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Considering spatial heterogeneity of cultivation conditions can effectively improve the assessment of nitrogen use at the provincial scale in China

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A B S T R A C T

Improving nitrogen (N) management are crucial for food security and ecological protection in China and globally. Assessing the contribution and influence characteristics of N input components on crop growth is a key component. There are challenges in conducting such assessments at large regional scales, particularly in developing models that fit regional N inputs and crop N uptake. An improved scheme that fit regional N inputs and crop N uptake with consideration of spatial heterogeneity of cultivation conditions was proposed. Based on the division of homogeneous cultivation conditions zones, linear models and Random Forest models were developed to assess the contribution and influence characteristics of N input components on crop growth at the provincial scale in mainland China. And synthetic N contribution rate (SNCR) and soil fertility N contribution (SFNC) were innovatively proposed to represent the contribution of fertilizer and soil fertility to crop growth. The results showed that the overall N use efficiency ranged from 35 % to 55 % in 1985–2020, and higher NUE could be seen in major grain producing provinces. The SNCR generally declined, with a spatial pattern higher in the southwest, northwest, and northeast regions. The SFNC showed an increasing trend, with a spatial pattern higher in the northeast than southeast than west. For each N input component, Synthetic N input was critical in the northwest, southwest regions and north China, positively affecting crop N uptake. The improved scheme, which incorporated considerations for spatial heterogeneity, demonstrated superior accuracy compared to the model fitted by year, increasing from 0.27 (0.11) to 0.42 (0.47). Over the past 35 years, the crop N uptake and N surplus of mainland China had experienced a process of extensive-unsustainable-sustainable-conservative pattern changes. The response of crop N uptake and N use efficiency to the regulation of N inputs in typical regions was simulated, providing reference for provincial N inputs regulation in China. This study can provide support for the design of N management strategies in China to reduce N pollution, and the method can provide guidance for other regions to assess N use in different scales.

1. Introduction

Food security is a global challenge closely related to the sustainable development of the human world (Chen et al., 2022; Willett et al., 2019). It is expected that by 2050, the global population will rise to 9 billion, and the demand for global crop production is expected to increase by about 50–60 % (Falcon et al., 2022). Over the past half-century, initiatives to fill the gap in food demand, such as expanding cultivated land, intensifying agrochemical use, and promoting high-intensity farming practices, have worsened the degradation of agroecosystems in numerous countries, particularly in developing countries (Gong et al., 2023; Huang et al., 2021; Yin et al., 2022). This has resulted in problems like soil erosion, waterlogging, acidification, and decreased organic matter content, endangering soil fauna and microbial communities, which poses a huge risk to future food security (Ren et al., 2022; Ye et al., 2022a; Ye et al., 2020). Exploring regionally appropriate paths for sustainable intensive agricultural use, i.e., using limited cultivated land to meet the growing demand for food while reducing environmental risks and protecting the stability of cultivated land and other ecosystems, has become an important challenge that needs to be urgently addressed (Du et al., 2024; Ren et al., 2023; Ye et al., 2024b).

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Efficient use of nitrogen (N) fertilizer is one of the central aspects of achieving sustainable intensification of agriculture (Yin et al., 2019). In 2020, total global crop N use reached 113 Tg, providing more than half of the world's population with the nutrients they need to survive (FAO, 2023). However, there are large differences in N use efficiency (NUE, i.e. the ratio of N uptake of crop harvests and residues to N inputs) in different countries (Yan et al., 2022; Zhang et al., 2015). In 2010, NUE in developed regions such as the USA and Europe were in the range of 50–70 %, whereas in developing countries such as China and India, NUE only reached 25–30 % (Zhang et al., 2015). Blindly increasing N fertilizer input under low NUE may not improve crop yields (Ju et al., 2004; Tilman et al., 2002). At the same time, excessive N inputs can exacerbate a number of environmental problems, including greenhouse gas emissions, water eutrophication and soil acidification (Bouwman et al., 2002; Domingo et al., 2021; Galloway et al., 2003).

As a country with less than 40 % of the world's average per capita cultivated land, China has long been responsible for high food production with 9 % of the world's cultivated land feeding nearly 20 % of the population, and has demonstrated a high reliance on N fertilizer input (Chen et al., 2016; Jin et al., 2024; Wu et al., 2018; Ye et al., 2022a). As the absolute mainstay of China's agricultural business, smallholders are limited by their own technological and cultural level and scale of operation, making it difficult for them to achieve the goal of "reduced fertilizer inputs increase yields" through improved farming techniques, and tend to over-fertilize to reduce the risk of yield loss in the farming process (Lowder et al., 2016; Wu et al., 2018; Yin et al., 2021). N consumption in Chinese agriculture has increased rapidly since the 1980 s (Gu et al., 2015). In 2020, as the world's largest N consumer, China's agricultural use of N amounted to 25 Tg, which accounted for 22.1 % of the global N consumption, showing high potential for NUE improvement (FAO, 2023). Therefore, taking China as an example, cognizant of the change process of N inputs and its impact on N output is important for optimizing the level of agricultural N management in China and thus reducing the negative impacts of excessive N inputs on global biodiversity and climate change (Cui et al., 2018).

The study of N use in agricultural systems requires the calculation of N flow (including N inputs and crop N uptake). At different scales, N inputs (fertilizer, manure, biologically fixed N, and N deposition) and crop N uptake are calculated in different ways (Howarth et al., 1996; Yang et al., 2007). On the one hand, at the field or farm scale, the specific N input and crop N uptake of a particular piece of cropland at a specific location with the amount of N contained in the soil can be accurately determined (Cui et al., 2011; Zhao et al., 2016). However, due to the high cost of equipment use and labor time, the study could not be carried out in a large region, and the results obtained were very limited (Liu et al., 2023b). On the other hand, in N use assessment studies conducted at regional or global scales, N inputs and crop N uptake are usually calculated from statistical yearbook data, which increases the uncertainty of the calculated results (He et al., 2018; Liu et al., 2020b; Zhang et al., 2015). For a large region such as China, the provincial scale is an appropriate scale to study N use on cultivated land. This is because at the provincial scale, the statistical yearbook data of provincial units released by the government administration are more detailed and accurate than the statistical yearbook data of municipalities or counties, and provinces in China often have the same fertilizer management policies within their borders (Liu et al., 2020a; Liu et al., 2023b; Liu et al., 2022b; Yan et al., 2014; Yan et al., 2022).

Currently, research on N use in agroecosystems can be divided into two main aspects: N use assessment and interpretation of indicators of NUE. Partial factor productivity (i.e., the ratio of crop yield to N inputs), partial nutrient balance (i.e., the ratio of crop N content to N inputs) and other indices were proposed in order to assess NUE by correlating the N output with N inputs (Cassman et al., 1998; Zhang et al., 2015). Recovery efficiency (i.e., the difference in crop N uptake between plots with and without fertilization divided by fertilizer N input) was proposed for assessing fertilizer use efficiency (Cassman et al., 2002; Yan et al., 2014). N surplus was proposed for the assessment of N pollution or N loss (Luo et al., 2018; Poore and Nemecek, 2018). For instance, Zhang et al. (2015) calculated the NUE of crop production in various regions of the world and found a pattern between N surplus and N inputs similar to an environmental Kuznets curve, which was a landmark study. He et al. (2018) assessed the temporal and spatial variation patterns of soil N balance and NUE in Chinese farmland from 1984 to 2014 based on the soil system N balance model and quantified each N input and output component, which was very informative for future studies. Yan et al. (2014) analyzed the recovery efficiency of synthetic N with and without considering the N residual effect by establishing a linear model of synthetic (total) N input and N output in each province of China, which was very inspiring for the study of N fertilizer use in China. Based on Yan's study, Yan et al. (2022) analyzed the temporal and spatial changes in NUE and cumulative synthetic and non-synthetic N fertilizer recovery efficiency of crop production in China during 1980–2014. Yan's method was innovative in calculating recovery efficiency at regional scales where it was difficult to set up a control group, and it helped to assess the use efficiency of synthetic N and the contribution of different N input from N sources to crop growth. However, in Yan's process of building a linear model to solve for recovery efficiency, data on annual N input per unit area and annual crop N uptake per unit area for 31 provinces in China for the same year were input as fitting samples. This implementation assumes all N sources other than synthetic N for crops in different provinces and crop N uptake from the soil as constants, ignoring the spatial heterogeneity of natural-socio-economic conditions in different regions. This drawback makes the method applicable only in small study areas with similar natural-socio-economic conditions and not suitable for provincial scale studies.

Regarding the interpretation of NUE indicators, most of the existing studies were modeled by deriving empirical relationships between NUE indicators and explanatory variables. Socio-economic variables, agricultural management practices, and natural attributes were chosen as explanatory variables, and together with NUE indicators, they were directly modeled using multiple linear regression, random forests, and other methods to explain changes in the NUE indicators (Li et al., 2020; Liu et al., 2020b)。For instance, Liu et al. (2020) used a stepwise multiple linear regression model to model partial factor productivity and partial nutrient balance at the provincial scale in China, and found that crop type, temperature, and soil properties were important variables in determining NUE, i.e., more soybeans, lower temperatures, and more soil carbon and sulfur had a positive effect on NUE. Li et al. (2020) modeled maize NUE using a random forest model based on a *meta*-analysis of global field observations and found that an increase in mean annual temperature was the most critical factor contributing to a decrease in NUE. Liu et al. (2022) used stepwise multiple linear regression and random forests to model county-scale partial factor productivity and partial nutrient balance in northeastern China, and found that vegetable and legume acreage indices, soil clay content, saturated water content, vegetation index in November and December, soil capacity and annual minimum temperature were the main explanatory variables for both indicators. The results obtained from these explanatory models demonstrate how NUE indicators correlate and respond to various environmental and socio-economic variables. However, the above studies have somewhat confused the indirect effects of natural-socio-economic factors on NUE and the direct effects of different types of N inputs on NUE. In the N process of the agroecosystem, variables such as natural attributes, socio-economics and agricultural management practices indirectly affect crop N uptake and thus NUE by influencing N inputs and soil N processes. Studying the direct effects of various types of N inputs on crop N uptake at the regional scale, and then simulating the response of crop N uptake and NUE to the regulation of N inputs, can provide decision support for regional fertilizer use regulation programs.

The above studies provide important inspiration and guidance for this study. The core objectives of this paper are (1) to propose a calculation method suitable for assessing synthetic N contribution rate and soil fertility N contribution at the regional scale, and to use this method to assess the N use status in mainland China; (2) to analyze the characteristics of the regional driving effect of the different N input components on the crop N uptake, and then to simulate the response of crop N uptake and NUE to the regulation of N inputs. To achieve these targets, first, the spatial and temporal characteristics of NUE in mainland China from 1985 to 2020 were analyzed. Second, the authors improved the method proposed by Yan et al. (2014). In the improved scheme, the K-means method and the subjective discriminant method were combined to divide the provincial units into several homogeneous cultivation conditions zones, with considering indicators such as the level of agricultural intensification, agricultural economic income, terrain characteristics, soil properties, farm scale, etc. Then, for each homogeneous zone, the annual N input and crop N uptake for the five adjacent years of the provinces contained in the zone were input as samples into linear models to fit to calculate its synthetic N contribution rate and soil fertility N contribution for a specific year. By applying this improved scheme, the spatial and temporal variations of synthetic N contribution rate and soil fertility N contribution of provincial units in mainland China from 1985 to 2020 were analyzed. Third, the Random Forest method was applied to analyze the characteristics of the effects of different components of N input on crop N uptake and their spatial variability. In the Discussion section, the improved scheme was validated to exhibit higher explanatory power than the Yan's scheme in fitting the linear relationship between N input and crop N uptake, and thus is more suitable for evaluating the regional scale synthetic N contribution rate with soil fertility N contribution. In addition, the provincial development patterns of N use from 1985 to 2020 were discussed. For typical regions, the response of crop N uptake and NUE to the regulation of N inputs were simulated and analyzed. This study can provide support for the design of N management strategies in China. The research methodology of this paper can also provide a reference for other countries to explore the path of NUE improvement.

