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Basin-Level Assessment of Irrigation Water, Food Production, and Nitrogen Losses and Inequality and Inequities in China

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Abstract

At the current stage, water resource shortages and significant regional disparities in resource distribution severely restrict China's food security. Existing research primarily focuses on resource use efficiency, while lacking a systematic framework to distinguish between equality and equity in the coupled distribution of irrigation water, grain production, and nitrogen pollution across major river basins. The core objective of this study is to utilize the Concentration Index (CI) to construct a unified equity assessment framework, quantify the evolution of equality and equity in irrigation water use, grain production, and nitrogen loss to surface water in different river basins in China from 1992 to 2017, and determine the key influencing factors. For positive production resources, a distribution that benefits low-income groups is equity, while for pollution burdens, this distribution pattern is inequity. The results show that water shortages in Northern China have intensified, and higher income groups have obtained excessive benefits. The distribution of grain production has shifted from favoring higher income groups to favoring low-income groups, with the Concentration Index changing from 0.214 to -0.052 , indicating an enhancement in equity. Irrigation water use has shown a certain degree of improvement, with the CI dropping from 0.023 to 0.017. However, nitrogen loss to surface water has exacerbated environmental inequality, with the CI dropping from 0.10 to 0.03, indicating that pollution burdens have shifted to low-income groups. Changes in equity across the country are driven by a small number of high-intensity grain production areas, and the key influencing factors include food security policies, urbanization, population size, and nitrogen fertilizer application. An asymmetric coupling relationship exists between water resource shortages and equity, and the regional economic foundation determines the formation of synergy or trade-offs. The findings underscore the necessity of transitioning from efficiency-focused to equity-focused agricultural governance in China. Targeted policies should include cross-basin ecological compensation mechanisms, differentiated technology promotion strategies, and integrated water–food–pollution management systems to balance food security, environmental protection, and social justice.



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1. Introduction

Agriculture serves as a potent instrument for eradicating extreme poverty and advancing economic development, generating two to three times the poverty alleviation benefits compared with equivalent growth in other sectors [1]. The stable operation of the agricultural system not only concerns food supply security but also directly affects global sustainable development processes, such as poverty reduction. However, a surging global population, sustained economic expansion, and intensifying climate change have subjected the global food system to unprecedented pressure. Currently, over 2 billion people worldwide face moderate or severe food insecurity, while a considerably larger population cannot access nutritious diets due to economic and resource constraints [2]. Among the multifaceted driving factors, the escalating scarcity of freshwater resources, especially for agricultural irrigation, has become a pivotal nexus interconnecting climate risks, food security sustainability, and poverty-related predicaments [3].

In the agricultural system, freshwater is crucial for maintaining food production and ensuring water resource security. Ensuring freshwater availability and security is a fundamental prerequisite for sustainable development; it is a direct goal of achieving clean water and sanitation (SDG 6) [4], an important method for eliminating poverty through livelihood security and health promotion (SDG 1) [5], and a key means to reduce social inequality by alleviating uneven resource access (SDG 10) [6]. Nevertheless, the contribution of water resources to these SDGs is undermined by worsening freshwater scarcity and water pollution. Irrigation agriculture contributes 40% of global food production but consumes over 70% of global freshwater [7], with more than 60% (171 million ha) of irrigated farmland under water shortage pressure [8]. Additionally, global agricultural nitrogen (N) pollution has transgressed surface water environmental thresholds [9], intensifying conflicts between food security and water security. Meanwhile, 2.2 billion people worldwide lack access to safely managed drinking water, 80% of whom live in rural areas and 50% in least-developed countries [10].

For China, despite the extraordinary achievement of feeding 22% of the world's population with only 7% of global arable land [11], its food system faces pressing challenges: per capita water resources are less than a quarter of the global average, arable land is scarce, and soaring protein demand has spurred massive feed crop imports. The spatial mismatch between water and arable land resources, coupled with the expansion of irrigated areas in water-deficient regions, has further exacerbated these challenges [12–14]. To advance the coordinated development of grain production, resource utilization, and environmental protection, the academic community in China has conducted extensive assessments and optimizations, such as improving water resource efficiency [15], transforming crop structures [16], and ensuring food production under water quantity and quality constraints [17]. Gu et al. (2024) proposed cross-regional agricultural trade as a dual-purpose strategy to address agricultural commodity demand and alleviate water scarcity [18], while Chen et al. (2025) optimized the grain trade to balance food security and sustainable water management [19]. However, these efficiency-oriented measures have paid insufficient attention to the disparate impacts of resource and environmental risks on different populations, especially issues of equality and equity. This oversight has impeded the formulation of targeted policies, hindering the balanced advancement of multiple SDGs. For China, irrigation water availability, grain yield, and water body nitrogen loss are the three core elements of

the agricultural water food environment nexus, which jointly determine the achievement of national food security, water security, and sustainable agricultural development [20]. Against this backdrop, we take water resources as the pivotal nexus and select these three core indicators to distinguish between inequality and inequity in resource allocation and pollution burden bearing.

In addition, a critical gap in existing research lies in the ambiguous definition and contradictory application of “equality” and “equity”: equality refers to the equal distribution of resources among all stakeholders, while equity denotes resource allocation based on needs and suitability. Furthermore, no clear definitions of equality and equity have been tailored to irrigation water, food production, and nitrogen losses to water bodies from crop production. Existing equity theory holds that individuals in society tend to compare themselves with others under similar conditions to evaluate their input–output ratio. Individuals perceive equity when the ratios between the two parties are comparable, and inequity when the ratios differ [21]. Notably, the existing literature on distributive justice also presents alternative interpretative frameworks for resource and burden distribution: (1) the utilitarianism-based efficiency framework, which prioritizes the maximization of total social welfare and may justify resource concentration in high-productivity regions regardless of income status [22]; (2) the contribution-based distribution framework, which allocates resources/burdens based on the proportion of regional contribution to national grain production or pollution generation [23]; and (3) the procedural justice-oriented framework, which emphasizes fair decision-making processes over end-state distributional outcomes [24]. The equity evaluation framework employed in this study prioritizes pro-poor distribution of positive agricultural resources and pro-rich distribution for negative environmental burdens. This framework is grounded in three core theoretical pillars of contemporary research on distributive justice and environmental justice: the difference principle [25], the capability approach to development, and the distributive justice dimension of environmental justice theory [26]. We do not negate the value of these alternative frameworks. Instead, our choice of the vulnerability-centered distributive justice framework is a context-specific normative decision tailored to China’s national conditions. We adopt the Concentration Index (CI) as our core analytical tool. The CI is a standard metric for quantifying distributional inequality across socioeconomic groups, with values ranging from -1 to 1 . A CI value of zero indicates perfect absolute equality of distribution, a CI value greater than zero represents a pro-rich distribution, and a CI value less than zero represents a pro-poor distribution. Building on this metric, we distinguish between positive resources and negative environmental burdens based on established environmental justice principles. For positive resources (irrigation water, food yield), a pro-poor distribution ($CI < 0$) is considered equitable because: (1) low-income populations exhibit higher livelihood dependence on agricultural resources, with agriculture constituting their primary income source and food security foundation [5,18]; (2) resource allocation to vulnerable groups aligns with the capability approach to development, which emphasizes matching resources to needs rather than uniform distribution [25,26]; and (3) empirical evidence demonstrates that agricultural resource concentration in low-income regions enhances poverty alleviation effectiveness and livelihood resilience [27].

Conversely, for negative environmental burdens (nitrogen loss, water pollution), a pro-poor distribution ($CI < 0$) is inequitable because: (1) low-income communities possess limited financial capacity, technological infrastructure, and institutional resources for pollution mitigation and health risk management [28–30]; (2) environmental burden concentration in disadvantaged areas violates the polluter-pays principle and distributive justice, as these populations contribute less to pollution generation but bear disproportionate health and ecological costs [31]; and (3) pollution exposure exacerbates existing socioeconomic vul-

nerabilities, creating feedback loops that perpetuate poverty and health inequities [28,31]. This equity evaluation framework, which distinguishes between positive agricultural resources and negative environmental burdens, is widely applied in environmental justice research and provides a solid theoretical basis for assessing trade-offs between resource allocation and pollution burden distribution in agricultural systems [18,29].

