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Integrated Assessment of Sustainable Development of the Agro-Industrial Complex in the BRICS Countries: Evidence from China, Russia and India

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Abstract

Achieving balanced development across economic, social, environmental, and agricultural domains remains a critical challenge for emerging economies. This study conducts a comparative assessment of sustainable development in the agro-industrial complex of China, Russia, and India over the period 2000–2023 within an extended SDG-based framework. The methodological approach combines a multi-dimensional indicator system (37 indicators) with the Entropy Weight Method to identify indicators with high temporal information contribution and the Equal Weighting Method to evaluate long-term performance, ensuring both sensitivity to structural changes and cross-country comparability. The results reveal differentiated development trajectories: China demonstrates steady and balanced growth across all dimensions; India shows consistent improvement driven by progress in social and infrastructure-related indicators; Russia exhibits a more volatile pattern with relatively strong social outcomes but persistent weaknesses in agricultural performance. The entropy-based analysis indicates that the indicators contributing most strongly to temporal differentiation vary significantly across countries, with infrastructure and energy transition prevailing in China, natural resource dynamics in Russia, and social and digital factors in India. These findings suggest that long-term development trajectories in the agro-industrial sector are associated with different configurations of resource interdependence, institutional capacity, and resource-use efficiency.

Keywords: agro-industrial complex; sustainable development; BRICS countries; entropy weight method; agricultural sustainability; comparative assessment



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1. Introduction

Sustainable development remains one of the central challenges for contemporary economies, as it requires a simultaneous balance between economic growth, social progress, and environmental protection [1]. The United Nations 2030 Agenda for Sustainable Development provides the main international framework for assessing these interrelated dimensions. Within this agenda, the BRICS countries occupy a particularly important position because of their demographic scale, resource significance, and growing influence on global development processes. Among them, China, India, and Russia represent three major emerging economies with markedly different development trajectories, institutional

settings, and sectoral structures, which makes them a relevant comparative group for the study of long-term sustainability dynamics [2].

At the same time, the agro-industrial complex remains a strategic sector in all three countries. Its significance extends far beyond food production and includes rural employment, land use, water consumption, energy demand, and the environmental consequences of resource-intensive production. In this sense, the agro-industrial complex should not be treated as a peripheral element of sustainable development assessment. In large emerging economies, it constitutes one of the main interfaces through which economic, social, and environmental processes interact. This is especially evident within the water–energy–food nexus, where agricultural production is directly linked to the efficiency of resource use, food security, and the resilience of national development models.

1.1. Theoretical Framework and Research Logic

In this study, sustainable development of the agro-industrial complex is understood as a long-term process in which agricultural production, processing, infrastructure, and related rural systems improve their economic performance and social contribution while maintaining the regenerative capacity of land, water, energy, and ecological resources. This interpretation emphasizes balanced progress across four interconnected dimensions: economic capacity, social outcomes, resource and environmental conditions, and sector-specific agricultural performance. It therefore refers not only to growth in agricultural output, but also to the capacity of the agro-industrial system to generate food, income, employment, and technological progress without creating disproportionate resource pressure or weakening long-term resilience.

The analytical framework of this study combines three complementary theoretical perspectives. First, the agro-industrial complex is understood as an integrated system that links primary agricultural production with processing industries, infrastructure, logistics, finance, public regulation, and rural labor markets. This system perspective implies that agricultural performance cannot be assessed exclusively through output indicators because its long-term trajectory depends on the coordination of production, resource, institutional, and social subsystems. Research on agro-food value chains likewise emphasizes that value creation in agriculture is shaped by interactions between upstream inputs, farm production, downstream processing, services, trade, and policy conditions [3].

Second, the water–energy–food nexus provides the resource-interdependence mechanism underlying the proposed evaluation structure. Agricultural production simultaneously depends on water availability, energy inputs, land quality, infrastructure, and environmental carrying capacity. Policy interventions in one subsystem may generate trade-offs or synergies in others; for example, irrigation expansion can increase food output while raising energy demand and groundwater pressure. The nexus approach therefore supports the joint assessment of agricultural, economic, social, and resource–environmental indicators rather than their isolated interpretation [4].

Third, sustainability-transition theory explains why long-term changes in agro-industrial systems are uneven across countries. Structural transformation is not limited to the diffusion of individual technologies; it also involves changes in institutions, regulation, infrastructure, investment patterns, producer practices, and market organization. From this perspective, the observed trajectories of China, Russia, and India can be interpreted as different configurations of system stability and transformation, conditioned by national resource endowments, institutional capacities, and the pace of technological and social change [5].

The four-dimensional model used in this study follows from the intersection of these perspectives. The economic dimension captures productive capacity, investment,

industrial structure, and digital connectivity; the social dimension reflects human capital, employment, inequality, and access to basic services; the resource and environmental dimension measures the pressures and constraints associated with energy, emissions, materials, forests, and water; and the agricultural dimension captures sector-specific productivity, land, irrigation, employment, and food-production characteristics. Agricultural sustainability is therefore treated as an independent dimension, but not as an isolated subsystem: its performance is analytically linked to the other three dimensions through resource flows, institutional coordination, and structural transformation.

The agricultural dimension is treated as a standalone analytical subsystem because the study evaluates the agro-industrial complex rather than national development in the abstract. Its purpose is to capture sector-specific outcomes that cannot be reconstructed from the general economic, social, or resource-environmental dimensions alone, including agricultural productivity, food-production dynamics, irrigation coverage, agricultural employment structure, and the role of agricultural land. These indicators describe the internal performance and structural configuration of agriculture, whereas conceptually related indicators in the other dimensions describe economy-wide conditions, social outcomes, or aggregate resource pressures.

Potential conceptual overlap is addressed through a distinction between context and sectoral manifestation. For example, total economic value added and agricultural value added are not treated as equivalent: the former reflects the overall production structure, while the latter measures the relative role of agriculture within that structure. Similarly, total employment conditions differ from agricultural employment structure, and economy-wide freshwater pressure differs from the agricultural share of water use. The indicators therefore refer to different analytical levels and are not duplicated under identical definitions.

An alternative framework would treat agriculture as a cross-cutting theme and distribute agricultural indicators across the economic, social, and resource-environmental dimensions. Such a design is useful when agriculture is only one component of a general national sustainability index. However, it would make it impossible to calculate a distinct agricultural score and would obscure whether a country's overall position is supported or constrained by the agro-industrial subsystem. The separate-dimension approach was therefore selected to preserve sectoral diagnostic value, while equal weighting of the four-dimension scores prevents the larger indicator groups from mechanically dominating the total index.

This theoretical integration yields two propositions that guide the empirical analysis. First, countries with more coordinated infrastructure, institutional capacity, and resource management should display more balanced development across dimensions. Second, the indicators contributing most strongly to temporal differentiation should vary across countries because the binding constraints of agro-industrial transformation are country-specific. The empirical methods used below do not test causality directly; instead, they provide a comparative measurement framework for identifying these structural patterns and generating theoretically grounded interpretations.

1.2. Literature Review

The literature relevant to this study can be organized into four interconnected research streams: multidimensional indicator-based assessment, agro-industrial development and agricultural sustainability, resource interdependencies within the water–energy–food nexus, and comparative analysis of emerging economies. The review draws on country-specific studies of China, Russia, and India as well as comparative BRICS research, allowing the theoretical framing to reflect both national particularities and common cross-country mechanisms. Multicriteria research provides a methodological basis for integrating het-

erogeneous economic, social, and environmental indicators, while broader development studies emphasize the need to interpret composite performance in relation to institutional and sectoral conditions [6,7].

The first stream concerns multidimensional and indicator-based assessment. Existing studies demonstrate the value of composite indices and multicriteria procedures for structuring complex development problems. However, such assessments frequently apply a single weighting approach and often incorporate agricultural variables into broader economic, environmental, or food-security dimensions. This limits the ability to distinguish sector-specific agricultural performance from general national development and to separate long-term comparative performance from indicators characterized by strong temporal variation.

Within the ecological–economic tradition, Shmelev’s dynamic assessment of Russia is particularly relevant because it applies multi-criteria methods to macro-level sustainability assessment during a transition period and shows how alternative policy priorities affect multidimensional evaluation results [8]. More recently, Shmelev’s comparative assessment of 12 OECD countries, China, and Brazil demonstrates the relevance of multidimensional indicators and alternative weighting assumptions for evaluating progress towards sustainability at the macro scale [9].

