ENGINEERING Agriculture

Engineering Journals

REVIEW

2026 / Volume 13 / Issue 6 / 26730

AI- and engineering-enabled maize population optimization for yield gap closure

Ning LUO, Yaru LU, Pu WANG, Qingfeng MENG (✉)

State Key Laboratory of Maize Bio-breeding, College of Agronomy and Biotechnology, China Agricultural University, Beijing 100193, China.

KEYWORDS

AI, maize, plant population optimization, sustainable agriculture, yield gap

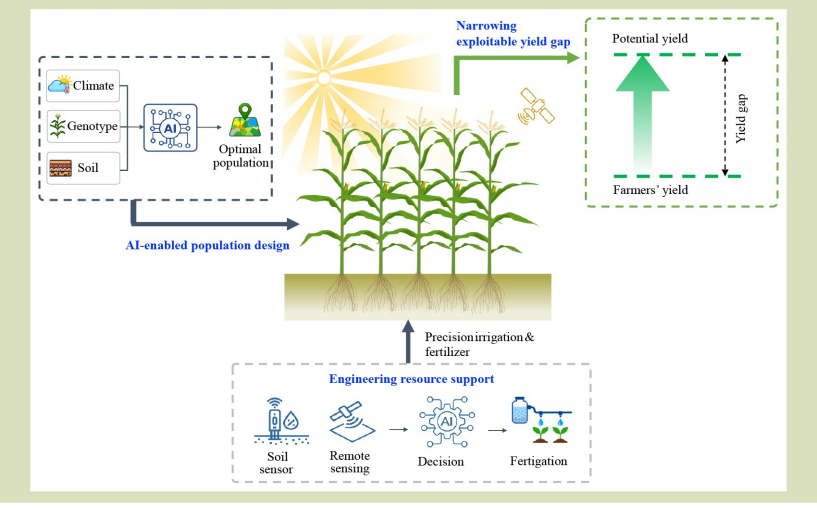
HIGHLIGHTS

- Optimizing maize plant populations provides an important way for narrowing exploitable yield gaps.
- AI enables locally adapted and field-achievable maize population optimization.
- Engineering resource support coordinates water and nutrient supply with optimized maize populations.
- Genotype × environment × management interactions shape the performance and adaptability of optimized maize populations.

Received September 1, 2026;
Accepted October 19, 2026.

Correspondence: mengqf@cau.edu.cn

GRAPHICAL ABSTRACT



ABSTRACT

Although the importance of maize plant population is widely recognized, suboptimal population management remains a relevant constraint on maize yield improvement, while identifying and achieving optimal populations could contribute to narrowing exploitable yield gaps in China and other major maize-producing regions. The review synthesizes evidence on historical plant population-yield trajectories, examines approaches to population optimization, and discusses how engineering support can coordinate water and nutrient supply with population demand. Evidence shows that historical yield gains have often coincided with increases in plant population and improved crowding tolerance, whereas recent trends in the USA indicate a growing contribution from per-plant productivity. In China, plant population development remains at an earlier stage than in highly intensified systems, suggesting further scope for locally adapted population optimization. AI-enabled machine learning, particularly when integrating genotype, climate and soil information, provides new opportunities to identify locally adapted and field-achievable population targets. Engineering systems that couple sensing,

AI-based decision support, and precision fertigation or variable-rate application can align resource supply with population demand and support the realization of optimized populations in the field. Future progress will depend on integrating AI-enabled population design, responsive resource engineering, and climate-resilient hybrids to sustain maize yield gains under increasing climatic constraints.

© The Author(s) 2026. Published by Higher Education Press. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0)

1 Introduction

Rising demands for crop production, driven by population growth and dietary shifts, together with increasing yield instability under climate change, pose major challenges to the global food system[1–3]. As one of the world's most widely cultivated staple crops, maize (*Zea mays*) has had a threefold increase in yield since the Green Revolution[4,5]. These gains have resulted from the combined effects of genetic improvement and advances in crop management[6]. Nevertheless, substantial gaps remain between current farm yields and potential yields across many maize-producing regions[7]. Recent global analyses further indicate that these gaps are not uniformly narrowing and may persist or widen in some regions, underscoring the need for practical strategies to capture unrealized local yield potential[8]. Plant population optimization represents one such pathway, as increases in maize yield per unit area have been strongly associated with increases in optimal plant population and improved crowding tolerance of modern hybrids[9–11]. The challenge, therefore, lies not simply in increasing the number of plants per unit area but in designing populations that are appropriately matched to local production conditions.

Larger crop populations can enhance yield per unit area by improving collective resource capture but they also intensify competition among plants for light, water and nutrients. The population that maximizes yield therefore depends on both the crowding tolerance of individual plants and how effectively population size is matched to the spatial and temporal availability of local resources. An optimal maize population thus maximizes productivity without inducing excessive interplant competition. This balance is jointly shaped by genotype, environment and management (G × E × M). Canopy structure is central to this balance because it regulates solar radiation interception and utilization, as well as resource distribution within the crop population[12]. Given that this balance varies across G × E × M conditions, optimal populations must be locally adapted rather than universally prescribed. Identifying and realizing such locally adapted populations is therefore essential for designing high-yielding maize systems.

A range of approaches has been developed to optimize maize populations across diverse production environments, including field experiments, statistical methods and crop models. Field experiments provide robust evidence for identifying locally adapted population sizes for specific hybrids and environments and for elucidating the physiological mechanisms underlying yield responses to population size. However, limited population treatments, genotype coverage and experimental locations constrain the extrapolation of these findings to broader regions[13]. Statistical methods and crop models extend the assessment of yield responses to population size across environments, but their predictions remain subject to uncertainties associated with data availability, model structure and parameterization[14]. More recently, data-driven approaches that combine machine learning with field validation have provided new opportunities for locally adapted population optimization[15]. Compared with established empirical or synthesis-based approaches, AI-enabled methods can more flexibly integrate multiple climatic, soil, genotype and management factors, capture nonlinear interactions among them, and support site-specific prediction across heterogeneous production environments represented in the available data. These advances provide a practical basis for moving beyond uniform population recommendations toward site-specific maize population optimization.

In this review, we synthesize current understanding of maize population optimization and its potential contribution to narrowing yield gaps. We first examine yield potential, yield gaps, and contrasting plant population-yield trajectories across major maize-producing regions to identify remaining

opportunities for population improvement. We then review the major approaches to plant population optimization and highlight the emerging role of AI in predicting locally adapted populations through the integration of multiple environmental and soil factors. We further discuss how coordinated fertilizer and irrigation management, supported by sensing and precision engineering technologies, can align resource supply with population demand and sustain optimal maize populations. Finally, we consider future challenges and opportunities for maize population optimization under climate change, resource scarcity, soil degradation, and other emerging production constraints.