2. Materials and methods

2.1. Data

In this study, 3 kinds of datasets are used to divide homogeneous cultivation conditions zones and estimate N inputs and crop N uptake. First, the provincial average cultivated land quality indicators dataset and the annual provincial agricultural intensification indicators dataset were used to divide homogeneous cultivation conditions zones. The provincial average cultivated land quality indicators dataset covered indicators such as slope, soil organic carbon content, mean patch size, cultivated land density, area-weighted mean shape index. The annual provincial agricultural intensification indicators dataset covered indicators such as farming input quantity of pesticides (unit: metric ton), fertilizer (unit: metric ton), agricultural diesel (unit: metric ton), labor force (unit: metric capita) and irrigation area proportion, agricultural output value (unit: RMB), income of rural residents (unit: RMB). Secondly, annual provincial rural population and livestock quantity dataset, annual provincial crop sown area dataset and annual regional N deposition rate dataset were used to calculate annual provincial N inputs. Annual fertilizer input in the annual provincial agricultural intensification indicators dataset were used to calculate synthetic N input. The annual provincial rural population and livestock quantity dataset covers annual total rural population and the number of livestock in mainland China, and was used to calculate manure N input. The annual provincial crop sown area dataset covered the annual provincial sown area (unit: ha.) of all major crop types in mainland China, which can be used to calculate crop N fixation. The annual regional N deposition rate dataset was referenced from Liu et al. (2013), where the fitted model was used to calculate the annual N deposition rate for each year in each region. Thirdly, the annual provincial crop production dataset was used to calculate crop N uptake, which covered the annual provincial production (unit: metric ton) of all major crop types in mainland China, same as the annual provincial sown area dataset. All data missing values above were interpolated using data from adjacent years. Table 1 shows the detailed dataset information.

Table 1
Detailed dataset information related to the division of homogeneous cultivation conditions zones and the estimation of N inputs and crop N uptake.

Dataset	Indicators	Data source	Applications
Annual provincial agricultural intensification indicators of China	Farming input quantity of pesticides (unit: metric ton); chemical fertilizer (unit: metric ton); agricultural diesel (unit: metric ton); labor force (unit: metric capita); irrigation area proportion; agricultural output value (unit: RMB); income of rural residents (unit: RMB)	China rural statistical yearbook	(Liu et al., 2020b; Ye et al., 2022a)
Provincial average cultivated land quality indicators of China	Slope (unit: degree); soil organic carbon content (unit: g kg^{-1}); mean patch size (unit: ha); cultivated land density (unit: ha); area-weighted mean shape index	ASTER GDEMV3; Liu et al., 2022; Ye et al., 2022a; Ye et al., 2022b; Ye et al., 2024	(Abrams et al., 2022; Liu et al., 2023a; Liu et al., 2022a; Ye et al., 2022a; Ye et al., 2024a; Ye et al., 2022b)
Annual provincial rural population and livestock quantity of China	Annual provincial total rural population and number of livestock, including cattle; pigs; cows; sheep; horses; mules and donkeys	China rural statistical yearbook	(Yan et al., 2014; Yan et al., 2022; Ye et al., 2023)
Annual provincial crop sown area of China	Annual provincial sown area of crop i (unit: ha.), including rice; maize; wheat; soybean; potatoes; peanut; oil rape; sesame; cotton; sugarcane; beet; tobacco; vegetable; fiber; fruit and tea	China rural statistical yearbook	(Yan et al., 2022; Zhang et al., 2015)
Annual provincial crop production of China	Annual provincial production of multiple types of crop i (unit: metric ton), including rice; maize; wheat; soybean; potatoes; peanut; oil rape; sesame; cotton; sugarcane; beet; tobacco; vegetable; fiber; fruit and tea	China rural statistical yearbook	(Yan et al., 2022; Zhang et al., 2015)
Annual regional N deposition rate of China	Annual provincial N deposition rate (unit: kg N ha^{-1} yr^{-1})	Liu et al., 2013	(Liu et al., 2013)

2.2. Soil N process model

As shown in Fig. 1, the soil N process model was established based on soil N balance, including N inputs, crop N uptake, N surplus, and soil N cycle (Oenema et al., 2003). Table 2 showed the detailed calculation equation for each N input component and crop N uptake. The specific parameters could be found in the Appendix (Table S1-S4). NUE was calculated as the ratio of N uptake (i.e., N_{uptake}) to total N input (i.e., N_{input}), as shown in Eq. (1). N surplus (i.e., N_{sur}) is calculated as the difference between N inputs and crop N uptake, as shown in Eq. (2). N_{sur} was regarded as a useful indicator of potential losses of N to the environment from agricultural soils, including N_2, N_2O, NO emissions and ammonia volatilization (NH_3) and NO_3^- leaching and runoff and N recycling within the soil.

$$NUE = \frac{N_{uptake}}{N_{input}} \tag{1}$$

$$N_{sur} = N_{input} - N_{uptake} \tag{2}$$

2.3. Evaluating the contribution of synthetic N input and soil fertility N to crop N uptake based on linear models

Yan et al. (2014) assessed the recovery efficiency of synthetic N and the contribution of soil N to crop N uptake by establishing linear equations, as shown in Eq. (3) and Eq. (4). N_{syn} represents the annual provincial synthetic N input per unit area (unit: kg N ha^{-1} yr^{-1}); N_{input} represents the annual provincial total N input per unit area (unit: kg N ha^{-1} yr^{-1}); N_{uptake} represents the annual provincial crop N uptake per unit area (unit: kg N ha^{-1} yr^{-1}); a_1 and a_2 are parameters obtained from linear fitting, expressing the effects of synthetic N and total N input on crop N uptake, respectively; b_1 represents the N absorbed by crops from all N sources other than synthetic N (including manure N input, biological N fixation, N deposition, soil fertility N); b_2 represents the N absorbed by crops from the soil (SFNC, Soil Fertility N Contribution). A higher a_1 indicates that more of the synthetic N input in the current year is used.

$$N_{uptake} = a_1 \times N_{syn} + b_1 \tag{3}$$

$$N_{uptake} = a_2 \times N_{input} + b_2 \tag{4}$$

According to the scheme by Yan et al. (2014), for a specific year, the N_{syn}, N_{input} and N_{uptake} of all provinces in mainland China were used as sample input to fit linear equations and calculate the constant terms b_1 and b_2. However, this scheme is inappropriate because it overlooks the spatial heterogeneity characteristics of b_1 (or b_2). This spatial heterogeneity is mainly caused by differences in regional natural-socio-economic conditions (including the level of agricultural intensification, agricultural economic income, terrain characteristics, soil properties, farm scale, etc.). Provinces with approximate natural-socio-economic conditions, or the same region in adjacent years, are more likely to have similar b_1 (or b_2).

In this study, the authors improved the implementation scheme of

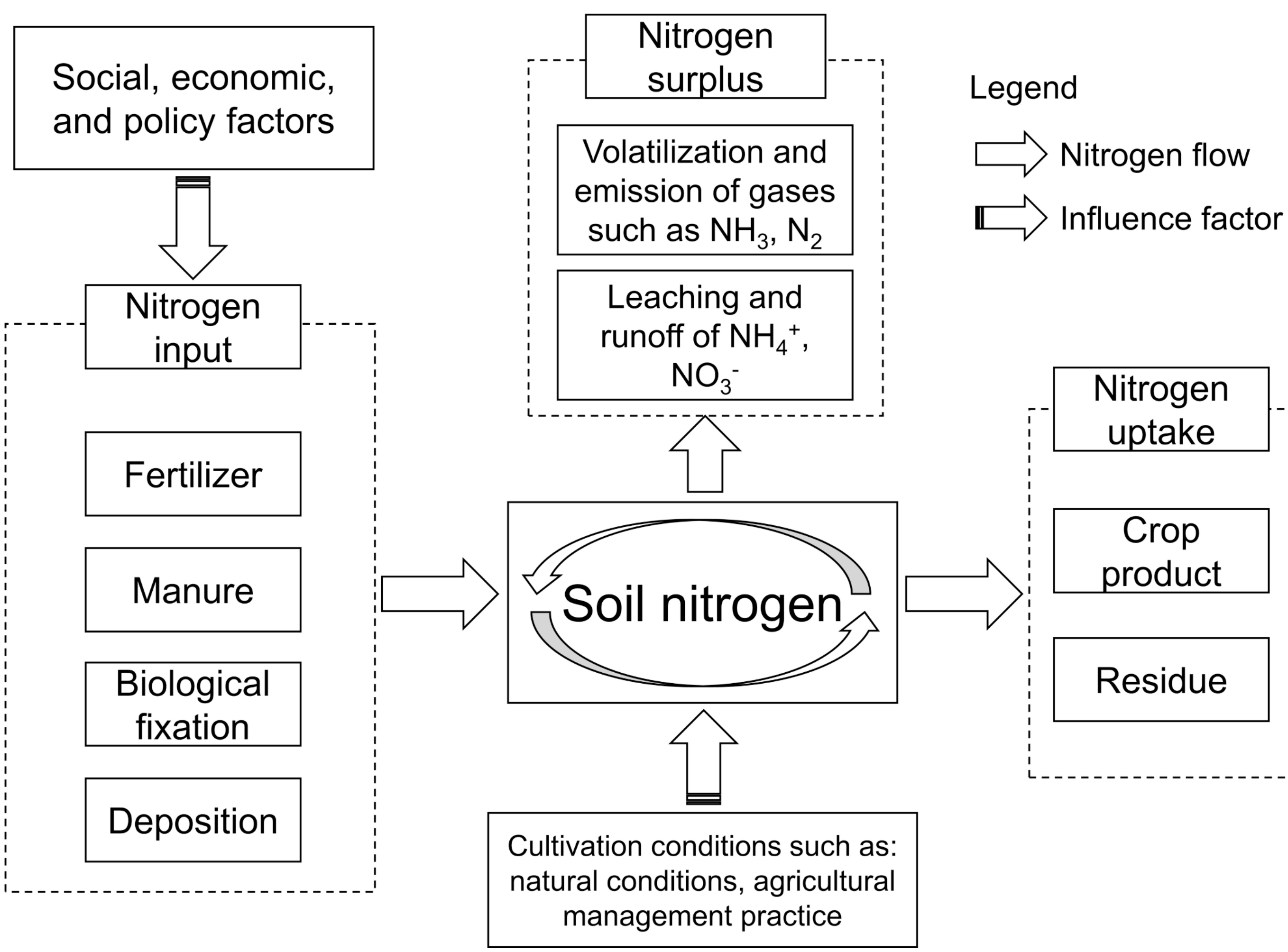


Fig. 1. Soil N process model. Social, economic, and policy factors affect N inputs. Cultivation conditions such as natural conditions and agricultural management practices affect the soil N process in agroecosystem.

Table 2
Calculation of N input components and crop N uptake.

