Examining Social and Climate Feedbacks: Linking Climate Opinions and Climate System in Social Networks

by

Athira Satheesh Kumar

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner:	Hao Wang Professor, Dept. of Mathematical and Statistical Sciences University of Alberta
Supervisor(s):	Chris Bauch Professor, Dept. of Applied Mathematics University of Waterloo
Internal Member:	Brian Ingalls Professor, Dept. of Applied Mathematics University of Waterloo
	Sue Ann Campbell Professor, Dept. of Applied Mathematics University of Waterloo
Internal-External Member:	Rebecca Saari Associate Professor, Dept. of Civil and Environmental Engineering University of Waterloo

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

- Chapter 2: The work in this chapter was performed by Athira Satheesh Kumar (ASK) under the supervision of Dr. Chris Bauch (CB) and Dr. Madhur Anand (MA), resulting in a co-authored paper accepted in PloS One [1]. Contributions were as follows: ASK, CB, and MA conceived of the study. ASK developed and analyzed the model, and wrote the first draft. All authors revised the manuscript.

- Chapter 3: This chapter is based on a manuscript in review with Journal of the Royal Society Interface. ASK conceived, developed, and analyzed this study. ASK wrote the first draft. Dr. Kresimir Josic, CB, and MA supervised the work. All authors revised the manuscript.

- Chapter 4: This chapter is based on a manuscript in preparation. CB and MA conceived and designed the work. ASK developed and analyzed the model and wrote the first draft. All authors revised the manuscript.

Abstract

Climate change is one of the most critical challenges that humanity faces, particularly due to its impacts on ecosystems, economies, and societies around the globe. Usually, climate models focus on physical and economic factors, often overlooking social dynamics. Despite identifying human contribution to the climate crisis, behavioral factors, such as public opinion and decisions about mitigation, remain unintegrated in climate models. This research highlights the role of human actions in addressing climate challenges. Human actions are controlled by social factors such as climate rumors. The rising popularity of social media exposes people to unverified information about climate change and its impacts. In addition to rumors, other factors, such as the high costs to switch to climate-friendly alternatives make mitigation less appealing to people. Although several models consider integrating social behaviour into climate models, these models usually treat human behaviour as a binary choice between mitigation and non-mitigation. However, choices are not too simple when it comes to climate change. People can have more or less intense climate opinions, demonstrating the importance of having a continuous range of opinions when it comes to understanding the issue of climate change. We adopt various modelling approaches to identify the factors leading to reduced response towards the issue of climate change. Our analysis reveals the important role larger groups play in determining future climate scenarios. The behaviour (mitigating or non-mitigating) of these large groups determines the overall emission levels of the population. We identified the importance of mitigation strategies to achieve our current climate targets. Moreover, frequent rumors regarding climate change can also enhance mitigative behaviour and reduce emissions. Factors such as frequent and unexpected social or climate events, stubbornness in individuals, opinion polarization, and high mitigation costs can greatly influence future climate predictions. Ignorance towards climate issues due to delayed response in switching to climate-friendly alternatives or completely forgetting about these issues are some of the major reasons for falling behind in meeting the world's climate targets. The global nature of climate issues makes finding common ground to adopt mitigative strategies difficult. This thesis underscores incorporating social dynamics into climate models, a more comprehensive framework for predicting policy outcomes. Policymakers could leverage the model outcomes to identify factors that minimize emissions by maximizing public response to climate change. Ultimately, this research emphasizes the necessity of integrating behavioral insights into climate models to support informed, and effective climate policy development.

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Dedication

I dedicate this thesis to my parents, Jyothi and Sateesh. Whatever I am today is because of them.

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Chapter 1

Introduction

Social and climate changes represent two inseparable elements examined separately, even though their interdependence is crucial to understanding the broader picture. However, there is a deep relationship between these two systems, and their profound influence on one another in multiple ways is often overlooked. In particular, people's opinions regarding climate and the phenomenon of climate change can substantially impact each other. This signifies the importance of understanding the intricate mutual feedback between these two systems. In this chapter, we shall conduct a retrospective analysis of various methodologies and models that examine these two systems, independently and collectively, by carefully understanding each system and recognizing the significant contributions already made in this field of study.

1.1 Social Networks

Social networks are a representation of human society. Moreover, human beings are called social beings, and they form a society. A society can be defined in multiple ways - it is a construct of social relationships [3], a center of political, economic, or social interactions [4], a complex association of individuals [5]. In simple words, a society can be defined as a network of social relationships, where the nodes are individuals, and the edges form the relation between individuals. "Social networks are social structures made up of a set of social actors, sets of dyadic ties, and other social interactions between actors" [6]. These are often used to understand behavior, particularly in large societies [7]. Furthermore, human relationships are part of social networks that are interconnected in various dimensions and influence behaviour, opinions, and actions. The study of social networks focuses

on understanding the properties of the interaction between individuals in a population, whereas human dynamics studies how the pattern of human activity changes over time [8, 9]. Integration between social networks and human beings is achieved by focusing on the connection between individuals and their characteristics, to understand how these networks work in different social contexts [10]. In addition, social networks act as a key area for understanding various human characteristics such as how people share knowledge, ideas, and resources, how they cooperate, how they respond and adapt to changes, reflecting and influencing interpersonal processes [11, 9, 12]. Various concepts in social networks, such as homophily, clustering, and preferential attachments, make it easier to understand human behaviour dynamics [11].

Social networks can be broadly classified as homogeneous and heterogeneous and are used to portray various real-life relations. Homogeneous social networks have nodes of the same kind, and all these nodes share similar relationships. On the other hand, heterogeneous social networks have a variety of node types and relationships. Homogeneous networks are simple, whereas heterogeneous networks are diverse, richer, and more complex. Moreover, heterogeneous networks are used in various applications like modelling community interactions, social phenomena, and social dynamics [13, 14, 15]. They are an important tool in predicting behaviours and social influence in various real-world situations [16, 17]. Transitioning to the power of social networks, social media platforms are examples of heterogeneous social networks, which are powerful tools in altering the behaviour and actions of individuals both online and offline, making them highly efficient in spreading and sharing information [18]. Many information-spreading dynamics are often modelled using social networks due to this characteristic. Hence, heterogeneous social networks are useful tools for analyzing and understanding human behaviour, which we use in our models to understand human dynamics, highlighting the potential of social networks in modern social and cultural scenarios [19].

Social networks are also used in climate modelling, where social networks help understand the interactions between individuals and groups that influence social behaviours and decisions related to climate action [20]. Moreover, social networks provide a better understanding of the potential of social influence in addressing climate challenges. Specifically, social networks are beneficial in understanding the collective behaviour of individuals, but the network structure can influence these dynamics [20, 21]. Climate researchers use social network analysis using social media data or simulations [22, 23]. Nonetheless, an increasing number of climate scientists use social networks as a tool for their analysis [21].

1.2 Social Models

Social models, which study the behavioural process in human beings, rely on mathematical models. The behaviour of human beings is complex and is influenced by various processes. However, psychology and social science researchers use mathematical models as tools in modelling human behaviour [24]. In this section we look at various social models which are used to understand human behaviour.

1.2.1 Compartmental models

Like diseases, social behaviour is also contagious [25]. Compartmental models, as the name suggests, divide behaviours into different compartments or states and analyze the flow between these states. It is generally used to model infectious disease dynamics, but it is also an essential tool for predicting behavioural dynamics in various systems. It has been used extensively to study the spread of misinformation in social networks. Compartmental models like Susceptible-Infected (SI), Susceptible-Infected-Recovered (SIR), Susceptible-Infected-Recovered-Susceptible (SIRS), etc., are widely used in epidemiology to understand disease spread [26, 27, 28, 29]. Inspired by these models, compartmental models are extended to describe complex behaviours in humans [30, 31] and to understand how rumors or misinformation spread [32, 33, 27]. The simplicity of these models lies in the use of ordinary differential equations (ODE) to describe the transition between states, making them computationally efficient and simple to implement [29].

In behavioral studies, compartmental models have been used to study smoking dynamics, voting dynamics, rumor propagation, malware spread, drug interactions, vaccination behaviour, etc. [34, 35, 36, 37, 38, 39, 40]. Moreover, social activity is represented as a parameter in these models to understand the impact of these parameters on the propagation behaviour of rumors and to find ways to optimally decrease the spread [41]. Apart from its usual use in analyzing disease spread, these applications of compartmental modelling make it a desirable tool for understanding social behaviour and interactions. However, researchers have not previously used compartmental models to understand social behavior in a coupled human-environment system. We use compartmental modelling in this thesis to understand how climate rumors spread in a network (Chapter 2).

1.2.2 Opinion Dynamics Models

Opinion dynamic modelling is another method used to understand human behaviour. In social networks, these models help us understand how individuals form and spread opinions

and how opinions evolve through social interactions. Three key factors to consider while developing these models are the opinion space, the interaction between individuals, and time-space. The opinion space represents what the opinions focus on and whether these opinions are discrete or continuous, whereas the network structure and its properties represent the interactions. Similar to the opinion space, the time-space could also be discrete or continuous.

Some of the classic models in opinion dynamics are the DeGroot model, the Friedkin-Johnsen model (FJ model), and the bounded confidence model (BCM). The DeGroot model uses a simple averaging mechanism using the concept of weights, where the weights determine how much the opinion of any other individual influences an individual [42]. On the other hand, the Friedkin-Johnsen model is an extension of the DeGroot model, which includes stubborn agents along with weights [43]. The bounded confidence model, also known as the Deffuant and Weisbuch model (DW model), considers a boundary or a radius inside which each agent considers the other agents' opinions, and the opinions of any other agent who lies outside the confidence range are ignored. These models are developed on the principle of homophily where like opinions attract each other [44, 45]. Some models use a combination of these models according to the specific problem [46, 47]. Continuous opinion dynamics models are well established, yet researchers have not previously used them to understand social behaviour in a coupled human-environmental system. In chapter 3, we use opinion dynamics modelling in a coupled social-climate model.

1.2.3 Evolutionary Game Theory

While social networks are a key factor influencing individual behaviour, several other factors influence opinions and behaviours in human beings. Factors such as network structure, education, and other social characteristics can influence these behaviours. However, developing mathematical models for human behaviour involves quantifying and interpreting these social behaviours. Multiple mathematical concepts have been used by researchers to understand human behavioral dynamics. Among other social models, evolutionary game theory (EGT) based models for human behaviour are gaining traction. This method is a robust approach to understanding human decision-making dynamics and social interactions. Concepts in EGT like prisoner's dilemma, replicator equations, and imitation dynamics in EGT focus on the evolution of behaviour over time, making it suitable to analyze complex human behaviour [48]. The replicator equation is a mathematical formula used in EGT to understand how individuals adopt strategies based on their payoffs. It highlights instantaneous payoffs while adapting to behaviours or strategies based on social and moral behaviours by comparing their payoff [49].



Figure 1.1: The 2015 Alaska fire season burned the second-largest number of acres since records began in 1940 (Image credit: Philip Spor)

Prisoner's Dilemma (PD) is a game studied using game theory, to understand decision-making processes [50, 51, 52, 53, 54]. They replicate several characteristics in human behaviour, such as the level of cooperation in real-world scenarios [55]. Moreover, PD has been used to assess the response of people in choosing strategies compared to the cost of volunteering in emergencies [56]. PD can also highlight a conflict between individual and collective rationality [55]. These theories help us understand how people choose between personal benefit and common good and are used to understand common pool resource (CPR) problems. CPRs are sometimes overexploited, leading to rapid depletion known as the tragedy of commons (TOC) [54, 53]. Game theory is used to understand the behavioral dynamics in common pool resource problems, and without regulations on use, people overuse the resources, leading to depletion [57].

1.2.4 Agent Based Models

Agent-based models (ABM) are powerful tools that help to examine social system behaviours. These models simulate individual behaviours through interactions by incorporating complexities into the human decision-making process [58]. ABMs have been widely used in studying collective behaviour to individual-level decisions based on environmental conditions [59]. ABMs are also employed in understanding growths and evolutions in so-

cial networks to reproduce real-world scenarios in online platforms [60]. There are ongoing debates on the power of ABMs regarding it being used for theory testing over precise prediction [61, 62]. Even though ABMs may not provide precise predictions in all cases, they have a vital role in simulating and understanding collective behaviours. Hence, ABMs are an invaluable tool for understanding complex social phenomena.

This section summarized the literature relating to different social models used in coupled human-environmental systems, but it is also important to discuss how these social models have been used in climate models. Social modelling methods have been used to analyze climate-related questions by linking social behaviour with the climate system [63]. Moreover, opinion dynamics models and evolutionary game theory provide a better understanding of human behaviour and address uncertainties in human responses to climate risks. On the other hand, tools like social networks and agent-based models enhance the analysis of climate systems by allowing researchers to consider various social factors. These models provide a better understanding of social and behavioural systems and allow researchers to explore the intricate relationship between human behaviour and climate change through coupled social-climate models [64]. The next section discusses this relationship between social and climate systems in detail.

1.3 Climate Change and Social Change

Human activities impact the environment, such as the atmosphere, hydrosphere, biosphere, and lithosphere, in several ways (Fig 1.1). The Industrial Revolution and urbanization led to social-economic development, but it came with a cost. Human-induced greenhouse gases have a severe impact on Earth's energy balance, leading to global warming [65, 66]. Rise in pollution levels, global warming, extreme weather events, sea level rise, biodiversity loss, and enteric diseases due to the accumulation of greenhouse gases and other pollutants are some of the consequences [67, 68, 69]. Burning fossil fuels and improper waste disposal have endangered the entire planet by disrupting the ecosystem and natural balance. Human actions, including deforestation for settlement and agriculture, have resulted in habitat loss, leading to a decline in biodiversity and degradation of natural resources (air pollution, soil pollution, water pollution, algae blooms) due to the increase in population and needs [67, 70, 71, 72], making mitigation and sustainable practices extremely important, eventhough they come at massive cost [73].

Similar to the influence of human beings on the environment, human beings are also impacted by various environmental issues. There is a relationship between the climate system and human beings. Human actions significantly influence environmental changes, but

these changes can greatly impact human attitudes toward the environment by influencing behaviour. The climate system can directly and indirectly affect our health, socioeconomic conditions, and general well-being. These effects are aggravated by the intensity and frequency of climate events like extreme precipitation, heatwaves, changing temperatures, sea level rise, etc. There are several physical health risks related to climate change ranging from heat-related issues to contagious diseases [74, 75]. Climate change-induced stress can lead to several well-being issues, which directly contribute to mental health issues, too [76, 77]. Events like climate-induced natural disasters and reduced availability of natural resources for basic needs can lead to displacement, economic and resource insecurity, further leading to severe psychological stress [76, 77]. Although there are several negative impacts on human life due to climate change, some people might find these changes helpful, too. Climate change in some regions can contribute to shorter winters, leveraging more business and outdoor activities [76].

In addition to the impact of climate change on humans, various factors intensify behavioral change in human beings, such as education, personal experience, adequate information, and the media [78, 79, 80, 81, 82]. These behavioral changes mostly depend on personal experiences and preferences. Social networks help in understanding how human behaviour evolves with changes in natural systems. In particular, social networks cause behavioral changes in adaptation to sudden and long-term environmental changes[11]. In addition, people's attitude towards uncertainty and risk is influenced by environmental factors when they have economic benefits from their behaviour[82]. In summary, social and climate change are interlinked, and it is important to examine this link using coupled social-climate models, to make better policies related to climate change by examining social factors, which is one of the main objectives of this thesis.

1.4 Climate Models

The previous section focused on the relationship between social and climate systems; now, we will have a closer look at the climate system and climate modelling. Climate models are sophisticated tools that predict Earth's climate scenario. These models include various systems of our planet that contribute to the climate, like the atmosphere, biosphere, oceans, and land surface. Since Earth is too big and complicated to experiment with, these models provide a digital laboratory for exploring and understanding various systems contributing to climate change by allowing experts to simulate various scenarios [83, 84]. They are crucial in planning carbon budgets and climate policies, especially for organizations like the Intergovernmental Panel for Climate Change (IPCC) and the United Nations (UN), to understand future scenarios and bring in relevant predictions and policy changes [85].

Although these models are extremely useful, they come with some drawbacks. There are certain uncertainties regarding climate models, which can affect the accuracy of the predictions they give [86] despite their high computational complexity and sophisticated algorithms. Generally, climate models face challenges in incorporating human dynamics in them. A system that integrates human behaviour completely is not possible due to the complexity of human behaviour [87], because of which researchers make simplifying assumptions and constant advancements. This drawback of climate models is the reason behind the development of coupled social-climate models, which will be discussed in the next section and used throughout this thesis.

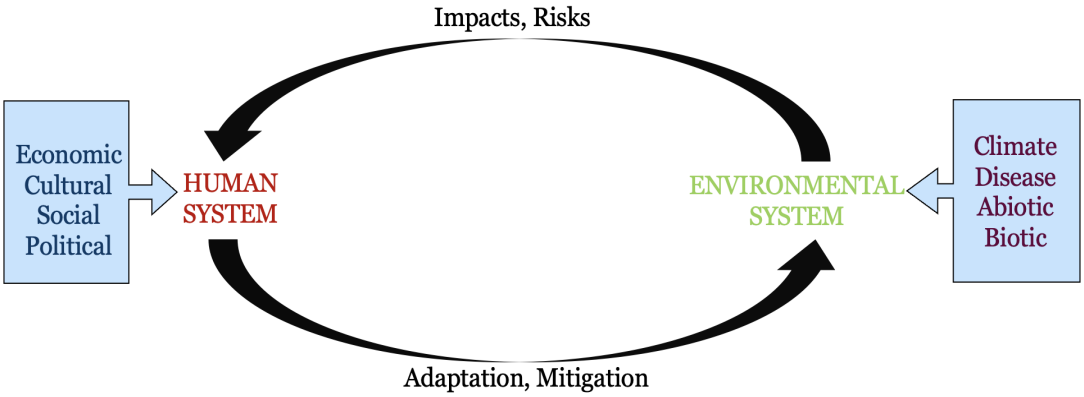


Figure 1.2: **Coupled social-climate model:** Mutual feedback loop between social and climate systems.

1.5 Coupled Social-Climate Models

Human beings and the environment are somewhat inseparable and significantly influence each other (as discussed in previous sections). However, most sophisticated behaviour and environmental models do not consider an active interaction and response between these independent systems (Fig 1.2). This leads us to the concept of coupled models, which are important tools for understanding the feedback loop between the two systems. Coupled human-environmental models integrate human behaviour with environmental systems to understand how human behaviour is influenced by environmental changes and how environmental changes are influenced by human actions.

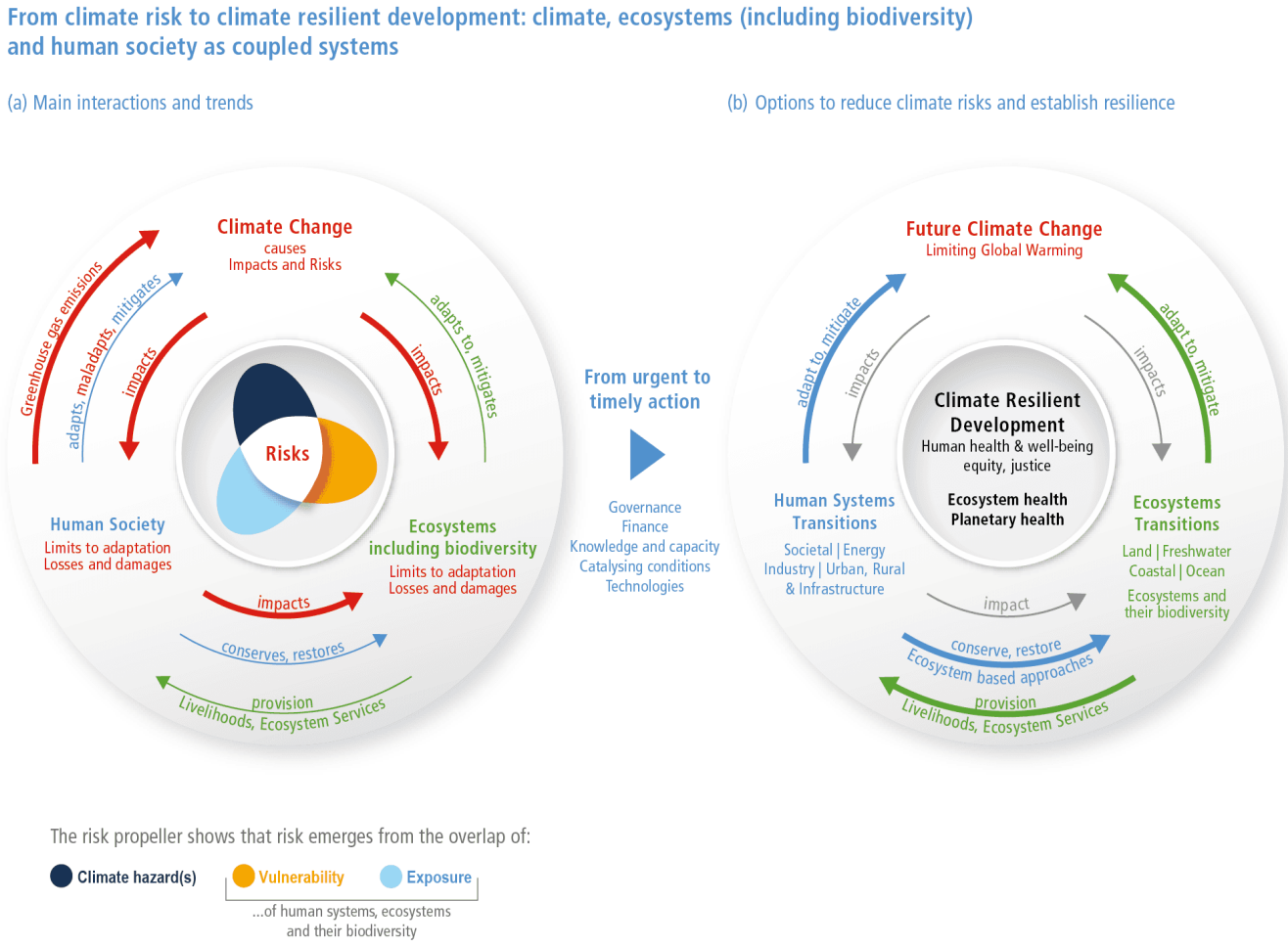


Figure 1.3: **Figure SPM.1 in IPCC, 2022** [2]

Coupled human-environmental models have been applied in various domains such as forests, land use, coral reefs, fisheries, and climate change mitigation (Fig 1.3). These models can provide insights that are impossible to obtain using uncoupled normative models [88, 89, 90, 91]. However, coupled models could lead to complexities due to the integration of various feedbacks. This could further lead to uncertainties and challenges in model precision, as in the case of integrated assessment models (IAM). Also, coupled models sometimes include various simplification assumptions and approximations too [92]. Although there are limitations to coupled models, they give a new, different perspective and insight into climate dynamics [93]. In general, coupled human-environmental models are crucial for

forming strategies to both mitigate and adapt to environmental changes. They promote sustainable development by thoroughly understanding the relation between human and natural systems [88, 92, 94, 95]. In this thesis, we look at several coupled social-climate models to understand the mutual feedback between the social and climate systems.

1.6 Aims and Objectives

Coupled social-climate models have rapidly grown over the past decade as researchers around the globe seek to understand the link between social attributes and the climate system to tackle the climate crisis we are experiencing [96, 97, 98, 99]. These models display great potential to understand the intricate relationship between human behaviour and environmental outcomes. Despite these advancements, the existing social-climate models do not consider several perspectives. This thesis aims to develop simple social-climate models that examine various social factors to provide insights that policymakers could use [100].

We aim to identify several social attributes, such as rumors related to climate change, opinions on climate change, mitigation costs, individual response to climate events, stubbornness in changing opinions, unexpected social and climate events, and impacts of climate change, among other factors, to understand the mutual feedback between human behaviour and the climate system. For this, we focus on two types of social behaviour: mitigative and non-mitigative. Mitigative strategies reduce the impacts of climate change, while non-mitigative strategies exacerbate them. We aim to quantify the social factors influencing climate outcomes by evaluating their influence on emission levels and temperature change. We also aim to understand how these social factors can influence climate behaviour in individuals when they experience climate change. Our objective is to simplify the complicated scientific models for policymakers and stakeholders for actionable real-world applications. This is achieved by analyzing various model parameters that we consider to predict their influence on climate outcomes and policy effectiveness.

In coupled models, behaviour dynamics are explored using several modelling techniques. However, none of them uses compartmental modelling for this purpose. Apart from its primary use in epidemiology, compartmental modelling is used to understand information spread in individuals [32, 33]. We use this concept to understand climate behaviour in individuals using climate rumors and how rumors about climate change can shape individual and group behaviours. Rumors act as a social factor, greatly influencing people and their actions. Our objective with this modelling technique is to understand the insights compartmental modelling of human behaviour can provide us in a social-climate model.

Social-climate models usually categorize opinions into binary categories: mitigative and non-mitigative. We identified this drawback in the existing coupled models and aimed to develop a model considering continuous climate opinions. In this case, our objective is to understand how social attributes act when the opinions are continuous. This model could help policymakers create realistic plans to enhance mitigative behaviour in the population.

Apart from how the opinions or attitudes are modeled, several attributes can contribute to the mutual feedback between behaviour formation and climate scenarios, such as the impact mitigation costs can have on mitigating behaviour, how well and fast people respond to climate change problems, individual reluctance to behaviour alteration (stubbornness) promoting mitigation, and experiencing frequent and unexpected social and climate changes (policies, economic, political, extreme weather events). We are also motivated to explore why people do not respond to climate change even after knowing the fatalities it can lead to. This thesis addresses the above mentioned factors that impact model predictions by incorporating various modelling strategies to get realistic and socially relevant predictions. The main objective of this thesis is to identify the aspects of social behaviour and climate opinions that can be incorporated into effective and efficient policy-making regarding climate change by exploring the different scenarios that can enhance mitigative behaviour and limit global warming. This thesis also aims to address the current knowledge gap in social-climate models by exploring the role of behavioral dynamics in shaping climate change outcomes by incorporating behavioral dynamics into climate models using social networks. Specifically, it seeks to answer the question: "How do changes in human behaviour influence emission trends and *vice-versa*?"

1.7 Thesis Outline

Our goal with this thesis is to develop simple coupled models that can help policymakers by giving significant information about the social factors that foster mitigation and limit warming. This thesis is structured as follows. We begin with a simple social-climate model in Chapter 2. In this model, we explore how rumors about climate change within a population can influence their attitude towards climate change and how temperature changes alter individual judgment regarding climate rumors and mitigative behaviour by considering rumor propagation between individuals and groups. Using this model, we try to better understand how factors like believing, rejecting, or forgetting climate rumors and the effectiveness of the mitigation strategies impact future climate scenarios, particularly temperature, and emissions. Modelling a climate system coupled to a social system has been explored before [98, 101], but the dynamics of rumor coupled to a climate system

is relatively new, and this work is the first to examine the mutual feedback between climate rumors and climate system using compartmental modelling, to our knowledge. We explored various factors that can promote mitigative behaviour in individuals when they encounter climate-related rumors. Factors such as believing and rejecting these rumors, forgetting about the rumors, and network characteristics, such as group size and information transmission frequency, can significantly impact shaping climate behaviour. This chapter is published in PloS One [1].

In Chapter 3, we introduce a novel model involving continuous opinions about climate change to explore the coupled dynamics. We look at different factors, such as the stubbornness of individuals, social influence, and the cost of mitigation. Although there are coupled models that consider human behaviour and climate systems, none consider opinions about climate change in a continuous space, making our work novel. This model explores how continuous opinions about climate change can affect the climate system and vice versa compared to binary coupled models. We also identified critical points where increased response towards climate change could foster mitigation even with high mitigation costs. This chapter is currently being prepared for submission.

In Chapter 4, we aim to further understand the factors contributing to individual behaviour differences between the pandemic and climate change. We explore the factors contributing to this behavioral difference despite climate change having more severe consequences than the pandemic. This chapter explores the difference in attitudes towards pandemics and climate change, focusing on factors such as mitigation cost, duration of impact, and benefits of mitigation. Our analysis gives critical information regarding this behavioral disparity, which can help in policy formation to limit warming. This chapter is currently being prepared for submission.

In Chapter 5, we discuss the implications of our results in a broader scope by summarizing the findings. We deduce how the results from these models can help policymakers develop climate-friendly policies that can help foster mitigative behaviour in the population. The future directions and extensions that can be employed using these models are also discussed in this chapter.

Chapter 2

Climate-denying rumor propagation in a coupled socio-climate model: impact on average global temperature

This chapter is based on the paper: Athira Satheesh Kumar, Chris T. Bauch, and Madhur Anand. Climate-denying rumor propagation in a coupled socio-climate model: Impact on average global temperature. PloS one 20.1 (2025): e0317338.

Abstract

Individual attitudes vastly affect the transformations we are experiencing and are vital in mitigating or intensifying climate change. A socio-climate model by coupling a model of rumor dynamics in heterogeneous networks to a simple Earth System model is developed, in order to analyze how rumors about climate change impact individuals' opinions when they may choose to either believe or reject the rumors they come across over time. Our model assumes that when individuals experience an increase in the global temperature, they tend to not believe the rumors they come across. The rumor rejectors limit their CO_2 emissions to reduce global temperature. Our numerical analysis indicates that, over time, the temperature anomaly becomes less affected by the variations in rumor propagation parameters, and having larger groups (having more members) is more efficient in reducing temperature (by efficiently propagating rumors) than having numerous small groups. It is observed that decreasing the number of individual connections does not reduce the size of the rejector population when there are large numbers of messages sent through groups. Mitigation strategies considered by the rejectors are highly influential. The absence of mitigative behaviour in rejectors can cause an increase in the global average temperature by 0.5°C. Our model indicates that rumor propagation in groups has the upper hand in controlling temperature change, compared to individual climate-denying propagation.

2.1 Introduction

Sustainability challenges have spanned multiple systems such as forest degradation [102, 103, 104], air pollution [105, 106, 107] and water systems [108, 109, 110], and accelerated anthropogenic global warming. Since the Industrial Revolution, humans have been emitting increasing amounts of greenhouse gases (GHG) into the Earth's atmosphere, leading to anthropogenic global warming. The Intergovernmental Panel on Climate Change (IPCC) reports [111, 112] outline the social transitions required to limit the increase in the average global temperature to between 1.5°C and 2°C. Lifestyle and behavioral changes like reduction in household and industrial energy consumption, switching to renewable energy, and changes in diet can assist in achieving this goal [113, 114, 115]. Climate models couple Earth system components like the ocean and terrestrial systems with atmospheric dynamics, in order to project future temperature, precipitation, and other variables [116, 117, 118, 119, 120, 121]. These model dynamics respond to atmospheric GHG concentration, the roots of which are human activities like fossil fuel usage and deforestation. These models typically assume a fixed trajectory for future GHG emissions as a model input, based on assumptions about socio-economic development. However, GHG emissions

are not fixed but rather they increasingly respond to climate change, as a result of the response from human populations and institutions [122, 123, 124].

Human perceptions of climate change, variation in individual behaviour driving climate change, and human responses and adaptation strategies are recognized as the three key aspects of human behavioral changes in response to climate change [124]. Human beings recognize and adapt to climate change based on personal experience [125, 126], for instance, individuals living in places with increased temperatures are more likely to perceive climate change than others [123]. This observation suggests that human behaviour and climate change are connected into a single coupled human-environment system [127, 128]. Changes in individual behaviours could also contribute to climate change mitigation strategies [128, 129]. Behavioral change alone can lead to significant reduction in emissions [130]. With monetary incentives and feedback, around 0.35 $GTCO_2$ per year reduction in emission levels can be observed from the residential sector alone [131, 132]. A study regarding potential behavioral changes on climate change in the European Union further establishes the importance of including human behaviour: changes to dietary habits, mobility, and household can reduce the emission levels by 6% to 16% leading to a decrease of 13.5% to 30% reduction mitigation costs [133]. These findings underscore the importance of behavioral transitions in climate change mitigation, which leads to substantial reduction in emissions.

Coupled socio-climate models have been gaining importance due to the growing recognition of the role of social processes. Such models have demonstrated the enormous influence of social norms and social learning on temperature projections [134, 128]. These models act as tools to understand the feedback loops between climate and human systems. Several behavioral theories could be potentially used in the coupled model [135, 136, 137]. Models involving frameworks for representing processing, spreading, and behavioral responses considering the heterogeneous nature of society have also been developed recently. Qualitative insights on socio-climate models portray the importance of social learning, and the associated cost for mitigation [128]. By integrating an Earth System Model with a social dynamics model, Bury et al. [128] observed that increasing social learning and reducing mitigation costs is the most efficient way to reduce global temperature anomalies. These models also help to analyze how different groups in a heterogeneous population respond and evolve [99].

