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A system dynamics modeling framework for endogenizing human behavior change in global-scale integrated assessment models

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Abstract. Integrated Assessment Models have come to occupy a pivotal role in evaluating the multifaceted and complex interactions of the human-climate systems for informing climate change mitigation and adaptation policies. However, current models often lack explicit representations of human behavior and social systems necessary for assessing demand-side policies. In this paper, we introduce and provide a detailed description of our modeling framework for endogenizing human behavior change in the global-scale FRIDA model, specifically focusing on behavioral processes related to environmentally significant diet choices. The framework models human behavior as a function of three sources of motivations (perceived accessibility, descriptive norms, and personal norms), constrained by accessibility and past behavior. Consistent with literature, our results show that endogenizing behavior change leads to lower baseline climate projections. However, we found that a pro-environmental behavioral response, indicated by both a reduction of consumption and substitution of animal products, may not be an enduring phenomenon: behavior change could reverse in the future from weakening threat perceptions over time. Our work contributes to the limited work on human behavior in climate models, extending current representations to include more dynamic complexity. It also contributes to the system dynamics field for modeling social norms and risk perceptions.

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Extended Abstract

Introduction

Anthropogenic climate change is recognized as a multifaceted and highly complex global problem, with interlocking feedback interactions between subsystems in the broader human-climate system [1]. Integrated Assessment Models (IAMs), designed to assess the impacts of such interactions, are used for scenario analyses to support mitigation and adaptation policies [2]. However, most IAMs today do not explicitly nor adequately represent social systems to account for human behavioral responses to climate change [3]—despite considerable evidence that demand-side pro-environmental behavior change could be a critical mitigation strategy [4–6]. The dominant approach, instead, is coupling separate behavior change narratives and scenarios with IAMs to exogenously drive relevant technoeconomic decisions [7–9]. Recently, scholars have called for engagement with other social scientific disciplines to improve representations of social-cultural processes within the human systems of IAMs [3,10].

The EU-funded WorldTrans consortium [see 11] has responded to such calls for endogenizing human behavior, among other objectives. The consortium has developed a novel IAM, FRIDA (Feedback-based knowledge Repository for IntegrateD Assessments), that aims to represent the co-evolution of the climate and human processes by closing all major feedback loops at the global aggregate scale [12,13]. In doing so, they endeavor to provide a fully endogenous, process-based explanation of system behavior. FRIDA version 2.0 introduced the Behavioral Change module, which endogenously models human behavior in animal-derived products demand. In the latest v2.1, this module was expanded to include total food demand. The modeling framework underpinning the module was developed by integrating knowledge from several sources, including an array of behavioral theories [e.g., 14–16], systematic reviews of extant literature [e.g., 17–19], and insights from participatory modeling [e.g., 20,21] and preliminary proof-of-concepts [e.g., 22,23].

In this paper, we formally introduce our fully endogenous behavior change modeling framework, operationalized as a system dynamics (SD) model embedded within FRIDA v2.1. After situating it within existing work, we provide the formal documentation of the framework as applied to human behavioral processes surrounding diet choices. Briefly, this behavior change framework represents consumptive behavior as a function of three main sources of motivations (perceived accessibility, descriptive norm, and personal norms), constrained by accessibility and past behavior. Importantly, the determinants are embedded within and responsive to feedback processes between human-climate systems. We then report the protocol employed for parameterization and analysis, while accounting for uncertainty. Thereafter, we present and explain the results pertinent to human behavior from a process-based perspective. We conclude with a discussion of the results, the framework's contributions and its limitations. Besides contributing to the nascent advancement of IAMs on this front, we further hope to contribute to the SD field more broadly for representing human behavioral processes in models.

Model description

Our endogenous modelling framework, encapsulated within FRIDA's Behavioral Change module, comprises three sub-modules: Animal Products Demand, Total Food Demand, and Climate Risk Perception (see Fig. 1). Total Food Demand captures changes in overall diet (total desired caloric intake), whereas Animal Products Demand computes changes in the share of animal products in the average diet. Vegetal products demand is calculated as the remaining share. We model the key behavioral processes that endogenously determine changes in total food demand (i.e., diet) and animal products demand (i.e., diet composition).

