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Research Article

Keywords: Two-stage network DEA, Agricultural eco-efficiency, Interregional grain flows, Carbon responsibility, Allocation optimization

Posted Date: September 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10687128/v1>

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Additional Declarations: No competing interests reported.

Interregional Grain Flows and Carbon Responsibility in China: Two-Stage Network DEA and Allocation Optimization for Low-Carbon Agricultural Governance

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Abstract: Climate risk governance in food systems increasingly requires identifying where carbon burdens arise, how they are redistributed through interregional production and consumption networks, and how mitigation responsibilities can be coordinated without reducing aggregate food supply. Interregional grain circulation complicates this task because conventional agricultural eco-efficiency assessments often treat regions as closed systems and overlook the spatial redistribution of environmental responsibilities. This study develops a computational decision-support framework combining two-stage network data envelopment analysis, interprovincial grain-flow accounting, carbon-responsibility attribution, a no-transfer counterfactual, allocation optimization, and Tobit regression. The framework treats interregional grain flows as transferable intermediate measures and incorporates cultivation- and transportation-related carbon emissions within a unified production–circulation–consumption boundary. Using panel data for 30 Chinese provinces from 2017 to 2021, we evaluate agricultural eco-efficiency, identify carbon-responsibility transfers, and explore low-carbon allocation pathways relevant to climate mitigation. Results show that grain-exporting regions generally achieve higher production efficiency but bear greater cultivation-related carbon burdens, while grain-importing regions benefit from lower locally recorded production emissions. The no-transfer counterfactual further reveals that closed-system assessments can misrepresent regional environmental performance and mitigation responsibilities. Under a fixed national grain-output constraint, reallocating production among net grain-exporting provinces reduces cultivation-related carbon emissions from 55.65 to 52.91 million tons, or about 4.9%. Tobit estimates indicate clear stage- and region-specific associations. The framework provides computational support for carbon accounting, ecological compensation, low-carbon grain allocation, and responsibility-aware climate risk governance in interdependent food systems.

Keywords: Two-stage network DEA; Agricultural eco-efficiency; Interregional grain flows; Carbon responsibility; Allocation optimization

1. Introduction

Effective climate risk governance increasingly requires identifying where environmental pressures arise, how resource-allocation and consumption decisions shift carbon burdens across regions, and how low-carbon transitions can avoid unintended spillovers in complex and interdependent systems (He et al., 2023; Zhong et al., 2024). Agricultural systems provide a representative context because they must maintain grain supply while reducing resource use and greenhouse gas emissions. Agricultural production consumes substantial land, water, and chemical inputs and generates environmental pressures, including land degradation, water pollution, and greenhouse gas emissions (Foley et al., 2011). These pressures become more difficult to govern when grain production, consumption, and associated carbon burdens span regional boundaries, creating cross-regional challenges for climate mitigation and responsibility allocation.

As regional specialization and interregional grain circulation deepen, agricultural systems increasingly rely on cross-regional flows of products, resources, and environmental burdens. Regions are connected by observable grain flows and less visible transfers of emissions and environmental responsibilities (Wu et al., 2024). The benefits generated in one region or stage may therefore be accompanied by environmental burdens borne elsewhere, especially when production-based and consumption-based environmental responsibilities diverge through trade and interregional flows (Foong et al., 2022; B. Liu et al., 2024). Grain-consuming regions may obtain food supplies, processing opportunities, and downstream economic value through interregional inflows, while grain-producing regions often bear a large share of production-side resource use and environmental pressure. If regions are evaluated as closed systems, consuming regions may appear cleaner and more efficient, whereas producing regions may be penalized for burdens partly generated to satisfy external demand. This bias arises because production benefits, consumption benefits, and environmental responsibilities are spatially separated. Accordingly, eco-efficiency assessment should move beyond closed systems to reveal how grain-flow networks redistribute ecological externalities and carbon responsibilities. This issue is particularly relevant to climate risk governance, because closed-system assessments may distort regional efficiency rankings and misallocate mitigation responsibilities, ecological compensation, and low-carbon policy support.

Data envelopment analysis (DEA) provides a suitable computational basis for addressing these cross-regional efficiency and responsibility linkages. As originally proposed by Charnes et al. (1978), DEA evaluates the relative performance of decision-making units with multiple inputs and outputs without imposing a predefined functional form on the production technology. Its nonparametric structure is particularly suitable for environmental efficiency assessment because desirable outputs, undesirable outputs, and disposability assumptions can be incorporated into a unified evaluation framework (Khezrimotlagh & Zhu, 2025). These features

are also relevant to climate risk governance, where decision makers must balance economic outputs, resource constraints, and heterogeneous environmental burdens across interconnected regions. DEA has therefore been widely applied to agricultural eco-efficiency assessment (Coluccia et al., 2020). Conventional DEA models, however, generally treat each region as an independent production unit and have limited ability to represent the internal and external linkages of networked grain systems. Two-stage and network DEA models partly address this limitation by opening the black-box structure and distinguishing production-stage performance from subsequent use, treatment, or transformation-stage performance. Recent methodological research has further improved the formulation and computation of two-stage network DEA models (Khezrimotlagh, 2026), while applied studies have extended two-stage dynamic DEA to evaluate efficiency and productivity changes in agricultural and industrial systems (Lu et al., 2023). Yet many existing two-stage formulations model intermediate products as within-DMU links, even when shared inputs or flexible intermediates are considered (Li et al., 2012). Consequently, existing models cannot fully identify which regions receive consumption benefits, which regions bear externally induced carbon burdens, or how these burdens should enter regional efficiency assessment. Such settings are restrictive for interregional grain systems, in which grain may be retained for local use, transferred to other regions, or received from elsewhere through the national circulation network.

To address these interregional carbon-responsibility imbalances, this study develops a two-stage network DEA framework for carbon-aware grain-allocation decisions. The framework consists of three connected models. First, the baseline two-stage network DEA model represents the actual production–circulation–consumption structure of the grain system, in which grain output generated in the production stage can be retained for local use or transferred across regions as an intermediate measure entering downstream activities. Second, the no-transfer model provides a counterfactual closed-system benchmark. By comparing this benchmark with the baseline model, we quantify the efficiency-evaluation differences associated with ignoring interregional grain circulation and identify the corresponding redistribution of carbon burdens. Third, the allocation optimization model moves the analysis beyond ex-post efficiency assessment, consistent with recent operations-analytics research that incorporates environmental sustainability into logistics and allocation decisions (Gong et al., 2024). Under a fixed national grain-output requirement, the model reallocates production responsibilities among net grain-exporting regions and identifies feasible pathways for improving aggregate production-stage performance and reducing cultivation-related carbon emissions. By linking efficiency evaluation, counterfactual diagnosis, carbon-responsibility attribution, and allocation optimization, the proposed framework provides an interpretable computational approach for supporting low-carbon grain allocation, mitigation planning, and responsibility-aware climate risk governance across interdependent regions.

China's interprovincial grain system provides a policy-relevant setting for examining climate risk governance under spatially uneven production, consumption, and carbon responsibilities. Its differentiated grain-supply pattern is closely associated with national food-security strategy, land-use policy, and rapid urbanization (Liu & Zhou, 2021), while provincial agricultural production efficiency varies substantially with resource endowments, technology, and development conditions (Ma et al., 2021). To operationalize the two-stage structure, the production stage converts land, water, fertilizer, pesticides, and machinery into grain output while generating cultivation-related emissions; intensive chemical-input use has been associated with substantial environmental risks in Chinese agriculture (Ju et al., 2009). The circulation–consumption stage uses locally retained and interregionally transferred grain together with grain-industry capital and labor inputs to generate downstream economic value while producing transportation-related emissions. Given the documented spatial differentiation in provincial AEE (Liao et al., 2021), this study uses panel data for 30 Chinese provinces from 2017 to 2021 to jointly evaluate production efficiency, circulation–consumption efficiency, overall eco-efficiency, and carbon-responsibility transfers.

This study contributes to the literature in three ways. First, it advances DEA-based environmental performance analysis by developing a two-stage network framework with transferable intermediate measures. Unlike conventional closed-system DEA models, the proposed framework allows grain output to be retained locally or transferred across regional boundaries, thereby extending two-stage DEA from internal process evaluation to interregional flow-based performance assessment. This design provides a more realistic representation of agricultural systems in which economic activities and environmental burdens are connected through spatial networks. Second, the study incorporates carbon-responsibility accounting into the production–circulation–consumption boundary of AEE analysis by jointly considering cultivation-related and transportation-related emissions. It traces how interregional grain circulation redistributes production-side carbon burdens between grain-exporting and grain-importing regions, thereby providing a quantitative basis for mitigation responsibility sharing and interregional ecological compensation. Third, the study moves beyond ex-post efficiency measurement by combining a no-transfer counterfactual with production-allocation optimization and explanatory regression analysis. Under a fixed national grain-output requirement, the framework identifies feasible production-reallocation pathways that reduce cultivation-related carbon emissions while preserving aggregate national grain output. The Tobit analysis further examines regional and stage-specific associations and provides additional evidence for differentiated low-carbon policy design. Together, these contributions extend computational approaches to climate risk governance by integrating nonparametric network evaluation, carbon-responsibility attribution, counterfactual diagnosis, and constrained allocation optimization within a unified interregional framework.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 develops the proposed two-stage network DEA framework, including the baseline model, the no-transfer model, and the allocation optimization model. Section 4 conducts an empirical investigation of China's interprovincial grain system to illustrate and validate the proposed approach. Section 5 analyzes carbon-responsibility transfers, allocation results, and heterogeneous efficiency drivers. Section 6 concludes and discusses the policy implications and limitations.

2. Literature review

2.1. Agricultural eco-efficiency and interregional carbon responsibility

The concept of eco-efficiency was introduced by Schaltegger and Sturm (1990) to evaluate the relationship between economic growth and environmental impacts, and was later refined by the World Business Council for Sustainable Development (Verfaillie, 2000). In agriculture, AEE assesses whether agricultural systems can maintain production while reducing resource consumption and undesirable environmental outputs (Picazo-Tadeo et al., 2011). It has subsequently been used to examine the temporal evolution and regional differentiation of agricultural environmental performance (Liu et al., 2020). However, most assessments define the evaluation boundary around regional production activities and pay limited attention to the environmental consequences associated with the subsequent circulation and consumption of agricultural products.

