Conceptualising Recognition Justice for Agent-Based Modelling in the Context of Resource Scarcity

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Thesis Report

by

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Preface

This first page of this master thesis report heralds the last page in the story of my time as a student of the Delft University of Technology. It has been a pleasure and a privilege, for which I have much more gratitude to express than I could ever fit on this half page, but I will try.

I started my thesis project in the fall of 2022. I wanted to do agent-based modelling, and for this reason I asked Igor Nikolic to be my first supervisor. I am still very happy he agreed, and I loved his enthousiasm and guidance in finding a topic that suited both me and him. I wanted it to have something to do with ethics, so Igor and I asked Neelke Doorn, whose course on water ethics I had enjoyed during my master's programme, to be the second supervisor and I was very excited that she agreed. I wanted to gain some experience in an organisation outside the university as well, and Frederique de Groen made this possible by offering me a position as a graduate intern at Deltares. This position came with a real-world case to focus my research on. Frederique proceeded to act as my daily supervisor, which was both fun and very helpful.

My thesis project took an unusual turn when I took a dive into someone's car windshield and suffered a concussion. This was unfortunate, but I am thrilled that despite it slowing down my progress, I was given so much support and understanding by my supervisors that I was able to finish the project while recovering. Even when it seemed to take forever, I never felt any pressure to hurry and was always able to prioritise getting better. I want to thank Igor, Neelke, and Frederique for their patience and their support, as well as their excellent and enthousiastic supervision of my thesis. Even after all this time they were still willing to have discussions and provide feedback, which have raised the quality of my work and thinking to levels I would not have achieved on my own. So thank you all, and I hope you enjoy reading the result.

Frederique left Deltares before my thesis project was finished, and I have Marnix van der Vat to thank for being able to finish my internship. So thank you Marnix for taking over Frederique's role.

The people in my life also deserve a place on this page. Thank you to my parents for supporting me in my studies and my sport my whole life. And many thanks to my brother Philip, who took such good care of me after the accident.

Finally I want to thank all the friends I made during my time in Delft before this page is full. Thank you all, the rowers, the coaches, the cyclists, the study friends, the committee members, the camp instructors, and many more. Thank you to my crew friends with whom I have worked so hard, but also had so much fun, and still do to this day. Thank you Simone, for being such a kind and fun roommate in our new city, and for being so patient with me. And to my roommates from Delft, the greatest group of friends anyone could ever wish to have: I love you and I hope we will stay friends for the rest of our lives.

My final remark is an expression of gratitude to Lisanne, for being my concussion mentor. Without your help, this whole process would have been infinitely harder. Thank you.

Annabel Oggel
Delft, April 2024

Executive Summary

Climate change and a growing population are putting more and more pressure on the Earth's natural resources. There are many places around the world where resources people depend on for their livelihood are already scarce. When different groups of people compete over these resources, conflicts start to emerge. People may perceive other parties as having more access to the scarce resources than they do. They will experience this as unjust and this will lead to discontent and eventually evolve into active dispute. Applying norms of recognition justice can prevent or de-escalate conflict, because recognition justice means accepting differences between the involved people and groups through mutual respect and understanding. It addresses people's feelings towards themselves and each other, hereby opening more entryways into achieving justice than solely focusing on equality in the amount of received resources, as distributive justice does. Distributive justice is the form of justice that is most commonly implemented in modelling, if justice is considered at all, and it is achieved when there is an equal distribution of resources and goods as well as burdens. Recognition justice on the other hand is a more subjective form of justice. It is achieved when all people can participate in society as equals, in the way they desire. It can be obstructed by recognition injustices, which are injustices caused by people from one group, that prevent people from another group from participating in society in the way they want. These injustices can be detected through people voicing their discontent about them, as well as through public debate where the norms of recognition justice are applied to all involved groups and people.

This research aims to conceptualise recognition justice for use in agent-based models (ABMs), with focus on the context of resource scarcity. Agent-based models are simulation models that use a bottom-up approach, which allows for global patterns to be modelled through local interactions. This property lets ABMs produce complex outcomes with a relatively simple set of rules. To do this, ABMs contain entities called agents, who live in the modelled environment and follow such rules. The agents interact with their environment and each other, contributing to the global patterns as they do so. Agent-based modelling is a suitable method for implementing a complex concept such as recognition justice, because a simplified decomposition of the concept can be modelled, yet ABMs can preserve its complexity due to the many interactions that take place in such models. Furthermore, recognition justice is the most emergent form of justice, as it can be detected through an expression of feelings of injustice by people subjected to injustices, making it suitable to be modelled in an ABM.

Recognition justice was conceptualised for agent-based modelling by using literature about recognition justice and emotions in the context of conflict to identify elements that could either narrow its definition down for modelling, or that could be implemented in models. From these elements, recognition justice was defined as the absence of recognition *in*justices. To conceptualise it for modelling, these injustices were further specified as a series of individual misrecognition events, each with a type and an intensity. Each misrecognition event that an agent in a model experiences, elicits an angry emotional response in the agent. These responses over time build up to form an angry emotional sentiment, which is a state of long-term anger towards another group. Anger can diminish after misrecognition terminates, so when agents do not experience any misrecognition for a while, their sentiment can also decrease again.

To implement this conceptualisation in an ABM, agents update their emotional sentiment every time they experience a misrecognition event. Their new sentiment is calculated from their current sentiment and their emotional response to the event, which in turn depends on the event type and intensity. The emotional sentiment is used as an indication of how unjust an individual, on the agent level, or a group, on the aggregate level, is treated. It is the main metric of the model.

To demonstrate the behaviour of the recognition justice conceptualisation, an ABM based on the resource scarcity situation in the Dosso region was built. In Dosso, one of seven regions in the West-African country of Niger, a conflict is arising due to increasing pressure on resources caused by

desertification of agricultural land, and by population growth. The decreasing yield of the agricultural land leads sedentery farmers of Djerma ethnicity to expand their lands, sometimes into areas that are traditionally used by nomadic Peuhl herders as transhumance corridors. Herders trek through these corridors with their herds in pursuit of the rain. They cross the Dosso region at the end of the rainy season, when farmers are pulling in their harvests. The intrusion of farmers into herder territory leads herders to feel threatened by farmers. Meanwhile, farmers feel threatened by herders, who have a history of raiding farms and villages they pass on their trek. A perceived inequality of access to resources is the result.

Because the model purpose is to explore the behaviour of the conceptualisation instead of accurately portraying a real-world scenario, no real-world input data from the Dosso region was used. Instead, fictional configurations were used for the geographical layout of the land, the farmer and herder population numbers, and the resource demand and availability. This made it possible to test the effects these input parameters have on sentiment outcomes. Experiments were done with different combinations of input parameters to explore the model's behaviour and to see what happens to the sentiment in different scenarios.

Results showed that the geographical layout input parameters had the strongest influence on the model's sentiment outcomes. Within each geographical layout, population ratio had the strongest effect. When modelling a real-world resource scarcity situation with the purpose of learning about recognition justice there, accurate data on these factors should be collected to get the best results.

Interestingly, no patterns emerged that could be attributed to resource availability, indicating that recognition justice indeed distinguishes itself from distributive justice, and offers entryways into achieving justice even in a resource scarcity situation.

Different input scenarios lead to different sentiment outcomes by changing how many misrecognition events occur in the model and by which agents they are experienced. This means that the recognition justice conceptualisation relies on distributive characteristics by representing feelings of injustice expressed as a result of an unfair distribution of burdens. If there were a situation in which misrecognition events could not take place, this recognition justice conceptualisation would define it as a state in which recognition justice was achieved.

It is recommended to implement the recognition justice conceptualisation into ABMs modelling resource scarcity, or other types of competitions between different groups in a society. The identification of misrecognition events can be tailored to a specific system by involving its stakeholders to define the misrecognition events and the emotions that come with them. Making the modelling process participatory is expected to help detect recognition injustice by facilitating debate. Simulating feelings of injustice helps validate feelings of injustice expressed by the involved parties, which should help them feel appreciated, and help authorities become aware of groups they need prioritise in their policy design.

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Nomenclature

Acronyms

ABM agent-based model.

CAS complex adaptive system.

CoSEM Complex Systems Engineering and Management.

NGO Non-Governmental Organisation.

ODD Overview, Design concepts, Details.

WPS Water, Peace, and Security.

1 Introduction

1.1. Research Problem

Climate change is often framed as a looming threat that has to be dealt with in the near future, but its consequences for food and water security are already being felt today. Especially in Africa, where a large share of the areas most vulnerable to climate impact is located, people are currently struggling to survive. Over the next two decades, multiple climate-induced disasters and humanitarian crises are expected to take place, even if large efforts to reduce greenhouse gas emissions will be made (IPCC, 2022). Assuming this means that natural resource scarcity is going to occur in vulnerable areas in the next two decades regardless of efforts to combat the underlying cause, adaptation to these circumstances is necessary to mitigate disaster.

When people depend on scarce natural resources such as water and fertile soil for their livelihood, competition over these resources leads to conflict (Herrero, 2006). To resolve this conflict, a fair distribution of the burdens of resource scarcity must be achieved. Obtaining a morally just distribution of costs and benefits is the end goal of distributive justice (Olsaretti, 2018). This type of justice has been gaining attention in climate change modelling. For example, Matczak and Hegger (2021) notice a trend that takes distributive justice into account in water management models, especially in the context of flood risk governance. Yet, available models that take justice into account at all focus solely on planning the actual distribution of either burdens or resources from an aggregate perspective, which does not always achieve a morally just end state. For instance, Jafino et al. (2021) acknowledge that a situation that is just from the aggregate level, can give rise to injustices on the individual level. They address this by forming requirements that should be fulfilled when aiming for morally just distributions. The factors that go into forming these requirements themselves are not modelled. This is because these aspects are qualitative and hard to define, whereas dividing resources to achieve justice is a quantifiable aspect of qualitative problem.

When operating under the assumption that there are not enough resources to fulfil the needs of all actors involved, other entrances for conflict resolution must be found. To inform conflict resolution tactics, it is necessary to gain insight into the qualitative aspects of justice. People may feel that they are treated justly even when their needs are not completely fulfilled, for example by being validated by the group they are in competition with. Mutual understanding may improve relations between groups and deflate tensions that fuel the conflict. Simulation models can help with gaining insights into complex and dynamic social systems, but simulating qualitative concepts in a mathematical model is challenging.

An agent-based model (ABM) is a type of simulation model where local interactions between agents, other agents, and their environment generate emergent patterns using a bottom-up approach (Nikolic & Kasmire, 2013). These properties make it an interesting option for gaining insight into the local interactions that are involved in people's feelings about being treated justly, but to do so a quantifiable representation of justice must be conceptualised, so that it can be modelled. This is currently not being simulated in models, apart from some models using equal distribution of resources as a proxy to simulate distributive justice as mentioned above.

Doorn (2019) describes more forms of justice: apart from distributive justice there is procedural justice which is concerned with the fairness of the process with which decisions about distributions are made, and there is justice as recognition. Out of the different forms of justice as described by Doorn (2019), recognition justice holds the best opportunity for achieving justice when there is no possibility of satisfying a resource need. This is because recognition goes beyond the resources people receive, and addresses the value of people's identity. Recognition justice holds space for differences and coexistence, which chips away at the competitive element of conflict.

The aim of this thesis is to develop a method that allows for the modelling of recognition justice in an agent-based model in the context of natural resource scarcity. These concepts will be explained in further detail in later chapters.

1.2. Research Questions

The main research question of this thesis is derived from the research problem described in the previous section.

> ***"How can recognition justice be conceptualised for agent-based simulation in the context of natural resource scarcity?"***

The main research question will be answered in parts, using sub-questions that are listed below.

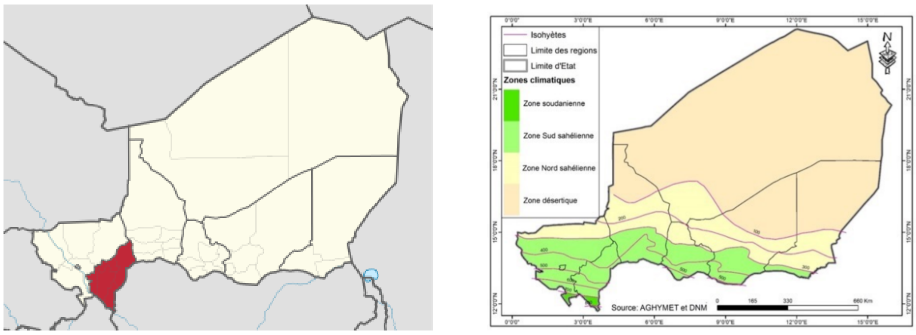
1. How can recognition justice be conceptualised in order to be modelled?
2. How must the model be built to allow for implementation of the recognition justice decomposition?
3. What insights can be gained from the model about recognition justice in the context of natural resource scarcity?

1.3. Context

To be able to demonstrate the recognition justice conceptualisation, an agent-based model will be constructed about a specific case involving conflict due to natural resource scarcity. The case will be the farmer-herder conflict currently taking place in the Dosso region in Niger. The Nigerien population largely relies on agricultural practices to sustain themselves, but desertification and degradation of natural resources are threatening the livelihood of many of Dosso's inhabitants. This leads to tensions and conflict between farmers and herders that depend on resources in the same area (Dimé & Abdoulaye Nakoari Tambandia, 2020; Frexus, 2022).

Niger is a landlocked country in West Africa, with over 80% of its surface covered by the Sahara desert. The southern part of the country lies in a region called the Sahel, which is a strip of land forming an ecoclimatic region of transition from the Sahara to the savanna. The Sahel spans all the way from the west to the east coasts of Africa. The Sahelian zone of Niger is indicated in figure 1.1b in green. Only 36% of the surface area of Niger is suitable for farming, yet over 87% of Niger's population of over 22 million relies on either agriculture or raising livestock for their livelihood (Dimé & Abdoulaye Nakoari Tambandia, 2020; Frexus, 2021). 25% of them depend on the Niger river for their water needs, others take their water from lake Chad on the border shared with Chad, or from aquifers located elsewhere (Dimé & Abdoulaye Nakoari Tambandia, 2020).

The Dosso region is one of Niger's seven regions. It is a southern region and lies in Niger's Sahelian zone, as can be seen in figure 1.1a. It is home to many farmers, as it is more habitable than the desert and lies in the catchment area of the Niger river. People that practice agriculture as their main method of securing their livelihood tend to be sedentary. These people may also own some livestock, but people that raise livestock as their main practice are usually nomadic herders, also called pastoralists. They practise the ancient tradition of transhumance (Frexus, 2021). Both professions are dominated by different ethnic groups. In Dosso, the main agriculturalist ethnicity is a farmer group called Djerma or Zerma, and the main pastoralist group are of Fulani ethnicity, also called Peuhl (Frexus, 2021).



(a) The country of Niger with the Dosso region highlighted in red (from "dosso region niger - Bing images" (n.d.))

(b) Climatic zones in Niger (from Dimé and Abdoulaye Nakoari Tambandia (2020))

Figure 1.1: Niger, the Dosso region, and the climatic zones

Niger deals with climate extremes, mainly floods and droughts, with high temperatures and strong winds, and even sandstorms as additional effects. These events seem to be increasing as the planet warms up. The climate extremes are paired with degradation of resources, such as water sources falling dry or silting (Dimé & Abdoulaye Nakoari Tambandia, 2020). Meanwhile, pressure on the resources increases due to the rapid growth of the Nigerien population (Dimé & Abdoulaye Nakoari Tambandia, 2020; Frexus, 2021). These factors combined cause low resource availability for Niger's inhabitants.

Niger has to deal with a turbulent history of colonisation as well as with its harsh climate (Frexus, 2021). In precolonial states, pastoralists enjoyed a claim on pastures and water points, but their transhumance corridors have not been protected by colonial and postcolonial governments. They favoured sedentary farmer authorities, causing pastoralists to feel that their access to natural resources is threatened by farmers (Herrero, 2006; Turner et al., 2011). Cultivated land has increased five times over the past decades, and intrudes on animal passage corridors and pasture areas (Frexus, 2021). Nowadays still, local religious and customary authorities as well as political representatives in Dosso, favour Djermas in access to and control over resources. But Peuhls are the original inhabitants of the area, and civil society actors such as Non-Governmental Organisation (NGO)'s still support the Peuhl claim to pastoral land and water resources (Frexus, 2021; Herrero, 2006).

The pastoral and agricultural areas have always had overlap, which has historically proven useful for collaboration between farmers and herders at times too, for example by the trade of goods and labour, and fertilisation of the soil by livestock manure. However, Peuhl herders also have a history of raiding farmer villages (Herrero, 2006). Currently, the relations between farmers and herders are dominantly hostile (Frexus, 2022). There is a conflict between them, according to Herrero (2006), who defines conflict as "the competition for scarce resources, namely water and fertile soil". This conflict comprises negative attitudes of the groups towards each other, and can amount to violence.

The conflict cannot be explained solely by resource scarcity and institutional failure (Turner et al., 2012). Indeed, according to Frexus (2022), lack of rainfall does not have to lead to conflict risk when pastoral areas are secured by the authorities. Although increasing pressure on resources due to demographic growth and climate change is a conflict factor, the main reasons for conflict are a network of social and political tensions (Herrero, 2006). Five conflict drivers were identified by Frexus (2021). They are: insufficient state management of resources, illegal or wrong use of land, insufficient mechanisms for sustainable resource use, perceived inequality of access to resources, and insufficient management of pastoral zones by customary authorities.

Land use rights for pastoralism in Dosso are documented in the Rural Code, designating about 130 pastoral zones and 274 transhumance corridors in Dosso. During the changing of the seasons, pastoralists travel through Dosso, starting from the pastoral region in the north of Niger, which has been designated as such in the law in 1961 as well as the revised law in 2010 (Frexus, 2021). They trek towards Burkina Faso and Benin and back in pursuit of the rain. Conflict between farmers and herders arises during the crossing of the herds, especially at the end of the rainy season around November, when the farmers are pulling in their harvests. Tensions rise because the farmers feel that the pastoral zones prevent them from expanding their farmlands, while the herders feel threatened by the farmers using their designated areas illegally (Frexus, 2021).

Frexus (2022) has facilitated local stakeholders to develop a common understanding of the situation through a causal loop diagram Frexus (2022, fig. 35). This diagram shows interactions between different environmental and conflict factors. The perception of inequality in access to resources is missing from this diagram, although it was identified as one of the main conflict drivers. The fact that it is perception instead of actual inequality that is driving the conflict, suggests that providing all actors with a sense of recognition might help deflate conflict and increase collaboration towards more sustainable land use. Therefore, this is a suitable case for building an ABM modelling recognition justice.

1.4. System's Perspective

This thesis aims to characterise recognition justice in order to model its role in conflict that emerges over natural resources. Emergent behaviour is the most important characteristic of a complex adaptive system (CAS). Other characteristics of CAS's include adaptivity, self-organisation, and nonlinear behaviour (Ridder et al., 2017). These are all traits that can be found in the resource scarcity conflict in Niger. The human subsystem comprises the farmer and herder groups. They interact with the available natural resources, which form the physical subsystem, to fulfil their needs. However, this is not always possible, causing subsystems to have to adapt to each other and within themselves. Modelling Niger's farmer-herder conflict is therefore expected to align well with the thesis requirements of the Complex Systems Engineering and Management (CoSEM) programme, as this programme teaches students to explore interactions in complex socio-technical environments.

1.5. Research Approach

As the main goal of the study is to conceptualise recognition justice for use in agent-based models, the modelling purpose is what Edmonds (2017) calls 'theoretical exposition'. This means that the model is being built to illustrate a hypothesis or theory. Prediction or system evaluation fall outside the scope of this modelling purpose.

A short justification for the use of an ABM has already been given in the problem statement, however an elaboration seems appropriate. To model a complex system, the model itself must be capable of complexity as well, according to Ashby's Law of Requisite Variety (Nikolic & Kasmire, 2013). The only method that is capable of reaching sufficient internal complexity is agent-based modelling Dam et al. (2013). Additionally, agent-based modelling allows for the representation of global connections that the modeller knows little to nothing about, simply by modelling interactions on a lower level. These advantages are decisive to select agent-based modelling over other modelling approaches for this project.

1.6. Outline

This thesis report uses research methods described in chapter 2. A theoretical decomposition of recognition justice into components that can be implemented in computational models can be found in chapter 3. Chapter 4 describes the conceptualisation and formalisation of the model, as well as experimental setup. Chapter 5 presents the results from the experiments. In chapter 6, the results are discussed. This chapter also contains recommendations for future research. Finally, the research questions are answered in chapter 7.

2 Methods

This chapter goes into detail regarding the research methods of this study. Firstly, the research gap is confirmed by a structured literature review. Then, the scope of the study is defined. The modelling process is described in the research framework. A research flow diagram provides a comprehensive overview of which research questions are addressed during different phases of the thesis project.

2.1. Research Gap

To identify the state of the art of justice in modelling, a structured search was done to find reviews of models that have attempted this in the past. A description of the search process can be found in appendix A.

Meijer et al. (2021) have reviewed studies on water-related human responses. They have aggregated different types of quantification methods and how they integrate a variety of human responses. In their set of studies, they identify no agent-based models that model conflict as a human response to shortage of water.

Matczak and Hegger (2021) describe flood risk mitigation strategies, but states that improving behavioural assumptions can be of significant impact on dynamic modelling using ABM. They do not however mention a specific example that models conflict.

Lindkvist et al. (2020) discuss the advantages of using ABMs in research about fisheries governance and management. A number of ABMs modelling interactions taking place in the context of fisheries have been reviewed, however none of them models conflict or justice.

DeAngelis and Diaz (2019) say that ABMs can be used where decisions are complex and in a setting of populations or communities. ABMs make for more realistic models of the decision-making process than classical models. Mostly movement decisions are described in this paper, as well as foraging decisions and population interactions. The authors also highlight that sometimes, ABMs borrow principles from machine learning and artificial life, which might make them more suitable for addressing complex social systems. However, no concrete examples of how to use this are given.

The goal of Eshragh et al. (2015) is to bridge the gap between research contributions made in automated negotiation from the disciplines of artificial intelligence, machine learning, and agent-based modelling to take advantage of the potential offered by automated negotiation in environmental resource management. The authors stress that automated negotiation methods are a supplement to human interactions and decision-making, not a replacement for them. Forward snowballing from this paper resulted in the paper by Akhbari and Grigg (2013) which describes a very simple model governing conflict scenarios over water as a game. This is however not focused on emotional decision rules or perceptions of justice of the individual and is therefore not relevant to this study.

None of the studies identified in this literature review focus on modelling people's feelings about conflict, let alone justice as an emergent property. Recognition justice specifically is never mentioned or modelled, suggesting it is not considered in simulation models in the context of resource scarcity. It is therefore expected that this thesis will contribute to the scientific body of system's research by offering a new perspective on modelling justice in the context of resource scarcity.

2.2. Scope

This study aims to conceptualise recognition justice for use in models that describe conflict in the context of water-related resource scarcity. Literature from the fields of philosophy and ethics is used to determine theoretical concepts that recognition justice can be decomposed into.

The real-world system to be modelled is the Dosso region in Niger, because this project is in collaboration with the Water, Peace, and Security (WPS) project with Deltares (WPS, 2022). Because Niger has a turbulent past with many conflicts, most of which unrelated to resource scarcity, the model will run from 2011 up to and including 2022. 2011 is the year that Niger established a democracy, which was in place until the military coup in the summer of 2023. Each year, model actors will make decisions every day for a period of three months, which represent the end of the rainy season. This is the time when farmers are pulling in their harvests and herders are crossing the region with their herds. Farmer agents in the model will represent entire farm households, and herder agents will represent the herders including their herds. The rainy period lasts from October to December. For the model, this means 90 days per year, where each day will be represented by one tick. When a year has finished, the model will immediately continue into October of the next year. The rest of the year is not modelled.

The actors that make the decisions are sedentary farmers and travelling herders. The herders follow the rain, trekking through the area from North to South each year, over pre-established routes. The farmers harvest resources from their own farms in the area.

To keep the model simple, many assumptions are made. A list of assumptions can be found in appendix B.

2.3. Modelling Framework

To demonstrate the recognition justice conceptualisation, an agent-based model will be made in which it will be incorporated. The model will be based on the resource scarcity conflict in the Dosso region in Niger. Dam et al. (2013) propose a 10-step framework for developing agent-based models. In this section, the steps from this framework will be explained for use in this thesis.

Problem Identification: In this step, the problem and research scope are defined. In this thesis, recognition justice in the context of resource scarcity will be conceptualised for agent-based modelling. This will be applied to the conflict in Dosso, Niger.

System Identification and Decomposition: In the second step, more data on the system is gathered and structured, including defining system boundaries and components. This is done using literature obtained from WPS, as well as a manual literature review.

During this step, a conceptualisation of recognition justice is formed using literature from philosophy and social sciences, as well as logical reasoning to identify elements from it that can be used in simulation modelling. This conceptualisation is the most important contribution of this thesis and can be applied to model a variety of situations. The model developed in this thesis is made to demonstrate the conceptualisation in a working ABM.

The result of the identification and decomposition step, on top of the recognition justice conceptualisation, is a conceptual model that can be formalised in the next step. This step is iterative, as new insights during the structuring of information may give the need to add or remove system components.

Concept Formalisation: In this step, the agents, their states and relationships, and the environment are identified.

Model Formalisation: In the model formalisation step, a model narrative is constructed involving the concepts from the previous step. This narrative is expressed in pseudo-code and/or flowcharts.

Software Implementation: This step translates the formal model into a computer model and implements it in a modelling environment. For this thesis, NetLogo (Wilensky, 1999) will be used to implement the model, as this software is very good at running agent-based models quickly and it is relatively easy to use. It also has extensive documentation as well as example models available.

Model Verification: In this step, the model will be verified. In reality, verification happens continuously throughout the modelling process. This will be done during the software implementation by removing bugs, but the model should also be carefully tested after completion, to see if it behaves as intended.

Experimentation: In this step, hypotheses are tested. For this thesis, it means that the conceptualisation of recognition justice is explored through experiments involving different input scenarios.

Data Analysis: In this step, the data resulting from the experimentation step are translated into information that can be interpreted by humans, mainly by visualisation. Python will be used for data visualisation and statistical analysis.

Model Validation: Models require validation before being applied to answer real-world problems. However, due to the abstract nature of this modelling project, classical validation is outside the scope of this thesis. When using the model, expert validation should be requested to determine the model's validity.

Model Use: The model is made as a contribution to the Water, Peace, and Security project (WPS, 2022). If the conceptualisation of recognition justice proves useful, the model can be used in this context to supplement existing models and broaden their opportunity for facilitating debate.

The steps from this framework will be carried out during different phases of the research project. The first two steps of this framework are combined into the background and data gathering phase. The problem and system identifications are discussed in chapter 1, whereas the recognition justice conceptualisation is described in chapter 3. This is the most important part of the system decomposition and therefore gets its own chapter.

The concept and model formalisation steps are combined with the software implementation and verification to form the modelling phase, described in chapter 4. The results of the experimentation and data analysis phases are presented in chapter 5 and discussed in chapter 6. This chapter also addresses recommendations for model use. The validation step is difficult due to the model purpose being theoretical exposition, section 4.3 addresses this further. Model use in decision-making falls outside the scope of this research project.

2.4. Research Overview

A research flow diagram is presented here to give an overview of the different phases in the study and the research questions that are answered as well as the methods that are used in each phase. The diagram is presented below in figure 2.1.

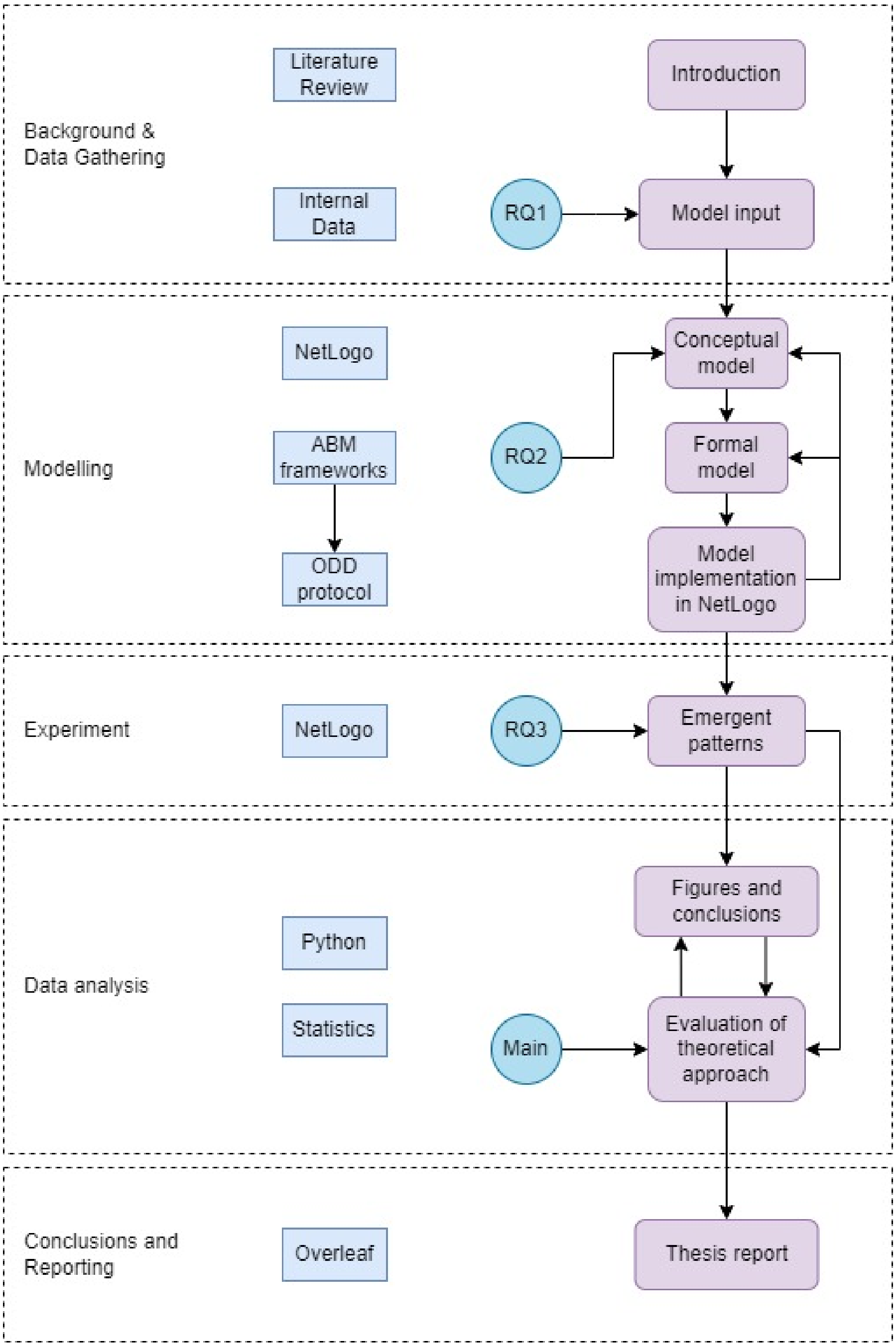


Figure 2.1: Research Flow Diagram. Phases are divided in boxes. The blue boxes contain methods, azure circles are the different research questions, and purple boxes represent the products resulting from different phases.

3
Theory

In this chapter, recognition justice is conceptualised for use in agent-based models. The conceptualisation is made using literature on recognition justice and related topics. From this literature, elements are identified that define or shape the process with which people experience recognition justice. The criteria to accept each of these elements as part of the process are that the element is either something that can be modelled, or it can help narrow down the definition of recognition justice for modelling. The elements are presented in boxes at the ends of the paragraphs in which they are identified, for a quick overview of the conceptualisation rationale. Also, a visual overview of the elements and their purpose is provided in this chapter.

