# Simulation of Migration Paths Using Agent-Based Modeling: The Case of Syrian Refugees

by

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Koç University

Graduate School of Sciences and Engineering

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*To my family*

# ABSTRACT


**Simulation of Migration Paths Using Agent-Based Modeling: The Case of Syrian Refugees**
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**Master of Science in Industrial Engineering**
**November, 2022**

The Syrian civil war, which has been ongoing for over a decade, has caused a massive migration wave in the Middle East. Turkey has been the most preferred destination for Syrian refugees seeking security. The primary purpose of our study is to develop a migration tool to simulate the paths of Syrian refugees en route to Turkey. In this way, we aim to facilitate humanitarian aid organizations to deliver services to refugees in future migration instances. We limited the scope of the study to a crisis moment. We simulated the southeastern Idlib aerial bombardment on December 16, 2019, and observed the outcomes of the sudden conflict-driven migration movements of refugees who started to migrate in a one-month period from December 16, 2019 to January 15, 2020. Due to the lack of reliable data on displacement during the crisis, we restricted the destination options to official refugee camps in Turkey. We developed an agent-based model (ABM) based on two attributes of refugee groups: risk sensitivity and agent type, which include four different information types. We expanded the A* algorithm with a cost metric to calculate the weighted average of distance and risk to a destination point. The proposed ABM has the flexibility to be easily adapted to migration instances in another geography and to enable various analyses under different parameters. The case study examines the southern Idlib crisis with five different scenarios. We obtained the total number of refugees, migration paths, camp occupancy rates, and heat maps of the densely populated regions for each scenario. We compared the obtained outputs with the situation reports and the official statements of the period and acquired several meaningful insights for policymakers.

# ÖZETÇE

**Ajan Tabanlı Modelleme Kullanılarak Göç Yolları Simülasyonu: Suriyeli Sığınmacılar Örneği**

**Özlem Güngör**
**Endüstri Mühendisliği, Yüksek Lisans**
**Kasım, 2022**

2011'den bu yana devam eden Suriye iç savaşı Orta Doğu'da büyük bir göç dalgasına neden olmuştur. Vatanını terk etmek zorunda kalan sığınmacıların yoğun olarak göç ettiği noktalardan biri Türkiye'dir. Çalışmamızın birincil amacı Suriye'den Türkiye'ye göç eden sığınmacıların göç yollarını simüle eden bir göç modeli geliştirerek ileride oluşabilecek yoğun göç dalgalarında sığınmacılara yardım ulaştırmayı kolaylaştırmaktır. Önceki benzer çalışmalardan farklı olarak bu modelin kapsamı bir kriz anıyla sınırlandırılmıştır. Örnek olarak 16 Aralık 2019'da gerçekleşen güneydoğu İdlib hava bombardımanı konu alınmış ve bombardımanın neden olduğu ani göç hareketinin etkileri gözlemlenmiştir. Kriz anında çatışma bölgesini terk eden sığınmacı gruplarının demografik verilerine erişim mümkün olmadığından kişisel tercihlerin etkisi ortadan kaldırılmıştır. Sığınmacı gruplarına risk duyarlılığı ve dört farklı bilgi çeşidini içeren ajan tipi özellikleri atanmış ve bunları baz alan bir ajan tabanlı model (ABM) geliştirilmiştir. ABM kapsamında, ajanların varış noktaları kamplar ile sınırlı tutulmuştur. Kamplara olan mesafelerinin ve yol boyunca karşılaşacakları risklerin ağırlıklı ortalamasını esas alan bir maliyet metriği eklenerek geliştirilmiş A* algoritması kullanılmıştır. Geliştirilen model farklı parametreler altında çeşitli analizler yapılmasını sağlamaktadır. Çalışmamızda sunulan göç modeli ile İdlib'de yaşanan kriz beş farklı senaryo altında incelenmiştir. Her senaryo için toplam sığınmacı sayısı, sığınmacıların göç yolları, kamp doluluk oranları ve sığınmacılar tarafından yoğun olarak tercih edilen bölgelerin ısı haritası sunulmuştur. Elde edilen çıktılar dönemin durum raporları ve basına yansıyan resmi açıklamalar ile karşılaştırılmıştır ve ele alınan durum için çeşitli çıkarımlar elde edilmiştir. Geliştirilen model başka bir coğrafyadaki göç durumlarına da kolayca adapte edilebilecek ve farklı parametreler altında analiz yapılmasını sağlayacak esnekliğe sahiptir.

# ACKNOWLEDGMENTS

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I am deeply grateful to my parents, Sevdaar and Kubilay, for their unfailing support, appreciation, continuous encouragement, and keen interest in my academic achievements. They have allowed me to be free in every decision I have made throughout my life, and they have respected and sincerely supported all of them. Words cannot express my gratitude to my family for making me the person I am today.

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## ABBREVIATIONS

| | |
|---|---|
| ABM | Agent-Based Model |
| EU | Europian Union |
| GIS | Geographic Information System |
| IDP | Internally Displaced People |
| US | United States |

# Chapter 1

# INTRODUCTION

This study focuses on conflict-induced displacements where people are forced to flee their homes for reasons such as violence, political oppression, human rights violation, and discrimination against race, religion, and nationality. The number of domestic and international displacements, which follows an increasing trend, has become alarming in the last decade. The total number of forcibly displaced people worldwide, which was reported as 42.7 million at the end of 2012, reached 89.3 million by the end of 2021 [UNHCR, 2022a]. According to this statistic, 1 out of 88 people had to leave home by the end of 2021. Recently, as a result of the war in Ukraine that broke out at the beginning of 2022, 7.1 million Ukrainians were displaced within the country from February to the end of May. From February 24, 2022, to August 23, 2022, more than 11 million refugees crossed the border from Ukraine [UNHCR, 2022b].

Conflicts over the past decade have resulted in the largest forced migration since the Second World War. Authorities emphasize that migration will increase yearly unless permanent solutions are proposed to the ongoing conflicts [UNHCR, 2022a]. In addition, the consequences of climate change become visible day by day. At the extreme point of pessimistic scenarios, it is predicted that 216 million people will be forced to migrate in 2050 due to climate change [Clement et al., 2021]. On the other hand, optimistic scenarios argue that urgent and concerted action to reduce global greenhouse gas emissions and promote green, inclusive, and resilient development can decrease these displacement numbers by up to 80 percent [Clement et al., 2021]. Thus, predicting the possible consequences of forced migration plays a vital role in taking measures within and between countries.

The Syrian civil war, which started in 2011, has caused migration waves in the Middle East. After more than ten years of conflict, loss of life and property, poor living conditions, and vulnerability caused Syrian civilians to flee to other countries. By the end of 2021, the number of refugees worldwide climbed to 27.1 million, of which 6.8 million were Syrian refugees [UNHCR, 2022a]. Most Syrian refugees preferred staying close to Syria. The neighboring countries (Turkey, Lebanon, and Jordan) host more than three-quarters of all Syrian refugees. Turkey has been the most preferred destination for Syrian refugees. The number hosted by Turkey at the end of 2021 was reported as 3.7 million [UNHCR, 2022a]. In this study, we focus on Syrian refugees en route to Turkey.

We limited the scope of the study to a crisis moment. As the Assad regime recaptured most of the territory in Syria, the invader-controlled Idlib (northwest Syria) became the last stronghold of refuge for almost 3 million people [Atrache, 2019]. An attack in Idlib was thwarted by the Sochi agreement signed between Russia and Turkey in September 2018. An upcoming attack in northwest Syria, mainly in Idlib, was alarming for Turkey. Turkey was already home to 3.5 million Syrians in September 2019, and a conflict in Idlib resulted in tens of thousands of people crossing the Turkish border [Atrache, 2019]. On December 16, 2019, the aerial bombardment intensified in southern Idlib. In this study, we aim to predict the impact of the aerial bombardment on the migration movements of Syrian refugees en route to Turkey. To achieve this, we developed an agent-based model (ABM) based on the interactions of agents with each other and their environment in NetLogo [Wilensky, 1999]. Using the developed model, we simulated Syrian refugee movements to official refugee camps in Turkey for one month between December 16, 2019, and January 15, 2020.

The contributions of this study can be explained as follows. The study simulates the actions and interactions of refugees using a novel agent-based model. The model reflects a crisis moment and examines the short-term effects of a large-scale conflict. We aim to eliminate the adverse effects caused by the difficulty of accessing the records and personal data of displaced people during a crisis. Therefore, we defined several agent properties that personalize the migration movements of refugee groups but do not require demographic data. To the best of our knowledge, this is the first study that integrates agents' risk sensitivities and levels for four different information types into the decision-making processes of refugee groups. Consistent with the risk sensitivities of the agents, a risk parameter is defined for the environment based on the number of conflicts occurring in the region. The model can increase or decrease the regional risk by defining the intermittent conflicts to ensure a dynamic environment. The model also creates leader-follower relationships among refugee groups depending on their agent properties. In this way, migration dynamics are adapted to the simulation model realistically. The developed model has the flexibility to be easily adapted to migration incidents in another geography and to enable analysis under different parameters.

We provide insights based on several investigations using the model. We examine five scenarios under different parameter values (presence of other conflicts, unlimited camp capacities, agents' knowledge of environmental risks, i.e., their vision, and different compositions of the migrating population). Four different agent types are defined in the model. Agent types determine the levels of four different types of information. Some of the parameters control the proportions of these agent types in the migrating population. This way, we examine the effects of different levels of each information type on migration decisions and paths.

The thesis is organized as follows. Chapter 2 gives an overview of the literature on agent-based modeling and its applications on Syria. Our agent-based model is explained in detail in Chapter 3. Chapter 4 presents the case study of Syrian refugees en route to Turkey, the study results, the discussion of the results, and future work directions. Finally, Chapter 5 concludes the study with some insights.

# Chapter 2

# LITERATURE REVIEW

We review the related literature in three main subjects: i) human migration in general (Section 2.1), ii) agent-based modeling (Section 2.2) and iii) displaced people in Syria (Section 2.3). Finally, we explain a preliminary study which constitutes a basis for the thesis (Section 2.4).

## *2.1 Human Migration*

Human migration is about people who move from one geographic area to another with the intention of permanent or temporary settlement. It reflects the changing living conditions in the world and causes cultural and economical changes in places where people leave and settle. Geography has been highly influential in human migration since prehistoric times. A study examined spatial patterns of human migration and its underlying decision processes in the context of the spatial development of societies [Lewis, 1982]. A spatial interaction model was applied to gain insight into the determinants of internal migration in Eastern and Western Russia [Sardadvar and Vakulenko, 2020]. Another study investigated long-term and short-term spatial mobility in Greece regarding urbanization processes and socio-economic development [Salvati, 2020]. Spatial mobility has required an understanding of migration paths. Researchers were able to study migration paths to unoccupied parts of Britain, even in prehistoric times, using factors such as geography and basic human needs [Vahia et al., 2016]. Their simulation results offered insights into human mobility about 2,000 years ago with only primitive factors. Factors that drive people to migrate (forced/voluntary, permanent/temporary) are referred to as the drivers of migration and can be attractive or repulsive. Such factors may be economic, demographic, social, political, or environmental.

A study using pull and push factors modeled mass movements toward a goal and avoiding obstacles [Christou, 2010]. The study assumed groups to move in varying sizes, each with an assigned leader and simulated human migration using the swarm theory. The impact of drivers of human migration have been studied with various modeling methodologies. A multi-class human migration network equilibrium model was developed based on migration costs between locations [Nagurney et al., 1992]. Defining costs in the model caused no individual to relocate under equilibrium conditions and required formulating these conditions as a variational inequality problem [Nagurney et al., 1992]. Kalashnikov and Kalashnykova [Kalashnikov and Kalashnykova, 2006] contributed to the migration literature by extending existing human migration models. They conducted a sequence of numerical experiments and examined the effects of migration costs and utility function and influence coefficient values on the state of equilibrium.

It is challenging to conduct experimental research on social sciences because of the high dynamics of social phenomena. Therefore, social scientists use modeling and simulation, a relatively new approach in human migration [Frydenlund, 2021]. A multi-evolutionary agent model was designed for an experimental study to understand the association between migration, communication, and social networks in a social simulation [Filho et al., 2013]. Human migration studies in the last decade have shifted their direction to environmental migrations as the habitability in many parts of the world is expected to decline significantly due to climate change. For example, large-scale human migration, driven by the sea-level change, is anticipated largely from vulnerable coastlines of Bangladesh [Davis et al., 2018, Chen and Mueller, 2018, Hauer et al., 2019, Bell et al., 2021]. Davis et al. [Davis et al., 2018] revised a diffusion-based model of human mobility with population, geographic, and climatic data to predict the origins, destination points, and flows of possible displaced people. Finally, studies on human migration inspired by the Covid-19 pandemic expanded migration models with additional regulations. For example, a recent study integrated migration costs and quarantine regulations into a system-optimized network model [Cappello et al., 2021]. On the other hand, agent-based modeling (ABM), which differs from all these models by focusing on the individual choices of migrants, has recently gained a place in the human migration literature.

## 2.2 Agent-Based Modeling (ABM)

The gravity model has dominated the migration literature for decades. It suggests that the number of individuals migrating between two points increases with the population size and decreases with the geographical distance [Klabunde and Willekens, 2016]. However in recent years, human migration models have become increasingly lifelike by including decision processes, especially using agent-based modeling (ABM). ABM focuses on unique agents, their decision-making processes, interactions with other agents and the environment, and the outcomes of the interactions. Agent-based dynamic modeling was used to investigate population shifts between countries given alliance networks, shared language networks, economic influence networks, and proximity networks among countries [Lin et al., 2016]. Similarly, another study proposed an aggregated agent-based model, developed as an extended form of the gravity model, to simulate European Union (EU) migration flows [Makarov et al., 2019]. This model integrated individual decisions of agents based on socioeconomic, geographical, and distinctive features of EU countries, such as migration quotas, unemployment benefits, and the lowest salary. Sharma et al. [Sharma et al., 2021] used ABM to address migration complexity and dynamic behavior in the Tehri Garhwal region of Uttarakhand and showed that migration is controlled both by internal and external factors.

ABM has been widely used in different areas of human migration literature. Migration caused by the economic imbalance between rural and urban regions that emerged in the early stages of industrialization has been well-studied in the last decades [Silveira et al., 2006, Cai et al., 2015, Fu and Hao, 2018]. The increase in displacements caused by climate change has caught the attention of many researchers. Recent studies have examined environmental migrations using ABM [Kniveton et al., 2011, Caterina, 2021, Best et al., 2021, Thober et al., 2018]. Migration caused by conflicts, the primary concern of our study, is at least as old as the history of war. For this reason, many studies in the literature use ABM to simulate conflict-driven migrations and to understand them further [Makowsky et al., 2006, Hébert et al., 2018, Al-Khulaidy and Swartz, 2020, Searle and van Vuuren, 2021].

