

Measuring the efficiency of agropastoral systems in Inner Mongolia: Parallel bounded adjusted measure with shared inputs and outputs

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Citation: Chen C.H., Song W.J., Wang R.Z., Ma C.Y. (2026): Measuring the efficiency of agropastoral systems in Inner Mongolia: Parallel bounded adjusted measure with shared inputs and outputs. *Agric. Econ. – Czech*, 72: 540–558.

Abstract: Inner Mongolia operates using integrated agropastoral systems comprising crop and livestock production subsystems. To evaluate the efficiency of these interconnected subsystems, we develop an innovative parallel-bounded adjusted measure (BAM) model with shared inputs and outputs. Unlike conventional data envelopment analysis (DEA) models, this approach explicitly accounts for parallel structures with shared inputs and outputs, allowing for a more precise and nuanced assessment of efficiency. Our results are as follows: (i) regional efficiency disparities: Hohhot City, Ordos City, and Wuhai City are efficient, whereas Ulanqab City performs the worst; (ii) subsystem performance: crop production subsystems generally outperform livestock production subsystems; (iii) inefficiencies: we observe significant input slacks in cultivated land area, total agricultural machinery power, and initial livestock numbers, whereas the disposable income of rural residents requires significant improvement.

Keywords: agriculture; crop; data envelopment analysis; livestock; shared resources

Agriculture plays a vital role in national development and economic stability. A robust agricultural system serves as the cornerstone of building a modern socialist country. For China, a nation with a population exceeding 1.4 billion, agriculture is of critical strategic significance. It ensures a stable and sufficient supply of essential agricultural commodities and also underpins national security. Inner Mongolia is renowned as China's meat production hub, dairy heartland, and granary. It ranks first nationwide in beef and mutton production, dairy cattle inventory, and milk production; it is also a leading grain sown area

with its total grain output (National Bureau of Statistics of China, 2025). This pivotal role creates significant pressure to sustain high productivity, especially amid growing resource constraints and environmental challenges. Therefore, enhancing the efficiency of the agricultural system in Inner Mongolia is critical to ensure regional and national food security and sustainable development.

Inner Mongolia's distinctive geoeconomic profile establishes it as a quintessential agropastoral transition zone, where crop farming and livestock production coexist and interact synergistically. In other words,

Funded by the High-level Talents Support Program in Public Institutions of Inner Mongolia Autonomous Region (Grant No. DC240001051), and the High-level and Outstanding Doctoral Talent Start-Up Grant Program at Inner Mongolia Agricultural University (Grant No. NDYB2023-21).

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<https://doi.org/10.17221/395/2025-AGRICECON>

agropastoral systems comprise crop and livestock production subsystems. These two subsystems operate independently and in close proximity. The crop production subsystems require inputs such as cultivated land and agricultural machinery to produce crops; the livestock production subsystems rely on livestock inputs to generate outputs, including meat, eggs, and milk. However, the two subsystems share common inputs, such as the agricultural and livestock workforce, and shared outputs, such as gross agricultural production value and rural residents' disposable income. Based on these characteristics, this study defines a configuration as a Parallel Structure of Subsystems with Shared Inputs and Outputs (PSSSIO) (Figure 1). Evaluating only one subsystem in isolation or neglecting the sharing mechanism between them may introduce bias into the efficiency results and undermine the reliability of the policy recommendations. Therefore, it is essential to construct an efficiency evaluation framework that is capable of accurately representing this integrated agropastoral structure.

Nevertheless, existing literature reveals substantial limitations in evaluating the efficiency of such complex parallel systems. First, mainstream studies have predominantly focused on single agricultural production systems, typically oriented toward regions where crop farming is the dominant activity, making them ill-suited for analysing regions where crop and livestock subsystems coexist with markedly different resource endowments (Zhao et al. 2019; Cheng et al. 2025; Wang et al. 2025). Second, conventional parallel or network data envelopment analysis (DEA) models often assume homogeneity across subsystem structures and limited interaction among resources. This prevents them from capturing pervasive resource competition and synergistic relationships within Inner Mongolia's agropastoral system. For example, the agricultural and livestock workforce exhibits clear competition

between the two subsystems. Moreover, both the gross agricultural production value and disposable income of rural residents are jointly generated by crop production and livestock production subsystems. Their input–output structures differ markedly from those of a conventional stand-alone crop production system.

To address these gaps, our study develops a parallel-bounded adjusted measure (BAM) model based on DEA tailored to the PSSSIO structure. This model can depict the shared input–output mechanisms, output heterogeneity, and structural interdependencies between crop and livestock subsystems, thereby enabling a more precise measurement of both overall system efficiency and subsystem-specific efficiency.

An accurate efficiency measurement framework for such a system is not merely a methodological exercise but has direct economic and policy relevance. For policymakers in Inner Mongolia, understanding where and how inefficiencies arise within and between crop and livestock production subsystems is crucial for evidence-based decision-making. These findings can directly guide more effective resource allocation, such as prioritising investments in agricultural machinery, irrigation, or pasture improvement, to yield the greatest synergistic returns. They can also guide targeted interventions in livestock management and infrastructure planning that benefit both subsystems equitably. Ultimately, this precise efficiency assessment provides a scientific basis for formulating policies that enhance overall productivity, sustainability, and resilience of the regional agropastoral economy.

Accordingly, this study aims to answer the following research questions: (i) How can a parallel DEA model integrating the BAM approach and shared resource allocation be formulated to accurately assess the efficiency of agropastoral systems characterised by PSSSIO?; (ii) What are the overall and subsystem-specific efficiency

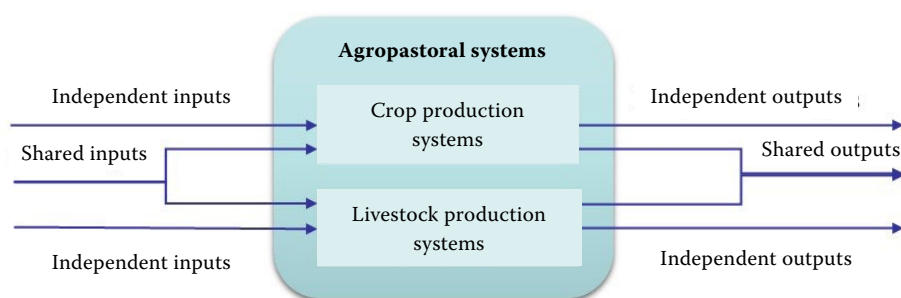


Figure 1. Conceptual framework of the parallel agropastoral system

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levels of agropastoral systems across different prefectures in Inner Mongolia, and how do they compare? and (iii) What are the primary sources of inefficiency, and what specific policy implications do they yield for resource management and subsystem development?

To contextualise this study, we present a comprehensive overview of relevant prior research.

Efficiency evaluation of agriculture. The challenges confronting agricultural systems, particularly in pastoral-agropastoral transition zones, transcend simple yield metrics. As Thornton et al. (2024) emphasised, enacting local and effective changes in these zones must account for complex socioeconomic factors. Spatial analyses have revealed that these transition zones are often characterised as complex coupling ecosystems (CCEs), where socioeconomic and natural systems interact intensely, concentrating drastic shifts in land use, economy, and ecology, thereby heightening their vulnerability and management complexity (Zhang et al. 2026). Furthermore, the success of adaptation and transformation in these regions is significantly influenced by policy interventions (Zhong et al. 2025). This multidimensional complexity, encompassing socioeconomic, spatial, and policy sensitivities, underscores why agricultural efficiency measurements have remained a central focus in global agricultural research. Consequently, scholars have extensively studied agricultural efficiency using both parametric and nonparametric methods.

Among parametric approaches, stochastic frontier analysis (SFA) is widely employed to evaluate technical and energy efficiency in agriculture (e.g. Yang et al. 2020; Hajihassani et al. 2022; Khan et al. 2023; Moulay et al. 2024; Song et al. 2024), largely because of its ability to distinguish between managerial inefficiency and random disturbances. However, the SFA requires a predefined production function and relies on a computationally-intensive maximum-likelihood estimation. More importantly, it is better suited to single-output or limited-output settings, making it less ideal for multi-input and multi-output agricultural systems.

