

Research Paper

Optimizing agricultural intensification and cropping structures in China to reduce nitrogen surplus

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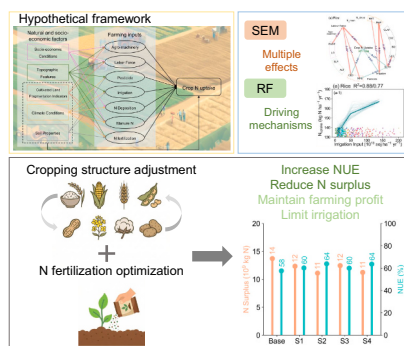
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HIGHLIGHTS

- N flows of eight major crops were modelled quantitatively in China.
- Multiple impact pathways affecting N uptake of eight major crops in China were revealed.
- Optimization of farming inputs and cropping structures were integrated to reduce N surplus.
- Under optimization, N surplus decreased by 9.2–19%, and overall NUE increased by 2.3–6.2%.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Nadine Andrieu

Keywords:

Sustainable agricultural intensification
Nitrogen use efficiency
Nitrogen surplus
Spatial optimization

ABSTRACT

CONTEXT: Minimizing nitrogen (N) surplus in croplands is a key objective of sustainable agricultural intensification and is crucial for climate change mitigation and adaptation strategies. Previous studies often focus on the cultivation of staple crops and lack integration between exploring the driving mechanisms of crop N uptake and adjusting cropping structures.

OBJECTIVE: This study focused on spatially explicit quantification and modelling of N flows and N use efficiency (NUE) of eight major crops (rice, maize, wheat, soybean, peanut, oilseed rape, cotton, and potato) from 2004 to 2020 at the regional scale in China. This study further provided strategies to reduce N surplus while ensuring food security and farming profit.

METHODS: Structural equation models and random forest models were used to analyse the multiple effects of natural and socio-economic factors and farming inputs on crop N uptake. Optimization models were applied to simulate the potential to reduce N surplus by optimizing N fertilization and adjusting the cropping structure

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<https://doi.org/10.1016/j.agsy.2026.104729>

Received 28 July 2025; Received in revised form 2 March 2026; Accepted 13 March 2026

Available online 17 March 2026

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under multiple scenarios, considering cropping calendars, maintaining stable farming profit, and limiting irrigation water use.

RESULTS AND CONCLUSIONS: The NUE of the eight major crops increased from 2004 to 2020. However, high yield per unit area did not always translate into high total production, reflecting constraints from sown area allocation, unrealized yield potential, and N surplus risk. Increased mechanization, reduced land fragmentation, appropriate N fertilization and irrigation increased crop N uptake, while excessive pesticide use and adverse soil or climatic conditions could limit it. The effects of farming inputs on crop N uptake usually reached saturation. For instance, the effects of N fertilization were saturated at 200 kg N ha⁻¹ yr⁻¹ and 70 kg N ha⁻¹ yr⁻¹ for wheat and soybean, respectively. Under various optimization scenarios, the N surplus decreased by 9.2–19%, and the overall NUE increased by 2.3–6.2%. Nationwide coordination of crop profits through transfer payments and optimizing N fertilization increased the NUE and reduced N surplus, resulting in approximately twice as many benefits. Adjustments to cropping structure could also reduce irrigation water use by 5.8–9.3%, especially in northern arid and semiarid regions.

SIGNIFICANCE: This study provides region-specific recommendations to optimize farming inputs and cropping structures, aiming to reduce environmental N losses while maintaining food security and farmer income.

1. Introduction

Nitrogen (N) is one of the most limiting nutrients in crop cultivation, as it increases crop growth and development (Oenema et al., 2003). To meet the increasing gap in food demand caused by global population growth and changes in dietary patterns, the intensity of N fertilization has gradually increased since the 1980s (Gao et al., 2025; Ju et al., 2004; Lv et al., 2025; Rosegrant and Cline, 2003; Tian et al., 2019). However, owing to limitations in cultivation conditions (including topographical features, soil properties, cultivation scale, and farmland infrastructure), the global average N use efficiency (NUE) is currently only approximately 40% (Govindasamy et al., 2023). A large surplus of N is lost to the environment, leading to a series of environmental challenges, such as increased greenhouse gas emissions (N₂O), eutrophication of aquatic ecosystems, soil acidification, and biodiversity loss (Guillaume et al., 2015; Poore and Nemecek, 2018; Springmann et al., 2018; Zamanian et al., 2021). To achieve sustainable intensification of agriculture, one of the most important tasks is to explore region-specific pathways to increase NUE, which aims to meet crop growth requirements while minimizing environmental problems caused by N surplus (Domingo et al., 2021; Du et al., 2024; Ren et al., 2022; Zamanian and Kuzyakov, 2019).

It is a major challenge for China to feed nearly 20% of the world's population with only 9% of the global cultivated land, especially because its cropping systems are largely dominated by smallholder farmers (Han et al., 2026; Kanter et al., 2019; Liu et al., 2023a; Ye et al., 2020). A major shortcoming of the current smallholder farming system is that agricultural operators generally have low education levels and small farming fields. They also lack access to capital and machinery, making it difficult to implement efficient N management practices, which leads to a tendency to apply excessive fertilizer to maintain high yields (Cui et al., 2018; Deng et al., 2024; Wu et al., 2018).

In 2020, China's agricultural N consumption accounted for 22% of the global total, making it the largest consumer of N in the world (FAO, 2024). There is a gap between the average NUE of cultivated land in China (30–55%) and that in other major agricultural regions of the world (52–70%) (Zhang et al., 2015). There is also high spatial heterogeneity in NUE among cropping regions and crop types in China (Chen et al., 2018; Jiang et al., 2024b). The Chinese government has made various efforts to increase NUE, such as implementing soil testing and formulated fertilization, “Double High Agriculture” (i.e., transforming from solely high yield to both high yield and high resource use efficiency), and “Zero Growth in Chemical Fertilizer Use by 2020” (Yin et al., 2019; Zhang et al., 2016). Regional crop-specific optimal strategies based on spatially explicit assessment and modelling of cultivated land N flows are urgently needed to better implement these nationwide measures.

Current assessments of cropland N flows are conducted at multiple scales. The main evaluation indicators include N inputs, crop N uptake,

N surplus (i.e., N inputs minus crop N uptake), and NUE (i.e., crop N uptake divided by N inputs). At the national scale, China's crop N surplus remains high, and estimates of fertilizer N inputs are highly uncertain (Zhang et al., 2015; Zhang et al., 2021b). High-resolution, grid-based studies capture spatial detail but face issues with inconsistent data and poor integration of socio-economic factors (Gu et al., 2015; Wang et al., 2020; Zhang et al., 2021b). The provincial or county scale is more suitable for China because of data availability and consistent management policies (Liu et al., 2020a; Liu et al., 2024). Recent studies at this scale have analysed spatial and temporal patterns of N flows and NUE and explored the contributions of various N sources, but most studies have focused mainly on staple crops (rice, maize and wheat) (He et al., 2018; Liu et al., 2024; Yan et al., 2022; Zhang et al., 2021a). Staple crops use only 54% of synthetic N, leaving research gaps for oil and economic crops. This study fills that gap by quantifying provincial-scale NUE for eight major crops (including rice, maize, wheat, soybean, peanut, oilseed rape, cotton, and potato) to better inform comprehensive N reduction strategies.

Optimizing agricultural management practices and adjusting cropping structures are the key strategies for reducing N losses. The former mainly involves modelling the impact of various practices on N losses to develop better solutions. Site-specific practices, such as the use of enhanced-efficiency fertilizers, biochar, crop rotation, no tillage, and the combination of organic fertilizers with synthetic fertilizers, can effectively reduce N losses and increase NUE (You et al., 2024; Duan et al., 2024). These studies also highlight that crop N uptake does not always increase linearly with fertilizer input and that there is saturation, beyond which additional fertilizer is ineffective (Cui et al., 2018). Optimized N management for specific crops, such as wheat and rice, can reduce both N input and loss without sacrificing yields (Cui et al., 2011; Cai et al., 2023). Adjusting cropping structures, often via linear optimization, is another key approach. These models optimize crop allocation to achieve sustainability targets, such as higher yields, lower greenhouse gas emissions, and reduced water use, while considering natural and socio-economic constraints (Xie et al., 2023; Folberth et al., 2020). Shifting production from low-yield, high-impact areas to high-yield, low-impact areas can greatly decrease CO₂ emissions and resource use, contributing to more sustainable agriculture. However, few studies have integrated crop-specific optimization of farming inputs with cropping structure adjustment. This study couples these two strategies for eight major crops in China to identify pathways to increase NUE and reduce N surplus while maintaining profits and limiting irrigation water use.

The core objective of this study was to assess how optimizing agricultural intensification and cropping structures can increase crop N uptake and reduce cultivated land N surplus at the provincial scale in China. To achieve this goal, provincial-scale NUE for eight major crops (rice, maize, wheat, soybean, peanut, oilseed rape, cotton, and potato) was assessed from 2004 to 2020. The multiple effects of natural and

socio-economic factors (including climate conditions, socio-economic conditions, topographic features, soil properties and cultivated land fragmentation indicators) and farming inputs on crop N uptake were subsequently analysed via structural equation models and random forest models. Finally, optimization models were used to increase NUE by optimizing N fertilization and adjusting the cropping structure under multiple constraints, such as safeguarding food security, stabilizing farming profit, and limiting irrigation water use. In the Discussion section, regionally appropriate farming inputs and optimization strategies for each major crop in China are discussed, along with the implication and trade-offs of farming profit and irrigation water use depending on the optimization scenario. This study supports the design of N reduction strategies, and the methods used here may also provide a reference for other countries to explore ways to increase NUE.

