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AI for Agri-Food Resilience under Compound Crises: A Conceptual Model Linking Climate Shocks, Supply Disruptions, Farmer Adaptation, and Food Security Governance

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Abstract

Agri-food systems increasingly operate under compound crises in which climate shocks, supply disruptions, market instability, ecological stress, and social vulnerability interact. These crises do not affect production, distribution, livelihoods, and food access in isolation. They move through connected risk pathways that can destabilise farms, supply chains, public institutions, and households at the same time. Artificial intelligence can support prediction, monitoring, early warning, and decision support in these contexts. However, technical forecasting alone does not constitute resilience when risks cascade across multiple domains. Agri-food resilience requires that predictive information be translated into adaptive decisions, coordinated response, and food security protection. This article develops a conceptual model of AI-supported agri-food resilience under compound crises. The model links climate shocks, supply disruptions, farmer adaptation, and food security governance as interacting domains. It treats AI as a decision-support function embedded within social, institutional, ecological, and market systems rather than as a stand-alone technological solution. The model identifies resilience mechanisms that connect risk detection, signal integration, uncertainty communication, adaptive decision support, institutional coordination, feedback learning, and accountability. It also clarifies boundary conditions that determine whether AI strengthens or weakens resilience. These include data quality, interpretability, local relevance, farmer participation, institutional response capacity, equity, and governance accountability. The article contributes a structured conceptual model for understanding how AI can support agri-food resilience when analytics are aligned with adaptation needs and food security objectives. It argues that resilient agri-food AI systems must connect prediction with human judgement, local knowledge, public action, and accountable coordination. The proposed model offers a basis for future empirical testing, policy design, and responsible innovation in crisis-sensitive food systems.

Keywords Artificial intelligence, Agri-food resilience, Compound crises, Climate shocks, Supply disruptions, Farmer adaptation

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Introduction

Agri-food systems are increasingly exposed to compound crises in which climate shocks, supply disruptions, market volatility, public-health emergencies, conflict, and livelihood insecurity interact across scales. In this article, agri-food resilience is understood as the capacity of food systems to sustain essential functions while absorbing disturbance,

adapting to changing conditions, and recovering from disruption. This framing is important because food-system failure rarely begins or ends at one point in the system; it emerges through linked vulnerabilities in production, distribution, access, governance, and social protection [1].

At farm level, resilience requires more than short-term survival after a shock. Farming systems must combine robustness, adaptability, and transformability so that producers can maintain livelihoods, adjust practices, and reorganise when existing arrangements become untenable. These capacities are shaped by farm resources, advisory systems, institutional support, market relations, ecological conditions, and the ability to learn from repeated disruption [2].

Food security adds a further conceptual layer because resilient production does not automatically guarantee stable access, utilisation, or equitable outcomes. Local food-system resilience depends on how communities, markets, and institutions absorb shocks while protecting vulnerable households and maintaining access to nutritious food. A conceptual model of AI-supported resilience must therefore link technical risk detection with food-security outcomes and crisis-response arrangements [2, 3].

The need for an integrated model is intensified by the possibility of simultaneous production shocks across major agricultural regions. When breadbasket regions experience overlapping climatic stress, the resulting risk can move through trade, prices, input systems, humanitarian demand, and public institutions. This article develops a conceptual model that connects four domains—climate shocks, supply disruptions, farmer adaptation, and food security governance—to explain how AI can support resilience only when predictive analytics are aligned with adaptive capacity and coordinated response [4].

AI and Agri-Food Resilience Under Compound Crises

AI-supported agri-food resilience depends first on the integration of data across farms, landscapes, supply chains, markets, institutions, and food-security monitoring systems. Big data in smart farming can improve situational awareness by combining sensor streams, weather data, machinery data, remote observations, farm records, and platform-based information. Yet these data streams become resilience-enhancing only when they are interoperable, interpretable, and connected to decisions that matter under crisis conditions [5].