Scholars in China and beyond have explored various methods for measuring AEE, among which DEA is one of the most widely adopted approaches (Moradi et al., 2018). As a non-parametric technique suited to multi-input and multi-output agricultural systems, DEA avoids subjective weighting and can incorporate undesirable outputs such as greenhouse gas emissions and water pollution. It therefore provides a flexible tool for evaluating ecological performance under heterogeneous production conditions (Vlontzos et al., 2014). Bonfiglio et al. (2017) assessed the eco-efficiency of arable farms in rural areas using DEA and identified heterogeneity in farm-level ecological performance. Coluccia et al. (2020) combined DEA with principal component analysis to examine the integrated ecological performance of agricultural systems in Italy, with attention to the relationship between land use and pollutant reduction. However, their analysis did not consider the link between agricultural production and consumption, limiting its applicability to large countries with spatially separated producing and consuming regions. In China, DEA and machine-learning methods have been integrated to examine the long-term evolution of provincial AEE (Sun & Sui, 2023). Although these studies improve the measurement of agricultural environmental performance, they generally evaluate production units independently and do not explicitly represent the connections between producing and consuming regions created by interregional agricultural-product flows.

An important development in AEE assessment has been the treatment of undesirable outputs. Early production-frontier research demonstrated that environmental pollutants should be incorporated into efficiency analysis rather than excluded from the production technology (Färe et al., 1994; Pittman, 1983). Picazo-Tadeo et al. (2011) showed that neglecting undesirable outputs may misclassify agricultural producers with low environmental impacts and lead to biased efficiency assessment. Pishgar-Komleh et al. (2021) incorporated undesirable outputs into a dynamic Window-SBM model at the European Union level and revealed substantial cross-country heterogeneity, with older member states generally performing better.

Using Chinese provincial panel data, Wang et al. (2025) further extended undesirable outputs by including CH₄ and N₂O, offering a more comprehensive evaluation of non-CO₂ emissions and strengthening the robustness of AEE assessment. These studies have improved the treatment of production-side environmental pressures. However, they pay less attention to circulation-related emissions and to the redistribution of carbon responsibility between producing and consuming regions.

Overall, existing AEE studies still tend to evaluate agricultural systems within regional production boundaries. This closed-system perspective may overlook environmental burdens embedded in interregional product and resource flows. Recent studies on trade-adjusted agricultural emissions and embodied land-use emissions have shown that production-based and consumption-based environmental responsibilities can diverge when agricultural products circulate across regions (Foong et al., 2022; Hong et al., 2022). This limitation may distort regional efficiency evaluation and weaken the policy relevance of AEE results. A more realistic framework should therefore integrate resource-flow mechanisms, heterogeneous production and consumption conditions, and circulation-related emissions.

2.2. Two-stage network DEA with interregional intermediate transfers

Traditional DEA treats each decision-making unit (DMU) as a black box and evaluates its performance using aggregate inputs and outputs. Two-stage and network DEA models relax this assumption by representing internal subprocesses and intermediate measures, making it possible to distinguish production-stage performance from subsequent use, transformation, or treatment (Kao & Hwang, 2008). This distinction is particularly relevant to AEE assessment. Grain production converts land, water, chemical inputs and machinery into grain output while generating cultivation-related emissions. The subsequent circulation–consumption stage uses grain as an intermediate input to generate downstream economic value, while interregional transportation produces additional carbon emissions. Network formulations incorporating undesirable outputs have therefore improved the ability of DEA to locate environmental inefficiencies within multistage systems (Song et al., 2014; Song et al., 2015).

Methodological developments have extended network DEA from simple closed serial processes to more flexible internal structures. Connected-division and network-production formulations established the basis for decomposing overall system efficiency across linked stages (Färe & Grosskopf, 2000; Tone & Tsutsui, 2009). Open multistage and extended two-stage models subsequently allowed stage outputs to leave the system, enter later stages, or interact with additional inputs (Cook et al., 2010; Li et al., 2012). These developments provide more realistic representations of internal production structures and reduce the information loss caused by treating all subprocesses as an aggregated black box. However, because intermediate links are still generally defined within individual DMUs, these models mainly explain how

intermediate measures affect the stage-level and overall performance of the originating decision unit.

Existing two-stage DEA studies have also emphasized the role of intermediate measures, shared resources, and flexible allocation in multistage efficiency evaluation. Cooperative two-stage frameworks allow common inputs to be allocated flexibly across stages, showing that shared-resource allocation can affect both stage-level and overall efficiency (Zha & Liang, 2010). Models incorporating undesirable inputs, intermediates, and outputs show that their treatment can systematically affect the production possibility set and the resulting efficiency estimates (Liu et al., 2015). Other studies show that the specification and distribution of intermediates—including cases in which only part of a first-stage output enters the second stage—can alter efficiency decomposition (Izadikhah et al., 2018; Kao, 2018). These studies demonstrate that intermediate measures are not merely fixed connectors between subprocesses. Their allocation, sharing, and transformation can directly affect stage efficiency and overall environmental performance. Nevertheless, even flexible formulations generally retain intermediate measures within the originating DMU.

This within-DMU restriction is problematic for interregional grain systems, where grain may be retained locally, transferred across provinces, or used in downstream activities. These flows also redistribute environmental burdens: cultivation-related emissions remain concentrated in supplying regions, while transportation emissions arise during circulation and consumption benefits accrue elsewhere. Evidence from China shows that the spatial separation of grain production and consumption has increased transport-related carbon emissions (Zuo et al., 2023). Therefore, intermediate grain should be modeled as transferable across DMUs so that network DEA can capture interregional product flows, circulation emissions, and carbon-responsibility redistribution within a unified production–consumption framework.

2.3. Prescriptive DEA models for resource allocation

DEA has been used not only for ex-post efficiency measurement but also for resource allocation and target setting. The allocative efficiency approach evaluates whether a DMU achieves an appropriate allocation of resources under given price or constraint information. Banker et al. (1984) developed the BCC model to distinguish scale efficiency from pure technical efficiency, thereby improving the applicability of DEA in resource-allocation analysis. Coelli et al. (2005) further emphasized that variable selection can significantly affect allocative efficiency results. These studies provide a methodological basis for extending DEA from performance assessment to allocation-oriented decision support.

DEA-based allocation methods have been applied to a range of environmental and agricultural problems. Inverse DEA has been used to allocate CO₂ emission quotas across regions while maintaining predefined efficiency conditions (Emrouznejad et al., 2019). Agricultural applications have examined allocative efficiency and regional disparities in factor

use (Ma et al., 2021; Wang et al., 2020), while network and supply-chain models have extended DEA to interconnected production and distribution systems (Vlachos et al., 2024). Counterfactual analysis has also been combined with regional green-performance evaluation to examine output losses under carbon constraints and the distribution of green-growth benefits across regions (Song et al., 2020). These studies demonstrate the potential of DEA to support resource allocation, environmental target setting, and low-carbon decision-making.

In grain systems, allocation decisions must further account for the spatial separation of production, circulation, and consumption. Agrifood supply-chain research has highlighted the importance of integrated production, logistics, and allocation decisions (Tsolakis et al., 2014). However, existing applications generally treat interregional product flows as fixed background conditions, focus on static factor allocation or within-chain efficiency, or allocate environmental quotas without jointly representing transferable grain intermediates and the carbon burdens embodied in those transfers.

For networked grain systems, ex-post efficiency scores alone cannot determine how regional production responsibilities should be adjusted while maintaining national food security. If interregional flows and consumption-induced carbon burdens are ignored, some regions may appear efficient partly because their environmental pressures are transferred elsewhere. A prescriptive framework should therefore combine circulation-adjusted efficiency assessment with a closed-system counterfactual and production reallocation under a fixed national grain-output requirement. Treating regional production responsibilities as optimizable within the interregional grain network makes it possible to identify feasible allocation pathways that improve systemwide eco-efficiency, reduce agricultural emissions, and provide a more transparent basis for distributing production and mitigation responsibilities.

3. Methods

In evaluating AEE, conventional approaches often treat each region as a closed production unit and therefore overlook interprovincial grain transfers, the spatial redistribution of agricultural outputs, and the carbon emissions generated by long-distance circulation. To address this limitation, this study develops a two-stage network DEA framework that integrates provincial production data, grain-flow information, cultivation-related emissions, and transportation-related emissions into a unified decision-support structure.

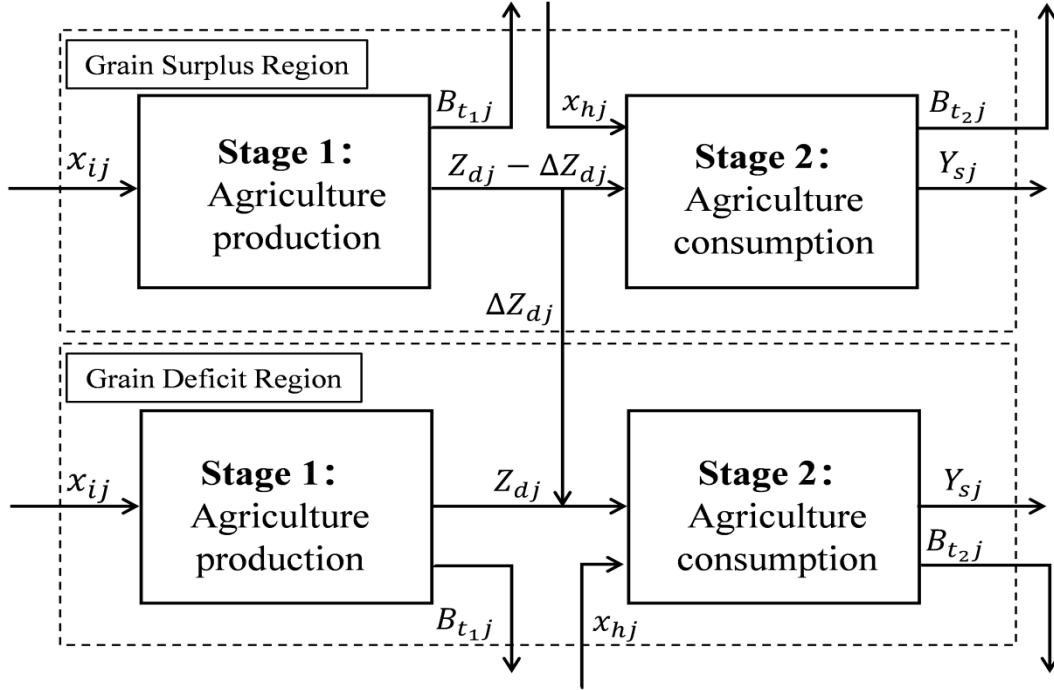


Fig. 1 Two-stage network for grain allocation and carbon-responsibility attribution

As illustrated in Fig. 1, Stage 1 represents agricultural production, where land, water, fertilizer, pesticides, and machinery inputs are converted into grain output while generating cultivation-related carbon emissions. Stage 2 represents agricultural consumption and circulation, where locally retained grain and interprovincially transferred grain are used together with grain-industry inputs to generate downstream economic value while producing transportation-related carbon emissions. In this structure, grain surplus regions may transfer part of their grain output to grain deficit regions, making interprovincial flows freely allocable intermediate measures between the two stages. Embedding these flows and emissions within one system allows the proposed framework to evaluate regional production efficiency, consumption efficiency, overall AEE, and carbon-responsibility transfers. It also provides the analytical basis for the subsequent no-transfer counterfactual model and allocation optimization model.

