# A review of model-based scenario analysis of poverty for informing sustainability

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## Abstract

Ending poverty in all its forms everywhere is the first goal being targeted by the United Nations 2030 Agenda for Sustainable Development. Poverty eradication is a long-term process that faces the challenges of many uncertainties and complex interactions with other Sustainable Development Goals (SDGs). In order to better understand poverty and contribute to addressing poverty in a sustainable manner, this paper aims to conduct a systematic review of model-based analysis for poverty scenario in the context of SDGs. We first review 144 studies from the perspectives of bibliometric information (i.e., publication types, research topics for poverty, research objects, research scales and geographic locations) and models information for poverty scenario analysis (i.e., model types, purposes, states, temporal and spatial range, sectors considered, poverty and other SDGs indicators). Second, we discuss the pros and cons of different types of models and identify seven representative models. We also discuss the synergies and trade-offs between poverty and other SDGs. Finally, we identify four potential research gaps in model-based poverty scenario analysis and provide suggestions for future research. The review shows that poverty scenario analysis was carried out mainly from a single perspective, such as economic, ecological, and agricultural. Few studies used effective models to analyze poverty under an integrated interactions analysis of multiple sectors. Comprehensive multi-sector models are needed for global and regional poverty scenario analysis over the medium- or long-term to enhance the ability of analyzing the combined effects, synergies, and trade-offs between poverty and a variety of other SDGs.

**Keywords:** Scenario modeling; Poverty analysis; Sustainable development; Survey

## 1 Introduction

The United Nations 2030 Agenda for Sustainable Development commonly known as the Sustainable Development Goals (SDGs) is committed to eradicating poverty, protecting the planet, and ensuring peace and prosperity for humanity through concerted actions (Cf, 2015). These SDGs are interdependent and interconnected, and together state the shared aspirations for a more sustainable future. The first goal (SDG 1) of the 17 SDGs, *ending poverty in all its forms everywhere*, is strongly associated with the well-being of every individual (United Nations, 2019). Although the proportion of people living in extreme poverty (less than $1.9 a day based on 2011 Purchasing Power Parities (United Nations, 2019)) has fallen from 36% in 1990 to 10% in 2015 globally, there are still more than 700 million people living in extreme poverty (United Nations, 2019) where their essential living needs (e.g., water, sanitation, health services, education) cannot be guaranteed. Poverty is still one of the most intractable social problems and the most important livelihood problems faced by humanity (United Nations, 2020).

To better understand poverty and evaluate progress towards SDG 1, researchers have conducted both qualitative and quantitative analyses aiming to identify poverty causes (B. W. Wang et al., 2019), measure the progress towards a set target (Vyas-Doorgapersad, 2018), understand linkages between poverty and other relevant factors (Suich et al., 2015), and formulate or evaluate the effects of poverty reduction policies (Alwang et al., 2019). However, poverty analysis, as in every other human-natural system analysis (Moallemi et al., 2020), is fraught with challenges of uncertainty (i.e., achieving SDG 1 is a long-term process that is vulnerable to external surprises and shocks) and complexity (interconnections between poverty and other economic, social, and environmental SDGs).

Model-based scenario analysis has been used to tackle these challenges in research on poverty. Regarded as a powerful analytical method to support sustainable development research (Swart et al., 2004), model-based quantitative scenario analysis aims to project possible future trends or consequences under the premise that a phenomenon could occur in the future with a certain likelihood, allowing policymakers to explore alternative futures and to take into account their consequences for decision-making (Kosow and Gaßner, 2008). Different from traditional forecasting methods, it emphasizes uncertainty instead of forecasting and works on the premise that there are a variety of possible trends in the future, hence diverse results will be obtained. Scenario analysis uses various sources of information and knowledge (e.g., experience and knowledge of experts, uncertain future trends, and human behaviors) to generate a series of internally consistent future scenarios, which involves highly uncertain long-term driving factors (e.g., demographics, climate change, and technological development) and includes trends or non-linear interactions that may differ significantly from past experiences.

Despite growing interest in model-based scenario analysis in dealing with poverty (Allen et al., 2021; Laborde et al., 2021), the depth and breadth of this area and opportunities for further studies have not been scoped so far. Here, we aim to fill this gap by conducting a systematic review of model-based poverty scenario analysis, mapping: (1) the topics addressed; (2) cataloging the quantitative models that have been developed; (3) the indicators used to measure poverty; as well as identifying representative models and research gaps in model-based quantitative poverty scenario analysis. Based on this systematic review we synthesize the field of scenario analysis for assessing poverty and chart a new research agenda for better integrating and mainstreaming this critically important aspect of sustainability into modelling studies.

## 2 Methods

We conducted a systematic review according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Moher et al., 2009) in three steps (Figure 1).

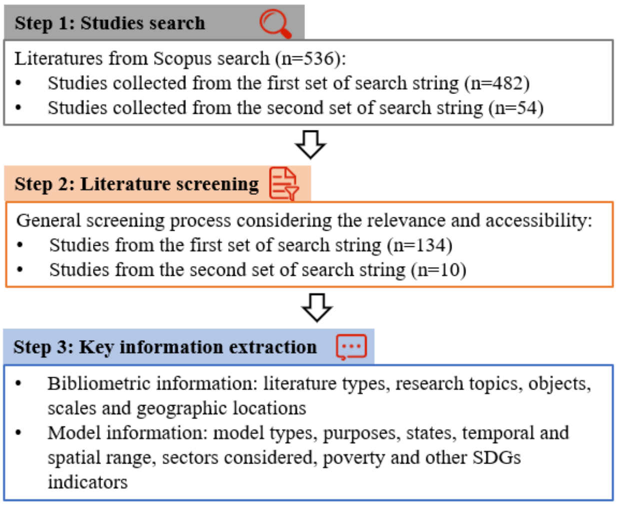


**Figure 1**. An overview of the steps used for the literature review.

### 2.1 Studies search

The Scopus database is adopted for the literature search because of its broad coverage in related research of poverty, SDGs, system dynamics, and scenario analysis, and internet-accessible full-text resources available in related journals (Mio et al., 2020). The literature search uses specific keywords and their combinations as indexes to search for related literature through titles, abstracts and keywords. The keywords are divided into two groups. The keywords in the first group contain *poverty, sustainable development goal 1,* and *SDG 1* while the second group consists of *scenario modeling, scenario analysis*, and commonly used scenario analysis model types derived from previous modelling reviews (Allen et al., 2016, 2017), namely *system dynamics, computable general equilibrium, integrated assessment model, input-output model, econometric model,* and *multi-agent model*. We set the search time span from January 2015 (the year when SDGs were adopted) to May 2021. We searched for all articles and reviews in English and published in journals from the Scopus database. Based on the information above, we found 482 papers by the following search string.

- TITLE-ABS-KEY ("*poverty*" OR "*sustainable development goal 1*" OR "*SDG 1*") AND TITLE-ABS-KEY ("*scenario analysis*" OR "*scenario modeling*" OR (*scenario* AND *model*) OR (*scenario* AND *modeling*) OR "*system dynamics*" OR CGE OR "*computable general equilibrium*" OR *IAM* OR "*integrated assessment model*" OR "*input-output model*" OR "*econometric model*" OR "*multi-agent model*"); SOURCE TYPE: (Journal).

