Ecological Economics 204 (2023) 107651

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Methodological and Ideological Options

A framework for agent-based models of human needs and ecological limits

Joël Foramitti *

Institute of Environmental Science and Technology, Universitat Autònoma de Barcelona, Spain
Institute for Environmental Studies, Vrije Universiteit Amsterdam, The Netherlands

ARTICLE INFO

Keywords:
agent-based modeling
social simulation
quality of life
human needs
bio-physical constraints

ABSTRACT

The social and ecological challenges of our time require a better understanding of the complex interactions between the multiple dimensions of human well-being and environmental impacts. This article introduces the Needs and Limits (N&L) framework, a theoretical and computational foundation for agent-based simulations of heterogeneous individuals who try to increase their quality of life through the satisfaction of human needs. Based on psychological research, human needs are described as satiable, adaptive, and interdependent with the social and bio-physical environment. The N&L framework represents a generic foundation that can be applied to a broad range of socio-economic and ecological scenarios. A comparison is provided with classical utility approaches. The framework is illustrated for the topics of income inequality and climate policy.

1. Introduction

Confronted with an increasing number of social and environmental emergencies, humanity faces the challenge of enabling a high quality of life for all people while staying within ecological limits (O'Neill et al., 2018). A system that would achieve such a balance between a social foundation on the one hand and an ecological ceiling on the other has been termed a 'safe and just operating space for humanity' (Raworth, 2012; Steffen et al., 2015). Moving into this space requires a more effective use of our energy, time, and resources towards the aim of increasing human well-being (Brand-Correa and Steinberger, 2017; Roberts et al., 2020; Rao and Wilson, 2021; Hickel et al., 2021).

Research on this topic is difficult due to the many interdependent dimensions that have to be taken into account. First, human well-being depends on the satisfaction of multiple human needs (Maslow, 1943; Max-Neef, 1991; Jackson et al., 2004; Royo, 2007; Gough, 2015; Sirgy, 2021). Second, each of these needs can be satisfied in different ways, with some being more resource-intensive than others. And third, there are numerous bio-physical limitations to consider, including both resource constraints and planetary boundaries like climate change and biodiversity loss (Steffen et al., 2015).

Social simulations are a useful tool to increase understanding within this complexity while taking into account that there is fundamental uncertainty about future outcomes (Arthur, 2021). Computational models can provide a structured way to think about real-world dynamics, show us the logical implications of our assumptions, help us to understand patterns of past events, and explore possible outcomes of future scenarios (Kucharski, 2021). Agent-based models (ABMs), in particular, are able to represent the world as a complex adaptive system (Arthur, 2021). They allow for the simulation of societal dynamics from the bottom-up, based on the interaction of autonomous agents with limited information and heterogeneous characteristics (Farmer and Foley, 2009). These features have lead to an increasing application of ABMs to economic and environmental policy analysis (Dawid and Delli Gatti, 2018; Castro et al., 2020). However, challenges remain to enhance the realism of such models through the integration of psychological theory — especially in regards to the representation of human needs (Jager, 2017).

The aim of this paper is to introduce a theoretical and computational foundation for ABMs aimed at addressing multiple dimensions of human well-being and environmental impacts: the Needs & Limits (N&L) framework. It describes the activities and choices of human individuals who try to improve their quality of life through the satisfaction of their needs while being subject to multiple bio-physical constraints. The presented approach is flexible enough so that different theories of human needs can be applied and provides a consistent way to describe how these needs translate into human behavior within a particular social, institutional, and bio-physical environment.

The N&L framework is designed to address research questions that focus on the understanding of mechanisms. It can be used to explore ways in which social and economic changes can achieve a reduction of ecological impacts that is consistent with high levels of well-being (Creutzig et al., 2021) — and how those changes could come about in a complex social setting. It further allows for policy analysis

* Correspondence to: Institute of Environmental Science and Technology, Universitat Autònoma de Barcelona, 08193 Bellaterra, Spain.
E-mail address: joel.foramitti@uab.cat.

https://doi.org/10.1016/j.ecolecon.2022.107651
Received 24 November 2021; Received in revised form 26 August 2022; Accepted 14 October 2022
Available online 4 November 2022

Table 1
Different categorizations of separate life domains that can be applied within the N&L framework.

Theory	Source	Categories
Basic needs — Theory of human motivation	Maslow (1943)	Physiological; safety; love; esteem; self actualization
Basic needs — Human scale development	Max-Neef (1991)	Subsistence; protection; affection; understanding; participation, idleness; creation; identity; freedom
Domains of life satisfaction	Cummins (1996)	Material well-being; health; productivity; intimacy; safety; community; emotional well-being
Basic human functional capabilities	Nussbaum (2011) (see also Sen, 1999)	Life; bodily health; bodily integrity; senses, imagination, and thought; emotion; practical reason; affiliation; other species; play; control over one's environment
Basic needs — Theory of human need	Gough (2015)	Physical health; autonomy of agency (mental health, cognitive understanding, opportunities to participate); critical autonomy
Decent living standards	Kikstra et al. (2021)	Nutrition; Shelter; Health; Socialization; Mobility

that takes a large number of dimensions into account, identifying potential synergies and drawbacks that are overlooked in simpler models. In line with current research agendas, this supports a focus on the intersection between environmental outcomes, equity, and well-being (Roberts et al., 2020; Rao and Wilson, 2021).

The remainder of the paper is organized as follows. Section 2 lays out the psychological foundation of this study. Section 3 presents an overview of needs-based simulation models in the literature. Section 4 provides a detailed description of the framework. Section 5 illustrates the framework for the topics of income inequality and climate policy. Section 6 discusses limitations and future applications.

2. The quality of life

The quality of life (QOL) is used to describe the overall assessment of human experience (Costanza et al., 2007). There are numerous philosophical and psychological approaches to this concept, and its relation to human needs remains contested (Jackson et al., 2004). A comprehensive overview can be found in Sirgy (2021). The two most influential schools of thoughts are described in the following.

The Benthamite tradition is based on the concept of hedonic utility. From this perspective, a high QOL describes a life that is pleasant — a state of contentment that contains a high amount of pleasure and a low amount of pain. This school of thought has originated the principle of 'choosing the action that leads to the greatest happiness of the greatest number' (Sirgy, 2021, p. 7) and is closely aligned to the concept of welfare that is prevalent in mainstream economic literature (Fellner and Goehmann, 2017).

The Aristotlean tradition of 'eudaimonia', in contrast, focuses less on outcomes and more on the process of living well (Ryan et al., 2008). From this perspective, a high QOL relates to a life that is engaging, meaningful, and fulfilling. It describes a state where an individual has the capabilities to reach 'their highest potential within the context of their society' (Brand-Correa and Steinberger, 2017, p. 44). Related concepts are human flourishing, psychological well-being, and perfectionist happiness (Sirgy, 2021).

Similar to Seligman (2004) and Sirgy (2021), we here refer to the QOL as subjective well-being in its broadest sense, relating not only to that which makes life pleasant (hedonic utility), but also to what makes it engaging and meaningful (eudaimonia). The aim of this work is to understand long-term patterns of well-being in regard to different social, economic, and ecological dynamics. The focus here is therefore not on momentary sensations, but on people's overall QOL over longer periods of time.

In the following, we describe eight key characteristics of human behavior and well-being (numbered C1–C8) that will serve as a psychological foundation for the N&L framework.

C1. **Motive.** The improvement of one's own QOL is a universal motive that governs most of human behavior (Sirgy, 2021). In other words, most choices and activities of an individual can be explained by the aim to enhance their own well-being. Adopting an eudaimonic understanding, this includes the fulfillment of values and goals and thus also relates to the well-being of others (Ryan et al., 2008).

