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Food packaging: identifying the socio-economic drivers and reduction opportunities through system dynamics modelling

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Abstract

Background Food packaging continues to create negative socio-ecological impacts. Current initiatives, including recycling and the use of sustainable packaging materials, address important aspects of sustainability, however, a more comprehensive approach is needed to tackle the underlying challenges of a growth-driven economy that significantly impacts food systems. There is currently limited research in identifying systemic policy changes aimed at reducing food packaging.

Methods Using a system dynamics approach, this study models the determinants that shape contemporary food systems and contribute to the increase in packaged food production and consumption. The resulting stock and flow model developed helps to understand and evaluate how globalisation, urbanisation and households dynamics are driving growth in packaged food.

Results Findings from this study highlight (1) the need to shift the conversation from food packaging to packaged food, the actual product traded; (2) that growth-driven globalisation is contributing to the dependence on packaging; and (3) policies, such as the introduction of a basic income, could foster a reorganisation of social reproduction to incentivise the consumption of fresh and unpackaged food.

Conclusion This paper concludes with an invitation to explore degrowth policy proposals that could reduce dependence on packaged food and highlights the need for systemic policy changes to transform food systems. The findings of this study can be extrapolated to other countries exhibiting growth in production and consumption of packaged food. In this study, environmental and public health lenses converge.

Keywords Packaging, Food systems, System dynamics, Degrowth, Sustainability

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Introduction

Since the 1960s, food systems have become increasingly dependent on packaged food [1]. Increased use of fossil fuels for petroleum-based packaging materials [2], air, water and land pollution are just some of the environmental impacts caused by food packaging production and consumption [3–5]. The environmental consequences of this growing reliance on packaging have been extensively researched [1, 6–9]. Despite efforts to mitigate the environmental impacts of food packaging [10], such as recycling schemes and the introduction of disposable "sustainable" packaging materials [11], broader systemic policy actions targeting the entire food system have remained largely neglected. The importance of comprehensive, systems-based approaches to effectively catalyse the necessary transformation in food systems has been emphasised in various studies [12–17].

This study adopts a systems approach as the foundational framework for the investigation of the socio-economic drivers of packaged food. Sterman's [18] systems modelling framework was adopted to develop, test, and apply a simulation model using a stock and flow model (SFM). These types of simulation models are pivotal for understanding and interpreting the dynamics associated with systemic socio-environmental system changes [19, 20]. Thus, adopting a system-based approach, this study investigates the following research question: What are the systemic socio-economic drivers of food packaging? This systems-based approach aids in examining the determinants and dynamics driving the increasing global dependence on packaging. The novelty of this study is to explore food packaging challenges beyond the materiality of packaging and beyond supply chain analysis. This study offers a cross-scale analysis of the drivers of packaging use, pointing out policy frameworks influencing food systems. Moreover, in this study, environmental and public health lenses converge. This research started by focusing on the use and reduction of food packaging, however, the reiteration in the systems modelling process shifted the attention to packaged food. Packaged food is the ultimate product exchanged in the market; food packaging is a side effect of the purchase of (packaged) food. Packaging impacts the environment in several ways (e.g. as a pollutant), while the processed or ultra-processed food contained within the packaging can lead to health issues (e.g. cardiovascular and cerebrovascular diseases) [21, 22]. Thus, this study links spheres that often remain disjointed in the literature. Food packaging studies, which primarily focus on material and technological innovation, remain disconnected from public health and nutritional research areas that analyse the health effects of consuming processed (packaged) food products.

The geographical focus of the SFM in this paper is the United States (US), selected because it is a leading contributor to global food packaging and because of the availability of data needed to parameterise and calibrate the SFM. However, this process-driven modelling methodology can be applied to analyse other countries or scaled up to model at a global level. This applicability (and scalability) is important given that packaged food production and consumption have increased at comparable rates across many other high-income countries [1, 23], and that the globalised food system is dominated by Western-style processed foods, which have also penetrated low- and middle-income countries [23–26].

The first part of the paper, section "Methods", explains the SFM development, parameterisation, and testing methods. section "Results" presents the model structure and the results of the sensitivity and scenario analyses. The discussion in section "Discussion" outlines how various policies, such as global free trade agreements, directly influence the use of food packaging. Additionally, this section introduces potential degrowth-aligned policies that could help reduce packaged food dependence, increasing socio-ecological wellbeing in food systems. Degrowth can be defined as a multidimensional, planned, and democratic transformation of the economic system that prioritises socio-ecological wellbeing over growth-dependent and growth-driven activities [27]. Degrowth aims at "an equitable downscaling of production and consumption that increases human wellbeing and enhances ecological conditions at the local and global level, in the short and long-term" [28, p. 512]. section "Conclusion" concludes with a call for action for policies that could foster a reorganisation of the socio-economic context in which food systems exist.

Methods

The systems approach

This study has employed the five-stage systems method outlined by Sterman [18], which includes: (1) problem articulation, (2) dynamic hypothesis formulation, (3) simulation model building, (4) model testing, and (5) policy design and evaluation. Stages 1 (problem articulation) and 2 (dynamic hypothesis formation) of this study are detailed in Chakori et al. [1]; Chakori et al. [29]. This paper provides details on stages 3 to 5, encompassing the development, testing, and application of the SFM.

Stock and flow model boundary and aggregation

A core requirement for developing a systems model is to 'model a problem, not a system' (i.e. the increasing global dependence on packaged food), which helps to define the model's boundary and the level of aggregation [18]. This approach allows us to delve into the macro socio-economic drivers of the problem. The US is chosen as the focus of this study primarily due to its notably high per capita plastic waste generation rate [9, 30]. Additionally, the US provides detailed, specific data on municipal solid waste, particularly in containers and packaging. This data is comprehensively documented by the US Environmental Protection Agency [31]. The study particularly considers containers and packaging as products that are typically discarded within the same year of purchasing the contained products. This category encompasses various materials, including glass, steel, aluminium, paper and paperboard, plastics, and other packaging types [31].

Stock and flow model development

An SFM is a graphical representation of a system defined by interconnected ordinary differential equations, as detailed in section "Introduction" of the supplementary material. To create and test this SFM, we employed the software Stella® Architect 2.2.2 (here, 'Stella'). The development of the subsystems of the SFM that together make up the whole model was guided by the 'modes of behaviour' approach using the time-series data obtained for each of the identified stocks [18] (i.e. Fig. S1 in the supplementary material). This approach aligns with a first-principles approach to systems modelling, where subsystem structure is inferred from the observed system behaviour as a 'dynamic hypothesis' [18]. The model encompasses a historical time horizon from 1960 to 2020, enabling the observation of decadal trends within the data.

Parameterisation data

Parameterisation of the model involved assigning values to all model constants, including initial values for stocks, rate constants, and coefficients. These values were primarily derived from scientific, peer-reviewed publications and reports from reputable institutions, such as the Food and Agriculture Organization of the United Nations (FAO). In cases where the literature did not provide specific parameter values, the authors made initial estimates. These estimates were subsequently refined during the model's calibration process. Details of the model parameters are listed in section "Methods" of the supplementary material (Table 1S).

Dimensionless multipliers

Dimensionless multipliers are a unique feature of system dynamics modelling [32]. These multipliers are essential for quantifying cause-effect relationships within a model, mainly when the analytical relationships between different components are not explicitly known but are vital for accurately modelling the problem [32, 33]. Systems modelling justifies using dimensionless multipliers to represent these relationships because the focus is on relating system structure to system behaviour rather than solely focusing on predictive accuracy. However, it is important to acknowledge that employing these multipliers can introduce greater uncertainty into the model's predictions [33]. Section "Results" (supplementary material) presents insights into the application and implications of dimensionless multipliers.