Machine learning can contribute to resilience through prediction, classification, anomaly detection, yield estimation, pest and disease identification, resource optimisation, and operational decision support. These functions can help identify emerging risks before they become acute, especially when climate stress, input scarcity, and market uncertainty converge. However, the conceptual role of machine learning is not to replace agricultural judgement but to extend the range of observable signals available for timely adaptation [6].

Deep learning expands the capacity of agricultural systems to interpret complex visual, spatial, temporal, and sensor-based data. It can support crop monitoring, disease detection, stress diagnosis, and other analytical functions relevant to crisis preparedness. In a resilience model, these capabilities must be connected to uncertainty communication and explainable decisions, because opaque signals are difficult to act on when farmers, supply-chain actors, and public agencies must make high-stakes choices under pressure [7].

Smart farming should therefore be understood through responsible innovation rather than technological determinism. AI can strengthen agri-food resilience when it supports anticipation, inclusion, reflexivity, and responsive governance, but it can also deepen vulnerability if tools are inaccessible, misaligned with farmer needs, or governed through narrow efficiency goals. The conceptual model developed here treats responsibility as a boundary condition that determines whether digital agriculture contributes to system-level resilience [6–8].

Climate Shocks and Agricultural Risk

Climate shocks are a central driver of agri-food vulnerability because they affect crop growth, water availability, livestock systems, pest pressure, labour conditions, and infrastructure reliability. Long-term climate change can slow agricultural productivity growth, which makes production systems more exposed to repeated disturbance and less able to recover between shocks. In conceptual terms, climate shocks represent an upstream risk pathway that can trigger downstream supply disruptions, adaptation demands, and governance responses [9].

Climate effects on food production are not uniform across crops, regions, seasons, or farming systems. This unevenness means that AI-supported climate-risk analytics must be spatially sensitive and crop specific rather than based on aggregate warning signals alone. Remote sensing, climate analytics, crop modelling, and machine learning can help identify where production risks are emerging, but their resilience value depends on whether they inform decisions that can still be changed in time [9, 10].

Drought and heat stress illustrate why climate shocks should be modelled as interacting hazards rather than isolated events. When heatwaves intensify water deficits, shorten crop-development windows, or coincide with sensitive growth stages, the resulting crop losses may exceed what single-hazard assessments anticipate. AI-supported risk systems should therefore detect compound climatic stress, communicate uncertainty, and connect alerts to adaptation options such as planting adjustment, irrigation prioritisation, crop switching, input planning, and emergency support [11].

Climate-shock detection must also be linked to farmer decision-making, local validation, and institutional response. A risk signal that cannot be interpreted by farmers, trusted by advisors, or acted upon by agencies may improve prediction without improving resilience. **Table 1** summarises AI-supported climate-shock detection and agricultural-risk interpretation functions for agri-food resilience. These functions clarify how analytical signals become useful only when they are connected to adaptation timing, uncertainty communication, and response capacity [9].

Table 1. AI-Supported Climate-Shock Detection and Agricultural-Risk Interpretation for Agri-Food Resilience: Risk Signals, Data Sources, Analytical Functions, Decision Uses, Adaptation Needs, and Failure Risks

Climate-shock or agricultural-risk signal	Potential data sources	AI-supported analytical function	Decision-support use	Farmer adaptation need	Food-security or governance relevance	Failure risk if poorly governed
Drought onset and soil-moisture deficit	Satellite imagery, soil sensors, rainfall records, evapotranspiration estimates, hydrological data	Detect spatial water stress and forecast likely production impacts	Irrigation prioritisation, drought advisories, water allocation, emergency planning	Adjust planting dates, select tolerant varieties, prioritise water use, reduce input exposure	Supports drought early warning, procurement planning, and anticipatory assistance	False confidence, late warnings, exclusion of rainfed farmers, weak local validation
Heat stress during sensitive crop stages	Weather stations, climate forecasts, crop phenology data, remote sensing, farm observations	Identify periods of yield vulnerability and likely heat-related crop stress	Heat advisories, harvest timing, crop-stage risk alerts, labour safety planning	Change planting windows, protect livestock, adjust field operations, manage	Helps anticipate crop losses, labour risks, and local food supply pressure	Overgeneralised alerts, insufficient uncertainty communication, poor fit to local crop calendars

