What do we know about
THE FUTURE OF FORESIGHT MODELING RELATED TO FOOD SYSTEMS?

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Key messages

- "Foresight modeling" is thinking about the future using a simplified representation of reality to inform choices we make today.
- Quantitative foresight modeling is increasingly used to inform decision-making related to food systems by analytically exploring alternative possible futures in a world that is becoming more complex and uncertain.
- Foresight modeling is improving in coverage and resolution, but various technical and institutional challenges remain.
- Artificial intelligence can help gather and synthesize information to improve foresight modeling, but it cannot replace the role of human expertise and foresight in testing assumptions and helping to shape the future.
- To be most effective, quantitative foresight modeling needs to be better linked with qualitative foresight approaches and complemented by engagement with decision-makers in an ongoing and systematic process.

RECENT TRENDS AND CHALLENGES

Food systems are inherently complex, involving biophysical and socioeconomic processes and interactions among the choices made by more than 8 billion people every day. It is impossible to measure and analyze all aspects of food systems, but it is possible to know quite a lot about some aspects and critical to understand their key features and how they are changing. As shown in this book, foresight modeling can help us do that.

Foresight modeling may sound like a mysterious and complicated process, but if you have ever asked a question starting with the words "What if…", you have used foresight. And if you have ever formed an opinion or drawn a conclusion based on incomplete information (which is what we all do, most of the time), you have used a model. Simply put, foresight is thinking about the future to inform choices we make today. And modeling is using a simplified representation of an object or a process to better understand it.

In this sense, we all use mental models implicitly, and all foresight involves modeling in some way. Farmers have used informal foresight models since the dawn of agriculture – including each time they make a decision about what, where, and when to plant a crop that will be harvested weeks or months later. Their models are based on past experience as well as assumptions about weather and market conditions in the future.

Foresight modeling can be simple or complex, subconscious or deliberate, implicit or explicit, and qualitative or quantitative, depending on the question at hand. Deciding whether to take an umbrella when you leave the house in the morning is a relatively simple foresight modeling exercise, based on looking out the window or at the weather forecast on your mobile phone. The weather forecast on your phone, on the other hand, is the result of very complex and sophisticated modeling. Similarly, the future of food systems involves the interaction of complex biological and physical processes (including weather) as well as social and economic processes (including the choices we make about what we eat and how we produce it). Understanding the future of food systems thus requires complex foresight modeling (Wiebe et al. 2018).