In setting up the dimensionless multipliers, we initially confined our choices to 's-shaped growth' or 's-shaped decay' from Stella's library of graphical functions. This approach was taken while maintaining the software's default settings for input and output ranges, as exemplified in Fig. S2b of the supplementary material. Our primary criterion in this selection was to determine whether the relationship between a predictor and its effect variable exhibited a positive correlation (growth) or a negative correlation (decay). Moreover, we specifically chose s-shaped functions as our initial model framework, ensuring that the upper and lower limits of the graphical function asymptotically bound the relationship between predictors and effect variables. Opting for Stella's default functions also provided a consistent and standardised basis for integrating these effects into our model.

Stock and flow model testing

The testing of the SFM involved a comprehensive application of best-practice systems modelling principles, along with a range of structural and behavioural tests. The primary goal of adhering to these best practices was to avoid potential errors arising from constraining the model inappropriately [20]. Our approach included two key strategies:

1. Allowing Negative Values for Stocks: In Stella, stocks can be set to 'non-negative', which can potentially mask scenarios where stocks should decrease into negative values. To avoid this, our model was configured to allow stocks to attain negative values, thus providing a more accurate representation of system dynamics.
2. Bidirectional Flows: Contrary to the common practice in SFMs, where flows (either inflows or outflows) are typically unidirectional [20, 34, 35], we specified all flows in our model as bidirectional. This is because unidirectional flows, by default, do not account for situations where a flow could be negative and, thus, should logically 'flow' in the opposite direction. In standard models, such scenarios would result in a flow defaulting to zero, which could misrepresent the true dynamics of the system.

Structural testing

Structural testing of the SFM involved examining its behaviour under various scenarios, a process crucial for validating the model's robustness [36]. These tests included ensuring unit consistency across all model variables and conducting extreme condition testing [18].

Stella's built-in unit checker to verify unit consistency was used. For extreme condition testing (i.e. section "Conclusion", Fig. S3, in supplementary material), the SFM was subjected to abrupt and significant changes during simulation runs, such as unexpectedly setting a stock or rate to zero. The model's output was then evaluated to ensure it displayed realistic and appropriate responses under these extreme conditions [18].

Behavioural testing – dimensionless multipliers

Behavioural testing of the SFM involved comparing the patterns generated by the model with historical data, a key aspect in model validation [36]. Using historical time-series data and Stella's built-in optimisation tool, we calibrated the SFM's state variables, including stocks and dimensionless multipliers. Stella's calibration and optimisation method utilises the BOBYQA algorithm for bound constrained optimisation without derivatives, using a local search technique to locate local minima to high accuracy [37]. We employed a heuristic strategy [38] with optimisation conducted on all the time series data. The model's performance was initially assessed using Stella's default s-shaped graphical functions for the dimensionless multipliers. Following this initial assessment, we adopted an iterative approach for further refinement. In this phase, each graphical function was systematically replaced with a sigmoid equation (referenced as Eq. 1 below) and recalibrated using Stella's optimisation function. This process allowed for a more precise adjustment of the multipliers, ensuring they were closely aligned with the observed historical patterns.

$$S(x) = \left(\frac{1}{1 + \alpha e^{-x.x_1 + x_2}}\right)\beta \quad (1)$$

In Eq. 1, x is the input value for the function, and four parameters allow adjustment of the x-axis scale (x_1, x_2), the steepness of the sigmoid function (a), and the magnitude of the sigmoid function (β). The parameter values $a = 2.5$, $b = 2.0$, $x_1 = 2$ and $x_2 = -2$) perfectly fit Stella's default s-shape growth function (i.e. Fig. S2b, supplementary material). We calculated the coefficient of determination (R^2) [18, 39, 40], discrepancy coefficient (U_0) [34, 36, 39] and Mean Absolute Percentage Error (MAPE) [41–44] to evaluate the model's performance after optimisation. Information explaining these three measures of fit are provided in the supplementary material (section "Discussion", supplementary material).

Behavioural testing – sensitivity analysis

A sensitivity analysis was conducted to test the model's performance and, by extension, its conclusions when assumptions vary over the plausible uncertainty range [18]. This test is vital for determining how uncertainty in the model's output can be apportioned to different sources of uncertainty in the model input [33, 45, 46]. It can highlight 'structural sensitivity' [33, 47], help identify leverage points within the model, and guide policy scenarios [39, 48].

Parameters used in the sensitivity analysis were input variables, parameters with a constant numeric value throughout the model run (e.g. initial conditions for stocks, rate constants) and the dimensionless multipliers. Each parameter was tested individually (univariate parametric sensitivity) at three different settings (base value and ±10%), and the system performance was evaluated by monitoring the values of two stocks: *Packaged food* and *Food trade*. This approach is consistent with other systems modelling studies [34, 39, 49, 50]. The sensitivity analysis focuses on *Packaged food* because of the scope of this study (i.e. packaging), and on the globalisation subsystem (i.e. *Food trade)* because, while other stocks might have a highest variation across countries (e.g. women employment), globalisation of food systems - and the related nutrition transition [51, 52] - leads to a global convergence of food systems that rely on packaged (processed) food. Hence, the analysis of this part of the system is of broader global interest and it aligns with the scope of the journal (i.e. globalisation).

Given the uncertainty dimensionless multipliers introduced, these parameters must be included in the sensitivity testing. There is sparse information on conducting a sensitivity analysis for dimensionless multipliers, specifically those represented as graphical functions [33]. Parametric sensitivity is run automatically within Stella and other comparable system dynamics modelling software. Here, sensitivity testing was undertaken using an incremental distribution, where values are evenly incremented between specified start (−10%) and end (+10%) values based on the number of samples ($n = 5$). Conversely, the sensitivity analysis on the effects of the graphical functions requires manual manipulation.

In this study, all dimensionless multipliers in the SFM were included in the sensitivity testing. All equation parameters were included in the sensitivity testing for dimensionless multipliers in the model that are based on an equation (e.g. *Effect of urban population on women employment*). For dimensionless multipliers that used Stella's built-in sigmoid graphical function (e.g. *Effect of global trade on packaged food production rate*), these were replaced by their equation form (Eq. 1) and the equation parameters univariately used in the testing.

Results

Stock and flow model of food system

The developed SFM (Fig. 1) consists of three interconnected subsystems: (i) the globalisation subsystem (green), (ii) the urbanisation subsystem (brown), and (iii)