The ABM serves as a tool for policymakers seeking answers to what-if scenarios regarding the influences of migration. A study conducted an agent-based simulation to develop an emergency medical response plan for a mass disaster [Wang et al., 2012]. Various response policies were evaluated, and responders were informed about the requirements and protocols of such an emergency plan. We need a programming platform to create and simulate scenarios. Even more simply, these platforms are essential for developing and running agent-based models. NetLogo, where we developed our agent-based model, provides an easy-to-use environment and the ability to monitor the simulation visually. Many migration researchers have preferred NetLogo. For example, using NetLogo, Deshmukh [Deshmukh, 2018] developed agent-based models of popular migration theories, such as the neoclassical approach, network migration, and pull-push migration. Also, Termos et al. [Termos et al., 2021] used NetLogo to investigate the consequences of international migration on urban dynamics.

## 2.3 ABM for Conflict-Induced Migration in Syria

Refugees fleeing the Syrian civil war have caused one of the largest refugee crises in history, and this international migration movement has agitated the refugee crisis in Europe. As observed in the case of Syria, the difficulty of accurately predicting the scale and dynamics of the sudden migration of masses can result in a refugee crisis in the receiving countries. The incomplete or unreliable data on the movements further complicate the functional principles of the estimation mechanisms. A study proposed a general framework for assisting in the development processes of ABM for conflict-driven migrations, considering the drawbacks of conflict instance modeling and the lack of reliable data on the movement patterns of the forcibly displaced [Searle and van Vuuren, 2021]. The study illustrates the practicality and applicability of the framework with a framework-based ABM concept demonstrator designed for conflict-driven forced migration in Syria (executed in AnyLogic for each year between 2011 and 2017). The ABM enables the computation of individuals' capacities to withstand conflict based on their attributes and quantified their decision-making in choosing a movement type. In this study, three displaced groups are defined according to their type of movement: legal refugees who seek refuge in neighboring countries, undocumented refugees crossing international borders, and migrants internally displaced within Syria. The type of movement influences the decision-making process of choosing a destination based on characteristics of the individual and external factors. The developed decision-support framework assists governments and humanitarian organizations by predicting the rates of three movement types among displaced Syrians and the number of refugees crossing international borders by destination countries.

Another study on conflict-driven migration in Syria focused on the migration paths of refugees crossing Syrian international borders [Hébert et al., 2018]. Hebert et al. [Hébert et al., 2018] developed a model that employs complex systems theory to simulate the migration movements of Syrian refugees from March 2011 to December 2015. They divided the model into three stages, each representing a decision-making process of agents: decision to leave, the choice of destination and path, and the decision to settle on the destination. Refugees, agents who decide to migrate, choose their mode of transportation according to their wealth. Alternative destination points include countries, cities, and refugee camps. Each destination has attractiveness indicators such as safety, life expectancy, reliability, education quality, infrastructure quality, freedom of the press, and government effectiveness. Refugees choose a destination considering their desires and needs. The model, which simulates a 5-year time period, focuses on the long-term effects of conflicts. Hence, migration motivations are not limited to the search for security but also the desire for better living conditions. After implementing the model in NetLogo, the study offers the number of Syrian refugees arriving in each neighboring country and a heat map of frequently used regions on the migration paths as outputs. A different study on Syria focuses only on internally displaced people (IDP) who urgently need protection, nourishment, water, and health care [Huynh and Basu, 2020]. They developed a forecasting framework for conflict-induced migration of IDPs to aid humanitarian organizations in effectively distributing resources.

The common difficulty of the aforementioned Syrian studies is the lack of reliable information experienced during conflict-related migration. Searle and van Vuuren [Searle and van Vuuren, 2021] handled this problem by realistic estimations of probability distributions where the data is not exact or not available and initializes agent attributes (gender, age, tertiary education, economic status, international family, and anticipated age of death) according to these distributions. Hebert et al. [Hébert et al., 2018] associated agents with a series of variables, including religion, ethnicity, wealth, age, gender, and familial status, to evaluate their tolerance to conflict and assigned random values to these variables. Both studies examine the long-term effects of the Syrian civil war. On the other hand, unlike these studies, we focused on the short-term effects of a crisis on migration movements. The primary purpose of refugees in times of crisis is to reach safety as quickly as possible. For this reason, we assigned agents risk sensitivities and information levels on destination locations, their remaining capacities, and environmental risks. We aimed to attain insights into migration movements in cases where there is no demographic record of migrating individuals, or the records are unreliable.

## 2.4 Preliminary Study

In a preliminary study of our current work, we simulated the refugee movements from conflict areas in Syria to the refugee camps in Turkey during a crisis [Güngör et al., 2022]. We proposed an agent-based model to predict migration paths. We assigned risk-taking preferences to the agents and categorized them as risk-averse, risk-neutral, and risk-seeker. However, in many ways, risk-taking preferences fall behind the risk sensitivity method developed in the current study. In our preliminary study, environmental risks restricted the movements of risk-averse and risk-neutral agents. It was assumed that the agents choose their paths through governorates compatible with their risk-taking preference. Thus, most agents' movement range was limited to their origin governorate. On the other hand, in our current study, we defined risk sensitivity for agents' destination and pathway choices. We have developed a new method based on the capability of agents to be exposed to risk rather than restricting their movements. This way, we simultaneously minimized the path length and risk exposure along the path. Moreover, in our current work, we have simplified the environment of the agents. In this way, even though we have developed a more complicated model that includes risk calculations, we have drastically reduced the run time through a simplified environment from 45 minutes to 30 seconds through algorithmic improvements. The simplified environment failed to reflect some details existing in our preliminary work, such as main roads and highways. However, this seems like an acceptable loss since we assume in our current study that walking is the only transportation mode.

# Chapter 3

# AGENT-BASED MODEL

We developed an agent-based model to simulate refugee movements. Refugees are represented by agents, and the environment includes sources, obstacles, and destinations. The model serves as a migration tool and can simulate any migration phenomenon with minor modifications. It is implemented in NetLogo. Each agent has two attributes in the model: risk sensitivity and agent type. Agent types specify the levels of multiple information types. Agents have information on destination locations, remaining destination capacities, patch risks, and risk sensitivities of other agents. The model takes the source and destination locations, destination capacities, risks of patches, and agent attributes as inputs. We obtain the emerging migration paths and the total number of refugees using these paths as an output. The model consists of three parts: i) migration decision, ii) interactions between agents, and iii) interactions between agents and the environment. In the following sections, we will explain each part of the model in detail. The data transferred between each part of the model is given in Figure 3.1.

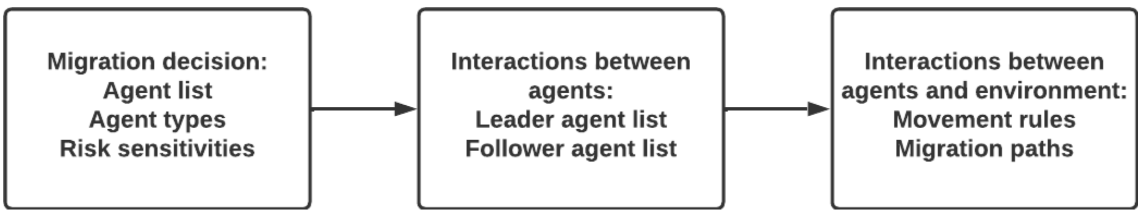



Figure 3.1: Transferred data between each part of the model.

Details of the model is described in the following sections. Assumptions of the model are listed in Section 3.1. Section 3.2 is based on mapping stages of the NetLogo world. Section 3.3 deal with the migration decision. Finally, Sections 3.4 and 3.5 describe the actions and interactions of agents among themselves and with their environment.

## 3.1 Assumptions

The model has some restrictions and assumptions. All destination points are assumed to be empty at the beginning and to serve at full capacity. Agents are classified into four different agent types. Each agent type is formed with assumptions based on the four different information type levels (see Section 3.3.1). These assumptions regulate actions and interactions of agents within themselves and with the environment. Agent movements after settling in destinations are omitted. In other words, an agent that settles in destination point does not leave that location.

## 3.2 NetLogo World Generation

We created a sample NetLogo world consisting of seven sources, one destination, and obstacles. The sample world is given in Figure 3.2. Green patches represent sources, blue represents destinations, and white represents obstacles. We defined patch risk between 0 and 1, with 0 being the lowest and 1 being the highest. We divided the terrain patches, excluding sources, destinations and obstacles, into three groups according to their risks. Dark gray has a risk of 0.25 and a light gray of 0.75; as it progresses from dark gray to light gray, the risk of patches increases by 0.25. Each terrain patch group is randomly distributed in the world.

The NetLogo user interface allows the design of a preferred map. The **setup** button clears the world. **Draw-map** creates a canvas consisting of only terrain patches. After activating the **draw** button, the user selects an element from the **element-to-draw** chooser and transfers this element to a patch by clicking on it. The **generate-map** button creates a random world using the number of sources and destinations and the percentage of the world covered with obstacles. The user can determine the values of these three variables from the sliders in the interface. The **setup-map** creates the sample world. Users can save the created maps for later use with the **save-map** button and import them later with the **load-map**. The Figure 3.3 shows all the features above through the interface.

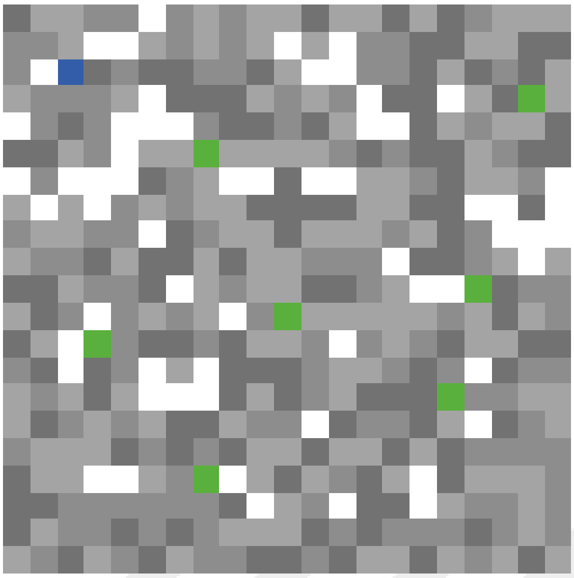


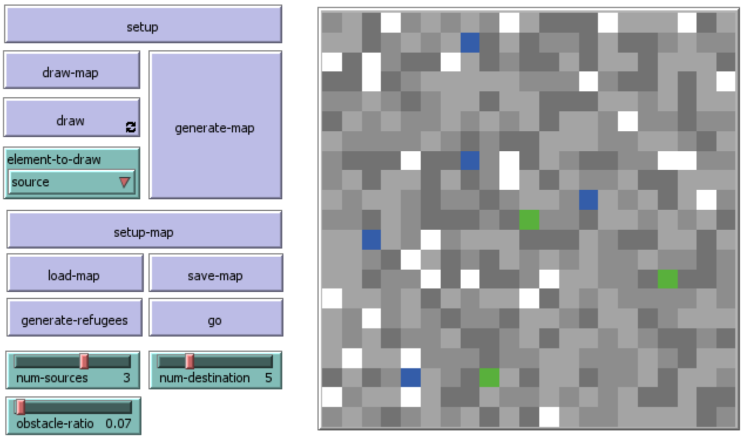
Figure 3.2: The sample NetLogo world.

### 3.3 Migration Decision

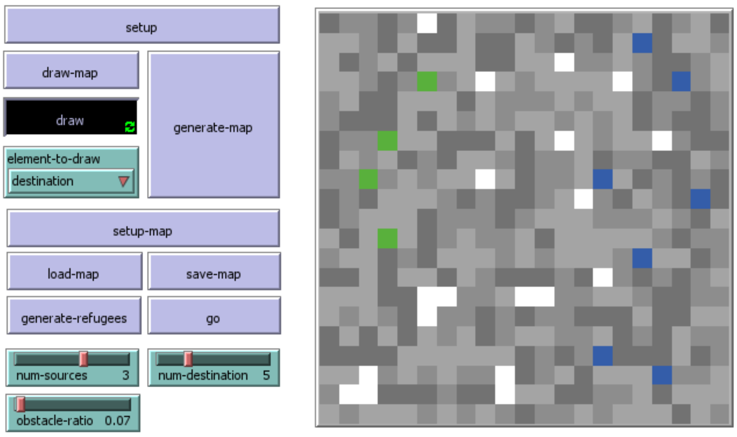
Agent generation procedure mimics the migration decision. In each tick, source patches generate an agent with a non-negative random probability. A random agent type is assigned to each agent during the initial generation process. Agent types carry some assumptions on the multi-level information attributes of agents. Each agent has a random risk sensitivity with values ranging from 0 to 1, where 0 represents the lowest and 1 represents the highest value. Risk sensitivity indicates the extent to which an agent's choice of path is affected by environmental risk. The detailed flowchart of the migration decision is given in Figure 3.4.

#### *3.3.1 Agent Types*

There are four different agent types: uninformed, household, well-informed and guide agents. Agents have multi-level information on destination locations, daily destination populations, risk of patches and risk sensitivities of other agents. Agent types define values of information attributes. Information on destination locations represents an agent's knowledge and experience with destination locations, and its value ranges between 0 and 1. It is assumed that the number of known destinations




(a)




(b)

Figure 3.3: The NetLogo user interface: (a) randomly generated map, (b) drawn map.

is proportional to an agent's information on destination locations. The number of known destinations is calculated by multiplying the information level on destination locations by the total number of destinations in the NetLogo world. The list of known destination points is generated by randomly selecting the calculated number of destinations from the possible destinations. Information on daily destination populations determines the ability of agents to control known destination occupancies and the frequency of control. Information on patch risks creates agents' visions.

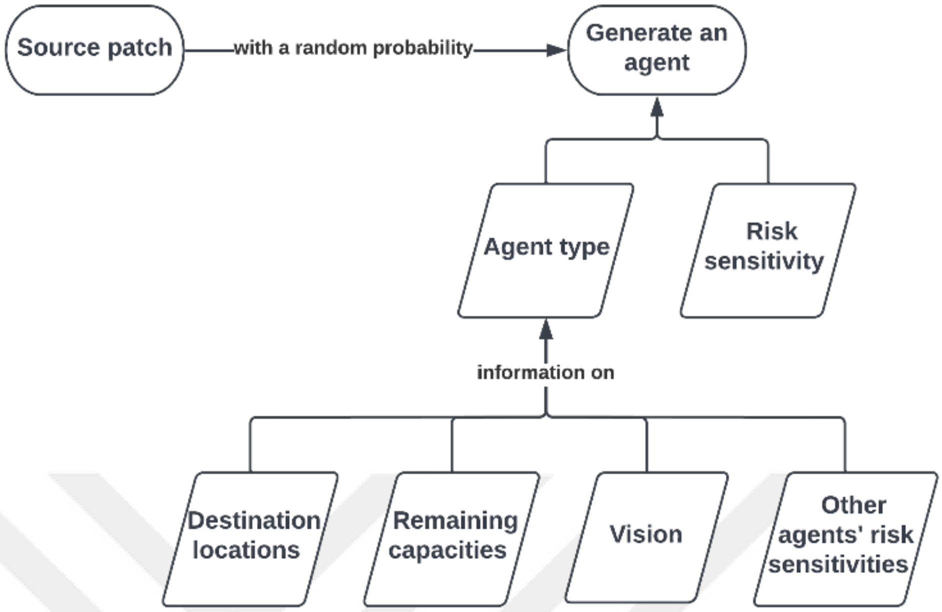



Figure 3.4: The flowchart of migration decisions.

