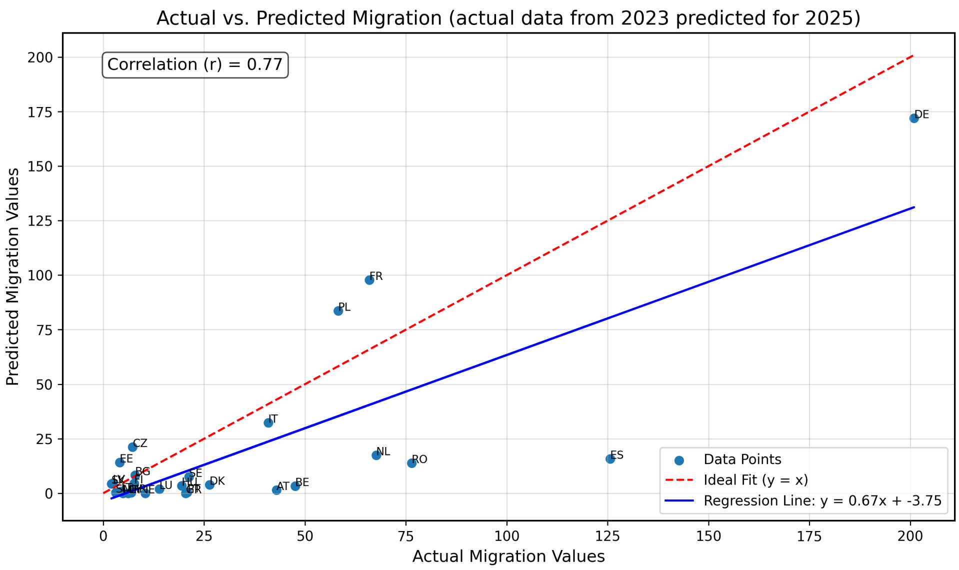


Figure 6: Actual migration numbers per sample of 10.000 within the EU (2023) and predicted migration numbers per sample of 10.000 within the EU (2025). These results stem from an average over 100 Monte Carlo runs utilising the base-climate scenario with no flooding. Predicted values were reduced to a uniform 10.000 per EU27 country utilizing population numbers from Eurostat [35].

One step further would be to look at the actual predicted migration flows between countries. Utilising the same data as before, it is possible to see which countries accounted for the largest share of migrants. This can then be compared to the model-predicted shares. This gives an indication of the accuracy of decisions within the agent-based model, reflected by the accuracy of the origin-country to destination-country flows.

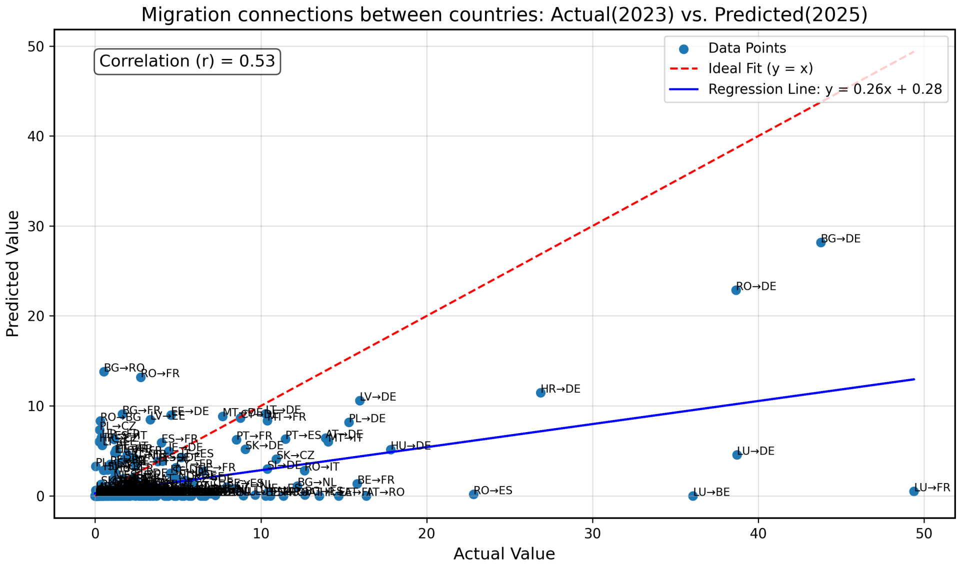


Figure 7: Actual migration flows per sample of 10.000 within the EU (2023) and predicted migration flows per sample of 10.000 within the EU (2025). These results stem from an average over 100 Monte Carlo runs utilising the base-climate scenario with no flooding. Predicted values were reduced to a uniform 10.000 per EU27 country utilizing population numbers from Eurostat [35].

Here, we observe a decrease in accuracy as predictions become more complex, since not only the number of migrants should be correct, but also the flows from the origin country to the destination country. For lower-wage countries, we see some overfitting. One reason might be that social ties are assumed in a very general way, resulting in lower-wage countries with higher populations standing out. We still observe the same underfitting for Spain; additionally, we notice an unexplored relationship between Spain and Romania. There is a long-lasting history of Spanish migrating to Romania and vice versa [51]. Due to the rough estimation of social ties utilising population and non-existing and cultural relations between Spain and Romania (according to Ronan and Shenkar [65]), effects like these are not well-captured.

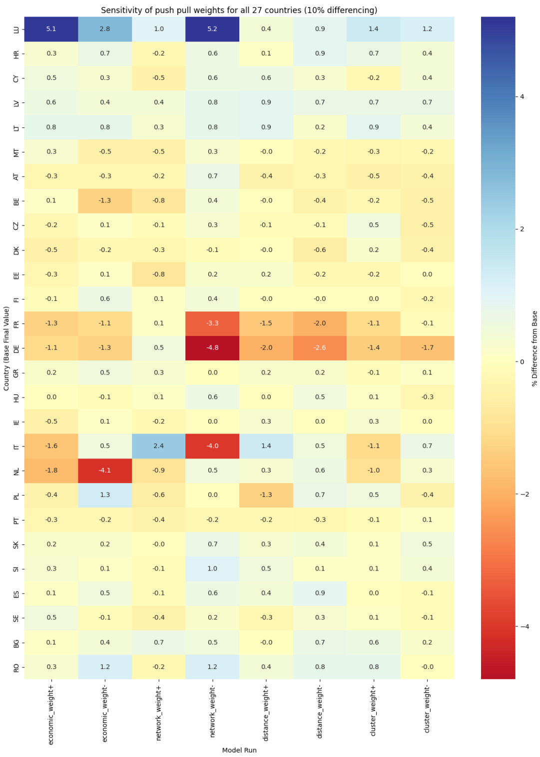
Additionally, it becomes apparent that high wages, such as those in Luxembourg [28], show less than expected emigration numbers. This is due to the high focus on economic weights and the lack of outliers resulting from the heterogeneity introduced by the literature weights. High-wage countries, therefore, have little to no people who have financial reasons to leave, creating a high reliance on social effects. These effects are probably not as heterogeneous as they should be in extremely wealthy EU27 countries. This effect is logical due to the current literature's weight inputs to the model. Currently, the raw model performance shows logical relationships but cannot capture some outliers that could be extracted from actual survey data. The model can, however, still capture differences in state, making it useful for policy analysis.

5.1 Sensitivity analysis

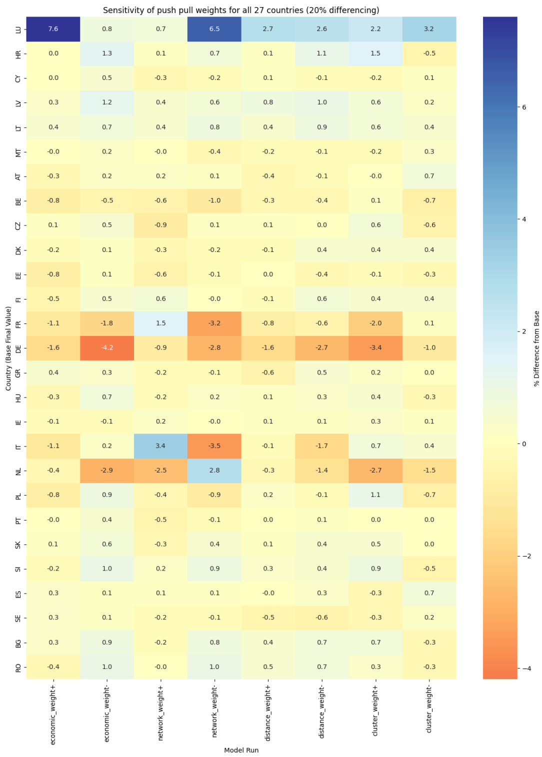
To gain a better understanding of the importance of the included weights, a sensitivity analysis is provided. For this analysis, just the added migration variables are considered. For the sensitivity of the economic system, one can refer to the paper by Taberna et al. [78]. The variables that matter most for migration are the heterogeneous weights assigned as push-pull weights. To analyse the sensitivity of migration behaviour, these weights will be increased by ±10 % and ±20 %, respectively. Table 13 in Appendix B shows these values.

Due to the computational power and time required to run the model, a single representative seed was selected from the previously collected 100 Monte Carlo runs. For the base scenario, seed 27 was found to be the closest to the average of all runs utilising the MSE. Locking stochasticity was possible for the base weight valuation, generating the same results. Deviating from the base weights, however, introduces new stochasticity as the random number generators are being called in different orders. This, unfortunately, means that the sensitivity results are only an indication, and directions do not necessarily have meaning. They do, however, indicate general sensitivity to the push-pull weights and stochasticity.

The sensitivity analysis results are presented in Figure 8. The model exhibited slight deviations from the base scenario, with greater deviations when the weights were shifted by 20%. It is also apparent that the emergence of migration flows makes it unpredictable what precise impact changes in weights have on macro-migration figures, as migration flows are complex. The main takeaway from this sensitivity analysis is that migration decisions are relatively stable for certain groups of countries. Luxembourg shows itself to be the most sensitive to the economic weights, logically gaining a lot of external migrants. Networking is holding back countries like Luxembourg, as the population becomes more heavily concentrated. Still, we see the effect of stochasticity influence the results, but the weights are reasonably stable. For smaller weights, such as distance and cultural clustering, we see more minor deviations affected mainly through stochasticity.



(a) deviation from the base household numbers for all EU27 countries when varying the push-pull weights by ±10%.



(b) deviation from the base household numbers for all EU27 countries when varying the push-pull weights by ±20%.

Figure 8: Sensitivity of final household numbers in each of the EU27 countries. The null value of this sensitivity is an average seed with the original push-pull weights, deviated according to Table 13 in Appendix B.

5.2 Migration Results

This chapter will highlight the most important results. Apart from the climate-induced scenario analysis, further use cases within evidence-based policy making will be showcased, such as economic environments within the EU27 countries, macro-based migration analysis, and micro-based decision making.

5.2.1 Scenario Analysis

As discussed in section 4.3.2, a flood map of the Rhine and Danube is selected to test the model on one of the potential use cases. Because the model enables the behavioural simulation of complex migration patterns, it provides insights into how the system changes due to household-level impacts when climate shocks are introduced. The choice for climate shocks primarily stems from the earlier-mentioned extensive research in the field of climate-induced migration. Consequently, this makes literature validations more reliable.

Previous research in this field is essentially unanimous in concluding that environmental changes have no significant direct impact on inter-European displacements [52]. It has been found that there are some slight indirect effects that ecological hazards have on migration within Europe [19]. Therefore, it is expected that flooding events in Europe can affect the economic environment of some households. Still, this effect is expected to have no lasting impact on household migration. To test the model, the Rhine and Danube will be flooded with the idea of destabilising the economy and testing the country's resilience to flooding hazards. Firms within flooded zones lose market position or go bankrupt, causing more unemployment and thus emigration pressure. In theory, however, this pressure should be minimal as the effect of a few firms losing market position should be quickly corrected if the model behaves in consensus with the literature. Although it should be noted that the literature on inter-EU climate-induced migration does not include modelling and relies heavily on theory. This novelty raises expectations to be more uncertain.

The Rhine and Danube are chosen because they are two big rivers that flow through both higher-wage countries and lower-wage countries. These rivers are not necessarily those with the highest flooding probabilities, but they can validate the model by introducing extreme climate shock events that affect a large number of people. Table 8 gives an overview of the two scenarios and the model's hypothesis.

To gain a simultaneous understanding of flooding impacts in the near and distant future, the decision has been made to trigger one flood in 2030 and one flood in 2045, as projected economic growth may impact the system differently in the future.

Table 8: Base and flooding scenario expectations.

Scenario	**Expected migration effects**
Base scenario (no floods)	Migration flows mostly follow current European trends [34].
Extreme flooding of the Rhine and Danube	The scenario is expected to have a very slight effect on migration, leading to short-term economic downturns. Still, these are quickly recovered [19] [14]. Although research indicates that the EU is seen as a destination country [14], it remains challenging to determine the effects of inter-EU migration.

The next section analyses the results by comparing the differences between the two states. By analysing the differences, conclusions can be drawn about the differences between two complex interactions within the model.

5.2.2 Scenario Analysis Results

To generate the results, 100 Monte Carlo runs were performed for each scenario. For the climate-based impact of the two river floods, only the affected countries will be examined more closely. Figure 22 in Appendix D.3 gives an overview of the total repair expenses in each country. This provides us with a total of 9 countries affected by the river flooding (HR, AT, FR, DE, HU, NL, SK, BG, and RO). Of these countries, the Netherlands is the most affected. This is expected, given that it has the most densely populated household sample living near one of the two rivers. It also becomes clear that repair expenses increase significantly over time, due to the model's general economic growth.

Firstly, we extract the results of the CGE-based macro environment. This is achieved by examining wages, unemployment and consumption. Wages exhibit minimal deviation in both model runs, with only slight downturns as firms are damaged. Figure 23 (appendix D.3) shows an apparent clustering of higher and lower income countries within the EU. Significant flooding events result in small wage reductions for short periods. These small wage reductions are overshadowed by overall system stochasticity and have no noticeable impact on average population-based wage perception. Therefore, the economic impact will not be significant enough to outweigh the stochastic and, in particular, country-specific differences in wages. Interestingly, wages tend to rise slightly when regions are flooded (see figure 9). This is a direct effect of the increase in consumption due to the need for repairs. This effect is delayed; therefore, the impact on wages only shows one quarter after the flooding event. In Figure 26, in Appendix D.3, it is visible that consumption differences trigger in sync with flooding, but wages take more time to catch up.

