Spatial and Temporal Discounting in a Social-Climate Model

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

This thesis analyzes how individuals' devaluation of distant impacts of climate change affects mitigation behaviours and projected climate conditions. To approach this question, spatial and temporal discounting is applied to a coupled social-climate model. This model represents a two-way feedback between human decision-making, social norms, and human behaviour with changes in the climate. This is achieved through coupling an evolutionary game theoretic model of opinion dynamics and a simple Earth System Model. The results showed that shifting from current-looking to future-looking behaviours (preferring lower discounting scenarios) and considering multiple locations and population groups, supports a higher proportion of the population choosing mitigation strategies. This shift produces a pathway to reducing temperature anomalies and carbon dioxide emissions. However, the approach to a better state of the climate is best achieved by targeting both discounting and social behaviours rather than just one or the other. These results highlight the benefits of including human behaviour in climate models and the need for a more multifaceted approach to mitigating the negative effects of climate change.

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Dedication

This is dedicated to my grandma, who always wanted me to pursue an education in something I loved.

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Chapter 1

Introduction

It is well accepted and observed that the Earth's climate has been changing, and the surface of the Earth has been warming [27, 28]. Earth's climate and radiative balance are influenced by many factors and their interactions with each other [17, 27, 29]. Some major drivers of climate change include greenhouse gas emissions, surface albedo, aerosols in the atmosphere, and land use [27]. These climate forcings are used as parameters in climate models [27]. The results from these climate models can be used to predict future climates, determine different effects certain parameters or interactions have on the changing climate, and influence mitigation and policy-making efforts [27, 28].

The standard practice in climate modelling has primarily focused on the physical processes of the climate, implementing predefined pathways of emissions into simple or extensive models, and using model ensembles and physical data (ocean circulation, atmosphere dynamics, etc.) [27]. Yet, through the standard practice of building and evaluating the model, a vital component of the changing climate is left out: humans. In an effort not to complicate the physical modelling further, scientists often choose not to account for human interactions with the climate beyond anthropogenic emission scenarios [27]. If climate models aim to represent the planet as best they can, the models will always maintain a gap in representation if they fail to implement human behaviour, which is the leading driver of climate change [17, 27]. And the problem is not humans as some abstract other; it is us: scientists, policymakers, emitters, mitigators, non-mitigators. And even within these specific groups, there is further diversity. Humans, individually and as groups, differ in experience and how they feel the effects of climate change economically, physically, mentally, and culturally, which has implications for climate-related behaviour [7, 11, 13, 19, 33]. This needs to be accounted for in climate models as much as the diversity in physical climate conditions across the globe. To gain a better understanding of the climate, its impacts by and on humans will need to be considered. As an emerging area of study, it is not yet possible to model the full complexity of human behaviour in the climate. However, even at a conceptual level, key drivers and deterrents of decision-making can be implemented [6, 9, 33]. This includes the impediments common to the majority of individuals and their differences, like how climate change issues are often considered as out of reach, meaning individuals are not frequently interacting with climate change issues in their everyday life [19, 31, 39, 40, 56].

Specifically, the adverse effects of climate change are often portrayed as "there and later", thus reducing the motivation to mitigate "here and now." This is called discounting, where we take value away from events that happen farther away in time, location, or socially [19, 46, 53]. When we discount climate change or consider environmental conditions to be worse off somewhere else, we reduce our motivation to mitigate, which means we do little or nothing to combat climate change [19]. And by doing so, unsurprisingly, the climate does not miraculously get better. This leads to the understanding that how climate change is portrayed and dealt with is fundamentally flawed in our everyday lives and climate models.

The aims of the research presented in this thesis focus on gaining more understanding of the relationship between how humans devalue climate change impacts and conditions as they occur farther away in time and geographic locations and the resulting changes in the climate. This understanding will help address the need for the dynamic inclusion of humans in climate models and support areas of improvement in the presentation and perception of climate change issues. The objectives of this research address the proposed aim through the development and analysis of an expanded behavioural model in a social-climate model. The first objective is to develop a coupled system of Ordinary Differential Equations (ODE) that incorporates spatial and temporal discounting as additional differential equations in a social-climate model and a time horizon approach, respectively. The second objective is to identify key changes in the proportion of mitigators and the temperature anomalies that result from running this coupled human-environment system. This thesis will be broken into four main chapters to address these aims and objectives.

Chapter 2 will cover the necessary background information and literature review that support this thesis. Specific problems like the portrayal of climate change in the media and barriers to mitigating the negative effects of climate change are presented as motivations for this research. The background of the thesis is rounded out with a short literature review of game theory in social dynamics and simple Earth System Models to support the methodology and modelling process, which is presented in Chapter 3. Chapter 3 is where the bulk of my contribution, the inclusion of spatial and temporal discounting into a social-climate model, is provided. This Chapter also explores the two-way feedback between the social system and the simple Earth System Model as established alongside the many parameters of the model. Chapter 4 implements the coupled model under various discounting regimes. This is done to assess the model's functionality and, most importantly, to address the fundamental relationships between how humans devalue future and distant climate impacts and the resulting changes on the climate. An analysis is completed in this Chapter to consider how the inclusion of additional human behaviour in the form of discounting into established opinion dynamics amplifies the adverse effects of non-mitigation on climate conditions. Chapter 5 discusses the implication of the results from my conceptual model in terms of pathways to increase uptake of mitigation strategies and decrease temperature anomalies. This Chapter also provides assumptions made during my modelling process as well as the limitations of the model I develop in Chapter 3. Finally, Chapter 5 also concludes this thesis and provides areas of potential future research in the field of social-climate modelling, and specifically on the phenomenon of discounting.

1.1 Research Questions and Hypotheses

In this thesis, the following main questions will be investigated:

1. Will modelling how humans devalue future climate impacts make sufficiently meaningful changes to projected future climate conditions?

2. How does the inclusion of additional human behavioural traits influence opinion dynamics? And will this more complex system provide greater insight into mitigation strategies?

Where I hypothesize that:

1. Forward-looking behaviours will act to increase mitigation and maintain moderate projected climate conditions.

2. Current-looking behaviour will act to reduce motivation to mitigate and result in extreme projected climate conditions.

3. Including discounting as additional human behaviour will enhance the negative effects of non-mitigation on the climate.

Chapter 2

Background

Important background information is presented in this chapter through a literature review. Topics and problems that motivate my research are presented in Sections 2.1, 2.2, and 2.3. As well, I provide support and definitions for fundamental aspects of my methodology, like game theory in mathematical models (Section 2.4), simple Earth System Models (Section 2.5), and social-climate models (Section 2.6).

2.1 Climate Change in the Media

The media plays a crucial role in how people receive, perceive, and share the issue of climate change. This can be through online or print newspapers, radio, social media, and even film and art. This media is presented on a range of scales from local to global levels. The mechanisms behind media that drive engagement with climate change do not operate to consistently support or promote engagement with environmental issues. In this section, I discuss how climate change is portrayed in the media (namely news media), the outcome of this framing, and better ways to approach the presentation of climate change issues. This discussion of climate change in the media is useful in understanding the motivation and necessity to incorporate discounting into a social-climate model, which is, at its core, my research topic.

Media has an important hand in shaping the way climate change is presented on a global, national, and local level. Climate change is presented in such a way that certain aspects of the issues are emphasized or made salient while others are pushed to the back or obscured [39, 40, 59]. This is known as framing and is used to stimulate the interpretation and evaluation of climate change [39, 40]. Issues can be framed in different ways depending on the desired audience, outcome, and even based on geographical origins of events and reporting [3, 59]. Issue frames are greatly influenced by politics, ideology, and socioeconomic factors [40, 59], as well as social norms and cultural factors [40, 59]. There is leverage over framing even at the level of news development. Major news corporations and their organizational and readership pressures and ideals play major roles in building the media frames [40]. Framing climate change is clearly a complex process that draws on factors beyond climate-related events and the environment. As an extension of the construction of frames, the implementation of frames also creates meaning. When select frames are used in rotation and others are abandoned, specific narratives and voices are valued or devalued respectively [39]. O'Neill [39, 40] eloquently defines how all the influences on framing climate change work together to "shape the possibilities of engagement with climate change". This engagement starts at the level of understanding, moves to awareness, and then moves to action. Yet the frames that news media turn to the most fail to spark positive, actionable engagement regarding climate change.

Some of the most common frames used when presenting climate change in the media are 'distant framing' and 'contested' or 'politicized framing' [31, 39, 40, 55, 56]. Distant framing removes the reader or general public from the climate change issue. This is achieved through casting geographical, temporal, or social distance in the preparation and distribution of media [56]. In other words, this framing places climate change as something psychologically isolated from the consumers' everyday [39, 40]. Frames can be implemented in media by showing specific types of images, through geographical scales of publications versus events, through discussion by specific actors, and more often than not, a combination of these. For example, this frame can be achieved through the use of particular images that evoke distance through the feeling of awe [39, 40]. Photos that present environments with very few to no humans or featureless photos, isolate the climate change threat from the media consumer. Frequently used photos that capture this feeling of distance are ice-landscapes on their own or more commonly seen with polar bears [39, 40]. Beyond the geographical distance photos can emulate, they can also create a physiological detachment between consumption and production. A famous example of this is through the image of smokestacks, specifically relating to the everyday use of energy versus the conceptually distant production of that energy [39, 40]. The distant framing in photos draws a line between some far away concept or location, and the consumer.

A less direct way to implement the distance frame is through prioritizing certain voices over others. The media uses only a few of many possible ways of discussing the climate crises (examples include driving narratives of specific voices and geographic locations) [39, 56]. This limited selection of reporting then restricts the ideas and issues people know and care about, fundamentally narrowing potential work on the climate crises. In one example of how climate is discussed in the media, it is suggested that when researcher's discourse is prioritized, their persistent use of projected global outcomes and events presents climate change issues as untouchable to the general public [56]. This forms a disconnect between everyday life and climate change, discouraging the understanding of climate change as a present problem. Another disconnect arises through the prioritization of scale. Often, climate change is portrayed on a large national, international and global scale. This scale is used even in local news media [31]. The large-scale climate issues presented then feel spatially and temporally distant to the individual, distorting their view of their local climate problems. The tendency of media to implement the distance frame through repeated narratives reinforces an understanding of climate change as happening elsewhere and as inaccessible on an immediate or local basis to the media consumers. This siphons off possible engagement and motivation to actively mitigate behaviours that result in climate change. The absence of the general public from images, debate, and local news that they consume aids in heightening the disconnect between the effects of climate change and the anthropogenic forces behind these consequences. After all, if climate change is constantly being portrayed as a problem somewhere else and later on, then individuals will be left with no sense or motivation to act.

Another highly adopted way to frame climate change issues is through 'contested framing,' which gives space in news media to the voices and faces behind policy, protest, debate, and skepticism. Images of politicians or protests are the stars of this frame [39, 40]. While it is good to humanize climate change interventions, restricting media coverage to climate action by politicians, celebrities, or other elite characters creates a gap between the everyday person (and their actions) and avenues for real change. Other less frequently employed frames are 'outcome,' 'impacts or consequences' (economic or natural), 'scientific,' and 'social progress framing' to name a few [3, 31, 35, 39, 40, 55, 56, 59]. Distance and contested framing are continually the most used in presenting climate change issues, but are not effective in promoting the shift from individual engagement with an issue into actual action. That gap remains a significant driver for inaction. Still, if climate change issues are framed differently, an increase in individual connection to the issue could be approached.

Alternate approaches to framing climate change issues should be dominated by one shift: making climate change an issue that is personally relevant to individuals' everyday lives. This can be done by stepping away from frames that break down individuals' motivation toward action, like the distancing frame, and moving towards frames that are empowering to the individual and larger population [55, 56]. This deliberate choice addresses the gap in previously used frames: there are very low rates of solutions or actions presented [31, 56]. This absence of potential action emphasizes the necessity to encourage changes in behaviour. Such encouragement or motivation could be through presenting and supporting solutions of individual mitigation or adaptation practices [31, 55, 56]. This draws climate change solutions and, thus, climate issues closer to the everyday individual. This flips the narrative: leaving behind the overwhelming use of climate change as some long-term complex spectacle, and heading towards a "here and now" form of communication of climate issues [55, 56]. This creates a closeness rather than a distant feeling which could lead to better engagement and action [55]. It has been suggested to present climate change and mitigation through a health and public health lens to bring the issues of climate change one step closer to the individual [40, 55]. This portrays climate change and its understanding as even more relevant to the individuals' everyday [55, 56]. In any of these cases, it is clear that creative and personal ways of framing climate change issues as relevant and open to the everyday and general public voices are needed to promote a mix of emotional connections that drive engagement and action.

However, if climate change issues are not covered in the news media, then framing becomes trivial. The type and magnitude of climate coverage in the media depends on various factors. Sociopolitical events, extreme weather events, and socioeconomic traits of geographical locations all contribute to media coverage [3, 31, 35, 39]. Planned IPCC reports, UN Climate Change Conference of the Parties, and less frequent events like Al Gore's *"An Inconvenient Truth"* and Nobel Peace Prize, capture media attention and are triggers for increased climate change coverage [3, 31, 35, 39]. In contrast, climate change issues are often under-covered, if at all, when other prominent regional and global events (sporting events, elections, etc.) are occurring [35]. While coverage peaks around environmental events, the coverage around extreme weather fails to emphasize connections to larger-scale anthropogenic climate contributions [3]. Due to this climate coverage and the common media frames, individuals are then disconnected from climate change problems. This disconnect is heightened by the use of reporting styles in carbon-emitting locations versus regions where the effects of climate change are felt [59]. In richer (higher GDP per capita) and carbon-emitting countries, coverage of climate change is scientifically framed and focused in the energy sector [59]. Whereas poorer countries experiencing climate change effects regularly, have media coverage relying on the 'natural impact frame' [59]. Framing and covering climate change in this way highlights a major divide between climate change causes and impacts. Down to the level of media consumers, the limited framing in specific geographic locations produces a distance between individuals and consequences of inaction towards the climate. The intensely varied framing of climate change issues from location to location reflects a more universal understanding. That much like how climate change does not affect all people equally, climate change related media does not reach everyone equally either.

Through media, individuals see climate change issues framed as distant from their everyday, as happening somewhere out of reach and if predicted, later in time. They may see news stories of climate-related events, but rarely climate change solutions like mitigation practices. This construction of climate change media reinstates barriers to positive environmental behaviour. They block or make it harder for individuals to feel motivated and engaged in climate change issues and solutions. Climate change in the media is just one area that supports the action of discounting climate change through space and time.

2.2 Barriers to Mitigation

An individual's willingness to take action, specifically towards the environment, is a behaviour that is easily influenced, both positively and negatively. These influences arise in many forms but ultimately target the mind. In terms of climate change, on the one hand, positive influences can lead to an increased uptake of mitigative action. On the other hand, negative influences can reduce the amount of mitigation an individual and a population take towards the climate. In this section, I discuss a variety of barriers to taking action, guided by Gifford's 2011 study [19], and ways to deal with those barriers that can promote positive action towards the environment. This idea of what inhibits an individual's motivation to mitigate is important in my thesis because the main problem I aim to address deals with a barrier to action: judgmental discounting.

By identifying psychological barriers to mitigating climate change, Gifford [19] highlights key behavioural aspects that should be included when studying climate change mitigation on a phenomenological level. In the context of social-climate models, considering these barriers in the social subsystem may better address the complex nature of human decision-making. In their 2011 study, Gifford [19] outlines seven central psychological barriers to pro-environmental behaviour. The barriers they present are not mutually exclusive, and in fact, the overlapping nature may enhance the lack of positive action toward the climate [19]. The developed barriers address three broad phases of climate inaction: ignorance (no action), being aware of the problem (no action), and action that has an inconsequential difference on the climate [19]. The seven major barriers or "dragons" as Gifford calls them include: limited cognition about the problem, ideological worldviews, comparisons with other people, sunk cost and behavioural momentum, discredence towards experts and authorities, perceived risks, and positive but inadequate behavioural changes [19]. Examples of these barriers may include actions that may be presented as solutions to climate change problems but are not substantial enough to have meaningful effects [63]. Thus, an individual's willingness to take pro-environmental action decreases [63]. I will discuss three barriers: place attachment, limited cognition, and judgmental discounting.

Place attachment, or lack thereof, refers to the psychological connection or belongingness to a "place", such that the place holds meaning to the individual [47]. This definition of place does not rely on stationary spaces but can refer to various scales, from objects to environmental and geographical scales. Most attachments form on scales larger than the human body and vary by demographic [47]. Place attachment operates to provide benefits to individuals through connection. Scannell and Gifford [47] derived thirteen categories of benefits from their 2017 survey; the most significant benefits provided by a place included memories, belonging, and relaxation. That being said, despite benefits gained on individual levels, too strong or too weak of connections may act counter-intuitively towards the climate [12, 19].

The two sides of place attachment, which support and discourage mitigation, represent the complexity of dealing with barriers to action. One example of the benefits of place attachment pairs with the framing of climate change in the media, as covered in Section 2.1. When combined with an individual's level of place attachment, local framing of messages promotes more engagement with climate change issues [46]. This lends some insight into the multifaceted approach needed to encourage pro-environmental action. That being said, place attachment can often act as resistance to mitigation. When the place attachment - the feeling of belongingness to a place, the emotional and psychological connection - is weak, it stands as an "obstacle" to pro-environmental behaviour [12, 19]. Moreover, place attachment can negatively affect the environment if an individual is attached to a place in such a way that hinders preservation [46]. This implies that there is not one way to approach the barrier of place attachment, and further, there could be different approaches to increasing the motivation to take mitigation behaviour.

Not all individuals are experts in the science of climate change. The information received about climate change issues does not always cover relevant information and sufficient action that can be taken [31, 56]. This leads to an incomplete understanding of the problem, which is another barrier to mitigating climate change impacts. The limited cognition barrier covers a variety of physiological behaviours and features that are associated with irrational thinking [19]. These include lack of knowledge about the problem, uncertainty in climate models, the common inability to be concerned with distant problems, and the perception that individual actions are insufficient, to name a few [19]. This reinforces the ideas associated with maintaining climate change as a distant threat and brings to light the inhibiting effects of skepticism around climate change issues.

Another major barrier to action is called judgmental discounting. Judgmental discounting, much like other definitions of discounting, is seen as taking value away from future risks. Yet, Gifford [19] breaks this barrier down into spatial and temporal components in direct relation to environmental action. They define discounting as acting against an individual's willingness to mitigate. Specifically, spatial discounting is defined as an individual perceiving environmental conditions and problems to be worse somewhere else, distant from where they are [19]. Along the same lines, temporal discounting focuses on the idea that environmental conditions will be worse in the distant future [19]. Judgmental discounting lays out a fundamental problem in climate change science and mitigation. It considers the fact that climate change poses a major threat in "other" locations in space and time, but the solutions lie "here and now."

While judgmental discounting is of utmost importance to this research, it is apparent that coupled human-environment models, through the nature of behavioural human dynamics, implement some form of these "barriers". For example, the social system in Bury et al.'s [9] and Menard et al.'s [33] models that rely on imitation dynamics subtly introduce the barrier focused on the comparison with others. Breaking their models down further, the perceived cost of climate change and the cost of mitigation behaviours are representative of the obtrusion that personal risks and financial risks cause to taking up mitigative action [19]. As an extension, Menard et al.'s [33] consideration of rich and poor groups is representative of the causes that inequality has on pro-environmental behaviour. These are just a few cases where human behaviour is implemented to asses what supports and what acts against taking mitigation action.

Ultimately, individuals' experiences in their everyday lives can act as influences that either push them toward choosing mitigation strategies or non-mitigation strategies towards the climate. When these influences hinder the willingness to or discourage the uptake of mitigation action, they are known as barriers [19]. Through these physiological barriers, a slightly more complete understanding of human behaviour in terms of climate change conditions and impacts can be gained. As an extension of this understanding, these barriers can be implemented through mathematical modelling in human-environment systems to analyze the behaviours dynamically.

2.3 Discounting The Climate

Section 2.2 outlines some barriers to pro-environmental behaviour as physiological behaviours that inhibit mitigation. Section 2.1 presents common ways climate change is presented in the media, which builds upon and into these barriers. In this section, I discuss discounting as it relates to environmental conditions and break it down into spatial and temporal reasoning. This section is particularly important in establishing how discounting is defined and eventually implemented into a coupled social-climate model in my thesis (Section 3.1).

Discounting in the ecological and environmental context can be understood generally as some process of devaluing environmental events or services depending on some dimension of concern [5, 19, 20, 48, 53, 64]. When looking at spatial and temporal dimensions, discounting can focus on the idea of environmental conditions being worse in other locations (spatial) and farther in time (temporal) [19]. That being said, discounting can also assess psychological or social distance, and foresight or the extent of decision making [5, 20, 24, 46, 48, 53]. For example, psychological distance can describe the degree of separation spatially, socially, and temporally between some object and an individual (and their sense of self) [53]. Commonly, the dimensions of space and time are used when studying discounting in environmental systems.

The idea of discounting in an environmental context is malleable enough to support the understanding of taking value away from environmental events or services while providing space for application in different research areas. When looking at one dimension, time discounting, a few researchers rely on the ideals of costs and benefits in terms of time [5, 20, 48]. Their implementation of temporal discounting follows the general understanding that future decision outcomes are valued less than short-term outcomes [5, 20, 48]. This is a reasonably general temporal discounting definition, and yet the context of intergenerational decision-making [20], time preference (prefer positive outcomes now and negative outcomes later) [20, 48], temporal perspective (influence of views on past, present, and future) [48], and time horizons (foresight of decision making) [24] easily guide how discounting is used to answer the researchers' questions. Time preference or perspective helps reduce the generalized definition of time discounting into individual human behaviour.

