# Modelling the Dynamics of Nature Experience and Nature Appreciation: An Agent-based Approach to Extinction of Experience

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**Abstract**

The decrease in humans' nature experience and appreciation represents a barrier to a sustainability transition. Nature experience and appreciation dynamically influence each other, which may lead to a vicious cycle, where nature experience and appreciation decrease over time (i.e., extinction of experience) or to a virtuous cycle, where both factors increase over time. This study investigates the emergence of a vicious or virtuous cycle by simulating the dynamics of nature experience and appreciation over time and across interacting individuals. An agent-based model was developed simulating interacting agents that experience and appreciate nature within an urban environment. The percentage of green spaces and the impact of assimilative social influence was evaluated via experimentation with the model. More green spaces foster the emergence of a virtuous cycle. A tipping point was identified when green spaces covered between 23-25% of agents' environment. Assimilative social influence had an accelerating effect on the dynamics of nature experience and appreciation. Limitations and implications will be discussed.

**Keywords**: nature experience, nature appreciation, extinction of experience, assimilative social influence, agent-based modelling

**Modelling the Dynamics of Nature Experience and Nature Appreciation: An Agent-based Approach to Extinction of Experience**

Climate change increasingly endangers the health and well-being of people, ecosystems, and biodiversity (IPCC, 2022). A major challenge is to address climate change as a complex problem and facilitate a societal transition towards sustainability. A growing line of research identifies the loss in humans' nature experience and appreciation as a fundamental hurdle to achieve a sustainability transition (Alcock et al., 2020; Miller, 2005; Collégony et al., 2017; Nisbet et al., 2009; Börgerholz, 2006; Martin & Czellar, 2017).

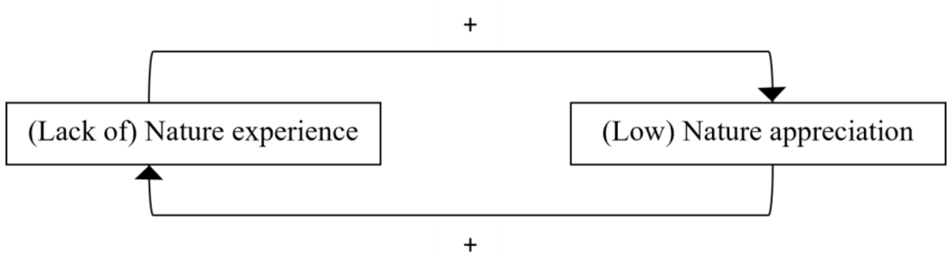
Nature experience (NE) describes situations in which an individual is engaged in contact (and interaction) with various types of natural environments, ranging from wilderness environments to managed green spaces (Gaston et al., 2020; Maller et al., 2006). Examples include spending time in forests or parks and gardening. Nature appreciation (NA) is referred to as a generic psychological phenomenon involving positive attitudes towards, emotional affiliation with, as well as connectedness to nature. Moreover, NA is positively associated with environmental concern (Brügger et al., 2011; Alcock et al., 2020; Kaiser et al., 2014; Perkins, 2010; Nisbet et al., 2009; Mackay & Schmitt, 2019).

NE and NA are conceptually closely related (Tuan, 1977). When delving deeper into their relationship, we find that they dynamically influence each other. The amount of individuals' NE impacts their level of NA. Likewise, individuals' NA affects their amount of NE. These two mutually reinforcing mechanisms may lead to two different outcomes. On the one hand, extinction of experience, coined by Pyle (1992), describes the progressive loss of humans' NE and NA. Specifically, the decline of NE (e.g., due to increasing urbanisation and spending leisure time indoors; Weinstein et al., 2015) relates to decreased individual's NA (Gaston et al., 2020; Miller, 2005). Subsequently, a low level of NA reduces individuals' tendencies to seek NEs, maintaining the vicious cycle. Put differently, human alienation from nature is equally cause and consequence of a vicious cycle of decreased experience and appreciation towards nature (Soga & Gaston, 2016; Bögerholz, 2006).

On the other hand, the dynamics of NE and NA may form a "virtuous cycle" (cf. Nyborg et al., 2016). Experiencing nature via mere exposure or interaction relates to increased NA (Hinds & Sparks, 2008; Weinstein et al., 2015; Bögerholz, 2006) and environmental concern (Clayton et al., 2018). A high level of NA in turn, promotes the likelihood to engage with nature in the future (Hinds & Sparks, 2008, Nisbet et al., 2009; Collégony et al., 2017), which closes the virtuous cycle.

**Figure 1**

*The association between NE and NA*




Still, the dynamics of NE and NA remain poorly documented and there have been some inconsistencies in the literature regarding these mechanisms over time (Gaston et al., 2020; Kaiser et al., 2014; Bögerholz, 2006). Empirical studies confirm that NE and NA are closely associated with each other (Collégony et al., 2017; Bögerholz, 1999; Kals et al., 1999). Yet, Clayton et al. (2018) found that NA in adults remains high, while NE and its enjoyment decreases compared to younger participants, suggesting that the mechanisms change across the lifespan. Scholars claim that childhood NE predicts NA in adulthood (Wells & Lekies, 2006;

Miller, 2005; Kals et al., 1999) and consider NE as the foundation for any environmental awareness and NA (Börgerholz; 2006). In a cross-sectional study however, Alcock et al. (2020) failed to establish causality and thus, assumed a bi-directional relationship of NE and NA. Even a time frame of two years seems not sufficient to study changes in NA (Kaiser et al., 2014), implying that a long-term perspective needs to be adapted to study how NE, NA and their dynamics develop over time.

Research on NE and NA has in common that it focusses on the intraindividual factors explaining NE and NA. In consequence, causes and consequences of extinction of experience are studied neglecting interindividual influences. If at all considered, interindividual influences only take a side role compared to intraindividual considerations (cf. Soga & Gaston, 2016). There are studies on the effect of NE on prosociality (e.g., Goldy & Piff, 2020), yet they do not comprehensively examine how socially embedded individuals experience and appreciate nature. NE and NA are inherently social as we share most green spaces with and often experience nature accompanied by others. NA, conceptualised as an attitude or emotional connection, is subject to various forms of social influence, such as persuasion (Wood, 2000; Prislin & Wood, 2005; Fischer et al., 2003). Extinction of experience and its consequences for a sustainability transition represents a societal challenge. Therefore, it needs to be addressed from the perspective of multiple interacting individuals.

The present study advances the current understanding of NE and NA dynamics in two ways: it investigates these dynamics 1) over time and 2) across interacting individuals. Applying a long-time perspective has several advantages: The relative stability of NA (cf. Kaiser et al., 2014) and small effect sizes can be accounted for while investigating dynamics that unfold in long timespans. To illustrate, a single walk in the park is unlikely to significantly increase a person’s level of NA. Still, differences in the amount that people appreciate nature may be explained by frequent and long-term exposure to nature. In addition, applying a longer time frame allows to draw causal inferences to some extent. Further, the social dimension is studied in the context of NE and NA dynamics. Little attention has been paid to the effect of social influence on the dynamics of NE and NA and the resulting vicious or virtuous cycle. The potentials and limits of social influence to solve large-scale problems remain unclear (Nyborg et al., 2016). To understand how social influence operates within NE and NA dynamics, it is important to integrate studies that analyse the effect of social influence on individuals and studies on aggregate-level variables such as the effect of social network structure and spatial environment (Mason et al., 2007).

Taking these two additions into account, the emergence of a vicious or virtuous cycle is investigated by examining the dynamics of NE and NA over time and across interacting individuals. Further, I explore critical tipping points of nature presence and social influence that shape the dynamics of NE and NA over time. A tipping point is where small changes trigger self-reinforcing mechanisms in a way that the dynamics generate either a vicious or a virtuous cycle (Lenton et al., 2022). Derived from this, I strive to answer the following research questions:

1. How do the dynamics of NE and NA unfold over time?
2. How does social influence affect the dynamics of NE and NA?
3. Do tipping points exist, where the dynamics of NE and NA generate either a vicious cycle of extinction of experience or a virtuous cycle?

## Green Spaces

NE takes place within various types of natural environments, ranging from wilderness environments to urban green spaces. In the present project, I focus on NE within urban green spaces as the share of people living in urban environments continuously increases and rising urbanisation is a major reason for extinction of experience (Soga & Gaston, 2016; Weinstein et al., 2015). In the following, green spaces are understood as urban environments where vegetation and other natural features are predominant compared to non-natural features. Following the criteria by Taylor and Hochuli (2017), the presence of green spaces is quantified by the percentage of green spaces across the full extent of the city. Thus, the percentage of green spaces describes the proportion of green to non-green spaces in urban environments.

Exposure to green spaces is associated with various health benefits (for a meta-analysis see Twohing-Bennett & Jones, 2018; Bratman et al., 2019; Maller et al., 2006) and residential satisfaction (Wang et al., 2019; Fornara et al., 2010). Moreover, the percentage of green spaces in individuals' surroundings predicts NE (Weinstein et al., 2015, Zhang et al., 2014), although the willingness to experience nature is more driven by individual preferences than by mere green space presence (Collégony et al., 2017; Alcock et al., 2020). Green spaces promote NE and therefore adds in a beneficial way to the dynamics of NE and NA. Yet, the entanglement of green spaces is more complex as it is also a dynamic factor. People with high NA are not only more likely to seek NE, but NA is also the most important motivator to further create opportunities for NE, such as gardening (Clayton, 2007). Not only the gardeners increase their opportunities for NE, surrounded people benefit from the created green space as well (Clayton, 2007; Kaplan & Kaplan, 1989). Hence, the mechanisms between green spaces, NE and NA are mutually reinforcing and green spaces may act as a catalysator for a virtuous cycle. On the other hand, the decline in NA may further promote the loss of opportunity, as people become unmotivated to invest in natural environments, strengthening the vicious cycle of extinction of experience (Soga & Gaston, 2016; Miller, 2005).

