Nitrogen Cycling

https://doi.org/10.48130/nc-0026-0009

Perspective

Open Access

Artificial intelligence empowers sustainable agricultural nitrogen management

Xiuming Zhang[1,2*], Chengkun Wei[3], Shaohui Zhang[1] and Baojing Gu[2,4,5]

Received: 30 March 2026

Revised: 24 April 2026

Accepted: 20 May 2026

Published online: 4 June 2026

Abstract

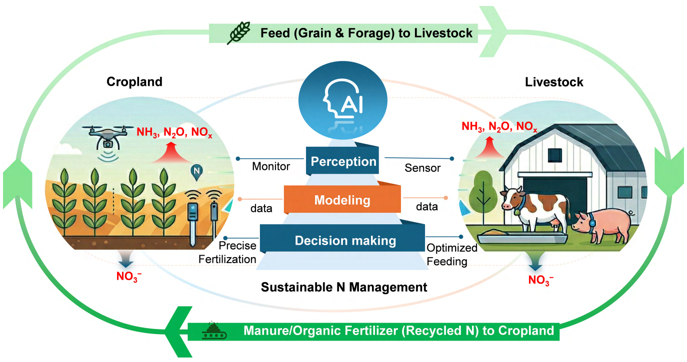
The global nitrogen (N) cycle is profoundly disrupted by the intensification of agriculture. Historically, the management of N has suffered from a critical decoupling between crop production and livestock farming, leading to severe environmental leakage. Addressing this imbalance requires an integrated approach that bridges the gap between agronomy and animal husbandry. This perspective explores the transformative potential of artificial intelligence (AI) in redefining sustainable agricultural N management. We propose a systemic, three-level framework transitioning from perception to integrated process modeling. First, we highlight how AI-driven multi-scale observations enable high-resolution sensing of N flows. Second, we emphasize the core integration of data-driven AI with mechanistic models, advocating for physics-informed neural networks (PINNs) to optimize not only soil biogeochemical processes but also animal nutrition and manure management. Furthermore, we examine the deployment of these integrated systems into actionable intelligence, showcasing the rapid global evolution of agricultural large language models (LLMs) specializing in both crop stewardship and precision livestock farming. By facilitating spatial optimization for crop-livestock integration, AI translates complex N-cycle insights into circular farming decisions. Finally, we address current challenges and future directions toward a smart, circular, and inclusive agricultural N management framework.

Keywords: Artificial intelligence, Nitrogen management, Crop-livestock integration, Precision agriculture, Nitrogen use efficiency, Agricultural large language models

Highlights

- AI bridges the gap between complex N-cycle mechanisms and the decoupled crop-livestock system.
- Coupling AI with mechanistic models optimizes soil biogeochemistry, animal nutrition, and manure recycling.
- Specialized agricultural large language models translate systemic N-cycle insights into actionable circular farming decisions.

Graphical abstract



* Correspondence: Xiuming Zhang (zhangx@iiasa.ac.at)

Full list of author information is available at the end of the article.

https://doi.org/10.48130/nc-0026-0009

Introduction

The alteration of the global nitrogen (N) cycle represents one of the most pressing environmental challenges of the 21st century[1,2]. While synthetic N fertilizers derived from the Haber-Bosch process have helped sustain the global population, the cascading effects of reactive N losses have caused severe ecological consequences, including air pollution, soil acidification, groundwater nitrate contamination, and the exacerbation of climate change through nitrous oxide (N_2O) emissions[3]. The modern agricultural N crisis is driven by the spatial and systemic decoupling of crop and livestock production across multiple scales. At the field scale, soil biogeochemists and animal scientists operate in silos, using disconnected models with incompatible data protocols. At the farm scale, manure is treated as waste while croplands simultaneously purchase synthetic N. At the regional scale, concentrated animal feeding operations (CAFOs) create massive, localized N surpluses through manure accumulation, while distant croplands remain highly dependent on synthetic inputs[4]. Achieving true sustainability requires re-establishing the nutrient loop, a paradigm known as crop-livestock integration (CLI) or circular agriculture[4].

The rapid maturation of artificial intelligence (AI) offers an unprecedented opportunity to bridge these scales[5]. AI possesses a strong capacity to uncover hidden patterns within massive, heterogeneous datasets, ranging from multi-spectral satellite imagery to high-frequency *in-situ* sensor networks. More importantly, the emergence of domain-specific Foundation Models and Large Language Models (LLMs) is revolutionizing the translation of these complex scientific models into actionable, whole-farm management practices[6]. Yet over 90% of existing AI-enabled N management studies focus on cropland or livestock single systems, ignoring this core root cause.

