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SOURCES OF VARIABILITY AND UNCERTAINTY IN FOOD-ENERGY-WATER NEXUS SYSTEMS

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Sources of Variability and Uncertainty in Food-Energy-Water Nexus Systems

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Review

Highlights

- Accounting for variability and uncertainty empowers stakeholders to make better-informed decisions.
- Considering spatial and temporal sources of variability contributes to more robust modeling systems.
- Stochastic methods that factor in uncertainty contribute to a better understanding of the FEW nexus systems.
- A robust modeling system will contribute to the design of resilient FEW nexus systems.

Abstract. *A nexus approach contributes to the strategic allocation of resources to secure food, energy, and water for the world population. Integrated models considering the complex interactions across food, energy, and water (FEW) enhance decision-making and strategic planning towards resilience. However, a significant number of the existing integrated models leave unaddressed the inherent variability and uncertainty present in the FEW sectors. Here, we review the importance of characterizing variability over spatial and temporal scales and the importance of decreasing the uncertainty present within a FEW nexus systems. The review also discusses existing modeling tools that address variability and uncertainty on single and paired elements of the FEW nexus systems, as well as integrated tools that address the sources of variability and uncertainty across the nexus. Finally, the review highlights the opportunity to address the limitations of existing models through multidisciplinary approaches and the potential to integrate publicly available models, as has already been the case for single and coupled elements of the FEW nexus. Addressing variability and uncertainty would improve the robustness of a FEW systems modeling and would provide stakeholders with the capacity to make better-informed decisions.*

Keywords. *Climate variability, Food-water-energy nexus, Modeling, Spatial variability, Temporal variability, Uncertainty.*

Food, energy, and water security are fundamental to sustainable development, for which balancing the social, environmental, and economic dimensions is of great importance to meet the world's increasing demand. A nexus approach studies the complex interactions within Food-Energy-Water (FEW) systems, exploring potential trade-offs and synergies toward the strategic allocation of resources.

While the nexus concept has evolved since it was presented at the 2011 Bonn Conference (Hoff, 2011), and some analytical frameworks have developed accordingly, there is a need to (1) account for relevant inherent variability over spatial and temporal scales, and (2) reduce uncertainty within the nexus to provide more reliable information to decision-makers and policy planning. So far, few studies have focused on dealing with variability and uncertainty within a FEW nexus framework to support decision-making and policy development.

This literature review presents existing approaches to manage variability and uncertainty within the FEW nexus. First, the review discusses the importance of characterizing variability over time and space and the importance of decreasing uncertainty in key elements of the FEW nexus. Second, the review analyzes existing modeling tools that account for variability and uncertainty on single or paired elements of a FEW nexus. Third, the review discusses the feasibility of integrating existent models to understand the interactions, trade-offs, and potential synergies among FEW integrated systems.

Food-Energy-Water Nexus Definition

The U.S. Geological Survey (USGS) defines the food-energy-water nexus as "the association of interactions that link water, energy, and food resources in a common system" (Friedel et al., 2021). Kurian (2017) expands the concept beyond the mere interaction of resources, defining the FEW nexus approach as "an expression of trade-offs, synergies, and resource optimization potential that is a function of the relationship between environmental resources and public service delivery, and institutional and environmental risks." Examining trade-offs and synergies under a nexus approach promotes integrated management and governance across sectors and scales while avoiding critical unintended

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consequences of policies developed in "silos" or that only consider one-way exchanges among coupled elements (Eftelioglu et al., 2017; Yillia, 2016). The concept of nexus increases the understanding of the inextricable links across food, energy, and water systems and provides a framework to develop multidisciplinary collaborations toward water, energy, and food security. In addition, the FEW nexus also embraces the economic aspects of decision-making and efficient resource allocation to harmonize economic growth with environmental and social responsibilities.

Although research, academic, and government institutions have worked to understand and simulate the interactions within the FEW nexus, more can be done to develop strategies with synergistic effects to enhance the resilience of food, energy, and water (D'Odorico et al. 2018). Given the natural variability inherent within biological systems, there is a need to account for spatial and temporal sources of variability (McGrane et al., 2019). Addressing potential vulnerabilities posed by the inherent variability and uncertainty affecting the FEW nexus is tied to the understanding of the systems resilience, availability, and access to all the resources linked to the FEW nexus (Hoff, 2011; Hussien et al., 2018; Bauer et al., 2014).

Concerns over water availability and water quality have become more prominent given the trends in climate change, growing population, demographic changes, the introduction of new technologies, and policy development (Eftelioglu et al., 2017; New et al., 2022; Samir and Wolfgang, 2017; Bauer et al., 2014). Existent climate models suggest that some highly productive lands may increasingly face extreme weather conditions such as drought and floods (Kling et al., 2017; New et al., 2022).