When considering other dimensions of discounting, similar varieties of definitions arise. Generally, discounting in a spatial or social sense is defined by value decrease when physical or physiological distance increases [5, 64]. Frameworks of physical distance (for example, ecosystem service values) [64], spatial preferences [5], and separation of self and others [19, 48] extend this baseline idea of discounting in terms of the environment to support an array of distinct definitions. That said, social and spatial discounting are not as straightforward as temporal discounting. Whereas temporal discounting follows linear time with exponential and hyperbolic smooth decay functions [5], spatial discounting may rely heavily on individual preferences. It is clear from these definitions presented that temporal and spatial discounting not only depends on physical and psychological distance but also individual preferences (prefer benefits sooner rather than later and at specific locations) [5, 20, 48]. Moreover, the application of discounting can be used in the areas of ecology, economy, and climate to name a few [5, 20, 24, 46, 48, 52, 53, 64].

More often than not, studies implement multiple dimensions of discounting to asses their research questions. This process can isolate different discounting measures to analyze effects individually or consider the possible overlap that the influence of discounting has on human decisions and the environment. For example, a study considered temporal and social distance when looking at climate risk perception in farmers, finding that two principal ideals arose: participants were either historically-oriented or future-orientated [48]. This implies that individuals make decisions based on prior experiences but vary in their willingness to acknowledge future generations, conditions, or to add external information to their own experiences [48]. As a result, future-oriented individuals acted in a more pro-environmental way than individuals with historically-oriented perspectives [48]. This study helps discover how the perception of climate-related events can influence an individual's behaviour in polarizing ways, one supporting beneficial action for the environment and another acting against it.

A second study found that when analyzing both spatial and temporal psychological distance, the two types of discounting were additive in their consequences, often with negative impacts on policy support [53]. This study from Sparkman et al. [53] considers a lens of "closeness" in space and time rather than "distance" when concerned with policy support. They identified that (in their region of interest) policies currently seem to frame environmental impacts in the distant future and farther away [53]. This leads to future events losing value through temporal and spatial discounting and then reducing policy support [53]. Their results reinforce the need to shift the way climate change is framed away from the distant frame in the media [55, 56], or in this case, climate policy (see Section 2.1). That being said, similar to the negative consequences of too strong of place attachment [19, 46], Sparkman et al. [53] acknowledge that closeness can lead to too high of concern level and become overwhelming. This study addresses two important factors of discounting. First, the overlapping nature of the dimensions of discounting influence, often negatively, the choice of pro-environmental behaviour (see Section 2.2) [19]. Secondly, discounting, even as presented through policies and the media, has a strong influence on individual decision-making.

When considering one dimension, like space or time, the application of discounting is distinct in study results. These results then reinforce the definition of discounting and provide evidence of the impacts of discounting on environmental decision-making. For example, one study incorporates spatial discounting into a mathematical model of ecosystem service distances through spatial welfare to analyze consumption, ecosystem services, and willingness to pay for services [64]. These drivers of discounting rate account for spatial preference and population density, which can represent wealth disparity based on location

[64]. Ultimately concluding that while a low magnitude of services increases ecosystem service value, an increase in physical distance from the ecosystem service results in a decay of the service value [64]. Another study implements temporal discounting through foresight in decision-making (time horizons) on forest-grassland mosaics [24]. The discount time horizons are integral for identifying vegetation cover, such that long time horizons for conservation boost natural land cover [24]. Subsequently, the discount time horizon for conservation has a more significant effect on the dynamics of land cover than the discount time horizon for the economy [24]. These two studies are important in the way they implement discounting. Yamaguchi and Shah [64] have a spatial discounting factor that influences their utility function governing their model, and Henderson et al.'s [24] time horizon factors for conservation or economic gains are used as foresight in their utility function that governs human behaviour. These studies highlight the important influences that discounting has on the outcome of environmental decision-making and human behaviour, which can be discovered by mathematically implementing even just one dimension of discounting.

Discounting the climate and environment does not always follow the clear-cut definitions of discounting as presented thus far. In fact, the idea of value and how it is given to or taken away from climate change events re-evaluates approaches to discounting [5]. In an attempt to focus on climate change adaptation instead of mitigation, Baum and Easterling [5] address the contrast between how individuals value costs and benefits versus how those costs and benefits should be valued. These values could take the form of intrinsic or instrumental value [5]. Additionally, discounting has even been applied to factors beyond distance. An example is through directly discounting carbon prices (taxes, payments) [52]. This form of discounting in Sjølie et al.'s [52] 2013 study takes an economic approach to assess the value of carbon in relation to forest carbon offsets. In particular, they determined that even with low discounting rates on carbon, mitigation efforts are still low in the short-term but increase in the long-term [52]. These studies highlight that the approach, assessment, and results of studying discounting on the climate are not always straightforward. Often, a different scientific perspective helps better understand the intricacies of discounting concerning the environment.

The presented temporal, spatial, and social discounting definitions establish a standard understanding of discounting in terms of the environment. In this thesis, the definition of spatial and temporal discounting concerning climate change is as follows: individuals devalue climate impacts as they occur in more distant locations and times. This follows the initial form of discounting defined by Gifford [19]. While the way discounting is enforced in this research differs from other implementations [5, 20, 48, 64], it is essential to consider overall how the functionality of discounting is applied in an environmental sense.

This brief literature review and dive into other instances of discounting being implemented in environmental studies highlight the influence that discounting plays on responses in decision-making and environmental conditions. Specifically, implementing distance in time and space as a foundation for discounting has major implications in climate science. It helps illuminate the fundamental issue of expressing and acting on climate change and climate-related issues as distant problems [31, 39, 40, 56]. Also, accounting for discounting in climate-related research provides evidence and support for policy changes that can address this type of physiological barrier to mitigation and climate-positive behaviours [53]. These definitions of discounting and how they are modelled in environmental and human systems help guide the understanding and implementation of spatial and temporal discounting as seen in Section 3.1.

2.4 Game Theory in Mathematical Models and Social Dynamics

Game theory is a valuable tool in modelling and assessing interactions between individuals and between and within groups of individuals [21, 43]. On a very basic level, game theory is a way to study the outcome of decisions when individuals consider and interact with other decision-making individuals [21, 41, 43]. On the level of the individual, or player, in these models, their main goal is to maximize their payoffs or utilities [43]. Generally, these payoffs are defined based on a player's chosen decision or strategy, which can take a couple of forms. Firstly, payoffs can be provided to a player as a utility after all players have chosen strategies and the game has ended [43]. Secondly, individuals can receive payoffs in the form of expected utility that depends on the chosen strategies of all individuals and themselves [43]. These payoffs represent the fundamental practice in game theory: the interdependence of other players' strategies and action choices [21, 43]. While this is a rudimentary introduction to game theory, it lays the basis for the necessary information covered in this section. Specifically, I will briefly discuss evolutionary game theory and social dynamics in a game theoretic context, as well as a few instances of the implementation of game theory in mathematical models. This discussion is essential in understanding the methodology of the social system presented in Section 3.1.

Evolutionary game theory focuses on the social dynamics in a group of individuals where others greatly influence behaviours of choosing strategies. The evolutionary component operates to weed out behaviours that do not perform well in the population [50]. More specifically, an individual will imitate another individual's choosing behaviour if the payoffs of that strategy are greater than the current or average population strategy [50, 57]. This is called imitation dynamics, where the rate of changing strategies depends on the difference in payoffs, such that the expected success increases when choosing a different strategy [21, 25, 57]. These dynamics are dependent on replicator equations where individuals imitate the actions, or strategy choices of others at a "probability proportional to the expected gain" [25].

Replicator equations are often used in biological applications of game theory [21]. These are equations mathematically modelling the dynamics of the frequency of strategies occurring or being chosen in a population [21, 25]. Replicator equations rely on the difference between the payoffs of strategies and the average population [25]. Through these equations, the success of strategies is reflective of the strategies' rate of increase in the population [25]. All that said, replicator dynamics represent the imitation process of individuals, which can be through the exchange of experiences and information [21]. Approaches to implementing imitation dynamics and replicator equations can follow continuous-time differential equations and even take on stochastic forms due to their "BOLTZMANN-like" origins [21]. Tilman et al. [57] use this form of evolutionary game theory to create a generalized model for environmental systems, where both other individuals and the environment influence decisions. Other forms of the application of game theory (not just evolutionary game theory) are in economics, infectious diseases, and ecology [4, 41, 57].

Game theory is easily applied in the context of economics as payoffs are simplified. That being said, the strategies and games defined may take various forms. Perman [41] focuses on the interdependence of countries and pollution reduction in the context of decision-making and the runoff effects of those decisions. Due to the nature of pollution not abiding by boundaries, the decision of one country to work to reduce pollution may benefit other nearby countries [41]. To consider this idea, Perman [41] implements a few different game theoretic approaches and cooperation levels (full or no cooperation): the prisoner's dilemma, the chicken game, and the assurance game. Through this analysis, they discovered different stable and unstable solutions, often resulting in the strategy choices of not abating pollution, or "free-riding" the benefits from the other player's decision in the prisoner's dilemma game [41]. The main environmentally beneficial solution they obtained was when both countries worked cooperatively to contribute to the public good in the assurance game [41]. That being said, the outcome of the games they studied in this context relied heavily on defining the payoffs and punishments of choosing different pollution abatement strategies. This study focused on only two countries in the context of economic benefits and pollution control. Games can have more than two strategy options. Sethi and Somanathan [50] focus on a common pool resource game with three strategy types. These types (enforcer, cooperator, defectors) were defined based on the reliance on norms or self-governance employed by communities concerning common resources [50]. Their use of evolutionary game theory is implemented through the standard form of differences in payoffs between strategies. A significant result they found through applying evolutionary game theory was the persistence of behaviours [50]. In other words, a temporary change in payoffs (and parameters) can result in irreversible changes in behaviour [50]. These two economically and environmentally-centred studies help to begin to identify the impact of social dynamics in different systems when multiple strategies or groups are present.

This intuition can be extended into systems and models that capture the feedback between a decision-making payoff system and a biological system. In an environmental sense, these are systems where payoffs for individuals rely on strategy choices concerning the population and the state of the environmental system [9, 33, 57]. To complete the feedback, the choices of populations also influence the environment [57]. In this way, Tilman et al. [57] create a general framework for what they call "eco-evolutionary games" that represent this feedback with arbitrary environmental systems. Immediately, an issue of timescale arises. Three timescales are present: intrinsic environment dynamics, strategy impacts on the environment, and the evolution of strategy choices in a population [57]. To deal with this issue, Tilman et al. [57] undergo linear transformations in their model and assume an equivalent timescale to compare the rate of environmental dynamics and strategy dynamics. This general model with a linear payoff structure was applied to a psychological model with fixed or flexible decisions, an ecological model of grass and legume competition relative to nitrogen fixation, common-pool resource harvesting in bio-economics, and an environment governed by tipping points in an eco-evolutionary game [57]. They conclude that the rate of environmental feedbacks plays an integral part in the dynamics of the system. Particularly, a complete understanding of the adaptive systems could not be obtained by considering either environmental or evolutionary game dynamics on their own [57]. This result highly supports the knowledge gap when these two types of systems are not dynamically considered together.

The connected influences modelled through evolutionary game theory and arbitrary environmental systems can also be observed in a biological sense. Bauch and Bhattacharyya [4] implement social learning guided by imitation dynamics and replicator equations. They focus on the feedback loop between disease incidence and vaccination behaviour modelled through coupling the behaviour model with a SIR model [4]. The addition of social learning provided important insight into risk perception and vaccination coverage. Some results from their model show that the coupled model fits data in vaccine coverage better than disease incidence and fit to historical data was overall better with social learning implemented [4]. Fundamentally, this study represents the strength of game theoretic interactions with individuals, vaccination responses, and disease incidence when a vaccine scare occurred in a population [4]. Additionally, this study highlights the beneficial outcomes achieved by implementing evolutionary game theory through social dynamics to represent better and model two-way feedbacks where human opinion dynamics are at the centre. Overall, evolutionary game theory is highly efficient as a methodological tool in modelling two-way feedbacks between social dynamics and another biological or ecological system.

2.5 Earth System Models

Earth System Models (ESM) are mathematical models that capture key dynamics of the Earth's physical system to produce climate simulations and projections. ESMs are used to test and gain an understanding of scientific or climate questions and theories, as well as an understanding of model components, systems, flaws, and areas of improvement. Because of the expanse of ESMs, these types of models range in complexity. In this section, I discuss some essential characteristics, variability, and difficulties of ESMs. Understanding the general components and functionalities of ESMs helps support the decisions and assumptions made in my modelling process.

An ESM is comprised of atmosphere, ocean, sea ice, and land surface components [42]. Each of these contains smaller systems that represent the many physical climate processes. These can include water processes, greenhouse gasses, ozone, aerosols, biochemistry processes, land vegetation, marine chemistry, terrestrial ice sheets, ocean biology, and biogeology [42]. The inclusion of biogeochemical processes is a key distinction between ESMs and other models like Atmosphere-Ocean General Circulation Models [27]. ESMs are coupled such that each component or sub-model exchanges variables with each other, representing vital feedbacks in the Earth's climate [42]. The representations of smaller physical processes are formulated through grid boxes and layers of the model [17, 42]. The grid boxes and model layers then determine the geological and computational scale.

ESMs sufficiently represent climate processes that occur over multiple geographic and time scales. Some chemical processes occur on smaller scales than larger atmospheric processes. For example, atmospheric cloud cover occurs on a much larger spatial scale and faster time scale than photosynthesis (uptake and storage of carbon dioxide) [2]. Similarly, some physical processes like turbulent eddies and mid-latitude weather systems operate on time scales of seconds to minutes and days to weeks, respectively [16]. ESMs must work to account for these mismatches in scale in the model subsystems. The resolution of the common scale mismatch is approached by choosing grid box sizes and then parameterizing any process that occurs on scales smaller than those boxes [17]. These "smaller" processes are often called sub-grid processes [42]. In other words, ESMs depend on parametrizations to help represent the interactions of both grid-scale and sub-grid scale processes on the climate [17]. As an extension, this process of parameterization not only better represents the

Earth's physical systems but also enables ESMs to pay specialized attention to particular topics and areas of scientific query.

While parametrization is a major point of development and attention for ESMs, it also comes with challenges. Dealing with processes that occur over multiple scales requires additional attention [42]. The parameterizations that aim to solve the mismatch problem bring additional uncertainty into the model and its results. To deal with these uncertainties, hypothesis testing and calibration are completed [17]. This process is vital to checking that the historical and observational data correspond with the simulated data from the parametrizations [17]. This approach addresses model, physical, and result uncertainty for climate models like ESMs [17, 42]. The multiple stages of model development, from parameterizations to model refinement, are heavy undertakings. Climate groups are constantly working to better capture and represent the Earth and its physical climate system, whether it's through parameterizations, ESMs, or other climate models [27].

While ESMs represent the many physical processes and feedbacks of the Earth's climate, they are implemented and used to assess different uncertainties, explore scientific challenges, and gain a new understanding of the climate system [27]. Two main ways that ESMs are used are through single-model or multi-model experiments [27]. Single-model experiments address new questions or theories, whereas multi-model experiments assess the structural features of the models and results [27]. The multi-model experiments are called ensembles. The ensemble results are often used in large level projections and uncertainty and robustness quantification through Model Intercomparison Projects (MIPs) [27, 22]. MIPs and their ensembles can be focused on specific areas or questions. For example, CMIP compares coupled climate models, AOMIP evaluates arctic ocean climate models, and PMIP explores the paleoclimate, to name a few [1]. The goal of running MIPs is to gain more complete interpretable results, which can then be used to guide future work on ESMs.

Climate models, like ESMs, are evaluated as boundary forcing problems. The results of the ESM simulations provide a space where existence is based on the boundary conditions and forcings [17]. Emission scenarios are one of the most consistent input data that drives these models. These have been systematically developed from Representative Concentration Pathways (RCPs) to Shared Socioeconomic Pathways (SSPs) and fundamentally maintain a fixed nature to human behaviour [6, 44]. SSPs are emission scenarios to represent plausible and implausible global emission levels and storylines [15, 27]. These storylines focus on policy with or without mitigation and adaptation strategies [18, 44]. Moreover, the implementation of SSPs into climate models, like ESMs, is used to understand potential successes and challenges with global climate action [18, 44]. ESMs require these forcings, boundary conditions, and mathematical processes to evaluate the model and approximate its solutions. The resolution of these models is implemented through spatial grids and vertical layers. Grids vary in size; the smaller the grids, the more computationally expensive simulations become [42]. Similarly, the larger the grids are, then the modelled processes become less precise [42]. To evaluate these models over the grids, methods such as spectral or gridpoint are used to approximate the solutions [42]. Similar to improving parameterizations, the way ESMs are evaluated is also constantly developed. One such development is looking at the type of grids used [42]. This approach aims to swap out the structured grids used in most ESMs with unstructured grids. These unstructured grids take on different geometries like triangles or hexagons [42]. While the development of models often takes precedence, the evaluation of ESMs is just as important to ensure data can be interpretable and achieve computational efficiency.

Efficiency is fundamental in climate models; thus, ESMs must be flexible in their complexity to approach the task at hand. Whether it is to answer specific scientific questions, gain an understanding of a climate topic, or produce large amounts of climate simulations. A model hierarchy has been developed to document the types of differences in complexity, mainly following differences in dimensionality [27]. These model differences fundamentally separate the complexity through computational time and energy, which is high in extensive models and lower in idealized simpler models [42]. That being said, complexity is not static in models. It can be increased in models by coupling different systems together or decreased by breaking apart major subsystems in ESMs [22].

On the one hand, complex models are suitable for simulations that require extensive details [22]. That gives the impression that complex ESMs must be all global and include general physical systems, but that is not always the case. The highly complex models can still narrow down to specific climate topics. For example, FESOM (finite element sea ice/ocean model) is a model that has the flexibility to be regionally specific to high latitudes or have global ocean domains [42]. On the other hand, simple models are crucial to enhancing understanding of results and the hypotheses they set out to test [22]. Some simple ESMs include Energy Balance Models (EBM) that have low dimensionality and focus on energy transfers (for example of an EBM see [14]) [27, 42]; Box Diffusion Models that have few layers of interactions [42]; and Radiative-Convection Equilibrium Models that can be used to interpret results from more complicated models [42, 62]. While comprehensive models, high in complexity, are the best tools for simulations, simplified idealized ESMs are fundamental in advancing understanding of the Earth's climate.

2.6 Coupled Social-Climate Models

Section 2.5 established that climate models generally do not implement a dynamic nature to human behaviour and responses to climate change because of the dependence on Shared Socioeconomic Pathways [6, 44]. Human responses to climate change can be in the form of altering opinions and beliefs on climate change due to experiencing extreme events, interactions with other individuals, and even influences from social media [6, 7]. These changes in behaviour influence mitigation practices, leading to changes in emissions and subsequently the changes in climate, which humans then experience [9, 33]. This is the common feedback loop that is idealized in social-climate models. These are useful in policy making and managing different natural resources and the climate because they help identify how humans make decisions about specific environmental issues [30]. In this section, I present social-climate models as a tool to understand the relationship between human behaviour and the changing climate. This discussion is vital in creating a foundation for the type of model that I use in this thesis.

In a more general lens, social-climate models are a form of coupled human-environment systems. These mathematical models capture the two-way feedback loop between human behaviour and environmental responses. The social and physical systems are coupled in such a way that the change in the human system will be fed into the environmental system, and its results will then fundamentally cause changes in the human subsystem [9, 23, 26, 30, 33, 51]. This concept of human-environment systems has been well applied to ecological processes through social-ecological models that consider a dynamic human behavioural component [26]. For instance, one study implements a social-ecological model to examine how opinions on conservation affect forest-grassland mosaics [26]. Another study focuses on how forest growth is altered due to decisions based on injunctive social norms or conservation priorities [51]. A final example of social-ecological modelling considers drivers of decision-making, like incentives and forest governance [23]. Each of these studies considered agent-based behavioural models with imitation dynamics and social norms as major components in their human subsystems. Particularly, these studies demonstrate that social-ecological systems are complex adaptive systems [30, 49, 57], and emphasize that real-world features may be missed if important characteristics of the coupled system are overlooked [30]. The social-ecological framework and research outcomes of human-environment systems can be extended into a social-climate context.

Shifting to the context of climate change, it is noteworthy to remember that these human-environment feedbacks are not well represented in current climate models. While Integrated Assessment Models (IAMs) consider both economic and physical processes [7, 61], they do not obtain a complete two-way feedback (see Figure 2.1) [6, 10]. By lacking the more complex human behaviour within a larger population size, IAMs lose inter- and intra-group dynamics that are present in more realistic social systems. This can be in the form of mitigator and non-mitigator groups and broken down even further through population heterogeneities [9, 33]. Social-climate models address the challenges present in IAMs and better incorporate human behaviour into the social system rather than narrowing down on socioeconomic processes seen with SSPs. Social-climate models idealize two-way feedbacks by coupling human and physical systems. The coupled models can also range in complexity as a whole and on the individual system levels [10].

Figure 2.1 from Calvin and Lamberty's [10] study presents a conceptualization of this complexity. Figure 2.1 presents the individual complexity of the coupled Earth systems and the human systems based on the amount of feedbacks present in the models [10]. This visualization is helpful in understanding the flexibility in both ESMs and their coupled human system counterparts. Even more so, Figure 2.1 shows that models with two-way feedbacks can vary from simple to complex in both components, giving insight into the functionality on the model level and on the level of understanding that two-way feedbacks provide. Models can pass different variables between the coupled system depending on the problem, question, or feedback they wish to approach. From the human to physical system, this may include greenhouse gas emissions, aerosol emissions, a measure of land use or land cover, carbon dioxide concentration, water demand, or even gross world product [10]. From the physical to the human system, this could be a measure of ecosystem service, crop yield, temperature, precipitation, or land and ecosystem productivity [10]. At a very basic level, evaluation of these coupled models can follow the process of passing data from subsystem to subsystem until the entire system converges [10]. This reinforces the wide range of two-way feedbacks that social-climate models can investigate to understand how social processes and the climate interact [33].