This perspective aims to synthesize the current advancements and articulate a future roadmap for AI in comprehensive agricultural N management. We structure our discussion from perception to process modeling, exploring: (1) AI-driven perception across croplands and livestock facilities; (2) the critical coupling of AI with process-based biogeochemical models; and (3) the application of agricultural LLMs in translating these coupled mechanisms into sustainable, precision management decisions. Building on this framework, we illustrate how AI-empowered agriculture could bridge the broken nitrogen loop across spatial scales (Fig. 1). Through this lens, we aim to inspire interdisciplinary collaboration to redefine the future of sustainable nitrogen management.

AI-driven perception of agricultural nitrogen

The inherent spatiotemporal heterogeneity of the agricultural N cycle presents a substantial challenge for traditional monitoring. The emergence of AI, integrated with advanced observation technologies, is fundamentally reshaping our capabilities to perceive both cropland and livestock systems. In cropland systems, AI enhances N perception at multiple scales. At the macro scale, multi-modal remote sensing coupled with deep learning architectures enables regional mapping of crop N status. Foundation models tailored for agricultural remote sensing, such as EarthGPT and AgroMind, can directly interpret satellite imagery to identify N-deficiency patterns and estimate canopy N concentration with unprecedented accuracy (Table 1)[7,8]. At the field