3.1. Baseline two-stage network DEA model

Consider n DMUs indexed by $j=1, 2, \dots, n$. Each DMU_j ($j=1, \dots, n$) participates in a two-stage network process. Stage 1 consumes m initial inputs x_{ij} ($i=1, 2, \dots, m$) to produce D intermediate outputs z_{dj} ($d=1, 2, \dots, D$) and undesirable outputs b_{t1j} , ($t_1 \in T^P$). Stage 2 takes the intermediate measures from Stage 1 and additional inputs x_{hj} ($h=1, 2, \dots, H$) to generate s desirable outputs y_{rj} ($r=1, 2, \dots, s$) and undesirable outputs b_{t2j} , ($t_2 \in T^C$), where $T^P \cup T^C = \{1, 2, \dots, \pi\}$ and $T^P \cap T^C = \emptyset$. Following Halkos and Petrou (2019), undesirable outputs are treated as conventional input variables without any data transformation. This treatment is consistent with the managerial objective of reducing both resource inputs and carbon burdens while increasing desirable outputs. Through this approach, our model efficiency reflects the simultaneous minimization of conventional inputs and undesirables while maximizing desirable outputs.

Intermediates are freely allocable: for each d , write $z_{dj}^{use} = z_{dj} - \Delta z_{dj}$, where z_{dj}^{use} enters Stage 2 locally and Δz_{dj} is the net interprovincial transfer (for grain surplus regions, $\Delta z_{dj} > 0$; for grain deficit regions, $\Delta z_{dj} \leq 0$). Accordingly, $z_{dj} - \Delta z_{dj}$ denotes the amount of grain available for local consumption and downstream grain-related activities in province j . The national balance condition is $\sum_{j=1}^n \Delta z_{dj} = 0$, meaning that total interprovincial net transfers cancel out at the national level. For net grain-exporting regions, Δz_{dj} represents the amount transferred to other regions, whereas $z_{dj} - \Delta z_{dj}$ represents locally retained grain. Moreover, since $d=1, \dots, D$, z_d is the same type of variable used throughout the entire process, the weights associated with these variables can be assumed to be equal in each stage.

We adopted a two-stage formulation consistent with Li et al. (2012). Namely, the overall efficiency of the process is defined as the product of the efficiencies of the two stages. Since Stage 1 emissions accounted for a significantly larger proportion of total emissions than Stage 2 and production-side carbon responsibility is central to the allocation problem, Stage 1 was treated as the leader, while Stage 2 was treated as the follower. Following a similar logic and building on the ratio efficiency of the CCR model (Charnes et al., 1978), we establish the following model for Stage 1 of the structure presented in Fig. 1 .

$$\begin{aligned}
 E_0^P &= \max \frac{\sum_{d=1}^D u_d z_{d0}}{\sum_{i=1}^m v_i x_{i0} + \sum_{t_1 \in T^P} \omega_{t_1} b_{t_1 0}} \\
 s.t. & \frac{\sum_{d=1}^D u_d z_{dj}}{\sum_{i=1}^m v_i x_{ij} + \sum_{t_1 \in T^P} \omega_{t_1} b_{t_1 j}} \leq 1, \\
 & \omega_{t_1}, u_d, v_i \geq \varepsilon, \\
 & j=1, \dots, n, \quad d=1, \dots, D, \\
 & i=1, \dots, m, \quad t_1 \in T^P.
 \end{aligned} \tag{1}$$

Let $t = \frac{1}{\sum_{i=1}^m v_i x_{i0} + \sum_{t_1 \in T^P} \omega_{t_1} b_{t_1 0}}$, and set $\psi_{t_1} = \omega_{t_1}$, $\mu_d = u_d$, $v_i = v_i$. Using the *Charnes and Cooper*

transformation, Model (1) can be transformed into the following linear program:

$$\begin{aligned}
E_0^P &= \max \sum_{d=1}^D \mu_d z_{d0} \\
s.t. \quad & \sum_{d=1}^D \mu_d z_{dj} - \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 j} - \sum_{i=1}^m v_i x_{ij} \leq 0, \\
& \sum_{i=1}^m v_i x_{i0} + \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 0} = 1, \\
& \psi_{t_1}, \mu_d, v_i \geq \varepsilon, \\
& d=1, \dots, D, j=1, \dots, n, \\
& i=1, \dots, m, t_1 \in T^P.
\end{aligned} \tag{2}$$

Model (2) calculates the value of environmental efficiency E_0^P in the agricultural production stage. The evaluated DMU is efficient in the agricultural production stage only when $E_0^P = 1$. However, part of each region's grain is traded across provinces rather than locally consumed. Hence, the consumption stage requires a distinct program in which each region's inputs include local grain entering Stage 2, as well as its net interprovincial transfer. Following the secondary-objective logic of Doyle and Green (1994), we adopted a second-target formulation to handle such cross-linked inputs.

Based on this approach, we constructed a model that maximizes efficiency in Stage 2 while fixing the efficiency in Stage 1 as the objective function. This model allows for an accurate assessment of the efficiency of the consumption stage while considering the ecological impact and circulation of agricultural products across regions. For detailed information on the calculation, please refer to Eq. (A.1) in the supplementary materials.

$$\begin{aligned}
E_0^C &= \max \sum_{r=1}^s \mu_r y_{r0} \\
s.t. \quad & \sum_{d=1}^D \mu_d z_{dj} - \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 j} - \sum_{i=1}^m v_i x_{ij} \leq 0, \\
& \sum_{r=1}^s u_r y_{rj} - \sum_{t_2 \in T^C} \psi_{t_2} b_{t_2 j} - \sum_{d=1}^D \mu_d (z_{dj} - \Delta z_{dj}) - \sum_{h=1}^H \eta_h x_{hj} \leq 0, \\
& \sum_{d=1}^D \mu_d (z_{d0} - \Delta z_{d0}) + \sum_{t_2 \in T^C} \psi_{t_2} b_{t_2 0} + \sum_{h=1}^H \eta_h x_{h0} = 1,
\end{aligned}$$

$$\begin{aligned}
& \sum_{d=1}^D \mu_d z_{d0} - E_0^{p*} \left(\sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 0} + \sum_{i=1}^m v_i x_{i0} \right) = 0, \\
& \psi_{t_1}, \psi_{t_2}, \mu_r, \mu_d, v_i, \eta_h \geq \varepsilon, \\
& d=1, \dots, D, r=1, \dots, S, \\
& i=1, \dots, m, h=1, \dots, H, \\
& j=1, \dots, n, t_1 \in T^P, t_2 \in T^C.
\end{aligned} \tag{3}$$

When we denote the optimal value for Model (3) as E_0^{C*} , then the efficiency for the entire two-stage system is $E_0^* = E_0^{p*} * E_0^{C*}$. Having established the two-stage AEE evaluation model, we next examine the efficiency dynamics under a no-transfer scenario.

3.2. AEE without interregional agricultural transfer

To evaluate AEE in the absence of interregional grain circulation, we first assume that each region produces solely for local consumption without relying on imports or exports. The following model calculates the change in overall input requirements when the interregional circulation of agricultural products is absent.

$$\begin{aligned}
& E_0^{p,NT} = \max \sum_{d=1}^D \mu_d (z_{d0} - \Delta z_{d0}) \\
& \text{s.t.} \sum_{d=1}^D \mu_d (z_{dj} - \Delta z_{dj}) - \frac{1}{E_0^{p*}} \left(\sum_{i=1}^m v_i x_{ij} + \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 j} \right) \leq 0, \\
& \sum_{i=1}^m v_i x_{i0} + \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 0} = 1, \\
& \psi_{t_1}, \mu_d, v_i \geq \varepsilon, \\
& d=1, \dots, D, j=1, \dots, n, \\
& i=1, \dots, m, t_1 \in T^P.
\end{aligned} \tag{4}$$

In Model (4), it is assumed that all provinces achieve the corresponding optimal efficiency value, denoted as E_0^{p*} , calculated by Model (2). On this basis, Model (4) evaluates the scenario without interregional transfers, yielding $E_0^{p,NT}$ and the associated input and ecological impacts. If $E_0^{p,NT} > 1$, interprovincial circulation improves regional resource use and reduces ecological burden; if $E_0^{p,NT} \leq 1$, the opposite holds.

$$\begin{aligned}
& E_0^{c,NT} = \max \sum_{r=1}^S \mu_r y_{r0} \\
& \text{s.t.} \sum_{d=1}^D \mu_d z_{dj} - \sum_{i=1}^m v_i x_{ij} - \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 j} \leq 0,
\end{aligned}$$

$$\begin{aligned}
& \sum_{r=1}^s u_r y_{rj} - \frac{1}{E_0^{C*}} \left(\sum_{d=1}^D \mu_d z_{dj} + \sum_{h=1}^H \eta_h x_{hj} \right) \leq 0, \\
& \sum_{d=1}^D \mu_d z_{d0} + \sum_{h=1}^H \eta_h x_{h0} = 1, \\
& \psi_{t_1}, \mu_r, \mu_d, v_i, \eta_h \geq \varepsilon, \\
& i=1, \dots, m, h=1, \dots, H \\
& d=1, \dots, D, r=1, \dots, s, \\
& j=1, \dots, n, t_1 \in T^P.
\end{aligned} \tag{5}$$

In Model (5), we assume that all provinces reached the corresponding optimal efficiency value E_0^{C*} noted in Model (3). $E_0^{C,NT}$ measures the proportional change in attainable grain-industry revenue under the no-transfer counterfactual, which reflects the specific impact of the agricultural transfer mechanism on the grain industry's sales revenue across provinces. Because interprovincial grain circulation is removed in the no-transfer scenario, interprovincial transportation emissions are excluded from the consumption-stage benchmark.