Currently, an array of human behaviour systems are being implemented, much like the variety of parameterizations of physical processes in ESMs. A few motivating studies implement agent-based models with imitation dynamics or planned behaviour, highlighting the benefits of using social-climate models to help inform mitigation efforts [6, 9, 33]. In Bury et al.'s [9] coupled model, they have a system of differential equations to analyze changes in global average temperature due to individuals conforming to mitigative or non-mitigative behaviours at a specific social learning rate. The social behaviour model implements social learning rate and social norms through a utility function that considers drivers of mitigation practices and the probability of individuals switching between being a mitigator or non-mitigator [9]. Similarly, Menard et al. [33] developed a human system that implements wealth heterogeneity to model the socioeconomic inequalities in populations and reflect the asymmetries in climate change. They altered the social-climate model

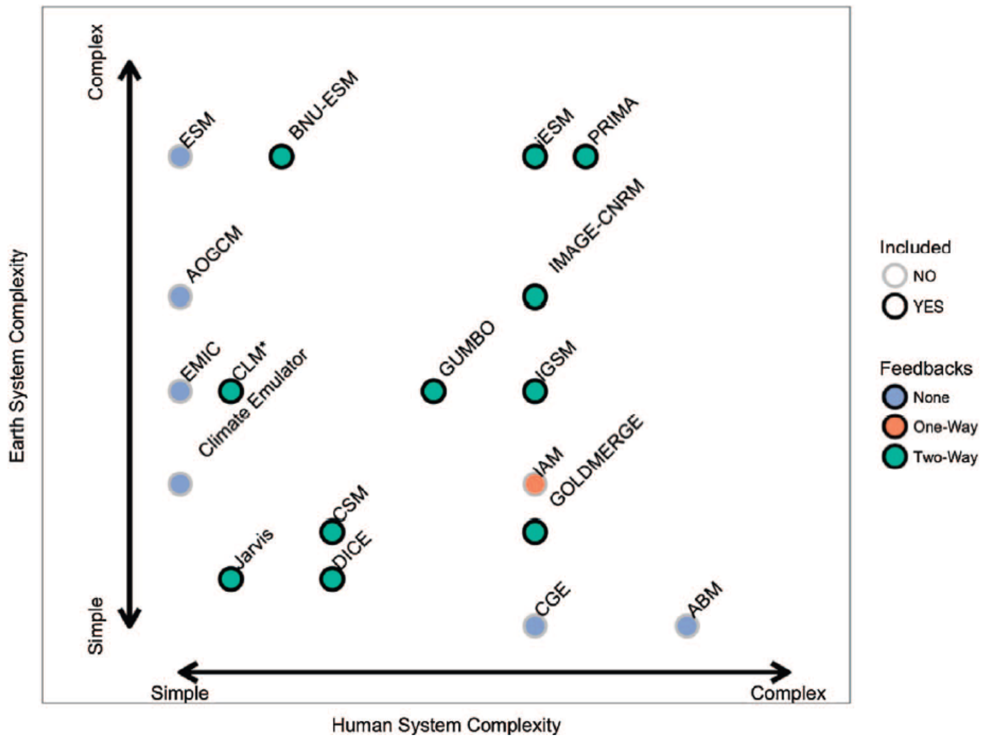

Figure 2.1: This plot from Calvin and Lamberty [10] demonstrates the coupling of human and climate systems as they vary in complexity. It is clear that agent-based models have the most complexity for human systems, but have no feedbacks on their own. When coupled with ESMs of varying complexity, the desired two-way feedbacks are achieved. This plot positions IAMs with other models, showing the level of complexity in IAMs' human system but only a one-way feedback.

from Bury et al. [9] to include a dissatisfaction term present among the poor group [33]. This ensures that the group interactions are modelled by imitation dynamics weighted by dissatisfaction in the poor group and homophily in both groups [33]. Both the Bury et al. [9] and Menard et al. [33] models consider drivers of switching between being a mitigator or non-mitigator as costs of taking on mitigation strategies, cost of rising temperature, the available resources, and the impacts of climate change on those resources [33]. These two social-climate models focus on representing the feedback between the drivers of mitigation action and climate conditions represented through a simple ESM.

Another human behaviour theory that has been implemented into social-climate models is planned behaviour. Beckage et al. [6] implement a planned behaviour social system focused on risk where behaviours depend on the frequency of extreme events. Their analysis considers multiple functional forms of planned behaviour: linear, logistic, and cubic [6]. Each represents different responses to climate extremes. The climate system that they couple their social model with is the Climate Rapid Overview and Decision Support climate model [54]. These three studies implementing social-climate models arrived at the following conclusions: a decrease in net mitigation cost and an increase in social learning rate is needed to reach the IPCC global temperature anomaly target of 2°C [9]; polarization in action occurred between groups based on separate socioeconomic parameters and asymmetric climate change impacts [33]; and high sensitivity in perceived risk to climate extremes, time frame for mitigation responses, and perceived social norms and behavioural control all impact emissions [6]. Despite each model varying in human behavioural processes, these conclusions show that the connection between the social and climate systems is too meaningful to ignore, even if the results of models are used for insight rather than robust climate projections.

Social-climate models often include ESMs that do not elaborate beyond the extent of what is needed to answer their questions. They employ elegant climate systems rather than fully comprehensive systems [22]. This helps to focus on gaining intuition and understanding rather than validated climate projections [9]. That being said, social-climate models also have limitations in their construction. One limitation is that through the implementation of simplified climate systems, there is a potential to miss complex physical processes unrelated to the subgrid-scale processes challenges. Another challenge includes dealing with the mismatched timescales. The human behaviour processes occur on a much faster time scale than the physical processes in the climate [57]. Due to the emergent framework of social-climate models, they lack the large-scale analysis and inclusion that is available to ESMs through Model Intercomparison Projects (MIPs) and ensembles. This produces an increased uncertainty due to the fewer number of models that have been developed independently.

Approaches to deal with these challenges can be done on singular model levels and larger ensemble levels. Müller et al. [37] deal with the issue of mismatched scale by implementing a stochastic process approach in part of their analysis of an anticipation-induced social-climate model. Before they couple the systems, they consider a static physical system (letting the time variable go to infinity) and a dynamic social system (that does not react to the climate system) that evolves at a faster time scale [37]. They then analyze when both systems occur on similar time scales and how the social system responds to the climate system [37]. Once the systems are coupled, they observe the changes in the stability of the systems on these varying timescales [37]. This is one representation of how stochastic analysis can be a tool to use when a mathematical model incorporates processes with dramatically different time scales like in social-climate models. The primary way to approach the challenge of model uncertainties is through an increase in models and involvement in ensembles [17, 27]. Developing more social-climate models that implement a variety of human behaviour theories into the social subsystem, like diversity of parameters, structure, and complexity, helps to address model uncertainties in the social subsystems better and increase robustness across social-climate models [7, 9, 10, 61].

Overall, recent studies developing and analyzing social-climate models are focused on understanding and investigating the impacts of the coupling of human behaviour and the changing climate rather than the climate projections [6, 9, 33, 34]. For that reason, social-climate models are a good tool for advancing the field of climate science. Not only do they draw humans and human behaviour directly into the model to better account for anthropogenic emissions dynamically, but they highlight the fact that climate science can and should be more interdisciplinary in structure [10, 38]. This multidisciplinary nature is already observed through the collaboration that is present in the collection, implementation, and use of proxy data in paleoclimate research. Regarding social-climate models, interdisciplinary collaboration between social scientists, psychologists, and climate scientists would help further evolve social-climate models and the field of climate science altogether.

Chapter 3

Methods

3.1 Human Behaviour Model

The social-climate model developed in this thesis builds on a coupled human-environment system model by Bury et al. [9]. Their model captures human behaviour through imitation dynamics based on social norms, social learning, and the costs of mitigation. The simple Earth System Model (ESM) used in Bury et al.'s [9] original system is a basic representation of the climate. It captures the carbon cycle and greenhouse gas emissions per Lenton's coupled carbon and temperature ESM [29]. These two systems, ESM and social dynamics model, are coupled through the perceived costs associated with climate change - a mechanism to represent the emotional, mental, and physical costs associated with climate change beyond *just* the monetary costs.

Spatial and temporal discounting are systematically implemented into this model so that both dynamics can be represented entirely while also maintaining the integrity of the social dynamics and ESM. The sections in this chapter will step through how both temporal and spatial forms of discounting are captured.

3.1.1 Spatial Discounting in Behaviour Dynamics

The individuals in the model can be mitigators or non-mitigators, meaning they follow one of two strategies: a mitigation strategy of reducing carbon emissions or a non-mitigation strategy of not reducing atmospheric carbon emissions. Individuals conform to these behaviours depending on social learning rates [9]. Similar to Menard et al.'s [33] extension of Bury et al.'s [9] social system into rich and poor groups, the social system in this model separates individuals into two arbitrary patches, patch 1 and patch 2. This effectively creates a two-patch social behaviour model, representing two spatially distinct groups of individuals.

The benefits for individuals of taking up mitigation or non-mitigation strategies are defined through utility functions. These utilities consider drivers of mitigation practices and the probabilities of individuals switching between behaviours. Behaviours depend on climate change costs associated with either behaviour type, social norms, and spatial discounting in either patch. The utilities of being a mitigator or non-mitigator for each patch are as follows:

$$e_{M,1} = -\alpha + c(\theta f_1(T_f) + (1-\theta)f_2(T_f)) + \delta x_1 \tag{3.1}$$
$$e_{M,2} = -\alpha + c(\theta f_2(T_f) + (1-\theta)f_1(T_f)) + \delta x_2 \tag{3.2}$$
$$e_{N,1} = -\gamma - (\theta f_1(T_f) + (1-\theta)f_2(T_f)) + \delta(1-x_1) \tag{3.3}$$
$$e_{N,2} = -\gamma - (\theta f_2(T_f) + (1-\theta)f_1(T_f)) + \delta(1-x_2) \tag{3.4}$$

where, M represents mitigation and N non-mitigation utilities (e) for patch 1 and patch 2. x is the proportion of mitigators and $1-x$ is the proportion of non-mitigators. The impact of the mitigation utility is weighted by the proportionality constant c, and α is the cost of adopting a mitigation strategy, and γ is the cost of non-mitigative behaviour. The costs associated with climate change when taking mitigative action include energy-efficient housing, choosing to drive electric vehicles, or switching to a plant-based diet [28]. Conversely, when conforming to non-mitigation behaviour, costs may arise through carbon tax [9]. δ is the strength of social norms, and $f_i(T_f)$ is the perceived cost associated with the projected temperature anomaly (T_f) for each patch [9]. θ is the spatial discounting factor, weighting each patch's perceived costs associated with climate change.

Spatial discounting is implemented into the social system through the spatial discounting factor, which follows the definition of spatial discounting used in this thesis (see section 2.3). Implementing spatial discounting in the model follows the idea of climate conditions being worse in other locations [19], but functions to determine where the perceived impacts of climate change are being viewed. The spatial discounting factor, θ, operates such that when $\theta = 1$ the population only considers itself and when $\theta = 0$ the population only considers the other population. Rather than holding these scopes as a binary of just "there" or "here," the populations in each patch can consider, to some fraction, themselves and the other patch. By incorporating spatial discounting in this manner, evaluating the standard devaluing of spatially distant environmental conditions and considering multiple spatially distinct conditions can be completed.

When θ takes on the value of 1, where population i only considers themselves, then Equations 3.1 and 3.2 become $e_{M,i} = -\alpha + cf_i(T_f) + \delta x_i$ and Equations 3.3 and 3.4 become $e_{N,i} = -\gamma - f_i(T_f) + \delta(1 - x_i)$. If θ takes on the value of 0, for population i paying attention to the other population j, then the utilities are $e_{M,i} = -\alpha + cf_j(T_f) + \delta x_i$ and $e_{N,i} = -\gamma - f_j(T_f) + \delta(1 - x_i)$. In the same manner, if θ takes on the value of 0.5, where each population equally considers themselves and the other, then, $e_{M,i} = -\alpha + \frac{1}{2}c(f_i(T_f) + f_j(T_f)) + \delta x_i$ and $e_{N,i} = -\gamma - \frac{1}{2}(f_i(T_f) + f_j(T_f)) + \delta(1 - x_i)$.

The key forcing in the social system is social learning, which is implemented through imitation dynamics. These dynamics follow the form such that individuals within each population group may alter their opinions based on the opinions of other individuals in their patch. An individual may switch opinions between mitigating or doing nothing towards climate change at a social learning rate of κ if the payoff of the other opinion is higher. These payoffs or utility gains follow an evolutionary game theoretic form [4, 9, 33]. The switching rate between mitigation and non-mitigation strategies ($M \to N$) and vice versa ($N \to M$) depends on the difference between the utilities of each strategy. For patch 1, these rates take the form:

$$r_{N \to M,1} = \kappa x_1(1 - x_1) max\{e_{M,1} - e_{N,1}, 0\} \tag{3.5}$$

$$r_{M \to N,1} = \kappa x_1(1 - x_1) max\{e_{N,1} - e_{M,1}, 0\} \tag{3.6}$$

Thus, the net rate of change for individuals in the population of patch 1 is:

$$\begin{aligned} \frac{dx_1}{dt} &= r_{N \to M,1} - r_{M \to N,1} \\ &= \kappa x_1(1 - x_1)(max\{e_{M,1} - e_{N,1}, 0\} - max\{e_{N,1} - e_{M,1}, 0\}) \end{aligned} \tag{3.7}$$

which is the difference between switching from a non-mitigation strategy to a mitigation strategy (Equation 3.5) and a mitigation to non-mitigation strategy shift (Equation 3.6).

To ensure that the rate of opinion change is capturing the switch to a higher utility, two cases are considered: first, when $e_{M,1} > e_{N,1}$ and second, when $e_{N,1} > e_{M,1}$. For the first case, the rate of change results in $\kappa x_1(1 - x_1)((e_{M,1} - e_{N,1}) - 0)$. The second case similarly reduces to $\kappa x_1(1 - x_1)(0 - (e_{N,1} - e_{M,1}))$. The net rate of change from Equation 3.7 for the proportion of mitigators in patch 1 is then represented as:

$$\frac{dx_1}{dt} = \kappa x_1(1 - x_1)(e_{M,1} - e_{N,1}) \tag{3.8}$$

Through the same reasoning, the proportion of mitigators for patch 2 is:

$$\frac{dx_2}{dt} = \kappa x_2(1 - x_2)(e_{M,2} - e_{N,2}) \tag{3.9}$$

These differential equations are also known as replicator equations [21, 25].

The utilities for each strategy and respective patches (Equations 3.1 - 3.4) are substituted into the replicator equations 3.8 and 3.9 to complete the social system:

$$\frac{dx_1}{dt} = \kappa x_1(1-x_1)(\gamma - \alpha + \theta f_1(T_f)(c+1) + (1-\theta)f_2(T_f)(c+1) + \delta(2x_1 - 1)) \quad (3.10)$$

$$\frac{dx_2}{dt} = \kappa x_2(1-x_2)(\gamma - \alpha + \theta f_2(T_f)(c+1) + (1-\theta)f_1(T_f)(c+1) + \delta(2x_2 - 1)) \quad (3.11)$$

To simplify the costs of taking up mitigation or non-mitigation behaviour, α and γ are combined into a net cost of mitigating climate change term: $\beta = \alpha - \gamma$.

Table 3.1: This table provides a list of social parameters in the model. Parameter values are presented as triplets to provide lower bounds, baseline values, and upper bounds, for example: (lower bound, baseline, upper bound).

Parameter	**Symbol**	**Values**
Social learning rate	κ	(0.02, 0.05, 0.2) yr^{-1}
Net cost of mitigation	β	(0.5, 1, 1.5)
Strength of social norms	δ	(0.5, 1, 1.5)
Spatial discounting factor	θ	(0, 0.5, 1)
Temporal discounting factor	δ_t	(0, 0.015, 0.05)
Time horizon	t_H	(1, 50, 100) yr
Proportion of emissions	α	(0, 0.5, 1)

3.1.2 Temperature Projection

It is understood that individuals' perceptions of climate change are influenced by climate forecasts [9, 60]. So, the social system in this thesis assumes that individuals use recent climate trends and experiences with longer-term extrapolations of future perceived climate to make decisions [9, 60]. The temperature projections that individuals consider are:

$$T_f(t) = T(t) + \left(\frac{t_f}{t_p}\right)(T(t) - T(t - t_p)) \quad (3.12)$$

where T is the current temperature, t_f is the number of years projecting forward, and t_p is the parameter governing the number of years projecting back. Therefore, T_f is the projected future temperature the population uses for decision-making, which relies on both current and past temperature values.

3.1.3 Temporal Discounting in Perceived Costs Associated with Climate Change

The personal perceived costs of climate change are psychological and physical benefits based on taking up mitigation behaviour or costs based on non-mitigative behaviour. On one side, costs arise through psychological processes surrounding perceived risks of climate change (for example, eco-anxiety, eco-emotions) based on non-mitigation behaviours [33]. On the other, co-benefits emerge through the synchronous benefits of personal and environmental health based on mitigative actions [28, 33].

To represent this human behavioural relationship with projected future temperature, a sigmoidal function is implemented [9]. In the absence of discounting, the perceived costs associated with climate change are of the form:

$$f(T(t)) = \frac{f_{max}}{1 + e^{-\omega(T(t)-T_c)}} \tag{3.13}$$

where f_{max} is the max cost of climate change, this determines the maximum value that Equation 3.13 can reach. ω is the degree of non-linearity, which can alter the abrupt changes in the sigmoidal form of Equation 3.13. T is the current temperature, and T_c is the critical temperature, such that the costs of climate change are most sensitive to temperature changes [9].

Equation 3.13 represents individuals projecting forward to a single point in time t_f. For temporal discounting, I strive to represent the impacts each year while still projecting forward. This is accomplished by summing the projected personal costs of climate change (Equation 3.13) over every year from the current time to some time horizon, t_H (normalized over this time horizon). As time passes, the future impact is discounted by our temporal discounting factor δ_t. Altogether, this gives the new forward projections for decision-making:

$$f(T(t)) = \frac{1}{t_H} \sum_{t_f=1}^{t_H} \frac{f_{max}(1-\delta_t)^{t_f}}{1 + e^{-\omega(T(t)-T_c)}} \tag{3.14}$$

where $(1-\delta_t)^{t_f}$ represents how much value is removed from the climate conditions at the time t_f.

The perceived costs of climate change now operate so that when temporal discounting increases, as a percentage per year, then 3.14 decreases. Similarly, when the temporal discounting factor (δ_t) decreases, then the perceived costs associated with climate change increase. In terms of mitigation, Equation 3.14 mathematically represents the understanding that a lower personal cost of climate change does not encourage mitigation behaviour, whereas a high personal cost of climate change does trigger mitigation behaviour.

By looking at the limits as the temporal discounting factor, δ_t, approaches its upper ($\delta_t = 1$) and lower ($\delta_t = 0$) bounds, a more complete understanding of temporal discounting and opinion dynamics can be achieved.

$$\lim_{\delta_t \to 0} f(T(t)) = \frac{1}{t_H} \frac{f_{max}}{1 + e^{-\omega(T(t)-T_c)}} \qquad\qquad \lim_{\delta_t \to 1} f(T_f(t)) = 0$$

The limit as $\delta_t \to 0$ will always be greater than 0. This holds because the limit takes the form of Equation 3.13, which is a strictly positive sigmoidal function [9], and the time horizon t_H is also positive. The above limits provide the relationship that:

> $\forall\, a, b$ *in* $[0, 1]$, *and* $f_a(T)$, $f_b(T)$ *representing perceived costs of climate change at temporal discounting values a and b. If* $a \geq b$ *then* $f_b(T) \geq f_a(T)$.

This distinction between different temporal discounting values is important in the model construction for two patches. Each patch will have a unique function (depending on the choices of parameters) for the perceived costs of climate change:

$$f_1(T(t)) = \frac{1}{t_{H,1}} \sum_{t_f=1}^{t_{H,1}} \frac{f_{max}(1-\delta_{t,1})^{t_f}}{1 + e^{-\omega(T(t)-T_c)}} \qquad\qquad f_2(T(t)) = \frac{1}{t_{H,2}} \sum_{t_f=1}^{t_{H,2}} \frac{f_{max}(1-\delta_{t,2})^{t_f}}{1 + e^{-\omega(T(t)-T_c)}}$$

The perceived cost of climate change function (Equation 3.14) is grouped with the factor of $(c + 1)$ from Equations 3.10 and 3.11 to simplify the social system:

$$\hat{f}_i(T(t)) = \frac{(c+1)}{t_{H,i}} \sum_{t_f=1}^{t_{H,i}} \frac{f_{max}(1-\delta_{t,i})^{t_f}}{1 + e^{-\omega(T(t)-T_c)}} \tag{3.15}$$

Grouping f_{max} and $(c + 1)$ together into a new $\hat{f}_{max}$ term gives:

$$\hat{f}_i(T_f(t)) = \frac{1}{t_{H,i}} \sum_{t_f=1}^{t_{H,i}} \frac{\hat{f}_{max}(1-\delta_{t,i})^{t_f}}{1 + e^{-\omega(T_f(t)-T_c)}} \tag{3.16}$$

where the patch identification is $i = 1, 2$. Equation 3.16 represents in the model the perceived costs associated with climate change over the projected future temperature (Equation 3.12), weighted by temporal discounting per year.