The second stream addresses agro-industrial development, agricultural productivity, policy, and institutional transformation across all three countries. Research on China emphasizes public investment, food security, cultivated-land protection, spatial differentiation, environmental efficiency, water-use efficiency, and the interaction between renewable energy and agricultural productivity [10–16]. Studies of Russia focus on institutional coordination, land allocation, environmental pressures, territorial constraints, post-Soviet restructuring, and the digital transformation of agri-food systems [17–20]. Research on India highlights water and energy constraints, irrigation dependence, the limited diffusion of improved agricultural practices, environmental regulation, access to finance, digital technologies, and biodiversity-related support mechanisms [21–24]. Considered together, these studies show that agricultural performance is shaped by a common set of production, institutional, technological, and resource factors, although their relative importance differs substantially among countries.

The third stream examines resource interdependencies through the water–energy–food nexus. Studies of China and India demonstrate that irrigation, agricultural energy consumption, land use, emissions, and food production cannot be assessed independently because changes in one subsystem generate trade-offs and synergies in others [14–16,21]. This literature supports an integrated resource perspective, but nexus studies are commonly conducted at the level of individual resources, regions, or production systems and are rarely combined with social and macroeconomic indicators in a unified cross-country assessment.

The fourth stream comprises comparative studies of emerging economies. Although the existing literature provides substantial evidence for individual countries, directly comparable long-term assessments of China, Russia, and India remain limited. Cross-country studies frequently use different indicator sets, time horizons, normalization procedures, and weighting assumptions. These methodological differences restrict the direct comparison of national trajectories and make it difficult to determine whether observed differences reflect substantive development patterns or the design of the assessment model.

Comparative BRICS research also confirms the relevance of resource interdependence and national heterogeneity. Ozturk identifies long-term links among food, energy, water, economic growth, and ecological pressure in the BRICS countries [25]. Egbo et al. show that freshwater withdrawals have heterogeneous effects on agricultural and industrial productivity across BRICS economies [26]. Ren et al. demonstrate that food-

security cooperation potential depends on differences in resource endowments, production capacity, trade structures, and technological capabilities among member states [27]. These findings provide an international comparative basis for interpreting why China, Russia, and India exhibit different combinations of agricultural, social, economic, and resource-environmental performance.

Taken together, the Russian, Indian, Chinese, and BRICS-oriented literature supports the comparative logic of the study. Russia provides evidence of institutionally and spatially uneven resource conversion, India illustrates the interaction between social inclusion, digital access, and water-energy constraints, and China demonstrates the role of coordinated infrastructure and investment capacity. The comparative literature shows that these differences should be analyzed within a common framework rather than through isolated country narratives.

International research provides several benchmarks for interpreting the present framework. The OECD/JRC handbook on composite indicators emphasizes that cross-country indices require an explicit theoretical framework, transparent normalization and weighting procedures, and sensitivity analysis to avoid misleading rankings [28]. In agricultural assessment, Henderson and Lankoski argue that productivity, environmental performance, and sectoral livelihoods should be examined jointly because partial indicators may conceal trade-offs between production growth and resource pressure [29]. These methodological principles support the use of a multidimensional framework and the separate presentation of dimension scores in this study.

The reviewed literature therefore reveals four specific research gaps. First, most studies are country-specific and do not provide a directly comparable assessment of China, Russia, and India over a common long-term period. Second, agricultural indicators are generally incorporated into economic, environmental, or food-security dimensions rather than treated as an independent analytical subsystem. Third, composite assessments commonly rely on a single weighting procedure and therefore do not distinguish between stable long-term performance and indicators with high temporal information content. Fourth, relatively few studies integrate economic, social, resource-environmental, and agricultural dimensions within a common framework using uniform normalization and aggregation procedures.

The goal of this study is to develop and apply a unified multidimensional framework for comparing the long-term development trajectories of the agro-industrial complexes of China, Russia, and India over 2000–2023, while distinguishing comparative performance levels from country-specific temporal information patterns.

Accordingly, this study addresses the following research questions:

- How did the integrated development trajectories of the agro-industrial complexes of China, Russia, and India change between 2000 and 2023?
- How do the three countries differ across the economic, social, resource-environmental, and agricultural dimensions?
- Which indicators demonstrate the highest information contribution and temporal differentiation in each country?

This study addresses the identified gaps by providing a unified comparison of three major BRICS economies over the period 2000–2023. Its contribution lies in treating agricultural sustainability as an independent but systemically connected dimension; combining equal weighting for long-term comparative assessment with entropy weighting for identifying high-information indicators; and integrating country-specific evidence from China, Russia, and India with comparative BRICS research on resource interdependence, institutional coordination, and structural transformation.

2. Materials and Methods

2.1. Data and Indicator System Construction

To dynamically monitor the sustainable development progress of BRICS countries, this study utilizes annual panel data of China, Russia, and India from 2000 to 2023. Guided by the United Nations 2030 Agenda for Sustainable Development (SDGs) framework, a global sustainable development evaluation indicator system is constructed. It is worth noting that agro-industrial complex, as a common strategic industry among BRICS countries, plays a critical role in food security, rural employment, resource utilization, and climate change response. However, existing evaluation systems under the SDGs framework tend to address the complexity of agricultural systems in a fragmented manner, making it difficult to comprehensively capture the overall performance of agricultural sustainability. To address this, this study introduces an additional “Agricultural Sustainability” dimension on top of the three traditional dimensions of economy, society, and environment, integrating seven core indicators to establish an independent sub-system for agricultural sustainability. This extension enables the evaluation framework to more comprehensively capture the dynamic changes in BRICS countries regarding agricultural modernization, intensive resource utilization, and agricultural resilience, while also providing a basis for analyzing differences in sustainable development pathways from an agricultural perspective.

The indicator system was constructed using five selection criteria: (1) theoretical relevance to the agro-industrial system, the water–energy–food nexus, and sustainability-transition framework; (2) consistency with the SDG architecture; (3) comparability of definitions across China, Russia, and India; (4) annual data availability for the period 2000–2023; and (5) avoidance of exact or near-duplicate indicators. The final set therefore reflects both conceptual coverage and the practical requirement of maintaining a balanced long-term panel.

Indicator direction was assigned according to the expected relationship between an indicator and the evaluated development outcome. Positive indicators represent variables for which higher values are generally associated with improved performance, whereas negative indicators represent pressures or adverse outcomes. Moderate indicators were used where both very low and very high values may indicate structural imbalance.

For moderate indicators, the normalization procedure assumes a non-monotonic relationship with the assessed outcome, under which both low and high values may indicate structural imbalance. The interval boundaries used in the calculations were derived from the pooled observed range for China, Russia, and India over 2000–2023 and were applied uniformly to all three countries. Because these boundaries are sample-dependent rather than externally established normative thresholds, the corresponding results should be interpreted as comparative scores within the analyzed dataset.

The classification follows an explicit monotonicity rule. An indicator is classified as positive when an increase is expected to improve the assessed outcome over the relevant range; it is classified as negative when an increase represents greater pressure, risk, or deprivation. An indicator is classified as moderate when neither a continuously increasing nor a continuously decreasing relationship is theoretically defensible and both very low and very high values may indicate structural imbalance.

The moderate classification applies to five indicators. Industry value added (C6) and services value added (C7) are treated as moderate because an excessively low share may indicate insufficient productive diversification, whereas an excessively high share may indicate structural concentration or an imbalanced sectoral composition. Agricultural value added (C31) is moderate because a very low share may reflect a weak agricultural production base, while a very high share may indicate limited structural transformation and excessive dependence on primary production.

Agricultural employment share (C34) is moderate because a very low value may indicate insufficient rural employment capacity, while a very high value may reflect low labor productivity and delayed structural transformation. Agricultural land share (C37) is moderate because insufficient land availability may constrain agricultural capacity, whereas an excessively high share may indicate land-use pressure, ecosystem conversion, or an extensive rather than productivity-based development model. For all moderate indicators, the same pre-specified interval-based transformation is applied consistently to all three countries.