3.1. Recognition Justice Introduction

As mentioned in section 1.1, justice is underrepresented in models, and if it is incorporated, almost exclusively distributive justice is considered. Distributive justice refers to how resources are distributed in society (Doorn, 2019). This is the easiest form of justice to model, as modellers can identify a quantifiable entity, distribute it equally over model actors, and call it justice. There are however more forms of justice, and within them interpretations also vary. Procedural justice is the second important form of justice, which aims for fairness with which decisions about fair distributions are made and who is involved in them (Doorn, 2019), and legitimacy of planning and decision-making processes in a broad sense (Jafino et al., 2021).

In 1996, Axel Honneth and Nancy Fraser laid the foundations for a new form of justice: recognition justice. According to Honneth (1996), this was at the time a new critical social theory, because it incorporated aspects of relationships based on mutual recognition into explanations for societal change. According to Fraser (1996), recognition justice went further than procedural and distributive justice, because it focused on accepting differences between people, such as differences in culture, race, or gender.

When recognition justice is achieved, minorities can participate in society without having to assimilate to dominant cultural norms (Fraser, 1996). Honneth (1996) identified three forms of recognition, each with a corresponding form of disrespect which hinders recognition justice and can contribute to the emergence of social conflicts.

Recognition justice is felt by individuals, as opposed to distributive and procedural justice which are being applied top-down by decision-makers. It is therefore the most emergent form of justice, which makes it the most suitable for use in agent-based modelling. However, this is not currently being done. Searching for the string '"agent based modelling" AND "recognition justice"' in Scopus does not yield any results as of April 2024.

Yet, as stated in section 1.1, recognition justice is expected to offer the best opportunity for achieving justice when other needs cannot be satisfied. The next sections will therefore explore aspects and interpretations of recognition justice, to identify elements that can be used to build a conceptualisation of recognition justice for agent-based modelling.

3.2. Recognition Justice Conceptualisation

van Uffelen (2022), builds on Honneth and Fraser by saying that there are two approaches to understanding recognition justice. The first one, called the status order model, is based on the premise that to achieve recognition justice means to be in the absence of injustice, and thus recognition justice can be disrupted by recognition injustices. Recognition injustices are actions or events that harm participatory parity. Participatory parity is the term coined by Fraser (1996) to describe a phenomenon that penetrates all social interactions. It refers to the ability of people to participate equally as peers in social life. Examples of recognition injustices that harm participatory parity include cultural domination, where people are forced to adhere to practices of a culture that is not their own, nonrecognition, where people are overlooked by authorities of their own culture, and disrespect. This last example encompasses being maligned in everyday interactions, as well as in public representation (van Uffelen, 2022).

Participatory parity can be evaluated through the cultural status order, by which Fraser (1996) means the institutionalised value system that contains the hierarchy of cultural value. If the status order allows all people to participate equally in society and social life, participatory parity is achieved and there is recognition justice.

The other approach to understanding recognition justice is called the self-realisation model. This approach is based on the premise that recognition injustices can happen in different ways and at different levels in society, and that they affect the practical relation to the self, as interpreted by Honneth (1996). According to the self-realisation model, people want to be recognised through love, law, and cultural appreciation. This form of recognition justice is much more personal than Fraser's: where participatory parity focuses on equal participation in society for all actors, the self-realisation model examines the self-confidence, self-respect, and self-esteem that individual people gain from recognition through the previously mentioned aspects of life.

van Uffelen (2022) combines the approaches of Honneth and Fraser, by stating that actors can be subjected to recognition injustices through love, law, and through the cultural status order. To conceptualise recognition justice for modelling, it can be understood as the absence of recognition injustices, and the recognition injustices can be modelled. This is the first element towards the full conceptualisation.

Element 1: Recognition justice is conceptualised for modelling as the absence of recognition injustices

All recognition injustices will from here on out be collected under the term 'misrecognition' for simplicity. Identifying misrecognition can be done with van Uffelen (2022)'s combined understanding of recognition justice, using complementary detection methods. The self-realisation model assumes that actors who feel misrecognised will articulate their discontent by resisting or protesting, and misrecognition can be detected by examining their experiences. This is the first detection method. However, people's feelings of injustice do not always mean that misrecognition is really occurring, therefore this method is incomplete.

On the other hand, misrecognition can also be present without the people subjected to it realising that they are being misrecognised. Or maybe people feel misrecognised but are not in a position to express their feelings. Therefore, the absence of an expression of feelings of injustice alone is not sufficient to draw conclusions about the absence of misrecognition itself. When people do not indicate that they are being misrecognised, misrecogition is harder to detect, as it must be identified by external parties who have nothing to gain from doing so. To ensure that efforts to do so are made, the second detection method must be executed by society periodically. It is done by holding public debates involving external parties and preferably also the misrecognised parties, where the norm of participatory parity is applied to the society as a whole. The decision whether misrecognition occurs must be made collectively, by multiple authorities who apply different perspectives. This method however requires participatory parity to ensure that all actors are part of the debate, and is therefore also not complete. Thus, both detection methods must be used continuously and in parallel, to maximise chances of misrecognition detection. This is the second element towards a full conceptualisation.

Element 2: Misrecognition must be detected by complementary methods

van Uffelen (2022) mentions detection methods for recognition injustices, but does not mention sources. To define recognition justice to fit into an agent-based simulation, misrecognition needs to originate somewhere. It can be a majority, an authority, or another individual, as suggested by Fraser (1996), but it needs to be another human party that hinders a first human party to participate in society. The hindrance leads to a discrepancy between how the first human party *wants* to act, and the reality in which they *have* to act. This is the third element in the recognition justice conceptualisation.

Element 3: Misrecognition happens when one party hinders another party in carrying out their activities as desired

The actors experiencing misrecognition will over time feel that they are treated unjustly by some human entity. To decompose misrecognition for agent-based modelling is therefore to understand it as the process of many events in which an actor is misrecognised by an actor from an adversary group, or by the group in total. The first actor experiences a difference between desired actions, and the reality in which these actions may not be possible. Over time, a feeling of discontent towards the group to which the second actor belongs accumulates, which the first actor can can express, and which can be detected by authorities to identify the injustice.

Element 4: Misrecognition can be decomposed into a string of misrecognition events

To measure feelings in any kind of software model, they must be quantified. If misrecognition is interpreted as a string of misrecognition events that lead actors to build up feelings over time, each event needs to be assigned an amount of feeling by the actor experiencing it. This can be done by defining types of events that elicit fixed amounts of feeling. The type of event includes the level on which it takes place, which as mentioned above can be love, law, or the cultural status order (van Uffelen, 2022). The event type describes how desired actions differ from experienced reality. However, different actors can experience the same event type at varying intensities. Thus, the type of the event and its intensity together determine the quantification of feeling each event elicits for each actor. This is the fifth element in the conceptualisation.

Element 5: Actors judge the severity of each misrecognition event by its type and intensity

This element is particularly subjective. For the purpose of conceptualising recognition justice for agent-based modelling it is assumed that recognition justice is an objective concept that can be modelled. This is justified only if the quantification of feelings that misrecognition events elicit in agents has come about in collaboration with the actors represented in the model. For this, these actors must first be identified and involved in the process. Then they must define the types of misrecognition events, the quantification of feeling that should be assigned to each, and how they can differ in intensity.

The next section explores literature about emotions, to understand how to quantify feelings that build up over time.

3.2.1. Emotion

Misrecognition is understood as a string of misrecognition events that each contribute to a feeling building up over time. To be able to calculate how this happens and to be able to use it as a metric, deeper insights into the development of emotions in the context of conflict are presented here.

A lot of research into emotions in the context of conflict has been done by the group of Professor Eran Halperin of Tel Aviv University, by studying the Israeli-Palestinian conflict. Most of this research investigates the role of emotions and emotion regulation in inter-group conflict, using psychological and political theories ("Eran Halperin", n.d.). This research group distinguishes emotions from emotional sentiments. An *emotion* is a response to a specific event, and an *emotional sentiment* is an emotional disposition towards an object, be it another person or group, that is not related to specific events but is temporally stable (Halperin et al., 2010). Emotional sentiments arise in long-standing conflicts because a pattern of emotional responses to events eventually establishes itself as a sentiment (Halperin & Pliskin, 2015). Emotional sentiments serve as the next element in the recognition justice conceptualisation.

Element 6: An emotion is a response to an individual event, emotions build up to form a long-term emotional sentiment

The group has developed a framework that aims to aid in understanding how emotions influence the manner in which both groups and individual people are affected by conflict (Halperin et al., 2010). The framework has two parts. The first part describes the way in which emotions and emotional sentiments shape the behaviour and attitude that people display to conflict-related events as four-step process.

First, a person is exposed to an event. Then, they judge this event and their judgement is influenced by the long-term sentiment towards the other person that has been formed over time, as well as by individual non-affective factors that differ per person. Lerner and Keltner (2000) adds to this that the emotional sentiment towards the injustice itself influences the judgment as well. The feedback of the sentiment on the emotional response is the seventh element in the recognition justice conceptualisation.

Element 7: The reactive emotion to an event is influenced by the long-term emotional sentiment

In the third step, reactive emotions arise from the judgment formed in the previous step. These emotions in turn shape the attitudes and actions of the person, and the group they identify with, in the fourth step. The framework is shown in figure 3.1.

The second part of Halperin et al. (2010)'s framework offers possible paths for emotion regulation, shown as dotted line boxes in figure 3.1. Halperin et al. (2010) explain how the the framework can be applied to three main stages in a conflict, namely outbreak and escalation, de-escalation, and reconciliation. Bar-Tal (2011) defines conflicts as *"situations in which two or more parties perceive that their goals and/or interests are in direct contradiction with one another and decide to* act *on the basis of this perception"*. This thesis however does not aim to model the people acting on their feelings of misrecognition yet, the aim is only to model recognition justice over time. Following the definitions of Bar-Tal (2011) and Halperin et al. (2010), there is a negative emotional sentiment involved in experiencing misrecognition, but there is no conflict in the modelled case of the perceived farmer-herder inequality in access to resources in Dosso. Yet, sticking to the definition by Herrero (2006) mentioned in section 1.3, it will still be referred to as such. Emotion regulation is however outside the scope of this research.

Furthermore, for the sake of simplicity, individual differences in personality will not be modelled. Especially as Halperin and Pliskin (2015) define emotional sentiments to be specific to reactive emotions, and not to another predisposition to respond to events in a certain way.

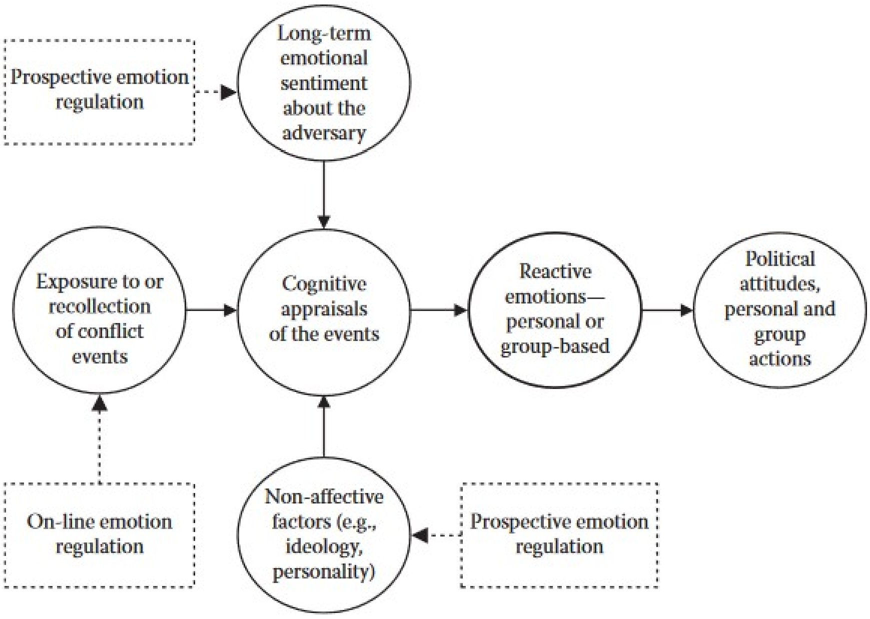


Figure 3.1: Framework by Halperin et al. (2010). The bold circles represent the process of emotions and emotional sentiments shaping people's attitudes and behaviour towards conflict-related events. The dotted line boxes show possible paths for regulation of these emotions.

Halperin et al. (2010) start applying their framework in the first main stage of conflict, the outbreak and escalation stage, where latent disagreement transforms into violence. At the very beginning of their definition of a conflict, a decision must be made to start confronting the so-called 'out group', and this decision is directly associated with the emotion anger. It is the relevant emotion in conflicts, which is the next element in the conceptualisation, therefore it will be elaborated upon in the following section.

Element 8: The emotion most associated with conflict is anger

3.2.2. Anger

According to Averill (1982), an individual feels angry if they perceive actions of others to be unfair or unjust, or to deviate from acceptable societal norms. It is experienced by people in conflict (Halperin et al., 2010), but views on the emotion itself differ (Silva, 2021). Silva (2021) states that the traditional view of the emotion anger holds central the desire for retribution. However, this requires an angry individual to have another party to be angry at, whereas one could also experience self-directed anger. Silva (2021) therefore argues for a pluralist view of anger in which there is a central desire for recognition, and this view can take a plethora of forms. One example is a desire for rectification, where the inflicted harm must be undone or terminated. Therefore, it is an appropriate response to disrespect experienced in misrecognition events. People feel angry after these events happen, and they want to be acknowledged so that these events are not repeated. This is the ninth element that is part of the recognition justice conceptualisation.

Element 9: Anger holds central a desire for recognition, and for misrecognition events to terminate

Now, to model anger that builds up over time into an angry sentiment, this information is interpreted so that anger is the emotion that arises from misrecognition events, and the intensity or 'amount' of anger depends on the event type and intensity, and also on the emotional sentiment of the individual at the time of the event. It is logical that the emotional sentiment becomes more negative if an individual experiences a lot of misrecognition events. The desire for the cause of the anger to terminate will only grow with the sentiment, until it does stop.

This leads to another question: what happens when the misrecognition does stop? It would mean that there is no more need for anger, but it is important in conflict regulation to understand the difference between an emotion and a sentiment, because a sentiment is much harder to get rid of once it has established (Halperin & Pliskin, 2015).

Na'aman (2020) explains that anger, like grief or regret, is a backward-looking emotion, and backward-looking emotions often diminish with time. According to Callard (2017), a reason to be angry at someone is anchored in the past and therefore cannot ever be changed again, hereby justifying the anger to persist for eternity. However, Na'aman (2020) argues that for the emotion to diminish, the reason does not have to change but the background conditions for the emotion could. In a more recent publication, Na'aman (2021) explicitly stresses that this does not mean that emotions always diminish due to time passing, but because the time does allow for background conditions to change.

For the purposes of this model, it will be assumed that if no misrecognition events take place for a long time, eventually the negative emotional sentiment an individual might have towards the other group will start to decrease. This is the last element in the recognition justice conceptualisation.

Element 10: When the cause for anger is not experienced for a long time, emotional sentiment will start to decrease

3.2.3. Conceptualisation Overview

A short overview of the conceptualisation of recognition justice for modelling based on the elements identified in this chapter is presented here as follows:

Recognition justice can be defined as the absence of recognition injustices, and then it can be inferred if indeed no injustices take place. The injustices, and the feelings that arise from them, can be modelled in an ABM. This satisfies the detection method of simulated people expressing that they feel misrecognised, and the model can be used by external parties in public debate which satisfies the second detection method. These elements form the demarcation of recognition justice made for the conceptualisation.

Recognition injustices must be caused by a rival party. They are conceptualised as misrecognition events that have a type and an intensity. Thus, misrecognition events are concepts caused by other agents with characterising parameters. These elements can be modelled.

People have emotional responses to these misrecognition events, and these reactive emotions build up over time to form an emotional sentiment. The emotional sentiment is the metric by which feelings of misrecognition are expressed in the model. On top of acting as a metric, the emotional sentiment influences the emotional response towards misrecognition events, along with the type and the intensity of the event. The emotion associated with misrecognition is anger. For the purposes of modelling, these elements form the part that must be quantified.

Anger is a reactive emotion that is based around a desire for recognition, and termination of misrecognition. When this desire is fulfilled, anger decreases after some time passes. This characteristic is added to the modelled concepts to allow for the metrics to decrease again.

The elements shape the recognition justice conceptualisation as visualised in figure 3.2. The blue bar shows the elements used for demarcation, the green bars the concepts that are modelled and the purple bar shows concepts that must be quantified and that are used as metrics.

Using theory described in this chapter, a misrecognition submodel for agent-based models is designed which is discussed in chapter 4.2.3, and explained in detail in appendix C.7.

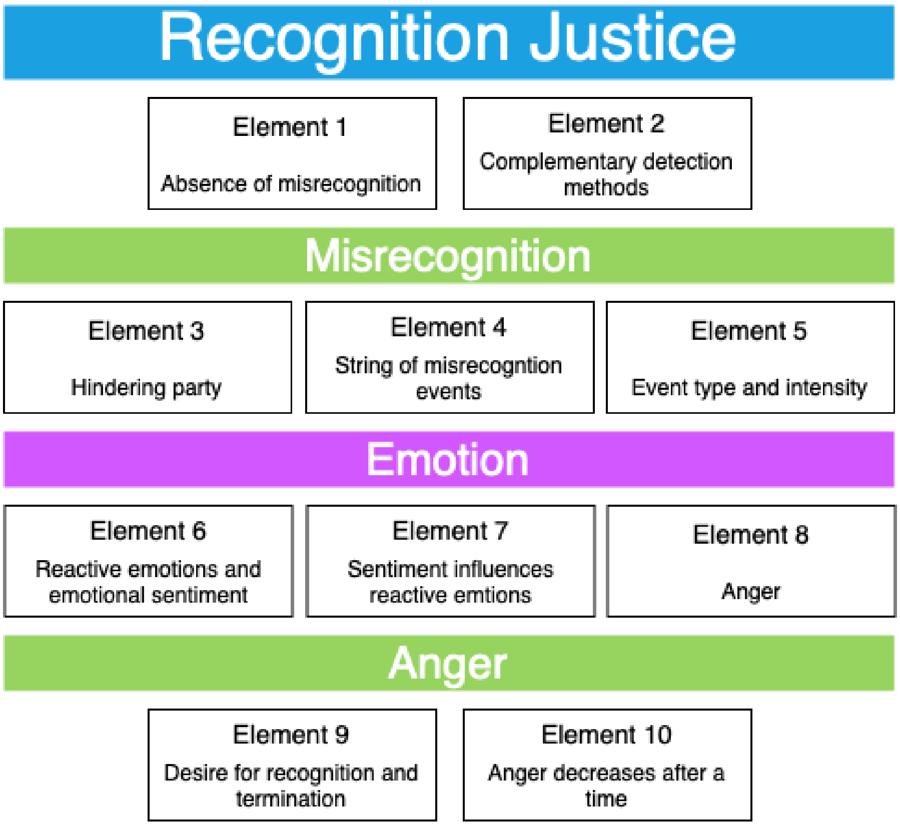


Figure 3.2: Overview of the elements in the recognition justice conceptualisation

3.3. Recognition Justice and Resource Scarcity

This section applies the theory from this chapter to the resource scarcity situation in the Dosso region.

To adapt the conceptualisation of recognition justice to be relevant in the context of natural resource scarcity in the Dosso region in Niger, misrecognition is considered at the level of daily interactions that stop people from participating equally in society. The assumption that the conflict takes place between groups with different cultural backgrounds, in the case of Dosso between farmer and herder tribes, suggests that recognition justice in the context of natural resource scarcity is best approached in the form of Fraser (1996)'s cultural status order. For example, the institutionalised value system in Dosso gives way to the conflict drivers identified by Frexus (2022) in section 1.3. Especially the perceived inequality of access to resources suggests that the cultural status order in the Dosso region does not allow for equal participation of all people in social life.

As resources are accessed every day, perceived inequality of this access must stem from everyday interactions. So, misrecognition in this case can be interpreted to mean that an individual from one tribe is misrecognised when they cannot perform their daily activities in the way they desire, because they are prevented from doing so through interactions with someone from the other tribe. This is an example of disrespect as defined by Honneth (1996).

Of course there are other sources of misrecognition, such as bad and biased government and laws, or even the industrialised countries emitting greenhouse gases and contributing to the decline of resource availability. However, it is assumed that these actions are so far away from the actor experiencing misrecognition that they are negligible compared to misrecognition experienced directly in daily interactions with another actor. Therefore, only direct misrecognition is taken into account to conceptualise recognition justice for modelling the resource scarcity situation in Niger.

To quantify the difference between desired actions and experienced reality for each misrecognition event in an ABM simulating the Dosso region recognition injustice, the following types of misrecognition events are defined.

Desired actions in a resource scarcity conflict are assumed to be that the actors can take resources from their land. After a misrecognition event has taken place, resources may no longer be present, or fewer resources are present than before the event, or maybe the order of visiting the land where resources are may need to change a little, or a lot. The event types in an ABM simulating this are therefore defined as either a presence event, where an agent finds fewer resources on her land than expected, or an order event, where an agent has to change her planned visiting order of locations in which she expects to find resources. Both of these events can have different intensities. So, when agents have to judge how they feel about being misrecognised, the metric for misrecognition becomes **"the feeling of the agent about the difference between the desired actions and the experienced reality, based on the extent to which actions are performed in the desired presence or order, and with the desired intensity"**.

For model simplicity, only individual agents in the model can experience and cause misrecognition events. It will be assumed that other factors that influence agents' desired reality, such as the climate reducing resource availability or agents that fall into the same group, will not be interpreted as misrecognition.

All agents can be misrecognised. All agents can also can misrecognise someone else, by obstructing them to perform actions as they desire. To call it misrecognition, agents need to be aware that what they are doing is wrong. To not overcomplicate this, it will be assumed that an agent will only misrecognise someone by taking resources from an area designated to another group and that they will not do so if they can satisfy their needs using their own resources.

An agent experiencing a misrecognition event and judging it by the presence or order, and by the intensity is visualised in figure 3.3. The evaluation of the difference between reality and desire is highlighted in blue, as quantifying this is a crucial contribution of this thesis to the decomposition of recognition justice for agent-based modelling.

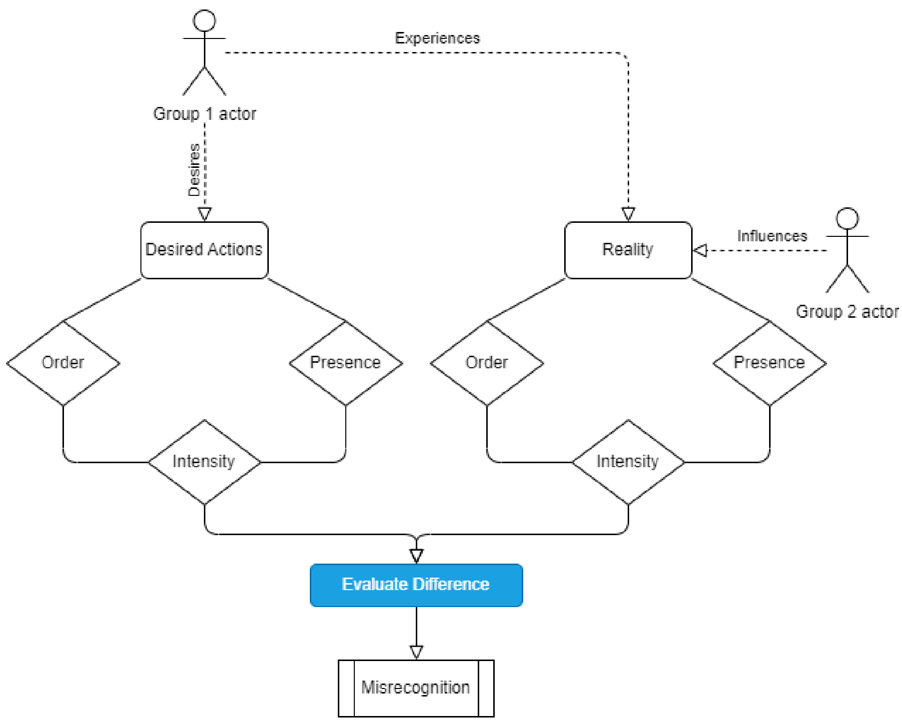


Figure 3.3: A misrecognition event experienced by an actor from group 1. Evaluation of the difference between reality and desired activities is highlighted in blue.

4 Model Description

This chapter provides an overview of the model design and implementation. It takes the recognition justice elements from chapter 3 and uses them to design a model that can be tested, hereby answering the second sub-question from section 1.2. A detailed model description can be found in appendix C.

4.1. Conceptual Model

According to Dam et al. (2013), in the conceptual model the agents, their states and relationships, and the environment are identified. This section will serve to identify these components from the context described in chapter 1.3.

The conceptual model is designed while keeping in mind that the purpose of this research project is to conceptualise recognition justice for agent-based simulation, not to accurately model the exact situation in Dosso, Niger. Furthermore, obtaining access to exact geographical and demographic data from the region falls outside the scope of this project. Therefore, concepts from the situation in Dosso are taken and simplified to be used in an abstract model. These are the following:

Agents: Two groups of agents are considered in the model. The Djermas are considered simply as sedentary farmers, and the Peuhls are considered simply as nomadic herders.

Relationships: The relationship within a group of agents is virtually nonexistent. When they have sufficient resources they stay on their own land. They only interact in the context of recognition injustice. In section 3.3, recognition injustice is defined to be caused by a person from an outside group. Therefore, there is a relationship between the agent groups. They misrecognise, and are misrecognised by, each other, which leads them to develop their emotional sentiment.

Environment: The environment is a two-dimensional map based on the Dosso region insofar that it has desert, farmland, and pastures. But the influence of the environment will be tested by changing it, so the layout of the environment has no connection to the real world.

Figure 4.1 shows the system relationships and the external factors, as well as the metrics. Sentiment is the most important metric of the system, remaining need can be used as a proxy to see if low access to resources correlates with high negative sentiment.

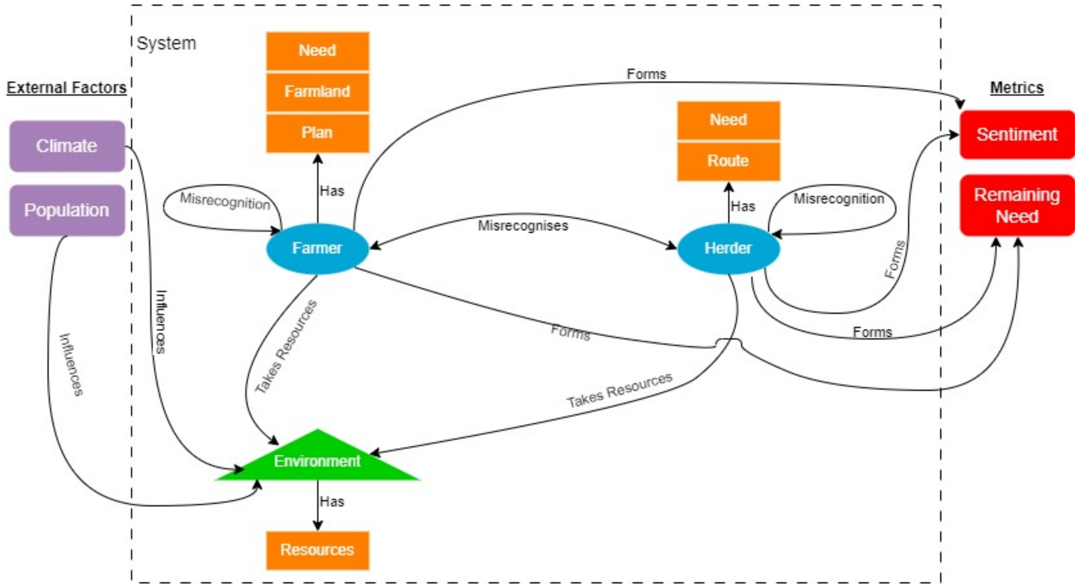


Figure 4.1: Relationship diagram of the modelled system

4.2. Model Formalisation

In the formalisation step, model parameters and states are designed, and the concepts are formalised by involving them in a narrative which can subsequently be implemented into software. This narrative is translated into flowcharts, which are shown and discussed in this section.

4.2.1. Parameters

System parameters are not to be confused with state variables. According to Grimm et al. (2020), *"Parameters are coefficients or constants used in model equations and algorithms"*. Table 4.1 shows the parameters used in the model. Global parameters are present in all model scenarios. Setup parameters can be set by the user at the beginning of every model run. All parameters are constant throughout a model run.

Due to the model's purpose being theoretical exposition, the parameters are given fictional values calibrated to be able to test the recognition justice decomposition in an agent-based model. The time parameters are set according to the time span discussed in chapter 2. The geographical layout is represented on a 180x180 patch grid, where colours represent different land types. The colours are taken from hypothetical drawings shown in figure 4.3, that have a basis in but no relation to the real world. The population numbers are calibrated to fit into the model, as are the resources. Resource scarcity is simulated by setting a need per cattle or family member and calibrating it so that the normal distribution used to grow the resources on each land type has a mean that for different settings of the 'rain' parameter equals 65, 75, 85, or 95% respectively of the average need of agents that use that land type. This means that pasture patches need more resources than farmland patches. It is assumed that pasture patches need to be able to accommodate the average need of two herder agents, while all farm patches are known to only be used by one farmer. To keep this calibration, the feed-need and family-need parameters are kept constant. The choice is made to use the 'rain' parameter only to simulate resource scarcity. The 'farmarea' limits the size of the farms so that the plans of farmer agents roughly stay within the same length as the routes of herder agents.

Lastly, the 'order' and 'presence' parameters represent the amount of anger each respective event elicits, regardless of the agents' previous experiences. These numbers are also calibrated through trial and error.