2. Materials and methods

2.1. Data

The study area covered the entirety of mainland China. Owing to data limitations, Taiwan, Hong Kong, and Macau were not included. Multiple datasets were used to assess the N use of eight major crops (rice, maize, wheat, soybean, peanut, oilseed rape, potato, and cotton) and to analyse their driving processes. The sown area of these eight major crops accounted for more than 75% of the total sown area of annual crops in mainland China in 2020 (calculated from sown area statistics in the China Statistical Yearbook 2021; excluding orchards and tea plantations).

Table 1
Detailed dataset information.

Dataset	Indicator	Unit	Data source
N budget dataset	Crop-specific sown area	ha	China rural statistical yearbook (2005–2021);
	Crop-specific yield	metric ton	
	Crop-specific fertilizer input	metric ton	National agricultural product cost–benefit data compilation (2005–2021); Yan et al., 2014; Ye et al., 2022a
	Rural population and number of livestock (including cattle, pigs, cows, sheep, horses, mules and donkeys)	–	
	N deposition rate	kg N ha ⁻¹	Liu et al., 2013
	Agricultural product cost–benefit dataset	Crop-specific pesticides input	RMB ha ⁻¹
Crop-specific agro-machinery input		RMB ha ⁻¹	
Crop-specific labour force input		RMB ha ⁻¹	
Crop-specific irrigation input		RMB ha ⁻¹	
Crop-specific farming profit		RMB ha ⁻¹	
Natural and socio-economic factors dataset		Per capita GDP	RMB
	Urbanization rate	%	
	Slope	degree	Abrams et al., 2015
	Altitude	m	
	Mean patch size	ha	Ren et al., 2025; Ye et al., 2024a
	Cultivated land density	ha	
	Mean annual temperature	degree	Peng, 2024a, 2024b; Ye et al., 2022b
	Mean annual precipitation	mm	
	Clay content	%	Shangguan et al., 2014; Ren et al., 2023
	Cation exchange capacity	cmol/kg	
	Bulk density	g/cm ³	
	Soil organic carbon content	%	

Table 1 presents information about the datasets. First, the N budget dataset derived from the 2005–2021 China Rural Statistical Yearbook (<https://data.cnki.net/Yearbook/>) and the National Agricultural Product Cost–Benefit Data Compilation (https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_1907941.html) was used to calculate crop N uptake and N inputs. This included annual provincial data on the sown area, yield, and N fertilizer input (synthetic N fertilizer only) for the eight major crops, as well as regional scale N deposition rates, the rural population and the number of livestock used to estimate manure N input. Second, the agricultural product cost-benefit dataset covers annual provincial farming profit and farming inputs for the eight major crops from 2004 to 2020, including expenditures on pesticides, agro-machinery, labour force, and irrigation. Farming inputs were converted into solar emery values to enable comparisons across different years and regions, which were calculated in unit of solar emjoules (sej) (see Appendix for details) (Ulgiati and Brown, 2009). Third, the natural and socio-economic factors dataset included socio-economic conditions, topographic features, cultivated land fragmentation indicators, climate conditions and soil properties (Detailed definitions could be found in Table S2). Except for socio-economic conditions, all other indicators were extracted via a cultivated land layer mask and then averaged at the provincial level. Fourth, the agricultural product cost–benefit dataset included the annual farming profit of each crop at the provincial level from 2004 to 2020.

2.2. NUE and N surplus

NUE is calculated as the ratio of crop N uptake (N_{uptake}) to total N input (N_{input}) (Eq. (1)), where crop N uptake mainly originates from the total N inputs applied in the current year, soil organic matter, and residual N from previous inputs. The total N input (N_{input}) includes N fertilization (N_{fer}), manure N input (N_{man}), biological N fixation (N_{fix}) and N deposition (N_{depo}) (Eq. (2)). The N surplus (N_{sur}) is calculated as the difference between the total N input and crop N uptake (Eq. (3)). N_{sur} is regarded as a useful indicator of potential N losses to the environment from agricultural soils, including N₂, N₂O, and NO emissions; ammonia volatilization (NH₃); and NO₃⁻ leaching and runoff (Ti et al., 2012; Zhang et al., 2015). The detailed calculation equations for each N input component and crop N uptake are shown in Table S3.

$$NUE = \frac{N_{uptake}}{N_{input}} \quad (1)$$

$$N_{input} = N_{fer} + N_{man} + N_{fix} + N_{depo} \quad (2)$$

$$N_{sur} = N_{input} - N_{uptake} \quad (3)$$

2.3. Exploring the influencing factors of crop N uptake via structural equation modelling

Structural equation modelling (SEM) is a powerful statistical tool (Bayard and Jolly, 2007). It is used to analyse the complex relationships among multiple variables and to construct theoretical models to describe the connections and interactions between variables (Grace and Keeley, 2006; Hou et al., 2025; Sarkar et al., 2021; Xu et al., 2025).

Eight crop-specific structural equation models were established to explore the multiple effects of natural and socio-economic factors and farming inputs on crop N uptake in China, including multiple explanatory variables (Fig. 1). We selected these variables based on prior literature and established agronomic knowledge to represent the key drivers of crop production and N uptake (Liu et al., 2020b; Wang et al., 2023). Specifically, we included variables plausibly causally related to provincial crop N uptake, covering: (i) farming inputs (N fertilization, pesticides, agro-machinery, labour force, irrigation) capturing management intensity; (ii) socio-economic conditions (per capita GDP, urbanization rate) reflecting technology adoption and input accessibility;

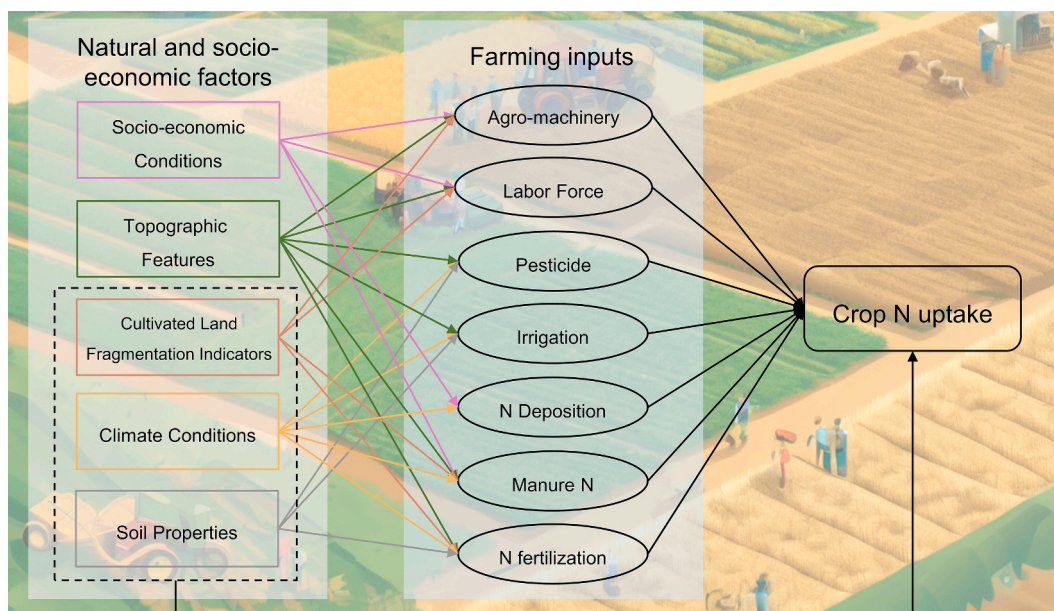


Fig. 1. Hypothetical framework of SEM. Socio-economic conditions include per capita GDP and urbanization rate. Topographic features include slope and altitude. Cultivated land fragmentation indicators includes mean patch size and cultivated land density. Climate conditions include mean annual temperature and mean annual precipitation. Soil properties include clay content, cation exchange capacity, bulk density and soil organic carbon content.

(iii) topographic features (slope, altitude) constraining cultivation and mechanization; (iv) cultivated land fragmentation (mean patch size, cultivated land density) indicating field size, contiguity and management efficiency; (v) climate conditions (mean annual temperature, mean annual precipitation) describing baseline hydro-thermal constraints; and (vi) soil properties (clay content, cation exchange capacity, bulk density, soil organic carbon content) representing soil fertility and water/nutrient retention. Accordingly, we specified a priori SEM with directional paths to test a hypothesized (not experimentally identified) causal structure; the estimated paths were modelled as monotonic and approximately linear (increasing or decreasing) effects. In the hypothetical framework, crop N uptake is directly influenced by farming inputs, cultivated land fragmentation indicators, climate conditions and soil properties, and indirectly influenced by socio-economic conditions, topographic features and other natural and socio-economic factors through their direct influence on farming inputs. The direction of the arrows indicates the proposed causal relationships among the variables, and all variables were standardized (z-score normalized) prior to SEM fitting to obtain standardized parameter estimates. The model fits were evaluated via the chi-square test (CHISQ), comparative fit index (CFI), goodness-of-fit index (GFI), and information theory (AIC) (Aguiar et al., 2022; Wang et al., 2023). χ^2/df should not exceed 5, and the GFI and CFI should be greater than 0.9 (Marsh et al., 1988). When the sample size is not large enough, the GFI and CFI from 0.8 to 0.9 are considered marginal levels and fall into acceptable ranges (Dang et al., 2014; Hsu and Lin, 2008). The AIC needs to be as small as possible to find a balance between explanatory power and simplicity. During the process of fitting these model parameters, the insignificant paths and corresponding indicators were gradually removed to further simplify the models and increase their explanatory power and adequacy.