**Social Influence**

Individuals are strongly influenced by their social context regarding their experiences and attitudes (Cialdini & Goldstein, 2004; Wood, 2000; Prislin & Wood, 2005), which also accounts for NA and (seeking) NE (Gaston et al., 2020; Börgerholz, 1999a; Collégony et al., 2017; Soga & Gaston, 2016; Kals et al., 1999). Social influence adopts various forms including assimilative social influence, which is referred to as predominant and persistent process in social interactions (Flache, 2018, Flache et al., 2017). Assimilative social influence means that individuals often adjust their attitudes in the direction of the attitudes of others they interact with. This influence is assumed to be bi-directional, indicating that the assimilation process occurs for both interacting individuals (Mason et al., 2007; Flache, 2018; Flache et al., 2017). Social influence in real life settings often involves multiple, heterogeneous actors and is dynamic as it occurs over time (Manson, 2007). By reducing attitude differences between multiple repeatedly interacting individuals, assimilative social influence causes the emergence of a stable consensus. This even accounts for social networks with initially strong (and polarised) attitudes (Mäs et al., 2013; Flache, 2018).

People interact with and have lasting connections to specific others, which constitutes a social network (Smith & Conrey, 2007). Within a social network, assimilative social influence operates via network links making connected individuals more similar (Mason et al., 2007). People vary regarding their position in their respective social networks, as well as in the extent to which they can influence and are influenced by others (Lenton et al., 2022; Jager & Ernst, 2017). Applied to the present context, individuals can influence and be influenced by their network and that their level of NA is likely to converge to the level of connected individuals.

Assimilative social influence has implications beyond the individual level. When many heterogeneous individuals recurrently interact over time, assimilative processes translate into non intuitive complex systems on the societal level (Mason et al., 2007; Flache et al., 2017; Smith & Conrey, 2007). Short term consequences of these interactions may differ from outcomes in the long term (Mäs et al., 2013). For example, assimilative social influence might initially hinder NA changes, while it accelerates NA changes after a critical mass altered their level of NA. Social processes can shape the behaviour of individuals on larger scales, which is crucial for societal change (Nyborg et al., 2016; Jager & Mosler, 2007). This is especially important for the present context as climate-related problems are often rooted in our social behaviour (Jager, 2021). Together, individuals have the agency to trigger positive tipping points of a societal transition towards sustainability (Lenton et al., 2022).

**Agent-Based Approach**

To investigate the dynamics of NE and NA within individuals and how this translates via social interactions to outcomes on the societal level, I will utilise an agent-based approach. Though influences of environmental and social factors on NE and NA have been demonstrated, we need theoretical models that account for the dynamic interdependencies between those factors. Especially theoretical modelling is appropriate to approach the dynamic relationship of NE and NA in combination with social networks (Flache et al., 2017). Agent-based modelling is considered as (the most) suitable method to address this type of research topics (Mason et al., 2007; Jager & Mosler, 2007).

Agent-based modelling (ABM) describes a computational simulation technique that aims to distil key theoretical elements of psychological and social processes. This enables better understanding of the dynamics that consist of these psychological and social processes and can reveal unexpected consequences of theories (Smith & Conrey, 2007; Jager 2021; Mäs et al., 2013). This modelling technique is "agent-based" as theoretical assumptions on the individual level pose the starting point for growing models. Based on a set of simple, theory deduced rules for agents' perceptions and behavioural options, each agent starts to process and behave uniquely. Their perceptions and behavioural options are heuristic and adaptive. Further, agents operate in a physical and social environment, which affects them and where they can gather information from. (Macy & Flache, 2011; Jager & Mosler, 2007; Smith & Conrey, 2007).

Agents are influenced by and can also influence their physical and social environment. Agents are inherently social and embedded in social networks (Flache et al., 2017). When many individuals interact over time, their behaviours are interdependent, creating a complex, dynamic system that may have unpredictable and not directly accessible outcomes (Smith & Conrey, 2007; Jager & Mosler, 2007). In other words, local interactions based on simple rules give rise to emerging macro (i.e., societal) level outcomes (Macy & Flache, 2011; Jager 2000), that cannot simply be inferred from aggregating individual actions (Flache, 2018; Macy & Flache, 2011; Schelling, 1971). Macro-phenomena in turn, affect individuals' behaviour (Kangur et al., 2017; Mason et al., 2007). In the present context, complexity arises from many assimilative social interactions on the micro-level, which cause population NA to emerge, which in turn affect NA on the individual level.

All models are incomplete, as they do not fully depict social reality. Still, ABM can be utilised to study theories of social behaviour (Smith & Conrey, 2007; Wilensky & Rand, 2015), by manipulating realistic, yet controllable conditions and compressing long term dynamic interactions into short experimental simulations (Mäs et al., 2013; Jager 2000; Jager & Mosler; 2007; Mason et al., 2007). Therefore, I need to balance simplicity and completeness. Models should be simple as additional, not conceptually critical assumptions obscure fundamental elements of the theory. Moreover, additional assumptions complicate model verification (Jager, 2021, Smith & Conrey, 2007; Wilensky & Rand, 2015). The analysis of simple abstract models may reveal new theoretical insights with wide applicability, beyond the model that produced them (Macy & Flache, 2011). Simultaneously, simple models with a strong theoretical and empirical foundation may validly represent real-world settings (Jager & Mosler, 2007).

ABM can be used for various goals. It supports studying how assumptions for individuals unfold on a societal level as soon as agents start interacting through networks. Further, with ABM tipping points of social complex systems can be explored, where equal starting conditions may produce entirely different outcomes (Jager, 2021). By visualising complex dynamics, ABM can be instrumentalised as a tool to inform and increase understanding among researchers and other stakeholders. Apart from analysing dynamics, intervention strategies can be explored, which makes ABM practically applicable for decision-making in policy and planning. Hence, ABM supports the political relevance of environmental psychology research (Jager & Gotts, 2019; Hansen et al., 2019; Jager & Ernst, 2017). Still, ABM is a relatively uncommon approach in psychology (Smith & Conrey, 2007). Acknowledging the potential of this method to address complex social-environmental dynamics, ABM attracts increased attention in the social sciences and the environmental psychology domain (Jager, 2021; Hansen et al., 2019; Flache, 2018; Grimm et al., 2006).

## The Present Project

The main purpose of this project is to understand the emergence of a vicious or virtuous cycle by simulating the dynamics of NE and NA over time and across interacting individuals. Within the vicious cycle, also called extinction of experience, NE and NA decrease over time, which is opposed to the virtuous cycle, where NE and NA increase over time. Building on central research on social influence, I extend this dynamic relationship with the effect of assimilative social influence on (changes in) NA. The conceptual model integrates the complex interactions between environmental and social factors that account for the evolution of NE and NA over time. By this, I assume that none of the factors are entirely stable but that they continuously affect each other.

**Figure 2**

*Dynamics of NE, NA, green spaces and assimilative social influence generating a virtuous cycle*

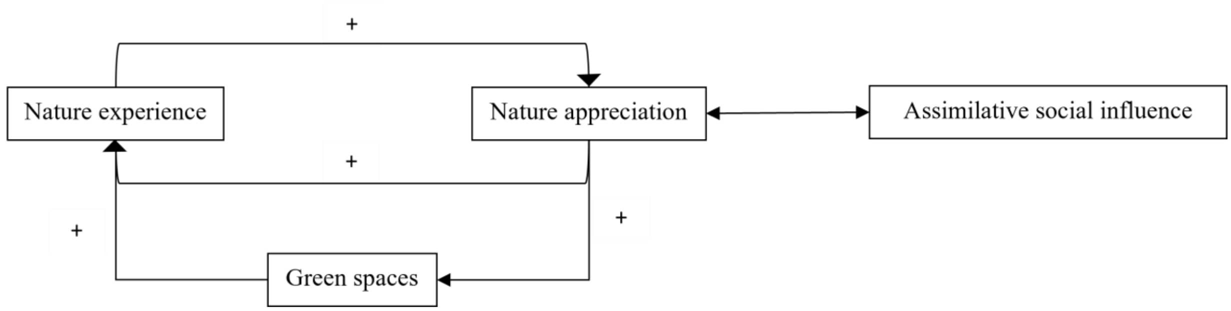



Figure 2 depicts the conceptual model for the case that the dynamics of NE and NA, interwoven with the effects of assimilative social influence and green spaces, generate a virtuous cycle. While it is comprehensible that the presence of green spaces positively relates to the NE and NA dynamics based on the theoretical background, the mechanisms of social influence remain unclear, which is why a research question is dedicated to this mechanism. For the dynamics that give rise to extinction of experience, lack of NE fosters low NA, which interacts with assimilative social influence and further decreases presence of green spaces. Few green spaces reinforce the lack of NE, maintaining the vicious cycle.

Supported by theory and empirical research, I outline the mechanisms of NE, NA, green spaces, and assimilative social influence that dynamically give rise to extinction of experience or a virtuous cycle. Based on these mechanisms, I derive assumptions that enables to implement the computational model. Specifically, a stochastic agent-based model is built simulating the dynamics of NE and NA within heterogeneous agents that are influenced by and influence their social and physical environment. The percentage of green spaces and the impact of assimilative social influence on the reinforcing mechanisms of NE and NA are evaluated through experimentation with the model. The model, procedure and experimentation are described according to the ODD protocol (Overview, design concepts and details; Grimm et al., 2006, 2010). Emerging patterns on the population level under different conditions are explored and analysed. Subsequently, I perform a sensitivity analysis to check the robustness of the findings. In the last part, I discuss findings, limitations, the model's validity, and implications, before drawing conclusions.