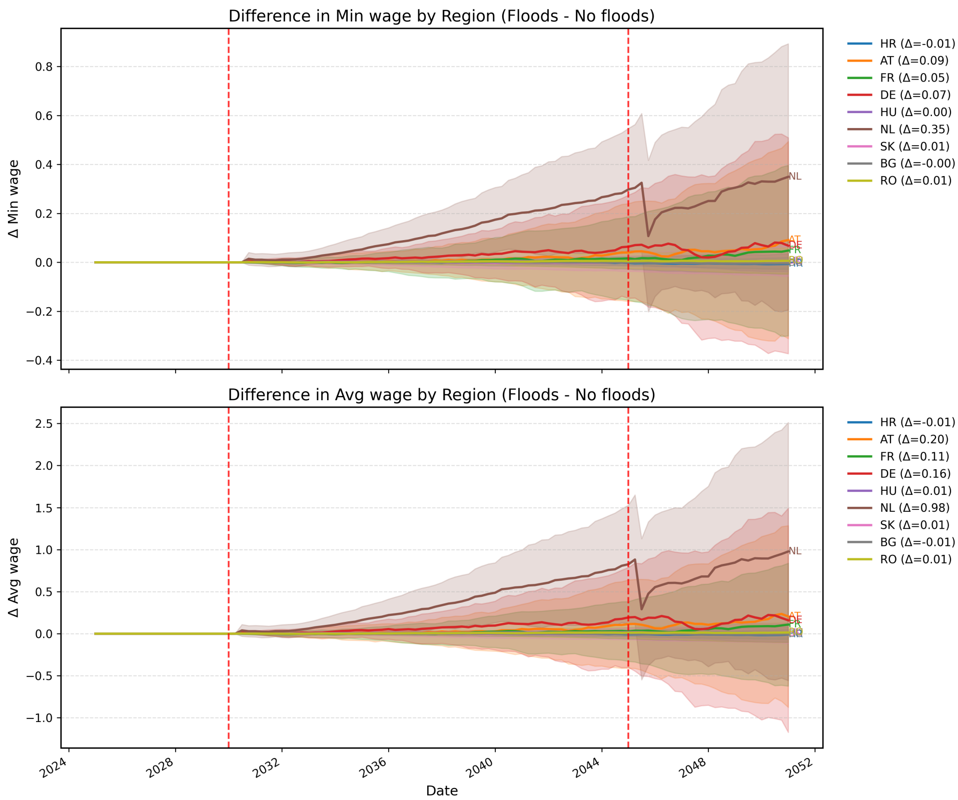


Figure 9: Differences in wages between the two scenarios. The red line resembles a flooding event, and the uncertainty bands represent the mean ± one standard deviation. Both scenarios were obtained from 100 Monte Carlo runs simulating 10.000 households in each of the EU27 countries.

For unemployment rates (Figure 27 in Appendix D.3), the effect of flooding is not enough to increase averages significantly. The number of firms within countries means households face less difficulty finding employment, even during a flood. As the model progresses, we do see more uncertainty in employment for lower-income regions such as Bulgaria. Slight increases in unemployment become possible as migration, combined with low consumption shares compared to other countries, makes it challenging to sustain employment for firms in lower-wage countries. This increase, however, is marginal, and according to model output, employment is not expected to suffer significantly from migration and flooding events.

The leading cause of migration flow changes in the model is increased consumption, which creates wage differences. Furthermore, there is a growing percentage of the population willing to leave the country due to climate hazards. This percentage goes up from 24% to 35% for affected households (see section 4.5.2). This effect will be small, as only a tiny portion of the population willing to leave will undertake action [50]. Figure 24 shows that migration does shift a little due to the increasing sample size of households that are willing to migrate. Most interesting here is that the outflow from lower-wage countries to higher-wage countries increases more than the outflow in higher-wage countries. As a result, higher-income countries experience a rise in the number of migrants, even if higher-wage countries experience a similar flooding event. This happens because lower-wage countries have more countries that meet household migration criteria and historically have higher probabilities of actually emigrating.

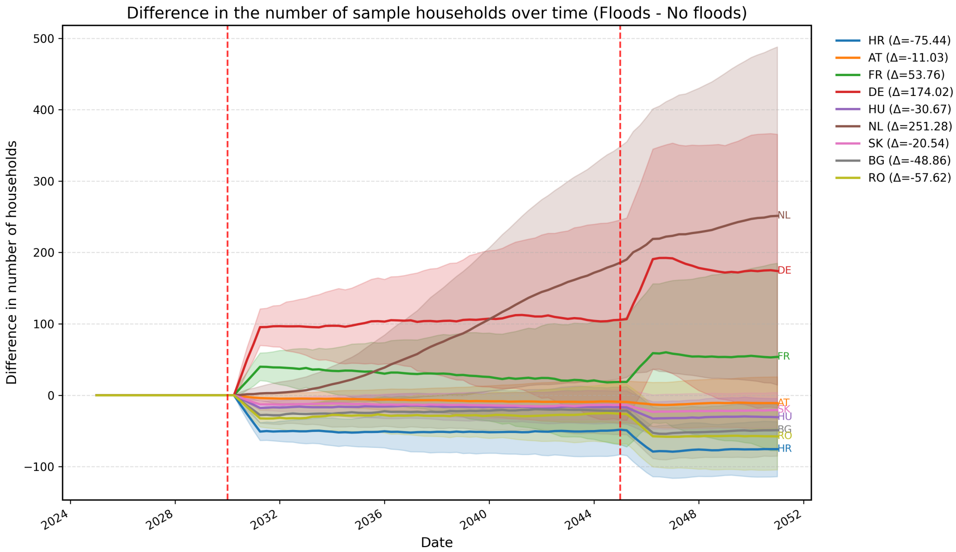


Figure 10: Differences in household numbers for flood-affected regions between the two scenarios. The red line resembles a flooding event, and the uncertainty bands represent the mean ± one standard deviation. Both scenarios were obtained from 100 Monte Carlo runs simulating 10.000 households in each of the EU27 countries.

As a result of higher consumption growth, wages go upwards in high-income countries. As the resilience of firms is high enough, short-term economic instability does not lead to a rise in unemployment. Therefore, the increase in consumption will actually have a bigger effect than the short-term shock has on the economy of a whole country. In this case, the Netherlands gets hit hard enough to see this effect; other countries see significantly less damage from the flooding (see Figure 22 in appendix D.3). It is essential to realise that consumption does not get affected positively in the short term, meaning there is a risk of hitting a tipping point where there is no resulting higher consumption growth after the system stabilises. Finally, the overall effect of increases in both economic and migration data sees little impact on the raw numbers of households in regions, as the differences are significant but small in the overall picture (see Figure 23 and Figure 24 in appendix D.3).

5.2.3 Migration results EU27

As previously shown, the model can be beneficial for climate-scenario analysis. It can, however, generate data for the entire EU and provide valuable insights into migration flows with more detailed behavioural information. To illustrate this, this section will provide additional insights into the types of data that can be extracted and explained for this model. These model results prove useful for system insights.

Firstly, the macro-based results will be extracted from the model. Macro-data can easily be collected and visualised. The model can generate migration results similar to gravity-based approaches while maintaining behavioural richness. To showcase this, Figure 11 gives an estimation of where the sample households are distributed in 2050:

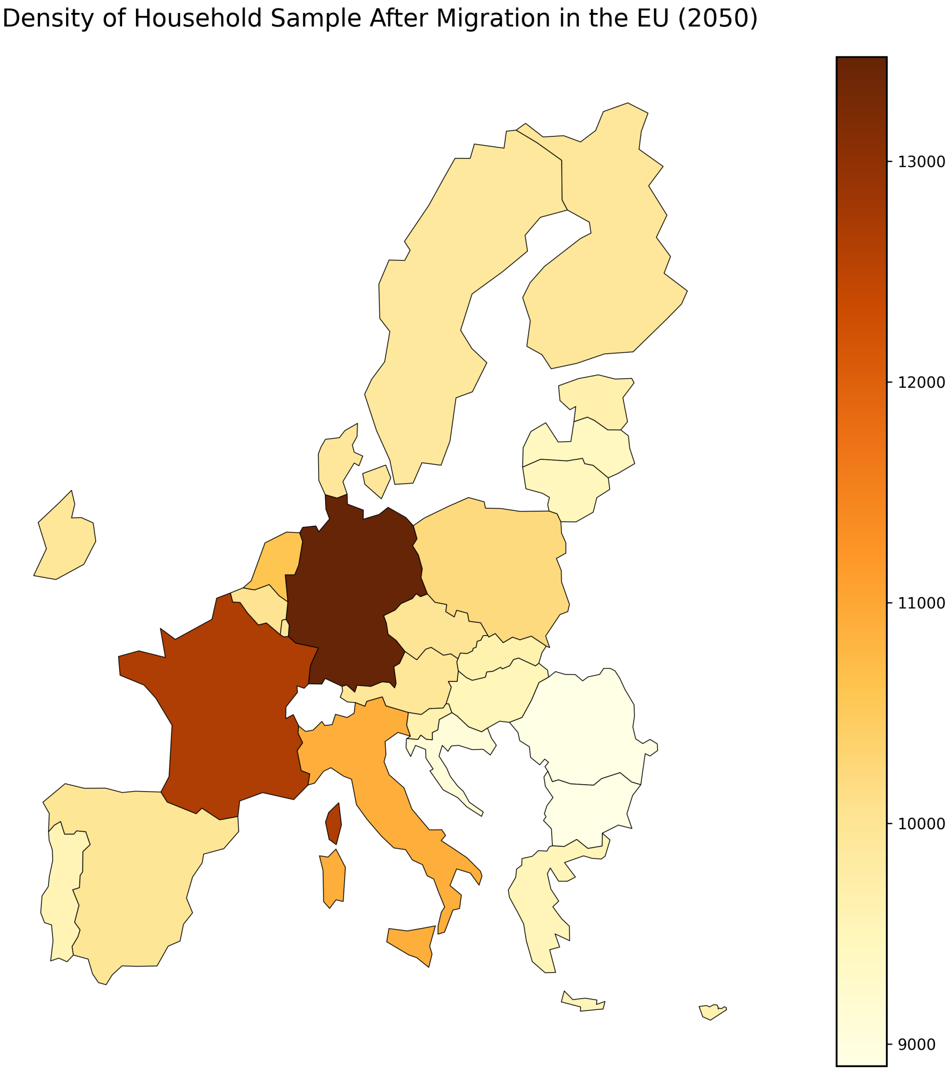


Figure 11: Heat map of the distribution of the household samples for the EU27 countries. Final values are averages from 100 Monte Carlo runs, starting with a sample of 10.000 households for each of the EU27 countries.

On the macro scale, various additional observations can be of interest. One sees that high-population countries tend to receive more households, especially those with higher wages. This is most likely due to the increased probability of social ties in highly populated countries. Countries close to the centre also seem to receive more migrants; this is logical, but relative importance cannot be observed in this macro perspective. Countries close to the centre often have higher relative wages and populations, making it difficult to say in this macro-perspective what the relative importance of individual factors is.

Secondly, one can further observe macro-migration flows for specific countries by looking at the countries of origin of the migrants. For example, Germany has the largest number of households that came from other countries. Figure 25 in Appendix D.3 shows where these households came from. Here, it is apparent that economic effects, in combination with network effects, outweigh the impact of culture and distance for many households in regions with lower wages. This is a logical result of treating the literature weights as normal distributions varying with the standard error. The cultural cluster of Germany consisted of just Austria; this cultural linkage did not weigh heavily enough for many Austrians to migrate to Germany. We do see a small portion of Austrians moving to Germany compared to lower-income regions. Germany, however, is the number one destination for Austrians. Still, this effect is overshadowed by the fact that up to 5 times as many people leave from lower-income regions in the model.

Lastly, the micro-based results can be extracted from the model. Due to the household-level modelling focus of the ABM, it is also possible to analyse the micro-level decision-making processes. For instance, it is easy to explore the distribution of wages between all 270,000 agents over all time steps. This helps in understanding economic differences. Figure 28 in Appendix D.3 shows this. From this wage distribution, it can be concluded that there are no outliers among countries with weaker economies. This modelling choice stems from the CRAB model, which serves as the basis for this model [78]. More relevant to this research would be to examine the migration results of individual agents. Figure 12 shows this distribution.