Agents can check the risk levels of patches that remain within their vision. Information on risk sensitivities defines the ability to check other agents' risk sensitivities. It takes the value of 1 if an agent can check and 0 if an agent cannot.

Uninformed agents do not have any information about the destination points. Their information on destination locations is at or near zero. Since they have no information about destinations, they cannot check the occupancy rates of destinations. This information type does not apply to them. They cannot check patch risks during their migration movements. They do not have any vision. Therefore, they cannot move on their own, and they need someone to lead them. Their information on other agents' risk sensitivities depends on the ability to communicate with other agents. The ability to check other agents' risk sensitivities is randomly assigned as 0 or 1. Information on risk sensitivities affects their interactions with other agents, i.e., follower-leader relationship.

Household agents differ from the previous agent type in the number of known destination locations. The number of destinations they know is greater than 0. On the other hand, it is less than eighty percent of the total number of destinations in the world. They do not have the ability to check the daily occupancy rates of the destinations. Household agents check the occupancy of their target destination only when they reach that point. It is assumed that they receive information from the authorities at the destination in case the destination location is full. They can move alone. They have a low vision. Their vision is defined by two inputs, a vision distance and the viewing angle. For household agents, the vision distance is the number of patches covered per tick and the viewing angle is 90 degrees. Agents can move 3 patches in a tick. It is assumed that they know the risks of patches within their vision. Whether they have information on the risk sensitivities of other agents is determined randomly.

The other agent type includes well-informed household agents. Well-informed agents have information on more than eighty percent of destination locations, but not all of them. They check the populations of their known destinations at each tick. They compare the population of destination with its capacity, and if it is full, they head to a different available destination. Their vision distance is longer than household agents. They can check risk levels of patches in a cone with a vision distance of six patches and 90 degrees. Well-informed agents do not check risk sensitivities of other agents. Hence, this information type is not defined for them. Well-informed agents do not need anyone to guide them. On the other hand, they can lead uninformed and household agents. Follower-leader relationships are described in detail in Section 3.4.

The last agent type is defined for guide agents. Guides know all destination locations. They check the occupancy of each destination in each tick. They have a high vision, so they know the risks of all patches. They do not check the risk sensitivities of other agents. It is the only agent type with complete information. All other agent types follow a guide if there is an agent with an agent type of guide around them. The levels of different information types for each agent type are given in Table 3.1.

Table 3.1: Information levels for each agent type.

| Agent Type | Information on | | | |
|---|---|---|---|---|
| | Destination Locations | Remaining Capacities | Vision | Risk Sensitivities |
| Uninformed household | 0% | N/A | N/A | Random (0 or 1) |
| Household | > 0% and < 80% | None | Low (3 patches) | Random (0 or 1) |
| Well-informed household | >= 80% and < 100% | 100% (known destinations) | Med (6 patches) | N/A |
| Guide | 100% | 100% | High (all patches) | N/A |

## *3.4 Interactions Between Agents*

Agents interact with the neighboring agents, i.e., the agents of their neighboring patches, within the framework of their agent types. Inter-agent communication allows the formation of follower-leader relationships among agents. Guide and well-informed agents do not follow any other agent. They can lead the agents with other two agent types on their migration paths.

Household agents do not need the leadership of other agents. However, if there are guide or well-informed agents among neighboring agents, they prefer to follow them. The leader assignment steps of household agents are as follows. First, they scan all agents within a one-patch radius circle and form a candidate set, if any, of guide agents. If the set consists of one guide agent, that agent is assigned as the leader of the corresponding agent. If there is more than one guide in the neighboring patches, we check whether the corresponding agent can check other agents' risk sensitivities. A household agent with information on risk sensitivities determines the guide with the closest risk sensitivity to her/his risk sensitivity as her/his leader. If there is a tie, one of them is randomly assigned as the leader. On the other hand, an agent with no information on others' risk sensitivities assigns one of the guides from the candidate set as her/his leader. If there is no guide agent in the scanned neighboring patches, the same scanning process is performed for the well-informed agents. All other steps are the same as for guides. The agent becomes her/his own leader if the candidate set is empty, i.e., no neighboring agent belongs to agent types of guide and well-informed. Figure 3.5 shows the flowchart of interactions of household agents with other agent types.

Uninformed agents need the leadership of another agent. As in the household agents, the guide agents in the neighboring patches are scanned first. The same scanning procedure is performed for the well-informed ones if there is no neighboring guide agent. Unlike the household agents, uninformed agents can designate household agents as leaders. They form a candidate set from the neighboring household agents. An uninformed agent chooses her/his leader based on her/his ability to check the risk sensitivities of other agents. Again, the same steps are followed depending on whether the agent's information on others' risk sensitivities is 0 or 1. The flowchart of interactions of uninformed agents with other agent types is given in Figure 3.6.

Followers assign their leader's target destination as their destination and start following the path of the leader. An agent cannot have more than one leader at the same time. Agents prefer to follow guides first and then well-informed agents. If there are no agents of these agent types in neighboring patches, uninformed agents follow the household agents. For this reason, agents check neighboring agents at each tick to see if there is a better candidate who meets their criteria. If they find such a candidate, they update their leader as the corresponding candidate and start following the new leader. In addition, when a leader leaves the system (settles in the destination), follower agents search for a new leader applying the same procedure based on their agent type. Due to this dynamic inter-agent communication, regular agents who are followers can become leaders and vice versa.

### 3.5 Interactions Between Agents and the Environment

The environment affects the agents through the risks associated with each patch, i.e., risk levels of patches. Agent types and follower-leader relationship between agents define the movement rules of the model. Note that destination points represent refugee camps. For the sake of clarity, destination patches will be referred to as camps in this section.

Guides and well-informed agents do not follow any other agent. Guides apply a destination choice process before leaving their origin point. It is assumed that they

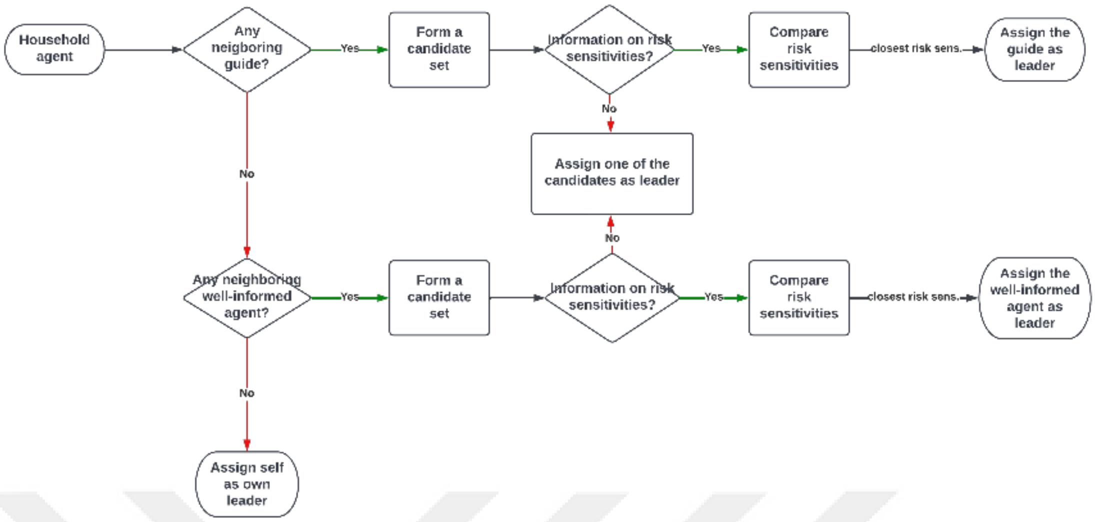



Figure 3.5: The flowchart of interactions of household agents with other agent types.


Figure 3.6: The flowchart of interactions of uninformed agents with other agent types.

know all refugee camp locations. They create a list of alternative camps with available capacity. Each guide calculates a cost for each camp as a weighted combination of its risk and distance using the A* path-finding algorithm [Hart et al., 1968]. The A* algorithm takes an agent's source and risk sensitivity and the camp locations as inputs and reports the optimal path, if one exists, as output. To determine the optimal path, at each iteration, in a recursive manner, the algorithm explores the neighboring patches that are not the source (i.e. current patch), a camp, or an obstacle and calculates a risk- and distance-based cost value, denoted by $f$, for each neighboring patch and destination pair. The value of $f$ for a neighboring patch and destination pair is calculated as the summation of a risk and a distance variable, denoted by $g$ and $h$, respectively. The risk variable, $g$, of a neighboring patch corresponds to the expected risk during the movement from the current patch to the neighboring patch and calculated as the average of the risk levels of these two patches. The distance variable, $h$, of a neighboring patch and a destination pair corresponds to the Manhattan distance from the corresponding neighboring patch to the corresponding destination, multiplied by the agent's risk sensitivity. At each iteration of the A* algorithm, the neighboring patch with the smallest total cost to a destination is selected to be included in the optimal path. Through the A* algorithm, a guide agent chooses the camp with the minimum cost and starts walking towards it together with her/his follower agents, i.e., the followers set the leader's destination as their destination. During their movements, guides can access the remaining camp capacity information for all camps. If the destination camp becomes full, the guide removes that camp from her/his alternative camp list and determines a new destination point using the A* algorithm. The algorithm uses the guide's current location and current risks of patches to find the next best destination. The flowchart of interactions of guide agents with the environment is given in Figure 3.7.

Well-informed agents calculate their distance to each camp location they know. They sort the distances from smallest to largest. They randomly select one of the two closest camps. If the destination is within the distance traversed in one tick, they find a path to that point using the A* algorithm mentioned above. Otherwise, they face their destination and select the patch which gets them closest to their destination from the area within their vision as a temporary target. They determine the optimal path to this temporary target point using the A* algorithm and proceed by following this path. If the patch they are on at the end of the tick is another destination patch, they settle in that camp. This procedure is repeated in each tick until the well-informed agent reaches her/his destination. Well-informed agents check the occupancy rates of their known camps at each tick. If the destination becomes full, they determine the closest available camp among their known camps as the new destination. Figure 3.8 shows the flowchart of the movement rules of well-informed agents.

Two different walking rules are defined for household agents, depending on whether they are followers or not. Non-follower household agents create a list of known camps. If there is only one camp in the list, they set this camp as the destination. If there are two camps, they randomly select one of them as the destination. If there are three or more camps, they calculate their distances for each of these camp locations. They list the calculated distances from smallest to largest and randomly select one of the two closest camps as the destination. The household agent type also has the same walking rules as well-informed agents. On the other hand, they have a narrower vision distance. Unlike well-informed agents, they cannot access the occupancy information of the known camps. They check whether there is available capacity in the destination only when they reach it. If there is available capacity, they settle in their destination. If the destination is full, they receive information about other camp locations from the authorities. Authorities direct agents to the nearest camp, i.e., they set the nearest camp with available capacity as their new destination. The interactions of household agents with their environment are summarized by the flowchart given in Figure 3.9.

Followers, uninformed agents and follower household agents, follow their leader. If they are not on the same patch as their leader, they find a path to the leader's location using the A* algorithm. When they arrive at the same patch, they assign the current path of their leader as their current path and walk on this path with their leader. They assign their leader's destination as their own destination. Uninformed agents cannot move without a leader; therefore, they check whether their leader has left the system (settled in a camp) during their movements. If the leader leaves the system and the remaining distance to the destination camp is shorter than the movement distance per tick, they find a path to the destination with the A* algorithm. They return to the leader search process if the distance exceeds their movement range. If no other leader is found in three ticks, their migration journey ends and they leave the system before reaching a destination. Followers face different conditions depending on their agent type at the time of arrival to the destination camp. If there is still capacity when their leader reaches the destination, they settle in the destination with their leader. If there is not enough capacity, the followers restart from the leader search process. If they find a new leader, they start to follow her/him to a new available destination point. If uninformed agents cannot find a new leader within three ticks, they leave the system before completing their migration. On the other hand, when a new leader is not found, household agents set themselves as their own leader. They follow the movement rules of the household agent type mentioned above. The flowchart of the movement rules of follower agents is given in Figure 3.10.

## 3.6 Simulation Instances

We tested our model on two NetLogo worlds: the customized sample world and the randomly generated world. The sample world contains only one destination patch. We defined additional destination patches on the sample world to get meaningful results from the simulation. In this way, we utilize the information levels of the different information types for each agent type. Each agent moves three patches per tick in both test simulations. Agents check for a leader in a circle with a radius of one patch. Red represents guide agents, and yellow represents uninformed agents. Different shades of orange represent well-informed and household agents. As the color fades, the overall information level of the agent types decreases. We will next present the numerical results of the test simulations. However, note that only locations of source, destination, and obstacle patches are fixed in the sample world, i.e., risks of terrain patches are randomly assigned. On the other hand, the type of

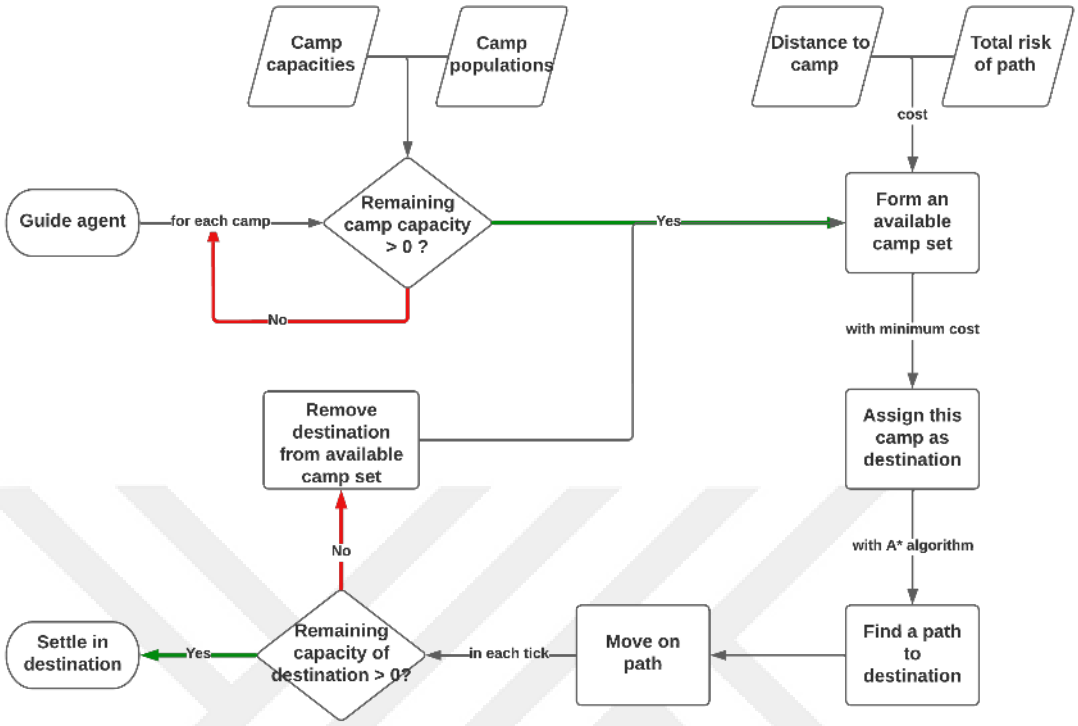



Figure 3.7: The flowchart of interactions of guide agents with the environment.

each patch is randomly assigned in the newly generated world. Therefore, results vary with the world generation and reflect only one instance.