## Method

The present ABM is developed using NetLogo (Wilenski, 1999; version 6.2.1). The purpose of the model is to understand the evolution of extinction of experience or a virtuous cycle based on the dynamic relationship of NE and NA over time and across interacting individuals. Specifically, dynamics of NE and NA are assessed while increasing the number of green spaces in the spatial model and either including assimilative social influence or not. For an illustration of the model's interface in NetLogo see Appendix A.

### Overview, Design Concepts and Details

**State variables and scales.** The model is comprised of three hierarchical levels: individual, social network and spatial environment. Individuals are characterised by their personal amount of NA which lies on a continuous 6-point scale developed by Brügger et al. (2011) and is drawn from a normal distribution. Further, individuals are characterised by their number of connections to other individuals. To model that people vary in the extent to which they can influence and are influenced by others (cf. Lenton et al., 2022), the number of links randomly varies per person but lie between 0 to 15 connections. Furthermore, individuals have the behavioural options to seek NE and to once create or remove a green patch (i.e., shape the physical environment) depending on their level of NA. The social network is composed of connected individuals and is characterised by the number of group members. Network links are assumed to remain unchanged over time and have equal influence weights (cf. Flache et al., 2017). Assimilative social influence operates via network links and is bi-directional. The environment is characterised by its proportion of green spaces compared to non-green (i.e., grey) spaces. Green spaces represent opportunities for individuals to experience nature.

**Process overview and scheduling.** The model proceeds in discrete time steps. Within each time step, five phases are processed in the following order: move, experience, appreciate, shape environment, and social influence. Agents move through the environment, which can be either aimless or directed towards a green space. Upon ending the movement, agents may be exposed to a green patch and experience nature. Alternatively, they are exposed to a grey patch. Within the next phase, agents on a green patch and thus, experiencing nature may increase their NA. Then, agents have the option to shape the environment by removing or creating a green patch, each once per simulation run. In the final phase, a random agent will be selected that experiences social influence. Agents' decision cycle within the phases are depicted in Appendix B. Following classical implementations, all agents update their level of NA simultaneously in one discrete time step, based on the state of the model that resulted after updating at the previous time point (Flache et al., 2017).

**Design concepts.** Population dynamics emerge from the behaviour and interaction of individuals, that are represented by empirical rules. Agents adapt their level of NA according to their own NE and the NA of their social network. They are assumed to know their own level of NA and the NA of individuals in their social network, as well as the nearest green space.

Three types of interactions are modelled: the interaction of NE and NA, social interaction and agent-environment interaction. First, if agents are exposed to a green space (indicated by agents turning green for the duration of experience), their NA may increase; exposed to a grey space, their NA may decrease. Agents adapt their behaviour (tendency to seek nature experiences) according to their level of NA. The higher agents' NA the more likely they will seek nature experiences. Second, the average NA in agents' social network influences their own degree of NA. The currently influenced agent is indicated by turning blue. The more links an agent has, the more agents a) they influence and b) influence them. Third, agents can influence their physical environment by either creating or removing a green patch depending on their level of NA. If individuals have a high level of NA they may create a green patch, if their level of NA is low, they may remove a green patch.

To represent uncertainty in simulation runs, the model is equipped with stochastic variables. Specifically, to describe variables and their relationships, parameter values are formalised as probability distributions, which are based on empirical data. For example, Alcock et al. (2020) found that 10% of the variance in individuals' NA is accounted for by NE, which is considered for modelling the effect of NE on NA. This means that with the same set of initial parameters different results emerge.

**Initialisation.** To set up the model, agents are randomly placed on a grey coloured grid of the size 20 x 20. Green spaces are randomly located within the grid, which means that these specific patches are coloured green. A set of 100 agents are randomly placed within the spatial model and links with other random agents are created per agent, building a social network. With the default value 5, agents direct a random number of connections to other agents in a range from 0 to 5. The social ties are visible via grey links. The agents are equipped with an initial amount of NA that is sampled from a normal distribution with the mean 4.88 and standard deviation of 1.026 (cf. Welsch & Kühling, 2018). Further parameters and their default values can be derived from Table 1. The default values for *green_spaces*, *effect_ne* and *max_connections_per_agents* are based on related literature (HUGSI, 2021; Alcock et al., 2020; Antonucci et al., 2004). To consider that NA is relatively stable across time even though NE may decrease (Kaiser et al., 2014; Clayton et al., 2018) the parameter *decrease_na* is chosen to be smaller compared to *effect_ne*.

**Table 1**

*Simulation parameters*

| **Name** | **Symbol** | **Range** | **Default** | **Description** |
|---|---|---|---|---|
| green_spaces | *gs* | (0, 40) | 25 | Proportion of green vs. grey patches, expressed by percentages. |
| n_agents | *N* | $\mathbb{N}$ | 100 | Size of the population of agents that are placed in the environment. |
| max_connections_per_agent | $n_{ij}$ | (0, 15) | 5 | Maximum of connections an agent can direct towards other agents. |
| mean_na | *M* | (0, 6) | 4.88 | Initial mean nature-appreciation in the population of agents. |
| sd_na | *SD* | (0, 3) | 1.026 | Initial standard deviation of nature-appreciation in the population. |
| decrease_na | *b* | $\mathbb{Q}^+$ | 0.05 | The amount nature-appreciation decreases when not experiencing nature. |
| effect_ne | *a* | $\mathbb{Q}^+$ | 0.148 | The increase in an agent's nature-appreciation when experiencing nature. |
| max_n_ticks | $n_t$ | $\mathbb{N}$ | 100 000 | Number of ticks at which the model stops. Duration of the run. |

**Submodels.** The level of NA of agent *i* will be determined based on a function of the constant effect of NE multiplied by their personal NE at that time point ($a * ne_{i,t}$), the constant decrease of NA in case of exposure to a grey patch $b$, and assimilative social influence of their personal network $k$ at that time point $\Delta si_{ik,t}$.

$$na_{i,t} = f(a * ne_{i,t}, b, \Delta si_{ik,t}) \tag{1}$$

Agents' NE is based on the constant likelihood to seek NE multiplied by their prior level of NA ($c * na_{i,t-1}$) and the amount of green spaces at that time point $gs_t$.

$$ne_{i,t} = f(c * na_{i,t-1}, gs_t) \tag{2}$$

Assimilative social influence is modelled as an averaging-function based on prominent model-representatives (Macy & Flache, 2011; Flache, 2018). Agents' NA moves towards the average of their personal NA and the NA of connected agents $j$.

$$na_{i,t+1} = na_{i,t} + \Delta si_{ik,t} = na_{i,t} + \frac{1}{2(N-1)} \sum_{i \neq j} (na_{jk,t} - na_{ik,t}) \tag{3}$$

Assimilative social influence can either increase (4) or decrease (5) agents' level of NA.

$$na_{i,t+1} - (na_{i,t} + si_{ik,t}) > 0 \tag{4}$$

$$na_{i,t+1} - (na_{i,t} + si_{ik,t}) < 0 \tag{5}$$

**Simulation Experiments**

Simulation experiments are performed using NetLogo's BehaviourSpace feature, running for 100000-time steps to explore how the dynamics of NE and NA unfold over time. To investigate potential tipping points between extinction of experience versus a virtuous cycle, I systematically vary the *green_spaces* parameter from 5 to 30 in steps of 5, which manages the percentage of green spaces on the grid. I further explore the effect of either including assimilative social influence or not, leading to 6 x 2 conditions (an overview over all conditions is displayed in Table 2). All other parameters are kept constant at their default value.

**Table 2**

*Overview over the 12 conditions within the simulation experiments*

| Condition | Percentage of green spaces | Social influence included? |
|---|---|---|
| 1 | 5 | yes |
| 2 | 5 | no |
| 3 | 10 | yes |
| 4 | 10 | no |
| 5 | 15 | yes |
| 6 | 15 | no |
| 7 | 20 | yes |
| 8 | 20 | no |
| 9 | 25 | yes |
| 10 | 25 | no |
| 11 | 30 | yes |
| 12 | 30 | no |

The following output is monitored during the simulation runs: the distribution of NA, the percentage of green spaces, the percentage of agents experiencing nature, as well as the total number and distribution of social connections. The BehaviourSpace output is a .csv file containing the output within each condition. I run 10 independent simulations per condition, realising a total of 120 simulation runs. Data is analysed using a separate R script (RStudio version 2022.02.2+492).

The average NA on the population level (i.e., mean NA) is instrumentalised as a proxy for determining whether the conditions give rise to a vicious (i.e., extinction of experience) or a virtuous cycle. A low mean NA corresponds to extinction of experience, a high mean NA to a virtuous cycle. To explore the emergence of a vicious or virtuous cycle based on the dynamics of NE, NA, green spaces and assimilative social influence, I examine the development of mean NA across time and conditions. In addition, the mean NA at the end of the simulation runs is compared between conditions. To assess the overall effects of percentage of green spaces and assimilative social influence, analyses of variances are performed. Akin to Mittal et al. (2019), I use unpaired two-sample two-tailed *t*-test with Welch's correction of unequal variances to compare different conditions. By comparing the mean NA under different percentages of green spaces and whether assimilative social influence is included or not, both across and at the end of the simulation runs, I can identify potential tipping points and explore the role of assimilative social influence. To assess the findings' robustness, sensitivity analysis is performed, giving special attention to the parameters *decrease_na b* and *max_connections_per_agent* $n_{ij}$.