3.2 Fully Discounted Social - Climate Model

The complete social-climate model with spatial and temporal discounting is as follows:

$$
\begin{aligned}
\frac{dx_1}{dt} &= \kappa_1 x_1(1-x_1)(-\beta_1+\theta_1\hat{f}_1(T_f)+(1-\theta_1)\hat{f}_2(T_f)+\delta_1(2x_1-1)) \\
\frac{dx_2}{dt} &= \kappa_2 x_2(1-x_2)(-\beta_2+\theta_2\hat{f}_2(T_f)+(1-\theta_2)\hat{f}_1(T_f)+\delta_2(2x_2-1)) \\
\frac{dC_{at}}{dt} &= \epsilon(t)\,\alpha\,(1-x_1)+\epsilon(t)(1-\alpha)(1-x_2)-P+R_{veg}+R_{so}-F_{oc} \\
\frac{dC_{oc}}{dt} &= F_{oc} \\
\frac{dC_{veg}}{dt} &= P-R_{veg}-L \\
\frac{dC_{so}}{dt} &= L-R_{so} \\
c\frac{dT}{dt} &= (F_d-\sigma T^4)a_E
\end{aligned}
$$

A comprehensive list of social and climate system variables and proccesses are presented in Table 3.2. A complete list of parameters can be found in Tables 3.1 and 3.3 (see Section 3.4).

Table 3.2: This table provides a list of variables and processes in the model.

Variables	**Symbol**	**Units**
Proportion of mitigators	x_1, x_2	1
Deviation of CO_2 in atmosphere	C_{at}	GtC
Deviation of CO_2 in ocean	C_{oc}	GtC
Deviation of CO_2 in vegetation	C_{veg}	GtC
Deviation of CO_2 in soil	C_{so}	GtC
Deviation in temperature	T	K
Processes	**Symbol**	**Units**
CO_2 emissions without mitigation	$\epsilon(t)$	GtC yr^{-1}
Carbon uptake from photosynthesis	P	GtC yr^{-1}
Respiration from vegetation	R_{veg}	GtC yr^{-1}
Respiration from soil	R_{so}	GtC yr^{-1}
Flux of CO_2 from atmosphere to ocean	F_{oc}	GtC yr^{-1}

Table 3.3: This table provides a list of climate and model parameters. Values are presented as constants or triplets to provide lower bounds, baseline values, and upper bounds.

Parameters	**Symbol**	**Values**
Initial CO_2 in atmosphere	C_{at0}	(590, 596, 602) GtC
Initial CO_2 in ocean reservoir	C_{oc0}	(1.4, 1.5, 1.6)$\times 10^5$ GtC
Initial CO_2 in vegetation reservoir	C_{veg0}	(540, 550, 560) GtC
Initial CO_2 in soil reservoir	C_{so0}	(1480, 1500, 1520) GtC
Initial average atmospheric temperature	T_0	(288,288.15,288.3) K
Photosynthesis rate constant	k_p	(0.175, 0.184, 0.193) yr^{-1}
Photosynthesis normalizing constant	k_{MM}	1.478
Photosynthesis compensation point	k_c	(26, 29, 32)$\times 10^{-6}$
Half-saturation point for photosynthesis	K_M	(108, 120, 132)$\times 10^{-6}$
Mole volume of atmosphere	k_a	1.773$\times 10^{20}$ moles
Plant respiration constant	k_r	(0.0828, 0.092, 0.1012) yr^{-1}
Plant respiration normalizing constant	k_A	8.7039$\times 10^9$
Plant respiration activation energy	E_a	(54.63, 54.83, 55.03) Jmol^{-1}
Soil respiration rate constant	k_{sr}	(0.0303, 0.034, 0.037) yr^{-1}
Soil respiration normalizing constant	k_B	157.072
Turnover rate constant	k_t	(0.0828, 0.092, 0.1012) yr^{-1}
Specific heat capacity of Earth's surface	c	(4.22, 4.69, 5.19)$\times 10^{23}$ JK^{-1}
Earth's surface area	a_E	5.101$\times 10^{14}$ m^2
Stefan-Boltzman constant	σ	5.67$\times 10^{-8}$ Wm^{-2}K^{-4}
Latent heat per mole of water	L	43655 mol^{-1}
Molar gas constant	R	8.314 Jmol^{-1}K^{-1}
Relative humidity	H	0.5915
Surface albedo	A	(0.203, 0.225, 0.248) yr^{-1}
Solar flux	S	(1231.2, 1368, 1504.8) Wm^{-2}
Methane opacity	$\tau(CH_4)$	(0.0208, 0.0231, 0.0254)
Water vapour saturation constant	P_0	(1.26, 1.4, 1.54)$\times 10^{11}$ Pa
Ocean flux rate constant	F_0	(2.25, 2.5, 2.75)$\times 10^{-2}$ yr^{-1}
Characteristic CO_2 solubility	χ	(0.2, 0.3, 0.4)
Evasion factor	ζ	(40, 50, 60)
Maximum of warming cost function $f(T)$	f_{max}	(4, 5, 6)
Non-linearity of warming cost function $f(T)$	ω	(1, 3, 5) K^{-1}
Critical temperature of $f(T)$	T_c	(2.4, 2.5, 2.6) K
# previous years used for temperature projection	t_p	10 yr
# years ahead for temperature projection	t_f	(0, 25, 50) yr
Half-saturation time for $\epsilon(t)$ from 2014	s	(30, 50, 70) yr
Maximum change in $\epsilon(t)$ from 2014	ϵ_{max}	(4.2, 7, 9.8) GtC yr^{-1}
Initial proportion of mitigators	$x_{0,1}$, $x_{0,2}$	(0.01, 0.05, 0.1)

3.3 Earth System Model

Section 3.2 presents the complete social-climate model where a simple Earth System Model (ESM) is coupled to the social system developed in Section 3.1. The ESM used, as previously developed by Lenton [29], sufficiently represents the carbon cycle and the greenhouse gas effect (averaged globally) and keeps computational cost low [9, 33]. The model implements various key carbon cycle components, including biochemical processes [9, 29, 33, 36]. I provide in this section the full ESM, including the physical processes implemented guided by Lenton, Bury et al., and Menard et al. [9, 29, 33, 36].

Atmospheric Carbon Dioxide

The ESM components presented here are altered to account for the two-way feedback between human behaviour and the climate and its processes. Specifically, the differential equation governing deviation in atmospheric CO_2 (C_{at}) is adjusted so that carbon emissions ($\epsilon(t)$) are weighted by the proportion of non-mitigators in each patch $(1 - x_i)$. Such that,

$$\frac{dC_{at}}{dt} = \epsilon(t)\,\alpha\,(1 - x_1) + \epsilon(t)(1-\alpha)(1 - x_2) - P + R_{veg} + R_{so} - F_{oc} \tag{3.17}$$

where $\epsilon(t)$ is the rate of CO_2 emissions without mitigation, α is the proportion of emissions patch 1 releases, $1 - \alpha$ is the proportion of emissions patch 2 releases, P is carbon uptake rate by photosynthesis, R_{veg} and R_{so} are outward carbon flux by plant respiration and soil respiration, respectively, and F_{oc} is net ocean uptake of carbon.

The functional form for $\epsilon(t)$ follows an increasing and saturating function:

$$\epsilon(t) = \begin{cases} \text{linear interpolation of historical emissions} & t < 2014 \\ \epsilon_{2014} + \dfrac{(t-2014)\epsilon_{max}}{t - 2014 + s} & t \geq 2014 \end{cases} \tag{3.18}$$

where ϵ_{2014} are emissions at the year 2014, ϵ_{max} is the maximum change in emissions from the year 2014, and s is the half-saturation time for $\epsilon(t)$ from 2014 [9].

Photosynthesis

Photosynthetic carbon uptake from the atmosphere takes the form:

$$P(C_{at}, T) = k_p C_{veg0} k_{MM} \left(\frac{pCO_{2a} - k_c}{K_M + pCO_{2a} - k_c} \right) \left(\frac{(15+T)^2(25-T)}{5625} \right) \tag{3.19}$$

where k_p is the photosynthesis rate constant, C_{veg0} is the initial carbon dioxide in the vegetation reservoir, and K_M is the half-saturation point for photosynthesis. k_{MM} is the photosynthesis normalizing constant which normalizes photosynthesis carbon uptake by initial ratio of CO_2 in atmosphere [29]. k_c is the photosynthetic compensation point governing the point carbon absorption through photosynthesis reaches zero [29]. Equation 3.19 follows the relationship that $pCO_{2a} \geq k_c$ and $-15 \leq T \leq 25$, and $P = 0$ otherwise [9, 29]. The mixing ratio in the atmosphere of CO_2 is pCO_{2a}. It is defined as the ratio of moles of CO_2 in the atmosphere to the total number of moles of molecules, k_a, in the atmosphere:

$$pCO_{2a} = \frac{f_{gtm}(C_{at} + C_{atm0})}{k_a} \tag{3.20}$$

The factor $f_{gtm} = 8.3259 \times 10^{13}$ converts from gTC to moles of carbon, and the initial level of carbon in the atmosphere is C_{atm0}. The Michaelis-Menton kinetics in pCO_{2a} is satisfied through photosynthesis [9, 29]. When $T = 2$, photosynthesis rates are optimized, and rates decline when temperatures increase past $T = 2$.

Respiration

Plant respiration occurs in the form:

$$R_{veg}(T, C_{veg}) = k_r C_{veg} k_A e^{-\frac{E_a}{R(T+T_0)}} \tag{3.21}$$

where k_r is the plant respiration constant and k_A is the plant respiration normalizing constant which normalizes impacts of temperature [29]. E_a is the plant respiration activation energy, R is the molar gas constant, and T_0 is initial average atmospheric temperature. Plant respiration increases with the amount of carbon present in vegetation and temperature [9, 29, 33].

Soil respiration follows similarly:

$$R_{so}(T, C_{so}) = k_{sr} C_{so} k_B e^{-\frac{308.56}{T+T_0+227.13}} \tag{3.22}$$

where k_{sr} is the soil respiration rate constant and k_B is the soil respiration normalizing constant which normalizes the impact of temperature [29].

Turnover

A constant fraction of plants is assumed to die over a given unit of time, following:

$$L(C_{veg}) = k_t C_{veg} \tag{3.23}$$

where k_t is the turnover rate constant governing the living biomass [29]. The turnover process $L(C_{veg})$ captures the flux of carbon from decaying plants into the soil reservoir [29].

Ocean Flux

CO_2 flux from the atmosphere to the ocean occurs in the form:

$$F_{oc}(C_{at}, C_{oc}) = F_0 \chi \left(C_{at} - \zeta \frac{C_{at0}}{C_{oc0}} C_{oc} \right) \tag{3.24}$$

where F_0 is the ocean flux constant, χ is the characteristic solubility of CO_2 in water, and ζ is the evasion factor [36]. C_{at0} and C_{oc0} are initial carbon dioxide in the atmosphere and ocean reservoir respectively.

Atmospheric Dynamics

Grey-atmosphere approximation from Lenton [29] is used to model atmospheric dynamics. The global average surface temperature changes are modelled based on changes in albedo (A), incoming solar flux (S), and the opacity of CO_2, $H_2O_{(v)}$, and CH_4. The net downward flux of solar radiation that the surface of the planet absorbs is provided by:

$$F_d = \frac{(1-A)S}{4} \left(1 + \frac{3}{4} \tau \right) \tag{3.25}$$

where τ is the opacity of greenhouse gasses in the atmosphere (CO_2, $H_2O_{(v)}$, CH_4). The opacity for the various gases is provided as:

$$\begin{aligned} \tau(CO_2) &= 1.73 (pCO_2)^{0.263} \\ \tau(H_2O) &= 0.0126 (H P_0 e^{-\frac{L}{RT}})^{0.503} \\ \tau(CH_4) &= 0.0231 \end{aligned}$$

and

$$\tau = \tau(CO_2) + \tau(H_2O) + \tau(CH_4) \tag{3.26}$$

where pCO_2 is the mixing ratio of CO_2 seen in Equation 3.20, H is relative humidity, P_0 is the water vapour saturation constant, L is the latent heat per mole of water, R is the molar gas constant, and T is temperature [29].

3.4 Parameters

Three lists of model variables (Table 3.2) and parameters (Tables 3.1 and 3.3) are provided throughout this Methods Chapter. The parameter tables are split into two components. Table 3.1 provides all social system parameters and their values, and Table 3.3 provides all other climate system parameter values. Parameter values are either stated as constants or as their parameter spaces' lower, baseline, and upper bounds. The parameter values are obtained from Bury et al. [9] or are standardly accepted values.

The value for the rate of discounting is varied in the literature and dependent on the field of interest, for example, economics, ecology, sustainability, and social discounting [20, 24, 32, 45, 58]. These values range from 0 - 6% discounting per year (sometimes they reach up to 10% discounting), and no clear consensus has been made [20, 32, 45, 58]. In this thesis, the temporal discounting parameter choice is guided by values found in ecological studies that implement time discounting and time horizons [24]. The range of the temporal discounting rate in this thesis is between 0 - 5% with a baseline at 1.5%. The upper bound is selected following the understanding that when temporal discounting begins to approach and exceed 5% discounting per year (while all other parameters are held at baseline), temperature anomaly projections begin to converge. A baseline of 1.5% was chosen to reflect consistent baseline climate and mitigation projections (similar to the baselines achieved in past social-climate models [9, 33]).

3.5 Simulation and Data

The social-climate model proposed in this thesis is simulated over the time period from 1800 to 2200. Where the model runs between 1800 and 2014 in the absence of social dynamics, statically forced by historical anthropogenic emissions [9]. Social dynamics are initiated in 2014, and initial conditions for the climate variables (values defined as deviations from pre-industrial values) are held at zero before 2014. Each patch's initial proportion of mitigators is $x_{0,1} = 0.05$ and $x_{0,2} = 0.05$.

The historical emissions data used in the model is from the CDIAC data repository [8]. The full emissions data in the model is comprised of the historical emissions data from the year 1800 to 2014 and concatenated with a subset of projected future emissions data. The model was run using the delay differential equations package (dde23) in MATLAB (R2021a) to approximate the solution to the coupled system of differential equations.

Chapter 4

Results

To best explore the research questions and hypotheses as outlined in Section 1.1, an understanding of the interactions of spatial and temporal discounting behaviour with itself and on established opinion dynamics is necessary. The model parameter and output analysis are broken up into two main components. The first is focused on understanding the interactions that spatial and temporal discounting behaviour has on itself (Section 4.1). The second component deals with the interactions discounting the climate has on established opinion dynamics (Section 4.2). These results aim to acknowledge the role that discounting plays in opinion dynamics in a social-climate model, through which a better understanding of how and why individuals and populations mitigate can be gained.

The results presented often consider two different discounting behaviours: current-looking and forward-looking. Current-looking behaviour refers to a discounting regime where individuals devalue future climate impacts at a high rate per year and only consider their geographic location. Forward-looking behaviour follows a more optimistic discounting regime where individuals maintain value in present and distant climate impacts and consider multiple geographic locations. These behaviours influence the mitigation strategy choices of individuals in the model.

4.1 Spatial and Temporal Discounting

In this section, I focus on how the interaction of spatial and temporal discounting together may influence changes in opinion dynamics and, consequently, climate conditions. Multiple different sources of obstacles to mitigation have been found to drive environmental inaction

[12, 19, 53]. While discounting the climate in this thesis is considered as one impediment to mitigation, it does manifest in two dimensions: space and time. In other words, these two dimensions of discounting may work together to enhance the lack of motivation to mitigate. Thus, the potentially additive nature that discounting in time and space has on willingness to mitigate must be considered. Section 4.1.1 investigates parameter spaces for the various discounting parameters, and section 4.1.2 provides results based on changes to how individuals perceive climate conditions in terms of discounting.

4.1.1 Parameter Planes

Varying both dimensions of discounting simultaneously will help to understand how shifting perceptions of climate change impacts can guide mitigation efforts. Specifically, looking at parameter planes of peak temperature anomaly and the year the peak temperature anomaly is reached helps map how temperature responds in a beneficial or consequential way to discounting while all other opinion dynamics parameters are at their baseline values. In this section, I show that there is an additive nature in the way individuals take value away from the future climate, require a long range of time to make decisions, and consider isolated geographic locations. Together, three main results are obtained. Firstly, high spatial and temporal discounting produce temperature anomalies that peak higher and later (Figure 4.1). Secondly, considering multiple geographic locations is as important as reducing temperature anomalies (Figure 4.3). And thirdly, the longer an individual discounts at a high rate, the quicker the rise in temperature anomaly occurs (Figure 4.4). A reduction in the discounting rate (or the shorter time frame for that discounting) or maintaining a diverse consideration of locations will drop temperature anomalies at a mild and saturating pace. That being said, reducing both temporal discounting factors and shifting to a spatial discounting mid-point is ideal.

While a fundamental aspect of our model and research question is spatial discounting, in Figure 4.1, I look at the parameter plane for just one patch, and the other patch is fixed at its baseline discounting behaviours. This choice focuses on the interactions of these two parameters isolated from other variations, even in the second patch. This allows for the exploration of how discounting in itself may alter the climate. Moreover, adding variations in the second patch parameter values, as in Figure 4.3, allows the investigation of how two different populations' opinion dynamics under varying strengths of discounting influence the climate. Both analyses are vital in the overall understanding of how removing value from climate conditions farther away in time and geographically works together to affect the environment.

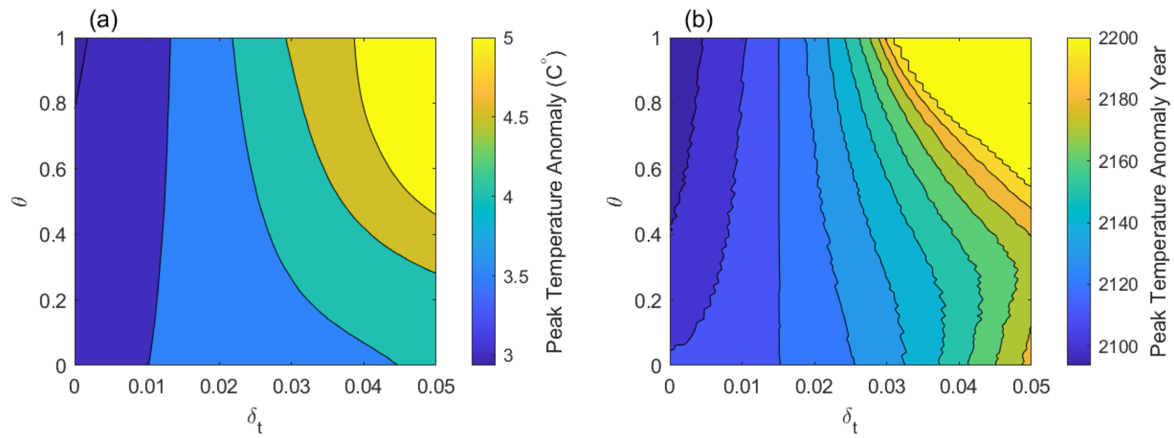

Figure 4.1: Contour plots show peak temperature anomaly (a) and the year the peak temperature anomaly is reached (b) at values of temporal discounting (δ_t) and spatial discounting (θ). All other parameters are held at their baseline values as defined in Tables 3.1 and 3.3.

Figure 4.1(a) shows the parameter planes for the peak temperature anomaly over specific spatial discounting (θ) and temporal discounting (δ_t) values. Although the parameter space is dominated by mid-range temperature anomalies, the pathway to reducing temperature anomalies is relatively slow, as seen through the large spaces between changing contour lines (Figure 4.1(a)). This direction of declining temperature anomalies is initially dominated by a simultaneous reduction in devaluing future environmental conditions and shifting geographical concern towards a more even share between both populations' locations. Eventually, as individuals shift towards forward-looking behaviour (considering future climate conditions), the population may consider in any proportion themselves and the other population when perceiving the impacts of the climate when making decisions. This is representative of the benefits of maintaining value in future climate impacts, as it acts to reduce temperature anomalies. It is important to note that this is only the case when one patch's discounting behaviour is fixed to a baseline 1.5% discounting per year while the other is varied.