3.3. Optimal agricultural allocation model

Building on these stage-wise scenarios, we construct an optimal allocation model that reallocates grain output among exporting regions under a fixed national output requirement. The model identifies feasible production-adjustment pathways that improve systemwide AEE and reduce cultivation-related carbon emissions. We assume that R_{out} denotes net grain-exporting regions and R_{in} denotes net grain-importing regions. Together, these regions form the set of provincial DMUs, $J = R_{out} \cup R_{in}$. Let E_0^{P*} be each region's benchmark production-stage AEE from Model (2). Let δz_{dk} denote the adjustment in grain output for exporting region k , and let $z_{dk} + \delta z_{dk}$ denote its optimized grain output after reallocation. The following optimization model can then calculate the overall optimal allocation of agricultural production resources across regions:

$$\begin{aligned}
E_0^{P,opt} &= \max \left[\sum_{p \in R_{in}} \sum_{d=1}^D \mu_d z_{dp} + \sum_{k \in R_{out}} \sum_{d=1}^D \mu_d (z_{dk} + \delta z_{dk}) \right] \\
s.t. \quad & \sum_{d=1}^D \mu_d z_{dp} - \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 p} - \sum_{i=1}^m v_i x_{ip} \leq 0, \quad \forall p \in R_{in}, \\
& \sum_{d=1}^D \mu_d (z_{dk} + \delta z_{dk}) - \frac{1}{E_0^{P*}} \left(\sum_{i=1}^m v_i x_{ik} + \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 k} \right) \leq 0, \quad \forall k \in R_{out}, \\
& \sum_{k \in R_{out}} \delta z_{dk} = 0, \quad -\alpha z_{dk} \leq \delta z_{dk} \leq \alpha z_{dk}, \quad \forall k \in R_{out},
\end{aligned}$$

$$\begin{aligned}
& \sum_{i=1}^m v_i x_{i0} + \sum_{t_1 \in T^P} \psi_{t_1} b_{t_1 0} = 1, \\
& \psi_{t_1}, \mu_d, v_i \geq \varepsilon, p \in R_{in}, k \in R_{out}, \\
& d=1, \dots, D, i=1, \dots, m, t_1 \in T^P.
\end{aligned} \tag{6}$$

In Model (6), the objective $E_0^{P,opt}$ maximizes an aggregate production-stage performance measure by reallocating grain output among net grain-exporting provinces while preserving total output. The adjustment term δz_{dk} captures the potential redistribution of grain outputs within output regions to achieve overall efficiency gains. To ensure the feasibility and realism of the reallocation, a proportional constraint $-\alpha z_{dk} \leq \delta z_{dk} \leq \alpha z_{dk}$ is used, with α representing the allowable adjustment ratio relative to each region's annual grain production. Existing international research indicates that modern agricultural technologies (e.g., precision management, smart irrigation, high-yield varieties) can raise crop yields by roughly 20–30% (Tilman et al., 2011), with similar potential existing in China (Foley et al., 2011). Accordingly, we set $\alpha = 30\%$ as the upper limit. The 30% adjustment bound is used as a scenario parameter representing an upper range of production flexibility rather than a direct estimate of realizable provincial output growth. With $\left| \frac{\delta z_{dk}}{z_{dk}} \right| \leq \alpha$, the optimized allocation remains consistent with China's practical conditions.

4. Empirical results

4.1. Data and variable selection

Building on the two-stage structure presented in Section 3.1, we select indicators for production (Stage 1) and consumption/circulation (Stage 2) following established practice in agricultural sustainability (Yang et al., 2023), with the precise definitions and units reported in Table 1.

For the grain production stage, the following inputs were selected to capture land, chemical, water, and machinery use: effective irrigated region (X_1^p); fertilizer application intensity (X_2^p); pesticide use (X_3^p); agricultural water use (X_4^p); total power of agricultural machinery (X_5^p). These variables collectively reflect the scale and intensity of resource utilization in crop production. Grain output (Z) represents the annual production of major cereals and serves as the intermediate product linking Stage 1 to Stage 2.

Grain consumption is constructed following Zuo et al. (2023). International imports, international exports, and changes in grain stocks are excluded so that the measure captures domestic circulation. Additional inputs are net fixed assets of the grain industry (X_1^c) and grain industry employment (X_2^c). These variables capture the capital and labor resources sustaining grain circulation and downstream processing. The desirable output is grain industry sales revenue (Y), which reflects the final economic value of domestically consumed grain products.

To capture environmental externalities, we include the following variables: (i) carbon emissions from agricultural production (B_1), computed by summing multiple on-farm emission sources multiplied by corresponding factors (Ji et al., 2024); (ii) carbon emissions from grain transportation (B_2), estimated by combining province-level transport carbon intensities with interprovincial trade volumes (Zuo et al., 2023). Detailed formulas and coefficients are provided in Appendix Tables B.1 and B.2.

Table 1 Input–output indicators for the two-stage DEA model

Stage	Indicator Type	Variable	Unit
Stage 1	Input	Land input (X_1^p)	1000 hectares
		Fertilizer input (X_2^p)	10,000 metric tons
		Pesticide input (X_3^p)	10,000 metric tons
		Water consumption (X_4^p)	10^8 m ³
		Agricultural machinery power (X_5^p)	10,000 kilowatts
	Intermediate output	Grain output (Z)	10,000 metric tons
Stage 2	Undesirable output	Carbon emissions from plantations (B_1)	10,000 metric tons
	Intermediate measure	Grain consumption ($Z-\Delta Z$)	10,000 metric tons
		Net fixed assets of the grain industry (X_1^c)	100 million yuan
		Grain industry employment (X_2^c)	10,000 people
	Output	Sales revenue of the grain industry (Y)	100 million yuan
	Undesirable output	Transportation emissions (B_2)	10,000 metric tons

This study focuses on crop cultivation rather than broad agriculture including livestock and fisheries. The sample covers 30 mainland provincial-level regions in China from 2017 to 2021, excluding Tibet, Hong Kong, Macao, and Taiwan. Data originate from the China

Statistical Yearbook (2018–2022), China Agricultural Statistical Yearbook (2018–2022), China Grain and Material Reserve Yearbook (2018–2022), China Environmental Statistical Yearbook (2018–2022), and the 2022 provincial yearbooks. These official sources adopt consistent statistical standards, thus ensuring comparability across regions and years. The compiled dataset is complete, with no missing values.

After more than two decades of development, China's North-South Grain Transportation Project has established the current agricultural geographical distribution pattern. We classify provinces into input (net-consuming) and output (net-producing) regions. Broadly, input regions cluster in southeastern coastal China and parts of the southwest, while output regions concentrate in the north and central belt (Fig. 2). The province-level classification and summary statistics for production/consumption are reported in Appendix Table B.3.

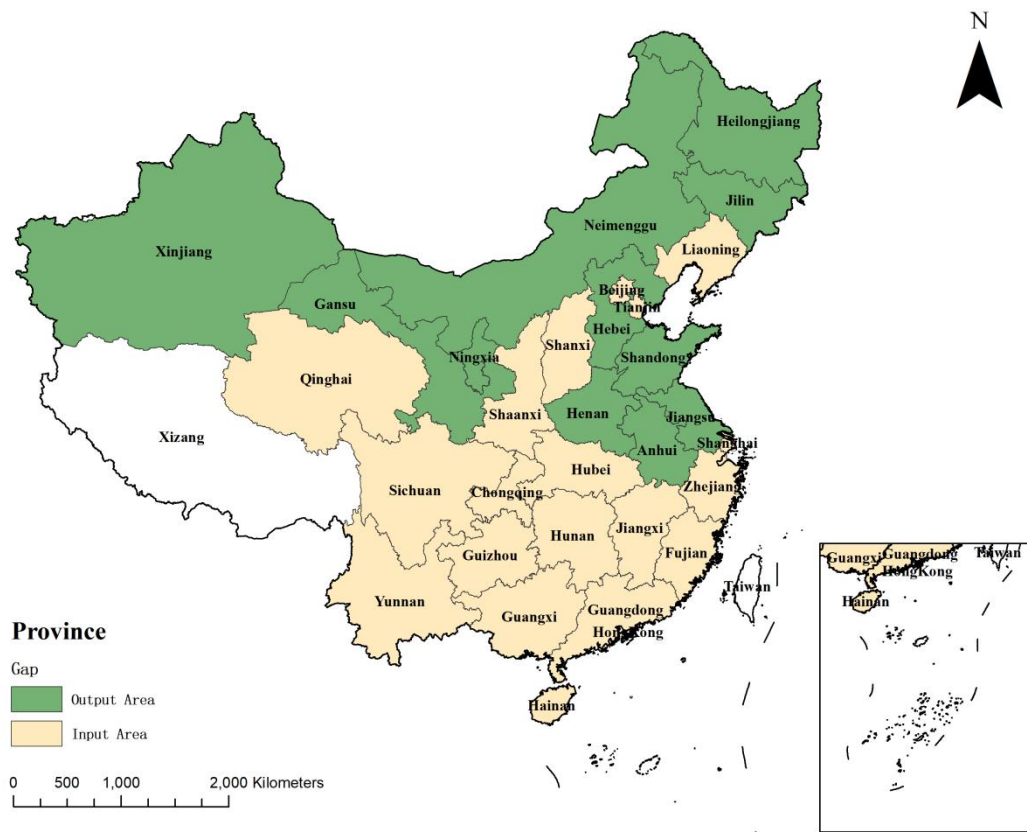


Fig. 2 Distribution map of agricultural input and output regions

Overall, the proposed methodological framework combines network DEA with spatial allocation optimization, thus providing a unified basis to assess AEE under interregional circulation and identify emission-reduction potential along both production and transport links.

4.2. AEE evaluation results

We apply the two-stage DEA model to 30 provinces from 2017 to 2021. Overall efficiency (EE), calculated as the product of production efficiency (PE) and consumption efficiency (CE), shows clear interprovincial heterogeneity (Fig. 3). The national mean EE is 0.432, with a mild U-shaped trend from 0.438 in 2017 to 0.406 in 2019 and 0.459 in 2021. Multi-year leaders

include Guizhou, Tianjin, and Shandong, while Zhejiang, Fujian, and Beijing remain among the lowest-performing provinces. These differences indicate that regional AEE is jointly shaped by production capability, circulation efficiency, and demand-side proximity.