Against the backdrop of growing scholarly attention to the water–food–environment nexus and calls for equity-centered assessment frameworks, this study advances the existing literature by quantifying multidimensional disparities across China’s basins. Specifically, we employ an integrated framework that links the irrigation water–food–agricultural nitrogen pollution nexus with rigorous inequality and inequity indicators. The specific objectives are to (1) uncover the evolution of inequity in irrigation water availability, food production, and agricultural water nitrogen pollution risk, clarifying the role of national grain security policies; (2) assess the magnitude of regional disparities and interlinkages among irrigation water–food–agricultural water pollution; and (3) identify key influencing factors behind such disparities. The innovation of this research lies in developing an integrated resource, environment, socioeconomic, and policy assessment framework that explicitly incorporates policy-driven production concentration; establishing a consistent equity evaluation standard (distinguishing positive resources and negative burdens); and realizing the synchronous quantification of inequities across three critical dimensions for the first time. This study not only provides empirical evidence for transitioning agricultural resource management from efficiency-prioritized to equity-oriented governance, but also offers actionable scientific support for targeted infrastructure investment and region-differentiated agricultural trade and subsidy policies that reconcile food security, environmental protection, and social justice.

2. Materials and Methods

2.1. Calculation of Water Resource Scarcity Index

We integrated grid-level ($0.25^\circ \times 0.25^\circ$) water consumption and available water resources (natural runoff minus environmental flow demand) to the county-level scale in China, calculating the Water Scarcity Index (WSI) for each county. For the calculation method, please refer to Gu et al. (2024) [6]. The WSI was derived by dividing total water consumption (agricultural, industrial, and residential) by available water resources (excluding environmental flow) in 1992 and 2017. Total water consumption data were sourced from Zhang et al. (2025) [32], and runoff data from Miao et al. (2020) [33]. The ecological base flow (EF) was set at 20% of the multi-year average surface runoff, following standards from the Ministry of Water Resources of the People’s Republic of China (MOW) [34]. For details, please refer to Equation (1):

$$WSI = \frac{WU}{WA} = \frac{W_{irr} + W_{ind} + W_{dom}}{R - EF} \quad (1)$$

where WSI represents the water scarcity index. WU indicates total water consumption. WA equals the total available water. W_{irr} , W_{ind} , and W_{dom} represent irrigation water, industrial water, and domestic water, respectively. R represents total runoff volume (average of the study year’s preceding and following five years). EF represents the runoff volume required to maintain the surface water ecosystem.

2.2. Equality and Equity of Irrigation Water, Food Yield, and N Loss Responsibility

2.2.1. Data Sources

Irrigation water resources and food yield: Irrigation water includes water requirements for grain crops (wheat, corn, rice, tubers, soybeans). Crop sowing area and yield data were

obtained from the National Bureau of Statistics of China (NBS) [35]. Regional crop-specific water requirement data were sourced from Zhou et al. (2020) [36]. We used the nutrient flows in food chains, environment, and resource use (NUFER) model [37,38] to quantify nitrogen (N) losses entering surface water bodies via surface runoff from crop production, considering N inputs (fertilizer, manure, irrigation, etc.), N surpluses, and loss pathways. Notably, this study focuses exclusively on N losses to surface water and does not include N losses via groundwater leaching. Important factors controlling N losses to surface water are slope, soil texture, land use, rainfall (intensity), and soil depth. For details, please refer to Equations (2)–(7).

$$N_{\text{surface runoff}} = (N_{\text{surplus}} - N_{\text{erosion}}) \times EF_{\text{surface runoff}} \quad (2)$$

$$N_{\text{surplus}} = IC_{\text{fixation}} + IC_{\text{deposition}} + IC_{\text{fertilizer}} + IC_{\text{manure}} + IC_{\text{irrigation}} + IC_{\text{straw}} - OC_{\text{products}} - OC_{\text{straw}} - OC_{\text{NH}_3} - OC_{\text{N}_2\text{O}} - OC_{\text{denitrification}} \quad (3)$$

$$N_{\text{erosion}} = N_{\text{surplus}} \times EF_{\text{erosion}} \quad (4)$$

$$OC_{\text{NH}_3} = IC_{\text{fertilizer}} \times EF_{\text{NH}_3, \text{fertilizer}} + IC_{\text{manure}} \times EF_{\text{NH}_3, \text{manure}} \quad (5)$$

$$OC_{\text{N}_2\text{O}} = IC_{\text{fertilizer}} \times EF_{\text{N}_2\text{O}, \text{fertilizer}} + IC_{\text{manure}} \times EF_{\text{N}_2\text{O}, \text{manure}} \quad (6)$$

$$OC_{\text{denitrification}} = IC_{\text{fertilizer}} \times EF_{\text{denitrification, fertilizer}} + IC_{\text{manure}} \times EF_{\text{denitrification, manure}} \quad (7)$$

where $N_{\text{surface runoff}}$ represents the nitrogen loss from the crops through surface runoff. N_{surplus} is the nitrogen surplus in the crop production system. N_{erosion} represents the nitrogen loss through erosion by the crop production system. IC_{fixation} is the nitrogen-fixing organisms. $IC_{\text{deposition}}$ is the nitrogen input through atmospheric deposition. $IC_{\text{fertilizer}}$ is the nitrogen input from fertilizers. IC_{manure} is the nitrogen input from manure. $IC_{\text{irrigation}}$ is the nitrogen input from irrigation. IC_{straw} is the nitrogen input from straw. OC_{products} is the nitrogen output from the produced crops. OC_{straw} is the nitrogen output from crop straw. OC_{NH_3} is the nitrogen loss through NH_3 emission from the applied chemical fertilizers and organic fertilizers. $OC_{\text{N}_2\text{O}}$ is the nitrogen lost through N_2O emission from the applied chemical fertilizers and organic fertilizers. $OC_{\text{denitrification}}$ is the nitrogen loss through denitrification from the applied chemical fertilizers and organic fertilizers. $EF_{\text{surface runoff}}$ is the coefficient of nitrogen runoff loss in the agricultural system. EF_{erosion} is the coefficient of nitrogen erosion loss in the agricultural system. $EF_{\text{NH}_3, \text{fertilizer}}$ is the NH_3 emission coefficient of chemical fertilizers. $EF_{\text{NH}_3, \text{manure}}$ is the NH_3 emission coefficient of manure. $EF_{\text{N}_2\text{O}, \text{fertilizer}}$ is the N_2O emission coefficient of chemical fertilizers. $EF_{\text{N}_2\text{O}, \text{manure}}$ is the N_2O emission coefficient of manure. $EF_{\text{denitrification, fertilizer}}$ is the denitrification emission coefficient of chemical fertilizers. $EF_{\text{denitrification, manure}}$ is the denitrification emission coefficient of manure.

2.2.2. Definition and Assessment of Equality and Equity

Equality refers to the uniform distribution of resources or burdens across populations/regions, quantified by the Concentration Index (CI). The CI is chosen as the core indicator for measuring inequality and equity in this study for its unique conceptual and applicative advantages over other methods, such as the Gini coefficient, in a resource-environment equity assessment of the water–food–environment nexus [39]. Conceptually, the Gini coefficient quantifies overall unordered variable inequality across the population, ignoring socioeconomic characteristics (e.g., income level) and only reflecting distribution disparity magnitude, with no linkage to social or environmental justice principles [40]. In contrast, the CI is a socially ordered indicator that quantifies resource/burden distribution relative to per capita GDP and ranked socioeconomic groups, directly connecting distribution patterns to distributive and environmental justice assessments—a core need of this

study—to evaluate if agricultural resources and environmental burdens are disproportionately concentrated in low- or high-income groups.

The CI is determined by calculating twice the area between the concentration curve and the absolute equality line. The concentration curve has the cumulative proportion of the population ranked by per capita GDP as the x -axis, and the cumulative proportion of agricultural resources as the y -axis. Absolute equality is represented by $CI = 0$, with larger absolute CI values indicating higher inequality. For details, please refer to Equation (8):

$$CI = 1 - 2 \int_0^1 L_w(P) dp = 1 - \sum_{i=0}^{n-1} (P_{i+1} - P_i)(W_{i+1} + W_i) \quad (8)$$

where $L_w(P)$ represents the concentration curve. n represents the population amount. i represents the rank of the population sorted by per capita GDP. W_i represents the cumulative proportion of resources or nitrogen loss of the first i populations. P_i represents the cumulative proportion of the population of the first i individuals. Due to the lack of individual-level data covering the entire country, the study assumes that the resource allocation for the population within the same grid is equal. Absolute equality is represented by $CI = 0$, meaning that the resource allocation or water body nitrogen pollution borne by all populations is equal. A larger absolute value of CI (e.g., $CI = 1$ or $CI = -1$) corresponds to a higher degree of inequality in resource allocation or nitrogen loss burden sharing among population subgroups.

