ENGINEERING Agriculture

Engineering Journals

REVIEW

2027 / Volume 14 / Issue 5 / 27756

Complex network-based resilience assessment and decision optimization of water-energy-food nexus systems in irrigation districts of northeastern China: a review

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KEYWORDS

Complex network, intelligent decision optimization, irrigation districts, northeastern China, resilience assessment, water-adaptive planting, water-energy-food nexus

HIGHLIGHTS

- Integrate network theory, resilience assessment and intelligent optimization
- Focus on the water-energy-food link in areas with excessive groundwater exploitation.
- Propose the CPSS paradigm as a unified framework.

Received July 4, 2026;
Accepted August 26, 2026.

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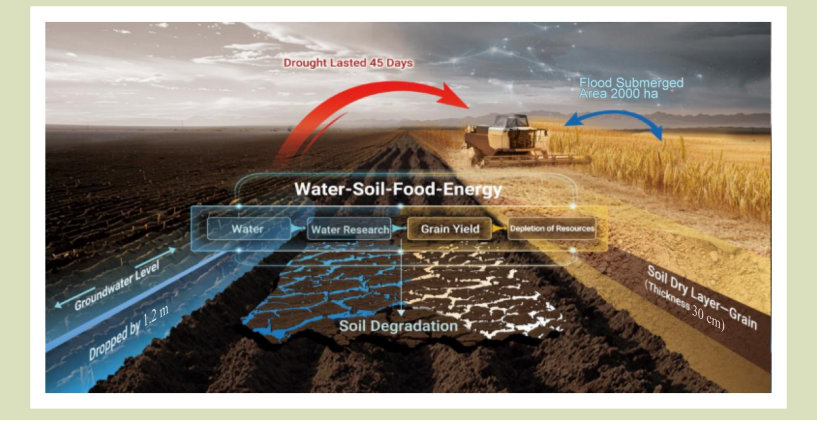
Special Issue: AI-Driven Reconfiguration of Climate-Smart Agricultural Systems

GRAPHICAL ABSTRACT



ABSTRACT

This study systematically reviewed complex network-based resilience assessment and intelligent decision optimization methods within the water-energy-food (WEF) nexus system in groundwater-scarce irrigation regions of northeastern China. While global research has advanced from conceptual frameworks to quantitative modeling, existing studies still rely on homogeneous coupling and static topological structures, failing to capture regional seasonal freeze-thaw dynamics and heterogeneous agricultural management characteristics. Three key gaps were identified: the absence of multilayer heterogeneous WEF network models tailored to local hydrogeological and institutional features; weak coupling between data-driven resilience indicators and mechanism-driven hydrological/crop models; and the

lack of operational frameworks to translate resilience diagnostics into climate-adaptive decisions. To address these gaps, a cyber-physical-social systems paradigm is proposed, mapping institutional actors within the region into social space. These findings indicate that WEF nexus resilience has improved over the last two decades but remains vulnerable to groundwater depletion, with mechanization intensity and irrigation coverage emerging as primary driving factors influencing resilience.

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1 Introduction

Global food production consumes about 70% of global freshwater withdrawals[1] and account for over 30% of total global energy consumption. The interdependence among water, energy and food systems is defined as the water-energy-food (WEF) nexus. This nexus means perturbations in one subsystem will spread across the entire coupled system. The spread happens through resource flows, price signals and institutional linkages[2]. Under accelerating climate change, groundwater depletion and geopolitical instability, understanding and managing WEF nexus system resilience has become a pressing scientific and policy priority[3].

Northeastern China includes the Songnen, Sanjiang and Liaohe Plains. It is a key commodity grain base for China, producing about 25% of the nation's rice and 40% of its soybean output[4]. However, long-term groundwater irrigation has created some of the world's largest groundwater depression cones in this region. In some counties, water tables decline at rates comparable to those documented in intensively irrigated regions such as the North China Plain (0.3–1.8 m·yr^{-1})[5]. The region faces structural tension among three policy imperatives. The first is maintaining national grain output targets. The second is achieving carbon peaking and neutrality goals. The third is enforcing groundwater abstraction caps under China's strictest water resource management system. In this context, the WEF nexus framework provides a natural analytical lens. It helps evaluate trade-offs and synergies among these competing objectives[6].

Several existing reviews have focused on WEF nexus literature from various angles. Albrecht et al.[7] provided a systematic review of WEF nexus methods. They identified persistent challenges in cross-sectoral integration. Zhang et al.[8] reviewed urban WEF nexus modeling approaches, with a focus on systems dynamics. D'Odorico et al.[9] examined the global WEF nexus through the lens of virtual water and land grabbing. More recently, Bian and Liu[10] reviewed WEF nexus research trends in China using bibliometric analysis. However, none of these reviews specifically study the intersection of complex network theory, resilience assessment and intelligent decision optimization for groundwater-dependent irrigation districts.

This review fills this gap by focusing on three dimensions. Geographically, it centers on typical irrigation districts in northeastern China's Songnen and Sanjiang Plains. It also makes selective reference to analogous semiarid irrigation systems worldwide. Thematically, it examines three interconnected methodological pillars. These pillars are complex network modeling of WEF interdependencies, quantitative resilience assessment frameworks, and intelligent optimization for decision support. The review analyzes each pillar individually and explores their interfaces. Temporally, it covers literature published from 2014 to 2025. This period captures the maturation of quantitative WEF methods after the Bonn Nexus Conference.

This review adopts a systematic-narrative hybrid approach. This approach helps ensure transparency in literature identification, screening and selection. Its narrative component synthesizes findings across heterogeneous methods, as formal meta-analysis is not feasible here. We conducted structured searches across Web of Science, Scopus and CNKI databases. We used Boolean combinations of keyword groups. These groups cover the water-energy-food nexus, resilience, complex network modeling, optimization and irrigation in northeastern China. We formulated explicit predefined inclusion and exclusion criteria to reduce screening bias. The inclusion criteria are as follows. First, the studies focused on irrigation districts in northeastern China journal articles published

between 2014 and 2025. Second, they must explicitly analyze interactions between at least two WEF subsystems. Third, they must have clear connections with irrigation district resilience assessment, complex network modeling or agricultural intelligent decision optimization. The exclusion criteria are as follows. First, conference abstracts, dissertations, book chapters and non-peer-reviewed gray literature are excluded. Second, studies without irrigation district research objects in northeastern China are excluded. Third, papers that only discuss a single water/energy/food subsystem without cross-resource coupling analysis are excluded. Fourth, qualitative commentary without quantitative modeling or empirical case verification is excluded.

All retrieved records first were put through title-abstract screening to remove irrelevant literature. The remaining papers enter full-text eligibility assessment. All excluded literature was categorized by rejection reason and quantified in the PRISMA flowchart. After multi-round screening, 118 qualified articles were retained for systematic synthesis. This paper aims to systematically review domestic and international research progress on resilience assessment and intelligent decision optimization of the WEF nexus from a complex network perspective. It focuses on the regional particularities of typical irrigation areas in northeastern China. It also clarifies the shortcomings and cutting-edge directions of existing studies. It provides references for constructing a theoretical framework of water-adapted planting decision optimization to enhance system resilience.

2 Conceptual connotation and theoretical framework of the water-energy-food nexus system

2.1 Conceptual evolution of the water-energy-food nexus

As shown in Fig. 1, the WEF nexus concept gained formal recognition at the 2011 Bonn Nexus Conference, which framed water, energy, and food security as inextricably linked policy domains[11]. The conceptual evolution since then can be periodized into three phases[12], moving from qualitative framing to quantitative modeling and, most recently, to complexity-informed resilience management. Phase I (2011–2015) centered on conceptual framing. Early scholarship focused on defining the nexus scope, developing qualitative frameworks and advocating for integrated governance. Representative contributions include Hoff's foundational positioning of the nexus within green economy discourse, as well as influential policy reports from the FAO[13] and the World Economic Forum[14]. Phase II (2016–2020) marked a quantitative modeling turn. Researchers shifted from defining

