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A meta-network analysis of methodological specifications for system dynamics modelling application in agricultural food systems

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A R T I C L E I N F O

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A B S T R A C T

This paper aims to review existing applications of system dynamics modelling in agricultural food systems and draw insights from the various modelling procedures in order to highlight best-practice guidelines on methodological specifications for SD modelling. A meta-network analysis was used to identify existing studies that have applied SD modelling in agriculture. Using an algorithm that automatically clusters closely connected research articles based on Boolean search strings that look at the title, keywords, abstract, and digital object identifier (DOI) of the journal articles, 354 journal articles were selected for in-depth content analysis.

Based on the synthesised trends, two criteria for determining the type of modelling process and model type to apply for the model conceptualisation step are: (*i*) the immediate end goal of the modelling process, and (*ii*) data availability. Participatory modelling is appropriate when there is limited data and model outputs will inform the implementation of interventions by stakeholders. For action research focusing on well-researched food systems with substantial data available, the semi-participatory modelling process can be adopted, and quantitative SD models can be solitarily used. A key contribution of this paper is the proposed procedure for emergent participatory scenario development within the system dynamics modelling process.

1. Introduction

Since the advent of Jay Forrester's system dynamics modelling as an analytical procedure for understanding complex adaptive systems in the late 1950s, and the subsequent publication of his book on Industrial Dynamics in 1961 (Forrester, 1997), there has been growing interest in the application of system dynamics in different fields. Agriculture is one of the fields that has seen a surge in system dynamics modelling applications. A prerequisite analytical skill for system dynamics modelling is systems thinking. Systems thinking provides the conceptual framework essential for understanding the structure and behaviour of systems (Sterman, 2000, p.4). Following a review of various definitions in the literature, Arnold & Wade (2015) defined systems thinking as an analytical skill to understand systems and predict behaviours. Notably, system dynamics modelling enables the realisation of the predictive aspect of systems thinking.

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However, there has been a bipartition among agriculture researchers about systems thinking as an epistemological tool (Bland & Bell, 2007). Researchers with the opposing stance state the limited integration of human behaviour in existing system dynamics models as a key drawback (Meijer et al., 2021). Nevertheless, with advances in the development of sophisticated software that support system dynamics modelling, coupled with the rising need to capture feedback effects, the unintended consequences of interventions, and the complexity in systems which are required for effective decision-making, the application of system dynamics (SD) modelling in different research fields has increased (Currie et al., 2018).

Gradually, the idea of systems thinking has grown among practitioners, policymakers, and researchers. Given that everyone uses mental models at some point in various analytical spheres, the popularisation of system thinking has aided in the concretisation of these mental models (Currie et al., 2018). The rise in SD modelling applications in agriculture relates to its ability to capture feedback, time delays, and dynamic behaviour (Muflikh et al., 2021); highlight production flow and facilitate ex-ante impact assessment (Aboah & Setsoafia, 2022; Rich et al., 2018a,2018b), and serve as a decision support tool (Aboah & Bahta, Wanyoike, et al., 2022; Wang & Davies, 2015). With SD modelling, an analyst can holistically investigate problems, assess the system's constantly changing behaviour, and estimate future (long-term) effects of decisions (Kazancoglu et al., 2021).

At the heart of system dynamics modelling is the exploration of potential futures (Meadows, 2008, p.47), a process facilitated by scenario development. Consequently, various approaches have been utilised in this endeavour. Among the spectrum of scenario planning methodologies—including probabilistic modified trend, La Prospective, and intuitive logic (Cordova-Pozo & Rouwette, 2023)—system dynamics modelling particularly aligns with the probabilistic modified trend approach. This connection is rooted in the exploration of causal relationships within SD models and the use of simulation and sensitivity analysis for evaluation. Although it shares common ground with the La Prospective approach in embracing both qualitative and quantitative techniques, system dynamics modelling distinguishes itself by enabling the determination of probabilities based on objective criteria rather than subjective assessments. The challenge in scenario development lies in seeking coherence and internal consistency (Gordon, 2020) while ensuring objectivity within the formulated scenarios amidst stakeholder participation (Cordova-Pozo & Rouwette, 2023). Needed is an approach that objectively identifies key drivers (Dhami et al., 2022) while accounting for the variability of impact and uncertainty to update the scenarios generated.

Moreover, despite the increase in the application of system dynamics modelling within the food and agricultural system contexts, no unifying framework exists to enhance the replicability of SD modelling procedures. Review studies that examined SD modelling applications in agriculture mostly focused on thematic areas like value chains (Muflikh et al., 2021), agri-food systems (Monasterolo et al., 2016), and policy decision-making in environmental health (Currie et al., 2018). Muflikh et al. (2021) reviewed the rationale for the application and operationalisation of system dynamics modelling for agricultural value chain analysis. Although the study offers an overview of the modelling process and emphasises the need to translate dynamic hypotheses into quantitative models to facilitate the evaluation of leverage points within the system, the procedural steps for achieving this are not covered. While Monasterolo et al. (2016) reviewed the performance and characteristics of the application of system dynamics modelling for climate smart agriculture, Currie et al. (2018) focused on the application of system dynamics modelling for policy and decision-making and explored the thematic issues addressed within an environmental health context. Missing in these reviews is the methodological specification for the application of SD modelling in agriculture and food systems. Hence, there is a need to harmonise how the modelling procedures are documented and implemented to enhance the replicability of SD models and inform future SD modelling applications in the agricultural sector.

This paper aims to review existing applications of system dynamics modelling in agricultural food systems and draw insights from the various modelling procedures employed to highlight best-practice guidelines on methodological specifications for SD modelling. A key contribution of this paper is the proposed procedure for emergent participatory scenario development within the system dynamics modelling process.

2. Methodology

2.1. Meta-network analysis

A meta-network analysis was used to select journal articles that have applied SD modelling in agricultural-related research, and to extract inferred data from these articles. The meta-network analysis followed four steps (Aboah & Lees, 2020) as shown in Fig. 1. These steps include the preliminary search, consolidation of articles, network analyses, and content analysis of the networked journal articles. The purpose of the content analysis was to collate inferred data from each journal article extracted from the network analysis. The inferred data covered the following methodological specifications: central theme, study area, modelling process, software usage, modelling type and structure, time step, scenario development procedure, data type, and simulation run.

Step 1; Preliminary Boolean search with inclusion criteria: Three bibliometric databases[1] – Scopus, Web of Science, and Science Direct were selected for the first step. The Boolean search string was used to search journal articles from the title, abstract and keywords of the Scopus and Science Direct databases, and the topic[2] section of the Web of Science database. The Boolean search string was:

("system dynamics" OR "systems thinking" OR "causal loop diagram") AND ("Agri*" OR "Food" OR "Crop" OR "Meat" OR "Animal" OR

[1] Although Google Scholar provides a comparatively broader coverage than Scopus, web of science, and Science Direct, it was not included because it is not considered a traditional bibliometric database (https://harzing.com/resources/publish-or-perish/tutorial).

[2] The title, abstract and keywords are captured as topic in the web of science database.