In contrast, non-parametric DEA does not assume a functional form and can handle multiple inputs and outputs directly, rendering it particularly suitable for complex agricultural systems (Fang 2016). Commonly applied DEA models include radial approaches such as the Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) models, which have been used extensively in regions such as the European Union and China (Rybczewska-Błazejowska and Gierulski 2018; Zhao et al. 2019; Wang et al. 2025). However, a key limitation of radial models is that they

may identify decision-making units (DMUs) as efficient, even when certain inputs or outputs can be improved. This condition is known as 'weak efficiency'. To overcome this problem and provide a more comprehensive assessment, non-radial DEA models have been introduced, allowing for non-proportional adjustments to inputs and outputs. A widely adopted non-radial model is the slacks-based measure (SBM), which has been frequently applied in agricultural efficiency studies (Kuang et al. 2020; Han et al. 2024; Liu and Li 2024; Wang et al. 2025).

The bounded adjusted measure (BAM) is a weighted additive model developed to address boundary issues in traditional DEA and offers higher discriminatory power. As a non-radial model, BAM allows DMUs to optimise inputs and outputs at different rates, thereby avoiding the issue of weak efficiency often associated with radial DEA models. More importantly, BAM was formulated as a linear programming model. This linear structure provides easier and more stable solutions, particularly when complex factors are incorporated. In contrast, other prevalent non-radial models, such as the SBM, become nonlinear programming problems under these conditions. Even after applying the Charnes–Cooper transformation, they often remain nonlinear, making it challenging to obtain a globally optimal solution. Furthermore, the BAM provides stronger economic interpretability. It directly uses slack as a shadow price and offers clear insights into the marginal value of resources. In SBM models, slack requires additional mathematical transformations to gain practical meaning, complicating the interpretation process. Therefore, BAM presents a methodologically robust and computationally tractable framework for efficiency evaluation in complex systems such as agriculture. However, based on our review of the literature primarily sourced from Web of Science using keywords such as 'DEA' and 'agricultural efficiency', few if any studies appear to have applied the BAM model to evaluate the efficiency of agricultural systems. This methodological lacuna was further illustrated by analysing the models and indicators used in literature. Table 1 confirms the absence of a BAM approach in this domain.

Efficiency evaluation of the agropastoral systems in Inner Mongolia. As a key agricultural region in China, Inner Mongolia is responsible for developing a nationally important agricultural and livestock production base, and plays a crucial role in advancing national agricultural development and policy formulation. He et al. (2019) used CCR and BCC to assess the economic, social, and ecological efficiency of modern

<https://doi.org/10.17221/395/2025-AGRICECON>

Table 1. The literature on the data envelopment analysis (DEA) efficiency evaluation of the agricultural sector

Reference	Input	Output	DEA model
Rybczewska-Błazejowska and Gierulski (2018)	energy; water consumption; chemical fertiliser; pesticides; air pollutants; waste	GDP	BCC
Zhao et al. (2019)	labour; agricultural machinery power; water consumption; sown area	grain output	CCR
Cheng et al. (2025)	sown area of crops; effective irrigation area; agricultural water use; agricultural plastic film use; power of agricultural machinery	production of major crops, gross agricultural output value	BCC
Kuang et al. (2020)	sown area; labour; agricultural machinery power; chemical fertiliser; agricultural plastic film; irrigation area	gross agricultural output value; grain output; agricultural carbon emissions	SBM
Han et al. (2024)	crop planting area; labour; mechanisation level; green technology; innovation; digitalisation of agricultural economy	gross agricultural output value; rural shared prosperity; agricultural pollution; agricultural carbon emissions	SBM
Liu and Li (2024)	labour; capital; land; chemical fertiliser; pesticide; agricultural plastic film; irrigation area; agricultural machinery power	gross agricultural output value; agricultural carbon emissions; agricultural non-point source pollution	SBM
Wang et al. (2025)	sown area of crops, rural employees, discounted fertiliser application amount, power of agricultural machinery, effective irrigated area, pesticide usage	grain production; CO ₂ emissions; CH ₄ emissions; NO ₂ emissions	SBM

BCC – Banker–Charnes–Cooper; CCR – Charnes–Cooper–Rhodes; SBM – slacks-based measure

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agriculture in Inner Mongolia. Zhao et al. (2019) focused on 12 prefecture-level divisions within Inner Mongolia and employed the BCC model to evaluate the sustainable agricultural production efficiency. Qimuge et al. (2023) employed the super-SBM model to evaluate the livelihood efficiency of herders in typical grassland areas of Inner Mongolia. Zhang et al. (2024) systematically analysed agricultural production efficiency and its influencing factors in Inner Mongolia using a three-stage DEA model.

However, research on the efficiency of agropastoral systems in Inner Mongolia is limited. The limitations of the current research can be summarised in two key aspects. First, existing studies have overlooked the allocation of shared inputs and outputs within agropastoral systems. Second, the research methodology relies

predominantly on traditional DEA models while neglecting the advantages of non-radial DEA approaches, particularly the BAM method.

DEA for parallel systems. In traditional efficiency evaluation methods, a system is typically treated as an indivisible whole, overlooking the interdependencies and interactions between its internal components. However, many systems consist of multiple interrelated subsystems, where one subsystem utilises the output of another as an input while simultaneously generating outputs for other subsystems. Such systems are referred to as series systems (Kao 2014). For example, in the medical waste recycling subsystem, the collection and transportation subsystem supplies the recovered medical waste to the disposal subsystem. In addition, various types of parallel systems exist (Kao 2009), as illustrated

in Figure 2. Some systems, such as a hospital's medical service system, consist of two independent parallel subsystems (Figure 2A). They can be divided into outpatient and inpatient subsystems, both of which function separately to address distinct healthcare demands. Other systems not only have their own inputs and outputs but also share certain inputs or outputs (Figure 2B). For example, multiple production lines within a factory may share specific equipment or resources that are considered intermediate resources, whereas each production line maintains its own distinct inputs and outputs. Furthermore, some systems exhibit the characteristics of both series and parallel structures, forming complex hybrid network structures (Phung et al. 2020; Stefaniec et al. 2020; Arya and Singh 2021; Zhang et al. 2022). A typical example is a supply chain system consisting of procurement, production, and sales subsystems arranged in series, whereas the production subsystem itself may comprise multiple parallel production lines (Figure 2C). Neglecting the operational dynamics of internal components in system efficiency evaluations may lead to misleading results. Given the presence of shared inputs and outputs between the crop and livestock production subsystems, this study reviews parallel systems with shared inputs and outputs to provide a more comprehensive analytical framework.

Beasley (1995) introduced a fractional multi-activity DEA (MDEA) model to evaluate the efficiency of DMUs with shared inputs across multiple activities. Molinero (1996) later linearised Beasley's MDEA

model using the Shephard distance function. Cook et al. (2000) applied the MDEA model to evaluate the efficiency of banking subsystems. Subsequently, Tsai and Molinero (2002) improved the model by incorporating variable returns to scale (VRS) and analysed the scale efficiency of multi-activity DMUs. Kao (2012) proposed a network DEA model for parallel systems. However, this model did not consider the allocation of shared inputs. Chen et al. (2013) introduced an enhanced MDEA model capable of handling shared inputs in parallel systems.