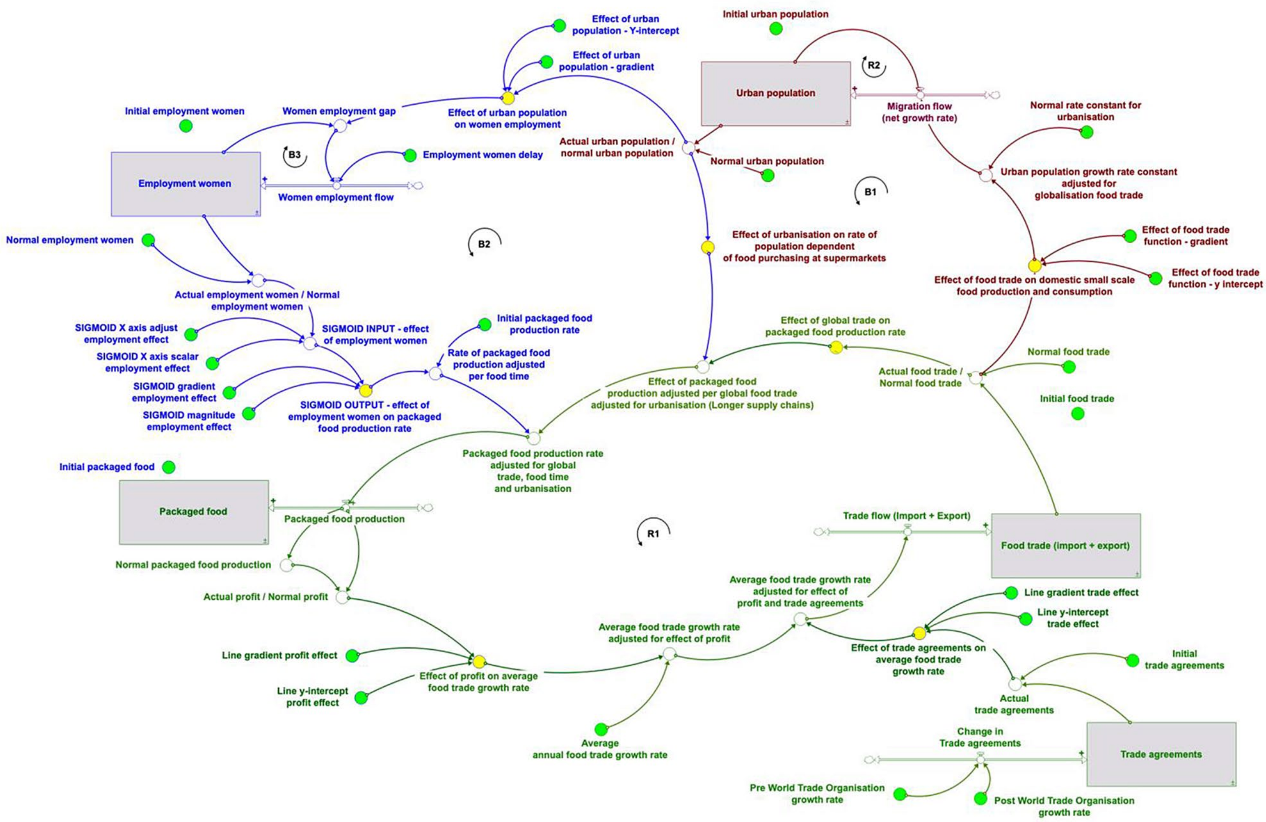

Fig. 1 Stock (grey boxes) and flow (bi-directional arrows feeding into stocks) model for the food packaging system showing subsystems of women employment (blue), globalisation (green), urbanisation (brown). Yellow nodes = dimensionless multipliers. Green nodes = constants. Feedback loops shown: R1, R2, B1 – B3 (*R* = reinforcing feedback and B = balancing feedback loop). The model is calibrated for USA data (1960 – 2020). Table S1 in the supplementary material presents the equations and values

household (women employment) subsystem (blue). Five stocks (*Packaged food, Women employment, Urban population, Trade agreements, Food trade*) and seven dimensionless multipliers (shown in yellow in Fig. 1) are used to integrate the different effects into the feedback loops. The equations and values adopted to build the SFM are presented in Table S1 in the supplementary material.

This model has two reinforcing loops (R1, R2) and three balancing loops (B1 – B3). R1 represents the globalisation loop, linking the *Food trade* and *Packaged food* stocks. It is an important feedback loop for matching system structure to the behaviour observed for *Food trade* and *Packaged food production* (Fig. 3). Specifically, it is responsible for enabling the exponential growth of *Food trade* and provides the exponential growth component of the s-shaped growth for *Packaged food production*. The urbanisation subsystem comprises R2, which provides density-dependent growth for the *Urban population*.

B1 integrates this stock into the globalisation loop (R1) and is responsible for decreasing the urban population growth rate in line with the overall trend observed in the data (https://data.worldbank.org/indicator/SP.URB.GROW?locations=US). The women's employment subsystem has two balancing loops (B2, B3). These two loops combine to facilitate the goal-seeking behaviour [18] observed in the time-series data (Fig. 3c).

Stock and flow model structure

Packaged food: The model sub-structure used to simulate packaged food was guided by available time-series data for *Packaged food production* and *Packaged food* (Fig. 2). *Packaged food* is an obvious candidate to be represented as a stock in the model because it is an accumulating variable, whilst *Packaged food production* is an obvious candidate to be represented as a flow because it has time in its units. However, there is disjoint in the dynamic behaviour between these two variables that means they both cannot be used. Specifically, the data for *Packaged food* plateaus after ca. 2000, indicating that the net rate of packaged food production has dropped to zero. However, the data for *Packaged food production* clearly shows that new production of *Packaged food* is increasing over the entire time horizon, and therefore, packaged food should be increasing. Thus, the data for *Packaged food production* might be more reflective of the real-world situation (i.e. that the rate of packaged food production

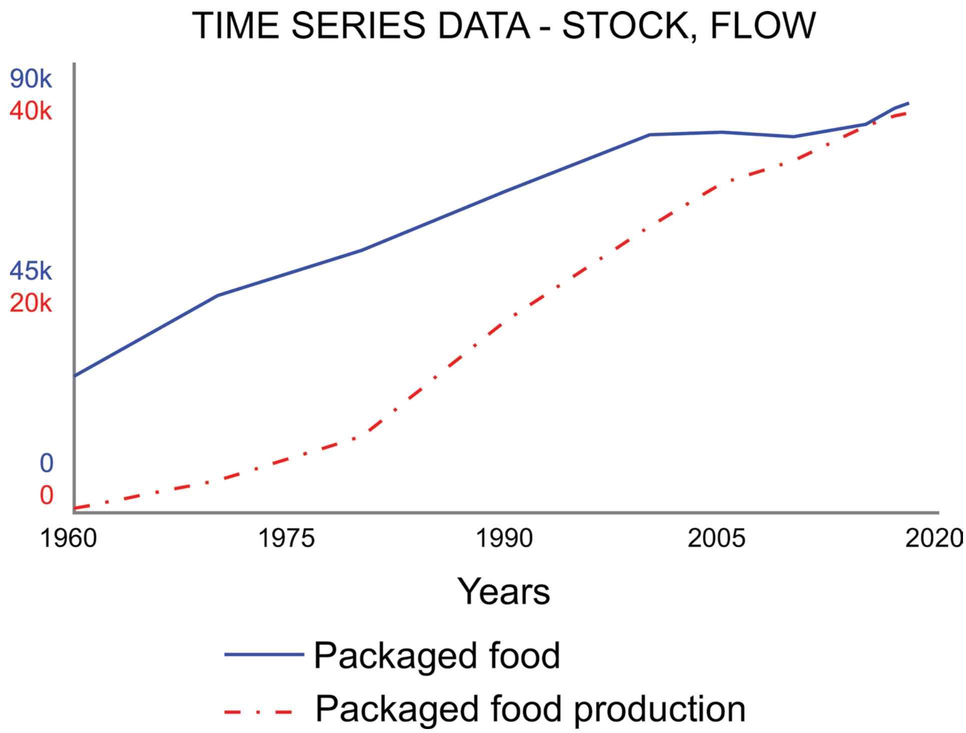

Fig. 2 Time-series (1960–2018) data for accumulated packaged food (stock, units: tonnes) and the rate of packaged food production (flow, units: tonnes year^{-1})

is increasing). Consequently, this model was based on the trend exhibited by *Packaged food production* and inferred from this the expected behaviour of *Packaged food* (i.e. exponential growth due to the increasing food production rate).