To investigate the relationship between spatial discounting and low temporal discounting, as observed in the left-hand side of Figure 4.1(a), multiple temperature anomaly projections are presented in Figure 4.2. The temperature anomalies follow a baseline parameter regime except for the specified spatial and temporal discounting values in the plot. These pairs of parameter values are drawn from the parameter plane in Figure 4.1(a). From Figure 4.1(a), the left-hand side of the plane provides the visualization that when

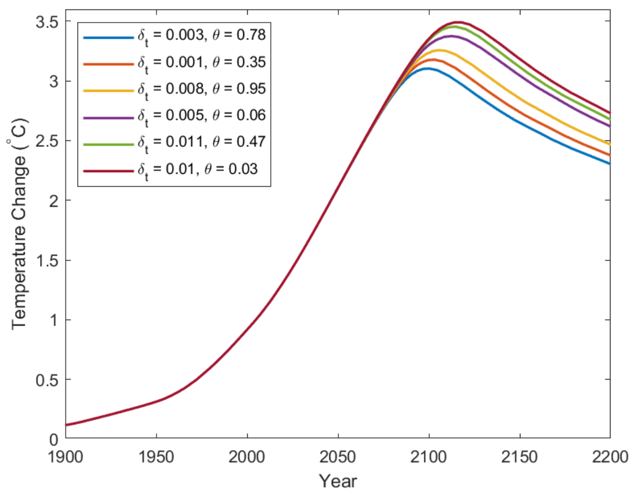

Figure 4.2: Temperature anomaly is plotted over time for various parameter pairs of temporal discounting (δ_t) and spatial discounting ($theta$) in patch 1 drawn from Figure 4.1(a). All other parameters are held at their baseline values as defined in Tables 3.1 and 3.3.

temporal discounting is less than 0.012 (individuals discounting less than 1.2% each year), then spatial discounting does not seem to influence the model. That being said, from Figure 4.2, there is a small relationship occurring between similar temporal discounting rates ($\delta_t = 0.001$ and 0.003, $\delta_t = 0.005$ and 0.008, and $\delta_t = 0.01$ and 0.011) based on the understanding that patch 2 follows a baseline temporal discounting rate of 0.015. Consider the pairs of parameters, that I will call Pair 1: $\{\delta_t = 0.003, \theta = 0.78\}$ and Pair 2: $\{\delta_t = 0.001, \theta = 0.35\}$. It would be easy to assume that the lower temporal discounting case in Pair 1 would result in a lower peak temperature anomaly, but that is not the result observed in Figure 4.2; it is found that Pair 2 produces a slightly lower peak temperature anomaly. Pair 1 follows the spatial discounting case where patch 1 is basing the majority of their perceived impacts of climate change on patch 2, which discounts each year at 1.5%. Meanwhile, Pair 2 follows the spatial discounting case where patch 1 is considering in the larger part their own perceived impacts, which are forced with a much lower temporal discounting rate than patch 2. This relationship reiterates the mathematical implementation of spatial discounting through Equations 3.1 - 3.4 and can be observed through other pairs of temperature anomaly trajectories in Figure 4.2. That being said, while it remains unclear from a model perspective why a temporal discounting range of about 1% produces a small change in peak temperature anomalies (less than half a degree) regardless of changes in spatial discounting, this behaviour is interesting (see Figures 4.1 and 4.2).

In addition to acknowledging values that peak temperature anomalies take under spatial and temporal discounting, it is equally interesting to consider the year in which those peaks are achieved (Figure 4.1(b)). In doing so, I can look for pathways that shift temperature anomalies to peak sooner rather than later. This is beneficial because it implies, by the definition of a peak or maximum, that temperature anomalies will start to decline after that year, which is ultimately the goal. Figure 4.1(b) shows the parameter planes for the year of the peak temperature anomaly for spatial discounting (θ) and temporal discounting (δ_t) while all other parameters are held at baseline. A peak temperature anomaly occurring in an earlier year implies an increase in mitigation efforts, resulting in the decline of temperatures in the years following the peak. Conversely, the farther out temperature anomalies reach their peak, if they reach a peak at all, narrows possibilities and opportunities for mitigation efforts (within the time frame of our simulations). That said, a peak temperature anomaly occurring in the year 2200 does not imply that temperatures decrease after that point. The year 2200 is the end of the simulation time. So when individuals are current-looking (not considering other locations or future generations' climate conditions), temperature anomalies reach their highest temperature in the simulation at the last time step. This suggests that either the year 2200 is the peak or more likely that temperatures continue to rise past that point in time.

Insight into how spatial and temporal discounting may augment climate conditions can be obtained by considering the joint influence of discounting on peak temperature anomalies and the year in which they occur. In a short argument, as discounting behaviours begin to favour the ideals of climate conditions being worse in another location (individuals will only consider themselves) and farther in time, this provides a population with the perception that climate change will not significantly impact them. Together, this suggests that temperature anomalies peak later and higher. This connection signifies how disadvantageous discounting is to climate conditions and willingness to mitigate. Unfortunately, as outlined in Section 2.1, conditions being worse somewhere else and later on is the most common way climate change is portrayed and considered. That being said, if the narrative and perceptions of climate change impact shift towards more forward-looking behaviour, then lower peak temperature anomalies can be achieved sooner (Figure 4.1).

Overall, Figure 4.1 represents what can happen due to maintaining how climate change is portrayed and understood as a far-off problem. Instead, by perceiving the impacts of climate change to be in a more present time and location, populations opt to switch to a mitigation strategy. As a beneficial result of this switch, peak temperature anomalies decrease and occur sooner. This provides more opportunity to decrease rising temperatures towards the IPCC targets [28]. These are targets that are not achievable under the typical portrayal of climate change. To support this finding, an extended analysis to consider how multiple populations value and devalue the impacts of climate change is completed and presented in Figure 4.3.

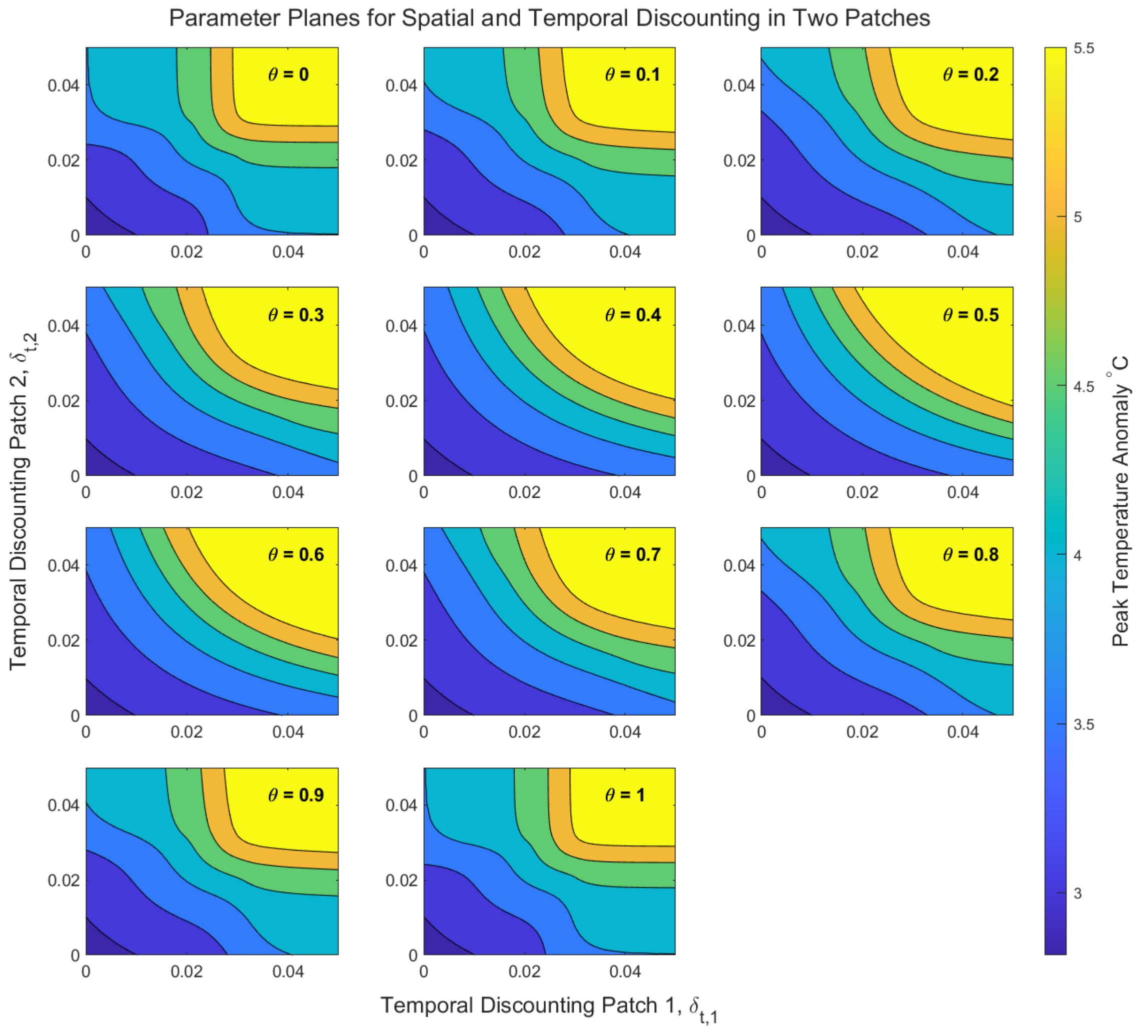

Figure 4.3: Contour plots showing peak temperature anomaly across the range of temporal discounting (δ_t) values in each patch at specific spatial discounting (θ) values. All other parameters are held at baseline as defined in Tables 3.1 and 3.3.

To understand the isolated interactions between spatial and temporal discounting on the climate between both patches in the model, a matrix of parameter spaces is provided in Figure 4.3. A relationship symmetry arises as a result of shifting where individuals in a population geographically base their perceptions of climate change impacts: when populations only consider themselves ($\theta = 1$) or only consider the other geographically distinct population ($\theta = 0$), the peak temperature anomaly has the same outcome. An incomplete idea of the climate is established when perceived impacts are based entirely on one location. This occurs because spatial discounting in the model, in these cases, isolates any influence from other geographic locations. For this reason, the transition from higher to lower temperature anomalies is slow and non-linear (Figure 4.3: $\theta = 0$, $\theta = 1$). Comparatively, the shift to lower temperature anomalies is quicker when both populations start to consider each other more equally and devalue future climate conditions less. This is observed in Figure 4.3 as the space between contour lines shrinks and becomes more uniform as spatial discounting approaches its midpoint ($\theta = 0.5$). These beneficial temperature changes slow (but do not stop) as both populations begin to value future climate conditions more. This concludes that forward-looking behaviour and considering a diversity of geographic locations is a pathway leading to lower temperature anomalies.

One consistency and one inconsistency arises through moving the gaze of perception from one patch to both patches. On the first side, populations acting under the same temporal discounting behaviour (forward or current-looking) produce a rapid and linear response in temperature anomaly consistent across which locations they consider. Conversely, when populations are fundamentally polarized in their temporal discounting behaviour, shifts in geographic considerations are not as consistent. The temperature anomalies in the parameter spaces in these cases become more varied as the populations look to each other rather than just one or the other. This is visualized through Figure 4.3 panels for $\theta = 0.5$ and $\theta = 1$ (or 0). When $\theta = 0.5$, and patch 1 is devaluing future climate impacts at a higher rate than the other, then a small increase in temporal discounting in the second patch can result in peak temperature anomalies changing by about a half degree. Yet, if a small shift like that is completed when a high proportion of future climate impacts are based in one location ($\theta = 0, 0.1, 0.2, 0.8, 0.9, 1$), then peak temperature anomalies are maintained or change very little. Together, this highlights the beneficial effects of maintaining a broader consideration of different locations and having fairly uniform discounting behaviour to approach lower temperature anomalies quickly.

Similarly, I carry out parameter analysis to understand the interactions between how much individuals devalue future climate events and how far into the future they consider or look when making decisions on taking mitigative or non-mitigative actions. Figure 4.4 provides a parameter space for the two temporal discounting parameters: temporal discounting rate (δ_t) and time horizon (t_H). Taking value away from future climate conditions and looking farther in time negatively impacts temperature. The pathway to lower peak

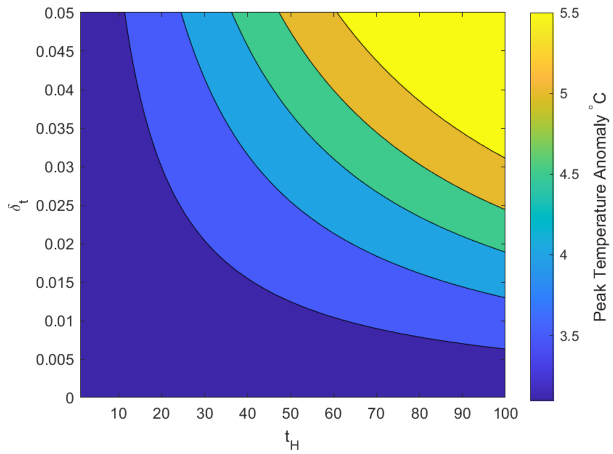

Figure 4.4: Contour plot showing peak temperature anomaly for temporal discounting (δ_t) and time horizon (t_H) values in patch 1. All other parameters are held at baseline as defined in Tables 3.1 and 3.3.

temperature anomalies is achieved the quickest by simultaneously devaluing the future climate at lower rates and shortening the time frame of decision-making based on future climate impacts. That being said, forward-looking behaviour provides the freedom to have an extended range for decision-making, and a reduced time frame for decision-making allows for a more extensive range in rates of devaluing the future climate. This slight flexibility between these two parameters can provide insight into discounting behavioural changes that promote mitigation. However, this span of low temperature anomalies may be misleading, as an individual with current-looking behaviour may also require a long period to shift their decision-making [9].

Overall, the best pathways to lower temperature anomalies are achieved when individuals take a forward-looking approach while considering multiple locations when determining their personal impacts of climate change. This discounting behaviour promotes mitigation the most and reduces temperature anomalies as a shared benefit.

4.1.2 Time Series: Emissions, Temperature Anomaly, and Proportion of Mitigators

The projected results in this section demonstrate the impediment that discounting plays in mitigation efforts. In this section, I show that forward-looking behaviour, following a lower discounting regime, supports a higher proportion of mitigation strategy uptake (Figures 4.5 and 4.6). But as motivation to mitigate decreases through a shift to current-looking behaviour, climate conditions are significantly worse, marked by about a 3°C increase in temperature anomaly (Figures 4.6 and 4.7). Also, through considering spatial discounting, I find that a more risk-averse and environmentally beneficial behaviour choice is to consider both population locations equally rather than just one location or the other on their own (Figure 4.8). Finally, I show that potential benefits from behavioural changes in the social system are muted by higher rates of temporal discounting (Figure 4.8).

Moderately to severely discounting climate change produces significantly worse climate conditions in the near and long term. That being said, even low levels of discounting behaviour produce temperature anomalies around 2.6°C (4.5(c)). Forward-looking behaviour takes the form in the model as 1.5% and 1% discounting per year, and each patch equally considers the climate conditions in their location and the other location. The forward-looking behaviour represents the consideration of future generations and the impact that mitigation efforts have on multiple spatially distinct locations. Further, it highlights potential changes in the climate as a result of bringing the climate change issue into an individual's everyday rather than maintaining it as some distant, abstract process [31, 55, 56]. Figure 4.5(a) shows explicitly that mitigation behaviour is facilitated under this forward-looking behaviour, as both patches reach full proportions of mitigators by the year 2100.

Subsequently, higher proportions of mitigators lead to reduced emissions as the population is actively undergoing action to better the environment under the mitigation strategy. Since both patches release equal proportions of emissions in Figure 4.5(b), their projected carbon dioxide emissions follow similar paths, peaking around the year 2050. These matching trajectories are a direct consequence of the two-patch model, as each patch is discounting under similar rates and considering each other's climate conditions equally. This relationship between patches and the proportion of total emission they produce is better observed in Figure 4.6(b). Each patch is under the same discounting scenario as in Figure 4.5, except now patch 1 produces 30% of total emissions and patch 2 produces 70%. This imbalance of emission production can be representative of the disproportionate breakdown of total emissions between high- and low-emitting locations. Even as our model projects one temperature anomaly for all population groups, providing the breakdown of emissions into both patches remains important. This breakdown better captures the patch with a more substantial influence on the climate.

Projections under forward-looking behaviour are significant as they visualize the impact of low discounting, representing the relationship between giving value to environmental conditions as they occur sooner and later and the changes in the climate. Compara-

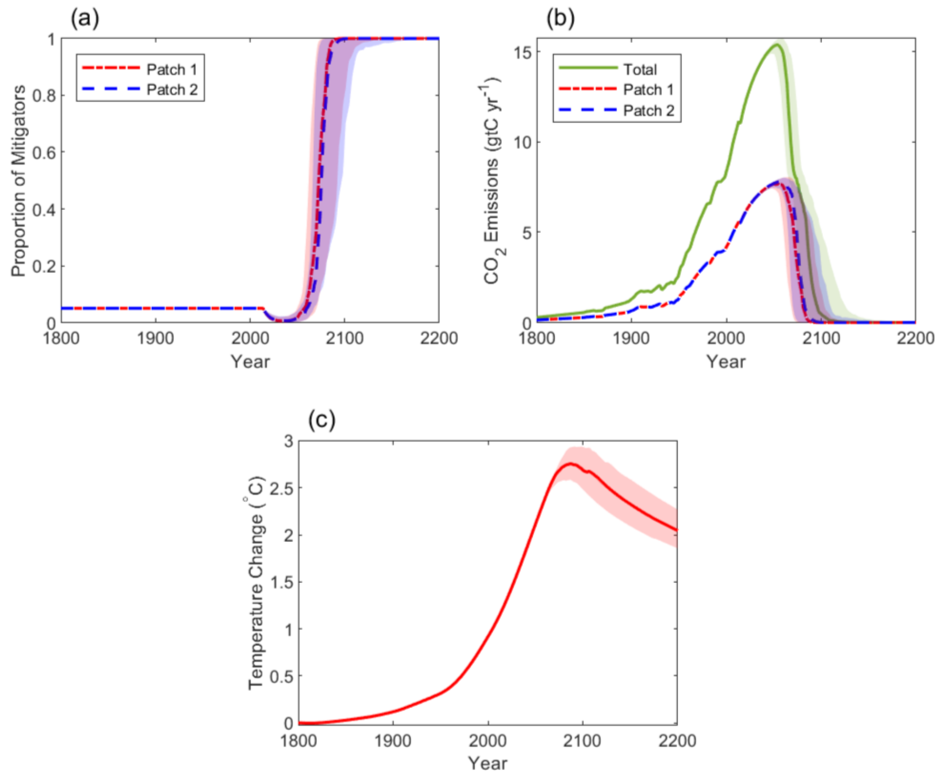

Figure 4.5: Forward-looking behaviour favours mitigation. Median trajectories (solid and dashed lines) and 20th and 80th percentiles are plotted to the year 2200 for the proportion of mitigators (a), carbon dioxide emissions (b) and temperature anomaly (c). With temporal discounting $\delta_{t,1} = 0.015$, $\delta_{t,2} = 0.01$, spatial discounting $\theta = 0.5$, time horizon $t_H = 50$, and proportion of emissions $\alpha = 0.5$. Medians and quintiles are computed over 100 simulations, where all other social system parameters are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

tively, observing the effect on climate conditions and strategy choices of the transition from forward-looking to current-looking behaviour provides valuable insight into discounting the climate. As expected, the resulting temperature anomalies drastically increase in this direction of decreasing motivation to mitigate (for example 4.5(c) and 4.7(c)). It is important to note that the shorter time horizon and low temporal discount rate dominate the climate projections, as predicted from the earlier parameter plane (Figure 4.4). These results still provide an immediate takeaway, such that shifting our perceptions of climate

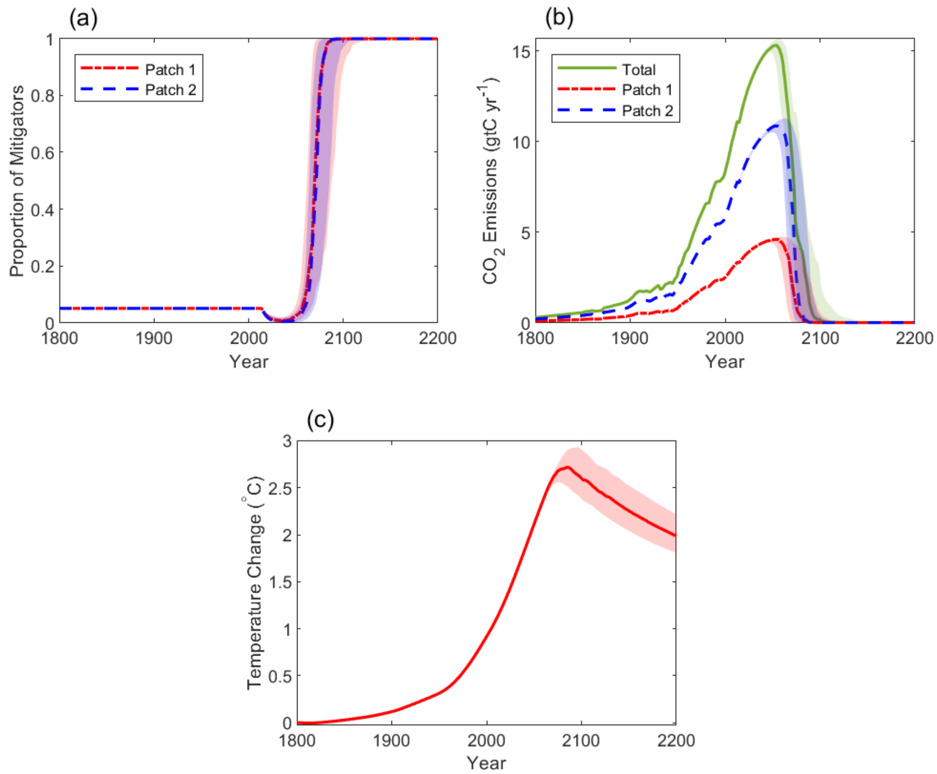

Figure 4.6: Patches may produce an uneven proportion of emissions. Median trajectories (solid and dashed lines) and 20th and 80th percentiles are plotted to the year 2200 for the proportion of mitigators (a), carbon dioxide emissions (b) and temperature anomaly (c). With temporal discounting $\delta_{t,1} = 0.015$, $\delta_{t,2} = 0.01$, spatial discounting $\theta = 0.5$, time horizon $t_H = 50$, and proportion of emissions $\alpha = 0.3$. Medians and quintiles are computed over 100 simulations, where all other social system parameters are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

change impacts from occurring later to sooner, may help moderate the effects of climate change.