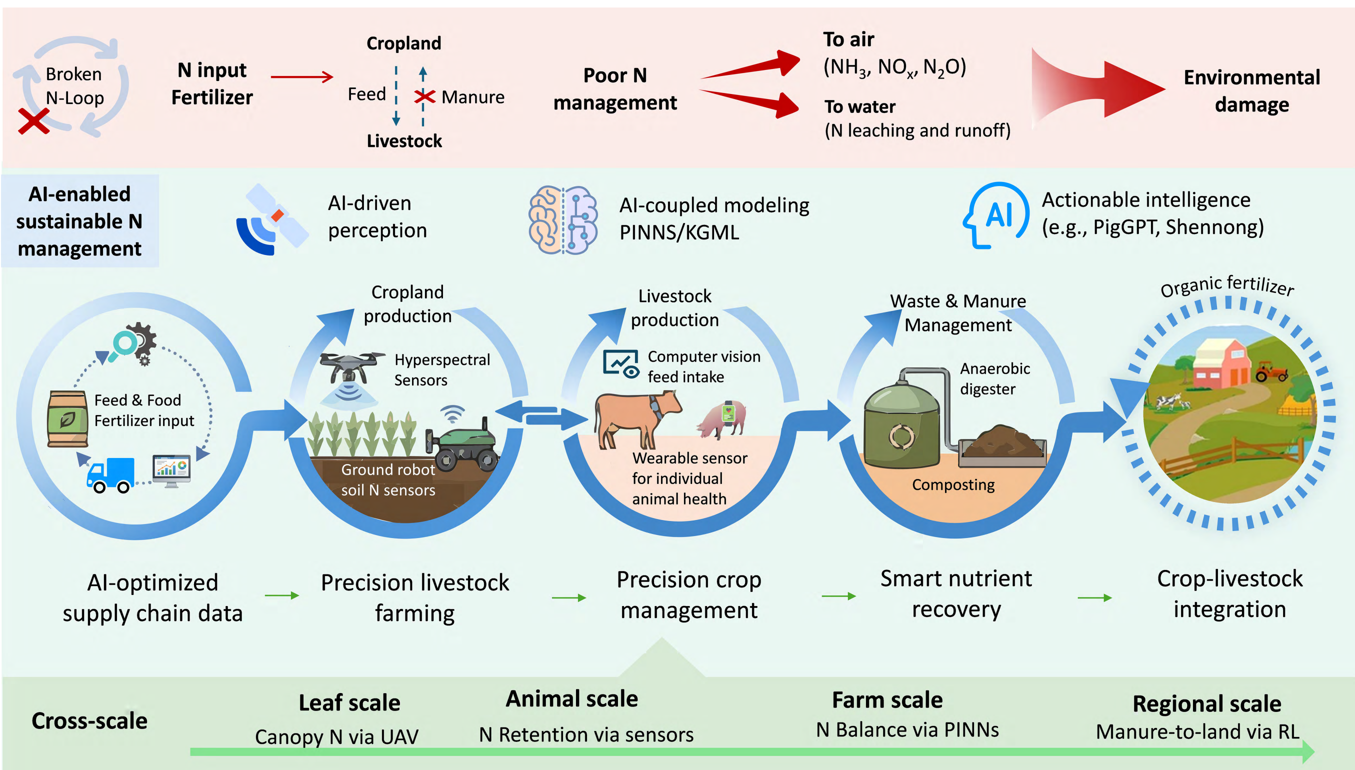


Fig. 1 AI-empowered roadmap for sustainable agricultural nitrogen management. By integrating AI-driven perception, process-based modeling (PINNs/KGML), and actionable intelligence, the framework enables precision nitrogen management across scale, and transition from a decoupled crop-livestock system to a sustainable, circular N economy.

Table 1 Summary of AI models in agricultural nitrogen management

Model name	Core AI technology/modality	Core applications in N management	Key advantages
AgroMind	Multi-modal remote sensing + deep learning	Regional crop N status mapping; canopy N concentration/deficiency detection	High-resolution N sensing; links remote sensing data to N-cycle dynamics
AgroLLM	Text-based LLM + agricultural knowledge graph	N fertilizer prescription Q&A; translates biogeochemical models to farm-level N management advice	User-friendly natural language interface; professional N stewardship support
AgroGPT	Vision-language model (VLM) + agricultural computer vision	Crop N-deficiency visual recognition; multi-modal agricultural scene interpretation for N stress	Accurate subtle N-deficiency detection; integrates visual/textual N knowledge
Sinong (司农)	Open-source agricultural LLM + federated learning	Smallholder-friendly N fertilization guidance; democratized agricultural N knowledge access	Low technical barrier; data privacy protection via federated learning
Shennong 3.0 (神农)	Text & reasoning LLM + 4R nutrient stewardship framework	Site-specific N fertilization decision-making; dynamic optimization of N source/rate/time/placement	Localized for Chinese agriculture; integrates soil/meteorological multi-source data
EarthGPT	Remote sensing foundation model + vision-language model (VLM)	Agricultural landscape N mapping; soil nitrate level inference; large-scale N-cycle pattern extraction	Strong object recognition; processes unstructured spatiotemporal remote sensing data
Nutrient Expert Smart Fertilization LLM	LLM (DeepSeek) + high-throughput soil sensing + knowledge distillation	Personalized precision N fertilization; soil N deficiency diagnosis	Higher recommendation efficiency; 18%–22% N fertilizer reduction (6%–14% yield increase)
IMAP	Comprehensive planting model + hybrid AI-optimization algorithm	Whole-chain N nutrient management; N-fertilizer-crop matching for large-scale farming	Improves NUE; integrates the entire agricultural production value chain
PigGPT	LLM + multi-source data fusion + 3D digital human interaction	Pig feed N formulation optimization; manure N recycling; regional pig farming N emission monitoring/early warning; crop-pig N cycle integration	Accurate N demand prediction; low operation threshold; boosts crop-livestock NUE
Smart Layer Chicken Model S1	LLM + computer vision + IoT sensor fusion + precision feeding algorithm	Layer feed N optimization; chicken house NH_3 monitoring; poultry manure N utilization; orchard-chicken N cycle integration	12%–18% feed N reduction; 20%–25% N fertilizer reduction
Suwu Smart Sheep Raising Model (苏武)	LLM + satellite remote sensing + grazing N-cycle model + precision supplementary feeding	Grassland N monitoring; sheep feed N optimization; manure N return-to-grassland; grassland-sheep N balance	10%–15% supplementary feed N reduction; 18%–22% grassland N fertility restoration
AI4DLLM Ruzi Niu Model (孺子牛)	Domain-specific LLM + agricultural knowledge distillation + federated learning + edge computing	Multi-source N data integration; lightweight N model development for edge devices; N management scheme generation	Supports edge deployment; low threshold for N data analysis

scale, machine learning serves as a 'smart filter' for high-frequency *in-situ* sensors, processing noisy data streams from soil probes to continuously monitor NO_3^- leaching and episodic N_2O fluxes while isolating confounding environmental variables[9−11].