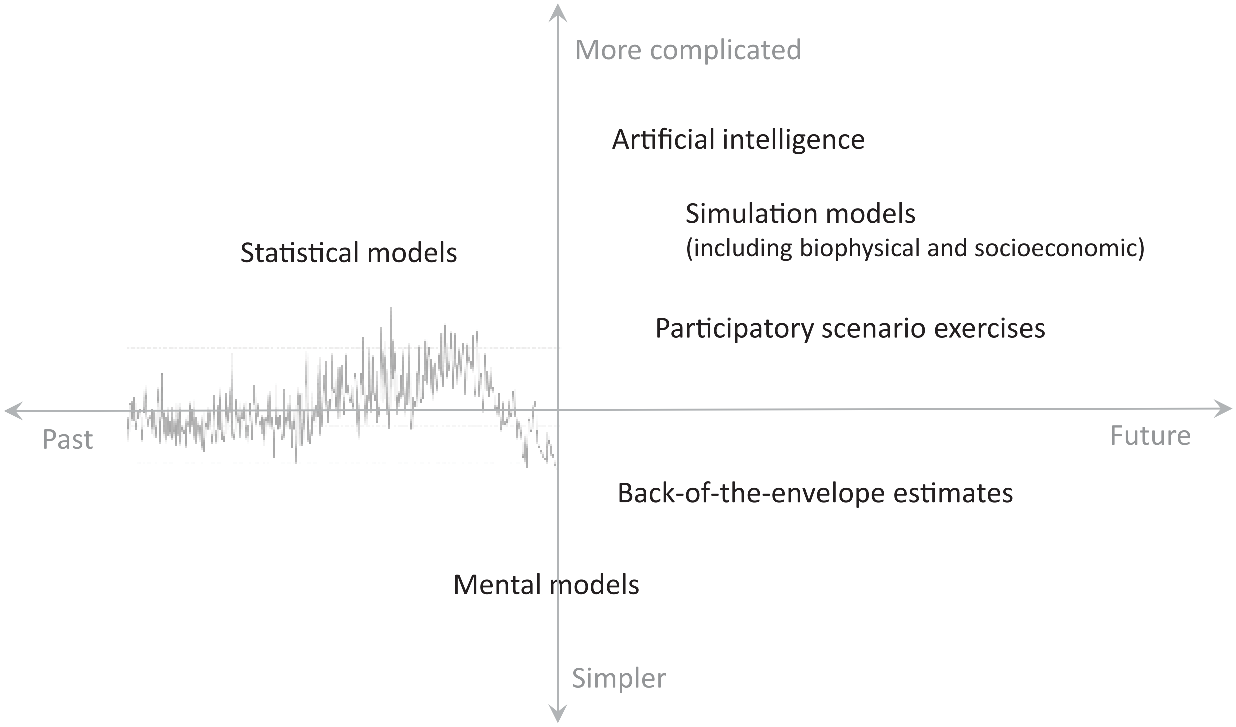
In recent years, food systems have become larger and more complicated in some ways (including the growing volume of production and complexity of global value chains), even while becoming simpler in other ways (including the increasing scale of production and focus on fewer major commodities in many areas). Over the same period, more formal foresight models have been developed to better understand food systems and how they may change in the future. These models vary in approach, complexity, and time horizon (Figure 1). Qualitative models may be based on structured dialogue with stakeholders about alternative future scenarios, usually resulting in a set of "storylines" about how various scenarios may unfold. Quantitative models include both statistical models that analyze historical data and simulation models that draw on historical patterns and explore how they might change in the future. These simulation models include specialized models, focused on specific biophysical and socioeconomic aspects of food systems, and are sometimes linked in integrated modeling frameworks. Foresight exercises often draw on both qualitative and quantitative models to bring together their complementary strengths.

Quantitative models are based on explicit assumptions about the model's components and how they interact with each other. This is sometimes seen as a weakness of these models, but it is actually their strength, because it makes those elements transparent and allows the assumptions to be tested – and changed if desired. (If someone does not make explicit assumptions about some things, it does not mean those things are not important. It just means that person has made *implicit* assumptions – for example, that those things do not change, or that they are not relevant. In fact, that person is using an implicit model, possibly without realizing it.)

These simplifying assumptions mean, as statistician George Box (1976) once wrote, that all models are "wrong" in that they do not capture reality completely or perfectly. (Box may have been writing about statistical models, but the same is true, by definition, for all models.) But as Box also noted, some models are still useful – specifically if they capture the features of an object or system that are essential for considering a particular question and omit features that are not relevant for that question.

No single model can capture all aspects of food systems, and indeed some aspects may not be captured by any model. But different models can be linked in various ways to capture multiple aspects of food systems. This chapter focuses primarily on economic simulation models linked

FIGURE 1 **Foresight models include a wide variety of approaches and time horizons**



Source: Authors' construction.

to other types of models that together capture some of the main features of food systems, including changes in population, income, technology, climate, land and water use, crop growth, diets, and health. By bringing together expertise about these different components of food systems, such modeling systems can help test assumptions and hypotheses about how food systems work, how they may change over time, and how the choices we make today can help direct those changes toward desirable outcomes in the future.