In mid-February 2021, the Central United States experienced extreme winter weather events that disrupted the supply and demand of food, energy, and water. The record cold temperatures and heavy snow damaged the energy infrastructure and caused a spike in energy demand. As a result, Texas reported more than 4 million customers without power. The power outages also affected the water supply, water quality, and food supply chain (U.S. Department of Energy, 2021).

Food insecurity was already rising before COVID-19, with the population affected by moderate or severe food insecurity going from 22.4% in 2014 to 25.9% in 2019 (United Nations, 2020). According to the World Bank, the COVID-19 pandemic triggered an economic recession that will add almost 90 million people to the extreme poverty group, the first increase since 1998 (International Monetary Fund, 2020; United Nations, 2020), and threatens the continuity of progress made on food, energy, and water security.

Both the pandemic and the record cold temperatures in Texas during 2021 exemplify the interconnections between food, energy, and water, and how constraints on any of these elements lead to vulnerabilities linked to other elements of the nexus system, including economic and social welfare. Stakeholders could prepare better to respond to these kinds of unanticipated events with a better understanding of the FEW nexus (Eftelioglu et al., 2017). Integrated modeling frameworks characterizing variability and reducing uncertainty would provide better information to decision-makers and policy planning.

Variability and Uncertainty in the FEW Nexus

Careful consideration of variability and uncertainty is relevant to supporting informed decision-making, increasing confidence in the estimates, facilitating more robust analyses, and providing critical information to the risk-assessment process. Some authors treat variability as a component of uncertainty, concluding that one contributes to the other. However, the National Research Council recommends treating them as separate concepts (Institute of Medicine, 2013; National Research Council, 2009).

Variability refers to the natural heterogeneity across observations. Since variability is an inherent property of a population, it cannot be reduced but can be better characterized. Variance and standard deviation are two common measures of variability (U.S. EPA, 2011). We can observe variability in biological processes within the FEW nexus systems over spatial and temporal scales.

Uncertainty arises from a lack of knowledge or data gaps; thus, it can be reduced with more or better data and a better understanding of the process (U.S. EPA, 2011). Quantitative modeling and futures thinking are two common approaches to addressing uncertainty. Quantitative modeling uses a probability distribution built upon the likelihood of a single outcome's value. Futures thinking embraces uncertainty by developing actions that respond to future trends or risks identified in the multiple scenarios considered (Yung et al., 2019). The futures thinking approach considers multiple possibilities that integrate quantitative and qualitative methods such as the Delphi method (expert panels), visioning (imagining the ideal future), and scenario planning (Begg et al., 2014; Maier et al., 2016; Yung et al., 2019).

Fuzzy cognitive maps (FCM) is a popular method based on scenario planning that incorporates fuzzy logic to quantify the nature of the interactions within the study case (Amer et al., 2013). For example, Ziv et al. (2018) applied FCM to analyze the consequences of Brexit for the food, energy, and water demand of the United Kingdom (U.K.). As a result, Ziv et al. (2018) highlighted the critical interactions involved in the FEW nexus and identified gross domestic product, regulation, U.K. population size, and net migration to the U.K. as four critical elements significantly impacted by the withdrawal of the U.K. from the European Union. In addition, the researchers concluded that energy demand would be the most affected by a change in gross domestic product, while the size of the U.K. population would affect water and food demand.

Modeling a FEW nexus with an inadequate characterization of variability and high uncertainty will reduce the confidence in the estimates and will fail to identify potential vulnerabilities of the FEW nexus. This section outlines the types of variabilities and uncertainties found in a FEW nexus.

Spatial Variability

Land and water characteristics exhibit sizeable spatial variability, explained by the soil characteristics, which determine the regional capacity to capture water, retain nutrients, produce food, and generate energy. Spatial variability is also tied to landscape position and to climate conditions (D'Odorico et al., 2018; Eftelioglu et al., 2017; Maestrini and Basso, 2018). Energy demand shows regional variability based on energy requirements for the water system, quality of water sources, and pumping needs (Bauer et al., 2014). Indicators such as water footprint and energy footprint also show spatial variation. Mekonnen et al. (2018) determined the value of measuring sustainability with these environmental indicators on a higher spatial resolution level. In addition, they demonstrated how the indicators at a state level provide more information than the same indicators at a national level.

Spatial variability in crop production has been managed through precision-agriculture technologies such as Global Positioning System (GPS), Geographic Information System (GIS), Reacting Technology (R.T.), Global Navigation Satellite System (GNSS), and nanobiosensors (Abobatta, 2020). The information available at a higher spatial resolution contributes to developing effective zone-specific management practices based on more specific nitrogen needs, water holding capacity, and water use patterns (Hatfield, 2012). However, the high costs of these technologies make the investment primarily feasible for more extensive agricultural operations, and access is still a challenge for small farmers (Castle et al., 2016).