Table 4.1: Model Parameters

Parameter Name	Parameter Type and Units	Meaning
	Global Parameters	
Time-step	Static, day	Each timestep, or tick, represents one day
Start-year	Static, year	The simulated year that the model starts running is 2011
End-year	Static, year	The simulated year that the model stops running is 2022
End-day	Static, day	The last day of the year after which a new year begins
Order	Static, amount of anger	The amount of anger that is elicited by an isolated order misrecognition event
Presence	Static, amount of anger	The amount of anger that is elicited by an isolated presence misrecognition event
	Setup Parameters	
Feed-need	Static, number of resources	The number of resources an individual cattle animal needs to eat in a day
Family-need	Static, number of resources	The number of resources an individual family member of a farmer needs to eat in a day
Rain	Static, number of resources	The mean of the normal distribution that assigns the number of resources that a patch grows every year
World	Static, land type	By choosing a different world, a different layout of colours that assign the landtypes to patches is loaded into the model
Number-of-herders	Static, number of agents	The number of herder agents in the model
Number-of-farmers	Static, number of agents	The number of farmer agents in the model
Farmarea	Static, number of patches	Maximum number of patches farmers can add to their farm

4.2.2. State Variables

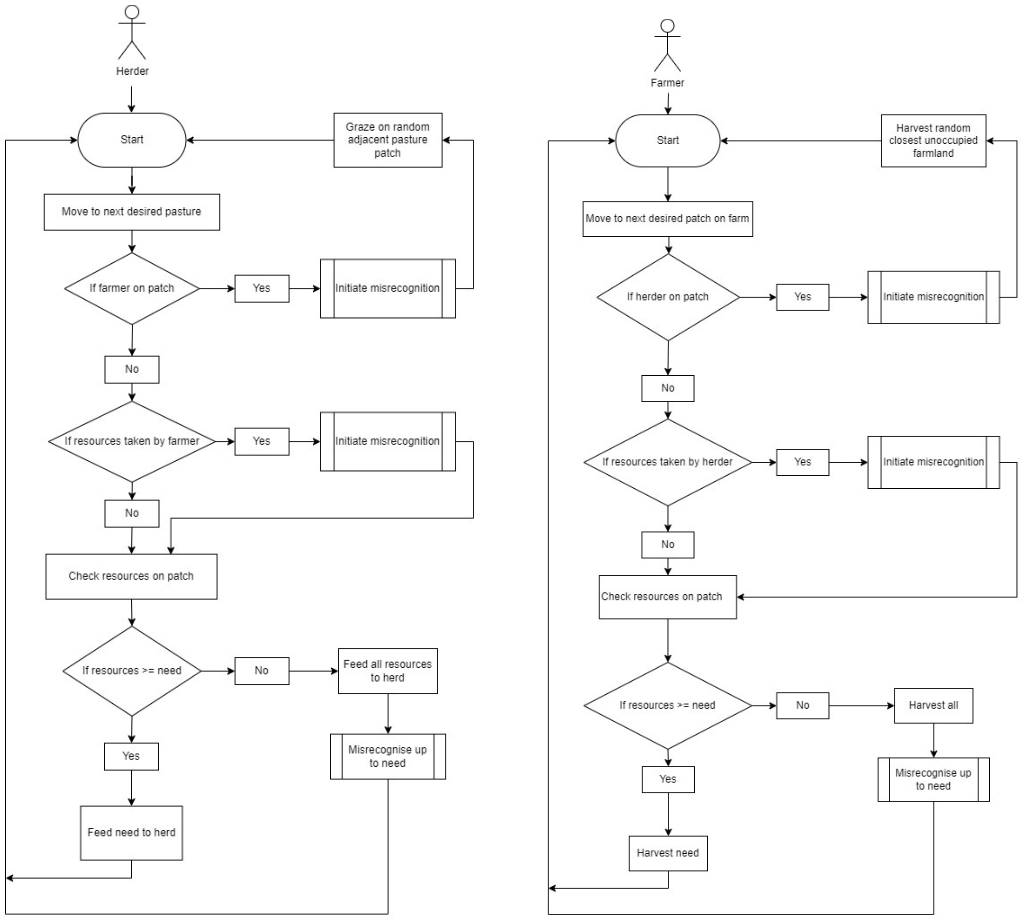
State variables differ from model parameters in that state variables determine the variety in an entity's state, either over time or between entities, whereas parameters are used in model equations and algorithms and are the same for all entities in the model (Grimm et al., 2020).

The sentiment is a state variable that also serves as the system's most important metric. Every agent has their own sentiment, but all agents start with an initial sentiment of 0,1. The initial value must be higher than zero because the new sentiment is multiplied by the current sentiment. The other agent state variables are used for moving each agent through the model and having them use resources, so that they can determine whether to update their sentiment or to misrecognise other agents. The environment state variables are there to provide agents with resources.

A detailed overview of state variables per entity can be found in appendix C subsection C.2.2.

4.2.3. Model Narrative

Figure 4.2 shows the narrative translated into flowcharts. These flowcharts represent the model formalisation and they are used for implementation of the model in NetLogo (Wilensky, 1999).



(a) Flowchart of a herder agent's daily decisions **(b)** Flowchart of a farmer agent's daily decisions

Figure 4.2: Farmer and herder narrative flowcharts

The model narrative is told from the perspective of the agents and takes place every day. Each agent has a daily need, which is the product of the need parameter for the specific agent group and the number of mouths they have to feed. Every day, the agents move to the next location on their plan to take the required resources from there. This is their expected reality. However, their expected reality can be disrupted. When an agent of the other group is present on the patch they were planning to go to, they choose to avoid conflict and instead are forced to move to and find resources on an alternative location, creating an order misrecognition event. When there is no other agent present but someone has been there previously and has stolen resources, the agent senses this and experiences a presence event. A presence event can only been experienced by the first agent who arrives on the patch after the theft has taken place. Each stealing event can therefore only be experienced once. For herder agents, this means the first agent who arrives on the patch after the event. Because farmer agents do not share their farmland, misrecognition events for farmers have a higher likelihood of going unnoticed, because the farmer may have already harvested that patch that year, and the events reset to zero at the end of each year. In both order and presence events, the agent knows the percentage of resources that were taken, this is used as a proxy to calculate the intensity of the event. The agent goes through the misrecognition submodel and updates their sentiment accordingly. A detailed description of the misrecognition submodel can be found in appendix C section C.7.

When no misrecognition has happened, agents either experience their desired reality, or they still find insufficient resources, but due to other factors than recognition injustice. In that case, the agent will not feel misrecognised, but they will go and misrecognise someone else. Table 4.2 shows the types of events agents can experience, and whether they are misrecognised when experiencing them.

Table 4.2: Possible misrecognition events

Farmer	Herder	Event Type	Misrecognised
Harvest	Graze herd	Desired Reality	×
Resources stolen	Resources stolen	Presence, intensity	✓
Resources occupied	Resources occupied	Order, intensity	✓
Resources insufficient	Resources insufficient	Bad Luck	×

After determining whether the agents need to invoke the misrecognition submodel, they graze their herds or harvest their crops. When this satisfies their need, they move on to the next day. When it doesn't, they take resources from the other agent group's land closest to them.

Every year, resources regrow on the land and agents get a new start day. Their routes and plans stay the same throughout each run. When agents have not been misrecognised for an entire year, their sentiment decreases by 10%.

The misrecognition submodel uses a function to update the emotional sentiment when a misrecogntion event is experienced. Following the elements defined in chapter 3, the emotional sentiment depends on the anger a prompted by the event, which in turn depends on the type of event e, and its intensity i. It is also influenced by the current emotional sentiment s_n. The new emotional sentiment s_{n+1} follows from these elements in the following manner:

$$s_{n+1} = s_n * (1 + a_e * i_e) \tag{4.1}$$

4.2.4. Assumptions

To create a model environment in which the recognition justice decomposition can be tested, the agents need a desired reality and the opportunity for other agents to mess with that. To keep it simple and abstract, a number of assumptions was made, the most important of which are discussed in this section. A table overview of the assumptions in more detail can be found in appendix B.

The first major assumption is made to be able to give the agents a desired reality with presence, order, and intensity. For this purpose they are given a list of patches they move through, and a daily resource need to meet using resources on the patches they visit. They are assumed to have land available to them where they plan their visit, and to repeat the same sequence every year. They are assumed to feel it is their right to use that land. They are assumed to know when someone has stolen from their land, and they are assumed to intentionally steal resources from the other agent's land when they fall short on their own.

The second major assumption is that misrecognition only happens when another agent causes the difference between desired and experienced reality. Other factors can cause the desired reality to not take place, but this will not be interpreted as misrecognition by the agents.

The third major assumption is that agents do not act on their negative sentiment. They may get very angry, but actual action to escalate the conflict is left outside the scope of this model.

The fourth major assumption is made regarding the inhabitants of the Dosso region. The model just speaks of herders and farmers. All herders are assumed to be nomadic Peuhls who herd cattle, all farmers to be sedentary Djermas who grow crops. In reality, this is more complex, sedentary herders exist, farmers keep animals as well, and many social and institutional structures govern intra- as well as inter-group behaviour. The agents in the groups are also assumed to operate on an individual basis, but the sentiment is assumed to represent the aggregate sentiment of the group. They only feel negative sentiment towards the other group, not towards their peers. This is a heavy simplification of human behaviour.

Lastly regarding the time frame, the period from 2011 up to and including 2022 was chosen in order to disregard any unrest due to political or other conflict. The 2011-2022 period was a relatively stable time for Niger. Each year only includes three months, or 90 days, because herders trek through the Dosso region at the end of the rainy season, which takes place during the months October, November, and December. Agents are assumed to do the exact same thing each year, although they do not always start on the exact same day. They cannot leave the model and will carry out their activities for as long as the model runs.

4.3. Model Evaluation

4.3.1. Verification

Model verification is done by using NetLogo's internal software to run individual scenario's and check the behaviour using the animation and dynamic plots, as well as printing and checking some of the results.

Because computers cannot generate true random numbers, the model should prove to be deterministic when run with the same input values using a random seed. This is tested by running ten replications of one model scenario with a fixed random seed. The results can be found in appendix D.1.

To test the model's internal stochastiticy, a hundred replications of this same scenario are run, without a random seed. This is necessary to determine the need for replications of each model run, and to determine the appropriate method for outcome aggregation. The results of the verification can be found in section 5.1.

4.3.2. Validation

It must be noted that this model is abstract, uses no external input data, and has no data to compare it with. Model validation will therefore not be possible for this specific implementation of the model. When implementing the methodology described in this report in a real-world scenario, it should be possible to validate it. For this research project, however, validation falls outside the scope.

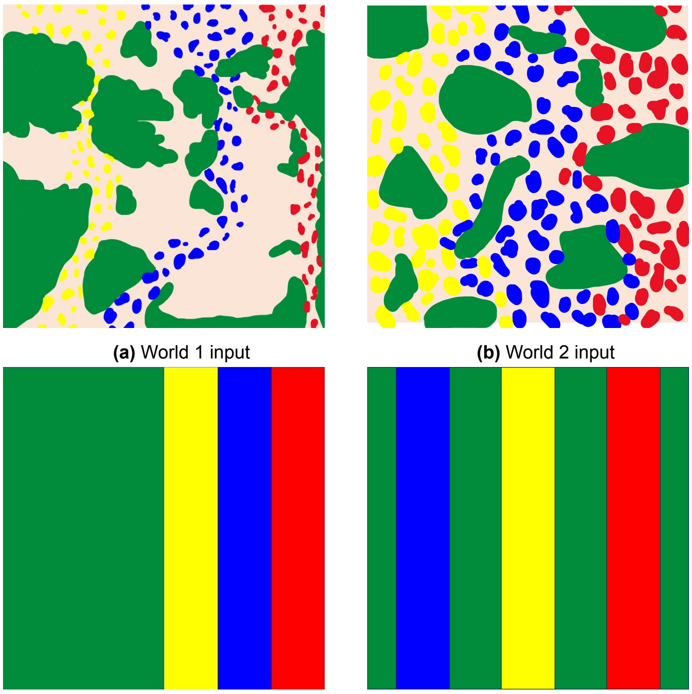
4.4. Experimental Setup

Model experiments will be run to answer research sub-question 3: What insights can be gained from the model about recognition justice in the context of natural resource scarcity?

Natural resource scarcity can occur due to higher need, higher population, or fewer resources. Because the number of experiments increases exponentially with every parameter varied, it was chosen to only test the effects of different populations, which can be varied by changing the 'number-of-farmers' and 'number-of-herders' parameters, and the resource availability, which can be varied by setting the 'rain' parameter.

The effect of available landtypes and their layout was tested by loading different colour images into the NetLogo model. These images are shown in figure 4.3. It must be noted that the worlds are numbered 1, 2, 4, and 5. World 3 was left out of the experimental setup after multiple problems arose during the verification process.

To account for stochasticity, ten replications are run for each scenario. The population of both agent groups is tested for four combinations of a low and a high value, in all four 'rain' scenarios, and for worlds 1 through 5 with the exclusion of world 3. This leads to a total of $4 * 4 * 4 * 10 = 640$ experiment runs. Table 4.3 shows an overview of the experimental setup for world 1. This setup is repeated for all of the worlds.



(a) World 1 input
(b) World 2 input
(c) World 4 input
(d) World 5 input

Figure 4.3: Input images for different geographical layouts

Table 4.3: Experimental Setup

world	rain	herder population	farmer population
1	1	50	50
		50	200
		200	50
		200	200
	2	50	50
		50	200
		200	50
		200	200
	3	50	50
		50	200
		200	50
		200	200
	4	50	50
		50	200
		200	50
		200	200

An additional experiment is done to see what would change if the sentiment is updated linearly instead of exponentially. For this, the same world and rain scenario as in the stochasticity and deterministic tests is taken, it is tested only for world 2 and rain 4. The misrecognition equation 4.1 is adjusted to the following equation:

$$s_{n+1} = a_e * i_e + s_n \tag{4.2}$$

This is tested for the same four combinations of herder and farmer populations as shown in table 4.3 and repeated ten times, so in total 40 runs are executed.

5
Model Results

This chapter discusses the behaviour of the recognition justice conceptualisation by analysing the results of running experiments with the ABM described in the previous chapter. The results provide insight into how the recognition justice conceptualisation behaves in a model.

First, the model stochasticity was tested to determine the need for running replications of each input scenario, and to compare methods for aggregating the outcomes. This is done by running one hundred replications of a single input scenario, and making multiple plots to gain insight in variability of outcomes that can be attributed to changes in initial conditions, and the influence of individual agent outcomes.

After this, the experiment results are discussed. The final aggregate sentiments of both agent groups are shown per run in an overview, where each data point represents the final aggregate sentiment of one agent group of one model run. This figure is then broken down to better highlight different emerging patterns that are found at more detailed levels. Then, to see if there are relationships between an agent group's final sentiment and other outcomes and metrics from the model, additional model outcomes are plotted over time per agent group, and each line is coloured on a gradient according to the final value of that agent group's sentiment in the same run.

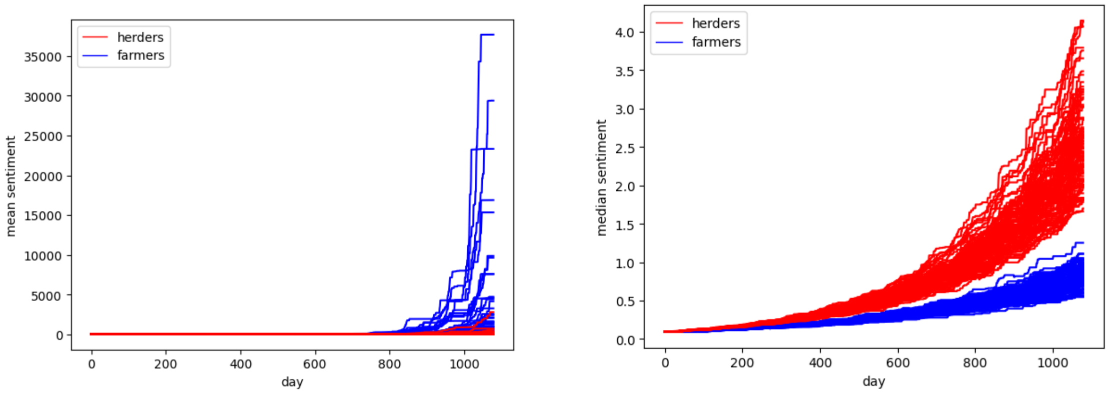
Lastly, the outcomes of experiments run with an alternative sentiment update function are plotted, to see how sentiment develops over time when using a linear function to calculate it. Ten replications of four scenarios were run with this function, and the outcomes of one of the scenarios are compared to the outcomes of the exponential experiments with the same input scenario.

5.1. Stochasticity

To gain insight into the variability of outcomes and the effects of aggregation, the model's internal stochasticity was tested by running one hundred replications of one scenario, and plotting two different aggregations of farmer and herder sentiments for each day of each run. Days are represented in the model as timesteps, and the 90 days of the rainy season are modelled per year, for 12 years. Figure 5.1a shows the mean sentiment of the herders in red and farmers in blue on the y-axis, at each timestep on the x-axis. Each line represents an agent group's mean sentiment at each point in time of one model run. Figure 5.1b shows the median sentiment of herders in red and farmers in blue on the y-axis over the days on the x-axis, where each line represents the median sentiment at each timestep of one agent group in one run. The input values that were used are:

- **world:** 2
- **rain:** 4
- **number of herders:** 200
- **number of farmers:** 200

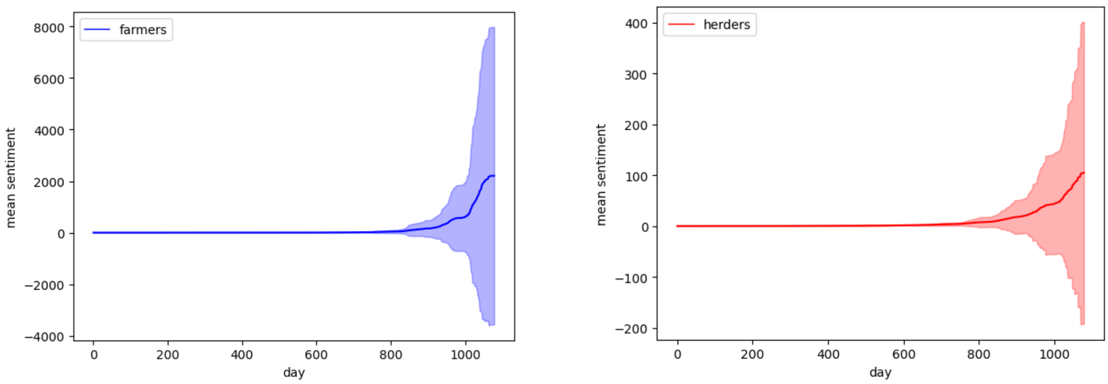
The order of magnitude of the highest mean final state of the sentiment of farmers, exceeds the highest median final sentiment of farmers by an order of magnitude of 10^4. To better visualise



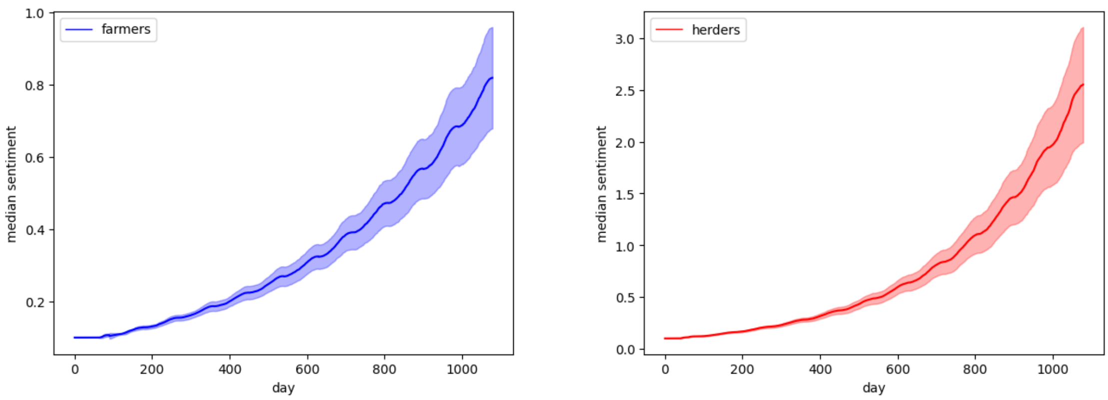
(a) Mean sentiment **(b)** Median sentiment

Figure 5.1: Mean and median farmer and herder sentiment over time for one hundred replications of a single set of input values

the internal variance of the mean and median outcomes, shaded error plots were created. At each timestep on the x-axis, the mean and standard deviations of one hundred sentiment data points for both aggregation methods per agent group were calculated and plotted on the y-axis. The mean outcomes of one hundred runs are shown as a dark line, and the standard deviations at each timestep are calculated around it. The area between the standard deviation and the mean is shaded with a lighter version of the same colour, again blue for farmers and red for herders. They are shown in figure 5.2.



(a) Mean and standard deviation of mean sentiment of farmers **(b)** Mean and standard deviation of mean sentiment of herders



(c) Mean and standard deviation of median sentiment of farmers **(d)** Mean and standard deviation of median sentiment of herders

Figure 5.2: Shaded errorplots of the mean and median herder and farmer sentiment outcomes. The line indicates the mean outcome of a hundred runs at each timestep, the shaded region indicates the standard deviation of a hundred runs at each timestep

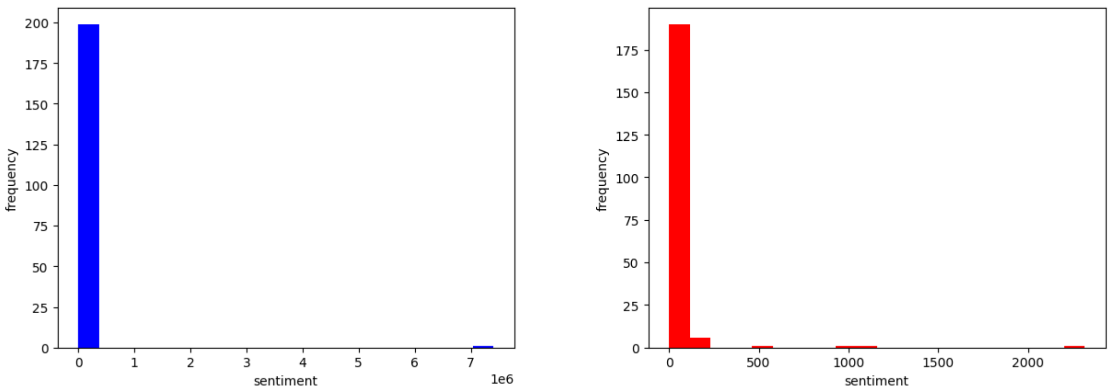
At the end of the modelled time span, mean sentiment outcomes have standard deviations three times as large as the mean of all replications. For median outcomes, the standard deviation at the end of the simulation is about a tenth to a fifth of the mean of all replications. Median outcomes are less prone to the effects of outliers, so the outcomes are more representative for the agent group as a whole, as it is less likely that a whole group of people changes their sentiment based on disproportionately strong feelings of an individual member.

Figure 5.1 and figure 5.2 provide a couple of important clues.

Firstly, the trajectories of the mean and median outcomes have very different shapes. Mean outcomes have a long warm-up period followed by an irregularly shaped exponential curve. Median outcomes have an exponential curve in which the yearly peaks in sentiment increase are clearly discernible.

Secondly, the farmers reach ten times higher mean sentiment end states than herders, but they have consistently lower median sentiment, and the median outcomes have a standard deviation that is more proportional to their value.

These two effects suggest that mean outcomes of a group are heavily influenced by individual agents who develop extreme sentiments over time, whereas median outcomes show the pattern that would be expected of multiple agents increasing the aggregate sentiment together in yearly waves, where most agents are active at the same time in the middle of the year and fewer agents are active during the beginning and end. It would be logical that farmers have more extreme outliers than herders do, because a sedentary farmer who lives in a bottleneck of herder routes would get misrecognised by a lot of passing herders. The exponential nature of the sentiment update function then ensures that this farmer's sentiment reaches extreme values. To get a look at individual agents, histograms were plotted which showed the distribution of sentiments at the end of the run that resulted in the highest final mean sentiment of farmers. Figure 5.3 shows sentiment on the x-axis, and the number of agents whose sentiment falls within a certain range on the y-axis. Each bin represents $\frac{1}{20}$ of the sentiment range between the lowest and highest individual sentiments.



(a) Farmer sentiment distribution

(b) Herder sentiment distribution

Figure 5.3: Sentiment distribution of farmers and herders for the highest end state of one hundred replications of one set of input values

In figure 5.3a, virtually all farmers have a sentiment in the lowest 5% of the range, and only one farmer has a sentiment of over 7 million, drastically increasing the mean. Figure 5.3b shows that the herder with the highest sentiment is at a sentiment in the order of magnitude 10^3 lower. This explains the higher mean and standard deviation of the mean farmer sentiment seen in in figure 5.2a versus 5.2b. Individual agents can drag up the mean with disproportionate effects.

The stochasticity outcomes have contributed to the decision to run ten replications of each input scenario during the experiments. For mean outcomes, even a hundred replications still yield a standard deviation in the exponential phase of the model that is very large, so more replications will not make this aggregate metric more reliable. Therefore, the trade-off between confidence and runtime falls in the favour of runtime. However, for median outcomes the standard deviation is within acceptable limits of the mean, therefore ten replications should suffice to obtain useful information from the experiments. Consequently, the median outcomes are considered as not only more representative for the agents as a group, but also as the most reliable aggregate outcome. Therefore, experiment results will be visualised in the next section using median sentiments as their main outcomes.

5.2. Experiment Outcomes

The model was run using world, herder and farmer population, and rain as input variables. The outcomes of 640 experiments, which consist of 10 replications of 64 combinations of input variables according to the experimental setup from table 4.3, for each of the worlds shown in figure 4.3, are visualised in this section.

First, a complete overview is shown in figure 5.4. In this figure, the median sentiment end states of the farmers and the herders are plotted for each individual run. So, 1280 data points are plotted in one figure. The y-axis represents the median sentiment. The x-axis represent the four different worlds. Outcomes have been given some noise on the x-axis to spread them over a column instead of a vertical line per world, so that individual data points are more visible.

The colours represent agent groups. All shades of blue are farmer sentiments and all shades of red are herder sentiments. The differences in shading, from light to dark, represent the population ratio, called combination in the legend. The combination shading from light to dark indicates that the data point is the median endstate of an agent group from a run with a population ratio compared to the other group of low-low, low-high, high-low, and high-high. So for example, light pink means that the data point indicates the median herder sentiment of herders in a run where the herder population and the farmer population were both low, whereas dark blue represents the median sentiment of farmers at the end of a run where both populations were high.

The shape of the data points represent the value of the 'rain' parameter for that run, this is the same for both farmer and herder outcomes.

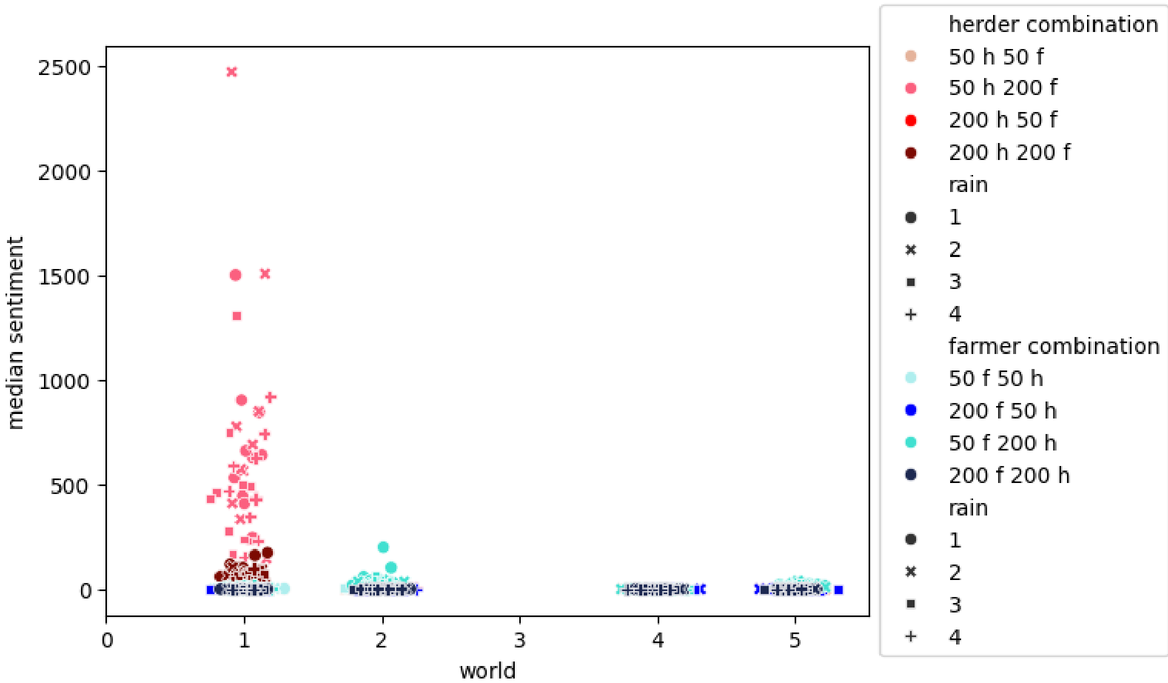
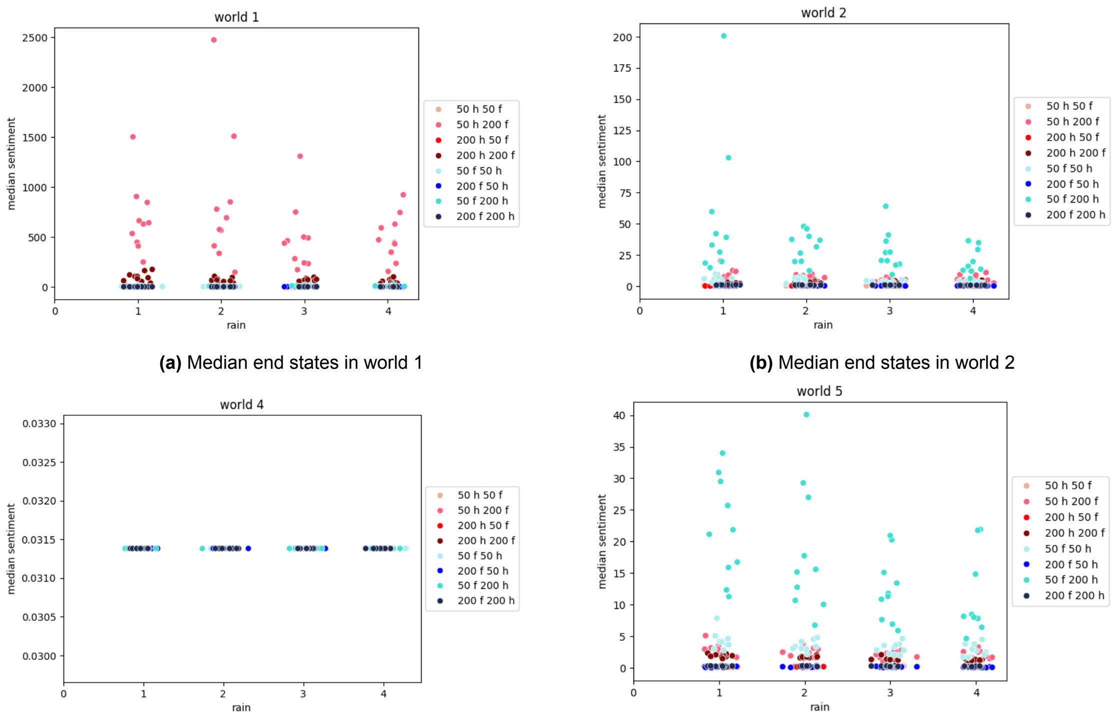


Figure 5.4: Median end state sentiments of individual experiment runs

The main thing to notice from figure 5.4 is that the height of sentiment values differs strongly per world. Also, the agent group that consistently reaches the highest sentiment end states seems to depend on the world. In world 1, the herders have 3165 pasture patches available to them, whereas there are 13265 farmland patches, and the herders have the highest end states. This suggests that land availability is important. However, in world 2 both groups have roughly 10.000 patches they can take resources from, but only the farmers reach elevated sentiment end states, although significantly lower than the herders in world 1. In world 4, where both groups have half the available patches, the sentiment values are not high enough to properly see what is going on. The same is true for world 5, where both groups have half the available patches too but arranged differently, although at first glance it looks like farmers can reach slightly elevated sentiments as well in this world. All highest sentiments are reached in scenarios with a population ratio where the group with the highest sentiment has a small population and the other group a large population.

To gain more insight in what goes on inside every world, each world's experiment outcomes are shown individually in figure 5.5. Since the different world inputs are now represented in different figures, the rain parameter can be represented on the x-axis instead of with the data point shape. Also, now only 320 data points are shown in one plot. These changes make the figures easier to interpret.