2 Yield gaps and plant population trajectories

2.1 Yield potential and yield gaps

The latest estimates from the Yield Potential and Yield Gap Atlas[16] quantify maize yield potential under representative climatic, soil, and cropping-system conditions. These estimates represent yield potential under non-limiting water conditions for irrigated maize and water-limited yield potential for rainfed maize, assuming adequate nutrient supply and effective control of biotic stress. Substantial variation exists among countries and production systems in both yield potential and yield gap closure, with yield gap closure defined here as actual yield expressed as a percentage of yield potential (Fig. 1). The USA and China, the world's two largest maize producers, together account for more than 50% of global maize production[5] and encompass both irrigated and rainfed production systems. According to the estimates from the Atlas, yield potential for irrigated and rainfed maize in the USA reaches 15.5 and 14.2 t·ha^{-1}, respectively, compared with 13.9 and 10.7 t·ha^{-1} in China. Considerable variation is also evident among other major rainfed maize-producing countries, with yield potential ranging from 8.2 t·ha^{-1} in Ukraine and 9.4 t·ha^{-1} in India to 10.8 t·ha^{-1} in Brazil and 14.4 t·ha^{-1} in Argentina.

Despite substantial yield potential across these regions, large gaps remain between actual and potential maize yields. Globally, actual yields average about 60% of yield potential, reaching 62% for irrigated maize and 50% for rainfed maize. The USA achieves about 80% of yield potential, whereas the corresponding values in China are 67% for rainfed maize and 59% for irrigated maize. Among other major producers, actual yields correspond to about 52%–70% of yield potential in Brazil, Argentina and Ukraine, but only about 17% in India. These differences indicate substantial scope for further maize yield improvement. Narrowing persistent yield gaps will require coordinated and locally adapted improvements in crop management, technology and production capacity under diverse environmental and resource constraints. Understanding how agronomic management has historically contributed to yield gains can therefore help identify practical opportunities for narrowing these exploitable yield gaps.

2.2 Contrasting plant population and yield trajectories

Historically, maize yield gains have generally resulted from a synergy between larger plant populations and the ability of successive hybrids to maintain reproductive growth under intensified interplant competition[17,18]. In North America, the optimal plant population increased by about 1.8×10^4 plants ha^{-1} between 1987 and 2016, accompanied by a yield gain of 3.5 t·ha^{-1}; increases in plant population were estimated to account for 8.5%–17% of historical yield gains[19]. Similar associations between plant population and yield have been reported in other major maize-producing regions. In Brazil, improved crowding tolerance of modern hybrids supported an increase in plant population from 7.1×10^4 plants ha^{-1} in the 1970s to 8.5×10^4 plants ha^{-1} in the 1990s[20]. In France, the approximately fourfold increase in maize yield between 1950 and 1984 was likewise associated with genetic advances that enhanced adaptation to higher plant populations[21]. Survey data from northern Italy further showed that on-farm yield increased from 9.8 to 11.7 t·ha^{-1}, accompanied by an increase in plant population from 6.5 to 7.5×10^4 plants ha^{-1}[22].

More recently, however, this historical coupling between plant population and yield has weakened in the USA. Maize yield in the USA initially increased in parallel with plant population, whereas recent yield gains have continued despite the stabilization of yield-maximizing plant populations (Fig. 2). Experiments further showed that potential yield per plant under weak interplant competition remained at about 275 g per plant among pre-1990 hybrids but increased to about 380 g per plant in modern hybrids, representing an increase of about 38%[23]. For hybrids released after 2010, further genetic yield gains have increasingly depended on greater per plant productivity and stress resilience within already dense crop populations, rather than on continued increases in population

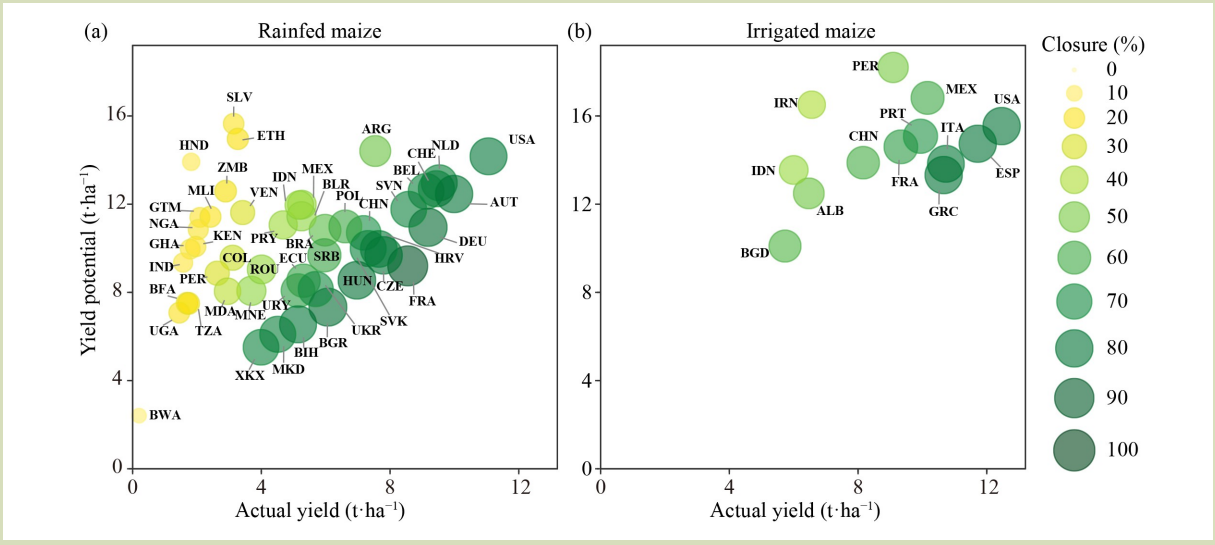


Fig. 1 Yield potential, actual yield, and yield gap closure for rainfed and irrigated maize across major global maize-producing regions. (a) Rainfed maize; (b) irrigated maize. Yield gap closure was calculated as actual yield expressed as a percentage of yield potential and is represented by circle size and a color gradient ranging from 0% to 100%. Larger, darker green circles indicate a greater proportion of yield potential achieved, whereas smaller, lighter yellow circles indicate lower yield gap closure. Data were derived from the Yield Potential and Yield Gap Atlas[16]. Country abbreviations are as follows: ALB, Albania; ARG, Argentina; AUT, Austria; BGD, Bangladesh; BEL, Belgium; BIH, Bosnia and Herzegovina; BGR, Bulgaria; BFA, Burkina Faso; BDI, Burundi; BWA, Botswana; BRA, Brazil; CAN, Canada; CHN, China; COL, Colombia; HRV, Croatia; CZE, Czechia; DNK, Denmark; ECU, Ecuador; EGY, Egypt; SLV, El Salvador; EST, Estonia; ETH, Ethiopia; FIN, Finland; FRA, France; DEU, Germany; GHA, Ghana; GRC, Greece; GTM, Guatemala; HUN, Hungary; IND, India; IDN, Indonesia; IRN, Iran; IRQ, Iraq; IRL, Ireland; ISR, Israel; ITA, Italy; JPN, Japan; KEN, Kenya; XKX, Kosovo; KGZ, Kyrgyzstan; LVA, Latvia; LBN, Lebanon; LTU, Lithuania; LUX, Luxembourg; MDG, Madagascar; MWI, Malawi; MYS, Malaysia; MLI, Mali; MRT, Mauritania; MEX, Mexico; MDA, Moldova; MNE, Montenegro; MAR, Morocco; MOZ, Mozambique; NLD, Netherlands; NZL, New Zealand; NIC, Nicaragua; NER, Niger; NGA, Nigeria; MKD, North Macedonia; NOR, Norway; PAK, Pakistan; PAN, Panama; PRY, Paraguay; PER, Peru; PHL, Philippines; POL, Poland; PRT, Portugal; ROU, Romania; RUS, Russia; RWA, Rwanda; SAU, Saudi Arabia; SEN, Senegal; SRB, Serbia; SLE, Sierra Leone; SVK, Slovakia; SVN, Slovenia; ZAF, South Africa; KOR, South Korea; ESP, Spain; LKA, Sri Lanka; SDN, Sudan; SWE, Sweden; CHE, Switzerland; SYR, Syria; TZA, Tanzania; THA, Thailand; TGO, Togo; TUN, Tunisia; TUR, Turkey; UGA, Uganda; UKR, Ukraine; GBR, United Kingdom; USA, United States of America; URY, Uruguay; VEN, Venezuela; VNM, Vietnam; YEM, Yemen; ZMB, Zambia; ZWE, Zimbabwe.