The time-series data for *Packaged food production* indicates s-shaped (sigmoid) growth behaviour. This fundamental behaviour model indicates a subsystem structure with interconnected reinforcing and balancing loops, and the 'loop dominance' is shifting from the reinforcing (exponential growth) to the balancing (goal-seek) loop. The reinforcing behaviour is provided in the SFM by R1, while B2 and B3 provide this balancing loop behaviour.

*Urban population:*A density-dependent feedback (exponential growth; R2) arrangement was used as the core structure for this stock. However, it is evident from the time-series data for this variable that the US urban population has exhibited approximately linear growth from 1960 to 2020 (Fig. 3b). We postulated that this was occurring because the annual urban growth rate, whilst positive, has generally been decreasing [53], and therefore, the net effect of these two loops (B1, R2) is producing the observed linear growth in population.

*Employment women:*This stock represents the proportion of women in employment. The time-series data (Fig. 3c) indicates goal-seek behaviour, evidenced in the data that appears to plateau over time. This goal-seeking behaviour is explicitly accounted for in the SFM by B3 and supplemented by B2.

Food trade (import + export): the time-series data indicate exponential growth (Fig. 3d). This is achieved through feedback loop R1, which relates the *Food trade* stock back to the input flow via *Packaged food production*.

Trade agreements: this stock uses a linear structure to match the linear trend observed in its data (Fig. 3e). The time-series data for trade agreements consisted of two distinct linear trends, with the change in gradient occurring around 1995, corresponding to the establishment of the World Trade Organisation (WTO), which led to changes in international trade agreements. To address this in the SFM, two auxiliary variables were used; one represented the linear growth rate pre-WTO (*Pre WTO growth rate*), and a second variable represented the linear growth rate post-WTO (*Post WTO growth rate*). Switching between these two growth rates was controlled in the SFM using a conditional (IF-ELSE) statement.

Stock and flow model structural testing

The dimensional consistency of the SFM was confirmed using Stella's built-in unit checker. Extreme condition testing comprised of allowing the SFM to run under default or business-as-usual (BAU) conditions from 1960 to 1990, after which the stock *Urban population* was set to zero for the remainder of the time horizon (1990–2020). The model performed correctly under this

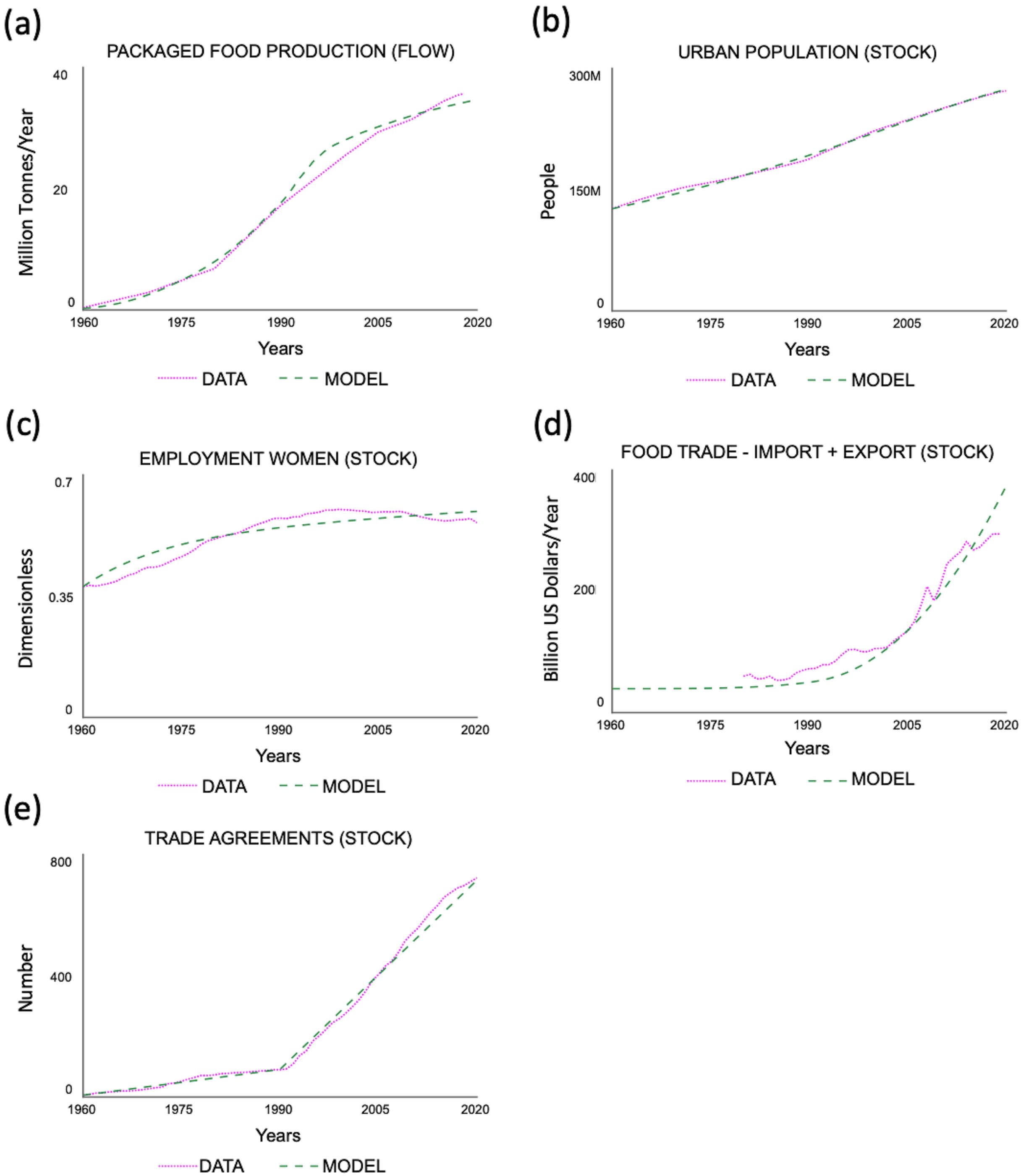

Fig. 3 Comparison between time-series data (DATA) and the calibrated simulation model (MODEL) for (**a**) packaged food production rate, (**b**) urban population, (**c**) employment of women, (**d**) food trade (imports and exports combined), (**e**) the number of trade agreements. All model variables shown represent state variables (stocks) in the model except for packaged food production (**a**), which is a flow. Calibrating data is comprised of annual data for the period 1960–2020, except for food trade (1980–2018) and packaged food production (decadal from 1960 to 2000, then 2005, 2010, 2015, 2017, 2018)

extreme condition with all stocks remaining non-negative. The results of this testing of the SFM are presented in the supplementary material.

Model parameterisation

The SFM was calibrated using the built-in payoff and optimisation functions in Stella using Powell's BOBYQA algorithm [37] and time-series data for *Urban population*, *Employment women*, *Food trade*, *Trade agreements* and *Packaged food production*.

A visual inspection of the SFM output highlights that it captures the behaviour of the time-series data (Fig. 3). The model output for *Packaged food production* reflects the sigmoidal shape of the data (Fig. 3a), *Employment women* (Fig. 3e) reflects the goal-seeking behaviour in the data and *Urban population* combines first-order growth dynamics (R2) and a balancing effect (B1) to capture the observed linear positive trend (Fig. 3b). The exponential growth observed for *Food trade* reflects the broad trend in the data but does not capture the short-term variability (Fig. 3c). However, the SFM structure was developed to reflect long-term trends in the system rather than short-term changes. Finally, the two-stage linear growth for *Trade agreements* (Fig. 3b) is captured.