Indicators	Description	Equations	Parameters descriptions
N_{syn}	Synthetic fertilizer N input per unit area	$N_{syn} = (N_{fert\_N} - N_{fert_{com}} \times R)/Area$	N_{fert_N} and N_{fert_com} are the total chemical fertilizer amount of single and compound, respectively. R is the N ratio of compound fertilizer. $Area$ is the sown area (unit: ha.).
N_{man}	Manure N input per unit area	$N_{man} = \sum_j (Num_j \times NE_j \times MR_j)/Area$	Num_j is the number of humans and livestock. NE_j is the amount of N content in excretion and urine in different humans and livestock (unit: kg N ha^{-1} yr^{-1}). MR_j is the returning field rate.
N_{fix}	Biological N fixation input per unit area	$N_{fix} = \sum_i (Area_i \times FR_i)/Area$	$Area_i$ is the sown area of crop (unit: ha.). FR_i is the amount of biological N fixation from different symbiotic and non-symbiotic crop (unit: kg N ha^{-1} yr^{-1}).
N_{depo}	N deposition input per unit area	$N_{depo} = DR$	DR is the amount of N content from atmospheric deposition (unit: kg N ha^{-1} yr^{-1}).
N_{input}	Total N input per unit area	$N_{input} = N_{syn} + N_{man} + N_{fix} + N_{depo}$	
N_{uptake}	Crop N uptake per unit area	$N_{uptake} = \sum_k (yield_k \times NC_k + yield_k \times RR_k \times NR_k)/Area$	$yield_k$ is the yield of crop. RR_k is the ratio of residue to crop product. NC_k and NR_k are the amount of N content in crop product and residue, respectively.

Yan et al. (2014). The 31 provinces in mainland China were divided into 10 homogeneous cultivation conditions zones based on indicators such as the level of agricultural intensification, agricultural economic income, terrain characteristics, soil properties, and farm scale. For each homogeneous cultivation conditions zone, a sliding time window spanning adjacent five years with a step length of one year was established. For a specific time window of a homogeneous cultivation conditions zone (e.g., t_0, $t_0 + 1$, $t_0 + 2$, $t_0 + 3$, $t_0 + 4$), the annual provincial N_{syn}, N_{input} and N_{uptake} from the corresponding years of provinces were used as sample input to fit linear equations and calculate the constants b_1 and b_2. Certain years might belong to multiple time windows simultaneously, and the corresponding constants b_1 and b_2 were averaged across the time windows. Subsequently, for a specific year and province, the synthetic N contribution rate ($SNCR$) was calculated by combining its N_{syn}, N_{uptake} and b_1 values, as shown in Eq. (5), where $SNCR$ represents the synthetic N contribution rate. A higher $SNCR$ indicates that more of the synthetic N input in that year is used for crop growth.

$$SNCR = \frac{N_{uptake} - b_1}{N_{syn}} \quad (5)$$

2.4. Division of homogeneous cultivation conditions zones

Based on the evaluation method proposed in this study for assessing the contributions of synthetic N and soil N to N uptake, the first step is to divide the provincial units of mainland China into several homogeneous cultivation conditions zones, considering indicators such as the level of agricultural intensification, agricultural economic income, terrain characteristics, soil properties, and farm scale. The specific steps for this division are as follows:

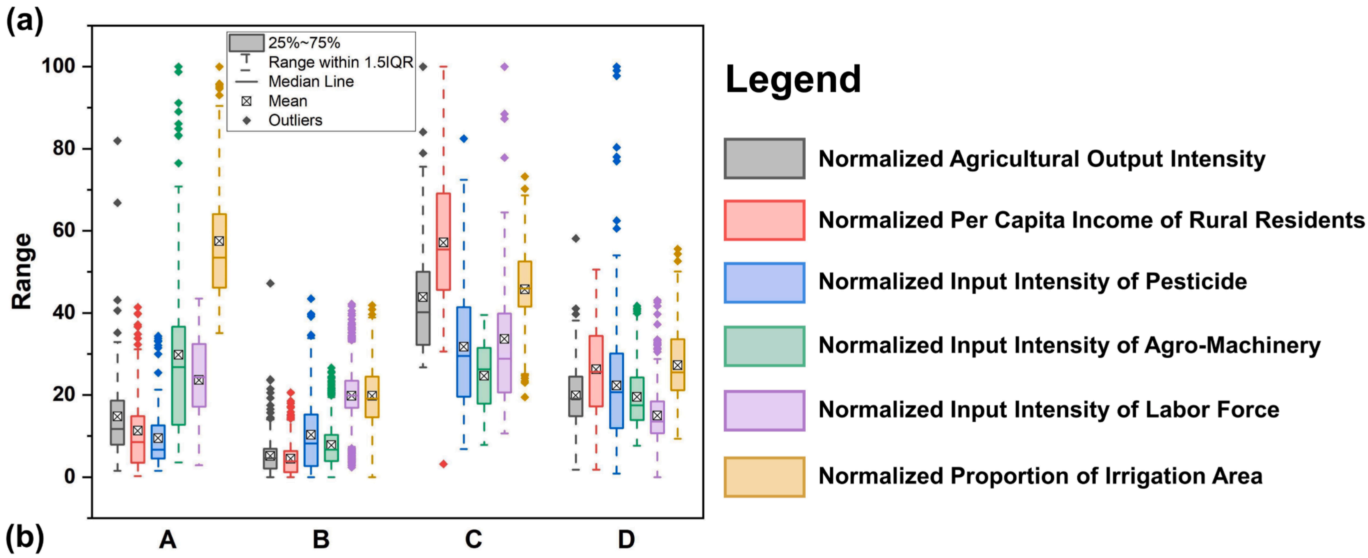
Step 1: Apply the natural breakpoint method to categorize cultivated land quality indicators, including provincial average slope, soil organic carbon content, mean patch size (MPS), density, and area-weighted mean shape index (AWMSI), into four levels (Fig. 2(b)). Higher levels indicate higher cultivated land quality, meaning higher soil organic carbon content, mean patch size, and density, as well as lower slope and area-weighted mean shape index.

Step 2: The K-means method is applied to categorize normalized agricultural intensification indicators of the provincial units, including farming input quantity of pesticides, agricultural diesel, labor force, irrigation area proportion, agricultural output value and income of rural residents, into four categories (Wilpon and Rabiner, 1985). As shown in Fig. 2(a), Class A corresponds to regions with lower agricultural output but higher levels of agricultural mechanization and irrigation; Class B represents regions with low agricultural output and inputs levels; Class C corresponds to regions with high agricultural output, economic development, and inputs levels; Class D corresponds to regions with relatively high agricultural output, economic development levels, and moderate levels of agricultural inputs.

Step 3: Integrating the hierarchical characteristics of cultivated land quality indicators and the clustering characteristics of agricultural intensification indicators, the 31 provincial units of mainland China are subjectively divided into 10 homogeneous cultivation conditions zones. These zones are as follows: (1) Northeast region, including Heilongjiang, Jilin, Liaoning, and Inner Mongolia; (2) Northwest arid region, including Ningxia, Gansu, and Xinjiang; (3) North China non major grain-producing region, including Beijing and Tianjin; (4) North China major grain-producing region, including Hebei, Shandong, and Henan; (5) Loess Plateau region, including Shaanxi and Shanxi; (6) Qinghai Tibet Plateau region, including Qinghai and Tibet; (7) Middle Yangtze Plain region, including Jiangxi, Hubei, and Hunan; (8) Lower Yangtze Plain region, including Anhui, Jiangsu, Shanghai, and Zhejiang; (9) Southwest region, including Chongqing, Sichuan, Guizhou, Yunnan, and Guangxi; (10) Southern China, including Fujian, Guangdong, and Hainan.

2.5. Analysis of the influence characteristics of N input components on N uptake by using Random Forest

Random Forest (RF) is an ensemble learning algorithm proposed by Breiman in 2001, which combines multiple decision trees to enhance the regression or classification performance of a single tree (Breiman, 2001). A decision tree represents a tree-like structure organized hierarchically from root to leaf nodes. When constructing a single decision tree, assuming there are N samples, N samples are randomly selected with replacement as the samples at the root node. Assuming each sample has M features, when a node of the decision tree needs to be split, m ($m \ll M$) features are randomly selected from these M features. Using a certain strategy, one feature is selected as the split attribute for this node from these m features. Each node in the decision tree formation process is split according to the previous step until it cannot be further split. The Random Forest model consists of hundreds or thousands of decision trees, each with a result. The most common category (or average value) among the voting results of the trees is the final prediction result of the model. In the Random Forest regression model, the importance of each feature is ranked based on the percentage increase in mean squared error with random replacement of out-of-bag samples, to evaluate the impact of each feature on the dependent variable. M−plots can be used to explore the specific effects of each feature on model predictions. As shown in Eq. (6), 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; $\widehat{f_{M,x_S}}(x_S)$ represents the predicted average marginal effect for a given



(b)

Homogeneous cultivation conditions zoning	Provinces	Slope	SOC	MPS	Density	AWMSI	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Northeast region	Heilongjiang	4	4	4	4	4	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D
	Jilin	3	4	3	4	4	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D
	Liaoning	3	2	2	3	3	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D
	Inner Mongolia	3	3	4	2	4	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D
Northwest arid region	Ningxia	3	1	4	3	3	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D
	Gansu	2	2	3	2	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D
	Xinjiang	4	2	4	3	4													A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
North China non major grain-producing region	Beijing	3	1	2	1	3	B	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	D	D	D	D	D	A	D	C	C	C	C	C	C	C	C	C	C	C
	Tianjin	4	1	2	3	2	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	C	C	C	C	C	C	C	C
North China major grain-producing region	Hebei	3	1	3	3	3	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	B	B	B	A	A	A	A	A	D	D	D	D	D	D	D	D	D	D	D	D	D
	Shandong	4	1	3	4	3	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	C
	Henan	4	1	2	4	4	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D
Loess Plateau	Shanxi	3	1	2	2	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D
	Shaanxi	2	2	2	1	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D
Qinghai Tibet Plateau	Qinghai	2	4	4	2	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	A	A	A	A	A	D	D	D	D	D	D	D	D
	Tibet	1	4	3	1	4	A	A	A	A	A	A	A	B	D	A	A	C	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
Middle Yangtze Plain region	Jiangxi	3	3	1	1	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D
	Hubei	2	3	2	2	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D
	Hunan	2	3	2	1	1	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D
Lower Yangtze Plain region	Anhui	3	2	2	3	4	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D
	Jiangsu	4	1	1	4	4	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D	C	C	C	C
	Shanghai	4	2	1	2	3	B	B	D	D	B	D	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D	C	D	C	C	C	C	C	C	C	C	C	C	C
	Zhejiang	2	3	1	1	3	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	C	C	C	C	C	C	C	C	C	C	C
Southwest region	Chongqing	1	3	1	2	1													B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D
	Sichuan	1	3	2	2	1	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D
	Guizhou	1	4	2	2	1	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D
	Yunnan	1	4	2	1	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D
	Guangxi	2	3	1	1	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D
Southern China	Fujian	2	3	1	1	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	D	C	C	C	C
	Guangdong	3	3	2	1	2	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	D	C	C	C	C
	Hainan	3	3	2	2	3				B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	D	D	D	D	D	D	D	D	D	D	C	C	C	C	C	C

Fig. 2. Division of homogeneous cultivation conditions zones of mainland China's provinces. (a) The boxplot results of K-means clustering of six agricultural input and output indicators for each province across various years. (b) The subjective discernment-based division of homogeneous cultivation conditions zones in China, integrating the hierarchical characteristics of cultivated land quality indicators (band 1–4) and the results of K-means clustering (A-D). The provinces marked with the green background are the major grain-producing provinces.

feature value S.

$$\widehat{f_{M,x_S}}(x_S) = \frac{1}{n}\sum_{i=1}^{n}\widehat{f}\left(x_S, x_C^{(i)}\right) \tag{6}$$

In this study, synthetic N input, manure N input, biological N fixation input, and N deposition input are used as independent variables, while N uptake serves as the dependent variable input into the Random Forest model. The data from all years in each homogeneous zone are divided into training and testing sets in a 4:1 ratio. The model is trained using the training set and evaluated using the testing set, with the R-squared value serving as the evaluation metric. Based on the obtained model, feature importance scores and M−plots for each N input component are used to interpret the effects of various N input components on N uptake within each homogeneous zone.