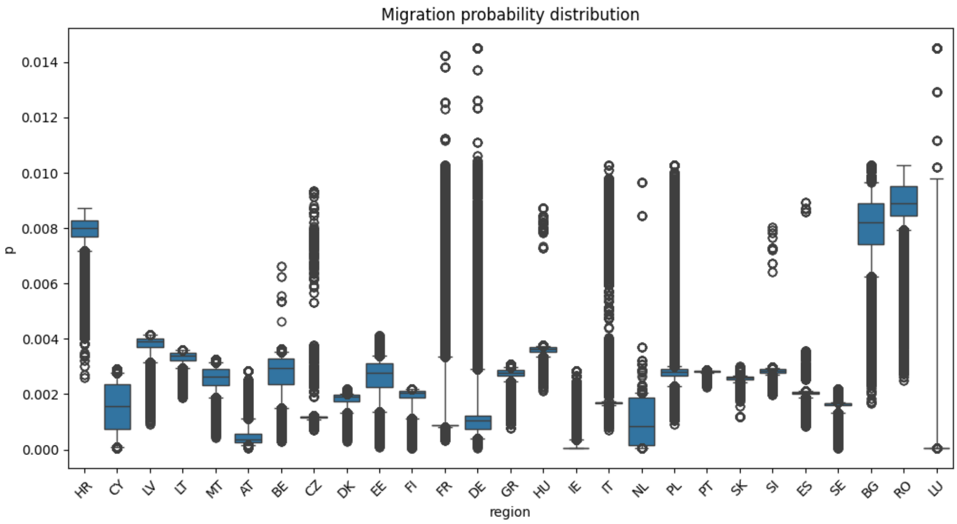
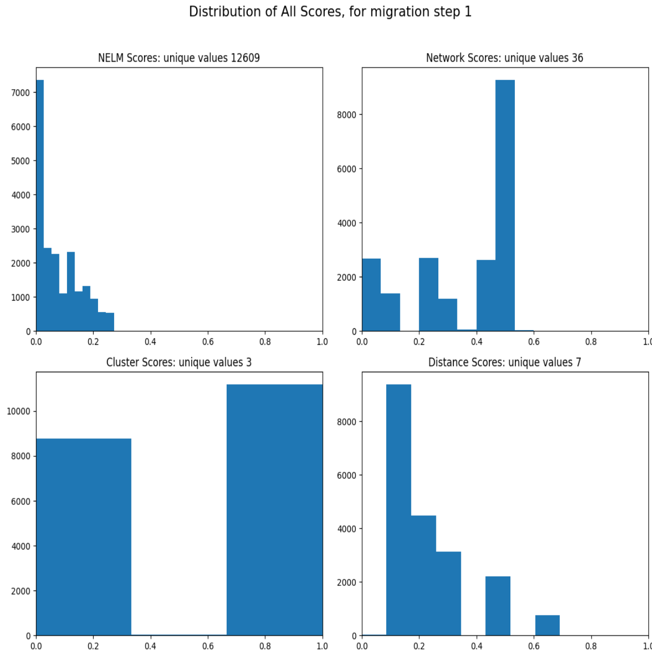


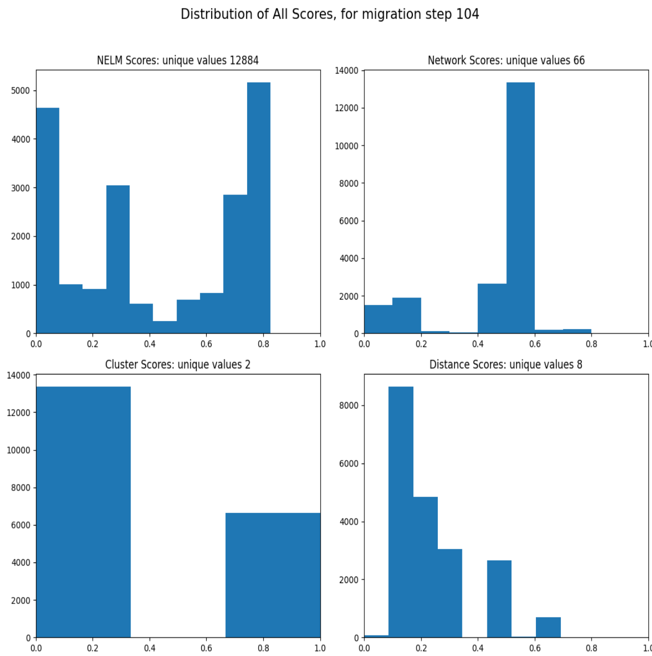
Figure 12: Box plot containing migration probabilities for all agents over all 124 time steps. The agents are categorised per region. Whiskers range from the 5th to the 95th percentile. This data has been obtained using the most representative random seed out of 100 Monte Carlo runs.

Here, we not only see the expected higher probabilities but also individual differences between EU27 countries. Outliers in high-income countries often have higher probabilities of migration, while outliers in lower-income countries tend to have lower migration probabilities. This provides insight into the origins of emergent macro-behaviours, making the model not only useful for policy analysis but also for a deeper examination of the underlying causes of observed macro-behaviours. As high-income countries see less pressure to migrate than low-income countries, the relative importance of the economic variables is relatively high in comparison. One probable reason for this behaviour is that social, cultural, and demographic variables are quite similar in magnitude across the EU27 countries. For instance, cultural similarities and distances between countries do not vary over time steps. Social weights do vary, but minimally. This suggests that the economic weight is most important for the migration probability as it changes the most between steps. Migration flows can change if cultural, environmental, social or economic environments change. Logically, it is way easier for economic environments to change. Therefore, existing migration flows are most easily changed by changes in financial environments, driving further differences in countries, explaining the high similarity of migration probabilities of agents with wages.

To confirm this theory, we can look at the distribution of the migration scores across the time steps. Here, it would be expected to see a high variance for the economic scores and relatively stable distributions for the social, cultural and distance-related scores. The distribution is shown in Figure 13



(a) Score distributions at the first step where migration is enabled. Values stem from one run with the most representative seed of the 100 Monte Carlo simulations. All values are for the maximum-scoring country the agent is considering.



(b) Score distributions at the last step where migration is enabled. Values stem from one run with the most representative seed of the 100 Monte Carlo simulations. All values are for the maximum-scoring country the agent is considering.

Figure 13: The distributions of the migration scores at the first and last step of migration. Values stem from one run with the most representative seed of the 100 Monte Carlo simulations. All values are for the maximum-scoring country the agent is considering. Due to size constraints, 20.000 values per score are considered; values are added randomly.

This figure shows that the prior assumptions hold in the course of the model's progression. NELM scores have significantly more unique values as individual economic differences are more precisely measured. The NELM scores furthermore show a growing distribution towards bigger values as economic differences increase within the EU27 countries, creating bigger economic migration pressures. This leads to economic changes being the driving factor in the change of migration probability within the model. The NELM scores start approaching one as the changes in wages increase. This function assumes that the value of one is a limit, contrary to other variables. This assumption results from the inability to use normalisation with the maximum value, as that would naturally add a large computational overhead. This assumption does not harm economic influences in the model, as seen in the resulting migration probabilities.

The social, cultural and distance factors show little to no changes during model progression. Social weights show very slight increases, indicating that a small portion of agents is receiving higher scores due to spillover effects as household connections leave the country. Cultural clusters show very low maximum migration score values of 0.5 (at value p=0.5 of the Ronan and Shenkar dendogram, see Figure 4). This is because the clusters at p=0.5 include countries with significantly better economies that are also in the cultural cluster at p=0.25, or they include countries that are economically much less advanced and are uncaptured within the social ties. This presents micro-level evidence on the absence of social relationships between specific countries, as social connections between clusters at p=0.5 are absent. Cultural cluster weights are furthermore, less than half of the valuation seen for economic and social weights (see Table 7). These missing micro-effects indicate that the social weights are oversimplified, leading to the underfitting observed in Figure 7.

6 Conclusion

In section 3.1.1, a research question was formalised, containing four sub-questions. The first of which being: "Given the macro and behavioural-micro requirements of the model, what modelling methodologies are most fit?". This first subquestion was answered in the section 3.2.1. It was found that CGE-ABM coupled models are the best fit, as the CGE keeps the behavioural modelling that the ABM provides intact, whilst delivering a detailed macro-economic environment. This combination was seen as best for migration, as economic environments play a significant role in migration decisions. Still, detailed economic macro-environments are difficult to simulate with just an ABM.

In section 4.2, the second subquestion was answered. Here, the included migration theories were selected. The foresight framework was chosen to pick the main elements of migration, being: economic, social, environmental, political and demographic. NELM was chosen for the economic micro-scores due to its close philosophical relation with ABMs. This was coupled with the push-pull theory to weigh the other foresight aspects. Later, it was determined that political weights do not hold significance for migration within the EU27 countries (see section 4.6.5).

In section 4.3, a first concept was developed. Input data and migrational behaviour were also created, giving a complete overview of model functionality. Climate scenarios and implementations were described, and model weights gathered. This provided an answer to the third subquestion, thus showing how a CGE-ABM coupled model can be developed for climate-induced migration.

In this section, the final subquestion is answered by examining the results of various metrics mentioned in section 5. These key metrics comprise the economic macro realism, which illustrates the effect of incorporating CGE models, and the macro-micro-based migration result, which highlights the novelty and implications of this model. This section further explains the model's contributions and impact; afterwards, the limitations are discussed, and finally, future research directions are given.

6.1 Key Findings

Table 9 shows the results of the key metrics described in the results of this thesis (5).

Table 9: Key model metrics and their corresponding results. These results stem from observations done in section 5. All results come from 100 Monte Carlo runs; if results imply comparisons between states, each state consists of 100 Monte Carlo runs.

Metric	**Result**
Effect of flooding on the differences in economic macro-environment for the EU27 countries.	Due to the increase in consumption caused by flooding events, wages experienced slight growth, as the flooding events were not extreme enough to bankrupt a significant number of firms, thus not driving unemployment up significantly. Single river flooding events were not disastrous enough, as country-wide economies showed resilience. This minimum effect showed to be in line with previous literature [19] [14], although inter-EU migration is little researched.
Effect of flooding on the different migration flows for the EU27 countries.	Due to simultaneous flooding, which increased the likelihood of movement within the sample population and increased consumption, lower-wage countries experienced a higher number of people leaving for higher-wage countries. This effect, combined with the lower emigration probabilities of high-wage countries, led to a minimal increase in flow to higher-wage countries, even when high-wage countries are simultaneously experiencing flooding.
Macro-based values regarding migration for the EU27 countries.	The CGE-ABM coupled model can generate macro-migration values built from micro-based decisions for the EU27 countries. This allows studying the flow within EU27 countries and identifying regions with large attraction, similar to what gravity models can offer. The correlation with real-world data for final population numbers (per sample of 10.000) was 0.77. Predictions of population flows within the EU27 countries correlated with 0.53, indicating a strong tendency towards under-fitting.
Micro-based values regarding migration for the EU27 countries.	Due to the micro-macro coupling, the model was able to look at individual household decision-making. For migration, the probability distributions of households showed that the relatively big differences in wages between EU27 countries had a significant impact on the probability of migration. Outliers for low-wage countries had lower migration probabilities. In comparison, outliers from high-wage countries had higher migration probabilities, indicating a larger migration pressure in the lower-wage countries. One explanation for this behaviour could lie in the observation that social, demographic and cultural effects are quite uniform within the EU27 countries. Economic differences cause the most significant differences in the sample population's migration probabilities. This is due to social, demographic, and cultural effects, which are more similar between countries.

Although the scenario analysis is not a focal point of this research, it must be noted that intra-EU climate-induced migration patterns remain a knowledge gap in current research. In academics, the EU is often taken as a destination point for migrants [14]. This, while inter-EU migration shows to be an interesting case-study due to the low costs associated with migration [66]. Due to the novelty, the scenario analysis does show interesting emergent relationships. Firstly, the flooding of just one river does not reach tipping points due to the resilience of higher-wage areas. The Netherlands showed to have endured the biggest impact from flooding. Still, it managed to recover within a time frame of 6 years (see Figure 26 in Appendix D.3). Due to the resilience of high-wage countries, they remained a migration hub even while suffering from flood-based events.

The final research question is: "Given the case of climate-induced migration, can a macro-micro coupled simulation model give more accurate behavioural insights while maintaining and utilising holistic realism?". To answer this final question, it was found that the model is capable of analysing and explaining micro-based behavioural aspects, as well as comparing states between climate scenarios. Determining holistic realism proved challenging, as the model exhibited underfitting for population flows. This shows to be a result of the lack of survey data and datasets containing accurate social ties. Even with a lack of data, a positive correlation of 0.53 and 0.77 was found for migration flows and migration numbers, respectively. Although not showing excellent holistic performance, results show there is reason for further data gathering and improvement of complex micro-macro-based behavioural modelling. Although the holistic realism is most challenging to obtain with such a model, it offers the benefits of explainability and more realistic evidence-based policy analysis.

6.2 Contribution and Implication

This thesis addressed the lack of micro-macro coupled climate-induced migration modelling, contributing to academic knowledge and evidence-based policy analysis in the process. As literature shows, macro-based methodologies lack accurate bottom-up decision-making processes and often struggle to include heterogeneity. This model bridges this gap in a novel way, allowing for the simulation of a precise macro-economy for household decisions. This model furthermore shows to be more explainable and transparent than the machine learning approach, as the ABM is programmed to follow the rules of migration theory, as opposed to black-box machine learning approaches.

This model additionally shows the possibility of climate-induced state comparison, which is beneficial for policy analysis. Model parameters regarding the economy are easily modified, aiding scenario-based policy analysis. Apart from policy state comparisons, climate-induced state changes can also be compared. To showcase this, an extemporary climate-scenario analysis was conducted. Due to the inclusion of a coupled CGE model, it becomes easier to analyse economic state changes as holistic economic realism is enhanced, giving policy makers and climate researchers a valuable tool for evidence-based policy analysis.

As a final contribution, the migration module, which consists of three migration theories, was submitted as a Reusable Building Block (RBB) [2]. The RBB project allows for the modularisation of (behavioural) modelling components. RBBs facilitate easier collaboration and provide access to well-regarded model-translated theories. The RBB includes purely the migration logic, making it possible to incorporate the migration logic for many different applications.

The implications of the model mainly consist of migration and policy analysis for the EU27 countries. The EU is constantly trying to incorporate modelling improvements into their policy assessments [26]. The ABM-CGE coupled model demonstrated that it is possible to examine the effects of flooding on migration numbers. Utilising different flood maps as input data, the model can be utilised to analyse household behaviours as a response to flooding. EU27 countries can furthermore utilise the model to test their policies; the model can be expanded to include flood-adaptation measures as described by Taberna et al. [78]. Leveraging the ample variable space: economic, social, cultural, and demographic aspects can be modified for policies. In the end, all these aspects come together to provide a tool that fosters a deeper understanding of the complex space regarding migration and informs sound policy.

The model furthermore showed interesting insights into the importance of economic variables within the EU. Showing that social, demographic, and cultural data are much more uniform across the EU27 countries than financial factors. Due to the asymmetry of mainly economics, this factor has a much bigger impact on the differences in migrant flows for the EU27 countries. Economic factors are furthermore much more volatile, meaning migration flows can be changed much more effectively with monetary policy as opposed to humanitarian policy.