Packaged food production: Stella's built-in library's default s-shaped graphical function produced the correct dynamics for this variable (s-shaped growth) but did not allow this stock to grow to the level observed in the data. The graphical function was replaced with a sigmoid function to address this, and the four associated parameters were adjusted during fitting (Fig. 3a).

*Urban population:*A key determinant of the dynamics of this stock is the dimensionless multiplier that links the globalisation loop (R1) with the urban population loop (B1). Initially, an s-shaped graphical function using Stella's default settings was used for this dimensionless multiplier. Preliminary model testing through optimisation indicated that a decreasing linear function (i.e. matching the general trend of the global urbanisation rate) produced behaviour for this stock that better matched the time-series data. This graphical function was then replaced with a linear function, and the two associated parameters (gradient, y-intercept) were adjusted during fitting (Fig. 3b).

*Employment women:*The default s-shaped function used to apply the urban population's effect on women's employment did not produce the desired goal-seek behaviour for this stock. Replacing the s-shaped graphical function with a sigmoid function and its four associated parameters (Eq. 1) resulted in a sigmoid approximating a linear (positive) trend. A linear function with two adjustable parameters (gradient = 0.504, y-intercept = 0.5) was used instead of the sigmoid function (Fig. 3c).

Food trade (imports + exports): The initial s-shaped growth function did not allow *Trade flow (import + export)* to exhibit the expected exponential behaviour observed in the time-series data. Further testing using Stella's library of graphical functions indicated that an exponential form improved the discrepancy between stock and data. The final approach was to use Stella's built-in exponential growth function (set to 'extrapolated') and adjust the *Average annual food trade growth rate* variable during fitting (Fig. 3d).

Applying the three measures of fit, the results of the coefficient of determination (R^2), discrepancy coefficient (U_0), and Mean Absolute Percentage Error (MAPE) (Table 1) indicate a good fit for the time-series data. All calibrated variables produced $R^2 > 0.90$, indicating a strong replication of the historical data by the model [54]. The values of U_0 range from 0.007–0.074 (0.7–7.4%), which are all within the thresholds for a good model fit [34, 36]. *Packaged food production*, *Urban population*, *Trade agreements* and *Women employment* have MAPE < 10%, representing a very accurate prediction, whilst *Food trade* (18.0%) represents a very reasonable prediction [43, 44] (equations are provided in Table 2S in the supplementary material).

Table 1 Statistical performances of variables

Variable name	Coefficient of determination (R^2)	Discrepancy coefficient (U_0)	Mean Absolute percentage error (MAPE)
Packaged food production	0.992	0.023	8.99
Urban Population	0.997	0.007	1.21
Food trade	0.964	0.074	18.0
Trade agreements	0.996	0.028	9.13
Women Employment	0.910	0.025	4.60

Sensitivity analysis

The outcome of the sensitivity testing on the two indicator variables, *Packaged Food* and *Food Trade*, are summarised as tornado plots in Figs. 4 and 5, respectively. These plots show that the most sensitive parameters for both indicator variables are dominated by dimensionless multipliers, re-affirming that these variables are likely sources of most significant uncertainty in this (and other) SFM.

Of the non-dimensionless multiplier variables tested, *Normal employment women* had the most significant influence on both indicator variables, followed by *Initial packaged food production rate*, *Initial urban population* and *Normal urban population*. A feature of these variables is that they are inputs into the R1 loop via balancing loops B1 (*Initial urban population*, *Normal urban population*) and B2 (*Normal employment women*, *Initial packaged food production rate*).

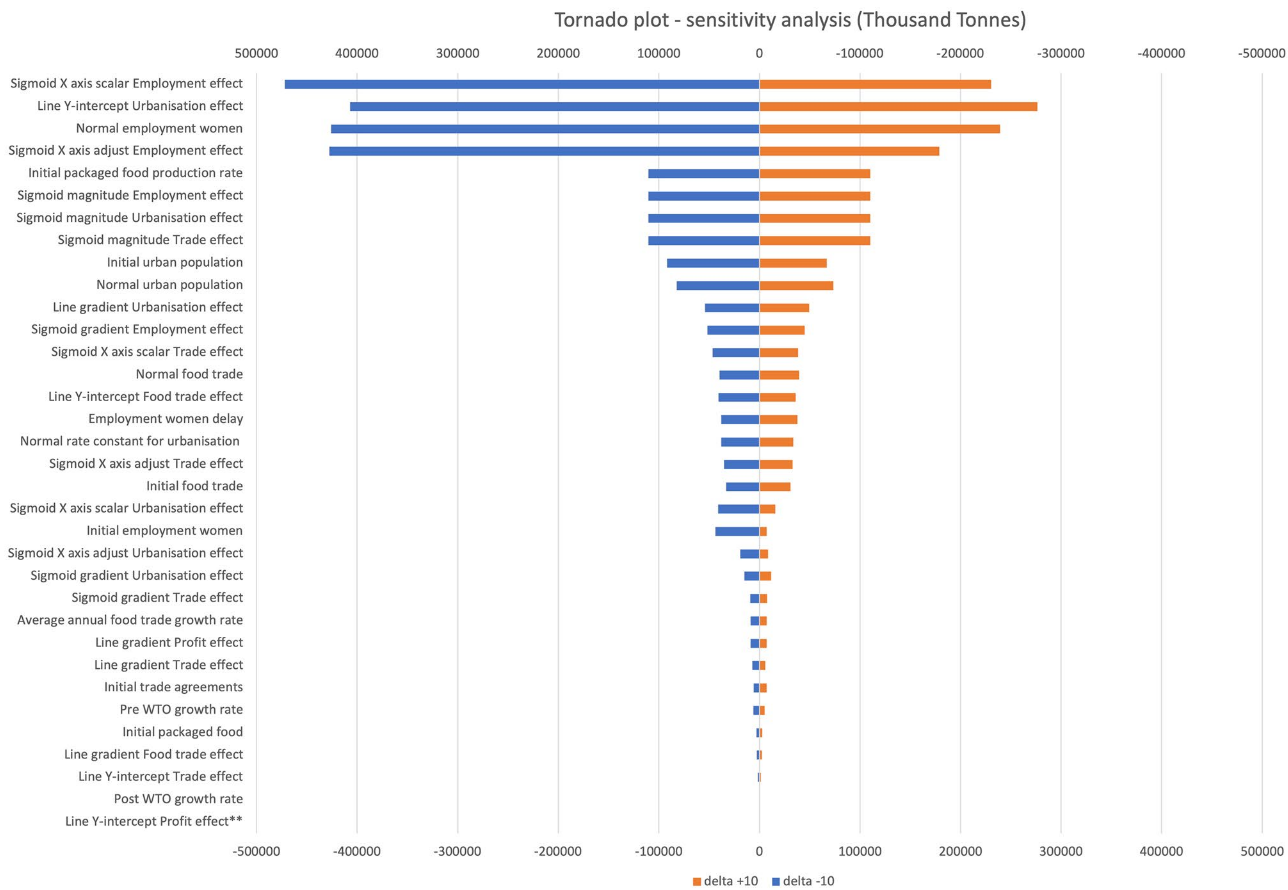

Fig. 4 Tornado plot of the sensitivity testing (Packaged Food). Parameters associated with a dimensionless multiplier are pre-fixed with 'sigmoid' or 'line' to indicate the type of function

In addition to evaluating the impact of parameter uncertainty on the model's performance, a sensitivity analysis can also aid the selection of variables used in the scenario analysis (the following section). We use the *Average annual food trade growth rate* as the primary variable for the scenario analysis because it relates directly to our focus on the globalisation subsystem. More importantly, it is the most sensitive parameter of the globalisation subsystem that is not (1) a tacit parameter belonging to a dimensionless multiplier or (2) a variable that could lead to counterfactual model outputs. Whilst the dimensionless multipliers dominate the sensitivity analysis (Figs. 4, 5), their utility for meaningful scenario analysis is questionable because they are difficult to define or translate into an intervention or policy. Other (non-dimensionless) sensitive variables are either an initial condition (*Initial urban population, Initial packaged food production rate*) or a historical reference variable (*Normal urban population, Normal employment women*), and therefore, manipulating these would cause the model to produce counterfactual outputs when backcasting.