Incorporating spatial information contributes to developing robust models (Monhollon, 2020) for crops, livestock, bio-industry, and agricultural activities in general. For instance, models accounting for spatial autocorrelation have been developed to improve decision-making related to logistics and the location of bio-industrial facilities (Sharma et al., 2017; Stewart and Lambert, 2011).

Nowadays, more geographic information is available and more advances in spatial data-driven solutions complement the strategies based only on social or physical science perspectives (Eftelioglu et al., 2017).

Regional economies develop based on available resources and other competitive advantages, incentivizing investment. Regions with a vast groundwater supply have a comparative advantage that favors local agriculture, livestock operations, and biofuel production, and regions with reduced access to water need to overcome more challenges to build a local economy around the FEW nexus. For example, optimal locations for bioethanol plants consider access to feedstocks, water availability, transportation infrastructure, and access to demand (Sharma et al., 2017; Stewart and Lambert, 2011). Stewart and Lambert (2011) concluded that access to feedstock, local incentives, and the absence of operating ethanol plants were critical factors in determining new ethanol plant locations during the expansion of the ethanol industry from 2000 to 2007.

It is not simply by chance that the six states with the highest ethanol production volumes are among the top 10 corn producers in the United States: Iowa, Nebraska, Illinois, Minnesota, Indiana, and South Dakota. These states are also part of the Corn Belt region, which is primarily rainfed but also has irrigation water sources such as the Ogallala Aquifer, the Platte River, and the Arkansas River (Green et al., 2018). Let us note that the corn belt also supplies corn and distillers' grains to the livestock industry, and the livestock industry offers manure as a fertilizer for crops. Besides, at the end of 2021, beef cattle production in these six states added up to 5.48 million heads, or 17% of the total beef cattle produced at the national level (USDA, 2022).

Temporal Variability

Temporal variability can be analyzed over different time scales based on the temporal resolution of the information available, the nature of the parameters being measured, and the purpose of the analysis. For example, crop models may require daily weather parameters, while land-use change models usually require annual parameters (Jones et al., 2003; Verstegen et al., 2012).

Much of the variability observed over time in the FEW nexus is influenced by climate patterns because climate affects water and sun radiation availability, among other resources needed for energy, agriculture, and livestock production. The increasing trend in ranges of climate variability and the number and intensity of extreme events prompts concerns about the resilience of agricultural and food systems and, therefore, water and energy systems.

Although natural and human systems have been dealing with climate variability for ages, it was until about 20 years ago that the IPCC projected that anthropogenic climate change would affect daily, seasonal, inter-annual, and decadal variability (IPCC, 2001). According to Holleman et al. (2020), climate variability and extreme events over agricultural areas have doubled since the 1990s.

Climate variations do not seem to follow a random distribution over space and time; rather, they frequently follow relatively consistent patterns over regions, while their amplitude, phase, and geographic position change over time (National Research Council, 1998).

Two key climate parameters are temperature and precipitation. The largest source of year-to-year variability in global temperatures typically comes from El Niño Southern Oscillation (ENSO). Rosenzweig and Hillel (2008) refer to El Niño Oscillation as the strongest, most predictable, and most well-known pattern recognized by climate scholars. Meteorological services and other agencies have used recurrent oscillation phenomena like ENSO to predict seasonal and year-to-year climate anomalies (IPCC, 2013). However, the uphill pattern shows that temperatures are increasing and becoming more variable even in the absence of large-scale global climate events such as ENSO (Holleman et al., 2020; NOAA, 2021).

In addition to the year-to-year variation, temperatures also show seasonal variation. For example, rising temperatures in the Northern Great Plains have resulted in shorter snow seasons and longer growing seasons that will likely benefit livestock production. In contrast, the warming and drying effects in the Southern Great Plains, Southwest, and northern Mexico anticipate a reduction in soil water availability and net primary productivity (Conant et al., 2018; Polley et al., 2013).

Despite the benefits of a longer growing season, the higher temperatures and wetter conditions projected for the Northern Great Plains can potentially lead to declining yield for crops and forages, an increasing presence of weeds and invasive species, and a decrease in forage quality to feed livestock (Polley et al., 2013).

Precipitation also exhibits high variability within and between years; however, the most recent 15-year period (2005-2020) shows most of the values above the historical mean, except for 2012 and 2020. The year 1915 reported the highest precipitation level on record (35.50 inches), and the year 2012 was the driest year on record (13.36 inches). During the summer of 2012, the drought combined with extreme heat had significant negative impacts on non-irrigated crop yield and pasture conditions (Franskon et al., 2017).