Currently, an increasing number of DEA models are being applied in various fields to address issues related to shared inputs and outputs. Ma (2015) proposed a two-stage network DEA model that incorporates intermediate outputs and shared inputs to assess hospital operational efficiency. Lozano (2015) developed a non-radial slacks-based measure (NSBM) model with shared inputs to evaluate the efficiency of production and pollution generation technologies in coal-fired power plants in EU and OECD countries. Lei et al. (2019) proposed a ratio-based parallel DEA approach that considers shared inputs and undesirable outputs to assess the efficiency of the transportation sector. Stefaniec et al. (2020) decomposed a transportation system into three parallel parts – social, economic, and environmental sustainability – and developed a hybrid-network DEA model with shared inputs to address the efficiency of the transportation system. Phung et al. (2020) used a hybrid network

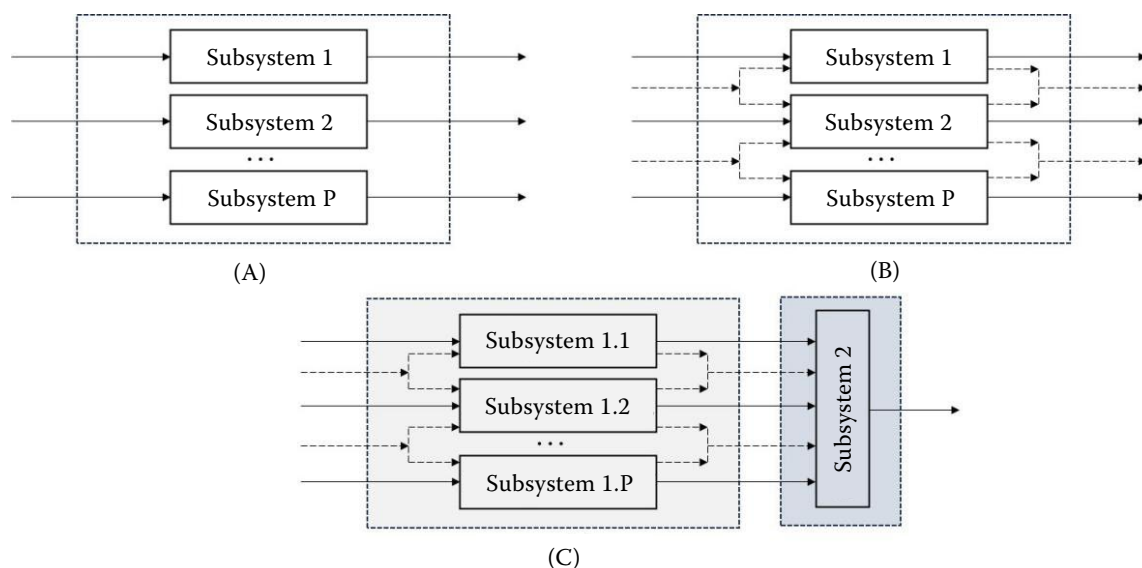


Figure 2. Parallel systems: (A) Parallel structure of independent subsystems. (B) Parallel structure of subsystems with shared inputs and outputs. (C) Complex hybrid network structure with series and parallel subsystems.

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structure with shared inputs to evaluate the efficiency of banking systems, focusing on processes such as fundraising, lending, investment, and non-interest income services. Bian et al. (2015) proposed a centralised DEA approach to evaluate the operational efficiency of railway companies with two parallel subsystems: passenger transport and freight transport. These subsystems share common inputs (e.g. the number of railway employees), dedicated inputs (e.g. the number of passenger dispatchers or freight-handling machinery), and shared outputs (e.g. other incomes). To evaluate the environmental efficiency of Chinese airlines, Li et al. (2022) developed a novel parallel range-adjusted measure (PRAM) method using shared inputs, desirable and undesirable outputs.

However, most existing studies on shared inputs and outputs have overlooked the role of non-radial models, and no study has applied BAM to address shared inputs and outputs. Moreover, the application of the BAM in parallel agropastoral systems with shared inputs and outputs has not yet been explored.

To evaluate the efficiency of agropastoral systems more accurately, this study proposes an innovative parallel BAM model with shared inputs and outputs. The model enhances efficiency assessment by considering system interdependence, thus providing a new approach to assessing the performance of agropastoral systems.

MATERIAL AND METHODS

As outlined previously, the BAM avoids the weak efficiency issue associated with radial DEA models. It also offers advantages over SBM and its extensions (e.g. network SBM) for two main reasons. First, its linear programming form ensures computational tractability. Second, it directly interprets slack variables as shadow prices, thereby providing stronger interpretability than the SBM approach, which requires complex mathematical transformation to yield meaningful economic interpretations. Moreover, compared to the range adjusted measure (RAM), BAM provides stronger discriminatory power and remains feasible under any returns-to-scale assumption, whereas RAM may lack a feasible solution under constant returns to scale (CRS). Hence, we selected BAM for this study.

Similar to other DEA-based approaches, the application of the BAM relies on several key assumptions that inform the interpretation of our results. First, our analysis adopts the VRS assumption, which is appropriate for heterogeneous and constrained

agropastoral systems because it does not require them to operate at an optimal scale. Second, we assume the free disposability of inputs and outputs, implying that excess inputs can be discarded and that output reduction is always possible. This assumption is justified because our study focuses on production and economic efficiency and excludes environmental externalities. Third, DEA is a deterministic frontier method that does not consider measurement errors or random noise. Thus, any estimated inefficiency can be attributed entirely to managerial practices or systemic factors, potentially overstating true inefficiency in the presence of data noise. Finally, BAM treats each agropastoral system as an independent DMU, implying that the efficiency of one unit is evaluated without considering possible spillovers or technological dependencies among the observed units. This implies that our results should be interpreted as relative technical efficiency within the observed sample, rather than as an absolute measure of productivity.

The traditional BAM model for black box systems.

Classical BAM is an advanced DEA efficiency evaluation model based on the additive DEA model (Cooper et al. 2011). However, similar to other traditional DEA models, it can only be used to evaluate the efficiency of an agropastoral system when the entire system is regarded as a black box (Figure 3). Under the assumption of variable returns to scale, the classical BAM can be represented as Equation (1):

$$\begin{aligned}
 E = \min & 1 - \frac{1}{M+T} \left(\sum_{m=1}^M \frac{S_m^-}{B_m} + \sum_{t=1}^T \frac{S_t^+}{B_t} \right) \\
 \sum_{j=1}^J \lambda_j x_{mj} &= x_{m0} - S_m^-, \quad m=1,2,\dots,M \\
 \sum_{j=1}^J \lambda_j y_{tj} &= y_{t0} + S_t^+, \quad t=1,2,\dots,T \\
 \sum_{j=1}^J \lambda_j &= 1 \\
 \lambda_j, S_m^-, S_t^+ &\geq 0, \text{ for all } j, m, t
 \end{aligned} \tag{1}$$

where: $DMU_j (j=1,2,\dots,J)$ – the agropastoral system of a region in Inner Mongolia, and it consumes M ($m \in M$) inputs to produce T ($t \in T$) outputs; $x_{mj} = (x_{1j}, \dots, x_{Mj})$ and $y_{tj} = (y_{1j}, \dots, y_{Tj})$ – the inputs and outputs, respectively; λ_j – the intensity variable associated with the j^{th} DMU; S_m^- and S_t^+ – the slack variables of inputs and outputs, respectively; $B_m = x_{m0} - \min(x_{mj})$ – the scope of inputs, while $B_t = \max(y_{tj}) - y_{t0}$ – the scope of outputs.

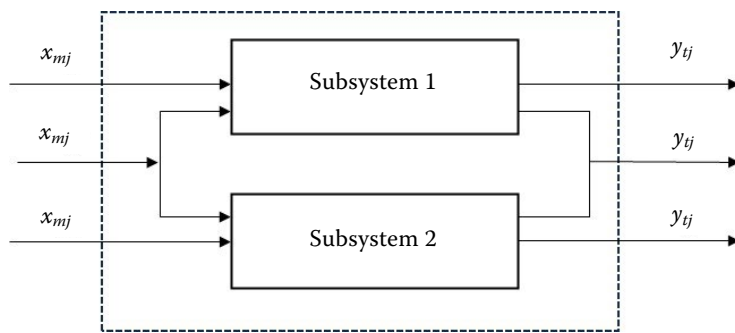


Figure 3. The black box system

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When the optimal value of the model's objective function is $E_0^* = 1$, it means that the DMU_0 is efficient. When the optimal value of the model's objective function is $0 < E_0^* < 1$, it means that the DMU_0 is inefficient. It should be noted that, to ensure that the model has a solution, it is necessary to make $\frac{S_m^*}{B_m} = 0$ when $x_{m0} = \min(x_{mj})$. Similarly, it is necessary to make $\frac{S_t^*}{B_t} = 0$ when $y_{t0} = \max(y_{tj})$.

However, treating the agropastoral system as a single black box is inadequate in regions such as Inner Mongolia. Ignoring its internal structure may obscure heterogeneous production processes, mask resource competition and synergies between the two subsystems and ultimately lead to biased efficiency estimates.

The parallel BAM model with shared inputs and outputs. In this section, we divide agropastoral systems into crop production and livestock production subsystems, exploring their internal structure to identify components that need improvement.