When individuals operate under current-looking behaviour, they are not motivated by their enviornmental experiences to mitigate. This occurs because they take enough value away from distant climate conditions, resulting in the perception that climate change will not impact them. This leads to populations dominated by non-mitigation behaviour, higher emissions, and finally, extreme rising temperature anomalies. Figure 4.7 is a representation of current-looking behaviour, where patch 1 discounts future climate impacts at 3% each

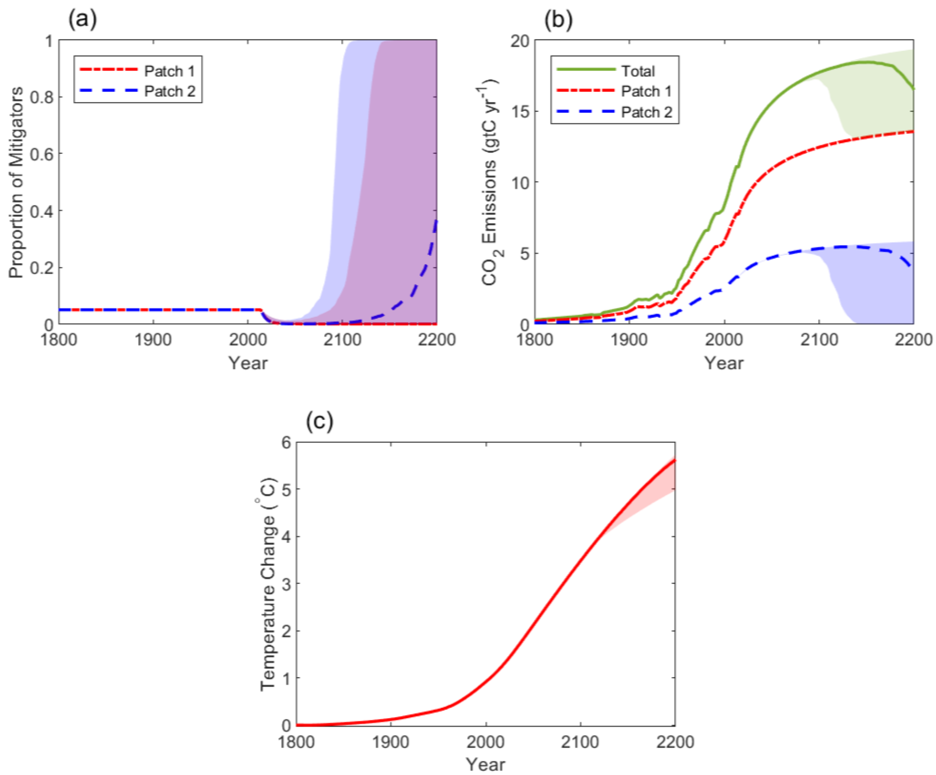

Figure 4.7: Current-looking behaviour favours non-mitigation. Median trajectories (solid and dashed lines) and 20th and 80th percentiles are plotted to the year 2200 for the proportion of mitigators (a), carbon dioxide emissions (b) and temperature anomaly (c). With temporal discounting $\delta_{t,1} = 0.03$, $\delta_{t,2} = 0.015$, spatial discounting $\theta = 1$, time horizon $t_H = 100$, and proportion of emissions $\alpha = 0.7$. Medians and quintiles are computed over 100 simulations, where all other social system parameters are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

year and produces 70% of total emissions, and patch 2 discounts at 1.5% each year and produces 30% of emissions. Each population assumes climate conditions are worse in the other location, and so only consider themselves when deciding which mitigation strategy is better and implements a time horizon of 100 years.

This current-looking behaviour (stronger in patch 1) supports the conformation to non-mitigation behaviour. So much so that the proportion of mitigators in patch 1 reaches zero almost immediately after social dynamics are initiated in 2014. While patch 2 (Figure 4.7(a,b)) is still valuing future climate impacts, similar to patch 1 from Figures 4.5 and 4.6, their population does not reach full mitigation by the end of the simulation run, nor do median emissions reach zero. This is a direct consequence of the longer time horizon implemented under this discounting scenario. From Equation 3.14, the longer the time horizon then, the longer out individuals are considering climate impacts. Moreover, they are removing value from future climate conditions for a longer time, and thus, they assume that climate change will not impact them greatly.

That being said, under these high discounting behaviours, emissions in patch 1 represent the increasing and saturating nature of the emissions function as defined in Equation 3.18. Since individuals are discounting distant climate impacts at higher rates, this fundamentally facilitates the case of emissions under no mitigation. But patch 2 in Figure 4.7(b) slightly moderates the total emissions as the median trajectories of total and patch 2 emissions peak and start to decline near the end of the simulation time. Even though patch 2 is showing signs of mitigation and reducing carbon dioxide emissions by the end of the simulations (Figure 4.7(a,b)), they are still only emitting a fraction of what patch 1 is producing. As a result, their mitigation efforts are overpowered by the non-mitigation strategy that is dominating patch 1, which functions to greatly increase the temperature anomaly (Figure 4.7(c)).

While a 5.5°C temperature anomaly seems unrealistically high, this result can be used to understand the magnitude at which a proportion of the total population (both patches together), discounting the climate at high rates, influences the overall climate. This result represents that decisions in one patch affect overall climate conditions and thus impact the total population through the model's two-way feedback. Essentially, from this case of high discounting, it can be understood that a population group's decision-making, to mitigate or not mitigate, has influential results on the climate: total carbon emissions and temperature anomalies.

A closer look at shifting perceptions of climate impacts between current and future-looking behaviours can show the negative consequences discounting has on the climate. For an example with temperature anomalies, forward-looking behaviour (Figure 4.6) peaks about 3°C lower than current-looking behaviour (Figure 4.7). That being said, the current-looking behaviour "peaks" at the end of the simulation, implying it will continue to rise for some period of time after. Similarly, under the high discounting behaviour, peak total emissions increase by about 3gtC/yr compared to lower discounting. Through comparing the disproportionate emission production between the two patches in Figure 4.6 and 4.7, it can be seen that the individual patches vary in emission productions from about 1 (30% emitting patches) to 3gtC/yr (70% emitting patches). Based on these examples, it is clear that the climate is negatively affected due to the non-mitigation nature of discounting distant climate conditions and impacts. This indicates that more considerable and uniform efforts in mitigation and promoting mitigation behaviour are needed across different groups and location types to obtain global beneficial climate impacts.

To fully recognize how spatial discounting can alter the perceived impacts of climate change in the model, I consider discounting scenarios where individuals base their personal impact of climate change on a different location. Now, their willingness to mitigate is driven by the perceived impacts of that other location. The shift in the location of perceived impacts causes issues when a population based on forward-looking behaviour relies on a second population's current-looking behaviour when choosing between mitigation strategies. Because now, they are switching between mitigation and non-mitigation strategies based on the current-looking behaviour of the higher discounting patch. So, where their perceived impacts could have been higher, triggering an increase in mitigation strategy uptake if they considered their own environmental conditions, they are now producing more emissions based on the other higher discounting behaviour. Figure 4.8 shows this type of switching discounting behaviour. In Figure 4.8(c), patch 1 discounts the future impact of climate change at a higher rate than patch 2, and both patches only look to the other when deciding which mitigation strategy to choose. That means that even though patch 2 has a lower discounting scenario, it is only patch 1 emissions that benefit because patch 1 only considers the perceptions in patch 2, and vice versa. So despite an expected lower emission production in patch 2, clearly from Figure 4.8(c) patch 2 (blue dashed line) is producing more emissions in part due to their proportion of emissions being higher and in part of patch 1's current-looking behaviour, they are relying on. Indeed, when patch 1 considers patch 2's perceived impacts of climate change instead of their own, they benefit as an individual patch. However, the climate conditions overall (total emissions and, subsequently temperature anomaly) do not gain as much benefit.

Spatial and temporal discounting influences model computations and evaluations as much as the climate projections themselves. Figure 4.8 represents the differences in model simulations under stronger discounting behaviour. Figure 4.8 (a) and (c) cover the carbon emissions when patch 1 discounts future climate impacts at 3% a year and produces 30% of total emissions, and patch 2 discounts at 1.5% per year and produces 70% of total emissions. Each patch completely considers the other patches' perceived impacts when making decisions. So, the lower discounting patch 2 will follow the higher discounting behaviour as in patch 1 and produce the majority of total emissions. Whereas Figure 4.8 (b) and (d) follow a discounting scenario that results, again, in the majority of emissions coming from the patch that perceives the personal impacts of climate change to be low (patch 1 discounting at 5% per year and patch 2 discounting at 3% per year).

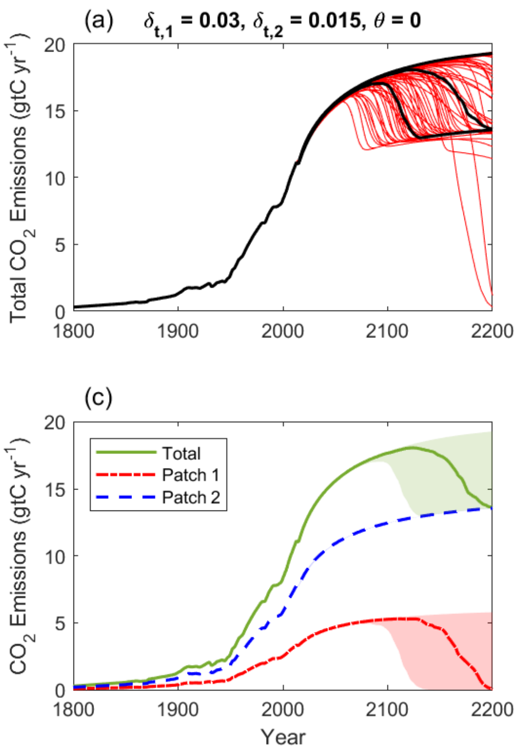

Figure 4.8: Emissions under current-looking behaviour increase and eventually saturate as equation 3.18 formulates. All 100 simulation runs (red) are plotted with median, 20th, and 80th percentiles (black) for total carbon dioxide emission (a),(b). Median trajectories (solid and dashed lines) and 20th and 80th percentiles are plotted to the year 2200 for carbon dioxide emissions (c),(d). Panels (a) and (c) are under temporal discounting $\delta_{t,1} = 0.03$, $\delta_{t,2} = 0.015$ spatial discounting $\theta = 0$, and proportion of emissions $\alpha = 0.3$. Panels (b) and (d) are under temporal discounting $\delta_{t,1} = 0.05$, $\delta_{t,2} = 0.03$, spatial discounting $\theta = 1$, and proportion of emissions $\alpha = 0.7$. Both have a time horizon of $t_H = 50$. Medians and quintiles are computed over 100 simulations, where all other social system parameters are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

Clearly, in the case where discounting in both patches is high (Figure 4.8 (b, d)), there is next to no variation from simulation to simulation. Whereas even the inclusion of devaluing future climate impacts at a lower rate and in smaller proportion still results in some variations across simulation runs (Figure 4.8 (a)). This highlights the strength of high temporal discounting or current-looking behaviour on the model results. Simulation runs are obtained by holding climate parameters at baseline (Table 3.3) and varying all social system parameters (Table 3.1). So even the variations of opinion dynamics are muted when the discounting rate per year rises. This leads to the understanding that temporal discounting overpowers the model in such a way as to diminish any beneficial changes in the social system. This implies the importance of focusing on shifting the way climate change is perceived towards being a problem affecting people here and now. By considering these two cases and over the 100 simulations, an understanding is gained on a mathematical level of how the developed model in this thesis, including behavioural discounting, impacts climate conditions.

In this Section 4.1, I covered results looking at the impacts that both spatial and temporal discounting have on the climate. Firstly, through parameter analysis and climate projections, I observed that forward-looking behaviour promotes mitigation and, as a result, provides an extended period for emissions and temperature to regulate. Secondly, current-looking behaviour supports non-mitigation strategies and thus negatively affects the climate on individual patch levels and globally. Thirdly, while reducing the rate at which individuals devalue future climate impacts, it is important to consider where these values are being deducted spatially. The spatial discounting analysis in this section emphasizes the idea that future climate conditions can be moderated better if multiple locations are considered at once. Altogether, this provides a clear picture of how bringing the issue of climate change into an individual's everyday life can promote willingness to mitigate. In other words, promoting individuals to take up forward-looking behaviour that reduces the distance between their everyday and climate issues will allow for meaningful environmental impacts.

4.2 Discounting and Opinion dynamics

In this section, I focus on how the interactions between spatial and temporal discounting and social behaviour may influence opinion dynamics and projected climate conditions. These connections help represent the influence that certain policy choices (economic focused, mitigation focused, etc.) under current or altered perceptions of climate change may have on climate and mitigation behaviours. Section 4.2.1 investigates parameter spaces for the various social and discounting parameters, and section 4.2.2 provides results based on changes to how individuals devalue climate conditions under various social dynamics.

4.2.1 Parameter Planes

Studies have shown that social learning should be a strong focus for climate interventions [9, 33]. A similar result is achieved in this thesis. In this section, I show that established relationships between social parameters (Figure 4.9) are altered by considering temporal discounting. This leads to the result that pathways to decreasing temperature anomalies are achieved by increasing the rate of social learning and reducing the strength of social norms while simultaneously decreasing temporal discounting (Figures 4.10(a) and (b) respectively). I also show that when analyzing discounting and drivers of decision-making, spatial discounting has a weaker influence on climate conditions than temporal discounting (Figure 4.11).

I begin by comparing two social dynamics parameters in Figure 4.9: the net cost of mitigation behaviour, β, and the strength of social norms, δ. The parameter space pro-

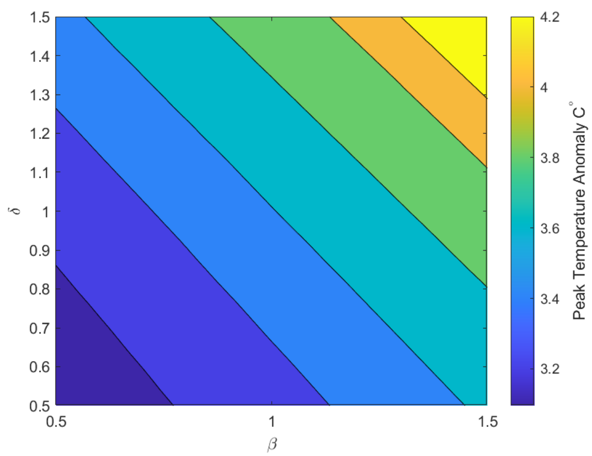

Figure 4.9: Contour plot showing peak temperature anomaly for values of the net cost of mitigation (β) and strength of social norms (δ) in patch 1. All other parameters are held at baseline as defined in Tables 3.1 and 3.3.

vides us with the understanding that as both costs and social norms are increased, then temperature anomaly also increases. The symmetric linear relationship observed through this plot conveys that δ and β tend to share influences on the system. This suggests that, as the economic burden of mitigative action increases, then the climate benefits only when social norms are weak (no prevalent majority behaviour in the population). This emphasizes the established understanding that social norms can act against mitigative action and be consequential to the environment, supporting an overwhelming non-mitigation strategy in a population [9]. For example, when mitigation action is expensive, a non-mitigation strategy choice becomes the majority behaviour, making it harder to switch strategies away from the norm. While these well-understood social dynamics are present in our model, it is imperative to figure out how they may change depending on the influence of spatial and temporal discounting.

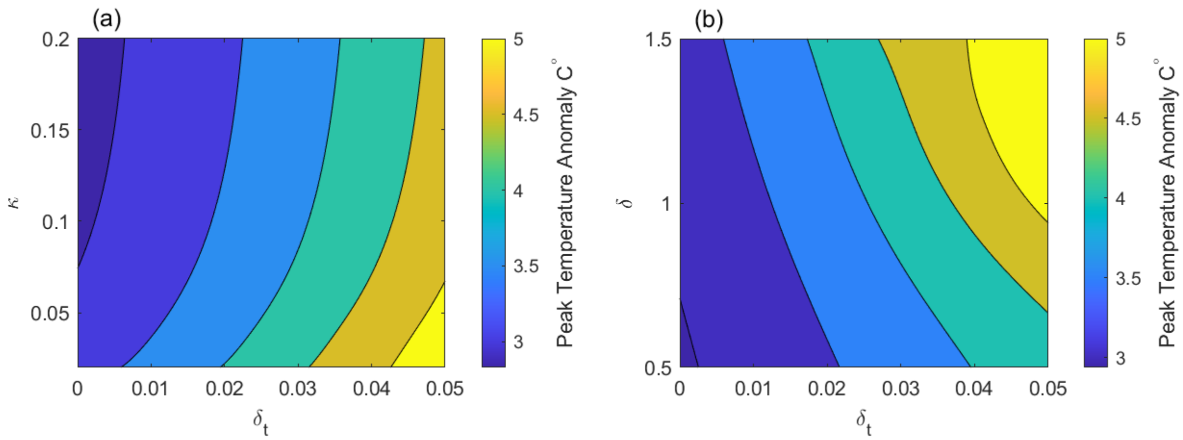

Figure 4.10: Contour plots showing peak temperature anomaly for temporal discounting (δ_t) and social learning rate (κ) (a) and strength of social norm (δ) (b) values in patch 1. All other parameters are held at baseline as defined in Tables 3.1 and 3.3

It is vital to understand how social learning and temporal discounting interact because social learning drives the imitation dynamics in the model [4]. As seen in Figure 4.10(a), a slow but sufficient reduction in temperature anomalies can be achieved by first focusing on increasing the rate at which individuals learn from each other and then reducing the rate at which those individuals devalue future climate impacts. Essentially, suppose individuals interact more with each other in discourse around climate change and climate impacts. In that case, the rate at which they devalue future climate impacts will not have as strong of an influence on the climate outcome. However, when individuals learn new behaviour from others over a long period, on generational timescales, temporal discounting has more substantial negative impacts on future temperature anomalies. Specifically, in the case of slow social learning, small increases in the rate at which future climate impacts are devalued produce a slightly more rapid increase in temperature anomalies. Effectively, even the simple action of talking about climate change promotes deeper awareness of the issue. Eventually, other social dynamics, like social norms, can lead to an increased uptake in mitigation behaviour and, subsequently, better environmental impacts. Temporal discounting seems to both strengthen dynamics and be amplified by the drivers of social dynamics (social learning and social norms).

Discounting can become more intense on the environment, considering that choosing a discounting behaviour, like current-looking behaviour, may be more enticing when everyone around an individual also holds that opinion of future climate impacts. This relationship holds consequences for environmental conditions when the majority of the population starts to remove value from future climate impacts. Figure 4.10(b) shows a parameter plane between values of temporal discounting (δ_t) and social norms (δ). The pathway to reducing temperature anomalies requires an initial reduction in the strength of social norms; this implies that it must become easier to switch mitigation strategies away from the majority behaviour. Peak temperature anomalies are reduced through this gradual shift in social norms alongside individuals giving value to future climate impacts. This pathway represents that as forward-looking behaviour and mitigation strategies become well accepted in a population, future temperature anomalies can be moderated.

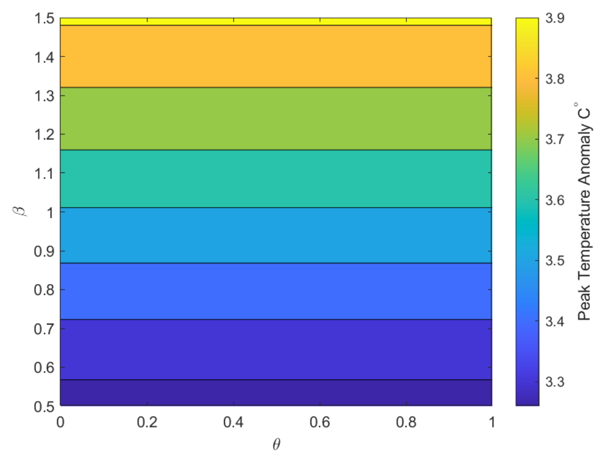

Figure 4.11: Contour plot showing peak temperature anomaly for spatial discounting (θ) and net cost of mitigation (β) values. All other parameters are held at baseline as defined in Tables 3.1 and 3.3.

Through the development of this conceptual model, both patches of arbitrary population groups only begin to differ when social parameters and temporal discounting are altered. Due to this mechanism of the model, spatial discounting does not have as strong of interactions with other human system parameters as temporal discounting. This can be understood through the way in which parameter planes are obtained for this model.

In the case when all parameters in Equation 3.16 are held at baseline for both patches during parameter analysis, then the perceived impacts of climate change are equivalent in each patch: $\hat{f}_1 = \hat{f}_2$. So, the spatial discounting factors in the social system (first two equations in Section 3.2) are eliminated. This reinforces the construction of the model and the functionality of spatial discounting. An illustration of this relationship can be observed in Figure 4.11. This plot shows the parameter space that the net cost of mitigation (β) and spatial discounting (θ) share, while all other parameters are held at baseline. Of course, this process results in the parameter plane where the peak temperature anomalies are consistent throughout the entire range of the spatial discounting parameter.

4.2.2 Time Series: Emissions, Temperature Anomaly, and Proportion of Mitigators

Projections in this section establish the magnifying effect that discounting, specifically temporal discounting, has on mitigation behaviour and temperature trajectories. In particular, a shift from forward to current-looking behaviour inflates the uptake of non-mitigation strategies and consequentially impacts the climate. In this section, four main results are obtained. First, I show that increasing temporal discounting amplifies the internal relationship of the social dynamics, often resulting in negative climate consequences (Figure 4.12). Next, I show that high rates of social learning offset some of the obstacles that devaluing distant climate impacts has on choosing the mitigation strategy (Figure 4.13). Then, I show how the economic hindrance of mitigation behaviours and temporal discounting work to promote the choice of a non-mitigation strategy (Figure 4.14). Finally, I show that stronger social norms, even at low temporal discounting values, are not always beneficial to enabling mitigation behaviour (Figure 4.15).