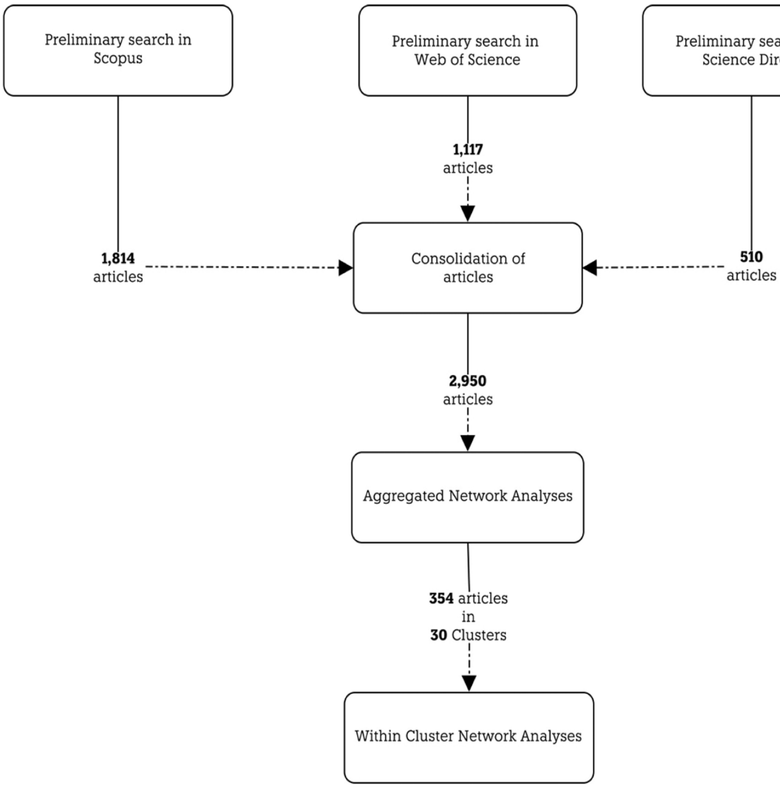


Fig. 1. Methodological framework for the meta-network analysis.

"Livestock"). The preliminary search yielded 2391 articles in the Scopus database 1444 articles in the Web of Science database, and 537 articles in Science Direct. After limiting the search to only journal articles published in the English language, the search resulted in 1814 peer-reviewed articles in the Scopus database, 1116 articles in the Web of Science database, and 510 articles in the Science Direct database.

Step 2; Consolidation of duplicate articles:

Articles with duplicates were identified using the digital object identifier (DOI) in the compiled list from step 1, and copies of the duplicated journal articles were deleted. In total, 2950 journal articles were combined from the three databases.

Step 3; Network Analysis:

The network analysis was performed in the Vosviewer software®. The unit of analysis was the journal articles. Unlike citation analysis which uses a high number of citations as an inclusion criterion for selecting a journal article, this present paper adopted a network approach that considered the level of connectedness between journal articles discounting the number of citations. This level of linkage (connectedness) was the basis for the network analysis. The information retrieved from the journal articles was used to determine the level of connectedness between two journal articles: (a) citation information: authors, title, year, volume, issues, pages, citation count, source and document type, publication stage, DOI; (b) bibliographical information: affiliation, serial identifiers, PubMed ID, publisher, editors, the language of the original document; (c) abstract: abstract, author keywords, index keywords; (d) other information: references.

A minimum number of citations for articles included in the network analysis was set at zero to allow currently published journal articles with no citations to be selected when the article is connected to other articles. A threshold of 1000 strongly connected journal articles was specified as the number of articles to be automatically selected in the network analysis. The Vosviewer® software selects closely connected articles based on two criteria: (i) forward-looking publication links, as later articles can reference earlier publications, but not vice versa; and (ii) acyclic network structures (van Eck & Waltman, 2014). In total, 354 closely connected articles in 30 clusters were generated in the network analysis. The nodes of the network are the journal articles, and the links represent the connection between two articles based on the bibliographic information. The closeness of the link between two nodes shows the level of connectedness of two articles in the network. The size of the node shows the in-degree centrality of the article in the network. Fig. 2 shows the network of closely connected journal articles included in the meta-network analysis. The colours show the differentiation of cluster themes.

Step 4; Content analysis and coding of inferred data:

All 354 connected journal articles were thoroughly read and inferred data on the key methodological specifications (including the year of publication, study area, central thematic area, modelling process, model type, model validation procedure, data source,

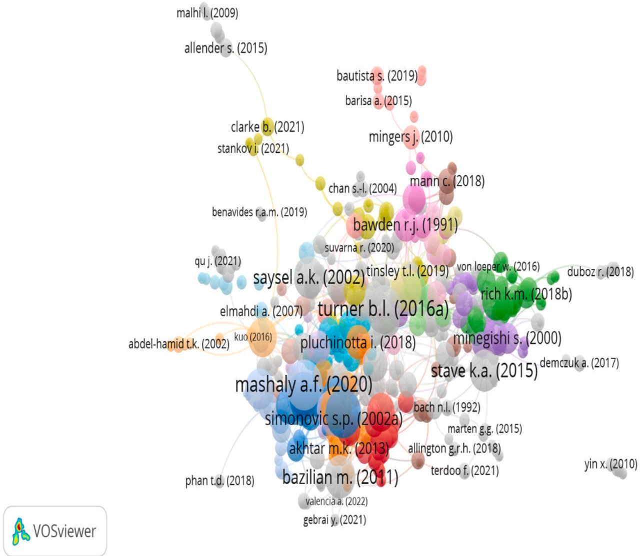


Fig. 2. Network of closely connected articles on SD modelling application in agriculture.

software, model segmentation, scenario development, time step, simulation period and units) were extracted, collated and curated in https://doi.org/10.5281/zenodo.6919643.

2.2. *Empirical analyses*

Using the year of publication as a proxy of the year the research was conducted[3], the methodological trends for the modelling process, model types, software usage, model segmentation, and model validation were analysed. The Fisher's Exact test (expressed in Eq. 1) was used to establish whether: (*i*) the modelling process can be associated with the model types used; (*ii*) the software used for SD modelling can be associated with the model segmentation; and (*iii*) model types can be associated with the model validation process.

$$P = (R_1!.\ R_2!.\ C_1!.\ C_2!)\ /\ N!.\Pi_{ij}\ (a_{ij}!) \tag{1}$$

Where P is the probability of a 2*2 contingency table; (R_1 and R_2) and (C_1 and C_2) are the row sums and column sums, respectively; N is the total number of observations, and Π_{ij} (a_{ij}!) is the product of the factorials of each cell in the 2 * 2 contingency table.

A Simulation Duration Scale (SDS) was estimated as a standardised measure of the simulation runs. SDS (expressed in Eq. 2) was used as a continuous variable to establish the correlation among the different methodological specifications adopted in SD modelling. The time step and SDS were estimated in the same units. Therefore, a model with daily and weekly time steps for a simulation run of 10 years will have an SDS of 3650 and 521.42, respectively.

$$\text{SDS} = \text{Sim}_{\text{duration}} / \text{Time step} \tag{2}$$

3. Results and discussion

The trend in Fig. 3 indicates a modest rise in the application of system dynamics modelling in agriculture from 1990 to 1999 with an average annual publication of eight peer-reviewed articles. The last two decades have witnessed a steady rise in the interest in system dynamics application in agriculture where on average 42.5 journal articles per year applied systems thinking in agriculture-related research were published between 2001 and 2010. However, the period from 2011 to 2021 has seen a very large increase of 210.4 journal articles per year being published that employed system dynamics modelling in agriculture. This trend highlights the growing importance of this methodology in modern agricultural research and thus the need for some guidelines.

3.1. *Synthesised trends of methodological specifications*

The synthesised methodological specifications discussed in the succeeding sub-sections are based on the system dynamics modelling steps (Rieder et al., 2021) illustrated in Fig. 4. For the problem definition and system conceptualisation step, the modelling

[3] Irrespective of the differences in the time it takes to publish an article, the year of publication is used as an objective indicator.