The number of indicators differs across dimensions because the dimensions were not populated to meet a predetermined numerical quota. Instead, the final composition reflects the availability of internationally comparable annual series and the need to cover the principal mechanisms identified in the theoretical framework. The economic, social, and resource and environmental dimensions each contain ten indicators, while the agricultural dimension contains seven sector-specific indicators. This difference does not give greater influence to dimensions with more indicators, because the indicators are first averaged within each dimension and the four-dimension scores are then assigned equal weight in the total index.

Potential redundancy was controlled at the indicator-definition stage by excluding measures with identical or nearly identical substantive content. Correlation alone was not used as an automatic exclusion criterion because statistically associated indicators may represent distinct mechanisms, such as income level, investment intensity, digital access, or resource pressure. The purpose of the index is descriptive multidimensional assessment rather than estimation of regression coefficients; consequently, preserving theoretically distinct information was prioritized over mechanical reduction of correlated variables. Residual overlap among indicators is acknowledged as a limitation and is addressed through dimension-level aggregation and the use of complementary weighting procedures.

To further reduce double-counting, the aggregation procedure is hierarchical. Indicators are first standardized and averaged within their assigned dimension, after which the four-dimension scores receive equal weight in the total index. Consequently, conceptually related indicators located in different dimensions do not enter the total index as unrestricted parallel weights; each contributes only through its dimension score. This design preserves the cross-cutting relationships among economic, social, resource-environmental, and agricultural processes while maintaining a distinct diagnostic measure of agricultural performance.

2.2. Data Sources and Processing Protocol

For each indicator, the source was selected according to a fixed hierarchy. Harmonized international series were used as the primary source because they apply common definitions and facilitate cross-country comparison. National statistical publications were used to verify unusual observations and to supplement a series only when the indicator definition and unit were consistent with the international metadata. The source assigned to each indicator is reported directly in Table 1.

The initial country-year matrix was checked for unit consistency, duplicate observations, changes in series definitions, and implausible year-to-year discontinuities. Monetary and percentage indicators were retained in the units reported in Table 1; no currency conversion was applied beyond that already incorporated in the source series. Where an international database published modelled or adjusted estimates, these values were retained as official harmonized observations and were not replaced by national estimates.

Table 1. A Multi-Dimensional Indicator System for Sustainable Development: Integrating Economic, Social, Environmental, and Agricultural Dimensions.

Dimension	Indicator ID	Indicator Name	Indicator Direction	Primary Source
D1 Economic Development	C1	GDP per capita (current US\$)	Positive	WDI
	C2	GDP growth (annual %)	Positive	WDI
	C3	GNI per capita (current US\$)	Positive	WDI
	C4	Foreign direct investment, net inflows (% of GDP)	Positive	WDI
	C5	Trade in goods and services (% of GDP)	Positive	WDI
	C6	Industry value added (% of GDP)	Moderate	WDI
	C7	Services value added (% of GDP)	Moderate	WDI
	C8	Gross fixed capital formation (% of GDP)	Positive	WDI
	C9	Research and development expenditure (% of GDP)	Positive	WDI
	C10	Individuals using the Internet (per 100 people)	Positive	WDI
D2 Social Progress	C11	Life expectancy at birth (years)	Positive	WDI
	C12	Under-5 mortality rate (per 1000 live births)	Negative	WDI
	C13	Maternal mortality ratio (per 100,000 live births)	Negative	WHO
	C14	Expected years of schooling (years)	Positive	UN SDG/ national statistics
	C15	Mean years of schooling (years)	Positive	UN SDG/ national statistics
	C16	Unemployment rate (% of total labor force)	Negative	WDI
	C17	Population using safely managed sanitation services (% of population)	Positive	WHO/UN SDG
	C18	Population using safely managed drinking water services (% of population)	Positive	WHO/UN SDG
	C19	Gini coefficient	Negative	WDI
	C20	Poverty headcount ratio at national poverty line (%)	Negative	WDI/ national statistics
D3 Resource and Environmental Sustainability	C21	CO ₂ emissions (metric tons per capita)	Negative	WDI
	C22	CO ₂ emissions per unit of GDP (kg per 2015 US\$ GDP)	Negative	WDI
	C23	Energy use (kg of oil equivalent per capita)	Negative	WDI
	C24	Renewable energy consumption (% of total final energy consumption)	Positive	WDI
	C25	Fossil fuel energy consumption (% of total energy consumption)	Negative	WDI
	C26	Forest area (% of land area)	Positive	WDI
	C27	Annual mean PM _{2.5} concentration (µg/m ³)	Negative	WHO/UN SDG
	C28	Domestic material consumption (tons per capita)	Negative	UN SDG
	C29	Freshwater withdrawal (% of internal resources)	Negative	WDI
	C30	Threatened species (Red List Index, 0–1)	Negative	UN SDG
D4 Agricultural Sustainability	C31	Agricultural value added (% of GDP)	Moderate	WDI
	C32	Agricultural productivity (US\$ per hectare)	Positive	WDI/BRICS statistics
	C33	Food production index	Positive	WDI/BRICS statistics
	C34	Agricultural employment share (% of total employment)	Moderate	WDI
	C35	Agricultural water withdrawal (% of total water use)	Negative	WDI/ national statistics
	C36	Irrigated land (% agricultural land)	Positive	BRICS/ national statistics
	C37	Agricultural land (% of total land area)	Moderate	WDI

Note: GDP = gross domestic product; GNI = gross national income; WDI = World Development Indicators; WHO = World Health Organization; UN SDG = United Nations SDG Indicators Platform; BRICS statistics = BRICS Joint Statistical Publication; PM_{2.5} = particulate matter with a diameter of 2.5 micrometers or less. National statistical publications were used for verification or supplementation only when definitions and units were comparable. Direction-classification note: Positive and negative indicators assume a monotonic relationship with the assessed outcome. Moderate indicators (C6, C7, C31, C34, and C37) assume a non-monotonic relationship in which both low and high values may represent structural imbalance; their scores are therefore calculated using the interval-based normalization specified in Equation (3). Moderate indicators are evaluated using an interval-based transformation derived from the pooled distribution of observations for the three countries over 2000–2023. The same normalization rule is applied to all countries. These intervals represent sample-specific comparative benchmarks rather than universal normative thresholds.

The final balanced panel contains 2664 country–year–indicator observations ($3 \text{ countries} \times 24 \text{ years} \times 37 \text{ indicators}$). Missing observations were not handled by listwise deletion. Isolated internal gaps of no more than two consecutive years were filled by linear interpolation between the nearest available observations, whereas leading and trailing gaps were not extrapolated. After harmonization and interpolation, the final analytical matrix contained no unresolved missing observations.

No indicator included in the final 37-indicator system was subsequently removed because of missing data. Data availability was instead applied as an ex-ante selection criterion: candidate indicators lacking a sufficiently complete and comparable annual series for all three countries over 2000–2023 were not admitted to the final framework. Where a comparable harmonized series could be identified from an alternative official source, that series was used under the source hierarchy described above.

All indicators were used in their observed annual levels after direction adjustment and normalization; they were not differenced, detrended, or transformed to achieve stationarity. Formal unit-root or stationarity tests were not required because the study does not estimate time-series regressions, long-run coefficients, or causal dynamic relationships. In the EWM, temporal variation in the level series is the information used to calculate entropy weights. Consequently, trends and structural changes are part of the descriptive signal rather than a violation of an econometric assumption. The entropy results should therefore be interpreted as measures of temporal information contribution within the observed period, not as parameters of a stationary stochastic process.

Cross-country comparability was assessed using the metadata provided by the original databases. When definitions differed across national publications, the harmonized international series was retained. The same indicator definition, unit, and source family were applied to all three countries whenever possible. The processed dataset was additionally inspected through descriptive time-series plots to identify abrupt discontinuities; values associated with documented methodological revisions were retained, whereas obvious transcription errors were corrected against the original source.

The main source families were the World Development Indicators (WDI) [30], the World Health Organization (WHO) [31], the United Nations SDG Indicators Platform [32], the China Statistical Yearbook [33], and the BRICS Joint Statistical Publication [34]. Table 1 identifies the source used for each indicator; the national publications served primarily as validation and supplementary sources where international metadata were incomplete.