In livestock systems, AI is establishing high-resolution monitoring of 'animal-end' N flows. Computer vision and wearable Internet of Things (IoT) sensors enable real-time tracking of individual animal health, feed intake, and metabolic efficiency, which directly govern N excretion rates[12]. Within livestock housing, AI-driven sensor networks continuously monitor the microclimate, employing recurrent neural networks to predict and detect NH_3 and greenhouse gas emissions[13].

Critically, our framework goes beyond isolated applications in either domain. By establishing a perception continuum across croplands and livestock facilities, it creates the foundational data infrastructure to trace N from fertilizer and feed inputs through to ultimate environmental fates, directly addressing the longstanding inability to track dynamic, 'invisible' N flows across disparate agricultural environments (Fig. 1).

Modeling and optimization: from process mechanisms to integrated systems

While data-driven AI models excel at pattern recognition, they lack physical and biological constraints. Our framework uniquely addresses this by advocating for the deep coupling of AI with mechanistic models across soil biogeochemistry, animal metabolism, and manure management, a paradigm known as Knowledge-Guided Machine Learning (KGML) or Physics-Informed Neural Networks (PINNs)[5]. This integration bridges three critical gaps in the fragmented N cycle: (1) field-scale discontinuity between crop and livestock science; (2) farm-scale asynchrony between manure generation and crop uptake; and (3) regional-scale spatial mismatch between CAFO nutrient surpluses and cropland deficits. In croplands, hybrid architectures are replacing highly uncertain empirical sub-modules (e.g., microbial kinetics governing N_2O production) within traditional models like DeNitrification-Decomposition (DNDC) with trained neural networks, while retaining overarching mass-balance frameworks[14]. This significantly enhances the robustness of N-loss predictions under climate extremes. In livestock systems, AI is being coupled with animal nutrition models to dynamically optimize dietary amino acid profiles, maximizing N retention (meat/milk protein) and minimizing urinary N excretion[15]. Additionally, machine learning models are deployed to optimize manure composting processes, predicting and mitigating N volatilization by adjusting aeration and carbon-to-nitrogen (C : N) ratios in real-time[16].

The ultimate systemic challenge is resolving the spatial mismatch between manure nutrient supply and crop demand across scales. At the regional level, utilizing multi-objective optimization algorithms and reinforcement learning, AI can process regional GIS data, transport logistics, and localized soil N deficits to formulate optimal manure redistribution networks[17]. By matching CAFO waste streams with the specific nutrient requirements of surrounding croplands, AI provides the mathematical blueprint for restoring the circular N economy, effectively substituting synthetic fertilizers with recycled organic N[18]. This bridges the regional-scale decoupling that has historically severed livestock nutrient concentration from crop nutrient demand.

https://doi.org/10.48130/nc-0026-0009

Actionable intelligence: agricultural LLMs empowering decision makers

The translation of integrated crop-livestock modeling into farm-level decision-making has historically been hindered by complexity. The rapid expansion of agricultural LLMs is bridging this divide, offering natural language interfaces for systemic N management (Table 1). For cropland management, global models like AgroLLM and AgroGPT interactively diagnose N deficiencies and formulate precise '4R' (Right source, rate, time, place) prescriptions. Within the rapidly advancing Chinese AI ecosystem, comprehensive platforms such as the IMAP planting model and the Shennong (神农) Large Model 3.0 provide sophisticated production reasoning to optimize fertilizer efficiency (https://shennong.cau.edu.cn/). Open-source models like Sinong (司农)[19] further democratize access to agronomic knowledge (Fig. 2). Pilot applications of the AI-driven 'Nutrient Expert' model have demonstrated an 18%–22% reduction in N fertilizer usage while simultaneously achieving a 6%–14% increase in crop yield.

Equally critical is the emergence of highly specialized livestock LLMs that optimize the animal N-footprint (Fig. 2). Models such as the AI4DLLM (孺子牛) focus on the dairy sector, optimizing feed efficiency and milk protein yield (https://news.cau.edu.cn/mtndnew/ff81332b045b49fbb623b5eb0cb0d725.htm). The Suwu (苏武) Smart Sheep Raising Model provides systemic herd management through the integration of satellite remote sensing-derived grassland nitrogen status with precision supplementary feeding algorithms. In the swine industry, the PigGPT platform, deployed in collaboration with the National Pig Big Data Center, integrates multi-source data from over 3,000 pig farms to provide real-time feed nitrogen formulation optimization. Early operational results indicate a 10%–15% improvement in whole-herd nitrogen use efficiency, with corresponding reductions in manure nitrogen loading per unit of pork produced. Furthermore, whole-farm crop-livestock integration is being realized through systems like the Smart Layer Chicken Model S1, which optimizes the orchard-chicken N cycle to achieve a 12%–18% reduction in feed N alongside a 20%–25% reduction in N fertilizer application (Table 1).