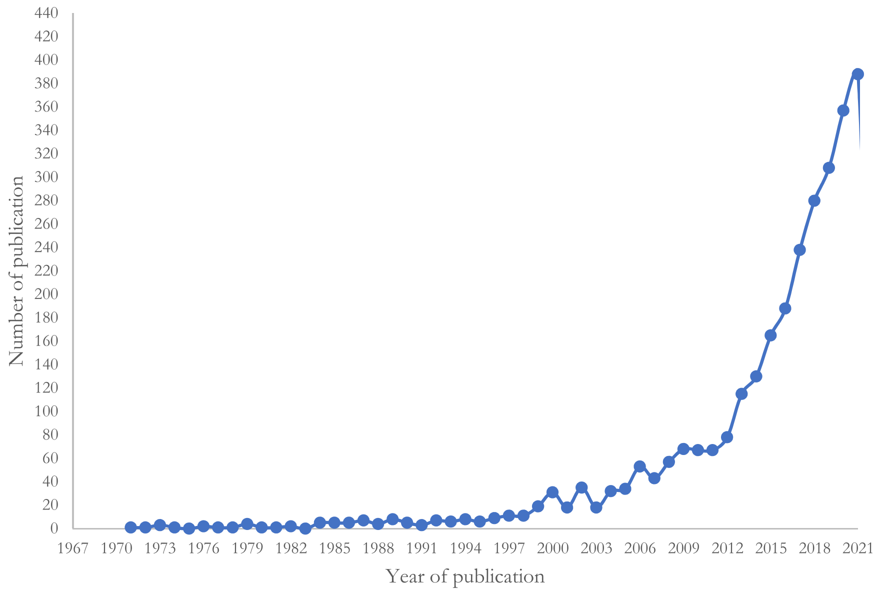


Fig. 3. A trend analysis of SD application in Agriculture.

process and model types applied in the selected articles from the network analysis are presented and discussed. For the model development step, lessons are drawn from the trends of software usage, model segmentation, and simulation specification in terms of the simulation duration and time steps. The trends in the different model validation procedures applied in the selected articles are the basis for proposing best practices for the model validation step. Finally, for the policy analysis step, lessons are drawn from the scenario development process adopted in the selected articles.

3.1.1. System conceptualisation: modelling process and model types

The synthesis of the model types from the selected articles in the network analysis indicates three categories of model types: (*i*) only qualitative model using causal loop diagrams (CLD), (*ii*) both qualitative and quantitative model using CLD and stocks and flow diagrams (SFDs), and (*iii*) only quantitative model using SFDs. Table 1 shows the types of system dynamics models and the modelling process that have been used in the articles. The trends of the types of system dynamics models (Appendix B) indicate that when qualitative and quantitative models were used in a study, the former served as an analytical foundation for the latter.

Results of the trend analysis suggest that the modelling processes applied in SD modelling are on a continuum based on the level of stakeholder inclusion. At the extreme ends of the continuum are the researcher-driven, and the group model building processes. Although participatory system dynamics modelling procedures are well documented, few researchers (13.8 % of 354 articles) adopted a participatory (group model building) approach. The low adoption of the participatory approach can be attributed to the fact that participatory approaches can be expensive. In between the two polar ends of this continuum is the semi-participatory modelling process (described as participatory modelling with a predeveloped model). For this type of modelling process, data triangulation (involving stakeholders' workshops, focus group discussions and experts' elicitation to augment secondary data) was used as a mechanism to incorporate some level of stakeholder inclusion in the modelling process by capturing insights from relevant stakeholders and experts concerning a model. The inclusion of stakeholders in this process also improves the stakeholders' ownership and buy-in of model results (Rich et al., 2018a,2018b).

Results showed that most researcher-driven modelling processes (69.04 %) were based on existing models. Here, data and the availability of an existing model served as the foundation that enabled researchers to begin their modelling efforts. Comparatively, the implementation of the participatory modelling process takes more time and resources than the researcher-driven modelling process. Therefore, resource constraints can be a prime reason for the prevalent use of the researcher-driven modelling process. Studies that were conducted in well-researched fields did not necessarily require a participatory modelling process for the model conceptualisation. However, the results reveal a gradual rise in the use of the participatory modelling process, i.e., group model building and quite recently, the spatial group model building which involves the incorporation of GIS into the group model building process (Rich et al., 2018a,2018b).

Results of a test of association using the Fisher's Exact test (p-value <0.05) indicate that there is a statistically significant association between the modelling process and the model type. This finding affirmed that the non-participatory (researcher-driven) modelling process is more likely to generate quantitative system dynamics models. It is worth noting that the reuse of models (i.e., applying a developed SD model to achieve more than one research objective) was observed in 13.3 % of the synthesised literature. These studies emanated from revised versions or extensions of existing models. Such studies separated the qualitative and quantitative analyses from a developed model in different journal articles. Notable examples include Tan & Yap (2019), and Tan et al. (2020) who looked at the modelling of water, energy, and food nexus in Malaysia. Other examples were Wang & Davies (2015), Pham et al. (2020),

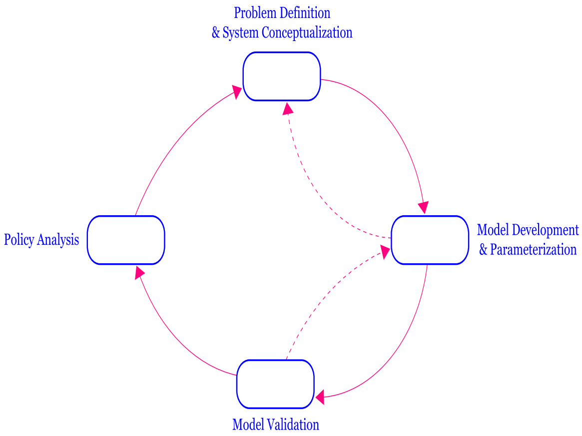


Fig. 4. System dynamics modelling procedure (adapted from Rieder et al., 2021).

Table 1
Model type and the modelling process employed.

Model Type	Non-participatory (Researcher-driven)	Participatory (pre-developed model)	Participatory (group model building)	Participatory (spatial group model building)
Qualitative (CLD)	52	0	23	2
Qualitative & quantitative	0	0	0	0
Quantitative	116	0	3	0

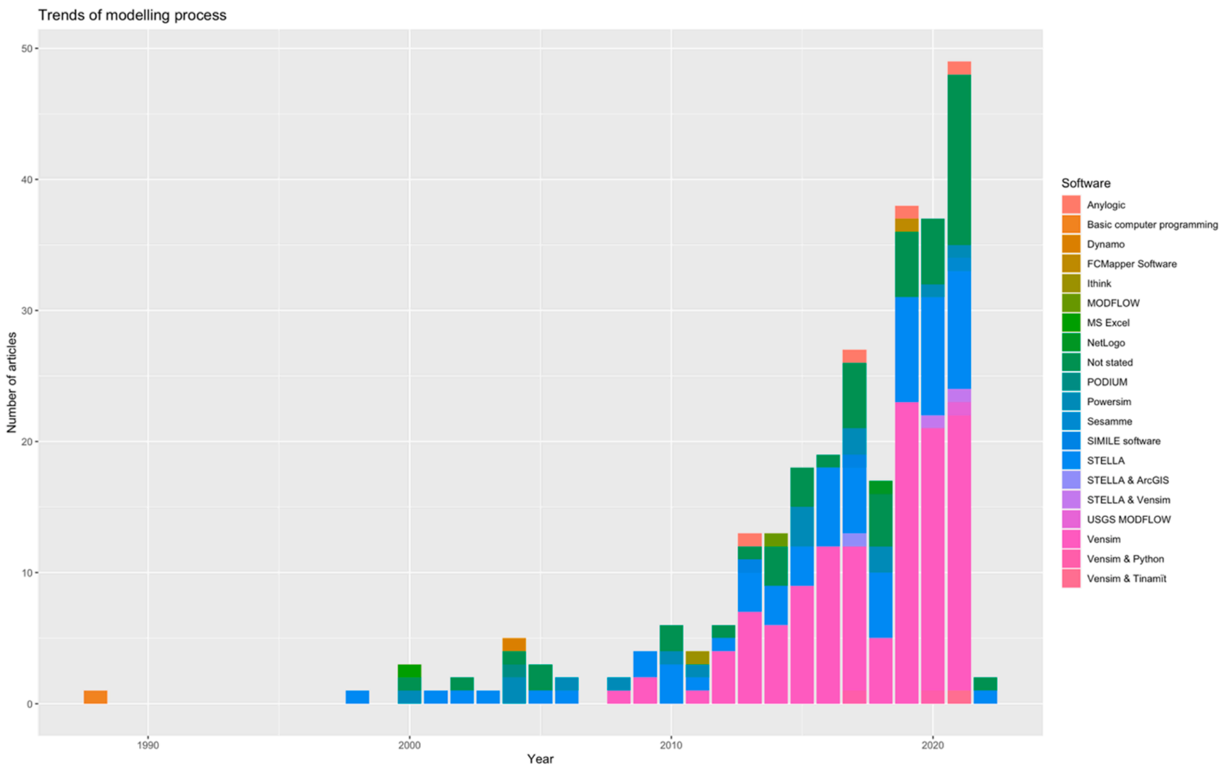


Fig. 5. Trend of software usage.

and Pham et al. (2021).