Despite seasonal variability, the spring and summer months are usually the wettest times of the year, with winter precipitation contributing to only 7% of the annual total (Franskon et al., 2017; Shulski and Williams, 2018). However, projections based on a high emissions scenario estimate an increase in winter precipitation of 15% across the state of Nebraska. Heavier winter precipitation may result in potential delays in planting summer crops, changes in crop yields, changes in crop types, increased runoff, flooding, reduction of water quality, and soil erosion (Franskon et al., 2017).

Forecasts based on ENSO seasonality are highly reliable and widely used to study the impacts of climate variability on crop yields. Current research estimates that precipitation variability associated with El Niño will intensify, and fewer frost days will occur in the Northern Hemisphere (Bathke et al., 2014).

The risk of seasonal supply variation hinders the availability of food and energy crops. Food crops and dedicated energy crops present significant seasonal supply variations that manifest in logistical challenges, regional supply imbalances, price variations, and shortages (Solomon et al., 2019).

An agricultural commodities shortage increases the likelihood of supply disruptions and has negative economic consequences for all stakeholders. On the contrary, excessive supply increases storage costs, handling costs, and losses due to degradation during storage (Kim and Kim, 2022). Therefore, the analysis of yield variability in space and time is essential to identify the potential risk of supply imbalances based on the probability of having high or low yield within years or within geographical regions (Golecha and Gan, 2016).

Table 1 presents examples of spatial variability and temporal variability for corn, water, ethanol, and beef sectors.

Uncertainties

Strategies to reduce uncertainty are necessary for sound decision-making. Sources of uncertainty are tied to a lack of information and the inability to predict the future precisely within the FEW nexus. Stakeholders face high levels of uncertainty when considering the complex and many interactions within the multiple components and multiple stakeholders associated with the nexus.

Examples of sources of uncertainty are public policies, dynamics of demand-supply balances, market fluctuations, emerging technology, multiple potential scenarios, the unconscious bias of decision-makers, input data, and model parameters (Mekonnen et al., 2018; Yu et al., 2020).

Incentives and Public Policies

Given the difficulty of predicting the impact of policies and decisions, public policies focusing on one sector may have unintended consequences for other sectors (Monhollon, 2020). Efforts to reduce uncertainty should consider the potential effects of policies that usually focus on single or coupled sectors of the nexus (Iizumi et al., 2013; Lazaro et al., 2021). Policymakers under a nexus approach may contribute to more robust policy choices that will perform as intended over multiple possible scenarios (Yung et al., 2019).

Environmental policies may encourage intensive monoculture, potentially creating water quality problems. For instance, policies promoting corn-based biofuels to reduce GHG emissions have been called to pay close attention to water sustainability. By 2019, Nebraska corn-based ethanol reported a 53% reduction in GHG emissions compared to gasoline, but it also reported a larger water footprint than conventional gasoline. On this matter, Mekonnnen et al. (2019) reported that about 66 liters of water are needed to travel 1 km with corn-based ethanol versus 0.4 liters of water per kilometer traveled with conventional fuel. Findings are conflicting, and environmental benefits cannot be guaranteed because they vary based on feedstock type, technology, land, and climate. The economic pressures on farmers to increase their productivity and size lead to excessive nitrogen applications, causing coastal and surface water eutrophication, groundwater contamination, and nitrous oxide emissions (Basso et al., 2021). A nexus approach would ideally strive for environmental benefits measured in water quality, land use, biodiversity, food prices, and co-product allocation across the system.

Some other policies created to reduce uncertainty for potential investors accelerate the creation of markets, facilitate access to financial resources, influence supply and prices, and create incentives to encourage consumption (National Research Council, 2011). However, in some cases, not all

Table 1. Sources of variability and uncertainties for a corn-water-ethanol-beef nexus.

Elements of the CWEB nexus	Spatial variability	Temporal variability
Corn	Crop yield variation within regions. Desertification and land degradation.	Crop yield variations within years (seasonal variation). Crop yield variation from year to year.
Water	Regional water demand. Regional water availability.	Seasonal variability of water needs and water availability. Climate effects resulting in floods and droughts that affect water quality and water availability.
Ethanol	Biomass yield variation within regions.	Seasonal biomass availability.
Beef	Nutrition quality of feed resources. Regional variation on water consumption.	Temporal variability within seasons.

results are as expected. One example is the shortfall in cellulosic ethanol production relative to the volume mandated in 2007 by the Energy Security Act (13.5 billion gallons per year by 2021). By December 2021, only three plants were producing ethanol from cellulosic biomass with a total production capacity of 0.075 billion gallons per year; seven biorefineries were registered as ethanol producers using corn/cellulosic-biomass/sorghum with a total capacity of 0.975 billion gallons per year (Cooper et al., 2021). The lack of biomass feedstock demand prevents farmers from growing cellulosic feedstocks like switchgrass and miscanthus. In addition, the high costs of transporting biomass to potential plant facilities hinder the development of a cellulosic market (National Research Council, 2011).