6.3 Limitations

Current results indicate the model can improve, especially holistically. Multiple points of improvement have been identified. Firstly, the lack of extensive global/continental survey data makes it challenging to include heterogeneity that closely resembles the population. Due to this lack of data, the model's push-pull weights are based on literature regression weights, which compromises the model's heterogeneity. Secondly, the absence of data on real-world social ties between EU27 countries causes unexplained variance. The model now combines population and cultural similarity as an estimate of the social relations between nations. Replacing this with real-world social relationships between countries is expected to increase accuracy significantly. These data could also be obtained through surveys, making it possible to initiate this process in a heterogeneous manner. An alternative to surveys would be the utilisation of expert knowledge, as mentioned in the knowledge gap of this thesis (3.1. Conducting expert interviews, unfortunately, fell outside the scope of this thesis, but they can provide valuable insights and feedback.

Secondly, this model has reached close to the limit of what is computationally possible with Python-based ABMs. The model already required running in parallel on a supercomputer to reduce stochasticity (special thanks to DelftBlue [22]). To keep scaling up micro-based models, either an increase in computational power or efficiency would be required. Python is known to be an inefficient language in terms of runtime. Frameworks for languages like Julia have risen as more performative alternatives [1].

Thirdly, ABM modelling has limitations that result in less accurate holistic behaviour due to compounded errors at the modelling scale [4]. This is more fundamental to the methodology and can therefore not be easily addressed. ABMs generate emergent behaviours of systems from low-level micro interactions. This causes emergence on higher scales. If there are assumptions or errors at lower levels, these errors have a greater effect on higher levels due to emergence. This thesis attempted to mitigate some of these effects by coupling with a CGE model, supplying the ABM with a more realistic economic environment. The migration decision, however, remains prone to assumptions and data quality limitations, compounding towards the holistic level.

Unfortunately, most of the direct model improvements require high-quality, large-scale data, which is not yet readily accessible. Once accurate macro-level longitudinal survey data are available for the EU27 countries, this model can be used to get more accurate results. However, the micro-macro-based approach of the model has already proven to be a valuable addition to current academic research.

[1] https://github.com/JuliaDynamics/Agents.jl

6.4 Future Research

The current model exposes knowledge gaps in the current state of qualitative research regarding climate-induced migration. Future research, therefore, should first focus on the gathering of more longitudinal survey data and expert opinions regarding climate-induced migration data for larger areas. Privatised organisations conduct extensive area surveys, such as Gallup's World Poll [41], which makes the data closed source and difficult to verify. By conducting such surveys openly and transparently, barriers are decreased for methodologies that include micro-based elements. The same can be achieved by gathering more expert opinions and attempting to find a consensus. These expert opinions give better insights into how migration can be modelled accurately, supporting a more theoretically sound modelling foundation.

Future research could furthermore focus on tight-coupling ABM-CGE models. This research is still built upon soft-coupling, where ABM results are not fed back into the CGE model. By tightly coupling these two methodologies, macroeconomic aspects adapt to a changing situation rather than assuming stability or a particular scenario. This method of coupling requires more computational overhead but allows for a more realistic modelling environment.

Future research, moreover, should find ways to address current computational limitations. Models like the one described in this thesis could benefit from complete translations into more efficient frameworks. As mentioned, Julia and even R are popular choices for ABMs. Parallelisation could be used to distribute model load more efficiently over the available resources. As this thesis already showed, Monte-Carlo simulations can be distributed over different CPUs, giving much more time-efficient solutions to remove stochasticity. Models like the ABM-CGE coupled models could further benefit by parallelising the other countries, thus making single runs more time efficient.

Finally, this model could benefit from introducing policy analysis. As previously described, this model can be used to design or validate polices. Although policy design and validation fell outside of this thesis's scope, it remains a valid use case for the ABM-CGE coupled model. Future research could validate existing EU policy or attempt to design new ones to measure the effects they will have on migration. The model also supports climate-adaptation measures, showing further flexibility in policy assessment.

To conclude, the following overview shows the different directions future research could take:

- Due to the lack of qualitative large-scale data in micro-oriented models for migration, future research could gather these using longitudinal surveys on a continental scale.
- Due to the difficulty of understanding migration decision-making, future research could focus on gathering more expert interviews that support migration theory within the models.
- Future research can increase realism by tight-coupling ABM and CGE models.
- Due to the computational requirements of ABM models, future research could focus on translating Python-based ABMs to R or Julia. Future research could furthermore parallelise large-scale models for better time efficiency.
- Due to policy design and analysis falling outside the scope of this thesis, further research could attempt to introduce policy validation or design for the EU.

References

[1] PRISMA statement. URL https://www.prisma-statement.org/.

[2] Agent blocks – reusable building blocks for agent-based modelling. https://www.agentblocks.org/about, n.d. URL https://www.agentblocks.org/about. Open Access platform for sharing Reusable Building Blocks (no date).

[3] George H. Allen, Cédric H. David, Konstantinos M. Andreadis, Faisal Hossain, and James S. Famiglietti. Global Estimates of River Flow Wave Travel Times and Implications for Low-Latency Satellite Data. *Geophysical Research Letters*, 45(15):7551–7560, 4 2018. doi: 10.1029/2018gl077914. URL https://doi.org/10.1029/2018gl077914.

[4] Li An, Volker Grimm, Abigail Sullivan, B. L. Turner II, Nicolas Malleson, Alison Heppenstall, Christian Vincenot, Derek Robinson, Xinyue Ye, Jianguo Liu, Emilie Lindkvist, and Wenwu Tang. Challenges, tasks, and opportunities in modeling agent-based complex systems. *Ecological Modelling*, 457:109685, October 2021. ISSN 0304-3800. doi: 10.1016/j.ecolmodel.2021.109685.

[5] James Anderson. The gravity model. Technical report, 12 2010. URL https://doi.org/10.3386/w16576.

[6] Kazeem Alasinrin Babatunde, Rawshan Ara Begum, and Fathin Faizah Said. Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. *Renewable and Sustainable Energy Reviews*, 78:61–71, 5 2017. doi: 10.1016/j.rser.2017.04.064. URL https://doi.org/10.1016/j.rser.2017.04.064.

[7] Calum Baugh, Juan Colonese, Claudia D'Angelo, Francesco Dottori, Jeffrey Neal, Christel Prudhomme, and Peter Salamon. River flood hazard maps for europe and the mediterranean basin region, 2024. URL http://data.europa.eu/89h/1d128b6c-a4ee-4858-9e34-6210707f3c81. [Dataset].

[8] A.R. Bell, D.J. Wrathall, V. Mueller, J. Chen, M. Oppenheimer, M. Hauer, H. Adams, S. Kulp, P.U. Clark, E. Fussell, N. Magliocca, T. Xiao, E.A. Gilmore, K. Abel, M. Call, and A.B.A. Slangen. Migration towards bangladesh coastlines projected to increase with sea-level rise through 2100. *Environmental Research Letters*, 16(2), 2021. doi: 10.1088/1748-9326/abdc5b.

[9] Robert Beyer, Andrea Milan, and IOM Global migration data anlysis center. CLIMATE CHANGE AND HUMAN MOBILITY. Technical report, 2023.

[10] Robert M. Beyer, Jacob Schewe, and Guy J. Abel. Modeling climate migration: dead ends and new avenues. *Frontiers in Climate*, 5, August 2023. ISSN 2624-9553. doi: 10.3389/fclim.2023.1212649. URL https://www.frontiersin.org/journals/climate/articles/10.3389/fclim.2023.1212649/full.

[11] Alessandra Carioli, Marcello Schiavina, Sergio Freire, and Kytt MacManus. Ghs-pop r2023a - ghs population grid multitemporal (1975-2030). Dataset, 2023. URL http://data.europa.eu/89h/2ff68a52-5b5b-4a22-8f40-c41da8332cfe.

[12] Diana Carney. Implementing the sustainable rural livelihoods approach. Technical report, Overseas Development Institute, London, 1998.

[13] N. Choquette-Levy, M. Wildemeersch, M. Oppenheimer, and S.A. Levin. Risk transfer policies and climate-induced immobility among smallholder farmers. *Nature Climate Change*, 11(12):1046–1054, 2021. doi: 10.1038/s41558-021-01205-4.

[14] Maria Cipollina, Luca De Benedictis, and Elisa Scibè. Environmental migration? A systematic review and meta-analysis of the literature. *Review of World Economics*, 3 2024. doi: 10.1007/s10290-024-00529-5. URL https://doi.org/10.1007/s10290-024-00529-5.

[15] ClimateCheck, Inc. What are the flood zones in fema maps – a-x. https://climatecheck.com/risks/flood/what-are-the-flood-zones-in-fema-maps, 2025. Accessed: 2025-09-03.

[16] European Commision. Floods, 7 2025. URL https://environment.ec.europa.eu/topics/water/floods_en#:~:text=Overview,for%20both%20people%20and%20nature.

[17] European commission. URL https://research-and-innovation.ec.europa.eu/research-area/social-sciences-and-humanities/migration-and-mobility_en.

[18] Fabien Cottier. Projecting future migration with Bayesian hierarchical gravity models of migration: an application to Africa. *Frontiers in Climate*, 6, 12 2024. doi: 10.3389/fclim.2024.1384295. URL https://doi.org/10.3389/fclim.2024.1384295.

[19] Hein De Haas. Mediterranean migration futures: Patterns, drivers and scenarios. *Global Environmental Change*, 21:S59–S69, 10 2011. doi: 10.1016/j.gloenvcha.2011.09.003. URL https://doi.org/10.1016/j.gloenvcha.2011.09.003.

[20] Hein de Haas. A theory of migration: the aspirations-capabilities framework. *Comparative Migration Studies*, 9(1):8, February 2021. ISSN 2214-594X. doi: 10.1186/s40878-020-00210-4.

[21] Alex de Sherbinin, Kathryn Grace, Sonali McDermid, Kees van der Geest, Michael J. Puma, and Andrew Bell. Migration theory in climate mobility research. *Frontiers in Climate*, 4, May 2022. ISSN 2624-9553. doi: 10.3389/fclim.2022.882343. URL https://www.frontiersin.org/journals/climate/articles/10.3389/fclim.2022.882343/full.

[22] Delft High Performance Computing Centre (DHPC). DelftBlue Supercomputer (Phase 2). https://www.tudelft.nl/dhpc/ark:/44463/DelftBluePhase2, 2024.

[23] B. Entwisle, N. Williams, and A. Verdery. Climate change and migration: New insights from a dynamic model of out-migration and return migration. *American Journal of Sociology*, 125(6):1469–1512, 2020. doi: 10.1086/709463.

[24] EU. volume 251. July 2021. URL http://data.europa.eu/eli/reg/2021/1147/oj/eng. Legislative Body: CONSIL, EP.

[25] EU, 2024. URL https://data.europa.eu/en/publications/datastories/unlocking-potential-open-data.

[26] European Commission. Modelling tools for eu analysis. https://climate.ec.europa.eu/eu-action/climate-strategies-targets/economic-analysis/modelling-tools-eu-analysis_en, 2025. Accessed: 2025-09-09.

[27] European Commission. Sweden – cap strategic plan. https://agriculture.ec.europa.eu/cap-my-country/cap-strategic-plans/sweden_en, 2025. URL https://agriculture.ec.europa.eu/cap-my-country/cap-strategic-plans/sweden_en. Accessed September 13, 2025.

[28] European Commission, Eurostat. Avarage wages. https://doi.org/10.2908/EARN_NT_NET, 2025.

[29] European Commission, Eurostat. Minimum wages. http://data.europa.eu/88u/dataset/gicnh24uvraqmknqji7s6q, 2025. Original work published 2009.

[30] European Union. Directive (eu) 2019/1024 on open data and the re-use of public sector information (psi directive). https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1561563110433&uri=CELEX:32019L1024, 2019. Accessed: 2025-09-01.

[31] European Union. Bulgaria – eu country profile, July 26 2025. URL https://european-union.europa.eu/principles-countries-history/eu-countries/bulgaria_en. Geraadpleegd op 26 juli 2025.

[32] European Union. Facts and figures on the european union. Online, July 2025. URL https://europeanâĂŞunion.europa.eu/principlesâĂŞcountriesâĂŞhistory/factsâĂŞandâĂŞfiguresâĂŞeuropeanâĂŞunion_en. Accessed 2025-07-21 at https://europeanâĂŞunion.europa.eu/principlesâĂŞcountriesâĂŞhistory/factsâĂŞandâĂŞfiguresâĂŞeuropeanâĂŞunion_en.

[33] Eurostat. Immigration by age group, sex and country of previous residence [migr_imm5prv]. Online database, 2024. URL https://doi.org/10.2908/MIGR_IMM5PRV. Accessed 2025.

[34] Eurostat. Migration and asylum in europe – 2024 edition: Free movement of persons in the eu. https://ec.europa.eu/eurostat/web/interactive-publications/migration-2024#free-movement-of-persons-in-the-eu, December 2024. ISSN 2600-3368. Interactive publication, accessed 2025-08-02.

[35] Eurostat. Population by educational attainment level, sex, and age (https://ec.europa.eu/eurostat/web/products-datasets/-/edat_lfs_9903, 2025. URL https://doi.org/10.2908/EDAT_LFS_9903. Accessed: 2025-07-20.

[36] Eurostat. Unemployment by sex and age – monthly data (une_rt_m). https://doi.org/10.2908/UNE_RT_M, 2025. Last update: July 7, 2025.

[37] Eurostat. Gdp per capita, consumption per capita and price level indices, June 18 2025. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=GDP_per_capita,_consumption_per_capita_and_price_level_indices. Geïnspireerd door de data van 18 juni 2025, geplande update 17 december 2025.

[38] Tatiana Filatova, Brayton Noll, Ariana Need, and Thorid Wagenblast. SCALAR household climate change adaptation and resilience survey, 2022. URL https://doi.org/10.17026/dans-x9h-nj3w.

[39] Jay W. Forrester. System dynamics, systems thinking, and soft or. *System Dynamics Review*, 10 (2–3):245–256, 1994. ISSN 1099-1727. doi: 10.1002/sdr.4260100211.

[40] A. S. Fotheringham. *Spatial Interaction Models*, page 14794–14800. Pergamon, Oxford, January 2001. ISBN 978-0-08-043076-8. doi: 10.1016/B0-08-043076-7/02519-5. URL https://www.sciencedirect.com/science/article/pii/B0080430767025195.