We first simulated agent movements on the sample world consisting of five sources and six destination points with unlimited capacity. The model generated agents for 30 ticks and the simulation continued until all agents reached their destinations. The simulation was completed in 43 ticks and the simulation time was approximately 2 seconds. One hundred agents arrived at their destination. During this simulation, we examined the interactions between the agent types and leader-follower relationships. Figure 3.11 shows the emerging agent paths.

We generated a random world consisting of three sources and five destinations. We limited the capacity of destinations. Thus, we observed agents' decisions when their preferred destinations were full. This test simulation shows the impact of relationships between agents and the environment, which is one of the main parts of the model, on path changes. The model generated agents for 30 ticks, and the

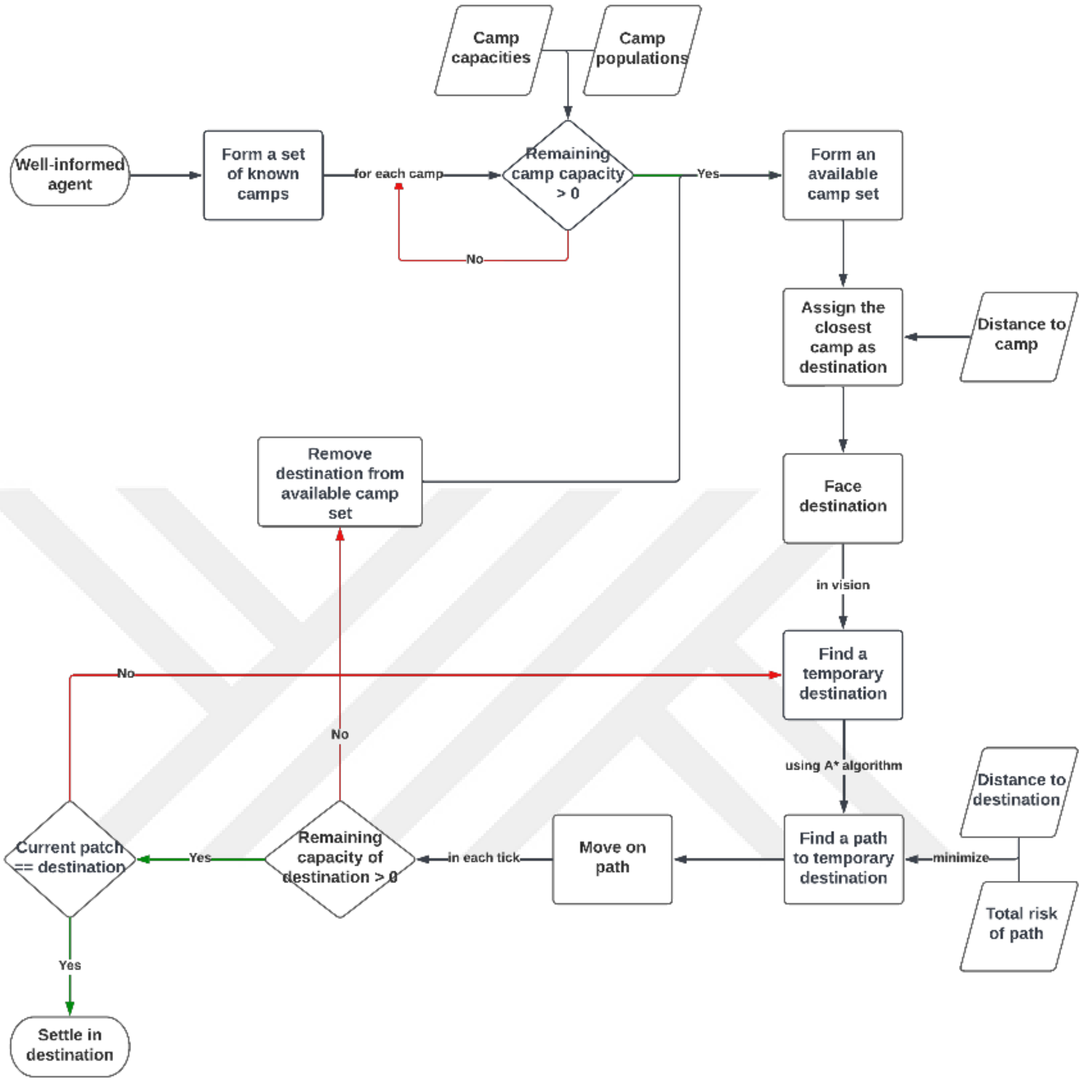



Figure 3.8: The flowchart of interactions of well-informed agents with the environment.

simulation was completed in 41 ticks. The simulation time was under 2 seconds. Forty agents reached their destination and completed their migration. We did not evaluate the situation where all destinations became full.

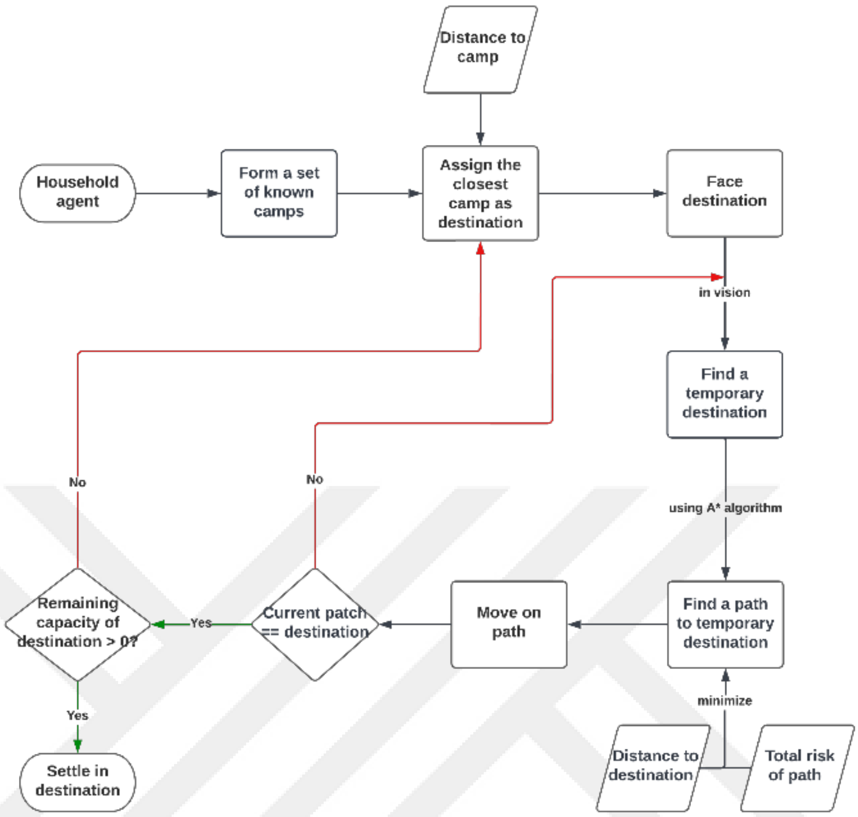



Figure 3.9: The flowchart of interactions of household agents with the environment.

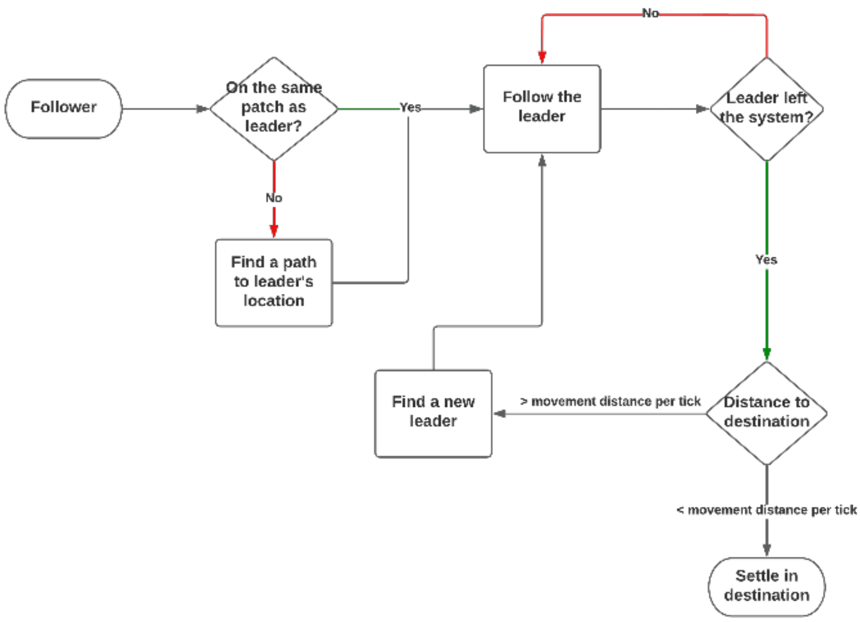
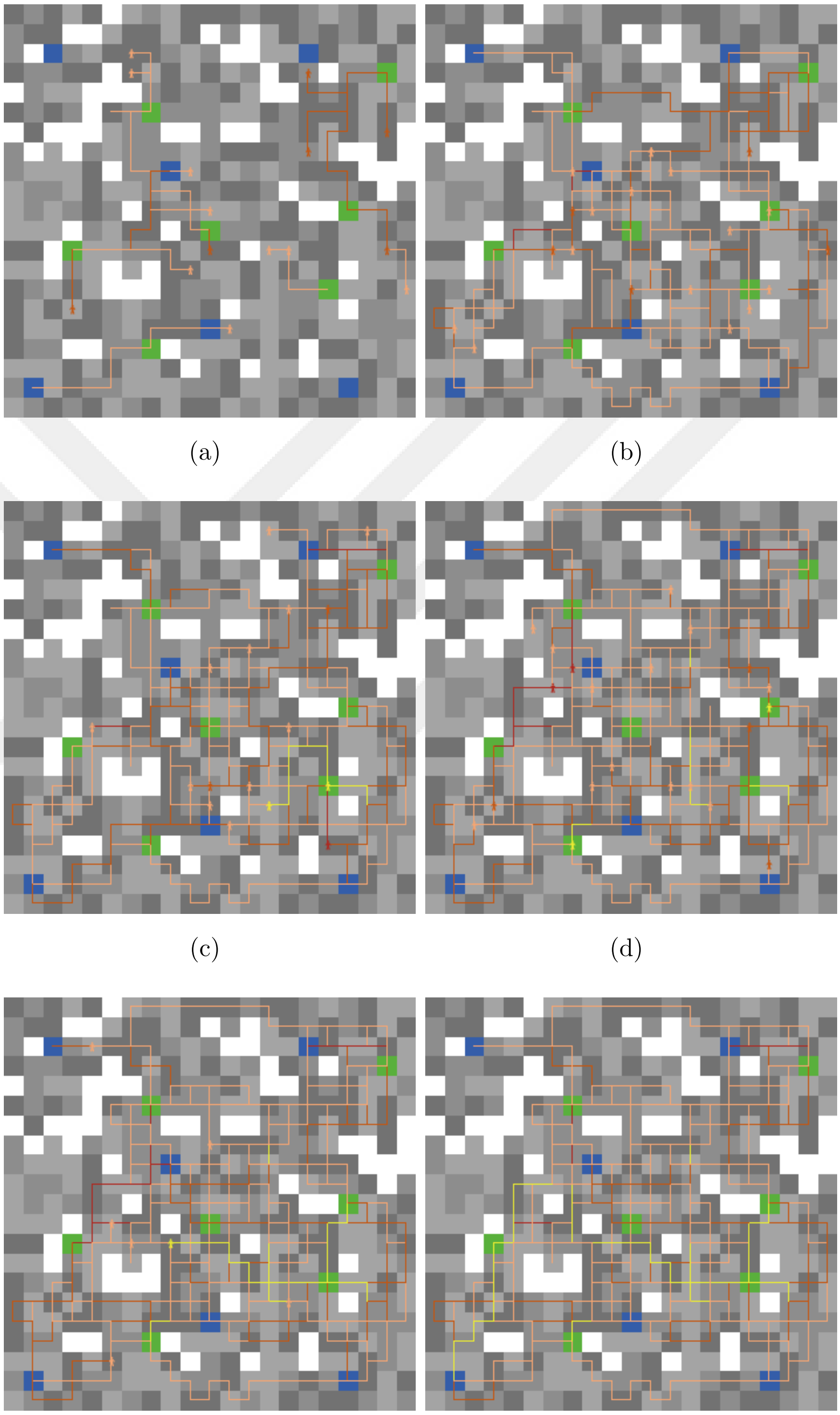



Figure 3.10: The flowchart of movement rules of followers.



(a) (b) (c) (d) (e) (f)

Figure 3.11: Agent movements at tick (a) 5, (b) 15, (c) 20, (d) 30, (e) 35, (f) 43.