2.4. Analysis of the response of crop N uptake to farming inputs via random forest models

Random Forest (RF) modelling is a powerful data analysis method based on the concept of ensemble learning, which combines multiple decision trees to increase the regression or classification performance of a single tree (Breiman, 2001). Marginal plots (M-plots) can be used to explore the specific effects of each feature on model predictions. As

shown in Eq. (4), x_s represents the feature value for a given feature; $x_C^{(i)}$ is the actual feature value for other features in the sample set; M represents the quantile interval for a given feature; n represents the number of samples in the quantile interval for the given feature in the sample set; and $\widehat{f}_{M,x_s}(x_s)$ represents the predicted average marginal effect for a given feature value S .

$$\widehat{f}_{M,x_s}(x_s) = \frac{1}{n} \sum_{i=1}^n \widehat{f}(x_s, x_C^{(i)}) \quad (4)$$

For each of the eight major crops, all the variables that had a direct and significant effect ($p < 0.05$) on crop N uptake obtained from SEM were taken as independent variables, and crop N uptake was input as the dependent variable in the RF model. For each crop-specific model, the data were divided into a training set and a testing set at a ratio of 4:1. Each model was trained on the training set and evaluated on the testing set, with the R^2 value used as the evaluation index. On the basis of the obtained models, M-plots were used to explain the response of each crop's N uptake to farming inputs, including N fertilization, pesticides, agro-machinery, labour force and irrigation, thereby facilitating the exploration of suitable crop-specific agricultural intensification strategies.

2.5. Optimization of cropping structures on the basis of optimization models

A single-objective optimization model is a mathematical framework designed to optimize (either maximize or minimize) a single objective function while satisfying a set of constraints (Guo et al., 2024). Single-objective optimization models were established to explore the provincial cropping structures that minimizes the total N surplus across China. Five scenarios were considered. The base scenario represented the situation in 2020. The unique constraints of Scenarios 1–4 are presented in Table 2. The objective was to minimize the total N surplus across China for eight major crops, among which rice was subdivided into early rice, middle-season rice and late rice, whereas wheat was subdivided into spring wheat and summer wheat (Eq. (5)), where p represents each provincial-level administrative region (except Taiwan, Hong Kong, and Macau), and c represents each of eleven crops. S_{pc} represents the sown area of a specific crop in a specific province. In scenarios 1 and 3, $N_{fer,pc}$

Table 2
Descriptions of scenarios 1–4.

	Unique Constraints	
	Farming profit	N fertilization
Scenarios 1	Non-declining overall national farming profit	2020-level N fertilization
Scenarios 2	Non-declining overall national farming profit	Optimized N fertilization
Scenarios 3	Non-declining provincial farming profit	2020-level N fertilization
Scenarios 4	Non-declining provincial farming profit	Optimized N fertilization

and $N_{uptake,pc}$ represent N fertilization and crop N uptake of a specific crop in a specific province in 2020, respectively. In scenarios 2 and 4, $N_{fer,pc}$ and $N_{uptake,pc}$ represent the modified N_{fer} and the predicted N_{uptake} obtained from the well-trained RF model of a specific crop. The specific operation involved multiplying N_{fer} by a change coefficient h ($h = 90\%, 91\%, 92\%, \dots, 110\%$) and simulating N_{uptake} while keeping the other independent variables unchanged. The values of N_{uptake}/h were then compared to determine the optimal N_{fer} and corresponding N_{uptake} that resulted in increased crop N uptake and reduced environmental N loss.

$$F(x) = \text{Min} \sum_{p=1}^{31} \sum_{c=1}^{11} (N_{fer,pc} + N_{man,pc} + N_{fix,c} + N_{depo,p} - N_{uptake,pc}) * S_{pc} \quad (5)$$

The constraints shared by scenarios 1–4 included cultivated land area, cropping calendars of rotating crops, crop nutrition demands and irrigation conditions. The constraint of cultivated land area and cropping calendars of rotating crops can be expressed by Eq. (6), where $Area_p$ represents the cultivated land area in a specific province, and where t represents a specific 10-day period starting from the first day of the year which is related to the cropping calendars of rotating crops (Table S4). The constraints of crop demands included no decrease in the nutritional content (i.e., protein, energy and fat) of staple crops (i.e., early rice, middle-season rice, late rice, spring wheat, summer wheat and maize) and no decrease in the yield of economic crops (i.e., soybean, peanut, oilseed rape, potato and cotton). The former can be expressed by Eq. (7), and the latter can be expressed by Eq. (8), where $Yield_{pc}$ represents the crop yield per unit area of a specific crop in a specific province, n_{ci} represents the content coefficient of a specific crop shown in Table S5, and S_{pc}^{2020} represents the sown area of a specific crop in a specific province in 2020. The constraint of irrigation conditions was that total irrigation water use in each province of the North China Plain, Loess Plateau and the northern arid and semiarid regions of China (including Beijing, Tianjin, Henan, Hebei, Shandong, Shanxi, Shaanxi, Ningxia, Gansu, Xinjiang and Inner Mongolia) did not increase (Yuan et al., 2018). It can be expressed by Eq. (9), where $Irri_{pc}$ represents the irrigation water use per unit area of a specific crop in a specific province.

$$\sum_{c=1}^{11} S_{pc} \leq Area_p, t = 1, 2, \dots, 36 \quad (6)$$

$$\sum_{c=1}^6 \sum_{p=1}^{31} Yield_{pc} * S_{pc} * n_{ci} \geq \sum_{c=1}^6 \sum_{p=1}^{31} Yield_{pc} * S_{pc}^{2020} * n_{ci}, i = 1, 2, 3 \quad (7)$$

$$\sum_{p=1}^{31} Yield_{pc} * S_{pc} \geq \sum_{p=1}^{31} Yield_{pc} * S_{pc}^{2020}, c = 1, 2, \dots, 5 \quad (8)$$

$$\sum_{c=1}^{11} Irri_{pc} * S_{pc} \geq \sum_{c=1}^{11} Irri_{pc} * S_{pc}^{2020}, p = 1, 2, \dots, 11 \quad (9)$$

In scenarios 1 and 2, no decrease in the overall national farming profit was taken as a constraint, whereas in scenarios 3 and 4, no decrease in the farming profit of each province was taken as a constraint, which can be expressed as Eq. (10) and Eq. (11), respectively, where $Profit_{pc}$ represents the farming profit per unit area of a specific crop in a

specific province.

$$\sum_{c=1}^{11} \sum_{p=1}^{31} Profit_{pc} * S_{pc} \geq \sum_{c=1}^{11} \sum_{p=1}^{31} Profit_{pc} * S_{pc}^{2020} \quad (10)$$

$$\sum_{c=1}^{11} Profit_{pc} * S_{pc} \geq \sum_{c=1}^{11} Profit_{pc} * S_{pc}^{2020}, p = 1, 2, \dots, 31 \quad (11)$$

3. Results

3.1. Spatial and temporal distributions of NUE and yield in major crops

The NUE of the eight major crops increased from 2004 to 2020 (Fig. 2). Soybeans and peanuts presented the highest NUE (70–90%), staple crops and oilseed rape presented moderate NUE (40–60%), and cotton and potato presented the lowest NUE (20–30% and 15–20%, respectively). Spatially, rice NUE was highest in Northeast China and the Sichuan Basin (60–80%), moderate in the Yangtze Plain (50–60%), and lowest in southern coastal regions (approximately 40%). Maize NUE peaked in Northeast China and North China (50–80%), but was much lower in the southwest and southern regions (20–40%). Wheat NUE was higher in the eastern region, exceeding 70% in Heilongjiang, Henan, and Shandong. Oilseed rape NUE was generally higher in the eastern and northern regions (Fig. S1). Cotton and potato NUE were higher in main production/northern areas than elsewhere, respectively. Crop N uptake was correlated with yield per unit area, but regions with high yield per unit area did not always have high total production, revealing constraints from sown area allocation, unrealized regional yield potential and N surplus risk (Fig. S1). For example, Northeast China had high soybean production but low yield per unit area, the rice yield per unit area is greater on the eastern coast than in the main production areas, and the maize yield per unit area is greater in Northeast China than in North China. Potato and oilseed rape also showed regional yield discrepancies, with high northern potato production and yield per unit area but lower yield per unit area in the southwest; the oilseed rape yield per unit area was balanced across regions.

3.2. Multiple effects of driving factors and farming inputs on crop N uptake

Fig. S2 shows the large regional differences in the farming inputs (N fertilization, pesticides, labour force, agro-machinery and irrigation) of the eight major crops. N fertilization had the highest path coefficient for oilseed rape (0.45), followed by cotton (0.39) and potato the lowest (0.04) (Fig. 3). Pesticide input had the opposite effect on crop N uptake for oil crops (Fig. 3d–f). For soybean, the path coefficient of pesticide input on crop N uptake was 0.51, whereas for peanut and oilseed rape, it was –0.17 and –0.18, respectively, indicating excessive pesticide input for peanut and oilseed rape in the southern regions (Fig. S2b).