[41] Gallup, Inc. Gallup world poll and global survey research. https://www.gallup.com/analytics/318875/global-research.aspx, 2025. Accessed: 2025-09-09.

[42] L.M. Harbach, D. Groen, A. Jahani, D. Suleimenova, M. Ghorbani, and Y. Xue. A conceptual approach to agent-based modelling of coping mechanisms in climate-driven flooding in bangladesh. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 14836 LNCS:421–428, 2024. doi: 10.1007/978-3-031-63775-9_31.

[43] Roman Hoffmann, Barbora Šedová, and Kira Vinke. Improving the evidence base: A methodological review of the quantitative climate migration literature. *Global Environmental Change*, 71:102367, 9 2021. doi: 10.1016/j.gloenvcha.2021.102367. URL https://doi.org/10.1016/j.gloenvcha.2021.102367.

[44] IOM. Drivers of international migration | EMM2, 2020. URL https://emm.iom.int/handbooks/global-context-international-migration/drivers-international-migration#:~:text=There%20are%20five%20primary%20macrolevel,from%20one%20location%20to%20another.

[45] O. Ivanova, d. Kancs, and M. Thissen. *EU economic modelling system – Assessment of the European Institute of Innovation and Technology (EIT) investments in innovation and human capital.* Publications Office, 2016. doi: doi/10.2791/184008.

[46] C. Jaipiam. Economic impacts of climate change in thailand: Theory and evidence. *Southeast Asian Journal of Economics*, 12(1):77–124, 2024.

[47] Pilat Krastev. Bounded rationality - the decision lab, 2025. URL https://thedecisionlab.com/biases/bounded-rationality.

[48] Everett S. Lee. A theory of migration. *Demography*, 3(1):47–57, 1966. ISSN 00703370, 15337790. URL http://www.jstor.org/stable/2060063.

[49] Seung Man Lee and Amy R. Pritchett. Predicting interactions between agents in agent-based modeling and simulation of sociotechnical systems. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 38(6):1210–1220, 2008. doi: 10.1109/TSMCA.2008.2001059.

[50] Silvia Migali, Fabrizio Natale, Guido Tintori, Sona Kalantaryan, Sara Grubanov-Boskovic, Marco Scipioni, Fabio Farinosi, Cristina Cattaneo, Barbara Benandi, Marco Follador, Giovanni Bidoglio, Thomas Barbas, and Simon McMahon. International migration drivers: A quantitative assessment of the structural factors shaping migration. Technical Report EUR29333 EN, Joint Research Centre, Publications Office of the European Union, Luxembourg, September 2018. URL https://publications.jrc.ec.europa.eu/repository/handle/JRC112622.

[51] Migration Policy Institute. Romanian migration to spain: Explaining an unexpected migrant flow. *Migration Policy Institute*, September 2022. URL https://www.migrationpolicy.org/article/romanian-migrants-spain. Online; accessed 2025-08-07.

[52] Mark Mulligan, Sophia Burke, and Caitlin Douglas. *Environmental Change and Migration Between Europe and Its Neighbours*, page 49–79. Springer Netherlands, Dordrecht, 2014. ISBN 978-94-007-6985-4. doi: 10.1007/978-94-007-6985-4_3. URL https://doi.org/10.1007/978-94-007-6985-4_3.

[53] E.L. Nelson, S.A. Khan, S. Thorve, and P.G. Greenough. Modeling pastoralist movement in response to environmental variables and conflict in somaliland: Combining agent-based modeling and geospatial data. *PLoS ONE*, 15(12 December), 2020. doi: 10.1371/journal.pone.0244185.

[54] K. Bruce Newbold. *Dynamic Migration Modeling*. 1 2005. doi: 10.1016/b0-12-369398-5/00363-7. URL https://doi.org/10.1016/b0-12-369398-5/00363-7.

[55] Leila Niamir, Olga Ivanova, and Tatiana Filatova. Economy-wide impacts of behavioral climate change mitigation: Linking agent-based and computable general equilibrium models. *Environmental Modelling Software*, 134:104839, 8 2020. doi: 10.1016/j.envsoft.2020.104839. URL https://doi.org/10.1016/j.envsoft.2020.104839.

[56] Z. Nourali, J.E. Shortridge, A. Bukvic, Y. Shao, and J.L. Irish. Simulation of flood-induced human migration at the municipal scale: A stochastic agent-based model of relocation response to coastal flooding. *Water (Switzerland)*, 16(2), 2024. doi: 10.3390/w16020263.

[57] numbeo. Understanding our Cost of Living Indexes, 2024. URL https://www.numbeo.com/cost-of-living/rankings_by_country.jsp?title=2024&region=150.

[58] OECD. *Taxing Wages 2025: Decomposition of Personal Income Taxes and the Role of Tax Reliefs*. OECD Publishing, Paris, 2025. doi: 10.1787/b3a95829-en. URL https://doi.org/10.1787/b3a95829-en.

[59] Publications Office of the European Union. EU economic modelling system : assessment of the European Institute of Innovation and Technology (EIT) investments in innovation and human capital., 2016. URL https://op.europa.eu/en/publication-detail/-/publication/74bde06e-e591-11e9-9c4e-01aa75ed71a1/language-en.

[60] Morton E. O'Kelly. doi: 10.1016/B978-008044910-4.00529-0. URL https://www.researchgate.net/publication/297714323_Spatial_Interaction_Models.

[61] P. Oliva. Migration and the environment: A look across perspectives. *Regional Science and Urban Economics*, 107, 2024. doi: 10.1016/j.regsciurbeco.2024.104005.

[62] Steven F. Railsback and Volker Grimm. *Agent-based and Individual-based Modeling*. 1 2012.

[63] Hugh B. Roland. Compelled and constrained migration: restrictions to migration agency in the Marshall Islands. *Frontiers in Climate*, 5, 8 2023. doi: 10.3389/fclim.2023.1212780. URL https://doi.org/10.3389/fclim.2023.1212780.

[64] Michele Ronco, José María Tárraga, Jordi Muñoz, María Piles, Eva Sevillano Marco, Qiang Wang, Maria Teresa Miranda Espinosa, Sylvain Ponserre, and Gustau Camps-Valls. Exploring interactions between socioeconomic context and natural hazards on human population displacement. *Nature Communications*, 14(1), 12 2023. doi: 10.1038/s41467-023-43809-8. URL https://doi.org/10.1038/s41467-023-43809-8.

[65] Simcha Ronen and Oded Shenkar. Mapping world cultures: Cluster formation, sources and implications. *Journal of International Business Studies*, 44(9):867–897, 2013. ISSN 00472506, 14786990. URL http://www.jstor.org/stable/43653701.

[66] Kristina Sargent. Unpacking migration costs: Heterogeneous effects in EU labor markets. *Economic Modelling*, 139:106816, 10 2024. doi: 10.1016/j.econmod.2024.106816. URL https://doi.org/10.1016/j.econmod.2024.106816.

[67] Thomas C. Schelling. Dynamic models of segregation†. *The Journal of Mathematical Sociology*, 1 (2):143–186, July 1971. ISSN 0022-250X. doi: 10.1080/0022250X.1971.9989794.

[68] K. Schewel, S. Dickerson, B. Madson, and G. Nagle Alverio. How well can we predict climate migration? a review of forecasting models. *Frontiers in Climate*, 5, 2023. doi: 10.3389/fclim.2023.1189125.

[69] Dagmar Schroter, Wolfgang Cramer, Rik Leemans, I. Colin Prentice, Miguel B. Araujo, Nigel W. Arnell, Alberte Bondeau, Harald Bugmann, Timothy R. Carter, Carlos A. Gracia, Anne C. De La Vega-Leinert, Markus Erhard, Frank Ewert, Margaret Glendining, Joanna I. House, Susanna Kankaanpaa, Richard J. T. Klein, Sandra Lavorel, Marcus Lindner, Marc J. Metzger, Jeannette Meyer, Timothy D. Mitchell, Isabelle Reginster, Mark Rounsevell, Santi Sabate, Stephen Sitch, Ben Smith, Jo Smith, Pete Smith, Martin T. Sykes, Kirsten Thonicke, Wilfried Thuiller, Gill Tuck, Sonke Zaehle, and Barbel Zierl. Ecosystem Service Supply and Vulnerability to Global Change in Europe. *Science*, 310(5752):1333–1337, 10 2005. doi: 10.1126/science.1115233. URL https://doi.org/10.1126/science.1115233.

[70] Barbora Sedova and Matthias Kalkuhl. Who are the climate migrants and where do they go? Evidence from rural India. *World Development*, 129:104848, 1 2020. doi: 10.1016/j.worlddev.2019.104848. URL https://doi.org/10.1016/j.worlddev.2019.104848.

[71] Filippo Simini, Marta C. González, Amos Maritan, and Albert-László Barabási. A universal model for mobility and migration patterns. *Nature*, 484(7392):96–100, February 2012. ISSN 1476-4687. doi: 10.1038/nature10856.

[72] Herbert A. Simon. A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69 (1):99–118, 1955. doi: 10.2307/1884852. URL https://doi.org/10.2307/1884852.

[73] Larry A. Sjaastad. The costs and returns of human migration. *Journal of Political Economy*, 70(5): 80–93, 1962. ISSN 00223808, 1537534X. URL http://www.jstor.org/stable/1829105.

[74] L.H. Speelman, R.J. Nicholls, and R. Safra de Campos. The role of migration and demographic change in small island futures. *Asian and Pacific Migration Journal*, 30(3):282–311, 2021. doi: 10.1177/01171968211044082.

[75] Oded Stark and David E. Bloom. The new economics of labor migration. *The American Economic Review*, 75(2):173–178, 1985. URL http://www.jstor.org/stable/1805591. Accessed 2 July 2025.

[76] Iván Claudio Suazo-Galdames, Mahia Saracostti, and Alain Manuel Chaple-Gil. Scientific evidence and public policy: a systematic review of barriers and enablers for evidence-informed decision-making. *Frontiers in Communication*, 10, 7 2025. doi: 10.3389/fcomm.2025.1632305. URL https://doi.org/10.3389/fcomm.2025.1632305.

[77] A. Taberna, T. Filatova, A. Roventini, and F. Lamperti. Exploring regional agglomeration dynamics in face of climate-driven hazards: Insights from an agent-based computational economic model. page 145–160, 2022. doi: 10.1007/978-3-030-92843-8_12.

[78] A. Taberna, T. Filatova, A. Roventini, and F. Lamperti. Coping with increasing tides: Evolving agglomeration dynamics and technological change under exacerbating hazards. *Ecological Economics*, 202, 2022. doi: 10.1016/j.ecolecon.2022.107588.

[79] L. Tierolf, T. Haer, W.J.W. Botzen, J.A. de Bruijn, M.J. Ton, L. Reimann, and J.C.J.H. Aerts. A coupled agent-based model for france for simulating adaptation and migration decisions under future coastal flood risk. *Scientific Reports*, 13(1), 2023. doi: 10.1038/s41598-023-31351-y.

[80] L. Tierolf, T. Haer, P. Athanasiou, A.P. Luijendijk, W.J.W. Botzen, and J.C.J.H. Aerts. Coastal adaptation and migration dynamics under future shoreline changes. *Science of the Total Environment*, 917, 2024. doi: 10.1016/j.scitotenv.2024.170239.

[81] T.T. Trinh and A. Munro. Integrating a choice experiment into an agent-based model to simulate climate-change induced migration: The case of the mekong river delta, vietnam. *Journal of Choice Modelling*, 48, 2023. doi: 10.1016/j.jocm.2023.100428.

[82] TutorChase. A2.1 hydrograph characteristics, n.d. URL https://www.tutorchase.com/notes/ib/geography/a-2-1-hydrograph-characteristics. Accessed: 2025-09-03.

[83] Katharina Van Baal, Stephanie Stiel, and Peter Schulte. Public Perceptions of Climate Change and Health—A Cross-Sectional Survey Study. *International Journal of Environmental Research and Public Health*, 20(2):1464, 1 2023. doi: 10.3390/ijerph20021464. URL https://pmc.ncbi.nlm.nih.gov/articles/PMC9859516/.

[84] Songmin Yu. An agent-based framework for policy simulation: Modeling heterogeneous behaviors with modified sigmoid function and evolutionary training. *IEEE Transactions on Computational Social Systems*, 10(4):1901–1913, 2023. doi: 10.1109/TCSS.2022.3196737.

[85] Wilbur Zelinsky. The hypothesis of the mobility transition. *Geographical Review*, 61(2):219–249, 1971. ISSN 00167428, 19310846. URL http://www.jstor.org/stable/213996.

[86] Zurich, October 2024. URL https://www.zurich.com/media/magazine/2022/there-could-be-1-2-billion-climate-refugees-by-2050-here-s-what-you-need-to-know.

A Statement on the use of generative AI

For the writing of this MSc. thesis, Grammarly [2] was used to check grammar errors and overall flow. AI wrote no text. For data analysis, GitHub Co-Pilot [3] was utilized, allowing for more swift analysis. All code has been thoroughly checked and implemented only when fully understood. For the model code, all code was written by hand. Co-Pilot did aid some debugging steps.

[2] https://app.grammarly.com/
[3] https://github.com/features/copilot

B Tables

B.1 Migration theories

In the review of Sherbinin et al. [21], different migration theories are discussed. To gain an understanding of the scopes of these theories, they are summed up in Table 10. Here, each of the theories has been given a scope. The smallest scope considers individual levels (e.g. neoclassical migration theory). The most extensive scope considers societies (e.g. Mobility transition theory). Households are the largest, still micro-based, assumed scope. The macro scope considers a description of a migration system as a whole without discussing individual behaviours. Meso falls in between these two, assessing the behaviours of particular groups of people.

Table 10: Overview of migration theories and their scopes [21]

Theory	**Scope (Micro, Meso, Macro)**
Neoclassical migration theory	Macro (Primarily), Micro
Push-pull theory	Micro, Meso
New economics of labour migration (NELM)	Micro
Mobility transition theory	Macro
Forced migration theory	Macro, Meso
Theories Addressing Sustained Migration	Macro, meso, micro
Aspirations and Capabilities	Micro
Livelihood framework	Micro

B.2 Climate-induced migration ABMs

Table 11: Literature that utilises ABMs to research human migration on a holistic system level. The following search query was utilized: "Abstract: agent-based OR 'ABM' AND migration AND climate". Scopus was utilized as a database for the search.