				shade and water		
Flooding and excess rainfall	Rainfall forecasts, river-level data, topography, drainage maps, satellite flood detection	Map inundation risk and identify exposed production and transport zones	Drainage action, field access planning, road-routing decisions, emergency logistics	Protect stored inputs, delay field operations, shift transport routes, manage crop damage	Supports food distribution planning and infrastructure response	Missed informal roads, poor coverage of small farms, delayed institutional action
Pest and disease pressure after climate anomalies	Field images, extension reports, weather anomalies, pest surveillance, farmer reports	Detect outbreak probability and classify visible symptoms	Targeted scouting, pesticide planning, extension alerts, regional surveillance	Apply timely control measures, coordinate local monitoring, adjust crop management	Helps prevent production losses and reduce unnecessary input use	Algorithmic misclassification, chemical overuse, inequitable access to diagnostics
Crop-yield anomaly and production shortfall	Remote sensing, crop models, historical yields, farm records, market arrivals	Estimate likely production deviations before harvest	Procurement planning, insurance triggers, food-balance assessment, market monitoring	Prepare storage, negotiate sales, diversify income, adjust household food planning	Supports early food-security assessment and supply planning	Poor calibration, hidden uncertainty, mis-targeted assistance, market panic
Rainfall variability and seasonal uncertainty	Seasonal forecasts, climate indices, local rainfall records, indigenous knowledge, advisory data	Translate probabilistic forecasts into locally meaningful risk scenarios	Planting advisories, input-purchase timing, credit and insurance decisions	Match crop choice and input intensity to expected conditions	Supports anticipatory planning across farming and public programmes	Probabilistic information misunderstood, weak trust, one-size-fits-all advice
Infrastructure exposure to climate hazards	Road networks, storage locations, flood maps, market nodes, transport data	Identify climate-sensitive bottlenecks linking production and distribution	Route planning, storage protection, emergency transport coordination	Protect harvest access, coordinate with buyers, shift delivery timing	Links climate shocks to supply-disruption governance	Focus on formal infrastructure only, neglect of remote communities

Supply Disruptions and Food-System Fragility

Supply disruptions reveal that food security depends on more than agricultural production. Transport failures, processing constraints, labour shortages, storage bottlenecks, border delays, and retail interruptions can prevent food from reaching households even when aggregate supply appears adequate. Food supply chains during crisis conditions show how logistics, labour, market access, and institutional coordination become resilience mechanisms rather than merely operational concerns [12].

Food-system fragility emerges when multiple nodes in production-to-consumption systems are disrupted at the same time. Input shortages can reduce farm capacity, transport barriers can delay distribution, and price instability can reduce household access even before physical scarcity becomes visible. AI-enabled supply-chain analytics can help detect these pressures, but disruption signals must be interpreted through food access, farmer livelihoods, and public-response needs [13].

Crisis conditions also show that resilience requires adaptive reconfiguration rather than simple restoration of pre-crisis flows. Food systems may need alternative procurement routes, decentralised storage, local processing capacity, flexible retail arrangements, and mechanisms to reduce waste when normal channels fail. In this sense, AI-supported supply monitoring should help actors identify feasible substitutions, not only predict where disruption may occur [14].

The conceptual model treats supply disruptions as mediating pathways between climate shocks, farmer adaptation, and food security governance. A drought may reduce production, but its food-security consequences depend on storage capacity, transport reliability, market concentration, import dependence, purchasing power, and emergency distribution. Supply-chain analytics can support resilience when they connect disruption detection to coordinated decisions about routing, procurement, market regulation, farmer support, and protection of vulnerable consumers [12].