size. This transition indicates that highly intensified maize systems may eventually shift from population-driven yield gains toward greater individual-plant productivity within an optimized population.

China remains at an earlier and more heterogeneous stage of this population-yield trajectory. Between 2009 and 2023, the national mean plant population increased by 14.6%, from about 5.4×10^4 to 6.2×10^4 plants ha^{-1}, corresponding to an average annual increase of about 353 plants ha^{-1}[24]. Over the same period, national maize yield increased from about 5.3 to 6.5 t·ha^{-1}[5]. Yield responses to increasing plant population nevertheless vary substantially among production regions, ranging from about 60 to 130 kg·ha^{-1} for each additional 1000 plants ha^{-1}. These trends indicate that population adjustment remains an important opportunity for yield improvement in China, particularly in regions where current plant populations remain below locally attainable levels.

The contrasting population-yield trajectories of China and the USA may partly reflect differences in both per plant productivity and farm structure. Published studies have reported ear-leaf net photosynthetic rates above 35 μmol·m^{-2}·s^{-1} CO_2 for modern US hybrids under favorable conditions, compared with about 22–24 μmol·m^{-2}·s^{-1} CO_2 for representative modern Chinese hybrids around silking[25,26]. Farm structure may further shape the feasibility of increasing and precisely managing plant population[27], and differs

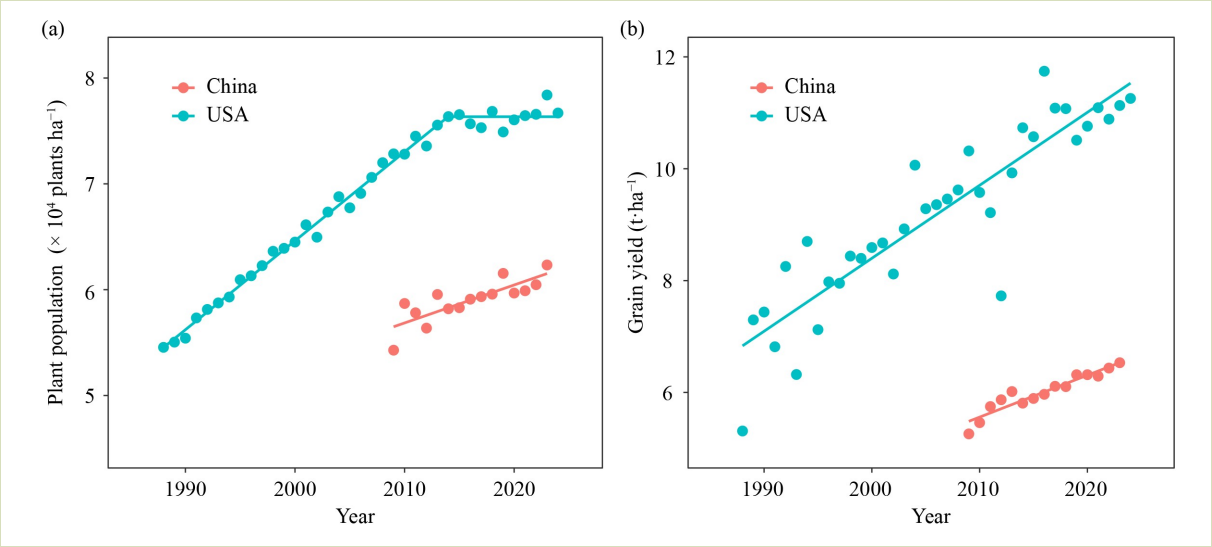


Fig. 2 Historical changes in maize population size and grain yield in China and the USA. (a) Population size; (b) grain yield. Population-size data for the USA reflect rainfed production in the US Midwest (including Iowa, Illinois, Indiana and Minnesota) from Borras et al.[23]; and nationwide data for China from Wang et al.[24]. Grain-yield data for both countries were retrieved from the FAO database[5].

markedly between China and the USA. Maize production in China remains dominated by small and fragmented farms, with historical estimates of maize farm size below 0.4 ha per household[24], whereas farms in the USA are typically much larger, averaging about 187 ha in recent agricultural censuses[28]. Larger farms generally facilitate mechanization, uniform stand establishment and coordinated management of plant population, fertilizer and irrigation, whereas land fragmentation can constrain these practices in smallholder systems. These physiological and structural contrasts highlight the need for locally adapted population optimization strategies that account for both crop performance and production conditions.

3 AI and engineering support for maize population optimization

3.1 AI-enabled design of maize populations

Methods for designing maize populations have evolved from empirical estimation based on individual environmental drivers and synthesis-based analyses toward more flexible data-driven approaches[14,29]. Empirical analysis of multi-environment field experiments represents an established approach for understanding how optimal population size responds to variation in environmental drivers. Solar radiation is a key determinant of population productivity, as greater radiation availability can support larger plant populations. Accordingly, accumulated solar radiation over the entire growing season has been related to optimal population size across environments, yielding a linear relationship between whole-season radiation and population size (y = 0.009895x – 3.249, Fig. 3(a))[30]. Such empirical relationships are straightforward and interpretable, but their predictive capacity may be limited when only a few environmental drivers are represented.