(a) Median end states in world 1

(b) Median end states in world 2

(c) Median end states in world 4

(d) Median end states in world 5

Figure 5.5: Median sentiment end states per world

In world 1, all median sentiment end states over 200 are herder sentiments in situations where there are 50 herders and 200 farmers in the model.

In world 2, where farmers have higher sentiment end states, only situations with 50 farmers and 200 herders have values over 25.

In world 4, the median sentiment end states of all agents is lower than the start value of 0,1. This means that the vast majority of agents does not experience any misrecognition event throughout the entire model run, as agents decrease their sentiment after they experience zero misrecognition events in a year.

In world 5, again only the situation with 50 farmers and 200 herders reaches values over 5.

These outcomes suggest two things. Firstly, if one group of agents has less land available to them, they are more easily misrecognised. This can be explained by noting that agents only steal from land that is assigned to agents from the other group, and when less land is available to one group, chances that the stealing happens on that group's routes or farms increase. Especially with herders, since routes can overlap, so misrecognition on one patch can be discovered by multiple herders in one year.

Secondly, having an equal amount of land available for both groups does not mean that the misrecognition problem is solved. Indeed, in worlds 2, 4, and 5 both groups of agents have roughly the same amount of land available to them. Although more land is available to both groups in world 5 as opposed to world 2, it leads to lower median sentiment but it does not eradicate misrecognition.

Within each world, the most influential factor on sentiment is population ratio. The highest median sentiment end states were reached by groups who had a small population, in a scenario where the other group had a large population.

This can be explained because fewer agents of one group means fewer farms or routes available for the other group to steal from, hereby increasing the chance that the same farm or route is misrecognised multiple times. And when the other agent group has a higher population, they create a lot of misrecognition events that have to be experienced by a smaller number of agents. So, the low population has to deal with a much higher chance of being misrecognised multiple times. Due to the exponential nature of the sentiment function, this will lead to much higher sentiments in these agents as opposed to when the experiments are distributed over a larger population, thus resulting in the highest aggregate sentiment end state over all.

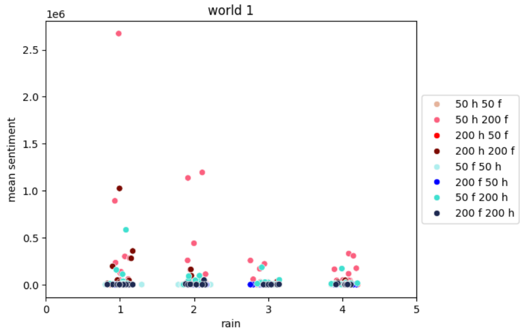
Rain, which determines the amount of resources on the land, appears to have very little significant influence on the median sentiment, as all the rain columns on the x-axis show sentiment end states in the same order of magnitude for the same input values. Since agents misrecognise when they don't have enough resources regardless of how big their deficit is, it is not surprising that the influence of this parameter is limited.

Figure 5.6 is the same as figure 5.5, except that it shows the mean sentiment end states per agent group for each run. The median outcomes per world are compared to the mean outcomes to confirm that outlier agents can affect the aggregate end states enough so that scenarios with the same input values result in a different group that ends up with the highest sentiment end states. Figure 5.1 already suggests this, but here end states from multiple scenarios are considered.

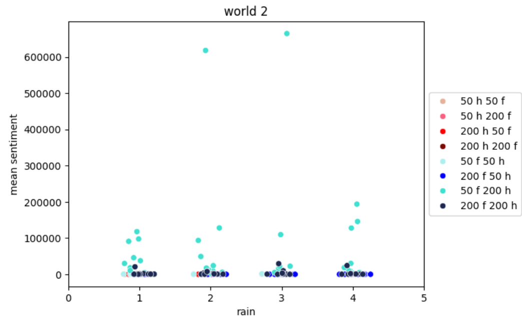
The difference between median and mean sentiment is greatest in world 4, between figures 5.5c and 5.6c. While the median sentiment end state for farmers is lower than its initial value of 0,1, the scale for the mean is in the order of magnitude 10^8 higher. Therefore, there must be a handful of farmers experiencing all misrecognition events, while the rest experiences none. This can be explained by the fact that farmers are sedentary, and some will live along the edges where herders pass by. Since agents steal only from the closest patches that belong to another agent, these farmers that live close to the herder routes will be misrecognised a lot. In world 4, there is only one border between farmland and pastures, so the farmers who live there will experience all the misrecognition, and reach extremely high sentiments due to the exponential nature of the sentiment update function. In world 5 there are more borders, so the misrecognition is distributed over more farmers. This leads to more farmers with high sentiments, but these sentiments will be less extreme and therefore the mean sentiment outcomes are lower than in world 4.

In worlds 1, 2, and 5, it is the same agent group that reaches the highest mean sentiment as the group that has the highest median sentiment, but the scales of the outcomes are much higher than the median outcomes. This reconfirms that individual agents can skew the mean upwards. Additionally, population ratios in runs that reach the highest mean sentiments of an agent group are not exclusively low-high anymore. Especially in worlds 4 and 5, where both agent groups have half of the land available to them, large populations of both groups can also result in high mean farmer sentiment end states. This can once more be explained by the extremely high sentiments that farmers living along the borders will form.

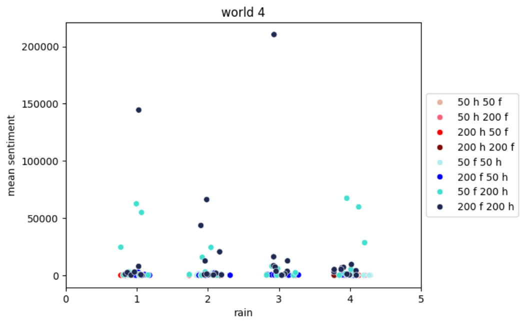
The timeseries outcomes of each individual input scenario can be found in appendix D.2.



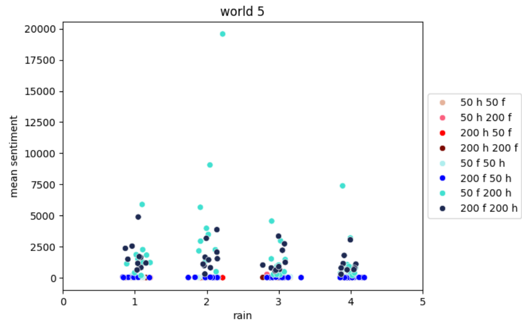
(a) Mean end states in world 1



(b) Mean end states in world 2



(c) Mean end states in world 4



(d) Mean end states in world 5

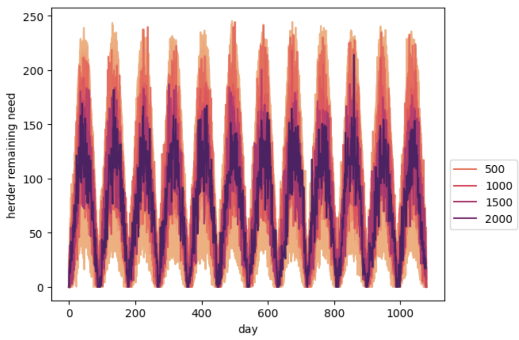
Figure 5.6: Mean sentiment end states per world

5.3. Outcome Relations

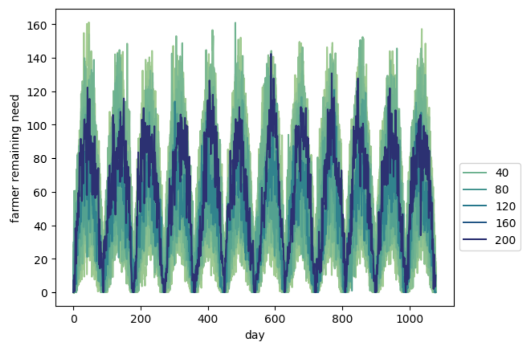
In addition to sentiment, the average amount of resources present on routes and farms, as well as the average remaining need are measured over time. The model also keeps track of the average number of stealing and misrecognition events over time. This section shows relationships between these measurements and the median sentiment of farmers and herders.

While the sentiment and number of events can only increase during a model run, the other outcomes reset to zero at the end of each year, making it useless to plot their end states. Instead, they are plotted as time series for each run for both agent groups side to side. Each of the outcomes are on the y-axes. The x-axes represent the timesteps in the model. The colours from light to dark indicate the lowest to highest median sentiment end state of each run for both agent groups: shades of red for herders, shades of blue for farmers.

Figure 5.7 shows the average remaining need of farmers and herders over time. It was to be expected that the remaining need of an agent group showed no strong relationship between its height and the agents' sentiment end state, because higher remaining need of an agent group indicates more agents who will resort to stealing, but this affects only the sentiment of the other group. Also, the amount of resources in the remaining need does not matter, for the agent will steal as soon as it is above zero.



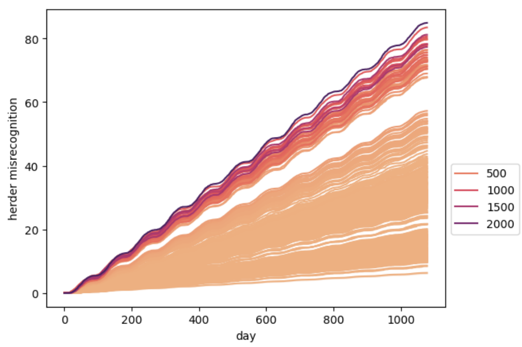
(a) Herder remaining need coloured by herder median sentiment



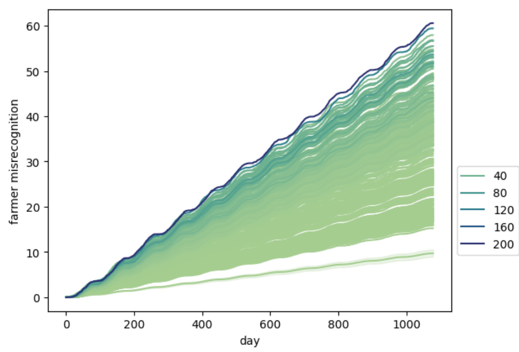
(b) Farmer remaining need coloured by farmer median sentiment

Figure 5.7: Remaining need over time coloured by sentiment

Figure 5.8 shows the average number of misrecognition events experienced by farmers and herders over time. It was to be expected that the run with the highest sentiment end state correlates directly with the run with the highest number of misrecognition events, which is why the darkest lines are the lines with the highest values.



(a) Herder misrecognition events coloured by herder median sentiment

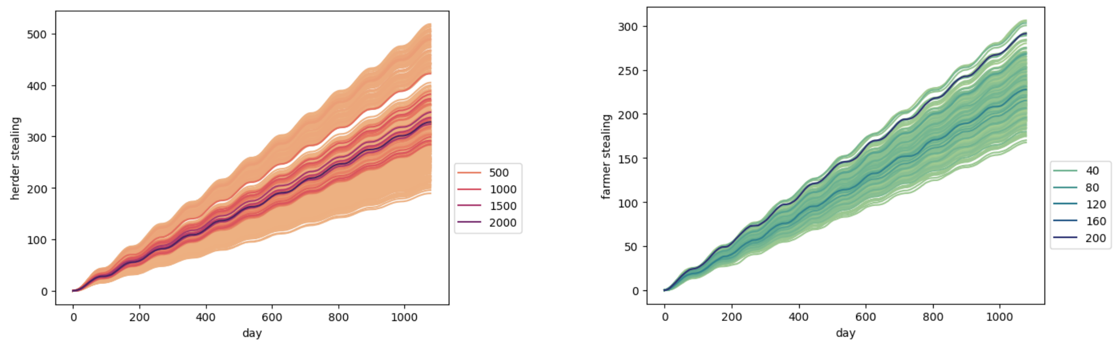


(b) Farmer misrecognition events coloured by farmer median sentiment

Figure 5.8: Misrecognition events over time coloured by sentiment

The average herder stealing events do not correlate with the highest herder sentiment, as shown in figure 5.9a, but the highest sentiment end states do form a distinguished band. The farmer sentiment is a bit more distributed over their average stealing events. A possible explanation for the herders could be that the stealing events group together per world, and they steal the most in world 1 due to having fewer resources available because more herders are forced to use the same pastures on their routes. For farmers it is unclear if there is a pattern. Stealing events do however seem to correlate with remaining need and available resources on the agents' own land, because in all of these graphs the highest sentiments end up in the middle of the spectrum of lines. This could be because low resource availability causes high remaining need, and thus more stealing events, suggesting that these outcomes would end up in the same place on their respective spectra for the same input scenario.

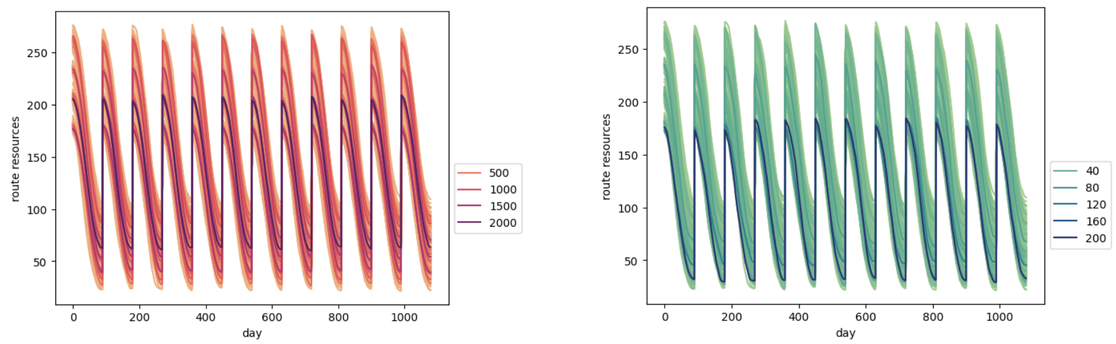
Herders consistently steal on a larger scale than farmers, but they are also misrecognised on a larger scale than farmers. This can be explained by the fact that farmers have a higher chance of letting a misrecognition event go unnoticed, as the event can occur on a patch they have already been to that year, and no other farmer is coming behind them. When farmers steal from a route patch, multiple herders might pass through there in the same year, increasing the chance one of them noticing the misrecognition.



(a) Herder stealing events coloured by herder median sentiment **(b)** Farmer stealing events coloured by farmer median sentiment

Figure 5.9: Stealing events over time coloured by sentiment

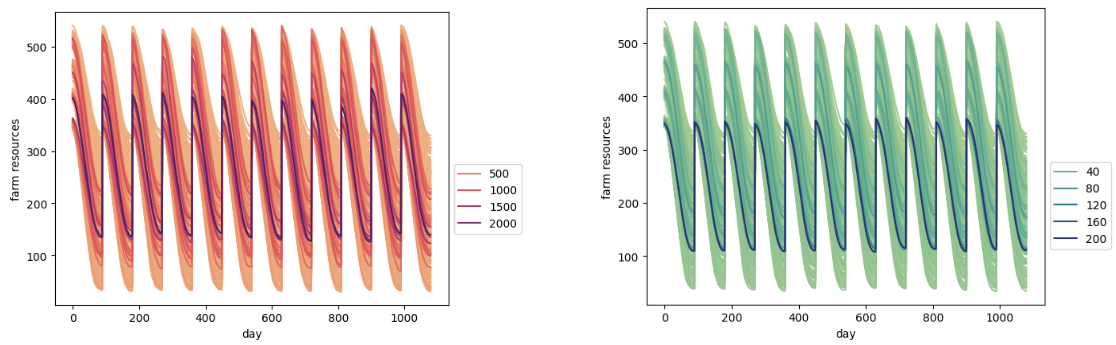
It would be expected that low resources on routes correlate with high farmer sentiment end states, and low resources on farms correlate with high herder sentiment end states, because when one group is low in resources, they will resort to stealing which leads to more misrecognition towards the other group. For the routes, this is true. The highest farmer sentiments correlate with low resources on the routes, as can be seen in figure 5.10b.



(a) Route resources coloured by herder median sentiment **(b)** Route resources coloured by farmer median sentiment

Figure 5.10: Route resources over time coloured by sentiment

The opposite is not true, however. The highest herder sentiments are on the low end of the middle of the farm resources spectrum, as shown in figure 5.11a. This suggests that the effect of herders having less land available to them than farmers is stronger than the effect of farmers having fewer resources available. The lack of a strong correlation between sentiment end states and the 'rain' parameter reinforces this conjecture.



(a) Farm resources coloured by herder median sentiment **(b)** Farm resources coloured by farmer median sentiment

Figure 5.11: Farm resources over time coloured by sentiment

It can also be seen in the correlation between agent sentiments and the resources on their own land. Extreme sentiments do not correlate with extremes in resource availability. This suggests once more that the effect of world and population ratio parameters on the aggregate sentiment is stronger than the effect available resources.

The experiments show how the input parameters influence sentiment outcomes by determining how likely agents are to experience misrecognition events. Different geographical layouts and population ratios expose agents to more or fewer events, which causes them to develop their sentiments towards the other group. So, the different scenarios change how many misrecognition events are caused and experienced, and if the distribution of agents who experience them is even or skewed. Therefore, the conceptualisation of recognition justice still has some characteristics of a distributive justice model, as different scenarios change the distribution of burdens, and this is in the end what makes agents express feelings of injustice. Nevertheless, the conceptualisation is of the reaction of people towards unjust distributions, and therefore it is a representation of recognition justice that needs the distribution of burdens to be expressed.

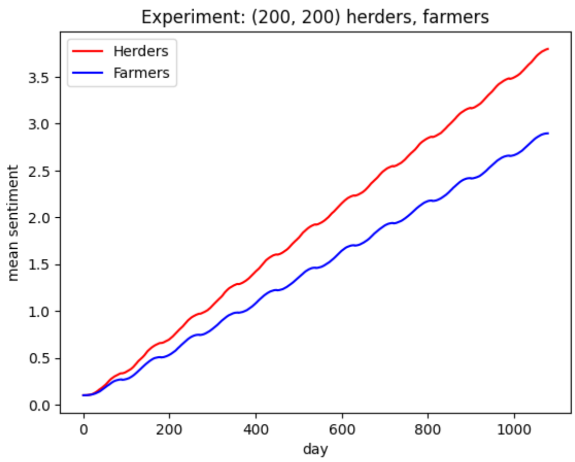
5.4. Alternative Sentiment Function Experiments

Lastly, some of the results from the experiments using a linear sentiment function are discussed in this section. They are compared to the outcomes obtained using the same initial conditions with the exponential sentiment function. This was done to perform some deeper model exploration by gaining more insight into the behaviour of the conceptualisation when the quantification is interpreted in an alternative manner.

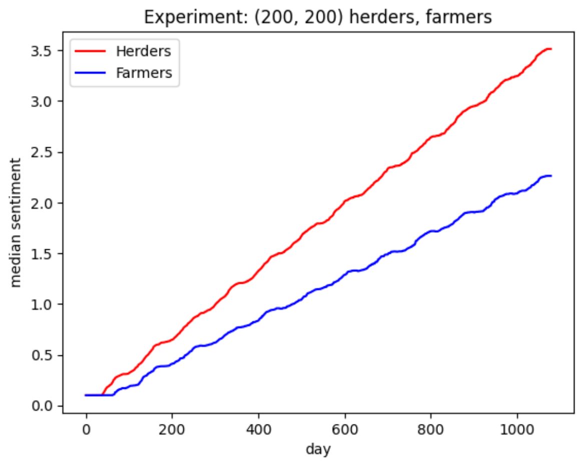
Figure 5.12 shows the mean outcome of ten replications of the scenario world 2, rain 4, and both agent populations 200, over time. The results in figures 5.12a and 5.12b were obtained with the linear sentiment function, and they are compared to the outcomes of the same scenario with the exponential sentiment function in figures 5.12c and 5.12d. The trajectories of the median outcome graphs are different between functions, but interestingly the linear median sentiment end state ends up in the same value range as the exponential median sentiment end state. This might be because the median of the exponential function is determined by agents whose sentiments never reach the true exponential phase of the function for this input scenario. The same cannot be said of the mean, which differs greatly from the median exponential outcomes as well as from the median and mean linear outcomes.

The mean outcomes with the linear function are very similar to the median outcomes with the linear function. The linear function does not allow for the same extreme sentiment values as the exponential function does, so individual agents with the highest sentiments cannot influence the mean by a lot. Therefore, the mean outcome with the linear function is similar to the median linear and exponential outcomes, but the mean exponential outcome is still very different because agents with the highest sentiment increase it by a lot. Moreover, the linear mean outcomes have local maxima and minima in each year, these are not as distinguishable in the exponential mean outcomes, again demonstrating that in the exponential outcomes the mean values depend more on one agent dragging the value upwards, instead of a lot of agents making small contributions to the aggregate sentiment.

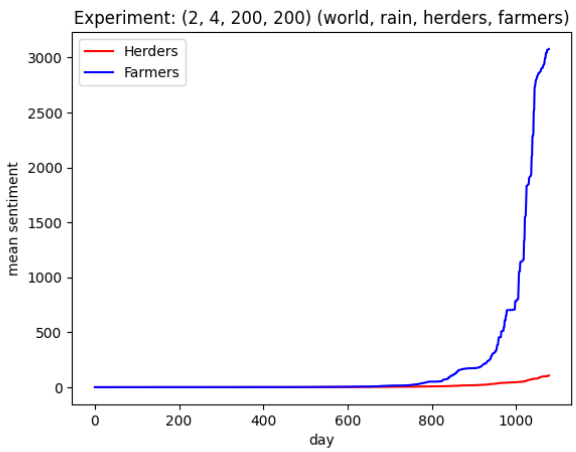
The purpose of testing with a linear sentiment function was to demonstrate the difference in outcomes with the results of the exponential sentiment function experiments. The linear function's advantage over the exponential function is that the mean does not have the large variance in it, so the linear function is more robust and easier to calibrate. However, the exponential function has a stronger basis in literature, as literature suggests that newly formed sentiment is influenced by the current sentiment, not just added to it. And when using the median outcomes, an aggregate outcome of the exponential function with acceptable variance can still be obtained. Additionally, the exponential function allows for quick identification of the presence of bottlenecks and misrecognition hot spots, which can be found by locating agents with extreme sentiments.



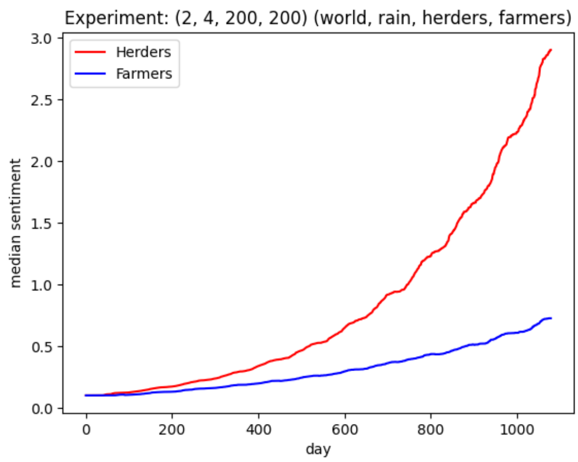
(a) Mean linear sentiment



(b) Median linear sentiment



(c) Mean exponential sentiment



(d) Median exponential sentiment

Figure 5.12: Comparing the mean and median farmer and herder sentiment over time averaged over ten replications of a single set of input values, using the linear and the exponential sentiment function

6 Discussion

This chapter discusses the experiment results and their limitations. Furthermore, it provides reflections on the context of the research process and outcomes, as well as recommendations for future research.

6.1. Model Limitations

Similar to the agents in the model, the modeller, too, does not have access to unlimited resources. This has resulted in limitations and simplifications that are discussed in this section.

Firstly, any conclusions that were drawn from testing with only one scenario need to be confirmed by testing additional scenarios. The stochasticity experiment and the experiments with the linear function now draw conclusions without taking into account the effect of different world and rain parameters, and also without the effect of population ratio. Since the world and population ratio affected the model outcomes the most, tests with different scenarios should be conducted to make more accurate statements about the results.

Secondly, it must be noted that all sentiment outcomes of this model have no absolute meaning. This is due to two reasons, the first being the lack of real-world data used in building the model.

The different geographical layouts are taken from hypothetical drawings that have no basis in the real world, but the world is the input parameter with the highest influence on the outcomes. Worlds 4 and 5 would never exist in reality and just have demonstrative purposes to show that layout matters too, not just equality in land distribution.

The population numbers were calibrated to fit into the model world instead of the other way around. This was done to keep the simulation going smoothly as too many agents slow the model down. In the case of farmers, it was also done because farmers cannot share land with each other and there is limited space for them.

Although the 'rain' parameter has no basis in reality either, this is considered less of a limitation to the model outcomes, because it did not show any significant effects on sentiment outcomes. Simulating resource scarcity was done using only the 'rain' parameter and not the 'feed-need' and 'family-need' parameters, which is also not expected to form a significant limitation on the sentiment outcomes, due to the resource availability's lack of an emergent pattern. However, if someone were to implement remaining need as a proxy for intensity, its influence is expected to increase and it would need to be calibrated more accurately.

The second reason for the model's lack of any absolute meaning is that although this model has attempted to decompose recognition justice into quantifiable elements, justice remains a qualitative and subjective concept. The sentiment outcomes from the model can only be compared to each other and their numerical values can only be used to draw qualitative conclusions. The values with which the sentiments increase, the order and presence parameters, are arbitrarily chosen values calibrated through trial and error, with all the other model parameters, just like the value of 10% with which an agent's sentiment decreases after they do not experience any misrecognition events for a year. The calibration depends on factors such as the size of the model world, the number of agents, the number of events, and the simulated time frame.

Unlike the other input parameters, the order and presence parameters were fixed throughout all experiments. This means that no experiments were done to see the effects of different input values for the misrecognition parameters. The start value for sentiment was supposed to be zero for all agents, but due to the recursive nature of the sentiment value it could not start at zero and was set to 0.1. Since any configuration of these parameters would have the same lack of quantitative meaning, this is not assumed to be a big limitation, but it is important to remember when interpreting model results, and when using the recognition justice decomposition for modelling other contexts.

Of course the function with which the sentiment is updated is also a choice and not an absolute truth. The linear function does not incorporate feedback from the current sentiment to the emotional response, but the exponential function makes individual agents reach sentiments so high that they might not even be meaningful compared to other agents in the same run anymore. More mathematical approaches could be used instead of either of these functions.

Thirdly, limitations show up in the outcomes of the experiments. Answering questions sometimes just raises more questions, and not all the information to answer them has been saved during the experiment runs.

One example of a question raising more questions is that the outcomes tell the model observer how many misrecognition events take place, but not which ones are presence events and which ones are order events. This information could be helpful when using the model to design interventions to address specific misrecognition events.

Another example is that it would provide more insight into the influence of geographical layout to identify the locations in the model where the agents with the highest sentiments reside. It has been deduced from the outcomes that farmer aggregate sentiment is susceptible to being heavily influenced by outliers. A heatmap of sentiment-increasing hotspots could provide better understanding of the influence of the geographical layout, but location and sentiment data of each individual agent should be recorded during the model runs to be able to visualise it.

6.2. Reflection

This section reflects upon the context of the research project as a whole. It adds nuance to the theoretical basis for the justice decomposition. Furthermore, the value of the conceptualisation and the model outcomes is discussed, and a translation from the model back to the real-world situation is made. Lastly, it reflects on what can be learned from the model about the recognition justice conceptualisation, and how the project contributes to the scientific body of research.

Firstly, a short positionality statement is made to provides some understanding of the researcher's background, including biases, assumptions, and values. The positionality of the literature used for the conceptualisation of recognition justice is also reflected upon.

In the case of this research project and the Dosso region, a European author who has never been subjected to recognition injustice or resource scarcity in their life, took a framework written by authors whose society was formed in the midst of an ethnic and religious conflict, and created a conceptualisation that is meant to be applicable to a variety of situations. Subsequently, this conceptualisation was applied to a region and a people neither of these parties know anything about culturally. Remembering to be careful when making and interpreting these universal statements is therefore strongly recommended.

It is however still considered useful to derive a general recognition justice conceptualisation from literature and to demonstrate it in a model. This is because the rationale of the conceptualisation process can be retraced, and because the model purpose is not to confidently and quantitatively measure a quality, but to show how the recognition justice conceptualisation reacts to being modelled.

To apply the recognition justice decomposition to a real-world scenario, it will benefit from tailoring it to the specific case. For this, firstly stakeholders should be carefully selected, which is a challenge in the context where the most important stakeholders are being misrecognised and may not be able to participate in the decision-making process on the implementation of the recognition justice conceptualisation. However, even if a model does not reflect the situation accurately it can be used to facilitate public debate by simulating hypothetical feelings of injustice and presenting the findings to other stakeholders as a starting point for discussion. This is expected to contribute to a better understanding of the situation by all parties, as public debate and feelings of injustice are the two factors van Uffelen (2022) argues are necessary to detect recognition injustice.

In the spirit of tailoring to specific situations, the translation back to Niger's Dosso region is made here. Although this case was used mainly for theoretical exposition of the recognition justice conceptualisation, a translation from the model to the real world is still useful for gaining a deeper understanding of its behaviour.

The original conclusion of Frexus (2022) was that lack of rainfall, and consequently a lack of resources, does not have to lead to conflict risk. Frexus (2021) provided the information that one of the main conflict drivers was a perception of inequality of access to resources, not the inequality itself. These statements are both supported by the lack of emergent patterns that can be attributed to resource availability resulting from the model.

The model has the capacity to display sentiments of farmers and herders who live in the Dosso region on both the local and aggregate level thanks to the bottom-up approach of ABM. This can help conflict mediators prioritise which group to engage in the debate first, by looking at which group has the highest negative sentiment, and which specific people from this group to engage, by looking at the sentiment distribution. Using accurate geographical data, these people can be located within the Dosso region. Accurate geographical data also contributes to the reliability of outcomes for this specific model.

The following aspects of the model are believed to be useful to facilitate discussions with Dosso's inhabitants:

The sentiment outcomes can be presented to inhabitants and used to validate feelings they may have, even without input data being accurate. The outcome relations can help put into perspective how much of the experienced recognition injustice is caused by perception. Model outcomes can be shown to inhabitants and even computed on demand, to answer questions they may have. The model may also be used in discussions with the region's authorities to help them understand the dynamics of recognition injustice. The model could also help with decision-making when it is applied to policy design, where recognition injustice can serve as a metric to be minimised.

In short, there are many ways the model can be used to open, facilitate, and structure public debate in the Dosso region, contributing to recognition justice not by telling people what their situation is like, but by inviting them to share their stories.

The model results show that the recognition justice conceptualisation's behaviour still depends on a distributive property. Different input scenarios essentially change the distribution of burdens. However, the recognition justice conceptualisation still represents recognition justice by making the translation from the burden distribution to how agents in the model feel about shouldering these burdens. Also, the burdens are modelled as the difference between what agents want, and how other agents obstruct them, hereby representing participatory parity which is an essential characteristic of recognition justice. When the burdens and their quantification are defined in collaboration with stakeholders of the modelled system, this is believed to go beyond the distributive characteristic and to be a useful representation of recognition justice.

Because of the aid in identifying recognition justice through expressed feelings of injustice and facilitation of public debate, the research project is believed to add value to the scientific body of system's research. No conflict models consider recognition justice yet. Using the outcomes of this research project helps fill that gap, and offers new entryways into conflict prevention and de-escalation.

6.3. Recommendations and Future Research

In this section, advice is given on how to use the key takeaways from the research project for real-world applications. The first key takeaway is the recognition justice conceptualisation itself. The second key takeaway is the implementation and behaviour of the recognition justice conceptualisation as done in the theoretical exposition ABM developed in this research project.