3.1.2. Model development: Software usage, model segmentation and simulation duration

Proprietary software like STELLA, Vensim, and Powersim have been widely used in SD modelling in recent times as shown in Fig. 5. Vensim and STELLA have relatively user-friendly interfaces and are the most used SD software packages (45.2 % and 21.2 %, respectively). Other software utilised include AnyLogic, FCMapper, Dynamo, MODFLOW, and Mental Modeler. While FCMapper and Mental Modeler are primarily employed for fuzzy-logic cognitive mapping, offering some quantitative modelling capabilities, their capacity for advanced complex simulations is relatively limited compared to widely used software such as Vensim and STELLA. AnyLogic stands out as a unique tool for hybrid modelling, combining elements of system dynamics and agent-based modelling. Results on the software usage for the model development step indicate a steady increase in the use of sophisticated software for performing system dynamics modelling. One of the earliest applications of SD modelling in agriculture is the work by Bala et al. (1988) that assessed the requisite time and volume of water application in an irrigated field. Although SD modelling was still in its infancy in terms of agricultural application, basic computer programming was used to capture the core components of modelling (i.e., causal loop diagram and stock and flow development, model validation and reporting of results).

Model segmentation is useful for documenting the different variable interactions that are aggregated to form the model structure. SD models can be segmented into sectors, components, sub-models, sub-systems, and modules, as shown in Fig. 6. Yet most of the articles reviewed in this paper (60.73 %) did not specify the way the different facets of a complex system were modelled. The results of a Fisher's Exact test of association (p-value <0.05) indicate that the model segmentation can be associated with the software used. For instance, the use of modules as a model segmentation approach is peculiar to the STELLA software.

Fig. 7 shows the trends of the timestep used for quantitative SD models. Results indicate that the annual timestep is the most used timestep in SD modelling applications in agriculture (52.8 %), followed by the monthly (11 %), daily (6.2 %), and weekly (2.5 %) timesteps. Other timesteps used were on biannual and quarterly. Due to the difference in the simulation duration specified in the models, the Simulation Duration Scale (SDS) was estimated as a standardised measure for simulation duration. The mean Simulation Duration Scale of 1742 was estimated from the quantitative SD models[4] included in this study. Thus, for daily, weekly, and monthly timesteps, an average simulation duration (run) of 1742 days, 248.9 weeks, and 145 months were specified, respectively.

The summary results (Table 2) show no statistically significant relationship between the simulation duration and these methodological specifications – modelling process, model type, thematic cluster, study year, and scenario development. As most SD modellers are interested in characterising the long-term dynamic behaviour of a system (Güneralp & Barlas, 2003), one must wonder, how long is considered adequate? Results showed that there is no consensus on the simulation duration. Differences exist in both timesteps and the duration of simulation runs. In some studies, timesteps were either generically defined or not explicitly stated, which hinders the replicability of the study. For instance, Sušnik et al. (2012) and Sušnik et al. (2013) used a generic 452 timestep without specifying what a timestep implies. Specifying the units of measure for the timestep (e.g., year, months, weeks) helps with the correct interpretation of simulation results.

3.1.3. Model validation

Generally, no model validation procedure was specified for studies that used qualitative SD models. Structural model validation with stakeholders is one way that existing studies focused on qualitative SD models have strengthened confidence in the modelling process. For the studies that adopted quantitative SD modelling, over 28 different combinations of model validation tests have been used. These model validation tests included structure validation with stakeholders and comparison of model results with historical data using relative error, MAPE, Theil U, and R^2. A summary of the empirical analysis presented in Table 3 shows that there was no statistically significant association between the year the studies were conducted and the model validation. Studies that used annual timestep tend to compare model results with historical data.

3.1.4. Scenario development in system dynamics modelling

A synthesis of text occurrence network using the title and abstract of selected articles indicates that out of a total of 45,964 different terms extracted from all the articles, only 1406 meet the minimum threshold of 10 appearances. Analysis of the most frequently used terms in system dynamics application in agriculture and food research, shown in Appendix C, indicates that the term "*scenario*" was the most used keyword. Thus, this paper highlights how scenarios have been developed for the policy analysis step of SD modelling and proposes an emergent scenario development procedure as an approach that synchronises scenario development within the system dynamics modelling process.

The trends of how scenarios have been developed for SD modelling application, shown in Fig. 8, highlight the predominant use (90.3 %) of researchers' discretion guided by the literature and their research questions. The formulation of scenarios based on expert opinions, stakeholders' insights, and policy documents are other ways that scenarios have been developed. According to Tiller et al. (2013), scenario development should draw a causal relationship between problems and interventions that are proposed as solutions. Indeed, the results confirm that most of the scenarios have been either developed based on subjectively determined leverage points (Bourgeois et al., 2017; di Vita et al. 2015) or using adaptations of reference scenarios (Murray-Rust et al., 2013; Therond et al., 2009). The use of software packages, like TOPSIS by Karamouz et al. (2013) to support the scenario development process is a good step to

[4] Qualitative SD modelling studies were excluded in this analysis because no timeframe was captured.

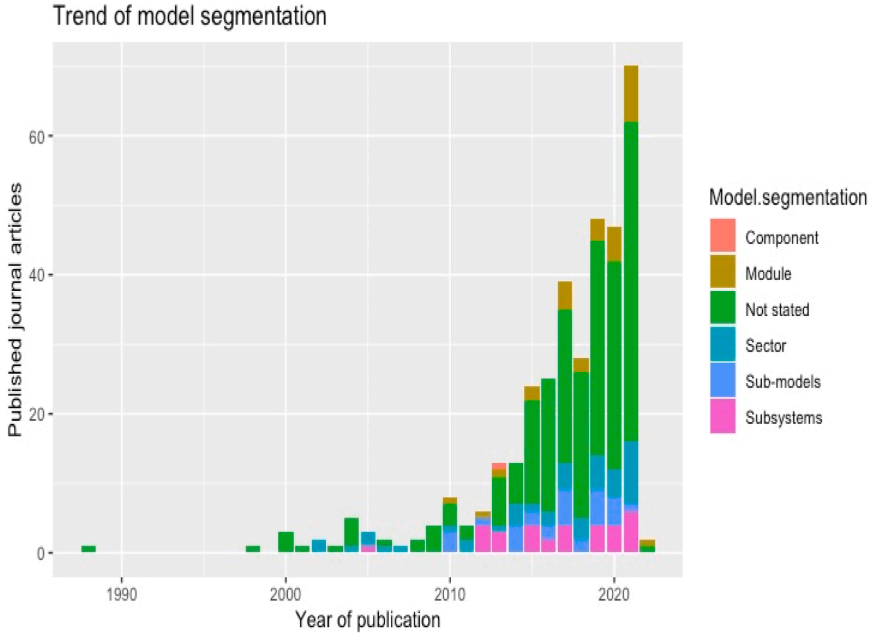


Fig. 6. Ways of segmenting SD models.