All data processing, normalization, entropy-weight calculation, equal-weight aggregation, sensitivity analysis, and figure preparation were performed using Microsoft Excel 2021 (Microsoft Corporation, Redmond, WA, USA).

2.3. Entropy Weight Method (EWM)

The Entropy Weight Method (EWM) is applied separately to each country using 24 annual observations for 2000–2023. For a fixed country c , t denotes year ($t = 1, \dots, T$; $T = 24$), j denotes indicator ($j = 1, \dots, m$; $m = 37$), X_{ij} is the raw value, and X'_{ij} is the standardized value. This country-specific implementation is used to identify indicators with high temporal information content within each national trajectory; it is not used to construct the cross-country ranking.

The method is applied to the normalized level series. Because EWM is a non-parametric weighting procedure rather than a time-series regression model, it does not require covariance stationarity. However, strong deterministic trends may increase an indicator's temporal dispersion and therefore its entropy-based information contribution; this property is acknowledged when interpreting the weights.

Entropy originates from information theory and measures a system's uncertainty or disorder [35]. In comprehensive evaluations:

The greater the variation in an indicator's values across different samples, the larger its information content, the lower its uncertainty (entropy), and the higher its weight in the evaluation.

Conversely, the smaller the variation in values, the smaller its information content, the higher its entropy, and the lower its weight.

Calculation Steps of the Entropy Weight Method:

Data standardization. The specific formula is as follows.

Positive indicators (1):

$$X'_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} \quad (1)$$

Negative indicators (2):

$$X'_{ij} = \frac{\min(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} \quad (2)$$

For the EWM calculations, the country index is held fixed and standardization is performed across the 24 annual observations. Accordingly, $\min(X_{ij})$ and $\max(X_{ij})$ denote the minimum and maximum values of indicator j for country over 2000–2023. This procedure preserves the temporal dispersion required for country-specific entropy weights.

Moderate indicators:

The optimal interval for the indicator is $[L, U]$, and the standardized formula is (3):

$$X'_{ij} = \begin{cases} 1 - \frac{L - X_{ij}}{L - \min(X_i)} & \text{if } X_{ij} < L \\ 1 & \text{if } L \leq X_{ij} \leq U \\ 1 - \frac{X_{ij} - U}{\max(X_i) - U} & \text{if } X_{ij} > U \end{cases} \quad (3)$$

Calculate the proportion of standardized indicator j in year t for country c , denoted y_{ij} (4). A small positive constant is used only where necessary to avoid $\ln(0)$; this technical adjustment does not affect the relative ordering of observations.

$$y_{ij} = \frac{X_{ij}}{\sum_{i=1}^n X_{ij}} \quad (4)$$

Calculate the information entropy of each indicator (5):

$$e_j = -\frac{1}{1/\ln n} \sum_{i=1}^n y_{ij} \ln(y_{ij}) \quad (5)$$

Calculate the coefficient of difference d_j (6):

$$d_j = 1 - e_j \quad (6)$$

Determine the weight of the indicators w_j (7):

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j}, j = 1, 2, \dots, m \quad (7)$$

Based on the standardized data X_{ij} and the calculated indicator weight W_j , use multiple linear functions to weight and obtain the comprehensive evaluation value S_i of sustainable development level (8):

$$s_i = \sum_{j=1}^m w_j \times y_{ij} \quad (8)$$

Among them, the larger the S_i , the better the level of sustainable development.

2.4. Equal Weighting Method

The Entropy Weight Method is sensitive to data volatility, as it assigns higher weights to indicators with greater fluctuations over time. Consequently, its weight structure tends to reflect the magnitude of change rather than the long-term average importance of each indicator. To complement this perspective and obtain a more stable assessment of long-term average performance, this study further adopts the Equal Weighting Method.

The Equal Weighting Method follows these steps:

Data standardization.

The same standardization formulas as in the Entropy Weight Method are applied to ensure consistency. To enable cross-country comparability, the standardized values X_{ij} are computed using the global minimum and maximum across all three countries and all years for each indicator.

Global min–max standardization was selected because the Equal Weighting Method is used for direct comparison of absolute performance levels across countries. Country-specific normalization would force each country's own minimum and maximum to 0 and 1 and would therefore remove level differences that are central to the comparative objective. The two normalization scopes serve different analytical purposes: within-country normalization supports the estimation of entropy weights, whereas global normalization supports cross-country performance comparison.

The principal limitation of global min–max standardization is its sensitivity to extreme observations. A very high or low value for one country–year can widen the common range and compress the standardized scores of the remaining observations. This may reduce the apparent magnitude of differences among countries, although it does not alter the ordering of observations for a given indicator.

Country-specific and year-specific normalization were considered as alternative schemes. Country-specific normalization is appropriate for examining the internal trajectory of each country, but it forces every country to span the same 0–1 range and therefore removes absolute cross-country level differences. Year-specific normalization is suitable for comparing relative positions within an individual year, but it prevents consistent intertemporal comparison because the reference range changes annually. For these reasons, global normalization is retained for the principal comparative index, while alternative normalization scopes are used only as diagnostic checks.

Dimension score calculation.

For each year, the score of each dimension is calculated as the arithmetic mean of the standardized indicators within that dimension. Let m_k denote the number of indicators in dimension k (where $k = 1, 2, 3, 4$ corresponds to the economic, social, environmental, and agricultural dimensions, respectively). The dimension score is given by (9):

$$D_k = \frac{1}{m_k} \sum_{j \in \text{dimension } k} X'_j \quad (9)$$

The number of indicators for each dimension is as follows:

$m_1 = 10$ (Economic Dimension, C1–C10)

$m_2 = 10$ (Social Dimension, C11–C20)

$m_3 = 10$ (Environmental Dimension, C21–C30)

$m_4 = 7$ (Agricultural Dimension, C31–C37)

Total index calculation.

The total sustainable development index for year i is the arithmetic mean of the four-dimension scores (10):

$$S_i = \frac{D_{1i} + D_{2i} + D_{3i} + D_{4i}}{4} \quad (10)$$

2.5. Complementarity of the Two Methods

The two methods are applied in parallel and serve different analytical purposes. The Equal Weighting Method is used as the principal scoring procedure because it applies a common global normalization and produces directly comparable annual composite indices, dimension scores, long-term averages, and country rankings. The Entropy Weight Method is applied separately to each country and is used only to identify indicators with the highest temporal information contribution within the corresponding national trajectory.

The analytical procedure consists of four consecutive stages. First, a common panel of 37 indicators is constructed and harmonized for China, Russia, and India for 2000–2023. Second, the dataset is processed through two parallel branches. Under the Equal Weighting Method, the indicators are normalized using global minimum and maximum values across all countries and years. Under the Entropy Weight Method, normalization and weight estimation are performed separately for each country using its annual observations. Third, the Equal Weighting Method produces comparable annual total indices and dimension scores, whereas the Entropy Weight Method produces country-specific indicator weights. Fourth, the two sets of results are interpreted jointly: the equal-weight scores describe comparative performance levels, while the entropy weights identify the indicators that contribute most strongly to temporal differentiation.

Country-specific entropy weights are not used for the principal cross-country ranking because they are estimated from different national time-series distributions and therefore do not form a common weighting vector. Direct comparison of entropy-weighted country scores would mix differences in development performance with differences in within-country variability. A globally estimated entropy-weighted index could be calculated as an alternative specification, but it would emphasize indicators with the largest pooled variation and would answer a different research question. For this reason, equal weighting is retained for comparative scoring, while entropy weighting is used for diagnostic interpretation.

This combination captures both comparative performance levels and country-specific temporal patterns, enabling a more comprehensive assessment of development trajectories in China, Russia, and India.

2.6. Sensitivity and Robustness Checks

To evaluate whether the country ranking depends on a single dimension, a leave-one-dimension-out sensitivity test was conducted (Table 2). The total index was recalculated four times, each time excluding one of the economic, social, resource-environmental, or agricultural dimensions and averaging the remaining three-dimension scores.

Table 2. Leave-One-Dimension-Out Sensitivity Analysis.