C2. **Behavioral biases.** Human behavior is subject to numerous behavioral biases that can diverge from this motive. A central reason for this is that people face fundamental uncertainty about both themselves and their environment. This means that it is not possible to know how to best enhance one's QOL. Most of our activities thus follow heuristics: routines, habits, and simple rules of thumb. However, this should not be seen as naive or irrational as the use of heuristics can lead to better results than more complicated ways of decision-making while using less cognitive resources (Gigerenzer and Brighton, 2009). Another reason is that the improvement of one's QOL governs most but not all of human behavior — which means that there are also factors of behavior that are unrelated to this central motive. Factors of behavior such as desires and wants are thus connected to but not the same as the factors of our well-being.

C3. **Human needs.** The QOL depends on the satisfaction of multiple human needs (Maslow, 1943; Max-Neef, 1991; Royo, 2007; Gough, 2015). These needs can be understood as 'universal motivations [that] underlie human behavior' (Jackson et al., 2004). A related view is that well-being requires fulfillment among different life domains (Rojas, 2006). To combine these two perspectives, we here adopt the simplified framing that the fulfillment of a life domain depends on the satisfaction of human needs within that domain. In other words, life domains are seen as categories of human needs.
The categorization of these domains can range from a small set of generic spheres of life to the almost infinite number of different aspects that affect the human experience (Rojas, 2006). The framework presented here is meant to be generic enough that different theories can be applied. An overview of different categorizations in the literature that are compatible with this approach is given in Table 1.

C4. **Need satisfiers.** There are different ways in which human needs can be satisfied. While needs themselves are universal, the set of possible need satisfiers and their effectiveness depends on an individual's personal characteristics as well as their cultural and institutional environment (Jackson et al., 2004). This means that people are heterogeneous regarding their needs in the sense that what they require to satisfy them is different for each individual. Most forms of satisfaction involve some sort of activity that requires resources and has an environmental impact. In other words, 'resources per se do not contribute directly to wellbeing. It is how people use resources that may enhance wellbeing' (Sirgy, 2021, p. 124). Note that these resources must not necessarily be physical materials, but could also regard the use of time, energy, or mental capacity. Finally, the fulfillment of personal values and goals can also contribute to the satisfaction of needs (Sirgy, 2021).

C5. **Need satiability.** Human needs are satiable from a temporary perspective (Jackson et al., 2004; Royo, 2007; Galak et al., 2014). This means that within a specific period of time, there is an amount of need satisfaction that is sufficient to fulfill a domain. Above this point, additional satisfaction will bring little additional fulfillment since that domain is already saturated. For example, additional income will lead to little additional well-being after a certain satiation point (Jebb et al., 2018).

C6. **Need deprivation.** If needs are not sufficiently satisfied within a specific period of time, they will become deprived. Such deprived needs have a stronger effect on QOL than satiated needs. This means that the deprivation of a need increases the relative importance of its life domain on the overall QOL. Basic needs can then be defined as needs whose deprivation results in a low QOL independent of other factors. In other words, one cannot have a high QOL if only a single basic need is not met. Once such basic needs are met, their relative importance will be reduced and 'higher-order needs (e.g., self-development and social relationships) gain prominence' (Sirgy, 2021, p. 267).

This relates to the idea of a hierarchy of needs (Maslow, 1943). However, the distinction between basic and higher-order needs is not clear (Jackson et al., 2004). The deprivation of higher-order needs can also lead to a low QOL, and higher-order needs can still play an important role even when basic needs are deprived. Therefore, we assume no fixed order between different needs as their relative priority will depend not just on their general importance but also on their current level of deprivation.

C7. **Interdependence.** Our needs are interdependent with our social and ecological environment. Some needs can be satisfied through pro-social behavior (Helliwell, 2014), some through being connected to nature (Pritchard et al., 2020), and some through social comparison (Sirgy, 2021). Identity-related characteristics like values and goals are formed through social interaction as well (Schachter, 2005). Note that this can also be undesirable in the sense that social interaction can lead to the formation of values and goals that are in conflict with other needs or harmful towards the well-being of others.[1]

C8. **Adaptation.** Both factors of behavior and factors of well-being can change over time. Based on the view that needs are universal (C3), the factors that can adapt are the set of available need satisfiers and their effectiveness as well as our behavioral biases. This can cause needs to be insatiable from a long-term perspective (Royo, 2007). Increases in income, for example, do not only fulfill basic needs but also lead to an increase in material desires (Jebb et al., 2018). This upwards adaptation is often called the 'hedonic treadmill', describing how the satisfaction gained from an activity can drop once people get used to it (Redden, 2015).[2]

It is an important difference whether this adaptation regards desire (factors of behavior, C2) or actual needs (factors of well-being, C3). In the first case, our behavior changes in a way that is less beneficial to our well-being. In the second case, we ourselves have changed in a way that makes it more difficult for us to live a good life. Finally, it is also often the case that the social and ecological environment in which we live has changed in a way that changes our capabilities for need satisfaction. The study of human behavior and well-being thus requires not only understanding about the satisfaction of human needs, but also about the psychological and social dynamics that determine what is both needed and wanted in the first place.

3. Needs-based models

Human needs have so far received little treatment in simulations of socio-economic dynamics. One reason for this is that the equilibrium models of mainstream economic literature require rigid assumptions of representative behavior, exogenous preferences, perfect rationality, and insatiable wants (Royo, 2007; Arthur, 2021). This makes it difficult to take a large number of dimensions into account. Nonetheless, there have been attempts to integrate a perspective of needs into classical economic approaches (Seeley, 1992; Woersdorfer, 2010; Lades, 2013; Baucells and Zhao, 2021).

A stronger emphasis on human needs and their satiability can be found in the literature of ecological and post-keynesian economics (Jackson et al., 2004; Costanza et al., 2007; Lavoie, 2014). However, not much work has been done to translate the theoretical debates and empirical insights around human needs into formalized simulation models. Agent-based modeling, which has long put an emphasis on a richer representation of psychological theory in social simulations, represents a promising method to fill this gap (Jager, 2017).

The best-known example of a needs-based ABM can be found in the popular computer game series 'The Sims', which represent the behavior and well-being of humans by describing them as needs-based artificial intelligences (Zubek, 2010). Inspired by Maslow (1943), each need is modeled as a reservoir that can be depleted and refilled through various actions. Bogdanovych and Trescak (2016) describe a similar model for virtual reality reconstructions of historical sites.

A research application of this approach can be found in the model of human activity patterns from Brandon et al. (2020). The agents' needs in this model are rest, hunger, income, and travel. The satiation of each need drops over time. During the simulation, agents continuously choose the activity that best satisfies the most urgent need. The aim of this model is to understand short-term patterns, i.e. the length and timing of different activities during a day.

Kangur et al. (2017), in contrast, regard need satisfaction from a long-term perspective. Their model simulates decisions of car use and purchase. Here, agents make use of different cognitive processes to seek information, which include optimization, repetition, imitation, and inquiry. They further regard four different types of needs: financial, functional, social, and environmental. To reach consumption decisions, each of these needs are evaluated through custom functions that describe car-related satisfaction.

A more comprehensive setting is considered in the urban development planning model of González-Méndez et al. (2021). Here, agents aim to satisfy the basic human needs described by Max-Neef (1991, see Table 1). Based on perceived information from their environment, agents choose a decision rule that they think will best satisfy their needs, and then make their decisions according to this rule. In contrast to the other models, this framework also includes a spatial dimension.