We assume that a system (Figure 2B) is composed of non-homogenous subsystems $p = (1, 2, \dots, P)$ operating independently and utilises M inputs to produce T outputs. The subsystem P of the DMU_j applies inputs x_{mj}^p to generate outputs y_{tj}^p , where $m \in M(p)$, $M(p) \subset M$, $t \in T(p)$, $T(p) \subset T$. Hence, $M(p)$ denotes the set of inputs consumed by the subsystem p , and $T(p)$ represents the set of outputs generated in the subsystem p . Thus, each subsystem uses its own set of inputs to produce its own set of outputs.

Figure 4 presents the network system with the parallel subsystems with their specific shares of inputs and outputs. The shares of input x_{mj} are denoted by parameters α_j^p assigned to each input m accordingly. The shares of output y_{tj} are denoted by parameters γ_j^p assigned to each output t accordingly. The parameters may take values from 0 to 1. The input x_{mj} is allocated completely across the subsystems. Hence, the sum of parameters α_j^p assigned to each input m for all the subsystems must be equal to 1 ($\sum_{p=1}^P \alpha_j^p = 1$). The output y_{tj} is allocated completely across the subsystems.

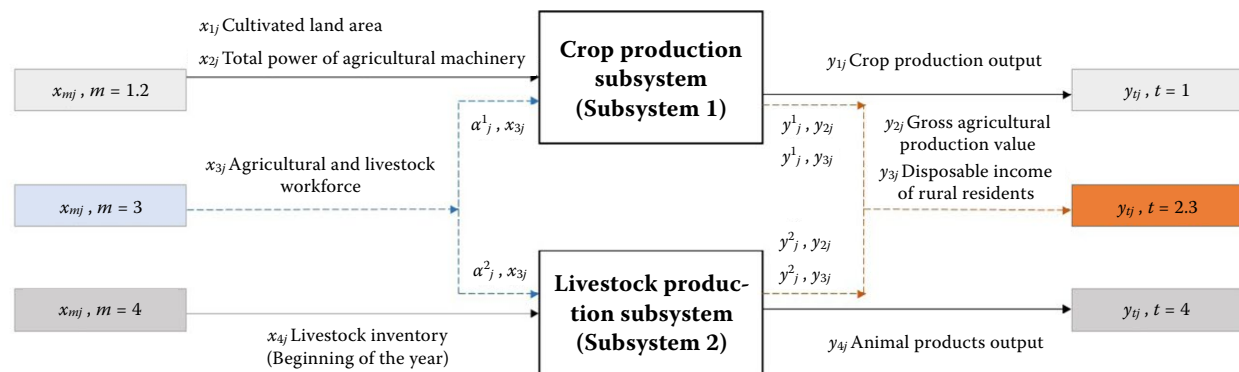


Figure 4. The parallel structure of agropastoral systems

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Therefore, the sum of parameters γ_j^p assigned to each output m for all the subsystems must be equal to 1 ($\sum_{p=1}^P \gamma_j^p = 1$).

Compared to the traditional black-box BAM model, introducing a parallel structure substantially enhances the discriminatory power of the proposed model, even when the number of DMUs is limited. This is because decomposing each agropastoral system into crop and livestock subsystems increases the variability in the observed production behaviour, and the endogenous allocation of shared inputs and outputs further differentiates the DMUs through subsystem-level slack. Consequently, inefficiencies that would otherwise be masked in an aggregate black-box setting can be detected more precisely in the parallel BAM framework.

According to Kao (2009, 2012), the overall efficiency is the weighted average of the efficiency of the subsystems. Moreover, the weight of the subsystem p is the total resources consumed by the subsystem out of the resources consumed by all subsystems, which is expressed by W_p . W_1 and W_2 can be expressed as Equations (2 and 3), respectively:

$$\begin{aligned}
 E = \min & 1 - \sum_{p=1}^2 \frac{W_p}{M(p) + T(p)} \left(\sum_{m=1}^M \frac{S_m^{p-}}{B_m^p} + \sum_{t=1}^T \frac{S_t^{p+}}{B_t^p} \right) \\
 & \sum_{j=1}^J \lambda_j x_{mj} = x_{m0}^p - S_m^{p-}, \text{ for } m=1,2, p=1 \\
 & \sum_{j=1}^J \lambda_j \alpha_j^p x_{mj} = x_{m0}^p - S_m^{p-}, \text{ for } m=3, p=1,2 \\
 & \sum_{j=1}^J \lambda_j x_{mj} = x_{m0}^p - S_m^{p-}, \text{ for } m=4, p=2 \\
 & \sum_{j=1}^J \lambda_j y_{tj} = y_{t0}^p + S_t^{p+}, \text{ for } t=1, p=1 \\
 & \sum_{j=1}^J \lambda_j \gamma_j^p y_{tj} = y_{t0}^p + S_t^{p+}, \text{ for } t=2,3, p=1,2 \\
 & \sum_{j=1}^J \lambda_j y_{tj} = y_{t0}^p + S_t^{p+}, \text{ for } t=4, p=2 \\
 & \sum_{j=1}^J \lambda_j = 1 \\
 & \sum_{p=1}^P W_p = 1 \\
 & \sum_{p=1}^P \alpha_j^p = \sum_{p=1}^P \gamma_j^p = 1, \text{ for all } j \\
 & \lambda_j, \alpha_j^p, \gamma_j^p, S_m^{p-}, S_t^{p+} \geq 0, \text{ for all } j, m, t, p
 \end{aligned} \tag{4}$$

Equation (2)

$$W_1 = \frac{\sum_{m=1}^M x_{mj}^1 + \sum_{t=1}^T y_{tj}^1}{\sum_{p=1}^P \sum_{m=1}^M x_{mj}^p + \sum_{p=1}^P \sum_{t=1}^T y_{tj}^p} = \frac{x_{1j} + x_{2j} + \alpha_j^1 x_{3j}^1 + y_{1j} + \gamma_j^1 y_{2j} + \gamma_j^1 y_{3j}}{\sum_{m=1}^M x_{mj} + \sum_{t=1}^T y_{tj}} \tag{2}$$

Equation (3)

$$W_2 = \frac{\sum_{m=1}^M x_{mj}^2 + \sum_{t=1}^T y_{tj}^2}{\sum_{p=1}^2 \sum_{m=1}^M x_{mj}^p + \sum_{p=1}^2 \sum_{t=1}^T y_{tj}^p} = \frac{\alpha_j^2 x_{3j}^2 + x_{4j} + \gamma_j^2 y_{2j} + \gamma_j^2 y_{3j} + y_{4j}}{\sum_{m=1}^M x_{mj} + \sum_{t=1}^T y_{tj}} \tag{3}$$

where: DMU_0 – the evaluated DMUs. The efficiency score of agropastoral systems can be obtained by combining the efficiency scores of subsystems 1 and 2 on a weighted average. Therefore, the parallel BAM model with shared inputs and outputs can be expressed as Equation (4).

It is necessary to consider lower-sided ranges for inputs and upper-sided ranges for outputs when using the BAM approach. The lower-sided range for the m^{th} input at (x_0, y_0) is determined by $B_m^p = x_{m0}^p - \min(x_{mj}^p)$, while the upper-sided range for the t^{th} output at (x_0, y_0) is determined by $B_t^p = \max(y_{tj}^p) - y_{t0}^p$.