Equity is a context-dependent concept distinguishing positive resources and negative burdens. For positive resource indicators (irrigation water, food yield), equity means allocating resources in a way that matches the demand and the degree of livelihood dependence. Pro-poor distribution ($CI < 0$) is equitable, as low-income groups rely on agriculture for survival, and resource concentration ensures food security and poverty alleviation. For negative indicators (N loss to water): Equity means matching the burden to the bearing capacity. Pro-rich distribution ($CI > 0$) is equitable, as high-income groups have a stronger governance capacity. Pro-poor distribution ($CI < 0$) is inequitable. Based on the aforementioned principles, this study calculates the CI across different river basins and per capita GDP groups to systematically analyze the spatial and socioeconomic disparities in the allocation or risk-bearing patterns of food yield, irrigation water resources, and water body nitrogen loss. Particular attention is paid to the equity differentiation among population subgroups within each river basin. This study simultaneously examines the equality and equity of the three indicators, thereby achieving a multidimensional evaluation of distributive equity in the water–food–environment system. The details of the evaluations of equality and equity for different indicators please see Table S1.

2.3. Factors Associated with Equity Variations

To quantify the marginal predictive contributions of each variable to the variations in the resource allocation equity index (CI) across China, this study employed the Shapley Value method. This method, rooted in cooperative game theory, is used to decompose and measure the relative contribution of each explanatory variable to the variations in the dependent variable (CI values) in our regression model [41]. The Shapley Value used in this study only quantifies the relative predictive contribution of each variable to the variations in CI values and cannot establish strict causal relationships between the variables and equity outcomes. The causal links between the selected variables and equity changes require further validation through targeted causal inference designs in subsequent research.

We selected seven key independent variables based on their theoretical relevance to agricultural resource allocation and environmental burden distribution: (1) population size—directly determines total resource demand and consumption scale [42]; (2) per capita GDP—reflects regional economic development level and resource acquisition capacity [43]; (3) urbanization rate—influences agricultural labor availability and production spatial patterns [44]; (4) crop yield per unit area—represents agricultural productivity and output intensity [45]; (5) crop water use per unit area—indicates irrigation intensity and water resource consumption [46]; (6) crop area share—measures the proportion of agricultural land use [47]; and (7) nitrogen fertilizer application—determines pollution generation intensity [48]. These variables comprehensively capture the demographic, economic, technological, and environmental dimensions that shape equity outcomes in the water–food–environment nexus. The definitions and data sources of the different variables are presented in Table S2.

In this study, the CI for various indicators serves as the dependent variable, while population size, per capita GDP, urbanization rate, crop yields, crop water use per unit area, crop area share, and nitrogen fertilizer application are employed as predictive independent variables. In machine learning, it is used to explain the contribution of each feature in the model to the prediction outcome. The analytical unit of this model is municipal administrative units on the Chinese mainland. After excluding Hong Kong, Macao, and Taiwan regions, the final valid sample comprises 333 municipal units, covering all major grain-producing areas and agricultural regions across China. First, we performed standardized preprocessing on all independent variables to eliminate the influence of dimensional differences between indicators. The preprocessed dataset was randomly split into a training set and a test set with a fixed random seed to ensure reproducibility. Seventy percent of the total sample was used to fit the XGBoost regression model and optimize hyperparameters. Thirty percent of the total sample was used to evaluate the out-of-sample prediction reliability of the model and to verify that the model has no severe overfitting.

For a model with n features, the Shapley Value of feature j (ϕ_j) is as follows. For details, please refer to Equation (9):

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(n-|S|-1)!}{n!} [f(S \cup \{j\}) - f(S)] \quad (9)$$

where N represents the set of all features, S represents the subset that does not include feature j . $|S|$ indicates the number of features in the subset S . n is the total number of independent variables. $f(S)$ represents the predicted value of the model under the feature subset S . $f(S \cup \{j\})$ represents the predicted value after adding feature j to the feature subset S .

This formula calculates the marginal contribution of feature j in all possible feature combinations (that is, the change in the predicted value after adding feature j) and, based on the weighted average of the probabilities of the combinations, obtains the contribution value of feature j to the model's prediction. The marginal contribution reflects the unique role of feature j in different combinations, and the weighted average ensures the equity and comprehensiveness of the result. This study primarily employs the XGBoost algorithm to construct a regression model and uses the SHAP (SHapley Additive exPlanations) method for model interpretation. Based on the shapviz package in R 4.4.3, the following analyses are conducted: a feature importance assessment, calculating the global contribution of each predictor variable to the CI, visualizing the SHAP value distribution of key variables through a beeswarm plot, and presenting their mean absolute SHAP values in a bar chart.

We conducted a rigorous circularity check between our predictors and the dependent variable (CI values). The CI is a distributional index calculated from cumulative population and core indicator shares, with none of the predictors mechanically included in its numerical calculation. Per capita GDP is only used for population ranking, and the nitrogen application rate is not a direct component of the distributional CI. All predictors are included with solid theoretical justification, with no circular prediction issues in our model design.

2.4. Quadrant Analysis of Water Scarcity and Equity Coupling

To systematically analyze the coupling relationship between water scarcity changes and equity evolution, we employed a quadrant classification method based on changes in WSI (ΔWSI) and changes in CI (ΔCI) in 1992 and 2017. For each county, $\Delta WSI = WSI_{2017} - WSI_{1992}$ represents the change in water scarcity (positive values indicate intensified scarcity, negative values indicate relief), and $\Delta CI = CI_{2017} - CI_{1992}$ represents the change in resource allocation or pollution burden equity (interpretation varies by indicator type).

Quadrant classification criteria:

- Quadrant I ($\Delta WSI > 0$, $\Delta CI > 0$): Intensified water scarcity coupled with increased pro-rich resource allocation or decreased pro-poor pollution burden—representing trade-offs where water stress worsens but equity improves for positive resources or deteriorates for negative burdens;
- Quadrant II ($\Delta WSI < 0$, $\Delta CI > 0$): Alleviated water scarcity coupled with increased pro-rich allocation or decreased pro-poor burden—representing synergy for positive resources where both water conditions and equity improve;
- Quadrant III ($\Delta WSI < 0$, $\Delta CI < 0$): Alleviated water scarcity coupled with increased pro-poor allocation or increased pro-poor burden—representing synergy for positive resources but trade-offs for negative burdens;
- Quadrant IV ($\Delta WSI > 0$, $\Delta CI < 0$): Intensified water scarcity coupled with increased pro-poor allocation or increased pro-poor burden—representing trade-offs where water stress worsens alongside equity deterioration.

For each quadrant, we calculated the population share and mean per capita GDP to characterize the socioeconomic profiles of affected populations. This quadrant analysis enables the identification of regions experiencing synergistic improvements (water relief + equity gains) versus those facing compounding challenges (water stress + equity deterioration), providing spatial targeting for policy interventions. The analysis was conducted separately for irrigation water, food yield, and nitrogen loss to reveal dimension-specific coupling patterns.

3. Results and Discussion

3.1. Differentiated Impacts on Water Scarcity and Policy-Driven Food Production

China's water scarcity exhibits a long-standing north–south asymmetry. In 1992, Northern and Northwestern China (key grain-producing regions) had a WSI above 0.6, with the North China Plain exceeding 1.0 (severe scarcity), while Southern and Southwestern China (diversified economies) had a WSI below 0.4 (Figure S2; Table S3). By 2017, the high-WSI areas expanded: the North China Plain, Northwest China, and the Huanghuai Plain saw their WSIs rise to above 0.8 (local areas > 1.0), and the southern regions (e.g., middle-lower Yangtze River) experienced significant WSI increases due to industrial/urban water use squeezing agricultural resources (Figures S2 and S3).

From 1992 to 2017, water stress and economic development co-evolved asymmetrically, a pattern intensified by national grain policy. Nationally, 61% of the population lived in areas with reduced water stress (WSI^-), while 39% resided in areas with intensified stress (WSI^+). Notably, the arithmetic mean and population-weighted per capita GDP of WSI^-

groups were consistently higher than WSI+ groups, indicating water stress relief disproportionately benefited economically developed regions (Figure S3). This asymmetric pattern of water stress relief in developed regions reflects multiple interacting mechanisms beyond grain policy alone. First, economically advanced regions underwent substantial industrial restructuring during this period, transitioning from water-intensive heavy industries (steel, chemicals, textiles) to service-oriented and high-tech sectors with significantly lower water footprints [16,49]. For instance, the Yangtze River Delta and Pearl River Delta regions reduced industrial water consumption by 30–45% through sectoral transformation and relocation of water-intensive manufacturing to inland areas.

Second, developed regions invested heavily in water-saving technologies and infrastructure, including industrial water-recycling systems, precision irrigation in remaining agricultural areas, and urban water conservation programs, achieving water use efficiency improvements of 40–60% [36,50]. Third, major inter-basin water transfer projects, most notably the South-to-North Water Diversion Project, strategically allocated water resources to economically developed but water-scarce regions, directly alleviating supply constraints in the North China Plain and benefiting over 100 million urban residents [51]. Fourth, market-driven water reallocation mechanisms enabled developed regions to reduce agricultural water use through crop structure adjustments and virtual water trade, importing water-intensive agricultural products while exporting high-value manufactured goods [52]. These technological, infrastructural, and economic factors synergistically contributed to water stress relief in developed areas, operating in parallel to, and sometimes reinforcing, the policy-driven concentration of grain production in low-income regions.