The work presented here extends this literature with a more general framework that is not limited to a specific application with a predefined set of needs or decisions. Drawing from the psychological insights of the previous section, it aims to provide a more generic foundation of how human needs translate into both human behavior and well-being. In addition, it connects the fields of social simulation and ecological economics by combining this multi-dimensional perspective on the quality of life with a detailed treatment of bio-physical constraints.

[1] In self-determination theory, such undesirable goals are often linked to extrinsic motivations like wealth or fame that rely on external indicators of worth (Fellner and Goehmann, 2017).

[2] The hedonic treadmill is sometimes also referred to as satiation. In contrast to the satiaton of needs discussed in C5, this describes the reduction of the effectiveness of a need satisfier.

4. Model description

The N&L framework describes a generic agent-based model, which can be fitted to different applied scenarios. Section 4.1 introduces the model's possible dimensions. Section 4.2 defines the model's variables. Section 4.3 presents the chain of events during each time-step of a simulation. Section 4.4 describes the computational implementation of this model.

4.1. Dimensions

The model is built upon the following dimensions:

- Human individuals $i \in I = \{1, \dots, n^I\}$ are the agents of the model. Their goal is to adapt their behavior in order to satisfy their needs and thus improve their overall quality of life.
- Activities $a \in A = \{1, \dots, n^A\}$ represent the various actions that agents can take. Examples are the use or acquisition of resources, trade, recreation, or social interaction.
- Choice sets $c \in C = \{1, \dots, n^C\}$ describe discrete decisions that agents can take from a set of available options $o \in O_c = \{1, \dots, n^O_c\}$. Examples are choices of employment, commitments, or investments.
- Life domains $d \in D = \{1, \dots, n^D\}$ describe distinct aspects of life that correspond to a specific category of human needs. Examples are given in Table 1 of Section 2, C3.
- Resources $r \in R = \{1, \dots, n^R\}$ represent any input or output of an activity that can be available to a single agent. They do not necessarily have to be physical. Examples are money, time, energy, goods, or materials.
- Environmental dimensions $e \in E = \{1, \dots, n^E\}$ describe factors of the social and ecological environment that can be impacted by human activities. Examples are emissions, biodiversity, or inequality.
- Time-steps $t \in T = \{1, \dots, n^T\}$ describes the discrete steps of the simulation. Based on the model's application, it can represent different units of time. Note that within each time-step, time can also be a resource.

4.2. Variables

The state of the model $\boldsymbol{X}_t$ denotes the vector of values for all variables in the model at a given time-step t. An agent's perceived state of a variable is denoted by a tilde ($\tilde{x}$). The perceived state $\tilde{\boldsymbol{X}}_{i,t}$ thus describes what an agent believes the current variables of the model to be. Variables that are not defined in the following subsections are free to be specified in custom ways for different applied scenarios.

4.2.1. Activities and choices

The activity intensity $\alpha_{i,a,t} \in \mathbb{R}_{\geq 0}$ describes the amount of which each activity a is performed by an individual i at time t. Choices differ from activities in the sense that they can only be chosen from a discrete choice set c. The option $\phi_{i,c,t} \in O_c$ denotes an agent's currently active choice.

As illustrated in Fig. 1, both activities and choices can have three different kinds of impacts (Section 2, C4). Activity impacts are denoted by $\delta \in \mathbb{R}$, and choice impacts by $\zeta \in \mathbb{R}$. The possible impacts are as follows:

1. An impact $\delta^R_{i,a,r,t}$ or $\zeta^R_{i,c,r,t}(o)$ on resource inventories.
2. An impact $\delta^E_{i,a,e,t}$ or $\zeta^E_{i,c,e,t}(o)$ on environmental factors.
3. An impact $\delta^S_{i,a,d,t}$ or $\zeta^S_{i,c,d,t}(o)$ on the satisfaction of needs.

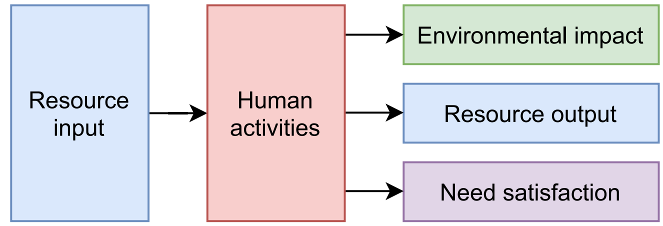

Fig. 1. Conceptualization of human activities and their impacts.

4.2.2. Resources

The resource inventory $\rho_{i,r,t} \in \mathbb{R}_{\geq 0}$ describes the stock of a given resource r in possession of an individual i. It depends on a default flow $\hat{\rho}_{i,r,t}$ as well as the impact of each activity and choice.

$$\rho_{i,r,t} = \hat{\rho}_{i,r,t} + \sum_{a \in A} \alpha_{i,a,t}\, \delta^R_{a,r} + \sum_{c \in C} \zeta^R_{i,c,r,t}(\phi_{i,c,t}) \tag{1}$$

If a particular resource r' can be kept from one time-step to the next (i.e. it is non-perishable), the default flow can be defined as $\hat{\rho}_{i,r',t} = \rho_{i,r',t-1}$. The first type of bio-physical limitations within this framework is represented by the fact that resource inventories must always be positive.

4.2.3. Environmental impacts

The environmental impact $\varepsilon_{e,t} \in \mathbb{R}$ describes the human influence on a given environmental dimension e. It depends on a default flow $\hat{\varepsilon}_{e,t}$ as well as the impact of all activities and choices.

$$\varepsilon_{e,t} = \hat{\varepsilon}_{e,t} + \sum_{i \in I} \left[\sum_{a \in A} \alpha_{i,a,t}\, \delta^E_{a,e} + \sum_{c \in C} \zeta^E_{i,c,e,t}(\phi_{i,c,t}) \right] \tag{2}$$

The difference between resources and environmental factors is that the former are a stock that is accounted for on the individual level while the latter can be any kind of systemic variable. Different kinds of environmental factors can be defined as functions of $\varepsilon_{e,t}$ to capture interdependencies between the agents' activities and the environment. Such feedback loops are the second type of bio-physical limitations that can be represented in this framework.

4.2.4. Satisfaction of needs

The satisfaction of needs $s_{i,d,t} \in \mathbb{R}_{\geq 0}$ within a given life domain d refers to an intermediate state that describes the total impact of satisfiers. It depends on its default satisfaction $\hat{s}_{i,d,t}$ and the impacts of different activities and choices.

$$s_{i,d,t} = \hat{s}_{i,d,t} + \sum_{a \in A} \alpha_{i,a,t}\, \delta^S_{i,a,d,t} + \sum_{c \in C} \zeta^S_{i,c,d,t}(\phi_{i,c,t}) \tag{3}$$

The fulfillment of a life domain $q_{i,d,t} \in [0,1]$ describes the resulting psychological state that arises from need satisfaction in a domain d. It is defined as a function of the current satisfaction $s_{i,d,t}$ and the satiation rate $k_{i,d,t} \in \mathbb{R}_{>0}$.

$$q_{i,d,t} = 1 - e^{-\,k_{i,d,t}\, s_{i,d,t}} \tag{4}$$

This equation represents the satiability of needs (Section 2, C5). The resulting fulfillment curves for different satiation rates $k_{i,d,t}$ are shown in Fig. 2. Note that this function transforms the unbounded space of satisfaction ($[0,\infty]$) into the bounded space of fulfillment ($[0,1]$).[3]

[3] If applied to a scenario with potentially negative impacts, the satisfaction $s_{i,d,t}$ must be capped at a minimum value of zero. Since this can create a lack of gradient for the algorithm in Section 4.3.2, such scenarios may require $q_{i,d,t}$ to be defined differently. One possible alternative would be to use a logistic function.