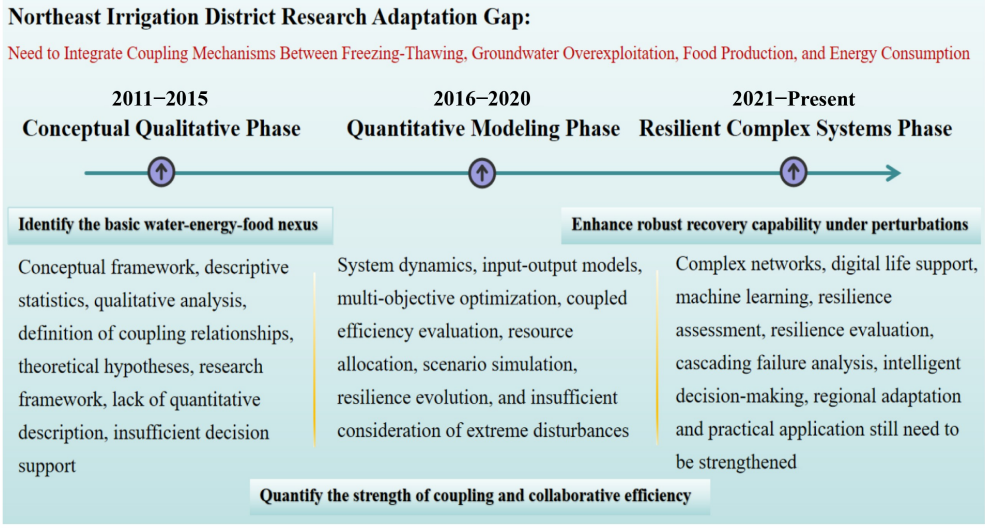

Fig. 1 Conceptual flowchart of the three-stage evolution of the water-energy-food coupling system.

the nexus to operationalizing it through empirical and simulation-based methods. Key approaches included system dynamics[15], input-output analysis[16], life cycle assessment[17] and integrated assessment models[18], which yielded nexus-specific tools such as WEF Nexus Tool 2.0[19] and MuSIASEM[20]. Phase III (2021–present) reflects a resilience and complexity turn. Growing recognition of WEF systems as complex adaptive systems susceptible to cascading failures has driven the integration of resilience theory[21] and network science[22] into nexus scholarship. The central question has shifted from static efficiency optimization toward dynamic resilience management under deep uncertainty. Overall, the three-stage evolution traces a clear trajectory from qualitative conceptual framing, through quantitative operational modeling, to the current emphasis on complex adaptive systems and dynamic resilience. This shift indicates a growing recognition that WEF systems are not merely optimization targets but complex adaptive systems whose long-term viability critically depends on their ability to absorb and recover from disturbances; a capacity captured by the concept of resilience, to which we now turn.

2.2 Resilience theory in the water-energy-food context

Table 1, resilience, as a concept, has undergone its own evolution from equilibrium-centered to adaptation-centered to transformation-centered perspectives[23]. In the WEF nexus literature, resilience has been operationalized along four canonical dimensions adapted from infrastructure systems research. An important distinction made by Folke et al.[24] and subsequently adopted in WEF literature[25] separates specified resilience from general resilience. For northeastern China irrigation districts, specified resilience to groundwater depletion and extreme drought constitutes the primary analytic concern (Fig. 2).

2.3 Complex network theory for water-energy-food systems

2.3.1 Network representation fundamentals

Complex network theory provides a structural language for representing WEF interdependencies. It goes beyond the aggregate, sector-averaged approaches of earlier nexus models[26]. The WEF linkage system can be formally represented as a multi-layered graph[27].

$$G = (V, E) \tag{1}$$

where G represents the multi-layer network diagram of the WEF linkage relationship, V is the set of nodes, and E is the set of edges.

$$V = V_w \cup V_e \cup V_f \tag{2}$$

where V_w, V_e, V_f respectively represent the node sets of the water resources, energy systems and food systems, and $\cup$ denotes the union operation of sets.

$$E = E_w \cup E_e \cup E_f \cup E_{inter} \tag{3}$$

where E_w, E_e, E_f respectively represent the edge sets within the water resources, energy systems and food systems, and E_{inter} represents the set of inter-subsystem layer edges.

Table 1 Four-dimensional resilience assessment index system for water-energy-food coupling system in irrigation areas

Resilience dimension	Core indicator	Calculation method	Target direction
Robustness	Irrigation district water resources Carrying capacity index Soil quality stability index Grain production capacity Fluctuation coefficient	Supply-demand balance ratio Soil parameter variation range Yield variation coefficient	Maximization of stability
Redundancy	Redundancy of available water resources Crop planting diversity index Soil water retention buffering capacity	Percentage of alternative water sources Shannon diversity index Soil available water capacity	Availability of alternative solutions
Resourcefulness	Water-adapted planting technology reserve rate Smart irrigation coverage Drought-resistant cultivar reserve coefficient	Proportion of technology library quantity Intelligent equipment proportion Drought-resistant cultivar area	Adaptation and adjustment capability
Rapidity	Irrigation system recovery rate Food production capacity recovery cycle Soil function recovery time post	Post-disaster recovery rate/time Capacity recovery slope Function recovery index	Post-disaster recovery speed

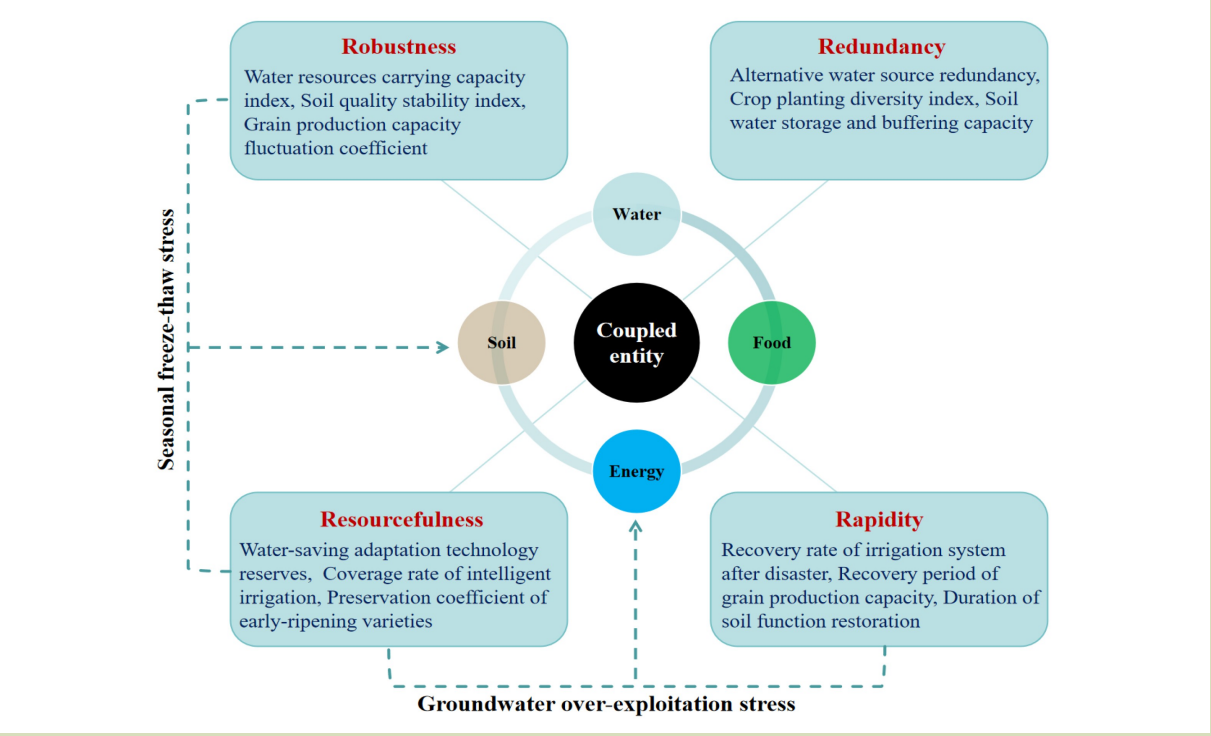

Fig. 2 Four-layer resilience coupling logic framework of the water-energy-food system. Robustness: the static stability capacity of the WEF system to maintain normal resource supply and grain production under mild disturbances, serving as one core dimension of system resilience. Redundancy: the multi-path alternative supply capacity of the WEF system to provide substitutable resource solutions when part of the resource supply chain fails, acting as an important support dimension of system resilience. Resourcefulness: the active adaptive adjustment capacity of the WEF system to mobilize existing technical and equipment resources to cope with stress shocks, being a key adaptive dimension of system resilience. Rapidity: the post-disaster rapid recovery capacity of the WEF system to restore resource functions and grain production level after being impacted, representing the efficiency dimension of system resilience.

$$G_\alpha = (V_\alpha, E_\alpha), \alpha \in \{w, e, f\} \quad (4)$$

where G_α represents the intra-layer network of the αth subsystem, V_α is the node set of this subsystem (such as irrigation wells, pumping stations, crop production units, etc.), and $E_\alpha \subseteq V_\alpha \times V_\alpha$ represents the intra-layer edge set that encodes the resource flow within each subsystem.

$$E_{inter} = \{(u, v)/u \in V_\alpha, v \in V_\beta, \alpha \neq \beta, \alpha, \beta \in \{w, e, f\}\} \quad (5)$$

where u, v represent the directed edge from node u to node v. V_α represents the set of nodes of the αth subsystem. α and β represent the indices of the subsystems, and their values are from the set $\{w, e, f\}$.