LATEST FORSIGHT RESEARCH

The past several decades have seen rapid growth in the development and use of biophysical and socioeconomic models to analyze various aspects of food systems. Many of these modeling systems have been further refined over the past decade through collaboration initiated as part of the Agricultural Model Intercomparison and Improvement Project (AgMIP). Among the global economic models involved in this collaboration are the AIM model developed by the National Institute for Environmental Studies (Japan), the CAPRI model developed by the Joint Research Centre of the European Commission, the ENVISAGE model developed originally at the World Bank, the GLOBIOM model developed by the International Institute for Applied Systems Analysis (IIASA), the IMPACT model developed by the International Food Policy Research Institute (IFPRI), the MAGNET model developed by Wageningen University & Research, and the MAgPIE model developed by the Potsdam Institute for Climate Impact Research. Other models used to analyze aspects of food systems include the EPPA model developed by the Massachusetts Institute of Technology and the GTAP model developed by Purdue University.

While these modeling systems share a general aim in exploring how food systems are changing, they also differ in important ways, depending on the specific purpose for which they were designed. Some focus on agriculture and food, while others incorporate other sectors of the economy. Some focus on global and regional scales, while others offer more detail at the national or even subnational level. Some offer greater detail on commodity production, trade, and diets, while others provide deeper analysis of land, water, energy, employment, income, or other indicators.

These models typically incorporate possible future changes in population, climate, and other factors as inputs from other modeling efforts, which enter these economic modeling systems as assumptions. These assumptions help define scenarios that may also reflect broader storylines about alternative possible futures (for example, a future characterized by slower population growth, increased investment in sustainable technologies, or more fragmented trade relations). These assumptions are then tested and their impacts compared in the context of dynamic economic relationships among production, trade, and consumption of different food and other commodities in different regions and over time.

While research in this area has expanded rapidly over the past decade, a few examples illustrate how these modeling systems can be used to explore key features of food systems. Using 10 global economic models, Valin et al. (2014) found that socioeconomic factors will have a bigger effect on global food demand than climate change in 2050. Nelson et al. (2014) analyzed results from 9 global economic models, 2 climate models, and 5 crop models to examine impacts of climate change on crop yields, area, production, prices, trade, and consumption. Wiebe et al. (2015) conducted a similar study with additional scenarios, finding that yield impacts increase at high emissions levels and vary with changes in population, income, and technology, but are reduced in all cases by endogenous changes in prices and other variables.

Further exploring interactions within food systems, Hasegawa et al. (2018) examined trade-offs among different policy goals, finding that climate mitigation policies need to be carefully implemented to avoid adversely affecting global hunger, particularly in sub-Saharan Africa and South Asia. Van Zeist et al. (2020) compared projections of future yields from five global economic models, finding that significant potential for further yield growth remains even in 2050 in some regions, particularly sub-Saharan Africa. Van Dijk et al. (2021) analyzed 57 studies projecting future global food demand and risk of hunger and found that most projected an increase in demand of 45–56 percent between 2010 and 2050. Rosegrant et al. (2024) used the IMPACT model to analyze how climate change will affect food security in different regions in 2035 and 2050 under multiple socioeconomic and climate scenarios. Most recently, 10 global economic models, as well as multiple input–output and optimization models, have been used to explore the impacts of dietary change on planetary boundaries and other food systems metrics, including livelihoods and incomes – and how policies and investments can help shape those outcomes – as part of the EAT-Lancet 2.0 Commission report (Rockström et al. forthcoming) and related background studies.