Model limitations

The SFM presented is a quantified version of a dynamic hypothesis for the food packaging system. The SFM attempts to explain the dynamic behaviour of key variables (represented by time-series data) through our interpretation of the system's structure. However, we acknowledge that the model is based on a series of assumptions and is, at best, a simplification of reality. However, consistent with the objectives of a systems approach to hypothesise the system's structure from the data, it captures the core dynamic behaviours of crucial system variables.

This study adopted a reflective mode, meaning that model testing was used to uncover flaws and expose assumptions for critique and improvement in future studies [18]. Contrary to a protective mode, which aims to prove a point (but hides assumptions, for example), this study promotes inquiry and contributes to more formal quantitative modelling of cross-scale analysis of macro-trends in food systems.

The SFM successfully replicates the historical data's modes of behaviour, as demonstrated in Fig. 3. This is further substantiated by the measures of fit detailed in

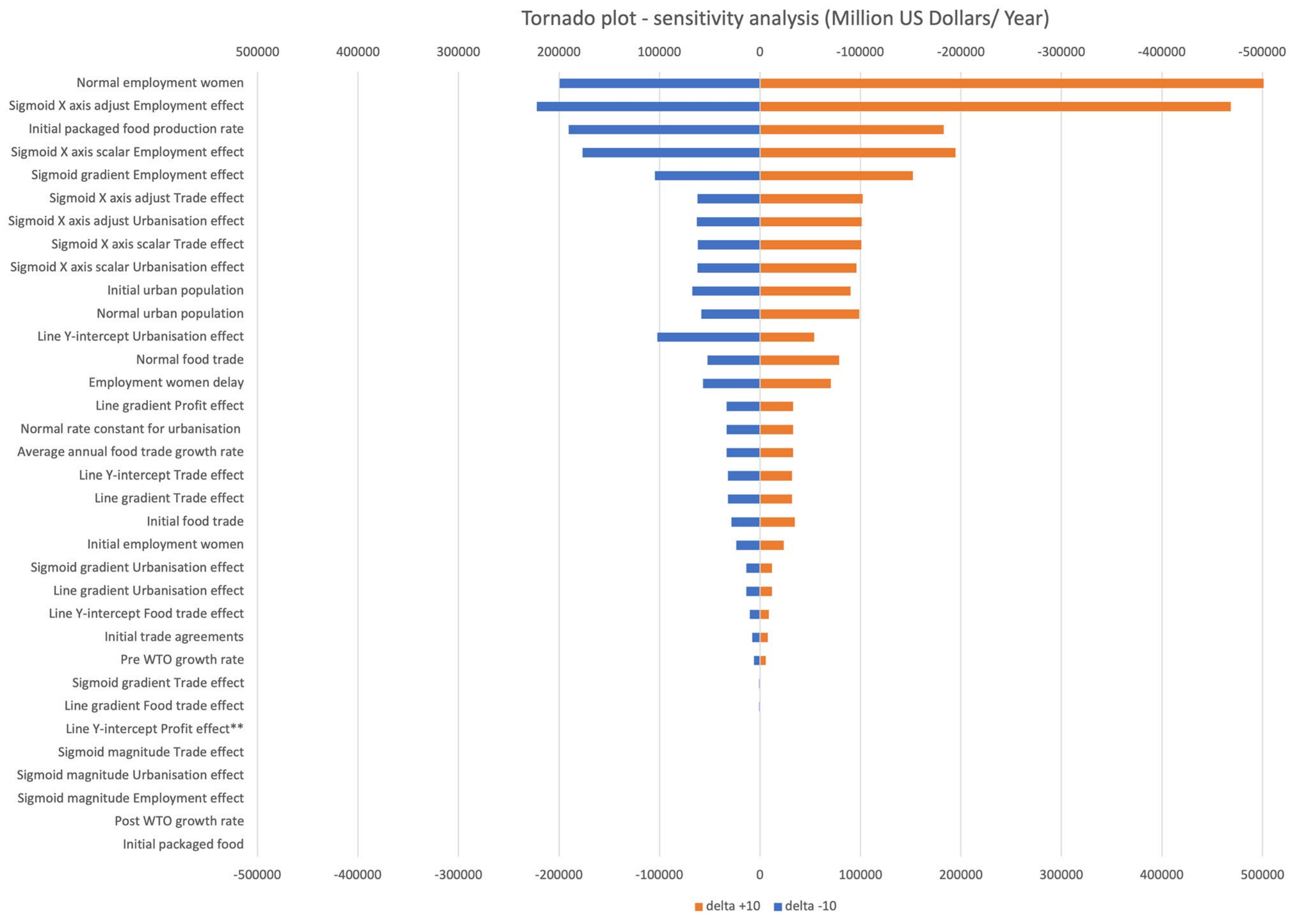

Fig. 5 Tornado plot of the sensitivity testing *(Food Trade)*. Parameters associated with a dimensionless multiplier are pre-fixed with 'sigmoid' or 'line' to indicate the type of function

Table 1. However, it is essential to clarify the definition and scope of the *Packaged food* stock depicted in Fig. 3a. In this study, the US Environmental Protection Agency's (EPA) definition of containers and packaging in municipal waste streams as a proxy for the packaged food stock was adopted. This category encompasses a variety of materials, including glass, steel, aluminium, paper and paperboard, and plastics. Typical examples of these packaging products are soft drink bottles (made of glass), cans (aluminium), and various bags and wraps (paper or plastic). It is crucial to note that the US data, as illustrated in Fig. 3a, only accounts for containers and packaging that end up in waste streams (i.e. unmanaged packaging materials that might, for instance, end up in the environment are not included). Thus, while the model aligns well with available historical data, the actual extent of packaged food production and consumption could be underestimated due to this limitation in the data.

Through the development of the SFM, this study highlighted the importance of including dimensionless multipliers (as graphical functions) in the model testing stage of the systems approach. Sensitivity analysis is a primary test for stock and flow modelling and has almost exclusively centred on testing auxiliary variables (parametric approach), often through a univariate approach [18, 33]. In systems modelling, sparse attention has been given to the sensitivity of the model behaviour to uncertainty in graphical functions [33]. In this study, much of the uncertainty in the SFM stems from the use of dimensionless multipliers. It, therefore, points towards these as potential leverage points (or at least points in the system where further research is required).

This study endeavoured to include the dimensionless multipliers in a structured sensitivity analysis, acknowledging that whilst these variables are central to the systems approach [33], they also introduce significant uncertainty. Using dimensionless multipliers (often graphical functions) in systems modelling enables the exploration of important interconnected concepts [33]. However, with this use comes the need to include these in calibration and sensitivity analysis – our study has shown that their presence is the primary source of uncertainty. We provide a template for this by utilising the equation forms of these variables, e.g. linear and sigmoid functions. Additionally, a potential limitation of our sensitivity analysis is that it was constrained to a univariate (one-variable-at-a-time approach). While multi-variable sensitivity analysis can be used [55], an univariate approach is almost universally applied in system dynamics models [39, 56].