Labour force input and agro-machinery input had opposite effects on crop N uptake (except for soybean). This reflected the advantages of mechanization in terms of crop cultivation efficiency. Except for maize and soybean, irrigation input was beneficial for the N uptake of all other crops, with path coefficients exceeding 0.2 for both cotton and potato and 0.17 for wheat. Reducing cultivated land fragmentation can increase crop N uptake. Specifically, the path coefficients of cultivated land density on the N uptake of rice, wheat, oilseed rape, and potato were 0.24, 0.33, 0.49, and 0.51, respectively, whereas the path coefficient for mean patch size on maize N uptake was 0.15.

Soil properties also had direct effects on crop N uptake, mainly through positive effects from bulk density, and negative effects from clay content and cation exchange capacity. The latter mainly reduced the water and nutrient use efficiencies due to their low permeability and intake rates (Liu et al., 2020b). Precipitation had a positive effect on peanut N uptake (0.62), and temperature had a negative effect on cotton

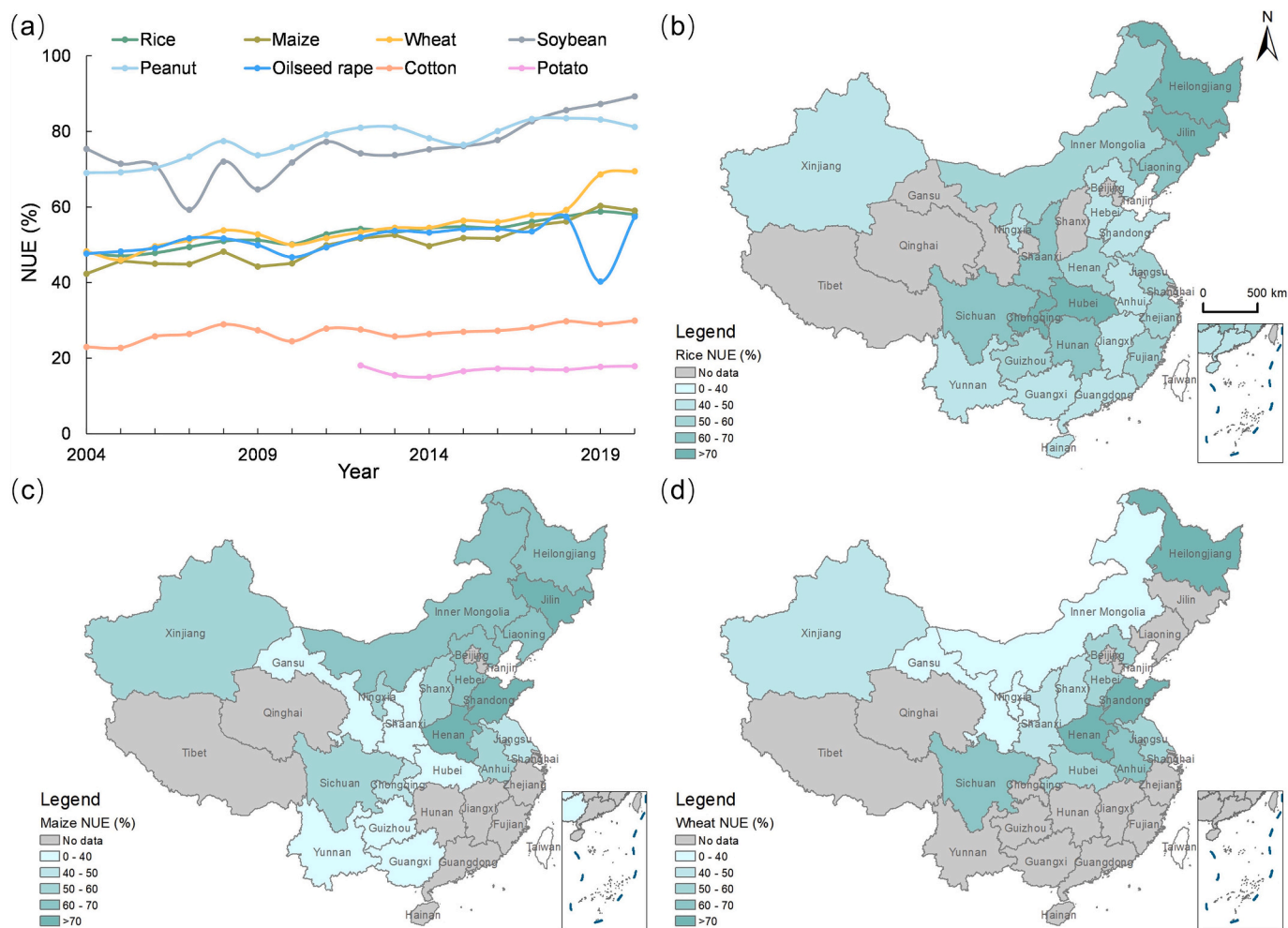


Fig. 2. Changes in the national average NUE for eight crops (2004–2020) and the spatial distribution of NUE for staple crops in 2020 (see Fig. S1 for the full details of yield per unit area, total production and NUE for eight major crops). (a) shows changes in the national average NUE for eight crops, 2004–2020. (b–d) show the spatial distribution of NUE in 2020 for rice, maize, and wheat, respectively.

N uptake (-0.18), which indicated that high temperatures constrain crop N uptake in sensitive crops, such as cotton (Cui et al., 2024).

Certain natural and socio-economic factors indirectly influence crop N uptake by affecting farming inputs. Regions with better economic conditions, lower slope and higher cultivated land density and mean patch size tend to rely more on agro-machinery than manual labour. For staple crops, a greater mean patch size generally increased N fertilization, whereas for oil crops the effect was the opposite. These findings suggest that large-scale cultivation of oil crops with their N-fixing capacities could effectively reduce N fertilization and the high demand of staple crops for N fertilization. An increase in clay content reduced the N fertilization for soybean and the irrigation input for wheat. An increase in precipitation led to a reduction in both irrigation and N fertilization.

3.3. Driving mechanisms of N uptake in major crops

According to the SEM results, for each major crop, only the indicators that had direct effects on crop N uptake were included in the random forest model to analyse the response of crop N uptake to changes in farming inputs (Fig. 4). Farming inputs and other indicators explained 52–97% of the variation in crop N uptake.

There were saturation levels in the effects of N fertilization on wheat, soybean, and oilseed rape. When N fertilization exceeded $200 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ for wheat and $70 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ for soybean, crop N uptake began to decrease. For oilseed rape, the increase in crop N uptake slowed

sharply when N fertilization exceeded $150 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. The crop N uptake of potato reached a saturation level of $210 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. Unlike other major crops, maize N uptake showed only a very slight increase in response to N fertilization: on average, every $10 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ increase in N fertilization resulted in only a $1 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ increase in crop N uptake.

Pesticide input mainly affected crop N uptake in oil crops. For soybean and peanut, pesticide input below $2\text{e}+13 \text{ sej ha}^{-1} \text{ yr}^{-1}$ increased crop N uptake, but further increases beyond $2.5\text{e}+13 \text{ sej ha}^{-1} \text{ yr}^{-1}$ reduced peanut N uptake. In northern China, lower pesticide input corresponded to greater crop N uptake, whereas in the humid southeast, greater pesticide use coincided with reduced crop N uptake. Agro-machinery input increased crop N uptake in maize, wheat, and oil crops, with a particularly strong increase for wheat, peanut, and oilseed rape. For maize, a saturation level occurred at approximately $7\text{e}+13 \text{ sej ha}^{-1} \text{ yr}^{-1}$, beyond which higher agro-machinery input did not increase N uptake (provinces above this threshold were mainly in the North China Plain and the Loess Plateau). For wheat, peanut, and oilseed rape, irrigation input exhibited an inverted U-shaped relationship with crop N uptake. Beyond saturation levels of approximately $30\text{e}+13$, $18\text{e}+13$, and $4\text{e}+13 \text{ sej ha}^{-1} \text{ yr}^{-1}$ for each crop respectively, higher irrigation actually reduced N uptake.