Subsidies and market interventions created to boost efficiency in the agricultural sector are necessary to achieve food and energy security, but uncertainty in subsidy renewals, tax incentives, and assistance programs also affects stakeholders' decisions (National Research Council, 2011; United States Government Accountability Office, 2016). In addition, foreign policies and changes in trade agreements are also sources of uncertainty that may negatively affect agricultural markets.

Market Fluctuations, Demand, and Supply

Although economic theory predicts how markets will react to changes in supply and demand and price movements, there is still considerable uncertainty about how these variations will interact with market structures within the FEW nexus. Policymakers would benefit from considering the allocation of resources within a market framework. Moreover, economic considerations beyond a single sector enable the analysis of markets emerging simultaneously from the multiple byproducts within a nexus.

For example, Shuster et al. (2017) studied the interaction between water and energy markets. Power stations and agricultural sectors will potentially adjust their water demand if water availability shrinks. In this case, the energy sector may deploy recirculation technologies to reduce water consumption or drive up water prices by competing with the agricultural sector for water. In this work, Shuster et al. (2017) constructed supply curves for water, considering several water sources that minimize cost and water use by the energy plants. Although having multiple water sources may increase the reliability of water and energy systems, the effects are still uncertain (Bauer et al., 2014).

Despite the incentives provided by the federal government and the improved conversion technologies, the commercial success of non-food crops for biofuels still faces many challenges. Some of the factors holding back the advanced biofuel supply are the low price of fossil fuels compared with advanced biofuels, high costs of converting lignocellulose feedstock, time and scale-up costs for new technologies at a commercial scale, uncertainty about the market, government policies, and barriers set by the logistics of the feedstock supply chain (United States Government Accountability Office, 2016).

In 2020, the decrease in ethanol demand due to the COVID pandemic resulted in lower ethanol production due to the decline in gasoline demand and, thus, a lower supply of distiller grains. As a result, the price of distiller grain was 110% higher than the price of corn. The volatility of prices is different for all products within a FEW nexus. Feeder cattle prices tend to be more volatile than live cattle prices because feeder cattle depend on more feeding resources. Livestock prices will also be affected by drought conditions and the location in the supply chain, which usually determines the ability of feedlots to process cattle (Dennis, 2020).

Another potential scenario that may affect water demand is the argument presented by several authors concerning a substantially higher water demand derived from the higher water footprint of ethanol production. Therefore, switching from fossil fuels to biofuels should be further analyzed across a FEW nexus to further study the potential effects on the biofuels market and other sectors involved (Mekonnen et al., 2018).

Emerging Technology

Future expansion of agricultural land is limited; consequently, a sustainable increase in food production will have to rely on strategies to achieve higher productivity using fewer resources. Technology research provides solutions by targeting advanced materials, cooling technologies, process efficiency, alternative fluids, and waste heat recovery (Bauer et al., 2014).

With the highest area of irrigated cropland in the United States, Nebraska is an example of how advances in irrigation technology and management practices in corn and soybean fields play a vital role increasing water productivity and conserving groundwater. For instance, in Nebraska, replacing surface irrigation with center pivot sprinkler irrigation systems reduced the field-level applied irrigation by 20% in cornfields and 8% for soybean fields from 2004 to 2013. Nevertheless, in some cases, evapotranspiration is more significant with a sprinkler system than with gravity systems, so despite the reduction in applied irrigation depth, the technology by itself alone cannot guarantee a reduction in actual consumptive water. Complementary measures such as deficit irrigation and no-till farming should be encouraged to monitor water conservation (Mekonnen et al., 2019). The challenge of quantifying the effects of new technology on water demand and land use adds uncertainty to the FEW nexus.

As the United States shifts its focus toward decarbonizing the energy industry, water management has become increasingly important, given that many decarbonization methods are even more water-intensive. In addition, researchers have also discussed the carbon footprint of renewable fuels such as bioethanol, leading them to optimize energy and water consumption in biofuel plants (Ahmetović et al., 2010; Mekonnen et al., 2019).

Due to the significant variations in water intensity by electricity technology and cooling systems, the potential expansion of the electric sector adds uncertainty to water demand (Davies et al., 2013).

New technology is more likely to be adopted when evidence of higher profit and productivity is compelling (Basso et al., 2021). Castle et al. (2016) studied five variables that may affect precision agriculture adoption: (1) operator age; (2) number of row crop acres farmed; (3) average yearly gross farm income; (4) use of irrigation; and (5) access to the internet using a cellphone. The study concluded that the two variables statistically significant for soy and corn producers in Nebraska were the size of the farm (number of row crops in operation) and access to smartphones.

