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Efficiency analysis of pond fishery in northern part of West Bengal, India: evidence from Data Envelopment Analysis (DEA)

Análisis de la eficiencia de la pesca en estanques en el norte de Bengala Occidental, India: evidencia del análisis de datos DEA

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ABSTRACT

North Bengal, a region in the Indian state of West Bengal, possesses abundant water resources and a growing pond-based fishery sector that plays a vital role in rural livelihoods and food security. Despite its potential, disparities in production performance and limited adoption of scientific practices have raised concerns about efficiency. In this study, the technical efficiency of pond fisheries in two districts of North Bengal has been assessed using the Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) DEA models. Findings reveal that the average technical efficiency of the sampled ponds is 74% under the BCC model, indicating a potential 27% improvement in technical efficiency if fish farming operates under variable returns to scale (VRS). Furthermore, over one-third (35.38%) of pond fishery farmers are classified as fully technically efficient within the BCC model, underscoring that a significant portion already operates at optimal efficiency. To validate the robustness of these findings, advanced machine learning techniques, Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE), have also been employed, confirming the consistency and reliability of the results. This suggests a pressing need for governmental intervention, particularly from the Department of Fisheries, to implement targeted measures aimed at enhancing productivity and boosting technical efficiency among pond fishery farmers.

PALABRAS CLAVE

Eficiencia técnica
Sostenibilidad pesquerías
Análisis Envolvente de Datos
Análisis de Componentes Principales
t-SNE
Acuicultura en estanques
Norte de Bengala

RESUMEN

El norte de Bengala, una región del estado indio de Bengala Occidental, posee abundantes recursos hídricos y un sector creciente de piscicultura en estanques que desempeña un papel vital en los medios de vida rurales y en la seguridad alimentaria. A pesar de su potencial, las disparidades en el rendimiento productivo y la limitada adopción de prácticas científicas han generado preocupaciones sobre la eficiencia. En este estudio se evalúa la eficiencia técnica de las pesquerías en estanques en dos distritos del norte de Bengala, utilizando los modelos DEA de Charnes–Cooper–Rhodes (CCR) y Banker–Charnes–Cooper (BCC). Los resultados revelan que la eficiencia técnica promedio de los estanques analizados es del 74% según el modelo BCC, lo que indica un margen potencial de mejora del 27% si la piscicultura operara bajo rendimientos variables a escala (VRS). Además, más de un tercio (35,38%) de los acuicultores en estanques fueron clasificados como plenamente eficientes en términos

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técnicos dentro del modelo BCC, lo que resalta que una proporción significativa ya opera a un nivel óptimo. Para validar la solidez de estos hallazgos, también se han empleado técnicas avanzadas de aprendizaje automático, como el Análisis de Componentes Principales (PCA) y la Integración Estocástica de Vecinos Distribuidos según t (t-SNE), confirmando la consistencia y fiabilidad de los resultados. Esto sugiere una necesidad urgente de intervención gubernamental, en particular por parte del Departamento de Pesca, para implementar medidas específicas orientadas a mejorar la productividad y aumentar la eficiencia técnica entre los acuicultores en estanques.

1. INTRODUCTION

A vital strategy for enhancing inland fish production to meet the rising domestic demand for fish in India is the widespread adoption of pisciculture. This approach not only supports the sustainable utilization of water resources but also holds promise for improving rural livelihoods and significantly boosting fish output. Recognizing the transformative potential of pisciculture as a driver of economic development, the Government of India initiated a beneficiary-oriented scheme during the 5th Five-Year Plan. This pilot initiative, known as the Fish Farmers Development Agency (FFDA), was designed to promote self-employment and provide financial, technical, and extension support to rural fish farmers (Bairagya, 2011). Since its inception, FFDA has evolved into a centrally sponsored flagship program, expanding its reach and impact across the country.

India's fisheries sector benefits from its vast and diverse aquatic resources, encompassing both inland and marine ecosystems that stretch from the Himalayan rivers to the coastal waters of the Indian Ocean. This ecological richness supports a thriving fisheries industry that includes both capture and culture fisheries (Aigner & Chu, 1968; Alam *et al*., 2005; Anand, 2013). The sector plays a crucial role in sustaining millions of livelihoods, particularly in rural areas, by contributing to food security, employment, and income generation. As population growth continues to drive up the demand for fish protein, the sustainable development of aquatic resources has become an urgent national priority (Anjani *et al*., 2005).