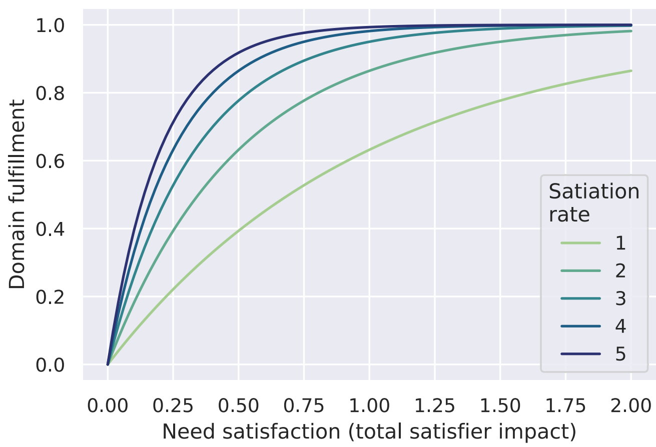

Fig. 2. Domain fulfillment function for different satiation rates.

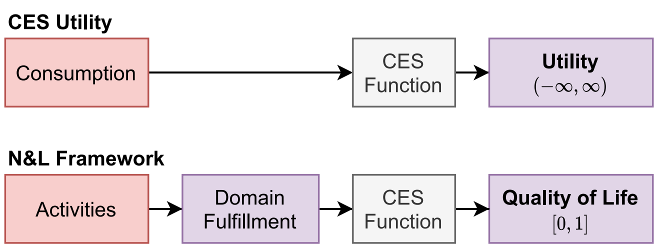

Fig. 3. Difference between CES utility and the N&L framework.

4.2.5. Quality of life

The quality of life $Q_{i,t} \in [0,1]$ is described as a bounded variable, representing a range from the worst possible life ($Q_{i,t} = 0$) to the best possible life ($Q_{i,t} = 1$). Following Rojas (2006), the relationship between the separate life domains and QOL is described by a constant elasticity of substitution (CES) function.

$$Q_{i,t} = \sum_{d \in D} \left(\bar{\omega}_{i,d,t} \, q_{i,d,t}{}^{\sigma_{i,t}} \right)^{\frac{1}{\sigma_{i,t}}} \tag{5}$$

The factor $\sigma_{i,t} \in \mathbb{R}_{>0}$ denotes the degree of substitution between domains. Note that an unfulfilled domain will gain greater relative importance if $\sigma_{i,t}$ is low, representing the effects of need deprivation described in Section 2, C6. The factors $\omega_{i,d,t} \in \mathbb{R}_{>0}$ denote the relative importance of each life domain. To stay within the bounds of $Q_{i,t}$, they are transformed into weights:

$$\bar{\omega}_{i,d,t} = \frac{\omega_{i,d,t}}{\sum_{d' \in D} \omega_{i,d',t}} \tag{6}$$

As illustrated in Fig. 3, this application of the CES function is different from its use for classical CES utility functions (Appendix A.4). Traditional models assume that utility is directly gained or lost from different kinds of consumption, resulting in potentially infinite values. Here, the CES function is applied to the fulfillment of life domains. This results in a bounded scale and allows for qualitative interpretation.

4.2.6. Networks

Finally, agents can be connected to each other through one or multiple networks. A network describes a graph in which the nodes are usually the agents themselves and the edges are connections between agents (Hagberg et al., 2021). However, there could also be networks between resources or environmental dimensions. The definition of such networks is not specified further here as it can vary greatly depending on the application.

4.3. Simulation procedure

The order of events per time-step t is given as follows:

1. Adaptation phase (perceived states)
   (a) Individuals update their (biased) perception.
   (b) Custom adaptive variables are updated.
2. Decision phase (desired states)
   (a) Individuals make discrete choices (if available).
   (b) Individuals decide on their desired activities.
3. Action phase (actual states)
   (a) Individuals perform their activities.
   (b) Activities cause impacts.

4.3.1. Adaptation phase (perceived states)

In this first phase of the simulation, agents update their perception of the world. This is described by the perceived state of the world $\tilde{\boldsymbol{X}}_{i,t}$, which describes what state the agent expects different variables of the model to be in. The way in which these perceptions are formed is not defined here so that it can be specified in custom ways for different scenarios.[4] Usually, they are a function of past states of the world:

$$\tilde{\boldsymbol{X}}_{i,t} = f(\boldsymbol{X}_{t-1}, \boldsymbol{X}_{t-2}, \ldots) \tag{7}$$

Any custom adaptive variables of a particular scenario are also meant to be evaluated in this phase. This can be used to represent the interdependence and adaptivity of psychological factors (Section 2, C7 & C8).

4.3.2. Decision phase (desired states)

The agents' factors of behavior are represented through the objective function $\tilde{Q}_{i,t}$. This adjusted form of the QOL is calculated like $Q_{i,t}$ (see Eq. (5)), but with the agent's perceived values (denoted by a tilde) being used for each variable. This means that agents aim to increase their QOL (Section 2, C1), but can diverge from this objective due to behavioral biases (Section 2, C2).

Agents are able to think about this objective in relation to any hypothetical context $\boldsymbol{X}'$. Their cognitive challenge represents a problem of non-linear multivariate constrained optimization.[5] The independent variable of this problem is the potential activity pattern $\boldsymbol{\alpha}'$, which describes a vector over all potential activity intensities. Constraints are given by the facts that activity intensities and expected resource inventories $\tilde{\rho}_{r,t}$ must be positive.

$$\begin{array}{lll} \text{maximize} & \tilde{Q}_{i,t}(\boldsymbol{X}', \boldsymbol{\alpha}') & \\ \text{subject to} & \alpha'_a \geq 0 & for\ a \in A \\ & \tilde{\rho}_{r,t}(\boldsymbol{\alpha}') \geq 0 & for\ r \in R \end{array} \tag{8}$$

In the computational model, this cognitive process is implemented through sequential least square programming (SciPy Community, 2021).[6] This algorithm works as follows. An agent starts from the last rounds' activity pattern $\alpha_{i,a,t-1}$. They then take discrete steps through the multi-dimensional space of activity combinations that are feasible within the given constraints, trying to follow

[4] See Dosi et al. (2020) for examples of different heuristic expectation rules.

[5] Optimization here refers to an individual's process of trying to improve an expected outcome, which is different from the traditional economic notion of optimality that would imply the result to be a perfectly known optimum for both the agent and the system.

[6] This algorithm has been chosen for its robustness and the possibility to represent generic behavioral biases which makes it suitable for many different applications. Performance can be enhanced by creating a custom algorithm for a particular scenario.

the gradient of the objective function. The algorithm stops when a maximum number of steps or a satisfactory threshold is reached.[7]

Different settings can be applied to this algorithm to represent additional behavioral biases. First, a threshold value can be set where the algorithm will stop looking for improvements. This reflects that there is a level of well-being above which the agent will be satisfied and not look for further improvements. This is also called satisficing. Second, the maximum number of steps within each use this algorithm can be used to represent the limited cognitive resources of agents.

Agents can apply this cognitive process to choose an option o from a discrete choice set c. For each option, they calculate the desired activities $\boldsymbol{\alpha}'(o)$ for each hypothetical expected context $\boldsymbol{X}'(o)$ where the option o is taken. Agents choose the option $\phi_{i,c,t}$ that leads to the highest value of $\tilde{Q}_{i,t}(\boldsymbol{X}', \boldsymbol{\alpha}')$. The related $\boldsymbol{X}'(\phi_{i,c,t})$ then becomes the new perceived context $\tilde{\boldsymbol{X}}_{i,t}$.[8]

After these discrete choices, agents apply the same process to decide on their desired activity pattern $\alpha^*_{i,a,t}$ for the current round. To do this, they evaluate $\boldsymbol{\alpha}'$ for the current perceived context $\tilde{\boldsymbol{X}}_{i,t}$.