Because it is difficult to predict the rate of technological adoption and its effects on water and energy demand, future water demand may be analyzed using different adoption rate scenarios. For example, the adoption of technologies should be examined from a nexus perspective, considering three different adoption rate scenarios: (1) no adoption of the advanced technology; (2) moderate adoption where 50% of all new power plants apply the new technology, and (3) a high adoption rate, where 100% of all new power plants adopt the new technology (Davies et al., 2013).

The Unconscious Bias of Decision-maker

The role played by human behavior and human activity within a FEW nexus is undeniable. The decision-making process is ultimately performed by humans, and the outcome depends heavily on the attitude toward risk, the group of different perspectives, different knowledge, and different experiences among each of the concerned parties (Begg et al., 2014).

Work has been done to integrate both different views of decision makers into the FEW nexus (Li et al., 2019). However, it is still necessary to explore how to incorporate aspects of social disciplines into the systems modeling.

We suggest that sources of uncertainties be assessed for each case according to the specific conditions of the FEW nexus system and with a multidisciplinary approach. Table 2 is an example of how one source of uncertainty has an effect across the CWEB nexus.

Table 2 provides an example of the systems thinking perspective when analyzing what case scenarios may come from a source of uncertainty. Stakeholders would study these conditions and decide what would be the best strategies and tools to reduce uncertainty.

Integrative Modeling Tools to Analyze the FEW Nexus Systems

Modeling the linkages and inter-dependencies across food, energy, and water comes with several challenges. Existing FEW modeling tools report limitations to designing appropriate and validated algorithms able to manage FEW data sets that come in different temporal and spatial scales. Additionally, the development of models and tools to analyze the FEW nexus should also consider the difficulties of identifying relevant links, balancing between increasing model details and solution efficiency, sparse data, and significant uncertainties (Liu et al., 2017). Furthermore, models do not usually address the effects of extreme events or increase climate variability in food, energy, and water, resulting in a limited understanding of the effects of climate variability within the FEW nexus (Godde et al., 2021; Khan et al., 2018).

Table 2. Uncertainty matrix for a corn-water-ethanol-beef nexus.

Source of uncertainty to analyze: Unintended consequences of environmental policies to promote corn-based ethanol.	
Corn	Uncertainty in subsidy renewals, taxes incentives, and assistance programs may affect farmers' decision on which crop to grow on their farms, and that may affect long term corn supply.
Water	Potential water quality issues may result from excessive nitrogen applications as a response of economic pressures to increase corn yield. There may be an increase in water demand due to corn-based ethanol's higher water footprint.
Ethanol	Prices may show dramatic changes due to a supply shock. For example, during the COVID pandemic, the decline in gasoline consumption reduced the demand for ethanol.
Beef	A lower supply of distillers' grains would spike up distillers' grains prices and would impact the supply chain of cattle feeders

Given that models of natural systems are never complete, researchers decide on the level of detail and rigor needed to achieve the model objective, as well as the data needed to estimate the parameters and input data, how to use the little information available to define or assume default values, and which uncertainties to leave unaddressed (National Research Council, 2009).

Stochastic methods and ranges of values defined by percentiles may adequately address parameters and input data uncertainties (Li et al., 2019; Mekonnen et al., 2018). Additionally, sensitivity analysis tests the influence of critical parameters and defines the range of values for which there is no change in the decision (Begg et al., 2014; Mekonnen et al., 2018; Wang et al., 2012). Often, a probabilistic approach to parameter uncertainty can provide an estimate of the likelihood of specific outcomes or future scenarios (Maier et al., 2016; Yung et al., 2019).

To account for the uncertainty of the future, it is also necessary to identify all coherent future pathways based on different sets of assumptions. To simplify the analysis, some of these possible future scenarios may be defined as mutually exclusive and can be assigned a probability of occurrence based on the current state of information and trends (Begg et al., 2014). However, some authors prefer to address uncertainty in terms of multiple plausible futures rather than probability distributions because not all future scenarios have an associated probability of occurrence or can even be ranked (Maier et al., 2016).

The failure to consider all possible events in an uncertain situation negatively affects the robustness of the system. Ideally, a robust system is one that performs well under a range of futures that are likely to happen. Maier et al. (2016) present a method to build three types of scenarios by answering three questions: (1) Predictive scenarios: What will happen? This can be answered through "trend" or "what-if" scenarios. (2) Explorative or exploratory scenarios: What could happen? Similar to "what-if" scenarios but considering longer timeframes and multiple perspectives. (3) Normative scenarios: How can a specific target be met? For example, how can access to electricity be achieved?

This section presents relevant models that have recognized the complexity of modeling temporal and spatial scales of variability and uncertainties within food, energy, and water relationships.