3. Results

3.1. Spatial and temporal variations of NUE

As shown in Fig. 3, China's overall NUE remained within the range of 35–55 % from 1985 to 2020. NUE decreased from 46.29 % in 1985 to 40.12 % in 1989. From 1990 to 1999, NUE fluctuated around 40 %. The decline in NUE continued from 1999 to 2003, reaching its lowest value of 36.44 % in 2003. NUE increased from 2000 to 2020, with the fastest increase observed from 2016 to 2020, reaching its highest value of 54.53 % in 2020.

Spatially, higher NUE could be seen in major grain producing provinces, including Heilongjiang, Jilin, Liaoning, Inner Mongolia, Henan, Shandong, Hebei, Anhui, Jiangsu, Jiangxi, Hunan, Hubei and Sichuan. Benefiting from intensive large-scale farm management in plain areas, NUE in provinces of North China and Northeast China increased from 1985 to 2020. Heilongjiang had the highest NUE, consistently exceeding 60 % from 1985 to 2020, with an average value exceeding 80 % from 2016 to 2020. The NUE in Shandong and Jilin increased to over 60 % after 2016. Provinces in the Qinghai Tibet Plateau region had relatively lower NUE, with Tibet having the lowest NUE, consistently below 10 %. Influenced by terrain or agricultural input levels, provinces in the southeastern coastal areas and central-western provinces such as Guizhou, Yunnan, Chongqing, Shaanxi, and Ningxia had lower NUE, ranging from 20 % to 40 %. Provinces in the

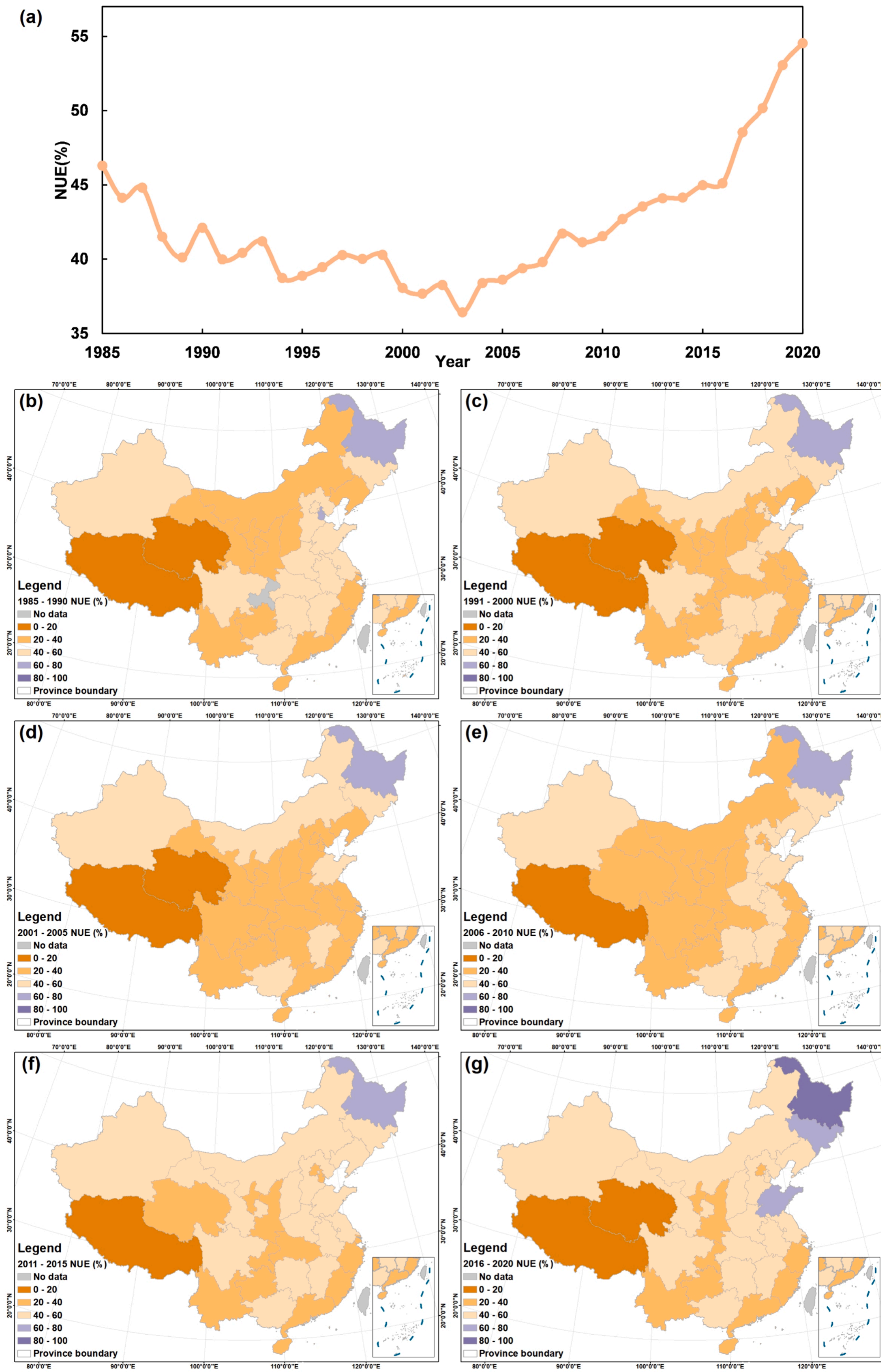


Fig. 3. Spatial and temporal variations of China's NUE from 1985 to 2020. (a) The temporal trend of overall NUE in mainland China; (b-g) The mean NUE across provinces in mainland China for the intervals 1985–1990, 1991–2000, 2001–2005, 2006–2010, 2011–2015 and 2016–2020. Hong Kong, Macau and Taiwan have no data.

Middle-lower Yangtze Plain, such as Jiangxi, Hunan, Hubei, and Anhui, maintained relatively stable NUE around 40 %.

3.2. Spatial and temporal variations of synthetic N contribution rate (SNCR)

A higher SNCR indicates that more synthetic N input was used for crop growth in the given year. Conversely, a lower SNCR suggests that the synthetic N input was not effectively used, or even exacerbated environmental risks, negatively impacting crop growth. As shown in Fig. 4, China's SNCR showed a slight increase from 2000 to 2010, but exhibited an overall downward trend in other periods. From 1985 to 1990, except for Inner Mongolia, SNCR in other regions was positive. From 1991 to 2000, with the increase in synthetic N input, SNCR in

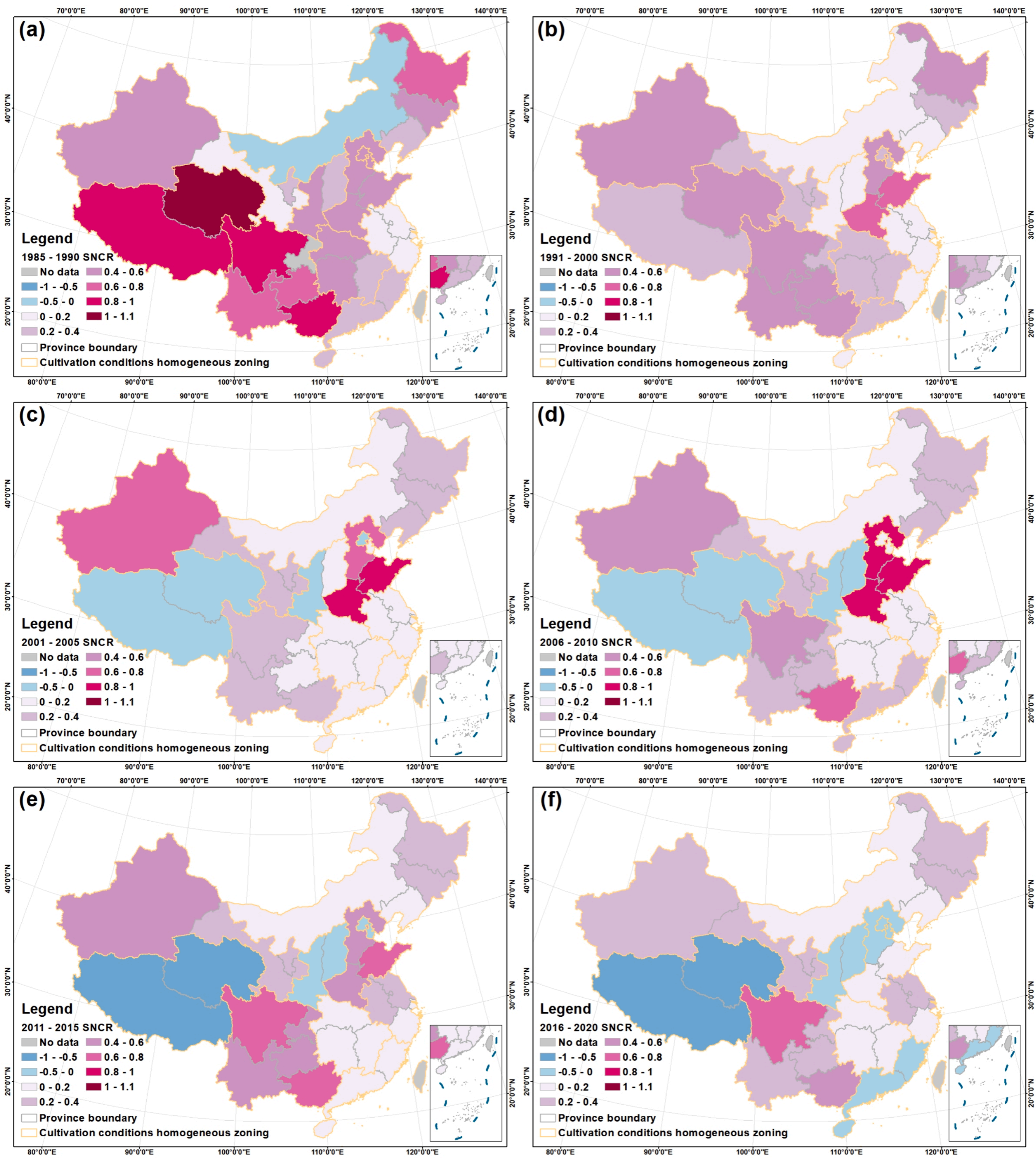


Fig. 4. Spatial and temporal variations of China's SNCR from 1985 to 2020. (a-f) The mean SNCR across provinces in mainland China for the intervals 1985–1990, 1991–2000, 2001–2005, 2006–2010, 2011–2015 and 2016–2020. Hong Kong, Macau and Taiwan have no data.

China decreased except for Shandong, Henan, and Inner Mongolia, and remained positive. From 2001 to 2010, SNCR in Tibet, Qinghai, Shaanxi, and Shanxi turned negative, while in Hubei, Hunan, and Jiangxi, SNCR dropped below 0.2. SNCR in Shandong, Hebei, and Henan increased to above 0.6. From 2011 to 2020, there was a general decline in SNCR, with SNCR in the North China Plain and southern China turning negative.