Our framework points toward integrating these domain-specific agents via APIs into a unified Whole-Farm Intelligent Agent, capable of co-optimizing crop fertilizer prescriptions, animal feed formulations, and manure recycling logistics simultaneously. This resolves the historical barrier of model complexity, translating highly technical, siloed biogeochemical data into natural language so that everyday farmers and decision-makers can actually execute sustainable N management.

Challenges, ethics, and future directions

Despite the immense potential, integrating AI into global N management faces critical challenges. First, data silos and heterogeneity remain primary bottlenecks[20]. High-resolution data on soil nitrogen fluxes and animal metabolism are held and managed by different institutions and protocols[21]. Building a unified, standardized agricultural nitrogen data platform, potentially via federated learning to protect commercial farm privacy, is imperative[22].

Second, the 'black-box' nature of deep learning hinders policy adoption. Explainable AI (XAI) is essential, particularly when AI outputs are used to guide environmental regulations or allocate

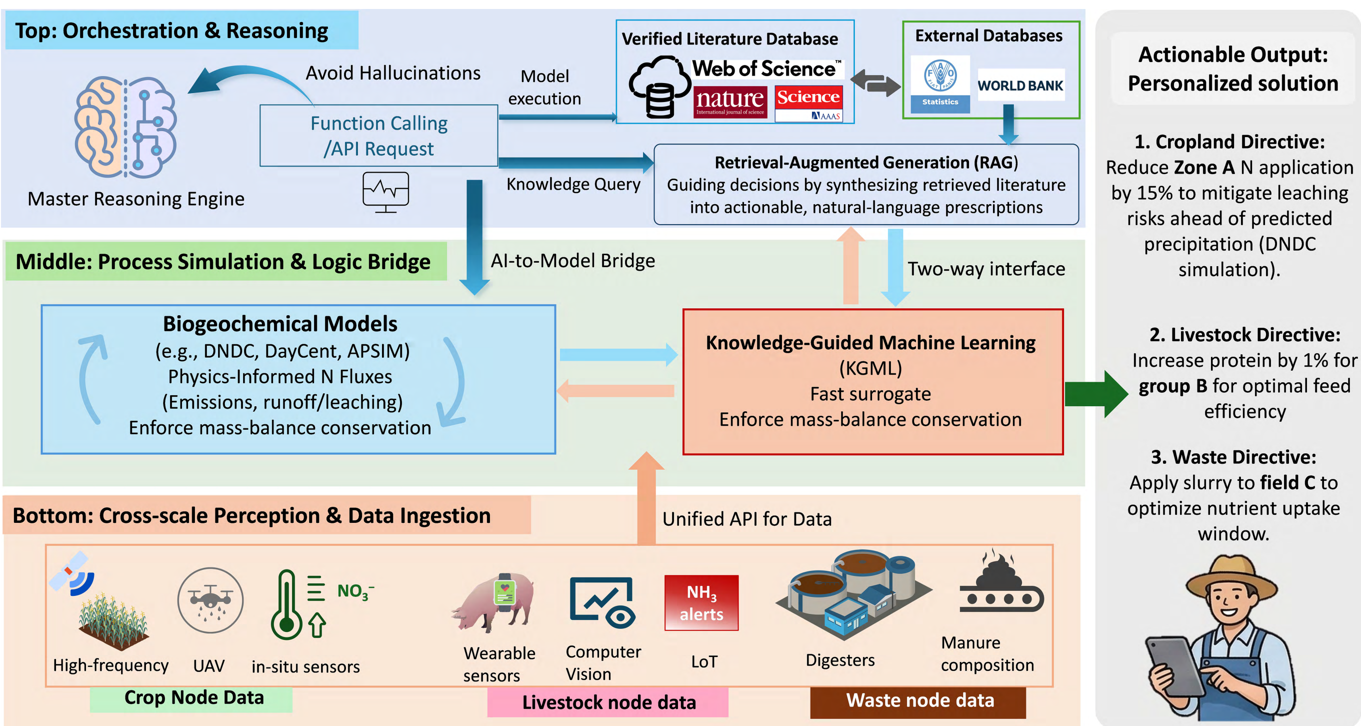


Fig. 2 Framework of the AI-Driven N management agent. The bottom layer continuously harvests multimodal, cross-scale data from crop, livestock, and waste nodes via *in-situ* sensors, UAVs, computer vision, and IoT (Internet of Things) networks. The middle layer serves as the mechanistic core, coupling traditional biogeochemical models with KGML to rapidly simulate N fluxes while strictly enforcing physical mass-balance constraints. Finally, the top layer acts as the cognitive engine. A master reasoning engine utilizes retrieval-augmented generation (RAG) and verified literature databases to synthesize model outputs and mitigate AI hallucinations.