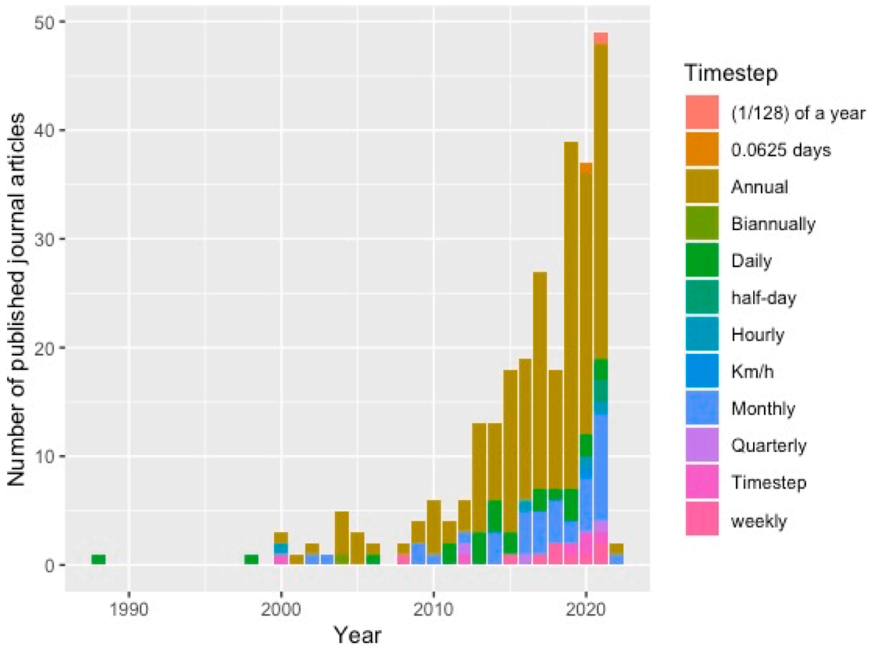


Fig. 7. The timesteps specified in the SD models.

improve consistency checking and robustness of scenario development.

The results show that the researcher-driven scenario development process was the most (97.5 %) common approach adopted in quantitative SD modelling. Sometimes referred to as multivariate sensitivity analyses in SD modelling, the researcher-driven scenario development process involves an exploration of the potential impact of different combinations of parameters (variables) at different alteration levels. This scenario development may suffer from implausibility, a condition that highlights the unrealistic combination of scenarios developed when consistency checks are not applied.

Table 2
Summary results of the test of difference for the SDS.

Focal variables	Kruskal-Wallis H	df	p-value
SDS & Modelling Process	7.00	6	0.3206
SDS & Cluster	38.91	28	0.08243*
SDS & Year	26.93	23	0.2589
SDS & Model type	4.85	3	0.1828
SDS & scenario development	3.00	6	0.8085
SDS & Timestep	107.40	11	2.2e−16***

*** sig at 1 % ** sig at 5 % * sig at 1 %

Table 3
Summary results of the Fisher's Exact test of association for the SDS.

Test variables	p-value
Model validation & Year	0.488
Model validation & Cluster	0.0005***
Model validation & scenario development	0.0005***
Model validation & Timestep	0.0004***

*** sig at 1 % ** sig at 5 % * sig at 1 %

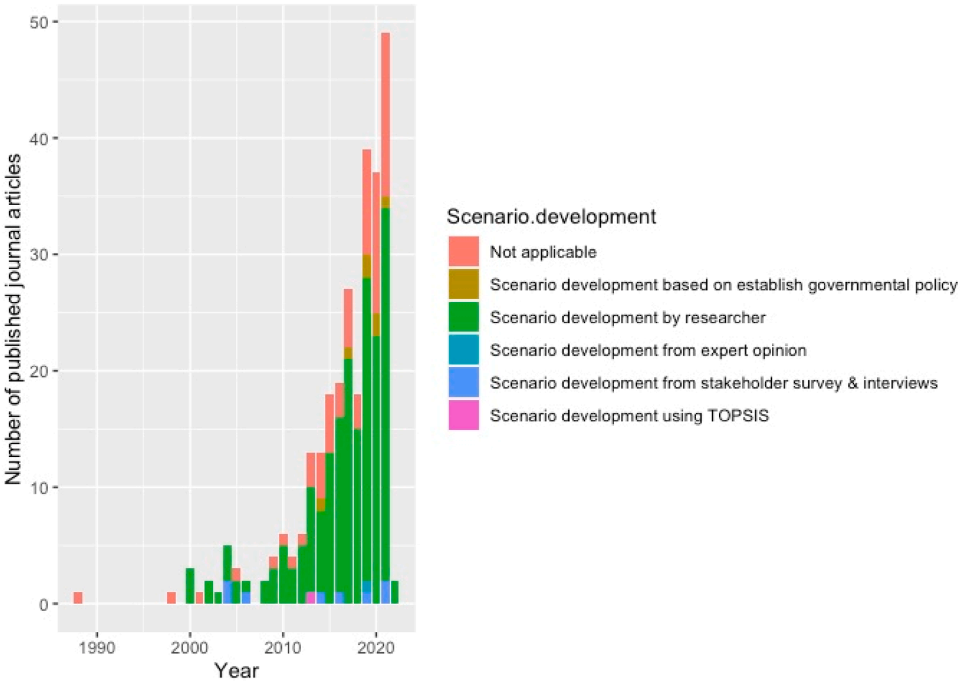


Fig. 8. Trend of scenario development for SD modelling application in agriculture.

According to Bishop et al. (2007), scenario development using systems modelling is the best approach for quantitative assessments. Within this scenario development approach, sensitivity analysis and dynamic scenarios serve as pivotal techniques. Although quantitative approaches use simulation and historical data for scenario generation (Dhami et al., 2022), there is a need to update scenarios based on the changes in the uncertainty and impact over time (van den Berg et al., 2021). The suggested procedures to update scenarios (van den Berg et al., 2021) are not synchronised in the modelling process. Also, the identification of key drivers, which is a crucial step for scenario development, is subjectively determined by analysts (Dhami et al., 2022). System dynamics modelling not only facilitates the application of both sensitivity analysis and dynamic scenarios, but also produces outcomes that identify the key system drivers and their evolving dominance over time, as proposed in the emergent participatory scenario development process.

3.1.5. Emergent participatory scenario development

An integrated framework for emergent participatory scenario development is presented as an analytical framework that can aid in developing intervention scenarios based on quantitatively identified dominant drivers of change in a system and a participatory stakeholder validation process. Unlike other dynamic scenario development processes that begin with a pre-modelling phase where scenarios are qualitatively determined (Therond et al., 2009), the emergent participatory scenario development process begins with a modelling phase to determine the dominant drivers of change for scenario development. The three phases of the emergent participatory scenario development process are shown in Fig. 9 and described in the ensuing sub-sections.

Phase 1 – Integrative Modelling: The first phase involves the integration of qualitative and quantitative system dynamics modelling procedures. The system is mapped out using causal loop diagrams to capture the causal relationships among variables that shape the system structure and behaviour and to highlight the inherent feedback in the system. The causal loop diagram is then translated into a quantifiable model, which is simulated to determine the baseline levels of key indicators. The simulation results also yield the dominant feedback loops.