Country	Baseline	Without D1	Without D2	Without D3	Without D4
China	0.5477	0.5477	0.4959	0.5833	0.5639
Russia	0.4757	0.4784	0.3823	0.4869	0.5551
India	0.4334	0.4677	0.4649	0.3780	0.4231

China remains first in all four specifications, indicating that its leading position is not determined by any single dimension. The baseline ranking China–Russia–India is also preserved when the economic, resource-environmental, or agricultural dimension is

excluded. When the social dimension is excluded, India moves ahead of Russia because Russia's comparative advantage is concentrated in social indicators. This result shows that the relative positions of Russia and India are dimension-sensitive and should be interpreted as structurally different profiles rather than as an invariant hierarchy.

The sensitivity analysis confirms the robustness of China's leading position while identifying a meaningful dependence of the Russia–India comparison on the social dimension. The baseline index is therefore retained as the principal summary measure, but its interpretation is supplemented by the dimension-specific results.

A normalization-scope diagnostic was also conducted for the annual total-index series. The country trajectories were re-expressed using each country's own minimum and maximum over 2000–2023. This monotonic transformation preserves the timing of increases, declines, and turning points within each national series, but it is not used to compare absolute country levels.

The diagnostic confirms the main temporal findings: China retains a sustained upward trajectory, India shows the strongest long-term improvement and convergence pattern, and Russia remains characterized by a post-2008 slowdown and greater volatility. The cross-country ranking reported in Table 3 is based exclusively on global standardization because country-specific normalization would mechanically assign each country both a value of 0 and a value of 1 within the study period.

Table 3. Dimension Scores and Total Index of Sustainable Development under Equal Weighting Method.

Country	Economic Dimension D1	Social Dimension D2	Environmental Dimension D3	Agricultural Dimension D4	Total Index
China	0.5476	0.7030	0.4410	0.4992	0.5477
Russia	0.4675	0.7557	0.4421	0.2374	0.4757
India	0.3306	0.3390	0.5997	0.4644	0.4334

Year-specific normalization was not adopted as a robustness specification because it would redefine the minimum and maximum in every year and would therefore eliminate the common intertemporal scale required for the 2000–2023 trajectory analysis. The robustness assessment consequently distinguishes between stability of within-country dynamics and comparability of cross-country performance levels.

Because the composite indices are deterministic functions of the observed indicator matrix, normalization rules, and aggregation scheme, conventional sampling-based confidence intervals are not applicable. Uncertainty is therefore assessed through specification sensitivity: the leave-one-dimension-out test evaluates sensitivity to the dimensional composition, while the normalization-scope diagnostic evaluates the stability of national trajectories under an alternative reference range.

3. Results and Discussion

Figure 1 presents the annual trends of the sustainable development total index for China, Russia, and India from 2000 to 2023, calculated using the Equal Weighting Method with global standardization. To avoid relying only on visual inspection, the dynamics are interpreted through three sub-periods that correspond to clearly distinguishable changes in the trajectories: 2000–2008, 2009–2015, and 2016–2023. This periodization is used as a descriptive sub-period analysis rather than as a causal test. The three sub-periods are used only to structure the descriptive interpretation; no formal structural-break test is performed.

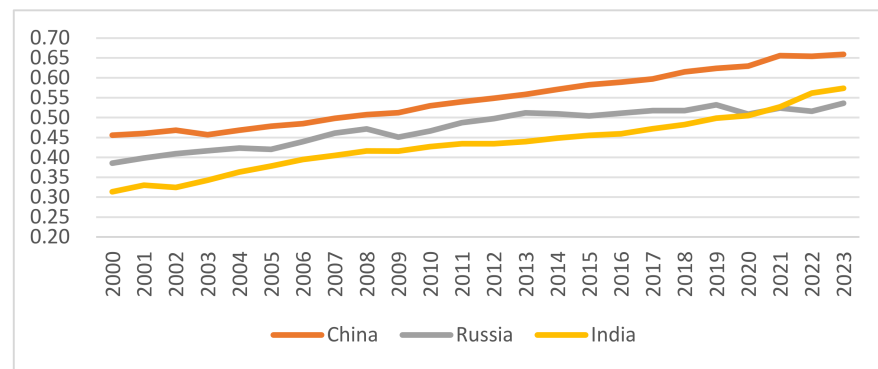


Figure 1. Trends of the Sustainable Development Total Index under the Equal Weighting Method. Note: The lines represent deterministic composite-index values rather than sample estimates. Conventional confidence intervals are therefore not applicable. Uncertainty associated with aggregation and normalization choices is assessed through the sensitivity analyses reported in Section 2.6 and Table 2.

China exhibits a sustained upward trajectory, increasing from 0.456 in 2000 to 0.659 in 2023. The index rose by 0.052 points in 2000–2008, by 0.075 points in 2009–2015, and by 0.077 points in 2016–2023. The absence of a prolonged decline after 2008 suggests that China’s trajectory was supported by a relatively coordinated combination of industrial expansion, infrastructure development, poverty reduction, and gradual environmental governance improvements. In terms of the theoretical framework, this indicates a higher degree of system coordination across economic, social, resource-environmental, and agricultural dimensions.

India demonstrates the strongest convergence pattern. Its total index increased from 0.314 in 2000 to 0.574 in 2023, while the gap with China narrowed from 0.142 points to 0.085 points. Growth was particularly pronounced in 2000–2008 (+0.102 points) and 2016–2023 (+0.119 points), whereas 2009–2015 was characterized by a slower increase (+0.039 points). This pattern indicates that India’s development trajectory is not linear but phase-dependent: the post-2015 acceleration is consistent with improvements in digital infrastructure, sanitation, electrification, and basic service provision, although the country still starts from a lower social and economic base.

Russia displays a different pattern. The index increased from 0.386 in 2000 to 0.472 in 2008, declined to 0.451 in 2009, and then fluctuated within a narrower range until 2023. The sharpest positive change occurred before 2008 (+0.086 points), while subsequent growth was much weaker: +0.033 points in 2009–2015 and +0.032 points in 2016–2023. This trajectory indicates a break in development momentum after the global financial crisis and a shift from rapid recovery growth to lower and more volatile long-term improvement.

The convergence analysis therefore reveals asymmetric dynamics. India moves closer to China over the full period, Russia falls further behind China after 2008, and India overtakes Russia in the total index by the end of the period. These trajectories support the interpretation that the three countries do not follow a single development path: China demonstrates balanced cumulative growth, India shows accelerated catching-up from a lower initial level, and Russia exhibits structural volatility with limited post-crisis acceleration.

Table 3 presents the average dimension scores and total index for China, Russia, and India from 2000 to 2023 under the Equal Weighting Method.

Table 3 shows that China ranks first in the total index (0.5477), followed by Russia (0.4757) and India (0.4334). This ranking should not be interpreted as a uniform hierarchy across all dimensions, since the national profiles are structurally heterogeneous.

In the Economic Dimension, the ranking China > Russia > India reflects differences in industrial scale, investment capacity, income level, and digital connectivity. China’s

leading score (0.5476) is consistent with sustained industrialization, high capital formation, and the expansion of digital infrastructure. Russia's intermediate score (0.4675) reflects a higher income base than India but weaker diversification and stronger exposure to energy-dependent growth. India's lower score (0.3306) corresponds to its lower initial income level, although the time-series pattern indicates gradual convergence.

The Social Dimension exhibits the most important structural contrast: Russia ranks highest (0.7557), followed by China (0.7030), while India remains substantially lower (0.3390). Russia's advantage is explained by accumulated human-capital assets inherited from a historically universal education and healthcare system, higher average schooling indicators, and relatively stronger access to basic social services. China's high score reflects rapid poverty reduction and expansion of basic infrastructure. India's lower position is associated with persistent disparities in health outcomes, schooling, sanitation, drinking-water access, and income distribution. This explains why the sensitivity test shows that excluding the social dimension changes the relative ranking of Russia and India.

In the Resource and Environmental Dimension, India records the highest score (0.5997). This result requires careful interpretation. It does not mean that India has no environmental constraints; rather, within the selected indicator system, India benefits from lower per-capita emissions, lower energy use per capita, and a relatively high renewable-energy share. China and Russia obtain similar scores, but for different reasons. China's result is constrained by industrial emissions, material consumption, and air-pollution pressures, whereas Russia's score reflects the tension between large forest resources and high energy intensity linked to its production structure and climatic conditions.