Several models have coupled climate dynamics and economic processes. For instance, integrated assessment models (IAMs) couple climate dynamics and economic processes by incorporating economic feedback in agriculture and energy expenditures [138, 139]. Dynamic Integrated Climate Economy (DICE) models couple climate change and economies with a focus on mitigation costs [140, 141]. However, human attitudes towards climate

change could be influenced by the social, religious, or political views of the population [142, 143]. Therefore, models that also include other relevant human processes–like social dynamics–are required for a more comprehensive picture. Machine learning models are also gaining popularity in studying climate systems to predict temperature and precipitation [144].

Various rumor propagation models have been developed and analyzed in different domains. Rumor propagation models inspired by compartmental models are not new [145, 74]. Due to the similarities between disease and rumor propagation in a population, rumor propagation models are sometimes constructed using mathematical epidemiology [27]. They also provide deeper insights on various factors that helps in understanding how to mitigate the effects of rumors. But most of these models focuses on individual rumor dynamics. There are very few models that discusses about propagation of rumors in groups [32]. Individual rumor propagation occurs when an individual spreads rumors by sharing them with other individuals whereas, in group propagation, an individual propagates the rumor to a group of individuals, such as via social media. Various aspects of group and individual rumor propagation have the power to affect individuals' attitudes toward climate change. Most of the population has only a superficial knowledge of climate change [146]. Perhaps as a result, rumors about climate change–especially climate misinformation–are common and there are empirical studies and statistical models that deal with myths and fake news regarding economic factors related to climate change [147, 148].

Several coupled models deal with climate change and various aspects of human behaviour, integrating features such as imitation dynamics and social norms [128, 99]. However, previous coupled social-climate models have not included misinformation campaigns, despite the fact that rumors which deny climate change are a major reason for individuals and groups not acknowledging the urgency of the climate emergency, and thus not taking effective mitigation strategies [149, 150]. Here, a coupled socio-climate model is developed where rumor propagation spreads through a mathematical approximation of a social network. Our objective is to demonstrate a simple yet novel way of modelling interactions between rumor spread as a contagious process and long-term climate dynamics to gain insights into potential social-climate dynamics. A simple Earth system model is used to capture temporal dynamics of the global temperature anomaly, and our rumor propagation model is correspondingly simple. Although social-climate systems are complex, a simple model to identify the regimes of climate-rumor dynamics, to start with and to suggest a framework for future, more sophisticated social-climate models.

2.2 Methods

A mathematical model linking climate-denying rumor propagation (including group dynamics) in heterogeneous networks with climate dynamics is proposed. The coupled rumor-climate change model is proposed by adding the climate dynamics into an existing rumor propagation model [32] in social networks by relating the human responses to rumors based on the range of climate change they experience. In this extension, the rumors are assumed to be false information about climate change. The model is developed by coupling the rumor-spreading model with an Earth System Model (ESM) to analyze the dynamics of the coupled system, in which the rumor propagation about climate change begins in 2021. The model considers a heterogeneous rumor model since real-life networks, including social networking sites, are heterogeneous in nature. This is done by incorporating emissions (mainly CO_2, an important greenhouse gas) and temperature into the model. The rumor model has two components: individual propagation and group propagation. The model helps us interpret how the parameters involved in rumor propagation influence emission levels and temperature change and how changes in temperature levels influence human attitude towards the rumors about climate change. The rumor-climate change dynamics are formulated such that when individuals understand that the rumors are false, they try to mitigate climate change. Similarly, individuals who experience climate change, through changes in temperature, believe that the rumors are not true.

2.2.1 Rumor Propagation Model

An existing rumor propagation model involving group propagation in heterogeneous networks is used [32]. Each node represents either an individual or a group in the social network, and the edges are connections between the individuals or between individuals and the groups they belong to. Each individual is assumed to be in one of the following states: s_k denotes the proportion of susceptible individuals who are susceptible to the rumor about climate change but are not exposed to the rumor, h_k, hesitator is the individual who is exposed to the rumor but hesitates to believe or reject the rumor. If they accept it, they propagate the rumor. Otherwise, they reject it. i_B is the proportion of believers who believe climate change is not real and share the rumor individually and in groups, and i_R is the proportion of rejectors who reject the rumor, believing that climate change is real, and do not forward the rumor. The possibility that people can forget about the rumor and be susceptible again is also considered in this model (Fig 2.1).

The equations for the rumor propagation involve ordinary differential equations and

are as follows [32]:

$$s'_k(t) = B - \beta\bar{c}ks_k(t)\frac{\sum_j(p(j|k))}{p_j}i_{B_j}(t) + \alpha\bar{c}k\frac{\sum_j(p(j|k))}{p_j}i_{B_j}(t) + \gamma\bar{c}ki_{R_k}(t) - \bar{G}\bar{m}\bar{d}\varsigma s_k(t)$$
$$i_{B_k}(t) + \bar{G}\bar{m}\bar{d}\sigma i_{R_k}(t) + \bar{G}\bar{m}\bar{d}\rho i_{B_k}(t) - \mu s_k(t)$$

$$h'_k(t) = \beta\bar{c}s_k(t)k\frac{\sum_j(p(j|k))}{p_j}i_{B_j}(t) - (\eta(T)+\varepsilon)\bar{c}k\frac{\sum_j(p(j|k))}{p_j}h_j(t) + \bar{G}\bar{m}\bar{d}\varsigma s_k(t)i_{B_k}(t) -$$
$$\bar{G}\bar{m}\bar{d}\omega(T)h_k(t) - \bar{G}\bar{m}\bar{d}\zeta h_k(t) - \mu h_k(t)$$

$$i'_{B_k}(t) = \eta(T)\bar{c}k\frac{\sum_j(p(j|k))}{p_j}h_j(t) - \alpha\bar{c}k\frac{\sum_j(p(j|k))}{p_j}i_{B_j}(t) + \bar{G}\bar{m}\bar{d}\omega(T)h_k(t) - \bar{G}\bar{m}\bar{d}\rho$$
$$i_{B_k}(t) - \mu i_{B_k}(t)$$

$$i'_{R_k}(t) = \varepsilon\bar{c}k\frac{\sum_j(p(j|k))}{p_j}h_j(t) - \gamma\bar{c}ki_{R_k}(t) + \bar{G}\bar{m}\bar{d}\zeta h_k(t) - \bar{G}\bar{m}\bar{d}\sigma i_{R_k}(t) - \mu i_{R_k}(t) \quad (2.1)$$

Social media features, like entering and leaving the network at any stage, are considered in this model. Individuals joining the network always fall into the susceptible category, and the number of individuals joining the network per unit of time is B. An individual can exit the network at any time, and hence the exiting rate at which an individual exits the network μ is included in each compartment. Since both individual and group propagation are considered, both parameters are considered separately. β is the hesitating probability with which a susceptible individual becomes a hesitator individual, whereas the hesitating probability in groups is ς. The probability that a hesitator individual believes the rumor is η, and in groups, this probability is ω. Similarly, a hesitator individual rejects the rumor with probability ϵ; in groups, this probability is ζ. A forgetting mechanism is also included in this model, along with believing and rejecting mechanisms. Individuals will forget the rumor and their opinion about it, as time passes and revert to the initial susceptible state. The probability with which the believer and rejector individuals forget the rumor is α and γ, respectively. The term $p(j|k)$ denotes the probability with which an edge with degree k connects to a node with degree j. The respective rates in groups are considered as ρ and σ. Apart from the probabilities, the average rate of individual contact is $\bar{c}$, and the average rate at which messages are transmitted per group is $\bar{d}$. The average network degree is k with X groups having m members on average, with the average degree for the group for an individual being $\bar{G}$. All these attributes make this rumor propagation model a simple and efficient way to assess various factors influencing information dissemination and opinion formation.

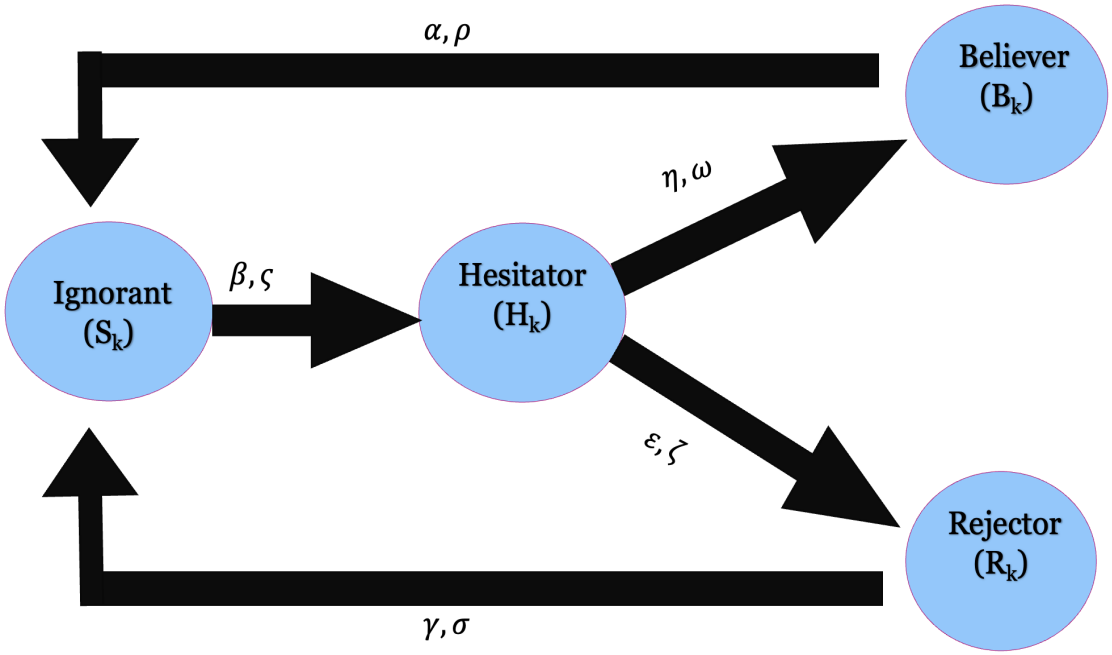


Figure 2.1: **Schematic representation of the rumor propagation model**

2.2.2 Earth System Model

A relation between emissions and temperature is required to understand the increase in temperature due to emissions. Earth system models (ESMs) describe climate-relevant Earth processes and how they influence climate dynamics. A simple existing Earth system model is used for this purpose [151]. An austere climate–carbon-cycle model for understanding the coupled climate-carbon–cycle system defines the global mean surface temperature anomaly (controlled by the upper ocean) as follows:

$$\frac{dT}{dt} = \frac{qF - T}{d} \tag{2.2}$$

$$F = \frac{F_{2x}}{ln(2)} \ln\left(\frac{C_{atm}}{C_0}\right) \tag{2.3}$$

where $F = \frac{F_{2x}}{ln(2)} ln(\frac{C_{atm}}{C_0})$ is the CO2 radiative forcing and C_0 is the pre-industrial atmospheric CO_2 level and $C_{atm} = C_0 + C$ is the atmospheric CO_2 level at the time point [151]. F_{2x} is the climate sensitivity, q is the thermal adjustment of the upper ocean, and d is the

thermal equilibrium for the upper ocean. The global mean surface temperature anomaly helps in understanding the change in temperature that has occurred over the years and projecting future changes concerning the emission levels (Table 2.1). This ESM has been used to calculate the temperature anomaly under different emissions scenarios [152].

2.2.3 Coupled rumor - climate change model

The rumor propagation model in section 2.2.1 is modified by incorporating climate dynamics. The coupling is accomplished by making the individual believing probability η and group believing probability ω a function of the change in temperature, T, defined as:

$$\eta(T) = \eta_0 e^{-vT} \tag{2.4}$$

$$\omega(T) = \omega_0 e^{-vT} \tag{2.5}$$

The parameters in the system Eq (2.1) are described in Table 2.1. According to Eq (2.4) and (2.5), the believing probability increases or decreases in response to the change in the temperature (T). As T increases, η and ω decrease: fewer individuals are convinced by the rumors since they experience the temperature change. This will decrease the believing probability and increase the rejecting probability.

The deviation of the global atmospheric CO_2 levels from the pre-industrial levels, C, is defined as:

$$\frac{dC}{dt} = \begin{cases} E(t) & t \leq 2021 \\ E_{2021} * exp(-\Psi \sum_k i_{R_k}) - \delta C & t > 2021 \end{cases} \tag{2.6}$$

where $E(t)$ is the anthropogenic emission data for each year until 2021, Ψ is a constant value at which the rejectors limit their emissions, which is any mitigation strategies considered by the rejector to reduce their emissions, like switching to renewable energy like solar energy for power consumption, using electric or hybrid vehicles, insulating walls during construction, etc. E_{2021} is the baseline carbon dioxide emissions level in the absence of rejectors (amount in 2021). According to Eq (2.6), CO_2 the equilibrium C value to which C trends exponentially depends as a negative exponential on the total rejector population. Apart from this, emission gets naturally dissipated due to various natural processes (sinks like ocean, land, and plants), and this natural dissipation rate is δ.

Usually, the time scale of rumor propagation and climate change is not comparable. Rumor propagation might last for weeks or months, whereas climate change takes place over decades. To overcome this issue, the long-term susceptibility and transmission of individuals are modeled to a collection of multiple related rumors. This means that an individual who is a believer (rejector), believes (rejects) various rumors that come up over time, and not just a single rumor.

Parameters	Description	Values	Units	Sources
β	Hesitating probability (individuals)	(0,0.7716,1)	1	calibrated
ς	Hesitating probability (groups)	(0,0.7924,1)	1	calibrated
η	Believing probability (individuals)	(0,0.3857,1)	1	calibrated
ω	Believing probability (groups)	(0,0.3115,1)	1	calibrated
ϵ	Rejecting probability (individuals)	(0,0.6143,1)	1	calibrated
ζ	Rejecting probability (groups)	(0,0.6885,1)	1	calibrated
α	Forgetting probability in believers (individuals)	(0,0.0003,1)	1	calibrated
ρ	Forgetting probability in believers (groups)	(0,0.0007,1)	1	calibrated
γ	Forgetting probability in rejectors (individuals)	(0,0.00009,1)	1	calibrated
σ	Forgetting probability in rejectors (groups)	(0,0.0007,1)	1	calibrated
$\bar{c}$	Average rate of contact for each individual	(1,27,50)	yr^{-1}	calibrated
$\bar{d}$	Average rate of transmitting messages per group	(1,11,50)	yr^{-1}	calibrated
δ	CO_2 dissipation rate	0.06	yr^{-1}	[152]
Ψ	Emission limiting constant by rejectors	10	1	calibrated
B	Proportion of individuals entering the network per unit time	(0,0.1730,1)	yr^{-1}	calibrated
μ	Rate of leaving or exiting the network	(0,0.1119,1)	yr^{-1}	calibrated
k	Average degree of the network	(1,5,20)	1	calibrated
X	Total number of groups	(1,40,100)	1	calibrated
$\bar{m}$	Average number of group members	(1,70,100)	1	calibrated
$\bar{G}$	Average group degree of an individual	3	1	calibrated
C_0	Pre-industrial CO_2 level	38.9	$GTCO_2$	[152]
F_{2x}	Forcing due to CO_2 doubling	3.74	Wm^{-2}	[151]
q	Thermal adjustment of upper ocean	0.41	$KW^{-1}m^2$	[151]
d	Thermal equilibrium for upper ocean	4.1	yr	[151]
v	Coefficient of exponential	0.35	C^{-1}	calibrated

Table 2.1: Table describing the model parameters and baseline values in Chapter 2.

2.2.4 Analysis

Time series, univariate, and bivariate (parameter plane) sensitivity analysis is used to understand the model's behaviour dynamics and parameter sensitivity. The baseline parameter values for the model were generated using Approximate Bayesian Computation (ABC) [153, 154], and the baseline climate parameters are obtained from the ESM [151], and the Global Carbon Budget [152]. The parameter range considered for sensitivity analysis depends on the upper and lower bounds of the model parameters. These bounds are chosen in accordance with the nature of the parameter. For example, the parameters representing the probability values are considered between 0 and 1, and hypothetical model parameters are given broad upper and lower bounds, specified in Table 2.1. The analysis was carried out over 180 years, beginning when the rumor propagation emerged in 2021.

2.3 Results

The model illustrates how social behaviour, through rumor propagation, influences temperature levels. Initially, the whole population is susceptible to the rumors ($s_0 = 1, h_0 = 0, i_{b_0} = 0, i_{r_0} = 0$). A time series examination of the model indicates that a growing proportion of rejectors in the population causes lower emission levels depending on their emission-limiting strategies, as expected (Fig 2.2(a) and (b)). The transmission of multiple rumors and that a believer (rejector) believes (rejects) all the rumors that come up over time is considered. The result shows an optimistic case where 80% of rejectors are present in the population, with strong emission-limiting strategies to keep the temperature anomaly below $1.5°C$ (Fig 2.2(b)), which is considered to be an important climate threshold [111] by the IPCC. The range of possible model outcomes is also analyzed (Fig 2.2(d,e,f)). The temperature anomaly lies between 1.3 to 1.8°C when the proportion of rejectors lies between 0.7 and 0.8.

Human actions predominantly affect climate through increased emissions, leading to the accumulation of greenhouse gases in the atmosphere, leading to severe and potentially irreversible changes. In this model, rumor propagation begins in 2021. The emissions and corresponding temperature anomalies before 2021 are computed using the anthropogenic emission data [152]. When individuals encounter rumors about climate change–such as climate change is not a serious problem or climate change is not real–they think about it and initially hesitate to decide whether to believe or reject it. The hesitating state can simply be considered as the state in which individuals are contemplating or checking facts before making their decision. Later, they decide whether to believe or not believe the rumors. The rejectors do not further spread the rumor, act like mitigators, and try to limit their emissions to reduce the impact of climate change, whereas the believers forward the rumor to more individuals, and the rumor spreads through the population.

Individuals stop believing the series of rumors when they experience a temperature change. As the proportion of rejectors increases in the population, the emission level slowly decreases, and so does the temperature. The temperature change is due to the cumulative amount of greenhouse gases in the atmosphere, especially CO_2. The atmospheric CO_2 does not reduce immediately but slowly dissipates, and the temperature decreases gradually as the CO_2 level decreases. Even though the population starts to act immediately, it takes more time to see a change since it takes more time to dissipate the CO_2 and even more time to see a drop in temperature.

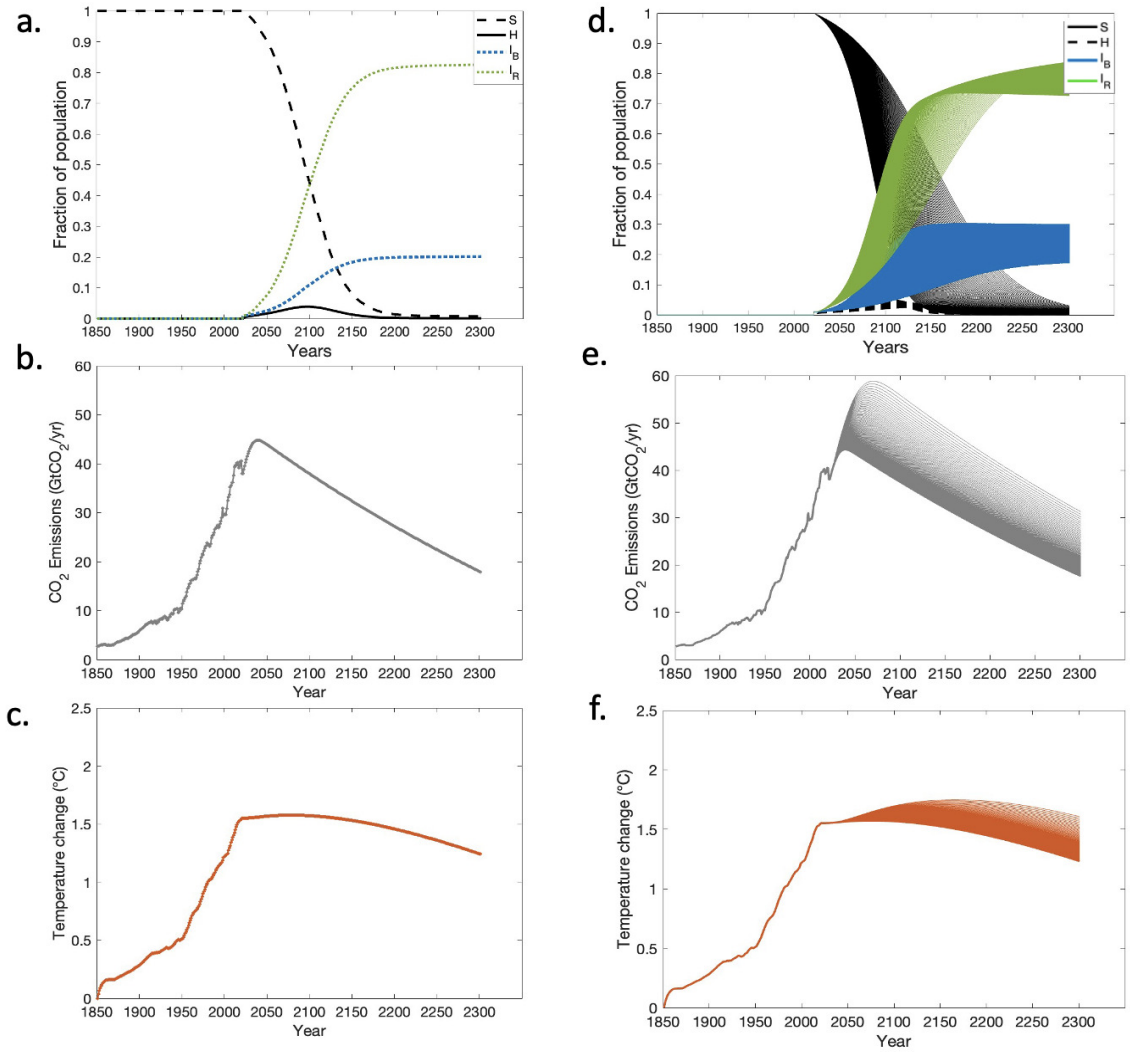


Figure 2.2: **Time series for the coupled socio-climate model for the baseline parameter values** (a,d) Times series showing the rumor dynamics for baseline parameter values (b,e) Time series of emission scenario ($GtCO_2yr^{-1}$) and (c,f) temperature anomaly ($^{\circ}C$) for baseline parameter values. (a,b,c) is the time series for the baseline parameter value and (d,e,f) is the time series plot generated using the accepted parameter values after applying ABC. Each of the multiple lines in (d,e,f) is a time series generated using each set of parameter values that were generated by ABC.

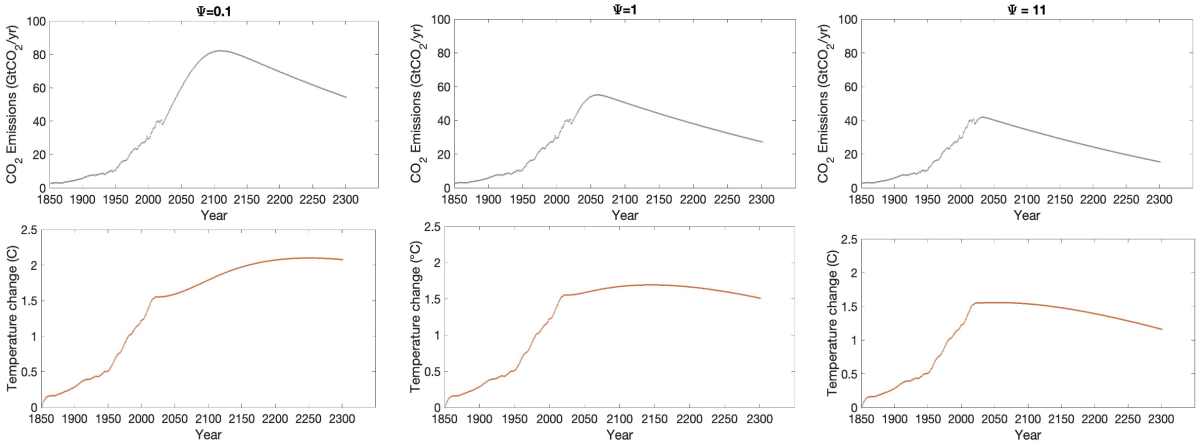


Figure 2.3: **Emission scenarios for limiting global temperature change** (a) Emissions levels at $\Psi = 0.1$ (d) Temperature anomaly $< 2.5°C$ at $\Psi = 0.1$ (b) Emission levels at $\Psi = 1$ (e) Temperature anomaly at $1.5°C$ (c)Emission levels when $\Psi = 11$ (f) Temperature anomaly at $< 1.5°C$ with all other parameters at the baseline values.

To understand the influence of the emission limiting strategies considered by the rejectors in the population, on the temperature anomaly, three cases are identified: a best-case scenario, which will be an ideal case where the temperature levels stay below the IPCC proposed levels [111], an average-case scenario, where the temperature increases little above the proposed level and a worst-case scenario, where the temperature increases far above the proposed level.

Best Case Scenario. An ideal case would be to limit the average global temperature change below $1.5°C$. When the emission limiting constant Ψ is high ($\Psi = 11$), the temperature stays below the desired level and accomplishes the world's climate goal (Fig 2.3(c) and (f)). The emissions decrease within a decade after the rumor propagation begins due to the strong mitigation strategies considered by the rejectors. Keeping the temperature rise below $1.5°C$ helps avoid irreversible changes like species extinction and adaptation problems. Our model suggests immediate mitigative actions are required to achieve our climate goals.

Average Case scenario. When the emission limiting constant Ψ takes a lower value indicating fewer mitigative actions ($\Psi = 1$), the emission increases for four decades before declining (Fig 2.3 (b) and (e)). In this case, the temperature rises above $1.5°C$ and decreases slowly, leading to irreversible environmental changes. Our model predicts that four decadal difference in emission reduction lead to a 200-year delay in achieving our climate goal.

Worst Case Scenario. If the emission level does not decrease for another nine decades, the temperature does not decrease till 2300 (Fig 2.3(a) and (d)). This situation arises due to poor or no mitigation steps taken by rejectors ($\Psi = 0.1$). The temperature increases above $2°C$ and does not decrease to a desired level, which could lead to unadaptable living conditions.

These three scenarios portray the importance of emission-mitigating strategies. Even though the population consists of 80% rejectors, the efficiency of their emission-limiting strategies plays a vital role. This result shows that understanding that climate change as a major issue is not enough but to efficiently mitigate it is also extremely necessary.

2.3.1 Sensitivity Analysis

The time series analysis gave an overall idea about how the model works but to further understand the influence of the model parameters, a sensitivity analysis is performed. The parameter planes generated by varying two model parameters simultaneously by retaining all other parameters at the baseline values help to understand how the simultaneous variation in two model parameters influences the model behaviour at different time points. Time snapshots of parameter planes for emissions and temperature levels in 2021, 2070, and 2200 are considered.

Emissions levels and temperature anomaly are more sensitive to changes in the emission-limiting value, Ψ, than the changes in believing and rejecting probabilities (Fig 2.4 and Fig 2.5). This means that the strength with which rejectors limit their emissions through various mitigation strategies can significantly reduce emission and temperature levels, which reestablishes the result from Fig 2.3. This also indicates that efforts to mitigate climate change are as important as the number of individuals who support mitigation. In other words, having individuals who adopt mitigative measures is as important as having individuals who acknowledge the climate crisis. Simultaneously increasing the probability of rejection and decreasing the probability of believing leads to lower levels of emissions and temperature (Fig. A.1). This was done to understand how the combination of both these probabilities would aid in reducing emissions and it was observed that both believing and rejecting probabilities contribute to the temperature anomaly equally. The emission limit constant (Ψ) has a greater influence on emission levels and temperature anomaly compared to the probabilities of believing (ω) and rejecting (ζ) (Fig 2.4 and Fig 2.5) when the emission limiting strategies considered are lower. Decreasing the emission-limiting constant value after achieving the desired temperature goal can also cause an increase in temperature, which implies that reducing the efficiency of mitigation strategies once the target is

achieved can take us to the initial scenario again. Hence it is important to maintain the efficiency in mitigating.

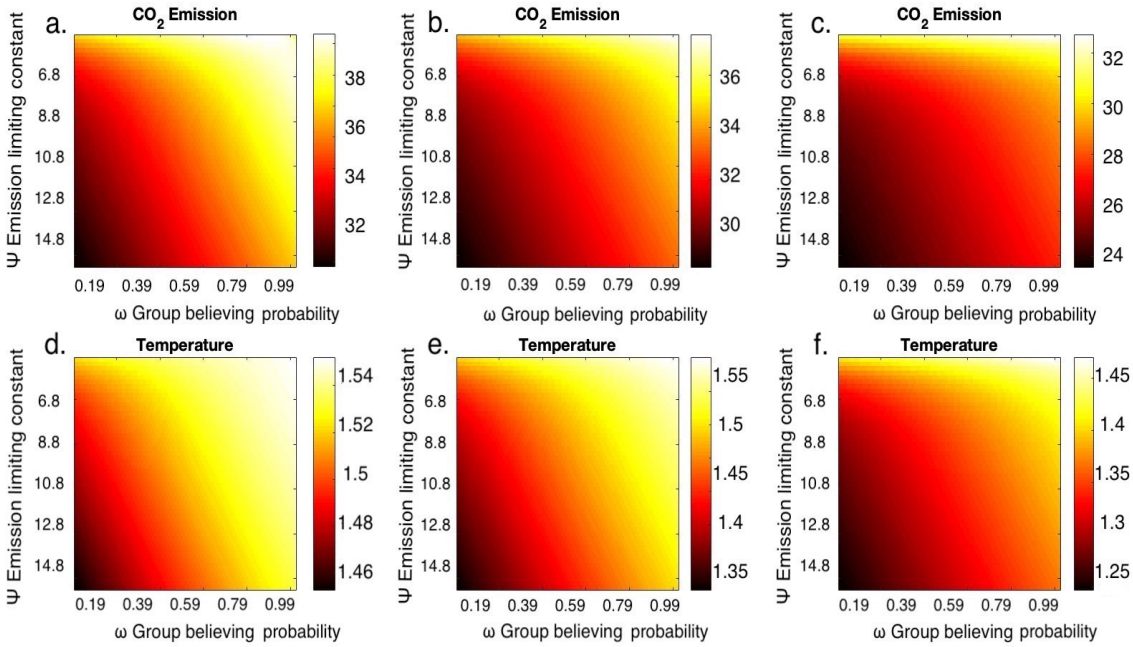


Figure 2.4: **Temperature sensitivity is more with variation in emission limiting constant than group believing probabilities.** Parameter planes of CO_2 emissions ($GtCO_2yr^{-1}$) at (a) 2021, (b) 2070, and (c) 2200 and temperature anomaly ($^{\circ}C$) at (d) 2021, (e) 2070 and (f) 2200 by varying group believing probability (ω) and emission limiting constant (Ψ).

The emission levels and temperature anomaly decrease as the forgetting probability in believers increases and the forgetting probability in rejectors decreases (Fig A.2). As more rejectors forget about the rumors, they become susceptible again, according to the rumor propagation model, and hence the mitigation strategies decrease with a decrease in the rejector population. Whereas when more believers forget about the rumors, this leads to reduced emissions. The snapshots display that emission levels and the temperature anomaly are equally sensitive to both parameters.

The global temperature anomaly becomes less sensitive to the variation in believing or rejecting probabilities along with their corresponding forgetting probabilities as time

passes (Fig A.3 and Fig A.4). Fewer parameter combinations lead to higher temperatures in 2200 than in 2070 and 2021, which implies that changing the believing (ω) or rejecting (ζ) probabilities and forgetting probabilities (ρ, σ) does not impact the temperature and emission levels after the rumor dynamics becomes stable. Also, the temperature anomaly is more sensitive to the forgetting probability in rejectors than the forgetting probabilities in believers (Fig A.3 and Fig A.4). High forgetting probabilities in rejectors lead to higher emissions and temperature levels. Maximum emissions are found at higher forgetting probabilities (in rejectors) and lower rejecting probabilities (Fig A.4). Rejectors forgetting the rumor have greater risks than the believers forgetting the rumor as rejectors act as mitigators and are the ones who adopt mitigative strategies to combat with climate change.