A glimpse at the impact of temporal discounting on temperature anomalies, carbon dioxide emissions, and the proportion of mitigators is presented in Figure 4.12. The temporal discounting parameter has been fixed at lower and higher discounting rates in the first and second rows of subplots, respectively. The model was implemented over the upper (blue line) and lower (red line) bounds of the social learning rate, cost of mitigation, and strength of social norms. One relationship between more current and forward-looking behaviour remains consistent across all three social dynamics parameters in Figure 4.12: the magnitude in temperature difference becomes more extreme when a higher (3%) discounting rate per year is implemented. The role of temporal discounting in these interactions is uncovered by isolating this analysis to one social behaviour parameter at a time.

Changes in temporal discounting do not alter the established dynamics of social learning

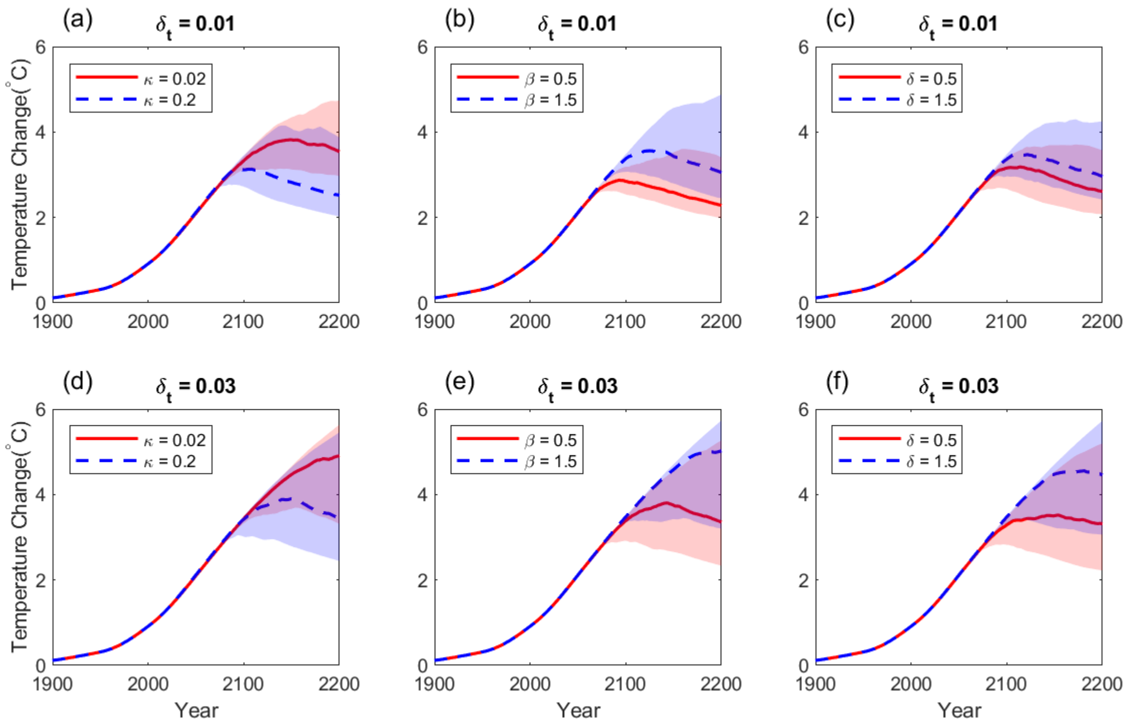

Figure 4.12: Current-looking behaviour amplifies the differences in temperature anomaly between weak and strong opinion dynamics. Median trajectories (solid and dashed lines) and 20th and 80th percentiles of temperature anomalies are plotted to the year 2200. The top row of plots shows anomalies for low yearly temporal discounting ($\delta_t = 0.01$), and the bottom row high temporal discounting ($\delta_t = 0.03$). The columns, from left to right, compare different parameter values for social learning rate (κ), net cost of mitigation (β), and strength of social norms (δ). Medians and quintiles are computed over 100 simulations, where all other social system parameters not specified in the panels are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

(Figure 4.12 (a) and (d)), where slow social learning leads to higher temperature anomalies. But when temporal discounting is higher, both slower and faster rates of social learning result in higher temperature anomalies in general. Of interest, the maximum distance between the temperature trajectories of different rates of social learning increases by 0.36°C and occurs about 16 years later when under current-looking behaviour (Figure 4.12(d)). Similarly, from Figure 4.12(a) to (d), the peak temperature anomalies are reached at a later time step and a higher degree. This connects to the result from Figure 4.1 in Section 4.2.1, where I investigated the implications of temperatures peaking sooner or later. The peak temperature anomalies occurring sooner and at a lower temperature highlight the beneficial effects on the climate of maintaining forward-looking behaviour and faster social learning rates.

Figures 4.12 (b) and (e) have a similar relationship when future climate conditions are discounted at higher percentages per year. Here, the maximum difference between the temperature anomalies under low and high cost of mitigation behaviour stretches from 0.90°C to 1.67°C and occurs 58 years later. Peak temperature anomalies when moving from low (4.12(b)) to high (4.12(e)) temporal discounting increase by 1.46°C for high costs and 0.93°C for low costs of mitigation. These significant shifts in temperature anomaly represent the extreme outcomes of opinion dynamics on the environment, even on a conceptual level. The interactions between the present economic costs of mitigation and the desire to look at climate change as something happening later in time amplifies the lack of motivation to mitigate (see also Figure 4.14 (d)) and thus increases temperature anomaly.

Following the same trends as the other human behaviour dynamics parameters, Figure 4.12 (c) and (f) also establish the strong influence temporal discounting has in the social-climate model. Specifically when looking at the interactions between temporal discounting and social norms, the maximum difference of the temperature projections between strong and weak social norms expands by 0.79°C when higher temporal discounting is implemented. Peak temperature anomalies occur more than four decades later and increase by 0.33°C under weak social norms and 1.08°C under strong social norms. When it gets harder to switch away from the majority mitigation strategy and there is a low perceived impact of climate change due to high temporal discounting, then the motivation to mitigate is low (see also Figure 4.15 (d)) and thus temperature anomaly increases drastically.

Together, these three relationships observed in Figure 4.12, identify that temporal discounting amplifies the relationship between the different rates of social learning, costs of mitigation, and strengths of social norms. This relationship reveals that if temporal discounting is not approached, then much greater efforts will need to be employed on shifting human behaviours to achieve noticable benefits on the envirnment. Overall, this implies that policies targeting mitigation costs or interventions in social behaviours will also need to consider the way individuals value future climate impacts.

The opinion dynamics of choosing a mitigation strategy or a non-mitigation strategy drives the feedback in the model: when there is a lower proportion of mitigators than non-mitigators, less carbon dioxide emissions will be reduced. As a consequence of higher anthropogenic emissions fed into the climate system from the social system, the global temperature rises. Shifts in up-taking mitigation behaviour are represented in Figures 4.13, 4.14, 4.15. Temporal discounting is held at 1% and 3% discounting per year, and the social parameters are held at their lower and upper bounds in patch 1. The social parameters for patch 2 are drawn randomly from their uniform distribution, see Table 3.1. From Figure 4.13, at a low rate of social learning, an increase in temporal discounting (Figure 4.13(a) to (b)), even by 2% significantly decreases the number of mitigators in patch 1. However, a high rate of social learning does not result in such a large shift in mitigators. In fact, at high social learning and high discounting (Figure 4.13(d)), patch 1 reaches the full proportion of mitigators, which could be a result of the simulation run and the large error bounds. Across these scenarios, a low rate of discounting and a high rate of social learning result in a full proportion of mitigators in the shortest amount of time.

A significant driver of pro-environmental behaviour is the costs of taking mitigative action [19]. This barrier to action is amplified when accounting for temporal discounting. Figure 4.14 plots the projections of the proportion of mitigators to the year 2200, between the patch with specified temporal discounting and net cost of mitigation parameter values (plotted in red) and the patch with a randomly chosen parameter set (plotted in blue). Most significantly, when the net cost of mitigation is high, then the jump from 1% discounting (4.14 (c)) to 3% discounting (4.14 (d)) per year results in a shift from a population with mitigators to a total population of non-mitigators. This interaction is representative of the value individuals put into current economic choices and the value they take away from future climate conditions [5, 20, 41]. The relationship between the costs of mitigation behaviour and temporal discounting as determined in Figure 4.12(b) and (e) is reestablished with the results from Figure 4.14.

The strength of social norms operates similarly on the proportion of mitigators to the net cost of mitigation. Figure 4.15 projects the proportion of mitigators for both patches, where δ_t and δ are varied in patch 1. In both lower and higher rates of temporal discounting, the stronger the social norms, then the population switches to mitigation behaviour slower (4.15(c)) or not at all (4.15(d)). Specifically, at a higher temporal discounting value, $\delta_t = 0.03$ (4.15(b)), if it is less socially taxing to switch behaviours, then the population in patch 1 is able to reach a full proportion of mitigators around the year 2130. Whereas, when social norms are strengthened (4.15(d)), meaning it is harder to switch to the non-dominant behaviour, the proportion of mitigators in patch 1 approaches zero. In other words, the population in patch 1 opts for the non-mitigation strategy. However, when future climate impacts are devalued, the magnitude of non-mitigators under weak or strong social norms moderately and drastically increases, respectively. This relationship can be visualized from Figure 4.15 (a) to (b) and (c) to (d). Fundamentally, the influence of temporal discounting on willingness to mitigate is linked to social dynamics like social norms, the net cost of

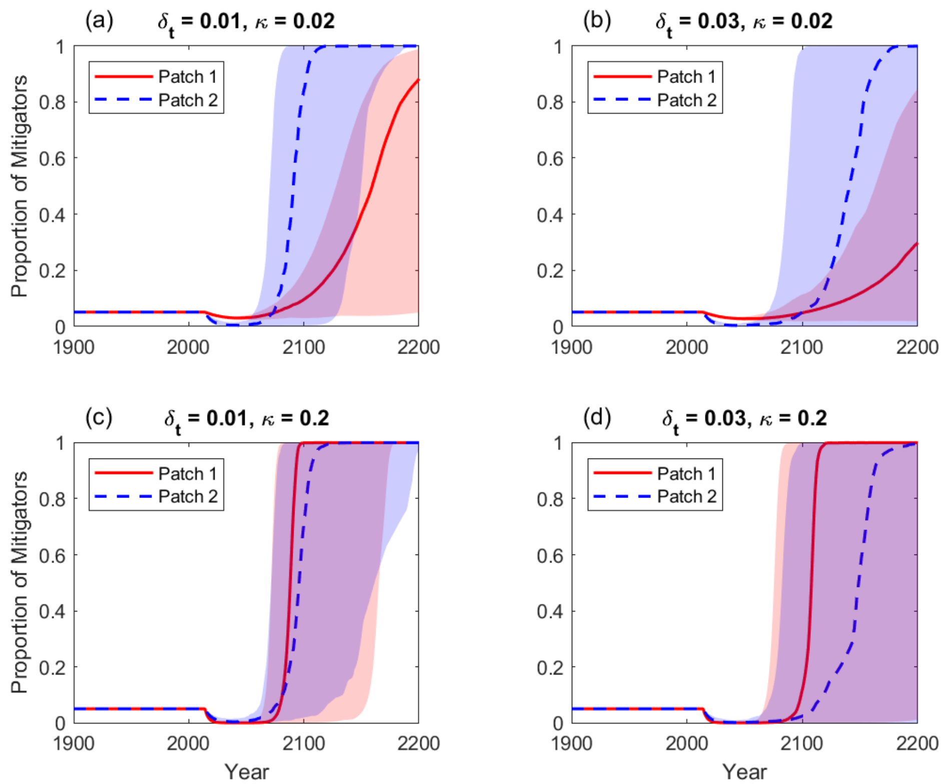

Figure 4.13: Stronger social learning offsets non-mitigation pressure from current-looking behaviours. Median trajectories (solid and dashed lines) and 20th and 80th percentiles of temperature anomalies are plotted to the year 2200. Panels show projections for specific discounting and social parameters. Temporal discounting (δ_T) increases from left to right, and social learning rate (κ) increases from top to bottom. Medians and quintiles are computed over 100 simulations, where all other social system parameters are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

mitigation, and social learning rates.

Overall, implementing discounting in the social system amplifies the underlying social dynamics and further amplifies the disadvantages felt in the climate by those behavioural decisions. Current-looking behaviour tends to overpower the system and amplify any minor differences between various social parameter values. It is essentially promoting, for the most part, more non-mitigative behaviour under higher discounting regimes. This also leads to the understanding that if the issue of discounting is targeted, approaching

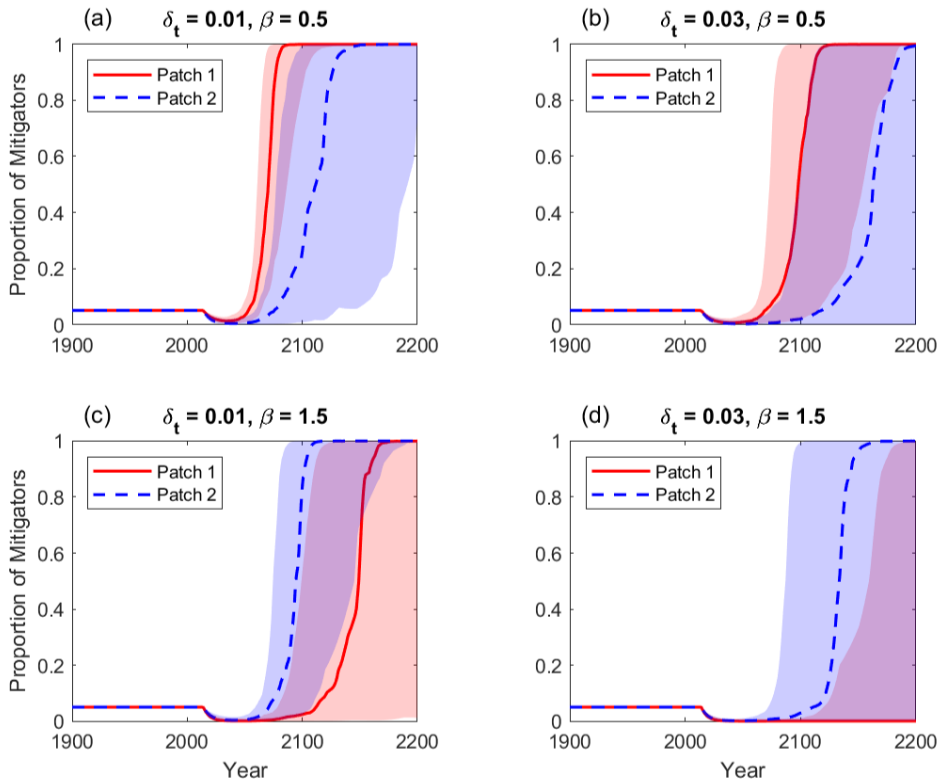

Figure 4.14: Reduction in discounting and net cost of mitigation promotes mitigation strategy. Median trajectories (solid and dashed lines) and 20th and 80th percentiles of temperature anomalies are plotted to the year 2200. Panels show projections for specific discounting and social parameters. Temporal discounting (δ_t) increases from left to right, and the net cost of mitigation (β) increases from top to bottom. Medians and quintiles are computed over 100 simulations, where all other social system parameters are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

a better climate state can be achieved quicker than if any of the other social parameters were tackled individually. Together, fostering a population that learns from each other at higher rates, is not economically burdened to take up mitigation practices, and allows for an ease of changing strategies can quickly lead to better environmental conditions by reducing temporal discounting. While this suggestion may seem unattainable, these results provide the understanding that changing how climate impacts are perceived is as crucial as dealing with other human behaviours related to climate change.

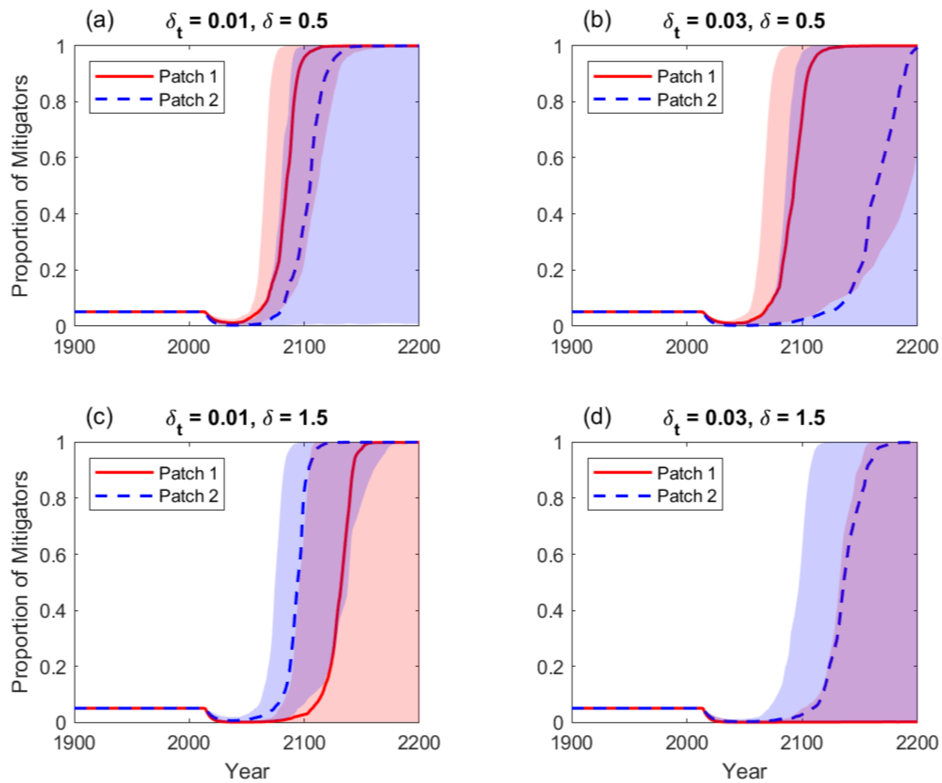

Figure 4.15: Resistance to switching mitigation strategies is amplified with an increase in yearly discounting. Median trajectories (solid and dashed lines) and 20th and 80th percentiles of temperature anomalies are plotted to the year 2200. Panels show projections for specific discounting and social parameters. Temporal discounting (δ_t) increases from left to right, and the net cost of mitigation (β) increases from top to bottom. Medians and quintiles are computed over 100 simulations, where all other social system parameters are randomly drawn from their uniform distributions (Table 3.1). All other parameters are held at baseline values (Table 3.3).

Chapter 5

Discussion

In this section, I conclude the thesis with a discussion of the key results found in this thesis, model assumptions and limitations, and the broader implications of this research.

5.1 Summary of Main Findings

This thesis aimed to identify the key interactions between how humans discount distant climate conditions and impacts and the changes in the climate under those behaviours. This was achieved through coupling a human decision-making model rooted in social dynamics with a simple Earth System Model (ESM). Historical emissions data was used throughout the full social-climate model, while the social dynamics were initiated in simulations in the year 2014. Imitation dynamics of evolutionary game theory and the flexibility of simple ESMs guided the modelling process. The main problem I set out to investigate in this thesis was motivated by the distant framing of climate change issues and impacts in the media and the psychological barrier to mitigation that discounting distant climate impacts has on the environment. The motivations and methodology work together to address the main questions of this thesis. As a result, a thorough line of understanding is raised. In this section, I summarize the main findings of this thesis as they relate to encouraging the choice of a mitigation strategy.

Our results clearly show that mitigation efforts are needed across multiple locations and population groups. When deciding between mitigation or non-mitigation behaviour, mitigation strategies are best supported when considering a more equal share of distinct geographic locations and population groups. Whereas, when only one population's perceived impacts of climate change are considered (either the current or other location), there is always a risk of entirely relying on opinion dynamics that are forced with a low personal impact of climate change. This fundamentally does not promote, nor has any small fraction of promotion for mitigation efforts. A quicker, more reliable pathway to temperature reduction is obtained from considering both patches, even if the other patch has a slightly worse discounting regime, rather than just one or the other (Figure 4.3). This understanding is essential as it supports the demand for bringing the issue of climate change to a closer, more local issue. This shift in the distance of climate change may help to maintain the connection between mitigation action and impacts “here” and “now” as they will inadvertently affect other locations too (see total emissions late peak and decline in Figure 4.7(b) and 4.8(c)) [41].

While focusing on a broader target of mitigation action is helpful, focusing on maintaining value in future climate impacts is just as important. Specifically because discounting climate conditions in space and time are additive in nature as determined through the model results. The more distant (spatially and temporally) climate change impacts are perceived to be, then individuals are more inclined to take up current-looking behaviour. Through this devaluing of personal impacts of climate change, motivation to mitigate is reduced, which negatively affects climate conditions as a result (this can be seen through the parameter planes in Section 4.1). The willingness to mitigate is almost entirely eliminated when even isolating the impact of temporal discounting on its own. Further, in the model, emissions are most sensitive to high temporal discounting (Figure 4.8). Together, this implies a required focus on shifting individuals’ behaviours to value climate impacts even as they occur farther out in time. This could be established by presenting climate change as both a current *and* future issue, not just a problem for future generations to deal with. This shift in perspective will also need to be supported by presenting pro-environmental actions [31, 55, 56].

Current-looking behaviour amplifies preexisting relationships between social dynamics and climate conditions. The differences in temperature anomalies for opinion dynamics that support mitigation strategies and those that do not are expanded when considering discounting future climate impacts. So much so that if policies are trying to encourage mitigative behaviour, then they will need to consider social dynamics and discounting equally. As much as current-looking behaviour becomes easy to choose when it’s harder to switch mitigation strategies, higher rates of social learning can moderate some of those adverse effects on the climate. A shift to forward-looking behaviour is additionally supported as the economic burden of mitigation decreases. Together, the understanding of how discounting interacts with human behaviour and social dynamics provides a clear picture for future motivation to mitigate. Specifically, challenging the way climate impacts are perceived has as much of an impact on future climate conditions as approaching a shift in human behaviour. As seen through the results in Section 4.2, the coupled alterations in discounting and opinion dynamics produce the best outcomes for willingness to mitigate.