In our modelling framework (see Fig. 2), dietary behavioral intention (desired demand) is adjusted by four groups of behavioral processes: (i) *past behavior* from habits that moderate desired changes in behavior; (ii) *perceived accessibility* in terms of socio-economic factors determining the affordability and availability of food products; (iii) *descriptive norm* that describes what others in the social environment are doing, which exerts a conformity pressure; and (iv) *personal norms* or standards that people hold and expect of themselves, which are shaped by perceptions of the social and natural environment.

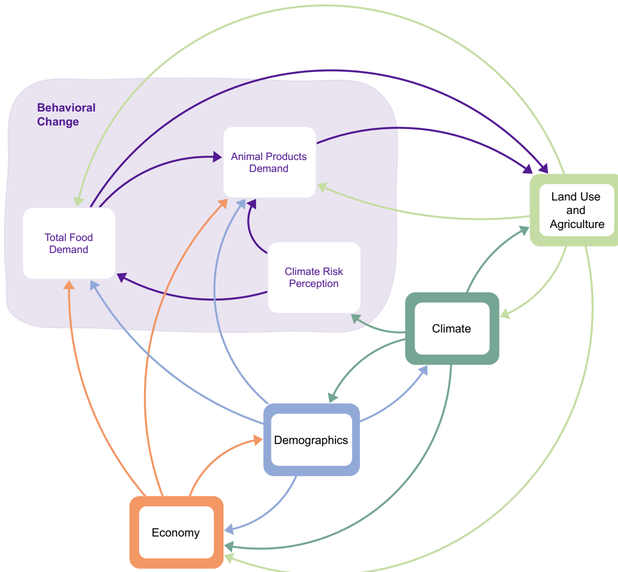

Figure 1: Subs-system diagram of Behavioral Change module (in blue) and its interlinkages with other relevant top-level modules in FRIDA v2.1.

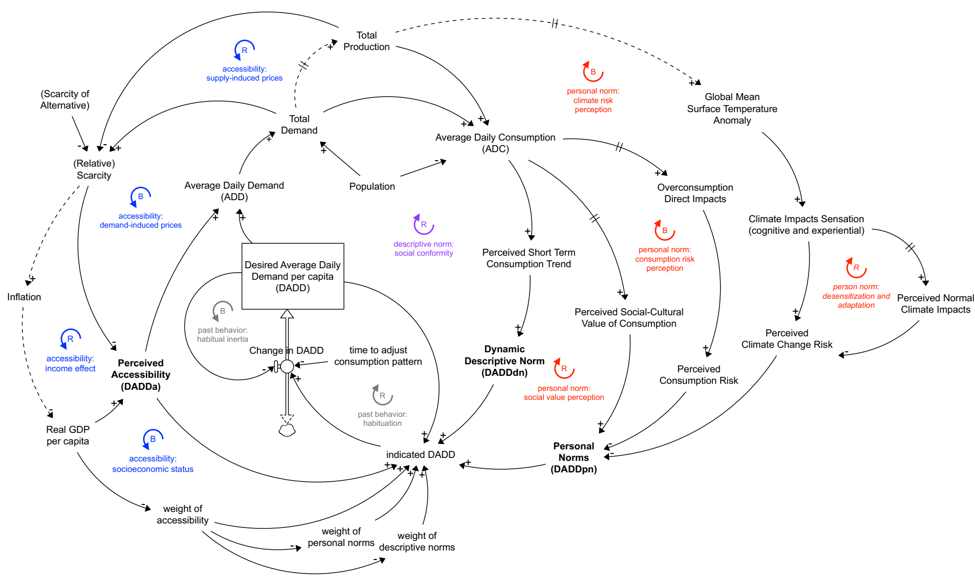

Figure 2: Simplified causal loop diagram of the endogenous modelling framework; grey labels: loops associated with past behavior; blue: loops associated with perceived accessibility; purple: loops associated with descriptive norm; red labels: loops associated with personal norms; R labels denote reinforcing loops (changes are amplified) whereas B labels denote balancing loops (changes are attenuated); double strokes on connectors indicate delays; solid connectors are internal to the Behavioral Change module while dashed connectors denote connections to other modules in FRIDA.