Researchers can use the Stella Architect software® Loops That Matter analysis to support the empirical determination of dominant drivers, which are the pathways of leverage points (Schoenberg et al., 2020). A Loops That Matter analysis produces three metrics – the link score, the loop score, and the relative loop score. The link score quantifies the contribution of change from one variable to another variable at a particular time. The loop score is the product of all link scores in a feedback loop at a point in time. The normalised loop score, which measures a loop's contribution to changes (in percentage) in all variables in a model, is a relative loop score (Schoenberg et al., 2020). The link score (LS) is estimated as in Eq. 3 below.

$$\text{Ls } (x. \rightarrow z) = [\Delta_x^z / \Delta_Z].\ \text{sign } [\Delta_x^z / \Delta_x] \tag{3}$$

Where Δ_x^z is the change in variable z concerning variable x. Δ_x represents the change in the variable x for time$_{(t)}$, and Δ_Z is the change in z from time $_{(t)}$ to time $_{(t+1)}$. $[\Delta_x^z/\Delta_Z]$ estimates the magnitude of the link score, and the sign $[\Delta_x^z/\Delta_x]$ represents the polarity of the link score.

Phase 2 – Scenario Development: The second phase consists of four steps. First, the scenario objectives are determined from the dominant drivers identified in Phase 1. Second, the formulated scenario objectives are presented to a reference group to brainstorm plausible scenarios that can be implemented to achieve the scenario objectives. Third, the scenarios are linked to specific parameters that need to be altered in the baseline model from phase 1. This step enables the translation of the qualitative scenario stories to quantitative scenarios. The consistency of the scenarios is tested by comparing the causal relationship among the identified parameters in step 3. A software like the Scenario Wizard® can help to determine the plausibility of scenarios.

Phase 3 – Ex-ante Analysis: The third phase is the post-scenario development phase, where formulated scenarios are used to revise the baseline model to facilitate an ex-ante analysis. Results from the baseline models (without scenarios) are compared with the results from the revised models (with scenarios). The difference between the two results is the impact of the scenarios, which can be interventions, strategies, and shocks.

3.2. Synthesised guidelines for SD modelling in agricultural and food systems

The proposed guidelines for each of the SD modelling steps are presented in this section. Fig. 10 is a schematic illustration of the different pathways that can be followed when conducting SD modelling. The red and blue dotted lines are the pathways for non-participatory and participatory SD modelling approaches, respectively. The circles in Fig. 10 are procedures to follow, the rectangles are key questions to answer before implementing a procedure, and the slanted square is the end of a pathway.

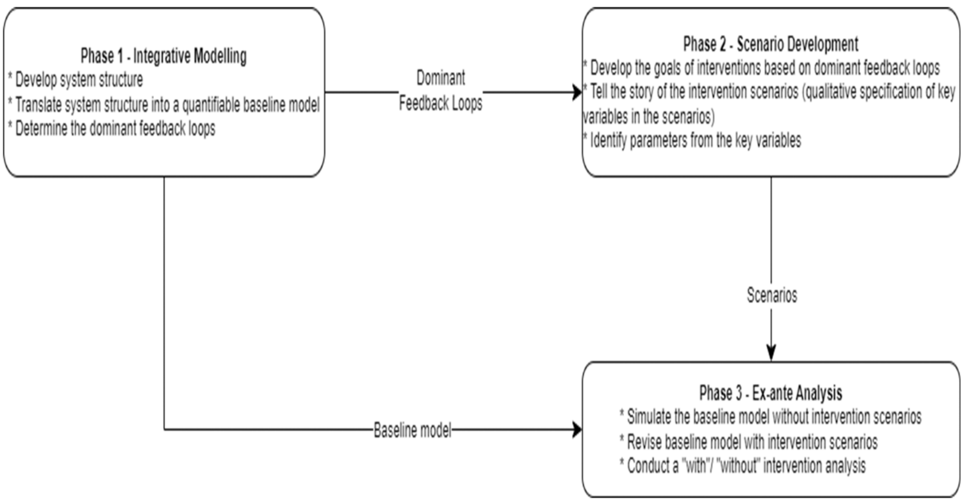


Fig. 9. The procedures of the emergent scenario development.

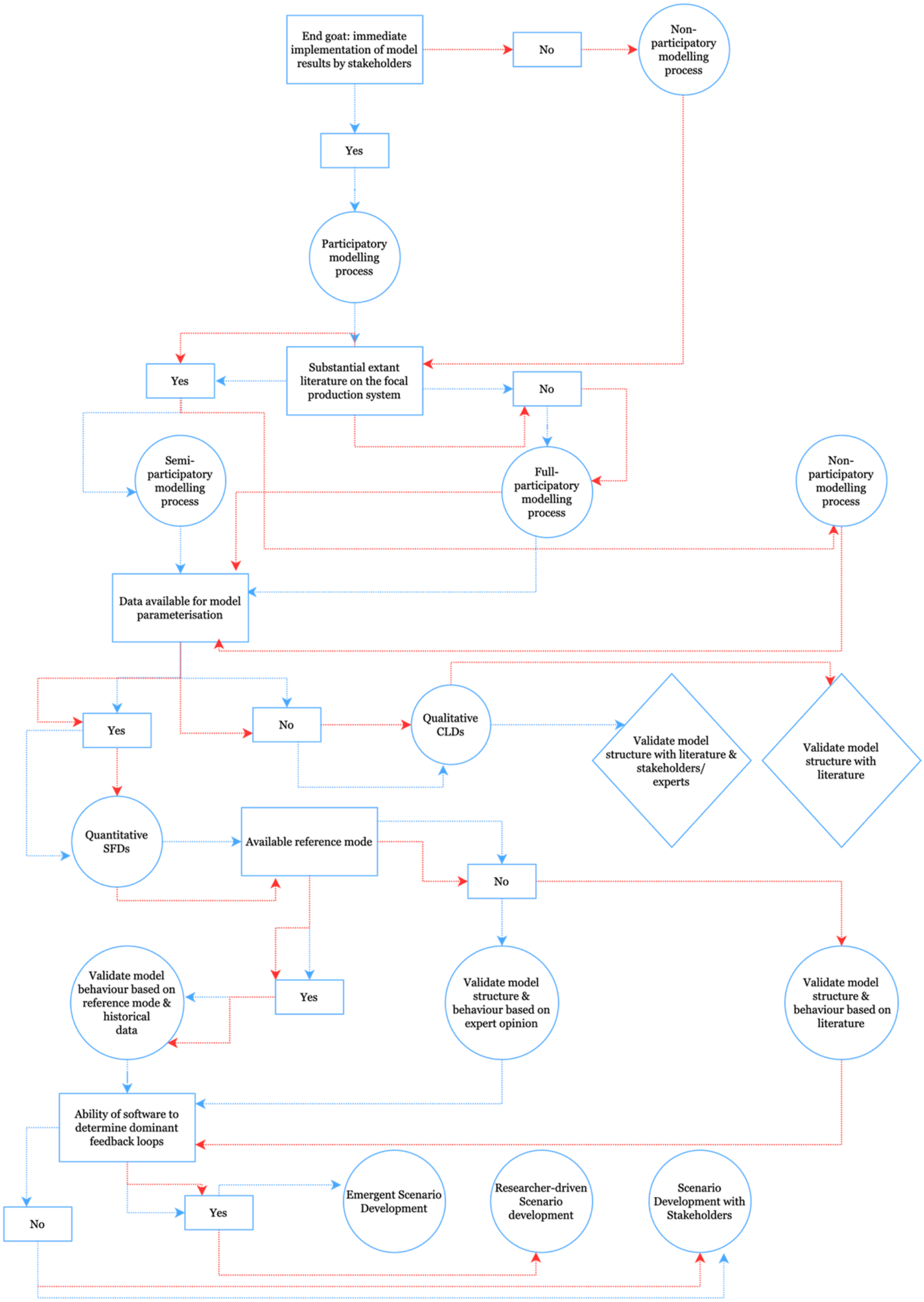


Fig. 10. Schematic diagram illustrating the pathways for SD modelling approaches.