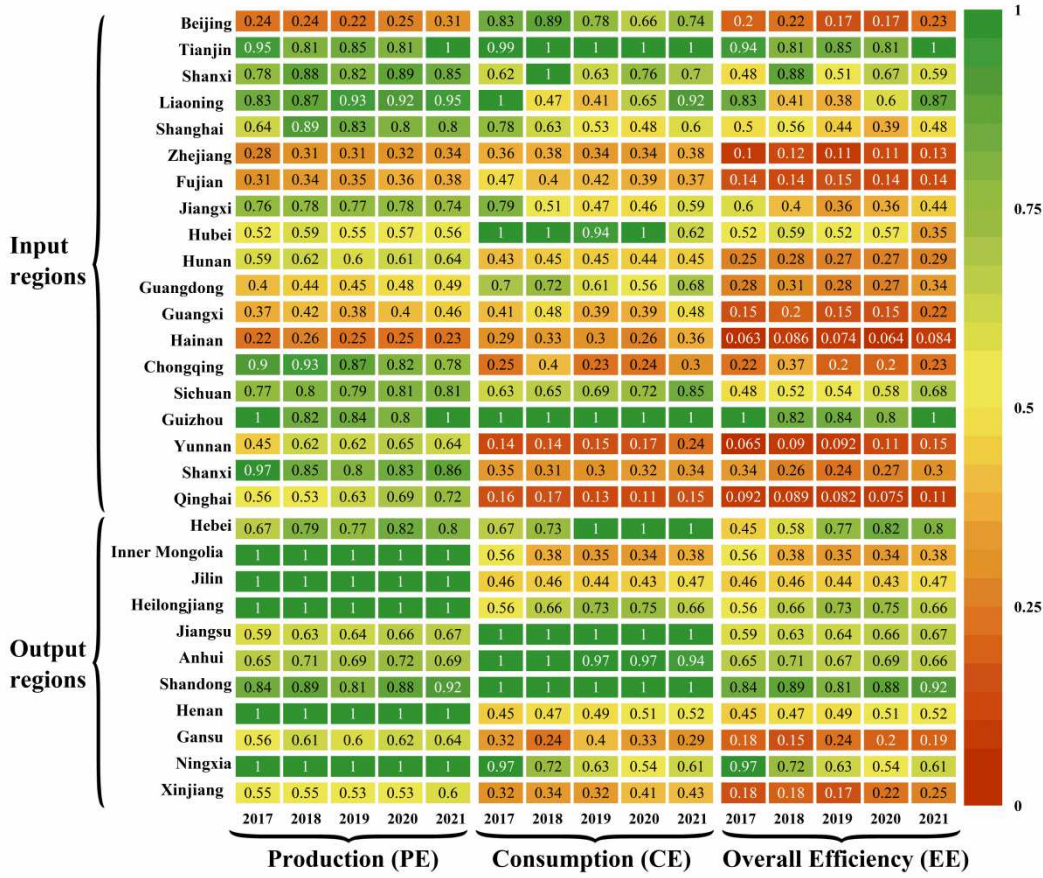


Fig. 3 AEE scores and stage components across 30 provinces

On the production side, grain-surplus provinces such as Jilin, Heilongjiang, and Henan generally perform better because large contiguous farmland, mechanized operations, and specialized grain production support more efficient input use (Mao et al., 2019). However, high PE does not eliminate ecological pressure. Some surplus regions also face rising marginal carbon burdens due to machinery redundancy, diesel use, and land-use stress. Thus, major producing regions contribute substantially to national grain security while bearing a disproportionate share of cultivation-related emissions.

By contrast, low-PE coastal provinces such as Fujian and Zhejiang are constrained by fragmented land, limited arable resources, high labor costs, and greater exposure to natural shocks. Their reliance on interregional inflows reduces the role of local production in grain security and weakens incentives for improving production-side efficiency. This contrast shows that interregional circulation safeguards food supply, but it also separates grain flows from the location where cultivation emissions are generated.

This structural asymmetry drives subsequent divergence in consumption-stage performance and, through the reverse transfer of carbon pressure, shows how circulation

reshapes production-side ecological outcomes. Specifically, exporting regions bear cultivation-related emissions, while importing regions must curb transport emissions and efficiently convert inflows into value. This decomposition motivates the optimization of interregional allocation and underpins the subsequent no-circulation and optimization analyses.

On the consumption side, CE is mainly shaped by processing capacity, logistics accessibility, and market organization. Coastal and transport-node provinces such as Jiangsu, Shandong, and Tianjin tend to perform better because shorter transport radii, denser processing networks, and stronger market connectivity reduce circulation frictions and improve value conversion. In contrast, inland regions in Southwest, Northwest, and parts of Northeast China generally exhibit lower CE because long-distance multimodal transport and weaker processing capacity increase time, energy, and emission costs per unit of grain.

Compared to coastal gateway regions, inland regions in Southwest, Northwest, and parts of Northeast China generally show lower CE (≤ 0.4). Long-distance multimodal transport raises the time and space costs per unit. Overall, production regions bear energy use and emissions from drying, grading, storage, and loading and unloading in the first leg, while consumption regions incur end-of-line cold chain and urban distribution costs; however, both channels elevate transport-related emissions. Meanwhile, inland processing often remains small-scale, with underutilized fixed assets and slower factor turnover that impede the conversion of inflows into industrial revenue.

Notably, the phased efficiency of China's agricultural input and output regions exhibits asymmetric evolution (Fig. 4). Average PE in input regions (0.65) is significantly lower than in output regions (0.86), consistent with standardized staple-crop technologies and large-scale operations in the latter. Provinces such as Henan, Inner Mongolia, and Heilongjiang enjoy notable advantages due to their specialization and mechanization. The example of Inner Mongolia (PE = 1), where the cost of agricultural machinery operation per unit region (312 yuan/ha) is 41% lower than the input region mean, underscores the cost control advantage of large-scale production (Zhu et al., 2022). In contrast, despite their relative economic advancement, input regions such as Beijing, Zhejiang, and Fujian face challenges, including fragmented land use, suboptimal economies of scale, and elevated labor costs, all of which contribute to reduced efficiency at this stage.

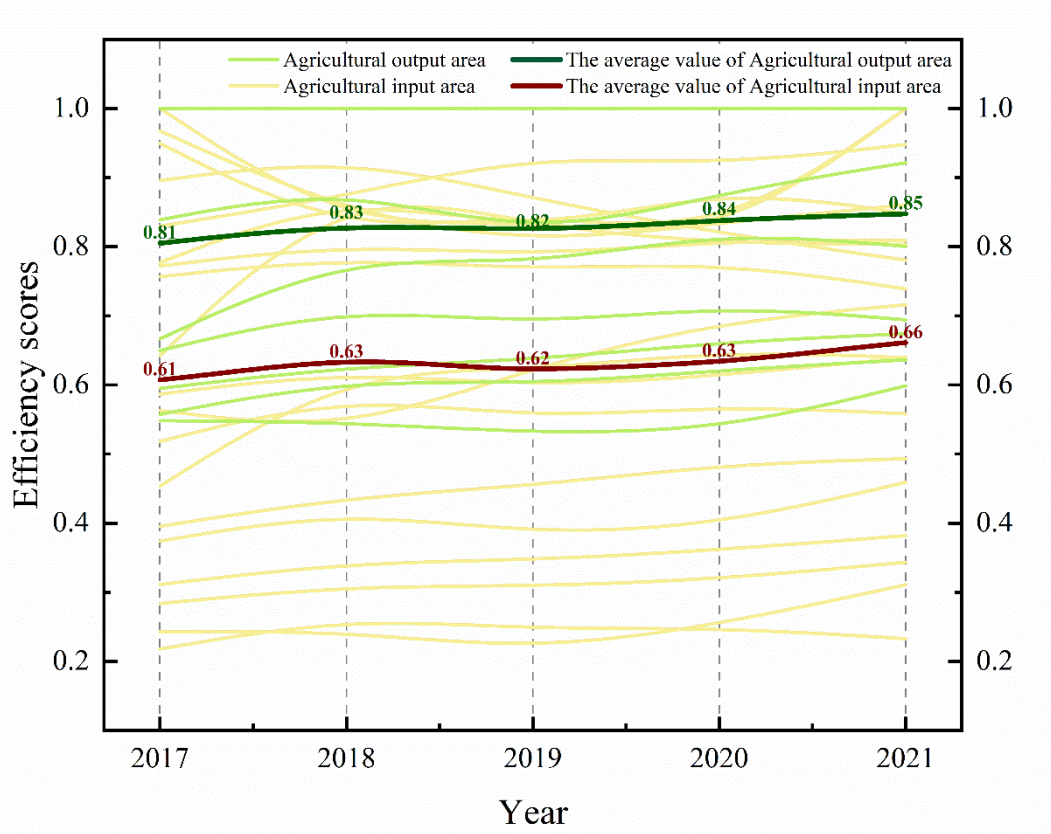


Fig. 4 Agricultural production efficiency of 30 Chinese regions (2015–2021)

In contrast, CE demonstrates a convergence trend: the average CE of input regions (0.55) is close to that of output regions (0.66), and this gap has narrowed over time. The mechanism behind this trend is the improvement of logistics technology. Specifically, the wider adoption of cold chains, integrated warehousing and distribution, and digitalized logistics spreads end-distribution costs and transport-emission intensity per unit of grain. Although input regions remain distant from core markets, deeper processing and faster turnover help convert inflows into revenue. Appendix Table B.4 details the PE lag in input regions, while CE differences are not significant, supporting the aforementioned convergence pattern.

4.3. Effects of agricultural transfers and regional allocation optimization

Building on the stage-wise results presented in Section 4.2, we first construct a scenario without interregional grain circulation to isolate the pure effect of transfers on ecological efficiency. Using Models (4) and (5), we calculated changes in agricultural carbon emissions and grain industry revenue (Fig. 5) across regions based on the efficiency values achieved during the production and consumption stages without circulation. Under the no-transfer counterfactual, the share of cultivation emissions borne by net-importing regions rises from 43% to 68%, indicating that actual interprovincial circulation shifts a substantial portion of production-side carbon burdens toward net-exporting regions. For instance, through the interprovincial transfer of agricultural products, the agricultural carbon emissions of Beijing

have decreased by approximately 96.2%, implying that counterfactual emissions would be about 26 times the current level. Conversely, the agricultural carbon emissions of Heilongjiang are approximately 3.3 times the no-transfer level, with approximately 80.77% of this increase being attributable to consumption-driven demand from importing regions.