If we consider only subsystem 1 and ignore subsystem 2, the corresponding model is given by Equation (5):

$$\begin{aligned}
 E_{(1)} = \min & 1 - \frac{1}{M(1) + T(1)} \left(\sum_{m=1}^M \frac{S_m^{1-}}{B_m^1} + \sum_{t=1}^T \frac{S_t^{1+}}{B_t^1} \right) \\
 & \sum_{j=1}^J \lambda_j x_{mj} = x_{m0}^1 - S_m^{1-}, \text{ for } m = 1, 2, \\
 & \sum_{j=1}^J \lambda_j \alpha_j^1 x_{mj} = x_{m0}^1 - S_m^{1-}, \text{ for } m = 3 \\
 & \sum_{j=1}^J \lambda_j y_{tj} = y_{t0}^1 + S_t^{1+}, \text{ for } t = 1 \\
 & \sum_{j=1}^J \lambda_j \gamma_j^1 y_{tj} = y_{t0}^1 + S_t^{1+}, \text{ for } t = 2, 3 \\
 & \sum_{j=1}^J \lambda_j = 1 \\
 & \lambda_j, \alpha_j^1, \gamma_j^1, S_m^{1-}, S_t^{1+} \geq 0, \text{ for all } j, m, t
 \end{aligned} \quad (5)$$

If we consider only subsystem 2 and ignore subsystem 1, the corresponding model is given by Equation (6):

$$\begin{aligned}
 E_{(2)} = \min & 1 - \frac{1}{M(2) + T(2)} \left(\sum_{m=1}^M \frac{S_m^{2-}}{B_m^2} + \sum_{t=1}^T \frac{S_t^{2+}}{B_t^2} \right) \\
 & \sum_{j=1}^J \lambda_j \alpha_j^2 x_{mj} = x_{m0}^2 - S_m^{2-}, \text{ for } m = 3 \\
 & \sum_{j=1}^J \lambda_j x_{mj} = x_{m0}^2 - S_m^{2-}, \text{ for } m = 4 \\
 & \sum_{j=1}^J \lambda_j \gamma_j^2 y_{tj} = y_{t0}^2 + S_t^{2+}, \text{ for } t = 2, 3 \\
 & \sum_{j=1}^J \lambda_j y_{tj} = y_{t0}^2 + S_t^{2+}, \text{ for } t = 4 \\
 & \sum_{j=1}^J \lambda_j = 1 \\
 & \lambda_j, \alpha_j^2, \gamma_j^2, S_m^{2-}, S_t^{2+} \geq 0, \text{ for all } j, m, t
 \end{aligned} \quad (6)$$

Data. We applied the proposed parallel BAM model with shared inputs and outputs to evaluate the efficiency of 12 agropastoral systems in Inner Mongolia. This study explored the factors and components that influence their development, thereby

providing theoretical insights and practical recommendations for decision-making.

Guided by established literature on agricultural productivity and regional characteristics, we selected four input and four output indicators to evaluate the efficiency of these systems. In the crop production subsystem, the input indicators included cultivated land area, total power of agricultural machinery, and agricultural and livestock workforce. The output indicators included crop production output, gross agricultural production value, and the disposable income of rural residents. In the livestock production subsystem, the input indicators included the livestock inventory (beginning of the year) and agricultural and livestock workforce. The output indicators included animal product output, gross agricultural production value, and the disposable income of rural residents. The agricultural and livestock workforce is a shared input across both subsystems, whereas the gross agricultural production value and disposable income of rural residents are shared outputs.

i) Cultivated land area (crop subsystem input). As the primary fixed production factor in crop farming, cultivated land determines the scale of planting activities and constrains potential output volume. It directly reflects land-use intensity and regional differences in arable land endowment, which are both fundamental drivers of crop production efficiency.

ii) Total power of agricultural machinery (crop subsystem input). Agricultural machinery power captures the degree of mechanisation, technological adoption, and capital input in crop farming. In regions such as Inner Mongolia, mechanisation has substantially improved labour productivity, expanded the operational scale of farming, and mitigated labour shortages. Therefore, this indicator reflects the levels of capital and technological investment.

iii) Livestock inventory (livestock subsystem input). Livestock inventory represents the core productive asset of livestock operations and determines meat, milk, and egg production capacity. This reflects both biological capital and herd management strategies, which correspond directly to the production technology of livestock husbandry.

iv) Agricultural and livestock workforce (shared input). Labour is a shared production resource in agropastoral regions, where households often simultaneously engage in farming and livestock raising. Labour allocation decisions, such as how workdays are distributed between cropping and herding, strongly affect subsystem-specific output levels. Therefore, treating the workforce as a shared input is essential to accurately model

<https://doi.org/10.17221/395/2025-AGRICECON>

the joint nature of agricultural labour markets and competition for labour between the two subsystems.

v) Crop production (crop subsystem output). This indicator reflects the economic and physical performance of crop farming, which is a direct consequence of land, machinery, and labour utilisation. This captures the primary market-oriented output of the crop subsystem.

vi) Animal product output (livestock subsystem output). Animal product output represents the physical production of livestock including meat, milk, and eggs. It is determined by livestock inventory, feeding practices, and labour input and therefore reflects the biological and economic behaviour of the livestock subsystem.

vii) Gross agricultural production value (shared output). Gross agricultural production value aggregates the monetary value generated by both crop and livestock operations. It captures the economic contribution of the entire agropastoral system and is co-determined by the efficiency of both subsystems. As a shared output, it reflects how subsystem-level productivity jointly shapes the regional agricultural economic performance.

viii) Disposable income of rural residents (shared output). Disposable income of rural residents is a comprehensive welfare indicator that reflects overall livelihood improvement derived from both crop and livestock production. In agropastoral regions, household income commonly results from a combination of crop sales, livestock products, and associated employment. Including this variable as a shared output highlights the socioeconomic outcomes of the agropastoral system beyond purely production-oriented metrics.

Because prices internalise land quality, labour scarcity and capital opportunity cost, the share of output value is a widely accepted proxy for resource use intensity in mixed-farming systems where physical input flows are non-separable (Thomassen et al. 2008; Low et al. 2023). Following this convention, we calculated the contribution of each subsystem to the total agropastoral output value, which was 56% for crop production and 44% for livestock production. These proportions were then directly applied as weights to allocate the shared resources between the two subsystems. Therefore, we assigned a weight of 0.56 to shared resources in the crop production subsystem and a weight of 0.44 in the livestock production subsystem, i.e. $\alpha_j^1 = \gamma_j^1 = 0.56$, $\alpha_j^2 = \gamma_j^2 = 0.44$.

The data for the remaining indicators were obtained from the Inner Mongolia Statistical Yearbook 2023 (Table 2). There were no missing data. According to the statistical standards of China's National Bureau of Statistics, the Agricultural and Livestock

Workforce indicator is a comprehensive annual aggregate. It aims to capture the total labour input over the course of the year. By definition, it encompasses all individuals whose primary economic activity falls within this sector. Consequently, this aggregate figure inherently includes contributions from full-time, part-time, and seasonal labour. The 'gross agricultural production value' and 'disposable income of rural residents' data were originally reported in Chinese Yuan (CNY). To present the results in more internationally accessible units, these values were converted to U.S. dollars (USD) using the 2022 annual average exchange rate of 1 USD = 6.726 1 CNY, as reported in the Statistical Communique of the People's Republic of China on 2022 National Economic and Social Development. This choice is methodologically sound and does not affect the efficiency evaluation results. The DEA approach satisfies the property of unit invariance, which means that a proportional transformation of all data (applying the same exchange rate to all monetary values) does not alter the relative efficiency scores. Therefore, the conversion was performed solely for the convenience of readers, and all comparative conclusions remain valid. Given that the data set is confined to 2022 and does not involve intertemporal comparisons, an inflation adjustment is not applicable.

RESULTS AND DISCUSSION

Results

Overall efficiency. We evaluated the overall efficiency of the 12 agropastoral systems using both traditional and parallel BAM models with shared inputs and outputs. As Table 3 shows, the two approaches produce markedly different efficiency patterns, indicating that the choice of modelling structure significantly affects the assessment of regional performance.