Farmer Adaptation and Adaptive Capacity

Farmer adaptation is a central resilience mechanism because farms are where climate information, input constraints, market signals, labour realities, and livelihood risks become practical decisions. Adaptive capacity depends on assets, knowledge, institutions, social networks, credit, land access, extension support, and the ability to act before losses become irreversible. Smallholder adaptation studies show that vulnerability cannot be reduced through information alone when farmers lack the material and institutional conditions required to respond [15].

Digital climate services can support adaptation by translating climate and production-risk information into locally relevant advisories. These services may guide planting dates, crop choice, irrigation scheduling, pest surveillance, input use, and risk management when they are accessible, trusted, and understandable. However, digital advice becomes resilience-enhancing only when farmers can evaluate recommendations against local knowledge, resource constraints, and livelihood priorities [16].

Climate-smart agriculture illustrates the importance of enabling conditions in adaptation support. Adoption depends not only on the technical promise of a practice but also on information access, financial capacity, institutional incentives, labour availability, land tenure, market opportunities, and perceived risk. AI-enabled advisory systems should therefore avoid one-size-fits-all recommendations and instead support context-sensitive decision pathways that reflect diverse farm realities [17].

In the proposed conceptual model, farmer adaptation links upstream risk detection with downstream food-security outcomes. Climate-shock analytics may identify water stress, and supply-chain analytics may detect input scarcity, but resilience depends on whether farmers can adjust practices in time. AI can support adaptive capacity when it strengthens farmer agency, communicates uncertainty clearly, incorporates local feedback, and connects farm decisions to advisory, financial, market, and governance support [15].

Food Security Governance and Coordinated Response

Food security governance is the institutional domain through which warnings, analytics, and adaptation needs become collective response. Early warning in agri-food systems is valuable only when alerts are actionable, trusted, timely, and connected to agencies capable of mobilising support. Drought early warning, for example, must move beyond risk detection toward anticipatory action, resource allocation, and protection of food availability and access [18].

Governance also determines whether crisis recovery reproduces vulnerability or reduces it. Food systems can become more resilient and just when policy responses address unequal exposure, household access, labour precarity, and the needs of marginalised producers and consumers. AI-supported governance dashboards should therefore be designed to identify vulnerability and response gaps, not merely to optimise flows or predict aggregate supply [19].

Coordinated response requires links among public agencies, market actors, community organisations, humanitarian providers, farmer groups, and emergency food systems. Governance during food-security crises shows that institutional coordination is often improvised under pressure, especially when shocks affect supply, income, access, and community support at the same time. AI can support coordination by organising risk signals, targeting assistance, modelling scenarios, and monitoring response, but it cannot substitute for accountable institutions and trusted relationships [20].

The governance function in the conceptual model is therefore both analytical and political. It interprets climate and supply signals, identifies who is at risk, determines which response mechanisms are activated, and evaluates whether interventions protect food security. **Table 2** maps supply disruptions, farmer adaptation needs, and food security governance functions in compound agri-food crises. The table emphasises that coordinated response must connect disruption pathways with farmer realities, institutional triggers, and risks of exclusion [18].

Table 2. Supply Disruptions, Farmer Adaptation, and Food Security Governance Under Compound Crises: Disruption Pathways, Adaptation Needs, Governance Functions, Response Triggers, and Coordination Risks