4.3.3. Action phase (actual states)

Agents want to follow their desired activity pattern $\alpha^*_{i,a,t}$. However, since agents do not necessarily know the exact impacts of their activities (Section 2, C2), this desired pattern can turn out to be infeasible. They can therefore be forced to make changes. However, agents still aim to stay as close as possible to their desired pattern.

In the computational model, this process is implemented through linear constrained optimization with the simplex algorithm (SciPy Community, 2021). The independent variables are the actually enacted activity intensities $\alpha_{i,a,t}$. The algorithm is configured to solve the following problem to keep the difference between desired and actual activity intensities minimal while staying within feasibility constraints.

$$\begin{array}{lll} \text{minimize} & \sum_{a\in A} \frac{|\alpha^*_{i,a,t} - \alpha_{i,a,t}|}{\alpha^*_{i,a,t}} & \\ \text{subject to} & \alpha_{i,a,t} \geq 0 & for\ a \in A \\ & \rho_{r,t}(\alpha_{i,a,t}) \geq 0 & for\ r \in R \end{array} \tag{9}$$

4.4. Software

The computational implementation of the N&L framework is written in Python 3. The software is build with the AgentPy package for agent-based modeling in Python (Foramitti, 2021), and makes use of multiple algorithms from the SciPy optimization module (SciPy Community, 2021) and NetworkX (Hagberg et al., 2021). The source code and documentation of this software is publicly available under an open-source license. The repository can be found under https://github.com/JoelForamitti/NeedsAndLimitsFramework.

5. Application examples

This section demonstrates the range of applications that are possible within the N&L framework. Section 5.1 introduces a simple demonstration scenario, which refers to a particular configuration of the framework with a specific set of dimensions and variables. Sections 5.2–5.5 present various numerical experiments based on this scenario. An interactive notebook able to replicate all of the presented results can be found in the software repository.

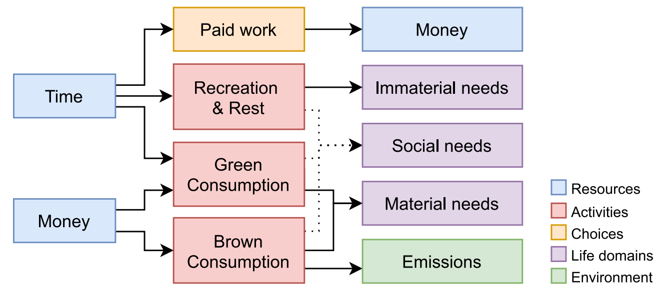

Fig. 4. Scenario configuration.

5.1. Scenario description

An overview of the demonstration scenario is given in Fig. 4. This scenario is meant to explore general mechanisms in an abstract setting, and does not represent a particular place or time. Following Klein and van den Bergh (2021), we focus on the interplay between the two resource dimensions of money and time. Each agent receives one unit of time per time-step (i.e. a default flow), while money has to be earned through paid work. The amount of work is a discrete choice and has two options: part-time and full-time.

Agents can further perform three different kinds of activities:

1. *Recreation & rest* uses time and satisfies immaterial needs.
2. *Green consumption* uses money and time, and satisfies material needs.
3. *Brown consumption* is similar to green consumption, but requires no time and instead causes emissions. The amount of money required for this activity can be increased through the carbon tax level τ.

The impacts of both activities and choices are described in Table 2 and Appendix A.1. This configuration is meant to roughly reflect two real-world aspects. First, that the use of time for leisure has a strong positive effect on QOL (Sirgy, 2021). And second, that sustainable activities often require more time than their polluting substitutes, as for example in regard to different modes of transportation.

The scenario includes an additional life domain that describes the social need to follow perceived norms (Helliwell, 2014; Konc et al., 2021). This assumes that people gain satisfaction from activities that appear to be popular. The more an activity is performed by their friends, the more it contributes to satisfaction in the life domain of social norms. The impact functions of this dynamic are also given in Appendix A.1.

The scenario is populated with 100 individuals.[9] As described in Appendix A.2, the agents are connected to each other through a small-world network of friendships. Their income rates follow the world's income distribution in the year 2016 (Helliwell et al., 2017).[10] Note that this only describes the default setting of the scenario. In some of the following experiments, income rates can be subject to growth and redistribution.

Finally, the agents' needs are assumed to be heterogeneous. The satiation rates $k_{i,d}$ of each agent and life domain are drawn from a normal distribution. As described in Appendix A.3, the mean and standard deviation of these distributions are calibrated so that the QOL

[7] In complex situations, this algorithm might get stuck in local or temporary maxima and thus lead to imperfect decisions. Note that this can also happen under heuristic decision-making (Section 2, C2).

[8] The structure of this decision-making process is similar to the Actor-Critic method of reinforcement learning (Lowe et al., 2020). The calculation of a desired activity pattern could be seen as the actor, and the estimation of well-being under this pattern as the critic.

[9] While this is a small number of agents, it is able to capture the mechanisms of interest and display the heterogeneity between the agents without requiring too many computational resources.

[10] This does not mean that these agents represent the global population. The intention is only to display the same degree of inequality as in the real world and to demonstrate how data can be used to parameterize a model within this framework.

Table 2
Dimensions and impacts of the demonstrated scenario. Non-constant values are defined in Appendix A.1.

Impact on	Type	Index	Activities			Choices
			Brown consumption a=1	Green consumption a=2	Recreation & rest a=3	Paid work c=1
Money	Resource	r=1	$-1-\tau$	-1	0	$\zeta^R_{i,c,o,r,t}$
Time	Resource	r=2	0	-1	-1	$\zeta^R_{i,c,o,r,t}$
Material needs	Life domain	d=1	1	1	0	0
Immaterial needs	Life domain	d=2	0	0	1	0
Social needs	Life domain	d=3	$\delta^S_{i,d,a,t}$	$\delta^S_{i,d,a,t}$	$\delta^S_{i,d,a,t}$	0
Emissions	Environmental	e=1	1	0	0	0