At the regional scale, the provinces in the southwest, northwest, and northeast of China generally exhibit higher SNCR, typically staying at or above 0.2. The elevated SNCR in the southwest and northwest can be attributed to rational synthetic N input (Table S5), while in the northeast, it's due to the region's higher level of intensification and the fertile black soil, resulting in lower demand for synthetic N. Over the past 35 years, crop N uptake in these regions had shown an overall upward

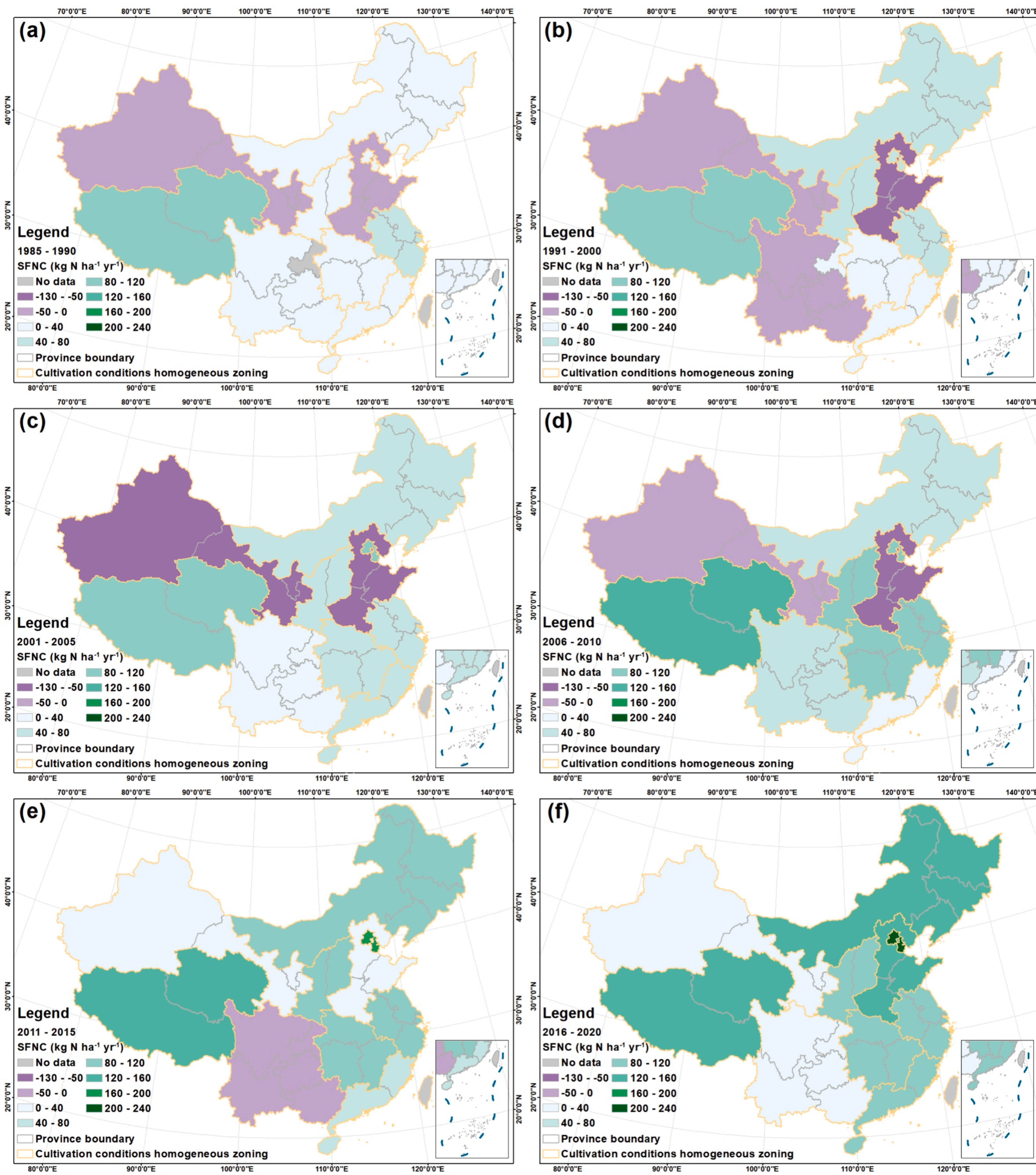


Fig. 5. Spatial and temporal variations of China's SFNC from 1985 to 2020. (a-f) The mean SFNC across provinces in mainland China for the intervals 1985–1990, 1991–2000, 2001–2005, 2006–2010, 2011–2015 and 2016–2020. Hong Kong, Macau and Taiwan have no data.

trend. Provincial SNCR in the North China major grain-producing region went through a phase of initial increase followed by decline, peaking at 0.8 between 2000 and 2010. During this period, there was rapid concurrent growth in synthetic N input and crop N uptake. However, after 2010, while synthetic N input remained stable from 2011 to 2015 and decreased after 2016 (Table S5), the SNCR gradually declined and reached below 0 after 2016, indicating that the benefits of synthetic N input on crop N uptake had reached saturation levels. Provinces in the Middle-lower Yangtze Plain region, generally maintain an SNCR around 0.2, with a slight downward trend with increasing synthetic N input. In the southern China, the SNCR fluctuated around 0.2 from 1985 to 2015, turning negative after 2015. Since 2010, synthetic N input of the provinces in the southern China reached very high levels (over 200 kg N ha^{-1} yr^{-1}) with no clear downward trend, while crop N uptake had not shown a corresponding increase. This corresponded to low use efficiency of synthetic N. Qinghai and Tibet experienced a transition from extremely high (around 1) to extremely low (around −0.5) SNCR over 35 years. Before 2000, synthetic N input in Qinghai and Tibet remained at relatively low levels (below 70 kg N ha^{-1} yr^{-1}), but increased to over 100 kg N ha^{-1} yr^{-1} in the past 20 years. The initial increase in synthetic N input brought about positive benefits in crop N uptake growth, which gradually disappeared in the later period. Consequently, the SNCR in Qinghai and Tibet exhibited a noticeable decline.

3.3. Spatial and temporal variations of soil fertility N contribution (SFNC)

A higher SFNC indicated a higher reliance of crop growth on N fertility within the soil. As shown in Fig. 5, SFNC showed an overall increasing trend over time, with values turning positive after 2016. Spatially, the pattern revealed higher SFNC in the northeast, followed by the southeast, and then the western regions. In Qinghai and Tibet, SFNC consistently remained above 60 kg N ha^{-1} yr^{-1}. This could be attributed partly to the low agricultural land area and low manure returning field rate, leading to overestimation when calculating manure N inputs, resulting in a relatively high slope in the fitted total N input and crop N uptake. It also suggested that the valley agricultural model and high labor input in these regions contribute to the N fertility of the soil. In the northeast region, SFNC remained positive and had exceeded 120 kg N ha^{-1} yr^{-1} since 2016–2020. This was primarily due to the fertility of black soil and the rapid increase in agricultural intensification in the Northeast Plain. In the North China major grain-producing region, SFNC was negative from 1985 to 2010, but around 2010, it transitioned to positive values and then increased rapidly, reaching over 120 kg N ha^{-1} yr^{-1} from 2016 to 2020. This shift indicated a gradual transition from dependence on N inputs to absorption of N fertility in the soil for crop growth. Provinces in the Middle-lower Yangtze Plain and southern China generally showed positive SFNC values over the 35 years, gradually increasing to over 80 kg N ha^{-1} yr^{-1} from 2016 to 2020. Since 2000, the low use efficiency of synthetic N in these areas had led to a significant portion of N inputs being lost to the soil and the environment,

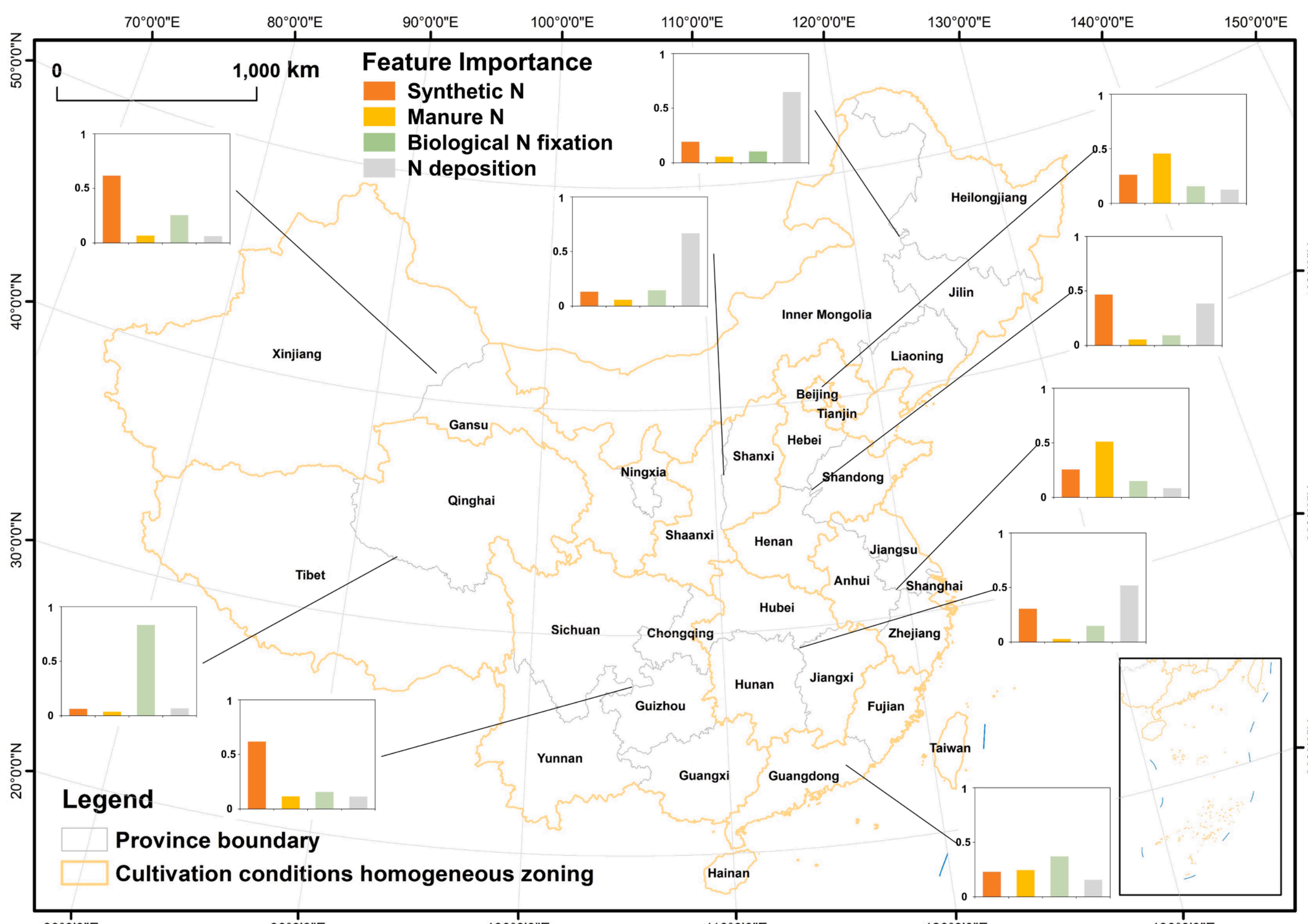


Fig. 6. The feature importance results of the Random Forest model for N input components in mainland China based on homogeneous cultivation conditions zones. Hong Kong, Macau and Taiwan have no data.

resulting in an increase in N content in the soil. In the provinces of the northwest arid region, SFNC was negative before 2010 but became positive after 2011. In the southwest region, SFNC fluctuated around 0, but since 2016, it had remained positive. Overall, there was a gradual decrease in the dependence of crop growth on N inputs, with an increasing role played by soil fertility N.