subsidies for manure applications. Integrating causal inference with machine learning ensures that AI explicitly elucidates the underlying biogeochemical and metabolic drivers of agricultural N cycling processes[23].

Third, the ethical implications of AI-driven agriculture must be addressed to prevent widening the socio-economic divide[24]. High-resolution perception tools, such as Unmanned Aerial Vehicles (UAVs) and wearable IoT sensors, require significant capital investment, risking a scenario where AI-optimized N management exclusively benefits large-scale farmers. To ensure equitable access, three architectural innovations address smallholder constraints (limited connectivity, heterogeneous plots, and minimal capital): (1) Federated learning frameworks (e.g., the Sinong platform) enable collective model training without raw data sharing; (2) Edge-computing (e.g., Ruzi Niu Model) shifts inference to low-cost local devices; and (3) Physics-informed models reduce data dependence via embedded biogeochemical constraints of N cycling. For small mixed farms in sub-Saharan Africa and South Asia, where synthetic fertilizers are cost-prohibitive, these systems offer immediate agronomic returns, extending the framework's benefits to diverse global contexts.

Looking ahead, AI will serve as the central nervous system of circular agriculture. Leveraging edge-computing architectures scalable from industrial CAFOs to remote smallholder plots, next-generation systems will autonomously coordinate smart barns and field robotics to continuously match nutrient outputs with localized N demands.

Conclusions

The profound disruption of the global nitrogen cycle necessitates a paradigm shift away from decoupled agricultural practices toward systemic, sustainable management. This work establishes a three-tier AI-enabled framework for closed-loop agricultural nitrogen management, unifying a full-chain perception continuum, physics-informed coupled modeling, and inclusive agricultural LLM decision-making. This framework addresses long-standing barriers of data silos, model black-box limitations, and inequitable technology access. Embracing this AI-empowered framework is essential to navigate the delicate trade-off between securing global food systems and restoring planetary nitrogen balance. Yet, realizing this vision will require unprecedented interdisciplinary collaboration among biogeochemists, animal scientists, agronomists, and computer scientists.

Author contributions

The authors confirm their contributions to the paper as follows: Xiuming Zhang: conceptualization, investigation, methodology, visualization, writing – original draft; Chengkun Wei: conceptualization, investigation, methodology, writing – review and editing; Shaohui Zhang: methodology, writing – review and editing; Baojing Gu: writing – review and editing. All authors reviewed the results and approved the final version of the manuscript.

Data availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Funding

This study was supported by the Grant Agreement Project-101149335-SynCAN-HORIZON-MSCA-2023-PF-01 funded by the European Union and the National Natural Science Foundation of China (Grant No. U24A20575).

Declarations

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author details

[1]International Institute for Applied Systems Analysis, Schlossplatz 1, A-2361, Laxenburg, Austria; [2]College of Environmental and Resource Sciences, Zhejiang University, Hangzhou 310058, China; [3]College of Computer Science and Technology, Zhejiang University, Hangzhou 310058, China; [4]State Key Laboratory of Soil Pollution Control and Safety, Zhejiang University, Hangzhou 310058, China; [5]Policy Simulation Laboratory, Zhejiang University, Hangzhou 310058, China

References

[1] Fowler D, Steadman CE, Stevenson D, Coyle M, Rees RM, et al. 2015. Effects of global change during the 21st century on the nitrogen cycle. *Atmospheric Chemistry and Physics* 15:13849−13893

[2] Galloway JN, Townsend AR, Erisman JW, Bekunda M, Cai Z, et al. 2008. Transformation of the nitrogen cycle: recent trends, questions, and potential solutions. *Science* 320:889−892

[3] Sutton MA, Oenema O, Erisman JW, Leip A, van Grinsven H, et al. 2011. Too much of a good thing. *Nature* 472:159−161