The Agricultural Dimension reveals the strongest sectoral imbalance. China (0.4992) and India (0.4644) achieve comparable scores because both countries combine large agricultural systems with relatively developed irrigation, food-production capacity, and high sectoral relevance. Russia's substantially lower score (0.2374) indicates that extensive land endowments are not converted into proportional agricultural performance. This gap can be attributed to lower output per unit of land, spatial dispersion of production, climatic constraints, uneven irrigation infrastructure, and institutional features of land use and agricultural modernization. Consequently, Russia's weakness is not resource scarcity but the limited transformation of natural endowments into agricultural productivity and resilience.

Taken together, the dimension-specific results deepen the interpretation of the time-series trajectories. China's leading position is based on a relatively balanced profile. India's improvement is driven by environmental and agricultural scores but remains constrained by economic and social gaps. Russia's intermediate total index masks a pronounced asymmetry: strong social outcomes coexist with weak agricultural performance and resource-dependent development dynamics.

Table 4 presents the top five weighted indicators for China, Russia, and India under the Entropy Weight Method.

This method is sensitive to temporal dispersion. A higher entropy weighting indicates that an indicator contributes more information to the differentiation of annual observations within a country. It does not measure causal influence, substantive importance independent of the data distribution, or the expected effect of a policy intervention. Accordingly, the indicators in Table 4 are interpreted as high-information indicators rather than as causal drivers.

For China, the five highest-weighted indicators are safely managed drinking water services (0.0679), renewable energy consumption (0.0506), agricultural value added (0.0409), CO₂ emissions per capita (0.0407), and GNI per capita (0.0381). This configuration indicates that the highest-information indicators of sustainable development in China are concentrated in infrastructure quality, energy transition, and the production base of the

agro-industrial complex. This interpretation is consistent with the findings of Zhang et al., who show that the sustainability of the water–energy–food system in China depends on the coordination of resource subsystems and their supply–demand balance [36]. It also corresponds to the results of Zou et al., who demonstrate that the coordinated development of the water–energy–food system is sensitive to environmental regulation [37], and to the conclusions of Guo et al., who emphasize the differentiated character of resource interdependencies across crop production systems [38].

Table 4. Top Five Weighted Indicators under Entropy Weight Method.

Rank	China	Weight	Russia	Weight	India	Weight
1	Population using safely managed drinking water services (% of population)	0.0679	Agricultural land (% of total land area)	0.1398	Unemployment rate (% of total labor force)	0.0769
2	Renewable energy consumption (% of total final energy consumption)	0.0506	Irrigated land (% agricultural land)	0.1183	Individuals using the Internet (per 100 people)	0.0621
3	Agricultural value added (% of GDP)	0.0409	Forest area (% of land area)	0.0768	Gini coefficient	0.0493
4	CO ₂ emissions (metric tons per capita)	0.0407	Agricultural employment share (% of total employment)	0.046	Renewable energy consumption (% of total final energy consumption)	0.0486
5	GNI per capita (current US\$)	0.0381	Renewable energy consumption (% of total final energy consumption)	0.0378	Agricultural value added (% of GDP)	0.0465

For Russia, three of the top five weighted indicators are agriculture-related: agricultural land (0.1398), irrigated land (0.1183), and agricultural employment (0.0460), together accounting for 0.3041 of the total weight. Forest area (0.0768) and renewable energy consumption (0.0378) also rank among the most influential indicators. These results suggest that sustainable development in Russia is strongly conditioned by land-resource structure and natural capital. At the same time, the low agricultural dimension score reported in Table 3 indicates that substantial resource endowments do not automatically ensure high long-term performance. This conclusion is consistent with Hamidov and Helming, who stress the importance of integrated resource management in irrigated agriculture [39], and with Kuzlyakina et al., who emphasize the role of technological modernization and rational land use in improving the sustainability of Russian agriculture [40].

This combination of a low agricultural dimension score and high entropy weights for agriculture-related indicators constitutes a specific Russian agricultural paradox. The two results capture different properties of the data. The low D4 score reflects the comparatively weak average level of agricultural performance over 2000–2023, whereas the high entropy weights indicate that land use, irrigation, and agricultural employment changed more unevenly over time than many other indicators.

Several structural mechanisms may explain this pattern. First, the post-Soviet restructuring of land ownership, farm organization, and rural labor markets created long-lasting discontinuities in the use of agricultural land and employment. Second, agricultural

policy shifted from institutional transition and market adaptation toward stronger state support, import substitution, and investment in domestic food production, producing uneven changes across sub-periods. Third, climatic variability, the concentration of production in a limited number of favorable regions, and the large spatial distance between production zones and processing or consumer markets increased volatility in output and infrastructure use. Fourth, the limited and regionally uneven development of irrigation and drainage systems constrained the conversion of extensive land resources into stable productivity gains.

The paradox therefore does not imply that agriculture is simultaneously strong and weak. Rather, it shows that Russia combines a low long-term average agricultural score with high temporal differentiation in several sectoral indicators. The entropy results identify the parts of the agricultural system that changed most markedly, while the equal-weight score shows that these changes were insufficient to raise the overall agricultural dimension to the levels observed in China and India.

This interpretation is consistent with the literature on Russia's institutional transformation, spatially uneven agricultural development, and the incomplete conversion of land and natural-resource endowments into productivity [15,17,18,38].

For India, the five highest-weighted indicators are the unemployment rate (0.0769), individuals using the Internet (0.0621), the Gini coefficient (0.0493), renewable energy consumption (0.0486), and agricultural value added (0.0465). This pattern identifies social differentiation, digitalization, and energy structure as the principal sources of temporal differentiation of sustainable development. The result is broadly consistent with Tarate et al., who show the growing importance of geospatial and digital technologies for agricultural water management [41]. It also aligns with the findings of Gupta and Rowan, who demonstrate that agricultural sustainability in India is closely linked to the efficiency of water and energy use within the broader water–energy–food–environment nexus [21].

Overall, the Entropy Weight Method reveals distinct patterns of temporal information contribution of sustainable development across the three countries: China's highest-information indicators are concentrated in infrastructure and energy transition, Russia's are highly reliant on natural resource endowments, and India's focus on social equity and digital inclusion. These findings complement the dimension scores obtained under the Equal Weighting Method presented in Table 3, together providing a more comprehensive understanding of sustainable development patterns in the three countries.

3.1. Mechanism-Oriented Interpretation of High-Information Indicators

To strengthen the interpretation of Table 4 without overstating causality, the high-information indicators were mapped to theoretically grounded transmission pathways. Table 5 summarizes the indicator groups, the corresponding theoretical pathways, their expected links to development outcomes, and the interpretive status of the proposed mechanisms. This procedure links the entropy results to the agro-industrial system, water–energy–food nexus, and sustainability-transition framework. The mapping is interpretative rather than causal: it identifies plausible channels through which the observed indicators may be associated with dimension scores and long-term trajectories.

For China, access to safely managed drinking water represents infrastructure and public-service capacity; renewable-energy consumption and carbon emissions reflect changes in the energy-production configuration; agricultural value-added captures structural transformation in the agro-industrial sector; and GNI per capita reflects income and investment capacity. For Russia, agricultural land, irrigated land, and agricultural employment describe the scale and utilization of the agricultural resource base, while forest area and renewable-energy consumption characterize natural-capital and energy conditions.

For India, unemployment and the Gini coefficient represent social inclusion constraints, Internet use captures digital access and diffusion capacity, renewable-energy consumption reflects energy transition, and agricultural value added indicates the changing economic role of agriculture.

Table 5. Mapping High-Information Indicators to Theoretical Pathways.

Country	Indicator Group	Theoretical Pathway	Expected Link to Development	Interpretive Status
China	Drinking water access; renewable energy; CO ₂ emissions; agricultural value added; GNI per capita	Infrastructure capacity, energy–system transition, structural transformation, and income-investment capacity.	Improved basic services and resource efficiency may support more balanced economic, social, environmental, and agricultural performance.	Association-based interpretation; no causal coefficient estimated.
Russia	Agricultural land; irrigated land; agricultural employment; forest area; renewable energy	Conversion of natural-resource endowments into productive capacity through irrigation, technology, and institutional coordination.	Large resource endowments may improve performance only when supported by productive use, infrastructure, and modernization.	Association-based interpretation; no causal coefficient estimated.
India	Unemployment; Internet use; Gini coefficient; renewable energy; agricultural value added	Social inclusion, digital diffusion, energy transition, and structural change.	Digital access and lower social disparities may facilitate technology adoption and broader participation in agricultural development.	Association-based interpretation; no causal coefficient estimated.