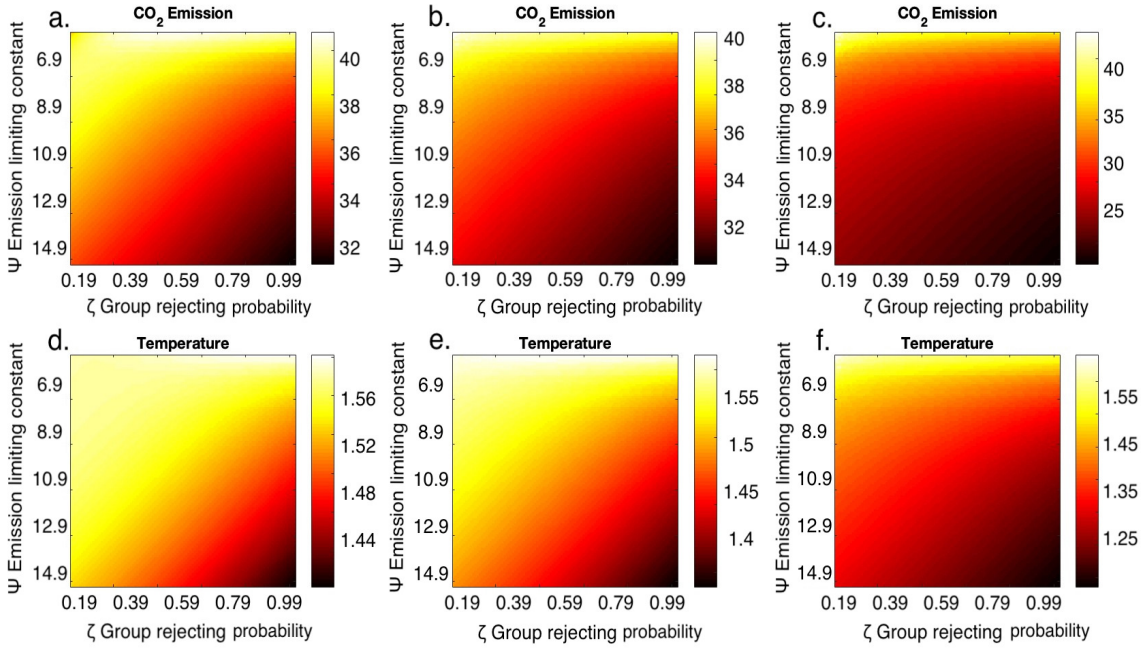


Figure 2.5: **Global temperature anomaly is more sensitive to the emission-liming constant than group rejecting probabilities.** (a-c)Parameter planes of CO_2 emissions ($GtCO_2yr^{-1}$) at (a) 2021, (b) 2070, and (c) 2200 and (d-f) temperature anomaly ($^{\circ}C$) at (d) 2021, (e) 2070 and (f) 2200 by varying group rejecting probability (ζ) and emission limiting constant (Ψ).

Univariate sensitivity analysis enables us to understand how sensitive the model is to a single parameter when it varies along its range by holding all other parameters at the

baseline value. Only three points in the time series are considered to generate the univariate sensitivity plot: the peak value, the value in 2050, and the value in 2200. Varying the total number of groups, X along its range (Table 2.1) helps to understand the sensitivity of the model compartments concerning the parameter (Fig A.5). The baseline value for X is 40. A lower number of groups in the system leads to a sluggish rumor spreading. At lower X values, most of the population belongs in the susceptible compartment, and few are in the believer and rejector categories. The emission and temperature levels are also higher at lower X values than the higher ones, which implies that more groups assist in propagating the rumor quickly and assist in reducing the temperature. This portrays the importance of group propagation as shown in [32].

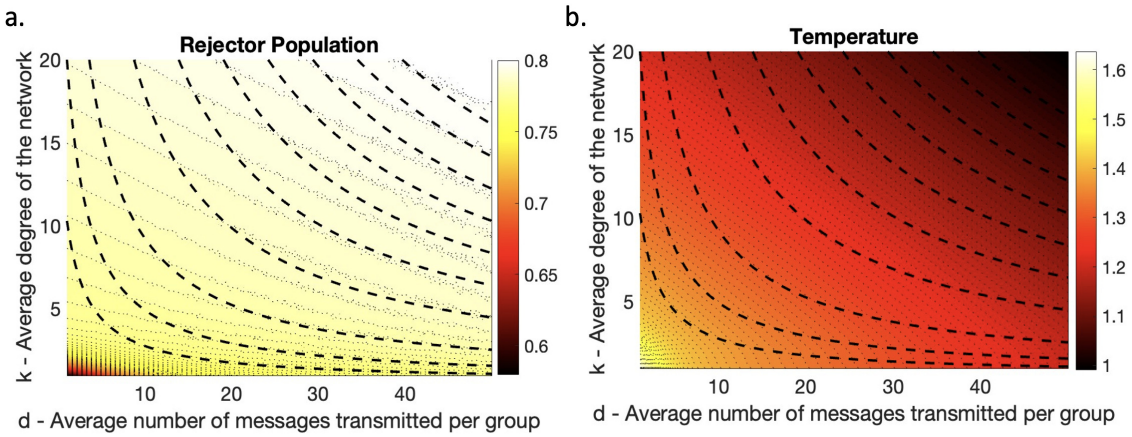


Figure 2.6: **Global temperature anomaly is unaffected by low network degree at a high number of group messages.** Parameter plane showing the changes in (a) rejector population and (b) temperature anomaly due to the variation in the average number of messages transmitted per group ($\bar{d}$) and the average degree of the network (k).The dashed lines show equal $\bar{d} * k$ values and the gray lines show equal size of rejector population and equal temperature anomaly.

The univariate sensitivity plot attained by varying the average number of group members (m) displays that rumor propagation is quicker when the average number of group members is higher (Fig A.6). The baseline value for m for the model is 70. At lower m values, rumor propagation is considerably slow. It also leads to a higher temperature and CO_2 emissions at lower m values which means that rumor propagation in groups with fewer members is less capable of spreading the rumor. Having more members in a group elevates the speed of the rumor propagation, making more individuals to decide at a time.

The univariate analysis for the parameter $\bar{c}$, which is the average number of contacts for each individual, shows that higher $\bar{c}$ (baseline value 27) does not aid much in decreasing the temperature or the rumor propagation (Fig A.7) whereas lowering it slows down the rumor propagation leading to an elevated temperature level. Even though having more individual connections does not help in reducing the temperature, having fewer connections can certainly increase the temperature anomaly by making the information spread more localized. Fig A.8 is the univariate analysis for the parameter $\bar{d}$, which is the average rate of transmitting messages per group. As the $\bar{d}$ value is decreased, the rumor propagation slows down, and the temperature shoots up. There is a considerable variation in the temperature anomaly as $\bar{d}$ decreases, implying that lowering the number of messages transmitted in the group can increase the temperature level, as it slows the rumor transmission among the population and making fewer individuals think about climate change.

The parameter plane by varying k and $\bar{d}$ illustrates that the temperature anomaly decreases as the average network degree and the messages transmitted per group increase (Fig 2.6). The hypothesis was that reducing the average degree of the network will not much affect the rumor propagation and temperature anomaly when the average number of messages transmitted in the groups is high. This hypothesis is tested using parameter planes by changing the parameters simultaneously, and the result supports our hypothesis. The dotted lines in Fig 2.6 represent equal products of the parameters $(d * k)$. The constant product value $(d*k)$, helps in analyzing how the rejector population and temperature anomaly vary, with changes in the parameter values. The distribution of parameters generated using ABC is shown in Fig A.9 - A.15.

The size of the rejector population determines the temperature anomaly, for instance, a higher rejector population leads to a lower temperature anomaly (Fig 2.6(a),(b)). Higher variations in the size of the rejector population (and temperature anomaly) are observed when the average number of messages transmitted is low. This implies that both rejector population and temperature anomaly are more sensitive to the variations in the average number of messages transmitted per group than the network degree. In other words, the messaging rate in groups is more important than the number of individual connections in terms of determining the size of the rejector population (and thus in determining how much climate change is mitigated). As long as the frequency of messages about climate change in groups remains high, reduction in individual connections does not influence the temperature anomaly.

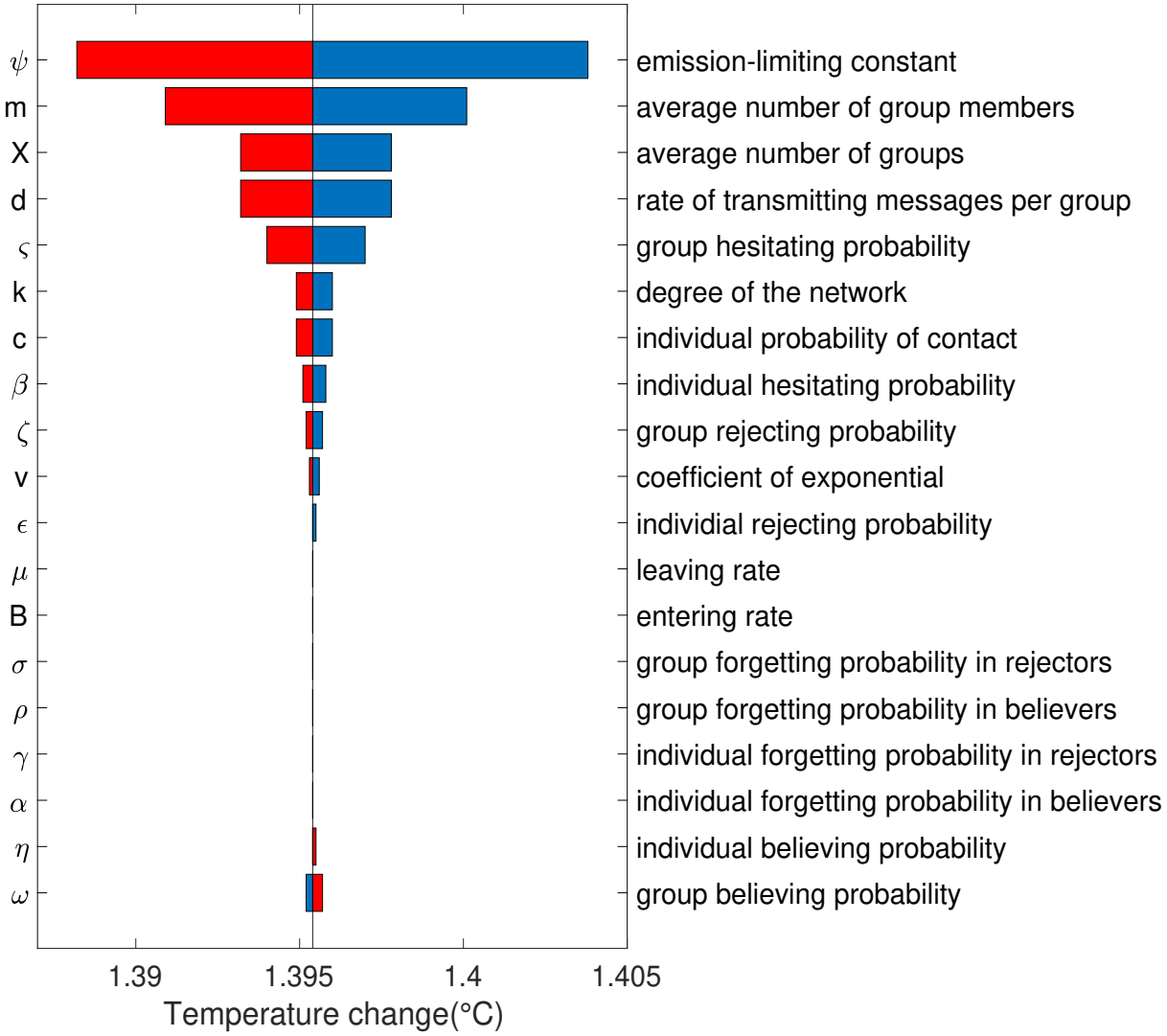


Figure 2.7: **Sensitivity of temperature anomaly at 10% change in parameter values.** Tornado plot showing the sensitivity of temperature change when parameters are varied individually, with a 10% increase and decrease from the baseline values. The red colour represents an increase in the parameter value and the blue colour represents a decrease in the parameter value, from the baseline value.

The interactions between rumor propagation parameters (group believing and rejecting probabilities) and the forcing due to doubling of CO_2 (Wm^{-2}) shows that temperature anomaly is more sensitive to changes in forcing than the changes in the believing or rejecting probability (Fig A.16). The forcing due to the doubling of CO_2 (F_{2x}), causes an increase in the temperature anomaly even at lower believing probability (higher rejecting probability). Being an environmental variable, forcing has its own upper hand in influencing climate change compared to human actions but human actions are the reason for these changes is also an underlying fact.

The tornado diagram is a sensitivity analysis tool that helps examine the model parameters' relative priority. The sensitivity of the temperature anomaly (in 2200) demonstrates the relative sensitivity of each parameter. Fig 2.7 is the tornado plot showing the temperature anomaly sensitivity when the model parameters vary individually at 10%. The analysis confirms the results from Fig 2.7 that temperature change is most sensitive to the emission limiting constant Ψ (Fig 2.7). The temperature is more sensitive to the group parameters than the individual parameters. The hypothesis that temperature change is more sensitive to forgetting probability in rejectors is also true in the case of 10% change in the parameters even though there are no visible changes because of the extremely low baseline value considered. The tornado plot reassures the results observed in sensitivity analysis and helps to understand the order of influence for each parameters.

2.4 Discussion

A rumor propagation model was linked with an Earth System model to understand how the spread of climate rumors responds to climate change, and how resulting behavioral change can feedback on climate. Differing from the existing literature, this model focuses on how rumors about climate change can influence the climate system itself, using methods from compartmental modelling and Earth System Modelling. The study has shown that the mitigation strategies by rumor rejectors to limit emissions are vital in reducing emission levels and temperature anomalies. Acknowledging that climate change is a major issue is not enough but working efficiently towards mitigation and adopting efficient mitigation strategies are vital in controlling the effects of climate change. The parameter planes and tornado plots suggest that temperature anomaly is most sensitive to these mitigation strategies by the rejectors. The mitigation plan is the crucial link that connects human behaviour and climate change in our model. Our results support that human mitigation strategies help in keeping climate change under control by avoiding undesirable and uninhabitable situations in the future, similar to the suggestions from various studies [130, 131, 132, 133]. The extent of climate change we will experience in the future depends on the strategies we adopt

today and how soon we start acting according to the strategies adopted. The more time we take to reduce our emissions, the higher the average global temperature anomaly will be. The coupled rumor-climate model suggests that misinformation via rumors is a significant issue. The effort the rejectors make to mitigate climate change is vital in controlling the time taken for decreasing the emission level, and temperature changes.

Our simple rumor-climate model shows that the temperature anomaly is more sensitive to mitigating strategies than believing or not believing the climate rumors. Surprisingly, the temperature becomes less sensitive to the variation in rumor propagation parameters as time passes. Our results show that larger groups assist in rapid rumor propagation and hence in temperature deviations. The univariate sensitivity plots infer that having larger groups with more members is more efficient in propagating rumors and reducing the temperature than having more groups with fewer members. In other words, the decision of a group with more members has more influence on the temperature levels than smaller groups. The coupled model also portrays that group propagation is faster than individual propagation and hence has more influence on the temperature anomaly. Decreasing the connectivity of individuals does not influence the number of rejectors in the population when a high volume of rumors is sent in groups. The average rate of messages sent in groups produces more variation in the temperature levels, and temperature is more sensitive to group propagation parameters than individual propagation parameters. Our model deals with arbitrary decision-making in the rumor propagation model by considering that the whole population either believes or rejects the rumors. In contrast, decision-making might be influenced by the individual's cultural, political, educational, or social views, which is not covered in this model. The spread of rumors about climate change can be controlled using various methods such as inoculations through educational approaches and social norms [155]. Proper climate education is necessary for individuals to distinguish between rumors and facts about climate change and take the right decisions by considering mitigation and adaptation strategies.

Several models deal with climate change, but models involving human influence on climate change are rare. The recent development of coupled social-climate models has included social and economic factors [128, 134, 99], but ours is the first social-climate model to include rumor propagation, to our knowledge. Social networks act as an essential medium of information circulation, therefore it is crucial to understand how rumor propagation in a heterogeneous social network can influence individuals' opinions on climate change. According to our model, social networks have a vital role in influencing the climate system. Coupled models can be beneficial in including dynamic social processes in climate models. Including these models in climate change research can provide different perspectives and predictions regarding climate change. Coupled models can also help in

policy-making by providing novel emission scenarios based on social mechanisms that are known to be important. Also, according to our model, using individuals in social networks to become aware of climate change issues could be beneficial to reduce emissions by increasing the number of mitigators in society. Social networks act as an important way of spreading information regarding climate change and inviting more individuals to act at the right time.

Chapter 3

From Opinion Polarization to Climate Action: A Social-Climate Model of the Opinion Spectrum

This chapter is based on the paper in preparation: Athira Satheesh Kumar, Krešimir Josić, Chris T Bauch, and Madhur Anand. From Opinion Polarization to Climate Action: A Social-Climate Model of the Opinion Spectrum. In review with Journal of the Royal Society Interface, 2025.

Abstract

We developed a coupled social-climate network model to understand the interaction between climate change opinion spread and the climate system and determine the role of this interaction in shaping collective actions and global temperature changes. Our model allows for a continuous spectrum of opinions about climate change, whereas previous social-climate models focus only on discrete opinions, and thus, we were able to study more nuanced interactions. The model shows that resistance to behaviour change, elevated mitigation costs, and slow response to climate events can result in a global temperature anomaly in excess of 2°C. However, this outcome could be avoided by lowering mitigation costs and increasing the rate of interaction between individuals with differing opinions (social learning). Our model is the first to demonstrate the emergence of opinion polarization in a human-environment system, predicting that polarization of opinions in a population can be extinguished, and the population will adopt mitigation practices when the response to temperature change is more sensitive, even at higher mitigation costs. It also indicates that even with polarized opinion, an average pro-mitigative opinion in the population can reduce emissions. Finally, our model underscores how frequent and unexpected social or environmental changes, such as policy changes or extreme weather events, can slow climate change mitigation. This analysis helps identify the factors that support achieving international climate goals, such as leveraging peer influence and decreasing stubbornness in individuals, reducing mitigation costs, and encouraging climate-friendly lifestyles. Our model offers a valuable new framework for exploring the integration of social and natural sciences, particularly in the domain of human behavioural change.

3.1 Introduction

Can changing human behaviour and social dynamics influence climate dynamics? To answer this question, social-climate models–models that describe both social or behavioural dynamics and climate dynamics and how the coupling of these two systems can influence each other– are increasingly being constructed [98, 156, 157, 97, 1]. It is apparent that social sciences and natural sciences need to come together to deal with the climate crisis [156, 157], and these models are an example of a broader class of coupled human-environment systems [158, 159, 160, 161] which are charting new and more hopeful pathways for sustainability science. Recent social-climate models have identified social factors such as policy, social interaction, social norms, and opinion polarization as having impacts on determining future emission trajectories [162, 98, 163, 164, 165]. Existing coupled social-climate models usually describe climate opinions as binary choices between mitigation and non-mitigation

[98, 99, 97, 1]. In reality, opinions lie on a spectrum [166, 167, 168] and climate opinions, in particular, can range from strong to neutral [169, 170].

Modelling opinion dynamics in human populations has been extensively studied in an uncoupled manner and these studies have elucidated the role of social influence, network interactions, and cognitive biases, in capturing the impact of social processes on opinion formation. One of the oldest continuous opinion models is the classic DeGroot model, which helps to understand how opinions are formed in social networks [42]. The DeGroot model focuses on how individuals update their own beliefs based on the opinions of their peers, by assigning weights. Another continuous opinion model is the Friedkin-Johnsen (FJ) model, which modifies the DeGroot model by including stubbornness [43], defined as resistance to changing one's opinion [171]. For instance, the FJ model was used to capture the negotiation process leading to the Paris Agreement, accounting for the stubbornness of nations during discussions [172]. Opinion models have been a topic of interest among researchers for almost a century as they provide insights into how human systems work. Yet, they have not been used in coupled social-climate models.

The weight given to the opinions of other individuals also plays an important role in opinion formation. In opinion models, weights can be assigned to each individual depending on proximity, opinion similarity, or other characteristics. Several social experiments show that individuals usually weigh their own opinion more than the opinions of others [173, 174, 175, 176]. People tend to be positively influenced by others with similar opinions [177, 178, 179, 175, 180, 181]. Sociological experiments also show that extremely different opinions tend to push opinions further apart [182, 183, 184, 185, 186, 187]. Weights can also be adaptive, meaning that they can change over time as opinions get updated, which is commonly observed in several social scenarios [188, 189, 190, 191, 192]. Based on these characteristics, opinion models with weights have considered different features in their analysis of opinion formation on a continuous spectrum [193, 194]. Although several social experiments support adaptive weights, only a few models have incorporated them.

Polarization is a commonly observed phenomenon in opinion formation on social networks in both theoretical models and empirical studies. Researchers have explored how exposure to opinions shared online influences opinion formation by linking it to the effects of personalization on polarization [195, 196]. Experiments on Facebook suggest that people adopt similar opinions and maintain distance from dissimilar opinions, which further establishes polarization. Such models are evaluated using empirical research to connect theoretical models with real-world data [197]. Factors such as politics, mass media, and social media also play an important role in shaping opinions and thus contributing to polarization [198, 199]. Particularly, the vast amount of information on social media introduces challenges in identifying credible sources [200, 201, 202, 203, 204] leading to polarization.

Some research also indicates that exposure to opposing opinions can increase polarization in social media [183]. The question of how polarization can emerge *de novo* is a topic of opinion modelling research [205, 206, 207].

Given the widespread literature on modelling the dynamics of continuously distributed opinions, it is surprising that these approaches have not been incorporated into coupled social-climate models. Similarly, it is surprising that the impact of environmental dynamics on continuously distributed opinion formation has not been explored in models, given that introducing human-environment coupling in binary decision models is known to create new regimes that are not possible in human or environment systems in isolation from one another [159, 208, 161, 209, 156, 97, 98, 99, 1]. Here, we address both knowledge gaps by modifying the FJ model with stubbornness and coupling it to an Earth system (climate) model. Stubborn individuals give a low weight to the opinions of other individuals while forming their opinions. The resulting coupled social-climate model is used to ask the following questions: how do factors like individual stubbornness, social influence, mitigation costs, and response to temperature change alter projected emission pathways and temperature trends? How might polarized opinions emerge in a population with an initially uniform distribution of opinion strength? Can polarization be removed from the population? How do environmental or social changes influence individual opinions and temperature trends?

3.2 Framework

3.2.1 Continuous opinion model

We start with a population of N individuals, each individual i having an opinion $o_i(t)$ about climate change. The opinion of individual i in a year t can take any value in $[-1, 1]$, where -1 implies a strong non-mitigative opinion, 1 implies a strong mitigative opinion and 0 implies neutral opinion. We modify the FJ model by adding vital dynamics and making individual opinion dependent on climate dynamics, specifically through a change in the mean global temperature anomaly.

Typically, opinion models are used to understand the formation of opinions over short periods of time. Climate change is a generational challenge; we wish to track opinion dynamics over multiple generations and hence include births and deaths when modelling the population. To do so, we randomly remove agents (death) from the population at a given rate and replace them with a new agent (birth). The opinion of the new agent is assigned by randomly choosing another individual's opinion. We also add Gaussian

white noise to the evolution of opinions to account for random events such as extreme climate events, celebrity speeches, and policy changes that can influence the decision-making process. Social networks are typically sparse [210, 211]. Hence, we consider that an individual i will only interact with 100 other randomly selected individuals from the network of N individuals at time t.

The continuous decision model with stubborn agents and temperature response is defined through a discrete-time formulation:

$$o_i(t+1) = \psi\left(w_{ii}o_i(t) + \lambda_i\left(\sum_{i\neq j} w_{ij}(t)o_j(t) + R(T)\right) + (1-\lambda_i)o_i(0)\right) + \varepsilon_i(t) \tag{3.1}$$

where $R(T)$ is the response of opinion to temperature change (defined below), and $0 < \lambda_i < 1$ accounts for the susceptibility of agents to influence (λ_i is the susceptibility of an individual to the opinions of others, and to the effects of climate change so that $1-\lambda_i$ is a measure of stubbornness) [43]. We assume that individuals are highly influenced by similar opinions and weakly influenced by more distant ones, in accordance with empirical observations [193, 206, 212, 213]. Accordingly, the weights by which individual j influences individual i is defined as $w_{ij} = e^{-\frac{d_{ij}}{A}}$ $(0 \leq w_{ij} \leq 1)$, where $d_{ij} = |o_j(t) - o_i(t)|$, the difference in opinions between i and j and A is the social influence of agents [193]; smaller A indicates a highly confident population that is only influenced by individuals with similar opinions, whereas a larger A allows for the influence of differing opinions. The factor ψ determines the time scale of opinion change to match the time scale (in years) of the climate dynamics. Since Eq (3.1) can result in an updated opinion outside the interval $[-1, 1]$, we also assume that when $o_i(t+1) < -1 \Rightarrow o_i(t+1) = -1$ and when $o_i(t+1) > 1 \Rightarrow o_i(t+1) = 1$. The term $\varepsilon_i(t)$ is Gaussian white noise which models random fluctuations in the opinion due to effects not explicitly included in the model. $R(T)$ (defined in Eq (3.4)) implicitly accounts for the outside interactions.

3.2.2 Earth System Model

We use the following Earth system model [214], which predicts future temperature levels depending on the atmospheric carbon dioxide levels:

$$\frac{dT_j}{dt} = \frac{q_j F - T_j}{d_j}; T = \sum_j T_j; j = 1, 2 \tag{3.2}$$

$$F = \frac{F_{2x}}{ln(2)} ln\left(\frac{C_0 + C}{C_0}\right). \tag{3.3}$$

Here T is the temperature, q_1 (0.33 $KW^{-1}m^2$) is the thermal adjustment of the deep ocean, q_2 (0.41 $KW^{-1}m^2$) is the thermal adjustment of the upper ocean [214], F is the CO_2 radiative forcing, C_0 (38.9 $GtCO_2$) [111, 112] is the pre-industrial atmospheric CO_2 level, F_{2x} (4.5 Wm^{-2}) [214] is the forcing due to CO_2 doubling, d_1 (239 yr) is the thermal equilibrium for the deep ocean, and d_2 (4.1 yr) is the thermal equilibrium for the upper ocean [214].

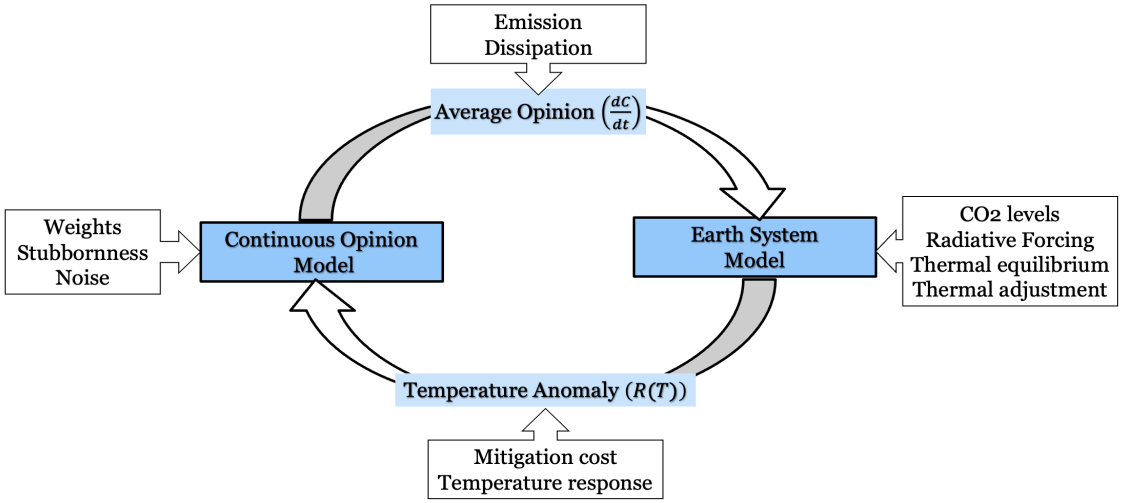


Figure 3.1: Schematic representation of the model with input variables for each component

3.2.3 Coupling between opinions and climate

We assume that all opinions, $(-1 \leq o_i \leq 1)$, translate into actions and that climate, in turn, impacts opinions. In particular, we model the impact of temperature T, on individual opinions using a sigmoid function [98, 215]:

$$R(T) = -m_{cost} + \left(\frac{R_{max}}{1 + e^{-\alpha\left(\frac{T(t)-T_0}{T_0}\right)}} \right) \tag{3.4}$$

depending on the cost of mitigation, $m_{cost} > 0$, the maximum impact due to temperature change, R_{max}, and the sensitivity to temperature change, α, which determines how sharply the response changes as the temperature T approaches T_0. Here, $T_0 = 1.2°C$ is the current average global temperature anomaly against which the changes are measured. We assume that every individual's emissions per unit of time are proportional to their opinion. A

schematic representation of the model is shown in Fig 3.1. We model the emission levels using:

$$\frac{dC}{dt} = E_0 \left(0.5 \left(1 - \frac{\sum_{i=1}^{N} o_i(t)}{N} \right) \right) - \delta C(t) \tag{3.5}$$

where E_0 is the baseline emission per year, and δ is the natural dissipation rate of carbon dioxide. This equation captures the decrease in emissions as the average opinion moves towards acceptance of mitigation, *i.e.* as $\langle o_i(t) \rangle$ increases, which allows the opinions to influence the climate system in a stepwise manner. We use Euler's method to solve the climate model numerically, with updates occurring at the same discrete time intervals (per year) as the opinion model to ensure consistency between the opinion and the climate model.

3.2.4 Model Parameters

We initialize opinion dynamics in the year 2022. The factor determining an individual's susceptibility to another opinion, λ_i, lies between $(0, 1)$, and we assigned them by sampling values independently, uniformly at random for each agent i in the population. The Gaussian white noise $(\varepsilon_i(t))$ added to the opinion dynamics was sampled from a normal distribution independently at each time step. For the baseline scenario, the noise is reduced to 3%, $\mathcal{N}(0, 0.03)$, to adjust the system's sensitivity to random fluctuations.

The temperature response function $R(T)$ depends on several parameters that connect the climate system to opinion dynamics. This function depends on the cost of mitigation (m_{cost}), maximum response to temperature change (R_{max}), the sensitivity to temperature change (α), the temperature anomaly (T), and the threshold temperature value ($T_0 = 1.2^\circ$ C) based on the current temperature anomaly. The values m_{cost}, R_{max}, and α do not have any particular range. However, these parameter values are chosen to give realistic temperature and emission predictions, which resonates with the RCP 4.5 scenario. Representative Concentration Pathways (RCP) are various climate change scenarios that help to project the future greenhouse gas levels formally adopted by the IPCC. RCP 4.5 is an intermediate scenario where the emissions peak around 2040 and then decline [216]. By exploring various parameter combinations through trial and error, we identified that $m_{cost} = 0.778$, $R_{max} = 1.37$, and $\alpha = 5.7$, give peak emissions in the year 2040. The parameter that accounts for the social influence of agents, $A = 0.35$ [193]. The scaling factor (ψ) determines the time scale of opinion dynamics. In the baseline scenario, we considered the scaling factor to be 0.7. This value moderates the pace of opinion dynamics to match climate dynamics to have peak emissions occur around 2040 (consistent with the RCP 4.5 scenario), enhancing the realism of our model predictions.

Parameters	Description	Values	Units	Sources
N	Total number of individuals	1000	1	calibrated
w_{ij}	Weight given to other opinions	[0,1]	1	[193]
λ_i	Susceptibility to other opinions	(0,1)	1	[43]
o_i	Opinion of individuals	[-1,1]	1	[193]
C_0	Pre-industrial CO_2 level	38.9	$GTCO_2$	[152]
F_{2x}	Forcing due to CO_2 doubling	4.5	Wm^{-2}	[217]
q_1	Thermal adjustment of deep ocean	0.33	$KW^{-1}m^2$	[214]
q_2	Thermal adjustment of upper ocean	0.41	$KW^{-1}m^2$	[214]
d_1	Thermal equilibrium for deep ocean	239	yr	[214]
d_2	Thermal equilibrium for upper ocean	4.1	yr	[214]
m_{cost}	Cost of mitigation	0.778	1	calibrated
R_{max}	Maximum response to temperature change	1.37	1	calibrated
δ	Natural dissipation rate	0.06	yr^{-1}	[152]
A	Social influence of agents	0.35	1	calibrated
α	Sensitivity to change in temperature	5.7	1	calibrated
ψ	Scaling for susceptibility and stubbornness	0.7	1	calibrated

Table 3.1: Table describing the model parameters and baseline values in Chapter 3.

The remaining parameters have been defined previously. The pre-industrial CO_2 is available in the IPCC reports [152], and the natural dissipation rate is calculated from the data in [152]. We estimate the E_0 value from Eq (3.5), and the data in [152] by substituting all other model parameters, which gave $E_0 = 4.8339$ $GTCO_2yr^{-1}$.

3.3 Results

We simulated the coupled model involving 1,000 individuals over 300 years to examine the interplay between opinion formation and climate dynamics. We treat $N = 1,000$ as a representative population. Opinions are initially assigned randomly to each individual, using a truncated normal distribution, $\mathcal{N}\left(0, \frac{1}{3}\right)$ which is then scaled to $[-1, 1]$ (with strong mitigative opinion represented as $o_i = 1$, strong non-mitigative opinion as $o_i = -1$). We then calculated the average opinion at 2150 (at the end of our simulation) and found that it is mitigating, with a value of 0.31.