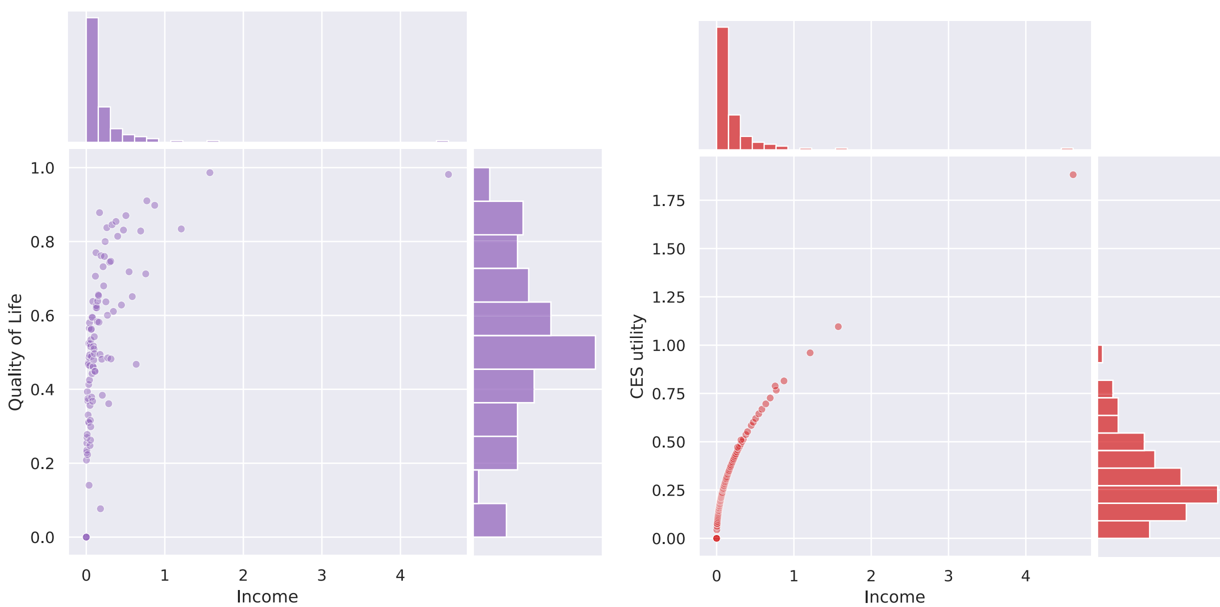

Fig. 5. Distributions of income and well-being within a single run.

outcome of the model follows a distribution that is similar to real-world values of life-satisfaction.

Note that some of the indices from Section 4 are omitted if a variable is constant over a specific dimension. For example, the index t is not used for the satiation rates $k_{i,d}$ here since they are assumed to be constant over time in this particular scenario.

5.2. Single run

In this first numerical experiment, we perform a single simulation run under the default setting. The left half of Fig. 5 presents the main results. There is a general trend that higher income leads to higher QOL with a diminishing rate of return. However, significant variations exist due to the fact that people's needs are heterogeneous. In line with the data that the model was calibrated to, the majority of people experience a QOL in the middle of the spectrum (Helliwell et al., 2017).

These results match two empirical observations. First, that a certain amount of income is necessary for a high QOL, but not sufficient (Kesebir and Diener, 2008). And second, that 'once people have high incomes [...], additional increases in wealth have a very small influence on [QOL] suggesting that added income beyond modest affluence no longer helps answer important desires and needs' (Diener and Biswas-Diener, 2002, p. 145).

For comparison, the right half of Fig. 5 shows how the same distribution looks like under a classical CES utility function which assumes that utility requires both money and time. The definition of this function is given in Appendix A.4. Since there are no heterogeneous needs and social interdependence in this case, there is a stronger correlation to income as under the QOL. In addition, utility can endlessly be increased through additional income.

Note that the agents' characteristics in this single simulation run are randomly drawn from a given probability distribution (Appendix A.3). All of the following experiments will be based on multiple runs, with results being given as averages and standard deviations over 20 such random configurations.

5.3. Growth and redistribution

We now explore the effects of changes in the economic system within this demonstration scenario. We consider two kinds of changes:

1. A proportional growth of income for all agents.
2. A redistribution of income between agents.

Fig. 6 presents the effects of these two interventions on well-being. In addition to QOL, comparative results are also presented for the measures of income and CES utility (Appendix A.4) — which are often used as a proxy for well-being. The first row presents the average well-being among agents. The second row presents the Gini coefficient in regard to well-being, with a low coefficient describing high equality of well-being between agents.

Income growth leads to an increase of average QOL. At the same time, the inequality of QOL is reduced as the well-being of low-income agents is increased to a larger extent than for high-income agents. The

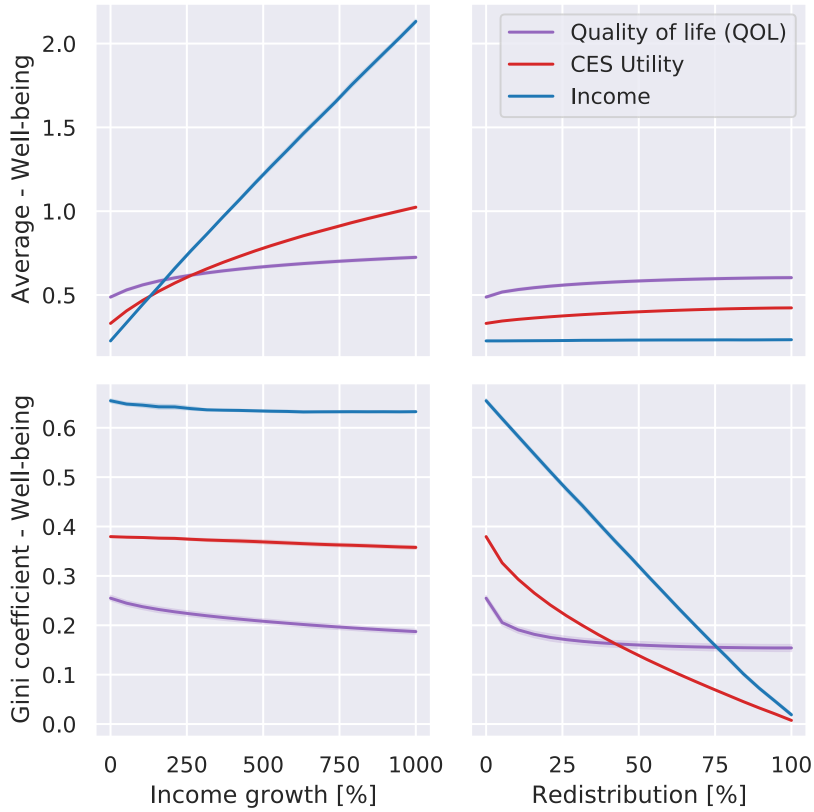

Fig. 6. Effects of income growth and redistribution on different measures of well-being.

increase of average QOL declines as material needs become saturated. The same is true for the increase of QOL equality. In other words, the effects of additional income display a decreasing rate of return to both QOL average and QOL equality.

Income redistribution similarly increases average QOL as the positive difference for low-income agents is larger than the negative effect on those with high incomes. As expected, the inequality of QOL is also reduced. However, a full equality of income (i.e. 100% redistribution) does not result in full equality of QOL. This is because people's needs are heterogeneous. Some agents are thus able to reach a higher QOL than others with the same amount of income.

For comparison, Fig. 6 also shows how the same analysis would look like under the assumption that income can serve as a proxy for well-being. Note that the results are not completely linear as income is affected by work-time choices. Income growth has a potentially infinite positive effect, and little effect on inequality. Redistribution, in contrast, has no effect on average income and leads to almost full equality.

The CES utility measure produces results that lie somewhere in-between the two other perspectives. Similarly to QOL, this function is able to describe decreasing marginal returns of additional income to well-being. However, utility has no upper bound and can reach potentially infinite values similar to the income perspective. The results on inequality are also similar to the income perspective. Income growth has little effect on inequality, and redistribution leads to an inequality close to zero.

5.4. Carbon pricing

Next, we look at the environmental dimension of emissions. We consider the effect of different carbon tax levels τ on both emissions and QOL. Following Klein et al. (2021), we also look at the tax's progressiveness ψ that defines how much income redistribution is caused through the recycling of tax revenue. The effective income redistribution that is caused by the recycling of tax revenues is then defined as $\tau\psi$.[11]

The left half of Fig. 7 presents the average and the inequality of both emissions and QOL. It shows that the carbon tax level reduces emissions. However, its effectiveness per unit of additional tax level declines for higher tax values. This is because green consumption gets in increasing competition with recreation & rest as they both require time.

The inequality of emissions is increased by a tax, meaning that the tax has a higher emission-reducing impact on low-income agents than on high-income agents. This is because the former are forced to change consumption habits due to income restrictions. Some of the latter, in contrast, only have an incentive to change due to relative price differences but can in principle afford to receive sufficient satisfaction through brown consumption.