As some comprehensive models that analyze the SDGs contain poverty modules but were not found by the keywords and search fields above, we used the following search string which returned an additional 54 papers:

- TITLE-ABS-KEY ("*sustainable development goals*" OR *SDGs*) AND TITLE-ABS-KEY ("*scenario modeling*" OR "*scenario model*" OR "*scenario analysis*"); SOURCE TYPE: (Journal).

### 2.2 Literature screening

Literature screening was then undertaken to process the collected 536 papers based on their relevance and accessibility. From the 482 papers obtained from the first search string, we selected 152 papers by browsing the title, abstract, and keywords and excluding irrelevant papers. Excluded papers include art-, psychology-, or medicine-related papers that were incorrectly captured; papers that only focused on energy poverty, fuel poverty, or food poverty and had no connections with SDG 1; papers that had little connection with poverty (e.g., "poverty" only appear in abstracts as future research). Moreover, we further excluded 18 papers because their full texts could not be accessed online, or the scenario analysis method or model presented was not used or could not be used for poverty analysis. From the 54 papers obtained from the second search string, 10 papers were selected by excluding duplicate and inaccessible papers and papers that did not mention poverty or SDG 1 in the full text. As a result, a total of 144 papers were retained for detailed review.

### 2.3 Key information extraction

By carefully reading each paper, the key information of each paper is recorded from bibliometric and model information and as shown in Table 1. From the perspective of bibliometric information, the research object in a paper represents the population or community studied in each paper. Research scales involve global, regional, national, and local, which cover almost all countries, multiple countries or economies, one country, and a part (e.g., one or more states, cities) of a country, respectively. Geographic locations of research areas are differentiated by country.

**Table 1.** Key information recorded.

| Key information | Meta-indicator | Description |
| --- | --- | --- |

| | | |
|---|---|---|
| Bibliometric information | Publication types | Research articles, review articles. |
| | Research topics | Socio-economy, agriculture, eco-environment, other, combinations. |
| | Research objects | Whole population, rural population, children, women, farmers, workers, etc. |
| | Research scales | Global, regional, national, local. |
| | Geographic locations | Differentiated by country. |
| Model information | Model types | CGE models, econometric models, SD models, microsimulation models, input-output models, BBN models, hybrid models. |
| | Model purposes | Ex-ante scenario analysis, ex-post scenario analysis, relationships exploration |
| | Model states | Static, dynamic. |
| | Model temporal scales | Short-term (2020≤t≤2030), medium-term (2031≤t≤2050), long-term (2051≤t≤2100). |
| | Model spatial range | Global, regional, national, local. |
| | Model sectors considered | Economic, social, environmental. |
| | Poverty and other SDGs indicators | Indicators (variables) proposed to measure poverty and other SDGs. |

Regarding to the model information, models for poverty scenario analysis were classified into seven types according to different modeling methods (Allen et al., 2016): (1) computable general equilibrium (CGE) models (Cantele et al.); (2) econometric models (Intriligator, 1983); (3) system dynamics (SD) models (Sterman, 2000); (4) microsimulation models; (5) input-output models (Ten Raa, 2009); (6) Bayesian belief network (BBN) models (Darwiche, 2009); and (7) hybrid models.

Each model targets one of the following three model purposes: ex-ante scenario analysis (i.e., estimation of future trends under different scenarios), ex-post scenario analysis (i.e., ex-post assessment of an event, policy, or behavior to analyze its influence), and relationships exploration (i.e., exploration of quantitative relationships between poverty and other factors under different scenarios). A model is considered to be *static* if it doesn't consider temporal factors and the process experienced, and *dynamic* if it can be used to examine the dynamic interactions in the system modeled and analyze the evolutionary process of these relationships over a time period. According to the maximum year ($t$) simulated by dynamic models, temporal scales of models can be classified as short-term, medium-term, and long-term.

## 3 Results

### 3.1 Bibliometric information

Model-based poverty scenario analysis covered a wide range of research fields since the collected 144 papers were published in 96 journals. The number of publications reached a peak in 2018 (Figure 2a). Only three reviews were relevant to poverty-related scenario analysis (Figure 2b). These reviewed global modeling efforts of farmer household bio-economy models for assessing the effects of new technologies on farming systems and livelihoods (Kruseman et al., 2020); the impacts of trade liberalization on poverty based on CGE models (Anderson, 2020); and the scenario modeling tools for assessing the implementation of national-scale SDGs (Allen et al., 2016).

The collected literature covered a wide range of research scales and areas. Among 144 papers, more than half (57.86%) were national scale, followed by local (22.14%) (Figure 2d). Countries that attracted the most attention are South Africa (10 cases) and China (9 cases) (Figure 3). Most studies (85%) defaulted to the entire population of the corresponding research area while only 15% considered specific research objects.

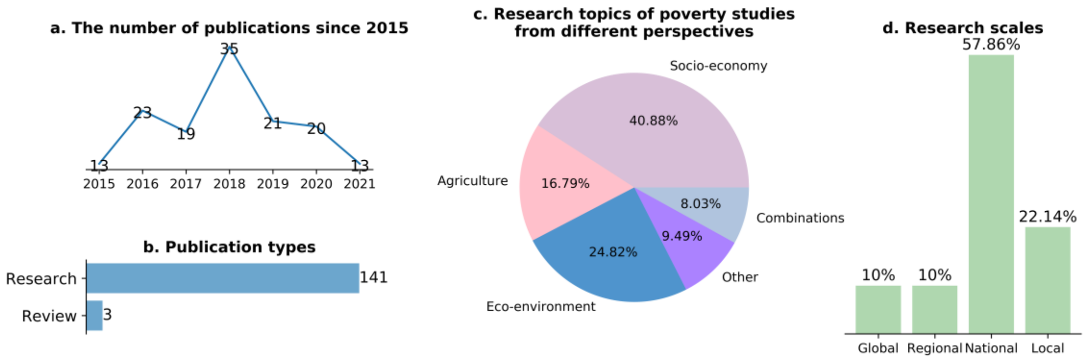


**Figure 2.** Distributions of the 144 selected papers in terms of (a) publication types, (b) the number of publications per year, (c) topics, and (d) scales.