Beyond relating population responses to individual environmental drivers, synthesis-based analyses provide an alternative means of identifying optimal populations directly from observed yield responses to population size. By integrating observations across numerous field experiments with contrasting population levels, synthesis-based analyses can characterize the relationship between yield and population size using a quadratic function. The population size corresponding to the maximum fitted yield is then defined as the optimal population size. A synthesis of 157 studies conducted across China during 2000–2017 derived a generalized quadratic relationship (y = –0.1246x^2 + 2.3483x,

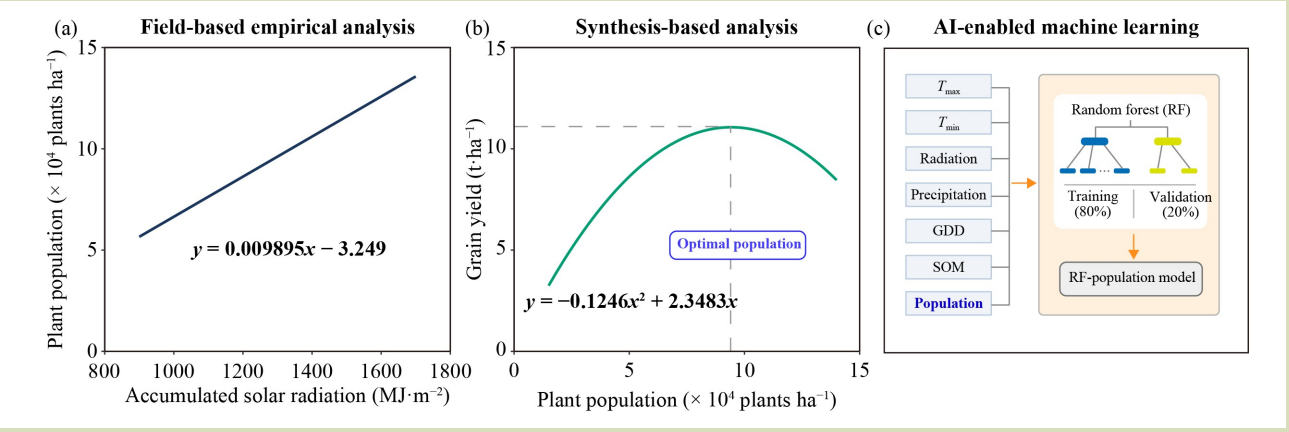


Fig. 3 Comparison of three methodological approaches for estimating optimal maize population size. (a) Field-based empirical analysis relating optimal population size to accumulated solar radiation using a linear relationship (y = 0.009895x − 3.249, conceptual model based on Liu et al.[30]); (b) synthesis-based analysis describing the relationship between grain yield and population size using a quadratic function (y = −0.1246x^2 + 2.3483x, quadratic model based on Luo et al.[31]); the dashed line indicates the derived optimal population size; (c) AI-enabled machine-learning framework (random forest-population) integrating climatic and soil variables, including maximum and minimum temperature, solar radiation, precipitation, growing degree days (GDD) and soil organic matter (SOM), to predict locally adapted optimal population sizes using a random forest model (framework based on Luo et al.[32]).

Fig. 3(b)) to estimate regional optimal populations[31]. Compared with individual multi-environment experiments, synthesis-based analyses integrate evidence across a broader range of regions and production conditions, thereby improving the spatial representativeness of population recommendations (Table 1). However, such aggregation can obscure variation in genotype, environment and management, thereby limiting the ability to identify locally optimal populations for specific sites.

These limitations have motivated the development of AI-enabled approaches that integrate multiple determinants of optimal population size simultaneously. Machine-learning algorithms provide greater flexibility than simple regression models by capturing nonlinear responses and complex interactions among genotype, environment and management. Building on this approach, a recent AI-enabled prediction framework integrated climatic and soil variables, including daily maximum and minimum temperature, precipitation, solar radiation, growing degree days and soil organic matter, to characterize the multidimensional controls on optimal population size (Fig. 3(c))[32]. Random forest, a nonparametric ensemble-learning method[33], was used to integrate these predictors and estimate optimal populations across the production environments represented in the dataset. This application provides a data-driven basis for identifying locally adapted population targets, although model performance remains dependent on the quality and representativeness of the training data (Table 1).

Table 1 Comparison of three approaches for quantifying optimal maize population size

Approach	Data basis	Model	Advantage	Limitation
Field-based empirical analysis[30]	Multi-environment field experiments	Linear model	Simple and interpretable; direct radiation-population relationship	Limited environmental drivers; limited spatial transferability
Synthesis-based analysis[31]	Multi-study field observations	Quadratic model	Broad regional coverage; generalized yield-population relationship	Loss of G × E × M specificity; limited site-specific prediction
AI-enabled machine learning[32]	Field observations with climatic, soil, genotype, and management data	Random Forest	Multivariable integration; nonlinear and interactive effects; site-specific prediction	Dependence on Training-data; limited extrapolation beyond represented conditions

Differences in estimation bias among the three approaches become evident when their national-scale estimates of optimal population size are compared with results from field validation experiments (Fig. 4). The field-based empirical and synthesis-based approaches estimated average optimal populations of 10.9×10^4 and 9.4×10^4 plants ha^{-1}, respectively, corresponding to about 40% and 17% overestimation relative to field validation results. Their corresponding grain-yield estimates were also about 30% and 15% higher, respectively. These discrepancies likely arise partly from model simplification, whereby complex environmental and management influences on population optimization are represented by a limited set of variables or generalized relationships. By comparison, the AI-enabled machine-learning approach predicted an average optimal population of 7.8×10^4 plants ha^{-1} and a corresponding grain yield of 11.7 $t \cdot ha^{-1}$, both showing closer agreement with field validation results than the other approaches[32].

3.2 Engineering resource support for optimal populations

Engineering support for optimized maize populations requires a closed-loop framework that integrates sensing of crop and soil status, AI-based interpretation of sensed data into resource prescriptions, and precision actuation through irrigation, fertigation and variable-rate equipment (Fig. 5). Given that fertigation depends on irrigation infrastructure, its application is mainly relevant to irrigated or supplemental-irrigation systems rather than strictly rainfed systems without irrigation facilities. Population size determines baseline resource demand, while productive population performance depends on matching water and nutrient supply to crop demand and avoiding both resource limitation and excessive inputs. The dynamic alignment of resource supply with crop demand across the growing season, however, depends on the response speed and spatial resolution of this sensing-decision-actuation loop. Increasingly, AI provides the computational layer that integrates multisource sensing, including soil and canopy sensors, UAV imagery, and satellite observations, with weather, soil and management information to generate site-specific and time-sensitive recommendations for N fertilization and irrigation.