Under the traditional BAM model, most regions receive an efficiency score of 1.000, which reflects the well-known limitation of black-box DEA models in distinguishing between DMUs when structural heterogeneity is ignored. After decomposing each agropastoral system into crop and livestock subsystems and accounting for shared inputs and outputs, the parallel BAM model yields a considerably greater dispersion in efficiency scores. For instance, Baotou City, Hulunbuir City, Hinggan League, Tongliao City, and Xilingol League, which were previously assessed as efficient, experienced a substantial decline when subsystem interactions were incorporated (efficiency scores ranging from 0.724 to 0.855). This demonstrates that the parallel structure

Table 2. The inputs and outputs of the agropastoral systems in 12 regions in Inner Mongolia

	Hohhot City	Baotou City	Hulunbuir City	Hinggan League	Tongliao City	Chifeng City	Xilingol League	Ulanqab City	Ordos City	Bayannur City	Wuhai City	Alxa League
crop production subsystems	cultivated land area (10 ³ ha)	290.04	1 878.20	1 107.15	1 444.62	1 371.89	244.13	688.74	479.28	758.71	6.12	64.92
	total power of agricultural machinery (10 ⁴ kW)	283.20	167.63	660.34	545.03	769.42	753.37	268.86	296.14	640.04	7.21	29.56
	livestock inventory											
	livestock production subsystems	278.66	308.84	820.79	897.84	971.75	1 255.06	438.37	911.80	864.99	11.99	98.09
shared inputs	agricultural and livestock workforce* (10 ³ persons)	15.80	16.10	41.70	52.80	52.00	51.20	50.30	18.30	54.60	4.10	17.40
	crop produc- tion output subsystems (10 ⁴ tonnes)	370.93	240.87	1 333.30	1 344.95	1 880.99	1 322.19	249.73	430.64	657.99	7.51	29.68
Outputs	livestock production subsystems	247.38	62.89	103.04	94.38	85.87	124.81	44.28	54.45	148.25	1.45	15.27
	gross agricul- tural produc- tion value* (10 ⁸ USD)	39.65	33.27	95.02	59.89	93.56	107.97	43.37	46.25	70.60	2.00	5.53
	shared outputs											
	dispos- able income of rural residents* (USD)	3 556	3 603	3 106	2 288	2 972	2 458	2 315	3 749	3 626	3 747	3 962

*shared inputs or outputs;

Source: Compiled by the authors based on the Inner Mongolia Statistical Yearbook 2023

<https://doi.org/10.17221/395/2025-AGRICECON>

Table 3. Comparison of efficiency results between the traditional BAM model and the parallel BAM model with shared inputs and outputs

DMUs	Traditional BAM model		Parallel BAM model with shared inputs and outputs	
	efficiency	ranking	efficiency	ranking
Hohhot City	1.000	1	1.000	1
Baotou City	1.000	1	0.807	5
Hulunbuir City	1.000	1	0.855	4
Hinggan League	1.000	1	0.729	7
Tongliao City	1.000	1	0.766	6
Chifeng City	0.791	9	0.717	9
Xilingol League	1.000	1	0.724	8
Ulanqab City	0.623	12	0.523	12
Ordos City	1.000	1	1.000	1
Bayannur City	0.670	11	0.594	11
Wuhai City	1.000	1	1.000	1
Alxa League	0.746	10	0.705	10
Average	0.9025	–	0.785	–

BAM – parallel-bounded adjusted measure; DMUs – decision-making units

Source: Authors' own calculation

uncovers inefficiencies masked by the aggregation of inputs and outputs. In the lower-ranked regions, Ulanqab City and Bayannur City consistently appear to be the weakest performers, but the parallel BAM model further widens the efficiency gaps (0.523 and 0.594, respectively).

Overall, the parallel BAM model offers a more realistic depiction of Inner Mongolia's agropastoral efficiency landscape by capturing the structural heterogeneity, resource competition, and joint output generation that traditional black-box models fail to reflect. The effectiveness of our model in revealing inefficiencies is further supported by a comparison with existing studies. Li et al. (2022) applied a parallel RAM model to evaluate airline efficiency and reported high average scores (> 0.98), with more than half of the airlines deemed efficient. By contrast, our parallel BAM model yields a markedly lower average efficiency (0.785) and identifies only three efficient DMUs. This pronounced difference underscores the stronger discriminatory power of the BAM-based approach than that of the RAM-based approach. Given that BAM inherently offers advantages over radial DEA, SBM, and RAM, our parallel BAM model has a comparative advantage over the parallel models derived from these methods.

The allocation of weights to shared resources in the parallel BAM may influence efficiency results. To test the sensitivity of these results, we conducted

a robustness analysis using five alternative weighting schemes alongside our baseline (Crop : Live-stock = 0.56 : 0.44): scenario 1 (0.5 : 0.5), scenario 2 (0.6 : 0.4), scenario 3 (0.7 : 0.3), scenario 4 (0.4 : 0.6), and scenario 5 (0.3 : 0.7). Table 4 presents the corresponding efficiency scores and rankings.

The results in Table 4 demonstrate a high degree of robustness in the relative performance evaluation. The top-performing DMUs, such as Hohhot City, Ordos City, and Wuhai City, remained fully efficient across all scenarios, whereas the poorest performers (i.e. Ulanqab City and Bayannur City) consistently ranked at the bottom. For the DMUs in the middle of the distribution, we only observed marginal shifts in ranking.

These findings indicate that although precise efficiency scores are sensitive to the choice of weights, the overall classification of DMUs is robust. This finding supports the credibility of the baseline analysis. However, to facilitate more nuanced and precise resource allocation decisions, we recommend that decision makers adopt a scientifically grounded approach when determining these weights.

The efficiency of subsystems. Figure 5 illustrates the relationship between the overall efficiency of each region and the efficiencies of its crop and livestock production subsystems. Clear differences are observed between the two subsystems. In several regions with a strong overall performance, the two subsystems

Table 4. Sensitivity analysis with different weighting schemes for shared resources

DMUs	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	efficiency	ranking	efficiency	ranking	efficiency	ranking	efficiency	ranking	efficiency	ranking
Hohhot City	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Baotou City	0.782	5	0.825	5	0.869	5	0.738	5	0.694	5
Hulunbuir City	0.836	4	0.869	4	0.902	4	0.804	4	0.771	4
Hinggan League	0.694	9	0.755	7	0.816	7	0.633	9	0.571	9
Tongliao City	0.736	6	0.789	6	0.842	6	0.683	7	0.630	8
Chifeng City	0.704	7	0.726	9	0.749	9	0.681	8	0.658	7
Xilingol League	0.688	10	0.750	8	0.813	8	0.626	10	0.563	10
Ulanqab City	0.510	12	0.532	12	0.554	12	0.488	12	0.466	12
Ordos City	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Bayannur City	0.579	11	0.605	11	0.632	11	0.553	11	0.526	11
Wuhai City	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Alxa League	0.701	8	0.707	10	0.713	10	0.695	6	0.689	6
Average	0.769	–	0.797	–	0.824	–	0.742	–	0.714	–

DMUs – decision-making units

Source: Authors' own calculation

exhibit balanced efficiency. However, subsystem disparities are pronounced in many other areas such as Ulanqab City, Bayannur City, Hinggan League, and Xilingol League. For example, Xilingol League achieves an efficiency score of 1.000 in its crop production subsystem, but only 0.376 in its livestock production

subsystem, indicating that weaknesses in livestock production significantly constrain its overall agropastoral efficiency. Generally, crop-production subsystems display higher efficiencies and stabilities across regions. Eight DMUs were efficient in crop production, with the lowest performer reaching 0.620. In contrast,