The spatial asymmetry between food production and economic development, which is consistent with the orientation of national food security policies, is further evident in agricultural spatial patterns: major grain-producing regions (northern water-scarce/low-income areas) face strict arable land protection and grain supply mandates, which may limit their industrialization and economic growth. In contrast, non-grain-producing regions, such as southern water-abundant and/or high-income areas, abandoned grain cultivation for industry/services, achieving far higher GDP growth. This led to (1) non-producing regions reducing grain shares via non-grain conversion/industrial land expansion and (2) widening GDP gaps, concentrating grain production in low-income areas (Figure S3).

3.2. Equity Changes and Asymmetric Transfer of Production-Environment Burdens

From 1992 to 2017, the CI of all three indicators declined ($\Delta|CI| > 0$), indicating improved equality, but equity implications varied by indicator (Figure 1). For food yield, the CI shifted from 0.214 (pro-rich) to -0.052 (pro-poor), marking enhanced equity. Policy-driven concentration ensured low-income regions' food security amid the looming climate/natural disaster risks, supporting poverty alleviation (SDG 1), contrary to prior claims that resource concentration hinders poverty reduction. Grain production is the main livelihood of low-income groups in producing regions, and resource concentration stabilizes their basic needs (Figure 1b). For irrigation water, the CI decreased from 0.023 to 0.017, with weakened pro-rich bias and modest equity improvement. Irrigation water followed grain production to low-income regions, but water scarcity and non-agricultural diversion limited equitable access (Figure 1a). For N loss to surface water, the CI decreased from 0.1 to 0.03, worsening environmental inequity. As grain production concentrated in low-income regions, N loss (an inevitable industrial agriculture byproduct) shifted to these areas, where weak governance capacity left them bearing pollution costs without compensation (Figure 1c).

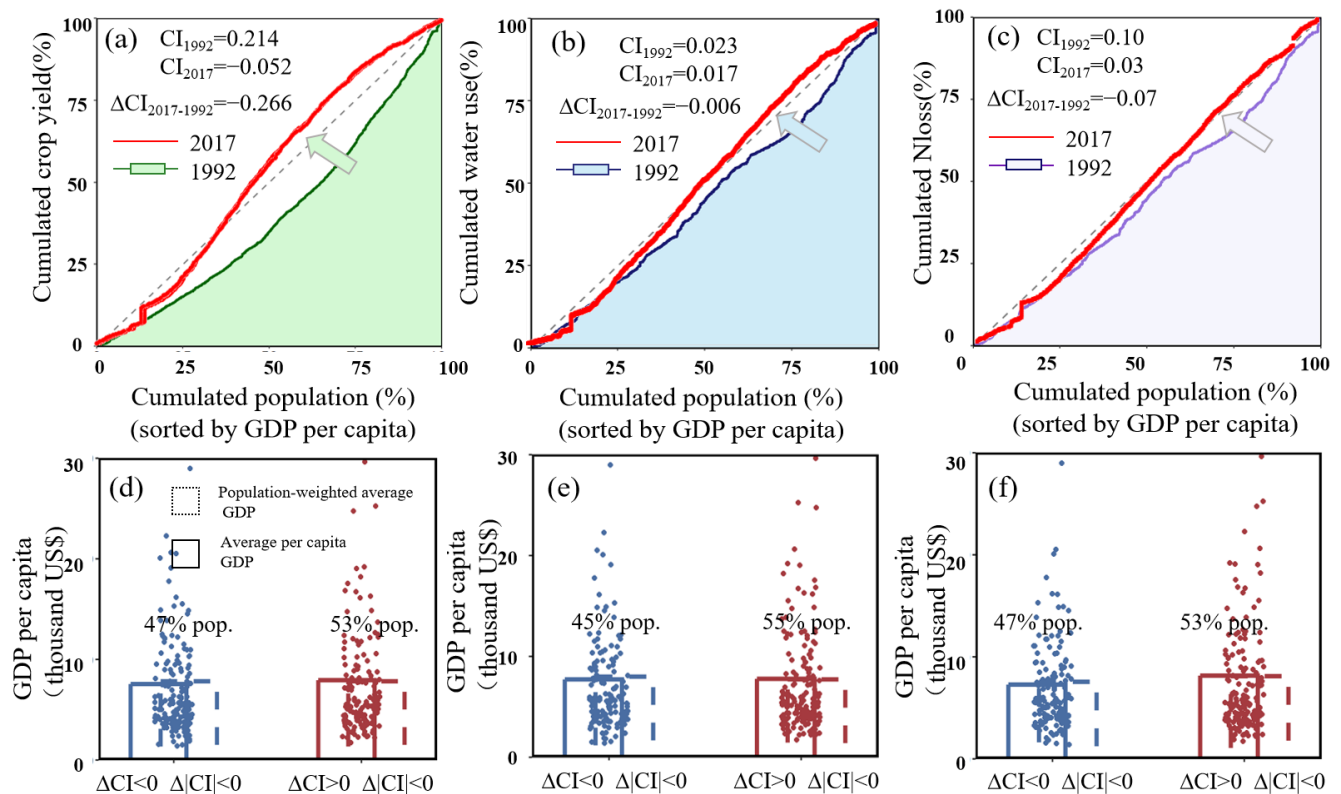


Figure 1. Temporal changes in equity of food yield, irrigation water, and nitrogen loss to surface water in China, 1992–2017. Panels (a–c) show concentration curves and changes in the Concentration Index (CI) for food yield, irrigation water, and nitrogen (N) loss, respectively. The concentration curve plots the cumulative population proportion (ranked by per capita GDP) against the cumulative resource or pollution burden proportion. CI values shifted from pro-rich to pro-poor for food yield (0.214 to −0.052), showed modest improvement for irrigation water (0.023 to 0.017), and worsened for N loss (0.10 to 0.03). Panels (d–f) show per capita GDP distribution (constant 2017 US\$ across groups experiencing different equity changes). Solid bars represent the arithmetic mean GDP per capita; dashed bars represent the population-weighted mean. Numbers above bars indicate population proportion in each group. Note: CI ranges from −1 to 1, where CI = 0 indicates perfect equality. For positive resources (food, water), CI < 0 (pro-poor) is equitable. For negative burdens (pollution), CI < 0 is inequitable. See Methods for detailed CI interpretation.

The improved food production distribution among poor people, however, was an outcome of national grain security policies. Since the 1990s, China has explicitly designated major grain-producing regions through the “Provincial Governor Grain Bag Responsibility System” and subsequent policies, which are predominantly located in economically underdeveloped areas [53,54]. These regions face strict arable land protection mandates and mandatory grain supply responsibilities, limiting their industrialization potential and economic diversification opportunities. The “Regulations on the Protection of Basic Farmland” (1998) and “National Main Functional Area Planning” (2010) reinforced the spatial constraints on non-agricultural development in major producing regions, effectively locking them into agricultural specialization [55]. In contrast, non-grain-producing regions, particularly coastal and economically advanced areas, have systematically abandoned grain cultivation to develop industry and high-value-added sectors, achieving far higher GDP growth rates. This policy-led division of labor has created a “grain production-economic development” trade-off: between 1992 and 2017, major grain-producing provinces (Heilongjiang, Henan, Shandong, Jilin, Hebei) maintained or increased their grain output shares

from 35% to 42% of national production, while their per capita GDP remained 60–75% of the national average [54].

Conversely, economically developed provinces (Guangdong, Zhejiang, Jiangsu) reduced grain production shares from 12% to 7% while achieving per capita GDP 150–200% of the national average. This spatial redistribution of grain production, which aligns with the implementation of national grain security policies, is associated with two key observed patterns: (1) non-grain-producing regions have reduced grain production shares through non-grain conversion and industrial land expansion and (2) the GDP gap between grain-producing and non-producing regions has widened from 1.8:1 to 2.5:1, which is accompanied by the increasing concentration of grain production in low-income areas [53]. This concentration of grain production improves food security equity for low-income-producing regions by stabilizing the livelihoods and income of local farming households whose subsistence depends primarily on grain cultivation amid climate and market risks, but it also transfers the associated irrigation water consumption and nitrogen loss burdens to these areas, creating a double-edged sword effect that necessitates targeted ecological compensation mechanisms.

The concentration of N losses to surface water in low-income grain-producing regions represents a critical environmental justice concern that extends beyond simple resource allocation patterns. This pollution transfer creates multidimensional health and socio-economic risks for vulnerable populations. N loss distribution (CI changed from 0.1 to 0.03) reflects an inequitable environmental risk transfer where low-income populations bear escalating pollution burdens without commensurate capacity for mitigation or compensation, a pattern that fundamentally contradicts environmental justice principles and threatens the sustainability of policy-driven agricultural intensification [26,28].