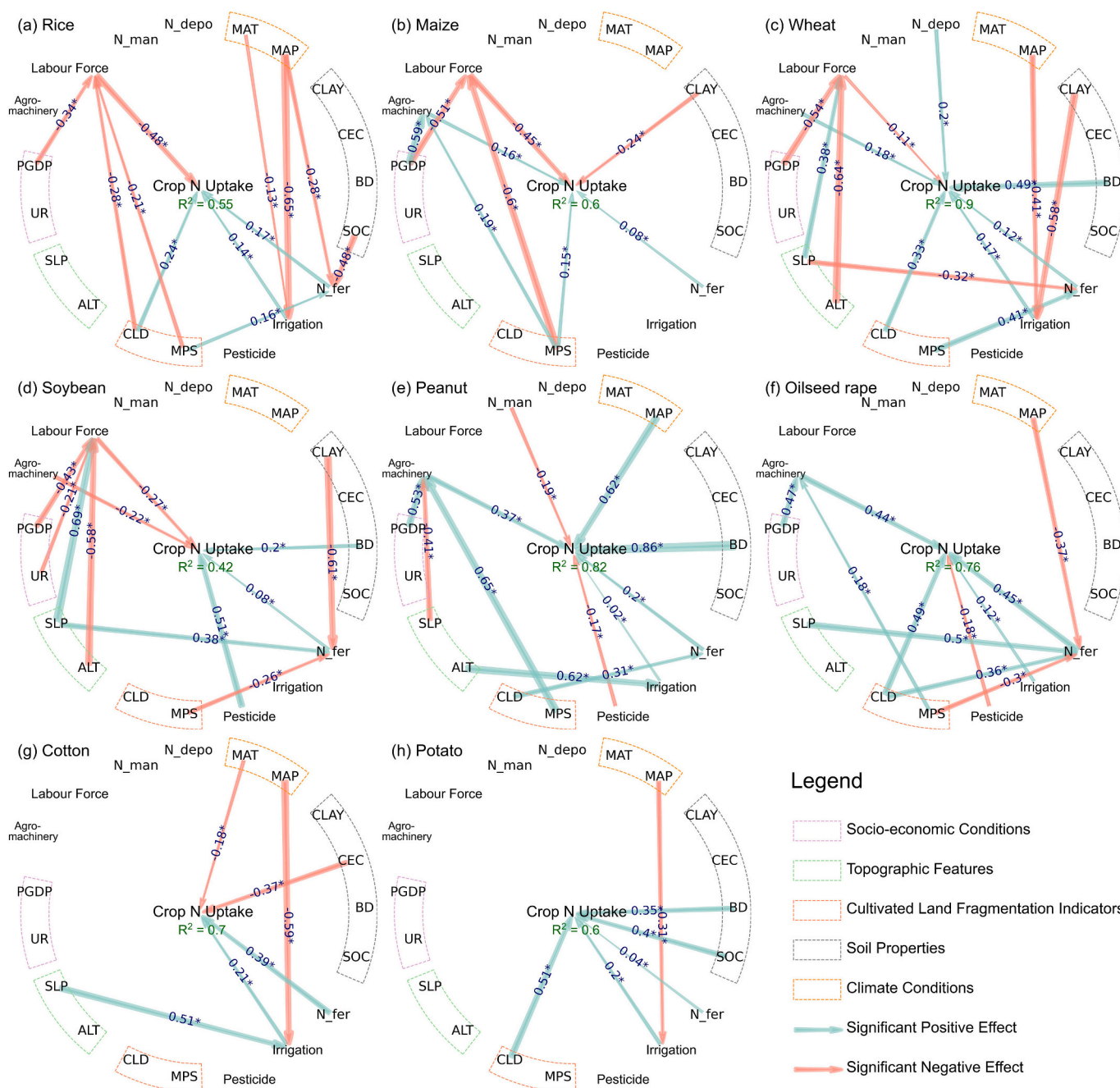


Fig. 3. Path diagrams of SEM results for crop N uptake of the eight major crops, showing the direct effects of farming inputs on crop N uptake, as well as the direct and indirect effects of natural and socio-economic factors on crop N uptake. Nonsignificant paths ($p \geq 0.05$) were omitted. (a–h) represent rice, maize, wheat, soybean, peanut, oilseed rape, cotton, and potato, respectively. PGDP represents per capita GDP. SLP represents slope. ALT represents altitude. MPS represents mean patch size. CLD represents cultivated land density. MAT represents mean annual temperature. MAP represents mean annual precipitation. CLAY represents clay content. CEC represents cation exchange capacity. BD represents bulk density. SOC represents soil organic carbon content.

3.4. Optimization of major crop cropping structures for different scenarios

In scenarios S1–S4, the total sown area decreased by 1850–2200 kha compared with that in the base scenario, mainly due to reductions in the sown areas of wheat, maize, soybean, oilseed rape, and potato (Fig. 5a). The total N surplus decreased by 9–19%, whereas the overall NUE increased to 60–64%, outperforming the base scenario (N surplus: 14e+19 kg N, NUE: 58%) (Fig. 5b). Nationwide coordination of crop profits through transfer payments (S1, S2) achieved greater N surplus reductions than did ensuring non-decreasing provincial profits (S3, S4). The joint optimization of N fertilization and cropping structures (S2, S4) was 1.9–2.0 times more effective in reducing the N surplus and 2.4–2.6

times more effective in improving NUE than the optimization of cropping structure alone (S1, S3). NUE for all major crops increased in the former scenarios (S2, S4), especially for rice, wheat, and oilseed rape (early/late rice and winter wheat, approximately 3%, oilseed rape, approximately 6%) (Fig. 5c–e). These results highlight the strong benefits of optimizing N fertilization. Details of the optimized strategies and crop N uptake per region are presented in Tables S6 and S7.

The cropping structure of major crops was spatially adjusted (Fig. 6). Under scenario S1, rice sown area decreased in parts of Northeast China, the North China Plain, and the southern regions (notably Guangxi, Yunnan, and Anhui) but increased in Heilongjiang, the Yangtze Plain (excluding Anhui), and the Sichuan Basin (especially Hunan and Hubei).

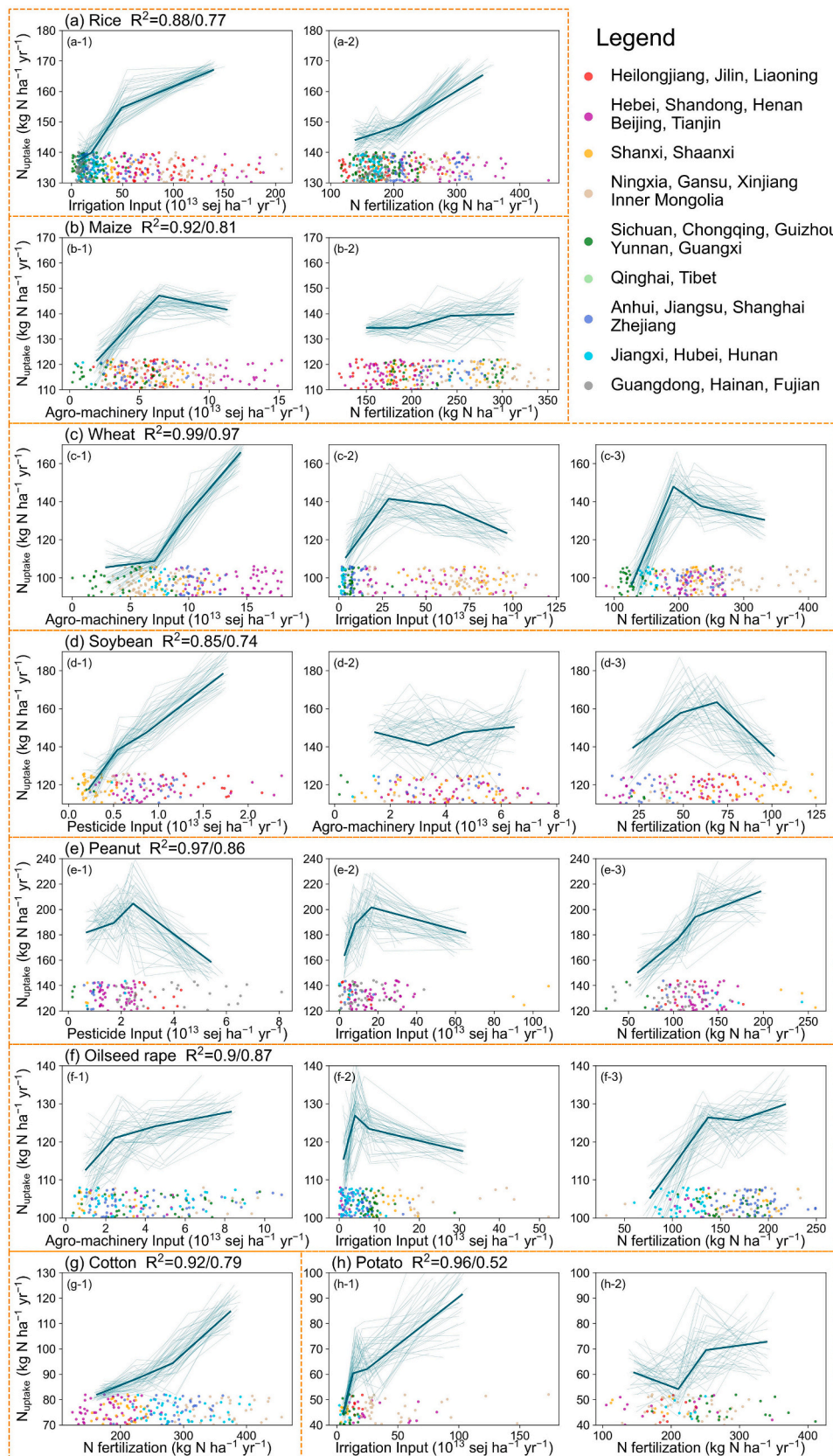


Fig. 4. M-plots based on the crop-specific random forest model showing the response of crop N uptake to certain farming inputs that presented significant path coefficients in the crop-specific SEM analysis for the eight major crops (see Fig. S3 for the full details of the farming inputs). The light-coloured lines represent the results of 50 Monte Carlo simulations. The data points above the X-axis indicate the farming inputs in different regions. (a–h) correspond to rice, maize, wheat, soybean, peanut, oilseed rape, cotton, and potato, respectively. The R-square values represent the training and testing R-square values of each crop-specific model.