## Results

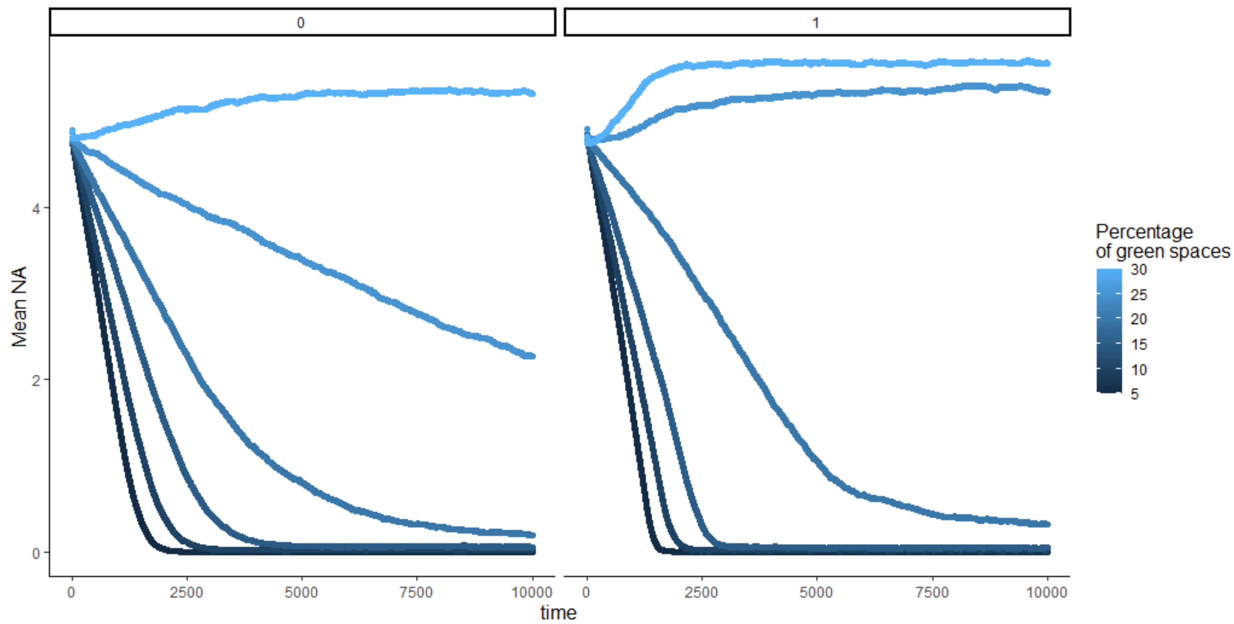
Figure 3 reports mean NA over time, averaged over ten simulation runs for either excluding or including social influence[1] per level of green space. Across all conditions and time steps, the mean NA is 2.15 ($SD$ = 2.26). The lowest mean NA is in condition 1 ($M_1$ = 0.37, $SD_1$= 1.03), which involves 5% green spaces and the highest mean NA is in condition 11 ($M_{11}$ = 5.58, $SD_{11}$= 0.2), which involves 30% green spaces. Both conditions include social influence. Within conditions that included social influence, agents have on average 3.96 connections ($SD$ = 0.08). Across conditions, the mean NA and NE are closely associated with each other, indicated by a high correlation coefficient ($r$ = .92, $p$ < .001). Likewise, there is a very strong, positive relationship between mean NA and percentage of green spaces ($r$ = .80, $p$ < .001). This is also illustrated in Figure 4, which shows the mean NA at the end of the simulation runs for either excluding or including social influence per level of green spaces. Overall, the mean NA increases with more green spaces being present and a F-test indicates that the percentage of green spaces is a main effect ($F$ (1, 43.32) = 21.95, $p$ < .001). Significant differences in the mean NA are found between all conditions (see Table 3); only the difference between 15% and 20% green spaces is not significant ($M_{15\%}$ = 0.06, $SD_{15\%}$= 0.01, $M_{20\%}$ = 0.26, $SD_{20\%}$= 0.47, *t (19.02)* = -1.95, p =

[1] In the following, social influence refers to assimilative social influence.

.066) according to unpaired two-sample two-tailed t-tests with Welch's correction of unequal variances.

**Figure 3**

*Mean NA over time per level of green space separated by either excluding (0) or including social influence (1)*




*Note.* Each line represents one of the 12 conditions.

Furthermore, Figure 3 illustrates that most conditions give rise to extinction of experience; three conditions enable a virtuous cycle. These trends are continuous, meaning that within these conditions, no qualitatively different patterns emerge. Put differently, I do not observe that the system tends towards extinction of experience but then suddenly gives rise to a virtuous cycle, or vice versa. All but one condition lead to a clear outcome at the end of the simulation runs, only the mean NA in condition 10 (i.e., 25% green spaces and social influence excluded) cannot be clearly categorised; yet, showing a trend towards extinction of experience.

**Table 3**

*Means and Standard Deviations of the average NA at the end of the simulations by condition*

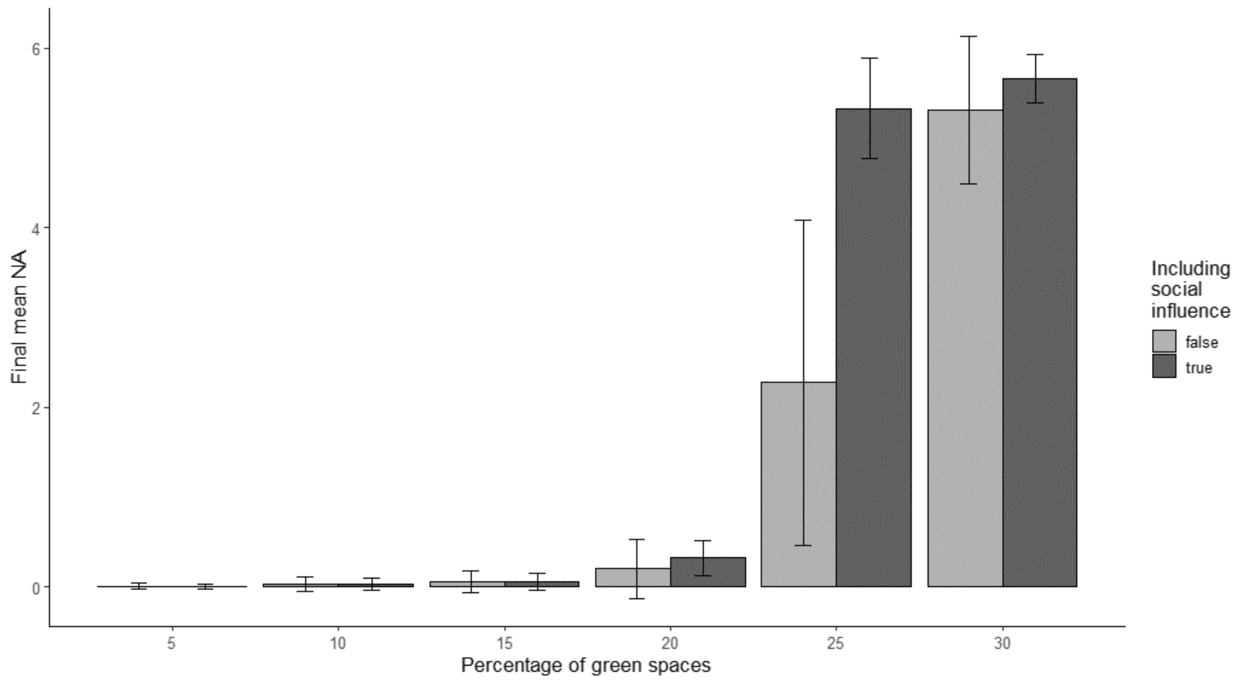
| Social influence included? | Percentage of green spaces | | | | | |
|---|---|---|---|---|---|---|
| | 5% | 10% | 15% | 20% | 25% | 30% |
| True | 0.01 (0.00) | 0.03 (0.01) | 0.05 (0.01) | 0.32 (0.65) | 5.33 (0.13) | 5.67 (0.03) |
| False | 0.01 (0.01) | 0.03 (0.01) | 0.06 (0.01) | 0.2 (0.2) | 2.27 (1.0) | 5.31 (0.21) |
| Both | $0.01_a$ (0.0) | $0.03_b$ (0.01) | $0.06_c$ (0.01) | $0.26_c$ (0.47) | $3.8_d$ (1.71) | $5.49_e$ (0.23) |

*Note.* Standard deviations are in parentheses. Means that do not share subscripts differ by $p < .05$ according to unpaired two-sample two-tailed *t*-test with Welch's correction of unequal variances.