The U.S. Geological Survey developed a soil-water-balance model that integrates spatially distributed soil properties, landscape properties, daily weather data, and estimated historical land-cover maps to calculate spatial and temporal variations in potential recharge (Peterson et al., 2016). This model serves as a tool to evaluate current and future groundwater availability.

The climate, land-use, energy, and water (CLEW) framework integrates an energy model (LEAP), a water model (WEAP), and a land-use model (AEZ) to evaluate the implications of policies and strategies under several assumptions that control for uncertainty (Howells et al., 2013). Howells et al. (2013) applied the CLEW framework to explore the implications of promoting a local biorefinery industry in the Republic of Mauritius. The study showed the increase of water withdrawals as an unintended consequence of the assumed policies based on the irrigation needed to offset future reduced rainfall. However, the authors omitted climate variability and the change effects from agricultural practices that may affect local biodiversity and land use.

The FAOS's nexus assessment methodology has a database with indicators used to perform analysis specific to a country and one type of intervention. The FEW nexus tool 2.0 provides a more holistic approach, allowing the user to create different scenarios to analyze the effects of changes in agricultural practices, water sources, energy sources, and even the share of imported food (Daher and Mohtar, 2015).

Anderson et al. (2018) developed an integrative modeling framework to explore the effects of nitrogen fertilizer in a corn-ethanol system. The framework connected two available models: the decision support system for agrotechnology transfer (DSSAT) and the greenhouse gases, regulated emissions, and energy use in the transportation model (GREET). Although the framework considered water consumption, the authors noted the complexity of adjusting the irrigation features on the DSSAT and GREET models. Additionally, the authors concluded that the tool's robustness could be improved by considering more economic and environmental aspects such as profitability and potential GHG emissions.

The Agricultural-Water-Energy-Food Sustainable Management model (AWEFSM), designed by Li et al. (2019), is a multi-objective nonlinear programming model that incorporates triangular intuitionistic fuzzy numbers to express the uncertainty of some parameters. AWEFSM considered the interactions between food, energy, and water. The model integrated economic and environmental aspects of the nexus by maximizing profit and minimizing CO2 emissions while rationally allocating limited water resources, energy resources, and land resources to different crops in different regions. However, the granularity of the model is limited because it excluded significant components such as the use of agricultural waste in bioenergy production. The authors concluded that this framework could be improved to increase its applicability and reduce the error introduced by uncertainties.

The Global Change Assessment Model (GCAM), developed by the Pacific Northwest National Laboratory, integrates energy, agriculture, and climate change. Davies et al. (2013) used GCAM to analyze future global water demands to produce electricity for 14 geopolitical areas from 2005 to 2095. The study included different electricity generation sources such as biomass, oil, hydrogen, wind, gas, coal, and geothermal energy. In addition, they accounted for uncertainty by considering potential changes to future water demands due to technological shifts. However, the study omits climate-energy-water links important to defining water availability, the electric generation technology choice under water scarcity, and the effect of environmental policies on electricity demand.

Khan et al. (2018) designed the SPATNEX-WE (Spatial and Temporal Nexus – Water Energy), a hard-link partial equilibrium linear optimization model solved in GAMS (General Algebraic Modeling System). This model captures the spatial and temporal variations in WE production and demand across their complete life-cycle. It also allows users to adjust spatial and temporal boundaries as needed. The model proved to be more robust in analyzing uncertainty in parameters related to demand patterns, policy constraints, and resource availability. One of the limitations of this model is that the optimization algorithm requires setting up each link as a linear equation even though nonlinear relationships best explain some connections within the WE nexus. Another significant limitation is that the SPATNEX-WE excludes WE demands from the agricultural and food sectors.

Table 3 summarizes the revised models that address variability and uncertainty for the FEW nexus and for corn, water, ethanol, and beef systems. This review is focused on whether these integrated models account for variability and uncertainty.

Conclusion

One of the goals set by the FEW nexus is to guarantee access to food, energy, and water while minimizing the detrimental consequences for any of these elements. Integrated planning tools under a FEW nexus approach enhance the understanding of the impacts of policies and management strategies across food, energy, and water, all three fundamental to sustainable development and national security.

Models have been developed to understand and predict trends, patterns, and the complex interactions between these three sectors. Two of the challenges of developing integrative tools are the required multidisciplinary collaboration and a clear strategy to connect publicly available models under a framework that simultaneously considers the technical, economic, and environmental aspects of interconnected sectors.