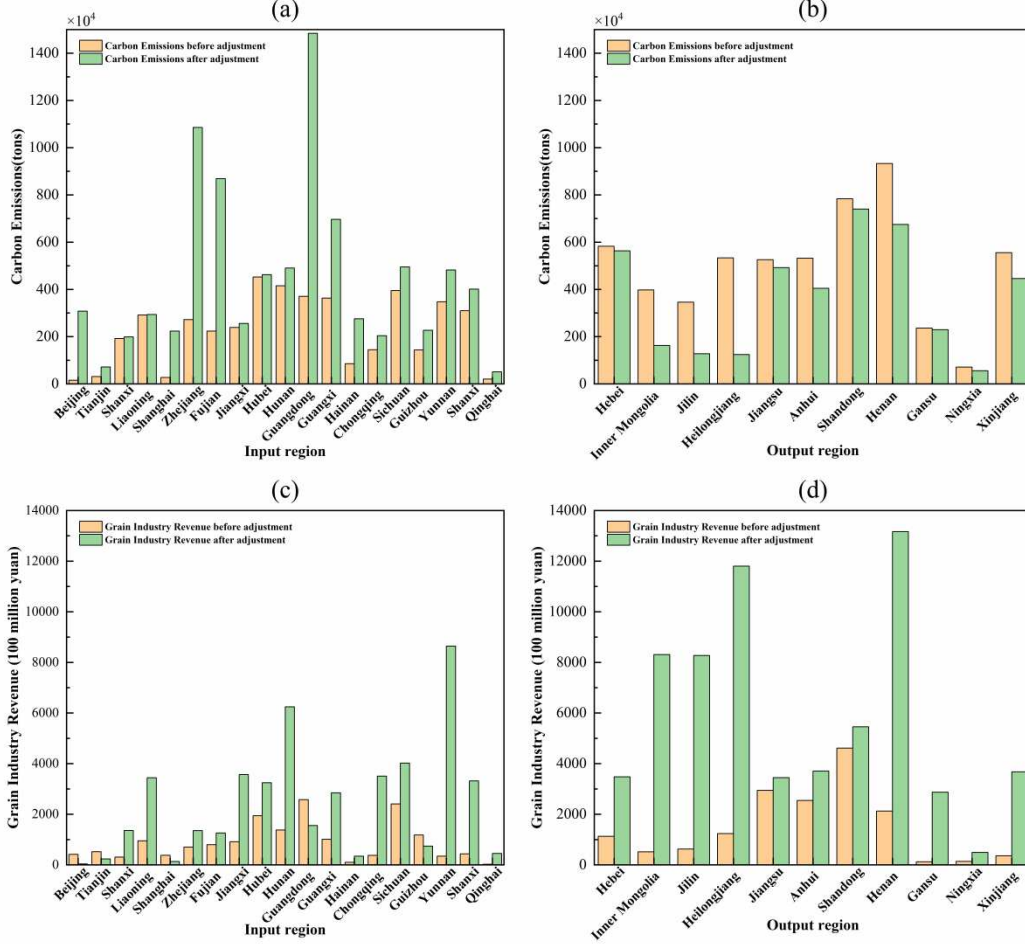


Fig. 5 Changes before and after agricultural transfer:

- (a) carbon emissions in input regions; (b) carbon emissions in output regions;
(c) grain industry revenue in input regions; (d) grain industry revenue in output regions

The no-transfer counterfactual produces asymmetric changes across regions. Removing interprovincial grain circulation increases cultivation-related carbon emissions in net grain-importing regions but reduces them in net grain-exporting regions, while modeled grain-industry sales revenue generally increases in both groups. At the national level, Table 2 reports the differences between the actual-circulation and no-transfer scenarios, calculated as the actual-circulation value minus the corresponding no-transfer value. The consistently negative values indicate that actual interprovincial grain circulation is associated with lower national cultivation-related carbon emissions and lower modeled grain-industry sales revenue than the no-transfer counterfactual throughout 2017–2021. These results reveal a trade-off: interprovincial circulation reduces aggregate cultivation-related emissions but also lowers

modeled downstream revenue relative to the closed-system benchmark, while redistributing a greater share of production-side carbon burdens toward net grain-exporting regions.

Table 2

Changes in various indicators caused by agricultural transfer (2017–2021).

Year	Difference in carbon emissions (10,000 metric tons)	Difference in grain-industry sales revenue (100 million yuan)
2017	-2479.43	-88607.65
2018	-2685.32	-82417.22
2019	-2839.49	-80221.15
2020	-2769.19	-73457.74
2021	-3012.95	-64644.26

To counteract this adverse pattern without sacrificing national output, we solve an allocation problem that maximizes systemwide AEE under fixed national grain output. Model (6) permits admissible provincial adjustments that reallocate production toward higher-AEE provinces while meeting provincial demand and accounting for transport-related externalities. Accordingly, the optimal solution reallocates production across exporting provinces while keeping total output constant (see Appendix Table B.5 for province-level changes). The Northeast Plain receives larger quotas, while several provinces, including Henan, reduce their grain production, resulting in lower national emissions. Fig. 6 visualizes the post-optimization distribution across exporting provinces.

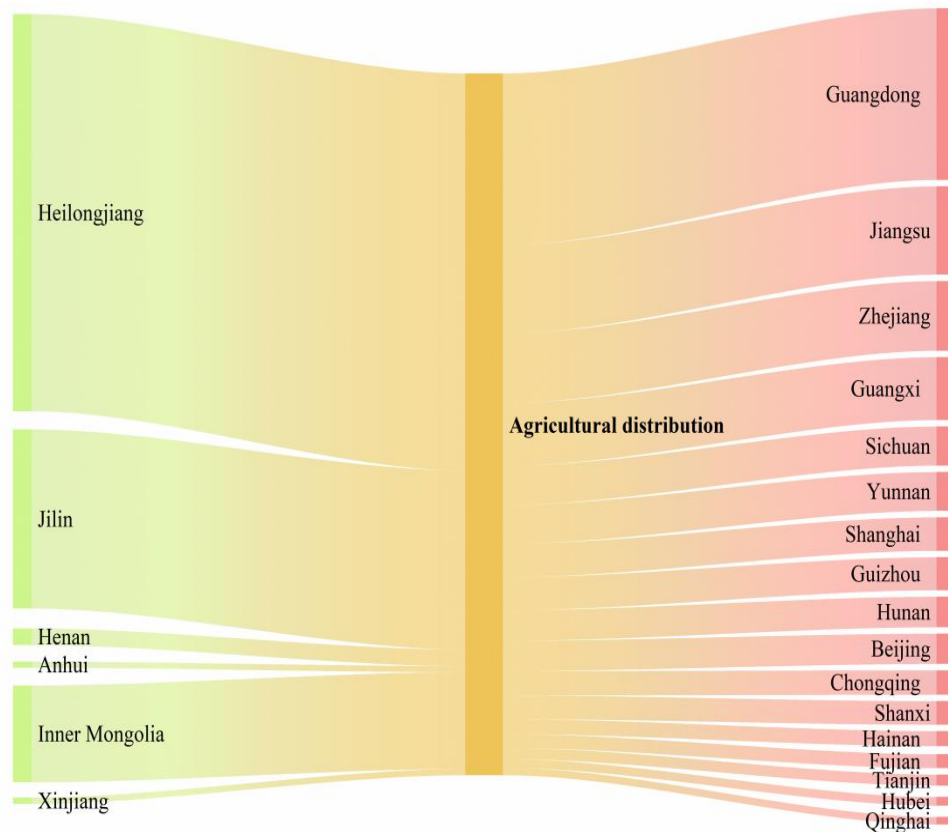


Fig. 6 Optimized grain allocation from net-exporting to net-importing provinces

AEE-guided reallocation favors the Northeast Plain, especially Heilongjiang and Jilin, because contiguous black-soil farmland, stable water conditions, large-scale operations, and

mechanized production support lower marginal carbon intensity. By contrast, provinces with more fragmented plots, higher machinery redundancy, or stronger ecological pressure face higher marginal emissions for additional output. The optimized allocation therefore shifts production toward high-AEE exporting regions while reducing the production burden in regions where further expansion is less carbon-efficient.

For the 11 exporting provinces, optimization delivers a national reduction in agricultural emissions of 55.65 to 52.91 million tons, implying a 4.9% decrease in total national agricultural carbon emissions while preserving total output (Fig. 7). This implies room for quota-style adjustments that shift marginal production toward high-AEE zones, accompanied by targeted investments in agronomic practices (e.g., conservation tillage), parcel consolidation, and cross-regional logistics coordination. Optimal allocation both strengthens high-efficiency zones and relieves high-emission regions, thereby supporting progress toward agricultural carbon neutrality.

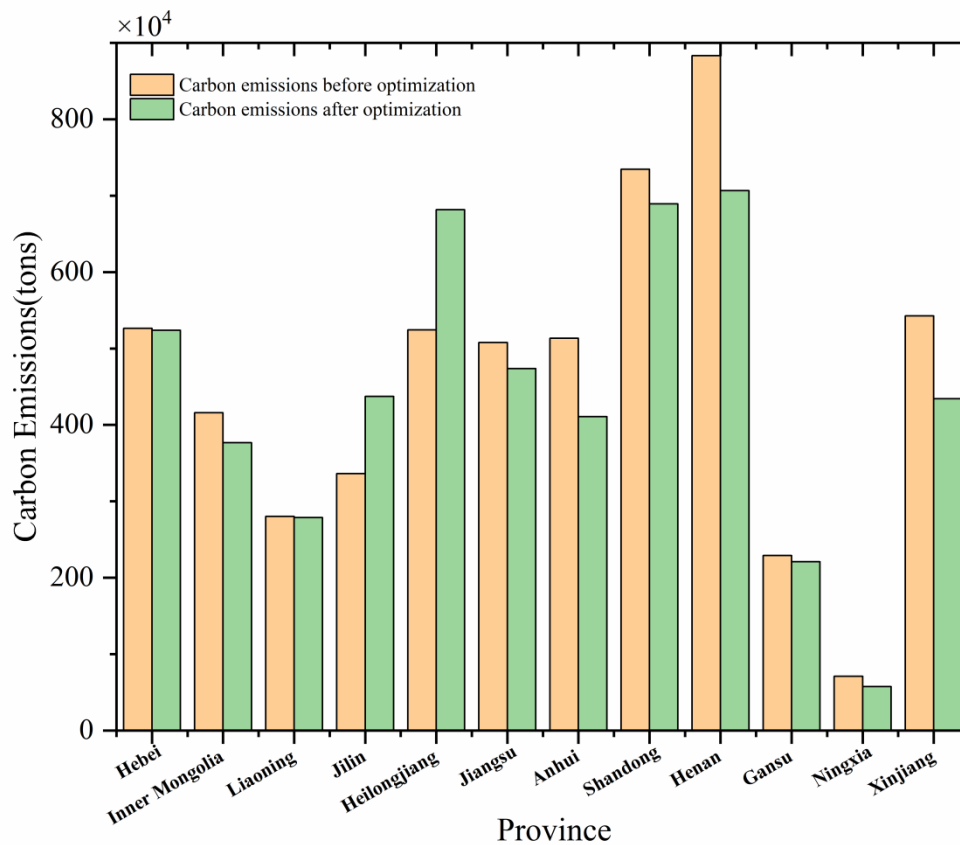


Fig. 7 Carbon emissions in output regions before and after agricultural allocation optimization

5. Explanatory analysis of AEE correlates and regional heterogeneity

5.1. Regression model

Previous studies on ecological efficiency have largely remained at the level of DEA estimation, lacking in-depth explanations for the sources of efficiency differences. In fact, linking ecological efficiency to factors such as environmental regulations and technological innovation holds significant policy implications. Since DEA efficiency scores range from 0 to 1, directly applying OLS regression may introduce estimation bias. Therefore, we estimate a panel Tobit model using maximum likelihood estimation. The standard Tobit model is expressed as:

$$y_{it}^* = x_{it}'\beta + u_i + \varepsilon_{it}$$

$$y_{it} = \begin{cases} 0, & y_{it}^* \leq 0, \\ y_{it}^*, & 0 < y_{it}^* < 1, \\ 1, & y_{it}^* \geq 1. \end{cases} \quad (7)$$

In this equation, i indexes provinces (DMUs), t indexes years, y_{it}^* denotes the AEE of province i in year t , x_{it}' are the variables that affect AEE, u_i captures the individual-specific random effect, β is the coefficient vector to be estimated, and ε_{it} is the random error term.