5 Simulation results

Figure 4 presents the baseline results of the key indicators for dietary behavior, comparing the performance of our endogenous modelling framework (i.e., EMB) to the more commonly GDP-driven approach of modeling. In general, we observe that future projections for GDP-driven food demand are higher than our EMB. On the other hand, our endogenous modelling framework captures people's dynamic response to changes in their social-ecological environment, which results in considerably lower future estimates across all food-related indicators.

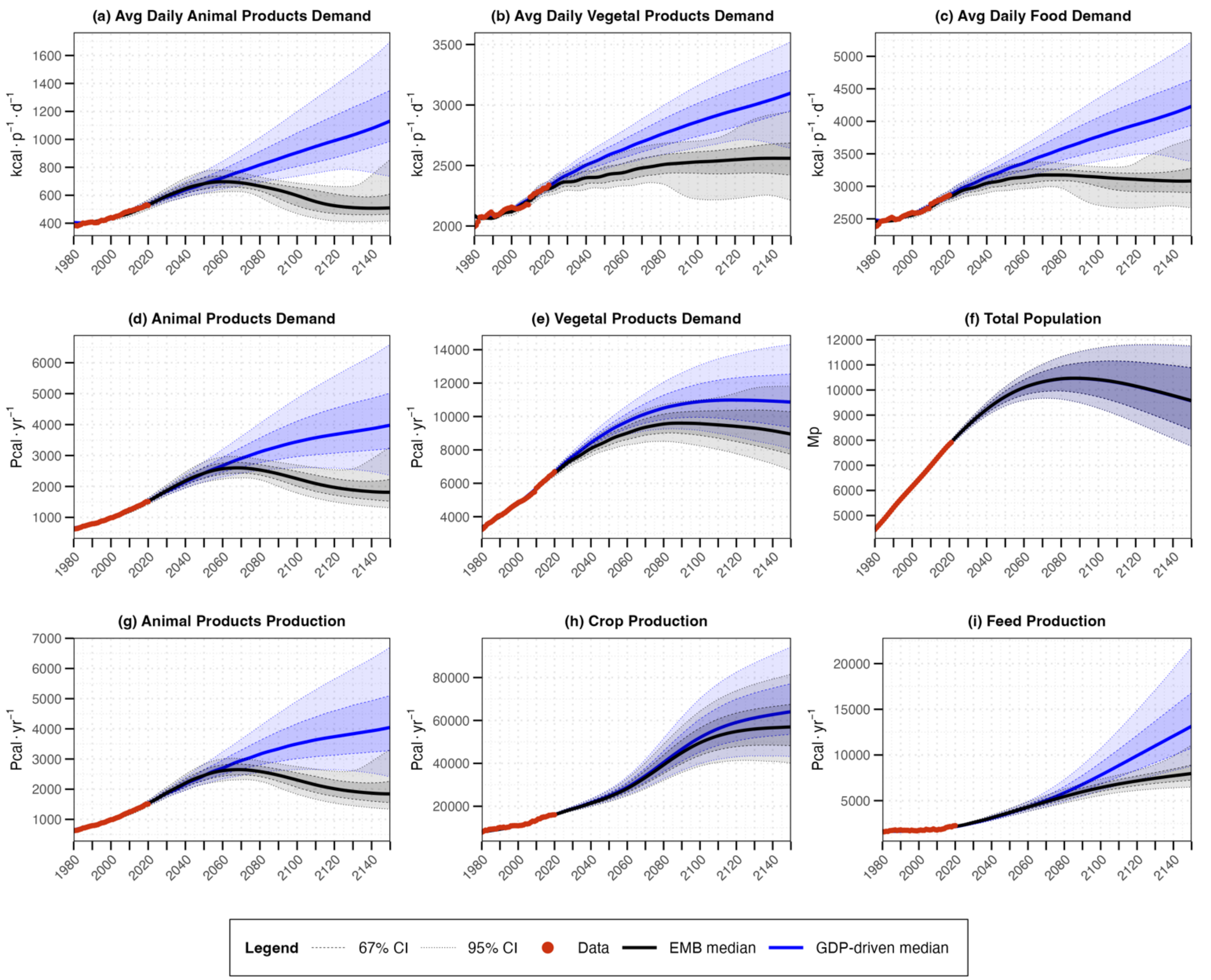

Figure 3: Comparison of simulation results for EMB (in black) and GDP-driven (in blue) 100,000-member ensembles across key dietary performance indicators in the human system, with confidence intervals.