While this study does not directly measure health outcomes or governance capacity, existing research provides robust evidence for the following potential pathways linking the observed pollution burden shift to adverse impacts on vulnerable populations. First, N pollution from agricultural runoff contaminates local drinking water sources through nitrate leaching and surface water eutrophication, directly threatening public health, particularly for infants (methemoglobinemia risk) and pregnant women in rural communities with limited access to treated water [4,9]. Epidemiological evidence indicates that chronic exposure to elevated nitrate levels in drinking water is associated with increased risks of gastric cancer, thyroid disorders, and adverse birth outcomes, with the health burdens disproportionately borne by low-income agricultural populations [55]. Second, existing empirical studies have shown that regional differences in financial resources, technical conditions, and institutional infrastructure for agricultural pollution control are highly correlated with the spatial distribution of agricultural non-point source pollution [56]. Combined with the empirical findings of this study, the concentration of grain production and associated nitrogen pollution burdens in low-income regions may further amplify the regional disparity in agricultural pollution pressure [56]. Third, the absence of modern agricultural management systems, extension services, and equipment in low-income areas leads to inefficient fertilizer application practices (over-application, poor timing, inadequate incorporation), exacerbating N losses per unit of grain produced [57]. This technological gap means that grain production concentration not only transfers pollution geographically but also amplifies pollution intensity due to lower production efficiency.

Notably, this study focuses on quantifying the spatiotemporal distribution of agricultural N pollution burdens across socioeconomic groups via the CI framework, rather than verifying causal links between the observed burden shift and specific health or governance outcomes. The pathways above are literature-based inferences, and the site-specific correlations, health-related causal links, and micro-policy mechanisms require further targeted research.

In addition, a detailed per capita GDP group analysis revealed a paradox: national equity improvements were driven by a minority of high-intensity grain-producing regions. For irrigation water, only 45% of the population saw concurrent equity ($\Delta CI < 0$) and equality ($\Delta |CI| < 0$) improvements, with 55% remaining in pro-rich allocation (Figure 1d). Similarly, food production and N loss equity gains were concentrated in major producing regions, masking uneven benefits among the broader population (Figure 1e,f). Notably, the prior contradiction between “water stress relief benefiting developed regions” and “resources concentrating in low-income areas” is resolved. It reflects a functional division of labor, developed regions gain industrial/ecological benefits, and low-income regions gain agricultural resources, an implicit equitable compensation for food security contributions.

3.3. Basin-Scale Equity Heterogeneity Driven by Policy and Resource Endowments

Equity evolution exhibited significant basin heterogeneity, shaped by policy, water resources, and economic bases.

For northern basins, the equity improved significantly in the lower Yellow River (core grain-producing region) due to state irrigation infrastructure investment. However, the upper-middle Yellow River, Haihe, and Songliao Basins showed limited improvement or decline, and cities like Shijiazhuang and Shenyang faced water scarcity and non-agricultural diversion, squeezing agricultural water for low-income groups (Figures 2 and 3). For southern basins, the equity increased in the upper Yangtze River and southwest (key grain-producing areas) but declined in the middle-lower Yangtze River, Pearl River, and southeast coast. Industrial/urban water demand diverted irrigation resources from low-income grain producers (Figures 2 and 3). These spatial patterns reflect the interplay between policy mandates and local resource constraints. State irrigation infrastructure investment in major producing regions (e.g., lower Yellow River) has partially offset water scarcity through improved water use efficiency and storage capacity [17]. However, in basins where industrial and urban water demand compete directly with agricultural use (e.g., Haihe, middle-lower Yangtze), market-driven water reallocation has favored high-value non-agricultural sectors, squeezing irrigation water access for low-income farmers despite policy intentions [12].

Food production equity improved most consistently, driven by policy mandates. For northern basins, the Songliao, Haihe, Huaihe, and lower Yellow River Basins (core producing regions) saw notable equity gains, with cities like Harbin and Shijiazhuang shifting to pro-poor distribution. The upper Yellow River and northwest showed modest improvements due to limited land/water resources (Figures 2 and 3). Meanwhile, for the southern basins, equity rose in the Yangtze River, Pearl River, and southeast coast, but was modest in the lower Yangtze (e.g., Nantong, Nanjing) due to non-grain conversion (Figures 2 and 3).

Nitrogen loss equity was the least stable when compared with that of irrigation water and food production. For the northern basins, equity improved in the upper-middle Yellow River (e.g., Xi'an) but deteriorated in the Haihe, Songliao, and lower Yellow River. Major producing regions bore heavy pollution burdens, while developed regions transferred pollution-intensive activities outward (Figures 2 and 3). Meanwhile, for the southern basins, equity improved in the Pearl River, southwest, and southeast, and declined in the

Yangtze River. In addition, the intensified grain production in the middle Yangtze increased N application and pollution (Figures 2 and 3). The instability of nitrogen loss equity across basins underscores the challenge of coordinating agricultural intensification with environmental protection. Developed regions have leveraged economic resources to adopt precision fertilization technologies and establish pollution monitoring systems, reducing nitrogen application rates by 15–25% while maintaining yields [58]. In contrast, low-income-producing regions face a “pollution lock-in” effect: policy-driven production concentration increases nitrogen input requirements, but limited financial capacity prevents the adoption of pollution mitigation technologies, resulting in nitrogen loss intensities 30–50% higher than developed regions [59]. This divergence highlights the need for targeted technology transfer and financial support to break the nexus between production concentration and pollution intensification.

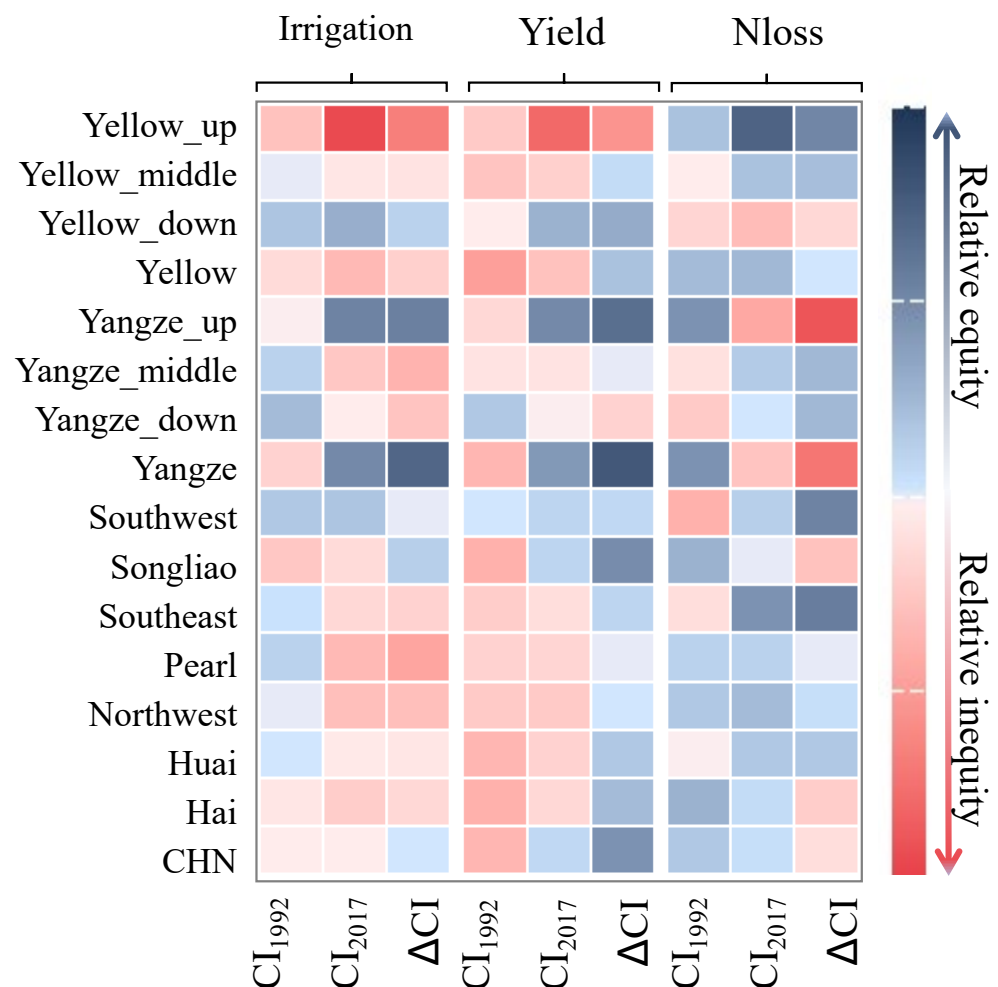


Figure 2. Spatial heterogeneity in equity changes across China’s river basins, 1992–2017. Maps show the Concentration Index (CI) values and their temporal changes ($\Delta CI = CI_{2017} - CI_{1992}$) for food yield, irrigation water, and nitrogen (N) loss to surface water across major river basins. Each row represents one indicator; the left column shows 1992 values, the middle column shows 2017 values, and the right column shows changes over the period. Blue colors indicate pro-poor distribution (equitable for resources, inequitable for pollution); red colors indicate pro-rich distribution (inequitable for resources, equitable for pollution). Color intensity represents the magnitude of CI values, with darker shades indicating stronger concentration. Note: Basin-level analysis reveals significant regional heterogeneity in equity evolution, with northern grain-producing basins (Haihe, Yellow River, Songliao) showing distinct patterns compared to southern basins (Yangtze, Pearl River).