3.2.1. Guidelines on model conceptualisation

Based on the synthesised trends, two criteria for determining the type of modelling process and model types to apply for the model conceptualisation step are proposed: (*i*) the immediate end goal of the modelling process, and (*ii*) data availability. A participatory modelling process is more suited and practical for action research where the end goal is to directly inform the interventions that are to be immediately implemented based on the results produced from the model. In action research, the involvement of stakeholders from the onset of the modelling process is essential to stimulate stakeholders' understanding of the model and buy-in of the results. Also, participatory modelling is useful when there is either limited data or little research on the specific topic. Opinions from stakeholders and experts become the primary sources of data; hence, both qualitative and quantitative models using CLDs and stocks and flow diagrams (SFDs), respectively are required.

For action research that focuses on well-researched production systems with substantial available data, the semi-participatory modelling process can be adopted, and quantitative SD models can be solitarily used. Basic research is conducted with the end goal of advancing knowledge and not immediate implementation of model results. When there is substantial data available, a non-participatory modelling process can be applied for basic research, and a quantitative SD model type alone can be used. When there is limited data available, a participatory modelling process involving experts can also be adopted for basic research. For this case, the use of a qualitative model (CLDs) becomes the backdrop for the quantitative model with SFDs.

3.2.2. Guidelines on model development

Model segmentation is an efficient way to manage the large volume of variable interactions and distinct equation formulations that characterise complex SD models. This approach allows modellers to compartmentalise various sectors or modules in a well-organised manner. For instance, a food system can be modularised based on key activities or layers such as production, marketing, and economic modules containing variable interactions that occur in different parts of the complex system.

The duration of simulation runs and specification of timesteps are relevant only to quantitative SD models. As a rule of thumb, the biological production cycle for the focal production system can be a key determining factor for deciding the appropriate timestep and simulation run. For instance, a daily timestep may be appropriate for a poultry production system but is likely to be too short for cattle production systems. Also, depending on research objectives, while a one-year simulation run may work for a broiler poultry system by incorporating two production cycles in a year, a one-year simulation will not be adequate to capture the entire production cycle for either a layer poultry or cattle production system. In the same vein, different simulation runs and timesteps are required for annual, biennial, and perennial crops.

3.2.3. Guidelines on model validation

Unlike econometric models, there are few goodness of fit tests for SD models. Thus, model validation in SD modelling tends to be more subjective. This subjectivity in the model validation process is more applicable to qualitative SD models and often regarded as the "Achilles' heel" of SD modelling. Therefore, model structure validation by stakeholders and experts is an integral procedure when qualitative SD models are developed from a participatory modelling process. The structure validation procedure precedes the behaviour validation procedure and offers the modeller an opportunity to revise the conceptualised system when key aspects of the model are not captured. During the validation of the structural model, the model boundaries and assumptions should be critically discussed by stakeholders to firm up the appropriateness of the model to answer the key research questions of interest.

For quantitative SD models, the use of objective statistical tests to compare the model results and historical data introduces objectivity in the model validation processes. However, this type of model behaviour validation is not possible with qualitative SD models. When data are readily available, a semi- and non-participatory modelling approach and quantitative SD model can be used. For semi and non-participatory modelling processes that produce a quantitative model, the model validation sequence suggested by Barlas (1997) is the main reference point.

3.2.4. Guidelines on scenario development for policy analysis

Emergent participatory scenario development can be conducted *a priori* or *a posteriori*. For *a priori* emergent participatory scenario development, the scenario planning is preceded by these modelling processes: model validation, baseline simulation and the synthesis of baseline results. In *a posteriori* emergent participatory scenario development, the modelling process is preceded by preliminary scenario planning, and the scenarios are revised after the baseline results are synthesised. For both types of emergent participatory scenario development, there is a need for plausibility and consistency checking of scenarios, which can be regarded as a post-model validation step. The plausibility and consistency checking step is a participatory process that enables stakeholders to qualitatively specify how the occurrence of one scenario influences another scenario in real-life.

A scenario matrix can be a simple alternative of the Scenario Wizard software to check the consistency of scenarios developed. A positive (+) polarity can be specified when Scenario "A" increases the likelihood that Scenario "B" occurs. A negative (-) polarity can be specified when Scenario "A" decreases the likelihood of scenario "B" occurring. A null polarity can be specified when the occurrence of Scenario "A" is unrelated to the occurrence of Scenario "B". The plausibility and consistency checking step can be combined with the scenario revision exercise when the *a posteriori* emergent participatory scenario development is adopted. Essentially, the Loops That Matter analysis, which is instrumental for the emergent participatory scenario development, is predicated on variables that are endogenized in a system. Therefore, important variables that are specified exogenously will be excluded in the dominant feedback loops. This can be seen as a drawback of the emergent participatory scenario development. However, the caveat is that modellers should endeavour to endogenize all key variables during the model conceptualisation phase of the modelling process.

4. Conclusions

This paper finds that the dominant modelling approach is non-participatory, but participatory methods like group model building are gaining traction, especially in qualitative system dynamics modelling. Researchers must weigh stakeholder involvement and model ownership against the time and budget demands of participatory processes.

System dynamics models support decision-making process. Hence, there is a need for the formulation of evidence-based scenarios. To enhance decision-making, it is crucial to measure the hypothesised changes resulting from the developed scenarios (Dhami et al., 2022; Lauer et al., 2024). Quantitative system dynamics procedures facilitate the testing of formulated hypotheses, estimating the expected proportion of change for various intervention scenarios, and confirming or refuting the hypothesised changes.

The emergent participatory scenario development process proposed in this paper will improve the transparency of scenario formulation in SD modelling. The process emphasises the synergistic potential of guiding expert opinions using emergent simulation results. However, this process cannot be easily implemented across various system dynamics software. To address this issue, multivariate sensitivity analyses can be conducted to identify the significant loops (Liu et al., 2020). Future research could explore new strategies for stakeholder engagement that can streamline the participatory process while maximising the benefits of stakeholder input and ownership (Dhami et al., 2022). Additionally, the scalability and generalisability of the proposed participatory scenario development process can be examined across different sectors.

CRediT authorship contribution statement

J. Aboah: Conceptualization, Data curation, Formal analysis, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review and editing. **M.M.J. Wilson:** Methodology, Project administration, Supervision, Writing – original draft, Writing – review and editing. **K. Bicknell:** Methodology, Project administration, Supervision, Writing – original draft, Writing – review and editing. **E.D. Setsoafia:** Methodology, Project administration, Supervision, Writing – original draft, Writing – review and editing.

Declaration of Competing Interest

The authors declare no conflict of interest that may be affected by the research reported in the enclosed paper.