Recent maize studies illustrate this transition from monitoring to prescription across both nutrient and water management. For N, an integrated precision-management framework combining crop modeling, canopy sensing, and machine learning improved prediction of the economically optimal side-dressing N rate. Across 28 site-years, the approach reduced N

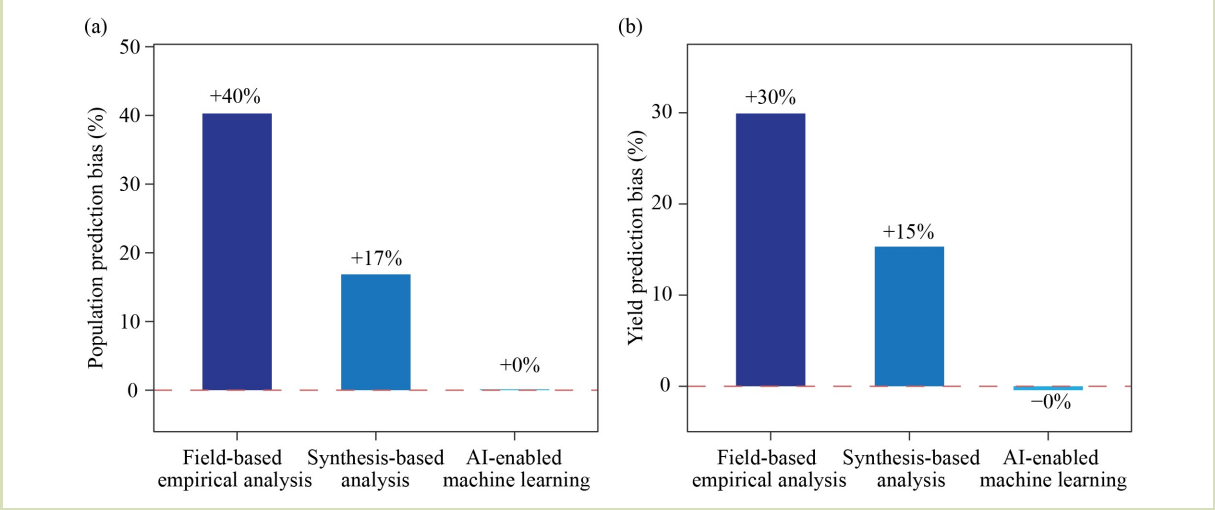


Fig. 4 Comparison of estimation bias among three approaches for identifying optimal maize population size. (a) Bias in estimated optimal population size relative to field observations for field-based empirical analysis, synthesis-based analysis, and AI-enabled machine learning; (b) corresponding bias in grain-yield estimates for the three approaches. Bias was calculated relative to field observations, with positive and negative values indicating overestimation and underestimation, respectively.

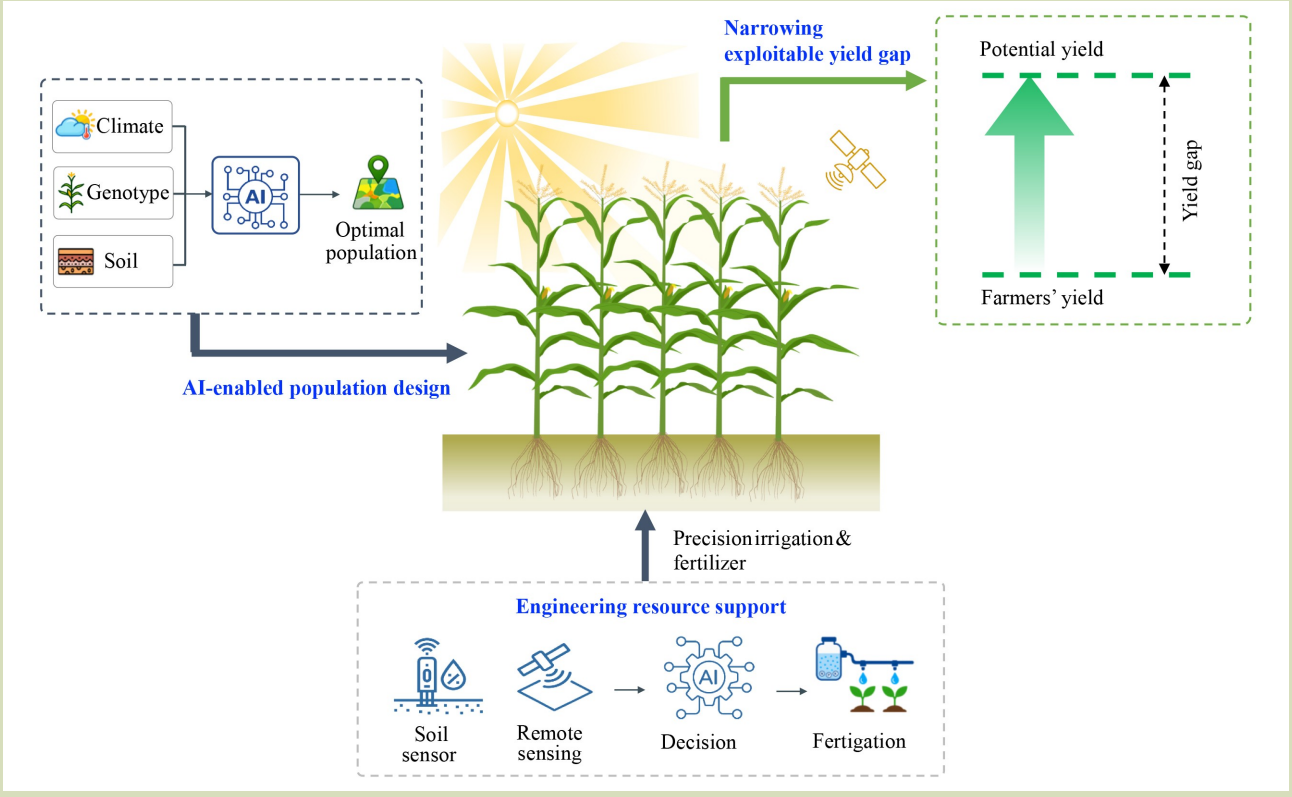


Fig. 5 Conceptual framework of AI-enabled maize population optimization and precision resource engineering to support the narrowing of exploitable yield gaps. The framework integrates multisource inputs, including climate, genotype, and soil information, through AI models to identify locally adapted optimal population sizes. It combines *in situ* sensor networks and remote sensing with AI-based decision support, and applies precision resource management, including fertigation where irrigation infrastructure is available, to coordinate resource supply with population demand and contribute to narrowing exploitable yield gaps.

inputs by 6%–16% and increased N-use efficiency by 8%–18% relative to standard practices, while maintaining high grain yield and marginal net return[34]. At the soil level, point-of-use sensors combined with machine learning can rapidly estimate soil nitrate status from ammonium measurements, together with conductivity, pH, weather and timing information, demonstrating how AI can translate sensor measurements into actionable nutrient diagnostics[35]. A parallel pathway is emerging for irrigation management. UAV-based multispectral and thermal sensing, coupled with machine-learning models, has been used to estimate maize crop coefficients, evapotranspiration and root-zone soil water status at the field scale, providing spatially explicit information for irrigation scheduling[36]. More recent work has further integrated UAV imagery with machine learning to map combined plant-soil water status across maize growth stages, strengthening the basis for spatially targeted irrigation decisions[37].

Building on these advances, resource management can move from uniform application toward an integrated, site-specific system in which sensing characterizes crop and soil status, AI translates these observations into resource prescriptions and precision equipment implements those prescriptions through irrigation and fertigation to support optimized maize populations. Such coordination is particularly important for high-yielding maize populations, where resource mismatches can rapidly intensify interplant competition and reduce per plant productivity. However, a persistent engineering challenge lies in synchronizing the sensing, decision and actuation components of this closed-loop system. Although sensing and computational inference can operate rapidly, hydraulic transport, valve response, nutrient injection and mixing introduce system-dependent delays that may limit the speed and precision of resource delivery[38]. Reducing these delays through faster actuators, improved hydraulic design, edge

control and predictive feedforward, or model-predictive control represents an important frontier for translating AI-derived resource prescriptions into timely field responses[39].