3.4. Contribution of N input components

Based on the division of homogeneous cultivation conditions zones, the direct relationship and response between various N input components and crop N uptake were revealed. Feature importance was used to indicate the sensitivity of crop N uptake to each N input component. As shown in Fig. 6, synthetic N input had higher feature importance in provinces of the northwest arid region and southwest region, all above 0.5. In the North China major grain-producing region, the importance was close to 0.5 (0.466). Manure N input had importance exceeding 0.5 in the Lower Yangtze Plain region, while it was lower in other major grain-producing regions. The importance of biological N fixation was generally low (except for Tibet and Qinghai), with importance exceeding 0.2 in the southern China and northwest arid region. N deposition played an important role in crop growth in the northeast, Loess Plateau, and Middle Yangtze Plain regions, with importance above 0.5.

As shown in Fig. 7, synthetic N input generally exhibited a promoting effect on crop N uptake in most regions. An increase in synthetic N input led to a noticeable increase in crop N uptake, but at high levels of synthetic N input, a decreasing trend in crop N uptake might be observed. This indicated a threshold for the promoting effect of increasing synthetic N input on crop N uptake. In the northeast, Middle-lower Yangtze Plain, and North China major grain-producing regions, the positive effect of synthetic N input on crop N uptake was sustained at levels above 200 kg N ha^{-1} yr^{-1}, while in coastal provinces in the southern China, synthetic N input no longer had a positive impact on crop N uptake above 180 kg N ha^{-1} yr^{-1}. Except for the northeast and North China major grain-producing regions, NUE decreased with increasing synthetic N input in most areas, indicating environmental risks associated with the decrease in NUE despite increased crop N uptake (Cui et al., 2018). In the northeast region, NUE initially increased and then decreased with increasing synthetic N input, stabilizing around 50 %. In the North China major grain-producing region, NUE fluctuated between 40–50 % with increasing synthetic N input. These reflected the influence of agricultural intensification on synthetic N use, where higher levels of intensification implied higher thresholds for the positive effects of synthetic N and more ideal NUE (Deng et al., 2024; Ju et al., 2016). Manure N input did not exhibit a significant positive effect on N uptake and even showed negative effects in the northeast, Middle-lower Yangtze Plain region, and North China major grain-producing regions, with crop N uptake and NUE decreasing with increasing manure N input. This suggested issues with the management and use of manure fertilizers in these regions, indicating they might not be effectively contributing to crop growth (Zhang et al., 2023). Biological N fixation showed a certain positive effect in coastal provinces in the southern China, with slight increases in uptake and NUE with increasing N fixation. In the northeast region, an appropriate increase in biological N fixation greatly enhanced NUE, indicating that the high NUE in this region was largely due to the extensive cultivation of N-rich oilseed crops such as soybeans and peanuts. An increase in N deposition generally led to an increase in crop N uptake in most regions. With increasing N deposition, NUE showed a trend of initially decreasing and then increasing (except in the southern China and southwest region), possibly corresponding to the adaptation process of crops and soil microorganisms to the increase in readily available N brought about by increased N deposition (Forsmark et al.,2024; Liu et al., 2013).

4. Discussion

4.1. Comparison of accuracy between fitting by years and fitting by regions

As shown in Fig. 8, the improved method was compared with the method of Yan et al. (2014) in terms of R-square. According to the method proposed by Yan et al. (2014), the synthetic N input, total N input, and crop N uptake from all provinces of mainland China in the same year were used as sample inputs to fit the model. However, this method fitting by years was not appropriate as it assumed b_1 (or b_2) in different provinces in the same year as constants and overlooked the spatial heterogeneity features of b_1 (or b_2) in different regions. The differences between b_1 (or b_2) in different regions were masked by the gradient formed between provinces with high N inputs and high crop N uptake versus those with low N inputs and low crop N uptake. Moreover, its linear models showed less ideal R-square performance after 2000, as shown in Figure S1. This also explained why the fitting R-square of the method fitting by years was relatively high in earlier periods (i.e., 1985–2000), ranging from 0.4 to 0.7; however, as the N inputs from previously low N input provinces gradually increased (i.e., the difference in NUE between different regions increased) (Table S5), the fitting R-square gradually decreased. In contrast, this study's linear model based on division of homogeneous cultivation conditions zones exhibited better R-square performance and also demonstrated advantages in the performance of the Random Forest model (negative R-square values indicated that the model fitted by year was not suitable for the dataset). This also indicated that the spatial variation of soil N processes in agroecosystems contributed more to the accuracy of model prediction than temporal variation (i.e., the spatial heterogeneity of soil N processes outweighed temporal heterogeneity). This underscored the importance and necessity of division of homogeneous cultivation conditions zones in studying and modeling soil N processes.

(synthetic N input, manure N input, biological N fixation input, and N deposition input) with crop N uptake. Fitting by regions meant that based on division of homogeneous cultivation conditions zones, the corresponding years in the same sliding time window of provinces in the same zone were used as sample input to fit linear models, and provinces in the same zone were used as sample input to fit Random Forest models. Fitting by years meant that all provinces within the same year from 1985 to 2020 were used to fit models. The R-square values of these models from different methods (fitting by regions and fitting by years) were compared.

With linear models, SNCR and SFNC were innovatively proposed in studies at regional scales. In previous regional scale studies, synthetic N fertilizer recovery efficiency was calculated by fitting a linear model by year to obtain an overall value for the current year's fraction without considering spatial heterogeneity. The SNCR and SFNC presented in this study were comparable in space and time while responding to the contribution of synthetic N fertilizer and soil fertility N to crop growth. Furthermore, compared to studies that directly model natural environmental factors and economic indicators to explore their relationships with N use indicators, this study adopts a more direct and targeted modeling strategy. By fitting N input components and crop N uptake using Random Forest models, clearer and more intuitive results were obtained, providing a more operational and accurate reference for the management and optimization of N inputs. The spatial partitioning-based modeling method used in this study was not only applicable to the provincial scale but could also be extended to other spatial scales, such as the county or even field and farm scale. At finer spatial scales, this method considers more specific local characteristics, thus generating more precise and reliable results.

4.2. Comparisons with previous studies

As was shown in Fig. 9, the general trends in NUE over time in this

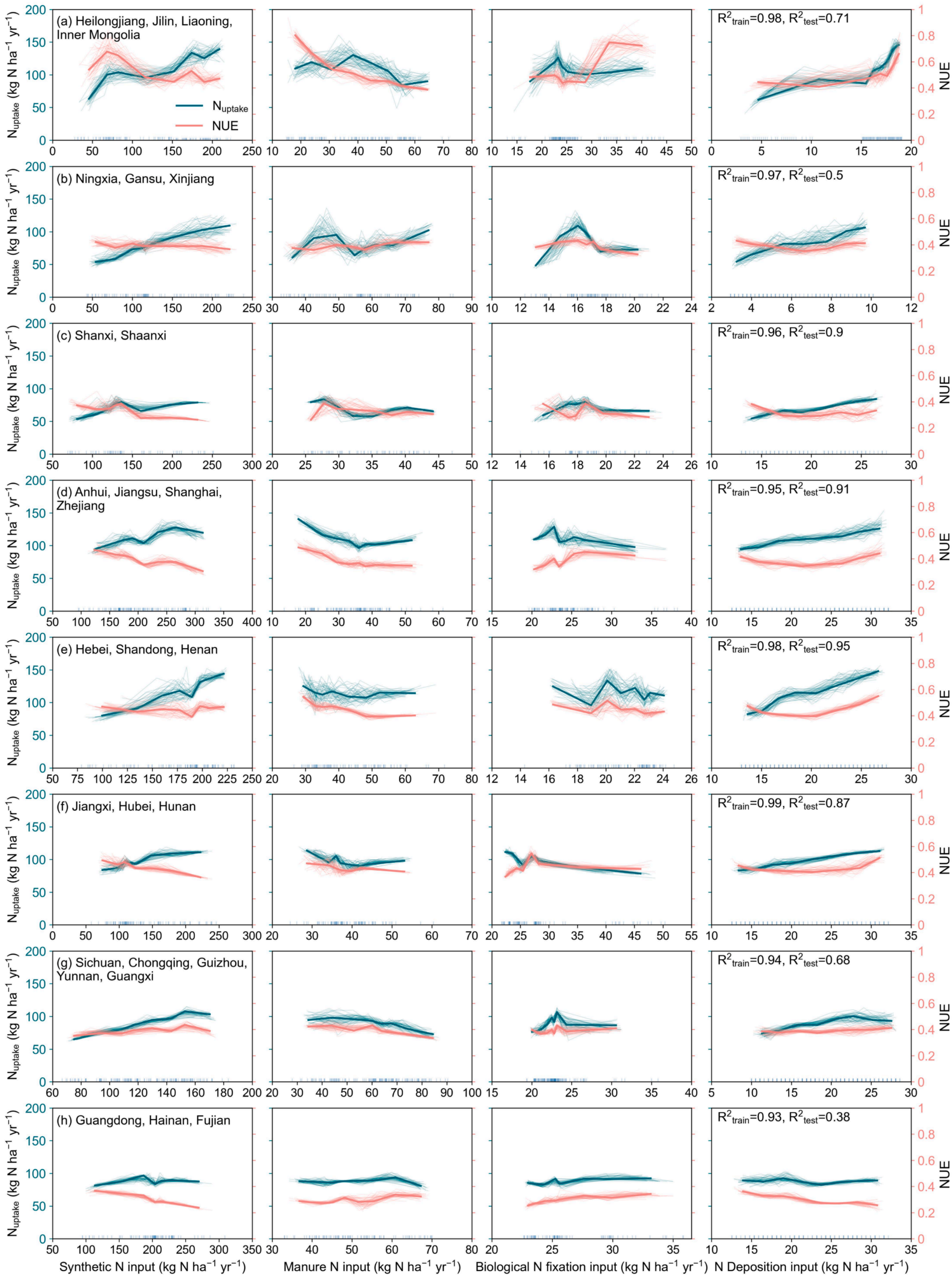


Fig. 7. Based on homogeneous cultivation conditions zones, the M−plot results of N_{uptake}, NUE, and various N input components in agricultural priority regions of China are presented. Lighter-colored lines represent the results of 50 Monte Carlo simulations. The blue lines on the X-axis indicate the distribution of data.

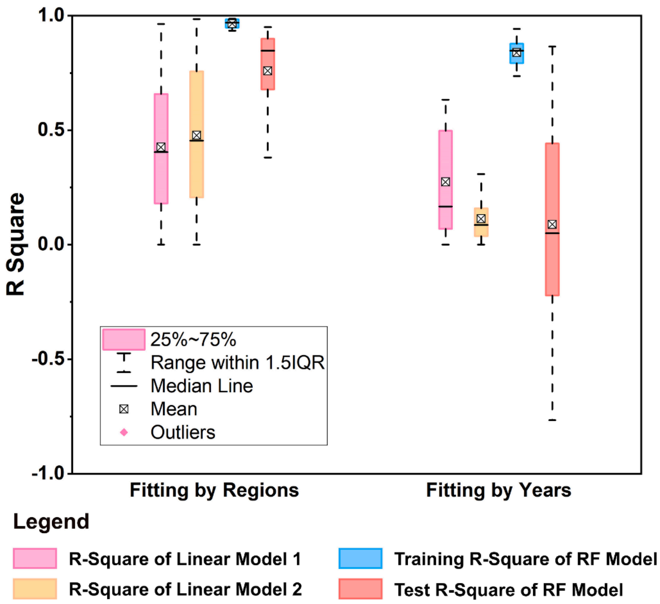


Fig. 8. Model accuracy comparison. Linear model 1 (Eq. (3)) fit synthetic N input and crop N uptake; linear model 2 (Eq. (4)) fit total N input and crop N uptake; RF model fit N input components.