Within this representation, several topological properties are particularly relevant to resilience assessment. The degree distribution P(k) captures the heterogeneity of node connectivity. Scale-free networks show robustness to random failures, but they are vulnerable to targeted attacks on hub nodes[28]. Betweenness centrality quantifies the extent to which a node serves as a bottleneck. The failure of such a node will maximally disrupt resource flows across the network[29]. The clustering coefficient measures local redundancy. Higher values of this index indicate more alternative pathways for resource delivery[30]. Network efficiency quantifies the ease of resource transmission. The degradation of network efficiency under sequential node removal can directly represent system vulnerability[31].

2.3.2 Core theoretical challenge of multi-layer coupling

The defining theoretical challenge for WEF network modeling lies in the heterogeneous multilayer coupling problem. Unlike single-domain infrastructure networks, WEF nexus networks

couple layers with fundamentally different physical characteristics. Water networks follow gravitational and hydraulic gradients, and they show dendritic topologies in canal irrigation systems[32]. Energy networks exhibit meshed topologies governed by Kirchhoff's laws[33]. Food networks have both spatial crop distribution patterns and market-mediated supply chain structures[34]. An open theoretical question remains. It is whether and under what conditions such heterogeneous multilayer networks can exhibit the same emergent properties as their constituent single-layer networks. These properties include small-worldness, scale-freeness and community structure. Buldyrev et al.[35] demonstrated through percolation theory that interdependent networks are more vulnerable to cascading failures than isolated ones. However, their model assumes identical degree distributions across layers. This assumption does not hold for the fundamentally asymmetric coupling structures of real WEF systems.

2.4 The cyber-physical-social systems paradigm

The cyber-physical-social systems (CPSS) paradigm acts as a unifying theoretical framework[36]. It maps the WEF nexus onto three interacting spaces. First, physical space covers water flows, energy generation and consumption, and crop growth dynamics. Second, cyber space spans IoT sensors, remote sensing, data transmission, digital twin models and cloud computing platforms. Third, social space covers farmer decision-making, irrigation district management institutions, water rights markets and agricultural policy instruments. This framework provides a systematic way to understand how resilience is generated or eroded across all three spaces at the same time. For northeastern China irrigation districts, this framework highlights the critical role of social-space factors. The coexistence of state farms and smallholder operations is a key feature. It mediates how physical-space water scarcity translates into food production outcomes[37]. Existing WEF nexus literature only provides a general conceptual introduction to the CPSS paradigm. It has not achieved localized mapping to northeastern China's unique institutional landscape. In the study area, large state-owned farms with unified water allocation authority coexist with scattered smallholder households that make independent irrigation pumping decisions. This forms a distinctive dual social subsystem. It reshapes how groundwater depletion, freeze-thaw soil degradation and grain yield fluctuation propagate across the WEF coupled system. This paper explicitly embeds this dual agricultural management structure into the CPSS social space layer. State farm management bureaus formulate regional groundwater extraction caps and large-scale irrigation infrastructure plans. Individual smallholders make micro-level real-time pumping and crop cultivar choices. This creates asymmetric feedback loops between social institutional rules and physical water-energy-food resource flows. This localized mapping distinguishes the present CPSS analytical framework from generic global nexus models. It targets the region-specific institutional heterogeneity ignored by prior studies.

3 Research progress on resilience quantification and intelligent decision optimization of water-energy-food nexus systems

3.1 Resilience quantification methods

3.1.1 Composite index methods

The methodological toolkit for WEF resilience assessment spans from purely statistical to fully simulation-based approaches. Composite index methods represent the most widely adopted statistical category. These methods aggregate multiple indicators into a single resilience score through weighting and normalization. The entropy-TOPSIS framework determines objective weights based on data dispersion, ranking alternatives by their distance to ideal and anti-ideal solutions. It has been applied to construct province-level WEF resilience indices in China[38,39]. The AHP-entropy hybrid method combines subjective expert judgment from the analytic hierarchy process with objective entropy weights, balancing domain knowledge against data structure. It has been used for basin-scale WEF sustainability assessment[40,41]. Projection pursuit techniques reduce high-dimensional indicator data onto a low-dimensional subspace while maximizing a projection index. Its genetic algorithm-optimized variants enable dynamic resilience assessment[42,43]. Despite their widespread use, composite index methods are inherently static. They cannot capture nonlinear interactions, feedback loops or dynamic trajectories. They also have a fundamental black-box problem. A single numerical score cannot provide any mechanistic explanation for why the system exhibits a given resilience level.

3.1.2 Network-based topological metrics

Network-based approaches quantify resilience through the structural properties of the coupling topology of the system[44]. They follow three operational steps. First, researchers identify functional entities such as irrigation zones, pumping stations and crop production units as nodes. Second, they establish edges based on material flows (water volume, energy consumption and crop output), information flows (market signals and policy directives) or spatial proximity. Third, they compute topological resilience indicators. These indicators include network efficiency degradation under random versus targeted node removal, the percolation threshold at which the giant component disintegrates, and the cascading failure extent triggered by a primary node failure[45]. Chilaka et al.[46] demonstrated that betweenness centrality outperformed simpler degree-based metrics in identifying critical groundwater pumping nodes. Kivela et al.[47] provided a comprehensive framework for extending single-layer metrics to multilayer graphs. However, empirical applications of this framework remain sparse. A key limitation of topological analyses is their abstraction from the magnitude and directionality of material flows. A node with high betweenness centrality may be physically insignificant if the actual flow volume it mediates is negligible.

3.1.3 Simulation-based methods

Simulation models explicitly represent the dynamic behavior of WEF subsystems under perturbation scenarios. System dynamics models capture feedback loops and time delays through stocks, flows and causal loop diagrams[48]. However, it entails high computational costs and considerable calibration complexity. Agent-based modeling simulates the adaptive behavior of heterogeneous decision-makers. These decision-makers include farmers, water managers and energy suppliers, who interact within a shared environment[49]. This modeling excels at capturing emergent social-spatial patterns but it has high computational cost and calibration complexity[50]. Coupled physically-based models include hydro-economic frameworks and integrated land-water-energy systems[51]. They link hydrological, crop growth and energy submodels through consistent boundary conditions and exchange variables. The IIASA WEF model is a typical example of this approach at the global scale. However, the computational demands of full coupling remain a barrier to widespread application.

3.1.4 Machine learning-augmented methods

Machine learning techniques are increasingly integrated into resilience assessment pipelines (Table 2). They are used for pattern recognition, dimensionality reduction and surrogate modeling. Standard ML methods include clustering algorithms (K-means and HO-KMA) and tree-based ensembles (random forest and XGBoost). They have been widely applied to classify resilience regimes and address the curse of dimensionality in composite index construction. In parallel, index decomposition analysis methods notably the logarithmic mean divisia index (LMDI) are used to identify driving factors of resilience change through additive or multiplicative decomposition of aggregate indicators; these are mathematical decomposition techniques rather than machine-learning algorithms. A new generation of advanced ML methods offers transformative potential for WEF resilience assessment. These methods explicitly account for network structure, physical constraints and temporal dependencies[52–54]. Graph neural networks (GNNs) represent a paradigm shift. They treat WEF system components as interdependent nodes within a graph structure, rather than independent features. GNNs operate directly on network-structured data through message-passing mechanisms. They learn node embeddings that encode both local topology and node attributes. In the WEF context, a GNN could be constructed with water wells, pumping stations and crop production units as nodes, and resource flows as edges[55]. Physics-informed neural networks (PINNs) embed physical knowledge, including both governing equations and process-based simulation models, as soft constraints in the neural network loss function. These include governing physical equations such as the groundwater flow equations (Boussinesq equation) and energy balance equations, coupled with process-based crop simulation models such as a decision support system for agrotechnology transfer (DSSAT) to represent crop growth dynamics. By enforcing physical consistency even in data-sparse regions, PINNs address a fundamental limitation of purely data-driven methods. That limitation is the inability to extrapolate to conditions outside the training domain. PINNs are particularly valuable for northeastern China irrigation districts. These districts have sparse long-term monitoring data, but the physical understanding of groundwater dynamics and crop physiology is well-established. For WEF resilience, transformer-based models can provide probabilistic forecasts. These forecasts can feed into risk-based decision frameworks. Despite these advances, a fundamental limitation persists across all ML-based approaches. ML methods are correlational rather than causal. The data-