The conditions differ in terms of speed by which the system stabilises. For the conditions generating extinction of experience, I observe that the lower the percentage of green spaces, the quicker the model stabilises at that outcome. For conditions generating a virtuous cycle, I observe a similar pattern although there is less data, demanding a more cautious conclusion. Within this stabilisation process, slopes are steeper when social influence is included, suggesting that social influence accelerates the dynamics and operates as a moderator variable in the model. This is supported by a F-test, reporting a significant interaction effect between the amount of green spaces and social influence ($F(1, 116) = 5.31$, $p = .023$). Figure 4 illustrates that for conditions characterised by 5- 15% green spaces, social influence did not yield significant differences for the mean NA at the end of the simulation runs. For conditions characterised by 20- 30% green spaces, the confidence intervals for the mean NA at the end of the simulation runs decreased when including social influence compared to excluding social influence. Yet, only in conditions with 25% ($M_9 = 5.33$, $SD_9 = 0.13$, $M_{10} = 2.27$ , $SD_{10} = 1$, $t(9.32) = 9.61$, $p < .001$) and 30% green spaces ($M_{11} = 5.67$, $SD_{11} = 0.03$, $M_{12} = 5.31$, $SD_{12} = 0.21$, $t(9.49) = 5.18$, $p < .001$) the mean NA differed significantly between including or excluding social influence. Notably, for conditions with 25% green spaces, social influence plays a crucial role for the final level of NA. Without social influence, the model tends towards extinction of experience, with social influence however, I observe a virtuous cycle. Thus, for 25% green spaces, social influence does not strengthen existing trends but is decisive in generating a vicious or virtuous cycle. Within the other conditions, social influence decreases the variation in NA and accelerates dynamics in both directions.

**Figure 4**

*Mean NA at the end of the simulation runs for either excluding or including social influence per level of green spaces*




*Note.* Error bars in the figure represent 95% confidence intervals.

### Tipping Points

In terms of tipping points, there seems to be a sensitive state of the system within 20-30% green spaces. For instance, the mean NA at the end of the simulation runs for condition 10 (i.e., 25% green spaces, social influence not included) range between 0.68, which corresponds to extinction of experience, and 5.40, corresponding to a virtuous cycle. This variation in outcome explains the high standard deviation for this condition that is depicted in Figure 4. To zoom into this sensitive system state, a second simulation experiment is run, this time varying the percentage of green spaces from 20% to 30% in steps of 1. Again, I run 10 independent simulations per condition.

**Figure 5**

*Boxplots of the mean NA at the end of the simulation runs per level of green spaces, not distinguishing whether social influence is included or not*

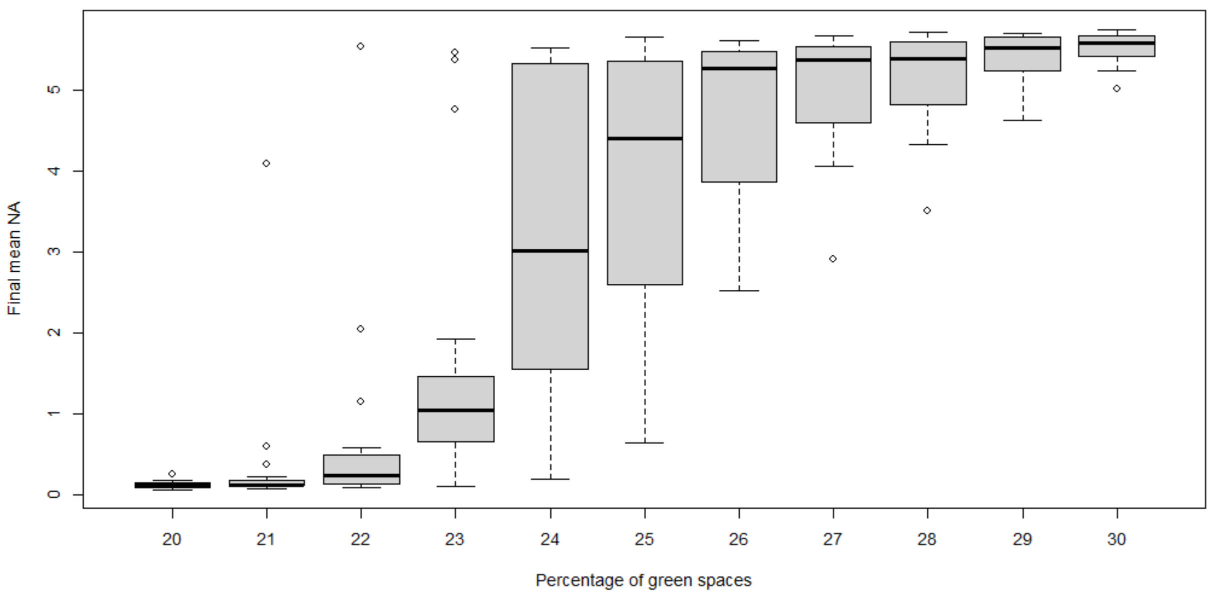
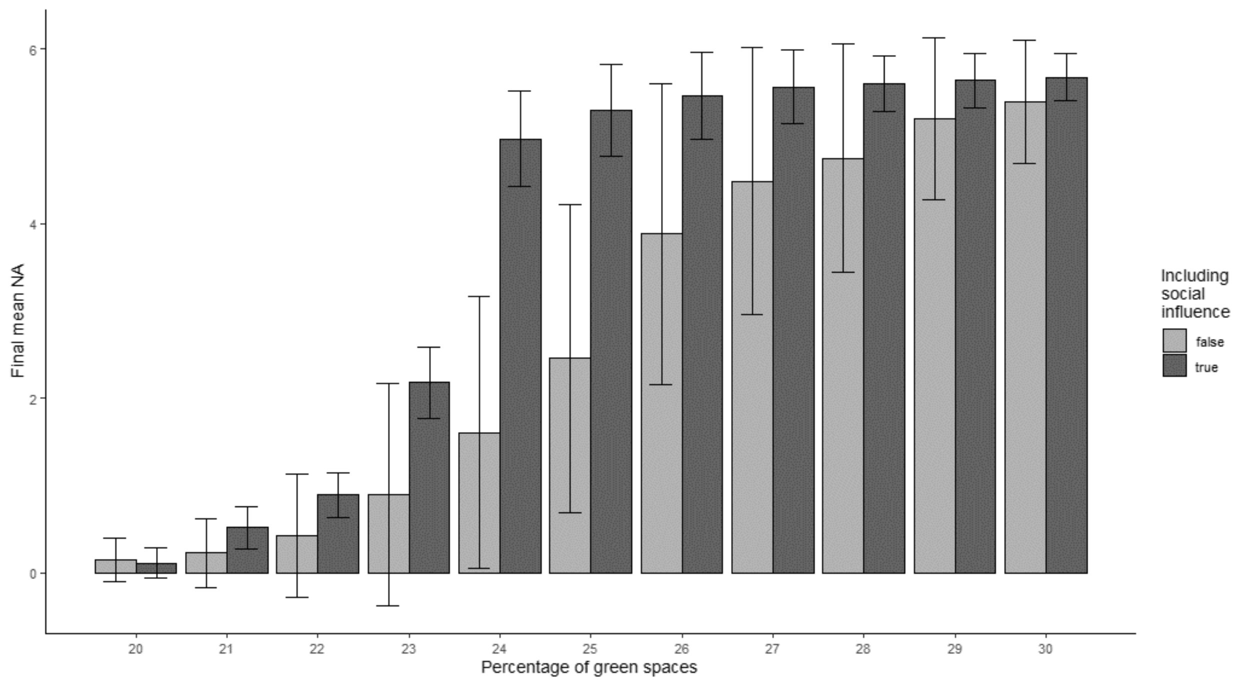



Figure 5 reports the mean NA at the end of the simulation runs per level of green space. The boxplots display a s-shaped transition (i.e., logistic growth rate, Kunzle et al., 2009) between extinction of experience and a virtuous cycle. Specifically, the increase in the mean NA grows slowly for 20-23% green spaces. With 20-21% green spaces, the model clearly generates extinction of experience and for 22-23% green spaces, the outcome would still classify as extinction of experience, although the variance already increases. Between 23-25% green spaces, the increase in mean NA reflects an exponential growth rate and a maximum in the variance between the simulation runs. This means that the same set of initial parameters generates a wide range of NA, which indicates a tipping point. The mean NA further increases for 26-30% green spaces, but the increase rate slows down (i.e., negative acceleration rate) and the outcome variance decreases.

**Figure 6**

*Mean NA at the end of the simulation runs for either excluding or including social influence per level of green spaces*




*Note.* Error bars in the figure represent 95% confidence intervals.

When distinguishing the patterns for either including or excluding social influence (see Figure 6), findings from above are mirrored here. Without social influence, the confidence intervals are larger and the increase in mean NA is more continuous, meaning that the growth rates between 23-25% is flatter. Including social influence, I observe that the transition from extinction of experience to a virtuous cycle is accelerated and a virtuous outcome emerges with a lower percentage of green spaces compared to conditions without social influence.

**Sensitivity Analysis**

**S**ensitivity analysis is performed to explore under which conditions the simulation findings are robust. By sweeping parameters I can inspect how sensitive the system reacts to these changes. First, I explore various NA decrease rates $b$, as there are no empirical references to set the default value and it is likely that this parameter shapes the dynamics of NE and NA. Second, I investigate the effect of differing the number of connections to other agents $n_{ij}$, which determines the size of their social network. As social influence operates via network links, the number of connections may impact tipping points within the system. For instance, more connections may accelerate the s-shaped transition but could also stabilise the mean NA in the population at the reference value.

Appendix C provides a comprehensive description of the sensitivity analysis. Robustness checks are performed with a total of 700 simulation runs. The simulation runs reveal that the model is highly sensitive to the specific NA decrease rate $b$ but robust to the size of the social network. Regarding the NA decrease rate, deviating 0.02 from the default parameter value $b$ = 0.05 neutralises the main effect of the percentage of green spaces and the social influence moderation effect. In a range of 0.04 < $b$ < 0.06, the main and moderation effect do shape the dynamics of NE and NA but are strongly influenced by the specific NA decrease rate. Hence, robustness checks indicate that the dynamics of NE and NA are highly sensitive to the specific decrease NA rate.