4 Future challenges and opportunities for maize population optimization

Despite the substantial yield gains achievable through population optimization, its practical implementation faces two major challenges that are spatial and temporal in nature[40,41]. Spatially, an optimal maize population is not a fixed physiological target but a production-system attribute that shifts with local climate, soil, genotype and management conditions; a population that performs well in one region may therefore be suboptimal elsewhere. This spatial heterogeneity also constrains the transferability of AI-based population models because their predictive reliability depends on the representativeness of the training data. Prediction uncertainty may increase when models are applied to environments, climatic extremes or crop cultivars that are poorly represented or absent from the training dataset. Temporally, the climatic baseline on which population recommendations are calibrated is increasingly non-stationary, as rising temperatures, altered precipitation regimes and more frequent extreme events may render historically optimal population targets less suitable under future conditions. Together, spatial heterogeneity and temporal climate uncertainty define a key frontier for population optimization, requiring a shift from static population recommendations toward context-specific and adaptive optimization frameworks.

China provides a useful example of how this spatial heterogeneity translates into different requirements for engineering support of maize populations optimization across production regions[42,43]. Rather than relying on uniform population recommendations, population optimization should be co-designed with the dominant resource constraints and available engineering infrastructure in each region. In northeastern China, where low temperature and episodic water limitation can constrain canopy development and reproductive stability, population design should prioritize stress-resilient hybrids together with management strategies that stabilize stand establishment and water supply[44]. On the North China Plain, where radiation and water-nitrogen interactions strongly influence canopy productivity, optimizing maize populations requires coordinated adjustment of population size, N supply, and irrigation, supported by field sensing and responsive management[45]. In northwestern China, where water availability is a dominant constraint, high-yielding populations increasingly depend on precision irrigation and fertigation systems that synchronize water and nutrient delivery with population demand[46]. In contrast, fragmented fields and topographic complexity in southwestern China increase the importance of site-specific sensing, machinery adaptability and spatially explicit population recommendations[47]. These regional differences illustrate that maize populations optimization involves not simply identifying an optimal population size but rather designing integrated genotype-population-resource systems that match local production constraints and technological capacity.

The implementation pathway should also be adapted to farm scale and management capacity. In smallholder and fragmented farming systems, regional decision-support platforms, agricultural extension services, cooperatives and shared machinery services may provide practical channels for accessing AI-based population recommendations and precision-management services, whereas larger farms with greater mechanization and infrastructure capacity may directly integrate sensing, AI-based decision support and precision equipment[48,49]. Economic feasibility represents an additional constraint, as the investment and operating costs of advanced precision technologies may limit their adoption and scaling, particularly in smallholder and resource-constrained farming systems[50]. Rapid advances in intelligent-agent and large-language-model technologies may further support the implementation of this framework by linking multisource environmental information and AI-based population models with user-oriented decision support, thereby lowering technical barriers to accessing locally adapted recommendations[51]. Such region-specific engineering strategies may provide a more practical pathway for narrowing exploitable yield gaps than uniform population recommendations.

Climate change compounds this spatial challenge by introducing temporal uncertainty into population optimization. Rising air temperatures can increase canopy temperature and atmospheric water demand through elevated vapor pressure deficit, intensifying crop water stress and potentially reducing the population that can be sustained without yield penalties[52]. Historical warming has already affected maize yields across many production regions, while

future increases in the frequency or severity of heat, drought, waterlogging, strong winds, low-radiation events and compound climate extremes are expected to increase yield instability and alter the suitability of current population strategies[53]. The effects of these extremes on optimal population size are likely to differ among stress types and growth stages. Under heat and drought, larger populations may intensify competition for water and increase vulnerability to atmospheric and soil water deficits, potentially favoring more conservative population targets under severe stress[54,55]. Strong winds can increase lodging risk, particularly in larger populations with greater canopy load, whereas waterlogging can induce root hypoxia and weaken anchorage, thereby reducing the capacity of the crop to sustain high population demand[56,57]. Periods of insufficient radiation can constrain canopy photosynthesis and dry matter accumulation, while excessive population size may further intensify within-canopy shading[58,59]. Population optimization for yield stability should therefore account for the type, timing and severity of extreme events rather than assuming a uniform population response. Denser canopies can also modify within-canopy temperature and humidity, potentially increasing susceptibility to pests and diseases, while climate-driven soil erosion and degradation may further reduce the resource base available to sustain productive populations[60]. As environmental conditions continue to shift, population targets calibrated to present-day climate may therefore become less suitable.

Future population optimization should move beyond fixed population recommendations toward AI- and engineering-enabled design of climate-resilient maize populations. AI can integrate seasonal climate forecasts, environmental information, and field observations to refine locally adapted population targets, while sensing and precision engineering can dynamically coordinate water and nutrient supply with population demand during the growing season. In parallel, breeding should target hybrids that maintain stable per plant productivity across a broader range of population levels. Together, these advances could transform population optimization from a fixed agronomic recommendation into an adaptive engineering strategy responsive to spatial heterogeneity and climatic non-stationarity.

5 Conclusions

Maize population optimization, supported by AI-enabled identification of locally adapted optimal populations and coordinated engineering of water and nutrient supply, can contribute to narrowing exploitable yield gaps. Evidence synthesized in this review shows that optimal population size varies with genotype, environment and management, limiting the transferability of generalized population recommendations and creating a clear role for machine learning in integrating multidimensional environmental and soil information. Realizing these optimized populations in the field further requires engineering systems that couple sensing, AI-based decision support, and precision delivery of water and nutrients to match resource supply with population demand. Population optimization should therefore move beyond fixed population recommendations toward locally adapted populations supported by dynamic resource management during the growing season. Future progress will depend on tighter integration of AI-enabled population design, responsive resource engineering and hybrids with stable productivity across population levels, providing a pathway toward maize systems that sustain high productivity under increasing climatic variability and resource constraints.

Acknowledgements

This work is supported by Shandong Provincial Key Research and Development Program, China (2024TZXD074), the National Key Research and Development Program of China (2023YFE0105000), the National Natural Science Foundation of China (42605248), the Disciplinary Breakthrough Project of Ministry of Education, China (00975101), the Chinese Universities Scientific Fund (2026RC049), and the 2115 Talent Development Program of China Agricultural University. During the preparation of this work, the authors used GPT-6 (OpenAI) solely to improvements to grammar and readability. The authors reviewed all AI-assisted revisions and take full responsibility for the content of the publication.