Moreover, stage five of Sterman's systems method is 'policy design and evaluation'. This is where a range of management scenarios are tested and analysed using the SFM. Scenarios should have a narrative accompanying them [57] and represent different possible future outcomes [58, 59]. Scenario analysis of stock-and-flow models enables comparisons across distinct scenarios and aims to illuminate the potential impacts of strategic interventions within a system. This study focuses on the exploration of the socio-economic drivers (behaviour over time and dynamics of the subsystems) of packaged food and does not include a scenario analysis; however, by manipulating key input variables, future studies could explore which interventions could lead to a reduction of packaged food, offering insights into more sustainable practices within the context of global food trade. Nevertheless, in the Discussion (section "Discussion"), a range of interventions that could reduce packaged food production and consumption are presented. Specifically, section "Discussion" discusses some degrowth solutions that have the potential to reduce reliance on packaged food, as outlined in the qualitative study by Chakori et al. [29].

This study provides information on the steps used to build the model, the equations and the datasets used. While limitations to the current model exist, future studies could expand and explore the macro socio-economic drivers of packaged food and further investigate leverage points, potentially, through scenario analysis and other systems approaches.

Discussion

Systemic change is defined as a fundamental change in the way the system is structured, and it can include, for example, the formation of new variables, changes in feedback loops, the reorganisation of network interactions, abrupt changes in functions and parameters, or changes in the spatial and temporal interactions [19]. This study stresses the importance of understanding the systemic drivers to explore systemic change possibilities.

Various studies and institutional reports emphasise consumers' responsibility to reduce, recycle, and choose more sustainable packaging options [60–63]. Individuals are encouraged to take 'small steps' towards a more sustainable lifestyle. In line with other research that emphasises the significance of examining food systems transformations by considering a diverse array of socio-economic factors [14, 15, 17], this study seeks to shift the conversation away from individual-focused solutions towards systemic and structural approaches. It is important to recognise that there are other avenues for transforming food systems. The following sections discuss in more depth some drivers and potential approaches that could help curb the production and consumption of packaged food. As presented below, the growth-driven economy is responsible for the dynamics of the current system. Therefore, with the intent to explore new socio-economic configurations and to respond to the increasing demands for food systems transformation, the discussion includes degrowth-aligned proposals that broaden the scope of potential interventions that could be employed to reform current food system practices. Table S3 in the supplementary material summarises the degrowth proposals and the SFM variables that could potentially be affected.

Globalisation: toward systemic and structural solutions

Since the 1960s, there has been a noticeable acceleration in the penetration of trade and large corporations worldwide [1, 64]. This period marks a significant shift in both the scale and geography of the food economy. Consequently, packaging has become an integral component essential for the transportation of food across global supply chains [52, 65, 66]. The globalisation subsystem of the SFM (green, Fig. 1) shows a reinforcing feedback loop R1 that characterises the increasingly open global food market driven by economic growth and trade policies (i.e. driver *Trade Agreements* influencing trade flow into the *Food Trade* stock) [66]. This subsystem captures the role of governments in promoting globalisation, incentivising imports and exports through increased free trade agreements.

With the establishment of the World Trade Organisation (WTO) in the mid-1990s and the suite of bilateral, multilateral and regional trade agreements (RTAs), food systems experienced an increase in international food trade and foreign direct investment (liberalisation) [67]. The *Trade agreements* stock in the model represents the increasing number of trade agreements, which is then used to drive increased global food trade. Trade agreements (e.g. RTAs) play a crucial role in international trade relations and, over the years, have increased in number, depth and complexity [68]. This stock modulates two distinct periods of linear growth (Fig. 3b). The first corresponds to the growth period preceding the establishment of the WTO (1960–1995), and the second corresponds to a higher growth period during the post-establishment period (1995–2020). Trade liberalisation, which involves the reduction of trade barriers, plays a significant role in fostering economic growth. Economic growth is achieved through several mechanisms, such as increased export opportunities in overseas markets, the attraction of foreign direct investment, and the reduced cost of imported goods [67]. Trade liberalisation agreements typically work towards diminishing tariff and non-tariff barriers, facilitating the movement of finance, technology, raw materials, and finished products across international borders [23, 67]. As a result, such liberalisation efforts significantly influence the likelihood of businesses entering, exiting, or sustaining their operations in the global market [69]. Furthermore, trade costs for both manufactured and agricultural products have seen a decline, attributable to changes in trade agreements (specifically tariff cost reductions) and transportation costs [66]. Free trade agreements expand global market opportunities for US producers and exporters [70]. The existing neoliberal capitalist ideological structure underlying the contemporary global food system treats food as a commodity to exchange, not a human need [71]. The meaning of ideology is the subject of extended debate, but this study adopts the definition of ideology as an underlying means to maintain a specific order of social interaction [71] – or mental models in systems thinking [18, 32]. Thus, to stimulate economic growth (i.e. GDP), countries reduced trade policy barriers [66].

The forces of globalisation are encouraged by free-market trade and capital flow [24]. Thus, the profit-driven private sector influences the *Food Trade* stock in loop R1. In the current growth-driven economy, the penetration of transnational corporations (TNCs) has led to a dramatic increase in the production and distribution of highly processed (packaged) foods [1, 29, 72]. Since the 1980s, TNCs' profits have increased exponentially and continue to depend on cheap ingredients and ultra-processed food products [73]. This phenomenon is represented by the feedback loop R1 in our model. Consequently, the *Trade flow (Import + Export)* in Fig. 1 is significantly influenced by the interests of TNCs. This dynamic underscores the critical role of private sector incentives in shaping global food systems and trade patterns. The global supply chain tends towards oligopoly, with a relatively small number of TNCs dominating the food economy [73]. The revenues of food corporations (e.g. Kellogg's, Unilever, Nestle, PepsiCo, Mondelez/Kraft, Coca-Cola, Mars, Danone, Associated British Foods, General Mills) amount to billions of dollars a day [21, 73]. TNCs monopolise local food systems and out-compete small producers through trade and market liberalisation [24]. This results in longer and more complex food supply chains that require packaging for transport and delivery (i.e. *Effect of food trade on domestic small scale food production and consumption* variable, Fig. 1).

The degrowth literature offers various policy suggestions to increase the sustainability of the (food) economy [29, 74]; [75; 76]). Some degrowth proposals include tools to shift the responsibility to producers, including taxing waste generation, environmental externalities and resource use, removing subsidies for resource extraction, and creating bans on harmful technologies (e.g. disposable packaging). These policies (i.e., Table S3 in the supplementary material) would help reduce social and ecological costs, or at least lead producers to internalise them. Internalising these costs would lead to a decrease in profit as a consequence. A degrowth economy would prioritise not-for-profit food systems [74].

Other possible changes include government regulations that could affect globalisation dynamics. Governments could disincentivise the global food trade of non-essential products (e.g. some ultra-processed food), reducing the need for food packaging. However, the opposite continues to happen. The saturation of markets in Global North countries has prompted TNCs to invest in low and middle-income countries, expanding their market for processed food [66, 77]. These mechanisms displace traditional diets with more processed, packaged products [78]. Thus, a not-for-profit food economy that serves human needs and not the growth-driven imperative might limit the market's expansion. Moreover, to counterbalance the globalised food economy, policies should promote the use of local resources, limit trade distances and volumes. The re-localisation of food production and consumption is one of the central objectives of degrowth [79, 80]. Re-localisation could be implemented to create bioregions and local networks, coherent social-spatial units that maintain self-sufficiency and autonomy in food production and consumption [80, 81].