Table 2 Comparative analysis of methods for assessing water-energy-food nexus system resilience and decision optimization

Method category	Temporal dynamics	Spatial detail	Cross-sector coupling	Data requirement	Uncertainty handling	Representative algorithm
Composite index	Static	Spatially aggregated	Implicit (via indicators)	Moderate	Sensitivity analysis	Entropy-TOPSIS, AHP-entropy
Network metrics	Static to pseudo-dynamic	Node-level	Explicit (interlayer edges)	Moderate-high	Scenario-based	Degree, betweenness, efficiency
System dynamics	Fully dynamic	Spatially aggregated	Explicit (feedback loops)	High	Monte Carlo	Causal loop, stock-flow
Agent-based model	Fully dynamic	Agent-level	Emergent from interactions	Very high	Monte Carlo	ABM-MODFLOW
Standard ML	Dynamic (time series)	Grid/node-level	Implicit (feature engineering)	Very high	Ensemble	K-means, XGBoost, random forest
Graph neural networks	Dynamic	Node-level	Explicit (graph structure)	High	Ensemble + graph	GCN, GAT, GraphSAGE
Physics-Informed NN	Dynamic	Grid/node-level	Explicit (physics constraints)	Moderate	Bayesian PINN	PINN, conservative PINN, Fourier PINN
Transformer-based	Dynamic (long sequence)	Grid/node-level	Implicit (attention)	Very high	Probabilistic	Informer, autoformer
Classical optimization	Static to dynamic	Basin/regional	Implicit (constraints)	Moderate	Scenario-based	LP/MILP, SP, RO
Evolutionary algorithms	Static	Regional	Implicit (objective weighting)	Moderate	Pareto ensemble	NSGA-III, MOEA/D, PSO
Deep reinforcement learning	Fully dynamic	Node/regional	Implicit (reward shaping)	Very high	Ensemble	DQN, PPO, SAC
Multi-objective DRL	Fully dynamic	Node/regional	Explicit (multi-reward)	Very high	Pareto + ensemble	MODRL, constrained DRL
Digital twin	Fully dynamic	Node/grid-level	Explicit (real-time coupling)	Very high	Real-time + MPC	MPC, IoT-cloud fusion

mechanism gap remains the central challenge for ML-based resilience assessment. That is, data-driven models fail to capture rare-but-catastrophic events that do not appear in the training data.

3.2 Intelligent decision optimization methods

3.2.1 Multi-objective optimization framework

While resilience assessment answers questions about the resilience of the system, decision optimization addresses the complementary questions about actions to improve resilience. As shown in Fig. 3, the methodological landscape spans from classical operations research to modern computational intelligence. The WEF nexus decision problem is inherently multi-objective and can be generically formulated as maximizing a vector of competing objectives. These objectives include grain output, groundwater conservation, energy efficiency and system resilience. The optimization is subject to constraints that encode water availability caps, land area limits and policy mandates. The decision variables include crop acreage allocation, irrigation quotas and groundwater pumping limits[56].

3.2.2 Established optimization approaches

Established optimization approaches offer complementary strategies to handle the trade-offs inherent in WEF nexus decisions. Linear and mixed-integer linear programming have been applied by Giordano et al[57]. They used this method to optimize crop patterns and water allocation in Mediterranean irrigation districts. The optimization balances farm income against water use. This method offers computational efficiency suitable for large-scale, multi-period problems, but it requires linearization of inherently nonlinear WEF interactions. Stochastic programming incorporates parameter uncertainty through probability distributions. It generates hedging strategies that perform robustly across multiple scenarios. It is particularly relevant for irrigation optimization under stochastic rainfall and streamflow conditions[58]. Robust optimization takes a more conservative approach. It optimizes

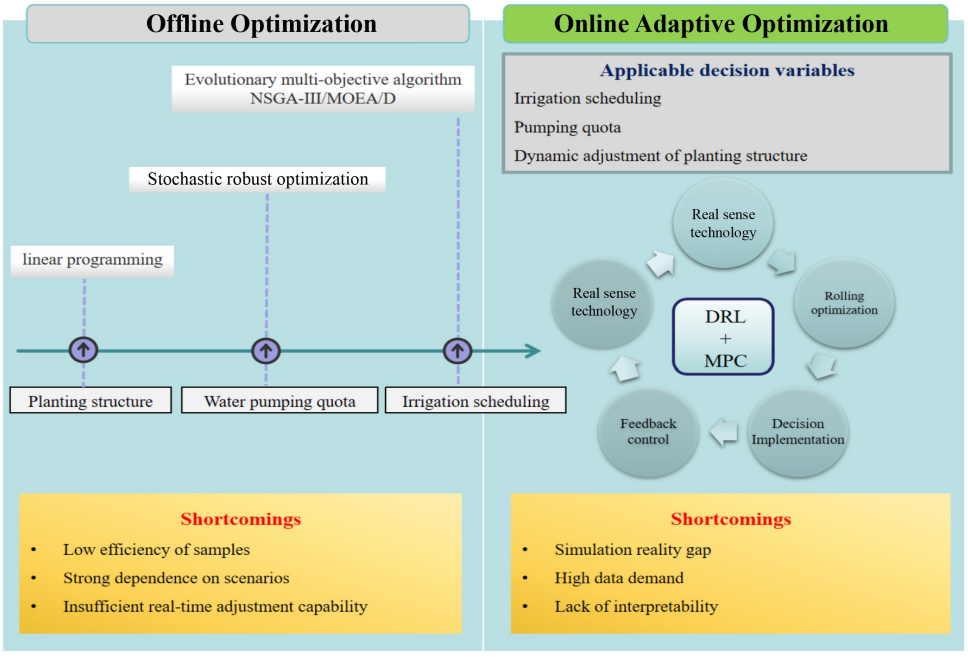

Fig. 3 Intelligent optimization technology evolution route map.

for worst-case realizations within specified uncertainty sets. Thus it guarantees feasibility under all admissible parameter values. This property provides reliable decision guidance for groundwater-dependent irrigation systems facing deep uncertainty about future recharge rates[59].

3.2.3 Evolutionary multi-objective algorithms

Evolutionary algorithms are population-based metaheuristics. They can approximate the Pareto front for the non-convex, non-differentiable multi-objective problems characteristic of WEF nexus optimization[60]. Of these, NSGA-II and NSGA-III are the most widely applied. Li et al.[61] used NSGA-III to optimize planting structures in irrigation districts in Heilongjiang Province under water resource resilience constraints. Their study showed that incorporating resilience as an explicit constraint shifted the optimal solution toward greater soybean and rice acreage and reduced maize planting area[62].

Complementary approaches include MOEA/D that decomposes the multi-objective problem into scalar subproblems solved simultaneously. It has been applied to basin-scale water-energy allocation in the Yellow River Basin[63]. Particle swarm optimization is a swarm intelligence algorithm that offers faster convergence than genetic algorithms for continuous-variable problems, such as irrigation scheduling optimization[64].

3.2.4 Deep reinforcement learning

Deep reinforcement learning (DRL) represents a paradigm shift from offline optimization to online adaptive learning. In this framework, an agent such as an irrigation district controller learns a policy. This policy maps observed system states to actions, such as water release decisions and planting area adjustments. The agent maximizes cumulative rewards through iterative interaction with the environment[65]. In WEF nexus applications, DRL has been explored for multiple scenarios. These include multi-reservoir release optimization under inflow uncertainty, adaptive irrigation scheduling that responds to real-time soil moisture and weather forecasts, and coordinated dispatch of groundwater pumping with variable renewable energy availability to reduce costs and carbon emissions[66–68]. DRL offers the distinct advantage of discovering non-intuitive policies and adapting to non-stationary environments, but it has three significant limitations. The first is sample inefficiency, which requires

millions of simulation episodes for training. The second is poor interpretability, as the learned policy remains a black-box neural network. The third is a fundamental simulation-to-real gap. Policies trained in simulation may fail under real-world conditions that are not represented in the training environment. Beyond single-objective DRL, multi-objective deep reinforcement learning has recently emerged as a powerful paradigm for WEF nexus optimization. It explicitly addresses the inherent trade-offs among competing objectives, including economic return, grain output, groundwater conservation and system resilience.