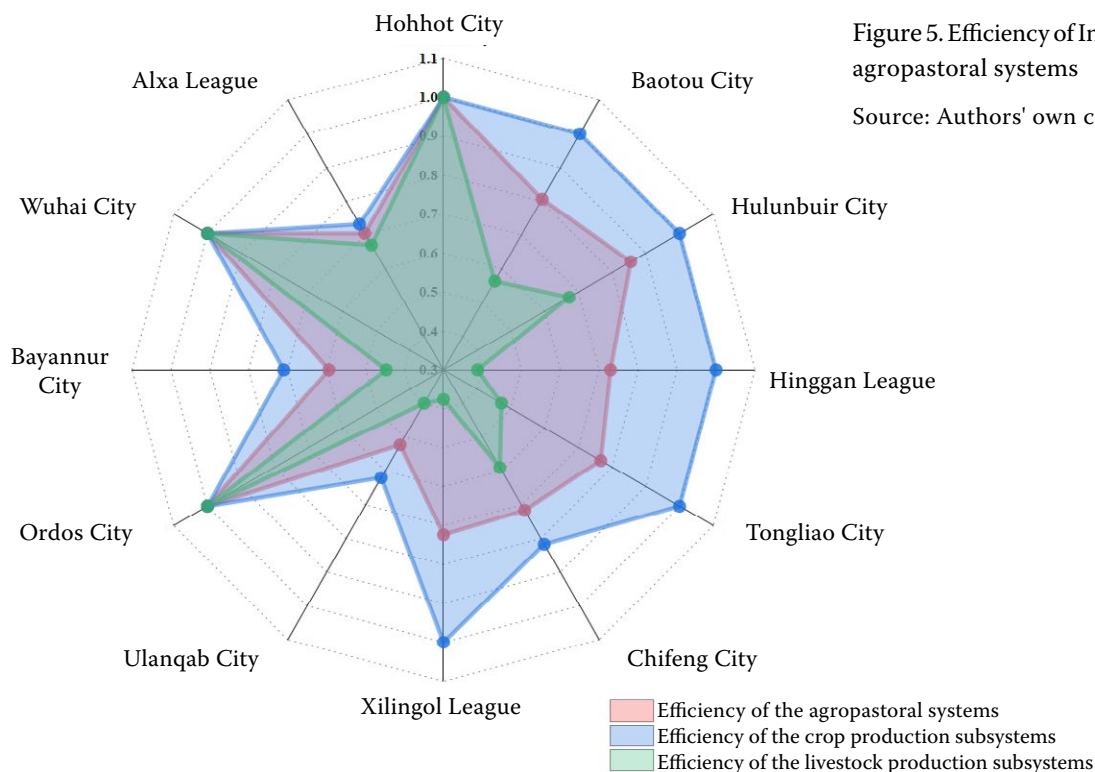


Figure 5. Efficiency of Inner Mongolia's agropastoral systems

Source: Authors' own calculation

<https://doi.org/10.17221/395/2025-AGRICECON>

livestock production subsystems exhibited greater variability, with efficiency scores ranging from 1.000 to 0.376. This variability underscores the role of livestock production as a primary source of inefficiency in many regions.

These disparities can be attributed to several factors. First, crop farming benefits from higher mechanisation levels, standardised cultivation practices, and more mature technological inputs, which collectively enhance productivity. In contrast, livestock production is more susceptible to natural constraints such as grassland carrying capacity, climate variability, and disease risks, all of which reduce operational stability. Second, policy support in the region has historically favoured crop farming through machinery subsidies, irrigation investment, and grain-oriented programs. Livestock policies essential for ecological restoration often impose grazing bans or stocking-density restrictions, which may suppress short-term production efficiency. Third, crop production is better integrated into established supply chains with relatively predictable market demand and pricing mechanisms. In contrast, livestock products face more fragmented market channels and higher transportation costs, particularly in remote grassland areas. These constraints limit market efficiency and undermine livestock operation productivity.

These interrelated technological, ecological, policy, and market constraints collectively explain the lower efficiency observed in livestock production subsystems, which represents a critical bottleneck for improving the overall agropastoral efficiency of Inner Mongolia. Therefore, addressing these structural challenges is essential for enhancing regional development outcomes.

Policy recommendations. Slack analysis of crop and livestock production subsystems provides targeted directions for improving the efficiency of agropastoral systems in Inner Mongolia. The results reveal that the inefficiencies stem primarily from input redundancy, output shortfalls, and imbalanced resource allocation between the two subsystems. These findings offer actionable insights for formulating region-specific optimisation strategies.

These observed efficiency patterns and slack values can be interpreted as an interplay of three key structural factors: agroecological conditions, investment patterns, and prevailing policy frameworks. First, agroecological conditions fundamentally constrain potential: regions with better water and land endowments (e.g. Hohhot City) show higher crop efficiency, whereas arid pastoral leagues (e.g. Xilingol League) exhibit massive livestock inventory slack, indicating overstocking beyond ecological carrying capacity.

Second, investment patterns revealed by input slack show distinct biases: significant machinery redundancy (e.g. Bayannur City) suggests potential over-mechanisation, whereas excessive herd size coupled with low output (e.g. Baotou City) indicates that capital is tied to scale rather than productive efficiency. Finally, these patterns are shaped by policy frameworks that support crop standardisation. Grassland conservation policies may limit scale-intensive livestock production; income support policies appear insufficient to fully translate production into rural welfare. Guided by this interpretive framework, we examine subsystem-specific slack values, which reveal how these structural factors manifest concrete inefficiencies at the regional level.

Table 5 shows the slack values for the crop production subsystems, which reflect either input excess or output shortfall. Chifeng City demonstrates output-oriented inefficiencies, requiring substantial increases in both crop production output (+46.445) and rural disposable income (+811.926), alongside a moderate reduction in cultivated land (−16.351). This highlights the need to enhance land productivity by improving agronomic practices and farmer income support policies. Ulanqab City, one of the weakest performers, exhibits large slack in cultivated land (−350.667), machinery power (−62.238), and labour (−13.115), accompanied by significant shortfalls in rural disposable income (+889.435). This combination indicates a structural over-input coupled with low production benefits. Therefore, optimisation strategies should consolidate farmland, eliminate outdated machinery, and promote income-enhancing diversification. Bayannur City needs to reduce redundant machinery power (−192.046) and labour (−11.253) while increasing crop production output (+25.448) and rural disposable income (+181.578). This indicates inefficiencies in mechanisation, labour matching, and insufficient value-added production. Alxa League shows overinvestment in cultivated land (−29.966), machinery power (−5.256), and labour (−6.199), highlighting the need to optimise resource allocation given its arid agricultural conditions.

Overall, the crop subsystem results suggest that regions should strengthen precision land management, optimise labour mechanisation structures and expand high-value crop production to enhance the economic contribution of agriculture.

The slack values presented in Table 6 demonstrate the prevalent inefficiencies in livestock production subsystems, with the most salient issues being excessive livestock inventory and inadequate output generation.

<https://doi.org/10.17221/359/2025-AGRICECON>

Table 5. The slack variables of the crop production subsystems obtained from the parallel BAM model with shared inputs and outputs

Region	Cultivated land area	Total power of agricultural machinery	Agricultural and livestock workforce*	Crop production output	Gross agricultural production value*	Disposable income of rural residents*
Hohhot City	0	0	0	0	0	0
Baotou City	0	0	0	0	0	0
Hulunbuir City	0	0	0	0	0	0
Hinggan League	0	0	0	0	0	0
Tongliao City	0	0	0	0	0	0
Chifeng City	16.351	0	0	46.445	0	811.926
Xilingol League	0	0	0	0	0	0
Ulanqab City	350.667	62.238	13.115	0	0	889.435
Ordos City	0	0	0	0	0	0
Bayannur City	0	192.046	11.253	25.448	0	181.578
Wuhai City	0	0	0	0	0	0
Alxa League	29.966	5.256	6.199	0	0	0

*shared inputs or outputs; BAM – parallel-bounded adjusted measure

Source: Authors' own calculation

Baotou City and Chifeng City need to reduce their livestock inventory (–75.634 and –103.268, respectively) and increase animal product output (+141.619 and +114.185). This highlights the low productivity of existing herds and underscores the necessity of improving breeding efficiency and disease prevention systems. Hinggan League and Xilingol League,

major pastoral regions, show very large slack in livestock inventory (–433.633 and –396.431) and labour (–12.833 and –8.116), together with animal products output shortfalls (+153.008 and +141.967). This implies overstocking relative to the ecological carrying capacity and insufficient modernisation of animal husbandry. Targeted interventions should include

Table 6. The slack variables of the livestock production subsystems obtained from the parallel BAM model with shared inputs and outputs

Region	Livestock inventory (beginning of year)	Agricultural and livestock workforce*	Animal products output	Gross agricultural production value*	Disposable income of rural residents*
Hohhot City	0	0	0	0	0
Baotou City	75.634	0.892	141.619	0	165.135
Hulunbuir City	0	0	80.844	0.449	393.563
Hinggan League	433.633	12.833	153.008	0	770.107
Tongliao City	0	2.018	88.662	6.626	455.215
Chifeng City	103.268	0.783	114.185	0	691.640
Xilingol League	396.431	8.116	141.967	0	296.642
Ulanqab City	126.821	14.973	203.103	0	757.667
Ordos City	0	0	0	0	0
Bayannur City	242.508	11.118	99.130	0	154.678
Wuhai City	0	0	0	0	0
Alxa League	61.252	5.515	8.507	0	0

*shared inputs or outputs; BAM – parallel-bounded adjusted measure

Source: Authors' own calculation

<https://doi.org/10.17221/395/2025-AGRICECON>

rotational grazing, smart livestock management, and improved forage quality. Ulanqab City and Bayannur City require reductions in both livestock inventory and labour, alongside significant increases in animal product output (+203.103 and +99.130). These regions should prioritise increasing productivity per animal through improved feed conversion ratios and genetic improvement techniques. Despite its rich natural pasture resources, Hulunbuir City shows gaps in animal product output (+80.844) and rural disposable income (+393.563), suggesting underutilised production potential.