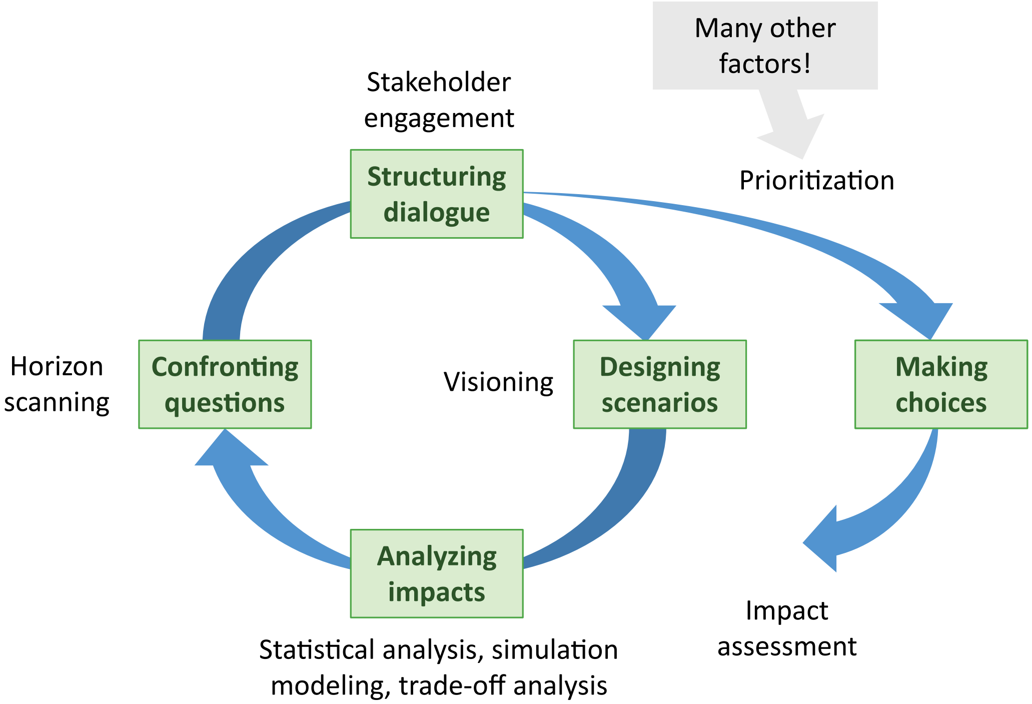
Foresight modeling studies like these have been used to inform policy and investment decisions by national governments, aid agencies, multilateral development banks, and private foundations, as well as intergovernmental processes like the Intergovernmental Panel on Climate Change. In addition to the global and regional models and studies noted above, country-level models such as IFPRI's RIAPA model are playing an increasingly important role in informing national governments (particularly in low- and middle-income countries) about impacts and policy options related to short- and medium-term shocks such as COVID-19 (Pauw et al. 2021) and the Russia-Ukraine conflict (Arndt et al. 2022). Many of these models include details at subnational levels, but they are most often used to explore interactions and challenges at larger scales.

KEY GAPS AND OPPORTUNITIES FOR FORESIGHT RESEARCH

Foresight models have evolved from an initial focus on commodities and production to capture more food systems features related to livelihoods, incomes, diets, health, natural resource use, the environment, and climate. Further attention to socioeconomic differences in access to resources and opportunities, biophysical differences in resource conditions, and spatial differences in both of these dimensions can help better target both the results provided by foresight modeling and the policy and investment choices made by decision-makers.

Different models are needed to address different questions, but end-users may find it difficult to make an informed choice about which models to use. Moreover, it can be challenging to find a model that can provide results for countries with small economies or territories (Mosnier et al. 2023). The FABLE Consortium, the Deep Decarbonization Pathways initiative, and the Foresight4Food (F4F) initiative are now developing a simple, collaboratively produced, and publicly accessible tool to help end-users identify the models that are

FIGURE 2 **Foresight modeling is part of a larger process to inform decision-making**



Source: Adapted by the authors from Wiebe et al. (2018)

best suited for their purposes. Three criteria guide this selection. First, can the model represent the actions the users want to test and the outcomes they want to observe before and after the implementation of these actions? Second, can the model produce results at the geographic scale required? And third, what is needed to access the model and how easy is it to adapt it? The tool is built upon a detailed database that includes different types of simulation models (not only economic models) that are relevant for food systems foresight. The database is currently being expanded by including more models, by capturing recent developments of models already included, and by adding more criteria to improve the tool's capacity to guide the choice of models.