3.2.5 Digital twin-enabled optimization

Digital twin technology couples real-time data streams from IoT sensors with high-fidelity simulation models of the physical system. It creates a responsive model that continuously updates and recalibrates[69]. In the WEF nexus context, a digital twin would integrate three layers. The first is a real-time monitoring layer that comprises soil moisture sensors, groundwater level loggers, energy meters, weather stations and satellite-derived evapotranspiration data. The second is a simulation layer that couples SWAT-MODFLOW for hydrology-groundwater dynamics, DSSAT/APSIM for crop growth and EnergyPlus for energy systems. The third is an optimization layer that uses model predictive control (MPC) algorithms to solve finite-horizon problems with rolling updates[70]. Rasheed et al.[71] reviewed digital twin applications in agriculture. They identified irrigation management as one of the most promising domains. However, full WEF nexus-scale digital twins remain aspirational due to unresolved computational and data integration challenges.

3.2.6 Transformer-based forecasting for decision support

While the optimization methods discussed above focus on solving the decision problem given current system states, effective WEF management also requires accurate forecasting of future states. These states include groundwater levels, crop yields, energy demand and extreme weather events. Transformer-based forecasting models have emerged as the state-of-the-art for time-series prediction in complex environmental systems. They offer three key advantages for WEF decision support. First, their superior long-range dependency modeling enables transformers to capture multi-year cycles in groundwater recharge, seasonal patterns in irrigation demand and lagged responses of crop yields to antecedent climate conditions. These relationships are challenging for standard RNNs or ARIMA models to capture. Second, multi-modal data integration allows transformers to jointly process heterogeneous data streams. These streams include time-series data (well levels and weather), spatial data (satellite imagery and soil maps) and categorical variables (crop types and management practices). The integration is realized through separate encoding branches with cross-attention mechanisms. This feature makes transformers uniquely suited for the multi-domain nature of WEF systems. Third, probabilistic forecasting, via autoregressive probabilistic frameworks such as DeepAR (built on recurrent neural network architectures) and transformer-based models with stochastic processes, provides prediction intervals rather than point estimates. This enables risk-aware decision-making under uncertainty, which is critical for groundwater-stressed irrigation districts. In these districts, the cost of over-pumping (depletion) must be balanced against the cost of under-pumping (crop failure). For the proposed WEF digital twin, a transformer-based forecasting module would serve as the predictive core of the MPC loop. It provides look-ahead estimates of system states to optimize rolling-horizon decisions.

4 Regional evidence: irrigation districts of northeastern China

4.1 Hydrogeological and agricultural context

The northeastern China Plain consists of three major alluvial plains: the Songnen Plain (18.3×10^4 km^2), the Sanjiang Plain (10.9×10^4 km^2) and the Liaohe Plain (3.7×10^4 km^2)[4]. Annual precipitation ranges from 400 to 600 mm with 70% to 80% of the precipitation concentrated in the July–September monsoon season. This creates a structural mismatch between water availability and the May–June peak irrigation demand for paddy rice[72]. Groundwater provides approximately 60% of irrigation supply in the Songnen Plain. It supplies over 80% of irrigation water in parts of the Sanjiang Plain[73]. Groundwater level declines of 0.3–1.8 m·yr^{-1} have been documented in intensively irrigated regions such as the North China Plain[5], with comparable declines reported in parts of the Sanjiang Plain. The deepest depression cone there exceeds 40 m below the historical water table. GRACE satellite gravimetry has been applied to quantify groundwater depletion rates in intensively pumped basins such as the Hai River Basin (1.4 ± 0.3 km^3·yr^{-1})[74]; analogous GRACE-based estimates for the broader northeastern China region remain limited.

4.2 Water-energy-food nexus studies in northeastern China

4.2.1 Resilience assessment studies

The empirical literature on WEF nexus resilience in northeastern China irrigation districts is nascent but growing. In the most comprehensive quantification to date, Li et al.[61] applied the HO-KMA clustering algorithm combined with LMDI decomposition. They evaluated WEF nexus system resilience in the Jiansanjiang Administration from 2000 to 2022. This administration is a major state farm complex managing 120 kha of irrigated paddy rice on the Sanjiang Plain. Their study revealed a three-phase resilience trajectory. The phases are stagnation (2000–2005), rapid growth coinciding with large-scale canal irrigation infrastructure investment (2006–2012) and fluctuating growth (2013–2022). The LMDI decomposition identified four dominant driving factors. They are mechanized cultivation ratio, rice paddy proportion, agricultural machinery power per unit area, and effective irrigation coverage ratio. Current empirical evidence targeting northeastern irrigation districts remains fragmented and under-synthesized. It is limited to isolated single-administration or provincial-scale case studies without systematic cross-site comparison. This review covers all published localized WEF resilience literature from 2014–2025. It provides a comprehensive thematic summary covering three dimensions. The first is temporal evolution characteristics of nexus resilience across Sanjiang and Songnen Plain irrigation zones. The second is core driving factor disparities between state farm and smallholder dominated regions. The third is the effectiveness of existing water-adaptive planting optimization schemes under groundwater over-extraction pressure. We further standardize the resilience evaluation indicator systems and optimization constraint settings adopted by Heilongjiang regional studies. We reveal consistent regional bottlenecks. These bottlenecks include insufficient long-term field monitoring datasets and neglect of seasonal freeze-thaw disturbance variables in local modeling frameworks.

4.2.2 Comparable studies from other irrigation systems in semiarid areas

Findings from geohydrologically analogous regions provide transferable insights for northeastern China. On the North China Plain, groundwater dependency and depletion severity mirror conditions in the northeast. Yang et al.[49] developed an agent-based model integrated with MODFLOW. They used it to simulate farmer irrigation adaptation to declining water tables in Hebei Province. Their study revealed a maladaptive pattern. Farmers initially increase pumping in response to well deepening. They only reduce consumption after wells exceed economic pumping depths. This behavioral dynamic likely applies to northeastern China's groundwater users. In the US High Plains Aquifer region, the Ogallala depletion crisis has motivated extensive WEF nexus modeling. Haacker et al.[75] quantified the spatial heterogeneity of aquifer depletion. They demonstrated that localized hotspot management, rather than uniform policies, is essential for effective resilience interventions. Network-based vulnerability analysis can identify priority intervention nodes for managed aquifer recharge and irrigation efficiency upgrades.

The Murray-Darling Basin in Australia provides a further international benchmark. Grafton et al.[76] documented how water trading, combined with environmental flow allocations and irrigation infrastructure modernization, improved system-wide resilience during the so-called Millennium Drought (2001–2009). The institutional mechanisms there, particularly the separation of water rights from land titles, offer relevant lessons for northeastern China's evolving water rights system.

4.3 Summary of regional evidence

The empirical base for WEF nexus resilience assessment in northeastern China's irrigation districts can be characterized as thin but informative. The available evidence confirms three key points. First, system resilience has improved over the last two decades, but it remains vulnerable to groundwater depletion. Second, mechanization intensity and irrigation coverage are the dominant drivers of resilience trajectories. Third, resilience-constrained planting structure optimization yields significantly different outcomes compared to unconstrained economic optimization.