To incorporate recognition justice into an agent-based model, a misrecognition submodel can be implemented. This requires defining misrecognition event types, an amount of anger that comes with each event, and a measure to assess the intensity of the events. Then, a formula must be devised that updates the emotional sentiment each time a misrecognition event is experienced. This formula should take into account the event type and intensity as well as the current emotional sentiment as an emotional response that shapes the new emotional sentiment. The sentiment update function presented in equation 4.1 is an example of how this can be done.

Choices about how to quantify the recognition justice conceptualisation must be made in collaboration with stakeholders from the modelled context. Doing so makes the model a participatory project, which is recommended for the benefit of both the accuracy of the outcomes, and for facilitating debate.

When executing this, the stakeholders will decide the amount of anger that arises in response to misrecognition events they define. It is however still advised to explore one or more base scenarios with a range of input values for misrecognition event anger, because the participatory process will likely benefit from the modeller knowing the effects of adjusting these values.

In the context of resource scarcity, misrecognition events were interpreted to pertain to perceived inequality of access to resources, however the misrecognition submodel used in this model may also be applied to other resource scarcity contexts in future research, as long as the misrecognition events are carefully defined.

When implementing the exact misrecognition submodel from the theoretical exposition model that was developed in this research project, obtaining data on the geographical layout should be prioritised, as this input parameter affected the misrecognition outcomes the most.

Secondly, population data must be obtained, as population ratio is the next most influential factor. However, in the modelled exposition population data is inherently connected to geographical layout, because each agent in the model 'owns' a number of patches. In situations where agents do not own any specific land areas, the influence of this factor should be reevaluated. Also, since it is not the population itself but the ratio that matters, this factor should be reevaluated for situations with more than two groups involved in the conflict.

Although the amount of resources did not display any emergent patterns in this model, it is still advised to obtain some data on the stakeholders' resource demand, and the resource availability for the sake of completeness. Furthermore, it is recommended to consider incorporating the remaining need into the sentiment function by using it to calculate intensity, and this might change the influence that the amount of available resources has. If this is done, it must be kept in mind that remaining need can also occur without the agent being misrecognised, therefore a distinction between misrecognition and other factors should be made.

It is recommended to implement the recognition justice conceptualisation as a sub-model into ABMs modelling resource scarcity situations even if they already incorporate distributive justice. After all, model results have shown that equal distribution of resources does not guarantee that people feel they are treated justly. Additionally, agents experience recognition injustice by being forced to carry burdens they consider unjust, even if others face the same problems.

Obtaining insights into recognition justice is expected to provide valuable information for handling resource scarcity conflict scenarios, by making more stakeholders feel included, and by serving as a possible metric to be minimised in future use for policy design.

Finally, it is recommended to apply the recognition justice conceptualisation to situations other than resource scarcity as well. Any agent-based model representing a society could benefit from considering recognition justice for all stakeholders.

7 Conclusion

In this chapter, all research sub-questions are answered one by one to ultimately answer the main research question of this thesis.

7.1. Sub-Question 1

"How can recognition justice be conceptualised in order to be modelled?"

This sub-question is answered using the theory from chapter 3. Recognition justice is defined as a form of justice that describes a situation as just when everybody is allowed to participate equally in social life. Recognition injustices prevent people from doing so. Recognition injustices can be identified by people expressing feelings of being treated unjustly, and through public debate that applies diverse perspectives. The source of recognition injustice must always be another party. In a resource scarcity situation, perceived inequality of access to resources between groups with different cultural backgrounds is a source of recognition injustice.

In order to be modelled in an ABM, agents need to be able to express feelings of recognition injustice. For this, they need to experience recognition injustice in the context of resource scarcity. To achieve this, recognition injustice is defined as a string of misrecognition events. A misrecognition event happens when agents have planned to perform certain actions, but are prevented from doing so in the way they want by another party. Each event is given a type and an intensity. These parameters indicates how much the reality differs from the desire. Experiencing a misrecognition event causes agents to update their emotional sentiment. The emotional sentiment represents an amount of anger and is calculated by a recursive function, where the new sentiment is calculated from the current sentiment and the emotional response to the event. This response is calculated from a fixed amount of anger that comes with the experienced type of event, and the intensity with which the agent experiences the event. Over time, the sentiment builds up. When no misrecognition events happen for a long time, sentiment can also go back down.

In short, recognition justice is defined as the absence of recognition injustices, which are conceptualised for modelling as a string of misrecognition events. Experiencing misrecognition events causes agents to update their emotional sentiment. Misrecognition is detected through the sentiment that agents form over time.

7.2. Sub-Question 2

"How must the model be built to allow for implementation of the recognition justice decomposition?"

To allow for implementation of the recognition justice decomposition in an ABM, agents need an environment where they can perform activities as they desire, and where their plans can be disrupted by another party. The agents need to be able to distinguish between event types, and they need to be able to determine the intensity of the difference between desired and experienced reality, to know by how much to update their sentiment. When their desired actions can't take place due to reasons other than obstruction by another party, they need to understand that this is not misrecognition.

To quantify the recognition justice conceptualisation, the type and intensity of misrecognition events must scored in cooperation with stakeholders that are to be modelled. Also, a formula must be devised to have emotional responses form the sentiment, and to have the sentiment influence the emotions in turn.

For the demonstration of the conceptualisation of recognition justice in a model, an ABM was created with an environment in which nomadic herder agents and sedentary farmer agents live. In this environment, the agents are entitled to the resources present on patches of land assigned to their group. All agents are given a list of land patches that they visit every year in a predefined order. They visit one patch a day, and their objective is to find enough resources on all patches they stop by to fulfil their daily need.

Sometimes, there are not enough resources present on the patches they visit, and in that case they steal from a patch that is not assigned to their group. The insufficient amount of resources may have been caused by another agent having stolen them, which is experienced as a misrecognition event with a type called 'presence', but environmental causes can also be responsible for the lower amount of resources. This last case is not interpreted as misrecognition by the agents. Additionally, a presence event is only experienced by the first agent to arrive on the patch after the event has taken place.

The predefined order of patches allows agents to experience misrecognition events with the type 'order', where they have to change their plan. In this model, the agents only deviate from their plan when an agent from the other group is stealing resources on the patch they were planning to go to at the exact time they were planning to go there. Agents can sense how many resources were stolen in both order and presence events, and this allows them to use this as a proxy for intensity of the experienced misrecognition event. Whenever an agent experiences such an event, she updates her sentiment accordingly.

7.3. Sub-Question 3

"What insights can be gained from the model about recognition justice in the context of natural resource scarcity?"

7.3.1. Quantification and Aggregation

In this research project, an exponential and a linear sentiment function were tested as formulas to calculate agent sentiments from events' types and intensities. The exponential function incorporates the feedback that the emotional sentiment gives back to the emotional response to an event, as literature suggests it does. This does however result in extreme outliers in the form of sentiments of agents that are misrecognised disproportionally often. The linear function does not have produce such outliers, but also doesn't incorporate the feedback of the emotional sentiment. In the tested scenarios, the linear function does not change the qualitative outcome of the model, because the same agent group ends up with the highest sentiment when using either of the functions for the same input scenarios. However, to draw a definitive conclusion about this, all scenarios should be tested with the linear function and compared to the exponential function outcomes.

Additionally, when looking at individual agent data, the differences in scale between the agents with the largest and smallest sentiment are very large in the exponential function, but the sentiment distribution per agent shows that most agents are in the lowest sentiment segment and only a couple of agents have a very high sentiment. This does seem representative of a normal society where extreme sentiments are usually only felt by a handful of people and not shared by everyone.

Because the exponential function incorporates the feedback of the emotional sentiment on the emotional response as found in literature, it is considered to be the superior option of the two functions, but other mathematical approaches must not yet be ruled out.

Assuming the exponential sentiment function is the best approach, the aggregation method must be carefully chosen to account for variance. The outliers produced by the exponential function can really skew the mean sentiment of a group. Median outcomes are more robust than mean outcomes, with the variance staying within the order of magnitude of the mean outcome of one hundred replications of the same input scenario. Median outcomes are therefore believed to better represent the aggregate sentiment than the mean. However, mean outcomes are interesting to see whether a scenario produces any outliers, indicating recognition injustice hotspots. Because the sentiment function is recursive, a very high mean suggests that one or a few agents are being disproportionally misrecognised.

In reality, when there is misrecognition happening between two groups in daily interactions, there will be some people who are more affected by this than others, and people who will be more angry than others. The median best represents the group sentiment, because its value is not influenced by how high the highest sentiment is. It is not expected that one angry person can cause an entire group to become irate, but chances are that as outliers with extremely high sentiment exist, the median sentiment is at least elevated.

7.3.2. Experiment Outcomes

The model uses world, herder and farmer population, and rain as input variables. This section summarises the insights gained by running experiments of different scenarios about the influence of each of the input parameters on the end state of the sentiment for each run.

The aggregated outcomes suggest that the world has the most influence on the scales of the sentiment end states, and on which agent group experiences the most sentiment. This is true for both the median and the mean outcomes.

The number of farmer and herder agents in the model was the next most significant factor, specifically the ratio of farmers and herders. Within each world, the highest median sentiments were reached when the group with the highest sentiment had a small population, and the other group a large population. Since an essential element of the recognition justice conceptualisation is the fact that it must be caused by another party, this is an important characteristic of the conceptualisation's behaviour in a model.

The last input variable, the 'rain', that controls the amount of resources that patches grow each year, does not seem to have any significant influence on the median sentiment end states. However, the absence of such a pattern is an emergent quality of the model as well.

For the conceptualisation to work in a model, there must be a situation where misrecognition events can occur. The resuls of this thesis project are specific to the Dosso model, and the population ratio and world parameters provide more information about the amount of misrecognition events that occur than about the recognition justice conceptualisation itself. However the lack of influence of the resource availability suggests that there is merit in modelling recognition justice instead of distributive justice. The recognition justice conceptualisation focuses on the emotional response of people as a result of what they feel is an unjust distribution of burdens, and therefore the conceptualisation of recognition justice relies on a distribution of misrecognition to be able to take shape. However, although the distributive property is a part of the conceptualisation, the misrecogntion events represent the harm to participatory parity and the quantification of feelings is advised to be made in collaboration with system stakeholders. Therefore the recognition justice conceptualisation is believed to provide insights beyond what a distributive justice representation can do.

7.4. Main Research Question

"How can recognition justice be conceptualised for agent-based simulation in the context of natural resource scarcity?"

In summary, recognition justice can be conceptualised for agent-based modelling as the absence of misrecognition, where misrecognition is modelled as a string of misrecognition events that must be caused by agents, which are judged by the agents who are subjected to them. The judgment is based on the event type and intensity, in the form of a quantified angry emotional response. This quantification must be decided upon with the stakeholders who are represented in the model. The responses to the misrecognition events build up over time to form an emotional sentiment, which is a temporally stable feeling towards another group that arises as a result of reactive emotions to misrecognition events caused by that group. This sentiment is a state variable of agents which in turn influences the emotional response each agent has to each single event. It can be evaluated on an individual and on an aggregate level and the function to update it must include the event type and intensity, as well as the current sentiment. The emotional sentiment is also the main metric of the recognition justice conceptualisation. When no misrecognition events occur for a long time, the sentiment can decrease again.

When using the recognition justice conceptualisation in an agent-based model of a certain system, the model must be built so that agents can misrecognise each other, and they can form a response and update their emotional sentiment after being misrecognised in a misrecognition submodel.

Such a model aids the detection of recognition injustice in two ways: the sentiment acts as a proxy for the expression of feelings of injustice by the system's stakeholders, and the model helps facilitate public debate with real-life stakeholders.

The recognition justice conceptualisation can be used in the context of natural resource scarcity by modelling a situation where individuals can realise their plan to take the resources they are entitled to without being obstructed in doing so by other parties.

The model demonstrating this conceptualisation of recognition justice showed that the conceptualisation of recognition justice can indeed be implemented in agent-based modelling. And because the amount of available resources in the model showed no emergent pattern in the outcomes, and it models agents' feelings resulting from harm to participatory parity, the recognition justice conceptualisation truly distinguishes the model from models that measure distributive justice, thus contributing to reducing the research gap of recognition justice implementation in agent-based modelling.

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A
Literature Review

Kable et al. (2012) provide guidelines for conducting a structured literature review to obtain a systematic approach. This framework has been used to identify a research gap in agent-based modelling of conflict.

The database used for a structured review was Scopus. To find reviews on agent-based models modelling justice, the search term consisted of three domains: ABM, justice, and literature review. Because injustice may lead to conflict, ”conflict” was used as an alternative search term for justice, to broaden the search. This lead to the following search string:

(”ABM” OR ”ABMS” OR ”agent-based model”) AND (”conflict” OR ”justice”) AND (”review” OR ”literature analysis”)*

This search yielded eight papers. Out of these, not all were about agent-based modelling. Twice, ABM stood for Agence de la Biomédecine, so these papers were rejected based on their abstracts. Another paper was rejected because it only mentioned agent-based modelling in minor detail and was about spatial planning instead of justice modelling. The remaining five literature reviews are shown in table A.1.

Table A.1: Results from the structured literature search

Author, year	**Title**
Meijer et al. (2021)	Quantitative modeling of human responses to changes in water resources availability: A review of methods and theories
Matczak and Hegger (2021)	Improving flood resilience through governance strategies: Gauging the state of the art
Lindkvist et al. (2020)	Navigating Complexities: Agent-Based Modeling to Support Research, Governance, and Management in Small-Scale Fisheries
DeAngelis and Diaz (2019)	Decision-making in agent-based modeling: A current review and future prospectus
Eshragh et al. (2015)	Automated negotiation in environmental resource management: Review and assessment

B
Assumptions

Table B.1: The list of assumptions

Number	Explanation
1	The amount of resources needed to satisfy the daily needs of the agents can be calculated
2	The agents have fixed desired activities
3	Resources are insufficient to satisfy everyone
4	When farmers and herders don't meet, there is no problem
5	There is insufficient management of resources by the authorities
6	There are no rebellions or other types of conflict that influence the emotional sentiment
7	Peuhls are the only ethnic group practising transhumance, Djermas are the only ethnic group practising agriculture
8	Peuhls and Djermas only meet between October - December
9	When Peuhls or Djermas take resources from land that is assigned to the other group, there is misrecognition
10	Misrecognition is an indicator for rising conflict and can be used as a proxy to indiacte where conflict is likely to escalate
11	When resources are sufficient, farmers and herders remain on their designated areas
12	Herders move through the model, farmers remain on their farms (this is not completely true in reality according to professor Lawali from Niger)
13	Interactions between agents are only relevant when it is between groups
14	There is no conflict within one agent group
15	The model area consists of farmer farms, transhumance corridors, pastures, and desert
16	The model runs from 2011 up to and including 2022, because the democracy has only been in place during that time
17	Farmers harvest at the end of the rainy season, when herders are crossing the area
18	The daily need of farmers is actually the part of their harvest they planned to pull in that day, their harvest lasts them the entire year
19	The daily need of herders is what their herd needs to be fed in a day
20	When needs aren't met by the pastures and routes, herders let their cattle graze the closest patch of farmland with resources on it
21	When farmer needs aren't met by their own farms, they steal resources from the closest patch of pasture land with resources on it

Continuation of table B.1	
Number	Explanation
22	Herders and farmers can always tell when their resources were taken by the other group
23	Herders and farmers cannot intrude on land designated to their own group
24	Every intrusion is represented as someone taking away water resources from an area of land
25	Everyone occupying or taking resources from a piece of land not intended for them is doing so intentionally, knowing it is wrong
26	After December, another November starts
27	No matter how high the sentiment gets, agents will not take any action that escalates the sentiment into conflict

C

Model Description

This chapter describes the model using the Overview, Design concepts, Details (ODD) protocol by Grimm et al. (2020), which is depicted in figure C.1. It provides a logical and standardised structure to help readers find and understand the different dynamics of ABMs.

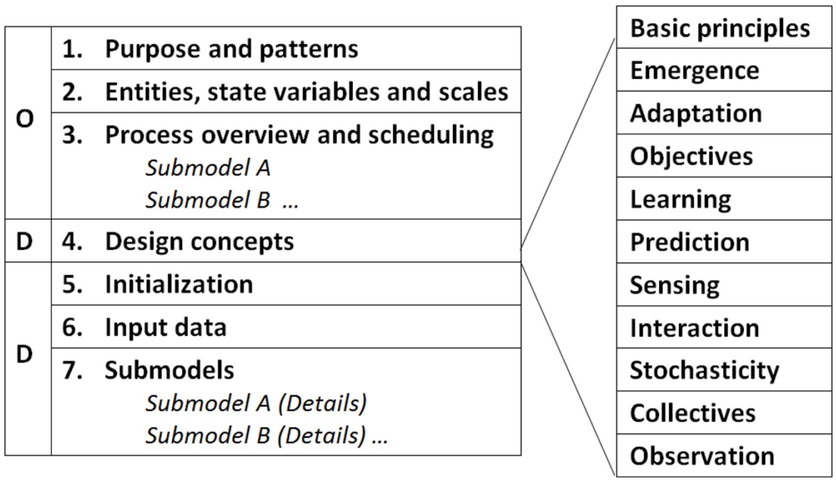


Figure C.1: The structure of model description using the most recent update of the ODD protocol, consisting of seven elements, as defined by Grimm et al. (2020).

C.1. Purpose and Patterns

C.1.1. Purpose

The purpose of this model is to demonstrate the behaviour of a recognition justice conceptualisation for agent-based modelling. According to Edmonds (2017), this model purpose is called 'theoretical exposition'. In his book, Edmonds (2017) states that *" 'Theoretical exposition' means discovering then establishing (or refuting) hypotheses about the general behaviour of a set of mechanisms (using a simulation)"*.

The specific purpose of this research project is to develop a theoretical decomposition of recognition justice which can be implemented in agent-based simulation. To do so, a model is developed in which the result of this decomposition is implemented to be assessed.

A few key aspects of this modelling purpose are mentioned in Edmonds (2017). Running a series of simulation experiments to see if a hypothesis should be refuted is important, and notice here that it does not definitively say to refute or accept it. Since the hypothesis pertains to a complex system, its value is not binary. To refute the hypothesis, a counterexample can be given. Otherwise, the hypothesis can be established, or partly established and otherwise improved upon. To be useful, the hypothesis cannot be very specific, it needs a certain generality so that it can be applied to different scenarios. And to test the hypothesis, the model does not necessarily need a direct relationship with the observed world in terms of data or evidence. It does however need to have some meaning in the real world, otherwise it would be a simulation model simulating nothing, which renders itself moot.

All these aspects can be argued to be present in this research. Especially since the model does have the real-world connection of being based on farmer-herder conflict in the Dosso region, but not using any of its geographical or demographic data. It is merely used to assess the usefulness of the proposed recognition justice decomposition. After drawing a conclusion about its utility, and perhaps improving upon it, it can then be implemented in simulations of real-world conflict as another factor to consider.

C.1.2. Patterns

The model is evaluated based on the following patterns:

1. **Lower amount of resources leads to more misrecognition events:** as the initial resource availability of the agents in the model model can be set to have fewer resources available due to drought, larger populations. increased need, or a combination of these factors, agents will try to fill their deficits by stealing resources from other agents.
2. **Increase in emotional sentiment due to increase in misrecognition events:** as the number of misrecognition events, in this case resource theft, goes up, agents will feel more negatively towards the other group.
3. **Geographical layout heavily influences the maximum sentiment experienced:** in an environment that is evenly distributed, the mean sentiment is relatively close to the median, whereas an environment that has bottlenecks for the herders to go through has a big difference between mean and median sentiment.

C.2. Entities, State Variables, and Scales

C.2.1. Entities

The following entities are considered in the model:

- **Farmers:** farmers are agents forming one side of the farmer-herder conflict which is modelled. Farmers are people that live on a farm and harvest their own crops there to provide for their families.
- **Herders:** herders are agents forming the other side of the farmer-herder conflict. Herders are people that cross the region every year during the rainy season to graze their herds.
- **Patches:** the patches represent virtual geographical locations, the region where the agents live and operate.
- **Observer:** the observer is an entity which describes the environment and simulated time.

C.2.2. State Variables

All entities have their own state variables. They are described per entity in this section.

Farmers

Table C.1: Farmer state variables

Variable Name	Variable Type and Units	Meaning
Need	Static, number of resources	The need of an agent is the amount of resources he needs to harvest graze every day
Start-day	Static	The day in each year on which the agent starts carrying out his plan
Farmland	Static, patch set	The farmland is a set of patches that belong to an agent
Family	Static, number of people	The family of a farmer is the number of people the farmer has to feed with his harvest
Plan	Static, list	The plan is an ordered list of the farmland set which stores the order in which the agent will harvest each year
Active	Dynamic, boolean	Describes whether the agent is working on his plan
Sentiment	Dynamic, anger	A score that expresses how negatively an agent feels towards the other agent group
Remaining-need	Dynamic, number of resources	The remaining need is a variable that holds the number of resources the agent is short in each timestep
Misrecognition-events	Dynamic, number of incidents	This variable counts how many misrecognition events an agent experiences over the years
Yearly-events	Dynamic, number of incidents	This variable counts how many misrecognition events an agent experiences per year. Used to determine whether the sentiment goes back down
Stealing-events	Dynamic, number of incidents	This variable counts how many times an agent misrecognises another agent each year
Location	Dynamic, internal model coordinates	The location shows where in the model world the agent is in each timestep, using coordinates inherent to the NetLogo software
Plan-position	Dynamic, step number	The plan-position is a variable that stores the current position of the agent in his plan

Herders

Table C.2: Herder state variables

Variable Name	Variable Type and Units	Meaning
Need	Static, number of resources	The need of an agent is the amount of resources he needs to graze every day
Start-day	Static	The day in each year on which the agent starts carrying out his plan
Route-flags	Static, agentset	The route-flags is a set of patches that the agent has designated to visit each year
Cattle	Static, number of cattle	The cattle variable is the number of cattle that an agent has to feed on the pastures each day
Route	Static, list	The route variable is a list of the patches the herder will visit in that order
Active	Dynamic, boolean	Describes whether the agent is working on his plan
Sentiment	Dynamic, anger	A score that expresses how negatively an agent feels towards the other agent group
Remaining-need	Dynamic, number of resources	The remaining need is a variable that holds the number of resources the agent is short in each timestep
Misrecognition-events	Dynamic, number of incidents	This variable counts how many misrecognition events an agent experiences per year
Yearly-events	Dynamic, number of incidents	This variable counts how many misrecognition events an agent experiences per year. Used to determine whether the sentiment goes back down
Stealing-events	Dynamic, number of incidents	This variable counts how many times an agent misrecognises another agent each year
Location	Dynamic, internal model coordinates	The location shows where in the model world the agent is in each timestep, using coordinates inherent to the NetLogo software
Route-position	Dynamic, step number	The route-position is a variable that stores the current position of the agent in his route

Patches

Table C.3: Patch state variables

Variable Name	Variable Type and Units	Meaning
Landtype	Static	States if the patch is a pasture, farmland, or desert
Landowner	Static, agent	States if the patch is owned by an agent, and if yes by which agent
Location	Static, internal model coordinates	Describes the location of a patch in coordinates inherent to the NetLogo software
Resources	Dynamic, number of resources	States the number of resources present on each patch at each timestep
Stolen	Dynamic, boolean	Shows whether an agent from a group who is not allowed on a patch has taken resources from there
Intensity	Dynamic, percentage of resources	States the amount of resources that have been stolen from a patch in a percentage of the number of resources taken divided by the total amount of resources on the patch at that timestep

Observer

Table C.4: Observer state variables

Variable Name	Variable Type and Units	Meaning
Day	Dynamic, day number	The simulated day at each timestep
Year	Dynamic, year number	The simulated year at each timestep
Newyear?	Dynamic, boolean	States whether it is the first day of a year or not

C.2.3. Scales

The model represents both time and space. Each tick in the model represents one day. The model runs for ninety days each year, for a period of twelve years. These ninety days are the approximate duration of the rainy season in which herders cross the Dosso region (Frexus, 2021). It runs for 12 years, for the duration of the rainy seasons of 2011 through 2022, as this is the period in which Niger had a relatively stable democratic government until the military coup in the summer of 2023.

The spatial component of the model is based on the Dosso region but does not use any actual geographical or demographic data and is therefore abstract. Three types of land are represented by the patches: desert, farmland, and pastures. The pastures are indicated by the colours yellow, blue, and red, and they represent transhumance corridors. Green patches indicate land suitable for farming, and the rest is desert. When farmland patches belong to a farm, they turn a lighter shade of green, and when pasture patches are part of a herder's route they turn pink. The model uses different compositions of these land type representations. Herders travel through the modelled Dosso region from the north to the south (Frexus, 2021) and the spatial component of the model represents land that the herders pass through and that is inhabited by sedentary farmers.

The maximum population of both herders and farmers possible in the model is 200, so there is a maximum of 400 agents present in the model at the same time. Farmers stay in the model, herders move through it in on average 30 days. An approximation of 3,6 km as the distance covered by herders per day is taken from Motta et al. (2018). This would mean that the 180x180 patch grid used in the model is about 108x108 km in reality. According to Wikipedia, the Dosso region has an area of 31.002 km^2 and a population of 2.754.500 (“dosso region niger - Bing images”, n.d.). This size is about a third of the real size of the Dosso region, and the maximum of 400 agents would mean the population density is about a 100 times less than the actual average population density, taken into account that every agent represents not one person but a household. Therefore, the spatial component of the model is abstract and must be adapted and calibrated to suit the user’s needs.

C.3. Process Overview and Scheduling

This section describes the process for every tick in the model after initialisation by the setup function for as long as the model runs. It goes as follows:

1. The observer updates the global variables. These are the day, and at the end of the year the year too, as well as resetting some yearly variables
2. Agents update their locations, moving on to the next patch on their plan or staying where they are if they are inactive
3. Agents check the patch for misrecognition
    - If misrecognition is true they go through the misrecognition submodel in which they update their sentiment
4. Agents check for resources on the patch, if there are enough to satisfy their need
5. Agents harvest or steal resources, depending on if their need is satisfied
6. The output is plotted

Figure C.2 shows a diagram of the process.

C.3.1. Rationale

The model includes the farmer and herder daily processes because it is a representation of the farmer herder resource conflict in the Dosso region. However, these processes are just there to provide context for the recognition justice decomposition. The misrecognion submodel is the one that specifies what happens when a misrecognition event occurs, which is why this is a submodel. This way, it can be used in other contexts as well.

The order in which the entities execute is random. Within a breed of agents the execution order is randomised. In the go procedure, herders go first and then farmers. This has no further meaning but is due to the way NetLogo executes code from top to bottom.

C.4. Design Concepts

C.4.1. Basic Principles

At the system level this model is quite abstract. However, the basic principle of the farmer-herder model is a conceptual decomposition of recognition justice as a series of misrecognition events that influence and are influenced by a sentiment towards the perpetrator. This interpretation of recognition justice may be considered to be implemented in models representing real-world conflicts. A more closely detailed description of it can be found in chapter 3 and figure **??**.

C.4.2. Emergence

Emergence refers to a global pattern that arises from local interactions in the model. The key metric for this model is the sentiment of agents. Sentiment develops when agents experience misrecognition events caused by other agents. These agents are forced to misrecognise due to their own environment not providing them with sufficient resources. So, the cumulative sentiment of agents depends on other agents misrecognising them, which depends on their environment not providing for them.

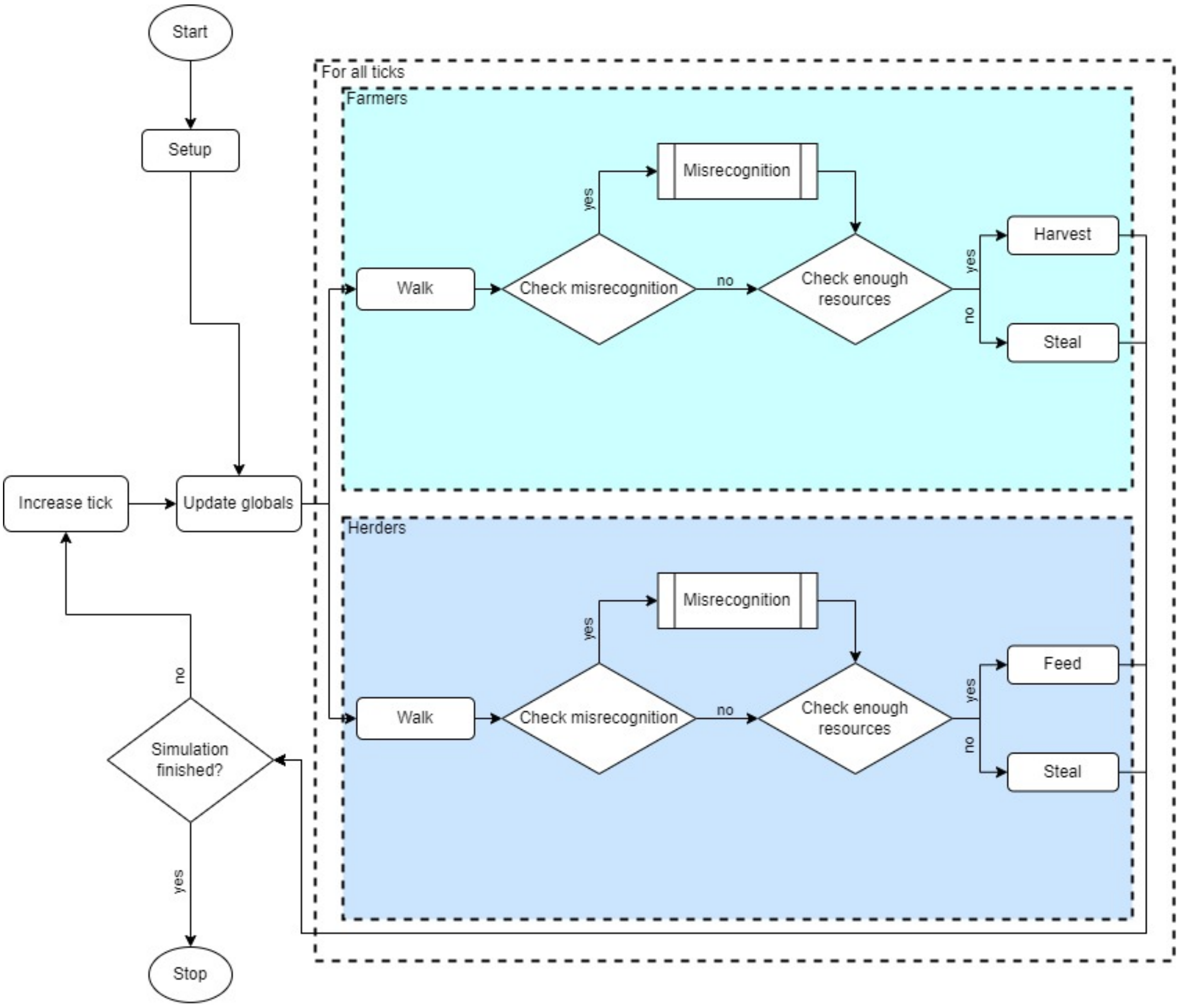


Figure C.2: Process overview and scheduling

C.4.3. Adaptation

Agents are only adaptive when they are active. They differentiate between their desired reality, called the route or plan, and their experienced reality. At the start of every day, they move to the next location of their plan. If they encounter an agent from the other group here, they update their sentiment and go to a place outside their plan to take resources from there, and they are done for the day. If they don't encounter an agent from the other group, they check if the location has been stolen from. If so, they update their sentiment again and then move on to checking the amount of resources. If they don't have enough resources to fulfil their need they misrecognise another agent. If they do, they fulfil their need. More information about this can be found in section 4.2.