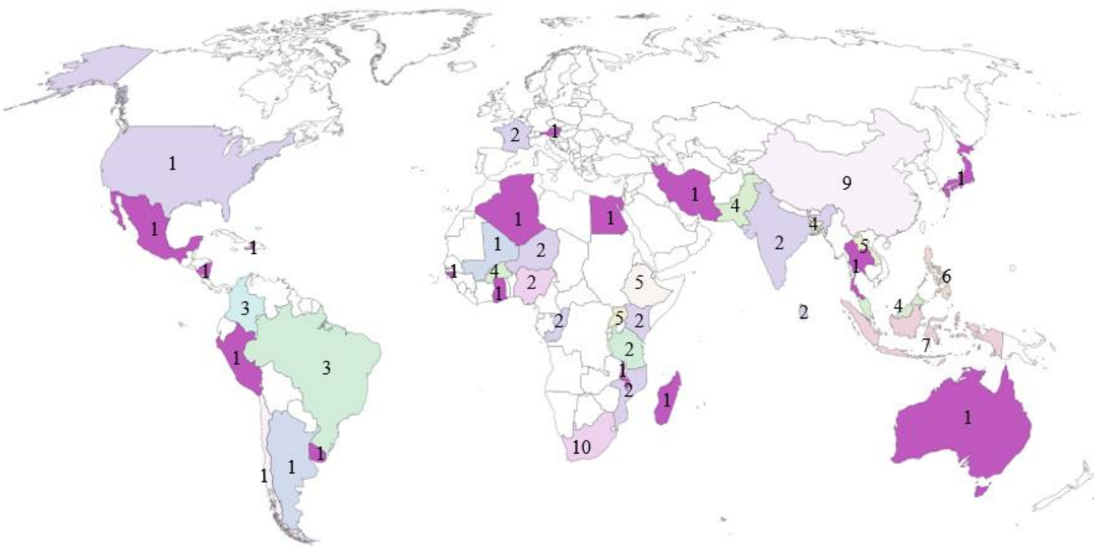

**Figure 3.** The number of national- and local-scale studies and their distribution. Country with 10 studies: South Africa; Country with 9 studies: China; Country with 7

studies: Indonesia; Country with 6 studies: Philippines; Countries with 5 studies: Ethiopia, Laos, and Uganda; Countries with 4 studies: Bangladesh, Burkina Faso, Malaysia, and Pakistan; Countries with 3 studies: Brazil, Colombia; Countries with 2 studies: Congo, France, India, Kenya, Tanzania, Mozambique, Niger, Nigeria and Sri Lanka; Countries with only 1 study: Algeria, Argentina, Australia, Austria, Chile, Egypt, Ghana, Guinea-Bissau, Haiti, Iran, Japan, Madagascar, Malawi, Mali, Mexico, Nicaragua, Peru, Thailand, United States and Uruguay.

Different poverty research topics have been addressed in previous studies (Figure 2c). Most of them (41%) investigated the impacts of socioeconomic activities on poverty from a variety of perspectives, including fiscal policies (e.g., cash transfer program (Gilliland et al., 2019), government redistributive policies (Mukarati et al., 2020; Salotti and Trecroci, 2018), tax reforms (Feltenstein et al., 2017; Llambi et al., 2016), public pension system (Inagaki, 2018), childcare policy (Cockburn et al., 2016)), trade liberalization policies (Liyanaarachchi et al., 2016), financial crises (Antoniades et al., 2020), and public investment adjustments in tourism (Banerjee et al., 2015), energy (Tiberti et al., 2017), and infrastructure (Medeiros et al., 2021). We found that economic growth, trade liberalization, and cash transfer have positive impacts on poverty reduction, in which the cash transfer has a significant impact in the short term, but has a limited role in the long run. A total of 26% of existing studies examined the connections between poverty and eco-environmental factors, such as climate policies (e.g., carbon tax) (Altieri et al., 2016), climatic risks (Aslam et al., 2018), natural resource degradation (Daregot et al., 2015), land deforestation (Siriban-manalang et al., 2016), and woodland ecosystem services (Zorrilla-Miras et al., 2018). These studies showed that eco-environmental deterioration increased poverty via increased food prices, decreased agricultural production and farmers' incomes. Moreover, some measures that could improve the environmental sustainability and enhance farmers' adaptability to climate change greatly reduced poverty, such as rational distribution of land, soil erosion management, and sewage treatment (X. Cheng et al., 2018).

The relationship between poverty and agriculture was also explored since the poorest households were thought to be more concentrated in agriculture (FAO, 2017). More than 16% of existing studies investigated the relationship and impacts of agriculture-related factors on poverty, which involve agricultural productivity variations (Zidouemba and Gerard, 2018), agricultural growth (Ndhleve et al., 2017), agricultural investment (Badibanga and Ulimwengu, 2020; Benfica et al., 2019), fertilizer use (van Wesenbeeck et al., 2021), and agricultural commodity price change (Solaymani, 2017; Solaymani and Yusoff, 2018). These studies suggested that poverty alleviation benefited from the growth of agricultural production and productivity, increased agricultural investment, appropriate amount and method of fertilizers application. In addition, around 9% of existing studies accounted for progress evaluation and interactions between SDGs (Allen et al., 2017; Allen et al., 2021), assessing the influence of various factors on poverty including health policies (Shrime et al., 2016), disease spread (Chitiga‐Mabugu et al., 2021), technical efficiency (Islam and Haider, 2018), population aging (X. Wang et al., 2017), and urban characteristics (Duque et al., 2015). Only 8% of studies analyzed the combined effects of multiple sectors on poverty, such as agriculture and climate (Montaud et al., 2017; Rosenzweig et al., 2018), agriculture and ecology (X. Cheng et al., 2018), agriculture and education (Karmozdi et al., 2020), and economy and ecology (Devarajan et al., 2015).

## 3.2 Model information

### 3.2.1 Overview of model information

In the selected studies, 138 papers presented models for poverty scenario analysis, while the remaining 6 papers were literature reviews or only introduced a conceptual model or framework. For these 138 papers, more than half of them (54.35%) used national-scale models, while 23.19%, 12.32%, 10.14% applied local, regional, and global scale models, respectively (Figure 4c).

The most widely used model type is hybrid (55 in total) which integrate at least two model types, followed by CGE models (Figure 4a). The majority (46) of the hybrid models are the combination of CGE and microsimulation models. Both hybrid and CGE models were used mainly for ex-ante scenario analysis. There were 24 econometric models, most of which were developed for relationship analysis. The remaining models were all used for ex-ante scenario analysis, including 16 system dynamics models, 10 microsimulation models, 2 input-output models and 2 BBN models. In terms of model states, dynamic models were slightly more widely used than static models (Figure 4b). All SD and BBN models were dynamic.

For studies presenting dynamic models that explicitly defined a simulation period, 58% were used for short-term (2020-2030) simulations, while only 12% were used for long-term (2051-2100) simulations (Figure 4d). Due to the close linkages between economy and poverty, all models considered the economy sector by modeling economy-related factors as variables and parameters in poverty scenario analysis, among which 31.16% of studies considered economic factors only while the remaining (68.84%) further considered social and (or) environmental factors to enhance their comprehensive analysis capabilities (Figure 4e).