A collective pro-mitigation opinion could constrain warming to 1.5°C

The baseline parameter values result in a reduction of emission levels from $40\,\mathrm{GtCO_2\,yr^{-1}}$ to $28\,\mathrm{GtCO_2\,yr^{-1}}$ when the average opinion of the population inclines towards mitigation.

This mitigating tendency in the population contributes to limiting the temperature rise beyond 1.5°C, which the IPCC recognizes as a critical threshold (Fig 3.2(a,b,c)). The time series shows that emissions decrease slowly as soon as the opinion dynamics begin. There is a steep increase in the average opinion, similar to the change in temperature levels. The opinions stabilize as the temperature starts to stabilize, which indicates the strong coupling between the average opinion and the temperature anomaly (Fig B.1).

Stubborn population can cause excessive warming

We next asked how stubbornness affects climate change. Specifically, suppose everyone in the population is unwilling to change their initial opinion (randomly assigned using truncated normal distribution as described above) regarding climate change. How does this shape our future climate scenario? We hypothesized that a stubborn population ($\lambda_i = 0$) reluctant to change their initial views on climate change could escalate emissions, resulting in a higher average global temperature when initial opinions are normally distributed between $[-1, 1]$. We examined a scenario in which individuals are extremely stubborn ($\lambda_i = 0$, which led to the average opinion at the end of our simulation closer to 0) and reluctant to change their perspectives (Fig 3.2d). In this case, emissions remain at their current levels (Fig 3.2e), while the temperature anomaly can exceed 2°C by 2100 (Fig 3.2f). This suggests that a highly stubborn population unwilling to revise their decisions can trigger irreversible climate change.

We also explored the best and worst-case scenarios to understand the various possibilities of opinion, emission, and temperature scenarios. We found a best-case scenario where the entire population has strong mitigative opinions (by setting $o_i(t) = 1$). In this situation, emissions drastically decline, resulting in a reduced temperature anomaly reverting to pre-industrial conditions. We further examined a worst-case scenario in which individuals refrain from choosing mitigative opinion due to a lack of response to temperature change (by setting $R_{max} = 0$), resulting in the average opinion of the population moving towards an average non-mitigative opinion (-0.8). Under such circumstances, emissions continue to escalate to nearly twice their existing levels, with the temperature anomaly surpassing 2.5°C by 2100 and continuing to increase thereafter.

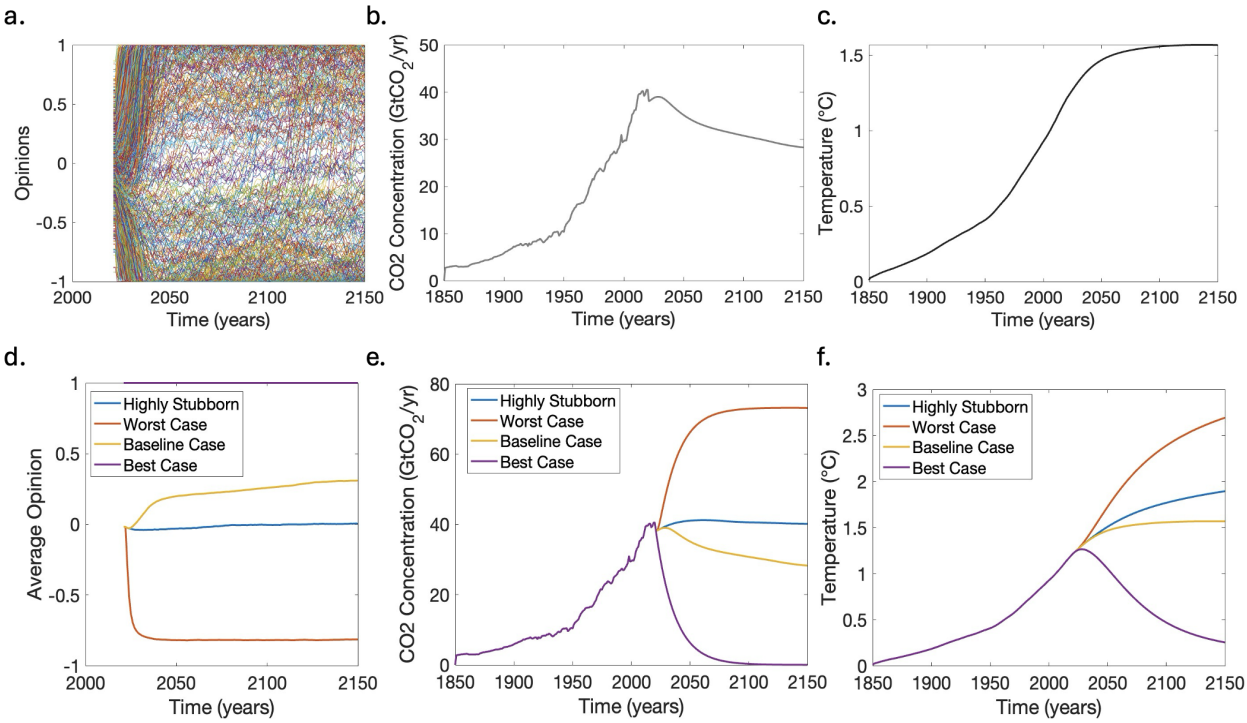


Figure 3.2: **Time series for the coupled social-climate model** Times series showing (a) the opinion dynamics (b) emission scenario ($GtCO_2yr^{-1}$) and (c) temperature anomaly (°C) for baseline parameter values. Time series for (d) average opinion (e) emission scenario ($GtCO_2yr^{-1}$), and (f) temperature anomaly (°C) for different parameter scenario.

Emergence of polarization

We did not assume that opinions are polarized *a priori* but observed that polarization emerges naturally in the baseline scenario (Table 3.1) despite the strong coupling with temperature. This observation also imply that a stronger coupling that diminishes the strength of our current temperature coupling could hinder mitigation. Although polarization emerges for a broad range of parameters in the FJ model, the coupling changes the balance in favour of mitigation. We examine the dynamics of opinion formation using the opinion distribution (Fig 3.3). The initial distribution of opinions follows a truncated normal curve, as mentioned above. Most opinion formation occurs within the initial decade (Fig 3.3). The population is divided into highly polarized perspectives of strong mitiga-

tive and non-mitigative opinions (Fig 3.3). As the coupled dynamics begin, the opinion distribution gradually evolves into a flat distribution, increasing the variance of the initial normal distribution. By the year 2026, cluster formation can be observed with less than 5% of the population in each cluster. By 2027, distinct polarization is apparent with fewer than 10% of the population with strong opinions on both mitigative and non-mitigative fronts. By 2040, the polarization intensifies with stronger mitigative opinions than non-mitigative. There are smaller subgroups between the extremities, although they constitute a small percentage($\leq$ 5%). By the end of our simulation (2150), more than 50% of the whole population opts to adopt mitigative opinions with around 20% with non-mitigative opinions and a small segment of individuals with less pronounced opinions in between.

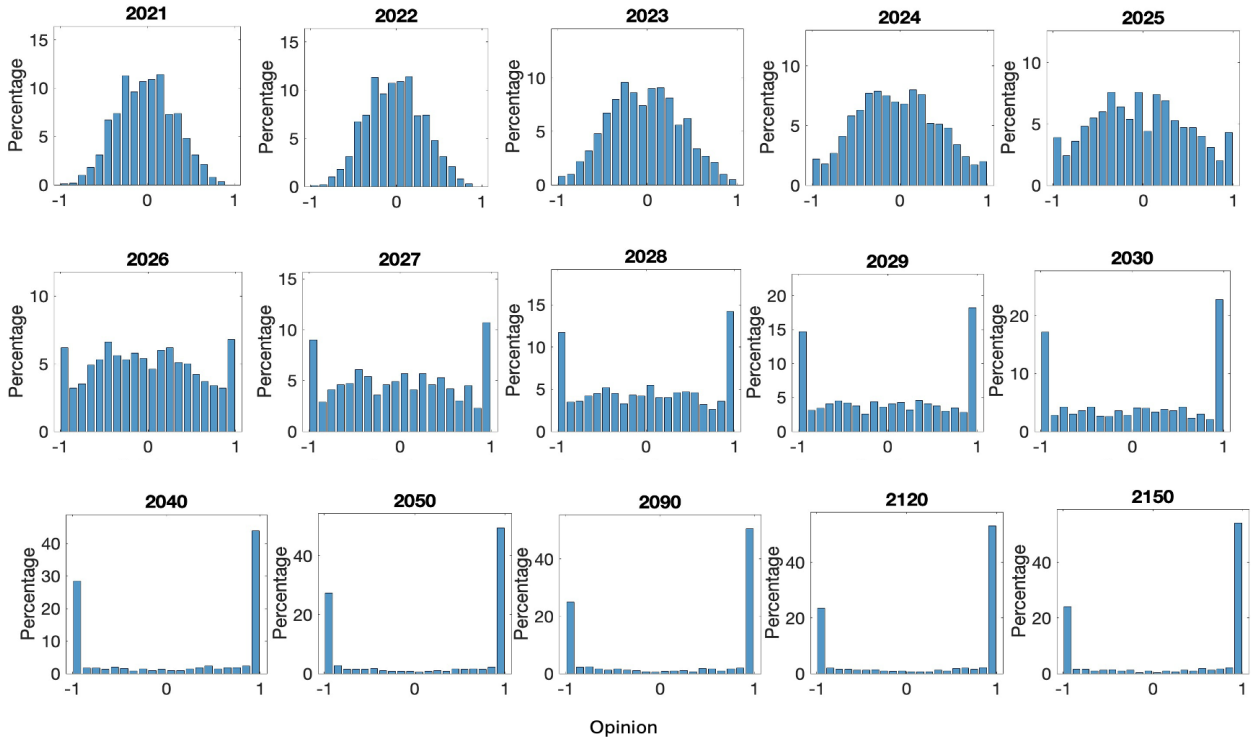


Figure 3.3: **Opinion evolution over time** Opinion distribution of the population at different time steps.

The evolution of opinions over time is shown in Fig 3.3 for our chosen baseline parameters (Table 3.1). The model dynamics indicate that polarization can occur naturally. Opinion polarization initiates after 5 years, showing slight increments as time progresses.

Distinct polarization is evident 20 years after the commencement of opinion dynamics. It is also noted that an initial polarization involving equal proportions of mitigative and non-mitigative opinions changes to a state of polarization with more mitigators and fewer non-mitigators by 2100. Our model simulation suggests that effective climate change mitigation is achievable even with 50% of mitigators in the population, provided that the average opinion is mitigative. Even though extreme mitigation is not essential, reducing emissions immediately is extremely important to stop warming (Fig 3.2(e,f)).

3.3.1 Sensitivity Analysis

We conducted a sensitivity analysis to understand the impact of changes in each parameter on the dynamics of the model. We executed both univariate and bivariate analyses, concentrating on how variations in model parameters influence the mean opinion, peak temperature, emission levels, and polarization. The univariate analysis is performed by changing a single parameter while maintaining all other parameters at their baseline values. This analysis helps to understand the effect of each parameter on the dynamics of the model. We investigate how these changes affect the mean opinion, emission levels, peak temperature, and polarization. In the bivariate analysis, two parameters are varied simultaneously, while all other parameters remain fixed at their baseline values. This analysis is particularly advantageous in understanding the combined effect of changes in the model parameters on the dynamics of the model. Polarization in our model is evaluated using bimodality coefficient. The bimodality coefficient (BC) is a function that measures the degree of polarization in a distribution based on skewness and kurtosis. Bimodality indicates the presence of two modes in the distribution. This value provides insights into the existence of distinct subgroups or opinions. BC values that exceed 0.55 ($BC \geq 0.55$) imply considerable differences between the opinions of these groups, suggesting a notable divergence in perspectives among individuals within the model.

Temperature response and mitigation costs impact peak temperature

Univariate analysis of the parameter that determines the impact of temperature fluctuations on opinions (R_{max}) reveals substantial effects on climate (peak temperature, emissions) and social (average opinion and polarization) dynamics (Fig 3.4). A heightened sensitivity to peak temperature and average public opinion is noted when the response to temperature changes is minimal ($R_{max} \leq 2$). Decreasing R_{max} can increase peak temperature ranging from 0.7 to 3.2 degrees within the projected future scenarios. Furthermore, a gradual transition in the average opinion of the population from a non-mitigative opinion

to one advocating for mitigation is observed with an intensified response to temperature change. Our model further suggests that elevated response values enhance mitigative opinions, reducing emissions and peak temperature levels, as anticipated.

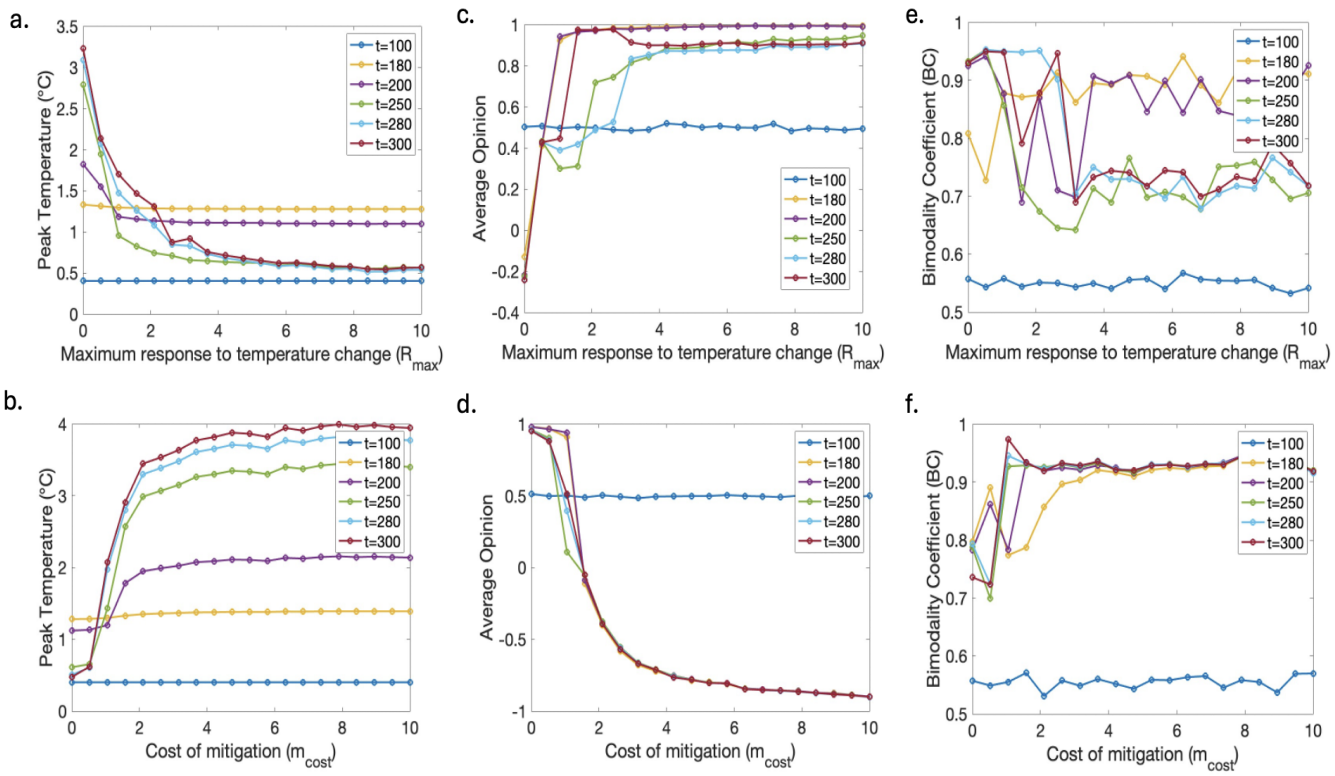


Figure 3.4: **Effect of variation in temperature response and cost of mitigation on opinion formation and climate change** Influence on (a) peak temperature levels, (c) average opinions, and (e) polarization using bimodality coefficient by varying R_{max}. Influence on (b) peak temperature levels, (d) average opinions, and (f) polarization using bimodality coefficient by varying m_{cost}.

A similar examination was conducted by altering the cost of mitigation (m_{cost}) (Fig 3.4). An increase in mitigation costs is associated with a notable increase in peak temperature values (ranging from 0.5 to 4 degrees) with a shift in the general opinion towards non-mitigative approaches. The elevated costs associated with mitigation reduce the mitigation efforts, resulting in more individuals choosing non-mitigative strategies resulting in an increase in emissions levels. Furthermore, a reduction in polarization (measured by a

decreased bimodality coefficient) is observed in contexts where mitigation costs are relatively low. In both scenarios with R_{max} and m_{cost}, more changes are evident within the parameter values spanning from 0 to 2 (Fig 3.4).

Increased perturbations delay mitigation

Incorporating random noise ($\varepsilon_i(t)$) into the framework of opinion dynamics introduces stochasticity that influences the evolution of individual beliefs over time. Random noise represents environmental or social changes that can influence individual opinions. We hypothesized that individuals are more likely to reassess and alter their opinions by intensifying these perturbations by applying random noise. To explore this hypothesis further, we conducted a univariate analysis by increasing the intensity of random noise ($\varepsilon_i(t)$). As the intensity of the random noise increases, the peak temperature shows a corresponding rise, while the mean opinion becomes less mitigative. Specifically, random noise alone was sufficient to elevate the peak temperature by 0.6°C, as illustrated in Fig B.3. This indicates that regular unexpected events (environmental, political, economic, and others) obstruct mitigation efforts as they can create uncertainty in long-term planning, ultimately delaying emission reduction. This finding highlights the influence that random factors can exert on the overall temperature behaviour within the system, even though these random events might seem neutral.

Social learning considerably reduces peak temperature anomaly

We analyzed the scaling parameter (ψ) that influences stubbornness and susceptibility to other opinions in the network by varying it from 0.1 to 1. This scaling factor is important in shaping the average opinion and temperature anomaly. We found that an increase in the scaling factor results in a notable decline in peak temperature, dropping from 2.8°C to 1.5°C. At the same time, this modification shifted the mean opinion from a neutral position towards mitigation, as illustrated in Fig B.2. This interaction among scaling, opinion dynamics, and temperature signifies the connections that govern social agreement and environmental reactions to climate change.

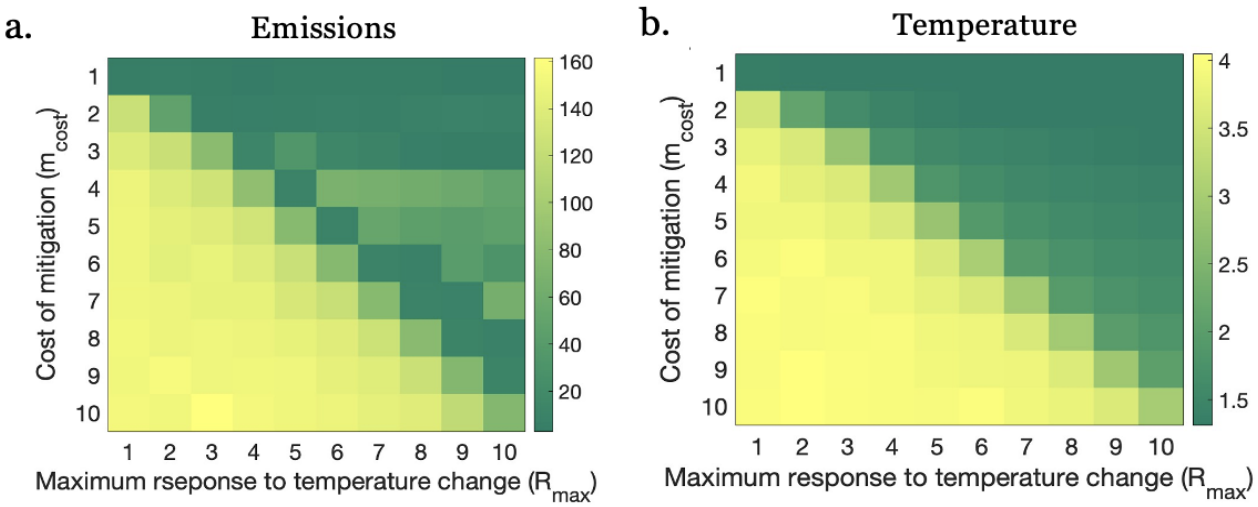


Figure 3.5: **Temperature response and cost of mitigation have a major influence on emission and peak temperature** Heatmap showing the influence of variation in R_{max} and m_{cost} on (a) emission levels and (b) peak temperature anomaly.

High mitigation costs with weak temperature response increases polarization

Conducting a bivariate analysis enabled us to evaluate and differentiate the impacts of changes in parameters on various important outputs like the peak temperature, emission rates, average opinion, and the level of polarization. Our bivariate analysis involving the variations in the parameters R_{max} and m_{cost}, revealed that both parameters had a similar influence on the outcomes we studied, illustrating that their influences are comparable in significance. We observed that a combination of relatively low costs with higher temperature responses led to lower peak temperatures and emissions, as shown in Fig 3.5, while simultaneously fostering mitigation through higher average opinions and an increased degree of polarization, as illustrated in Fig 3.6. This indicates that lowering the cost of mitigation and increasing the response to temperature can effectively diminish emissions and polarization.

Heightened response to temperature changes drives unified mitigation efforts

Comparing Fig 3.5a and 3.6a shows a crucial pattern relating emission levels with polarization. Despite the general trend revealing that high mitigation costs with low response

increase peak temperature levels, emissions, polarization and decrease average opinion, the emission levels and polarization act differently at certain specific points. Low polarization is observed with an increased response to temperature change even when the mitigation cost is high, which suggests the possibility of unified mitigation when the individual response to mitigate these changes. The high cost of mitigation is no longer a concern for individuals at this stage. This indicates a threshold effect in which a specific interplay of R_{max} and m_{cost} results in reduced polarization and temperatures.

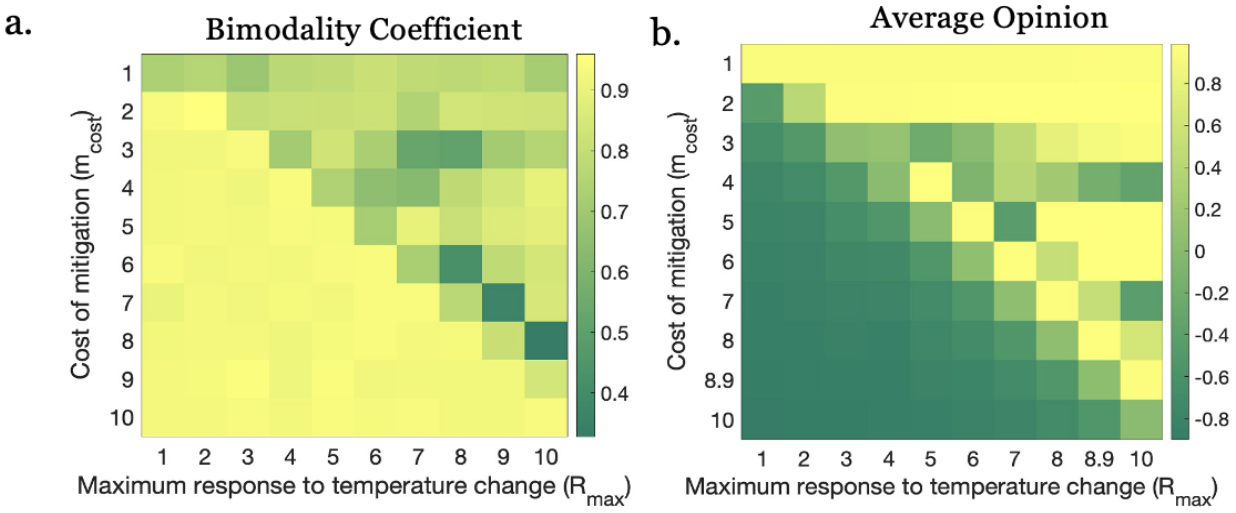


Figure 3.6: **Temperature response and cost of mitigation have a major influence on opinion formation** Heatmap showing the influence of variation in R_{max} and m_{cost} on (a) polarization using bimodality coefficient and (b) average opinion.

R_{max} and m_{cost} considerably influence model dynamics

A bivariate analysis conducted to assess the influence of the scaling factor (ψ) along the cost of mitigation (m_{cost}), clearly illustrates that the effect of the scaling factor is considerably reduced when compared to the overall impact the cost of mitigation has on the peak temperature anomaly. In particular, in circumstances where the cost of mitigation remains relatively low ($m_{cost} \leq 2$), the scaling factor has a considerable influence over the average opinion of the population; however, as the cost of mitigation begins to increase, the scaling factor's impact on the average opinion of the population is reduced (Fig B.6 (a,b) and B.7 (b)). In this model, the scaling factor is linked to the social learning component typically

incorporated in social-climate models that aim to understand human behaviour and climate change. An increase in social learning enhances efforts toward mitigation, similar to the findings in various discrete social-climate models [98, 99, 209].

An examination focusing on the connection between the scaling factor and the temperature change response, denoted as (R_{max}), revealed that heightened social learning, as signified by the scaling factor, can elevate peak temperatures when the response is constrained ($R_{max} \leq 2$) (Fig B.4). As social learning rises with reduced temperature responses, the collective opinion of the population transitions from a non-mitigative to one that supports mitigation (Fig B.5 (b)). In essence, the findings indicate that the scaling factor exerts a stronger influence on peak temperatures, emission rates, and the opinion of the population when both mitigation costs and temperature responses are relatively minimal. An examination of polarization while adjusting these parameters shows that polarization is directly tied to the scaling factor rather than being a consequence of variations in the temperature response (Fig B.5 (a)). Conversely, the scaling factor appears to exert minimal influence when the cost of mitigation is higher (Fig B.7 (a)). Furthermore, the analysis of the impact of additional model parameters with fluctuations in R_{max} and m_{cost} suggests that elements such as the social influence of agents (A) and the sensitivity to temperature variations (α) have considerably less effect on the overall dynamics compared to the roles of R_{max} and m_{cost} (Fig B.8 - B.15). Our findings suggest that enhancing the response to temperature change and lowering the cost of mitigation is ideal for addressing climate change.

3.4 Discussion

This model highlights the role of opinion dynamics on social networks and coupled social-climate feedbacks in shaping views on climate change and thus intensifying or mitigating climate change impacts. Climate opinions reflect not just personal beliefs but also the influence of external factors such as social interaction, individual responses to climate events, and the costs associated with mitigation. Our model shows how opinion polarization can arise in a broad parameter regime for all three of these factors. Moreover, opinion formation depends on the climate scenario and individual interactions.

This is the first demonstration of the emergence of opinion polarization in a human-environment system, to our knowledge. Our simulations also indicate that even with polarized opinions, an average pro-mitigation opinion in the population can enhance mitigative behaviour and reduce emissions. Although having an entire population with a strongly pro-mitigation opinion is not essential, a minimum of 50 percent of the population em-

bracing mitigation is necessary to limit our emissions and halt warming. The ideal way to boost the number of mitigators in the population is to lower the mitigation costs and increase individual response to climate change by adopting mitigation-friendly lifestyles. However, our simulation also points out some critical values of mitigation costs that could eliminate polarization. These critical points suggest that a heightened response to climate change can lessen the concerns over the cost of mitigation at certain points.

Feedback from the environmental systems influences long-term opinion distribution. According to our analysis of the climate change issue, frequent and unexpected social or environmental changes could also result in lower average pro-mitigation opinion in the population, leading to elevated peak temperatures. Our findings show that social learning (represented by the scaling parameter) is important in forming opinions on climate change, and that a high social learning rate can reduce temperature anomalies. However, a highly stubborn population can result in an average global temperature anomaly in excess of 2°C. Elements such as increased responsiveness of individuals to climate change, reduced mitigation costs, and enhanced social learning can promote mitigation, especially in tandem.

Although this model offers a new perspective on coupled social-climate dynamics, it does not include all relevant aspects. Several social factors might contribute to opinion shifts regarding climate change, including climate education, media representation, economic circumstances, and political influence [198, 199, 172]. These factors were not explicitly represented in our social learning model. There is a possibility for global consensus on certain mitigative strategies, free from biases related to politics, geography, or cultural influences [172]. This could give rise to other issues when individuals do not express their true opinions to align with the prevailing political, cultural, or geographical ideologies. Incorporating these elements could serve as a valuable extension to the model, enabling deeper exploration of several aspects of society that may promote or hinder mitigation. Even without these aspects, simple coupled models like the one presented in this work can provide valuable insights into the interplay between opinion and climate systems. More sophisticated social-climate models that build on these insights could help policymakers create targeted strategies that address prevailing opinions, ultimately enhancing the effectiveness of climate change mitigation initiatives.

Chapter 4

Space, time and altruism in pandemic and the climate crisis

This chapter is based on the paper in preparation: Chris T Bauch, Athira Satheesh Kumar, Karoline Wiesner, Simon A. Levin, and Madhur Anand. Space, time and altruism in pandemic and the climate crisis. In preparation 2025.

Abstract

Anthropogenic climate change exemplifies a common-pool resource (CPR) problem that requires quick action, and yet progress on climate change mitigation has been slow and incomplete. In contrast, COVID-19 is also a CPR problem, but human populations reacted much faster and achieved partial success in mitigating the worst possible impacts of COVID-19. Why has the human response to the climate change crisis been so different from the response to COVID-19? We hypothesize that the answer has to do with not only the spatial and temporal scale of the problem, but also the 'altruistic scale' that governs whether individual actions primarily affect self or others. We develop an agent-based network model to explore this question. We identified many factors that influence the behavior of individuals in both systems, such as the spatial scale and duration or severity of the impact, the perceived benefits derived from mitigation, the associated costs of mitigation, and the costs linked to impacts, among others. The framework is able to replicate both the lack of inaction in the case of climate change mitigation as well as the faster response that humans exhibited to COVID-19. The framework also suggests how behavioural responses to climate change can be accelerated. We suggest how these insights can be used to inform climate mitigation and infectious disease control.

4.1 Introduction

The Intergovernmental Panel for Climate Change (IPCC) called for rapid, unprecedented social change to combat climate change [217, 218]. However, progress has been inadequate despite the risk to lives and the economy. In contrast, the COVID-19 pandemic stimulated rapid, unprecedented social change in a very short period of time [219, 220, 221], even to the extent of reducing global greenhouse gas emissions by 14% during shutdowns [222]. This difference in our collective response calls for an explanation [223].

To explore this issue, we consider climate change and COVID-19 as common pool resources (CPRs): a natural resource is available to all members of a population, but its supply is finite, hence self-interested actions could lead to overuse and depletion of the resource [224, 54, 225, 226]. Preventing overuse is best for the group as a whole, but this outcome may be prevented because non-cooperating might be beneficial at the individual level [227, 228, 229].

Natural systems such as forests, waterways, and fisheries exemplify CPRs [230, 231]. Similarly, addressing the ozone hole problem required a coordinated response [232]. Although a top-down ban on ozone-depleting substances like chlorofluorocarbons was im-

posed, an important impetus for government action on CFCs was public pressure [233]. A stable climate also represents a common good that is threatened by the overuse of fossil fuels that harm everyone [234, 226]. To preserve a stable climate, individuals must adopt behaviours that could be costly, such as switching to solar energy by installing solar panels in a house or buying a more expensive electric vehicle [217]. This benefits everyone, but the individual incentive to avoid costly measures means some individuals ('free riders') may not adopt them [196, 235, 236]. Effective coordination is important to prevent or mitigate a tragedy of the commons [237, 238, 239]. Infectious disease control can also be viewed as a CPR [240]: public health is a shared and finite resource, but the reluctance of some individuals to follow public health measures leads to uncontrolled infection spread, affecting everyone [241, 242]. To mitigate the epidemic, individuals must pay a real or perceived cost, such as wearing a mask [243].

Climate change and infectious diseases both involve CPRs, but are dissimilar in other respects. The climate crisis concerns a well-mixed system (the atmosphere) where emissions from a single tailpipe are dispersed planet-wide after a relatively short period of time, whereas infections spread locally. If neighbours of Patient Zero act quickly to contain the outbreak, then the outbreak is stopped and the larger population is spared costly mitigation measures. However, if neighbours fail to act and become infected, they may in turn pass the infection to their own neighbours. As a result, the infection percolates through the entire population and between populations, eventually reaching almost every corner of the planet. This tug-of-war has been termed the 'race to trace' in the context of ring vaccination for smallpox [244]. A few people acting decisively can prevent morbidity and mortality for more people further down the chain of transmission. In contrast to the smallpox endgame, we lost the 'race to trace' during COVID-19 due to behavioural and epidemiological factors, and we fell back on mitigation measures that nonetheless saved many. It could be said that COVID-19 represents a CPR problem that propagates through local networks. Pandemics originate when infection control in the initial stages are a failure, due either to properties of the pathogen, lack of knowledge, or lack of adherence to infection control, the latter of which is our particular focus.