Looking beyond existing models, artificial intelligence (AI) offers considerable potential but also risks in relation to foresight modeling of food systems. In planning for the future, as in understanding the past, we want to be informed by the best available evidence. Collecting data has historically been a challenge, but today we live in a world saturated by data, to the point that processing and interpreting that data is as much of a challenge as gathering it. While quantitative foresight models offer a tool to process such complex information, this complexity can also make these models difficult to use. AI approaches increase our capacity to collect and synthesize information from a wide spectrum of sources, which could help improve the representation of complex systems in quantitative foresight models, increase the speed at which these models can be updated and validated, identify previously overlooked relationships, and inform the development of a broader range of relevant scenarios. Machine-reading and learning approaches, for example, can speed up the process of reviewing previous research to find key coefficients and relationships to parameterize model behavior (Brandtner and Mates 2021;Ködding et al. 2023). AI approaches could also help summarize and simplify the results of quantitative foresight models, making it easier to communicate them to a broader audience, including decision-makers and other stakeholders.

Despite these opportunities to improve foresight modeling, AI approaches are unlikely to replace human expertise entirely. First, the systems we are interested in are complex and ultimately chaotic, and increased data will not be able to fully eradicate uncertainty (Geurts et al. 2022; van der Sluijs 2005). If not applied carefully, AI can contribute to overconfidence in our knowledge of complex systems, increasing the risk of unintended consequences (Mason-D'Croz et al. under review; Suckling et al. 2021; De Zwart 2015). Second, AI applications are not perfect, and as they are often black boxes, they can introduce errors and biases in opaque ways (Chen 2023; Vicente and Matute 2023). As a result, human expertise will be critical in responsible AI use to assess the quality of data used by AI as well as the design of AI applications. And finally, while AI may help improve our ability to understand past trends and forecast future ones, ultimately foresight goes beyond trying to predict the future; it is about helping shape and define the future. Defining the future is not just about preparing for what will come, but also deciding which futures we want to achieve or avoid. That requires answering fundamental questions about what we care about most, which AI cannot do for us.

While foresight modeling tools continue to be improved, experience has shown that they are most useful as part of an iterative process that also includes qualitative foresight approaches to engage with decision-makers and other stakeholders, while recognizing that results from foresight exercises are themselves part of a larger set of factors that influence decision-making (Figure 2). This linkage improves effectiveness in multiple ways, including before and during the modeling stage by informing the framing of the scenarios and the modeling assumptions, and afterward by ensuring that the results are accessible and useful for decision-makers.

As noted at the beginning of this chapter, we all use models implicitly, whether we realize it or not. But understanding food systems and exploring options to improve them in the future requires more formal foresight modeling. The goal is not for everyone to become quantitative foresight modelers, and certainly not for all decisions to be made by such models. It is important, however, to help decision-makers *think* more like modelers – that is, to identify the key features of food systems that are important for particular decision-making contexts, to be explicit about the assumptions that are made about those features in a complex and uncertain world, and to be willing to test – and if necessary, change – those assumptions to better understand the likely future impacts of choices we make today.

This chapter was supported by the CGIAR Research Initiative on Foresight and the CGIAR Science Program on Policy Innovations. We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund.

This chapter was developed jointly with the Foresight4Food Initiative, which is hosted by the Food Systems Transformation Group of the Environmental Change Institute at the University of Oxford.

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Related chapters on the future of food system drivers and impacts, regional and national perspectives, food commodities, and foresight tools are available in our Table of Contents.

Citation: Wiebe, K., A. Mosnier, D. Mason-D'Croz, A. Petsakos, J. Svensson, and M. Zurek. 2025. "What Do We Know About the Future of Foresight Modeling Related to Food Systems?" In *What Do We Know About the Future of Food Systems?*, eds. K. Wiebe and E. Gotor, Chapter 37. Washington, DC: IFPRI. https://hdl.handle.net/10568/175019

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CAPRI: https://www.capri-model.org/

ENVISAGE: https://www.gtap.agecon.purdue.edu/models/envisage.aspx

EPPA: https://globalchange.mit.edu/research/research-tools/eppa

GLOBIOM: https://iiasa.ac.at/models-tools-data/globiom

GTAP: https://www.gtap.agecon.purdue.edu/models/current.asp

IMPACT: https://www.ifpri.org/project/ifpri-impact-model/

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MAgPIE: https://www.pik-potsdam.de/en/institute/departments/activities/land-use-modelling/magpie

RIAPA: https://www.ifpri.org/project/riapa-model/

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