Disruption pathway	Farmer adaptation need	AI-supported monitoring or decision function	Governance response function	Possible response trigger	Food-security objective	Coordination risk
Input shortage affecting seed, fertiliser, fuel, or veterinary supplies	Substitute inputs, adjust planting plans, reduce exposure to costly inputs, coordinate purchasing	Input availability tracking, price anomaly detection, supplier-risk mapping	Temporary procurement support, input distribution, credit adjustment, market oversight	Rapid price increase, stockout reports, delayed import or transport data	Protect production capacity and farmer livelihoods	Support may favour larger or better-connected farms
Transport or logistics breakdown	Shift delivery timing, use alternative routes, coordinate with buyers, protect perishable goods	Route-risk modelling, transport delay detection, network bottleneck identification	Emergency logistics coordination, road access support, local storage activation	Road closure, fuel scarcity, severe weather, port congestion	Maintain food flows and reduce post-harvest losses	Informal routes and remote communities may be invisible
Labour constraint	Adjust crop operations,	Labour availability	Labour mobility rules, worker	Harvest delay, public-health	Prevent production	Labour rights may be

during crisis	mechanise selectively, cooperate locally, prioritise critical tasks	monitoring, harvest-risk forecasting, scheduling support	protection, emergency staffing, advisory support	restriction, migration disruption	and harvest losses	subordinated to supply continuity
Market closure or demand collapse	Diversify channels, store produce, process locally, shift sales strategy	Market-access mapping, demand forecasting, price volatility detection	Public procurement, local market reopening protocols, buyer coordination	Sharp farm-gate price decline, unsold produce accumulation	Protect farmer income and food availability	Procurement may be slow or poorly targeted
Food price spike affecting consumers	Adjust household consumption, seek support, rely on social networks or safety nets	Price monitoring, vulnerability targeting, food-access risk dashboards	Cash transfers, food assistance, price regulation, safety-net expansion	Rapid staple-price increase, household food insecurity indicators	Protect access to affordable and nutritious food	Targeting systems may miss informal or undocumented households
Storage or cold-chain failure	Reallocate produce, change harvest timing, use local processing, reduce spoilage	Storage-capacity monitoring, cold-chain risk detection, spoilage prediction	Infrastructure support, emergency storage, public-private coordination	Power outage, storage saturation, temperature excursions	Reduce waste and stabilise supply	Data may privilege formal supply chains
Compound climate and market shock	Combine agronomic adaptation with income and risk-management strategies	Multi-hazard scenario modelling, farm-risk profiling, livelihood-risk dashboards	Integrated agricultural, market, and social-protection response	Concurrent yield loss, price volatility, and household vulnerability	Protect production, livelihoods, and access together	Agencies may respond in silos rather than as a system

Proposed Conceptual Model

The proposed conceptual model begins by asking what resilience is for, who benefits, which shocks are considered, and through which mechanisms system functions are protected. Food-system resilience concepts emphasise that resilience must specify the object of resilience, the disturbance, the affected groups, the temporal horizon, and the desired outcomes. In this article, the object is the agri-food system, the disturbances are compound crises, the affected groups include farmers and food-insecure households, and the desired outcome is sustained food security with adaptive capacity [21].

The model includes four core domains: climate shocks, supply disruptions, farmer adaptation, and food security governance. AI connects these domains through decision-support functions such as risk detection, signal integration, scenario analysis, targeting, uncertainty communication, and feedback learning. Yet AI can also create new vulnerabilities when optimisation is narrow, data gaps are ignored, externalities are displaced, or accountability is weak [22]. **Figure 1** presents the proposed conceptual model showing how AI-supported risk detection, signal integration, adaptive decision

support, governance coordination, feedback learning, and accountability connect climate shocks, supply disruptions, farmer adaptation, and food security protection under compound crises.