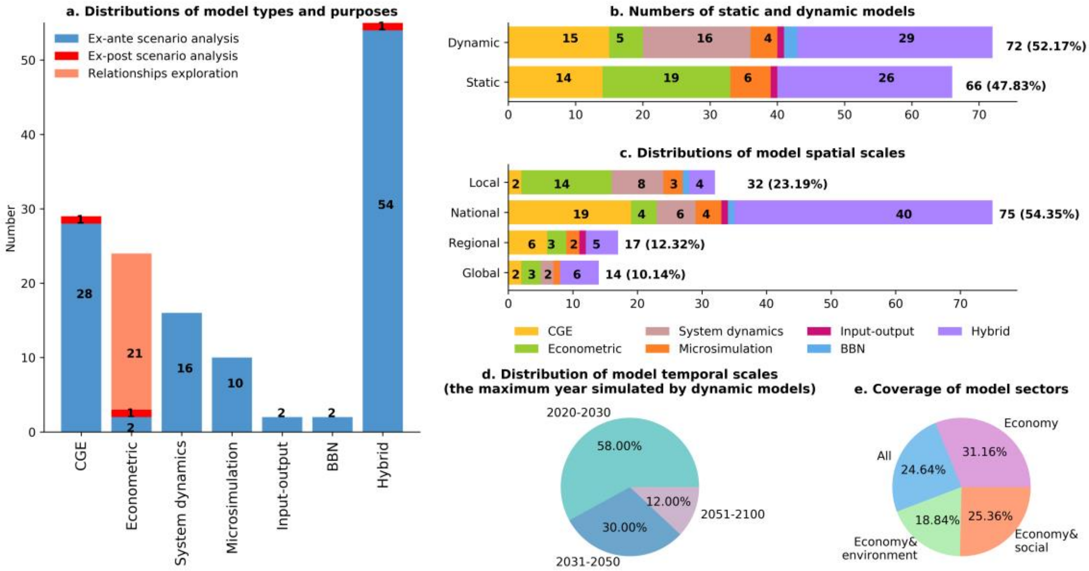


**Figure 4.** Overview of model information in selected studies.

### 3.2.2 Poverty and other SDG indicators

A total of 11 indicators were defined to measure poverty in model-based scenario analysis. More than two-thirds of studies only adopted one indicator, and the remaining used multiple indicators. These indicators are classified into direct and indirect indicators, and their usage counts are shown in Table 2.

The most commonly used indicator is the poverty rate, which is defined as the ratio of the number of people living below a given poverty line to the overall population. The ratio of people living below the poverty line has been calculated by income distribution (Cuaresma et al., 2018), household income (Lázár et al., 2020), household consumption (Ahmed et al., 2018), and growth of gross domestic product (GDP) (Ashimov et al., 2019; Ndhleve et al., 2017). Some models estimated poverty rates based on labor productivities and education levels (Cristea et al., 2020) or ecological factors such as topography, rainfall, and desertification (Zhou et al., 2020). The poverty population indicator is similar to the poverty rate, which is defined as the number of people living below a given poverty line. It has been obtained based on income per capita (Xin Cheng et al., 2018), economic growth (Supriyadi and Kausar, 2017), and the relationships between multiple factors (e.g., GDP, population, unemployment, agricultural investment) (Bafadal et al., 2020).

However, the two indicators mentioned above ignore the depth of poverty, signifying that the poverty rate remains constant if the poor become poorer (Foster et al., 2010). Some researchers thus used the poverty gap index to measure the depth of poverty, which is defined as the ratio by which the average income of the poor falls below the poverty line (C. Cororaton et al., 2018; Islam and Haider, 2018). Although the poverty gap index can indicate the depth of poverty, it cannot capture the inequality between the people living below the poverty line. The poverty severity index is thus proposed, which is defined as the average of the squared poverty gap ratio. It is a form of the weighted sum of the poverty gap, with the weight proportionate to the poverty gap. By squaring each poverty gap ratio of the poor who live below the poverty line, the larger the poverty gap of a person, the greater its weight in the poverty severity index calculation (Foster et al., 2010; Siriban-manalang et al., 2016). In addition, Duque et al. (2015) proposed a slums index to represent urban poverty by the number of slums in a city. Some researchers proposed multidimensional indicators to measure poverty from multiple dimensions of economy, health, education, basic living conditions, and environment, including multidimensional poverty index (Antoniades et al., 2020; W. Wang et al., 2018), binary poverty status (Nguyen and Nguyen, 2019) and poverty trap (Borgomeo, Hall, et al., 2018).

Indirect indicators (income returns, capital, and GDP) evaluate poverty though wealth data indicating the economic status of the population. The income returns indicator, representing the income return to unskilled labor, was seen as an alternative measurement of poverty (Jeong-Soo and Kyophilavon, 2015; Kyophilavong, Bin, et al., 2017), because the income gap is narrowed and poverty is reduced if the increased income return of unskilled labor is greater than it of skilled labor (Kyophilavong, Bin, et al., 2017). Indicators of capital (Garchitorena et al., 2017) and GDP (Glomsrød et al., 2016) assess poverty through their growth and distribution.

**Table 2.** Usage count of different poverty measurement indicators in the collected literature.

| Categories | Indicators | Times used |
|---|---|---|
| Direct indicators | Poverty rate | 108 |
| | Poverty gap | 38 |
| | Poverty severity | 31 |
| | Poverty population | 6 |
| | Multidimensional poverty index | 5 |
| | Binary poverty status | 4 |
| | Poverty trap | 2 |
| | Slums index | 1 |
| Indirect indicators | Income returns | 2 |
| | Capital | 1 |
| | GDP | 1 |

In addition to poverty indicators, other SDG indicators have been considered in poverty scenario analysis models (Tables 3, 4). Variables for SDG 2 (zero hunger) (El Wali et al., 2021) and SDG 13 (climate change) (Marcinko et al., 2021) were most often used together with poverty. Only iSDG (MI, 2021) and IFs (Hughes, 2019) developed variables for all SDGs and can be used to analyze poverty and SDG 3 (good health and well-being), SDG 9 (industry, innovation, infrastructure), SDG 11 (sustainable cities and communities), or SDG 16 (peace, justice, strong institutions) simultaneously. Except for some indicators (e.g., maternal mortality for SDG 3, occupational accident rate for SDG 8) that were developed to be completely consistent with SDGs agenda (United Nations, 2021), many models used proxy indicators to measure SDGs (Table 4). For instance, crop yield could be used to measure SDG 2 (El Wali et al., 2021) while agricultural water withdrawal could be used to measure SDG 6 (Byers et al., 2018).

**Table 3.** Models that considered synergies and trade-offs between SDG 1 and other SDGs.

| Model types | Model names | SDGs coverage |
|---|---|---|
| CGE models | GTAP-POV [a] | SDG 1, 7, 8, 13, 17 |
| | MAMS [b] | SDG 1, 2, 3, 6 |
| | Inter-temporal Computable Equilibrium System [c] | SDG 1, 10 |
| SD models | iSDG [d] | All 17 SDGs |
| | Phosphorus supply [e] | SDG 1, 2, 5, 6, 8, 12 |
| Hybrid models | GIDD [f] | SDG 1, 4, 8, 10 |
| | IMPACT [g] | SDG 1, 2, 6, 13, 15 |
| | IFs [h] | All 17 SDGs |
| | An IAM framework [i] | SDG 1, 2, 10, 13, 14, 15 |
| | An IAM framework [j] | SDG 1, 2, 6, 7, 13, 15 |

[a] Hertel et al. (2011). [b] Lofgren et al. (2013). [c] Campagnolo and Davide (2019). [d] MI (2021). [e] El Wali et al. (2021). [f] Bussolo et al. (2009). [g] Robinson et al. (2015). [h] Hughes (2018). [i] Marcinko et al. (2021). [j] Byers et al. (2018).