The difference in locality of impact illustrates one difference in the spatial scale of climate change mitigation and infectious disease control. These challenges also differ with respect to their temporal timescales. Epidemics pass through populations in a matter of weeks [245, 246], while the impacts of GHG emissions take generations to be felt [247, 248, 249, 250].

Finally, there is a difference in what could be called the altruistic scale of climate change mitigation and infectious disease control. If a single individual chooses to adopt a costly climate mitigation measure, the benefit to the individual of the resulting reduction in GHG

emissions is the same for all individuals, since everyone benefits from the small incremental reduction to the global temperature anomaly. However, the benefit to the individual from adopting infection control measures protects the individual more than the others in the population. Many vaccines not only block transmission but also prevent disease in the vaccinated individual [251]. Moreover, for an infectious disease intervention to protect others in the population, it faces a double barrier: it has to be effective both in protecting the mitigator, and also protective in terms of the mitigator not passing on the infection to their neighbourhood. Similarly, preventing infection through masking also prevents onward transmission, but a masker who does get infected might reduce their disease severity while also passing on the virus to a more vulnerable neighbour who is more affected [252]. Here we are not considering other social or psychological factors that might support climate change mitigation [253].

Our objective is to develop a network-based framework to help us understand how individual and group behaviour in common pool resource problems (CPRs) depend on the spatial, temporal, and altruistic scales of the system. Exploring these three scales provides a structured way to examine and compare behaviour in these common pool resource problems and thus better understand the difference in population reactions to COVID-19 versus the climate crisis. Comparing pandemic and climate systems can provide valuable information regarding the reason why mitigating the pandemic was partly successful, whereas mitigating climate change remains a challenge [217, 254, 255, 218, 256].

4.2 Methods

We hypothesize that three dimensions of common pool resource problems explain many differences in population responses to COVID-19 versus the climate crisis (Fig 4.1).

- Spatial scale: How widely is the change in individual behavior felt in the natural system? How widely do changes in the natural system impact populations?
- Temporal scale: How long does it take for an individual behavior change to be felt in the natural system? How quickly do changes in the natural system impact populations? In other words, how long do populations wait to experience the feedback of their collective decisions?
- Altruistic scale: Does a given change in an individual's behavior benefit only the individual, only others, or somewhere in between? This quantifies the relative impact of strategy choices on self versus others and reflects whether altruism can play a role in decision-making.

These dimensions of common pool resource problems appear in Fig 4.1 and each scale is government by a parameter, Q, ε and δ. These parameters differ by orders of magnitude between the two systems. In the case of climate change, the timescale δ will be very small, since greenhouse gases persist for a long time in the atmosphere. In contrast, acute infections resolve quickly, on a timescale of days or weeks, hence δ is large in that case. Greenhouse gas emissions spread globally, so the relevant spatial scale is a fully connected network with $Q = N - 1$, while infectious diseases spread locally thus $Q \ll P$. Finally, the incremental impact of a single individual on GHG emissions provides only a small direct benefit to the mitigator in proportion to the total population N of potential mitigators, hence $\varepsilon = \frac{1}{N}$, whereas infectious disease interventions can provide a significant benefit to self, regardless of whether they are effective in protecting others or how large the population size is ($0 \ll \varepsilon < 1$).

We illustrate this framework through an agent-based network model. We consider a network of individuals who can adopt behaviors that impact the abundance of a natural agent that spreads through network edges (e.g., viral load in the case of infectious diseases, or GHG concentration in the case of climate change). We assume N individuals each with Q network neighbors. When $Q = N - 1$, we have a fully connected network where every individual is connected to every other individual in the population. This corresponding to climate change, since emissions generated by a single individual are felt planet-wide, once enough time has passed to allow atmospheric mixing. When $Q << P$, we have a locally connected network, where each individual is only connected to a small neighborhood of individuals, corresponding to infectious disease transmission through a contact network (Fig 4.1).

The prevalence of the natural agent influences individual behavior and their well-being. The behavioral states are either mitigator (M) or non-mitigator (N) and is denoted as $B_i \in N, M$. In each timestep, an individual can switch between behavioral states with a transition probability (P_{MN}, P_{NM}) that depends on how attractive mitigation or non-mitigation appears to them at that time. Similarly, each individual has a physical state corresponding to their well-being, either well (W) or impacted (I), where impacted individuals have been infected, or suffered a climate change impact. The physical state of an individual i is denoted by $H_i \in W, I$. Individuals can switch between physical states with a transition probability (P_i^M, P_i^N) that depends on how the natural agent spreads through the network and how likely individuals will be impacted by it.

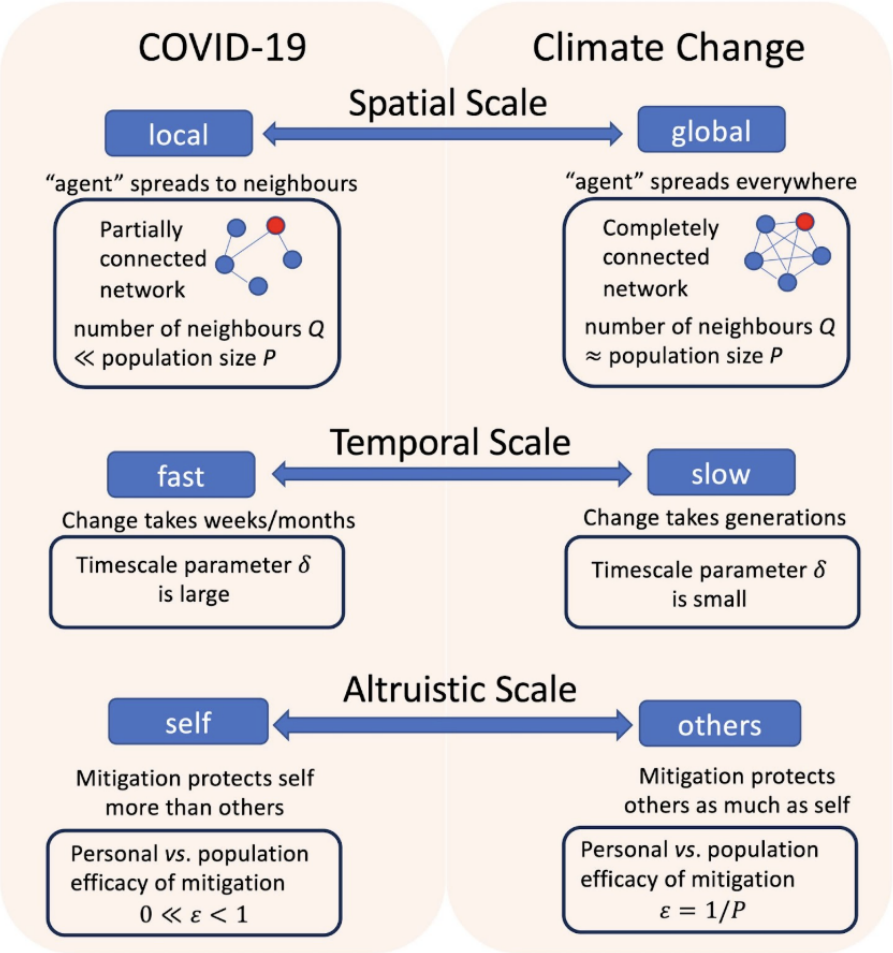


Figure 4.1: **Schematic representation of the model :**Representation of the cases identified depending on the spatial, temporal, and altruistic scale.

Both transition probabilities depend only on the perceived cost of being a mitigator (c_M), the perceived cost of being impacted (c_I), how long the individual remains impacted (D), the rate (probability per timestep) that the natural agent spreads along a network edge (β), the extent to which mitigation benefits oneself more than others (ε), and how strongly the differing attractiveness of mitigation or non-mitigation influences decision-making (σ).

Individuals are more likely to switch from non-mitigation to mitigation if the costs of mitigation (c_M) are less than the probability of being impacted (β) multiplied by the cost of the impact (c_I), although other factors may come into the decision. Individuals

can move from impacted back to well depending on how long it takes them to recover from an impact. The prevalence of the natural agent that node i is subject to at time t is denoted as $A_{i,t}$ (which is the local prevalence of virus for an infectious diseases, or greenhouse gas (GHG) concentration corresponding to extreme climate event risks for climate change). This quantity determines the probability of impact (Eq (4.4) and Eq (4.5)). In each timestep, the behavioral state, physical state, and prevalence of the natural agent are updated according to transition probabilities.

4.2.1 Behavioral Transitions

An individual i who is a non-mitigator (N) transitions to the mitigator (M) state with a probability

$$P_{NM} = \frac{1}{1 + exp[-\sigma(e_N - e_M)]} \tag{4.1}$$

where e_M is the payoff for being a mitigator, e_N is the payoff for being a non-mitigator, and σ controls how important the payoff differential is for decision-making. Similarly, an individual i who is a mitigator transitions to the non-mitigator state with probability

$$P_{MN} = \frac{1}{1 + exp[-\sigma(e_M - e_N)]} \tag{4.2}$$

The payoffs are given by

$$e_{N,i} = L - p_i^N c_I D \tag{4.3}$$

$$e_{M,i} = L - p_i^M c_I D - c_M \tag{4.4}$$

where c_M is the cost of being a mitigator, c_I is the cost of being impacted, L is a baseline payoff, D is the duration of the impact, p_i^M is the probability of being impacted if node i is a mitigator, and p_i^N is the probability of being impacted if node i is a non-mitigator. These two functions are, in turn, given by

$$p_{i,t}^M = 1 - [1 - \beta(1 - \varepsilon)]^{A_{i,t}} \tag{4.5}$$

$$p_{i,t}^N = 1 - [1 - \beta]^{A_{i,t}} \tag{4.6}$$

where $0 < \beta < 1$ controls the spread of the natural agent along edges, and $0 < \varepsilon < 1$ is the efficacy of mitigation for protecting the individual from being impacted. These equations represent the benefits of being a mitigator in protecting the individual against impacts.

4.2.2 Physical Transitions

In each timestep t, a non-mitigator (N) produces a fixed amount of natural agent $A_{i,t}$. This corresponds to individual behaviour that causes greenhouse gas emissions, or the spread of infection during the acute infection when the virus is multiplying in the host. Mitigators produce the natural agent to a lesser extent according to the efficacy (ε). Individuals can also be exposed to the natural agent from neighbours, although they are exposed less if there are more mitigators in their neighbourhood. The natural agent that the node is subject to decays in each timestep, at rate δ. If node i is a mitigator then the dynamics of $A_i(t)$ are given by:

$$A_{i,t+1} = \frac{1-\varepsilon}{Q+1}A_{i,t} + \frac{1}{Q+1}\sum_{j\neq i, j=N}^{Q} A_{j,t} + \frac{1}{Q+1}\sum_{j\neq i, j=M}^{Q} A_{j,t}(1-\varepsilon) + (1-\delta)A_{i,t}$$

and if node i is a non-mitigator:

$$A_{i,t+1} = \frac{1}{Q+1}A_{i,t} + \frac{1}{Q+1}\sum_{j\neq i, j=N}^{Q} A_{j,t} + \frac{1}{Q+1}\sum_{j\neq i, j=M}^{Q} A_{j,t}(1-\varepsilon) + (1-\delta)A_{i,t}$$

According to these equations, the prevalence $A_{i,t+1}$ of the natural agent experienced by node i at time $t+1$ is the prevalence $A_{i,t}$ that remains from the previous timestep, which decreases by an amount that disappears due to decay at rate δ, and increases by the amounts created through current activity in time t. Each node generates an amount $\frac{A_{i,t}}{Q+1}$ of the natural agent if they are a non-mitigator (N), and an amount $\frac{(1-\varepsilon)A_{i,t}}{Q+1}$ if they are a mitigator(M).

We note that $A_i(t)$ is analogous to the infection state in compartmental epidemic models for a disease that is normally mild or subclinical–especially when an environmental reservoir is involved–whereas the impacted state corresponds to a state of disease/morbidity brought on by the infection. The dynamics of a compartmental SIR model will not correspond on a one-to-one basis with these dynamics. The natural agent is only produced in proportion to the current amount. This means that if there is no natural agent in the network, it cannot be produced. In the case of COVID-19, this means that if the virus is extinct, it cannot be spread. In the case of climate change, this dependence occurs because a node that does not currently emit greenhouse gases will not emit them in the next time step. Rather, non-mitigating behaviour needs to be learned from adjacent nodes in the network.

The efficacy of protection depends on the behavior of both the node and its neighbors. This determines the probability of impact at time t according to equations (4.5) and (4.6).

An impacted individual recovers with probability $p_R = \frac{1}{D}$, where D is the duration in the impacted state. We express the total prevalence of natural agent in the population at time t as $A_t = \sum_{j=1}^{N} A_{j,t}$.

4.2.3 Simulation design

We consider a network with 1000 agents to explore these scenarios using MATLAB. We start with an initial population comprising of entirely susceptible non-mitigators. We use a static network and do not consider births and deaths. The network is formed by connecting random pairs of nodes until the desired degree (Q) is achieved. The natural decay of the natural agent (δ) is considered as 20 with a personal efficacy (ε) of 0.3 and $Q = 5$ in the case of COVID-19. In the case of climate change, the natural decay of natural agents occurs at a rate of δ, which is considered 0.01 and with ε as $1/N$ and $Q = N - 1 = 999$. Other baseline parameter values are the same for the pandemic and climate change scenarios (Table 4.1). The simulation begins by calculating the probabilities of being impacted, and switching strategies based on these parameter values. The physical and behavioral states of the individuals change according to the calculated values. We also calculate the number of individuals in each state (physical and behavioral) at each time step. The probabilities of being impacted and the switching strategies are updated at each time step until the simulation ends. Finally, the number of individuals in each state in the final time step is plotted.

4.3 Table of Parameters and Functions

4.4 Results

4.4.1 Four scenarios for COVID-19 and climate change

The scale differences for COVID-19 and climate change (Fig 4.1) generate four scenarios: successful containment/mitigation of COVID-19 (scenario 1) or lack of control leading to spread and partial reductions in case burdens (scenario 2), and a (hypothetical) strong mitigation (scenario 3), or lack of control (scenario 4). These can be obtained from the network model by varying the values of δ, Q, and ε to obtain the limiting cases described in Fig 4.1, but also, as the relative cost of mitigation (c_M), cost of impacts (c_I) and duration of impact (D) are varied in the model, it is possible to go from one scenario to another.

Parameters	Description	Values
N	Total number of individuals	1000
Q_{covid}	Neighbourhood size (node degree) for covid	25
$Q_{climate}$	Neighbourhood size (node degree) for climate	N-1
ε_{covid}	Personal efficacy of mitigation for covid	(0,0.3,1)
$\varepsilon_{climate}$	Personal efficacy of mitigation for climate change	$1/N$
δ_{covid}	Natural decay rate for covid	20
$\delta_{climate}$	Natural decay rate for climate change	0.01
c_M	Cost of being a mitigator	2000
c_I	Cost of being impacted	1000
D	Duration of impact	30
σ	Constant controlling the importance of payoff differential	10
β	Constant controlling impact probability	(0,0.24,1)
Function	Description	
p_i^M	Probability of being impacted in mitigators	calculated
p_i^N	Probability of being impacted in non-mitigators	calculated
e_M	Payoff of being a mitigator	calculated
e_N	Payoff of being a non-mitigator	calculated
P_{MN}	Probability of a mitigator transitioning to a non-mitigator	calculated
P_{NM}	Probability of a non-mitigator transitioning to a mitigator	calculated

Table 4.1: Table describing the model parameters and baseline values.

For the special situation where the initial population consists entirely of mitigators except for one non-mitigator, we can obtain equations that shed light on system behaviour. In this situation, $A_{i,0} = 0$ for all i except for node $i = 0$, with $A_{0,0} = 1$), a mitigator neighbor of node $i = 0$ remains a mitigator if $e_{M,i} < e_{N,i}$, thus

$$c_M < c_I D((1 - \beta(1 - \varepsilon))^{A_{i,t}} - (1 - \beta)^{A_{i,t}}), \tag{4.7}$$

(see Appendix for derivation). In other words, if the cost of mitigation (c_M) is sufficiently low relative to the probability and costs of being impacted. If c_M is too high and the inequality no longer holds, then some or all of the neighbours will switch to non-mitigation, causing the agent to spread to the neighbourhood and beyond: the population loses the 'race to trace'. These correspond to scenarios 1 and 2. We note that for the climate change system where acting to mitigate is primarily for the benefit of others, when $\varepsilon = \frac{1}{N} \approx 0$, we obtain

$$c_M < c_I D((1 - \beta(1 - \varepsilon))^{A_{i,t}} - (1 - \beta)^{A_{i,t}}) \approx 0 \tag{4.8}$$

hence implying failure to mitigate even when the cost to mitigate is very low. In this case, c_M must be very low for climate change mitigation to be successful. Mitigation could fail for climate change on account of the low value of δ (slow timescale) and the fact that

the prevalence of natural agents is initially very small and the impact is spread among $Q \approx N$ neighbors. However, a possible outcome in this situation is that climate change initially worsens, but later, it is contained/mitigated once the impact becomes sufficiently widespread on account of mounting GHG concentrations. In a situation where climate change mitigation occurs due to locality of impacts, such as microclimate, Q is smaller, although not as small as COVID or measles or mitigation is seen to protect both self and others, which is valued. Hence ε is significantly larger than $1/N$. In either case, individuals will eventually begin mitigating, even if they do not react immediately, as in the case of COVID-19.

It is possible to show from Eq (4.3) and (4.4) that if there is one unit of natural agent present, the individual will choose to mitigate ($e_M > e_N$) if and only if,

$$\beta > \frac{c_M}{\varepsilon c_I D} \tag{4.9}$$

The derivation of Eq (4.9) is in supplementary information.

4.4.2 Simulation Results

The four scenarios are illustrated by simulation of our network model. For COVID-19, with a relatively low neighbourhood size Q, fast decay rate δ, and high personal efficacy ε, the neighbours of any initial non-mitigator nodes quickly adopt mitigation measures, since having a single neighbour who adopts risky non-mitigating behaviour, and the availability of efficacious means of protection, are sufficient to convince all neighbours to adopt mitigation and thus contain the virus immediately (Fig 4.3, top left). It is only for a large mitigation cost that this finally fails, and the virus percolates through gaps in the neighbourhood to eventually reach the entire population (Fig 4.3, top right). Neighbours may temporarily adopt mitigation, but at insufficient rates and not long enough to prevent viral spread in the entire population. The switch between behaviours occurs at $c_M = c_I D((1-\beta(1-\varepsilon))^{A_{0,0}} - (1-\beta)^{A_{0,0}})$.

In the case of climate change, mitigation is more challenging. The population is completely connected and hence spatial localization does not occur–the population is homogeneously mixing when $Q = N - 1$. Personal efficacy ε is very small, so non-mitigation grows rapidly. Climate change can only be prevented if the cost of mitigation c_M is very small (Fig 4.3, bottom).

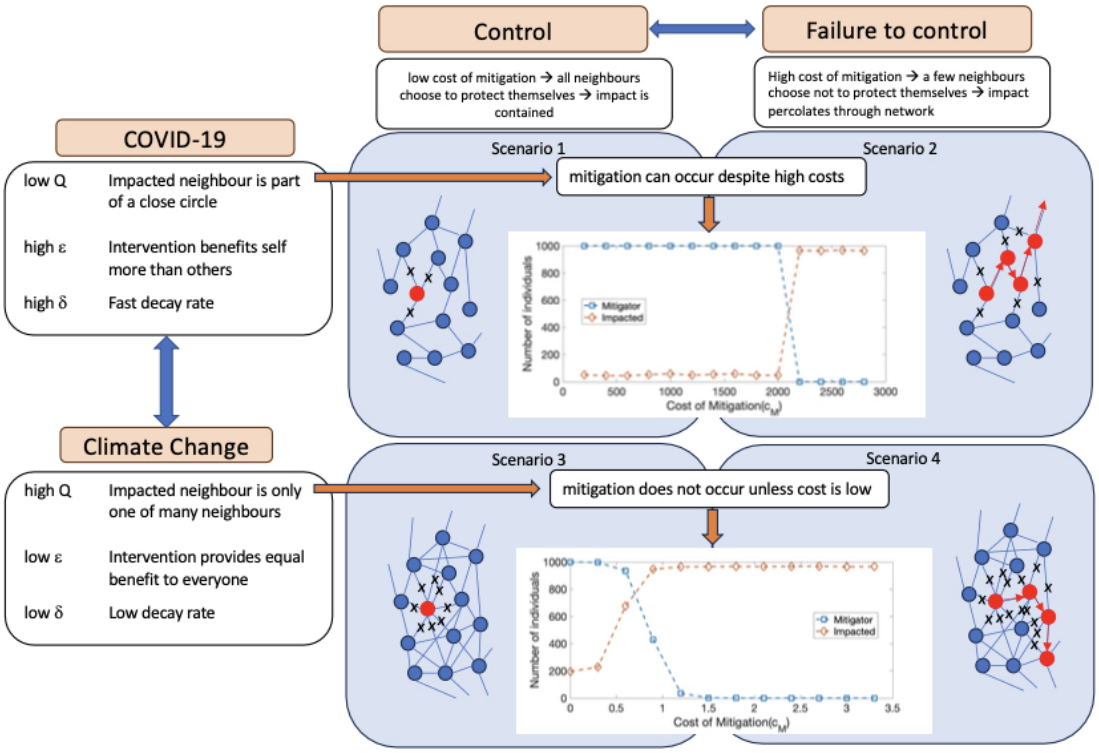


Figure 4.2: **Four scenarios with simulation results.** Parameters for scenario 1 and , scenario 2: $Q = 25$, scenario 3 and scenario 4: $Q = N - 1 = 999$. Remaining parameters are in Table 4.1.

It is possible to transition between the extremes of COVID-19 and climate change by varying the neighbourhood size, decay rate, and efficacy (Q, δ, and ε, Fig 4.3a-c). As these parameters change, the population switches between strong mitigation (few impacts, many mitigators) and no control (widespread impacts, few mitigators). Transitions in the timescale parameter δ result in a more gradual switch between these two regimes. There is also a broad intermediate regime of partial mitigation, for both COVID and climate change, where mitigation is sufficiently attractive that many individuals are adopting it at any given time, but it is not attractive enough to maintain strong coherence to the mitigation and thus impacts are also significant (Fig 4.3d). In the case of climate change, this corresponds to the expected initial failure to take up climate change mitigation on account of low ε. However, since the decay rate δ is slow, eventually there are enough greenhouse gases to force more of the population to choose mitigation, although by this time there are widespread impacts already.

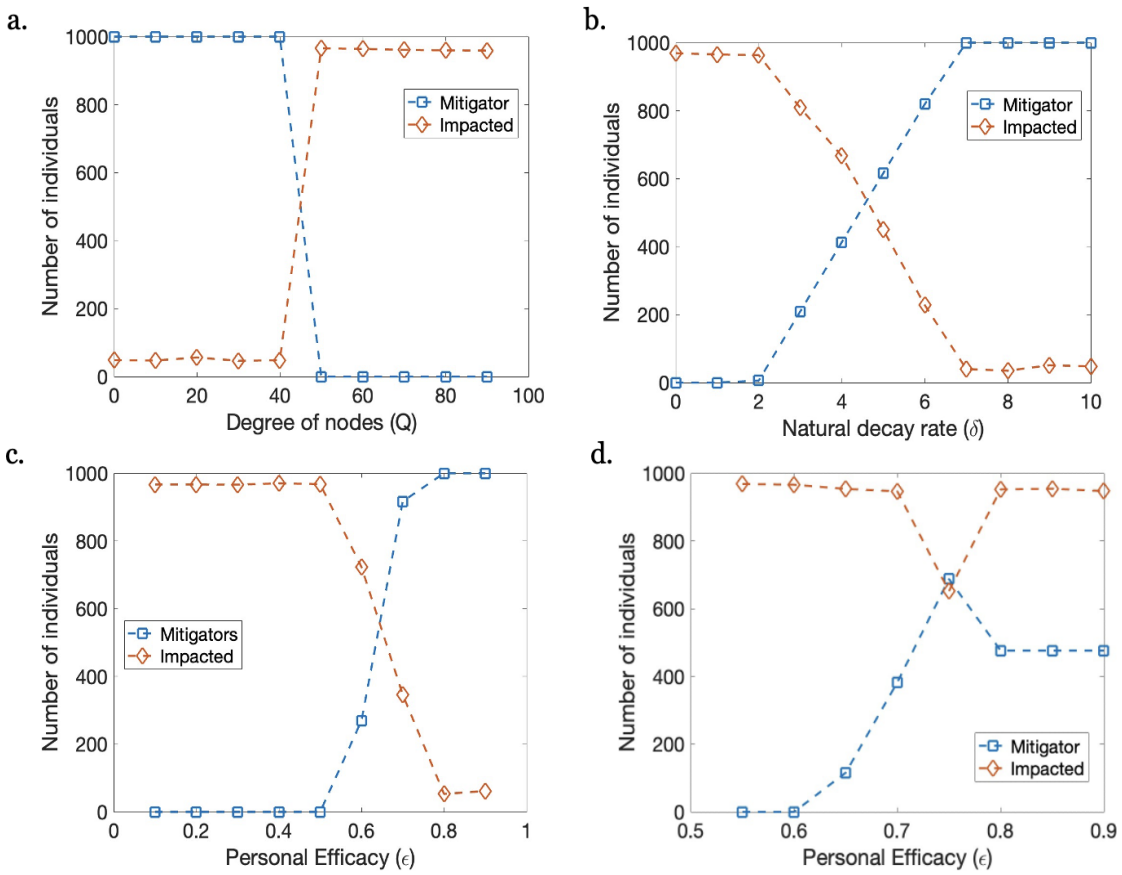


Figure 4.3: **Effect of scaling parameters on dynamical regimes.** Number of mitigators (squares) and impacted individuals (diamonds) under variation for (a) neighbourhood size Q, with $\beta = 0.03$, and $\delta = 2$, (b) decay rate δ, with $\beta = 0.03$, and $Q = 60$, (c) personal efficacy ε, with $\beta = 0.3$, and $Q = 500$ and (d) a regime of partial mitigation, with $c_M = 500$, $Q = 500$, $\beta = 0.7$, $\delta = 0.4$. Remaining parameters are in Table 4.1.

Exploring the distribution of impacts among mitigators and non-mitigators is also illuminating. For COVID-19, we observe a simultaneous switch from healthy mitigators to impacted non-mitigators as the cost of mitigation increases beyond its threshold (Fig C.2.1). But for the climate system, notable changes occur near the threshold in c_M that separates control from non-control (Fig C.2.2). As c_M increases past the threshold, the number of impacted mitigators increases as the population of non-mitigators grows, causing spreading impacts. As c_M continues to rise, mitigation behaviour disappears, and the

entire population consists of impacted non-mitigators. Variation in ε creates a similar pattern (Fig C.2.3). Low values of ε suppress mitigation and result in widespread impacts in the population. As ε is increased, an intermediate regime occurs where non-mitigators become more widespread, but suffer impacts from remaining non-mitigators. At the highest values of ε, mitigation is universal and impacts are minimal.

4.5 Discussion

The effects of spatial and temporal scales on systems is a frequent topic of study in many fields [257]. However, the impact of these scales on common pool resource problems is less studied [258, 259] and comparative analysis for specific types of systems is rare. Here we propose an explanation for the widely differing reaction to the emergency of COVID-19 versus that of climate change in terms of not only spatial and temporal scales, but also an altruism scale that quantifies the relative extent to which a behaviour benefits self or others. The altruism scale emerges naturally once common pool resource problems are moved into a human-environment framework, where we are forced to consider how actions affect a natural system, which in turn affects the human population again, in a two-way feedback loop [260, 159, 261].

Our framework identifies the cost of mitigation as one of the main determinants of uptake of control and mitigation measures, for both climate change and COVID-19, as expected. However, the population may adopt control measures at a higher cost for COVID-19 than for climate change. This reflects how, during the COVID-19 pandemic, individuals during the first wave were willing to adopt not only contact precautions like handwashing, mask wearing and social distancing, but also more expensive measures such as school and workplace closures. In contrast, control or even mitigation against climate change requires a very low cost to control or mitigate, on account of the large neighbourhood size, slow decay rate, and low personal efficacy. If this low cost can be achieved, then the switch to mitigation behaviour is predicted to be quick. This switch might be accelerated by a change from net costs for renewable energy to net savings relative to carbon-based energy sources, for example [262].

Our framework made simplifying assumptions that could affect the outcomes. For instance, we assume that individuals have perfect knowledge of their impact risk, and that decisions are based solely on parameters such as payoffs, mitigation costs and cost of impact. We also intentionally modelled the natural system dynamics in similar ways for COVID-19 and climate change, aside from differences in the parameter values used. Although the scale of time, space and altruism are important, other factors can be crucial

in CPRs, such as the level of organization complexity of the system [263]. For instance, better results in resource management have been observed when combined community and governmental efforts lead to sustainable transitions [264, 265]. In addition to sustainability, CPR management focuses on multiple factors, such as government and community interactions along with cultural, economic, and ecological factors, by looking at the interaction between human and environmental systems [266, 267]. This could be explored in future work. Similarly, there is a strong influence on human decisions by the choice of their neighbors, especially in the case of environmental decision-making [268, 269], and the framework could be extended in this direction, which would also benefit from the extensive literature on complex network structure [270]. Our primary objective was to demonstrate the value of comparing CPR problems with different characteristic scales, as opposed to creating a realistic model of either system.

This framework suggests possible strategies to accelerate the uptake of climate change mitigation. For instance, the framework suggests that turning a problem from a global one to a local one (smaller Q) could help support uptake. For climate change, this could occur through emphasizing co-benefits of reduced GHG emissions, such as air pollution reduction [271]. Approaching climate change as a local problem can also leverage faster behavioral change by considering the local and shorter-term impacts (high δ) of extreme weather events like heatwaves, floods, and droughts. Finally, expanding the definition of 'self' to include future generations or other individuals through deepending altruism [259] could increase the perceived personal efficacy ε [272, 259], in the same way that protecting immediate family was a powerful motivator for uptake of COVID-19 contact precautions [273]. In conclusion, comparing common pool resources problems with very different spatial, temporal, and altruistic scales may not only explain differences in human behaviour but also suggests ways in which more sustainable behaviours could be supported.

Chapter 5

Conclusion

5.1 Summary of findings

The purpose of this thesis is to examine the relationship between human behavior and climate change. An increasing number of researchers are working on coupled socio-climate models, as they are extremely useful in understanding and identifying the factors that motivate people to adopt mitigation strategies. In the first work, we linked a rumor propagation model with binary outcomes (mitigating or non-mitigating) to an earth system model to understand how climate rumors influence human attitudes toward climate change (Chapter 2). In the second work, we developed an opinion model with continuous opinions on climate change (Chapter 3). We linked the continuous opinion model with an earth system model to understand the dynamics between the two systems. In the third work, we explored the difference in people's attitudes towards climate change by comparing it with COVID-19, looking into temporal, spatial, and altruistic aspects of these two systems(Chapter 4).

The rumor propagation model is inspired by compartmental modelling to understand how rumors about climate change and temperature anomalies influence each other by considering individual and group propagation. In this age, where social media plays a significant role in shaping public opinion, we looked at how rumors about climate change can influence individual emissions and how their experience with the changing climate shapes their attitude towards climate change. We considered rumors about climate change, like climate change is a myth or not a real issue, with two categories of individuals – people who believe that climate change is not real (believers or non-mitigators) and people who reject this rumor (rejectors or mitigators). The findings of this model suggest that mitigation strategies by individuals who reject rumors are vital in reducing emissions and, hence,

temperature levels. This mitigation strategy is the component that links human behaviour with climate change in our model. Further, we investigated how social aspects, such as believing or rejecting the rumors, the properties of group propagation, and mitigative actions influence temperature levels. The results of this investigation show that rejecting the rumors by acknowledging climate change as a real issue is insufficient, but people should adopt mitigative strategies that limit their emissions. We also recognized that the opinions of larger groups have more influence on the temperature anomaly compared to a large number of smaller groups, suggesting the relevance of collective climate decisions on future climate scenarios compared to local or individual efforts, which suggests the importance of making a global effort towards mitigating climate change. A higher average rate of messages in groups also influences the temperature anomaly, linking the importance of discussions and sharing information about climate change to temperature anomalies.

Human decisions are not always discrete, and we all have a spectrum of feelings regarding various topics, which is not always binary, making our opinions more or less extreme. We modified a classic FJ model in continuous opinion dynamics by adding a parameter that influences opinions based on the changes in global temperature. We identified that the individual responses to the changes in climate they experience, and the costs that are required to make amends in their lifestyle to mitigate these changes act as vital parameters that collectively shape the opinions of individuals. We also explored how polarization emerges in the population and whether unified mitigation is possible. The findings revealed that an increased response to temperature variations and social learning, along with low mitigation costs and stubbornness, can gradually decrease the global temperature. We also identified that noises in the form of environmental or social changes can lead to higher temperature anomalies. Our discrete models suggested that at least 80% of mitigators with efficient mitigation strategies are required to decrease emissions to a desired level. The continuous opinion model suggests reducing emissions even with fewer mitigators if the average opinion supports mitigation. This also suggests that if all the individuals choose to be mitigators, we can reduce the emissions much more than what is targetted and return to the pre-industrial scenarios by 2100.