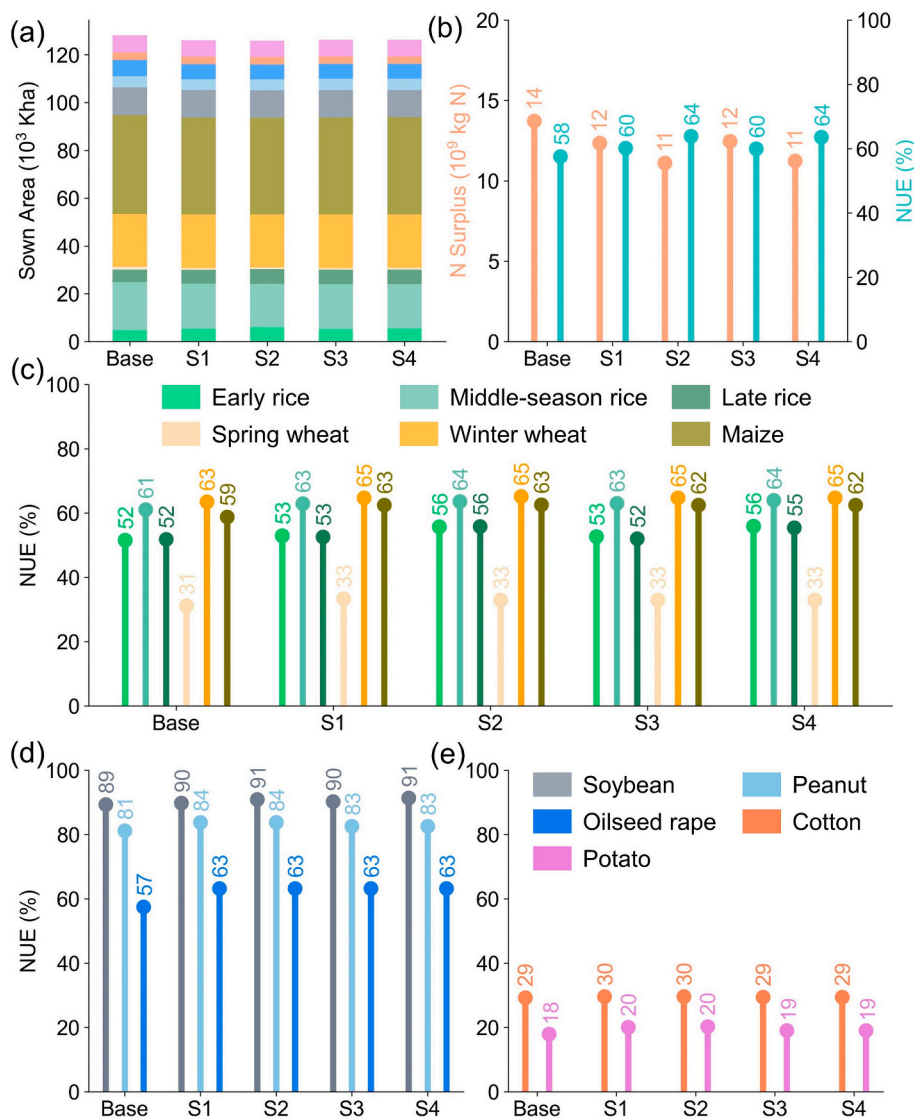


Fig. 5. Changes in N surplus and NUE under multiple optimization scenarios. (a) The total sown area of major crops across China under multiple scenarios. (b) Changes in overall N surplus and NUE in China under multiple scenarios. (c–e) Changes in NUE for crops under multiple scenarios, including staple crops, such as early rice, middle rice, late rice, spring wheat, winter wheat, and maize (c); oil crops, such as soybean, peanut, and oilseed rape (d); and cotton and potato (e).

Wheat sown area fell in Henan and the northwestern regions but grew in Anhui, Hubei, and the North China Plain (excluding Henan). Maize sown area declined in parts of the North China Plain, southwestern regions, and northwestern regions (excluding Xinjiang) (notably Yunnan and Shaanxi) but increased in Anhui, Henan, and Northeast China. Soybean area decreased in Northeast China, shifting to Inner Mongolia, Shanxi, and Jiangsu. Peanut sown area declined in Liaoning, Henan, Sichuan, and part of the Yangtze Plain but increased in Hebei, Shandong, Guangdong, and Guangxi. Oilseed rape and potato planting shifted towards the Sichuan Basin. Xinjiang remained the main cotton producer, with sown area above 2500 kha. Under the scenarios with adjusted N fertilization (S2, S4), rice sown area increased in the southwest regions, as most regions preferred to reduce N fertilization to lower the N surplus, which also led to reduced crop N uptake. Under scenarios ensuring no decrease in provincial profits (S3, S4), changes in crop sown areas became more conservative, as reductions in the sown area of high-profit crops and increases in low-profit crops for each province were restricted.

4. Discussion

4.1. Optimizing farming inputs for staple crops

A high NUE does not necessarily indicate high crop N uptake; it may correspond to low yield and low N fertilization (Xiong et al., 2022). Simply pursuing high NUE may not meet crop yield requirements. This study provides inspiration for exploring more efficient planting systems in China and offers optimized agricultural intensification strategies for major crops.

Rice yield per unit area is low in the main production areas of southern China, and NUE in the southern coastal regions is below the national average. The spatial optimization results suggest that reducing rice cultivation in these regions is appropriate, especially in Hainan, where the province's primary role shifts from grain production to breeding experiments (Zhu, 2016). In the middle Yangtze Plain (e.g., Hubei and Hunan), rice NUE is high, indicating that these areas are well suited to assume a greater share of rice production. In Hunan and Jiangxi, both rice yield per unit area and N fertilization are low, and increasing yield to achieve greater crop N uptake and planting benefits is necessary. A reasonable approach is to moderately increase N

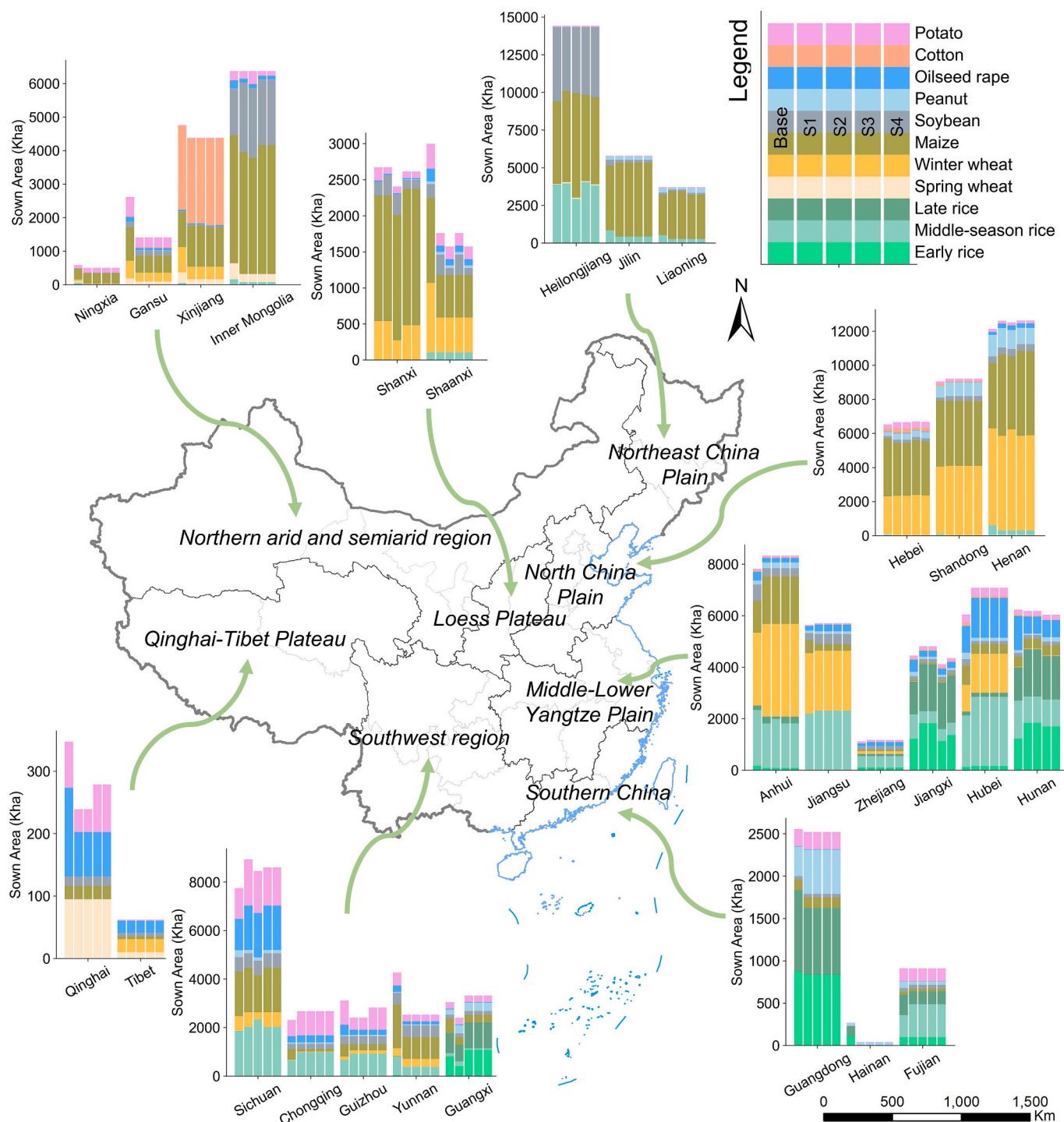


Fig. 6. Changes in the cropping structure of major crops under multiple optimization scenarios. Bar charts show the sown area of major crops in eight regions under multiple scenarios.

fertilization to 200 kg N ha⁻¹ yr⁻¹, which is consistent with the N management strategy recommended for double-cropping rice by Cai et al. (2023). Irrigation is recommended to increase to 50e+13 sej ha⁻¹ yr⁻¹, with reduced labour force input and increased agro-machinery input.