If no income redistribution is caused through revenue recycling, average QOL is negatively affected by the tax. However, the effect starts to become positive around a tax progressiveness of $\psi > 0.1$. This is because redistribution provides a higher income for those in most (material) need for consumption. Notably, this progressiveness does not increase the average emissions but instead makes the carbon tax even more effective.

The right half of Fig. 7 shows how the different activities and choices are affected by the tax. As expected, brown consumption is gradually replaced by green consumption. Progressiveness increases the amount of green consumption even further. The intensity of recreation & rest is reduced, since it competes with green consumption for the use of time.

[11] Note that this is not a full economic model that involves firms and trade, so the carbon tax is only assumed in terms of its effect. For example, if $\tau = 1$ and $\psi = 0.1$, consumption will get 1 monetary unit more expensive for each unit of embedded emissions, and 10% of total wealth will be redistributed.

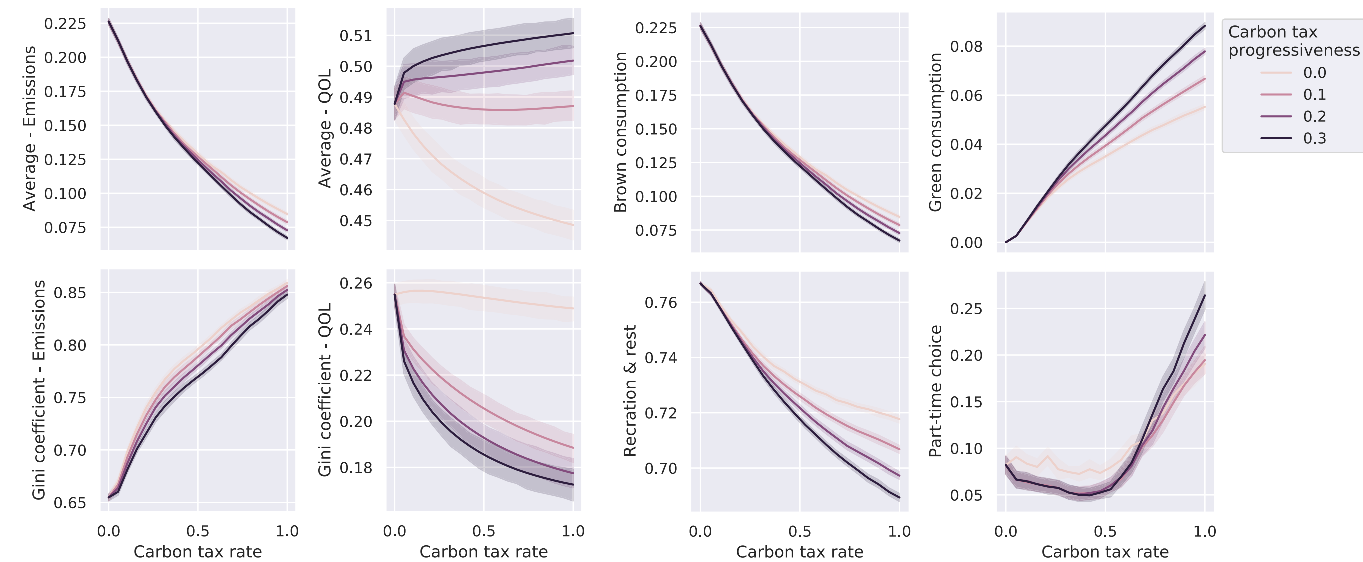

Fig. 7. Effect of a carbon tax on QOL and emissions (left half) and activity intensities and choices (right half).

Finally, let us regard the choice to work either part-time or full-time. The last panel of Fig. 7 shows the fraction of agents who choose to work part-time. This fraction is slightly decreased by low levels of the carbon tax. However, after a threshold around $\tau = 0.5$, the tax leads to a reverse effect and increases the percentage of people who choose to work part-time.

There are two reasons for this. First, the carbon tax increases the need for money as brown consumption gets more expensive. And second, it also increases the need for time as people increasingly switch to green consumption. The non-linear results can be explained by the combination of these two dynamics, with the latter becoming more dominant for higher tax levels.

5.5. Social multiplier

Following Konc et al. (2021), we now look at how the effectiveness of a carbon tax is affected by social interaction. As described in Section 5.1, the assumption in this scenario is that people want to behave similar to their friends. When the carbon tax level changes someone's behavior, it thus indirectly affects the behavior of their friends. This dynamic is also called the social multiplier of environmental policy (Konc et al., 2021).

To explore this effect, we vary the perceived importance of social norms ($\tilde{\omega}_{d=3}$). The higher this value, the more social norms are perceived as important compared to both material and immaterial needs. In addition, we also vary the weight $\tilde{\vartheta}_{a=3}$ (Eq. (A.3)), which defines how important recreation & rest is perceived to be for the fulfillment of social needs relative to the two other activities that regard consumption.

Note that this experiment looks at how much people think they need to follow norms, not how important it actually is for their well-being. This reflects a behavioral bias (Section 2, C2). The variables $\tilde{\omega}_{d=3}$ and $\tilde{\vartheta}_{a=3}$ are varied, while the actual states (without a tilde) are kept constant. In other words, we look at differences in people's behavior (i.e. their wants and desires) without differences in their needs.

The top panel of Fig. 8 presents the effects of these biases on emissions. When only consumption matters ($\tilde{\vartheta}_{a=3} = 0$), the effects of social interaction lead to a positive social multiplier effect on emission reduction. This means that the tax leads to a lower emission level than it would without social interaction. This is in line with results from the model of Konc et al. (2021), where agents similarly have the choice between two activities of green and brown consumption.

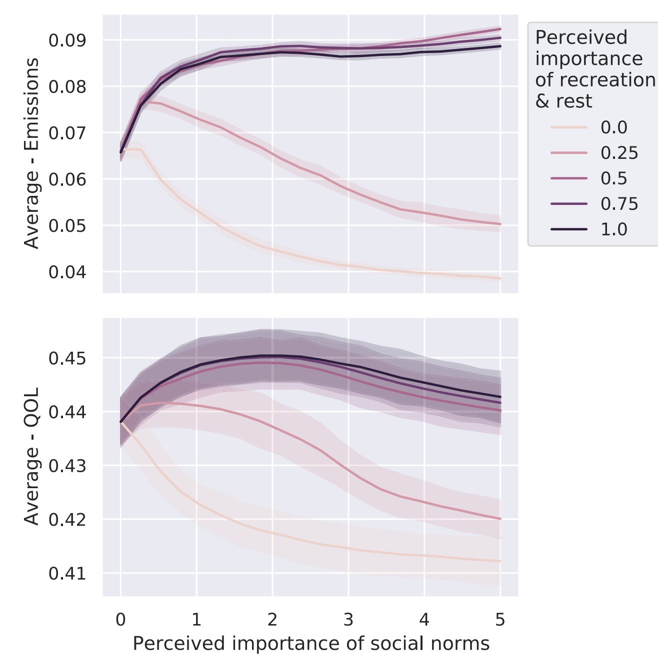

Fig. 8. Effect of a carbon tax on QOL and emissions under different behavioral biases.

A stronger perceived importance of recreation & rest ($\tilde{\vartheta}_{a=3} > 0$) – an additional dimension that is not accounted for in Konc et al. (2021) – can reverse this effect. This is because when people are able to fulfill a large part of their need to follow social norms through recreation & rest, they are less inclined to spend their extra time on green consumption as the two activities compete for time.