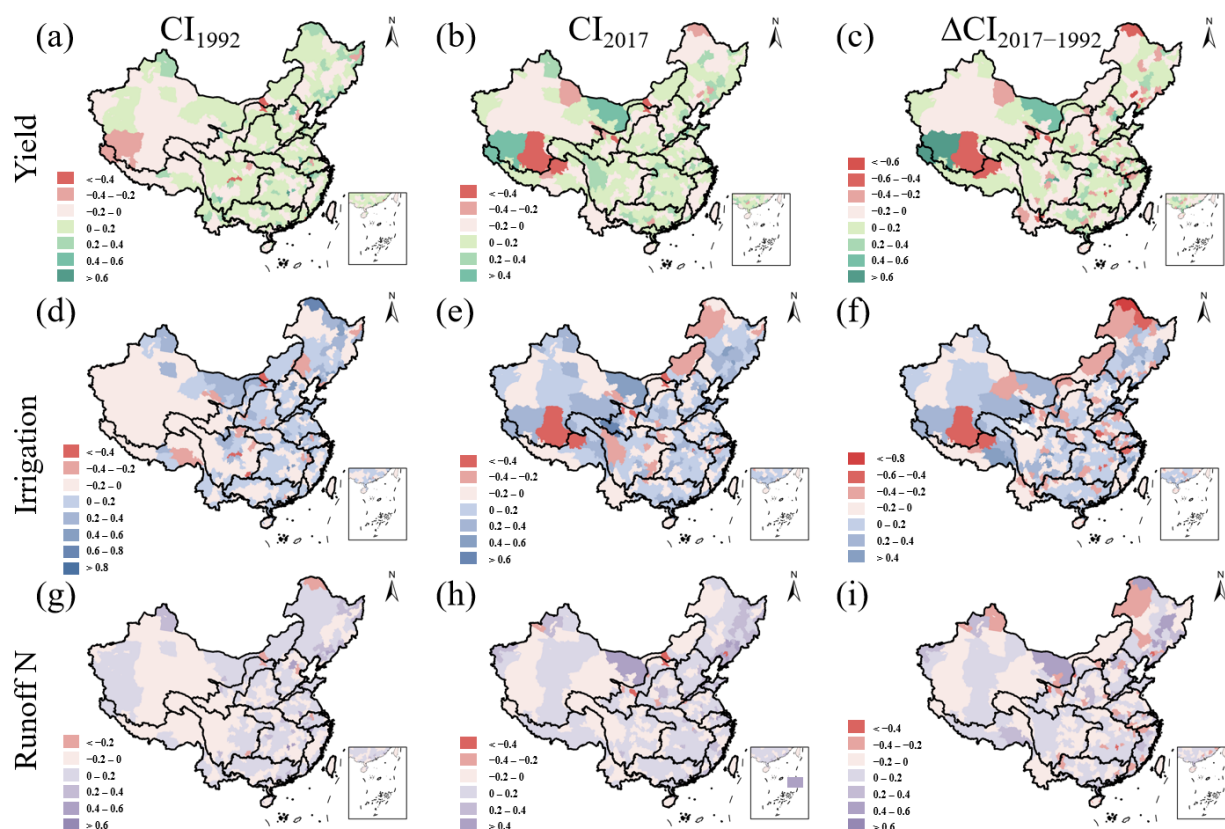


Figure 3. City-level equity patterns and changes in food yield, irrigation water, and nitrogen loss, 1992–2017. Maps display Concentration Index (CI) values and temporal changes (Δ CI) at the city level for (a–c) food yield, (d–f) irrigation water, and (g–i) nitrogen (N) loss to surface water. For each indicator, maps show 1992 CI values, 2017 CI values, and the change over the period. This fine-scale analysis reveals substantial within-basin heterogeneity, with major cities (e.g., Beijing, Shanghai, Guangzhou) showing distinct equity trajectories compared to surrounding agricultural regions. Blue indicates pro-poor distribution; red indicates pro-rich distribution. Color intensity represents CI magnitude. Note: City-level resolution captures local-scale equity dynamics masked in basin-level aggregation (Figure 2), particularly the urban–rural divide in resource allocation and pollution burden distribution.

Key discrepancies emerged across these dimensions, particularly in the Haihe, upper Yangtze, and Yellow River Basins: while food production equity improved, irrigation water allocation and N loss burdens failed to align with this progress, reflecting tensions between policy-driven production concentration and local resource or environmental constraints. The spatial concentration of grain production is typically coupled with elevated irrigation water consumption and greater accountability for N loss, leaving grain-producing basins to bear concurrent resource depletion and environmental pressure. For instance, in the lower Yellow River, Songliao Basin, and upper Yangtze River, both grain production and irrigation water use are markedly concentrated among low-income populations, who additionally shoulder substantial N loss burdens, objectively constraining these basins' capacity to develop high-value-added industries. In contrast, the Haihe and Huaihe Basins exhibit a mismatch between production obligations and resource access amid extreme water scarcity: grain production remains concentrated in low-income regions, yet irrigation water allocation has shifted toward high-income groups. Meanwhile, the Pearl River Basin and parts of the middle-lower Yangtze River show moderate or even improved trends in irrigation water, grain production, and nitrogen loss burden distribution, driven by robust economic foundations that enable coordinated grain production, resource allocation, and pollution

control. Overall, under China's food security framework, the redistribution of resource consumption and environmental burdens displays substantial spatial heterogeneity across river basins, with cross-dimensional synergies or trade-offs closely tied to local policy implementation, resource endowments, and economic development levels.

3.4. Factors Associated with Equity Variations: Policy, Socioeconomic Structure, and Agricultural Inputs

The SHAP (SHapley Additive exPlanations) analysis identified distinct predictive factors for CI variations across dimensions, with variables related to national grain security policy implementation showing the strongest predictive contribution (Figure 4). For irrigation water CI, the factors with the largest predictive contributions are population size, grain yield level, and variables related to national irrigation and grain security policies. Population size shows a consistent positive association with CI (positive SHAP values), which is linked to amplified total irrigation demand and the concentration of irrigation water allocation in densely populated food-producing regions. This pattern may lead to reduced equity in water-scarce basins, where non-agricultural water use tends to squeeze agricultural irrigation resources (Figure 4a). While food production is closely linked to irrigation water (positive CI influence), with high-yield regions securing priority water access, this is equitable for agricultural use but distorted by non-agricultural diversion. The regulation policy is playing as a regulatory factor, such as irrigation infrastructure investment in producing regions mitigated inequity, while industrial/urban water preference in developed regions amplified it.