With respect to the second parameter, increasing the number of connections per agent yield similar outputs compared to the default value $n_{ij}$ = 5. When decreasing the number of connections, outcomes for the mean NA start to resemble the patterns when social influence is excluded. Still, the data supports the conclusion that the dynamics of NE and NA are robust to various number of connections to other agents.

**Discussion**

This study investigates the emergence of a vicious or virtuous cycle by simulating the dynamics of NE and NA over time and across interacting individuals. The percentage of green spaces and the impact of assimilative social influence on these dynamics is evaluated via experimentation with the model. Simulation results indicate that indeed, the reinforcing mechanism of NE and NA give rise to either a vicious or a virtuous cycle. The trends are continuous, meaning that once the system tends towards one outcome, the dynamics are reinforcing and do not allow the system to evolve towards the other outcome. The increase in NA across the conditions is primarily driven by the percentage of green spaces: The higher the percentage of green spaces the higher the mean NA. This relationship is moderated by social influence, which accelerates the dynamics in either way. Still, social influence has little effect within conditions that clearly lead to either a vicious or virtuous cycle. In contrast, when the system becomes unstable, social influence has a crucial role in determining the outcome. A tipping point is identified when green spaces covered between 23 to 25% of agents' physical environment. The system evolves in a s-shaped transition from extinction of experience to a virtuous cycle.

The model seems to be robust to the size of the social network, but highly sensitive to the decrease of NA rate. The sensitivity analysis reveals some further noteworthy trends. The robustness check on number of connections hints that social influence follows a logarithmic function. While the first couple of connections each have a large effect on an individual, adding more connections increases the social influence only marginally. Further, comparing the 25%

green spaces conditions for excluding social influence and for maximum 2 connections (see Figure 3 and A2) shows that the decrease in the mean NA is slower when social influence is included compared to excluded. This suggests that around a tipping point, assimilative social influence may stabilise the mean NA at the initial value. Thus, in addition to the accelerating function of social influence from the main analysis, the robustness check also displayed that around a tipping point social influence may have a deaccelerating effect.

Akin to Schelling's (1971) model of spatial segregation, the present model displays a conflict between the perceptions of individuals and outcomes on the population level. Although individuals begin with a high level of NA, which can easily be increased by NE and is comparatively stable across time, for most simulation runs, a negative feedback loop leads to extinction of experience. Further, the crucial role of assimilative social influence within the 25% green spaces conditions depicts that multiple individuals have the agency to jointly trigger positive tipping points. When the percentage of green spaces reaches a critical size, social influence triggers a cascade of NA changes that rapidly increases the mean NA on the population level and strengthens the reinforcing mechanisms of NE and NA. Although individuals and assimilative social influence are operationalised based on simple rules, the model generates complex effects on the macro social level, which stresses that societal outcomes cannot be inferred from aggregating individuals' actions without considering complex interactions (cf. Lenton et al., 2022; Flache, 2018).

The progressive loss of NE and NA poses a challenge for a societal transition towards sustainability. Increasing opportunities and motivation to be in contact with nature may counteract extinction of experience and promote a sustainability transition (cf. Miller, 2005; Collégony et al., 2017). The present findings support that green spaces overall have a positive effect on NE and NA. However, other scholars state that interventions based on increasing opportunities for NE are unlikely to achieve changes in NA (Kaiser et al., 2014; Nisbet et al., 2009). My results partly agree since not every increase in the percentage of green spaces yield significant differences in the mean NA. Hence, a certain amount of green spaces is needed to approach a tipping point where small changes can shift the system. Around a tipping point, 1% increase in green spaces may accomplish lasting changes in NA.

**Limitations and Model Validity**

Challenges to the quality of the present study mostly stem from the lack of appropriate data to calibrate and validate the model, which is common for empirically parameterised ABMs (Jager & Ernst, 2017). Researchers acknowledge the lack of empirical documentation of the extinction of experience phenomena (Gaston et al, 2020), which makes it especially difficult to build the model. More established theories in environmental psychology, such as protection motivation theory (Rogers, 1975, 1983), often provide a better empirical foundation but are sequential and depend on static predictors. However, considering the dynamic relationship of NE and NA is crucial as extinction of experience and the opposed virtuous cycle describe gradual processes. Dynamic relationships assume causal associations between factors. Yet, only correlational associations between NE and NA are profoundly confirmed, which does not account for causality conclusions. Further, robustness checks reveal that the dynamics are highly sensitive to the NA decrease rate, which is especially critical as the parameter value is an estimation due to missing data. Likewise, the mechanisms behind assimilative social influence are not quantitatively monitored, although it is already an established phenomenon (cf. Flache et al., 2017). This means that ABMs with assimilative social influence cannot be reliably calibrated or validated. Therefore, I have to acknowledge uncertainty regarding the validity of the model.

To face the lack of appropriate data, I base assumptions on existing models as it has been recommended by Flache et al. (2017). For example, scholars repeatedly state that continuous attitudes are more realistic models of mental representations (e.g., Mason et al., 2007), which is implemented in the ABM by using a ratio scale for NA instead of discrete categories (e.g., high vs. low NA). When modelling human social behaviour, Smith and Conrey (2007) pose that providing agents with enduring links to other agents, with whom they interact and form a social network is most realistic, which is also reflected in the present ABM. By this, I build on plausible parameters and display general principles. As Lenton et al. (2022) put it, although I may not have enough data to calibrate the model, it still illustrates how the system operates in an area around the tipping point. Likewise, I try to compensate for the lack of data by testing assumptions in term of their robustness. Still, I do not explore the entire parameter space of a model, and therefore it does not allow testing robustness of results for all possible values of a given parameter, an endeavour that requires increased computing power and advanced analytical approaches (cf. Mäs et al., 2013).

Furthermore, I recognise the artificial setting that does not capture the richness of NE and how this translates to NA and vice versa. Simultaneously, this simplicity is a strength as the model is not overly complicated that it would mask crucial underlying processes. To illustrate, by advancing the mechanisms of social influence, the analyses would become more complicated and focussed on individual patterns that may mask the general principle that social influence has a moderating effect on the population level. Still, the present model incorporates the most important principles for ABMs located in the sustainability discussion. It incorporates adaptive and heterogeneous agents, regarding their initial level of NA and social connections, as well as interactions between agents. The model attempts to mirror non-rationality by adding uncertainty to the functions that are based on explained variances in corresponding literature. For instance, the explained variance for the effect of NE on NA is $R^2$ = 0.1 (Alcock et al., 2020), which is translated to changing the level of NA for only 10% of NE. In addition, people are always exposed to mixed environments composed of various proportions between green and non-green features. Thus, although there may be a lack of empirical validation, face validation is provided.

**Implications**

On the theoretical dimension, the model generates new insights regarding the dynamics over time and across individuals. The development of mean NA across time shows that once the system tends towards one outcome, the reinforcing mechanisms support the dynamics, and it is unlikely that the system entirely shifts towards the other outcome. This implies that transformation of a vicious cycle into a virtuous one requires an external trigger. Simulation results suggest that externally increasing the percentage of green spaces in peoples' environment could represent a trigger. However, I only tested this factor between conditions. Follow up studies could explore the effect of changing the percentage of green spaces externally, which could represent the top-down instalment of urban parks, during the simulation run to investigate system changes within conditions. The effect of installing influential individuals, which could represent politicians publicly lobbying for or against NA, could also operate as a trigger that fosters system change.

When decreasing the number of connections, the outcomes for the mean NA start to resemble the patterns when social influence was excluded. This suggests that social influence cannot be conceptualised as being present or not, and that gradual perspective seems more appropriate. Moreover, sensitivity analysis showed that the first couple of connections each have a large effect on an individual, adding more connections increases the social influence only marginally. These patterns sketch that the effect of assimilative social influence is more complex than the basic mechanism suggests. As this was not the main focus of the study, specifically designed experiments are needed to support my conclusions. In this context, future research should include weighted connections that mirror variation in the strength of social influence. Furthermore, directing links should consider reciprocity, triangulation (i.e., people are more likely to befriend friends' friends), homophily and other empirically confirmed mechanisms. In this model, most agents are connected within an overarching network. Advancing the social influence mechanisms allows to study specific patterns on the population level, such as polarisation.

The model assumes a constant effect of NE on NA and vice versa, which does not capture inter- and intraindividual differences. Likewise, green spaces did not qualitatively differ and thus, all green spaces influence agents equally. As it is acknowledged that forests enable different experiences than grass fields (Bratman et al., 2019), green spaces with differing characteristics should be considered in more advanced models. Considering crowding in green spaces and its effect on NE and NA may also reveal interesting principles, especially for models representing urban environments. Most importantly, to advance within the present topic, empirical data on the NA decrease rate, also in comparison to NA increase rate when experiencing nature, is urgently needed.

On the methodological dimension, social-climate models are gaining increased attention in the sustainability transition debate (for an example see Moore et al., 2022). Although, this model falls short in addressing the entire picture, it aims to be a building block within an emerging research area. ABM is a bridge for interdisciplinary work that is needed in the context of climate change, and it forces us to conceptualise climate change on both the macro and micro level. Understanding extinction of experience as an outcome of individual agents and their interactions is a necessary step to understand how key mechanisms develop across time. The present results report patterns that may not be discovered with empirical studies outlining the fruitful synergy of empirical studies and theoretical modelling.