The discrete and continuous models point toward the same factors: increased social learning and response to climate change, reduced mitigation costs, and collective efforts to achieve our current climate target of limiting warming at 1.5°C. They also suggest that reducing emissions immediately is important to limit warming by 1.5°C. To further understand why people were ready to make a quick transition during the pandemic but are still reluctant to make changes to combat climate change led to the analysis of comparing climate change and the pandemic at three different levels - temporal, spatial, and altruistic scales. We identified four cases as the potential reason behind this difference in behaviour.

Our analysis revealed that the future outcomes vastly depends on the initial responses and the evolution of these decisions over time. This comparative study also pointed toward the same factor, the cost of mitigation, as a major reason for the difference in behaviour. The low mitigation cost in the case of the pandemic greatly motivated people to switch to mitigating strategies and stop the spread of the disease. We identified a threshold cost beyond which people choose to stay as non-mitigators. Also, the efficacy of mitigation is much less in the case of climate change compared to COVID-19 because individual mitigation efforts have low evident changes in the case of climate change, which reduces motivation. Climate change is a global issue compared to the localized nature of the pandemic, where only people who come into contact with each other get affected, which makes its impact widespread.

This thesis has provided a deeper insight into coupled social-climate models by acknowledging the existing knowledge gap. The work in this thesis suggests various social aspects that lead to enhanced mitigation behaviour in individuals to reduce the impacts of climate change. Our objective was to develop coupled socio-climate models that can overcome the challenges posed by traditional climate models and to address the knowledge gap in the current socio-climate models. We used modelling techniques that were previously not used in coupled human-environment models, such as compartmental and opinion models, to understand social dynamics. We identified certain social aspects like mitigation costs, social learning, response to temperature change, group and individual decisions, and the benefits of mitigation that contribute to determining the future climate scenario. Our findings revealed that collective response is extremely impactful in combating climate change since climate change is a global issue that cannot be separated based on geographical, cultural, or political interests. Mitigative strategies of groups and policies to reduce mitigation costs can significantly change the current emission trajectory and encourage unified mitigation. This demonstrates the relevance of nations coming together to reduce mitigation costs and encourage mitigation with higher payoffs.

Along with reducing costs, educating people about climate change and increasing their awareness is vital in making the right decisions regarding mitigation and adaptation strategies. We found that social networks, such as social media platforms, can efficiently enhance mitigation when people identify climate change as a major issue and are reminded about it. Actions taken by larger communities have a greater impact on reducing temperature anomalies. Moreover, our model suggests that we could achieve our climate targets even with a polarized population if more individuals adopt mitigative strategies. We also identified scenarios where polarization could be removed from the population when the response to climate change is at its peak.

5.2 Future Directions

Although our models give a concrete idea about the factors influencing climate opinions and systems, various other factors could also be considered to improve the model predictions. One of the main challenges in modelling human behaviour is quantifying it. Social media data can be used to estimate the parameters of social dynamics. We adopted methods like Approximate Bayesian Computation to find parameter values that give realistic predictions. The ideal way to quantify these parameters would be to use social media data or surveys combined with statistical methods like Approximate Bayesian Computation to quantify these parameters better.

Several areas could be explored individually using these models. One of them is the factors contributing to an individual's social status. Factors like education, profession, and beliefs can all contribute to the opinion formation of an individual. This also connects to the economic status of the individuals. In this thesis, we focused on individual attributes contributing to climate change. Climate change is a global issue, so analyzing both individual and national interests can be beneficial based on both social and economic situations. However, the importance of individual behaviour cannot be overlooked in this case, as collective individual decisions can force nations to change their policies.

Another interesting factor that could be examined is the influence of media, like social media, newspapers, magazines, and news channels, on influencing climate opinions. The power of mass media is significant in convincing people regarding various topics, and people consider media opinions as factual information and accept them without many questions. However, the media is not always impartial. Mass media promotes particular opinions based on political ideologies, geographical locations, or press freedom. Also, individuals follow media that support their ideologies and beliefs, making media a powerful tool for enhancing behaviour alterations. In some situations, personal ideologies might not match group ideologies, in which case there can be two levels of opinions: personal and group opinions. Analyzing how these factors shape our climate scenario is interesting and impactful.

Sudden, unexpected events can also significantly influence our prediction. These events can also be called abrupt events that are not expected by the population and can quickly alter their opinion regarding climate change. This need not be extreme weather events like heatwaves, droughts, or floods but policy changes or economic changes. We looked at the influence of these unexpected changes on opinion formation in general, but a more strategic and specific analysis could give more information regarding their effects, which could either foster mitigation or reduce it. The impact of extreme weather events might not be the same as sudden changes in economic situation or policies. Analyzing these

systems individually can give more information regarding these systems.

Coupled human-environment systems (HES) can provide different perspectives regarding issues like climate change. These models are simple enough to use in policymaking to change social aspects that can alter attitudes and beliefs regarding climate change. However, the observations made using coupled HES are sometimes questioned due to their simplicity. Coupled models are gaining popularity among researchers; it might take more time for them to get the attention of policymakers. Future research in this field could explore various social models to develop sophisticated coupled HES that can provide results similar to existing climate models. Having said that, human decisions and actions are always unpredictable, and it will remain a challenge for a model, by definition, to fully capture any social phenomenon. There is, therefore, a definite need for continued efforts in coupled HES models to understand the links between social and climate systems.

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APPENDICES

Appendix A

Climate- denying rumor propagation in a coupled socio-climate model

A.1 Additional Figures

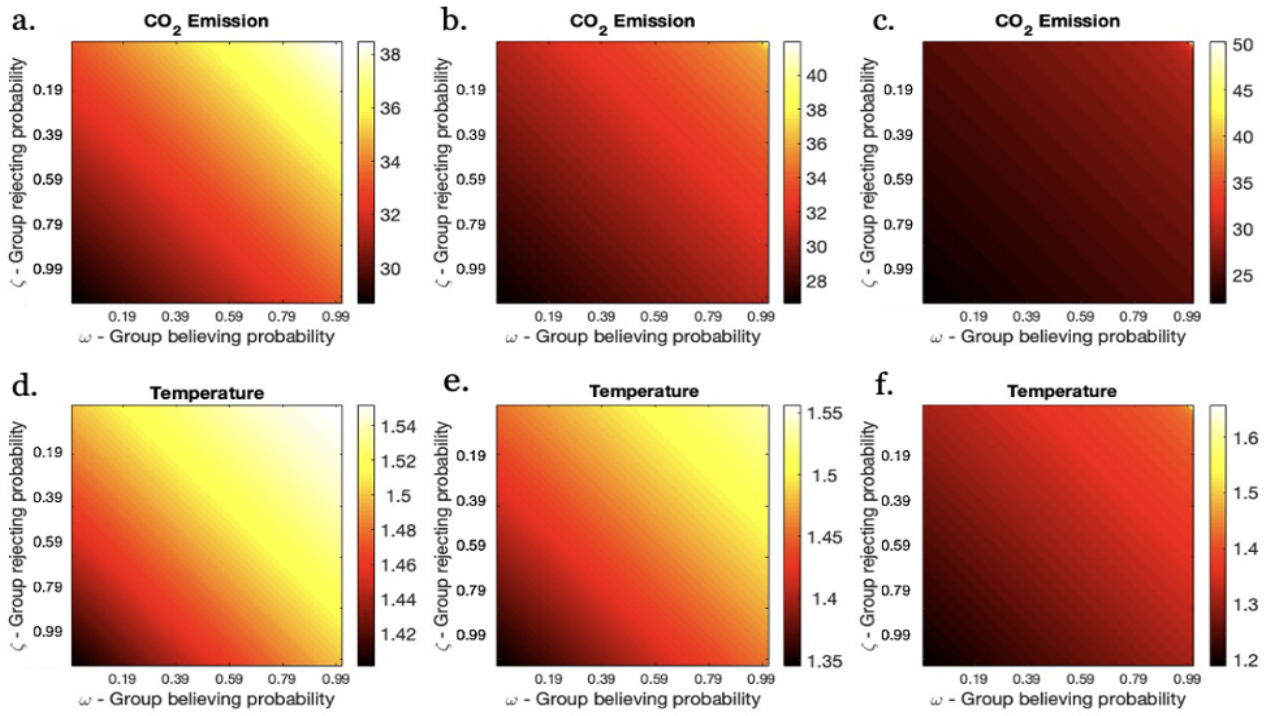


Figure A.1: **Temperature change is sensitive to both believing and rejecting probability in groups.** (a-c)Parameter planes of CO_2 emissions ($GtCO_2yr^{-1}$) at (a) 2021, (b) 2070, and (c) 2200 and (d-f) temperature changes (°C) at (d) 2021, (e) 2070 and (f) 2200 by varying group believing probability (ω) and group rejecting probability (ζ).

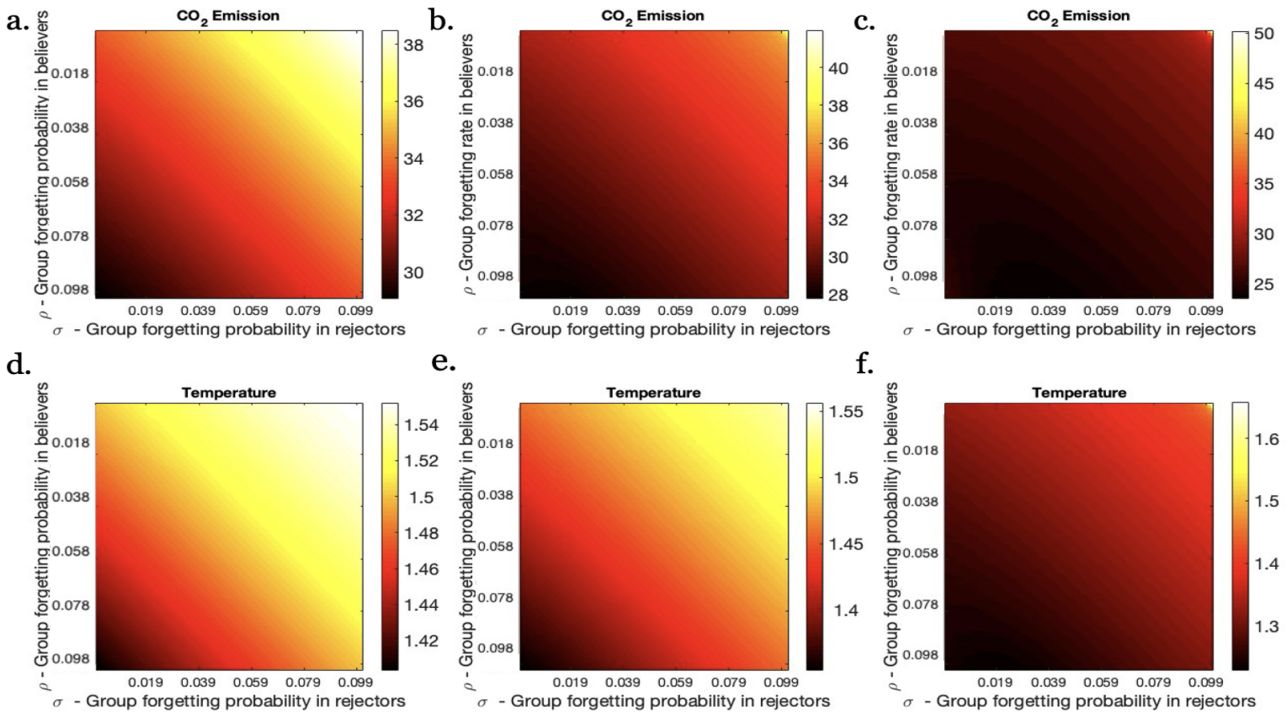


Figure A.2: **Temperature change is sensitive to forgetting probability in both believers and rejectors.** (a-c)Parameter planes of CO_2 emissions ($GtCO_2yr^{-1}$) at (a) 2021, (b) 2070, and (c) 2200 and (d-f) temperature changes (°C) at (d) 2021, (e) 2070 and (f) 2200 by varying group forgetting probability in believers (ρ) and group forgetting probability in rejectors (σ).

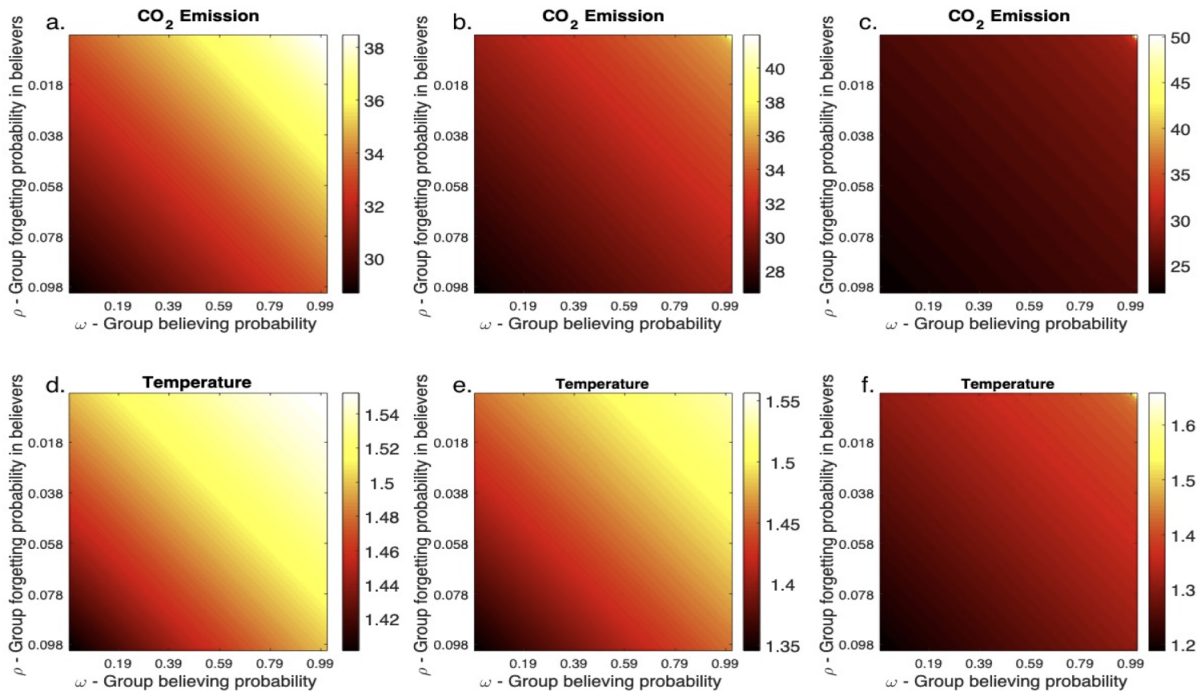


Figure A.3: **Effect of variations in a group believing probability and forgetting probability on temperature levels.** (a-c)Parameter planes of CO_2 emissions ($GtCO_2yr^{-1}$) at (a) 2021, (b) 2070, and (c) 2200 and (d-f) temperature changes (°C) at (d) 2021, (e) 2070 and (f) 2200 by varying group believing probability (ω) and group forgetting probability in believers (ρ).

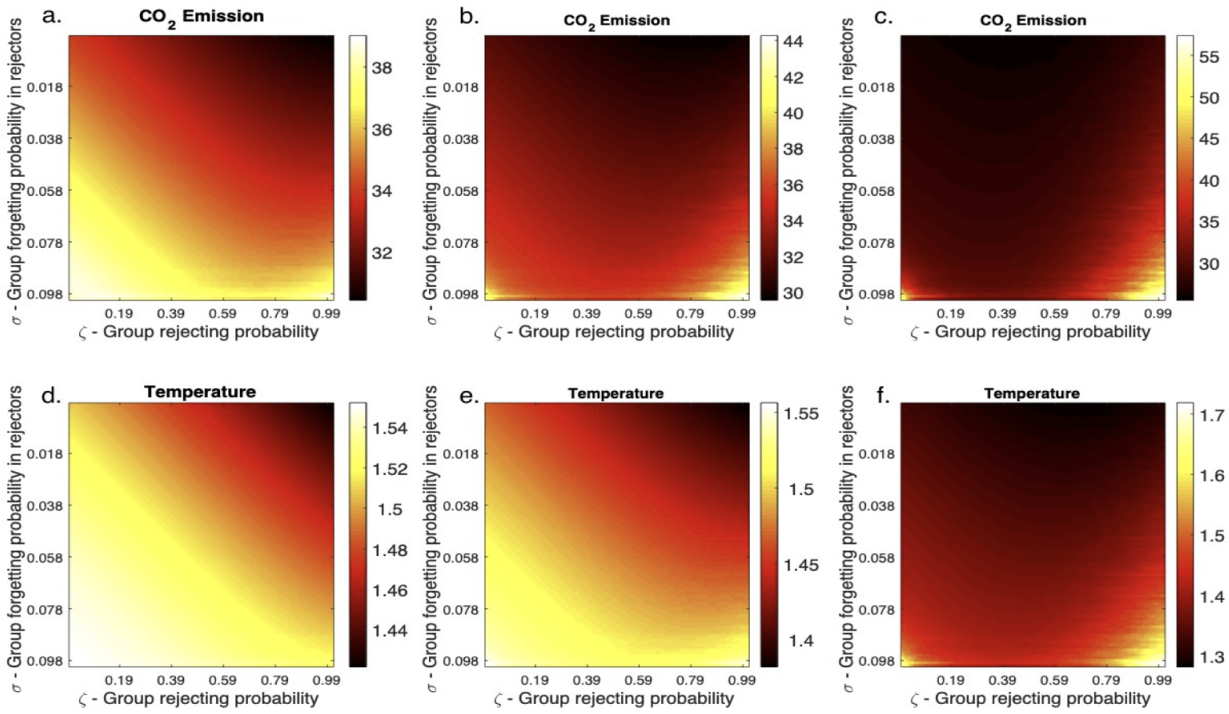


Figure A.4: **Low forgetting probability in rejectors leads to higher temperatures.** (a-c)Parameter planes of CO_2 emissions ($GtCO_2yr^{-1}$) at (a) 2021, (b) 2070, and (c) 2200 and (d-f) temperature changes (°C) at (d) 2021, (e) 2070 and (f) 2200 by varying the group rejecting probability (ζ) and group forgetting probability in rejectors (σ).

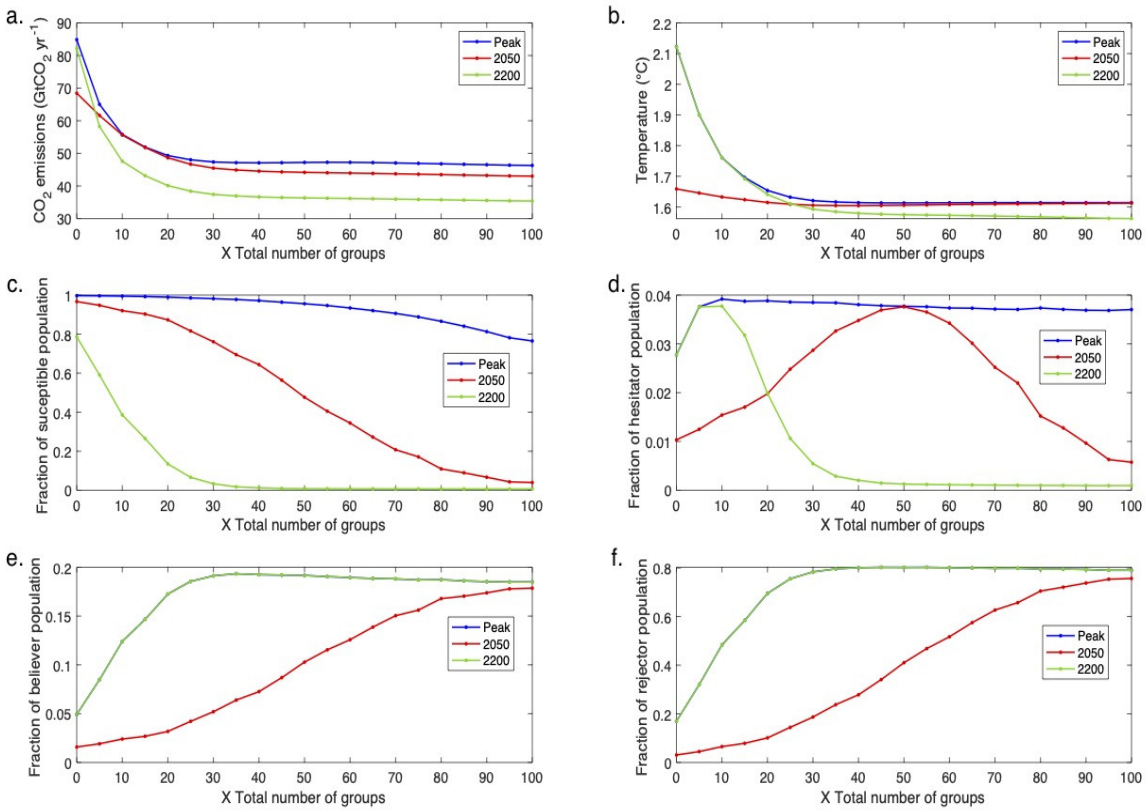


Figure A.5: **Temperature rises when the total number of groups is less.** Univariate sensitivity of (a) CO_2 emissions, (b) temperature, (c) susceptible, (d) hesitator, (e) believer and (f)rejector population by varying the parameter X, the total number of groups.

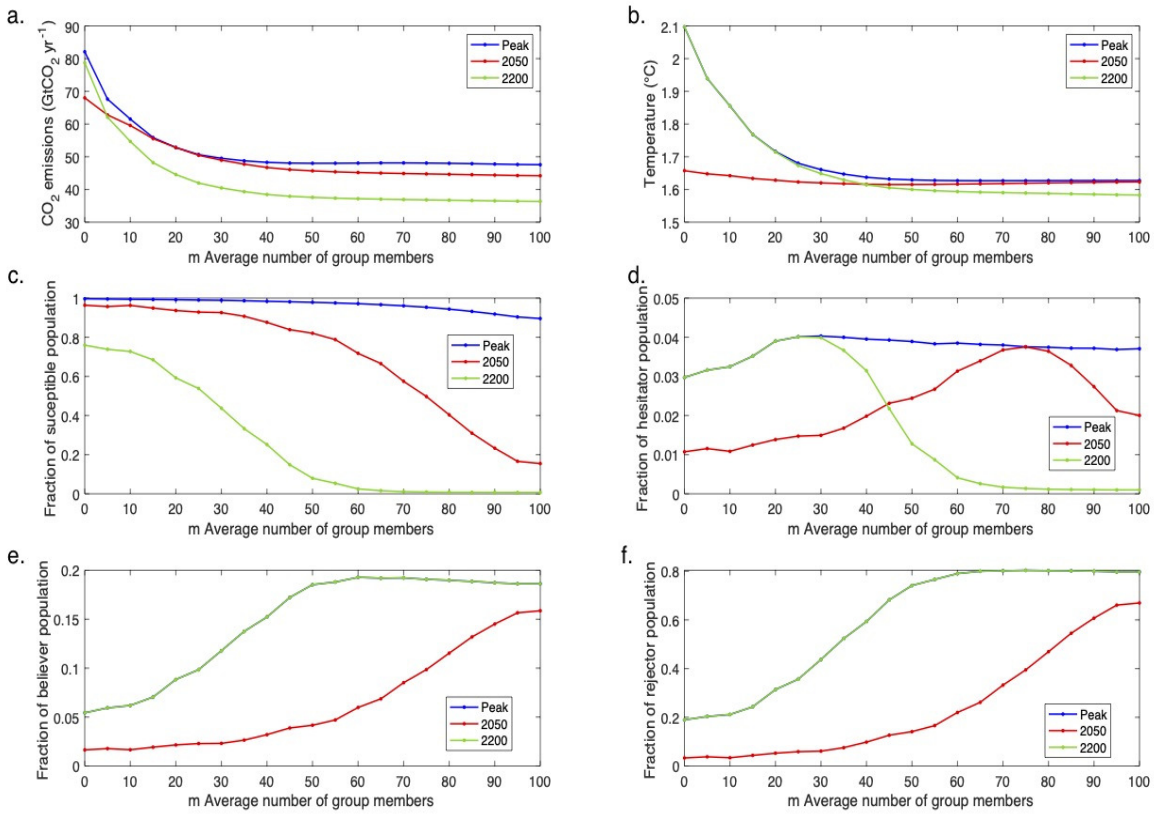


Figure A.6: **Higher average number of group members aids in rumor propagation.** Univariate sensitivity of (a) CO_2 emissions, (b) temperature, (c) susceptible, (d) hesitator, (e) believer, and (f) rejector population by varying the parameter m, the average number of group members.

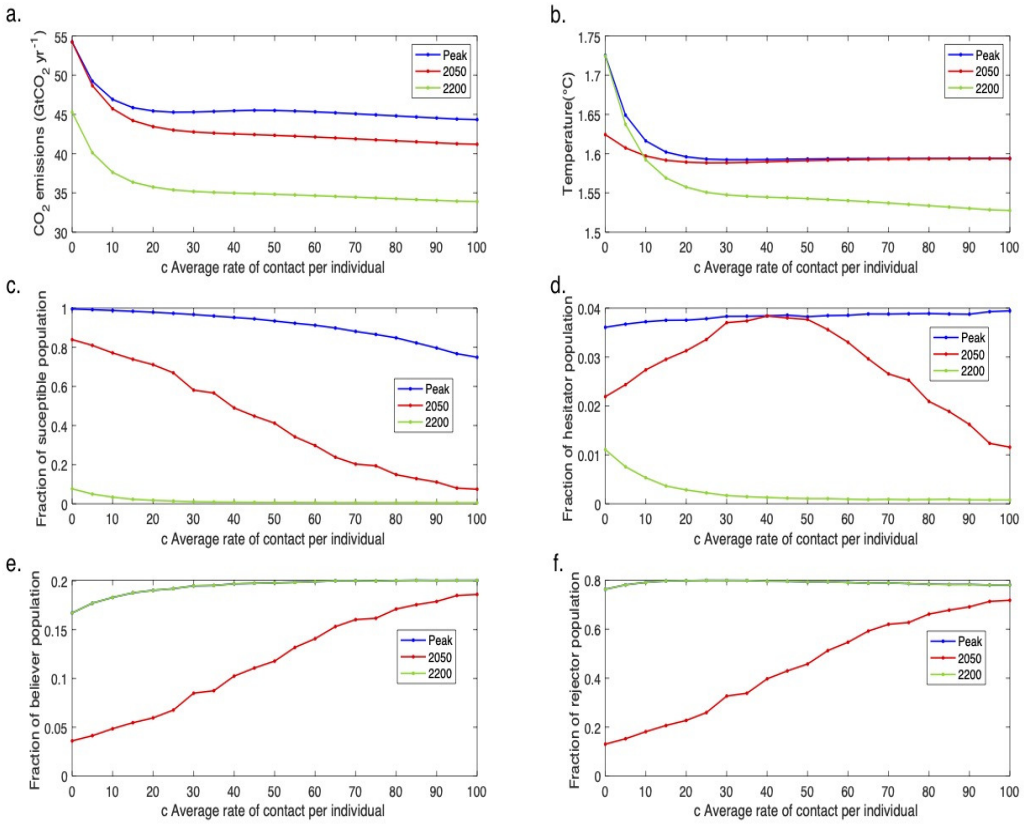


Figure A.7: **Rumor propagation is not affected by changes in an average number of individual contact.** Univariate sensitivity of (a) CO_2 emissions, (b) temperature, (c) susceptible, (d) hesitator, (e) believer, and (f) rejector population by varying the parameter $\bar{c}$, the average number of contact for each individual.

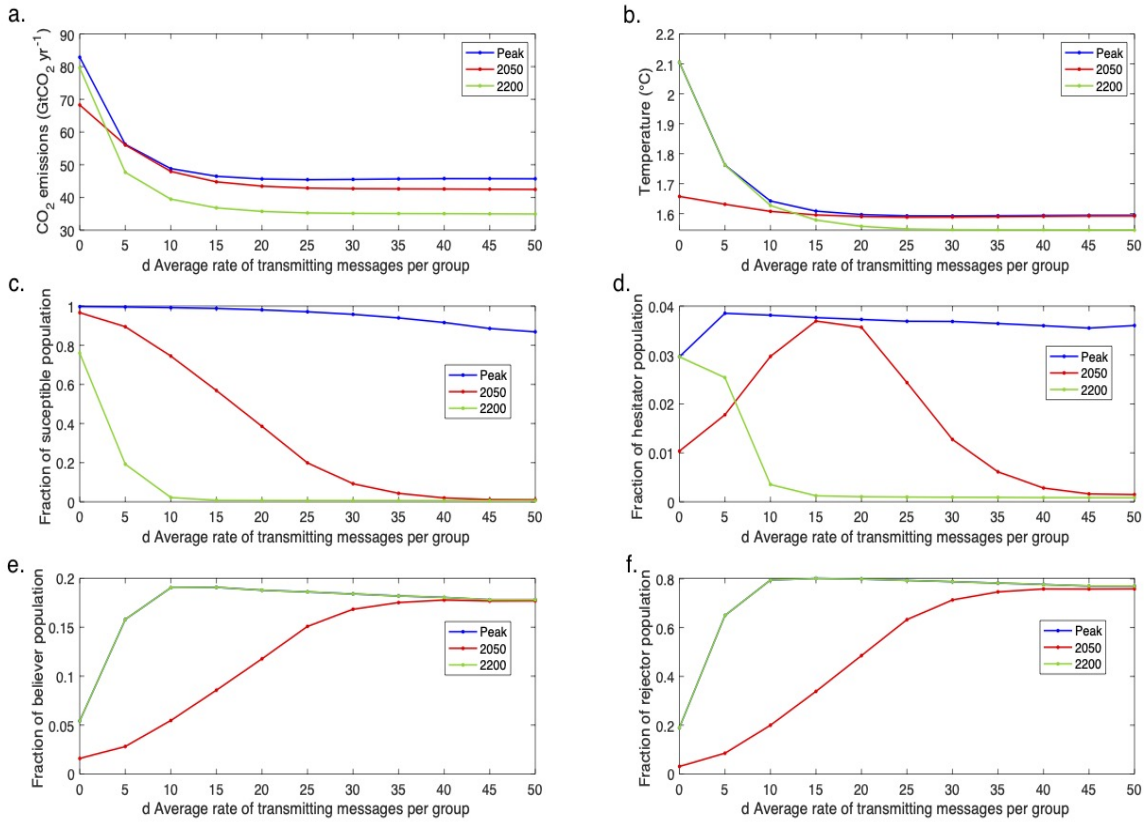


Figure A.8: **Lower rate of group message transmission leads to slower rumor propagation.** Univariate sensitivity of (a) CO_2 emissions, (b) temperature, (c) susceptible, (d) hesitator, (e) believer, and (f) rejector population by varying the parameter $\bar{d}$- the average rate of transmitting messages per group.

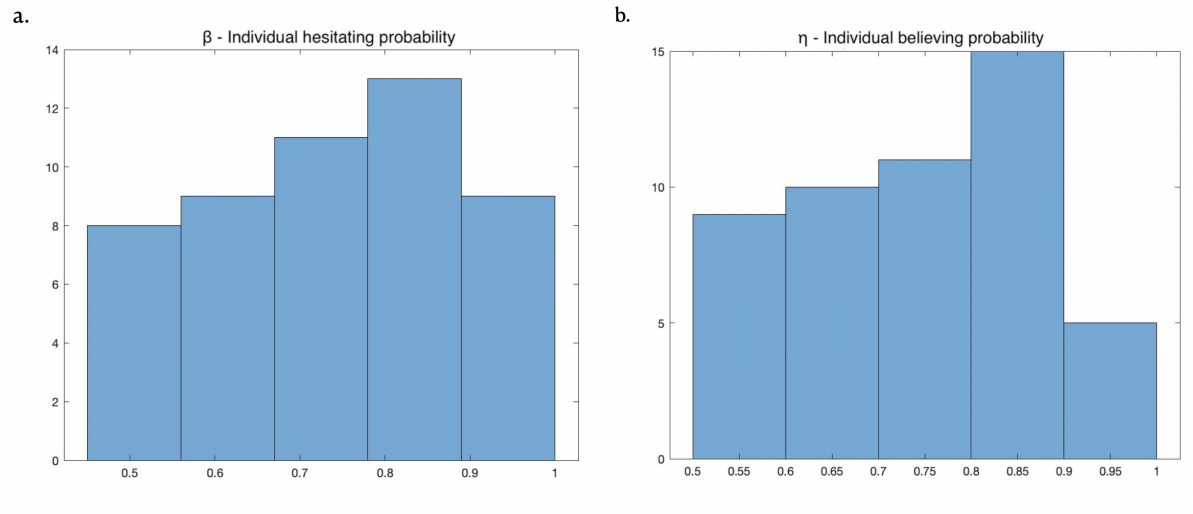


Figure A.9: Parameter values distribution of (a) β Individual hesitating probability and (b)η Individual believing probability generated using ABC.