**Table 4.** Measurement indicators for other SDGs mentioned in Table 3.

| SDGs | Indicators aligned with the SDGs agenda | Proxy indicators |
|---|---|---|
| SDG 2 Zero hunger | Food security calculated by nutrition, life expectancy, education, access to water. | Crop yield, phosphorus security [a] |
| SDG 3 Good health and well-being | The mortality rate of children; maternal mortality. | - |
| SDG 4 Quality education | Education penetration rate; educational level of different groups of the population. | - |
| SDG 5 Gender equality | Female share of employment in managerial positions, contraceptive prevalence rate. | Employment rates for males and females [a] |
| SDG 6 Clean water and sanitation | Proportion of access to safely managed water source, access to safely managed sanitation facility. | The proportion of human water demands relative to available renewable surface water supply, drought intensity, non-renewable groundwater, agricultural water withdrawal [b]. |
| SDG 7 Affordable and clean energy | Percentage of population with access to electricity, renewable share in total final energy consumption, energy intensity level of primary energy. | Fraction of access to clean cooking [b] |
| SDG 8 Decent work and economic growth | Real GDP per capita growth rate, GDP per employed person growth rate, material | Livelihood of employees [a] |

| | | |
|---|---|---|
| | footprint index, domestic material consumption, unemployment rate, share of youth not in education employment or training | |
| SDG 9 Industry, innovation, infrastructure | Rural access index, industry production, industry employment as share of total employment, $CO_2$ emissions per unit of value added. | Rural roads [c] |
| SDG 10 Reduced inequality | Bottom 40% income growth to average income growth gap, proportion of population below half median income. | The Palma Ratio, income inequality Gini index [c,d] |
| SDG 11 Sustainable cities and communities | Urban air quality, population affected by disasters. | - |
| SDG 12 Responsible consumption and production | Material footprint, domestic material consumption. | Phosphorus balance in circulation [a] |
| SDG 13 Climate change | GHG emissions, population affected by disasters | Heat events [b] |
| SDG 14 Life below water | Proportion of fish stocks sustainably exploited; proportion of territorial waters effectively protected. | Fisheries changes [e] |
| SDG 15 Life on land | Habitat degradation, proportion of territorial areas effectively protected. | Land-use change [h] |
| SDG 16 Peace, justice, strong institutions | Bribery incidence, mortality rates caused by violence. | - |
| SDG 17 Partnerships | proportion of domestic budget funded by domestic taxes, grants as share of domestic revenue. | Government investment [c,i] |

[a] El Wali et al. (2021). [b] Byers et al. (2018). [c] Hughes (2019). [d] Campagnolo and Davide (2019). [e] Marcinko et al. (2021). [h] Garchitorena et al. (2017). [i] Hertel et al. (2011).

### 3.2.3 Model application

- Computable general equilibrium (CGE) models

Most CGE models aimed at the ex-ante analysis of possible future poverty changes influenced by different social, economic, or natural changes (Figure 4a). Static CGE models compared the poverty levels in the initial and final equilibrium states affected by tax changes (Beckman et al., 2019), cash transfer programs (Yusuf, 2018), trade liberalization (Jeong-Soo and Kyophilavon, 2015; Kyophilavong, Wong, et al., 2017), and agricultural productivity and efficiency improvements (Solaymani and Yusoff, 2018). Dynamic CGE models simulated the dynamic impacts of various influencing factors on poverty over time. These factors involve energy (Breisinger et al., 2019), education subsidies changes (Mardones, 2015), agricultural productivity (van Wesenbeeck et al., 2021) and investments (Badibanga and Ulimwengu, 2020; Benfica et al., 2019), tax reforms (Mahadevan et al., 2017), carbon emissions (Altieri et al., 2016; Campagnolo and Davide, 2019), and climate changes such as rainfall shocks (Borgomeo, Vadheim, et al., 2018). However, around two-thirds of them were only applied to project the trends between 2020-2030, and the remaining was applied to projections between 2031-2050.

In previous studies using CGE models, about two-fifths (37.93%) of previous studies involved economic variables only in CGE models, 24.14% and 27.59% of them contained economic and social, and economic and environmental variables, respectively, while the remaining 10.34% involved economic, social, and environmental variables. Common economic variables include labor types, trade activities, capital classification, GDP and income, government financial allocation, agricultural products, and productivity (Badibanga and Ulimwengu, 2020; Borgomeo, Vadheim, et al., 2018). The social variables most often modeled include population growth, employment and unemployment, and education development (Breisinger et al., 2019; Mardones, 2015). The environmental variables mainly are land types and shares, greenhouse gas emissions and energy access (Campagnolo and Davide, 2019; Fujimori et al., 2020).

- Econometric models

Most applications of econometric models for poverty analysis aimed to investigate the connections of poverty and various influencing factors modeled in the entire system (Figure 4a). On one hand, relationships between poverty and socioeconomic activities (e.g., tourism economy (Supriyadi and Kausar, 2017), financial crises (Antoniades et al., 2020), urban fabric characteristics (Duque et al., 2015)) were examined to analyze their impacts. Bafadal et al. (2020) constructed an econometric model to assess government expenditure and its impact on agricultural output performance and poverty. On the other hand, linkages between poverty and natural resource degradation (Daregot et al., 2015) and the vulnerability of households to climatic disasters (Taupo et al., 2018) were identified. In addition to relationship analysis, two global multi-country econometric models were utilized for ex-ante analysis, one of which only predicted the consequences of various economic measures to fight poverty until 2020 (Ashimov et al., 2019), and the other evaluated absolute poverty changes at the global level under different shared socioeconomic pathways until 2030 (Cuaresma et al., 2018).

Static and dynamic econometric models introduced panel data (a set of survey data that occur at the same time) and time-series historical data as sample data, respectively, to estimate model parameters for poverty analysis. Most econometric models are static (Figure 4b). The economic model variables that are often considered in econometric models for poverty analysis include capital, GDP, income, labor categories, agricultural efficiency, government investments, and trade activities. Education level, employment situation, population growth, and demographic characteristics are common social variables modeled in econometric models. Several environmental variables were also constructed in four econometric models, such as ecological situations (e.g., degree of desertification and soil erosion, precipitation, geological disasters) (Zhou et al., 2020), and accessibility of natural resources like water, energy, and land (Abraham, 2018; Daregot et al., 2015; W. Wang et al., 2018).

- System dynamics (SD) models

Based on their dynamic and evolutionary characteristics, SD models in the selected literature were all used to project possible future trends of poverty under different scenarios, which can be classified into three groups according to three different modeling themes. The first group, also the most researched, is the nexus of ecosystem, economy, and poverty (Cheng et al., 2019; Garchitorena et al., 2017). For example, Grace et al. (2017) applied a national-scale SD model to illustrate that poverty traps may arise through the inter-relationships between ecosystem services damage, health, and well-being outcomes. Xin Cheng et al. (2018) established the interaction mechanism between the ecological environment, disasters, and poverty in China's reservoir regions, and simulated the effects of different environmental protection and poverty reduction strategies on poverty eradication.