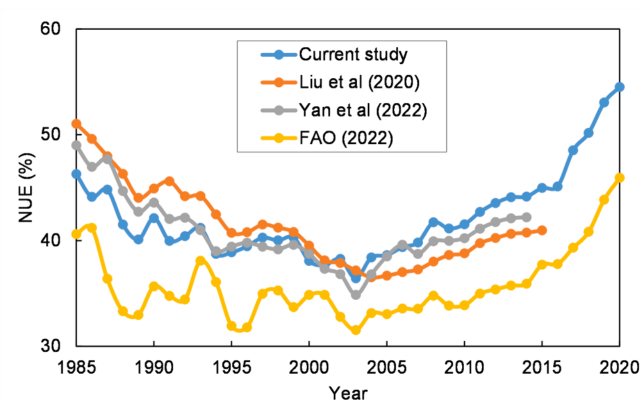


Fig. 9. Comparisons of NUE in mainland China for 1985–2020 according to various estimates (including Liu et al., 2020; Yan et al., 2022; FAO data from Ludemann et al., 2024).

study was broadly consistent with estimates from previous studies. At the numerical level, the provincial-scale studies (this study; Liu et al., 2020; Yan et al., 2022) estimated NUE roughly 10 % higher than FAO's estimates, because FAO's national-scale estimates might not account for the N content in the crop types that had limited data (Ludemann et al., 2024). Compared with the NUE estimated by Liu et al. (2020) and Yan et al. (2022), the NUE estimated in this study was slightly lower before 1990 and slightly higher after 2008. It might be due to the fact that in this study, all major crops were considered, including rice, maize, wheat, soybean, potatoes, peanut, oil rape, sesame, cotton, sugarcane, beet, tobacco, vegetable, fiber, fruit, tea and green manure which was widely cultivated before 1990 and had high N fixation.

4.3. Assess provincial N use in China from 1985 to 2020

As shown in Figure S2, synthetic N input in mainland China increased from 88.1 kg N ha^{-1} yr^{-1} to 182.0 kg N ha^{-1} yr^{-1} in 1985–2013 and then decreased to 148.7 kg N ha^{-1} yr^{-1} in 2014–2020. However, an increase in synthetic N input did not imply an increase in crop N uptake, but posed the environmental risk of an increase in N surplus. The annual provincial change of crop N uptake and N surplus from 1985 to 2020 was shown in Fig. 10. N inputs and crop N uptake in each region was shown in Table S5. Over the past 35 years, the crop N uptake and N surplus of mainland China had experienced a process of extensive-unsustainable-sustainable-conservative pattern changes.

In the first decade, most regions exhibited extensive patterns, suggesting that the generalized elevation of synthetic N input brought about a simultaneous rise in N surplus and crop N uptake. Especially in the northwest region and North China, SFNC in these areas acted negatively in the decade, indicating that crop growth was mainly dependent on synthetic N input. This was supported by the high feature importance of synthetic N input for the Random Forest model.

During the period 1996–2000, most regions gradually shifted towards unsustainable patterns. This suggested that excessive inputs of synthetic N did not bring positive benefits to crop N uptake but exacerbated the environmental risks associated with N surplus. The Middle-lower Yangtze Plain was dominated by unsustainable patterns due to low SNCR (0–0.2), experiencing a decline in NUE. The sustainable pattern was also highly proportioned during this period. This was particularly manifested in the northeast region, where the sustainable patterns alternated with the unsustainable patterns, suggesting that the increase in N inputs was at the tipping point of balancing crop N uptake and N surplus. But in terms of mainland China in general, heavy reliance on high N inputs led to substantial loss of environmental N and a decline in NUE during this period (Cui et al., 2018).

During the period 2001–2005, extensive patterns dominated in most regions, accompanied by unsustainable and sustainable patterns. The northeast region was dominated by sustainable patterns, with NUE at a high level (over 40 %). The North China major grain-producing region was dominated by sustainable and excessive patterns, with SNCR reaching a very high level (over 0.6), while SFNC was negative. The Middle-lower Yangtze Plain and the southern China were dominated by unsustainable patterns, with a decreasing SNCR and a slight increase in SFNC, indicating that N inputs exceeded the threshold required for crop growth. Excessive patterns dominated in the western region, with SNCR exceeding 0.2 in the northwest and southwest, indicating that increased N inputs still had a positive effect on crop growth, but at the same time, the level of N management was low (NUE was basically below 0.4).

From 2006 to 2015, extensive and unsustainable patterns were rapidly abandoned, and sustainable patterns gradually became mainstream. During this period, China's NUE continued to increase (from 36.44 % to 44.98 %). A slight decrease in SNCR and a rapid increase in SFNC were found. The decrease in SNCR did not necessarily indicate an increase in N loss. Its residual effect would play an important role in future crop growth (Vonk et al., 2022). As confirmed by the increase in SFNC, studies of soil sample profile data also indicated an improving trend in soil fertility (including total N) in the southern and northeastern regions in the 2010 s compared to the end of the 20th century (Deng et al., 2023). Research by Yan et al. (2022) indicated an overall improvement in the cumulative recovery efficiency of synthetic and non-synthetic N from 2003 to 2014. N inputs from sources other than synthetic N (such as manure N, N deposition, and biological N fixation) might be important sources supporting crop growth (Gu et al., 2017).

After 2015, although there was a clear increase in NUE, the main reason was the reduction in synthetic N input (from 179.6 kg N ha^{-1} yr^{-1} to 148.7 kg N ha^{-1} yr^{-1}), rather than a clear increase in crop N uptake (from 120.0 kg N ha^{-1} yr^{-1} to 127.2 kg N ha^{-1} yr^{-1}). The number of provinces adopting unsustainable patterns further decreased, while the number of provinces adopting conservative patterns increased, indicating a decrease in N surplus along with a decrease in crop N uptake. Southwest region and Middle-lower Yangtze Plain tended to adopt conservative patterns, with SNCR around 0.4, implying that reducing synthetic N input carried the risk of reducing crop uptake. Continuing to reduce N inputs in these regions might lead to adverse consequences of reduced crop N uptake. Future efforts need to focus on

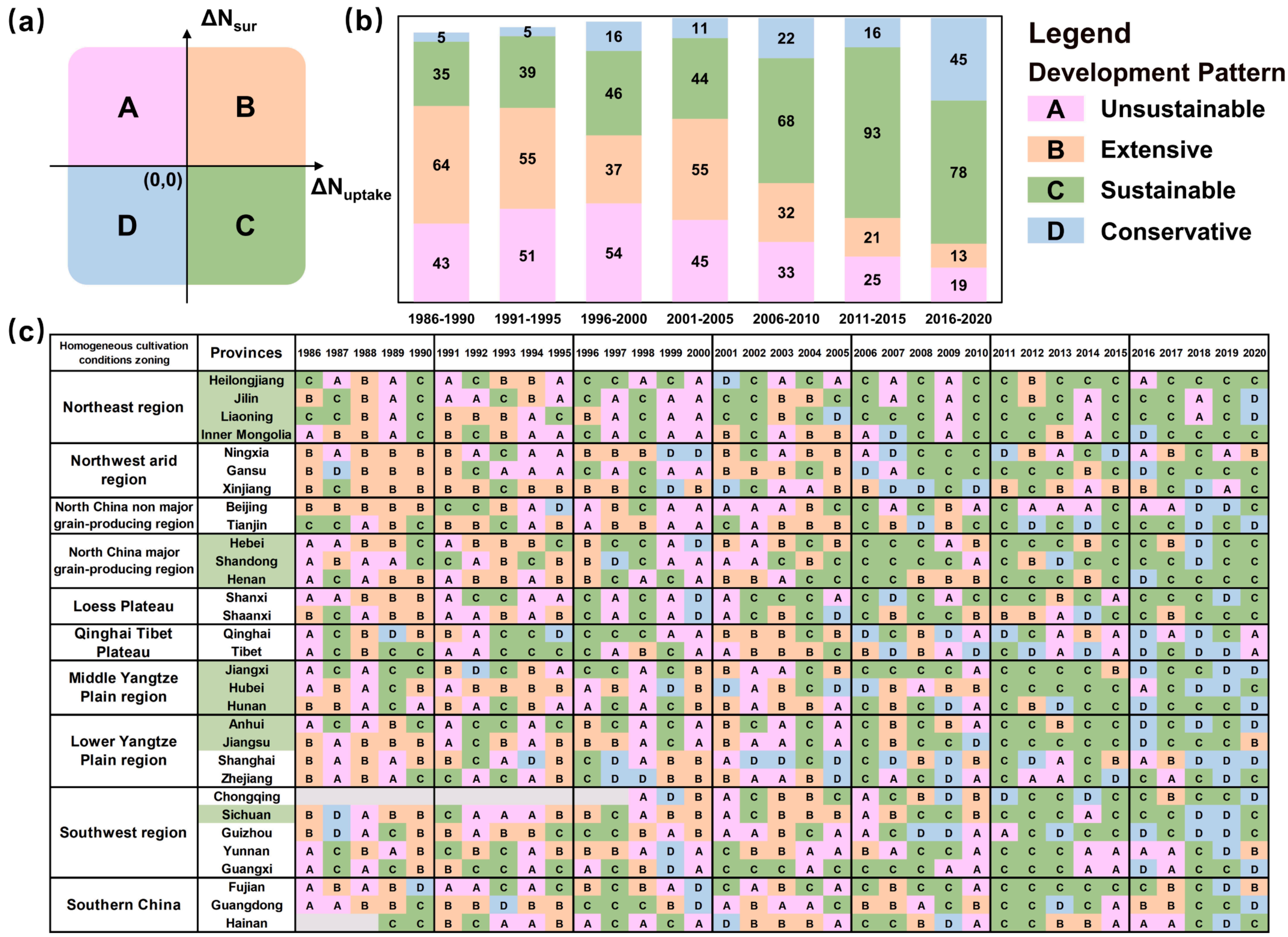


Fig. 10. The annual provincial change of crop N uptake and N surplus from 1985 to 2000. ΔN_{uptake} (ΔN_{sur}) respectively represent the difference in crop N uptake (N surplus) between the following year and the current year. (a) The schematic diagram of ΔN_{uptake} and ΔN_{sur} corresponding to four N use development patterns; (b) The stacked bar chart of these patterns over the 35-year period; (c) The specific patterns of each province in each year.

reducing environmental risks associated with N surplus while ensuring crop N uptake.

Previous studies had indicated that N surplus generally followed a pattern similar to the Environmental Kuznets Curve (EKC): N surplus increased in the early stages of agricultural development (Phase I) with rising income and pursuit of food security. However, in more affluent stages (Phase II), N surplus decreased with further income growth, eventually approaching the asymptote determined by the theoretical limit of crop system NUE (Zhang et al., 2015). Fig. 11 showed the trajectories of N surplus-NUE for the major grain-producing provinces over the past 35 years. Provinces such as Heilongjiang, Inner Mongolia, Sichuan, Henan, and Shandong, which were major grain-producing provinces, had found the turning point of the EKC. In the past five years, NUE had also increased to some extent along with the rise in crop N uptake, leading to a reduction in fertilizer expenditure while enhancing agricultural productivity. However, as was shown in Figure S3, the future trend for non major grain-producing provinces like Fujian, Guangdong, Guangxi, Guizhou, Yunnan and Zhejiang was unclear, as they were far from reaching the turning point of the EKC. Provinces in the southwest region faced the challenge of increasing crop N uptake; provinces in southern China needed to work on reducing N surplus.