5 Research gaps and future directions

5.1 Identified research gaps

Four critical research gaps emerge from this review. First, multilayer heterogeneous network models remain underdeveloped. Despite well-established theoretical

foundations in network science, no study has constructed and validated a three-layer water-energy-food coupled network model for an entire irrigation district. The specific properties of real WEF nexus networks, such as whether they exhibit scale-free, small-world or community structure properties, remain unknown. Researchers also have not systematically compared the robustness of coupled networks to cascading failures initiated from different subsystem nodes. These nodes include groundwater well nodes, power substation nodes and crop disease outbreak nodes. Second, a persistent data-mechanism integration gap exists. Purely data-driven resilience assessments cannot extrapolate to extreme events absent from training records or reveal causal mechanisms. Process-based models are limited by parameter uncertainty at the nexus scale and high computational cost. No existing framework has successfully fused the pattern-recognition power of machine learning with the causal consistency of physically-based hydrological, crop and energy models. Third, optimization frameworks inadequately incorporate resilience objectives. Current WEF nexus optimization studies predominantly optimize for economic efficiency or resource use minimization. Resilience, when considered at all, is treated as a post hoc constraint rather than an integral optimization objective. The specific path of translating "the system has resilience score X" to "decision Y improves resilience by ΔX" is not operationalized. Fourth, several knowledge gaps remain regarding northeast China. There are no long-term longitudinal WEF nexus resilience monitoring programs. The interaction effects between freeze-thaw dynamics and WEF resilience have not been examined. The behavioral dimensions of heterogeneous state farm and smallholder coexistence on resilience trajectories remain unexplored. There is also a lack of system-level evaluation of China's virtual water strategy for relieving pressure on groundwater-stressed areas.

5.2 A structured future research agenda

As shown in Fig. 4, we propose four priority research directions along the theoretical-methodological-applied continuum. First, at the theoretical level, multilayer WEF network resilience should be formalized. A domain-specific three-layer network model should be constructed for a typical

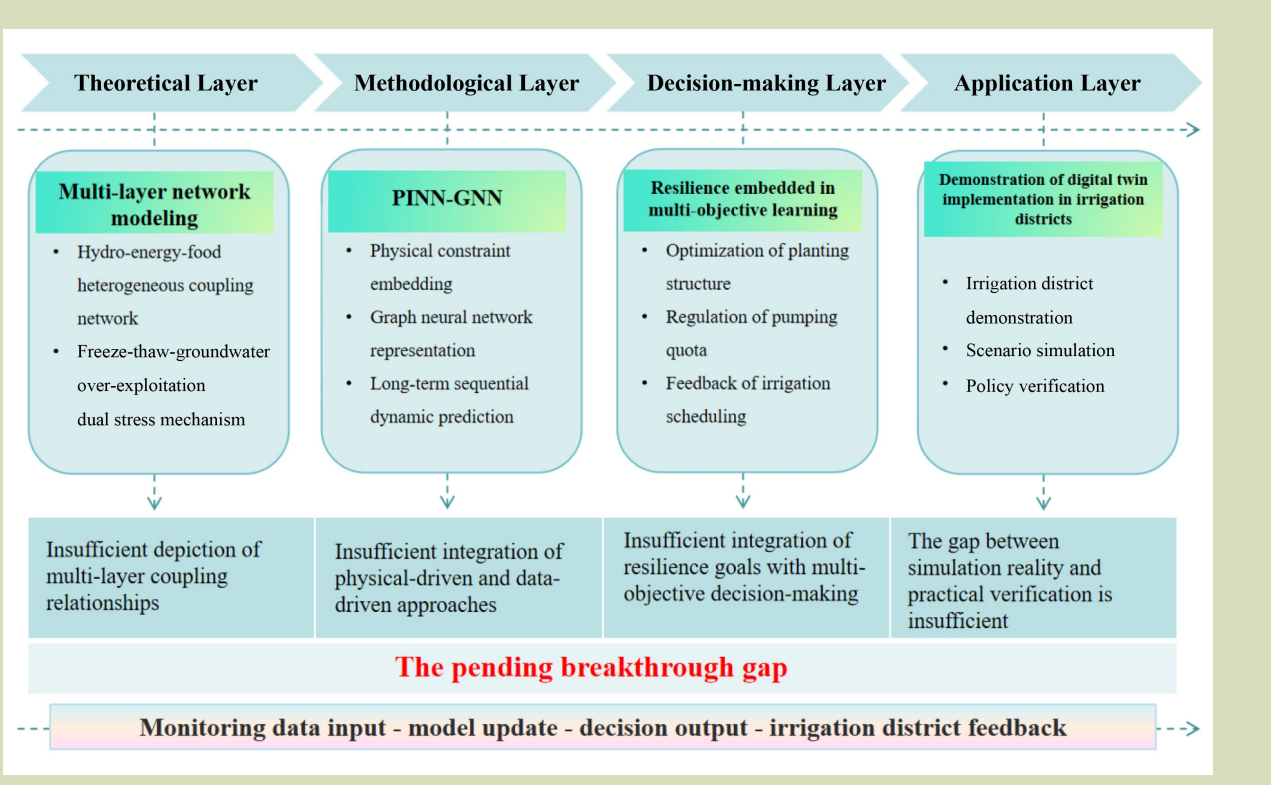

Fig. 4 The full-process technical roadmap for the water-energy-food digital twin of a northeastern irrigation district.

northeastern China irrigation district. Wells and irrigation zones serve as water-layer nodes. Substations and pumping stations serve as energy-layer nodes. Crop management units serve as food-layer nodes. Topological properties and interlayer coupling patterns should be empirically characterized for each layer. Targeted attacks should be simulated to measure cascading failure propagation across layers. Inter-layer coupling strength should be developed as a tunable parameter. This will reveal how varying coupling magnitudes affect system robustness. This direction directly addresses the first research gap. Second, at the methodological level, the data-mechanism gap should be bridged. PINNs should be applied to embed groundwater flow equations as soft constraints. This ensures physical consistency even in data-sparse regions. Graph neural networks should serve as surrogate models for computationally expensive coupled simulations. This enables Monte Carlo-style resilience analysis across thousands of perturbation scenarios. Copula-based extreme event generators should be developed to synthesize physically plausible compound events. These include simultaneous drought, heat wave, and energy price spikes. Such events should be derived from historical marginal distributions. This direction addresses the second research gap. Third, at the decision support level, resilience-embedded multi-objective optimization frameworks should be developed. Resilience should be formulated as an explicit fourth objective. It should sit alongside economic return, grain output, and resource efficiency. Resilience should be quantified using the multilayer network metrics from the first direction. These metrics should be applied under extreme climate scenarios from the second direction. The framework should be solved via multi-objective deep reinforcement learning. This should be benchmarked against classical NSGA-III and MPC approaches. This direction addresses the final research gap. Fourth, at the applied level, a prototypical WEF digital twin should be developed. It should be deployed for a representative irrigation district in the Songnen or Sanjiang Plain. IoT sensors should be integrated via LoRaWAN or NB-IoT. These sensors provide real-time field data. A SWAT-MODFLOW coupled model should simulate hydrology-groundwater dynamics. A DSSAT crop model should capture crop growth responses. An energy accounting module should be included. The multilayer network resilience engine should be embedded within a rolling-horizon MPC controller. This controller ingests real-time data. It recommends weekly planting and irrigation adjustments. Expected outcomes include a validated digital twin workflow. They also include quantification of the added value of dynamic over static decision rules. Finally, they include a replicable template for groundwater-dependent irrigation districts across China and globally.

6 Conclusions

This systematic review has examined the state of knowledge at the intersection of complex network theory, resilience assessment, and intelligent decision optimization for WEF nexus systems. The review focuses specifically on the groundwater-stressed irrigation districts of northeastern China. Three principal conclusions emerge. First, the theoretical foundation is strong but empirically untested. Multi-layer network theory and resilience frameworks provide a rich conceptual vocabulary. However, the empirical realization of multilayer WEF network models, complete with validated coupling topologies and calibrated flow magnitudes, remains an open frontier. For northeastern China specifically, the seasonal freeze-thaw regime and the coexistence of state farms and smallholders introduce unique structural features that are not captured by generic global network models. Second, resilience assessment and decision optimization remain disconnected. Despite sophisticated tools for resilience quantification (including composite indices, network metrics and simulation models) and advanced tools for decision optimization (including evolutionary algorithms, deep reinforcement learning and MPC), these two research streams seldom intersect. The critical missing link is an operational definition of resilience that can serve as a tractable objective function within standard optimization frameworks. Third, the empirical evidence base for northeastern China is inadequate for robust policy guidance. Despite the strategic importance of this region to China's food security and the severity of its ongoing groundwater crisis, only a handful of WEF nexus resilience studies have been conducted. Most existing studies are limited to the Jiansanjiang Administration or Heilongjiang Province-scale analysis. These preliminary findings point to improving resilience trajectories driven by mechanization and irrigation infrastructure investment, but these results have not been replicated across other irrigation districts, nor extended to evaluate specific targeted policy interventions. The future research agenda outlined here is organized around the CPSS paradigm and structured along theoretical, methodological, technological and applied dimensions. It offers a clear roadmap for closing all identified gaps. The ultimate objective is enabling a transition from reactive crisis management to proactive resilience governance in northeastern China's irrigation districts. This effort will contribute both to national food security and to global knowledge on sustainable groundwater-irrigated agriculture in semiarid regions.