Article	Goal	Modeling technique
Coastal adaptation and migration dynamics under future shoreline changes [80]	To develop a model that shows migrational dynamics and adaptation of households under sea level rise	ABM, gravitational model
A Conceptual Approach to Agent-Based Modelling of Coping Mechanisms in Climate-Driven Flooding in Bangladesh [42]	To develop a model in helping to understand the social and economical challenges Bangladesh faces in combating increased flooding risks	ABM
Simulation of Flood-Induced Human Migration at the Municipal Scale: A Stochastic Agent-Based Model of Relocation Response to Coastal Flooding [56]	To narrow down human flood migration models to a municipal scale to capture areas often overlooked in migrational research	ABM
A coupled agent-based model for France for simulating adaptation and migration decisions under future coastal flood risk [79]	To research flooding-induced human migration in France, coupling an ABM with a gravitational model (DYNAMO-M)	ABM, gravitational model
Integrating a choice experiment into an agent-based model to simulate climate-change induced migration: The case of the Mekong River Delta, Vietnam [81]	To enhance migration decision of ABM agents in the Mekong Delta using a choice experiment and multiple climate-induced decision factors	ABM
How well can we predict climate migration? A review of forecasting models [68]	To review the literature on the effectiveness of different climate migration models	ABM, gravity, radiation, agent-based, systems dynamics, statistical extrapolation models, CGE models, ...
Coping with increasing tides: Evolving agglomeration dynamics and technological change under exacerbating hazards [78]	To research the effects floodings have on the economic and spatial dynamics of inland and coastal migration	ABM
Exploring Regional Agglomeration Dynamics in the Face of Climate-Driven Hazards: Insights from an Agent-Based Computational Economic Model [77]	To research the trade off between agglomeration economics of firms and environmental hazards with an out-of-equilibrium approach	ABM
Risk transfer policies and climate-induced immobility among smallholder farmers [13]	To research the effect of temperature rise on farmer behaviors, including migration	ABM
The role of migration and demographic change in small island futures [74]	To research the effects of environmental changes on small island migration streams	ABM
Migration towards Bangladesh coastlines projected to increase with sea-level rise through 2100 [8]	To research the effects of flooding on the migration to Bangladesh coastlines, considering socio-economic influences	ABM

Article	**Goal**	**Modeling technique**
Modeling pastoralist movement in response to environmental variables and conflict in Somaliland: Combining agent-based modeling and geospatial data [53]	To research the effects of multiple climate variables and conflict on the movements of pastoralists in Somaliland	ABM
Climate change and migration: New insights from a dynamic model of out-migration and return migration [23]	To research the effects of climate change on migration using a case study looking at the impact of floods and droughts in Northeast Thailand	ABM

B.3 ARIMA(1,0,0) model for unemployement

Due to unemployment not always directly caused by not being able to find work, a threshold is established using a simple time series model. This model is extracted from historical unemployment figures for the EU27 countries. Table 12 shows the coefficients found. Not all values are significant when taking a threshold of p=0.1; these time series did not go back far enough for some countries. This insignificance causes the time series to be less representative for the first time steps. Still, as these time series quickly converge to the average, it does not hold significant implications.

Table 12: ARIMA(1,0,0) coefficients for unemployment across the 27 European countries. * AR value not significant ($p < 0.1$)

Country	**c**	ϕ_1	ϵ_t	U_1
FR	0.853753	-0.171451	7.022148	6.0
IT	0.882657	-0.928387	7.304730	5.7
RO	0.582930	0.073221	5.664927	4.2
ES	0.834315	0.051866	15.059533	10.2
GR	0.903711	-0.435781	12.612889	9.4
DE	0.841291	0.433202	4.293651	3.0
BE	0.637876	0.234284	5.911225	4.7
BG	0.787376	0.461442	6.858112	3.8
AT*	0.423333	-0.149161	4.817540	4.5
HU	0.792925	1.002540	5.756901	3.8
PL	0.763841	0.724899	5.050569	2.3
CZ	0.753644	0.490556	3.873403	2.2
PT	0.785888	0.596358	8.566701	5.3
SK	0.692716	0.293359	8.157013	4.6
HR	0.866366	-0.254063	7.673314	4.2
IE	0.728408	0.917876	7.402329	3.4
NL	0.856236	0.296390	4.066526	2.6
SI	0.866161	0.244626	5.079563	3.1
LU*	0.388850	0.583632	4.617364	5.1
SE	0.300114	0.222626	5.726035	6.2
LT*	0.530515	1.323538	8.933793	6.5
FI	0.483378	0.949455	6.548194	7.1
CY	0.867091	-0.566431	6.436154	4.3
EE	0.647310	1.899655	7.542702	6.5
LV	0.595925	1.370853	9.899834	6.4
MT*	0.248578	-0.059840	3.972017	2.5
DK*	0.340376	0.868658	5.011550	4.7

B.4 Sensitivity variations of weights

The sensitivity analysis varies the weights for the economy (α), distance (β), cultural similarity (γ), and social networking (ϵ). Table 13 shows how these weights have been varied.

Table 13: Sensitivity variations of the push-pull weights by ± 10% and ± 20%, respectively.

Variation	α	β	γ	ξ
Base values	0.4256	0.433	0.149	0.1842
$\alpha + 10\%$	0.4682	0.433	0.149	0.1842
$\alpha - 10\%$	0.3830	0.433	0.149	0.1842
$\alpha + 20\%$	0.5107	0.433	0.149	0.1842
$\alpha - 20\%$	0.3405	0.433	0.149	0.1842
$\beta + 10\%$	0.4256	0.4763	0.149	0.1842
$\beta - 10\%$	0.4256	0.3897	0.149	0.1842
$\beta + 20\%$	0.4256	0.5196	0.149	0.1842
$\beta - 20\%$	0.4256	0.3464	0.149	0.1842
$\gamma + 10\%$	0.4256	0.433	0.1639	0.1842
$\gamma - 10\%$	0.4256	0.433	0.1341	0.1842
$\gamma + 20\%$	0.4256	0.433	0.1788	0.1842
$\gamma - 20\%$	0.4256	0.433	0.1192	0.1842
$\epsilon + 10\%$	0.4256	0.433	0.149	0.2026
$\epsilon - 10\%$	0.4256	0.433	0.149	0.1658
$\epsilon + 20\%$	0.4256	0.433	0.149	0.2210
$\epsilon - 20\%$	0.4256	0.433	0.149	0.1474

C Model input data processing

C.1 CGE input data

The CGE input data consists of capital output ratios, consumption shares, demand for intermediate goods, import shares and export shares. These variables are utilised to regulate the economy in the ABM model. In this section, a short overview of these variables is given.

Firstly, the capital to output ratios are utilised to determine the production of firms, thus influencing the productivity in general of the EU27 countries. This variable represents the amount of capital it takes to produce one unit of output. The distribution of the capital to output ratios is given in the Figure.

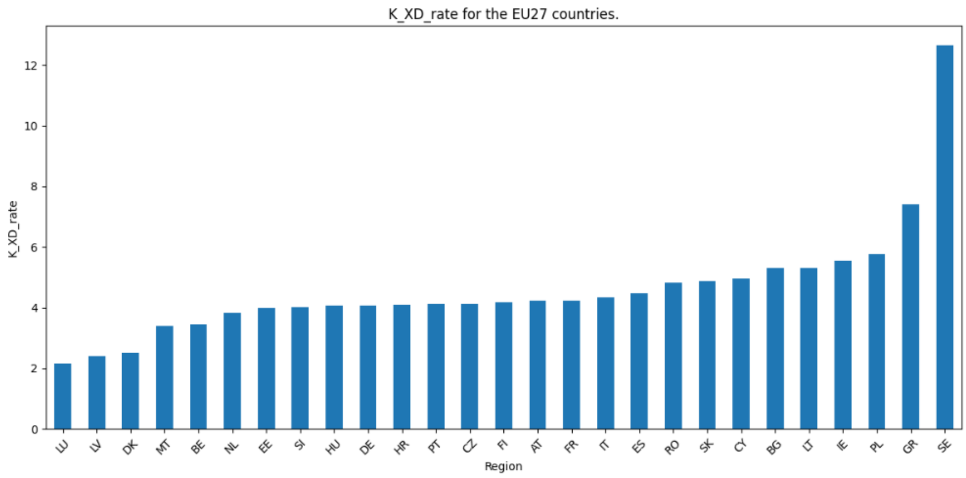


Figure 14: Capital to output ratios as input data from the CGE model, ratios are averages of the normalised fractions of all nine industries.

The reason Sweden has such a high ratio is solely due to the Agriculture sector. This sector has a value of almost 90. Agriculture makes up less than 1% of Sweden's GDP [27], meaning the impact is negligible.

Secondly, household consumption is normalised for each of the sections to serve as a fraction of the total market. Consumption is the consumer consumption, as it is calculated by multiplying the household's consumption by the firm's production. This way, regional demands for each sector are a fraction of the total consumer consumption. The demand gets calculated by each government of the EU27 countries, feeding the market shares to the firms. The distribution for the consumer consumption of the EU27 countries is given in Figure 15.

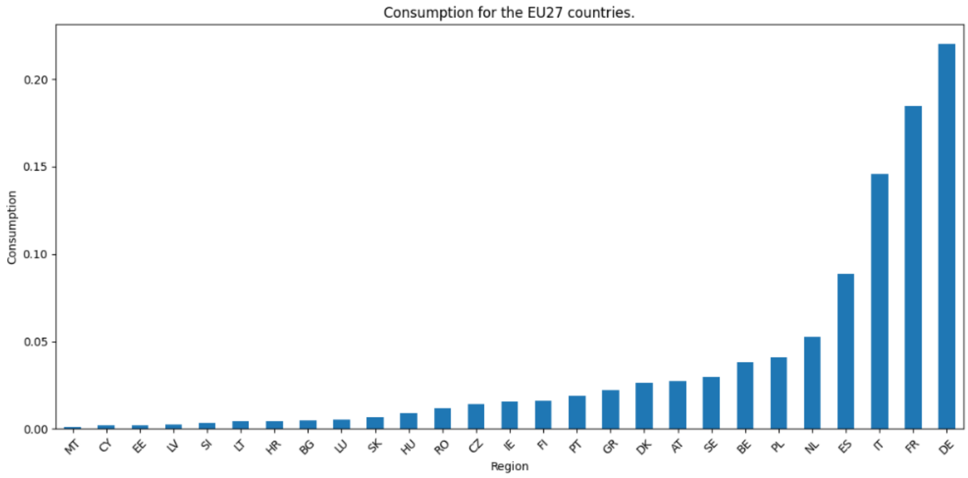


Figure 15: Consumer consumption fractions as input data from the CGE model, fractions are averages of the normalised fractions of all nine industries.

Thirdly, regional demands are enhanced by the needs of firms. This is achieved by adding the demands of firms to the total regional demand. This shows how much firms consume in relation to the domestic market. This demand factor is often called the intermediate demand. The distribution in Figure 16 shows this intermediate demand factor.

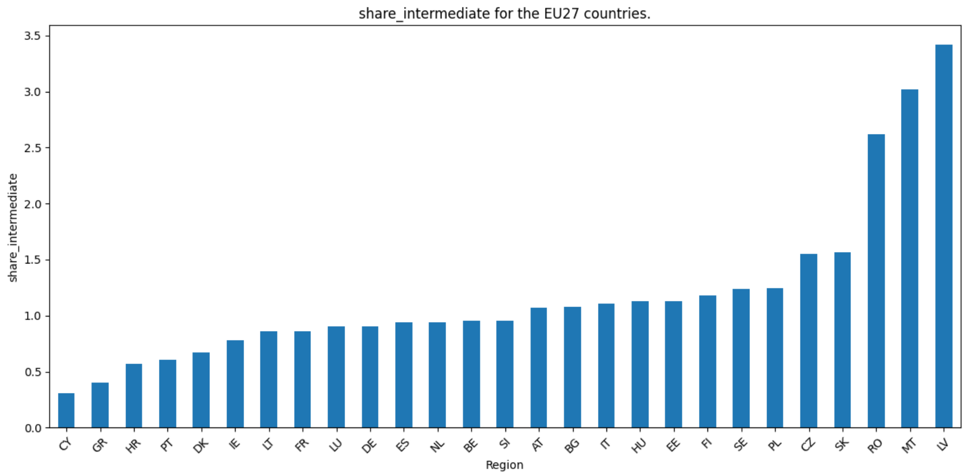
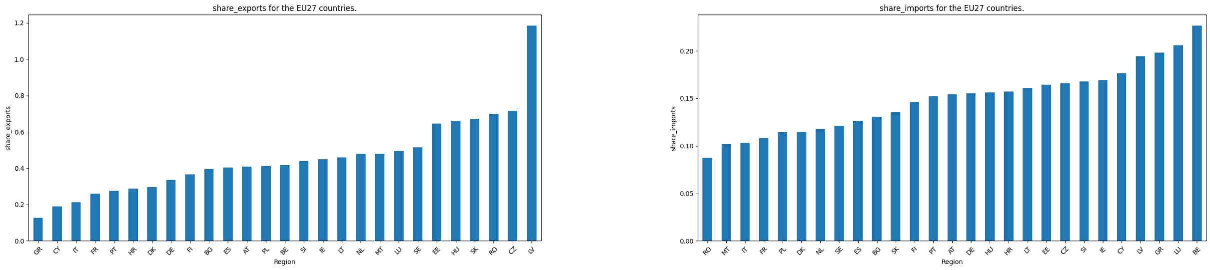


Figure 16: The intermediate demand as a factor of overall local consumer consumption as generated by the CGE model. Values are averages of all nine firm types.

The final two variables are import and export factors in relation to the overall domestic market. As factors, they can be easily multiplied by the regional demands. If countries have high export factors and low import factors, it means they need productive firms to bridge these gaps. Figure 17 provides the import and export distributions.