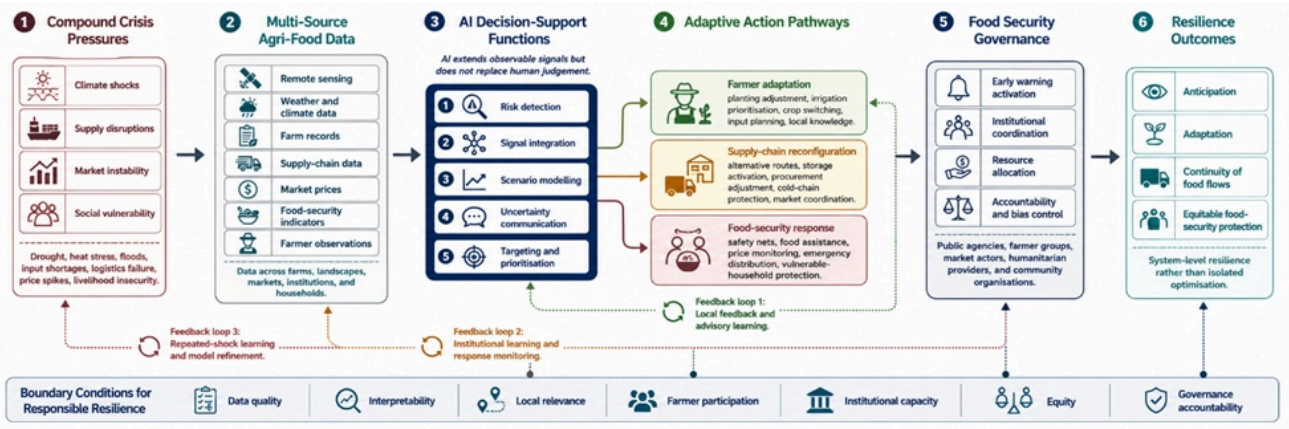


Figure 1. AI-Supported Agri-Food Resilience Under Compound Crises: Linking Climate Shocks, Supply Disruptions, Farmer Adaptation, and Food Security Governance

The model therefore includes boundary conditions that determine whether AI strengthens or weakens resilience. Precision-agriculture and digital decision-support tools must account for unequal access, labour implications, knowledge politics, power relations, and uneven distribution of benefits. These conditions matter because a tool that improves aggregate efficiency may still reduce resilience for farmers or communities excluded from data systems, advisory services, or institutional response [23].

The first feedback loop in the model connects climate-shock detection with farmer adaptation. Agricultural knowledge and advice networks translate climate, crop, and market signals into usable recommendations, making them essential intermediaries between AI systems and farm-level decisions [24]. A second feedback loop connects farmer data, institutional learning, and system improvement, but this loop depends on trust, transparency, and benefit-sharing in smart farming data relations [25].

The third feedback loop connects supply-disruption monitoring with food security governance. When analytics identify logistics bottlenecks, market instability, or food-access risk, governance actors must decide whether to activate procurement, safety nets, transport support, market regulation, or emergency assistance. Table 3 presents the proposed conceptual model of AI-supported agri-food resilience under compound crises. The model treats Agriculture 4.0 technologies as part of governed transition pathways rather than universal solutions, because responsibility and diversity are central to resilient food-system transformation [26].

Table 3. Proposed Conceptual Model of AI-Supported Agri-Food Resilience Under Compound Crises: Climate Shocks, Supply Disruptions, Farmer Adaptation, Food Security Governance, Resilience Mechanisms, Feedback Loops, and Boundary Conditions

Conceptual model component	Core construct	AI-supported decision function	Resilience mechanism	Feedback loop	Boundary condition	System-level outcome
Climate-shock domain	Drought, flood, heat stress, rainfall anomaly, crop	Remote sensing, early warning, crop-risk modelling, anomaly detection	Anticipation of production risk before	Climate signal to farmer advisory and	Local calibration, uncertainty	Earlier adaptation and reduced