C.4.4. Objectives

The agents' objective is to obtain enough resources every day to satisfy their total need. This is evaluated by comparing the amount of resources on the patch the agent is currently on to the daily need the agent has, at every tick.

C.4.5. Learning

Learning has not been implemented in this model.

C.4.6. Prediction

Agents do make predictions in the same way they do not learn, they stick to their plan as much as possible. But the implied assumption of increased sentiment is that at some point the sentiment will lead to action (as shown in figure 3.1) so the model can be used to determine where to start implementing conflict de-escalation measures.

C.4.7. Sensing

Agents can sense the amount of resources on a patch and whether it satisfies their need. They also know their current sentiment and use it to update their sentiment when they are misrecognised.

Patches sense when an agent steals from them, and in turn the next agent that lands on the patch senses this.

C.4.8. Interaction

Interactions between agents are mediated by the environment. Agents only interact through misrecognition events. When someone misrecognises them, they update their sentiment.

C.4.9. Stochasticity

Stochasticity occurs in a number of places in the model, during both the setup and the go phase.

C.4.10. Setup

Farmers are assigned a random set of farmland patches with a maximum that can be chosen by the user, and in a radius around them that allows for this maximum to occur. They create a randomly ordered list as their plan. They own a random number of family members that has a maximum value. They are assigned a random start day so that their chances of encountering other agents differ.

Herders sprout on one of the patches with the pasture land type, on the highest y coordinate. They create their route by moving to the bottom of the model over pasture patches where each patch they land on gets added to their route, and each next patch is a random pasture patch which has a y coordinate that is a certain step length below the current one. They own a random number of cattle that has a maximum value. They are assigned a random start day so that their chances of encountering other agents differ, and they have different probabilities of finding enough resources.

The environment grows resources according to a normal distribution, whose mean and standard deviation can be set by the user, using the 'rain' chooser button.

C.4.11. Go

During the go procedure, stochasticity is present in the order in which agents execute. Also, at the beginning of each new year, resources regrow and the start days are reassigned in the same way as during the setup procedure.

C.4.12. Collectives

The farmers and herders are modelled as explicit collectives. Both have their own state variables and although they are similar, they have opposing objectives. They interact through misrecognition, and although they do not interact within their own group, they are assumed to have a strong social cohesion and shared group values.

C.4.13. Observation

The model interface shows land types in the model world via patch colour. It also shows the agents as dots, and updates their locations for each tick.

Plots on the side of the model world show some summary statistics. The mean sentiment, remaining need, and mean numbers of misrecognition and stealing events are shown per agent breed, and a histogram of sentiment per agent breed is also shown. The last plot shows the average amount of resources that is present on farms and routes.

Lastly, two counters show the current year and day at every tick.

To get more insights from the experiments, the mean and median as well as individual farmer and herder sentiments are measured at each tick and saved to the output file. Furthermore, mean remaining need and mean recognition and stealing events are saved at each tick, and the average amount of resources on the farms and routes.

C.5. Initialisation

The setup function initialises each model run. All different model scenarios are created by setting different initial conditions.

First, the model is completely cleared of all data. Then the global variables are set up. Day and year state variables are set to the desired start date. The newyear? state variable is set to false at each initialisation.

Next, the world is set up. Their location is specified as their coordinates in the grid. Land types are determined by importing the colours from images, to initialise the model with different geographical layouts. Figure 4.3 shows the images used for this purpose.

The resources that grow on the model patches are drawn from a normal distribution. A normal distribution is used because this is one of four available distributions in NetLogo, and the most common distribution found in nature, as well as the (Patel & Read, 1996). The other state variables are set to zero.

Subsequently, agents are set up. The number in which they sprout is set by the user. The need of an agent is determined by multiplying the need per animal or family member set by the user, with the random number of family members or cattle the agent is assigned. Farmers are placed randomly around the farmland patches and take ownership of a set of patches in a radius around them, up to a maximum set by the user. They set their plan by shuffling the list of patches they own. Herders are placed on pasture patches on the highest y coordinate and create a route by randomly walking down over patches of their landtype. Initially the agents are all inactive. Each agent is assigned a start day that is lower than the amount of time in a year and the length of his route. The other state variables are set to 0.

The setup function concludes by resetting the ticks to 0.

C.6. Input Data

This model does not use any external input data.

C.7. Submodels

The most important metric, sentiment, is an agent state variable. Agents update their sentiment in the misrecognition submodel. This submodel is described here.

Following the analysis in chapter 3, agents evaluate the difference between the order, presence, and the intensity of their desired reality versus the experienced one, as shown in figure 3.3. Each occurrence of another agent causing the experience to differ from desire is called a misrecognition event. Recognition injustice is interpreted as a string of misrecognition events that give rise to an emotional sentiment. Each individual misrecognition event causes an agent to go through the misrecognition submodel and is given a score that indicates the amount of anger that follows from the event. This amount of anger a depends on the type of event e, and its intensity i, as well as the agent's current emotional sentiment s_n . The amount of anger leads to a new emotional sentiment s_{n+1} which will be used as a proxy for measuring recognition injustice experienced by that agent. This way, the equation for emotional anger sentiment can be written down as equation 4.1.

The misrecognition submodel contains all possible misrecognition events, which all use equation 4.1. They differ in the parameter they use for the amount of anger a, which is defined as *presence* for a presence misrecognition event, and *order* for an order misrecognition event. The intensity of the misrecognition event is defined as the percentage of resources that was stolen from the patch on which the event occurred.

Figure C.3 shows how the misrecognition submodel updates the sentiment. It starts at the current sentiment and arrives at the new sentiment via whichever misrecognition event type occurs.

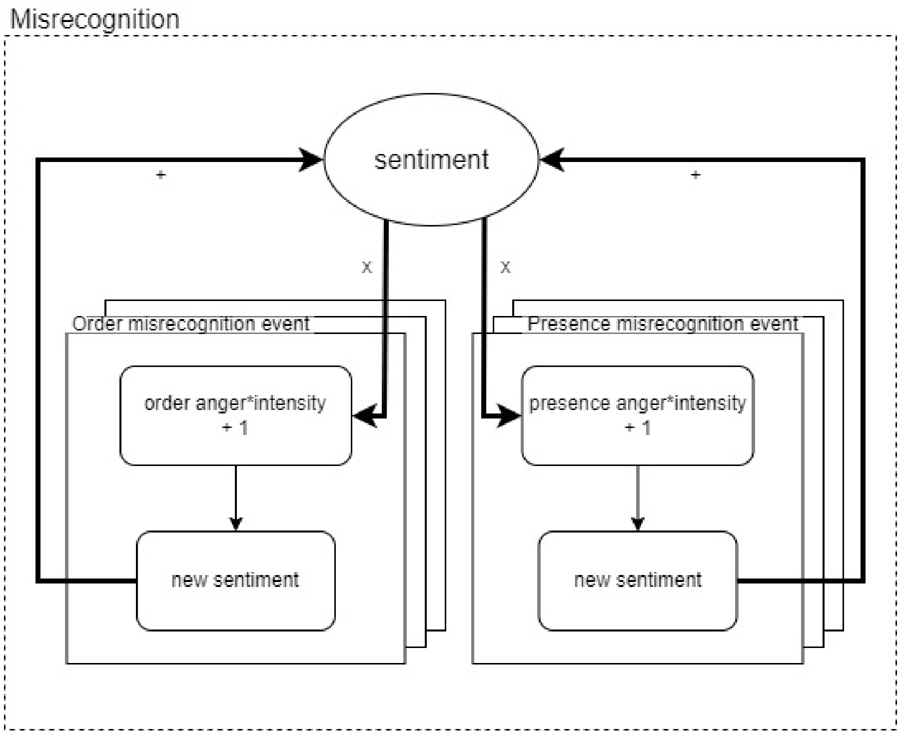


Figure C.3: Misrecognition Submodel Diagram

D

Supplementary Outcomes

D.1. Determinism

Since computers can only use pseudo-random numbers, even stochastic models are deterministic in reality. To see if this holds true for the model in this research as well, the model was run ten times with the exact same input scenario, and a random seed of 45. The input values used for this scenario are:

- **world:** 2
- **rain:** 4
- **number of herders:** 200
- **number of farmers:** 200

The mean sentiment over time was plotted for each run. Figure D.1 shows the resulting plot.

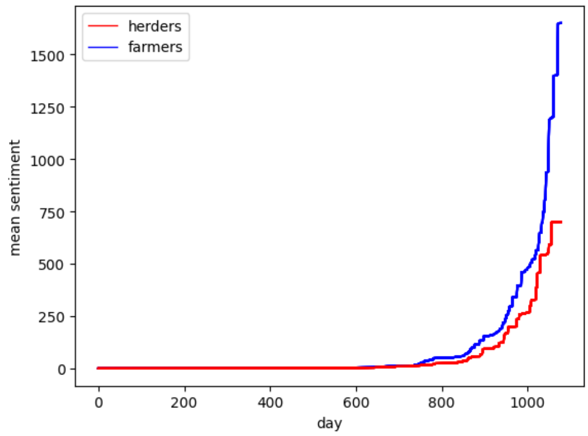


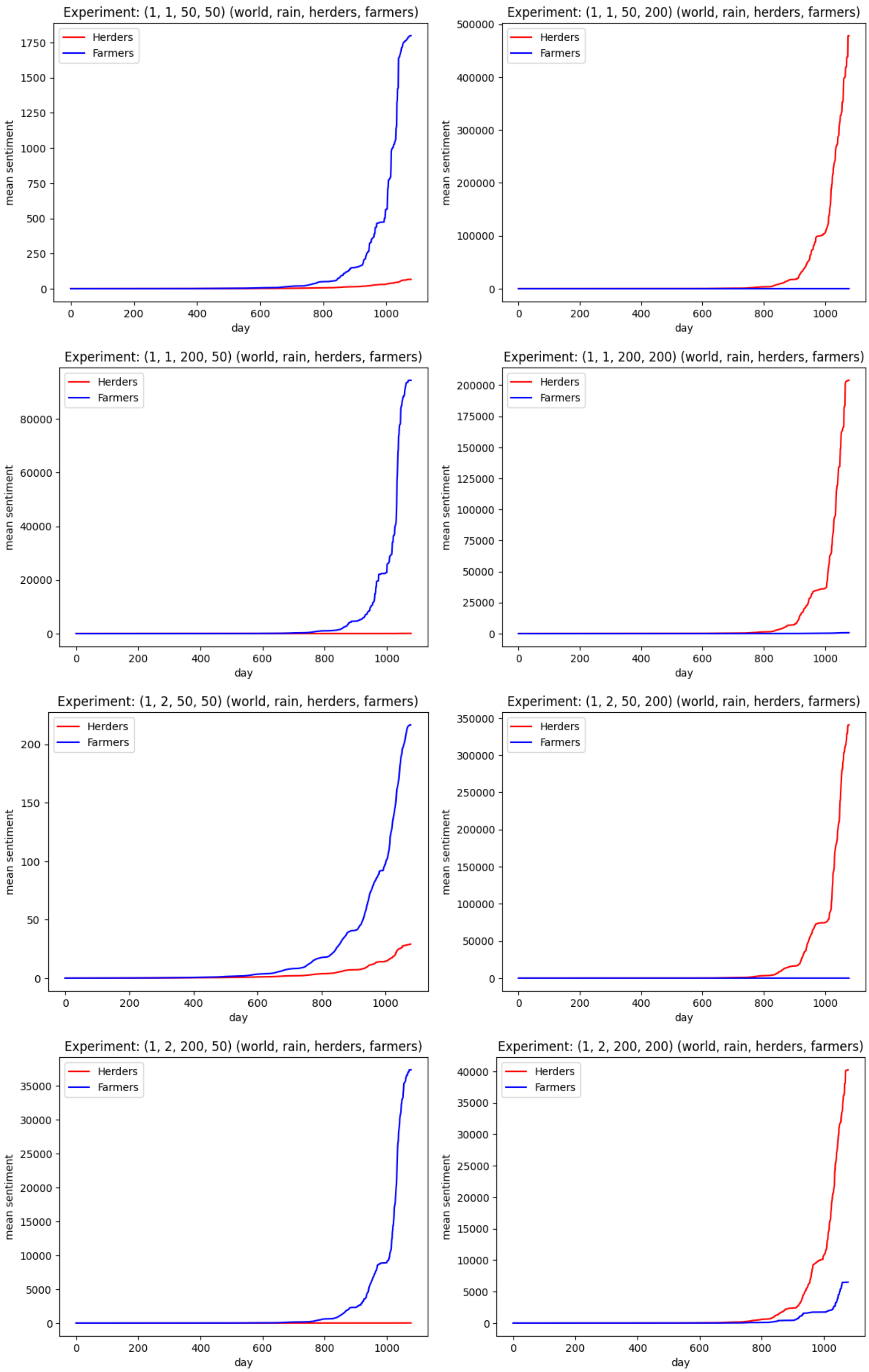
Figure D.1: Mean sentiment over time for ten replications of one input scenario with a random seed

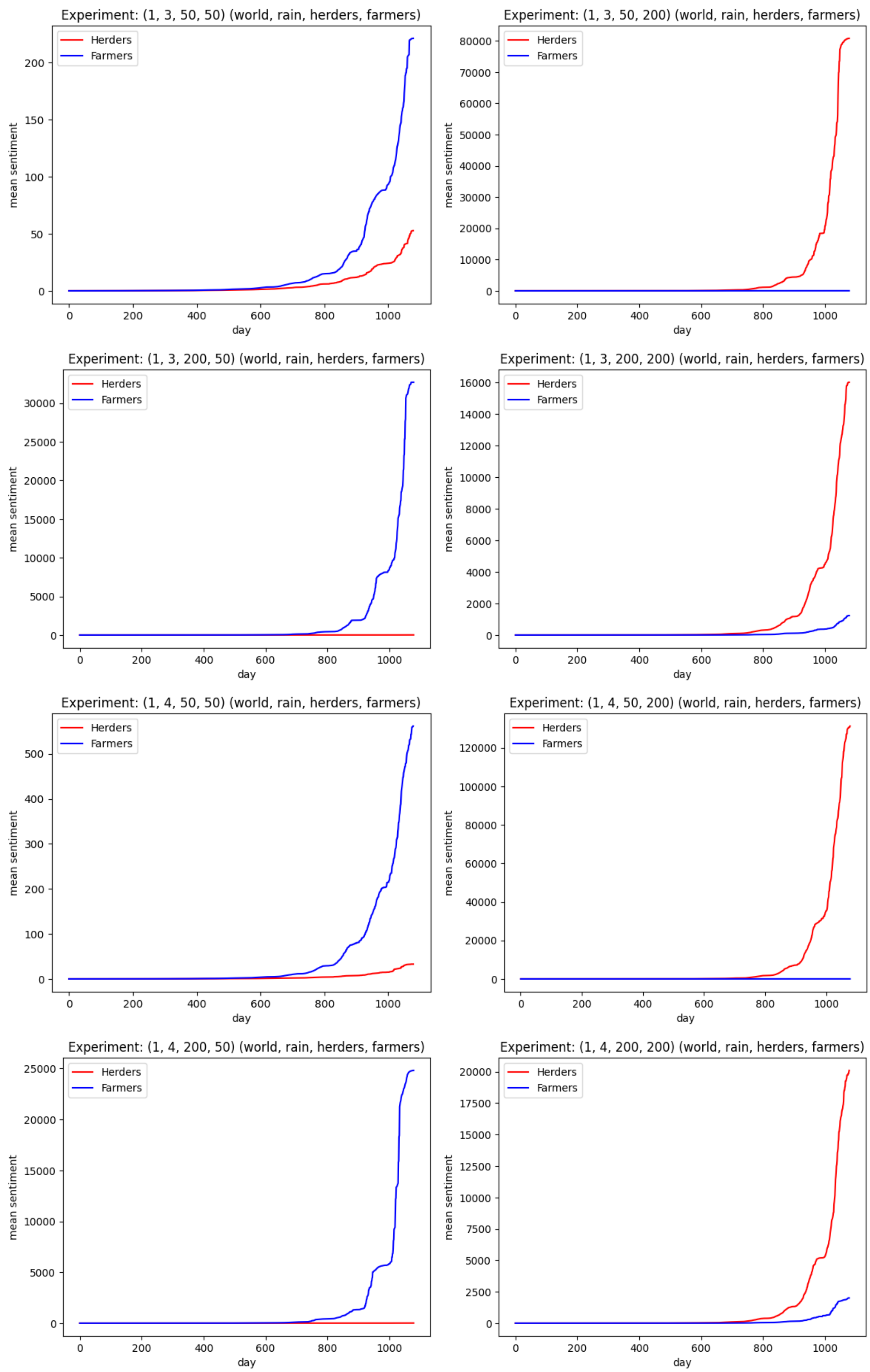
All the lines in figure D.1 follow the exact same trajectory, therefore it can be concluded that the model is deterministic in reality.

D.2. Outcomes per Experiment

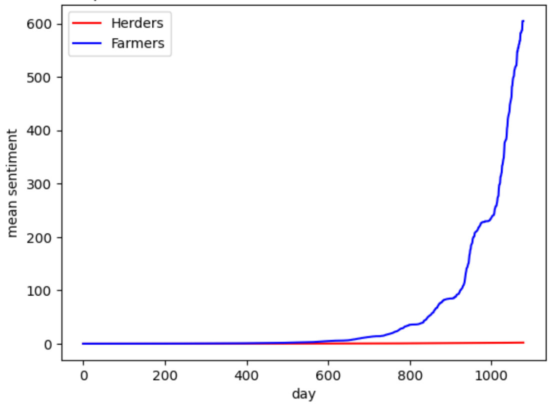
The next pages contain plots of the mean and median sentiment outcomes of herders and farmers, for each input scenario.

Mean Outcomes

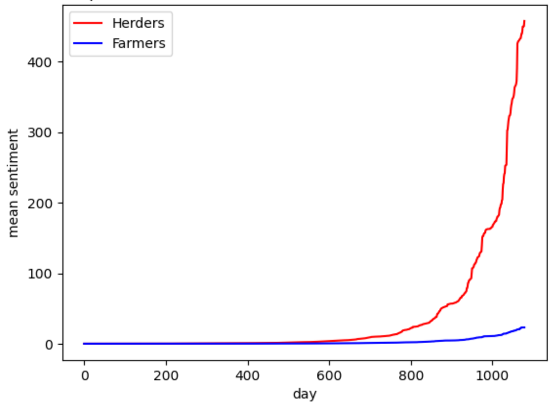



Experiment: (1, 3, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (1, 3, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (1, 3, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (1, 3, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (1, 4, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (1, 4, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (1, 4, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (1, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

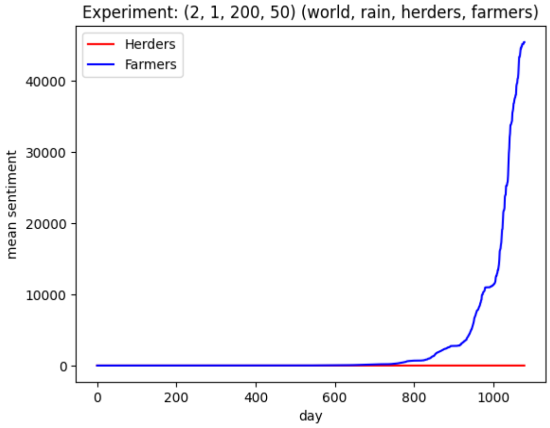
Experiment: (2, 1, 50, 50) (world, rain, herders, farmers)



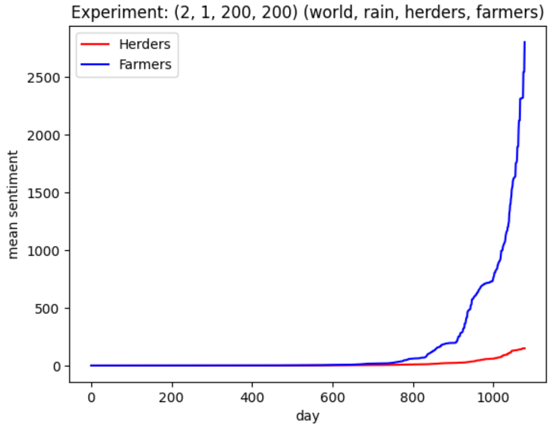
Experiment: (2, 1, 50, 200) (world, rain, herders, farmers)



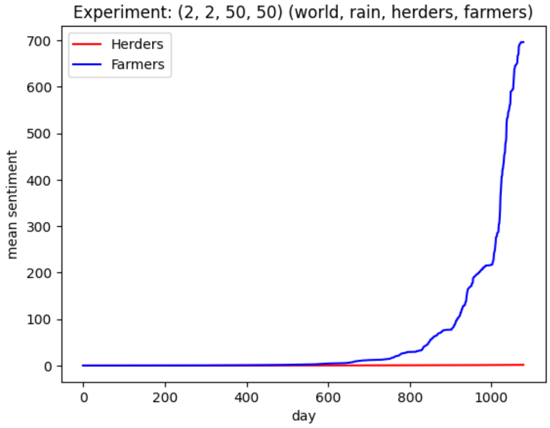
Experiment: (2, 1, 200, 50) (world, rain, herders, farmers)



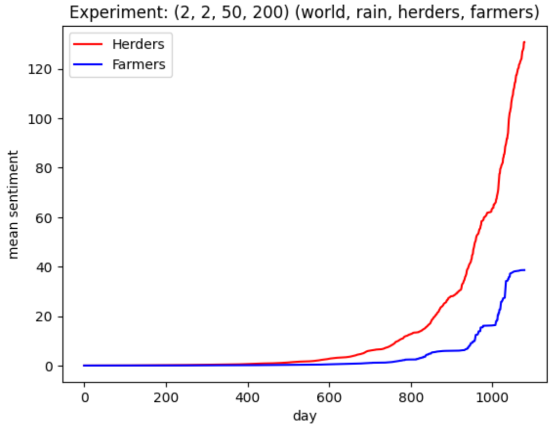
Experiment: (2, 1, 200, 200) (world, rain, herders, farmers)



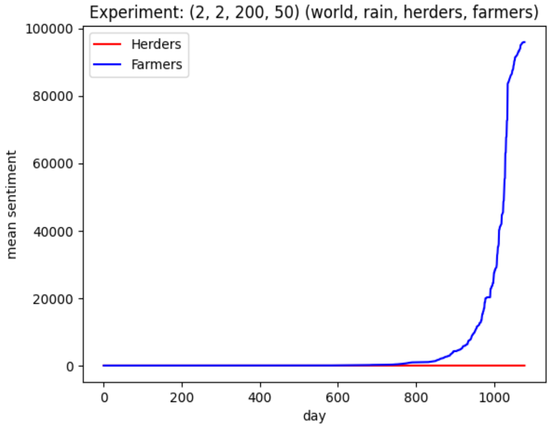
Experiment: (2, 2, 50, 50) (world, rain, herders, farmers)



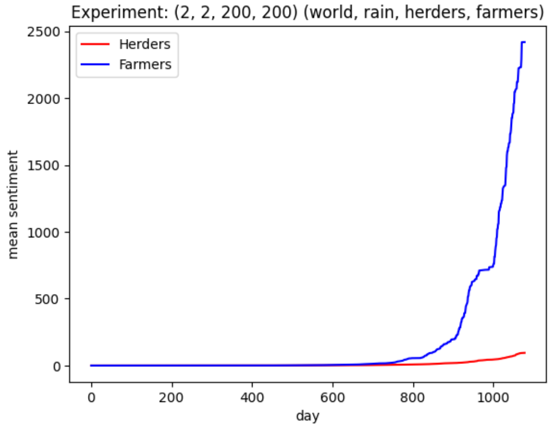
Experiment: (2, 2, 50, 200) (world, rain, herders, farmers)

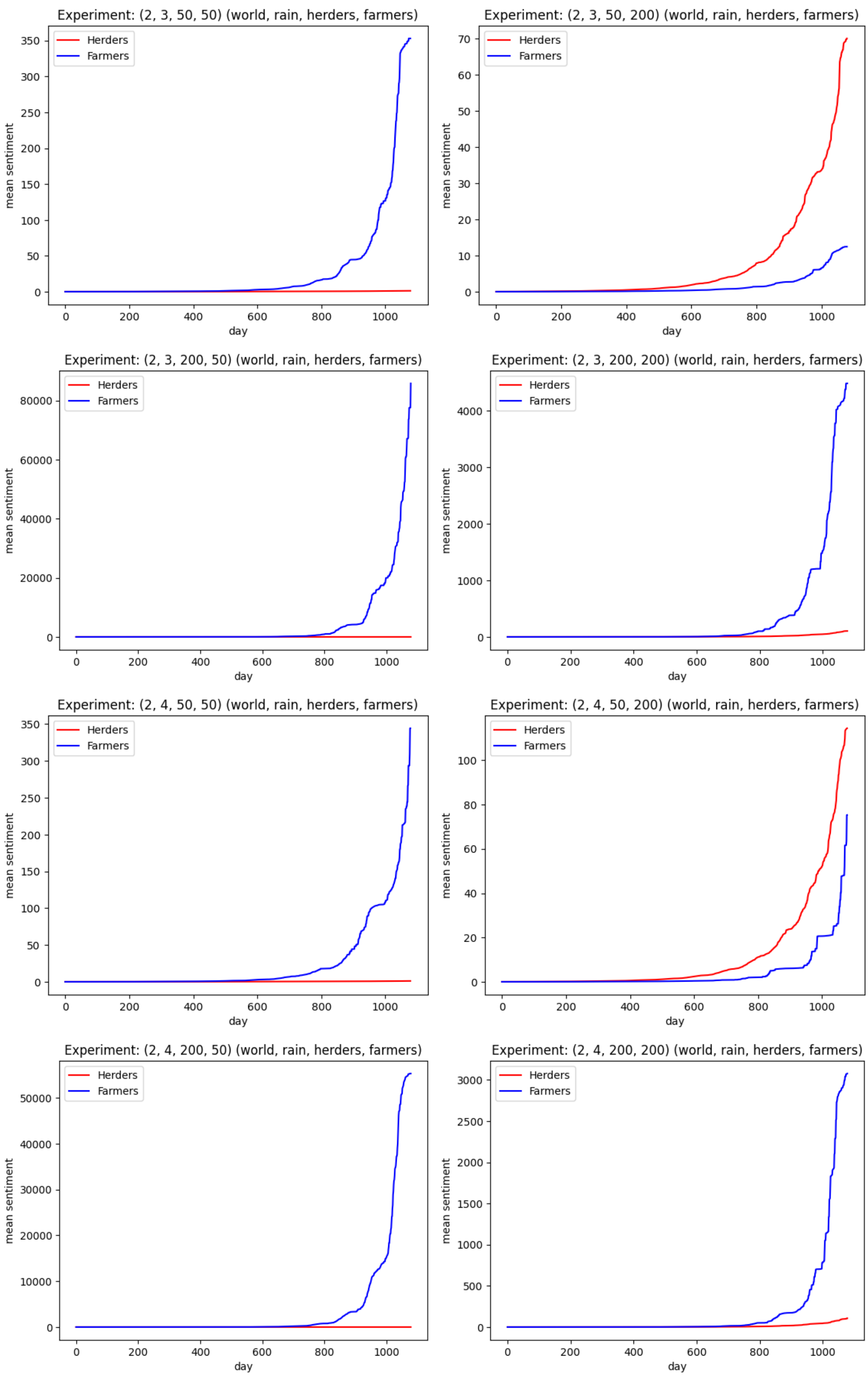


Experiment: (2, 2, 200, 50) (world, rain, herders, farmers)

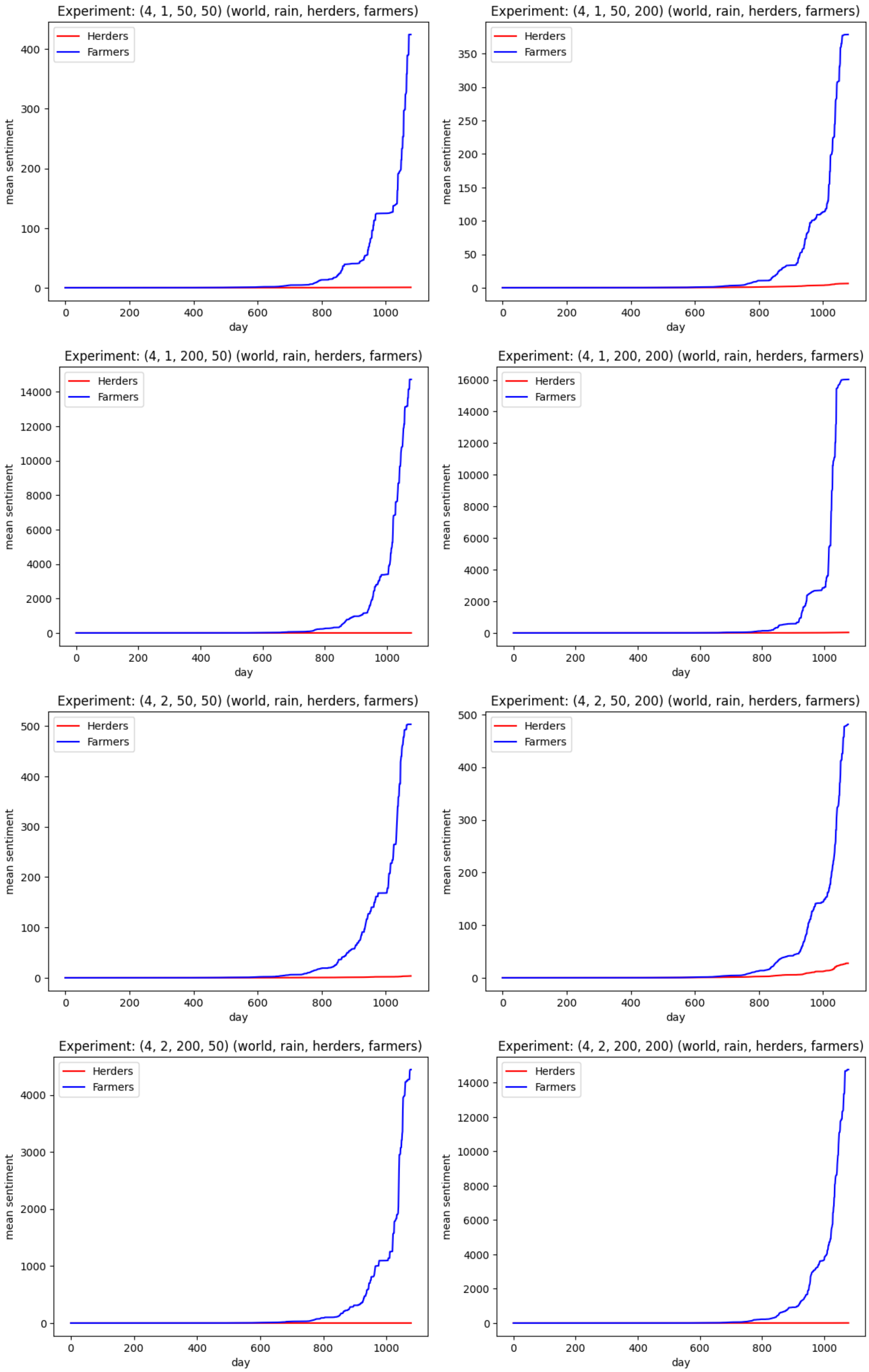


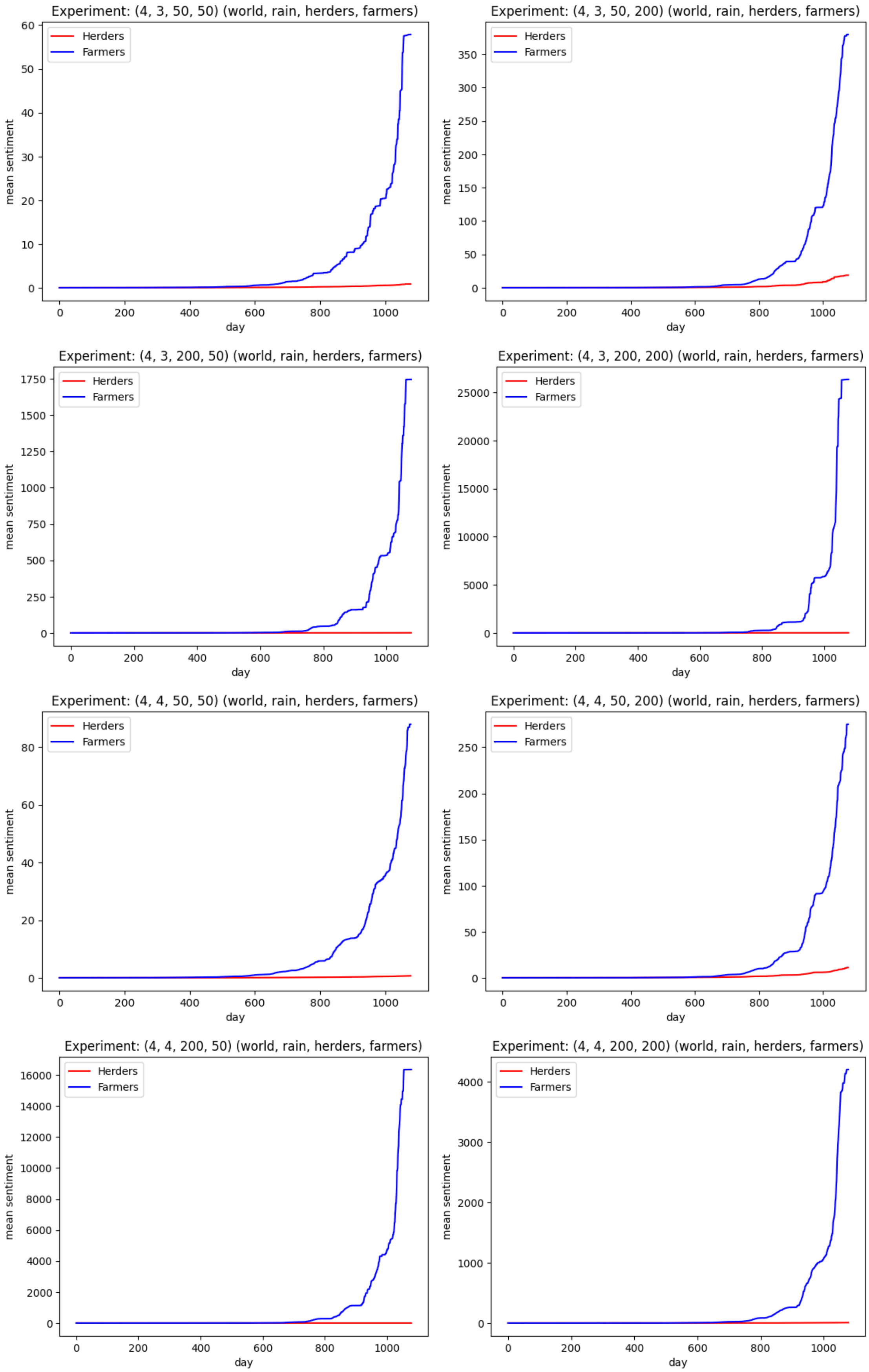
Experiment: (2, 2, 200, 200) (world, rain, herders, farmers)