(a) Share exports of overall domestic market numbers for the EU27 countries. Values are averages of all nine firm types.

(b) Share imports of overall domestic market numbers for the EU27 countries. Values are averages of all nine firm types.

Figure 17: CGE generated import and export shares that act as a factor of the overall domestic market of the EU27 countries. Values are averages of all nine firm types.

Figures 16, 17, show factors of the overall domestic market demands. This means that they are all derived from the consumption shown in Figure 15. Therefore, the most important for the overall model economy are the consumption figures and labour to output ratios. It is important to note that the values shown are averages of nine types of firms. Therefore, some firm types may skew these averages, but they might only make up a small portion of the regional market.

C.2 Flood depth inputs

In this section, the preprocessing of the flood depth map will be described. The flood depth map was used to generate flood depths along the Rhine and Danube; this required modifications to an EU-wide flood depth map. The original flood map contains a very high amount of depth points all across Europe [7]. This was first reduced with a geographic filter to just the Rhine and Danube. Next, the flood depths were scaled with a density filter [11].

Examining flood depths at the level of entire countries reveals that when just one River in the country floods in an extreme manner, many of the country's flood depth points fall outside the flooded areas. Among all EU27 countries along the Rhine and Danube, the Netherlands has the highest population density in flooded areas. The distribution of flood depths for the Netherlands is given in Figure 18.

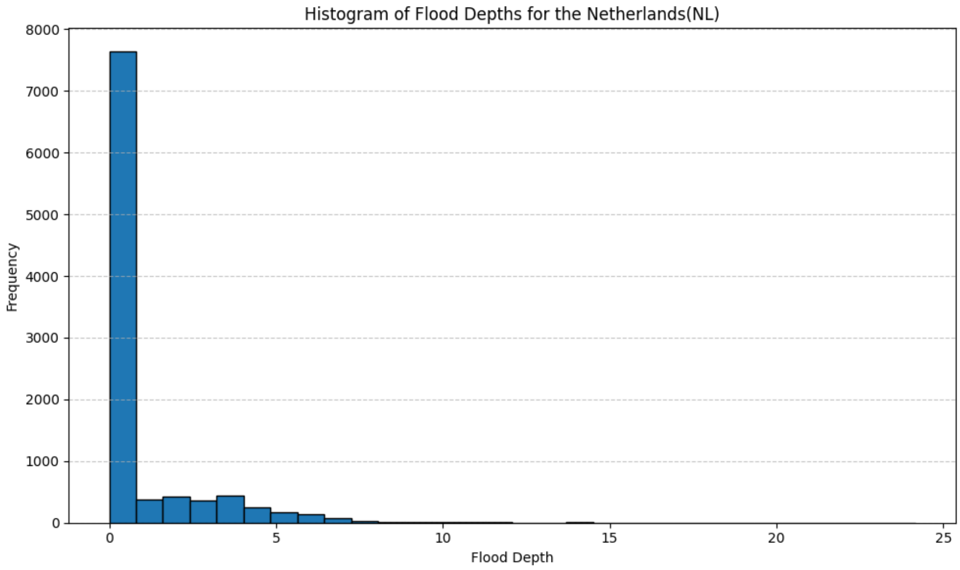


Figure 18: Flood depth distribution for the Netherlands after adjusting for population density. Flood depths are taken from a 100Km band along the Rhine and Danube.

The distribution shows that there are considerable flood depths for a small portion of the Population in the Netherlands. It also shows that on the population level, the EU27 countries have few households affected by floods. This highlights the need to flood large areas to protect a significant portion of the population affected by floods. The model still showed that countries are nonetheless affected by the flooding of the Rivers, affecting migration. The scale effect is, however, small, as can be explained in part by the skewed flood depth distribution.

D Additional materials

D.1 Climate worry among households

An attempt was made to extract climate perception from Dutch household survey data using a mixed logit. In the survey, questions were asked regarding how worried households were about climate change. Further in the survey, the respondents were introduced to a choice experiment. Here respondents got three options: move, stay and adapt. The options were for three scenarios: no flooding, moderate flooding and heavy flooding. If there was a relationship between climate worry and willingness to move, this could be introduced as a heterogeneous aspect in the model. From the analysis, no significance was found.

Figure 19 already shows that there is little relation between worry and willingness to move in the data. Very few datapoints expressed the highest level of worry, already indicating there is a low probability of finding population-wide significance.

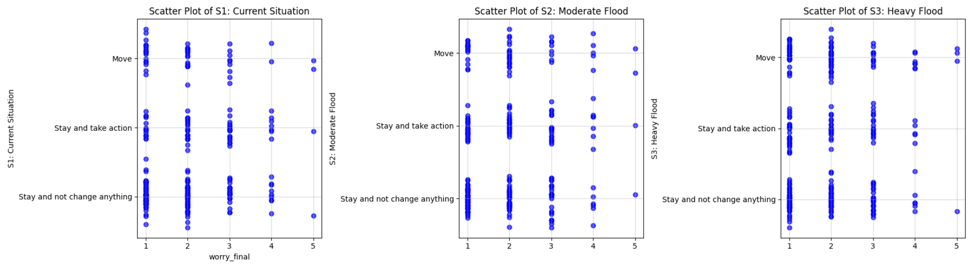


Figure 19: Household sample data illustrating the relationship between worry and willingness to move/adapt across three scenarios, varying in flooding severity. Later in the analysis, no significant difference between these variables was found.

D.2 Model architecture

Figure 20 shows how a migration decision is made by the decision-making unit (households).

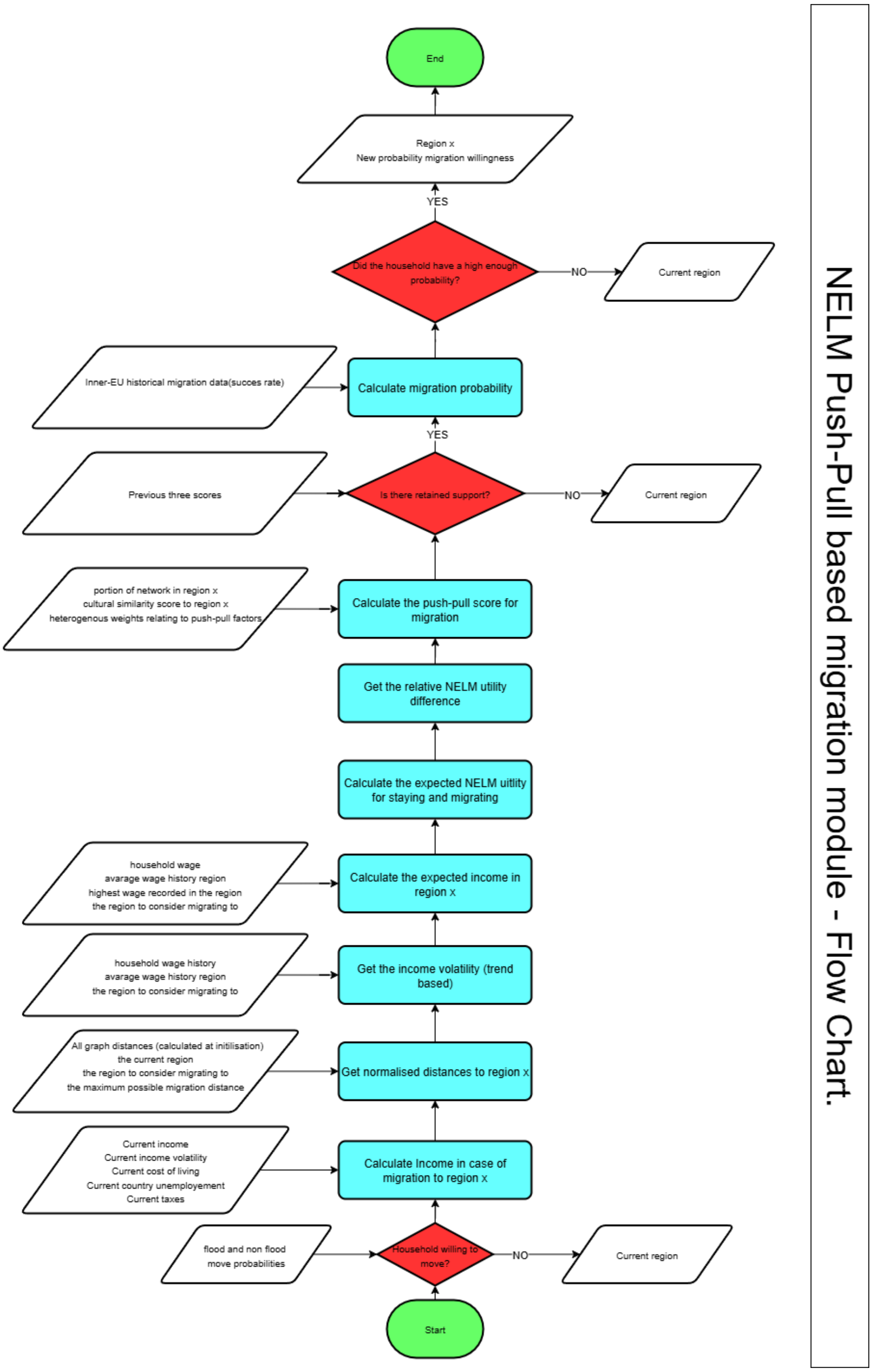


Figure 20: Migration flow chart as it is modelled.

Figure 21 shows the entire model's functionality for one time step and where the migration model fits.

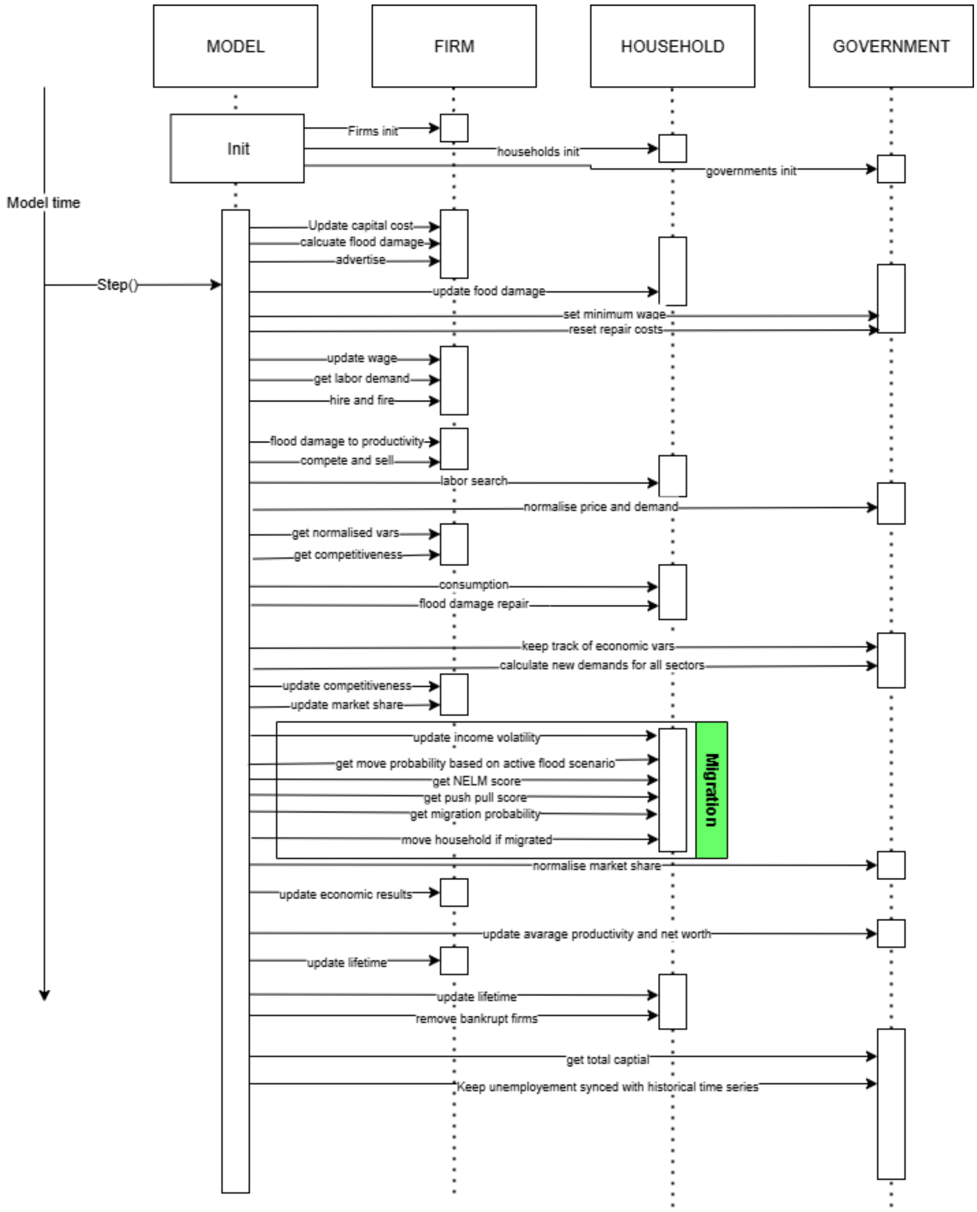


Figure 21: Full model sequence for 1 step. Migration is highlighted in green.

D.3 Model results

When running the model, there are additional characteristics of interest. Figure 22 shows what regions were affected by flooding of the Rhine and Danube. In the legend of the figure, repair expenses are noted. Countries not in proximity to either river show repair expenses of zero. The Netherlands shows the highest repair expenses as it has the most densely populated areas affected by the flooding.