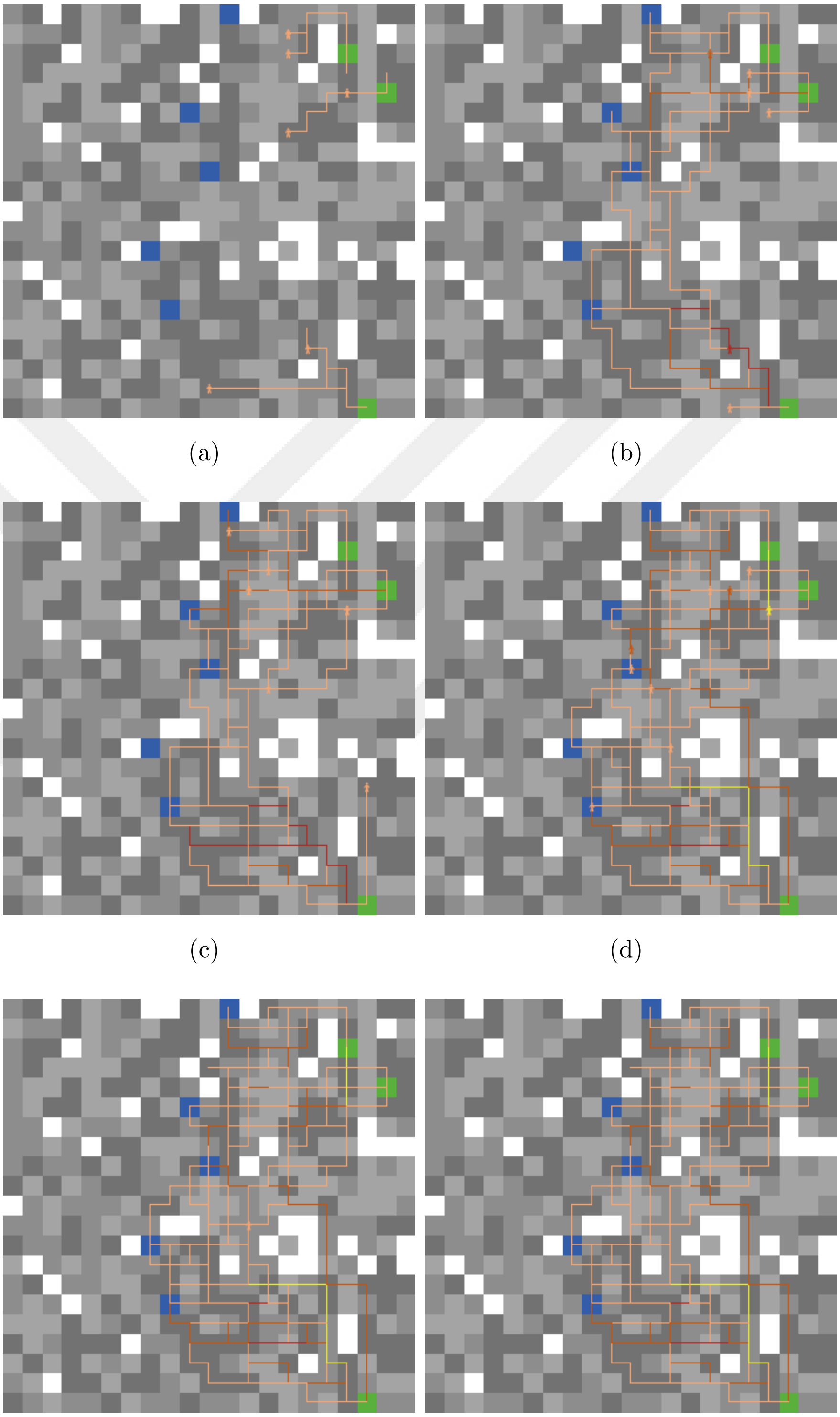

(a) (b) (c) (d) (e) (f)

Figure 3.12: Agent movements at tick (a) 5, (b) 15, (c) 20, (d) 30, (e) 35, (f) 41.

# Chapter 4

# CASE STUDY: SYRIAN REFUGEES EN ROUTE TO TURKEY

We designed a case study to test the performance of the developed agent-based migration model. The Syrian civil war has been ongoing for over a decade and has caused large migration waves to its neighboring countries, especially Turkey. Therefore, in our case study, we simulate the movements of refugee groups migrating from Syria to refugee camps in Turkey to observe the density of refugees, their migration paths to Turkey, and refugee camp preferences. We customized the developed agent-based model for the Syria case and simulated migration movements between December 16, 2019, and January 15, 2020, including the southern Idlib bombardment on December 16, 2019. We clarified the changes made to the model in the next section (see Section 4.1).

The chapter is organized as follows. Section 4.1 clarifies changes in the agent-based model customized to simulate the migration movements of Syrian refugees en route to Turkey. Section 4.2 describes the parameter settings of the customized model. Within the scope of this case study, five scenarios are considered, and Section 4.3 explains them in detail. Section 4.4 presents each scenario's numerical and visual results and lists the insights that can be drawn from them. In Section 4.5, we compare simulation outputs with real-life data gathered from international reports and news sources of the period (the southern Idlib bombardment). Finally, Section 4.6 presents the limitations of the study and suggests future work directions.

## *4.1 Agent-Based Model Customized to the Syrian Case*

We updated the agent-based model to simulate refugee movements after the southern Idlib bombardment. An agent represents a refugee group of 1,000 individuals, and the environment includes the governorates of northern Syria in addition to Turkish cities hosting official refugee camps. In the customized model, refugee camps replace destination points. We have not defined any specific sources, i.e., any patch in Syria can generate agents. We have removed the terrain patch groups from the updated model. Instead, we have assigned each Syrian governorate's risk value to the patches within that governorate. As a result of this migration simulation, we obtain the emerging migration pathways, the total number of refugees using these paths, the occupancy rate of each refugee camp, and the most preferred walk-through areas as output.

Changes in the model are given in the following sections. Additional assumptions on the Syria case are listed in Section 4.1.1. Section 4.1.2 shows the mapping stages of the NetLogo world and calculations of governorates' risk levels. Finally, Section 4.1.3 describes the agent generation processes and explains the migration decision steps in detail. No changes occurred in the other two parts of the model: interactions between agents (see Section 3.4) and interactions between agents and the environment (see Section 3.5).

### *4.1.1 Assumptions*

In addition to the assumptions of the agent-based model, we specify some assumptions and limitations for the case study. The set of possible destination points is restricted to official refugee camps in Turkey. Although only 1.3% of Syrian refugees arriving in Turkey stay in camps, this is a valid assumption since displaced people try to reach the nearest safe areas during a crisis [Refugees Association, 2022]. In our case, refugee camps are the closest settlements to the Turkish border. We assume that all refugee camps are empty at the beginning of the simulation and can serve at full capacity. In the model, border gates are not defined, so it is assumed that agents can cross over into Turkey from any point on the Syria-Turkey border. Also, we assume that the number of agents is less than the total camp capacity; hence, we have not evaluated the utilization of all camp capacities. In addition to these general assumptions, there are some scenario-based assumptions which will be explained in detail in Section 4.3.

### 4.1.2 Map Generation

We built a map covering the governorates of northern Syria and Turkish cities hosting official refugee camps using the geographic information system (GIS) software ArcMap (see Figure 4.1 and 4.2). Shape information of these locations is kept as polygon data in the ArcGIS database. The polygon data of Syria includes the risk of each governorate. Environmental risk is defined between 0 and 1, with 0 being the lowest and 1 being the highest. We calculated the risk as the ratio of conflicts in a governorate to the total number of conflicts in Syria. We accessed the Armed Conflict Location  Event Data Project (ACLED) database using the data export tool to acquire the number of armed conflicts in each Syrian governorate between July 2018 and November 2019 [ACLED, 2020]. We assumed that Turkish cities are risk-free. On the other hand, the shape information of the camps is kept as point data with the coordinates, city, name, and capacity. There are 23 refugee camps located in 10 different Turkish cities. We gathered all the required information about these camps from the reports of the Turkish Disaster and Emergency Management Directorate [AFAD, 2022].

The NetLogo GIS extension furnishes GIS aid and the capability to load polygon, line, and point data to NetLogo. Using the GIS extension, we adapted datasets (Syrian governorates, Turkish cities, refugee camps) to NetLogo from the GIS data space. We transformed the GIS map into a NetLogo world with 125 by 125 dimensions, where each patch represents 3 pixels. As a result of this transformation, a NetLogo patch represents an area of 7x7, i.e., 49 km$^2$. Patches inherit the unique characteristics of Syrian governorates or Turkish cities, depending on their locations. For this reason, we defined a risk attribute for patches within Syria. The risk of each governorate is transferred from the Syrian polygon data to NetLogo patches. While transferring, the model randomizes risks by employing a user-controlled parameter. Attributes other than risk are transferred to NetLogo patches from GIS data without any changes.

Figure 4.1: A realistic view of the map on a topographic basemap.

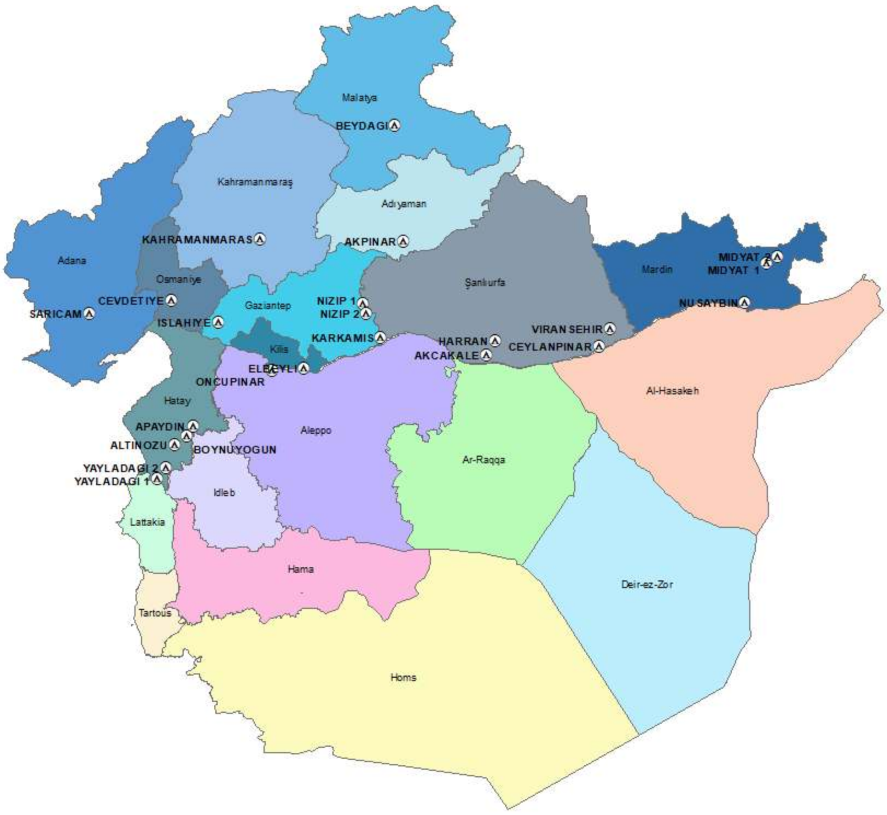



Figure 4.2: The portion of the map transferred to NetLogo.

### 4.1.3 Migration Decision

Agents decide to migrate based on the risk of patches around them. In each tick, the model calculates the average risk of neighboring patches for each patch in Syria. A sigmoid function is used to obtain a non-negative probability, $p$, of generating an agent at any value of mean risk, $x$, where $p(x) = \frac{1}{1+e^{-x}}$. Hence, the probability varies according to the risk. The model compares the obtained probability of each patch with a control parameter, which consists of two components, one of which is a constant and the other is a random number. The random number reflects the unpredictable side of the migration decision. The value of the constant number is determined through numerical experiments to keep the number of migrating agents reasonable. In each tick, patches with a probability greater than the control parameter generate an agent. The detailed flowchart for the migration decisions of the customized agent-based model is given in Figure 4.3.

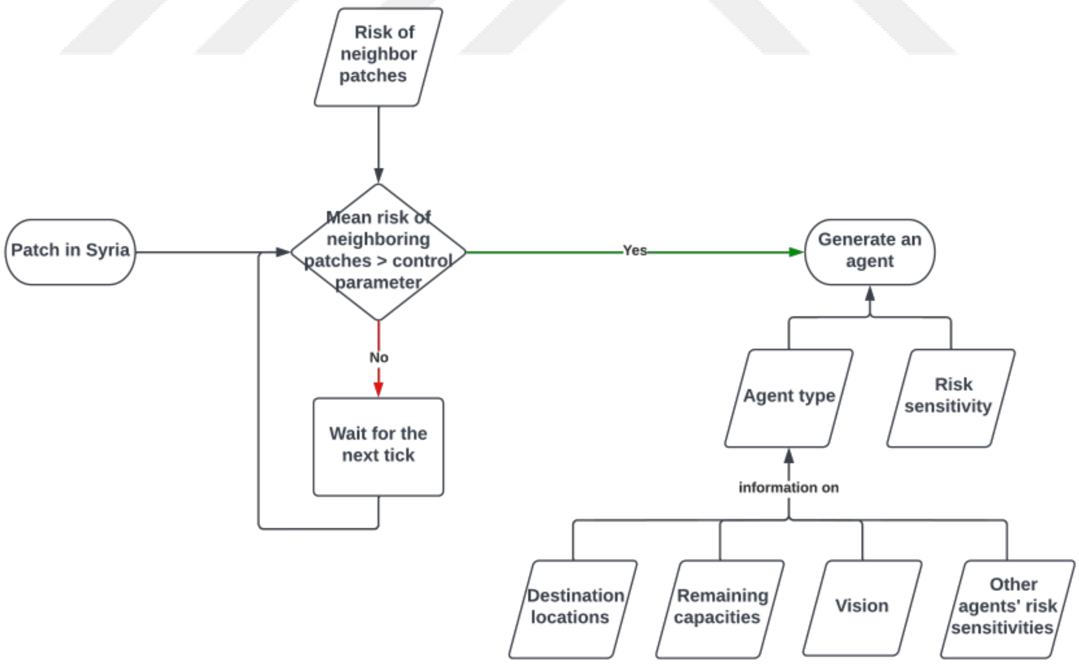



Figure 4.3: The flowchart for the migration decision part of the customized agent-based model.