5.2 Model Assumptions and Limitations

The results presented in this thesis represent the impact that spatial and temporal discounting have on the future climate and on an individual's willingness to mitigate. That said, certain assumptions were made throughout the modelling process that influenced the results. In this section, I will cover the assumptions and limitations of the model. These include the decision of a simplified ESM, the simple implementation of the temporal discounting time horizon, social parameter variations, and non-normalized emissions.

An imperative component of social-climate models is the physical climate model that is coupled to the social system. In this model, as represented in Section 3.3, a simple ESM is implemented. The simplified ESM does not elaborate beyond the extent of what is needed to answer my research questions. Through the atmosphere, ocean, vegetation and soil, the carbon cycle is represented by biological and chemical processes [9, 29, 36]. The ESM also captures the greenhouse gas effect and overall temperature response [9, 29, 36]. Employing this elegant climate system rather than a fully comprehensive system, as guided by Lenton [29], allows for the human behaviour dynamics in the coupled model to drive the two-way feedback equally. This space given to the social system helps to focus on gaining intuition and understanding into humans' dynamic influence on the climate rather than just validated climate projections [9].

The goal of understanding how the devaluing of distant climate conditions and impacts influence climate change was also prioritized throughout model realizations. The many simulations run to obtain the results presented in Chapter 4 maintain the common feature of only choosing the social system parameters at random. In contrast, the climate system parameters were held at their baseline values. More simply, there was only variability in the social system. This follows the focus on understanding how the variations in human behaviour under the new addition of discounting impacts the climate. This decision has limitations, as the natural variability in the environment is not accounted for in the model simulations. This is a significant limitation as the lack of potential physical climate process variability will increase the uncertainties in our model.

That being said, when climate processes were varied across model realizations through the random selection from uniform distributions of parameters (see Tables 3.1 and 3.3), the projections were ambiguous. 20th and 80th percentiles spanned almost the entire set of axes. No discernible relationship between spatial and temporal discounting and mitigation activity or climate conditions could be obtained. Under those variable conditions, the research questions and hypothesis set out to be tested in this thesis could not be approached. This led back to the focus on understanding interactions rather than just projections of future climate within the conceptual model. Approaching a more variable social-climate model through simulation runs could be dealt with in future research. This could be completed by identifying parameters with the most influence on the model and sorting out some climate model uncertainty.

Throughout the model development process, a difference arose from the coupling of the social system to the climate system in this model compared to another similar social-climate model. Menard et al. [33] implemented normalization of total emissions. This functions to account for the differences in size and resources between the rich and poor groups in their model [33]. Normalizing emissions in each population group by the total impact of non-mitigation across both groups captures the individual group influences on emissions [33]. The model presented in this thesis does not normalize emissions based on the initial proportion of non-mitigators. The implication of missing the normalization in our model fails to capture each patch's relative impact on emissions. That being said, the α term forces this impact on a proportional scale (α is the proportion of emissions each patch produces). While our model is conceptual, the lack of normalization fails to account for potential differences in patches that may arise when altered to represent more specific population group types. Future research to address normalization and apply the model to specific geographic and climate scenarios should be completed.

5.3 Implications of Research

While our model is conceptual, the results presented in Chapter 4 provide an understanding of human behaviour as it is related to devaluing the impacts of climate change. This provides a key takeaway: that maintaining value in climate change impacts is fundamental to any pathway of temperature reduction and encouraging mitigation. This leads to the idea that climate change must be presented differently if we want to change the perception of future and farther climate to a problem that is here and now. This shift then subsequently results in a less extreme climate in the future. In this section, I discuss the implication of our results in the context of promoting mitigation through shifts in discounting regimes.

Surrounding the main focus of discounting distant climate impacts, I found that shifts in perception of climate change impacts directly produce shifts in climate conditions. On the one hand, when individuals perceive climate change issues as out of reach (happening somewhere else and later in time), they do not act in ways to mitigate worsening climate conditions, resulting in negative consequences for the environment. On the other hand, if individuals' perspectives change to give value to climate conditions regardless of where and when they occur, their willingness to mitigate climate change is increased, which produces beneficial impacts on the environment. While these are simple takeaways, a more significant impact of these relationships is obtained. Specifically, a pathway to increasing climate change mitigation is an interdisciplinary effort, not just on the level of one individual's actions. Due to the evolutionary game theoretic approach in this social-climate model, individuals imitate other individuals' mitigation strategies. This provides the understanding that there are influences on decision-making (and perceived impacts of climate change) from other individuals in the population, environmental conditions, and the media's framing of climate change issues. And so, interventions aiming to support the uptake of mitigation action must approach these multiple interactions. Interventions should ideally consider the benefits of supporting social learning in a population, maintaining value in climate impacts, and shifting the presentation of climate change issues into the everyday.

The research questions (Section 1.1) have been answered through the results and discussion presented in this thesis. I am left with the understanding that by including a common barrier to mitigation behaviour, like spatial and temporal discounting, into a social-climate model, projections of the future climate capture the dynamic nature of human behaviour. As an extension, this relationship between discounting, human behaviour and the climate may better inform policy-making and decisions. And more importantly, this research addresses and supports the need for a better portrayal of climate change in the media. One that brings the issue and impacts of climate change into an individual's everyday life. As seen in Chapter 2.1, presenting climate in the media as a less distant problem can help promote engagement with the issue of climate change. If individuals are more engaged, they may talk about it more, increasing social learning on the topic of climate change. As seen from the results in Sections 4.2.1 and 4.2.2, the best outcomes can be obtained when human behaviour dynamics are accounted for alongside a shift from current to forward-looking behaviour.

Beyond policy-making and guiding perception and behavioural shifts, the model developed in this thesis could aid in expanding the field of coupled human-environment models. Through representing social dynamics with an additional behavioural influence, this model situates itself in the emergent area of social-climate modelling. Further, the results in this research support the need to increase climate models that include a dynamic human component. Finally, future research accounting for climate variability and applying the model to geographically and demographically specific populations will help increase the model's robustness and application of the results.

References

[1] Catalogue of Model Intercomparison Projects. https://www.clivar.org/clivar-panels/former-panels/aamp/resources/mips [Accessed: 2023-09-27].

[2] Climate (chemical processes). https://www.aoml.noaa.gov/general/nchem.html [Accessed: 2023-12-19].

[3] Ralf Barkemeyer, Frank Figge, Andreas Hoepner, Diane Holt, Johannes Marcelus Kraak, and Pei-Shan Yu. Media coverage of climate change: An international comparison. *Environment and Planning C: Politics and Space*, 35(6):1029–1054, September 2017.

[4] Chris T. Bauch and Samit Bhattacharyya. Evolutionary game theory and social learning can determine how vaccine scares unfold. *PLoS computational biology*, 8(4):e1002452–e1002452, 2012.

[5] Seth D Baum and William E Easterling. Space-time discounting in climate change adaptation. *Mitigation and adaptation strategies for global change*, 15(6):591–609, 2010.

[6] Brian Beckage, Louis J Gross, Katherine Lacasse, Eric Carr, Sara S Metcalf, Jonathan M Winter, Peter D Howe, Nina Fefferman, Travis Franck, Asim Zia, Ann Kinzig, and Forrest M Hoffman. Linking models of human behaviour and climate alters projected climate change. *Nature climate change*, 8(1):79–84, 2018.

[7] Brian Beckage, Katherine Lacasse, Jonathan M Winter, Louis J Gross, Nina Fefferman, Forrest M Hoffman, Sara S Metcalf, Travis Franck, Eric Carr, Asim Zia, and Ann Kinzig. The earth has humans, so why don't our climate models? *Climatic change*, 163(1):181–188, 2020.

[8] T.A. Boden, G. Marland, and R. J. Andres. Global, regional, and national fossil-fuel co2 emissions (1751 - 2014) (v. 2017), 2017. https://www.osti.gov/biblio/1389331.

[9] Thomas M Bury, Chris T Bauch, and Madhur Anand. Charting pathways to climate change mitigation in a coupled socio-climate model. *PLoS computational biology*, 15(6):e1007000, 2019.

[10] Katherine Calvin and Ben Bond-Lamberty. Integrated human-earth system modeling-state of the science and future directions. *Environmental research letters*, 13(6):63006–, 2017.

[11] Noel Castree, William M Adams, Peter Newell, Luigi Pellizzoni, Kate Rigby, Paul Robbins, Libby Robin, Deborah Bird Rose, Andrew Ross, David Schlosberg, Sverker Sörlin, Paige West, John Barry, Mark Whitehead, Brian Wynne, Daniel Brockington, Bram Büscher, Esteve Corbera, David Demeritt, Rosaleen Duffy, Ulrike Felt, and Katja Neves. Changing the intellectual climate. *Nature climate change*, 4(9):763–768, 2014.

[12] Susan Clayton. *Understanding responses to climate change: Psychological barriers to mitigation and a new theory of behavioral choice*. Academic Press, an imprint of Elsevier, London, United Kingdom, 1st edition edition, 2018.

[13] Susan Clayton, Patrick Devine-Wright, Paul C. Stern, Lorraine Whitmarsh, Amanda Carrico, Linda Steg, Janet Swim, and Mirilia Bonnes. Psychological research and global climate change. *Nature climate change*, 5(7):640–646, 2015.

[14] Brady Dortmans, William F Langford, and Allan R Willms. An energy balance model for paleoclimate transitions. *Climate of the past*, 15(2):493–520, 2019.

[15] Sondoss Elsawah, Serena H. Hamilton, Anthony J. Jakeman, Dale Rothman, Vanessa Schweizer, Evelina Trutnevyte, Henrik Carlsen, Crystal Drakes, Bob Frame, Baihua Fu, Celine Guivarch, Marjolijn Haasnoot, Eric Kemp-Benedict, Kasper Kok, Hannah Kosow, Mike Ryan, and Hedwig van Delden. Scenario processes for socio-environmental systems analysis of futures: A review of recent efforts and a salient research agenda for supporting decision making. *Science of The Total Environment*, 729:138393, 2020.

[16] Christian L. E Franzke, Terence J O'Kane, Judith Berner, Paul D Williams, and Valerio Lucarini. Stochastic climate theory and modeling. *Wiley interdisciplinary reviews. Climate change*, 6(1):63–78, 2015.

[17] Andrew Gettelman and Richard B. Rood. *Demystifying Climate Models: A Users Guide to Earth System Models*, volume 2 of *Earth Systems Data and Models*. Springer Berlin Heidelberg, Berlin, Heidelberg, 2016.

[18] M. J. Gidden, K. Riahi, S. J. Smith, S. Fujimori, G. Luderer, E. Kriegler, D. P. van Vuuren, M. van den Berg, L. Feng, D. Klein, K. Calvin, J. C. Doelman, S. Frank, O. Fricko, M. Harmsen, T. Hasegawa, P. Havlik, J. Hilaire, R. Hoesly, J. Horing, A. Popp, E. Stehfest, and K. Takahashi. Global emissions pathways under different socioeconomic scenarios for use in cmip6: a dataset of harmonized emissions trajectories through the end of the century. *Geoscientific Model Development*, 12(4):1443–1475, 2019.

[19] Robert Gifford. The dragons of inaction: Psychological barriers that limit climate change mitigation and adaptation. *The American psychologist*, 66(4):290–302, 2011.

[20] Conrad Heilmann. Values in time discounting. *Science and engineering ethics*, 23(5):1333–1349, 2017.

[21] Dirk Helbing. *Quantitative Sociodynamics: Stochastic Methods and Models of Social Interaction Processes*. Springer-Verlag, Berlin, Heidelberg, 1. aufl. edition, 2010.

[22] Isaac M. Held. The Gap between Simulation and Understanding in Climate Modeling. *Bulletin of the American Meteorological Society*, 86(11):1609–1614, November 2005.

[23] Kirsten A Henderson, Madhur Anand, and Chris T Bauch. Carrot or stick? modelling how landowner behavioural responses can cause incentive-based forest governance to backfire. *PloS one*, 8(10):e77735–e77735, 2013.

[24] Kirsten A. Henderson, Chris T. Bauch, and Madhur Anand. Alternative stable states and the sustainability of forests, grasslands, and agriculture. *Proceedings of the National Academy of Sciences - PNAS*, 113(51):14552–14559, 2016.

[25] Josef Hofbauer and Karl Sigmund. *Evolutionary games and population dynamics*. Cambridge University Press, Cambridge, 1998.

[26] Clinton Innes, Madhur Anand, and Chris T Bauch. The impact of human-environment interactions on the stability of forest-grassland mosaic ecosystems. *Scientific reports*, 3(1):2689–2689, 2013.

[27] Intergovernmental Panel On Climate Change. *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the*

Intergovernmental Panel on Climate Change. Cambridge University Press, 1 edition, 2023.

[28] Intergovernmental Panel On Climate Change. *Climate Change 2022 - Mitigation of Climate Change: Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, 2023.

[29] Timothy M. Lenton. Land and ocean carbon cycle feedback effects on global warming in a simple earth system model. *Tellus. Series B, Chemical and physical meteorology*, 52(5):1159–1188, 2000.

[30] Simon Levin, Tasos Xepapadeas, Anne-Sophie Crépin, Jon Norberg, Aart de Zeeuw, Carl Folke, Terry Hughes, Kenneth Arrow, Scott Barrett, Gretchen Daily, Paul Ehrlich, Nils Kautsky, Karl-Göran Mäler, Steve Polasky, Max Troell, Jeffrey R Vincent, and Brian Walker. Social-ecological systems as complex adaptive systems: modeling and policy implications. *Environment and development economics*, 18(2):111–132, 2013.

[31] Xinsheng Liu, Arnold Vedlitz, and Letitia Alston. Regional news portrayals of global warming and climate change. *Environmental Science & Policy*, 11(5):379–393, August 2008.

[32] Anil Markandya and David W. Pearce. Development, the environment, and the social rate of discount. *The World Bank research observer*, 6(2):137–152, 1991.

[33] Jyler Menard, Thomas M Bury, Chris T Bauch, and Madhur Anand. When conflicts get heated, so does the planet: Coupled social-climate dynamics under inequality. *Proceedings of the Royal Society. B, Biological sciences*, 288(1958):20211357, 2021.

[34] Frances C Moore, Katherine Lacasse, Katharine J Mach, Yoon Ah Shin, Louis J Gross, and Brian Beckage. Determinants of emissions pathways in the coupled climate-social system. *Nature (London)*, 603(7899):103–111, 2022.

[35] Rendani Mulaudzi and Joseph Kioko. Understanding broadsheet newspaper attention to climate change objective facts in South Africa. *Environmental Research Communications*, 4(12):125001, December 2022.

[36] K. E. Muryshev, A. V. Eliseev, I. I. Mokhov, and A. V. Timazhev. A lag between temperature and atmospheric co2 concentration based on a simple coupled model of climate and the carbon cycle. *Doklady earth sciences*, 463(2):863–867, 2015.

[37] Paul Manuel Müller, Jobst Heitzig, Jürgen Kurths, Kathy Lüdge, and Marc Wiedermann. Anticipation-induced social tipping: can the environment be stabilised by social dynamics? *The European physical journal. ST, Special topics*, 230(16-17):3189–3199, 2021.

[38] Kristian S Nielsen, Susan Clayton, Paul C Stern, Thomas Dietz, Stuart Capstick, and Lorraine Whitmarsh. How psychology can help limit climate change. *The American psychologist*, 76(1):130–144, 2021.

[39] Saffron O'Neill. More than meets the eye: a longitudinal analysis of climate change imagery in the print media. *Climatic Change*, 163(1):9–26, November 2020.

[40] Saffron J. O'Neill. Image matters: Climate change imagery in US, UK and Australian newspapers. *Geoforum*, 49:10–19, October 2013.

[41] Roger Perman. *Natural resource and environmental economics.* Pearson Addison Wesley, Harlow, Essex, 4th ed. edition, 2011.

[42] David A. Randall, Cecilia M. Bitz, Gokhan Danabasoglu, A. Scott Denning, Peter R. Gent, Andrew Gettelman, Stephen M. Griffies, Peter Lynch, Hugh Morrison, Robert Pincus, and John Thuburn. 100 Years of Earth System Model Development. *Meteorological Monographs*, 59(1):12.1–12.66, December 2018.

[43] Eric. Rasmusen. *Games and information : an introduction to game theory.* Blackwell Pub., Malden, MA, 4th ed. edition, 2007.

[44] Keywan Riahi, Detlef P van Vuuren, Elmar Kriegler, Jae Edmonds, Brian C O'Neill, Shinichiro Fujimori, Nico Bauer, Katherine Calvin, Rob Dellink, Oliver Fricko, Wolfgang Lutz, Alexander Popp, Jesus Crespo Cuaresma, Samir KC, Marian Leimbach, Leiwen Jiang, Tom Kram, Shilpa Rao, Johannes Emmerling, Kristie Ebi, Tomoko Hasegawa, Petr Havlik, Florian Humpenoder, Lara Aleluia Da Silva, Steve Smith, Elke Stehfest, Valentina Bosetti, Jiyong Eom, David Gernaat, Toshihiko Masui, Joeri Rogelj, Jessica Strefler, Laurent Drouet, Volker Krey, Gunnar Luderer, Mathijs Harmsen, Kiyoshi Takahashi, Lavinia Baumstark, Jonathan C Doelman, Mikiko Kainuma, Zbigniew Klimont, Giacomo Marangoni, Hermann Lotze-Campen, Michael Obersteiner, Andrzej Tabeau, and Massimo Tavoni. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global environmental change*, 42(C), 2017.

[45] Tracy M. Rout and Terry Walshe. Accounting for time preference in management decisions: An application to invasive species. *Journal of Multi-Criteria Decision Analysis*, 20(3-4):197–211, 2013.

[46] Leila Scannell and Robert Gifford. Personally relevant climate change: The role of place attachment and local versus global message framing in engagement. *Environment and behavior*, 45(1):60–85, 2013.

[47] Leila Scannell and Robert Gifford. The experienced psychological benefits of place attachment. *Journal of environmental psychology*, 51:256–269, 2017.

[48] Rachel E. Schattman, Martha Caswell, and Joshua W. Faulkner. Eyes on the horizon: Temporal and social perspectives of climate risk and agricultural decision making among climate-informed farmers. *Society natural resources*, 34(6):765–784, 2021.

[49] Maja Schlüter, L. Jamila Haider, Steven J Lade, Emilie Lindkvist, Romina Martin, Kirill Orach, Nanda Wijermans, and Carl Folke. Capturing emergent phenomena in social-ecological systems: An analytical framework. *Ecology and society*, 24(3):11, 2019.

[50] Rajiv Sethi and E. Somanathan. The evolution of social norms in common property resource use. *The American economic review*, 86(4):766–788, 1996.

[51] Ram P Sigdel, Madhur Anand, and Chris T Bauch. Competition between injunctive social norms and conservation priorities gives rise to complex dynamics in a model of forest growth and opinion dynamics. *Journal of theoretical biology*, 432:132–140, 2017.

[52] Hanne K Sjølie, Greg S Latta, and Birger Solberg. Dual discounting in climate change mitigation in the forest sector. *Journal of forest economics*, 19(4):416–431, 2013.

[53] Gregg Sparkman, Nathan R Lee, and Bobbie N.J Macdonald. Discounting environmental policy: The effects of psychological distance over time and space. *Journal of environmental psychology*, 73:101529, 2021.

[54] John Sterman, Thomas Fiddaman, Travis Franck, Andrew Jones, Stephanie McCauley, Philip Rice, Elizabeth Sawin, and Lori Siegel. Climate interactive: the c-roads climate policy model. *System dynamics review*, 28(3):295–305, 2012.

[55] Kristen Alley Swain. Mass Media Roles in Climate Change Mitigation. In Wei-Yin Chen, Toshio Suzuki, and Maximilian Lackner, editors, *Handbook of Climate Change Mitigation and Adaptation*, pages 167–219. Springer International Publishing, Cham, 2017.

[56] Alexandre O. Tavares, Neide P. Areia, Sinead Mellett, Julia James, Diego S. Intrigliolo, Laurence B. Couldrick, and Jean-François Berthoumieu. The European Media Portrayal of Climate Change: Implications for the Social Mobilization towards Climate Action. *Sustainability*, 12(20):8300, October 2020.

[57] Andrew R. Tilman, Joshua B. Plotkin, and Erol Akçay. Evolutionary games with environmental feedbacks. *Nature communications*, 11(1):915–915, 2020.

[58] Alexey Voinov and Joshua Farley. Reconciling sustainability, systems theory and discounting. *Ecological economics*, 63(1):104–113, 2007.

[59] Hong Tien Vu, Yuchen Liu, and Duc Vinh Tran. Nationalizing a global phenomenon: A study of how the press in 45 countries and territories portrays climate change. *Global Environmental Change*, 58:101942, September 2019.

[60] Elke U. Weber. What shapes perceptions of climate change? *Wiley interdisciplinary reviews. Climate change*, 1(3):332–342, 2010.

[61] John Weyant. Some contributions of integrated assessment models of global climate change. *Review of environmental economics and policy.*, 11(1):115–137, 2017.

[62] A. A. Wing, K. A. Reed, M. Satoh, B. Stevens, S. Bony, and T. Ohno. Radiative–convective equilibrium model intercomparison project. *Geoscientific Model Development*, 11(2):793–813, 2018.

[63] Seth Wynes and Kimberly A Nicholas. The climate mitigation gap: education and government recommendations miss the most effective individual actions. *Environmental research letters*, 12(7):74024, 2017.

[64] Rintaro Yamaguchi and Payal Shah. Spatial discounting of ecosystem services. *Resource and energy economics*, 62:101186, 2020.