[4] Jin S, Zhang B, Wu B, Han D, Hu Y, et al. 2021. Decoupling livestock and crop production at the household level in China. *Nature Sustainability* 4:48−55

[5] Aderele MO, Srivastava AK, Butterbach-Bahl K, Rahimi J. 2025. Integrating machine learning with agroecosystem modelling: current state and future challenges. *European Journal of Agronomy* 168:127610

[6] Yin S, Xi Y, Zhang X, Sun C, Mao Q. 2025. Foundation models in agriculture: a comprehensive review. *Agriculture* 15:847

[7] Zhang W, Cai M, Zhang T, Zhuang Y, Mao X. 2024. EarthGPT: a universal multimodal large language model for multi-sensor image comprehension in remote sensing domain. *arXiv* 00:2401.16822v3

[8] Li Q, Zhang Y, Mai Z, Chen Y, Lou S, et al. 2025. Can large multimodal models understand agricultural scenes? Benchmarking with AgroMind. *arXiv* 00:2505.12207

[9] Haq SIU, Wang G, Khan SN, Song C, Ma C, et al. 2025. Multi-dimensional optical remote sensing in agriculture: spectral, angular, and spatial scaling for crop stress monitoring. *Smart Agricultural Technology* 12:101583

[10] Fei S, Hassan MA, Xiao Y, Su X, Chen Z, et al. 2023. UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat. *Precision Agriculture* 24:187−212

[11] Dhaliwal JK, Panday D, Robertson GP, Saha D. 2025. Machine learning reveals dynamic controls of soil nitrous oxide emissions from diverse long-term cropping systems. *Journal of Environmental Quality* 54:132−146

[12] Tedeschi LO, Lopez PG, Menendez HM III, Seo S. 2025. Advancing precision livestock farming: integrating artificial intelligence and emerging technologies for sustainable livestock management. *Animal Bioscience* 39(4):250289

[13] Bordignon F, Provolo G, Riva E, Caria M, Todde G, et al. 2025. Smart technologies to improve the management and resilience to climate change of livestock housing: a systematic and critical review. *Italian Journal of Animal Science* 24:376−392

[14] Liu L, Xu S, Tang J, Guan K, Griffis TJ, et al. 2022. KGML-ag: a modeling framework of knowledge-guided machine learning to simulate agroecosystems: a case study of estimating N_2O emission using

data from mesocosm experiments. *Geoscientific Model Development* 15:2839–2858

[15] Condotta ICFS, Tedeschi LO. 2026. ASAS-NANP Symposium: mathematical modeling in animal nutrition: revolutionizing animal farming with artificial intelligence: trends, challenges, and opportunities. *Journal of Animal Science* 104:skaf441

[16] Aydın Temel F, Cagcag Yolcu O, Turan NG. 2023. Artificial intelligence and machine learning approaches in composting process: a review. *Bioresource Technology* 370:128539

[17] Yan J, Yan B, Shi W, Feng Y. 2025. Selecting suitable sites for livestock manure composting via the integration of machine learning, Median center and geographic information system. *Agricultural Systems* 226:104300

[18] Saha S, Bhardwaj A. 2025. A narrative review of artificial intelligence to optimize the use of fertilizers: a game changing opportunity. *Crop, Forage & Turfgrass Management* 11:e70027

[19] Nanjing Agricultural University & Nanjing University of Science and Technology. 2016. *Sinong*. https://github.com/njauzzx/Sinong

[20] Durrant A, Markovic M, Matthews D, May D, Enright J, et al. 2022. The role of cross-silo federated learning in facilitating data sharing in the agri-food sector. *Computers and Electronics in Agriculture* 193:106648

[21] Zhang X, Davidson EA, Mauzerall DL, Searchinger TD, Dumas P, et al. 2015. Managing nitrogen for sustainable development. *Nature* 528:51–59

[22] Basso B, Antle J. 2020. Digital agriculture to design sustainable agricultural systems. *Nature Sustainability* 3:254–256

[23] Ouyang Z, Ma Y, Kou Y, Liu X. 2025. Data governance, core technologies, and application challenges of China's agricultural large models. *Transactions of the Chinese Society of Agricultural Engineering* 41:153–162 (in Chinese)

[24] Mehrabi Z, McDowell MJ, Ricciardi V, Levers C, Martinez JD, et al. 2021. The global divide in data-driven farming. *Nature Sustainability* 4:154–160