Appendix A

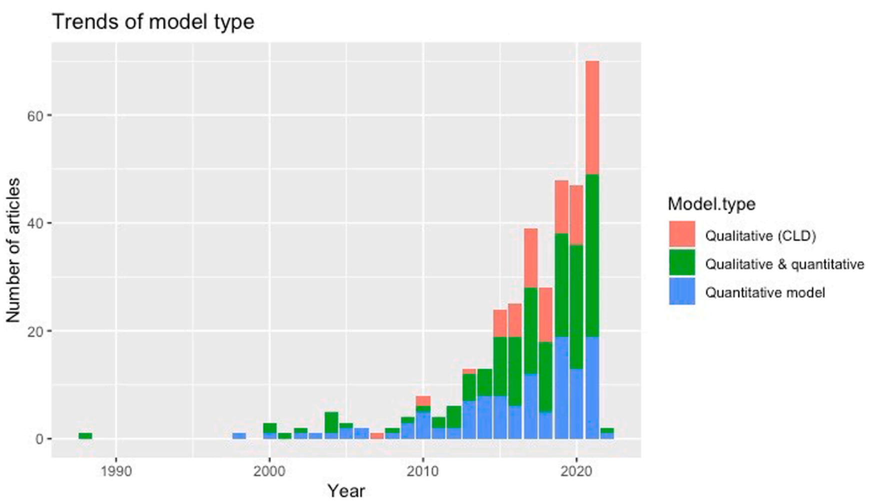
Cluster	Central (common) theme examined	Study areas
1	– Water-energy-food nexus/ system modelling – Irrigated agricultural system – Climate change impact on water availability for agriculture	Canada, Pakistan, Spain, Iraq, Greece, Sardinia, Indonesia, Latvia, Taiwan, China
2	– Ex-ante impact assessment of production technologies/ interventions (pig, cattle beef, fruits & vegetables) – Climate change impact on cattle production – Ex-ante impact assessment of disease management	Myanmar, India, Indonesia, Botswana, Tanzania, USA, Australia, Kenya, Guatemala, Mexico, Uganda, Vietnam, Ghana, Generic
3	– Sustainable water (ground & fresh) system management (including irrigation) for agriculture – Water reuse system	Iran, USA, Japan, China, Indonesia, South Korea, Taiwan, Ghana
4	– Vulnerability assessment in crop value chains – Technology adoption in agricultural production (citrus, pigeon pea) – Socioecological system interaction – Eco-agricultural system (Agroecosystem)	Ghana, Generic, Bangladesh, Brazil, China, Malawi, Colombia, Zambia
5	– Water system for agriculture – Replenishment policy (capacity planning) and performance monitoring and assessment in food supply chains	Generic, Bangladesh, Greece, Turkey, Iran, China, India, Nigeria, United Kingdom, France, Iran, Mexico, Turkey
6	– Irrigation (water) system for agriculture – Water sustainability for agriculture and industry – Soil water nutrients	USA, Australia, Bangladesh, India, China
7	– Impact of climate on society and economy – Water-energy-food-nexus (system) – - Irrigated agricultural system	Canada, Iran, Brazil, Vietnam, China, Italy, Generic, Taiwan
8	– Food system & sustainability – Land use & agriculture – Food system & communication and logistics management	Generic, China, Vietnam, Indonesia, Australia, USA
9	– Farming systems	USA

(continued on next page)

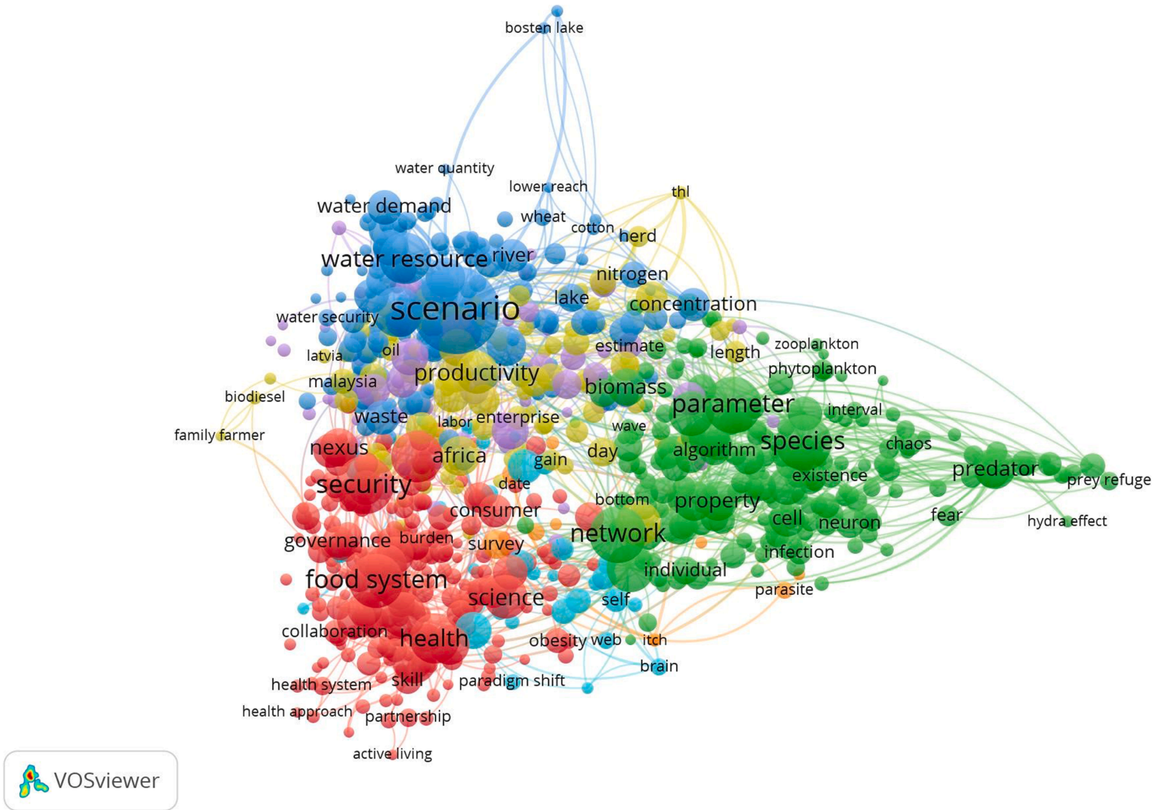
(*continued*)

Cluster	Central (common) theme examined	Study areas
10	– Biofuel (crop-based), sustainability & policy strategy – Agricultural system & policy	Latvia, Italy, Colombia, USA, Iran, Austria, Denmark
11	– Crops (maize & beans) & livestock (sheep, dairy, beef) value chain modelling	Ethiopia, Guatemala, Nigeria, Kenya, Indonesia
12	– Aquatic ecosystem and food chain – Climate change and sustainability of water systems for agriculture	Iran, Generic, Taiwan, Azerbaijan, USA, Japan, Mexico, China, Taiwan
13	– Impact of the animal production system (sheep, donkey, cattle) on profitability and efficiency – Assessment of leverage points in animal production system	China, New Zealand, USA, Argentina, Hawaii,
14	– Irrigation system for crop production – Water system sustainability	Bangladesh, Hong Kong, Iran, Turkey, USA, China, Tunisia
15	– Economic viability and ecology or crop production – - Ecology and water system	South Africa, USA, China
16	– Climate change impact on society and economy – Food and nutrition (humans & cattle) modelling	South Korea, Canada, Generic
17	– Climate change impact (drought) on agriculture – Water sustainability for economy (agriculture & industry)	China, Horn of Africa (Somalia, Ethiopia, Kenya), Mongolia, Canada, Vietnam
18	– -Agriculture system and policy – Farming and livelihoods	-Ghana, Indonesia, Nigeria, Zimbabwe, EU
19	– Technology adoption & profitability of agricultural systems – Food supply sustainability & resilience	Austria, Malawi, Generic, Mexico, Indonesia, Uganda, Brazil
20	– Food-water-energy nexus modelling	Egypt, China, Ethiopia, USA
21	– Sustainability of agricultural policy & agricultural production	Italy, Taiwan, Australia
22	– Sustainability of agricultural food production – Water system and fishery – Livelihood & policy	Vietnam, China, Ghana, USA
23	– Climate change impact on agricultural systems – Agricultural systems & sustainable development	India, Uganda, Iran, South Africa, Malaysia, Slovenia
24	– Water system sustainability for agriculture – Agricultural land use	Iran, USA, China
25	– Crop, animal, or aquaculture production dynamics – Biofuel & sustainability	Malaysia, Bangladesh, South Africa, Colombia
26	– Land use & agriculture – Urbanisation & sustainable development	Mongolia, China
27	– - Ex-ante impact assessment of agricultural policy and farm management decisions	Zambia, Switzerland, Czech Republic
28	– Sustainability and resilience of agro-ecosystem	Turkey, Slovenia, China
29	– Sustainability of water (irrigation) system for agriculture	Iran, USA, China
30	– Aquaculture production dynamics – Species population dynamics	France, Generic, China, South Africa, Cayman Island

Appendix B



Appendix C



Network of most used terms in SD modelling application in agriculture

Data Availability

I have shared the link in the manuscript

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