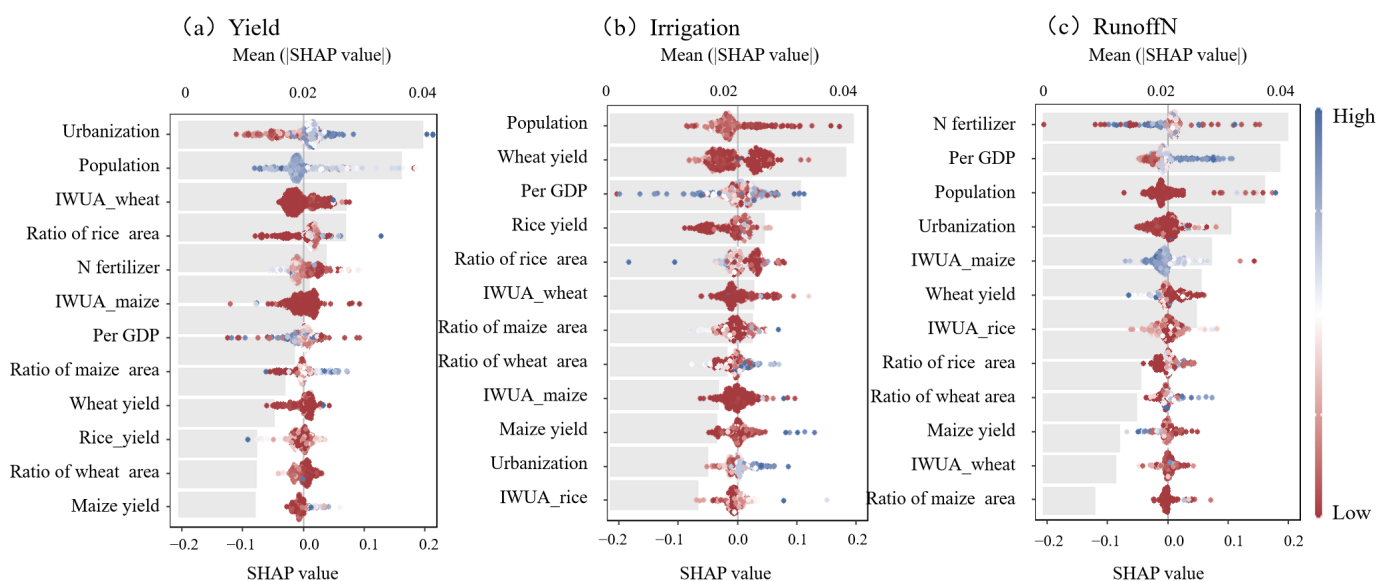


Figure 4. Factors predictive of CI variations identified through SHAP (SHapley Additive exPlanations) analysis. Beeswarm plots show the contribution of seven predictor variables to Concentration Index (CI) variation for (a) food yield, (b) irrigation water, and (c) nitrogen (N) loss to surface water. Each dot represents a county-level observation. Horizontal position indicates the SHAP value (contribution to CI prediction), and dot color represents the feature value magnitude (red = low, blue = high). Variables are ranked by mean absolute SHAP value (shown in gray bars on the right), indicating overall importance. Positive SHAP values indicate the variable increases CI (pro-rich distribution); negative values indicate decreased CI (pro-poor distribution). Note: SHAP analysis quantifies each variable's marginal contribution to model predictions while accounting for interactions among all features. See Methods Section 2.3 for details.

For food production, the national grain security policy, urbanization rate, and agricultural input intensity play key roles. Variables associated with the implementation of national grain security policies, including the designation of major grain-producing regions, arable land protection regulations, and agricultural subsidy schemes, are the strongest predictive factors for the spatial redistribution of grain production. These policy arrangements are closely associated with the growing concentration of grain production in low-income regions and may constrain the industrialization development of these areas. The urbanization rate shows a significant negative association with food yield CI (negative SHAP values), acting as a mitigating factor for the pro-rich concentration of grain production. The existing literature suggests two interconnected mechanisms underlying this association [42]: (1) Urbanization provides more nonagricultural employment opportunities for rural labor forces. This process reduces the reliance of low-income groups on grain production and further eases the pressure brought by production concentration. (2) Urban development and the associated infrastructure construction facilitate the spread of advanced agricultural technologies, including mechanization and precision agriculture. These advances improve production efficiency in non-major grain-producing regions, narrow the yield gap between major and non-major producing areas, and, thus, reduce the spatial concentration of grain production. (Figure 4b). Agricultural input intensity shows a positive association with grain yield CI (positive SHAP values), which is linked to a reinforced concentration of grain production, as major producing regions form high-input and high-output production advantages. This pattern is generally aligned with improved equity, as it matches the livelihood needs of low-income farming groups in major producing regions.

For N losses to water, the key roles are N fertilizer application, population pressure, and socioeconomic factors. The nitrogen fertilizer application rate has the largest predictive contribution to nitrogen loss CI variations, with a consistent positive association with CI values (positive SHAP values). Higher fertilizer application rates are linked to an intensified concentration of nitrogen pollution burdens in major grain-producing regions, which is associated with diminished environmental equity, as low-income regions generally have weaker technical and institutional capacity for pollution governance (Figure 4c). Population size acts as a secondary predictive factor (positive influence on CI values), with larger population scales associated with higher agricultural production intensity and elevated nitrogen pollution risk in grain-producing regions. Socioeconomic factors show weak and indirect predictive contributions: existing evidence indicates that developed regions can reduce local nitrogen pollution burdens via the adoption of clean production technologies, while low-income regions often face financial and technical constraints on effective pollution control.

3.5. Asymmetric Coupling Between Water Scarcity, Policy, and Equity

Agricultural production involves resource consumption and allocation, with inevitable tradeoffs and synergies among diverse resources. Approximately 44% of the population showed no clear coordination or tradeoffs across the three dimensions (Figure 5d). For food yield, population distribution was balanced across quadrants, but with significant socioeconomic disparities: in water stress-relief areas, 36% of the population had production resources concentrated among high-income groups, while 28% saw concentration among low-income groups (with opposite per capita GDP levels). In water stress-intensified areas, the proportions of favorable and disadvantaged populations were similar ($\approx 18\%$), indicating water pressure increases did not lead to one-sided yield concentration in wealthy areas. A distinct asymmetric coupling exists between water scarcity changes (ΔWSI) and concentration index shifts (ΔCI). For irrigation water inequity, 34% of the population lived in “alleviated scarcity + pro-rich water allocation” (high per capita GDP),

31% in “alleviated scarcity + pro-poor allocation” (low per capita GDP), and 21% in “intensified scarcity + pro-rich allocation” (high economic development). Coupling outcomes depend heavily on regional economic bases, with significant differences in irrigation water equity evolution even amid national water stress relief. For runoff N, most populations were in areas with slight Δ WSI changes but adjusted inequity, with 33% in “alleviated scarcity + high-income pollution burden” and 30% in “alleviated scarcity + low-income burden.” Even with improved water conditions, nitrogen loss distribution evolved along different socioeconomic paths. Water-stressed areas (16–21% of the population) had significantly higher per capita GDP, becoming concentrated zones of nitrogen pollution burden (Figure 5c).