The second group focused on the relationships between agriculture-related influencing factors and poverty. Karmozdi et al. (2020) constructed a local sustainable rural development model to simulate the impact of agricultural support, non-agricultural support, and environmental education on multidimensional poverty. Brinkmann et al. (2021) developed a local SD model for projecting possible trends in farmer crop management to 2045 and simulating their impacts on the family economy and environment. Ndhleve et al. (2017) investigated causality between agricultural public expenditure, agricultural growth, and poverty, and the driving factors of poverty reduction in South Africa, and found that investments in agricultural research, rural infrastructure and rural education had the greatest impact on poverty alleviation.

The third group analyzed the influence of socioeconomic scenarios on poverty. An integrated iSDG-Fiji model was constructed to perform a national-scale scenario analysis for Fiji (Allen et al., 2021), with a business-as-usual future scenario and six alternative scenarios within global Shared Socioeconomic Pathways, which evaluated the progress of each SDG by 2030 and the trends of environmental changes by 2050 in terms of planetary boundaries. Similarly, an integrated iSDG-Australia model was developed to project the future performance and assess the progress of 17 SDGs under four development scenarios by 2030 in Australia (Allen et al., 2019).

- Microsimulation models

Microsimulation models were usually used to analyze the impacts of economic and climate changes on poverty. A tax-benefit model EUROMOD, a form of microsimulation model, was applied to analyze the impact of subsidy reform policies on finances, income distribution, and poverty risks (Fuchs et al., 2017), and simulate a set of scenarios of increasing subsidies for childcare and mothers' employment and estimate their impacts on child poverty (Hufkens et al., 2020). The impact of climate change on household-level poverty by 2030 was assessed by combining the physical impact assessments of climate change in various sectors with a global database of household surveys in 92 countries (Hallegatte and Rozenberg, 2017). Agent-based models, as another type of microsimulation models, were implemented to evaluate the impact of healthcare policies on health, poverty and income distribution by 2050 in

Uganda (Shrime et al., 2016), and explored the long-term interdependence between agroforestry adoption decisions of farmers, poverty, and ecological environment in Indonesian rural areas (Nöldeke et al., 2021).

- Bayesian belief network (BBN) models

BBN models are suitable to estimate the probability of possible causes, consequences, or subsequent events from learning from data, which have been used to simulate the impact of agricultural policy on poverty in Ghana (Banson et al., 2016) and analyze the contribution of forest ecosystem services to rural household assets and multidimensional poverty in Southern Mozambique during 2015-2035 (Zorrilla-Miras et al., 2018).

- Input-output models

Only two studies applied input-output models for poverty scenario analysis. Input-output models were utilized to evaluate the effects of different carbon tax rates on income distribution and poverty in Mexico by combining with household survey data (Renner, 2018), and the potential impact of climate policies and employment on poverty by 2030 in more than 40 countries (Malerba and Wiebe, 2021).

- Hybrid models

Most hybrid models are CGE with microsimulation analysis (CGE-MS) models, with the modeling framework combines macro-CGE models with microsimulation models to capture the impact of macro-shocks on micro-distributions (Bussolo and Cockburn, 2010). CGE-MS models use the output of the CGE model as the input of the microsimulation model to analyze the micro impacts on income distribution and poverty from different scenarios, including taxes reforms (DIZON, 2021; Mohammed, 2018), cash transfer programs (Cury et al., 2016), trade policies (Boysen and Matthews, 2017; Shuaibu, 2017), agricultural policies (Boysen et al., 2016; C. B. Cororaton and Yu, 2019), energy subsidies (Cockburn et al., 2018), health (Chitiga‐Mabugu et al., 2021; Kabajulizi et al., 2017), and ecological changes (C. Cororaton et al., 2018; Siriban-manalang et al., 2016).

Only several hybrid models integrate other model types. A local integrated assessment model, combining an improved FAO CROPWAT model for agricultural yields estimation and an agent-based model for wellbeing projection, was applied to predicting poverty and inequality under different climate and socio-economic scenarios by 2100 in the southwestern coastal area of Bangladesh (Lázár et al., 2020). A static local hybrid model that combined four climate models was employed to study the pressures on food security, multidimensional poverty, and environment brought by climate changes in 2035, 2065 and 2085 in southern Pakistan (Aslam et al., 2018). Belem and Saqalli (2017) proposed a national comprehensive model combining system dynamics, Bayesian networks, and agent-based techniques to assess the impact of climate change, agricultural ecosystems, and demographic transitions on a West African country's ecosystem services, poverty reduction, and food self-sufficiency. Furthermore, several global hybrid models were utilized to study the consequences of various climate change scenarios (Byers et al., 2018; Rosenzweig et al., 2018). The most famous one is the International Futures (IFs) model, which is a large-scale integrated assessment model with interconnected sub-models of economy, population, education, agriculture, energy, and environment. The IFs model was adopted to explore the possible potential progress in poverty eradication in fragile countries by 2030 (Milante et al., 2016) and analyze the progress of SDGs and the potential for economic growth by 2100 (Hughes and Narayan, 2021).

## 4 Discussion

### 4.1 Model comparison

Table 5 summarizes the pros and cons of models commonly used for poverty scenario analysis. CGE models can construct linkages of various economic sectors and industries to reflect a coordinated interaction mechanism within the economy. Due to the theoretical foundation of the general equilibrium modeling method, CGE models have some limitations. First, they rely on the assumption that the economy will move toward an equilibrium state (an ideal state), which may be inconsistent with the actual economic situation. Second, they cannot respond effectively to future uncertainties (e.g., the unexpected occurrence of the COVID-19 pandemic, drastic changes of economic structure) because the trend relies on a large amount of historical data (e.g., social accounting matrix), which limits the understanding of poverty issues that arise over time from the interactions of multiple sectors. Third, some global CGE models that focus on long-term poverty scenario analysis are inherently difficult to verify, due to the difficulty in collecting required high-quality data for all countries (Jin et al., 2017). For econometric models, model verification is relatively easy, because it is usually carried out together with the parameter estimation to maximize the goodness of fit of the model. However, they are only suitable for short-term poverty projections and the situation of which the future socioeconomic trends are in line with past experience. In the case of rapid socioeconomic, the model effectiveness in the projection of poverty indicators will be seriously affected (Rey, 2000). SD models can track cause and effect, allowing the exploration of complex systems with poverty feedback loops and promoting the understanding of the causes and influences of poverty. SD models can be used for poverty scenario analysis outside of the experience of historical data, but they have some parameters and functional forms that are difficult to estimate. Their verification is also complicated, and not only involves assessing the quality of parameter estimations using a variety of data, but also evaluates the effectiveness of model structure (Jin et al., 2017). Microsimulation models can effectively simulate the impact of different poverty alleviation policies on different groups or individuals, but they require more behavioral assumptions and more accurate microeconomic data compared with traditional macroeconomic models (Ballas et al., 2013).