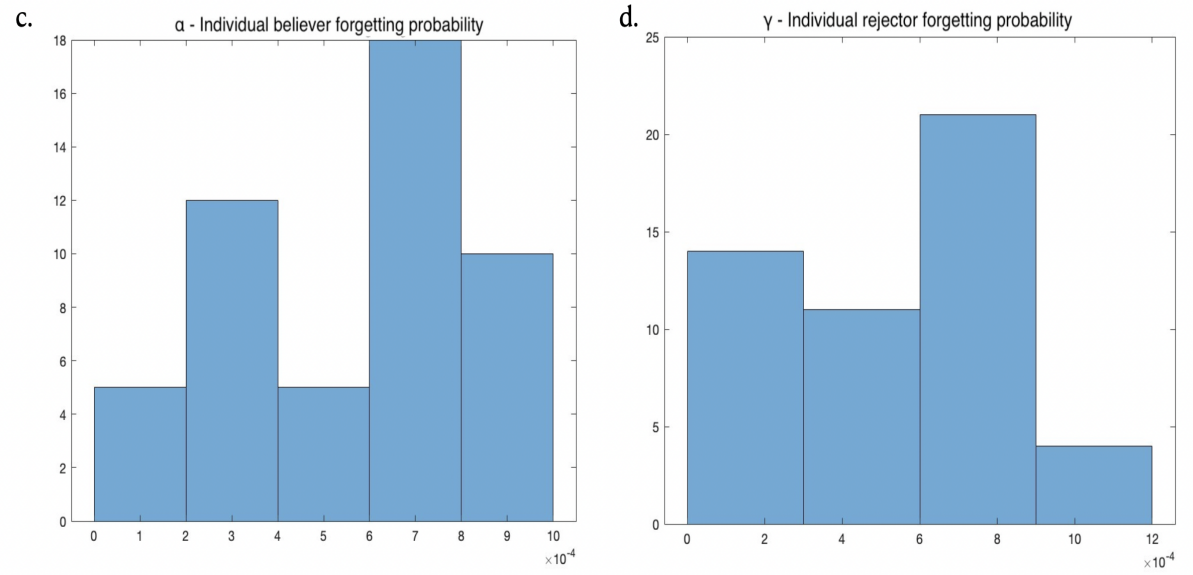


Figure A.10: Parameter values distribution of (c) α Believer forgetting probability and (d) γ rejector forgetting probability generated using ABC.

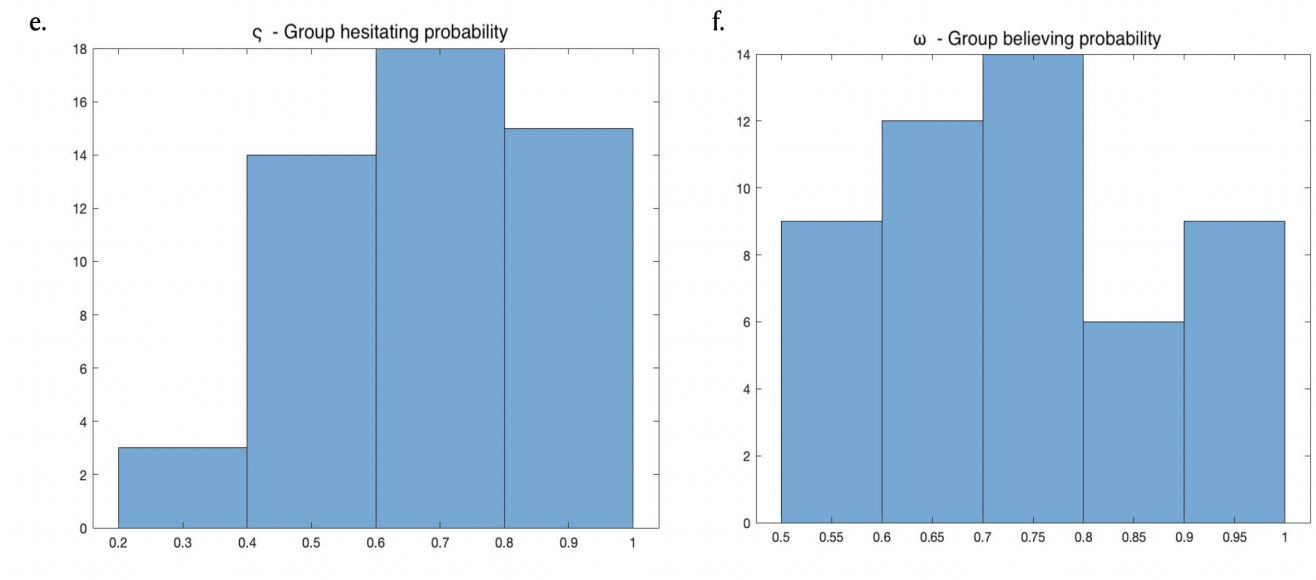


Figure A.11: Parameter values distribution of (e) ς Group hesitating probability and (f) ω Group believing probability generated using ABC.

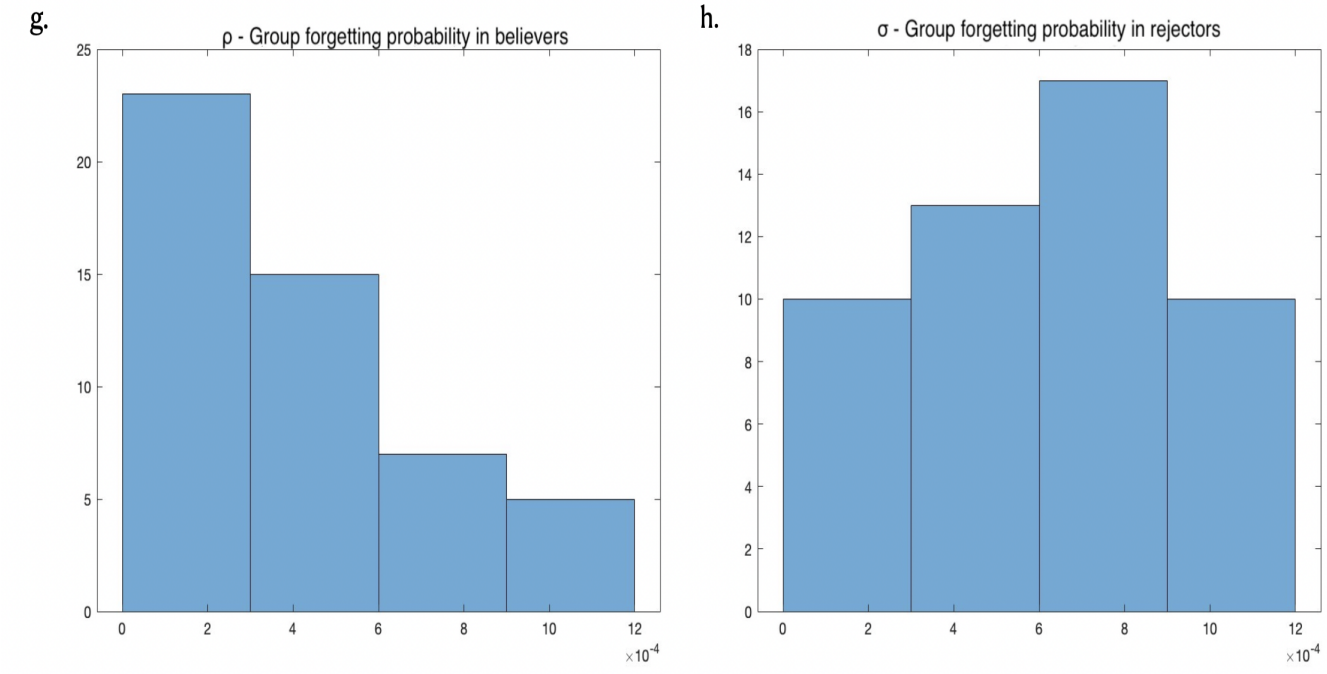


Figure A.12: Parameter values distribution of (g) ρ Group believer forgetting probability and (h) σ Group rejector forgetting probability generated using ABC.

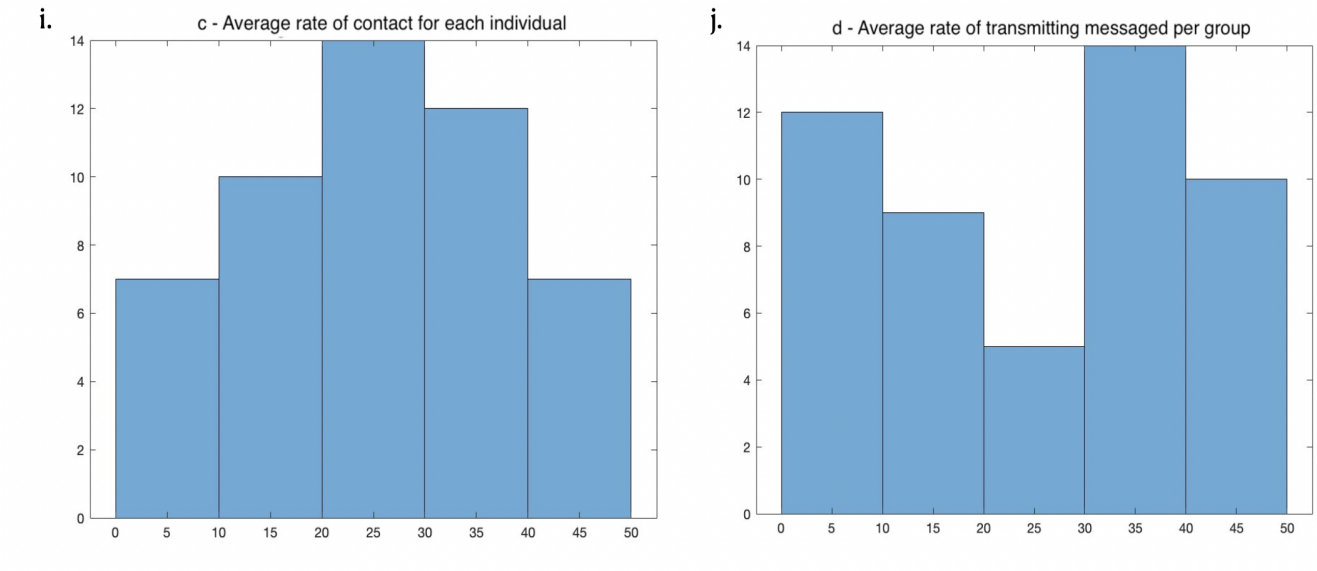


Figure A.13: Parameter values distribution of (i) $\bar{c}$ Average rate of contact per individual and (j) $\bar{d}$ Average rate of transmitting message per group generated using ABC.

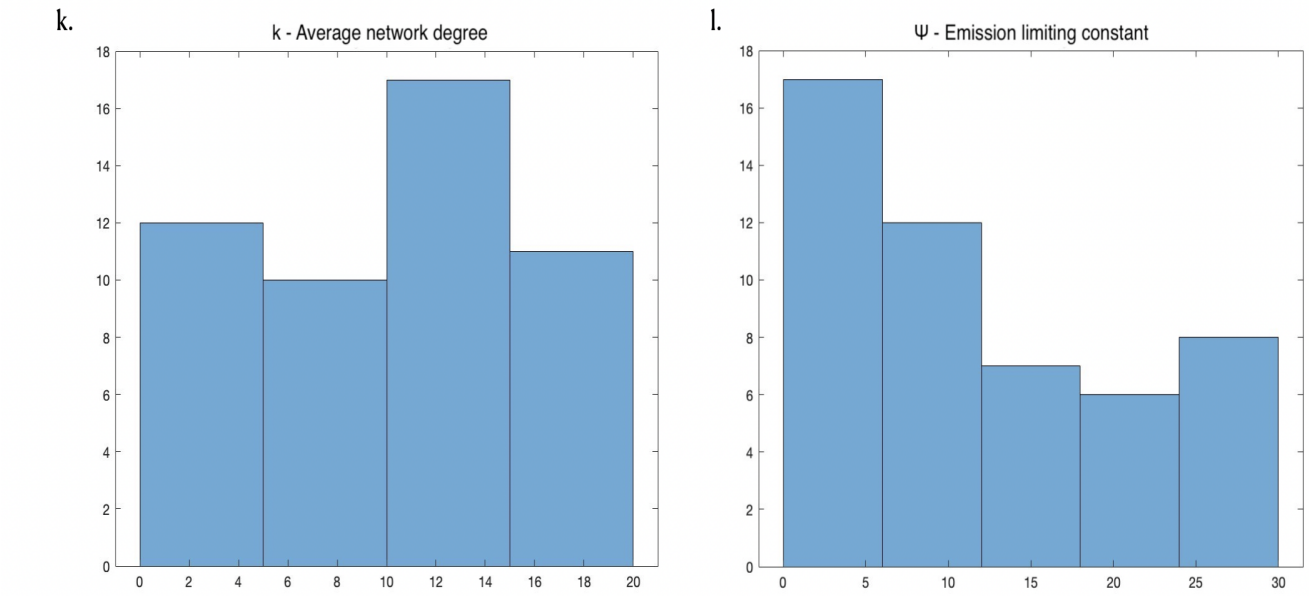


Figure A.14: Parameter values distribution of (k) k Average degree of the network and (l) Ψ Emission limiting constant generated using ABC.

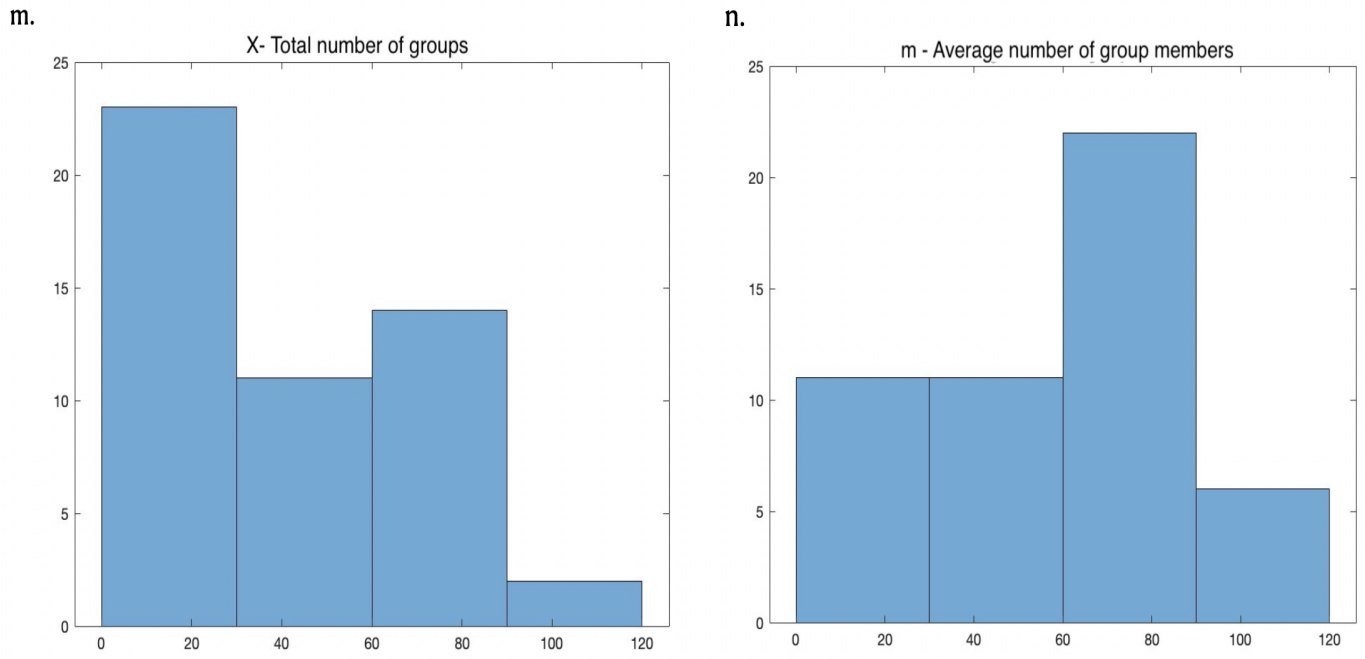


Figure A.15: Parameter values distribution of (m) X Total number of groups and (n) m Average number of group members generated using ABC

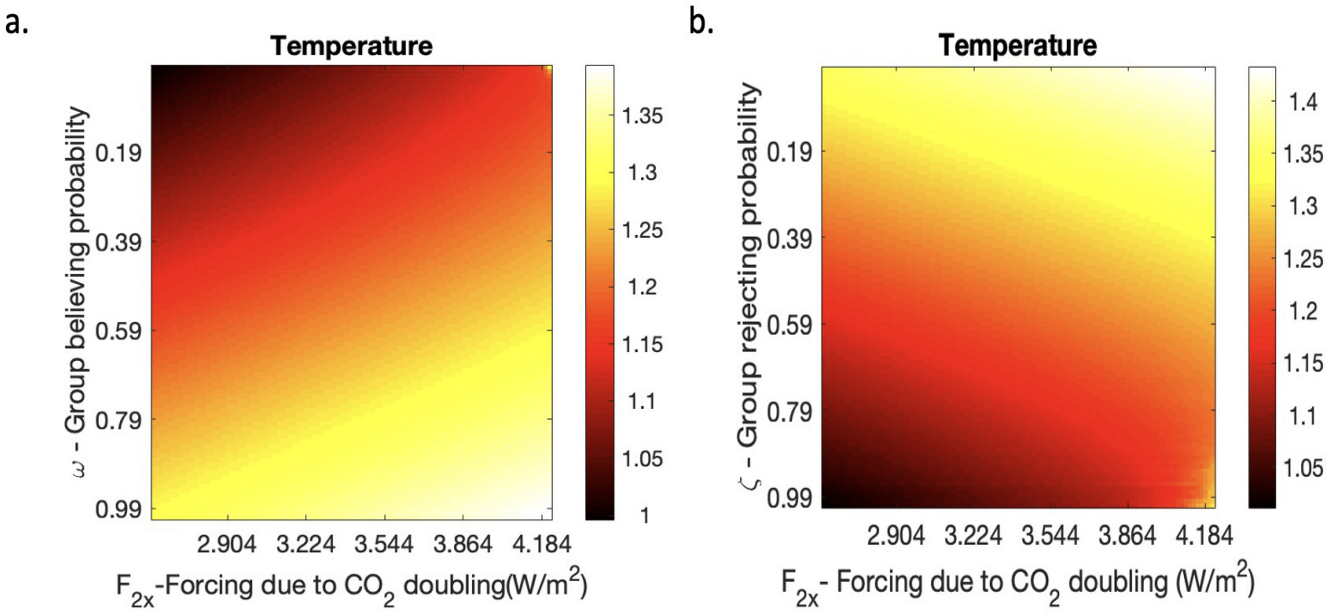


Figure A.16: **Interaction between forcing due to CO_2 doubling and rumor parameters.**

Appendix B

From Opinion Polarization to Climate Action: A Socio-Climate Framework for Continuous Opinions

B.1 Additional Figures

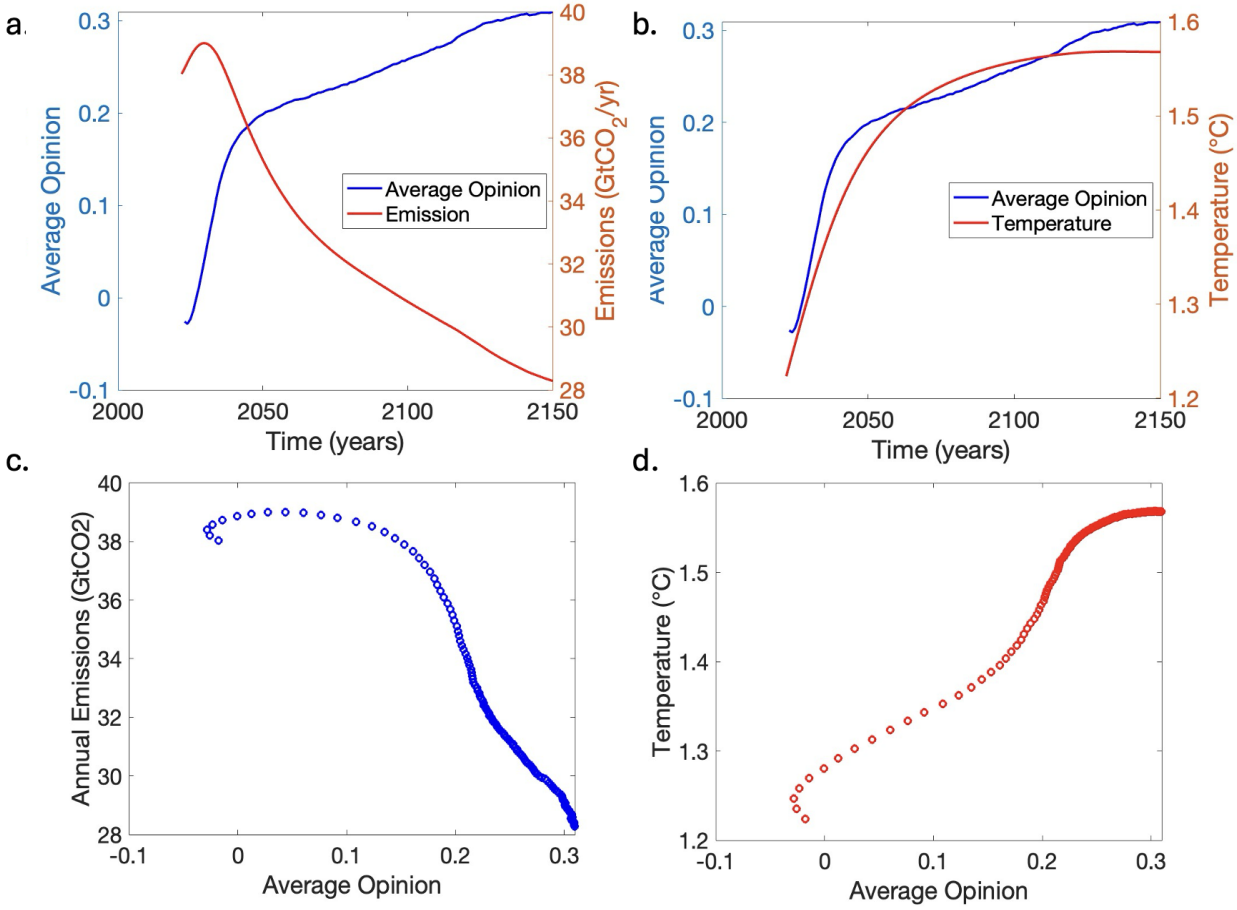


Figure B.1: **Relation between average opinion, emission, and temperature:**Time series of (a) average opinions and emissions ($GTCO_2yr^{-1}$), (b)average opinion and temperature (°C), and correlation between (c) average opinions and emissions ($GTCO_2yr^{-1}$), (d))average opinion and temperature (°C).

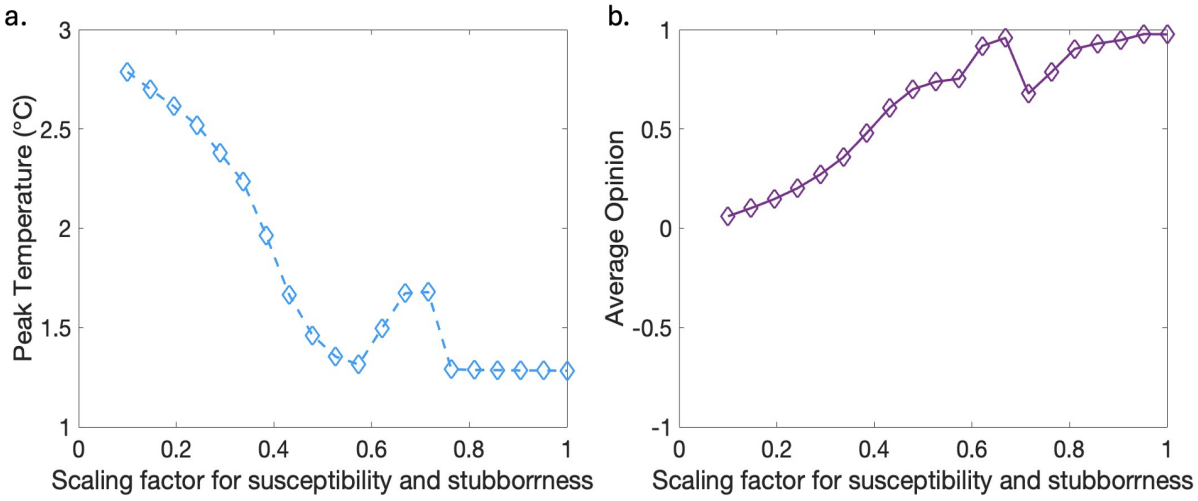


Figure B.2: **High social learning mitigates climate change:** Univariate sensitivity of (a) peak temperature (°C), (b) average opinion with variation in scaling factor of susceptibility and stubbornness.

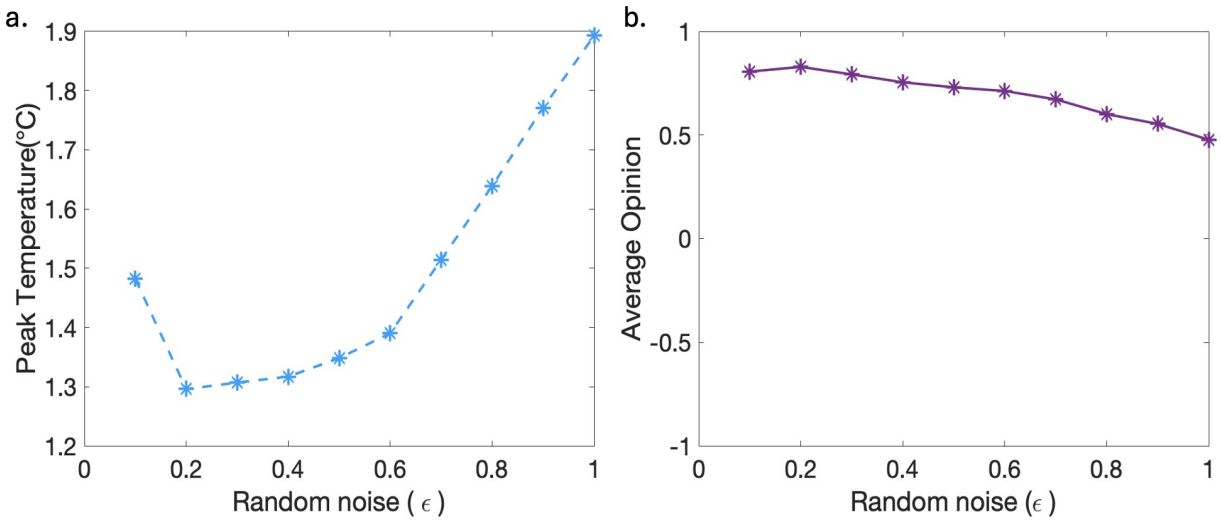


Figure B.3: **Increased stochasticity increases the peak temperature:** Univariate sensitivity of (a) peak temperature (°C), (b) average opinion with variation in random noise added to the opinion dynamics.

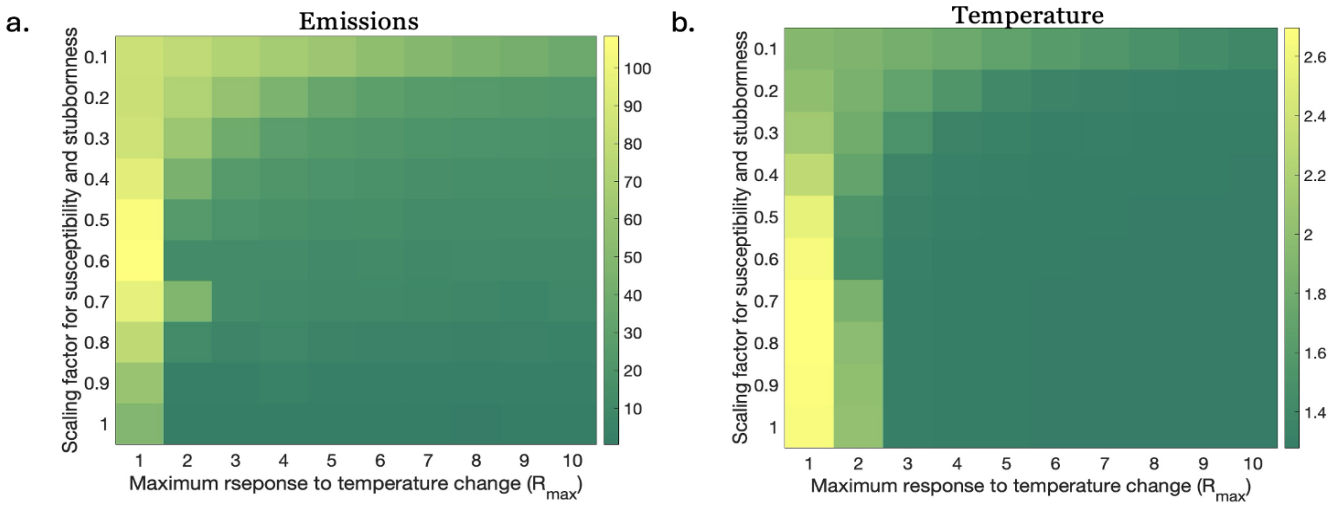


Figure B.4: **Scaling the opinion has minimal influence with high response:** Bivariate sensitivity of (a) emissions ($GTCO_2yr^{-1}$), (b) peak temperature (°C) when scaling factor is varied with the maximum response to temperature change (R_{max})

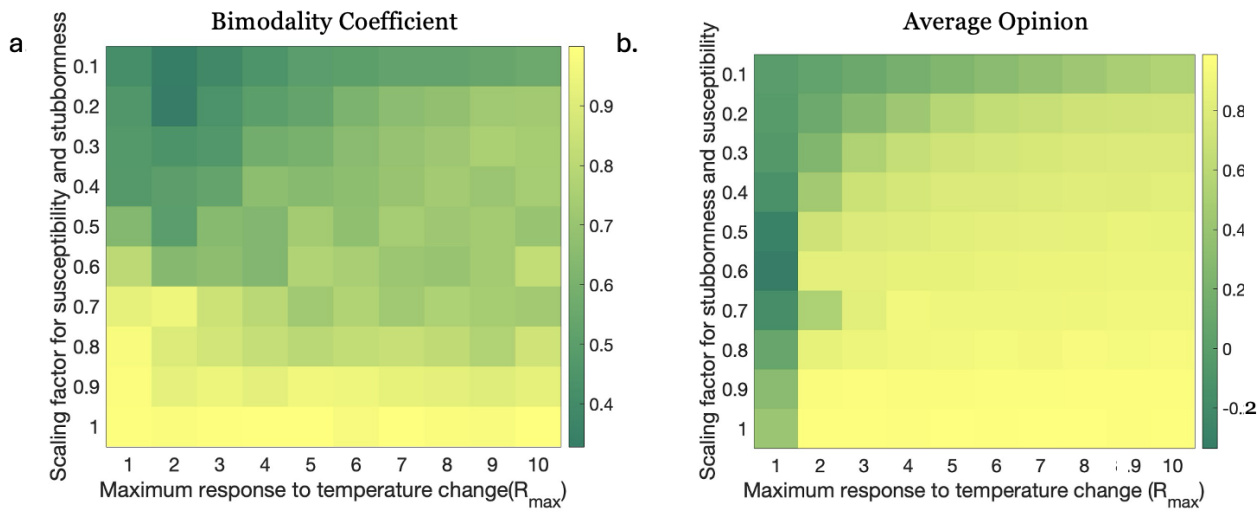


Figure B.5: **Scaling the opinion influences polarization:** Bivariate sensitivity of (a) bimodality coefficient, (b) average opinion when scaling factor is varied with the maximum response to temperature change (R_{max})