5.2. Selection of influencing factors

To explain the interprovincial variation in AEE measured by two-stage DEA, this study draws on prior literature and the present research focus to select a set of indicators that capture production structure, market demand, and ecological–governance constraints. Table 3 summarizes the implications of the aforementioned influencing factors. The data window and sources follow Section 4.1, covering data from national and provincial yearbooks for the 2017–2021 period. A small number of missing observations in the regression covariates were interpolated using. Therefore, this paper selects six factors for analysis, as follows:

Table 3 Indicators of influencing factors

Variable	Variable definitions
Ecological efficiency (EE)	Agricultural eco-efficiency
Agricultural structure (AS) (Wang et al., 2022)	Seeded area of grain crops/total seeded area of cultivated land
Consumer demand intensity (UR) (Y. Liu et al., 2024; Zhao et al., 2023)	Urban residential population/total population
Market stability of agricultural products (AP) (Liu et al., 2020)	Agricultural producer price index (log processing)
Conservation land constraint (PAS) (Köthe et al., 2023; Ouyang & Wen, 2025)	Area of nature reserve/total area of the region (excludes scenic and cultural heritage zones)
Environmental governance intensity (EPI) (Gou et al., 2025)	Environmental pollution control investment/GDP
Agricultural capital deepening (Stock) (Vander Donckt et al., 2021)	Agricultural capital stock/total capital stock (log processing)

The dependent variable is EE, obtained from the two-stage network DEA model. The explanatory variables capture three dimensions: production structure, represented by AS and Stock; demand and market conditions, represented by UR and AP; and ecological–governance constraints, represented by PAS and EPI. AS reflects the grain orientation of agricultural production, UR proxies consumption-side agglomeration and logistics demand, AP captures producer price fluctuations, PAS measures conservation-related land constraints, EPI reflects environmental governance intensity, and Stock captures agricultural capital deepening.

5.3. Tobit regression results and analysis

5.3.1. Benchmark regression results

The Tobit regression results presented in Table 4 indicate that AS and UR have significant positive effects on EE, while AP and PAS have significant adverse effects. EPI is shown to have a weakly positive effect, while the effect of Stock is positive but not statistically significant. The specific analysis is presented as follows.

Table 4 Baseline regression results

Variables	EE	PE	CE	CCR
AS	2.3995*** (2.8664)	0.7092* (1.6747)	1.5369* (1.8716)	2.2665** (2.4094)
UR	2.9710*** (3.3209)	1.1107** (2.2080)	2.4423*** (2.8913)	3.6766*** (4.0434)
AP	-0.5189** (-2.1431)	-0.0495 (-0.4144)	-0.5188** (-2.0490)	-0.6139** (-2.3606)
PAS	-3.2388*** (-3.0779)	-0.6431 (-1.0759)	-1.4227* (-1.9132)	-1.4943* (-1.6886)
EPI	0.0742* (1.7195)	-0.0362 (-1.5131)	0.1005** (2.2983)	0.0755 (1.6159)
Stock	0.0094 (0.6086)	-0.0080 (-1.1649)	0.0163 (0.9904)	0.0354** (2.0401)
_cons	-1.5871 (-1.2015)	-0.9975 (-1.4427)	-0.5639 (-0.4076)	-1.2193 (-0.8482)
sigma_u	0.6804*** (7.0405)	0.4861*** (6.3982)	0.5457*** (6.8586)	0.6405*** (6.2172)
sigma_e	0.1611*** (14.2873)	0.0749*** (13.7400)	0.1665*** (13.5265)	0.1627*** (12.6494)
N	150	150	150	150

Note: *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(1) The benchmark Tobit results reveal several important associations between regional characteristics and AEE. First, AS has a significant positive effect on EE, PE, and CE, indicating that agricultural structural upgrading plays a systemic role in improving eco-efficiency. In the production stage, a higher share of crop farming can promote more concentrated use of land, and machinery, facilitate scale operation, and support green production practices such as water-saving irrigation and precision fertilization (Wang et al., 2022). These mechanisms improve resource-use efficiency and reduce undesirable outputs. In the consumption stage, a more grain-oriented structure can strengthen standardization, stabilize supply, reduce transportation and storage losses, and improve interprovincial circulation efficiency.

(2) UR is significantly positive across stages, suggesting that urbanization improves AEE

through both production- and consumption-side channels. Urbanization enhances the mobility of labor, capital, information, and technology between urban and rural areas, thereby improving factor allocation (Y. Liu et al., 2024). In the production stage, it can promote land consolidation, mechanization, and the adoption of efficient agricultural technologies. Its effect is particularly evident in the consumption stage, where urban agglomeration supports cold-chain logistics, warehousing, processing capacity, and market connectivity. These improvements reduce distribution losses and energy use per unit of grain and enhance the scale effect of environmental governance.

(3) AP exhibits a significantly adverse effect on EE and CE. Rising agricultural prices tend to induce higher input use, including fertilizers and pesticides, increasing carbon emissions and other pollutants (Liu et al., 2020). Simultaneously, fluctuations in AP affect the consumption stage through market transmission mechanisms: excessively high prices suppress market demand, causing a decline in the operational efficiency of logistics and storage/transportation systems while increasing the energy consumption and emissions per unit of product.

(4) PAS is significantly negative, suggesting that a higher share of protected areas currently reduces measured AEE. This occurs because regions with higher PAS often restrict the use of high-quality farmland, forcing agricultural production activities to expand into marginal or low-yield areas. These areas feature poor soil quality and unfavorable production conditions. To maintain yields, farmers typically increase fertilizer, pesticide, and irrigation inputs, leading to higher pollutant emissions and reduced resource utilization efficiency (Köthe et al., 2023). Additionally, the fragmentation effect of protected area spatial layout may increase agricultural product transportation distances and energy consumption, further weakening overall ecological performance (Ouyang & Wen, 2025). In other words, while ecological spatial controls safeguard ecological security, they simultaneously constrain efficient agricultural production space, creating structural tension between efficiency and conservation.

(5) EPI has a relatively weak positive effect that is mainly characterized by a consumption-stage effect. Based on the previous analysis, the scale benefits of environmental pollution control are relatively high. Environmental governance investments, conceived within agro-socio-ecological systems linking urbanization, agricultural development, and environmental change, improve rural infrastructure for sewage treatment, waste recycling, and agricultural nonpoint-source pollution control. At the firm level, Pirtea et al. (2021) similarly show that environmental and governance dimensions are important for the sustainable financial performance of agricultural companies. Moreover, through spatially differentiated ecological infrastructure such as check dams, environmental investment can reduce soil erosion and undesirable-output intensity while raising land productivity and the green conversion efficiency of agricultural products during storage, transportation, processing, and consumption (Gou et al., 2025). Simultaneously, the public's educational level and environmental awareness will be

enhanced, and their attention to environmental management will also increase. These factors will effectively enhance the efficiency of the input elements for pollution control.

(6) Agricultural capital deepening (Stock) is positive but not statistically significant, indicating that capital deepening has not yet stably translated into EE gains during the sample period. Considering that capital allocation may be biased toward traditional mechanical expansion, which exhibits significant time lags, this variable is retained as a control in the baseline model without overinterpretation. In the robustness analysis of 5.3.2. Robustness test, its potential mechanisms and sensitivity to measurement methods will be further explored in the robustness analyses.

5.3.2. Robustness test

To test the robustness of the explanatory analysis, this study replicates the regression process described above using the CCR efficiency model as the dependent variable instead of EE, following the methodology of Chen and Chen (2019). The CCR model assumes constant returns to scale and treats the production system as a black box without explicit intermediate links. Therefore, it provides an independent assessment of coefficient direction and significance. As reported in Table 4 and CCR, the main patterns are stable. AS and UR remain significantly positive, while AP continues to exert a significant adverse effect. Moreover, the coefficient on PAS stays negative with slightly reduced significance, while EPI becomes statistically insignificant and Stock turns significantly positive.

EPI exhibits only weak significance in the two-stage framework and becomes insignificant in the CCR model. This primarily reflects that its effects are channeled through the second stage, including cleaner production, energy efficiency management, and enhanced environmental compliance, while the CCR model merges both stages into a black box and weakens this transmission channel. Furthermore, governance funds often prioritize end-stage interventions and involve time lags, thus making it difficult to achieve statistically significant overall efficiency gains in the short term (Ren et al., 2022). Notably, Stock represents a long-term, general-purpose asset (Vander Donckt et al., 2021). Within the two-stage model, if technical or circulation bottlenecks exist in intermediate stages or if there are lags, the marginal effect of capital becomes dispersed, making it difficult to achieve statistical significance. However, the CCR model directly links inputs to final sales revenue, reducing stage constraints and transmission losses, thereby increasing its statistical significance. Overall, the coefficient signs and core relationships are highly consistent with the benchmark results, confirming the robustness of the empirical findings.

5.3.3. Heterogeneity analysis

Within the interprovincial grain allocation framework, producing regions mainly bear production-side and ecological constraints, while receiving regions reflect demand and circulation conditions. Based on net grain flows, provinces are divided into input and output

regions and estimated separately (Table 5). Although overall coefficient signs are consistent with the benchmark results, key drivers differ in strength across the two groups.