Regarding practical implications, the model is a tool to visualise and raise awareness about the dynamics of NE and NA and their consequences on the individual and societal level. Hence, the model can be instrumentalised to communicate findings and implications to researchers and other stakeholders. Eventually, this may contribute to designing and testing interventions to effectively promote NE and NA. The present study implies that it is worth investing in green spaces for the sake of promoting NA. I propose that interventions aiming to promote NA should not only focus on NE but adopt a systemic approach and consider the crucial role of assimilative social influence.

In a broader sense, these findings aim to communicate that human-environment interactions can be mutually beneficial and are worth investing in to create sustainable environments. Apart from the study's narrow focus on NE and NA, creating green spaces in people's living environment is beneficial on both climate change mitigation and adaptation dimensions. Regarding climate change mitigation, green spaces, especially rich natural environments, function as a carbon storage and moreover, foster NA and pro-environmental concern and behaviour on the individual level (Brügger et al., 2011; Mackay & Schmitt, 2019; Bögerholz, 2006). In terms of climate change adaptation, green spaces contribute to resilient cities as they can be designed as buffers for floodings or heat islands (Wild et al., 2020). On the individual level, green spaces have various physical and mental health benefits and promote psychological resilience (Twohing-Bennett & Jones, 2018; Samuelson et al., 2020; Grey, 2019; Ingulli & Lindbloom, 2013).

## Conclusion

This study contributes to the line of research that identifies the loss in humans' nature experience and appreciation as a fundamental hurdle to achieve a societal transition towards sustainability. The dynamics of nature experience and appreciation have the power to give rise to the vicious cycle of extinction of experience or to a virtuous cycle characterised by beneficial human-environment interactions. This study aspires to contribute to the understanding of these underlying processes, which is needed to ultimately foster a virtuous cycle that brings us closer to a sustainable future. Applying an agent-based approach deals with the complexities of the co-evolution of nature experience, appreciation, green spaces, and social influence. I believe that agent-based modelling will be key in facilitating and applying psychological research that addresses pressing environmental and societal challenges. Investigating sustainability related issues from a bottom-up and dynamic perspective is crucial for theory, society, and the future of our planet.

## Model Documentation

The full NetLogo code and model is stored on google drive and can be accessed under the following URL:

https://drive.google.com/drive/folders/1oXdJTkSfvSsBpySUbCI556szkcXuIaxK?usp=sharing

The data and R-script can be found in the same storage folder.

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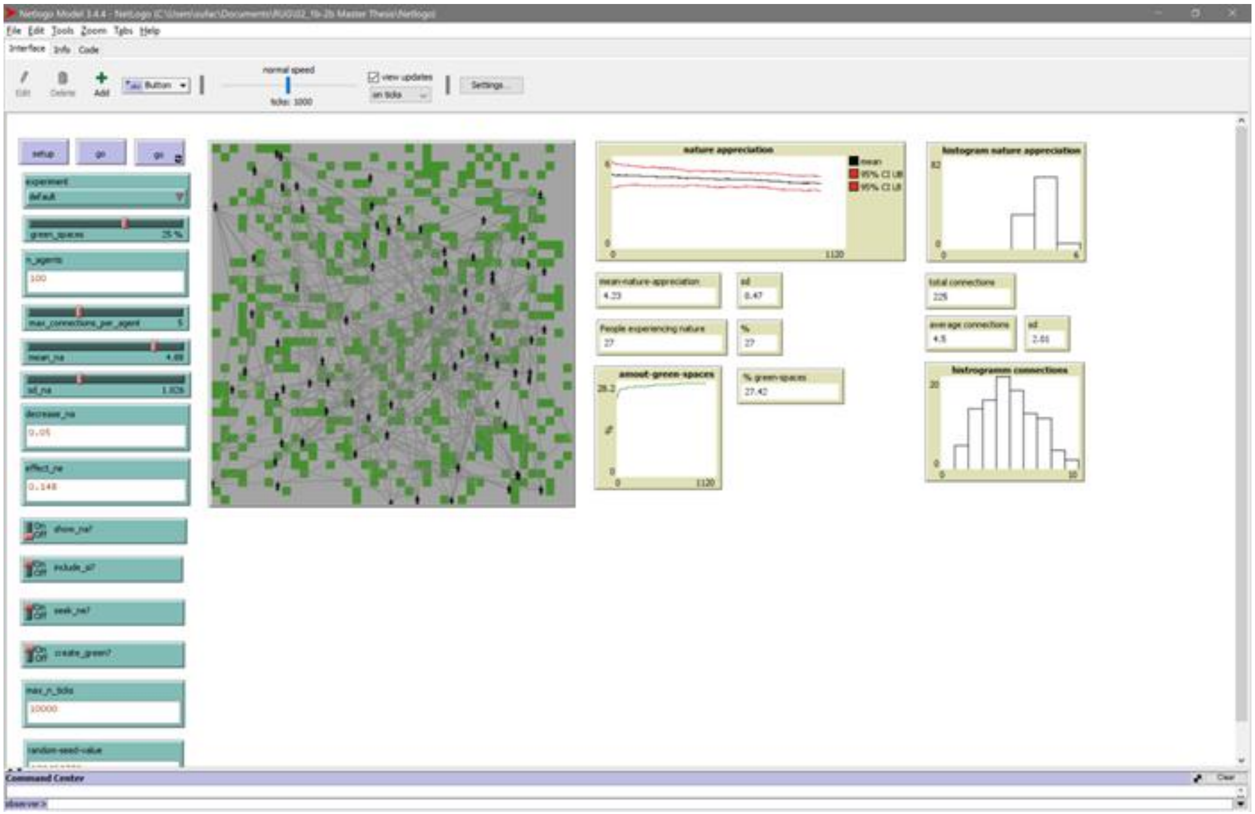
# Appendix A

## Figure A1

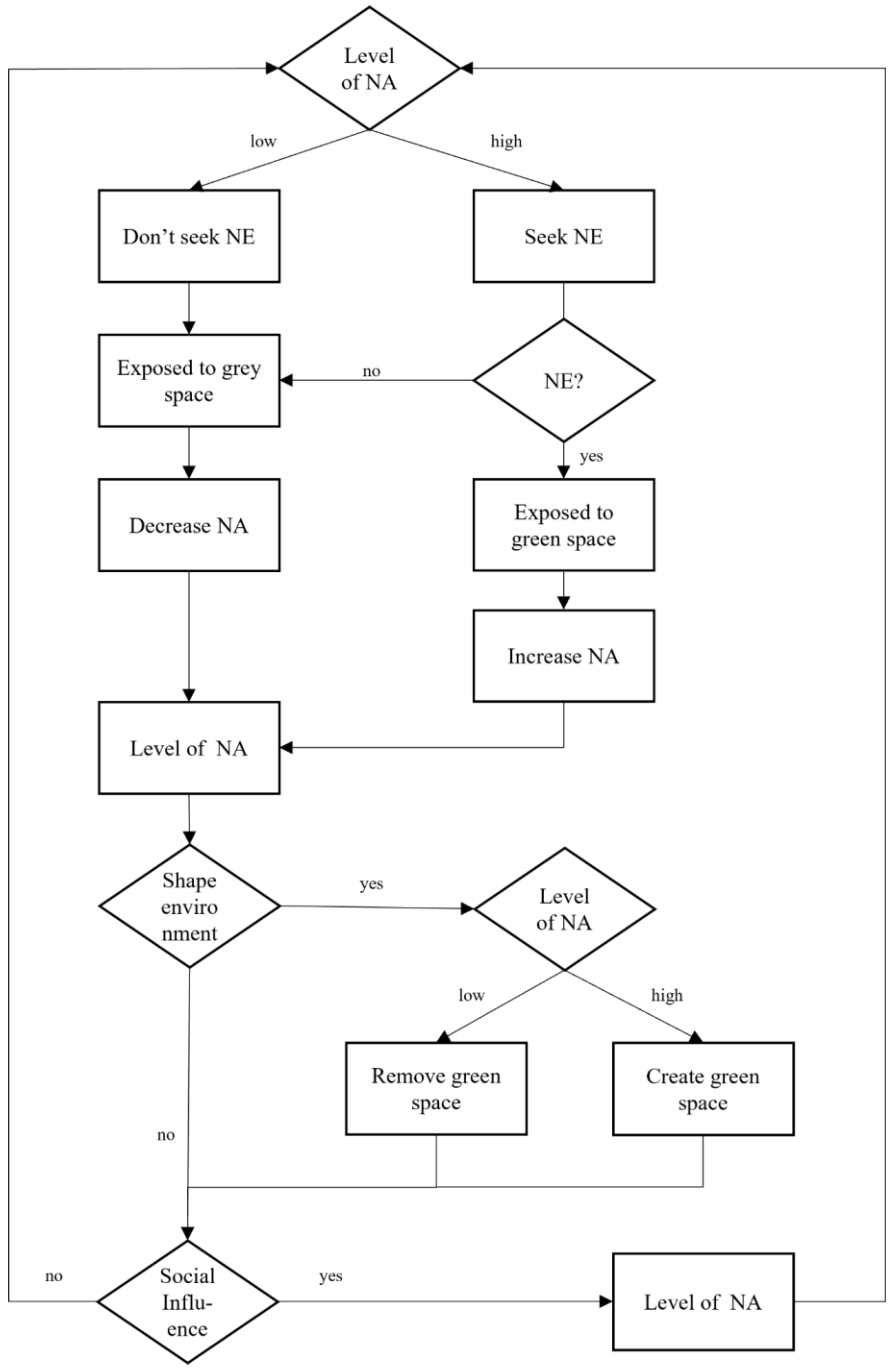
*NetLogo interface of the model, simulating the dynamics of NE and NA based on the default value*



## Appendix B

**Figure A2**

*Decision flowchart*




*Note.* Agents' decision cycles within the five phases: move, experience, appreciate, shape the environment, and social influence.