Models accounting for variability enable more robust analysis because they consider the natural heterogeneity present in biological systems. Uncertainty added by input data affects model parameters and, consequently, output reliability. While existing models and tools are available to address sources of variability and uncertainty for single or paired elements of the FEW nexus systems, this review found that no tools have been developed to address temporal and spatial scales of variability and sources of uncertainty for a complete FEW nexus. Integrative tools to analyze the temporal and spatial scales of variability and uncertainty will enable the user to assess the resilience of the FEW models and will set a reference to identify potential vulnerabilities that will contribute to setting a course of action for strategic decision-making based on a regional and time basis.

Table 3. Models that address variability and uncertainty for food, energy, and water sectors.

Reference	Temporal Variability	Spatial Variability	Uncertainties	Applied methodology, methods, and tools	Description and Outputs
FEW nexus					
Spatial dependence of controls on groundwater vulnerability in the FEW nexus (Gurdak et al., 2017).		✓		Logistic regression models of GIS-based explanatory variables based on Source, Transport, and Attenuation (STA) factors.	Predict vulnerabilities to NPS NO_3^- contamination in the Coastal California basin aquifer system. A limitation is that the vulnerabilities models may not be appropriate to forecast future vulnerability conditions.
Spatial Decision Support System (Verstegen et al., 2012)			Uncertainty of input values and model parameters.	Spatial Decision Support System, the PCRaster model construction framework and Monte Carlo analysis.	The spatial decision support system integrates simulation, uncertainty analysis, and visualization. The model accounts for uncertainty distribution in space and time. The model provides visualization tools for end users that have no specialist knowledge of statistics.
Climate, land-use, energy, and water strategies (CLEWS) (Howells et al., 2013)			Commodities prices. Accuracy of climate models.	A module-based approach that integrates existent models.	Analyze potential policy implications based on current knowledge and the uncertainty of future scenarios. The study case explored the effects of a policy to promote a local biofuel industry in the Republic of Mauritius.
A DSSAT-GREET integrated framework (Anderson et al., 2018)			Fertilizer use	The DSSAT-GREET integrated wrapper.	Assess the effects of several critical parameters on a crop-biofuel system under different scenarios.
Agricultural Water-Energy-Food Sustainable Management (AWEFSM) (Li et al., 2019)			Parameter uncertainties associated with the fluctuations of natural resources and variation of socioeconomic activities.	Integration of multi-objective programming, nonlinear programming, and intuitionistic fuzzy numbers.	Maximize system profit and minimize CO_2 emission by optimally allocating water, energy, and land to different regions and crops.
Corn					
Spatial patterns of water and nitrogen response within corn production fields (Hatfield, 2012)		✓		Spatial Analysis.	To determine the spatial relationships between corn yield and the vegetative indices across different fields.
Integrating a crop model into OptiCE (Zhang et al., 2018)	✓	✓		Integrates a crop model into OptiCE, an open-source code for clean energies simulations and optimizations.	The effects of drought on corn yield and the implications for water management. The integrated model explores climate variability over time and space.
Water					
A PCA application to GPCP precipitation data and a CAM5 simulation over the tropics. (Trammell et al., 2016)	✓	✓		Principal Component Analysis.	To explore temporal and spatial variability of precipitation in the tropics.
Ethanol					
A framework to incorporate spatial variability into life cycle analysis of Agricultural Systems (Monhollon, 2020)		✓		LCA.	To integrate spatial soil and weather data into an LCA for corn-based ethanol.

The interconnected nature of the FEW nexus provides an excellent framework to reinforce essential systems-thinking competencies and risk management. In addition, efforts toward a better characterization of variability and reducing uncertainty empower stakeholders to make better-informed decisions related to the strategies to allocate resources, minimizing potential unintended consequences that may be detrimental.

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Table 3 (continued). Models that address variability and uncertainty for food, energy, and water sectors.

Reference	Temporal Variability	Spatial Variability	Uncertainties	Applied methodology, methods, and tools	Description and Outputs
Water - Energy					
Global Change Assessment Model (GCAM) (Davies et al., 2013)	✓		Adoption rates of water-saving technologies. Power plant cooling system changes. Water consumption intensities. Water withdrawal.		Estimate future water demand for electric power production. The model considered water demand uncertainties related to potential technological advances in electric power production and water conservation technologies.
Spatial and Temporal Nexus – Water Energy (SPATNEX-WE) (Khan et al., 2018)	✓	✓	Energy and water demand patterns. Policy constraints related to emissions limits. Climate Change. Resource availability.	A partial equilibrium linear-optimization model, and life cycle analysis.	To analyze cross-sectoral issues and policies related to a coupled water-energy model. The framework accounts for several uncertain parameters, and different temporal/spatial scales.
The NETL Water-Energy Model (NWEM) (Shuster et al., 2017)	✓	✓	Water availability. Energy and water demands. Water markets. Power plant water use. Power generation forecasts.	Multi-period linear programming (L.P.) model.	Model the energy-water interactions to minimize the cost of satisfying local water demand.

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