Compliance with ethics guidelines

Ning Luo, Yaru Lu, Pu Wang, and Qingfeng Meng 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. Lentz E, Baylis K, Michelson H, Kim C. Official estimates of global food insecurity undercount acute hunger. *Nature Food*, 2025, **6**(12): 1196–1208
2. Tilman D, Balzer C, Hill J, Befort B L. Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, 2011, **108**(50): 20260–20264
3. Tuninetti M, Davis K F. Addressing global hotspots of drought-related crop production losses. *Nature Communications*, 2026, **17**(1): 6605
4. Aramburu-Merlos F, van Loon M P, van Ittersum M K, Grassini P. High-resolution global maps of yield potential with local relevance for targeted crop production improvement. *Nature Food*, 2024, **5**(8): 667–672
5. Statistics Division of the Food and Agriculture Organization of the United Nations (FAOSTAT). Crops and Livestock Products. *FAOSTAT*, 2026. Available at FAO website on August 10, 2026
6. Duvick D N. The contribution of breeding to yield advances in maize (*Zea mays* L.). *Advances in Agronomy*, 2005, **86**: 83–145
7. Aramburu-Merlos F, Tenorio F A M, Mashingaidze N, Sananka A, Aston S, Ojeda J J, Grassini P. Adopting yield-improving practices to meet maize demand in Sub-Saharan Africa without cropland expansion. *Nature Communications*, 2024, **15**(1): 4492
8. Gerber J S, Ray D K, Makowski D, Butler E E, Mueller N D, West P C, Johnson J A, Polasky S, Samberg L H, Siebert S, Sloat L. Global spatially explicit yield gap time trends reveal regions at risk of future crop yield stagnation. *Nature Food*, 2024, **5**(2): 125–135
9. Lacasa J, Gaspar A, Hinds M, Jayasinghege Don S, Berning D, Ciampitti I A. Bayesian approach for maize yield response to plant density from both agronomic and economic viewpoints in North America. *Scientific Reports*, 2020, **10**(1): 15948
10. Zhang G X, Cui C G, Lv Y F, Wang X Y, Wang X F, Zhao D H, Hu F S, Wen X X, Han J, Liao Y C. Is it necessary to increase the maize planting density in China? *European Journal of Agronomy*, 2024, **159**: 127235
11. Tokatlidis I S, Koutroubas S D. A review of maize hybrids' dependence on high plant populations and its implications for crop yield stability. *Field Crops Research*, 2004, **88**(2–3): 103–114
12. Wang Z L, Liu W M, Liu G Z, Guo X X, Wang Z T, Jin S, Zhang L, Yang Y S, Li S K, Hou P. Optimal canopy structure and radiation thresholds for sustaining maize yield under low solar radiation. *Field Crops Research*, 2026, **343**: 110494
13. Zhang Y H, Xu Z G, Li J, Wang R. Optimum planting density improves resource use efficiency and yield stability of rainfed maize in semiarid climate. *Frontiers in Plant Science*, 2021, **12**: 752606
14. Assefa Y, Vara Prasad P V, Carter P, Hinds M, Bhalla G, Schon R, Jeschke M, Paszkiewicz S, Ciampitti I A. Yield responses to planting density for US modern corn hybrids: a synthesis-analysis. *Crop Science*, 2016, **56**(5): 2802–2817
15. Luo N, Wang J H, Graversgaard M, Umburanas R C, Liu D L, Li Q R, Storkey J, Willcock S, Wang P, Meng Q F. AI-designed crop populations for sustainable intensification. *Trends in Plant Science*, 2026 [Published Online] doi: 10.1016/j.tplants.2026.07.010
16. Yield Potential & Yield Gap Atlas. Yield Potential and Yield Gap Atlas (YPYGA). *YPYGA*, 2026. Available at YPYGA website on August 10, 2026
17. Tollenaar M, Lee E A. Yield potential, yield stability and stress tolerance in maize. *Field Crops Research*, 2002, **75**(2–3): 161–169
18. Zhang M M, Zhao X R, Han X Q, Chen Y J, Dang P F, Xue J Q, Qin X L, Siddique K H M. Optimizing planting density for enhanced maize yield and resource use efficiency in China. A meta-analysis. *Agronomy for Sustainable Development*, 2025, **45**(3): 29
19. Assefa Y, Carter P, Hinds M, Bhalla G, Schon R, Jeschke M, Paszkiewicz S, Smith S, Ciampitti I A. Analysis of long term study indicates both agronomic optimal plant density and increase maize yield per plant contributed to yield gain. *Scientific Reports*, 2018, **8**(1): 4937
20. Sangoi L, Gracietti M A, Rampazzo C, Bianchetti P. Response of Brazilian maize hybrids from different eras to changes in plant density. *Field Crops Research*, 2002, **79**(1): 39–51
21. Derieux M, Darrigrand M, Gallais A, Barrière Y, Bloc D, Montalant Y. Estimation of genetic progress achieved in grain maize in France between 1950 and 1985. *Agronomie*, 1987, **7**(1): 1–11 (in French)
22. Rolando G, Aramburu-Merlos F, Ferrero F, Tabacco E, Borreani G, Tenorio F A, Grassini P. Simultaneous changes in climate and management explain yield trends in a major maize system in Europe. *Field Crops Research*, 2026, **345**: 110545
23. Borras L, Ruiz A, Krause M D, Zinselmeier C, Hoffman N, Podlich D, Smalley M. US maize yield gains have decoupled from the need for higher plant densities. *Field Crops Research*, 2026, **342**: 110456
24. Wang X J, Gao S, Yang H Y, Li E, Xie R Z, Wang K R, Zhang G Q, Yu H B, Ming B, Li S K. Spatiotemporal dynamics of maize planting density in China: yield responses and region-specific intensification thresholds. *Crop and Environment*, 2026, **5**(2): 100116
25. Hou J M, Luo N, Wang S, Meng Q F, Wang P. Effects of

increasing planting density on grain yield, leaf area index and photosynthetic rate of maize in China. *Scientia Agricultura Sinica*, 2021, **54**(12): 2538–2546 (in Chinese)