### *4.2 Parameter Settings*

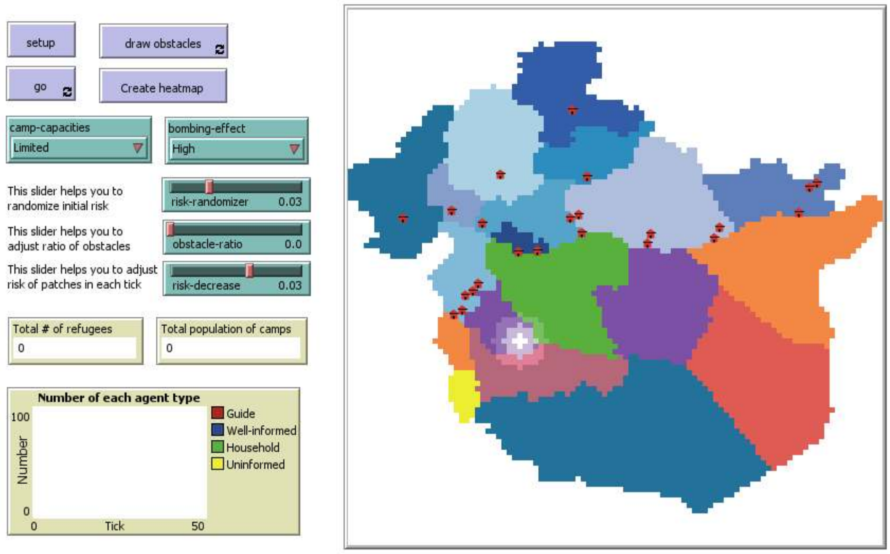
The model simulates the migration phenomenon through parameters. The simulation tool allows running different scenarios on the model with minor modifications on parameters. Some of these parameters are integrated into the code, and some are available in the NetLogo user interface. Users need to halt the simulation to be able to change the values of parameters integrated into the code. The change can be observed instantly as the simulation continues. The parameters integrated into the code are as follows. The **vision** parameter specifies the vision distance of agents with well-informed and household agent types. The **guide-ratio**, **well-informed-ratio**, **household-ratio**, and **uninformed-ratio** parameters indicate the percentage of each agent type in the total agents generated. There is no need to specify the value of each agent type parameter. For example, it is possible to specify the value of one and randomize the occurrence of the other three agent types. In the agent generation phase, **control-parameter** determines the agent generation condition on a patch, and it is a combination of a constant and a random number (see Section 3.3).

The parameters in the NetLogo interface are easier to use. Users can change parameter values by using buttons, sliders, and choosers. These parameters reflect the environmental changes that occur before and during the simulation. The **camp-capacities** parameter is a boolean parameter that controls whether camp capacities are limited or unlimited. The **risk-randomizer** parameter, determines the amount of change in the default risk level of patches and increases the uncertainty of the environment. This parameter represents the maximum value at which the patch risks can increase or decrease. In other words, the model sums the default risks with a random value between [-risk-randomizer, risk-randomizer]. It is only used to assign the initial risk values during the setup phase, while the NetLogo world is being created. The **obstacle-ratio** parameter specifies the percentage of random obstacles that appear in Syria. A reboot is required to change its value. Also, the user can specify the effect of bombing, i.e., the diameter of the bombing using the **bombing-effect** chooser from the NetLogo user interface. The **risk-decrease** parameter determines the amount of decrease in the risk of patches after the increase due to dangerous events in the environment. Patches reduce their risks at the specified parameter value when their risk level exceeds 0.5.

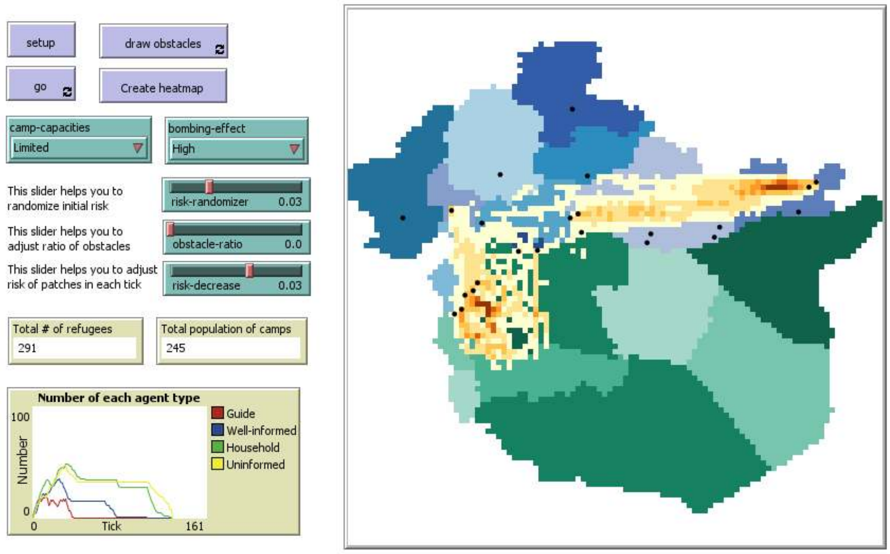
Table 4.1 summarizes the parameter properties and descriptions, both integrated into the code and available in the interface. Figure 4.4 gives the snapshots of the NetLogo user interface before (Figure 4.4(a)) and during a run (Figure 4.4(b)). Figure 4.4 shows the parameters that can be controlled from the interface. Sliders allow users to change parameter values easily, and the interface explains how to use these sliders. The user can track the total number of generated agents, and the number of agents settled in the camps from the interface. The time-dependent change in the number of agents belonging to four agent types is given graphically. Buttons enable creating the map (setup), adding obstacles to the environment (draw obstacles), starting the simulation (go), and creating a heat map at the end of a simulation (create heat map).

Table 4.1: Parameter properties and descriptions.

| Parameter Name | Location | Description |
|---|---|---|
| camp-capacities | Interface | 0-1 parameter standing for limited (1) or unlimited (0) capacities |
| bombing-effect | Interface | Specifies the diameter of the bombing (High/Med/Low) |
| risk-randomizer | Interface | Determines the amount of change in the default risk level of patches in initial set up |
| obstacle-ratio | Interface | Specifies the percentage of random obstacles |
| risk-decrease | Interface | Determines the amount of decrease in the risk of patches after an increase due to a dangerous event |
| vision | Code | Specifies the vision distance of agents with well-informed and household agent types |
| guide-ratio | Code | Represents the percentage of guide agents |
| well-informed-ratio | Code | Represents the percentage of well-informed agents |
| household-ratio | Code | Represents the percentage of household agents |
| uninformed-ratio | Code | Represents the percentage of uninformed agents |
| control-parameter | Code | Determines the agent generation condition |




(a)




(b)

Figure 4.4: Snapshots of the NetLogo user interface (a) before, (b) after a run.

## *4.3 Scenario Characteristics*

We developed five scenarios to observe the changes in the number of refugees and their migration paths under different conditions. All five scenarios simulate the movements of refugees who started to migrate in a one-month period from December 16, 2019 to January 15, 2020. One tick in the simulation is equivalent to one day in real life. The model generates agents for 30 ticks; after 30 ticks, the simulation ends when all agents settle in the refugee camps. In each scenario, a bombing with a high impact occurs at the beginning of the simulation (at tick 0). An agent represents a group of 1,000 refugees. We determined the group size by considering the model's run time and lucidity of visual outputs. As mentioned in Section 4.1.2, a patch represents an area of 49 $km^2$. Accordingly, an agent walks three patches in a tick, corresponding to a walking distance of 21 km per day. The first four scenarios do not set any condition on the distribution of agent types in the population. In other words, the model generates a random number of agents of each agent type. Table 4.2 provides the parameter settings for each scenario, which are explained next.

**Scenario 1 (Base scenario):** This is the base scenario. During the period covered by the simulation, the three most risky governorates within Syria, sorting in decreasing order of risk level, were Idlib, Hama, and Aleppo. Scenario 1 simulates the aerial bombardment in southern Idlib, and no other conflicts occur in Syria. The bombing raises the area's risk level to the highest level defined, which is equal to 1. Therefore, we expect a massive migration wave from the bombing site. Scenario 1 observes the impact of bombing on the number of refugees, their paths, and arrival times to camps where camp capacities are limited.

**Scenario 2:** Scenario 2 modifies the environment defined in the base scenario. This scenario analyzes random conflicts within Syria, other than the main bombardment in southern Idlib, that increase the environmental risk. The increased risk causes more refugees originating from these conflict areas. In addition, conflict zones become obstacles, where refugee groups cannot walk through. The user can determine the number of random conflicts by the **obstacle-ratio** parameter. While the parameter value is 0% in other scenarios, it is increased to 3% in Scenario 2.

**Scenario 3:** Scenario 3 removes the capacity constraint on the camps. This scenario investigates which camps are preferred when there is unlimited capacity so that the required capacity level for each camp can be determined.

The first three scenarios focus on environmental changes, while the last two analyze the changes in refugee groups.

**Scenario 4:** Scenario 4 explores the influence of vision distances of household and well-informed agent types on path choices. It employs **vision** parameter. In other scenarios, the vision distance of household agents is three patches, i.e., walking distance in one tick. The vision distance of well-informed agents is six patches. Scenario 4 doubles the vision of these two types of agents. In this way, these agents' knowledge about their environment increases. This scenario examines the effect of increased information on the distance and risk value of patches on agents' decisions.

**Scenario 5:** Scenario 5 analyzes the different compositions of agent types in the population. It alters the values of the **guide-ratio**, **well-informed-ratio**, **household-ratio**, and **uninformed-ratio** parameters. This scenario consists of two scenarios, 5a and 5b. Scenario 5a increases the number of well-informed household agents and guides in the population. Thus, it examines the effect of increasing information level (for each information type) on the number of agents that can reach the camps and migration paths. On the other hand, Scenario 5b increases the ratio of household and uninformed household agents in the population. This scenario aims to gain insights into the migration behaviors of populations with different levels of information.

In summary, with these five scenarios we aim to cover the following: a base scenario with the main bombardment (Scenario 1), the effects of other conflicts (Scenario 2), unlimited camp capacities (Scenario 3), vision distances (Scenario 4), and different compositions of agent types (Scenario 5). Note that these scenarios represent a small proportion of all potential cases. We think that they cover an interesting range of situations and can be extended in future studies.

## *4.4 Simulation Results*

The simulation model was run ten times for each scenario, and we report the average values of the obtained results. To facilitate tracking the camp occupancy results, we assigned numbers to the camp locations, which can be observed in Figure 4.5. The visual outputs of the resulting paths for each scenario are given in Figure 4.6.

Table 4.2: Parameter settings for each scenario

| Parameter | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 | Scenario 5 a | Scenario 5 b |
|---|---|---|---|---|---|---|
| camp-capacities | Limited | Limited | **Unlimited** | Limited | Limited | Limited |
| obstacle-ratio | 0% | **3**% | 0% | 0% | 0% | 0% |
| bombing-effect | High | High | High | High | High | High |
| risk-randomizer | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| risk-decrease | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| constant part of control-parameter | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 |
| vision (in patches) | 3 - 6 | 3 - 6 | 3 - 6 | **6 - 12** | 3 - 6 | 3 - 6 |
| guide-ratio | N/A | N/A | N/A | N/A | **0.8** | - |
| well-informed-ratio | N/A | N/A | N/A | N/A | **0.5** | - |
| household-ratio | N/A | N/A | N/A | N/A | - | **0.5** |
| uninformed-ratio | N/A | N/A | N/A | N/A | - | **0.8** |

Densely populated regions on the paths can be observed from the heat maps given in Figure 4.7. Table 4.4 provides camp numbers, names, and their average occupancy rates for each scenario.

**Scenario 1:** An average of 300 agents are generated in 30 ticks. The bombing takes place in the southern part of Idlib, close to Hama and Aleppo. Agents originate for these three risky regions, Idlib, Hama and Aleppo. While every patch of Idlib and Hama has a high probability of generating agents, the migration movement in Aleppo starts from the southwest region close to Idlib. While most migration paths pass through Idlib and Aleppo, some pass through Ar-Raqqa and Lattakia. Since agents randomly choose their known camp locations, path differences occur between the runs. When we examine Table 4.4, we can see that the population of each camp is different from zero. Hatay and Kilis are border neighbors to Idlib, and the agents frequently preferred the refugee camps in these cities. The capacities of the camps in Hatay (camps 3, 4, 6, 22, and 23) are used completely or almost completely. The population of camp 4 in Kilis almost reaches its maximum capacity. The randomness of camp preferences brings along various migration paths. The agents, who assign camps in Şanlıurfa (camps 8, 21) or Mardin (camps 14, 15, and 18) as their destination, pass through the Al-Hasakah governorate. The emerging paths are given in Figure 4.6(a). The heat map provides a more meaningful outcome (see Figure 4.7(a)). Follower-leader relationships between agents cause some points on the migration paths to be more populated. Rather than addressing individual agents, we focus on the movement of the community in the heat map. Governments and humanitarian organizations can utilize the emerging densely populated areas in the heat map to deliver aid to en route refugees. At the end of the simulation, an average of 250 agents settle in the camps. If uninformed agents cannot find a leader to follow for three consecutive days, they leave the system before reaching any camp (see Section 3.5). In this scenario, an average of 50 agents cannot leave the conflict zone due to insufficient environmental knowledge. The simulation is completed at an average of 120 ticks with a walking distance of 3 patches per tick.

**Scenario 2:** In Scenario 2, we define dangerous events in a random 3% of patches within Syria (see the white patches in Figure 4.6(b) in addition to the single white patch in the other Figures 4.6(a), (c)-(f) corresponding to the single bombing event in all scenarios). Thus, an increase compared to the base scenario is observed in the average number of people migrating, reaching an average of 425 agents. In addition to Idlib, Hama, and Aleppo, i.e., the riskiest regions; migration originates from the governorates of Deir ez-Zor, Homs, Tartus, Lattakia, Ar-Raqqa, and Al-Hasakah. Origin points in nine governorates initiate a scattered migration movement (see Figure 4.6(b)). Agents perceive dangerous events as obstacles and cannot walk through these patches. The agent movement restriction leads to shifted migration paths. This change can be observed visually in Figure 4.6(b). As in the base scenario, at least one agent settles at all camp points in this scenario. The increasing number of agents increases the occupancy rates of the camps. The occupancy rates of especially Gaziantep (camps 11, 13, 16 and 17), Şanlıurfa (camps 10 and 21), and Mardin (camps 14, 15 and 18) camps increase significantly with migrations from east Syria. Idlib and its surroundings are the primary sources of migration; therefore, most migration paths pass through these areas close to the bombing site. In addition, Şanlıurfa and Mardin are densely populated areas (see Figure 4.7(b)). An average of 345 agents reach the camps. The increasing number of agents and the limited camp capacities increased the workload on the model, and the simulation is completed in an average of 135 ticks.

**Scenario 3:** In Scenario 3, the camp capacity constraints are removed. An average of 300 agents are generated, and an average of 250 of them settle in the camps. Table 4.4 shows the average number of agents arriving at each refugee camp in Turkey (for Scenario 3 only). Accordingly, most agents settle in camps 22 and 23 in Hatay. Camp 9 in Kilis and camps 6 and 4 in Hatay are preferred when the camps' capacities are unlimited, respectively. In addition, some agents prefer camps further away from the border, such as camp 1 in Şanlıurfa. Limited knowledge of camp locations makes agents' destination choices different from each other when they do not designate any guide as a leader. As the agents head to camps close to the bombing site, the densely populated areas are limited to Idlib and Aleppo. With the removal of camp capacities, the simulation time is reduced to an average of 60 ticks, half that of the base scenario.