The pathway mapping provides a more disciplined interpretation of country heterogeneity. China’s pattern is consistent with a coordination mechanism in which infrastructure and energy-system changes are linked to broad-based performance. Russia’s pattern points to a resource-conversion mechanism: abundant land and natural capital do not generate high agricultural scores without irrigation, technological modernization, and institutional coordination. India’s pattern is consistent with an inclusion-and-diffusion mechanism in which social conditions and digital access influence the capacity to adopt technologies and improve resource use.

For Russia, the mechanism is best understood as a volatility-without-convergence pattern: substantial changes in land use, irrigation, and agricultural employment generated high information weights, but these changes did not produce a comparable increase in the average agricultural dimension score. Institutional transition, spatial concentration, climatic exposure, and uneven infrastructure modernization help explain this divergence.

Because the study contains only three countries and is designed as a comparative composite-index assessment, regression or spatial causal identification would be statistically weak and potentially misleading. The revised manuscript therefore avoids causal terminology and treats the mechanism analysis as theoretically grounded interpretation. A larger-country panel would be required to estimate causal effects, spillovers, and mediated pathways.

3.2. Comparison with International Research

The empirical results are broadly consistent with international research but also extend it in several respects. First, the balanced position of China corresponds to comparative studies that associate its performance with infrastructure expansion, investment capacity,

and coordinated resource governance. However, the present results also show that this advantage is not uniform: China's environmental score remains constrained by emissions, material consumption, and air-pollution pressures. This finding is consistent with international evidence that rapid productivity growth may coexist with substantial resource and environmental costs [25,29].

These findings also extend earlier ecological–economic studies of macro-level sustainability assessment. Shmelev's analysis of Russia demonstrated the usefulness of dynamic multi-criteria assessment for countries undergoing structural transition [8], while the comparative macro-scale study of OECD countries, China, and Brazil highlighted how country rankings and trajectories depend on the choice of indicators and policy-priority weights [9]. The present study advances this line of research by focusing on the agro-industrial complex and by separating agricultural sustainability as a distinct analytical dimension.

Second, Russia's profile supports the distinction between resource availability and resource conversion efficiency. The high information contribution of agricultural land, irrigated land, and forest area is consistent with BRICS studies emphasizing the role of freshwater and natural-resource management in sectoral productivity [26]. At the same time, the low agricultural dimension score indicates that extensive land and natural capital do not automatically generate high productivity. This result adds a country-specific dimension to the international literature by showing that infrastructure, spatial organization, and institutional coordination mediate the productive use of resources.

Third, India's trajectory is consistent with international evidence that agricultural transformation depends on the interaction of social inclusion, digital access, energy structure, and resource efficiency. The narrowing gap with China after 2015 supports the view that improvements in infrastructure and diffusion capacity can accelerate convergence from a lower initial level. At the same time, India's comparatively low social score confirms that technological and agricultural progress does not automatically eliminate inequalities in health, education, income, and access to basic services.

The comparison with BRICS food-security research also reinforces the interpretation of national heterogeneity. Ren et al. show that cooperation potential is shaped by complementary resource endowments, production structures, and trade capacities [27], whereas Ozturk demonstrates that food, energy, water, and ecological outcomes are jointly determined within BRICS economies [25]. The present study extends these findings by integrating social and macroeconomic dimensions, separating agricultural performance as an independent dimension, and applying a common 24-year framework to China, Russia, and India.

The marginal contribution of the study therefore lies in three elements: a common long-term comparison of three major BRICS economies; the treatment of agricultural sustainability as an independent but interconnected dimension; and the distinction between comparative performance and temporal information contribution through the combined use of equal and entropy weighting. This structure enables the findings to be positioned within international debates on composite indicators, agricultural productivity, food security, and the water–energy–food nexus.

3.3. Country-Specific Policy Implementation Pathways

The policy implications are derived from three layers of empirical evidence: the dimension scores in Table 3, the country-specific high-information indicators in Table 4, and the structural interpretation summarized in Table 5. The recommendations are therefore differentiated by country and linked to the specific constraints identified in the analysis. They are structured by implementation horizon, responsible institutional actors, and measurable monitoring indicators.

Across all three countries, implementation should account for the water–energy–food nexus. Irrigation expansion should be approved only together with an assessment of water availability and energy demand; renewable-energy projects should be evaluated for their effects on land use and food production; and agricultural modernization programs should include social-access criteria. Urban–rural industrial linkages can be strengthened through regional processing clusters, cold chains, logistics platforms, and procurement arrangements that connect farms with urban markets. Coordination between smallholders and large agricultural entities should rely on cooperatives, contract standards, shared infrastructure, and transparent access to digital platforms.

For India, the policy priority follows from its relatively strong resource–environmental and agricultural scores but weak social and economic performance. The central objective is to combine agricultural modernization with social inclusion, digital access, and water–energy constraints. In the short term, policy should target districts with high unemployment, low digital access, and high dependence on groundwater irrigation. Extension services should provide smallholders with mobile-based agronomic advice, water-use information, and access to credit and insurance. In the medium term, support should be directed to energy-efficient pumps, micro-irrigation, decentralized renewable energy, farmer–producer organizations, and shared storage and processing facilities. In the long term, agricultural and social policy should be coordinated to reduce disparities in access to sanitation, drinking water, education, digital services, and market infrastructure. Monitoring indicators should include Internet access among rural producers, unemployment, the Gini coefficient, micro-irrigation coverage, groundwater-use intensity, and agricultural value added per worker.

For Russia, the policy priority is derived from the combination of the lowest agricultural dimension score and high temporal variation in land, irrigation, and agricultural employment indicators. The main task is therefore to convert extensive land and natural-resource endowments into stable productivity gains. In the short term, federal and regional authorities should conduct a spatial audit of underused agricultural land, irrigation and drainage infrastructure, and logistics bottlenecks. In the medium term, capital support should be concentrated on rehabilitation of irrigation and drainage systems, digital land monitoring, precision-agriculture technologies, and regional programs for increasing output per hectare. Implementation should distinguish between large agricultural holdings and small and medium-sized producers: large entities can be subject to investment and efficiency targets, while smaller producers require shared machinery, advisory services, cooperative logistics, and access to concessional finance. In the long term, interregional planning should connect land use, transport, storage, processing, and water availability. Monitoring indicators should include agricultural output per hectare, irrigated-land share, utilization of agricultural land, post-harvest losses, and the share of producers using digital monitoring systems.

For China, the policy priority follows from its leading but environmentally constrained profile. The country records the highest total index and balanced economic and social scores, while its resource–environmental score remains limited by emissions, material use, and energy intensity. In the short term (1–3 years), provincial authorities should identify irrigation systems and agro-processing clusters with the highest water and energy intensity and introduce digital monitoring of water withdrawals, energy use, and emissions. In the medium term (4–7 years), investment programs should prioritize water-saving irrigation, renewable-energy integration in processing and cold-chain infrastructure, and reuse of treated water where technically feasible. In the long term (8–10 years), performance-based support should link public financing to reductions in water intensity, energy intensity, and emissions per unit of agricultural value added. Progress can be monitored through

irrigation-water productivity, renewable-energy share in agricultural energy use, CO₂ intensity, and safely managed water-service coverage.

The proposed policy pathways are based primarily on the dimension scores and country-specific structural constraints. China's pathway focuses on resource efficiency within an already integrated agro-industrial system; Russia's on converting land and infrastructure potential into stable productivity; and India's on combining modernization with social inclusion, digital diffusion, and water-energy management. The entropy results are used only to identify areas of pronounced temporal differentiation and do not, by themselves, justify policy priority or causal effectiveness. Table 6 summarizes the proposed implementation sequence and the indicators that can be used to monitor policy delivery.

Table 6. Country-Specific Policy Implementation Framework.