26. Ying J, Lee E A, Tollenaar M. Response of maize leaf photosynthesis to low temperature during the grain-filling period. *Field Crops Research*, 2000, **68**(2): 87–96
27. Hao W, Yi Y Y, Cao Y, Liu X W, Zhang Z X, Cai M Y, Hu X D, Zhou H. How farmland fragmentation affects crop yields through irrigation and labor input: an empirical study based on maize production in China. *Energy Nexus*, 2026, **23**: 100793
28. USDA National Agricultural Statistics Service (NASS). Census of Agriculture. *Department of Agriculture*, 2024. Available at USDA NASS website on August 10, 2026
29. Djaman K, Allen S, Djaman D S, Koudahe K, Irmak S, Puppala N, Darapuneni M K, Angadi S V. Planting date and plant density effects on maize growth, yield and water use efficiency. *Environmental Challenges*, 2022, **6**: 100417
30. Liu G Z, Liu W M, Hou P, Ming B, Yang Y S, Guo X X, Xie R Z, Wang K R, Li S K. Reducing maize yield gap by matching plant density and solar radiation. *Journal of Integrative Agriculture*, 2021, **20**(2): 363–370
31. Luo N, Wang X Y, Hou J M, Wang Y Y, Wang P, Meng Q F. Agronomic optimal plant density for yield improvement in the major maize regions of China. *Crop Science*, 2020, **60**(3): 1580–1590
32. Luo N, Meng Q F, Feng P Y, Qu Z R, Yu Y H, Liu D L, Müller C, Wang P. China can be self-sufficient in maize production by 2030 with optimal crop management. *Nature Communications*, 2023, **14**(1): 2637
33. Breiman L. Random forests. *Machine Learning*, 2001, **45**(1): 5–32
34. Wang X B, Miao Y X, Dong L W, Mi G H, Batchelor W D, Kusnierek K. Precision nitrogen management for maize based on crop modeling, remote sensing and machine learning. *Computers and Electronics in Agriculture*, 2025, **239**: 111124
35. Grell M, Barandun G, Asfour T, Kasimatis M, Collins A S P, Wang J N, Güder F. Point-of-use sensors and machine learning enable low-cost determination of soil nitrogen. *Nature Food*, 2021, **2**(12): 981–989
36. Shao G M, Han W T, Zhang H H, Zhang L Y, Wang Y, Zhang Y. Prediction of maize crop coefficient from UAV multisensor remote sensing using machine learning methods. *Agricultural Water Management*, 2023, **276**: 108064
37. Ma M J, Zhao J H, Hong M, Yang T R, Fu Q P. Assessing integrated water status in drip-irrigated maize fields using UAV multispectral data and machine learning algorithms. *Agricultural Water Management*, 2026, **333**: 110554
38. Yuan W, Zhang Z H, Dai J J, Liu Z X, Cidoncha R S. Change-aware online identification and adaptive PI control for robust electrical conductivity regulation in fertigation mixing systems. *Smart Agricultural Technology*, 2026, **14**: 102110
39. Nahar J, Liu S, Mao Y W, Liu J F, Shah S L. Closed-loop scheduling and control for precision irrigation. *Industrial & Engineering Chemistry Research*, 2019, **58**(26): 11485–11497
40. Messina C, Ciampitti I A, Berning D, Bubeck D, Hammer G, Cooper M. Sustained improvement in tolerance to water deficit accompanies maize yield increase in temperate environments. *Crop Science*, 2022, **62**(6): 2138–2150
41. Lei R Q, Fang Y T, Du C W, Zhou J M, Hang S, Xiang H T. Navigating yield-density trade-offs in maize production: a Bayesian-ML framework for uncertainty attribution and management. *Field Crops Research*, 2026, **342**: 110480
42. Ming B, Xie R Z, Hou P, Li L L, Wang K R, Li S K. Changes of maize planting density in China. *Scientia Agricultura Sinica*, 2017, **50**(11): 1960–1972 (in Chinese)
43. Meng Q F, Cui Z L, Yang H S, Zhang F S, Chen X P. Establishing high-yielding maize system for sustainable intensification in China. *Advances in Agronomy*, 2018, **148**: 85–109
44. Liu Z J, Yang X G, Hubbard K G, Lin X M. Maize potential yields and yield gaps in the changing climate of Northeast China. *Global Change Biology*, 2012, **18**(11): 3441–3454
45. Meng Q F, Liu B H, Yang H S, Chen X P. Solar dimming decreased maize yield potential on the North China Plain. *Food and Energy Security*, 2020, **9**(4): e235
46. Shi L, Wang Q, Zhang G Q, Li S K, Xue J. Increasing maize production and advancing rational water allocation and usage based on the optimal planting density and irrigation levels in northwest China. *Water*, 2023, **15**(3): 529
47. Cheng Y, Wei P C, Chen D, Zheng Y X, Song B. Optimizing planting density and variety allocation synergistically to improve maize yield and resource utilization efficiency in different agroecological zones of southwest China. *Annals of Applied Biology*, 2025, **187**(3): 330–344
48. Mizik T. How can precision farming work on a small scale? A systematic literature review. *Precision Agriculture*, 2023, **24**(1): 384–406
49. Zou B L, Mishra A K. Modernizing smallholder agriculture and achieving food security: an exploration in machinery services and labor reallocation in China. *Applied Economic Perspectives and Policy*, 2024, **46**(4): 1662–1691
50. Kroupová Z Ž, Aulová R, Rumánková L, Bajan B, Čechura L, Šimek P, Jarolímek J. Drivers and barriers to precision agriculture technology and digitalisation adoption: meta-analysis of decision choice models. *Precision Agriculture*, 2025, **26**(1): 17
51. Tzachor A, Devare M, Richards C, Pypers P, Ghosh A, Koo J, Johal S, King B. Large language models and agricultural extension services. *Nature Food*, 2023, **4**(11): 941–948
52. Lobell D B, Roberts M J, Schlenker W, Braun N, Little B B, Rejesus R M, Hammer G L. Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. *Science*,

2014, **344**(6183): 516–519

53. Lesk C, Anderson W, Rigden A, Coast O, Jägermeyr J, McDermid S, Davis K F, Konar M. Compound heat and moisture extreme impacts on global crop yields under climate change. *Nature Reviews Earth & Environment*, 2022, **3**(12): 872–889
54. Hernández M D, Alfonso C, Cerrudo A, Cambareri M, Della Maggiora A, Barbieri P, Echarte M M, Echarte L. Eco-physiological processes underlying maize water use efficiency response to plant density under contrasting water regimes. *Field Crops Research*, 2020, **254**: 107844
55. Lobell D B, Deines J M, Di Tommaso S. Changes in the drought sensitivity of US maize yields. *Nature Food*, 2020, **1**(11): 729–735
56. Xue J, Xie R Z, Zhang W F, Wang K R, Hou P, Ming B, Gou L, Li S K. Research progress on reduced lodging of high-yield and-density maize. *Journal of Integrative Agriculture*, 2017, **16**(12): 2717–2725
57. Jafari F, Wang B B, Wang H Y, Zou J J. Breeding maize of ideal plant architecture for high-density planting tolerance through modulating shade avoidance response and beyond. *Journal of Integrative Plant Biology*, 2024, **66**(5): 849–864
58. Zhang Y R, Ren J H, Liu S S, Zhang X R, Liu G Z, Du X, Cui Y H, Gao Z. Low light stress at tasseling threatens high-density maize production by impairing silk emergence. *Journal of Integrative Agriculture*, 2025 [Published Online] doi: 10.1016/j.jia.2025.12.010
59. Zheng B, Li Y T, Wu Q P, Zhao W, Ren T H, Zhang X H, Li G, Ning T Y, Zhang Z S. Maize (*Zea mays* L.) planted at higher density utilizes dynamic light more efficiently. *Plant, Cell & Environment*, 2023, **46**(11): 3305–3322
60. Qiao L, Wang X H, Smith P, Fan J L, Lu Y L, Emmett B, Li R, Dorling S, Chen H Q, Liu S G, Benton T G, Wang Y J, Ma Y Q, Jiang R F, Zhang F S, Piao S, Müller C, Yang H Q, Hao Y N, Li W M, Fan M S. Soil quality both increases crop production and improves resilience to climate change. *Nature Climate Change*, 2022, **12**(6): 574–580