Input-output models can reflect the structural relationships of industries via detailed industry information, and data are required to show the income and expenditure of each economic sector to support poverty analysis. However, they are difficult to split and integrate relevant data reflecting the industrial linkages among regions and countries under some circumstances. Similar to other model types that rely heavily on historical data, they cannot effectively respond to future uncertainties (Rey, 2000). BBN models use conditional probability to express the causal and conditional relationships between poverty and various elements, which can learn and deduce the probability of occurrence of some outcomes under conditions of limited, incomplete, and uncertain information. However, they are constructed based on the assumption of sample attribute independence, and the model effectiveness gets worse if the sample data violate this assumption (Oladokun, 2014). Hybrid models encompass combinations of a variety of models and thus can conduct both macro and micro poverty scenario analysis, cover wider sectors and have higher applicability for poverty in more complicated systems. However, using hybrid models have to face the difficulties of complicated model development and evaluation as well as the higher unavailability of historical data.

**Table 5.** Advantages and disadvantages of various models commonly used for poverty scenario analysis.

| Model types | Model advantages | Model disadvantages |
|---|---|---|
| CGE models | Link various economic sectors and industries. | Relying on the assumption of equilibrium;<br>unable to respond effectively to future uncertainties;<br>difficult to verify the global model and organize the data; |
| Econometric models | Easy to verify the model by fitting historical data. | Suitable for short-term development research instead of long-term research;<br>unable to respond effectively to future uncertainties. |
| SD models | Exploration of causal mechanism and dynamic complex relationships;<br>can be used for scenario analysis beyond the trend of historical data. | Difficult to obtain values of some parameters;<br>difficult to evaluate models' effectiveness. |
| Microsimulation models | Analyze the impacts on different populations and even individuals. | Need more behavioral assumptions and more accurate and true microeconomic data;<br>difficult to evaluate models' effectiveness. |
| Input-output models | Reflect the structural relationships of industries by detailed industry information. | Difficult to split and integrate relevant data reflecting the industrial linkages among regions and countries;<br>unable to respond effectively to future uncertainties. |
| BBN models | Causal and conditional relationships exploration. | Use the hypothesis of sample attribute independence. |
| Hybrid models | Macro and micro combination;<br>wider sectoral coverage;<br>suitable for studying complex issues. | More complicated model development;<br>more data demand;<br>difficult to evaluate models' effectiveness. |

In summary, it is recommended to use CGE or econometric models if a study focuses more on economic activities and poverty. Input-output models are more suitable to explore the relationship between poverty and each single industry (e.g., agriculture, forestry, fishery, manufacturing, transportation). Microsimulation models are appropriate to conduct the poverty analysis at the micro level (e.g., individuals, communities). SD and BBN models are the better choice if the dynamic causal mechanisms covering poverty and multiple other sectors need to be explored. Hybrid models can be utilized to research poverty in complex systems with dynamic causal mechanisms, relationships of various sectors and industries by combining multiple types of models at macro and micro levels.

### 4.2 Representative models

We derived seven representative models (Table 6) from more than 100 candidate scenario analysis models in the literature. A model is regarded as representative if it meets the following standards: (1) The model can be used for different countries or global setting instead of for only one country; (2) The model is developed by an authoritative organization (i.e., international organizations or well-known universities); (3) An introductory document or official website for this model is accessed publicly. Representative models include two CGE models, one SD model, one microsimulation model, and three hybrid models.

One CGE model, the Global Trade Analysis Project (GTAP) model embedding a poverty module (GTAP-POV), is an extension of the GTAP model to analyze the dynamic impact of global economic and environmental changes on national poverty, which was developed by an alliance composed of institutions such as the World Bank, World Trade Organization, European Commission, Organization for Economic Cooperation and Development (OECD), and International Monetary Fund (Hertel et al., 2011). GTAP is a multi-region and multi-sector CGE model, accompanied by a multi-country input-output table that includes production, consumption, bilateral trade and transportation data. Another CGE model, Maquette for MDG Simulations (MAMS), is a dynamic country-level model designed by the World Bank to analyze the national progress for the Millennium Development Goals (MDGs) of poverty, health, education, water and sanitation (Lofgren et al., 2013). MAMS was applied for World Bank country analysis, such as Public Expenditure Reviews and Poverty Assessments (Hans and Carolina, 2009).

**Table 6.** Representative poverty scenario analysis models and their characteristics.

| Model types | Model names | Model purpose and states | Spatial and temporal scales | Main variables coverage | Poverty measurement |
|---|---|---|---|---|---|
| CGE models | GTAP-POV | ex-ante scenario analysis; dynamic | Global, regional, national (140 regions); up to 2100 | GDP, income distribution, energy, climate, trade, government finance, etc. | PR calculated by income |
| | MAMS | ex-ante scenario analysis; dynamic | National (developing countries); up to 2030 | GDP, income, education, health, water, sanitation, trade, government finance, etc. | PR calculated by income or consumption |
| SD models | iSDG | ex-ante scenario analysis; | National; | GDP, income, population, health, education, agriculture, | PR calculated by income |

| | | | | | |
|---|---|---|---|---|---|
| | | dynamic | up to 2050 | land, water, climate, energy, infrastructure, etc. | |
| Micro-simulation models | EUROMOD | ex-ante scenario analysis;<br>static | Regional, national (EU countries, United Kingdom) | GDP, income, households, government finance, etc. | PR calculated by income |
| Hybrid models | GIDD | ex-ante scenario analysis;<br>dynamic | Global, regional, national (121 countries);<br>up to 2100 | GDP, income, trade, education, etc. | PR calculated by income |
| | IMPACT | ex-ante scenario analysis;<br>dynamic | Global, regional, national (159 countries);<br>up to 2100 | GDP, income, climate, agriculture, water, food supply, demand, trade, prices, land use, nutrition and health, etc. | GDP |
| | IFs | ex-ante scenario analysis;<br>dynamic | Global, regional, national (186 countries);<br>up to 2100 | GDP, income, population, education, agriculture, technology, government finance, international politics, health, energy, water infrastructure, environment, governance, etc. | PR calculated by income |

The integrated Sustainable Development Goals (iSDG) is a SD model constructed by Millennium Institute (MI, 2021). This model extends the concept of CGE models to a wider range of dynamic connections and policy issues to support national development planning and sustainable scenarios analysis, and explore the impact of policies on the country's progress in achieving all SDGs. iSDG has been used to formulate many countries' reports of SDGs' achievement progress (MI, 2021). A static tax-benefits model EUROMOD is a microsimulation model proposed by the European Union (EU), which can be used to analyze and compare the impact of different taxes and benefits policies on poverty, inequality and budget at individuals and households levels for each EU country and the United Kingdom (Sutherland and Figari, 2013).