Country	Empirical Constraint	Short-Term Actions (1–3 Years)	Medium/Long-Term Actions	Implementation Actors	Monitoring Indicators
China	Leading overall performance, but persistent emission, material-use, and resource-efficiency pressures	Audit high-intensity irrigation and processing clusters; introduce digital resource monitoring	Modernize irrigation; integrate renewable energy and water reuse; link support to efficiency targets.	Central ministries, provincial governments, water and energy agencies, agro-industrial firms	Water productivity; energy intensity; renewable-energy share; CO ₂ intensity; water-service coverage
Russia	Lowest agricultural score; volatile land, irrigation, and employment indicators; weak conversion of resource endowments into productivity	Map underused land, irrigation, drainage, logistics, and regional productivity gaps	Rehabilitate infrastructure; expand precision agriculture; support cooperatives and regional processing-logistics systems.	Federal and regional authorities, agricultural holdings, cooperatives, extension and finance institutions	Output per hectare; irrigated-land share; land utilization; post-harvest losses; digital adoption
India	Strong environmental and agricultural scores, but low social and economic performance, uneven digital access, and water-energy constraints	Target vulnerable districts; expand digital extension, credit, insurance, and water-use information	Scale micro-irrigation, efficient pumps, decentralized renewable energy, producer organizations, storage and processing.	Central and state governments, local agencies, farmer-producer organizations, financial institutions	Rural Internet access; unemployment; Gini coefficient; micro-irrigation coverage; groundwater intensity; value added per worker

3.4. Critical Discussion, Practical Significance, and Future Research

The multidimensional framework provides a structured basis for comparing heterogeneous agro-industrial systems, but its results should be interpreted critically. Composite indices inevitably simplify complex national systems and depend on the selected indicators, normalization rules, direction classifications, and aggregation assumptions. Equal weighting allows transparent comparison but assumes full compensation among indicators within each dimension; consequently, a high score for one indicator may offset a weak score for another. The separate agricultural dimension improves sectoral diagnosis, although some conceptual interaction with the economic, social, and resource-environmental dimensions remains unavoidable.

Additional limitations arise from data availability and comparability. Harmonized international databases improve consistency, but they may conceal national methodological differences and may include modelled observations. The sample-dependent intervals used for moderate indicators are appropriate for comparison within the analyzed dataset but should not be interpreted as universal normative thresholds. The three-country design also

limits the generalization of the results to the entire BRICS group. Finally, the composite-index approach identifies patterns and relative positions but does not establish causal relationships between individual indicators and development outcomes.

The practical significance of the study lies in its use as a diagnostic and monitoring instrument. Public authorities can apply the dimension scores to identify whether national or regional agro-industrial performance is constrained primarily by economic capacity, social conditions, resource pressure, or agricultural productivity. The high-information indicators can be used to identify variables requiring closer monitoring, while the country-specific implementation pathways in Table 6 provide examples of how the results can be translated into phased measures, responsible institutional roles, and measurable monitoring indicators.

The framework can also support future research. It may be extended to Brazil, South Africa, and other emerging economies; adapted to regional or sectoral datasets; and combined with panel regression, spatial analysis, scenario modelling, or coupling-coordination methods. Future studies may test alternative weighting and normalization procedures, validate the moderate-indicator thresholds against external benchmarks, and examine how policy interventions affect the relationships among water, energy, food production, social inclusion, and agricultural productivity.

4. Conclusions

The findings of this study allow several conclusions to be drawn regarding the long-term sustainable development of the agro-industrial complex in China, Russia, and India. Based on the comparative assessment results obtained through the Equal Weighting Method and the Entropy Weight Method, the main conclusions are as follows.

1. China demonstrates the highest overall level of sustainable development among the three countries over the period 2000–2023. Its results indicate the most balanced performance across the economic, social, environmental, and agricultural dimensions, which distinguishes China from the more uneven profiles observed in Russia and India.
2. India shows a sustained positive development trajectory, with relatively strong positions in the environmental and agricultural dimensions. At the same time, its lower scores in the economic and social dimensions indicate that long-term progress remains constrained by structural disparities in income, employment, and social development.
3. Russia occupies an intermediate position in the overall index and performs best in the social dimension, but its agricultural sustainability remains the weakest among the three countries. The simultaneous presence of a low agricultural dimension score and high entropy weights for land, irrigation, and agricultural employment reflects temporal volatility rather than high performance. This pattern is consistent with post-Soviet institutional restructuring, spatial and climatic constraints, and uneven modernization of agricultural infrastructure.
4. The indicators with the highest temporal information contribution differ substantially across countries. In China, they are associated with drinking water access, renewable energy consumption, agricultural value added, carbon emissions, and income dynamics. In Russia, they concern agricultural land, irrigated land, agricultural employment, forest area, and renewable energy consumption. In India, they concern unemployment, Internet use, income inequality, renewable energy consumption, and agricultural value added. These patterns support mechanism-oriented interpretation but should not be read as causal estimates.
5. The results confirm the analytical value of using the Equal Weighting Method and the Entropy Weight Method as complementary procedures and of treating agricultural

sustainability as a separate dimension of assessment. Equal weighting identifies long-term comparative performance, while entropy weighting identifies country-specific structures of temporal information contribution. The latter should not be interpreted as causal importance or policy leverage; the pathway mapping provides only theoretically plausible, association-based interpretation.

In general, the study demonstrates that sustainable development in the agro-industrial complex of the three countries is multidimensional and structurally heterogeneous. The comparison shows that similar strategic sectors may develop under substantially different configurations of economic, social, environmental, and agricultural factors. This confirms the importance of integrated comparative models for identifying both common trends and country-specific development features in the BRICS context.

Compared with international research, the findings confirm that BRICS agro-industrial development is shaped by heterogeneous combinations of resource endowments, institutional capacity, infrastructure, and social inclusion. The study adds to this literature by demonstrating that the same countries may occupy different positions across economic, social, resource-environmental, and agricultural dimensions, making a single aggregate ranking insufficient without dimension-specific interpretation.

The policy implications are formulated as differentiated implementation pathways linked directly to the empirical profiles of the three countries. For China, the emphasis is on reducing resource and emission intensity; for Russia, on improving the productive use of land and infrastructure; and for India, on integrating agricultural modernization with social inclusion, digital access, and water-energy management. Each pathway specifies implementation horizons, responsible institutional levels, and measurable monitoring indicators.

From an applied perspective, the proposed framework can be used as a repeatable monitoring tool for comparing national or regional agro-industrial trajectories, identifying dimension-specific constraints, prioritizing areas for detailed policy analysis, and evaluating changes in the selected indicators over time.

Methodological limitations should be noted. Entropy weights measure temporal information variation rather than causal influence, substantive importance independent of the data distribution, or policy leverage. The indicators were used in annual levels rather than being differenced or detrended, because EWM is a descriptive non-parametric weighting procedure and does not require stationarity. Accordingly, persistent trends and structural changes may increase entropy-based information contribution and should not be interpreted as causal effects. The composite indices are deterministic outputs of the selected indicator set, normalization rules, and aggregation scheme; conventional sampling-based confidence intervals are therefore not applicable. The interval boundaries used for moderate indicators are sample-dependent and reflect the pooled distribution of observations for China, Russia, and India over 2000–2023. They should therefore be interpreted as comparative benchmarks within the analyzed dataset rather than as universal normative thresholds. Uncertainty is assessed through leave-one-dimension-out and normalization-scope sensitivity checks rather than through probabilistic error bands. Global min-max normalization provides a common scale for cross-country and intertemporal comparison but may be sensitive to extreme country–year observations and may compress the scores of other observations. Country-specific normalization confirms the direction and turning points of the national trajectories but cannot be used for absolute cross-country ranking, while year-specific normalization would prevent consistent comparison over time. The mechanism-oriented mapping added to the Discussion is interpretative and does not quantify direct effects, mediated effects, or spillovers. The leave-one-dimension-out test confirms the stability of China’s leading position but shows that the relative ranking of Rus-

sia and India depends partly on the social dimension. Future research should combine the composite-index framework with stochastic uncertainty analysis, larger country samples, and causal econometric or quasi-experimental designs.

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Abbreviations

The following abbreviations are used in this manuscript:

SDG	Sustainable development goals
BRICS	Brazil, Russia, India, China, South Africa
EWM	Entropy weight method
WDI	World development indicators
GNI	Gross national income
AHP	Analytic hierarchy process

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