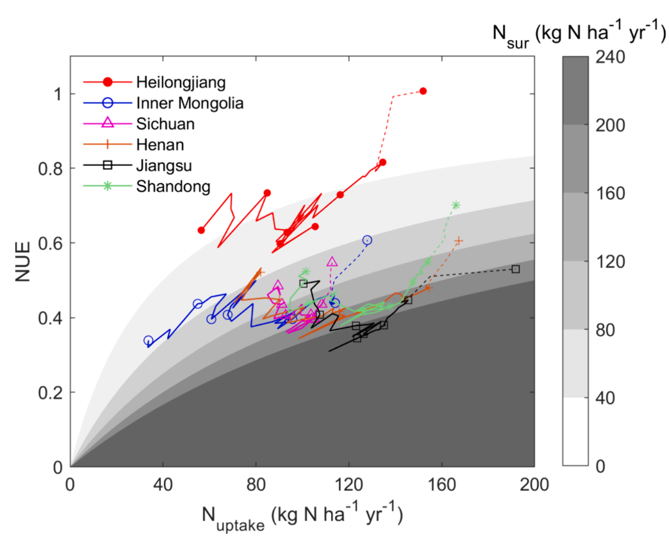


Fig. 11. The historical trends of NUE, N_{sur}, and N_{uptake} in the major grain-producing provinces were shown. The grayscale indicated the levels of N_{sur}, with darker colors representing higher N_{sur}. Solid line indicated 1985–2015; dotted line indicated 2016–2020.

4.4. Simulation of crop N uptake and NUE responded to the regulation of N inputs components in typical regions

As shown in Fig. 12, the potential effects of increasing or decreasing synthetic N input, manure N input, and biological N fixation input on crop N uptake and NUE in selected regions were simulated, using the 2020 N input for agroecosystems as a baseline. In provinces such as Shandong and Jilin, a certain increase in synthetic N input led to a clear rise in yield. This indicated that increasing fertilizer input in areas of high agricultural intensification, such as the northeast and North China Plain regions could enhance crop yield without exacerbating environmental risks associated with N surplus, suggesting a need for appropriate increases in future fertilizer input. Conversely, in provinces like Yunnan and Hainan, reducing synthetic N input did not negatively impact crop N uptake, while leading to an increase in NUE. Therefore, these regions dominated by small-scale agricultural operations should consider reducing future fertilizer input appropriately (Wu et al., 2018). Moderate increases in manure N input in provinces like Shaanxi and Anhui resulted in increased crop N uptake without a decrease in NUE. Conversely, reducing manure N input in provinces such as Liaoning and Zhejiang had positive effects on crop N uptake and NUE. While counterintuitive, this suggested a saturation point for manure N input. Regarding crop structure, to improve crop N uptake and NUE, provinces like Yunnan and Shandong might benefit from increasing the cultivation of N-fixing crops such as soybeans and peanuts. Accordingly, the latest agricultural plan encourages farmers to intercrop soybean–corn strip to expand soybean production (Deng et al., 2024). On the contrary, provinces like Heilongjiang and Anhui should consider reducing the cultivation of leguminous crops.

In recent years, the agricultural sector and research institutions in China have made significant efforts to promote sustainable agriculture. Policies are implemented to promote better N management practices among farmers, with the dual objectives of enhancing NUE while reducing pollution (Kanter et al., 2019; Meier et al., 2021; Zhang et al., 2016). Over the past decade, these initiatives have gradually gained acceptance and adoption among farmers, with significant results (Ju et al., 2016; Xia et al., 2017a; Xia et al., 2017b). However, China's crop production NUE still lags behind global leaders like the United States and Canada (which reached 68 % in 2014) (Zhang et al., 2015). This discrepancy is partly due to differences in agricultural production types and partly due to the varying levels of N management and intensification, which may limit further reductions in N inputs and affect crop N uptake (Lassaletta et al., 2016). There is still a need to explore better N management models that can reduce N inputs while increasing crop yield (Ju et al., 2016; Xia et al., 2017a; Xia et al., 2017b).

This study provides valuable insights for policy formulation by the Chinese government. It suggests that strict reduction of fertilizer use across all regions is inappropriate if the goal is to increase NUE while maintaining or even increasing crop yields. Instead, authorities should tailor their approach to each region, scientifically adjusting the use of chemical fertilizers and manure while also considering crop planting structures. For instance, in the northeast and North China Plain regions, appropriate increases in fertilizer use may be beneficial, while in the southern China and southwest regions, reducing fertilizer use might be more suitable.

4.5. Limitations, uncertainty and perspectives

This study extends the assessment of N use in China to the last 35 years and provides important guidance for future research on soil N processes and N use assessment. However, there are limitations in data and research scale. The provincial scale is relatively coarse for providing detailed recommendations to farmers (Wei et al., 2023). At the same time, data limitations may affect the accuracy of the results. The

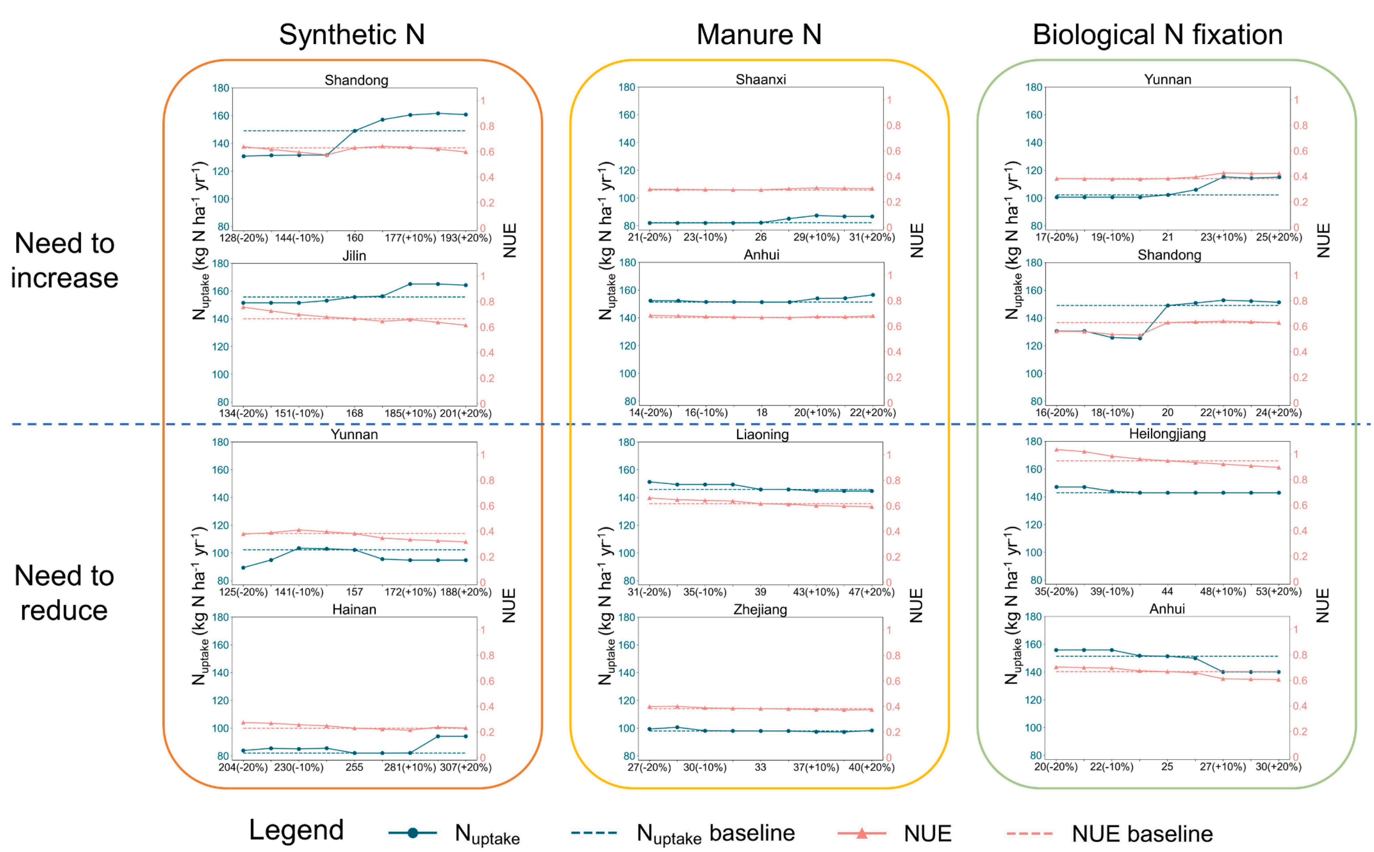


Fig. 12. Simulations of typical regions' crop N uptake and NUE resulting from five scenarios: reducing by 20%, reducing by 10%, no change (baseline), increasing by 10%, and increasing by 20% in synthetic N input, manure N input, and biological N fixation input.

estimations of N flow tend to have large uncertainties (Ludemann et al., 2024). To be specific, synthetic N input and crop N uptake have a high confidence rating level since it has been reported consistent nationwide (Liu et al., 2020a). The biological N fixation rate used in this study is estimated based on legume crop types (Table S2), but the N fixation rate is different due to changes in soil and climate. According to He et al. (2018), the confidence for biological N fixation should be moderate. N deposition has very great relative uncertainty while N deposition is a small contributor to the overall N budget (Figure S2), so that its contribution to overall uncertainty is also small. The known uncertainties in the estimates of manure application rates for China is very high, and this study refers to the parameters of Yan et al. (2014) (Ludemann et al., 2022; Zhang et al., 2023).

In the future, it is necessary to collect N balance field experiment data or county-level agricultural statistical yearbook data to obtain more precise and accurate results. Achieving these goals requires an urgent need for satellite-ground fusion imaging and high-performance spatial data processing and analysis technologies (Jiang et al., 2023; Jiang et al., 2024; Wan et al., 2021).

5. Conclusions

This study considered the spatial heterogeneity of mainland China's provinces from the perspective of natural-socio-economic to divide homogeneous cultivation conditions zones, based on which linear models and Random Forest models were established. Synthetic N contribution rate (SNCR) and soil fertility N contribution (SFNC) were innovatively proposed to represent the contribution of fertilizer and soil fertility to crop growth. The nitrogen (N) use in China's agroecosystems from 1985 to 2020 was assessing.

The results indicated: Firstly, N use efficiency (NUE) in China ranged from 35 % to 55 % and higher NUE could be seen in major grain producing provinces. Secondly, the SNCR slightly increased from 2000 to 2010 but generally decreased in other periods, with a spatial pattern higher in the southwest, northwest, and northeast regions. Thirdly, the SFNC showed an upward trend over time, with the spatial pattern higher in the northeast, followed by the southeast, and then the western regions. Fourthly, synthetic N input was critical in the northwest, southwest regions and north China, positively affecting crop N uptake. And higher levels of agricultural intensification implied higher thresholds for the positive effects of synthetic N and more ideal NUE. Manure N input was highly influential in the Lower Yangtze Plain region, negatively affecting crop N uptake. N deposition played a significant role in crop growth in the northeast, Loess Plateau, and Middle Yangtze Plain regions, showing a clear positive effect.

The crop N uptake and N surplus of China's provinces had experienced a process of extensive-unsustainable-sustainable-conservative pattern changes over the past 35 years. The simulation of the response of crop N uptake and NUE to the regulation of N inputs in typical regions indicated: in the North China Plain and northeast regions, appropriate increases in fertilizer use might be beneficial, while in the southern China and southwest regions, reducing fertilizer use might be more suitable. This study provides suggestions for formulating future N inputs and management strategies, and the analysis method of can provide guidance for other regions to assess N use in different scales.

CRediT authorship contribution statement

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

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.112603.

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