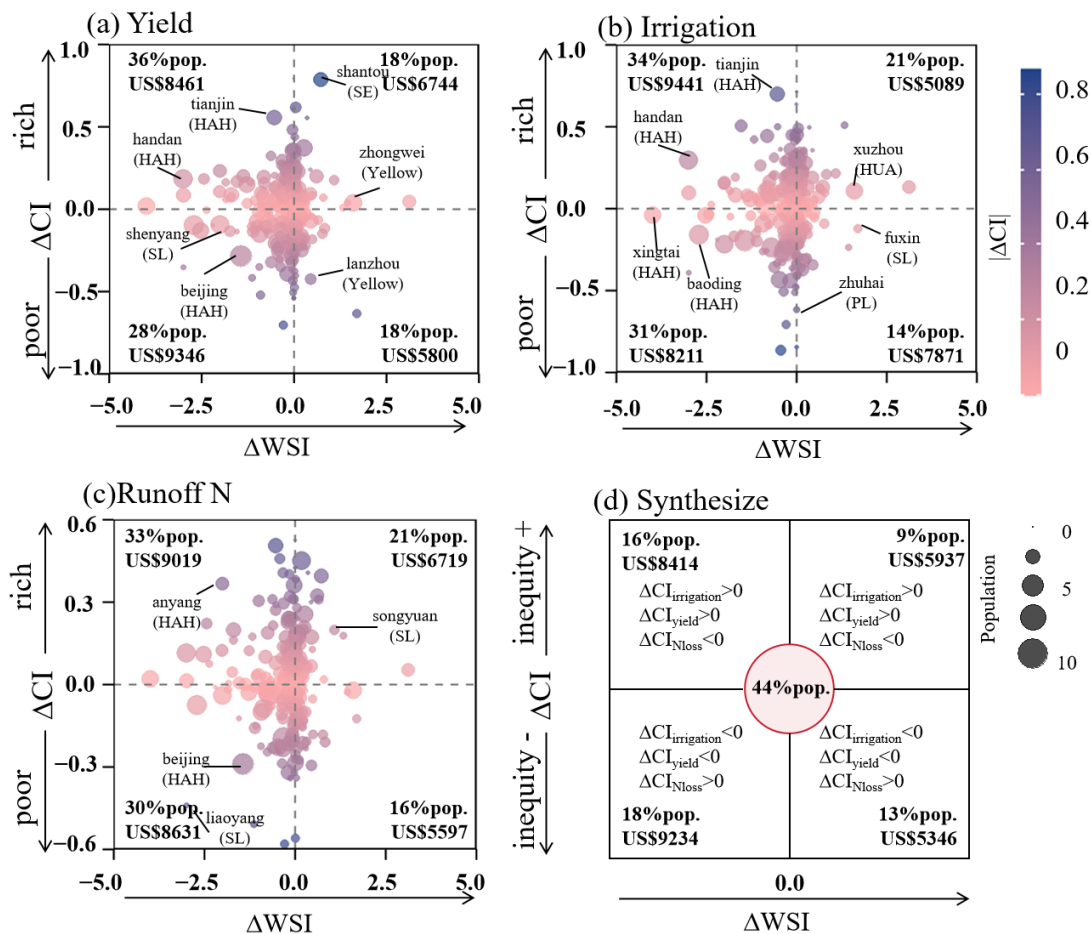


Figure 5. Coupling relationships between water scarcity changes and equity evolution, 1992–2017. Scatter plots show the relationship between changes in water scarcity (Δ WSI, x-axis) and changes in equity (Δ CI, y-axis) for (a) food yield, (b) irrigation water, and (c) nitrogen (N) loss to surface water. Panel (d) synthesizes patterns across all three dimensions. Each circle represents a city. Circle size indicates population; circle color indicates the direction of equity change (blue = toward pro-poor, red = toward pro-rich). Quadrant interpretation: Quadrant I (Δ WSI > 0, Δ CI > 0): intensified water scarcity with increased pro-rich allocation (trade-off for resources, synergy for pollution control); Quadrant II (Δ WSI < 0, Δ CI > 0): alleviated scarcity with increased pro-rich allocation (synergy for resources); Quadrant III (Δ WSI < 0, Δ CI < 0): alleviated scarcity with increased pro-poor allocation (synergy for resources, trade-off for pollution); Quadrant IV (Δ WSI > 0, Δ CI < 0): intensified scarcity with increased pro-poor allocation (trade-off). Population share and mean per capita GDP (constant 2017 US\$) are labeled for each quadrant. Note: Positive Δ CI indicates a shift toward pro-rich distribution; negative Δ CI indicates a shift toward pro-poor distribution. Equity implications differ for positive resources (food, water) versus negative burdens (pollution). See Section 2.4 for quadrant classification methodology.

3.6. Limitations

First, the endpoints-only design with 1992 and 2017 as the assessment time points can only quantify the distribution patterns and equity changes of irrigation water, grain yield, and nitrogen loss at the study's start and end. In addition, major changes in agricultural policies, land use patterns, and production systems may have altered the structural conditions of grain production and environmental burden distribution. These background changes may influence the interpretation of temporal shifts in equity, but they do not undermine the overall validity of the comparative analysis. Future studies with continuous time series data can better account for dynamic policy and methodology changes to improve interpretability.

Second, limitations exist in the selection and robustness validation of the core Concentration Index (CI). While this study conceptually compares CI's advantages over the Gini coefficient for distributive justice analysis, it does not empirically validate the consistency across multiple inequality indicators. CI results are also sensitive to socioeconomic-ranking variable selection, and this study exclusively uses per capita GDP to rank county-level units. Future research can enhance robustness by comparing results across multiple inequality metrics and alternative ranking criteria.

Third, the environmental burden assessment is narrowly focused on agricultural nitrogen losses to surface water from grain production, without assessing other pollutants or pollution sources. The environmental equity conclusions are thus only applicable to the studied nitrogen pollution and cannot be generalized to other pollution types.

Fourth, data spatial aggregation relies on the assumption of the uniform distribution of resources and pollution burdens within each county-level unit. This necessary simplification for national-scale assessment may mask within-county heterogeneity and slightly underestimate micro-scale inequity.

3.7. Future Implications

The core equity challenge revealed by this study lies in the fundamental imbalance between the production responsibilities and development rights of major grain-producing regions: low-income areas bear dual burdens of food security provision and environmental pollution while facing industrialization constraints that perpetuate poverty. This paradox, where policy-driven grain concentration improves food security equity but simultaneously exacerbates environmental inequity through N pollution transfer, demands an integrated governance paradigm shift from efficiency-prioritized to equity-oriented resource management. To address these multidimensional inequities and achieve sustainable development, we propose four strategic pathways that combine technological innovation with institutional reform.

First, establish a comprehensive production compensation equity fiscal mechanism. The mechanism can directly link cross-regional transfer payments to grain output, irrigation water consumption, and nitrogen loss control. This mechanism should prioritize water-scarce producing regions, such as the Haihe Basin, with differentiated transfer standards. It should also require grain-consuming developed regions to provide corresponding support according to their consumption levels. In this way, the environmental costs of food security can be effectively included in the regional responsibility system.

Second, deploy integrated water-saving and pollution reduction technologies suitable for the development conditions of low-income producing regions. Promote drought-tolerant crop substitution, such as wheat and millet, instead of water-intensive rice. Use drip and sprinkler irrigation systems to improve water use efficiency and agricultural equity at the same time. For nitrogen loss control, popularize precision fertilization technologies, including soil testing, slow-release fertilizers, and optimal fertilization timing. Provide

policy support for environmentally friendly practices such as crop–livestock integration and cover cropping. These measures can reduce pollution intensity per unit of grain output while maintaining stable yields. These technological interventions should be supported with professional extension services, equipment subsidies, and farmer training to help low-income regions overcome technical and financial barriers to pollution mitigation.

Third, market-oriented and administrative instruments should be integrated to improve cross-regional agricultural trade and water allocation. A national agricultural resource information platform can be established to guide the rational spatial adjustment of grain production, encouraging southern regions with abundant water resources to increase grain output and providing ecological compensation for water-saving practices in northern areas to reduce water-intensive grain exports from water-scarce regions. Typical cross-regional cooperation models, such as collaboration between northeast grain-producing provinces and developed coastal provinces, can be referenced, while equity principles should be incorporated into trans-basin water transfer projects to protect the water use rights of low-income agricultural groups and strengthen groundwater extraction control. Closer cooperation between grain-producing and non-producing regions is also proposed, where developed regions can invest in irrigation infrastructure, pollution control, and technology promotion in major producing areas in exchange for a stable grain supply, so as to coordinate food security and environmental justice.

Fourth, formulate targeted policies according to the characteristics of different river basins. This can alleviate the conflicting equity outcomes among irrigation water, food production, and nitrogen pollution. For basins with serious mismatches, such as the Haihe and Huaihe Basins, grain production is concentrated in low-income groups, while irrigation water is often used by high-income urban and industrial users. Strict non-agricultural water quotas should be set to ensure priority water use for low-income farmers. Local governments can promote the comprehensive management of groundwater over extraction in the Haihe Basin and agricultural non-point source pollution control in the Huaihe Basin as specific policy practices. Properly relax industrial development restrictions in major grain-producing regions. Support the development of low water footprint industries, including agricultural product processing and rural services. This will improve the local economic development capacity while protecting basic arable land resources. The spatially targeted policy fully considers the differences of resource endowments, economic foundations, and equity challenges in different river basins in China.

By integrating these technological and institutional innovations, China can transition from the current “efficiency-first, equity-later” paradigm to a holistic “production-compensation-technology-equity” framework that balances food security, resource conservation, environmental protection, and social justice, offering a replicable model for other developing nations confronting similar water, food, and environment nexus challenges in pursuit of multiple Sustainable Development Goals.

4. Conclusions

This basin-level assessment of China’s irrigation water, food production, and nitrogen loss inequities from 1992 to 2017 reveals a fundamental paradox: policy-driven grain production concentration in low-income regions has improved equity in food security but has simultaneously exacerbated environmental inequity through the transfer of nitrogen pollution risks. National changes in equity were primarily driven by a small number of high-intensity grain production areas, while 55% of the population still experienced pro-rich inequity in irrigation water allocation. A SHAP analysis identified grain security policies, urbanization, and nitrogen fertilizer application as the main influencing factors. An asymmetric coupling relationship exists between water scarcity and equity, which is further

determined by regional economic foundations. The integrated resource–environment–socioeconomic–policy framework established in this study provides scientific support for the transition from efficiency-prioritized to equity-oriented governance. Future policy efforts should establish comprehensive “production-compensation-technology-equity” mechanisms that integrate fiscal transfers, precision agricultural technologies, cross-regional coordination, and basin-specific differentiated policies. These strategies can help achieve a balanced improvement in food security, resource conservation, environmental protection, and social justice, and provide a replicable model for other developing countries to achieve multiple Sustainable Development Goals.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/agriculture16060645/s1>, Figure S1: Simple Nitrogen Flow Diagram of the Food System; Figure S2: China’s spatial distribution and relative changes of water scarcity index in 1992 and 2017; Figure S3: The asymmetric impact of water scarcity index in different river basins on different populations in China; Figure S4: The density curves of per capita GDP for different river basins in China; Figure S5: Single-factor analysis of irrigation water concentration index; Figure S6: Single-factor analysis of yield concentration index; Figure S7: Single-factor analysis of N loss to surface water concentration index.; Table S1: The evaluations of equality and equity for different indicators; Table S2: The definitions and data sources of different variables; Table S3: China water scarcity index and relative change in different river basins in 1992 and 2017; Table S4: Performance metrics of the XGBoost regression models.

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