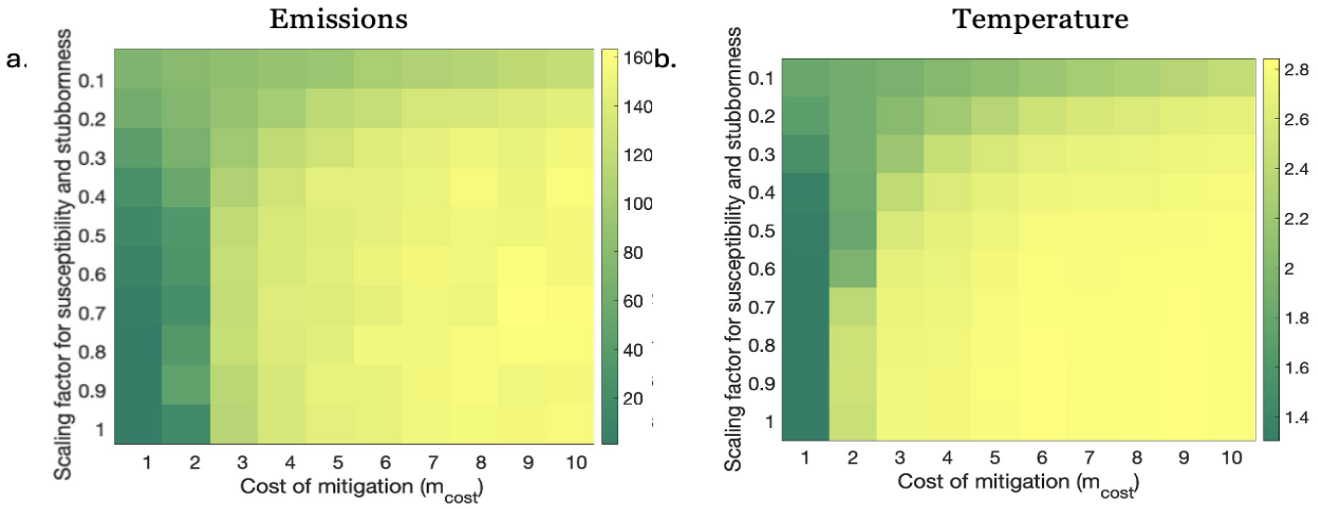


Figure B.6: **Scaling the opinion has minimal influence with high mitigation cost:** Bivariate sensitivity of (a) emissions ($GTCO_2yr^{-1}$), (b) peak temperature (°C) when scaling factor is varied with the cost of mitigation (m_{cost})

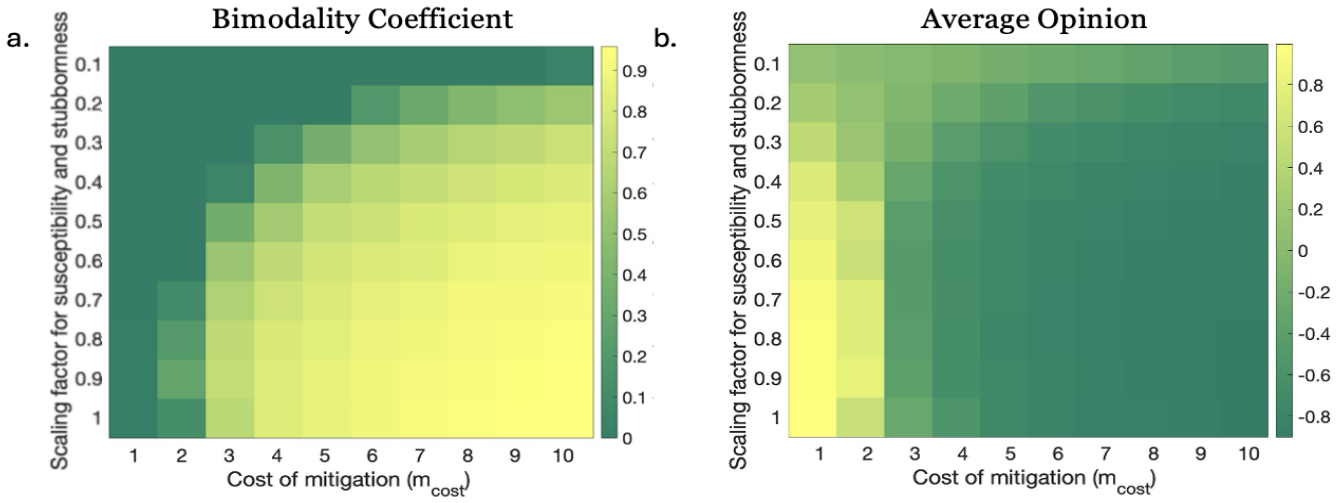


Figure B.7: **Scaling the opinion influences polarization with mitigation cost:** Bivariate sensitivity of (a) bimodality coefficient, (b) average opinion when scaling factor is varied with the cost of mitigation (m_{cost})

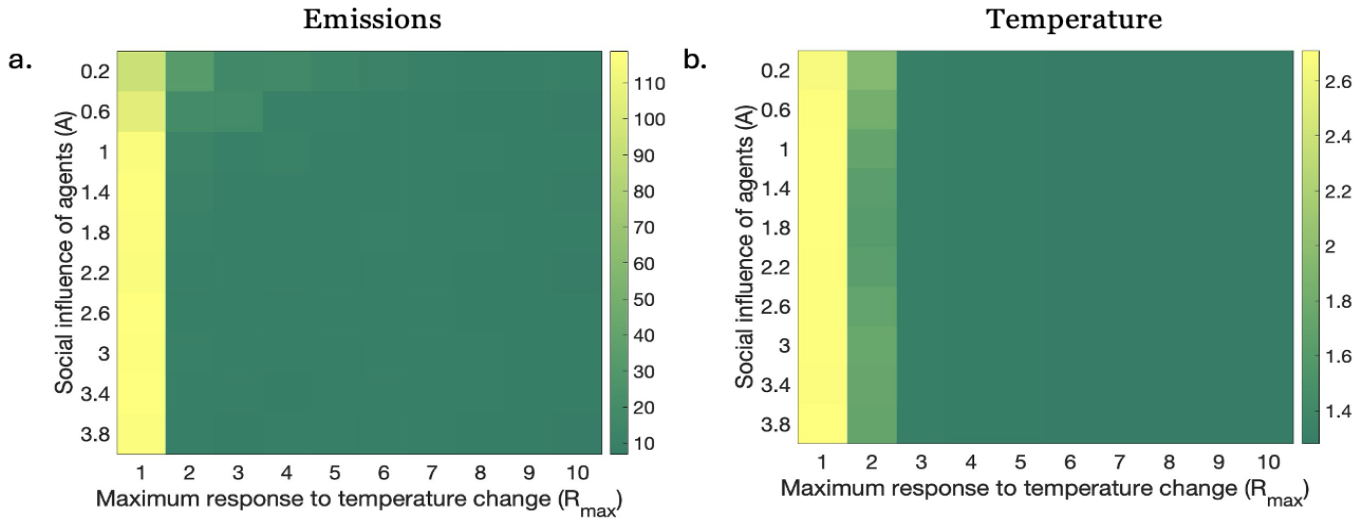


Figure B.8: **Social influence has minimal influence on emissions with high response:** Bivariate sensitivity of (a) emissions ($GTCO_2yr^{-1}$), (b) peak temperature (°C) when social influence(A) is varied with the maximum response to temperature change (R_{max})

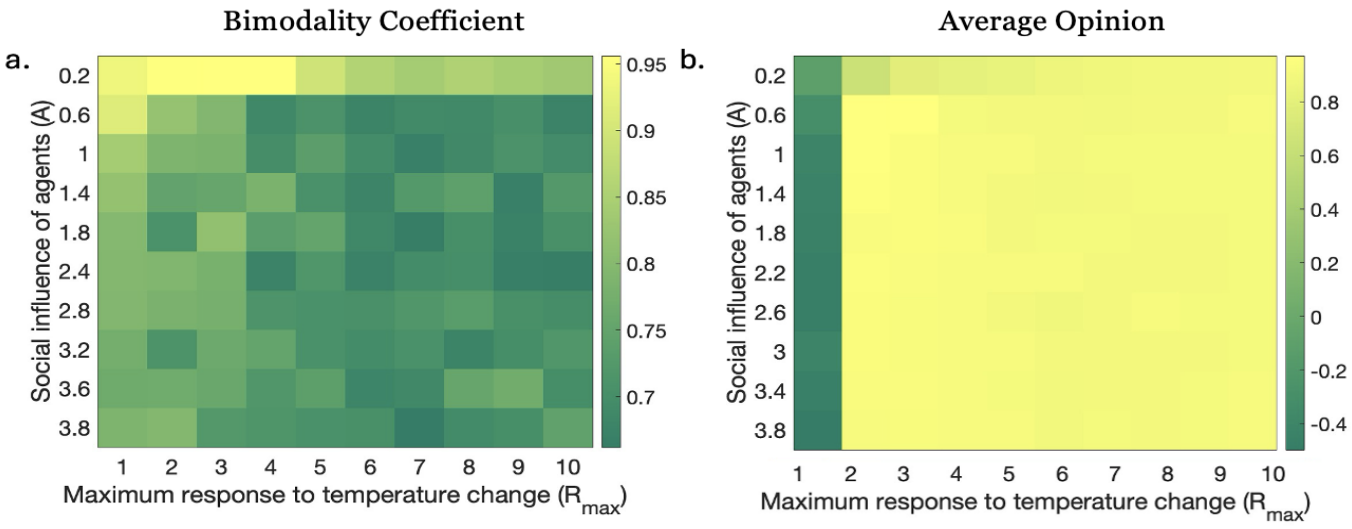


Figure B.9: **Social influence has minimal influence on average opinion with high response:** Bivariate sensitivity of (a) bimodality coefficient, (b) average opinion when social influence(A) is varied with the maximum response to temperature change (R_{max})

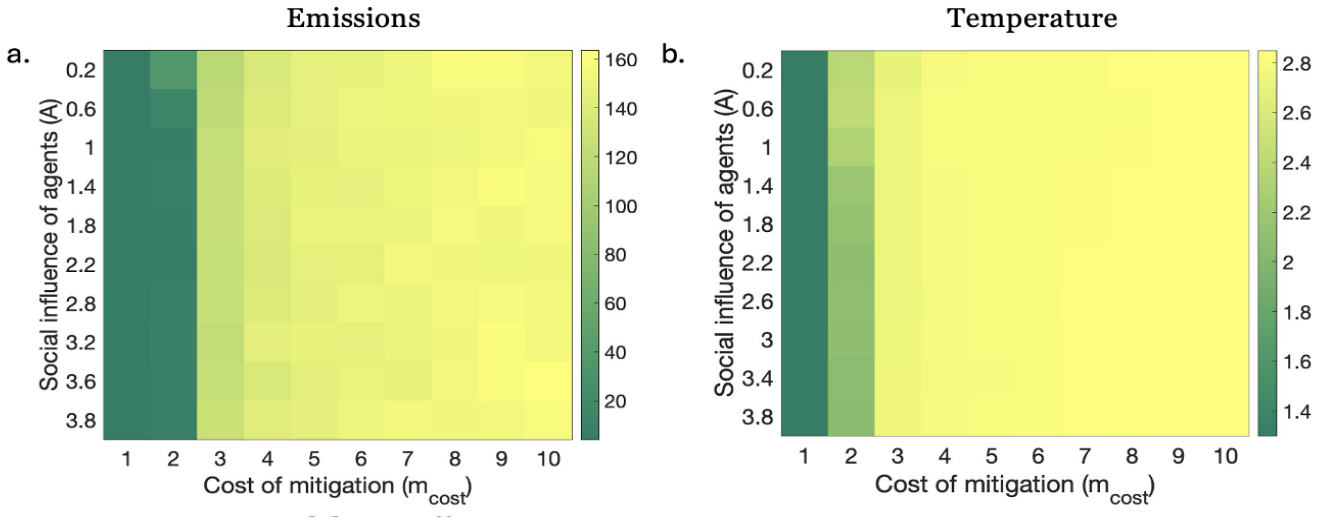


Figure B.10: **Social influence has minimal influence on emissions with mitigation costs:** Bivariate sensitivity of (a) emissions ($GTCO_2yr^{-1}$), (b) peak temperature (°C) when social influence(A) is varied with the cost of mitigation (m_{cost})

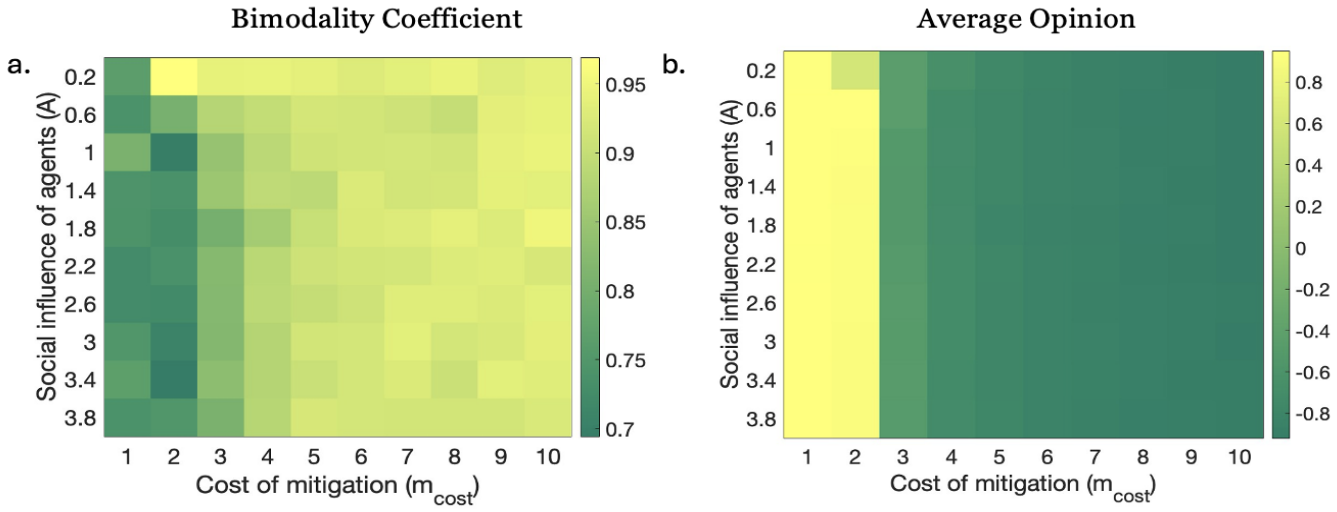


Figure B.11: **Social influence has minimal influence on average opinion with high mitigation costs:** Bivariate sensitivity of (a) bimodality coefficient, (b)average opinion when social influence(A) is varied with the maximum response to temperature change (R_{max})

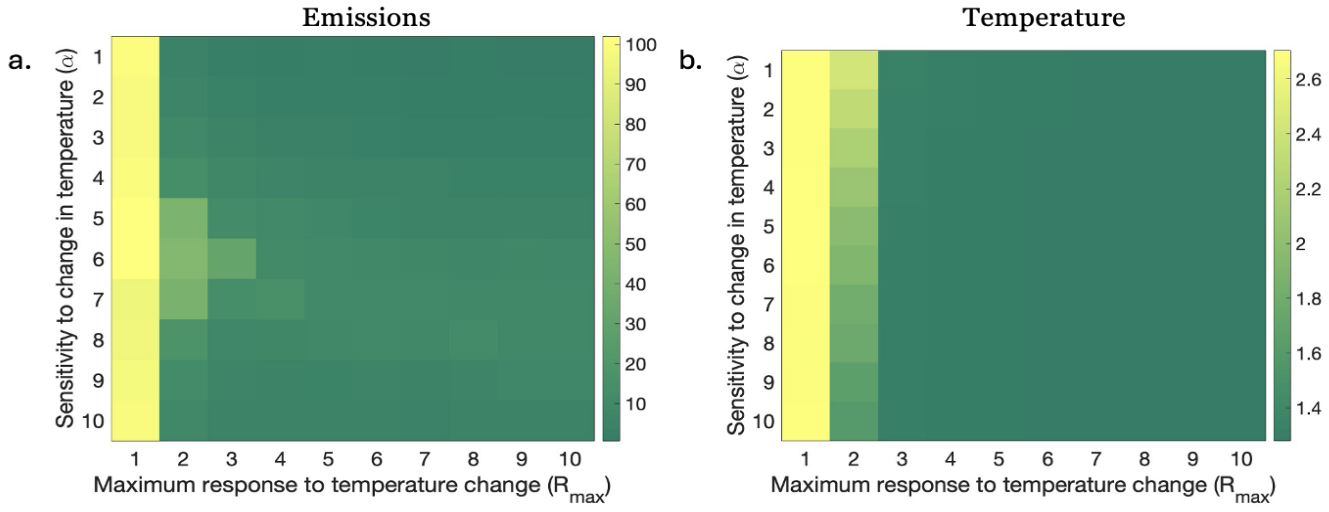


Figure B.12: **Sensitivity to temperature change has minimal influence on peak temperatures with high response:** Bivariate sensitivity of (a) emissions ($GTCO_2yr^{-1}$), (b) peak temperature (°C) when sensitivity to the temperature change (α) is varied with the maximum response to temperature change (R_{max})

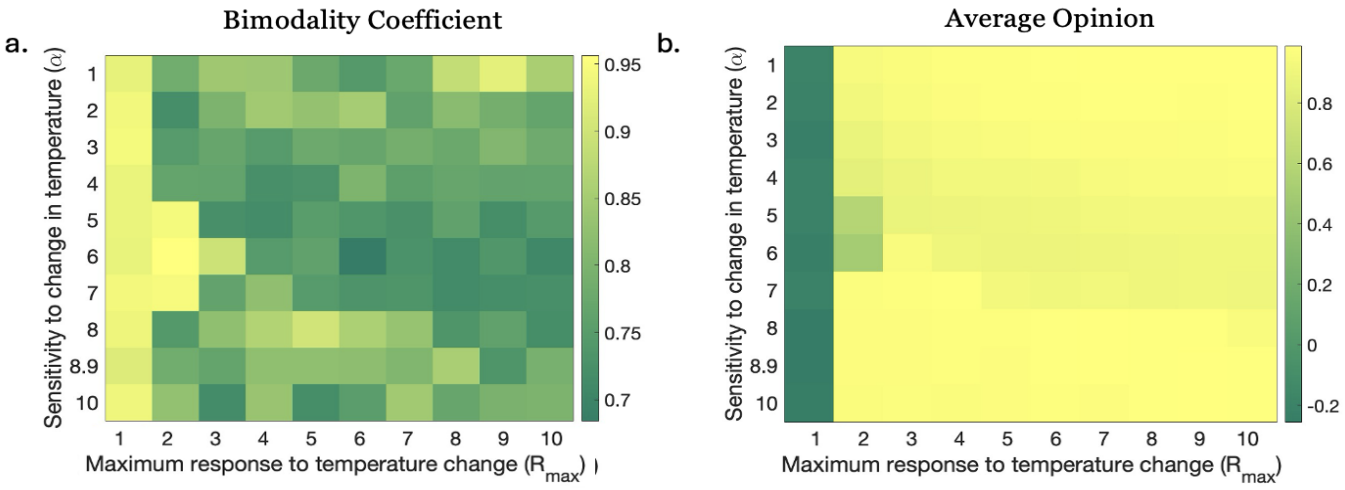


Figure B.13: **Sensitivity to temperature change has minimal influence on emissions with high response:** Bivariate sensitivity of (a) bimodality coefficient, (b) average opinion when sensitivity to the temperature change (α) is varied with the maximum response to temperature change (R_{max})

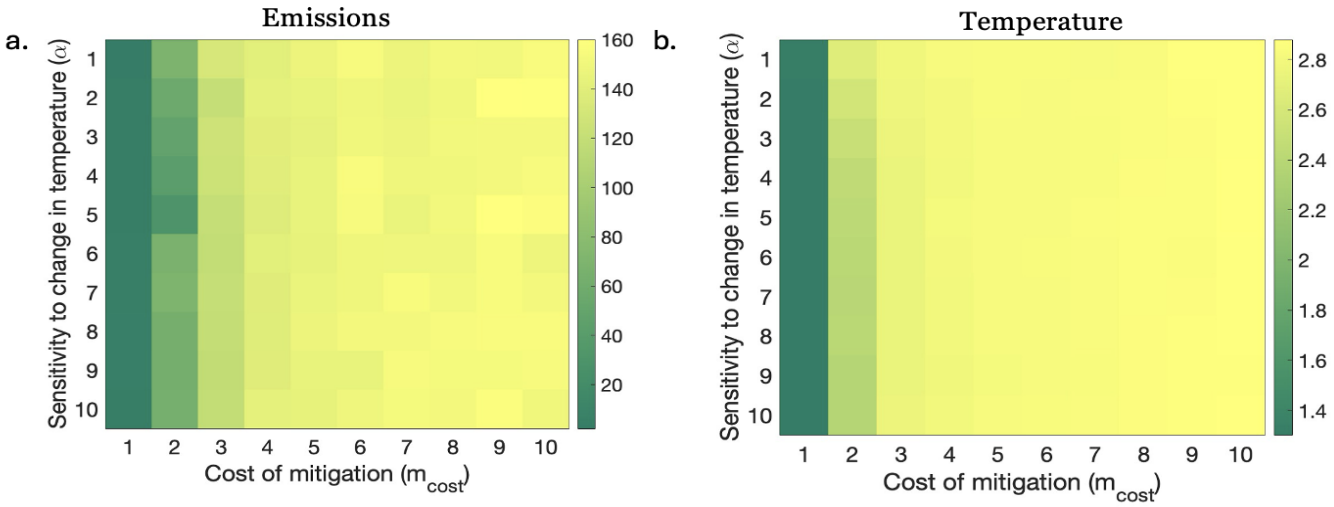


Figure B.14: **Sensitivity to temperature change has minimal influence on peak temperatures with high mitigation costs:** Bivariate sensitivity of (a) emissions ($GTCO_2yr^{-1}$), (b) peak temperature (°C) when sensitivity to the temperature change (α) is varied with the cost of mitigation (m_{cost})

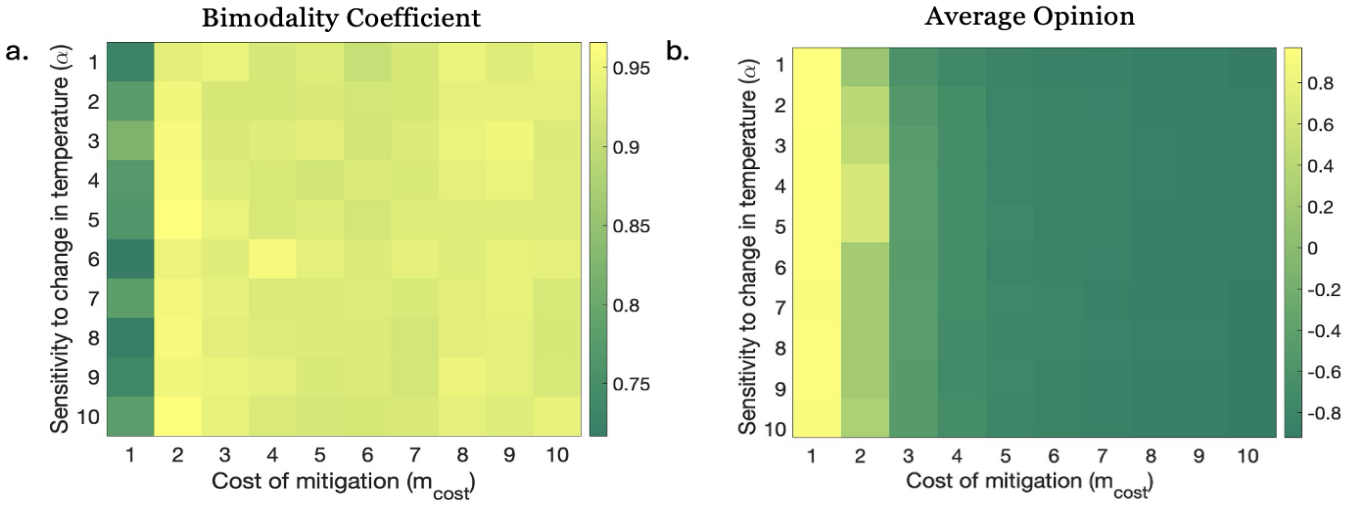


Figure B.15: **Sensitivity to temperature change has minimal influence on polarization with high mitigation costs:** Bivariate sensitivity of (a) emissions ($GTCO_2yr^{-1}$), (b) peak temperature (°C) when sensitivity to the temperature change (α) is varied with the cost of mitigation (m_{cost})

Appendix C

Space, time and altruism in pandemic and the climate crisis

C.1 Derivation of the control condition

If there is one unit of natural agent present $A_t = 1$, then from equations (4.5) and (4.6), the probabilities of being impacted evolve as:

$$P_i^N = 1 - [1 - \beta] = \beta$$
$$P_i^M = 1 - [1 - \beta(1 - \varepsilon)] = \beta(1 - \varepsilon)$$

Hence, the payoffs from equation (4.3) and (4.4) evolve as:

$$e_{N,i} = L - \beta C_I D$$
$$e_{M,i} = L - \beta(1 - \varepsilon)C_I D - C_M$$

For the non-mitigators to choose to mitigate, the payoffs of being a mitigator should be greater than that of being a non-mitigator:

$$e_M > e_N \Rightarrow L - \beta(1 - \varepsilon)C_I D - C_M > L - \beta C_I D$$
$$\Rightarrow \beta > \frac{C_M}{\varepsilon C_I D}$$

This means that $e_M > e_N$ if and only if $\beta > \frac{C_M}{\varepsilon C_I D}$.

C.2 Derivation of the condition for the limiting scenarios

Here we derive the condition which helps us to explore the limiting scenarios. An individual will choose to mitigate only if the payoff of being a mitigator e_M is larger than the cost of being a non-mitigator e_N. From equation (4.3) and (4.4):

$$e_{M,i} > e_{N,i}$$
$$\Rightarrow -{p_i}^M c_I D - c_M > -{p_i}^N c_I D$$
$$\Rightarrow c_M < {p_i}^N c_I D - {p_i}^M c_I D$$
$$\Rightarrow c_M < c_I D({p_i}^N - {p_i}^M)$$
$$\Rightarrow c_M < c_I D((1 - \beta(1 - \varepsilon))^{A_{i,t}} - (1 - \beta)^{A_{i,t}})$$

When $\varepsilon = \frac{1}{N} \approx 0$,

$$(1 - \beta(1 - \varepsilon))^{A_{i,t}} \approx (1 - \beta)^{A_{i,t}}$$

And,

$$c_M > c_I D((1 - \beta(1 - \varepsilon))^{A_{i,t}} - (1 - \beta)^{A_{i,t}} \approx 0$$

This means that the neighbors will not adopt mitigation, even for large $A_{0,0}$. Similarly, if Q is large, as for climate change, then $A_{i,0}$ is initially almost zero since the emissions of the index node are distributed equally among its $Q = N - 1$ neighbors.

C.2.1 Additional Figures

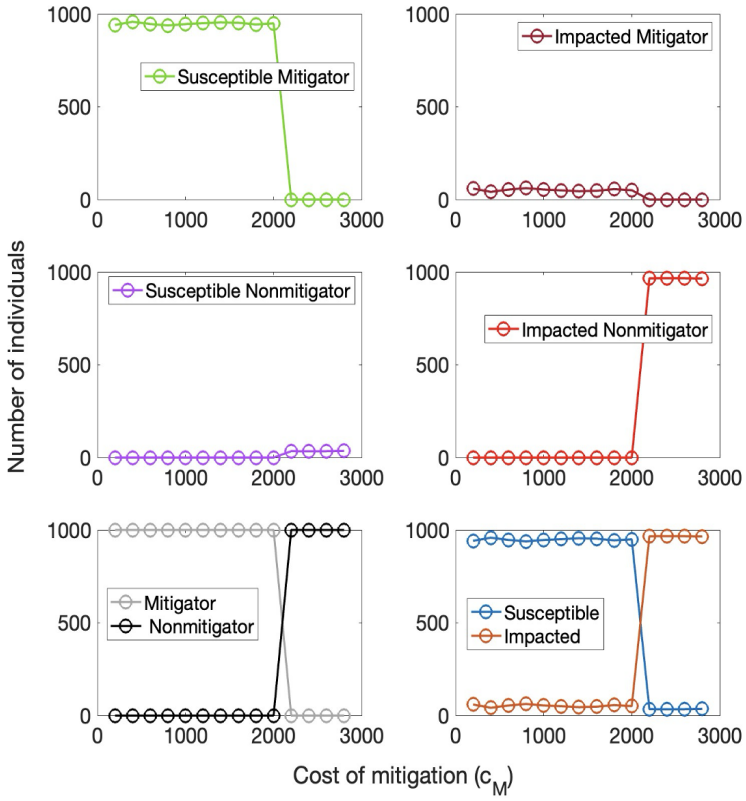


Figure C.2.1: **Effective of cost of mitigation on population composition, COVID-19 system:** Univariate sensitivity of physical and behavioral states in the population under variation in the cost of mitigation, c_M. Parameters are described in Table 4.1.

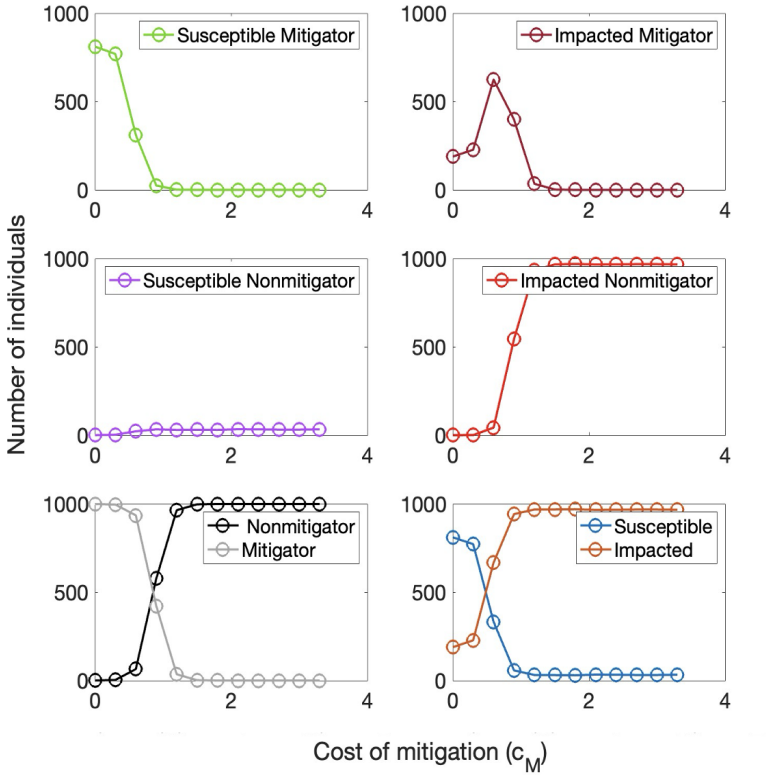


Figure C.2.2: **Effect of cost of mitigation on population composition, climate system.** Univariate sensitivity analysis of physical and behavioral states under variation in the cost of mitigation, c_M. Parameters are described in Table 4.1.

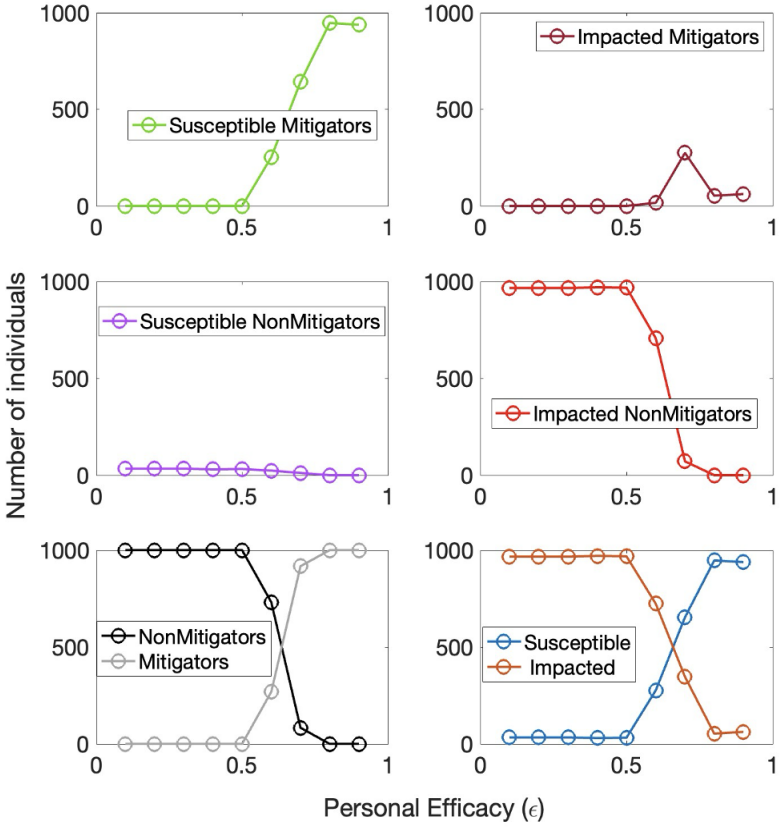


Figure C.2.3: **Effect of personal efficacy on population composition, climate system.** Univariate sensitivity analysis of physical and behavioral states under variation in the personal efficacy, ε. $\beta = 0.3$, and $Q = 500$, other parameters are described in Table 4.1.