For maize, yield per unit area is greater in Northeast China than in the southwestern regions. The spatial optimization results indicate that the former is suitable for more extensive maize cultivation, whereas the latter should have reduced maize planting. The random forest model reveals that, in the northwestern and southwestern regions, reducing

maize N fertilization to 240 kg N ha⁻¹ yr⁻¹ does not decrease crop N uptake. This result is consistent with field evidence reported by Tang et al. (2022) and would effectively reduce the N surplus. In the North China Plain, maize yield per unit area is lower than that in Northeast China and the northwestern regions (e.g., Ningxia and Xinjiang). Therefore, increasing N fertilization may be considered. Lu et al. (2024) showed that an application rate of 180 kg N ha⁻¹ yr⁻¹ was optimal.

Wheat production and yield per unit area show strong spatial consistency, with high values concentrated in the North China Plain and in the middle and lower Yangtze Plain (e.g., Anhui), where the NUE is also

relatively high. In contrast, wheat NUE and yield per unit area are low in western China. Given the limitations of agricultural irrigation water use in North China, Anhui and Hubei are more suitable for additional wheat cultivation, which is consistent with the environmentally sustainable crop planting optimization strategy proposed by Xie et al. (2023). To ensure production and reduce the N surplus, adjusting the irrigation input to $30e+13 \text{ sej ha}^{-1} \text{ yr}^{-1}$ is suitable for wheat cultivation in the North China Plain. In the southwestern and northwestern regions, increasing agro-machinery input and reduce N fertilization to $200 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ is recommended (Liu et al., 2016).

SEM did not identify a significant path coefficient between precipitation and crop N uptake for staple crops, suggesting that precipitation in the eastern monsoon region is not being fully utilized. Therefore, developing improved rainfed systems is necessary (Zhang et al., 2025).

4.2. Optimizing farming inputs for oil and economic crops

Northeast China is the main soybean-producing region, accounting for more than half of total soybean production. However, its yield per unit area was lower than that of the North China Plain and the middle and lower Yangtze Plain (Di et al., 2023). The spatial optimization results suggest that a slight reduction in soybean sown area in Heilongjiang, with a corresponding shift to Inner Mongolia and Jiangsu, would be appropriate. Increasing soybean production remains a priority

under China's current supply-demand context. Specific optimization strategies include increasing agro-machinery input in Northeast China and adjusting N fertilization to $70 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ (Wu et al., 2020).

Peanut cultivation is mainly concentrated in East China, with major production areas including the North China Plain, Anhui, and Guangdong. Compared with other major production areas, peanut crop N uptake in Guangdong exhibits a greater potential for improvement. The recommended agricultural practices include reducing pesticide input to $2.5e+13 \text{ sej ha}^{-1} \text{ yr}^{-1}$, increasing agro-machinery input, and increasing irrigation input to $20e+13 \text{ sej ha}^{-1} \text{ yr}^{-1}$. For oilseed rape, Sichuan appears more suitable for cultivation, with both high yield per unit area and high NUE. The suitable N fertilization for oilseed rape cultivation is approximately $150 \text{ kg N ha}^{-1} \text{ yr}^{-1}$, and the effectiveness of high N fertilization is relatively low. At the same time, in rice-oilseed rape rotation regions, N fertilization needs to be strictly controlled (Ma et al., 2020). Oilseed rape cultivation also has a relatively high demand for agro-machinery input, so in areas with sufficient resources, more agro-machinery should be used to replace the manual labour force.

Cotton has a relatively high demand for irrigation and N fertilization, and large-scale cultivation in Xinjiang is relatively advantageous. Therefore, in other regions, it is appropriate to moderately reduce the sown area (Baird et al., 2024). Potato production is mainly concentrated in the southwest region, where NUE and yield per unit area are low. The recommended agricultural practices include increasing irrigation input

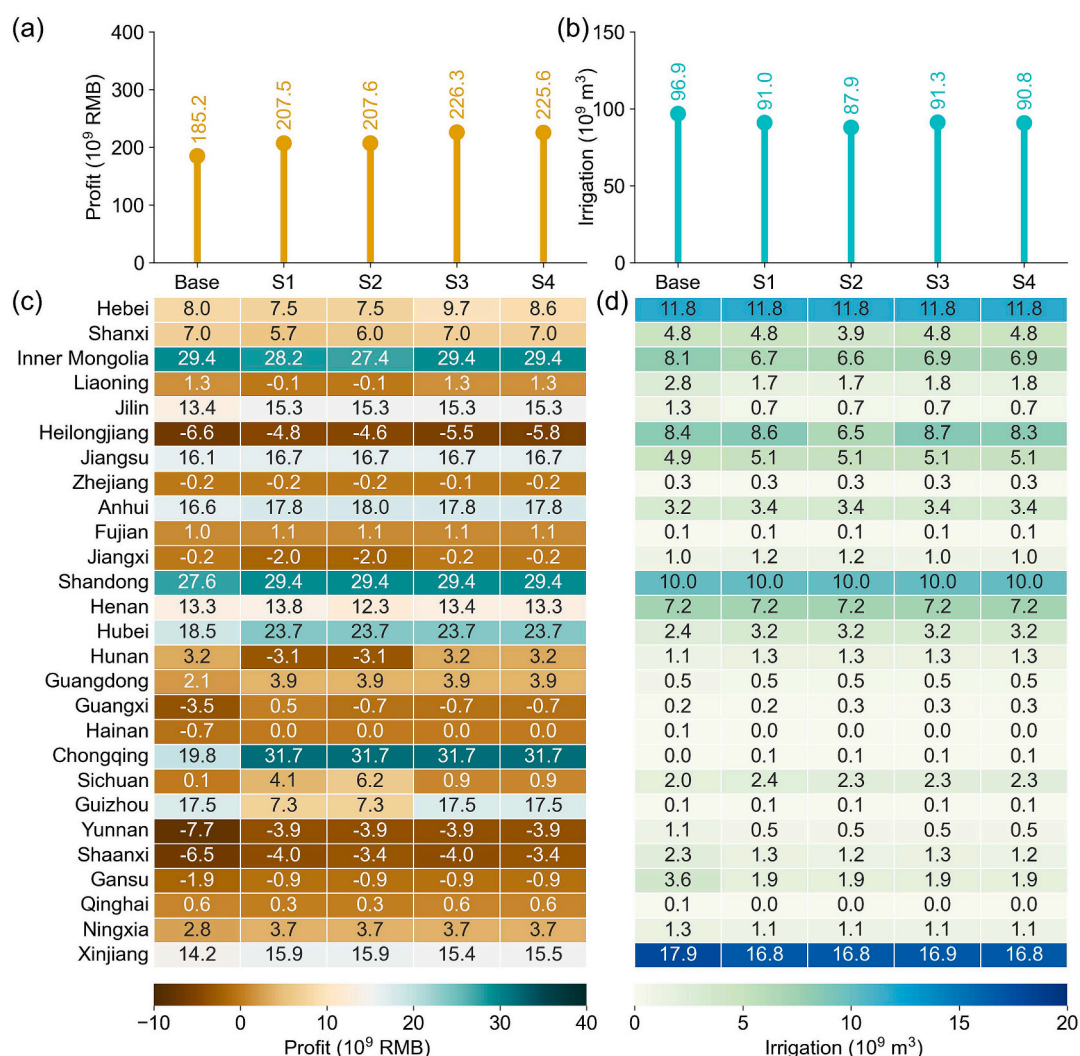


Fig. 7. Changes in farming profit and irrigation water use depending on optimization scenarios (Base, S1-S4). (a-b) Changes in the overall farming profit and irrigation water use under multiple scenarios; (c-d) Changes in the provincial farming profit and irrigation water use under multiple scenarios.

and controlling N fertilization to approximately $250 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ to balance crop N uptake and N surplus.

4.3. Implications of scenario-dependent trade-offs between farming profit and irrigation water use

Optimizing the cropping structure could yield both greater farming profit and reduced irrigation water use (Fig. 7). The total annual profit for the eight major crops rose from $185\text{e}+9$ RMB for the baseline to $208\text{e}+9$ RMB under S1 and S2, with most provinces gaining, especially Hubei, Chongqing, Sichuan, and Yunnan (each up to $3\text{e}+9$ RMB). These gains were due mainly to expanded rice and potato areas and the reduced planting of less profitable crops in Yunnan. Profits fell in Hunan, Jiangxi, Inner Mongolia, and Liaoning due to increases in low-profit crops or shifts from high-profit to low-profit crops. With regional profit safeguards (S3, S4), total profit further increased to $226\text{e}+9$ RMB, with profit stability maintained by limiting sown area shifts.