**Scenario 4:** Scenario 4 doubles the vision distance of well-informed and household agent types. An average of 315 agents are generated, and 260 of them reach the camps. The simulation is completed in an average of 115 ticks. There is no difference in the number of agents, simulation time, and camp occupancy rates compared to the base scenario. In the base scenario, the vision value is 3 for the household agent type and 6 for the well-informed. With Scenario 4, these numbers are increased to 6 and 12. However, since the distance walked per tick is three patches, it is difficult to visually observe the effect of increased visibility on the paths of the community. Focusing on individual agents shows that their information level on patch risks increases with increasing vision distance. This way, agents can scan more patches while searching for a path to their temporary targets (see Section 3.5). Vision restrictions are loosened. In other words, agents are more unrestricted in finding a path compatible with their risk sensitivity. Scenario 4 will produce more visible results when the vision is less than the walking distance in the base scenario.

**Scenario 5a:** Scenario 5a modifies the ratio of well-informed and guide agent types in the population. This scenario employs **well-informed-ratio** and **guide-ratio** parameters. The **well-informed-ratio** parameter value is set to 0.5. More clearly, half of the newly generated agents in each tick are assigned to the well-informed agent type. The **guide-ratio** parameter value is set to 0.8. Eighty percent of the remaining (newly generated) agents are assigned to the guide agent type. The rest of the newly generated agents have either the household or the uninformed agent type. An average of 310 agents are generated. An average of 300 agents settle in the camps within 115 ticks. The number of agents leaving the system without completing their migration path is reduced from 50, in the base scenario, to 10 in Scenario 5a. Camps close to Idlib have higher camp occupancy rates than the base scenario. For example, the occupancy rates of camp 19 in Kilis and camp 11 in the west of Gaziantep increase significantly. Increasing well-informed and guide agent numbers cause a decrease in the number of followers. Neither of these two types of agents follows other agents. Consequently, there are no highly populated areas in the heat map of Scenario 5a (see Figure 4.7(e)).

**Scenario 5b:** Scenario 5b creates a different composition for the population. It employs **household-ratio** and **uninformed-ratio** parameters to change the ratio of these two agent types in the population. The **household-ratio** parameter value is set to 0.5, i.e., half of the newly generated agents in each tick are household agents. The **uninformed-ratio** parameter value is set to 0.8. Eighty percent of the remaining (newly generated) agents are assigned to the uninformed agent type. The rest of the newly generated agents have either the well-informed or the guide agent type. An average of 315 agents are generated, and only 225 can reach the camps in an average simulation time of 110 ticks. Decreased environmental knowledge results in agents leaving the system before reaching safe areas. Uninformed agents need a leader to move. Therefore, the number of followers is much higher than in other scenarios. Household agents know fewer camp locations than well-informed agents. Choosing from their limited list of camps, a household agent may make strikingly different choices from another household agent (see Figure 4.6(f)). Also, household agents can only check the occupancy of their target camp after reaching it. For this reason, their migration duration and path can be longer than expected.

Table 4.3 summarizes the total number of agents, the number of agents settled in the refugee camps, and the total simulation times for each scenario. Considering the numerical results, Scenario 2 differs from other scenarios in the total number of generated agents. Scenario 3 removes camp capacity constraints and the simulation time is significantly reduced. In scenario 5b, the number of agents settling in the camps decreases. The camp occupancy rates (in %) for each scenario are given in Table 4.4. All camps are preferred by at least one agent in each scenario, except for unlimited camp capacities.

Table 4.3: Numerical results for all scenarios.

| | Scenario | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5a | 5b |
| Total number of agents | 300 | 425 | 300 | 315 | 310 | 315 |
| Total number of agents settled in camps | 250 | 345 | 250 | 260 | 300 | 225 |
| Total simulation time (in ticks) | 120 | 135 | 60 | 115 | 115 | 110 |

The time-dependent graphs of the number of agents belonging to each agent type are given in Figure 4.8. In the first four scenarios, the agent type is determined randomly. In these scenarios, the number of household and uninformed agents is usually higher than in the other two agent types. The number of guide agents is always less than the other three types. The obtained agent type distributions are quite successful in reflecting real life. On the other hand, Scenarios 5a and 5b create extreme cases to examine the effect of environmental knowledge on migration.

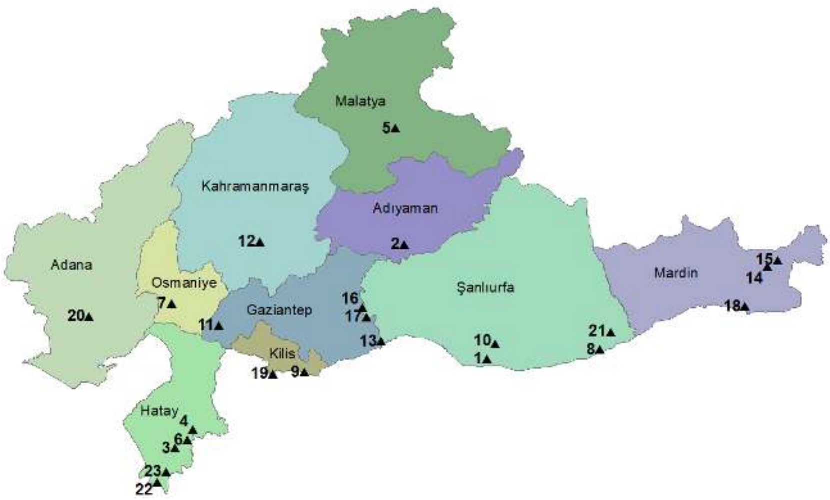



Figure 4.5: Numbered camp locations.

Table 4.4: Camp occupancy rates in % for Scenarios 1-2 and 4-5b, number of agents for Scenario 3 (since there is no capacity).

| Number | Name | Scenario 1 | Scenario 2 | **Scenario 3** | Scenario 4 | Scenario 5a | Scenario 5b |
|---|---|---|---|---|---|---|---|
| 1 | Akçakale | 53 | 50 | 11.8 | 30.6 | 43 | 22.3 |
| 2 | Akpınar | 26 | 22 | 0 | 11.6 | 20 | 32.4 |
| 3 | Altınözü | 98.5 | 100 | 9.4 | 100 | 100 | 94 |
| 4 | Apaydın | 86.9 | 97.5 | 15.9 | 99 | 100 | 92 |
| 5 | Beydağı | 10 | 11 | 0.8 | 41 | 40 | 24.5 |
| 6 | Boynuyoğun | 96 | 100 | 19.8 | 100 | 100 | 93.5 |
| 7 | Cevdetiye | 2.4 | 17.6 | 0.5 | 25.2 | 36.4 | 8 |
| 8 | Ceylanpınar | 47.3 | 41.3 | 1.2 | 13.3 | 50 | 42 |
| 9 | Elbeyli | 94.3 | 95.6 | 38.5 | 98.6 | 99 | 74 |
| 10 | Harran | 4.6 | 67 | 4.4 | 12.3 | 38 | 10 |
| 11 | Islahiye | 21.2 | 67.2 | 1 | 16.4 | 61.6 | 29.2 |
| 12 | Kahramanmaraş | 20.3 | 26.3 | 1.2 | 20.3 | 50 | 23.6 |
| 13 | Karkamış | 45.2 | 74.4 | 8.8 | 55.2 | 56.4 | 26 |
| 14 | Midyat1 | 1.5 | 43 | 0.9 | 36 | 21 | 31 |
| 15 | Midyat2 | 4 | 25.5 | 0 | 20 | 24 | 8.5 |
| 16 | Nizip1 | 35.6 | 69.6 | 1.2 | 17.6 | 14.8 | 24 |
| 17 | Nizip2 | 43.2 | 70.4 | 0.6 | 24.8 | 38.8 | 32 |
| 18 | Nusaybin | 41 | 75.5 | 0.1 | 21 | 18.5 | 14.5 |
| 19 | Öncüpınar | 44 | 88 | 7.3 | 77.9 | 91 | 51.3 |
| 20 | Sarıçam | 13 | 30.3 | 0.2 | 26.6 | 19.3 | 24.6 |
| 21 | Viranşehir | 28.6 | 42.6 | 0.4 | 40.3 | 20.3 | 12.3 |
| 22 | Yayladağı1 | 100 | 100 | 73.1 | 100 | 100 | 100 |
| 23 | Yayladağı2 | 100 | 100 | 73.5 | 100 | 100 | 100 |

### *4.4.1 Insights*

We can derive the following insights from the simulation results:

- Agents' information level on camp locations influences their camp choices. Agents can only choose their destination among the camps they know. They differ in their destination preferences from other agents. Thus, the individual decision processes of the agents are reflected in the model.

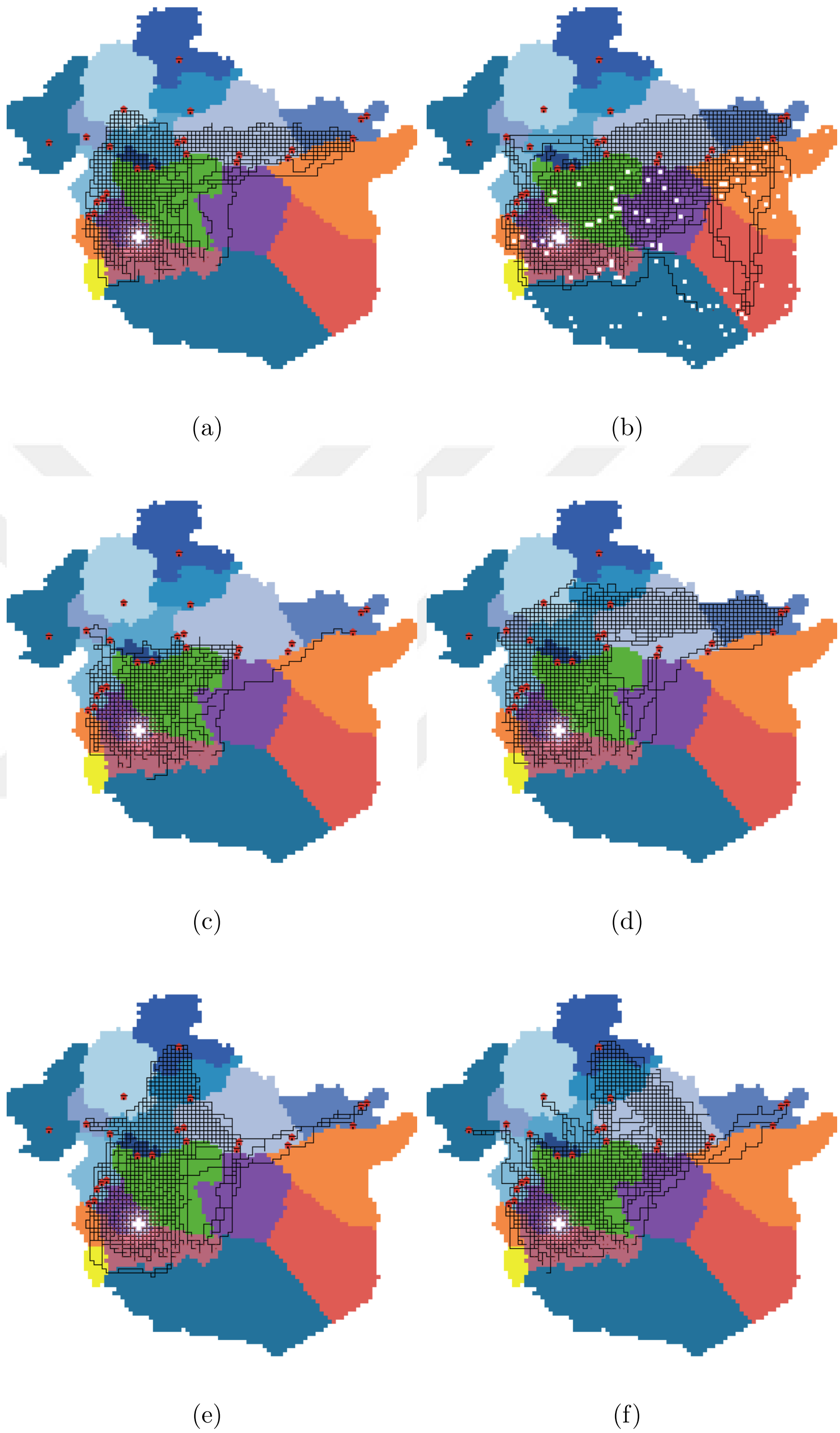



Figure 4.6: Migration paths for: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4, (e) Scenario 5a, (f) Scenario 5b.