## Appendix C

## Sensitivity Analysis

In the following, sensitivity analysis is conducted to explore under which conditions the simulation findings are robust. I focus on various NA decrease rates $b$ = {0.03, 0.04, 0.05, 0.06, 0.07} and on a range of the number of connections to other agents $n_{ij}$ = {2, 5, 8, 11, 14}. Robustness checks are performed on the same simulation experiments that are used for the main analyses.

### NA Decrease Rate

For the NA decrease rate, there are no empirical references to set the default value. In the NetLogo model, this parameter corresponds to the *decrease_na* input. The default value 0.05 was an educated guess using the scale of the parameter effect of NE *a* and reflecting the relative stability of NA that was found in empirical studies. The NA decrease rate is likely to influence the dynamics of NE and NA. To assess the impact of high versus low NA decrease rates, I run the simulation experiments varying the NA decrease rate *b* from 0.03 to 0.07 in steps of 0.01. To reduce the number of simulations, I focus on the tipping point environment which lies between 15-30% green spaces. A set of 5 x 4 x 2 conditions - NA decrease rates, percentages of green spaces, including social influence, respectively - is realised, for which I run 10 independent simulations per condition. This leads to a total of 400 simulation runs.

Figure A1 reports the mean NA over time for either excluding or including social influence per level of green spaces separated by five different NA decrease rates. The graphs depict very different outcomes for sweeping the decrease rate between 0.03 and 0.07. The NA decrease rate *b* = 0.03 generates a virtuous cycle regardless of the percentage of green spaces and whether social influence is included. This outcome is detrimental opposed to the outcome for *b* =

0.07, which generates a vicious cycle regardless of the other experimental parameters. Thus, deviating 0.02 from the default value cancels the main and moderating effect from the main analyses out. For *b* = 0.04, the outcomes show similar patterns to the main analyses but the outcomes per level of green spaces corresponds to the next higher level of green spaces for the other parameter. To clarify, the outcome for *b* = 0.04 and 15% green spaces corresponds to the outcome for *b* = 0.05 and 20% green spaces. Hence, with a lower NA decrease rate, fewer green spaces are needed to yield the same results. When increasing the rate by 0.01, this comparison applies when social influence is excluded. In this case, the outcome for *b* = 0.06 and 30% green spaces corresponds to the outcome for *b* = 0.05 and 25% green spaces. In general, we observe that for *b* = 0.06, all conditions tend towards extinction of experience although for 30% green spaces, social influence deaccelerates this trend.

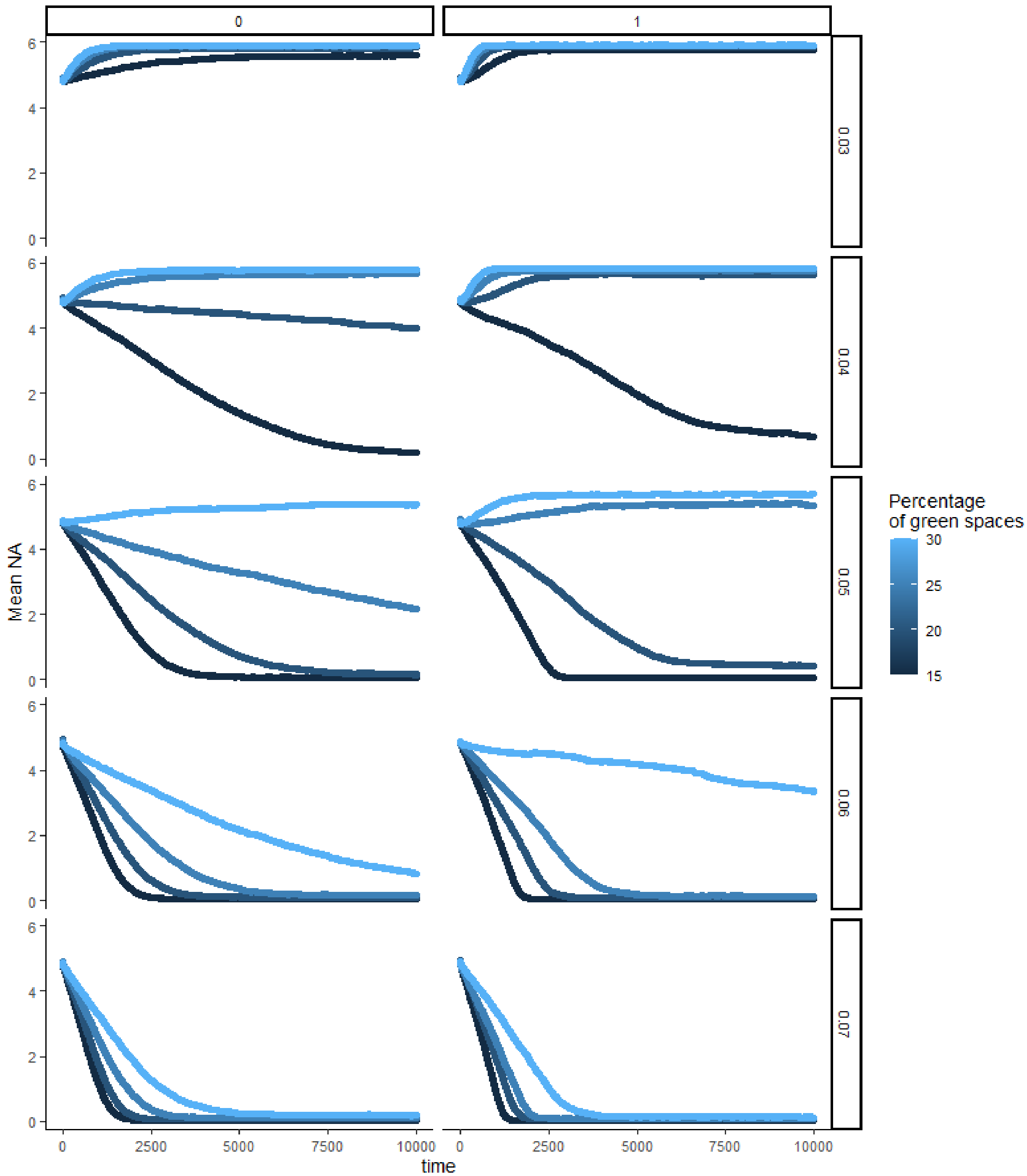
To conclude, this robustness check indicates that the main findings are strongly sensitive to the specific decrease NA rate. Deviating 0.02 from the default parameter value *b* = 0.05 neutralises the main effect of the percentage of green spaces and the social influence moderation effect. Deviating 0.01 from the default parameter preserves the overall pattern to some extent. Still, the outcome is far from being robust towards different NA decrease rates.

**Number of Connections**

Next, I check the robustness of findings from the main analyses varying the number of connections agents have with others. The parameter can be adjusted in the NetLogo model by using the slider *max_connections_per_agent* and the default value is 5, meaning that agents direct a random number of connections to other agents in a range from 0 to 5. The more connections agent *i* has with other agents *j*, the larger the social network *k* and the more agents they influence and influence them. Hence, the number of connections may impact tipping points

**Figure A1**

*Mean NA over time for either excluding (0) or including social influence (1) per level of green spaces separated by five different NA decrease rates*



within the system. For instance, more connections may accelerate the s-shaped transition but could also make the mean NA in the population more robust to changes due to NE. Sensitivity analysis is performed varying the maximum of connections from 2 to 14 in steps of 3. This results in 5 x 6 conditions, five levels for the maximum number of connections and six levels of green spaces. Note that this robustness check only applies for conditions from the main analyses that include assimilative social influence. Again, 10 independent simulations are performed per condition, resulting in 300 simulation runs.

The mean number of connections per agent for the range of the parameter $n_{ij}$ can be derived from Table A1. Considering robustness, Figure A2 explicates that increasing number of connections per agent does not systematically impact the outcome which we observe in the main analysis with the default value $n_{ij}$ = 5. Conditions that give rise to extinction of experience or to a virtuous cycle, have the same outcome with an increasing number of connections, respectively. The pattern across time does change for 15% green spaces as the mean NA decreases more slowly after timestep 5000 compared to the default value. For $n_{ij}$ = 14 and 15% green spaces, the mean NA decreases more slowly across the entire simulation run compared to $n_{ij}$ = 5.

Decreasing the number of connected agents yields a qualitatively different outcome for 25% green spaces compared to the other values for $n_{ij}$ by tending towards extinction of experience. Being connected to on average only one other agent corresponds to the results when social influence was excluded, although the decrease in the mean NA for 25% green spaces is slower. On a side note, it seems that the effect of number of connections resembles a logarithmic function. While the first couple of connections each have a large effect on an individual, adding more connections increases the social influence only marginally. In general, the sensitivity analysis supports the conclusion that the findings from the main analysis are robust under a range of $n_{ij}$. Hence, assuming various number of connections does not strongly impact the dynamics of NE and NA.

**Table A1**

*Mean and standard deviations of connections per agent for the range of the parameter $n_{ij}$*

| $n_{ij}$ | *M* | *SD* |
|---|---|---|
| 2 | 0.99 | 0.03 |
| 5 | 3.94 | 0.11 |
| 8 | 6.91 | 0.14 |
| 11 | 9.7 | 0.18 |
| 14 | 12.6 | 0.15 |

**Figure A2**

*Mean NA over time for including social influence per level of green spaces separated by five different number of connections per agent*