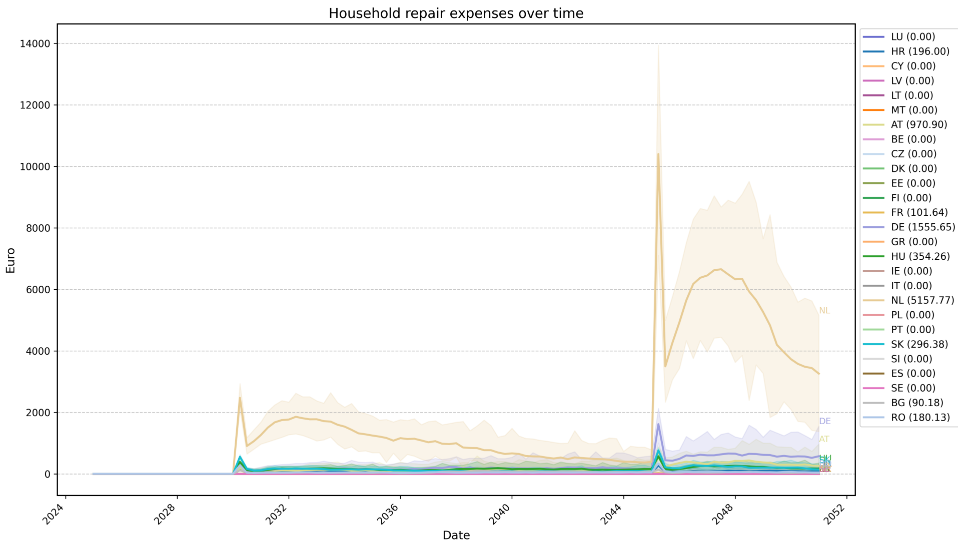
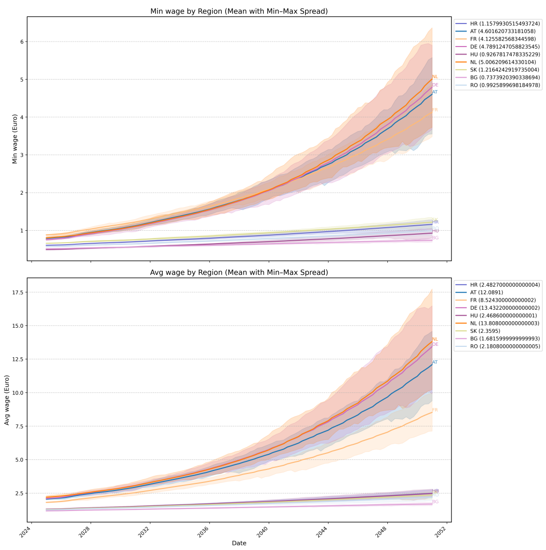
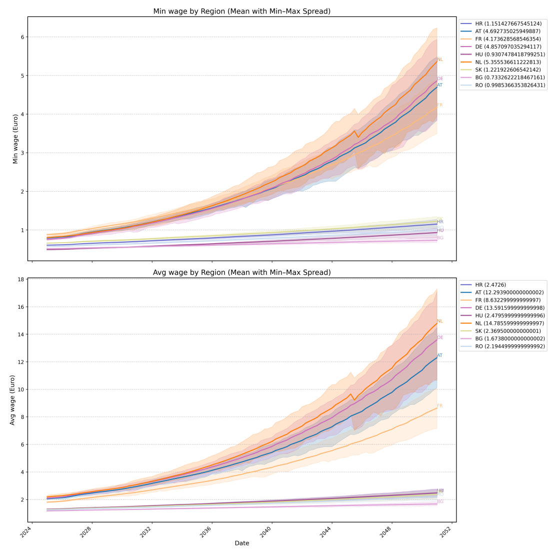


Figure 22: Repair expenses for each country when the model is hit with a flooding event of the Rhine and Danube. Repair expenses are the total sum for 10.000 households. To calculate country-wide repair expenses, divide the number by 10.000 and multiply by the country's population, as the flood maps have been filtered for density. Results are averages with min-max spreads of the 100 Monte Carlo runs.

Looking at the wages, the raw data shows apparent clustering of low- and high-wage countries. This is better seen when looking at raw data than when looking at differences between the scenarios. High-wage countries are in closer proximity to the Rhine, and low-wage countries are in closer proximity to the Danube. Wages are a direct result of CGE-generated economic variables.



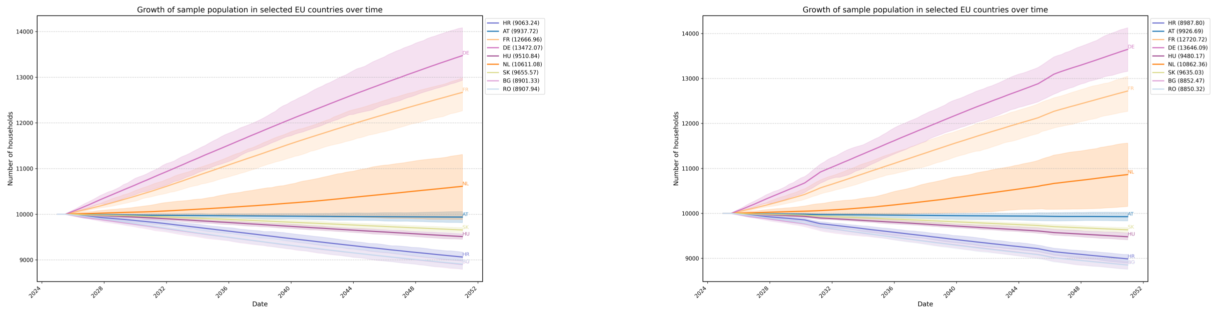
(a) Raw wage data of countries along the Danube and Rhine, excluding flooding events.



(b) Raw wage data of countries along the Danube and Rhine, including flooding events.

Figure 23: Raw average and minimum wage data for the EU27 countries without flooding events (a) and with flooding events (b). Results are averages with min-max spreads of the 100 Monte Carlo runs.

The final household numbers differ slightly between scenarios when compared in raw form. Small bumps can be seen during times of flooding.



(a) Number of sample households in potentially affected countries along the Danube and Rhine, excluding flooding events.

(b) Number of sample households in potentially affected countries when flooding of the Rhine and Danube takes place.

Figure 24: Number of sample households in potentially affected countries without (a) and with (b) flooding events. Results are averages with min-max spreads of the 100 Monte Carlo runs.

When looking at the migration flows for the most popular destination country (Germany), it becomes apparent how important the economic factors are, especially for lower-wage countries. Due to its large population and central location, it becomes evident why Germany ranks so high as a destination country, particularly when considering its social importance. Keep in mind that these numbers are based on sample values of 10.000 households; if one country has more people migrating than another country, that does not scale to the full population size.

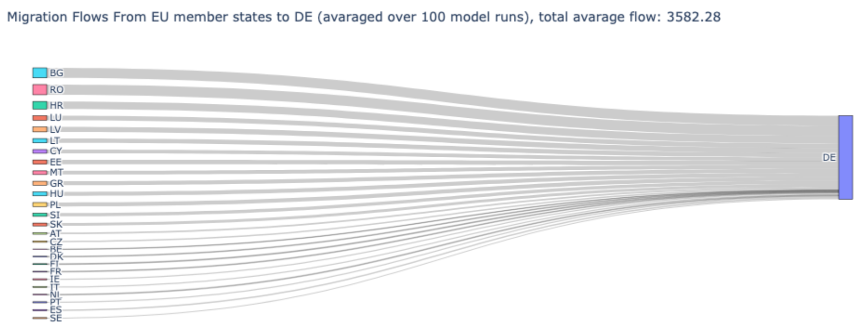


Figure 25: Migration flows for Germany (DE), showing high values for lower-income countries significantly outperforming culturally similar countries. Results are averages of the 100 Monte Carlo runs

When looking at the differences in consumption between the regions affected by floods, one can see that initially, consumption takes a hit. There is, however, a quick recovery from the damage, leading to forced consumption. This effect means that consumption can actually recover beyond the scenario without floods.

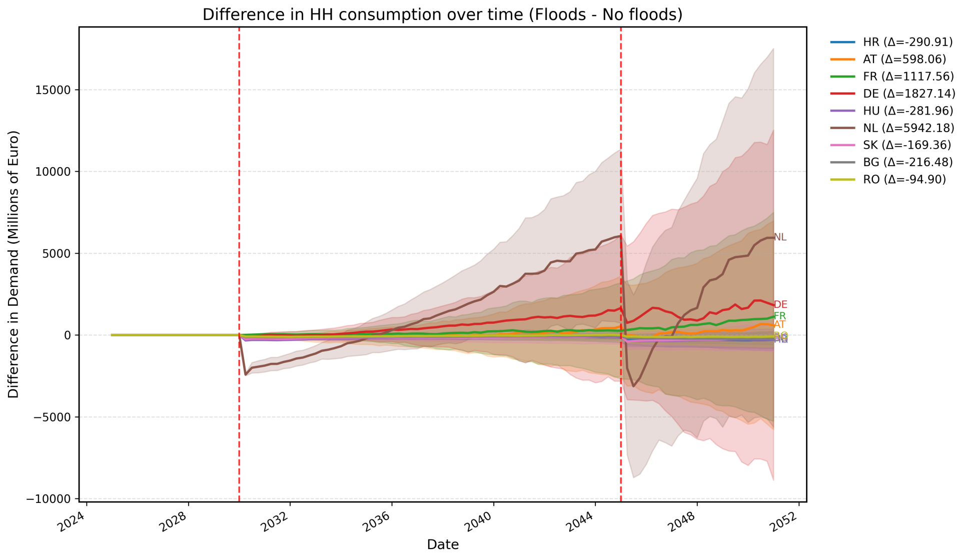
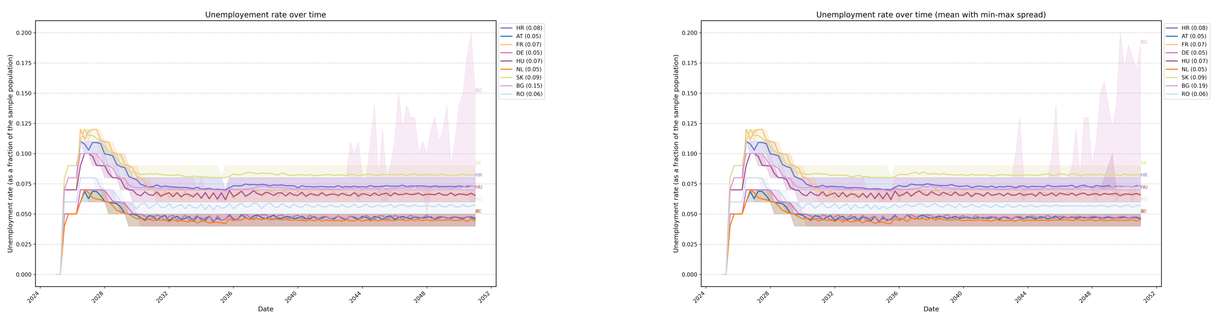


Figure 26: consumption differences when regions are flooded. These differences are gathered from 100 Monte Carlo runs of 10.000 households per EU27 country. Uncertainty bands represent the mean ± one standard deviation.

The model unemployment rarely exceeds the threshold set by the time series, indicating that there is enough work for all households, regardless of flooding events.



(a) Unemployment of EU27 countries along the Danube and Rhine, excluding flooding events.

(b) Unemployment of EU27 countries when floodings of the Rhine and Danube take place.

Figure 27: Unemployment rates in each of the 27EU countries without (a) and with (b) flooding events. Unemployment has a minimum average value based on time series from Eurostat [36]. Results are averages with min-max spreads of the 100 Monte Carlo runs. Uncertainty bands reflect the min-max differences of the 100 runs.

Finally, the model allows for the research of micro-based effects. Looking at wages, there are no outliers in the sample of 10.000 households for any of the regions, meaning the comparison does not include households with extreme wealth in any of the regions. However, the distribution of wealthier countries is more skewed.

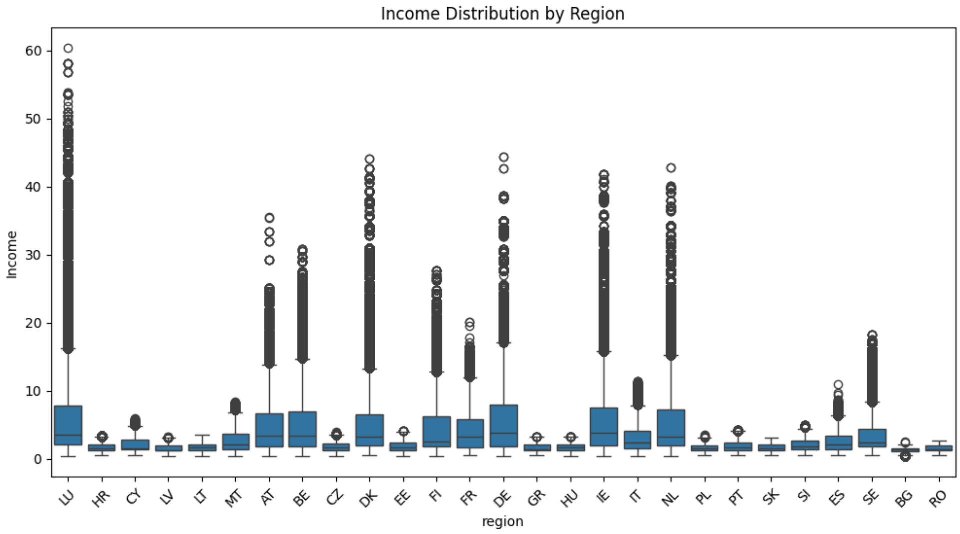


Figure 28: Box plot of the income distribution of all agents. For the results, seed 27 is utilised, which is most representative of the average of the Monte Carlo runs.

E Data Availability

As of this version, data is not publicly available; therefore, it should be requested from the faculty of Technology Policy and Management at the TU Delft. Two data repositories have been created, consisting of an analysis repository that allows for running the model once, viewing all data analysis, and serves as a repository for modifying the model. A second repository consists of a parallelised version of the model with only the necessary files to run the model. This repository can be used to conduct Monte Carlo model runs.

With access to the repository, please refer to *analysis.ipynb* for all data preprocessing. For the analysis of a single model run used to generate household-level data, refer to $single-run-analysis.ipynb$. For this analysis, seed 27 was used, which was found to be the most representative of all the Monte Carlo simulation runs. For the analysis of 100 runs for both flooding scenarios, refer to $multi-run-analysis.ipynb$.