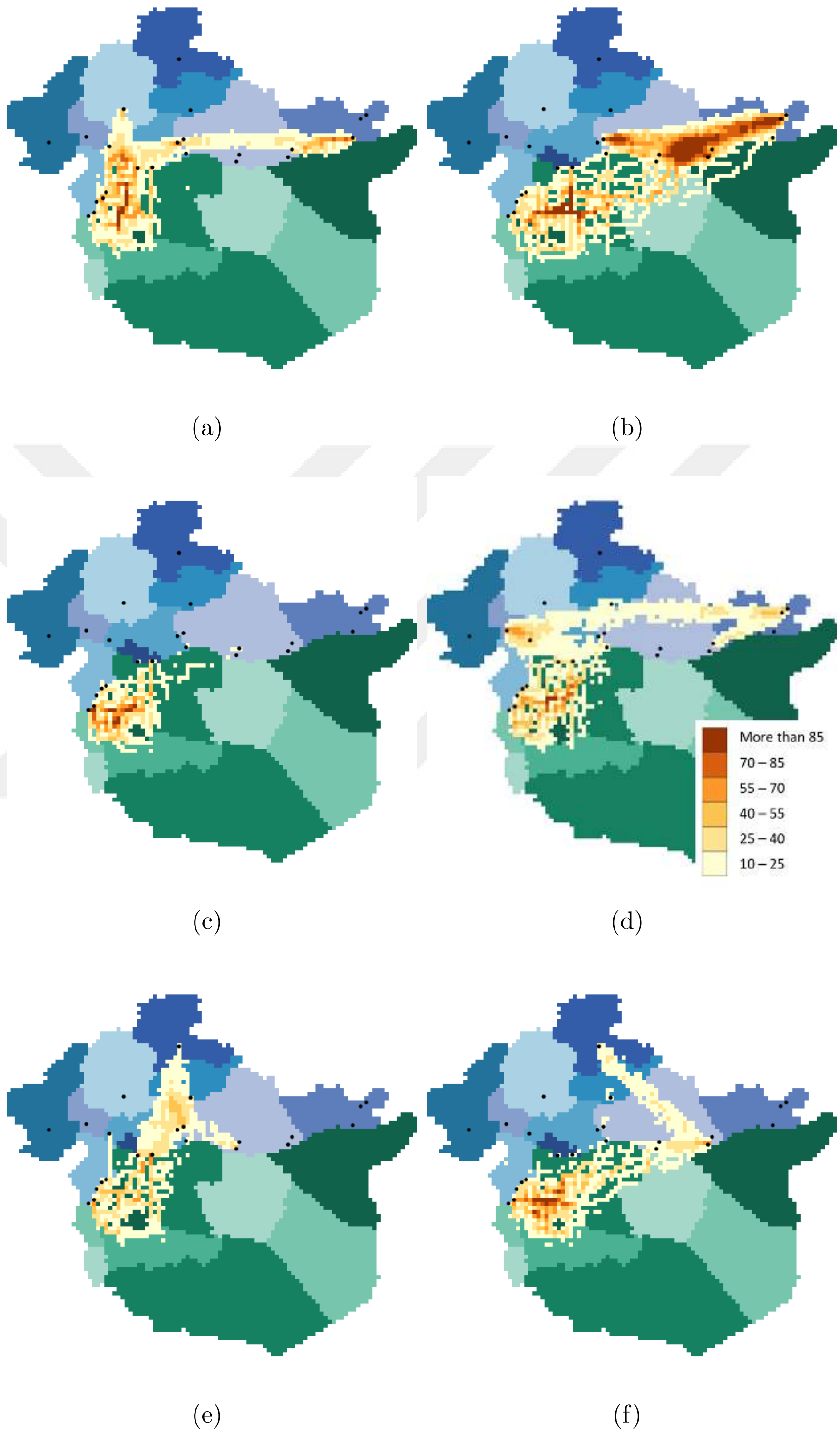
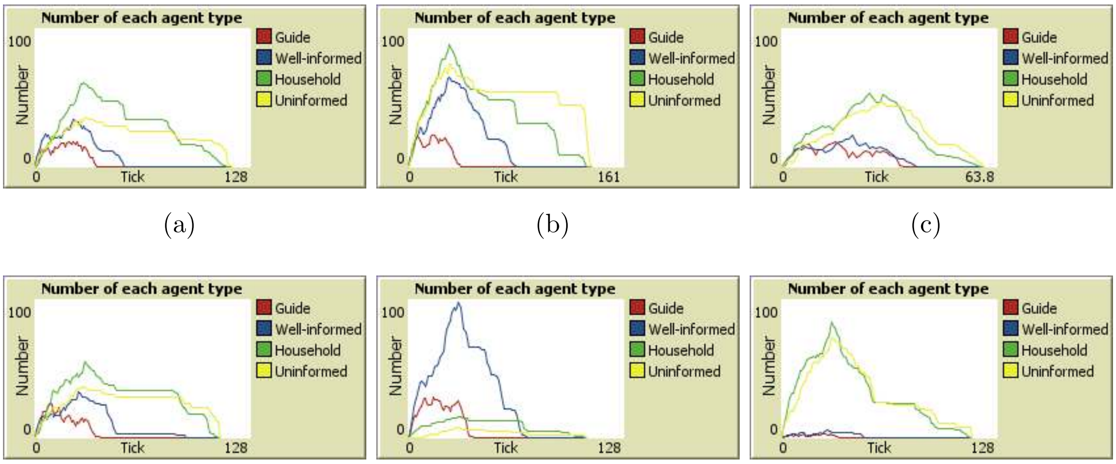



Figure 4.7: Heat maps for: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4, (e) Scenario 5a, (f) Scenario 5b.




(a) (b) (c)

(d) (e) (f)

Figure 4.8: Time-dependent graphs of agent types for: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4, (e) Scenario 5a, (f) Scenario 5b.

- Agents' ability to control camp occupancies prevents disruptions in their movements. Thus, instead of stopping at a camp with no remaining capacity, they proceed directly to their next destination camp.

- Randomly determining the known camps of each agent brings with it the possibility that at least one agent can occupy each camp's capacity. The uncertainty on camp preferences makes it difficult to prepare an emergency response plan for a crisis.

- The results obtained from the unlimited camp capacity scenario can be used as the upper limit by the decision-makers. The camps in Hatay provide temporary protection for many people. Especially in times of crisis, the service capacity of the nearest safe settlement areas can be increased.

- Increasing environmental risks forces more people to flee their homes. Thus, the number of agents increases, originating from patches closer to conflict areas.

- The probability of not reaching safety increases as the agent's environmental knowledge decreases. For this reason, refugees fleeing the conflict areas should have as much access to the camp locations, their occupancies, and up-to-date environmental risks as possible.

- Refugee camps also act as information centers for household agents. If the camp becomes full at arrival time, agents acquire information about the nearest camp with available capacity from the camp authorities for their next destination.

- Highly populated areas given in heat maps are essential findings for decision-makers. Mobile aid vehicles installed in these areas can be used to fulfill the needs of en-route refugees and access up-to-date information [Bayraktar et al., 2022].

- Agents' vision attribute restricts the patches that agents can check their risk levels. The vision constraint needs to be relaxed so that agents can find a path compatible with their risk sensitivity. In cases where the vision distance is restrictive, agents advance to the determined point regardless of their individual attributes.

- Each agent type has a range of values for four different types of information. These values define the movement rules of agents. Guide and well-informed agents are always leaders, while uninformed agents are always followers. Household agents can be both leaders and followers. Followers consider whether they know other agents' risk sensitivities during leader selection.

- Followers follow the path of their leader. This follower-leader relationship causes some regions to be densely populated in a society where followers are the majority.

- The guides head to the closest camp suitable for their risk sensitivity. Therefore, they are the first to reach their destination. Then, well-informed agents, who know a higher number of camps than the other two agent types, arrive at their destination camps. The household agents become their own leaders, and uninformed agents start to follow them. Household agents advance to their destination camp with their followers and settle into the camp, first the leaders and then the followers. This pattern can be observed from the graphs given in Figure 4.8(a)-(d).

## *4.5 Comparison with Real-Life Data*

We compared the simulation results with the real-life data declared in OCHA reports on developments in northwest Syria published before and after the bombing incident [OCHA, 2019a, OCHA, 2019b, OCHA, 2019c, OCHA, 2020a, OCHA, 2020b, OCHA, 2020c]. Table 4.5 summarizes the displacement numbers. The aerial bombardment, which continuously increased its intensity after December 16, accelerated the migration movement that commenced in November, mostly from densely populated cities such as Saraqab and Ma'arrat An-Numan [OCHA, 2019a]. As the bombing increased its devastating effects on local life, tens of thousands of displaced people flocked to northern parts of Syria, such as urban centers like Idlib, Saraqab, and Ariha, and IDP camps in northwest Idlib along the Turkish border. Although it is difficult to reach the exact number of displaced people in the early stages of the incident, the humanitarian community reported 130,000 displacements between December 11-23, 2019. As of December 26, displaced people reached 235,000 [OCHA, 2019b] and 284,000 displacements occurred between December 1-29, 2019 [OCHA, 2019c]. Ma'arrat An Numan and its countryside became almost empty during this period. Fearing the attack would spread to a wider area, the internally displaced people (IDP) began to flee from the eastern part of Saraqab. In addition, newly displaced individuals headed for northern Aleppo's Afrin, A'zaz, and Al-Bab areas. From December 1, 2019, to January 1, 2020, almost 300,000 individuals fled their homes, mostly from southern Idlib, and headed north, using a pathway within Idlib [OCHA, 2020a]. The total number of displacements seeking safety exceeded 312,000 by January 8 [OCHA, 2020b]. About 30,000 newly displaced advanced to Aleppo in search of refuge and service. From December 1, 2019, to January 14, 2020, nearly

350,000 individuals fled their homes and traveled further north to move away from militancy [OCHA, 2020c]. Most recently displaced moved to urban centers such as the city of Idlib or Ariha or areas where the IDP population is significantly high such as Dana, Maaret Tamsrin, or Atareb. During this period, the number of displaced individuals moving to the regions of the northern Aleppo governorate reached 45,000.

Unfortunately, in the reports mentioned above, there is no information on the number of displaced people crossing the Turkish border or the number of people resettled in the camps on the Syrian-Turkish border. For this reason, we compared our outputs with the official statements that appeared in the media. On December 19, The Turkish Presidency announced that in the three days following the bombardment of Southern Idlib, approximately 50,000 Syrian refugees crossed from Northern Idlib to the Turkish borders [Al Jazeera, 2022a]. Supporting the Turkish Presidency's statement, United Nations observers stated that at least 18,000 refugees left the bombing site on December 21 [Al Jazeera, 2022b]. According to the news of the Anadolu Agency, on January 9, 20,000 more civilians migrated from Idlib to the Turkish border in the last two days [Karacaoğlu et al., 2022]. About a week later, according to the news dated January 17, approximately 13,000 more civilians were displaced to the Turkish border in the last two days due to the intense attacks of the Bashar Assad regime and its supporters in the western and southern countryside of Aleppo within the borders of the Idlib De-escalation Zone in Syria [Musa and Karacaoğlu, 2022].

Table 4.5: Total number of displacements documented in situation reports.

| Situation report | Date | Total displacements | Displacements to Aleppo |
|---|---|---|---|
| Report 1 | 11-23 December | 130,000 | - |
| Report 2 | 11-25 December | 235,000 | - |
| Report 3 | 11-30 December | 284,000 | - |
| Report 4 | 11 December - 1 January | 298,354 | - |
| Report 5 | 11 December - 8 January | 312,000 | 30,000 |
| Report 6 | 11 December - 14 January | 350,000 | 45,000 |

Looking at the simulation results, we see that they match with the real-life data. In scenarios where the environmental risk does not change (Scenarios 1, 3, 4, 5a, and 5b), the numbers of generated agents are similar with the total displacement numbers in the official reports, as each agent represents a group of a thousand refugees. Besides the scenarios where the environmental risk does not change, in Scenario 2, the number of generated agents increased with increased environmental risk, as expected. As a result, the impact of environmental risk on the number of refugees is evident. In addition, the cost metric that we employed within the A* algorithm (the weighted combination of risk and distance) makes the environmental risk important for migration paths. Therefore, determining the environmental risk is the first step to obtaining a meaningful output from the migration model.

## 4.6 Limitations of the Study and Future Improvements

The proposed ABM gives a new direction to the human migration literature by simulating agents' interactions with each other and the environment during a crisis. Limiting the migration model with the moment of a crisis causes a few essential points to be ignored. One of them is related to the personal preferences of agents. In addition to the risk sensitivity and agent type, to highlight personal preferences, demographic characteristics such as education level, income, age, gender, religion and ethnicity can be defined as agent properties in the model. An agent represents a group of one thousand refugees. Agents should represent individuals or smaller collective entities such as households to incorporate demographic data in the model. Based on demographic characteristics such as age and income, different modes of transportation for agents can be incorporated into the model. Transportation modes such as cars, trains, or planes, much faster than walking, will increase the daily movement distance. However, new transportation modes will make a comprehensive map arrangement necessary. Additional transportation-related details such as the roads that cars can move on, train lines, and the starting and ending points of flight routes should also be included in the map. The more details that the model captures, the closer its results to the real-life. However, it should be kept in mind that accessing demographic data of displaced people and up-to-date terrain data during a crisis is one of the biggest challenges. As seen from the simulation results, the agents are generated within one month, and it takes more than two months for them to reach the camps. This is because the agents' transportation mode is limited to walking only. Faster transportation modes will diversify the time it takes for refugee groups to settle in their destination camp. Also, fatigue status can be added to the model. The portion of fatigue per tick of the agents can be determined based on their age, health status, and mode of transportation.

Another improvement point is the camp preferences of agents. Agents' destination choices can depend on some camp attributes. The number of shelters, emergency relief items such as blankets, sleeping bags, clothes, personal care kits, access to clean water and sanitation kits, quality of food, health services, and psychological counseling can determine the attractiveness level of refugee camps. Refugees prefer camps that offer registration and legal aid. Registered refugees are not forced to return and can stay with their family members. The fact that household refugee groups know some camp locations can be explained by the presence of their family members in these camps. The addition of camp attributes will deepen the migration story this study tells. Also, the existing environment can be made more detailed. One can define a new patch type for natural obstacles, such as lakes and water sources. These small details make the migration simulation model more realistic. The assumption of refugee groups crossing the Turkey-Syria border at any point can be removed, and border crossings can be restricted to border gates only. Future studies can examine the open/closed status of these border gates. This way, we can study the impacts of refugee policies on migration decisions and paths.

# Chapter 5

# CONCLUSION

The number of forcibly displaced worldwide has increased sharply over the past decade to an alarming level. If ongoing conflicts remain unresolved, or even new ones arise, the number of people forced to flee will increase continuously in the 21$^{st}$ century, and the options for the displaced will become dire. Striking statistical migration trends and current displacement numbers, including refugees, asylum seekers, and internally displaced, reveal that forced migration has become a global problem.

This study aims to simulate the migration paths of displaced people to help humanitarian organizations deliver aid. For this reason, we developed an agent-based model (ABM), which has recently become widespread in the human migration literature. The ABM simulates a crisis moment and analyzes the short-term effects of a large-scale conflict. The sudden migration of large groups of people causes data to be largely incomplete or unreliable. The lack of data further complicates predicting the scale and dynamics of such a migration. We try to minimize this complexity by defining agent attributes that do not require demographic data. Agents have information on destination locations, remaining capacities of destinations, risk levels of areas within their vision, and risk sensitivities of other agents. The level of each information type depends on the agent type. Agents perceive environmental risks based on their risk sensitivity value. The ABM investigates decision-making through these agent attributes and environmental risks. Agents interact with each other depending on their agent types and, if they have the ability to learn the risk sensitivities of other agents, their risk sensitivities. As a result of interactions among agents, a follower-leader relationship is formed between them. The ABM defines different walking rules for agents of each agent type, depending on whether they are leaders or followers. The ABM tries to reflect the dynamics of mass migration by focusing on the individual decisions of agents.

We developed a case study to examine the migration movements of Syrian refugees during the crisis initiated by the aerial bombardment in southern Idlib. We examined the impact of the bombing on the size of the migration wave from Syria to Turkey and their migration paths. We analyzed the effects of other conflicts in addition to the bombardment in Idlib, unlimited camp capacities, increased vision distance, and changing compositions of agent types in the population with five different scenarios. As a result of the simulation, we obtained the migration paths and the total number of refugees using these paths, the occupancy rate of each refugee camp, and the densely populated areas for each scenario. We limited refugee groups' destination choices to refugee camps only. Therefore, the obtained camp occupancy rates can define an upper limit for decision-makers. Emerging paths and densely populated areas can constitute an essential reference point for governments and humanitarian organizations to aid en route refugee groups. Acquired insights can help decision-makers develop effective emergency response plans and enable the rapid implementation of emergency response protocols during a crisis. In case more insight is needed, the model has been developed with the flexibility to generate other scenarios under different parameter values. Moreover, the model can simulate migration in other regions with slight modifications.

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