The bottom panel of Fig. 8 presents the effects of these biases on QOL, making it possible to account for the difference between observed behavior (wants) and actual well-being (needs). The results show that the behavioral biases of this experiment have a similar effect on QOL as they have on emissions. This suggests that the additional emission reduction that can be achieved through the social multiplier effect could be connected to a reduction in well-being.

6. Conclusions

This paper has presented the Needs and Limits (N&L) framework, a theoretical and computational foundation for agent-based models aimed at addressing multiple dimensions of human well-being and environmental impacts. It describes the adaptive behavior of human individuals who are trying to improve their quality of life. This makes it possible to represent the connection between individual decision factors and emergent patterns of the whole system. The framework is further able to account for the satiability of human needs, the effects of need deprivation, the influence of social interaction and behavioral biases, the adaptive nature of human well-being, and the existence of multiple bio-physical constraints.

This approach can be used to explore how complex social and economic dynamics can affect people's capabilities to enhance their quality of life within specific institutional and bio-physical environment. To illustrate this, application examples have been presented for the topics of income inequality and climate policy. The results suggest that the inclusion of additional dimensions can change or even reverse existing results from simpler models. A key insight from these experiments in line with existing literature is that the availability and use of time plays a central role in trade-offs between well-being and environmental objectives (Jalas, 2002).

The main strength of the N&L framework is that it can be applied to a broad range of socio-economic and ecological scenarios. It can incorporate any number of agents, networks, life domains, activities, choice sets, resources, and environmental factors. To provide some examples, the scenario presented in Section 5 could be extended by a differentiation between distinct types of green and brown consumption, the inclusion of unpaid work in addition to paid work, the representation of environmental values as an additional life domain, or the presence of further environmental factors to account for environmental problem shifting (van den Bergh et al., 2015).

The framework's capacity of such high levels of complexity is also its main limitation. The large amount of variables and the generic structure of the model result in long computation times. These aspects make it difficult to calibrate and validate any applied scenario, which can partly be overcome through the use of detailed empirical data like in Kangur et al. (2017). However, for the stated aim of understanding mechanisms, relevant insights can often be found in stylized models with a small number of agents. Performance can further be increased by replacing the generic optimization algorithm with custom code that is optimized for a specific application.

Another limitation is the fact that any quantitative approach to human well-being represents an extreme simplification of the human experience. From the empirical side, every existing measure of well-being provides an incomplete picture (Joshanloo et al., 2019). From the theoretical side, behavior that improves well-being from a certain philosophical perspective might appear undesirable in a model that is based on another. For example, the focus on the long-term perspective that is taken here will categorize choices that prioritize the short-term as a behavioral bias. This difficulty regarding time-related trade-offs has already been pointed out by Jager (2017) and remains a challenge to be addressed.

Future applications of this framework will be able to explore ways to achieve a higher quality of life for all people with a lower environmental impact. Putting human needs and well-being at the center of analysis makes it possible to shift away from increasingly controversial objectives like economic growth (O'Neill et al., 2018; Hickel et al., 2021). At the same time, it provides a more realistic description of human behavior that can be used to improve the demand-side description of economic models — leading to a fuller understanding regarding the social and ecological impacts of different policies. In addition, the framework is not methodologically limited to consider only incremental changes to the current system. It can also be used to explore fundamentally different cultural and institutional settings that include alternative forms of ownership, employment, currency, production, and trade.

Data availability

A link to a public repository is provided in the paper.

Acknowledgments

This study has received funding through an ERC Advanced Grant from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement no 741087).

I am grateful to Franziska Klein, whose ideas have greatly benefited the application examples. I further thank Jeroen van den Bergh, Ivan Savin, Théo Konc, Manuel Scholz-Wäckerle, Tania Treibich, Jarmo Kikstra, and Yannick Oswald for their helpful comments and support.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Scenario configuration

This appendix provides additional information about the demonstration scenario described Section 5.

A.1. Impact functions

This section describes the custom impact functions from Table 2. The impacts of the choice of working-time on the resource of time reflect a job of 30 and 40 h per week respectively.

$$\zeta^R_{i,c=1,r=2,t}(o) = \frac{-1}{168} * \begin{cases} 40 \ \dots \ if \ o{=}1 \ (full-time) \\ 30 \ \dots \ if \ o{=}2 \ (part-time) \end{cases} \tag{A.1}$$

The gained money per time-step is calculated as an agent's income rate γ_i times their chosen amount of work-time.

$$\zeta^R_{i,c=1,r=1,t}(o) = -\gamma_i \, \zeta^R_{i,c=1,r=2,t}(o) \tag{A.2}$$

The impact of activities on the domain of social needs depends on the activity-specific weights ϑ_a and the average activity intensity among an agent's set of friends J_i.

$$\delta^S_{i,d=3,a,t} = \frac{\vartheta_a}{|J_i|} \sum_{j \in J_i} \alpha_{j,a,t} \tag{A.3}$$

A.2. Parameter values

The demonstration scenario describes an abstract setting. Parameter values are thus not calibrated to a particular time or place, but are chosen to be within realistic ranges.

Each agent is connected to a set $J_i \subseteq \{j \mid j \in I\}$ of other agents that they consider friends. This network is randomly generated using the Watts–Strogatz algorithm for small-world graphs (Hagberg et al., 2021), with 2 default neighbors per agent and a rewiring probability of 0.1.

The simulation length n^T is set to 3 time-steps, allowing agents to observe the behavior of their friends and adapt their perception multiple times. The substitution degree σ is set to a constant value of 0.01. This low value means that the deprivation of needs in one of the three life domains cannot be compensated by fulfillment in another (Section 2, C6).

The income rates γ_i follow the world's income distribution in the year 2016, as reported in World Inequality Lab (2021). These income rates are normalized so that the average income per agent equals one unit of money if all agents work full-time. All relative importance factors ω and ϑ are set to a value of 1.

Table A.1
Calibrated parameters for the satiation rates $k_{i,d}$.

Domain	Index	Mean	Standard deviation
Material needs	d=1	8.35	1.78
Immaterial needs	d=2	1.33	2.92
Social norms	d=3	5.49	8.84

Perceived states simply reflect values of the previous round:

$$\tilde{\boldsymbol{X}}_{i,t} = \boldsymbol{X}_{t-1} \tag{A.4}$$

Note that these parameters regard default values, which can be subject to change in some of the presented experiments.

A.3. Calibration

The satiation rates $k_{i,d}$ for each of the three life domains are heterogeneous amongst agents, and drawn randomly from a normal distribution that is truncated to include only positive values. The mean and standard deviation of these distributions are calibrated to be in a similar range as global self-reported life-satisfaction between 2014–2016, as reported in Helliwell et al. (2017).

The calibration procedure is set to minimize the difference between this desired QOL distribution and the outcome of the model, using the Powell minimization algorithm (SciPy Community, 2021). The life-satisfaction data consists of discrete values from 0 to 10, which are mapped to QOL as eleven equally sized ranges between 0 and 1. The difference between the two distributions is measured with a chi-squared statistic. The resulting values are shown in Table A.1.

A.4. CES utility

The CES utility measure $U_{i,t}$ presented in Sections 5.2 and 5.3 assumes that individuals gain utility from the consumption of each resource (money and time) with equal weights. The substitution degree $\sigma_{i,t}$ is set to the same value as for QOL.

$$U_{i,t} = \sum_{r \in R} \left(\frac{1}{n^R} \left[\sum_{a \in A} \alpha_{i,a,t} \; \delta^R_{a,r} \right]^{\sigma} \right)^{\frac{1}{\sigma}} \tag{A.5}$$

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