Production dynamics has consequences for climate projections, as depicted in Fig. 6. CH_4 and N_2O emissions are directly influenced by animal products production and crop production; while land use transitions for food production affect CO_2 emissions [24]. After 2060, greenhouse gases emission rates from Land Use and Agriculture (Fig. 6a-c) are projected to be considerably lower in the EMB. In turn, we project a slightly cooler climate baseline in the future, as shown in Fig. 6d: EMB median STA of 3.16 [2.07, 4.83] °C in 2100 and 3.56 [2.14, 6.17] °C in 2150, compared to the projected 3.21 [2.11, 4.90] °C in 2100 and 3.67 [2.22, 6.31] °C in 2150 from the GDP-driven model. Similarly, we observe a slightly lower EMB median SLR of 0.65 [0.41, 1.05] m in 2100 and 1.13 [0.67, 2.03] m in 2150, compared to the GDP-driven 0.66 [0.41, 1.06] m in 2100 and 1.16 [0.68, 2.07] m in 2150 (Fig. 6e). There is considerable overlap in the confidence bounds for STA and SLR, as dietary behavior only contributes a fraction of total emissions. Other high-impact behaviors influencing energy demand are still modelled as functions of GDP in FRIDA v2.1 [for more details, see 25]. Including endogenous behavioral change for these other sources of human behavior could result in more significant differences in STA and SLR projections.