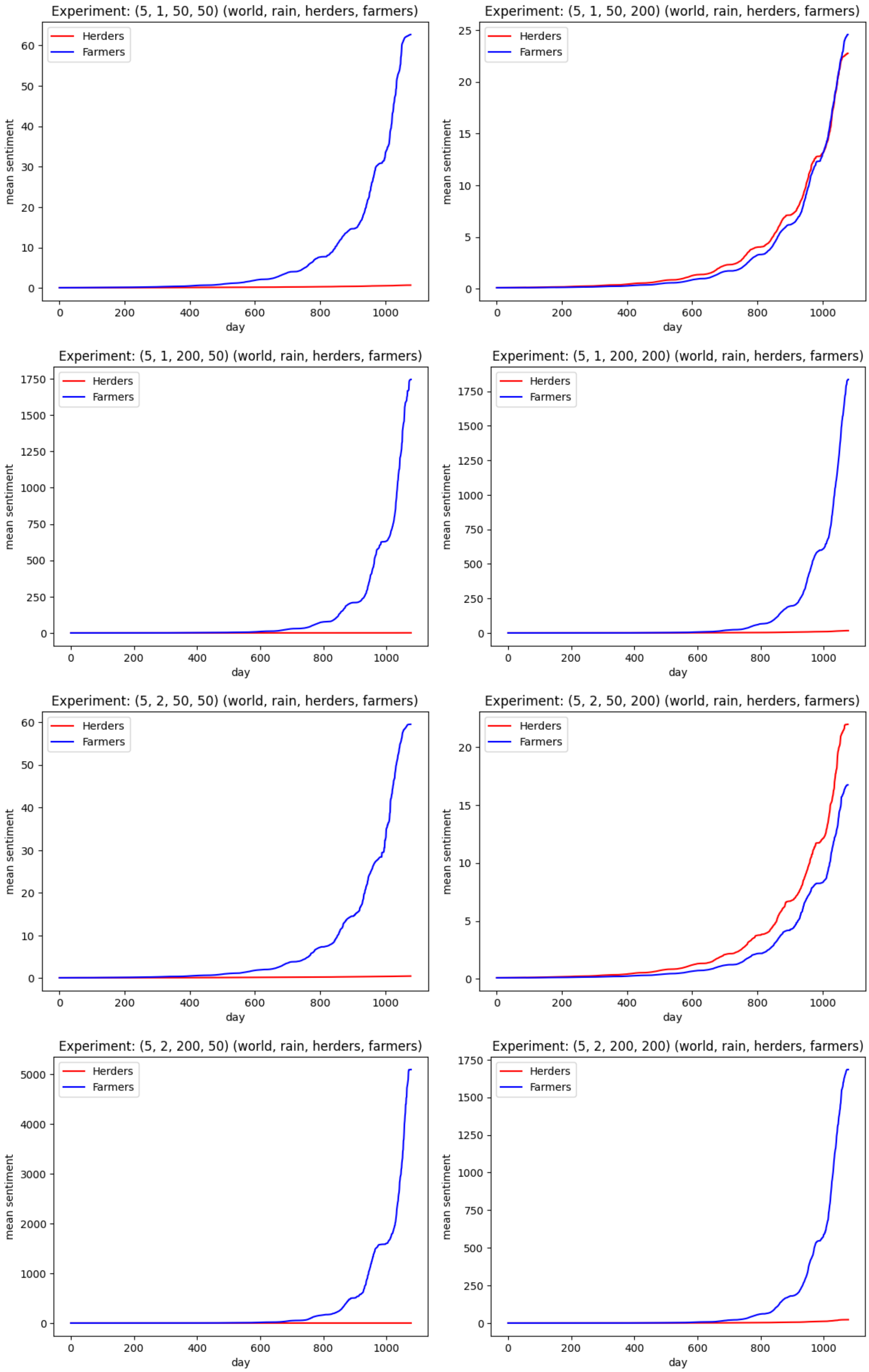




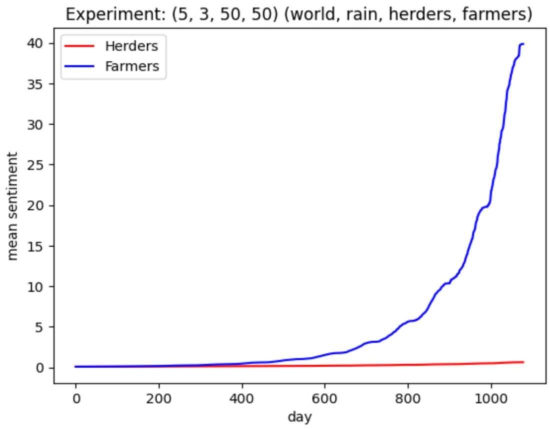
Experiment: (2, 3, 50, 50) (world, rain, herders, farmers)
Experiment: (2, 3, 50, 200) (world, rain, herders, farmers)
Experiment: (2, 3, 200, 50) (world, rain, herders, farmers)
Experiment: (2, 3, 200, 200) (world, rain, herders, farmers)
Experiment: (2, 4, 50, 50) (world, rain, herders, farmers)
Experiment: (2, 4, 50, 200) (world, rain, herders, farmers)
Experiment: (2, 4, 200, 50) (world, rain, herders, farmers)
Experiment: (2, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

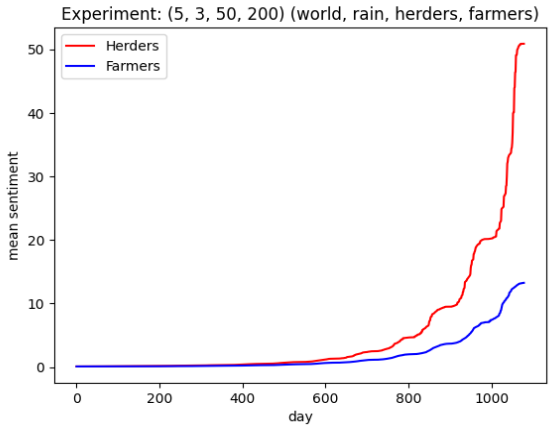

Experiment: (4, 1, 50, 50) (world, rain, herders, farmers)
Experiment: (4, 1, 50, 200) (world, rain, herders, farmers)
Experiment: (4, 1, 200, 50) (world, rain, herders, farmers)
Experiment: (4, 1, 200, 200) (world, rain, herders, farmers)
Experiment: (4, 2, 50, 50) (world, rain, herders, farmers)
Experiment: (4, 2, 50, 200) (world, rain, herders, farmers)
Experiment: (4, 2, 200, 50) (world, rain, herders, farmers)
Experiment: (4, 2, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

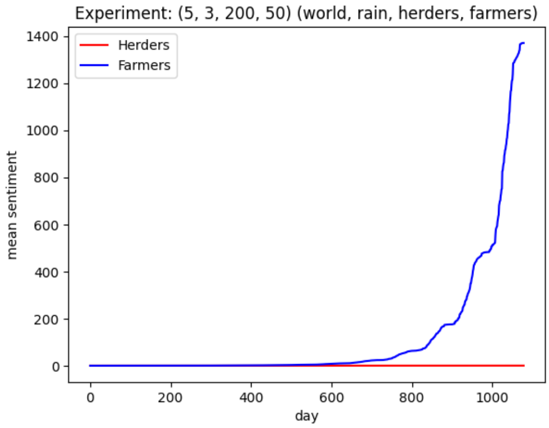

Experiment: (4, 3, 50, 50) (world, rain, herders, farmers)
Experiment: (4, 3, 50, 200) (world, rain, herders, farmers)
Experiment: (4, 3, 200, 50) (world, rain, herders, farmers)
Experiment: (4, 3, 200, 200) (world, rain, herders, farmers)
Experiment: (4, 4, 50, 50) (world, rain, herders, farmers)
Experiment: (4, 4, 50, 200) (world, rain, herders, farmers)
Experiment: (4, 4, 200, 50) (world, rain, herders, farmers)
Experiment: (4, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

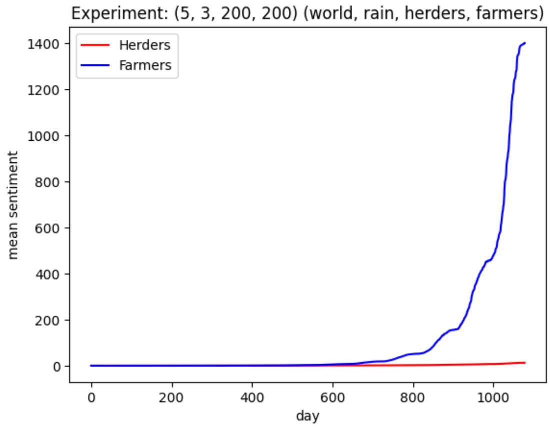


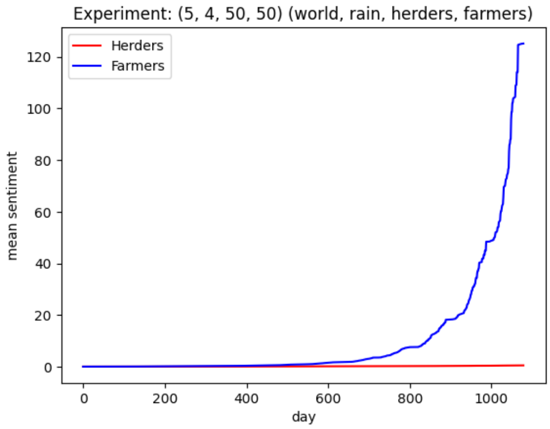
Experiment: (5, 1, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (5, 1, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (5, 1, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (5, 1, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (5, 2, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (5, 2, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (5, 2, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day
Experiment: (5, 2, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

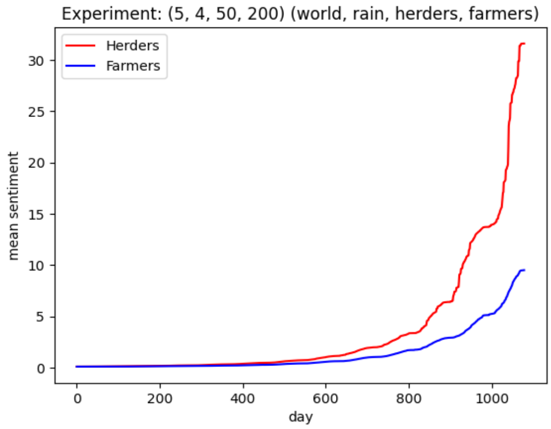

Experiment: (5, 3, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

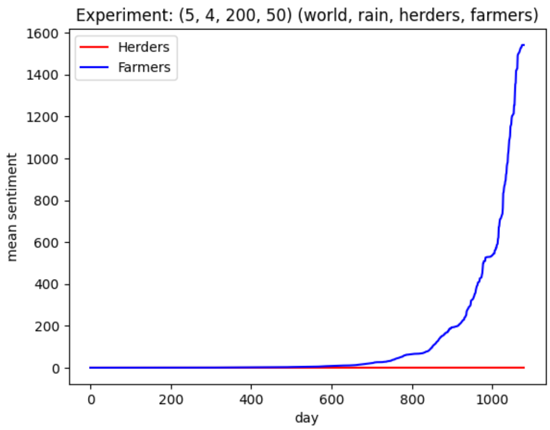

Experiment: (5, 3, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

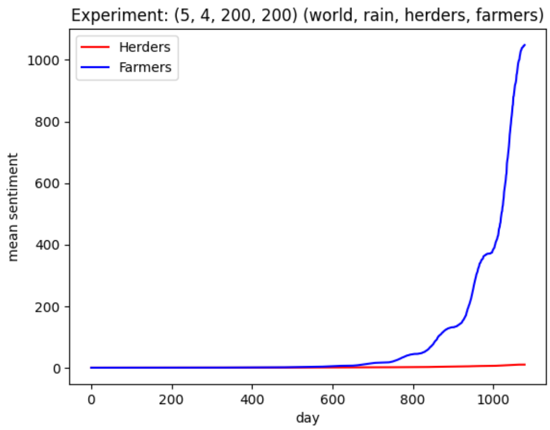

Experiment: (5, 3, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day


Experiment: (5, 3, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day


Experiment: (5, 4, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

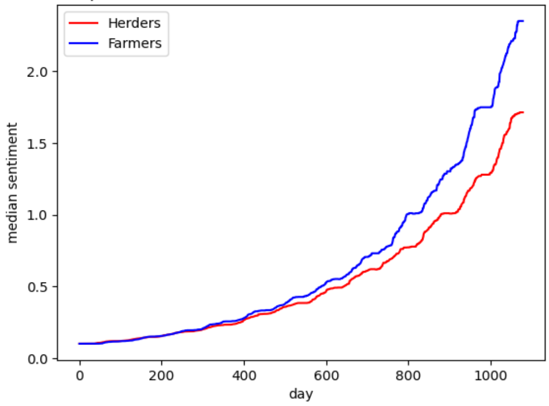

Experiment: (5, 4, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day


Experiment: (5, 4, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

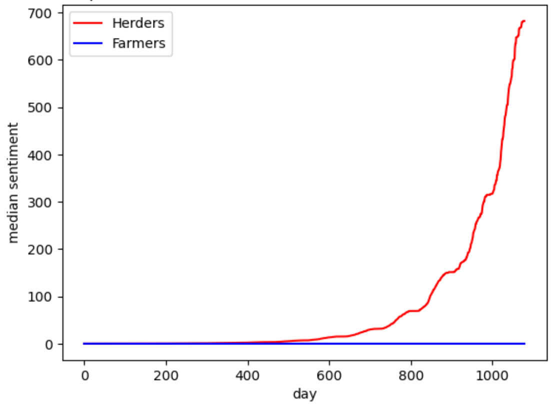

Experiment: (5, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
mean sentiment
day

Median Outcomes

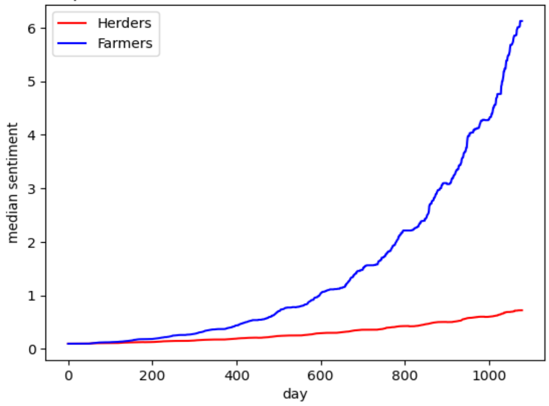
Experiment: (1, 1, 50, 50) (world, rain, herders, farmers)



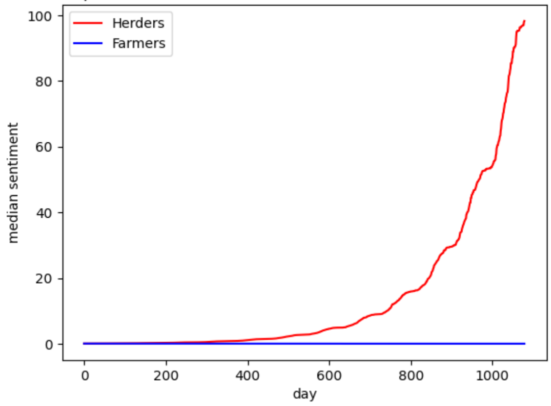
Experiment: (1, 1, 50, 200) (world, rain, herders, farmers)



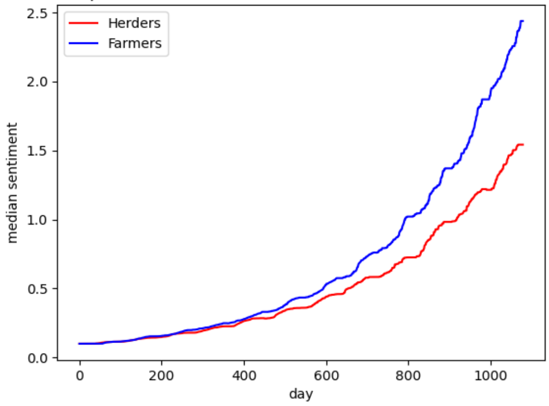
Experiment: (1, 1, 200, 50) (world, rain, herders, farmers)



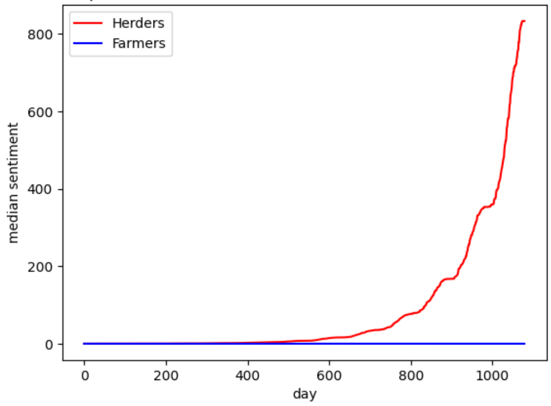
Experiment: (1, 1, 200, 200) (world, rain, herders, farmers)



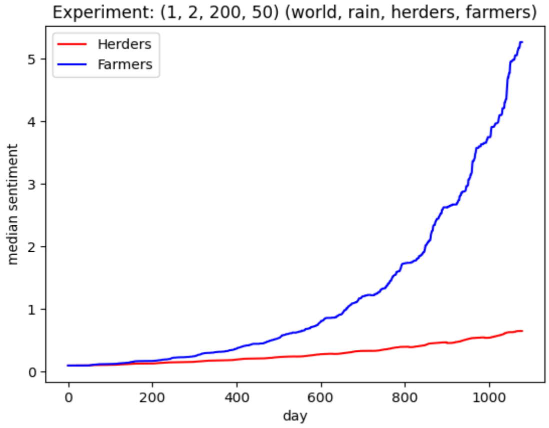
Experiment: (1, 2, 50, 50) (world, rain, herders, farmers)



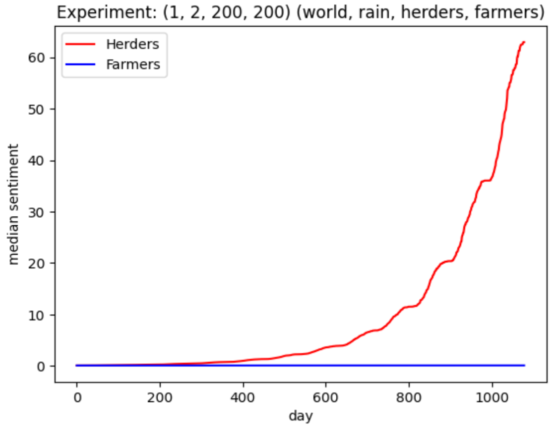
Experiment: (1, 2, 50, 200) (world, rain, herders, farmers)

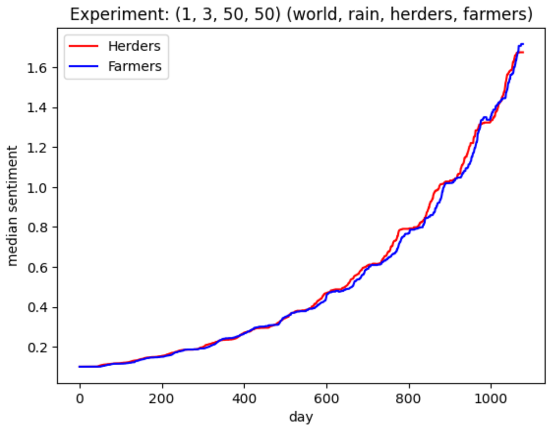


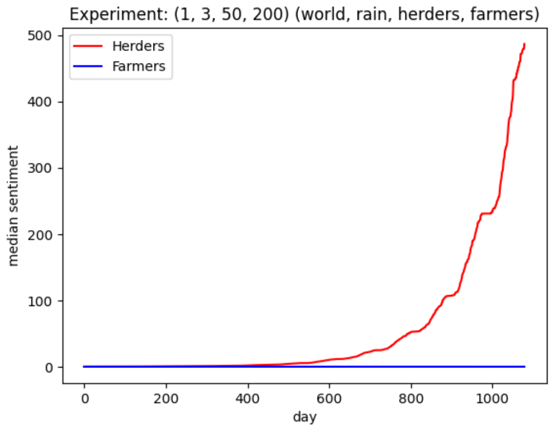
Experiment: (1, 2, 200, 50) (world, rain, herders, farmers)

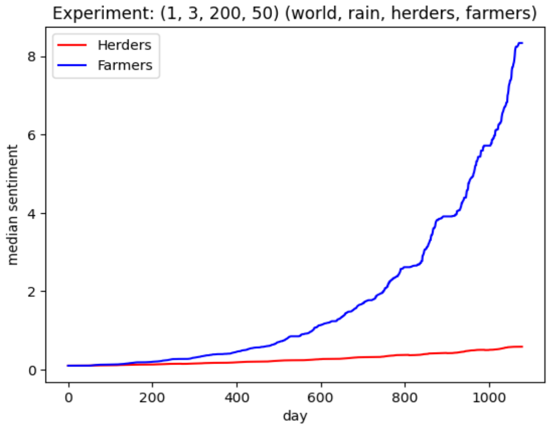


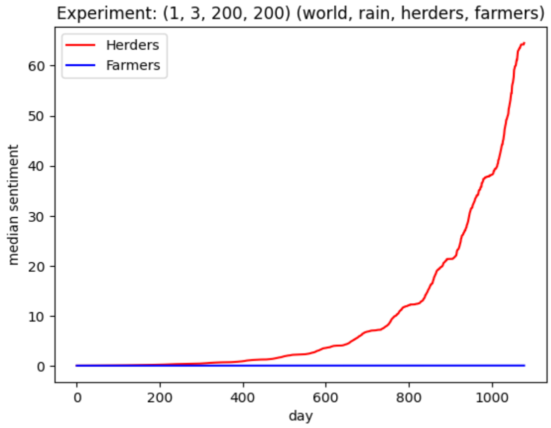
Experiment: (1, 2, 200, 200) (world, rain, herders, farmers)