In summary, efforts to improve livestock subsystems should focus on (i) reducing redundant and ecologically unsustainable stocking levels, (ii) improving output efficiency through upgraded breeding and feeding systems, and (iii) enhancing the link between livestock production and rural household income.

Across both subsystems, the slack analysis demonstrates that efficiency enhancements require addressing both factor redundancy and output insufficiency with tailored interventions for different regional resource endowments. Therefore, enhancing the overall performance and sustainability of Inner Mongolia's agropastoral economy requires integrated strategies that simultaneously address agroecological constraints, rationalise investment incentives, and refine the policy frameworks identified in our analysis. Specifically, this entails strengthening technology adoption, optimising labour structures, maintaining an ecological balance in livestock activities, and ensuring that agricultural policies effectively translate production gains into rural household income.

Discussion

Inner Mongolia is a typical agropastoral transition zone in which crop and livestock production subsystems operate independently and interdependently. To evaluate the efficiency of such complex systems, this study proposed an innovative parallel BAM with shared inputs and outputs. The empirical analysis revealed significant regional efficiency disparities, identified livestock production as the primary constraint on the overall system performance, and derived policy implications directly from each subsystem's specific input redundancies and output shortfalls. Compared to existing studies on agropastoral efficiency in Inner Mongolia (He et al. 2019; Qimuge et al. 2023; Zhang et al. 2024; Zhong et al. 2025), our study offered greater practical value. Previous studies have overlooked the allocation of shared inputs and outputs in agropastoral systems.

They also relied on traditional DEA models while neglecting the advantages of non-radial approaches such as BAM.

In terms of the overall efficiency assessment, we observed regional efficiency disparities: Hohhot City, Ordos City, and Wuhai City were efficient, whereas Ulanqab City performed the worst. The results also demonstrated that our parallel BAM model offered clear advantages over alternative approaches (Cooper et al. 2011; Li et al. 2022), underscoring its stronger discriminatory power as a more nuanced tool for evaluating complex multi-subsystem production systems.

Our finding that livestock production subsystems consistently underperformed compared to crop production subsystems aligns with that of Qimuge et al. (2023), who identified significant efficiency losses at the herder household level in Inner Mongolia's typical steppe areas. While Qimuge et al. (2023) attributed these losses primarily to social capital redundancy at the household level, our results suggested that systemic constraints, including grassland-carrying capacity, climate variability, and grazing restrictions under ecological conservation policies, played a more fundamental role. This interpretation aligns with the characterisation of agropastoral transition zones as multidimensional complex systems (Thornton et al. 2024; Zhong et al. 2025; Zhang et al. 2026).

Beyond identifying aggregate inefficiencies, our study offered granular, region-specific policy recommendations that previous studies have not provided. By analysing the subsystem-level slack variables, we identified the exact input redundancies and output shortfalls for each region. The identified redundancies, particularly in cultivated land areas and agricultural machinery power, are consistent with the results of He et al. (2019) and Zhang et al. (2024). However, by decomposing these redundancies at the subsystem level, our model revealed a more nuanced pattern: in regions such as Bayannur and Ulanqab, land and machinery redundancies were concentrated in the crop subsystem, whereas in pastoral leagues such as Hinggan and Xilingol, livestock inventory redundancy was the dominant issue. This subsystem-level diagnostic capacity represents a significant advancement in aggregate-level analysis.

This study has limitations that highlight promising avenues for future research. First, while the current model focused on economic efficiency, the exclusion of undesirable outputs (e.g. carbon emissions) limited its capacity to assess environmental sustainability and eco-efficiency. Future research could extend this framework to incorporate such variables for a more

comprehensive efficiency evaluation. Second, the cross-sectional design based on the 2022 data captured only a static snapshot. Applying the model in a dynamic setting with panel data would enable the tracking of efficiency changes over time and the identification of key drivers. Third, because the analysis was confined to Inner Mongolia, the generalisability of the findings remains untested. Adapting the model to other agropastoral regions would allow for cross-regional comparisons and validation. Fourth, although the model accounted for shared inputs and outputs, it did not explicitly consider spatial spillover effects or climatic variables. Integrating these factors can better capture the geographical and environmental heterogeneity. Addressing these research directions will deepen our understanding of agropastoral system performance and support more nuanced policymaking.

This study advances the existing literature in two ways. Theoretically, we developed a novel parallel BAM model with shared inputs and outputs that captures the structural interdependencies between crop and livestock subsystems, a feature overlooked in traditional DEA studies in Inner Mongolia. In practice, by quantifying the exact input redundancies and output shortfalls of each region's subsystems, we provided locally tailored strategies that move beyond the generic recommendations of conventional efficiency analyses. This study demonstrated that conventional black-box models mask critical inefficiencies within subsystems. Therefore, the parallel BAM approach is not merely a methodological refinement but a necessary tool for accurately diagnosing and addressing the structural constraints that limit agropastoral performance.

CONCLUSION

This study developed and applied an innovative parallel BAM model that incorporates shared inputs and outputs to evaluate the efficiency of agropastoral systems in Inner Mongolia.

Methodologically, the proposed model makes a significant contribution by explicitly representing the parallel structure of crop and livestock production subsystems and their shared critical resources: the agricultural and livestock workforce as a common input and gross agricultural production value and rural residents' disposable income as shared outputs. This framework overcomes the key limitations of conventional 'black-box' DEA approaches, enabling a more nuanced, accurate, and structurally coherent assessment of interconnected systems.

The empirical analysis yielded substantive insights. First, we observed clear regional efficiency disparities, with Hohhot, Ordos, and Wuhai operating efficiently and Ulanqab performing the least efficiently. Second, crop production subsystems generally outperformed livestock production subsystems, indicating that the latter acts as a primary constraint on overall agropastoral efficiency. Third, the model identified specific sources of inefficiency, highlighting widespread underutilisation or surplus in key inputs such as cultivated land area, total agricultural machinery power, and initial livestock numbers across multiple regions. Meanwhile, rural residents' disposable income was flagged as an output, requiring substantial improvements in most prefectures.

These findings have significant policy implications. For policymakers in Inner Mongolia, the efficiency measures and slack variables generated by this model provide a practical evidence-based toolkit for targeted resource management and subsystem development. Specifically, the analysis suggested three strategic actions:

i) Strengthen the livestock subsystem. Policies and investments should prioritise strengthening the livestock production subsystem, which has been identified as a primary weakness.

ii) Reallocate resources according to local needs. Resource allocation should be tailored to the inefficiencies of each region. For instance, policies should encourage the rationalisation of cultivated land use in Chifeng, Ulanqab, and Alxa, optimise herd structure and size in regions with significant livestock inventory surpluses, such as Hinggan, Xilingol, Ulanqab, and Bayannur, and rationalise agricultural machinery power in areas such as Ulanqab and Bayannur to eliminate excess capacity.

iii) Increase rural residents' income. Boosting rural residents' disposable income is crucial. Efforts should be intensified in regions with significant income gaps such as Ulanqab, Chifeng, Hinggan, and Tongliao.

We recommend that future research focus on the following topics. First, extending the model by incorporating undesirable outputs, such as carbon emissions, could provide a more comprehensive evaluation of environmental sustainability and eco-efficiency. Second, applying the framework in a dynamic setting using panel data would enable the tracking of efficiency changes over time and identify the drivers of productivity growth or decline. Third, adapting and testing the model to other agropastoral regions would examine its broader applicability and facilitate cross-regional comparisons. Finally, integrating spatial factors or climatic variables can further enhance the ability of the model to account

<https://doi.org/10.17221/395/2025-AGRICECON>

for geographical and environmental heterogeneity. These research directions will improve our understanding of agropastoral system performance and support more nuanced, sustainability-oriented policymaking.

Acknowledgement: The authors would like to greatly appreciate the editors and the reviewers for their remarkable comments.

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Received: August 31, 2025

Accepted: May 4, 2026

Published on-line: September 7, 2026