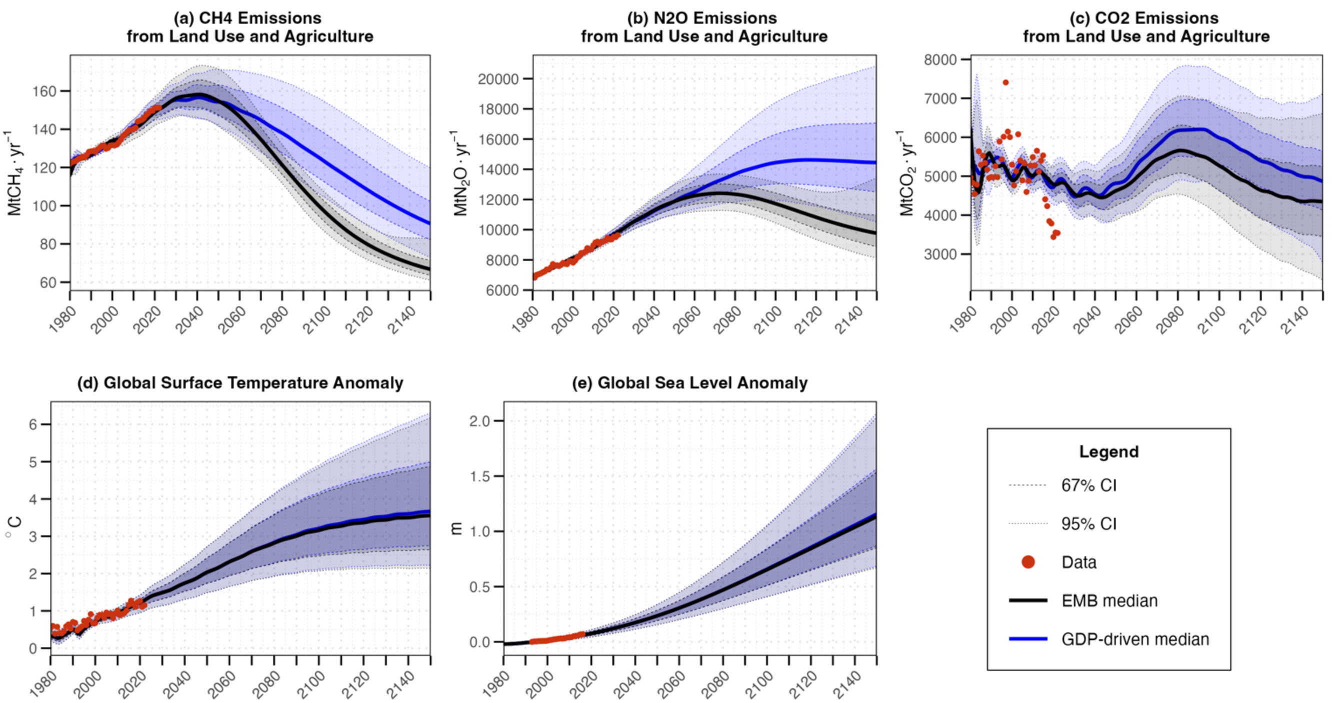

Figure 4: Comparison of simulation results for EMB (in black) and GDP-driven (in blue) 100,000-member ensembles across key performance indicators in the climate system with confidence intervals.

6 Discussion

To evaluate the performance of our endogenous modelling approach, we compared the results of our baseline EMB against the baseline produced by the more common GDP-driven model. Our findings indicate that while both approaches can acceptably reproduce historical data, our approach results in considerably lower future projections across key human-climate system indicators. This is because people adapt to their changing social-ecological environments, altering dietary behavior favorably from a climate mitigation perspective even in the absence of specific policies for facilitating pro-environmental behavioral change. We consequently observe relatively cooler future baseline climate projections by endogenizing human behavior. In the GDP-driven model, by contrast, humans primarily respond to changes in income: increasing demand proportionally as they become richer. Since real GDP increases for most of the simulation horizon in most IAMs, we may end up with higher demand projections that do not account for behavioral changes. Such inflated projections feed into the climate system and result in relatively warmer climate futures.

Using an uncertainty approach, our simulation results account for a range of plausible behaviors within the 95% confidence bounds. Beckage et al. [26] contend that the increased input uncertainty space from endogenizing human behavior may not necessarily increase output uncertainty since behavioral responses create balancing feedback. While we do not disagree with this premise, our results suggest that this is only the case if the balancing loops dominate the model behavior. Compared to the GDP-driven model, our endogenous framework results in tighter confidence bounds since we account for important balancing loops. However, we also observe an expanding uncertainty space (e.g., see animal products demand) towards the end of the simulation due to the shift in dominance from balancing to reinforcing processes. This highlights the need for sufficient dynamic complexity in any representation of behavioral processes to fully account for output uncertainty.

Our uncertainty analysis further shows that while climate-friendly behavioral change may occur in the future, this shift may not endure. While the second nutrition transition [cf. 27] occurs as more people become responsive to the downward pressures from personal and social norms, embedded reinforcing social-cultural processes may facilitate a third unfavorable transition from the system's resistance. Such reversals in behavior change have not been reported been in existing models, likely due to their lower dynamic complexity.

Our work contributes to the SD field in multiple ways. First, our model contributes to the very limited SD work in explicit social norms modeling: in a recent systematic review of social simulation models, Prawitz et al. [28] only found four such models that use the SD method. Secondly, none of the 49 reviewed models represented dynamic norms (changing trends) and most represented injunctive norms as external inputs [28]. Our model incorporates both descriptive and injunctive social norms endogenously and, to our knowledge, is the first to model dynamic social norms. Here, we have demonstrated the efficacy of Sterman's TREND function [29] for modeling dynamic norms, opening up an avenue for future SD applications in this regard. Lastly, we call for the inclusion of reference dependence and desensitization in behavioral models in other contexts. For instance, COVID-19 models include a balancing feedback from risk perception, typically with a logistic function, for modeling the behavioral response [e.g. 30]. Osi and Ghaffarzadegan [31] have included additional balancing feedback for adherence fatigue and societal learning to capture resistance to stringent policies. Including the reinforcing adaptation feedback from updating reference conditions of normality, instead, could perhaps explain waning risks even in the absence of policy.

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