Acknowledgements

This work was funded by Special Project for the Construction Project of Double First-Class Initiative in Heilongjiang Province "Green and Low-Carbon of Grain Crops", China (LJGXCG2022–107); Basic Resources Survey of Science and Technology, China (2025FY100702); National Key R&D Program Subproject, China (2024YFD1700102 and 2023YFD1701804); and The Construction of the National Modern Agricultural Industry Technology System of the Ministry of Finance and the Ministry of Agriculture and Rural Affairs of China (CARS-02–24). We used the Doubao AI web version to develop the image concept, and the image was finally produced by Handan Awakening Technology Co., Ltd.

Compliance with ethics guidelines

Yuzhou Jiang, Tong Li, Yan Zhang, and Qingli Liu declare that they have no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

REFERENCES

1. Food and Agriculture Organization of the United Nations (FAO). The State of the World's Land and Water Resources for Food and Agriculture–Systems at Breaking Point (SOLAW 2021). Rome: *FAO*, 2021
2. Simpson G B, Jewitt G P W. The development of the water-energy-food nexus as a framework for achieving resource security: a review. *Frontiers in Environmental Science*, 2019, **7**: 8
3. Rasul G, Sharma B. The nexus approach to water-energy-food security: an option for adaptation to climate change. *Climate Policy*, 2016, **16**(6): 682–702
4. Li W, Ward P J, van Wesenbeeck L. A critical review of quantifying water-energy-food nexus interactions. *Renewable and Sustainable Energy Reviews*, 2025, **211**: 115280
5. Cao G L, Zheng C M, Scanlon B R, Liu J, Li W P. Use of flow modeling to assess sustainability of groundwater resources in the North China Plain. *Water Resources Research*, 2013, **49**(1): 159–175
6. Liu J, Yang H, Cudennec C, Gain A K, Hoff H, Lawford R, Qi J, de Strasser L, Yillia P T, Zheng C. Challenges in operationalizing the water-energy-food nexus. *Hydrological Sciences Journal*, 2017, **62**(11): 1714–1720
7. Albrecht T R, Crootof A, Scott C A. The water-energy-food nexus: a systematic review of methods for nexus assessment. *Environmental Research Letters*, 2018, **13**(4): 043002
8. Zhang C, Chen X X, Li Y, Ding W, Fu G T. Water-energy-food nexus: concepts, questions and methodologies. *Journal of Cleaner Production*, 2018, **195**: 625–639
9. D'Odorico P, Davis K F, Rosa L, Carr J A, Chiarelli D, Dell' Angelo J, Gephart J, MacDonald G K, Seekell D A, Suweis S, Rulli M C. The global food-energy-water nexus. *Reviews of Geophysics*, 2018, **56**(3): 456–531
10. Bian Z Y, Liu D. A comprehensive review on types, methods and different regions related to water-energy-food nexus. *International Journal of Environmental Research and Public Health*, 2021, **18**(16): 8276
11. Hoff H. Understanding the nexus. In: Hoff H, ed. Background Paper for the Bonn 2011 Conference: the Water, Energy and Food Security Nexus. Stockholm: *Stockholm Environment Institute*, 2011
12. Endo A, Tsurita I, Burnett K, Orencio P M. A review of the current state of research on the water, energy, and food nexus. *Journal of Hydrology: Regional Studies*, 2017, **11**: 20–30
13. Food and Agriculture Organization of the United Nations (FAO). The Water-Energy-Food Nexus: A New Approach in Support of Food Security and Sustainable Agriculture. Rome: *FAO*, 2014
14. Waughray D. Water Security: the Water-Food-Energy-Climate Nexus. Washington: *Island Press*, 2011
15. Wang Q, Li S Q, He G, Li R R, Wang X F. Evaluating sustainability of water-energy-food (WEF) nexus using an improved matter-element extension model: a case study of China. *Journal of Cleaner Production*, 2018, **202**: 1097–1106
16. White D J, Hubacek K, Feng K S, Sun L X, Meng B. The water-energy-food nexus in East Asia: a tele-connected value chain analysis using inter-regional input-output analysis. *Applied Energy*, 2018, **210**: 550–567
17. Al-Ansari T, Korre A, Nie Z G, Shah N. Development of a life cycle assessment tool for the assessment of food production systems within the energy, water and food nexus. *Sustainable Production and Consumption*, 2015, **2**: 52–66
18. KC S, Lutz W. The human core of the shared socioeconomic pathways: population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*, 2017, **42**: 181–192
19. Tian G L, Li J W, Wu Z, Zhao Q Y, Xia Q, Zhang J Y, Niu X C.

Unveiling the resilience of the water-energy-food nexus: a context-specific framework and evolutionary insights for the Yellow River Basin. *Agricultural Water Management*, 2025, **315**: 109514

20. Giampietro M. Multi-scale integrated analysis of societal and ecosystem metabolism. In: Villamayor-Tomas S, Muradian R, eds. The Barcelona School of Ecological Economics and Political Ecology. Cham: *Springer*, 2023, 109–121
21. De Bruijn K, Buurman J, Mens M, Dahm R, Klijn F. Resilience in practice: five principles to enable societies to cope with extreme weather events. *Environmental Science & Policy*, 2017, **70**: 21–30
22. Drobinski P, Rivera Ferre M G, Monem M A, Abu Hatab A, Behnassi M, Chfadi T, Cramer W, Debolini M, Driouech F, El-Kenawy A, García-Vila M, Guiot J, Lamonaca E, López-I-gelats F, Malek Ž, Papadopoulou M P, Santeramo F G. Nexus approach to enhance water-energy-food security and ecosystems resilience under climate change in the Mediterranean. *npj Climate Action*, 2025, **4**(1): 115
23. Francis R, Bekera B. A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety*, 2014, **121**: 90–103
24. Folke C, Carpenter S R, Walker B, Scheffer M, Chapin T, Rockström J. Resilience thinking: integrating resilience, adaptability and transformability. *Ecology and Society*, 2010, **15**(4): 20
25. Hogeboom R J, Borsje B W, Deribe M M, van der Meer F D, Mehvar S, Meyer M A, Özerol G, Hoekstra A Y, Nelson A D. Resilience meets the water-energy-food nexus: mapping the research landscape. *Frontiers in Environmental Science*, 2021, **9**: 630395
26. Kurian M, Scott C, Reddy V R, Alabaster G, Nardocci A, Portney K, Boer R, Hannibal B. One swallow does not make a summer: siloes, trade-offs and synergies in the water-energy-food nexus. *Frontiers in Environmental Science*, 2019, **7**: 32
27. Boccaletti S, Bianconi G, Criado R, del Genio C I, Gómez-Gardeñes J, Romance M, Sendiña-Nadal I, Wang Z, Zanin M. The structure and dynamics of multilayer networks. *Physics Reports*, 2014, **544**(1): 1–122
28. Barabási A L, Albert R. Emergence of scaling in random networks. *Science*, 1999, **286**(5439): 509–512
29. Freeman L C. A set of measures of centrality based on betweenness. *Sociometry*, 1977, **40**(1): 35–41
30. Watts D J, Strogatz S H. Collective dynamics of 'small-world' networks. *Nature*, 1998, **393**(6684): 440–442
31. Latora V, Marchiori M. Efficient behavior of small-world networks. *Physical Review Letters*, 2001, **87**(19): 198701
32. Gómez-Gardeñes J, Reinares I, Arenas A, Floría L M. Evolution of cooperation in multiplex networks. *Scientific Reports*, 2012, **2**: 620
33. Pagani G A, Aiello M. The power grid as a complex network: a survey. *Physica A: Statistical Mechanics and its Applications*, 2013, **392**(11): 2688–2700
34. Puma M J, Bose S, Chon S Y, Cook B I. Assessing the evolving fragility of the global food system. *Environmental Research Letters*, 2015, **10**(2): 024007
35. Buldyrev S V, Parshani R, Paul G, Stanley H E, Havlin S. Catastrophic cascade of failures in interdependent networks. *Nature*, 2010, **464**(7291): 1025–1028
36. Wang F Y. The emergence of intelligent enterprises: from CPS to CPSS. *IEEE Intelligent Systems*, 2010, **25**(4): 85–88
37. Zhang X D, Vesselinov V V. Integrated modeling approach for optimal management of water, energy and food security nexus. *Advances in Water Resources*, 2017, **101**: 1–10
38. Liu H Y, Liu Y C, Meng L H, Jiao K Q, Zhu M Y, Chen Y K, Zhang P F. Research progress of entropy weight method in water resources and water environment. *Journal of Glaciology and Geocryology*, 2022, **44**(1): 299–306 (in Chinese)
39. Sun C Z, Yan X D. Security evaluation and spatial correlation pattern analysis of water resources-energy-food nexus coupling system in China. *Water Resources Protection*, 2018, **34**(5): 1–8 (in Chinese)
40. Saaty T L. Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, 2008, **1**(1): 83–98
41. Xu S S, He W J, Shen J Q, Degefu D M, Yuan L, Kong Y. Coupling and coordination degrees of the core water-energy-food nexus in China. *International Journal of Environmental Research and Public Health*, 2019, **16**(9): 1648
42. Liu J M, Chang F L, Yang J H, Jie X Y, Lu C Y, Wang C, Xie L, Ma L H, Su H Y. Deep reinforcement learning for irrigation optimization: advantages, opportunities, and challenges. *Agricultural Water Management*, 2025, **322**: 110030
43. He L X, Zhou S Y, Zhang Z, Li Z H. Water-energy-food-population system security evaluation based on projection pursuit model. *Yellow River*, 2024, **46**(4): 73–78 (in Chinese)
44. Gao J X, Buldyrev S V, Stanley H E, Havlin S. Networks formed from interdependent networks. *Nature Physics*, 2012, **8**(1): 40–48
45. Motter A E, Lai Y C. Cascade-based attacks on complex networks. *Physical Review E*, 2002, **66**(6): 065102
46. Chilaka C, Rinehart A J, Wang H Y, Ward F A. Optimizing the economic cost of sustainable pumping in the Southern High Plains aquifer. *Journal of Hydrology*, 2025, **662**: 134006
47. Kivela M, Arenas A, Barthelemy M, Gleeson J P, Moreno Y, Porter M A. Multilayer networks. *Journal of Complex Networks*, 2014, **2**(3): 203–271
48. Zheng D F, Tang H, Wang J Y, Lv L T. Multifunctionality evaluation and coupling coordination analysis of the water-energy-food system. *Journal of Economics of Water Resources*, 2026, **44**(4): 1–9 (in Chinese)
49. Yang Y C E, Cai X M, Stipanović D M. A decentralized optimization algorithm for multiagent system-based watershed management. *Water Resources Research*, 2009, **45**(8): W08430
50. An L. Modeling human decisions in coupled human and