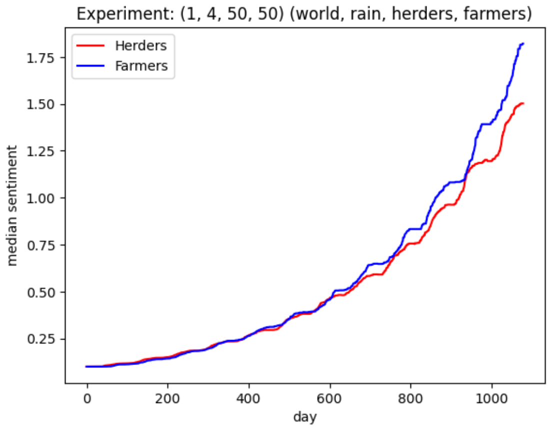


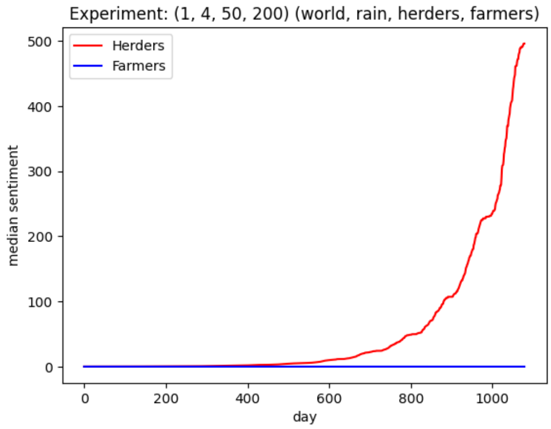

Experiment: (1, 3, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

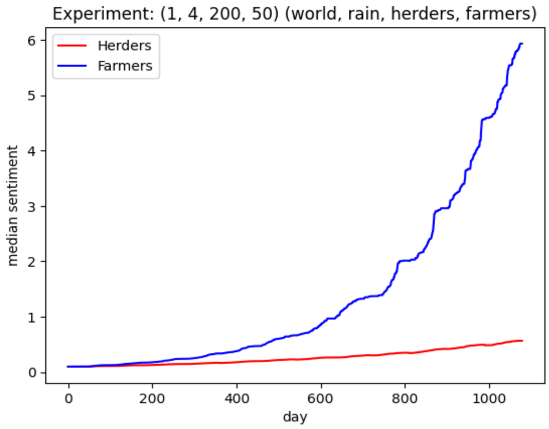

Experiment: (1, 3, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

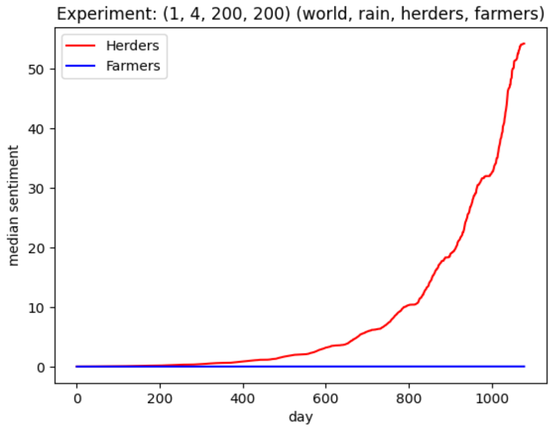

Experiment: (1, 3, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

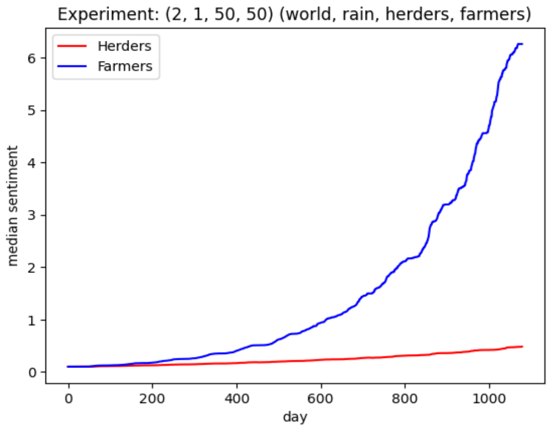

Experiment: (1, 3, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

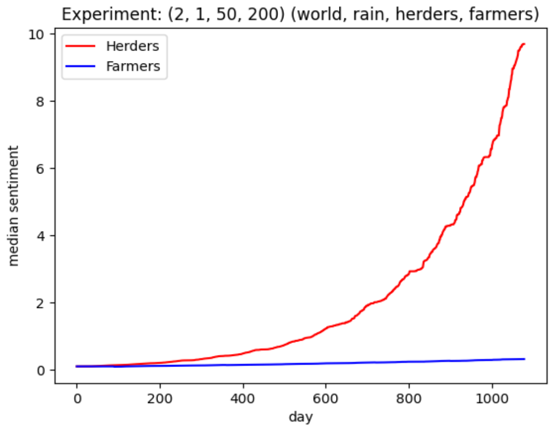

Experiment: (1, 4, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

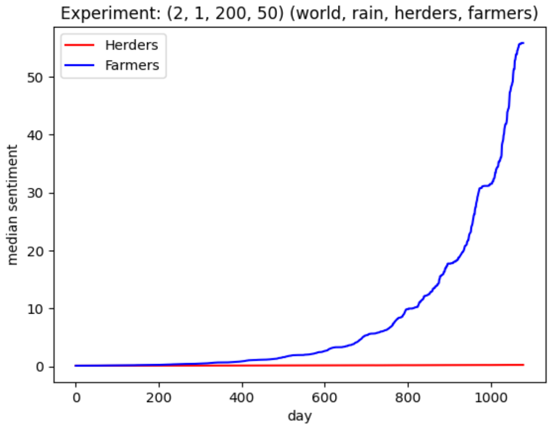

Experiment: (1, 4, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

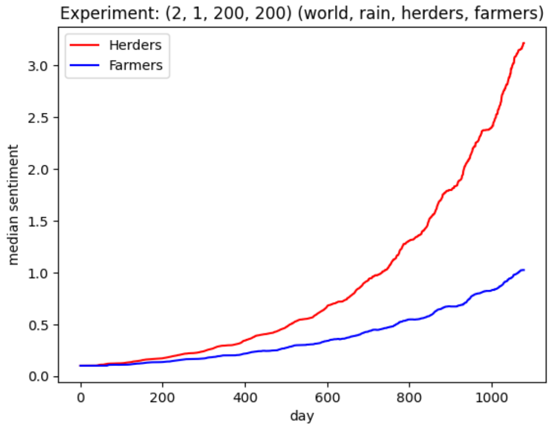

Experiment: (1, 4, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

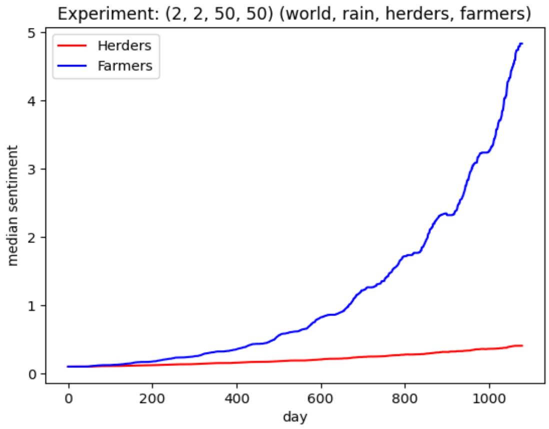

Experiment: (1, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

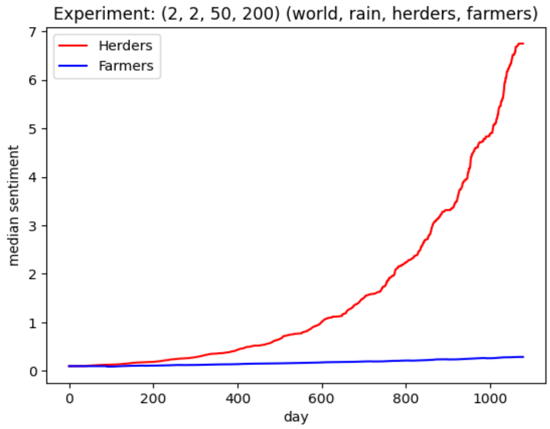

Experiment: (2, 1, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

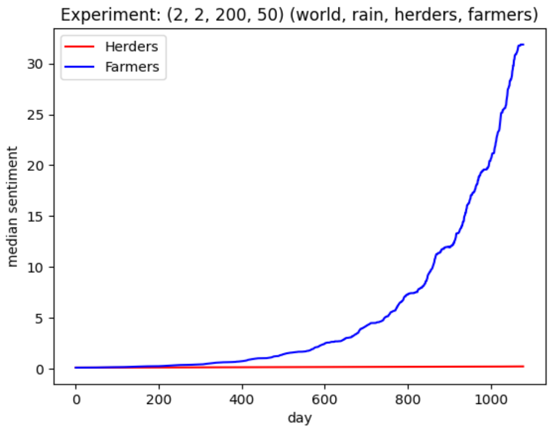

Experiment: (2, 1, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

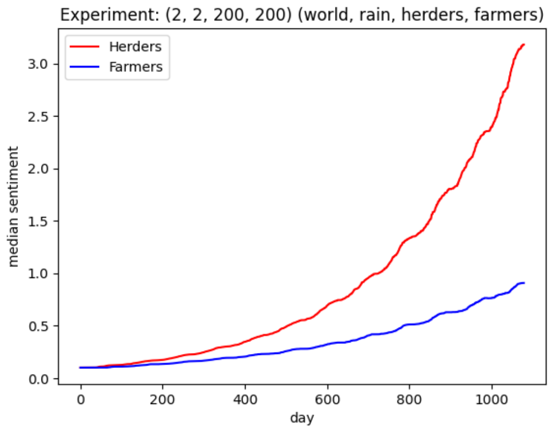

Experiment: (2, 1, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

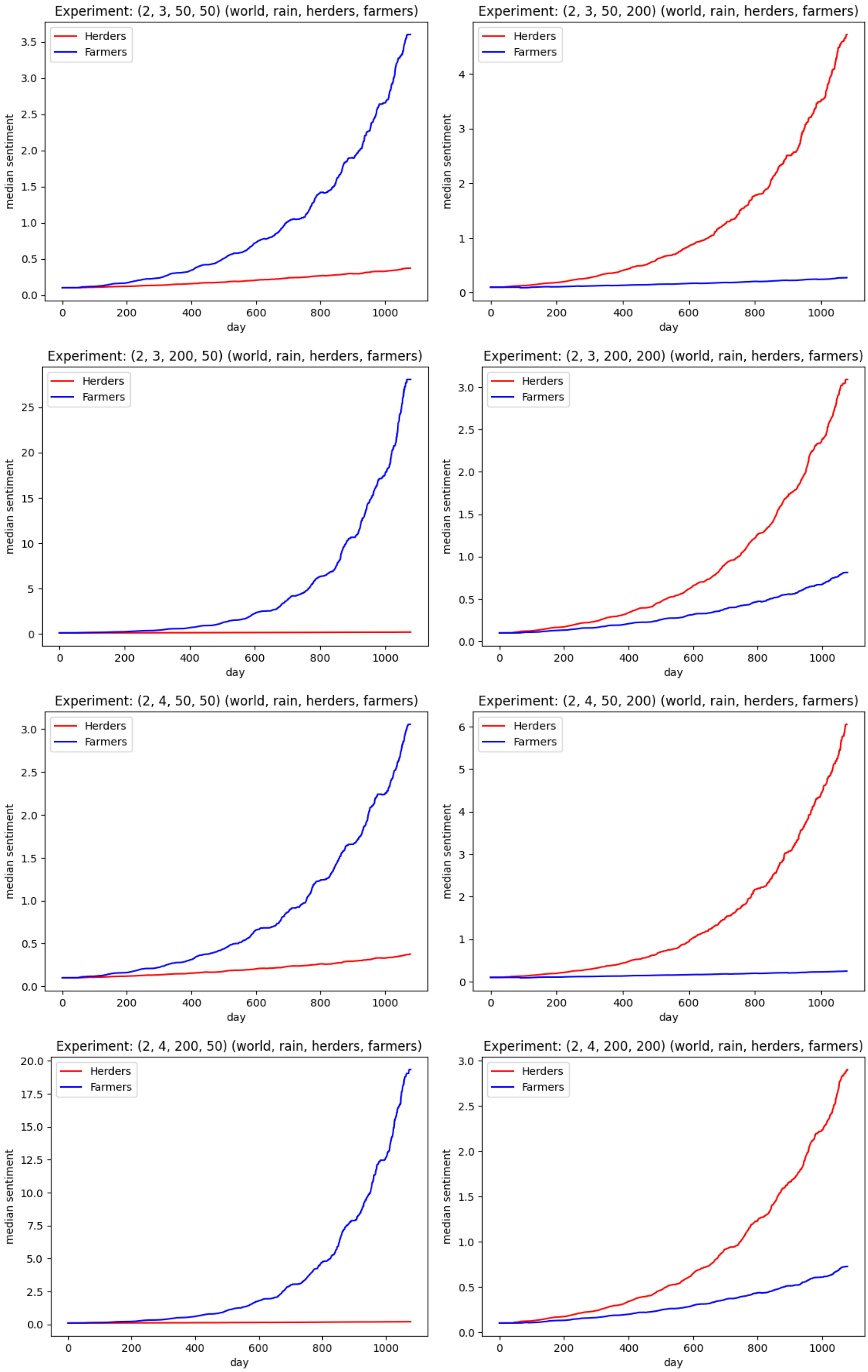

Experiment: (2, 1, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

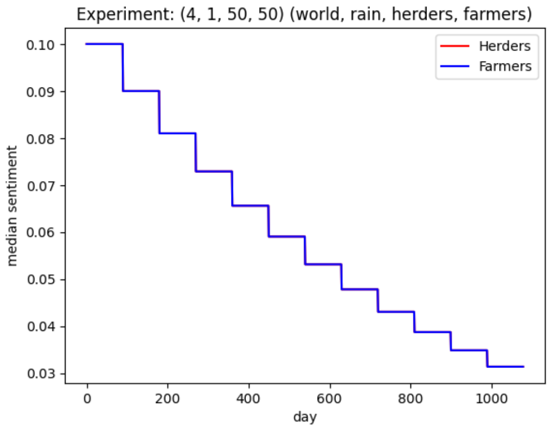

Experiment: (2, 2, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

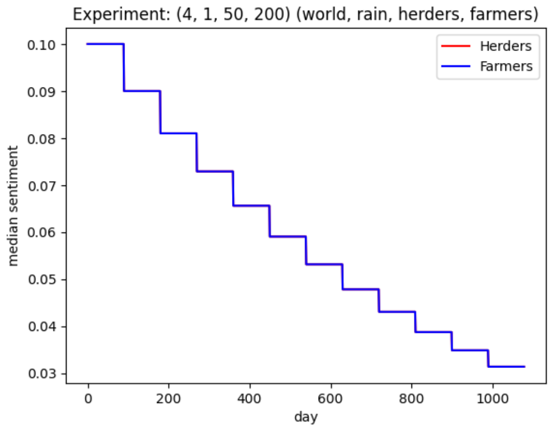

Experiment: (2, 2, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

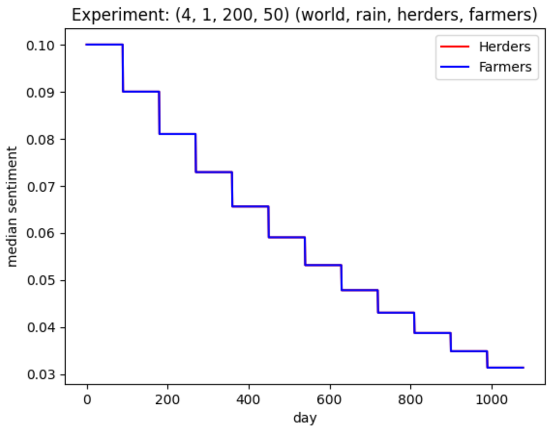

Experiment: (2, 2, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

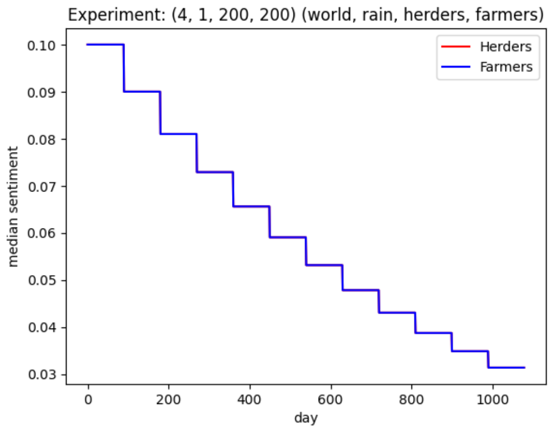

Experiment: (2, 2, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

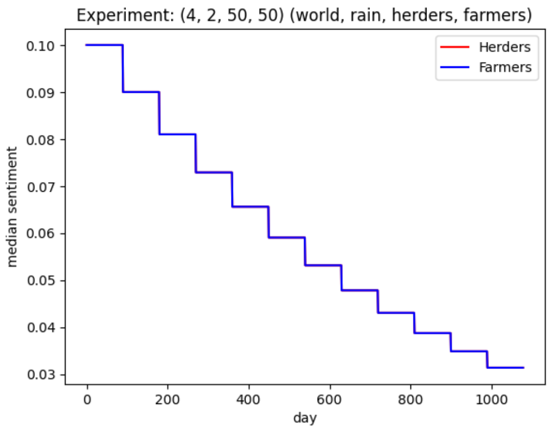

Experiment: (2, 3, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (2, 3, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (2, 3, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (2, 3, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (2, 4, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (2, 4, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (2, 4, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (2, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

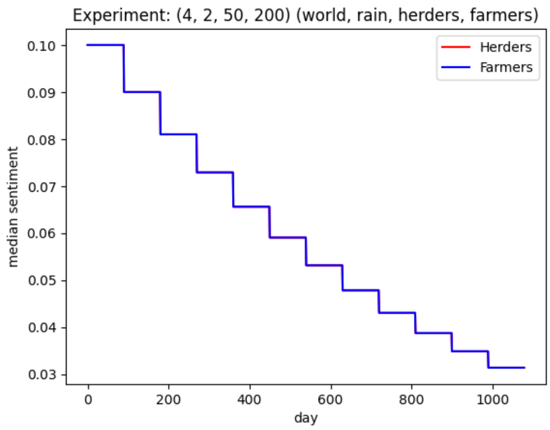

Experiment: (4, 1, 50, 50) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

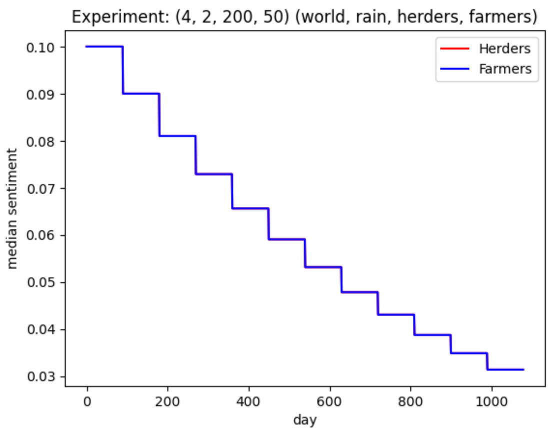

Experiment: (4, 1, 50, 200) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

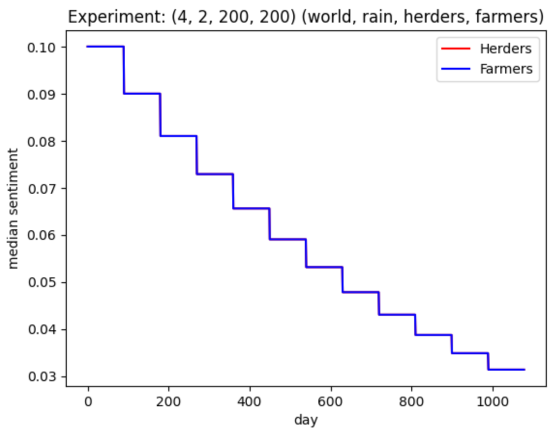

Experiment: (4, 1, 200, 50) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

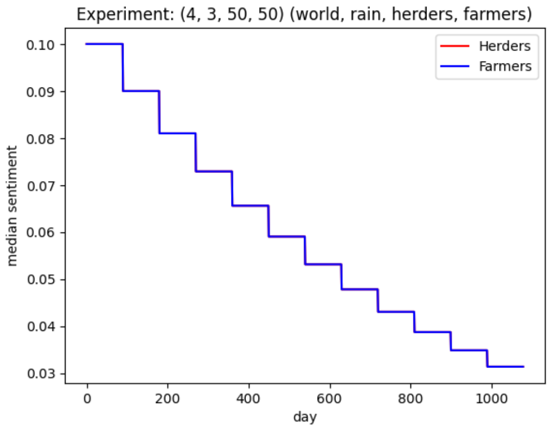

Experiment: (4, 1, 200, 200) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

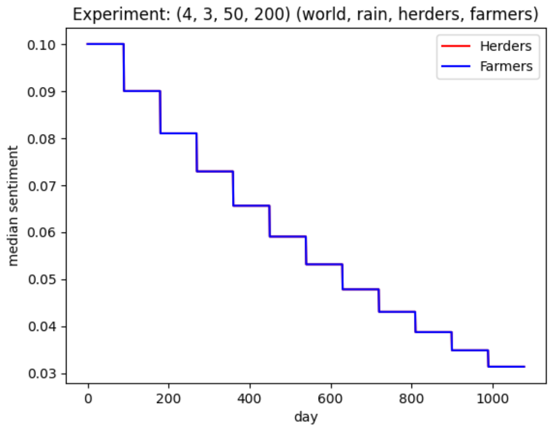

Experiment: (4, 2, 50, 50) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

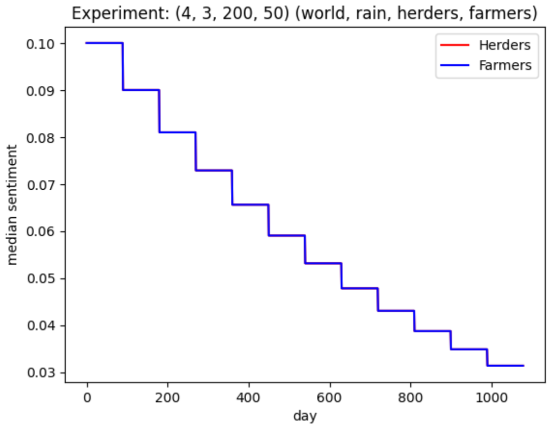

Experiment: (4, 2, 50, 200) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

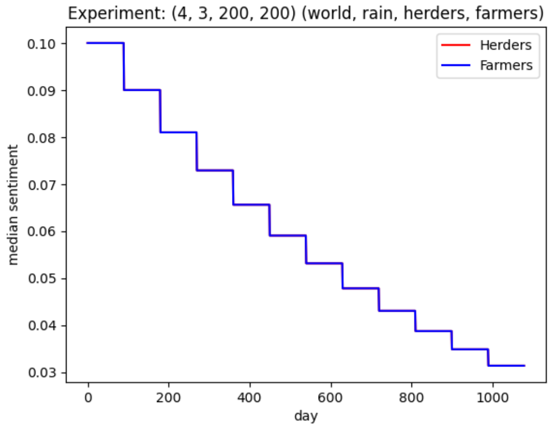

Experiment: (4, 2, 200, 50) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

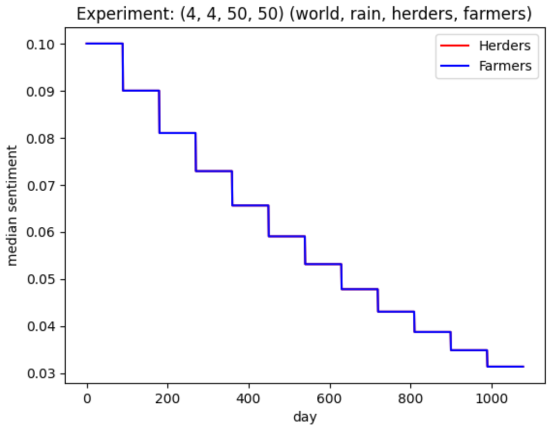

Experiment: (4, 2, 200, 200) (world, rain, herders, farmers)
median sentiment
day
Herders
Farmers

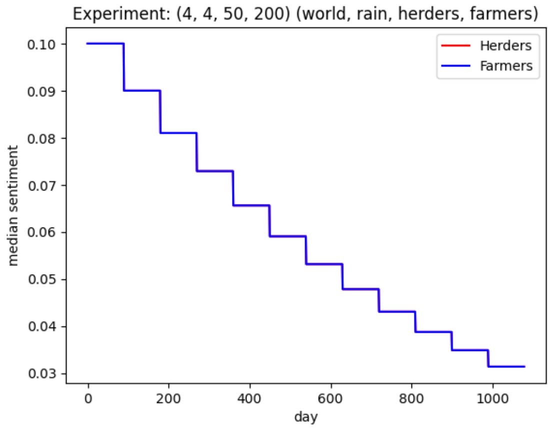

Experiment: (4, 3, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
200
400
600
800
1000
day


Experiment: (4, 3, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
200
400
600
800
1000
day


Experiment: (4, 3, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
200
400
600
800
1000
day


Experiment: (4, 3, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
200
400
600
800
1000
day


Experiment: (4, 4, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
200
400
600
800
1000
day


Experiment: (4, 4, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
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0.05
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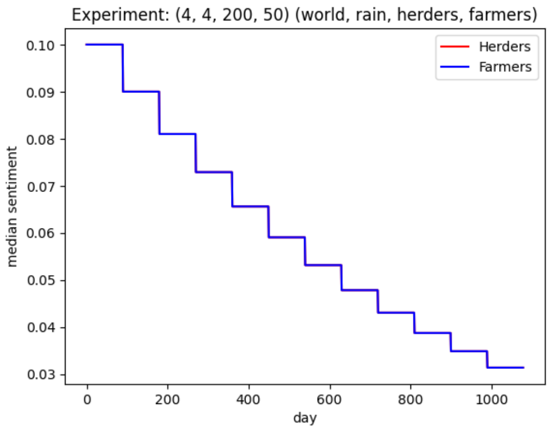
0.03
0
200
400
600
800
1000
day


Experiment: (4, 4, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
200
400
600
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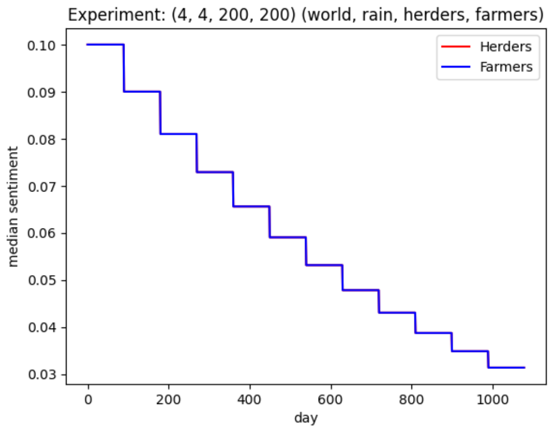
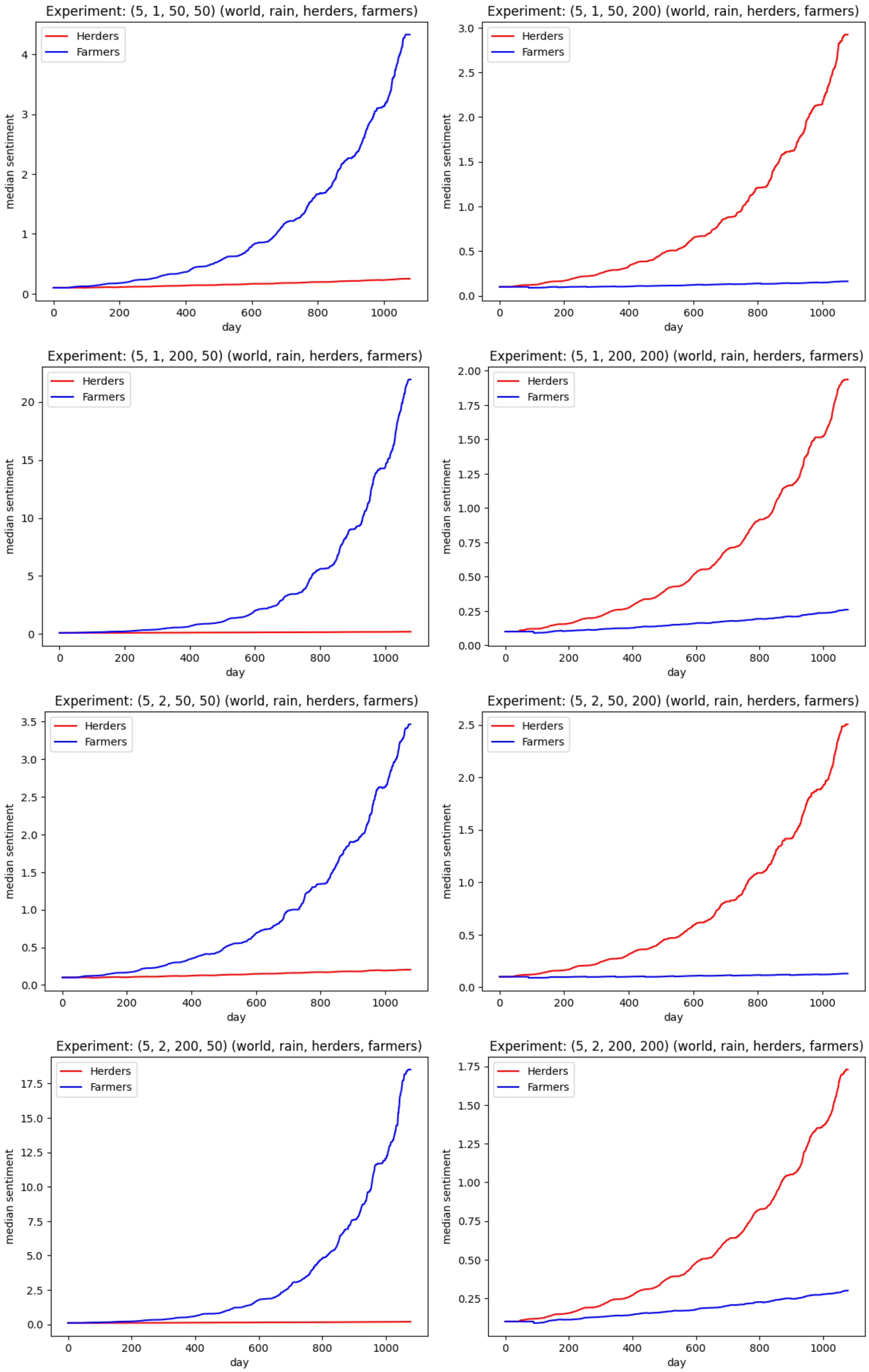
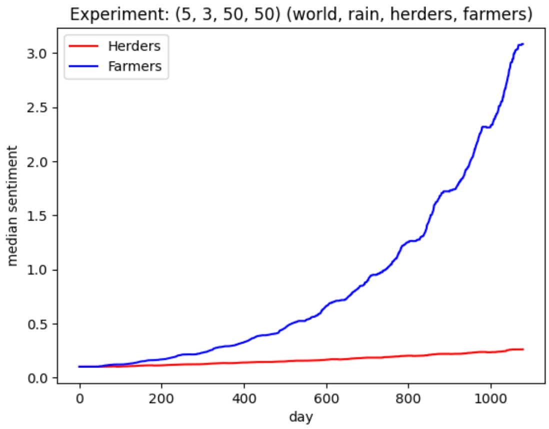
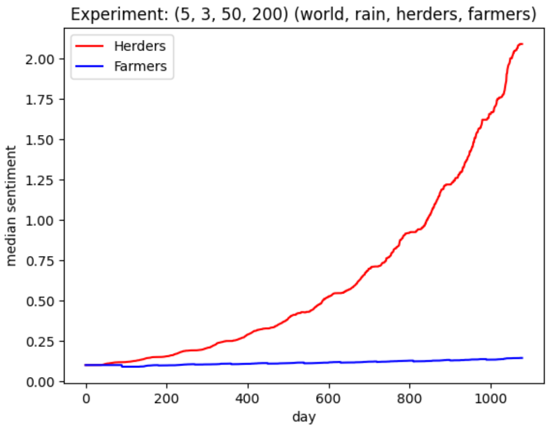
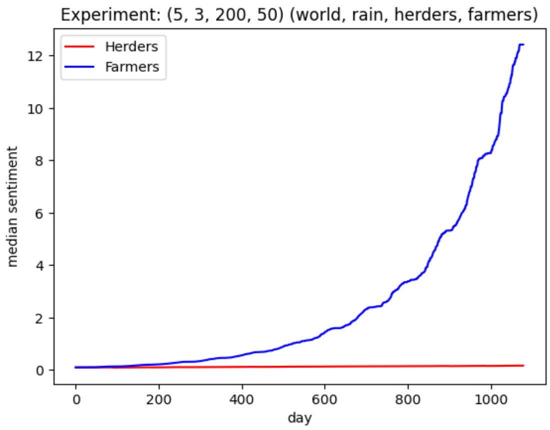
1000
day

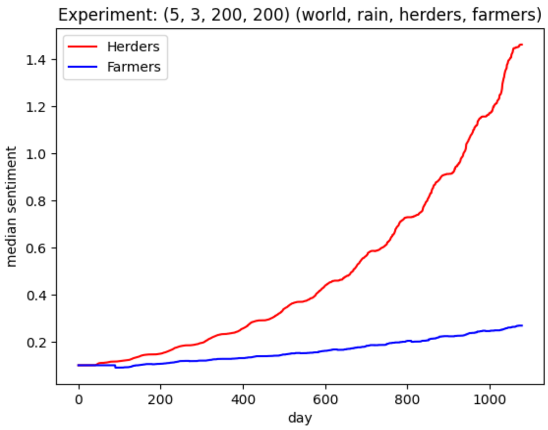

Experiment: (4, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0
200
400
600
800
1000
day

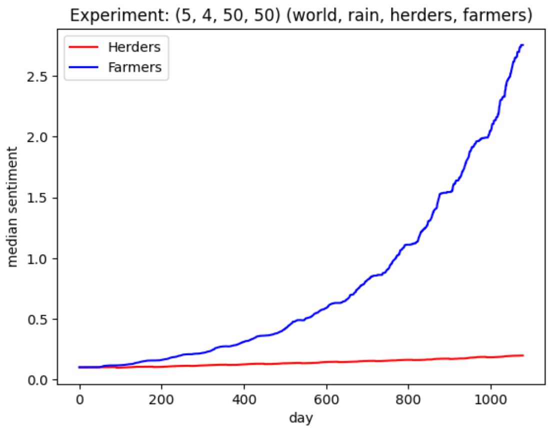

Experiment: (5, 1, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (5, 1, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (5, 1, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (5, 1, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (5, 2, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (5, 2, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (5, 2, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day
Experiment: (5, 2, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

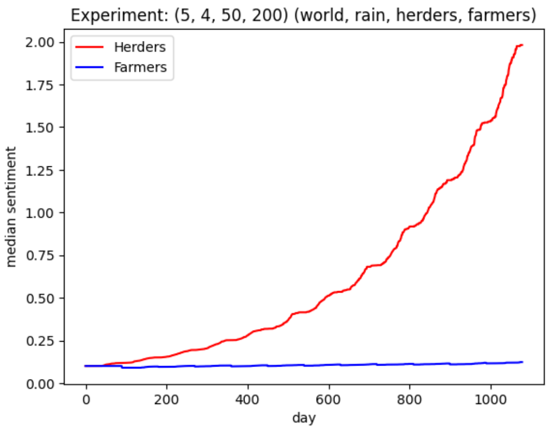

Experiment: (5, 3, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

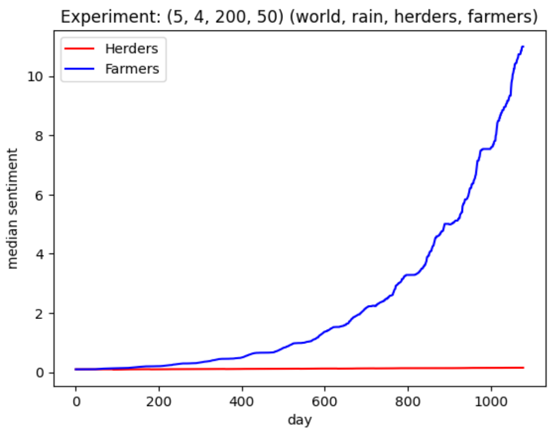

Experiment: (5, 3, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day

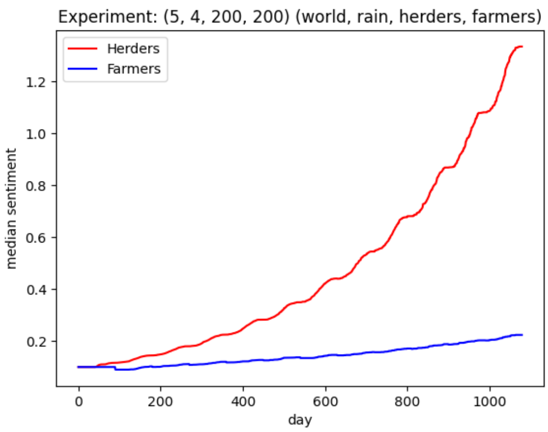

Experiment: (5, 3, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day


Experiment: (5, 3, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day


Experiment: (5, 4, 50, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day


Experiment: (5, 4, 50, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day


Experiment: (5, 4, 200, 50) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day


Experiment: (5, 4, 200, 200) (world, rain, herders, farmers)
Herders
Farmers
median sentiment
day