Global Income Distribution Dynamics (GIDD) is developed by the World Bank, which is a global hybrid model with the macro-micro framework integrating a dynamic CGE model and a microsimulation model. It could be used to analyze the impact of different global policies scenarios on global economic growth, income distribution and poverty (Bussolo et al., 2009). GIDD has been adopted widely in previous studies, such as working papers and reports by OECD (Bourguignon and Bussolo, 2013). The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) proposed by the International Food Policy Research Institute (Robinson et al., 2015), is also a global hybrid model integrating climate models, crop simulation models, water models with a core global partial equilibrium multi-market economic model. IMPACT has been applied to addressing how to reduce poverty and feed the world while protecting natural resources in the future (Rosegrant et al., 2017), and also used in the World Bank's reports for interdisciplinary analysis (World Bank, 2007). International futures (IFs), proposed by the Pardee Center for International Futures in the University of Denver (Hughes, 2019), is a large-scale, multi-issue long-term integrated assessment model integrating multiple sub-models, including a general equilibrium economic sub-model, and sub-models of population, agriculture, education, energy, environment, and international politics (Hughes, 2019). IFs allows projecting the progress of all SDGs in 186 countries influenced by different economic, social and environmental changes throughout the 21st century, which has been utilized in many international reports like the United Nations Human Development Report and the Global Environment Outlook (Hughes, 2018).

### 4.3 Modelling synergies and trade-offs between SDG 1 and other SDGs

As a complex social issue, poverty eradication is inseparable from the interaction of the entire socioeconomic and environmental system (e.g., socioeconomic changes, demographics, land, food, energy and climate). The SDG framework integrates key environmental, social and economic goals to promote sustainable development, and almost all SDGs influence poverty elimination (Kroll et al., 2019; Pradhan et al., 2017). For instance, taking unsustainable actions (e.g., a large amount consumption of fossil fuels to satisfy the energy demand for rapid economic growth, vigorous industry development without paying attention to environmental governance) to promote economic growth and further eliminate poverty may be the most convenient and quickest way in the short term (Adger and Winkels, 2014). However, some side effects will appear over a longer time horizon, such as increased greenhouse gas emissions and climate changes (SDG 13) (Bowles et al., 2014), environmental degradation (e.g., water (SDG 6) and soil (SDG 15) pollution, deforestation), biodiversity loss (SDG 15), and increased risk of pandemics (SDG 3) (Schleicher et al., 2018). In the long run, these side effects will affect economic growth (SDG 8) and then eventually increase poverty (SDG 1).

However, most existing models for poverty scenario analysis overlooked the importance of synergies and trade-offs among SDGs (section 3.2.2). On one hand, only ten models clearly developed variables for other SDGs, and only iSDG and IFs had variables for all 17 SDGs. SDGs 5-7, 9, 10, 12, and 14 were measured by proxy indicators, indicators that were fully in line with the sub-goals of these SDGs have not been constructed in collected models. Although other SDGs could be evaluated by indicators that were consistent with the SDGs agenda, one SDG contains multiple sub-goals and quite a few sub-goals have not been modelled. On the other hand, although some models covered some variables that could be used to evaluate some SDGs, the mechanisms of their interactions are still elusive. Analysis of these mechanisms by cross-disciplinary innovation is critical to understand their synergies and trade-offs, which need various challenging efforts, including integrating various systems involved in the economy, society and the environment, and identifying the interrelated factors and behaviors in systems, and then establishing their dynamic relationships. These efforts will promote a comprehensive understanding of the evolution mechanism of poverty in a complex system instead of the simple behavioral association between poverty and certain factors, which ultimately help uncover better poverty reduction strategies with consideration of synergies and trade-offs for other SDGs.

## 5 Conclusions and suggestions for future poverty scenario analysis

This paper reviewed 144 papers on model-based poverty scenario analysis. We classified these models into seven types, including computable general equilibrium, econometric models, system dynamics models, microsimulation models, input-output models, Bayesian belief network models, and hybrid models. These models were used for ex-ante scenario analysis, ex-post scenario analysis, and relationships exploration. We also identified seven representative poverty scenario analysis models. We found the following research gaps based on the review of bibliometric and model information, and the discussions on different model types and interactions between poverty and other SDGs.

(1) Around 80% of previous studies were carried out at national and local levels and models that could be used for medium- and long-term poverty simulations were very limited. However, in the context of increasing international cooperation and integration, poverty research from global to local scales is indispensable. It is conducive to understanding the evolution mechanism of poverty and their interactions with other SDGs and other related international agendas (e.g., the Paris Agreement), guiding global to local poverty strategies in a long-term perspective (Hughes et al., 2015).

(2) Poverty scenario analysis was mainly carried out from the single perspective of the economy, eco-environment, and agriculture, while comprehensive analyses that integrate multiple sectors (e.g., economic, social, and environmental) was seldom reported. Few models can address synergies and trade-offs between SDG 1 and other SDGs, but the interactions between poverty and other SDGs and their potential impacts are essential for reducing poverty and the resulting negative impacts (De Neve and Sachs, 2020), and poverty alleviation needs to be dealt with scientifically in a more comprehensive and integrated way (Adger and Winkels, 2014).

(3) The hybrid models used in poverty scenario analysis were mainly the integration of CGE and microsimulation models. The advantages of these models were not fully reflected for modelling dynamic causal mechanisms and multiple sectors relationships in complex systems.

(4) The poverty rate was the most widely used indicator to measure poverty in previous studies. However, due to the complexity of poverty and its diverse driving factors, this indicator cannot represent the diverse information of poverty, such as the depth and inequality of poverty.

As a result of the literature review about model-based poverty scenario analysis, some suggestions for future research are provided below to fill up the research gaps in existing studies.

(1) It is desirable to develop effective scenario analysis models for more medium- and long-term simulations of poverty changes under different future scenarios, especially global and regional models for understanding the evolution of global or regional poverty.

(2) The second promising direction is to develop scenario analysis models covering multiple sectors and a broad range of variables for these sectors so that the combined effects of multiple poverty alleviation policies can be evaluated. These variables include economic growth, population, education, health, agriculture, climate change, land use, water use, and energy use.

(3) It will be helpful to enhance the modeling of synergies and trade-offs between poverty and other SDGs, particularly with the relevant SDGs that are considered to have significant synergies or trade-offs (e.g., SDGs 2-3, SDGs 7-9, SDG 13) (Griggs et al., 2017; Kroll et al., 2019), or with the SDGs that are rarely modeled (e.g., SDGs 4-5, SDGs 11-12, SDG 14).

(4) To model complex systems effectively, it is critical to develop hybrid models by the integration of multiple single models that can complement with each other. For example, integrating system dynamic models with CGE concepts is capable of modelling dynamic causal mechanisms and multiple sectoral linkages.

(5) To measure poverty in a comprehensive manner, future work could measure economic poverty from multiple aspects (e.g., poverty rate, poverty gap, poverty severity, poverty trap), and integrate it with other dimensions of poverty (e.g., energy, water).

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## CRediT authorship contribution statement

**Qi Liu:** Conceptualization, Methodology, Visualization, Writing - original draft. **Zhaoxia Guo:** Conceptualization, Methodology, Writing – review & editing. **Gao Lei and Yucheng Dong:** Methodology, Writing - review& editing. **Jing Yang:** Visualization, Writing – review & editing. **Enayat A. Moallemi, Sibel Eker, Michael Obersteiner and Brett A. Bryan:** Writing - review& editing. **Xiaofeng Li:** Supervision, Project administration.

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