natural systems: review of agent-based models. *Ecological Modelling*, 2012, **229**: 25–36

51. Howells M, Hermann S, Welsch M, Bazilian M, Segerström R, Alfstad T, Gielen D, Rogner H, Fischer G, van Velthuizen H, Wiberg D, Young C, Roehrl R A, Mueller A, Steduto P, Ramma I. Integrated analysis of climate change, land-use, energy and water strategies. *Nature Climate Change*, 2013, **3**(7): 621–626
52. Li M, Fu Q, Singh V P, Liu D, Li T. An optimization-based multi-sensor fusion approach for daily streamflow estimation. *Journal of Hydrology*, 2020, **586**: 124890
53. Ang B W. LMDI decomposition approach: a guide for implementation. *Energy Policy*, 2015, **86**: 233–238
54. Chen T Q, Guestrin C. XGBoost: a Scalable Tree Boosting System. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. San Francisco, CA, USA: *ACM*, 2016, 785–794
55. Kipf T N, Welling M. Semi-supervised classification with graph convolutional networks. In: Proceedings of the 5th International Conference on Learning Representations. Toulon, France: *OpenReview.net*, 2017
56. Mardle S. Nonlinear multiobjective optimization K. M. Miettinen. *The Journal of the Operational Research Society*, 2000, **51**(2): 246–247
57. Giordano R, D'Agostino D, Apollonio C, Scardigno A, Pagano A, Portoghese I, Lamaddalena N, Piccinni A F, Vurro M. Evaluating acceptability of groundwater protection measures under different agricultural policies. *Agricultural Water Management*, 2015, **147**: 54–66
58. Birge J R, Louveaux F. Introduction to Stochastic Programming. 2nd ed. New York: *Springer*, 2011
59. Ben-Tal A, El Ghaoui L, Nemirovski A. Robust Optimization. Princeton: *Princeton University Press*, 2009, 1–565
60. Gaspar-Cunha A, Covas J A. Robustness in multi-objective optimization using evolutionary algorithms. *Computational Optimization and Applications*, 2008, **39**(1): 75–96
61. Li M X, Zhang Z W, Liu D, Zhang L L, Li M, Khan M I, Li T X, Cui S. Optimization of agricultural planting structure in irrigation areas of Heilongjiang province considering the constraints of water resource system resilience. *Journal of Cleaner Production*, 2024, **434**: 140329
62. Deb K, Jain H. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. *IEEE Transactions on Evolutionary Computation*, 2014, **18**(4): 577–601
63. Zhang Q F, Li H. MOEA/D: a multiobjective evolutionary algorithm based on decomposition. *IEEE Transactions on Evolutionary Computation*, 2007, **11**(6): 712–731
64. Kennedy J, Eberhart R. Particle Swarm Optimization. In: Proceedings of ICNN'95 — International Conference on Neural Networks. Perth, WA, Australia: *IEEE*, 1995, 1942–1948
65. Sutton R S, Barto A G. Reinforcement learning: an introduction. *IEEE Transactions on Neural Networks*, 1998, **9**(5): 1054
66. Castelletti A, Pianosi F, Restelli M. A multiobjective reinforcement learning approach to water resources systems operation: Pareto frontier approximation in a single run. *Water Resources Research*, 2013, **49**(6): 3476–3486
67. Berghuijs W R, Harrigan S, Molnar P, Slater L J, Kirchner J W. The relative importance of different flood-generating mechanisms across Europe. *Water Resources Research*, 2019, **55**(6): 4582–4593
68. Mnih V, Kavukcuoglu K, Silver D, Rusu A A, Veness J, Bellemare M G, Graves A, Riedmiller M, Fidjeland A K, Ostrovski G, Petersen S, Beattie C, Sadik A, Antonoglou I, King H, Kumaran D, Wierstra D, Legg S, Hassabis D. Human-level control through deep reinforcement learning. *Nature*, 2015, **518**(7540): 529–533
69. Grieves M, Vickers J. Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Kahlen F J, Flumerfelt S, Alves A, eds. Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches. Cham: *Springer*, 2017, 85–113
70. Mayne D Q, Rawlings J B, Rao C V, Scokaert P O M. Constrained model predictive control: stability and optimality. *Automatica*, 2000, **36**(6): 789–814
71. Rasheed A, San O, Kvamsdal T. Digital twin: values, challenges and enablers from a modeling perspective. *IEEE Access*, 2020, **8**: 21980–22012
72. Piao S L, Ciais P, Huang Y, Shen Z H, Peng S S, Li J S, Zhou L P, Liu H Y, Ma Y C, Ding Y H, Friedlingstein P, Liu C Z, Tan K, Yu Y Q, Zhang T Y, Fang J Y. The impacts of climate change on water resources and agriculture in China. *Nature*, 2010, **467**(7311): 43–51
73. Zheng C M, Liu J, Cao G L, Kendy E, Wang H, Jia Y W. Can China cope with its water crisis? Perspectives from the North China Plain. *Groundwater*, 2010, **48**(3): 350–354
74. Yin W J, Hu L T, Zhang M L, Wang H R, Han S C. Statistical downscaling of GRACE-derived groundwater storage using ET data in the North China Plain. *Journal of Geophysical Research: Atmospheres*, 2018, **123**(11): 5973–5987
75. Haacker E M K, Kendall A D, Hyndman D W. Water level declines in the High Plains Aquifer: predevelopment to resource senescence. *Groundwater*, 2016, **54**(2): 231–242
76. Grafton R Q, Pittock J, Davis R, Williams J, Fu G B, Warburton M, Udall B, McKenzie R, Yu X B, Che N, Connell D, Jiang Q, Kompas T, Lynch A, Norris R, Possingham H, Quiggin J. Global insights into water resources, climate change and governance. *Nature Climate Change*, 2013, **3**(4): 315–321