Table 5 Heterogeneity analysis results

Variables	EE	Input region	Output region
AS	2.3995*** (2.8664)	2.5678** (2.2114)	0.4883 (0.4229)
UR	2.9710*** (3.3209)	2.7539** (2.3866)	3.2945** (2.5687)
AP	-0.5189** (-2.1431)	-0.8706*** (-2.7632)	0.0535 (0.1406)
PAS	-3.2388*** (-3.0779)	-2.3919** (-2.4311)	-4.6625** (-2.3893)
EPI	0.0742* (1.7195)	0.0496 (0.6670)	0.1234** (2.3616)
Stock	0.0094 (0.6086)	0.0090 (0.4323)	0.0128 (0.5835)
_cons	-1.5871 (-1.2015)	-0.1556 (-0.0865)	-3.0526 (-1.6273)
sigma_u	0.6804*** (7.0405)	0.7602*** (5.4315)	0.3090*** (4.2111)
sigma_e	0.1611*** (14.2873)	0.1638*** (10.7420)	0.1506*** (9.2352)
N	150	95	55

Note: *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

AS is significantly positive in input regions but nonsignificant in output regions. In input regions, where farmland is often highly fragmented and intensification remains relatively low (Xu et al., 2020), increasing the proportion of crop cultivation enhances standardization, improves factor allocation, and reduces per-unit emissions. Since large-scale specialized patterns are already established in output regions, marginal structural adjustment yields limited additional gains. AP only shows a significant adverse effect in input regions. Rising agricultural product prices encourage farmers to increase inputs such as pesticides and fertilizers, which leads to higher pollution emissions in grain-importing regions where farming is fragmented (Liu et al., 2020). In output regions, price signals are largely smoothed by minimum purchase prices and contractual agreements, making it difficult for field-to-factory price fluctuations to translate into efficiency changes; therefore, the net effect is weak and not significant. EPI is insignificant in input regions but positive and significant in output regions. The lack of statistical significance for EPI in input regions may reflect that governance funds are concentrated in urban endpoints. Thus, pollution control investment is more effective where source emissions are concentrated (i.e., major output regions).

Overall, the heterogeneous results observed here suggest that input-region efficiency is more sensitive to price and structural signals, whereas output-region efficiency is more constrained by ecological red lines and source governance, highlighting the need for differentiated regional policies.

6. Conclusions and policy implications

6.1. Conclusions

From a climate risk governance perspective, this study examines how interprovincial grain circulation reshapes agricultural eco-efficiency and carbon responsibility when production benefits, consumption benefits, and environmental burdens are spatially separated. Using panel data for 30 Chinese provinces, we develop an interpretable two-stage network DEA framework that incorporates transferable grain intermediates, cultivation-related emissions, transportation-related emissions, and a no-transfer counterfactual within a unified production–circulation–consumption boundary. This framework makes it possible to identify how interregional grain circulation redistributes environmental burdens between grain-exporting and grain-importing regions and provides a more realistic basis for coordinating agricultural emission reduction, aggregate grain supply, and regional responsibility sharing.

The results reveal pronounced provincial heterogeneity and clear stage-specific differences. Production efficiency is generally higher in major grain-producing regions characterized by contiguous farmland, mechanized operations, and relatively mature production conditions. Circulation–consumption efficiency tends to be stronger in coastal provinces and transport nodes with denser logistics, processing, and market networks. Provinces with fragmented farmland, limited production scale, weak circulation infrastructure, long transport distances, or relatively severe ecological constraints tend to exhibit lower stage-specific performance. These findings indicate that assessments confined to production locations cannot fully distinguish production capability, circulation efficiency, and downstream value conversion, and may therefore provide an incomplete basis for regional low-carbon governance.

Interprovincial grain circulation substantially reshapes both efficiency evaluation and carbon-responsibility attribution. Grain-importing regions reduce locally recorded cultivation emissions by sourcing grain from surplus provinces, whereas major grain-exporting regions bear additional production-side carbon burdens associated with external demand. The no-transfer counterfactual shows that treating provinces as closed systems can overstate the environmental performance of importing regions and understate externally induced burdens borne by supplying regions. This mismatch is relevant not only to efficiency rankings but also to climate mitigation, regional responsibility sharing, and interregional ecological compensation. The allocation optimization further shows that, under a fixed national grain-output requirement, reallocating production among net grain-exporting provinces can reduce cultivation-related carbon emissions from 55.65 million tons to 52.91 million tons, representing a reduction of approximately 4.9%. This result indicates that emission reductions can be achieved while preserving aggregate national grain output and that production responsibilities can be adjusted toward regions with stronger production-stage eco-efficiency and more favorable cultivation-related emission performance.

The Tobit results provide further evidence on the structural and institutional correlates of these efficiency patterns. Agricultural structure and urbanization are positively associated with overall, production, and circulation–consumption efficiency, suggesting that specialization, scale operation, population agglomeration, and improved circulation capacity may be related to more efficient resource use and value conversion. Agricultural producer prices are negatively associated with overall and circulation – consumption efficiency, while protected-area coverage also exhibits a negative association with measured AEE. Environmental protection investment shows a weak positive relationship, whereas agricultural capital deepening is positive but not robust across alternative specifications. Separate estimates for grain-importing and grain-exporting regions further suggest different coefficient patterns across the two groups, although these differences should be interpreted cautiously in the absence of formal cross-group coefficient tests. Taken together, these findings suggest that low-carbon agricultural governance should account for regional roles within the national grain network rather than applying uniform efficiency standards or mitigation requirements.

6.2. Policy implications

Based on the circulation-adjusted efficiency results, the no-transfer counterfactual, allocation optimization, and explanatory analysis, this study derives several implications for climate risk governance in food systems, with particular attention to agricultural emission reduction, interregional carbon responsibility, and the maintenance of aggregate grain supply.

(1) Develop circulation-adjusted agricultural carbon accounting and interregional responsibility-sharing mechanisms. Agricultural carbon accounting should move beyond a production-location-only boundary and incorporate the redistribution of environmental burdens associated with interprovincial grain circulation. The results show that grain-importing regions can reduce locally recorded cultivation emissions by relying on supplies from other provinces, while major grain-exporting regions bear additional production-side emissions associated with external demand. Accordingly, regional environmental performance should be evaluated by jointly considering origin-borne emissions, consumption-induced responsibilities, and transportation-related emissions, rather than treating lower local production emissions as evidence of an absolute reduction in carbon responsibility. A circulation-adjusted accounting framework would help prevent the environmental performance of importing regions from being overstated and the externally induced burdens of supplying regions from being understated. On this basis, interregional ecological compensation could be linked to measurable demand-induced carbon burdens, verified emission reductions, and improvements in agricultural eco-efficiency. Such an arrangement would allow regions benefiting from grain inflows to share part of the mitigation and environmental-governance costs borne by major supplying regions, while avoiding rigid compensation rules that disregard differences in emission intensity,

efficiency, and ecological constraints. This would improve both the accuracy of agricultural carbon accounting and the fairness of responsibility allocation within the national grain network.

(2) Optimize regional production responsibilities under national grain-output and ecological constraints. Grain-production planning should incorporate eco-efficiency, cultivation-related emission performance, and resource suitability into the allocation of regional production responsibilities. The optimization results indicate that, while maintaining total national grain output, reallocating production among net grain-exporting provinces can reduce cultivation-related carbon emissions from 55.65 million tons to 52.91 million tons, corresponding to a reduction of approximately 4.9%. This finding supports a gradual shift from production targets based primarily on historical output and administrative allocation toward a more coordinated approach that considers production efficiency, carbon intensity, and regional resource conditions. Higher measured AEE, however, should not automatically be interpreted as unlimited capacity for production expansion. Regional adjustments should also account for water availability, arable-land quality, ecological protection requirements, and the potential environmental consequences of further intensification. The allocation model should therefore be viewed as a scenario-screening and decision-support tool for identifying feasible adjustment directions rather than as a rigid production mandate. Priority may be given to provinces that combine relatively high production-stage eco-efficiency with lower cultivation-related emission intensity and adequate ecological carrying capacity, while production expansion in regions with persistent low efficiency or fragile resource conditions should be approached cautiously. A phased adjustment process accompanied by continuous monitoring of output, emissions, and resource pressures would help pursue emission-reduction objectives while maintaining aggregate national grain supply.

(3) Implement stage-specific and regionally differentiated low-carbon governance. The substantial differences between production efficiency and circulation–consumption efficiency indicate that uniform agricultural environmental policies are unlikely to address the main constraints faced by all provinces. In regions with relatively low production efficiency, governance should focus on reducing excessive input intensity, improving land-use and production organization, promoting the effective adoption of green production technologies, and controlling cultivation-related emissions at source. In regions with relatively low circulation–consumption efficiency, greater attention should be paid to storage, processing, transportation organization, grain-loss reduction, and the conversion of grain flows into downstream economic value with lower unit emissions. Policy design should also distinguish between the roles of grain-importing and grain-exporting regions. The separate Tobit estimates suggest that importing regions may be more responsive to structural and price conditions, whereas exporting regions show stronger associations with ecological constraints and source-oriented environmental governance. These patterns support differentiated policy design,

although they should not be interpreted as formal evidence of statistically significant differences between regional groups. Performance assessment should therefore combine stage-specific efficiency indicators with each province's position in the national grain network rather than applying identical efficiency standards or mitigation obligations across all regions. Such differentiated governance can better align production organization, market incentives, environmental constraints, and regional carbon responsibilities.

Several limitations should be acknowledged. First, the current allocation model focuses on reallocating grain production among net grain-exporting provinces and does not endogenously optimize bilateral grain flows or transportation routes. It therefore cannot fully capture potential trade-offs between cultivation-related emission reductions and changes in transportation-related emissions. Second, the framework is static and does not explicitly model dynamic multi-period adjustments in regional production responsibilities. Uncertainties associated with grain demand, climate shocks, and transportation conditions are also not incorporated into the current analysis. Third, the Tobit results describe statistical associations and should not be interpreted as causal effects, while the allocation outcomes may be sensitive to the assumed adjustment bounds and DEA specification. Future research could extend the framework by integrating detailed origin–destination flow data, dynamic network DEA structures, and stochastic or robust optimization methods. Predictive and causal analytics could also be introduced to examine how changes in climate, markets, and policy interventions affect grain allocation, carbon-responsibility redistribution, and regional eco-efficiency over time. These extensions would strengthen the framework's capacity to support adaptive and responsibility-aware climate risk governance in food systems under changing climatic and socioeconomic conditions.

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Statements and Declarations

Funding

This work was supported by the National Natural Science Foundation of China [grant numbers 72571081, 72071066, 42271293, and 72188101].

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Zhixiang Zhou: Writing—original draft, Data curation, Software, Validation. Xianzhe Xu: Visualization, Conceptualization, Formal analysis, Writing—review & editing, Funding acquisition. Baohuan Zhou: Conceptualization, Resources, Project administration. Shaomeng Zhang: Supervision, Methodology, Validation.

Data availability

Data will be made available on request.

Supplementary Files

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