	stress, water scarcity		irreversible loss	public response	communication, timeliness	crop-loss exposure
Supply-disruption domain	Logistics breakdown, input shortage, labour constraint, market instability, price spike	Supply-chain monitoring, bottleneck detection, price prediction, network analysis	Continuity of food flows and identification of vulnerable nodes	Supply signal to procurement, routing, and safety-net response	Inclusion of informal markets and remote communities	More stable availability and improved access protection
Farmer-adaptation domain	Adaptive capacity, livelihood decisions, technology use, local knowledge, resource constraints	Localised recommendations, digital extension, risk profiling, decision support	Translation of risk information into feasible farm action	Farmer feedback to advisory systems and model improvement	Accessibility, trust, affordability, farmer participation	Strengthened agency and context-sensitive adaptation
Food-security governance domain	Early warning, coordination, safety nets, procurement, accountability, crisis response	Dashboards, scenario planning, targeting tools, resource allocation, monitoring	Coordinated institutional response to protect food security	Governance feedback to data systems and response protocols	Accountability, bias control, institutional capacity	More equitable and timely food-security response
Cross-domain integration	Compound-crisis linkage across climate, supply, farms, and institutions	Multi-source data integration, scenario modelling, decision prioritisation	Alignment of prediction, adaptation, and governance	System learning across repeated shocks	Interoperability, explainability, data quality	System-level resilience rather than isolated optimisation
Risk pathway	Shock transmission from production stress to access insecurity	Cascading-risk detection and vulnerability mapping	Identification of where risk becomes food insecurity	Household and community indicators inform response refinement	Protection of vulnerable groups and avoidance of exclusion	Reduced likelihood that shocks become food-security crises
Accountability layer	Governance of AI design, deployment, and evaluation	Audit trails, participatory evaluation, performance monitoring, bias assessment	Correction of harmful or ineffective decision-support systems	Evaluation results reshape models and institutions	Transparency, contestability, benefit-sharing	Responsible AI aligned with food security and resilience

Practical Implications and Future Research

For policymakers, food-security agencies, farm advisors, humanitarian organisations, and agricultural technology firms, the model implies that AI tools should be designed around crisis decisions rather than around prediction alone. Practical implementation should include safeguards for fairness, transparency, accountability, privacy, robustness, and environmental sustainability. Ethical and responsible AI in digital agriculture is therefore not an optional add-on but a condition for using analytics in high-stakes resilience decisions [27].

For farmer organisations and public institutions, the model highlights the need for smallholder-centred digital ecosystems. Infrastructure, connectivity, digital literacy, advisory capacity, and locally relevant data systems are necessary for AI-supported adaptation to reach farmers who face the greatest exposure to climate and market shocks. Sustainable digital agriculture for smallholder farmers requires inclusion, capacity building, and governance arrangements that prevent digital tools from widening existing inequalities [28].

Future research should empirically test the proposed model across different crops, regions, crisis types, supply-chain structures, and governance systems. Studies should evaluate whether AI-supported risk detection actually improves adaptation timing, institutional response, food access, and livelihood outcomes under compound crises. Research on AI and global food security in developing agricultural contexts should also examine implementation barriers, data limitations, local participation, institutional uptake, and the conditions under which digital tools support rather than undermine resilience [29].

Conclusion

This article has developed a conceptual model of AI-supported agri-food resilience under compound crises. The model links climate shocks, supply disruptions, farmer adaptation, and food security governance as connected domains rather than separate technical problems. Its central contribution is to show how resilience depends on the movement from risk detection to adaptive action, coordinated response, and food-security protection.

The model argues that AI can support resilience only when predictive analytics are connected to human judgement, farmer agency, institutional capacity, and accountable governance. Climate-risk detection, supply-chain monitoring, adaptation advice, and governance dashboards may all be useful, but none is sufficient by itself. Their value depends on whether they help actors understand uncertainty, respond in time, protect vulnerable groups, and learn from repeated shocks.

Agri-food AI systems should therefore be designed as crisis-sensitive, farmer-centred, food-security-oriented, and governance-aware decision-support systems. The future of AI for agri-food resilience lies not in automation alone but in building systems that help societies anticipate shocks, adapt under uncertainty, coordinate response, and protect food security during compound crises.

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