These patterns imply an important policy-relevant trade-off between national efficiency and local acceptability. When profit is safeguarded at the national level (S1–S2), the model can implement larger interprovincial reallocations to achieve systemwide gains. However, the provincial profit losses observed in several regions indicate that such reallocations may create “winners and losers”, potentially reducing adoption feasibility without compensation. In contrast, scenarios safeguarding non-declining provincial profits (S3–S4) effectively act as an equity constraint, but they can also restrict adjustments by limiting reductions in locally high-profit crops and constraining the expansion of low-profit alternatives. Therefore, if cropping structure adjustment is promoted as an N reduction pathway, it may need to be supported by cross regional compensation and transfer mechanisms (e.g., ecological compensation, targeted subsidies, or benefit sharing arrangements) to align provincial incentives with national environmental objectives.

The irrigation water use decreased by 5.8–9.3% (from $97\text{e}+9 \text{ m}^3$ to $88\text{–}91\text{e}+9 \text{ m}^3$), especially in arid and semiarid regions of North China and the Northeast China Plain. Specifically, rice area expansion increased irrigation demand in Heilongjiang, the middle and lower Yangtze Plain, and the southwest regions. The scenarios with N fertilization optimization (S2, S4) used less irrigation than those without, as more rice was shifted to other regions, such as Guangxi, which has lower irrigation demand. These results suggest that, at the national scale, reallocating cropping areas can be consistent with water-saving goals. However, the provincial signals indicate that local water pressure hotspots may still emerge when irrigated crops expand. Thus, policy design should combine N surplus reduction targets with region-specific water constraints (e.g., groundwater caps, water rights quotas, or differentiated irrigation cost) to avoid shifting environmental burdens across regions. The energy content of staple crops remained stable across the scenarios, ensuring that there was no impact on dietary structure (Table S8).

4.4. Model accuracy and results validation

In previous studies on N use, driving factors and crop N uptake have often been modelled directly, while the complex interactions among these drivers have rarely been investigated. SEM is an effective method for examining causal relationship networks among factors by considering all variables simultaneously. Drawing on prior research, both natural factors and farming inputs were modelled as factors influencing crop N uptake, and path analysis was used to estimate the quantitative relationships by which these drivers affect crop N uptake (Chen et al., 2023; Liu et al., 2022; Liu et al., 2020b). The goodness-of-fit indices indicated good explanatory power of the fitted models (Table S9).

Field-measured NUE data for the eight major crops were obtained from published papers, all of which met the local requirements for common growth conditions and fertilization levels (see Table S10 for details). A paired-sample *t*-test was used to compare the results of this

study with those from the field sampling, as shown in Fig. S4. The *t* statistic was -0.29 and the *p* value was 0.77 , indicating that there was no significant difference between the means of this study and the field data. This suggests that estimations at the regional scale provide valuable references for guiding decision-making at finer spatial scales.

4.5. Strengths, limitations and uncertainties of the integrated framework

This study integrates (i) provincial N flows assessment to quantify crop-specific N inputs, crop N uptake, N surplus and NUE; (ii) SEM and RF models to diagnose dominant correlates of crop N uptake and capture potentially non-linear input–uptake responses; and (iii) scenario-based optimization to explore feasible pathways for reducing N surplus while meeting food security, farming profit and irrigation water use constraints. Compared with studies that only report N budgets and NUE, the integrated “assessment–diagnosis–optimization” framework helps translate spatiotemporal patterns into actionable levers. Compared with regional optimization only approaches using fixed coefficients without an explicit diagnosis step, coupling SEM and RF models with optimization provides data-driven evidence on which inputs matter most and where diminishing returns may occur, thereby supporting crop- and region-specific prioritization.

Despite these strengths, several limitations and uncertainties should be noted. First, the SEM and RF analyses rely on observational data. Therefore, the SEM path coefficients should be interpreted as associations conditional on the specified SEM structure and the analysed dataset, rather than definitive causal effects. In addition, RF marginal plots summarize empirical response patterns from the available samples; they may not fully represent management heterogeneity, measurement errors, or interactions not captured by the selected predictors. The fitted models also do not fully explain the variance in crop N uptake, indicating that unmeasured factors (e.g., cultivar changes, soil management, extreme events, and within-province agronomic heterogeneity) may contribute to residual uncertainty.

Second, scale and parameterization constrain the interpretation and implementation relevance of the scenario optimization. The provincial scale is relatively coarse and therefore insufficient for designing detailed within-province cropping plans, and it cannot explicitly represent sub-provincial water availability, farm level constraints, or adoption costs that may limit real world reallocations (Wei et al., 2023). Moreover, uncertainty in regional N flows estimation remains non-negligible (Liu et al., 2023b). Specifically, N fertilization and crop N uptake for each crop have high confidence, as they have been reported to be consistent nationwide (Liu et al., 2020a). The biological N fixation rates used in this study were estimated according to legume crop type, and according to He et al. (2018), confidence in biological N fixation should be considered moderate. N deposition estimates have particularly high relative uncertainties. Because N deposition contributes little to the overall N budget, its impact on the total uncertainty is also limited (Jiang et al., 2024b). The uncertainty in estimates of manure N input in China is high. This study adopted the parameters from Yan et al. (2014), which have been widely used in previous studies (Ludemann et al., 2022; Zhang et al., 2023). Owing to the lack of data on manure application rates for crops, it was assumed that the amount of manure applied to each crop within a province was equal, resulting in greater uncertainty.

Third, the optimization results should be interpreted as scenario-based outcomes conditional on the adopted profit accounting and irrigation coefficients. Prices, costs and irrigation requirements can vary across years and management systems. Thus, the magnitude of estimated farming profit and irrigation water use trade-offs may shift under alternative economic or hydrological conditions.

Future work could strengthen this framework by extending it to finer spatial scales (county/field/farm), incorporating farm surveys to better allocate manure application and biological N fixation by crop, improving parameterization under diverse cropping systems, and using

additional field experiments to constrain key N loss processes (e.g., ammonia volatilization, nitrate leaching, and runoff). Introducing dynamic price scenarios and explicit regional water-availability constraints would further improve robustness and policy relevance of the integrated profit–water–N assessments.

5. Conclusions

To explore appropriate agricultural intensification strategies and cropping structures at the regional scale in China, the spatiotemporal variations in provincial NUE and yield per unit area for eight major crops (rice, maize, wheat, soybean, peanut, oilseed rape, cotton, and potato) from 2004 to 2020 were evaluated. Structural equation modeling and random forest models were used to analyse the multiple effects of natural and socio-economic factors and farming inputs on crop N uptake. Optimization models were used to increase the NUE and reduce the N surplus across mainland China by optimizing N fertilization and adjusting the cropping structure under multiple scenarios (ensuring food security, maintaining stable farming profit, and limiting irrigation water use).

The NUE of the eight major crops tend to increase from 2004 to 2020. The NUE of soybean and peanut ranged from 70 to 90%, whereas that of staple crops and oilseed rape fell between 40% and 60%. For cotton and potato, the NUE was 20–30% and 15–20%, respectively. There was a contradiction that regions with high yield per unit area did not necessarily have high total production because of constraints from sown area allocation, unrealized regional yield potential and N surplus risk.

Increased mechanization, reduced cultivated land fragmentation, and N fertilization and irrigation increased crop N uptake, while excessive pesticide use and adverse soil or climatic conditions could limit it. Crop N uptake had a clear saturation level for farming inputs: for wheat, soybean, oilseed rape, and potato, N fertilization above 200, 70, 150, and 210 kg N ha⁻¹ yr⁻¹, respectively, did not further increase N uptake and may even reduce it. Similar saturation or diminishing effects were observed for inputs of pesticides, agro-machinery, and irrigation.

Under various optimization scenarios, the N surplus decreased by 9.2–19%, and the overall NUE increased by 2.3–6.2%. Nationwide coordination of crop profits through transfer payments and optimizing N fertilization could achieve higher NUE and lower N surplus, resulting in approximately twice as many benefits.

Spatially, it was optimal for the middle Yangtze Plain to assume greater responsibility for rice cultivation. The northwest region was suitable for reducing wheat and maize cultivation and shifting the crop area to Anhui and the North China Plain. Peanut cultivation was more suitable in Hebei, Shandong, Guangdong, and Guangxi. The planting centres for oilseed rape and potato were suitable for shifting towards the Sichuan Basin. Adjustments to cropping structure could also reduce irrigation water use by 5.8–9.3%, especially in the northern arid and semiarid regions of China.

CRedit authorship contribution statement

Jiayi Jiang: Writing – original draft, Visualization, Methodology, Data curation. **Changqing Song:** Supervision, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Leina Zhang:** Resources, Investigation, Data curation. **Peichao Gao:** Project administration, Methodology, Formal analysis. **Sijing Ye:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Yakov Kuznyakov:** Writing – review & editing, Methodology.

Declaration of competing interest

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.

Acknowledgments

This research was funded by National Natural Science Foundation of China [Grant No. 42171250, 42230106, 42271418]. We would like to thank the high-performance computing support from the Center for Geodata and Analysis, Faculty of Geographical Science, Beijing Normal University, and the RUDN University Strategic Academic Leadership Program.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.agsy.2026.104729>.

Data availability

Data will be made available on request.

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