Urbanisation and household dynamics: additional systemic and structural solutions

While this study primarily concentrates on the dynamics of the globalisation subsystem, it is crucial to recognise the significant impact that both urbanisation and the household subsystems also have on food systems. These subsystems, interlinked with globalisation, can exert considerable influence on food systems. For example, TNCs influence consumer preferences and consumption of packaged food due to their production capabilities and advanced marketing strategies, thereby making society dependent on global food supply chains [24]. Exposure to their commercial marketing and convenient, ready-to-eat products reduces home food preparation [23]. Thus, packaging symbolises the perpetuation of the growth-driven economy and is not a consumer responsibility issue only. The growth-driven economy relies on continually expanding consumer demand [82]. Understanding these interactions is critical to developing a comprehensive view of the challenges and opportunities within food systems.

The urbanisation subsystem (Fig. 1 - brown) is another crucial driver of changes in consumption patterns and the transformation of food systems [26]. The demand for food is affected, for example, by changes in the total population (i.e. population growth drives the demand for and trade of food in terms of volume) and demographic changes (i.e. population distribution affects food consumption patterns and composition) [66]. As the population becomes urbanised, with people moving and living further away from agricultural production areas, the demand for food processing rises, as food needs to be stored and transported over longer supply chains [26, 66]. Longer supply chains involve increased use of food packaging. By 2050, 68% of the world's population is projected to live in urban areas [83]. However, in this study, we do not provide an in-depth discussion on the changes in the urbanisation subsystem because the importance of urbanisation may be diminishing with the increased penetration of TCNs' supply chains into rural regions [23].

Nevertheless, here we highlight the fact that in urban settings, there is less ability, time and desire to prepare food at home, which leads to increased consumption of convenient packaged food. Since the 1960s, adults in the US have decreased food consumption at home and reduced time spent cooking, increasing consumption of ready-to-eat meals or food requiring minimal or no preparation [84]. Contrary to cooking 'from scratch' - using basic ingredients - home cooking often translates into heating pre-processed food [84, 85]. Adults in the US appear willing to spend only about an hour a day cooking, which translates to approximately 20 minutes per meal [84, 86, 87]. Time has been reported as the major barrier to preparing meals, which prompts people to 'buy' time by relying more heavily on packaged and convenience foods (e.g. pasta sauce jars, frozen pizzas) [13, 88–93]. Earners have to balance productive work and reproductive work [94]. Complementary to productive work, which refers to working for an income ('outside the home'), reproductive work relates to unpaid work ('inside the home'), which includes food preparation [94, 95]. Households have less time for food work due to an increased number of adults involved in productive work [1, 23, 78, 85, 94, 96, 97].

The household subsystem (Fig. 1 - blue) represents the influence of labour time on the increase in packaged food consumption, particularly regarding female participation in the workforce. In urban areas, the rate of people entering the workforce is driven by the increasing need for a higher income [24]. Urbanisation has also resulted in higher female labour participation [78] (i.e. *Effect of urban population on women employment* variable, Fig. 1). The model represents the influence on female labour participation using a stock for *Women employment*, which influences *Effect of employment women on packaged food production rate* (Fig. 1). The increased percentage of women's employment and the associated shift to dual-worker households influence family meals, as well as the opportunity cost of women's time. There has been a shift away from time-intensive food preparations towards an increase in the demand for processed, precooked, convenience food at home, fast food and snacks for outside meals [1, 23, 78, 85, 96, 97]. There is a negative correlation between trends in women's employment and non-market work (e.g. cooking) [85]. Moreover, a non-equitable distribution of household work between men and women persists across the world [98]. The consumption of packaged 'convenient' food should also be analysed from a feminist political economic perspective, which looks at how work-life balance, employment and gender relations influence food habits [94]. In the US, even if men are increasingly playing a role in the kitchen, they have not increased their cooking hours enough to compensate for women's decreased hours, and a gender gap in performing these tasks persists [98, 99]. As a consequence, packaged food increasingly represents the bulk of store purchases [84, 100], and there has been a shift towards increased grazing and snacking (e.g. portable pre-packaged snacks) instead of meals [86, 101].

Therefore, although the focus of this study was on the globalisation subsystem, addressing aspects of the household and urbanisation subsystems is also important. Strategies in row no. 3 and 4 (Table S3 in the supplementary material), present propositions that could potentially reduce *Packaged food* if time availability increases. Generally, policies that reduce working hours, such as limiting mandatory overtime, implementing flexible work, and sharing work or basic income mechanisms, can boost people's ability to prepare healthy food at home with more time available. Time is required to cook from natural, package-free, local ingredients and accomplish tasks such as growing or purchasing food, especially if food shopping entails visiting many local, decentralised stores [94]. Degrowth proposals call for reprioritising social reproduction and food work [94, 102–105]. Additionally, improving a better work-life balance for everyone (i.e., reproductive and leisure time) would help reduce the gendered division of food preparation, which is a requirement to reduce women's employment and domestic duties overload. Easy steps to implement include formal (e.g. school courses) and informal promotion (e.g. family education, general advertising) of food work among boys and men can increase their involvement in domestic cooking [106, 107].

Conclusion

While the real world presents complexities beyond the scope of any model, the SFM presented illustrates the interplay among globalisation, urbanisation, and household subsystems in perpetuating a food system heavily reliant on packaged foods. Future studies could explore the model further to investigate leverage points, potentially, through scenario analysis and other systems approaches. Yet, it is clear that the reliance on packaged food is a symptom of a broader, growth-driven, globalised, food system, where packaged food is merely the tip of the iceberg.

Urgent actions are required to enhance the sustainability of food systems. Reducing global food trade, for instance, could significantly decrease the demand for packaging. The interplay between market forces and human choices is a dynamic process; markets shape preferences, and consumer choices influence market structures. As Lane and Husemann [108 p. 51] wrote: "If globalisation is inevitable, then why is so much human action necessary to create and maintain the structures for free trade? History indicates that "free" markets do not arise by chance, but by deliberate and sustained intervention. Conversely, as people experience it, is globalisation upheld solely by the momentary wishes and interpretations of human agents?" Complex systems are not beyond the influence of human agency and responsibility.

The urbanisation and household components of our model shed light on the unintended consequences of consumer choices within the intended purpose of the growth-driven economy. Time poverty leads people to opt for packaged food. A socio-economic reorganisation is necessary to incentivise the consumption of fresh, unpackaged food. Simple measures like encouraging recycling are insufficient; a more fundamental shift towards better work-life balance can significantly enhance food preparation practices, reducing reliance on packaged foods. Degrowth-aligned food strategies warrant more attention and the responsibility for transforming the food system should be a shared endeavour involving governments, businesses, communities, and individuals. The challenge of packaged food reduction requires collective action and extends beyond individual responsibility.

Supplementary information

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Supplementary Material 1

Author contributions

S.C: Conception and design of the project; Acquisition of research data; Modelling; Contribution of knowledge; Drafting significant parts of the publication. A.A. A: Conception and design of the project; Supervision; Critically revising the manuscript. R. R: Conception and design of the project; Supervision; Modelling; Contribution of knowledge; Drafting significant parts of the publication.

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Data availability

All data generated or analysed during this study are included in this published article and its supplementary information files. Clinical trial number: not applicable.

Declarations

Competing interests

The authors declare no competing interests.

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