Fisheries in India are not only a source of nutrition but also a cornerstone of rural economies. More than 16 million individuals are directly engaged as fishers and farmers, with many more employed in ancillary industries such as processing, transportation, and marketing (Anon. Handbook of Fisheries, 2013–14, 2014–15, 2015–16, 2017–18). Over the years, the sector has transitioned from traditional subsistence practices to a more commercialized enterprise, aligning with government goals to double the incomes of those involved (Banerjee, 2018; Barman, 2014). Despite impressive growth in fish production—from 7.54 lakh tonnes in 1950–51 to 95.79 lakh tonnes in 2013–14—challenges persist, especially in maintaining a balance between marine and inland fisheries (Anon. Handbook of Fisheries, 2013–14, 2014–15, 2015–16, 2017–18).

Inland fisheries, in particular, have experienced a decline in their share of total national fish production. This trend is attributed to factors such as habitat degradation, overexploitation, and inefficient resource management. To counter these issues, the Indian government has launched several initiatives, including the Pradhan Mantri Matsya Sampada Yojana (PMMSY). This scheme aims to modernize the fisheries sector by upgrading infrastructure, encouraging sustainable practices, and enhancing value chains (Cooper & Brand, 2007; Department of Animal Husbandry, Dairying, & Fisheries, 2018–19). Ensuring the long-term sustainability of fisheries requires effective governance, which involves coordination between central and state authorities and active participation from local communities. This is especially critical in the context of climate change and increasing environmental pressures (Clark, 1973; Coelli *et al*., 1997; Nayak & Kumar, 2019; Das *et al*., 2021).

In North Bengal, the expansion of pisciculture has been relatively slow for decades. However, recent years have witnessed a notable surge in fish farming activities across the region, leading to a structural transformation of inland fisheries toward commercialization. This shift began in the 1980s, with privately owned pond fisheries emerging as the dominant form of pisciculture. Today, pond-based fish farming is a rapidly growing enterprise in districts such as Uttar Dinajpur, Dakshin Dinajpur, Malda, Jalpaiguri, Coochbehar, and parts of Darjeeling (Agarwalla & Chatterjee, 2024). These areas are naturally endowed with extensive water bodies, making them well-suited for pisciculture development.

The increasing consumer preference for fresh fish in regional markets has further fueled the growth of pond fisheries. Nevertheless, merely expanding the number of fish ponds is insufficient to meet the escalating demand for fish. It is imperative to enhance the efficiency of fish production to maximize output. This can be achieved either by adopting advanced technologies that elevate the production possibility frontier or by optimizing the use of existing technologies to their full potential (Kumar *et al*., 2005; Katiha *et al*., 2005). The latter approach emphasizes improving resource use efficiency, which is crucial for achieving the highest possible yield and addressing future demand challenges (Mishra & Mishra, 2014; Chatterjee & Agarwalla, 2024).

1.1. Background of the study

Fisheries are a vital component of rural economies worldwide, offering food security, employment, and income to millions, especially in agrarian societies. In India, the fisheries sector is deeply embedded within the agricultural framework, with smallholder farmers forming its backbone. West Bengal stands out for its abundant water resources, positioning it as a key center for inland fisheries (Kundu, 2011). Despite this prominence, regions like North Bengal suffer from limited scholarly attention regarding the operational and efficiency dimensions of pond fisheries. Existing studies highlight that inefficiencies in fish production often stem from constraints such as small farm sizes, outdated practices, and inadequate access to extension services (Alam *et al*., 2005; Olaniyi, 2012; Sathiadhas *et al*., 2011). Addressing these gaps is essential for fostering sustainable growth and optimizing economic returns from small-scale aquaculture.

This research focuses on pond-fishery systems in North Bengal, India, but draws parallels with similar aquaculture models in Mediterranean regions like the Albufera lagoon in Valencia and the Doñana wetlands in Andalucía, Spain. These semi-intensive, family-run pond systems face comparable challenges, including inefficient input use, fragmented institutional support, and technical limitations (Pérez-Ruiz, 2021; De-los-Ríos-Mérida *et al*., 2017). In both Spanish regions, overdependence on organic fertilization and poor stocking strategies have undermined ecological balance and production efficiency, despite favorable natural conditions (Pérez-Ruiz, 2021). By juxtaposing Indian and Mediterranean experiences, this study underscores that inefficiencies in smallholder pond aquaculture are not region-specific but reflect broader systemic issues in resource-sensitive fisheries (Avnimelech, 2011).

To evaluate performance and identify areas for improvement, Data Envelopment Analysis (DEA hereafter) has emerged as a robust tool in fisheries research. Misra & Misra (2014) applied DEA to assess technical efficiency across fish farms and revealed significant disparities linked to farm size, ownership, and regional characteristics. These insights suggest that DEA could be effectively employed in North Bengal, where smallholders face persistent challenges such as overfishing, environmental stress, and market limitations (Roy, 2008). The present study aims to bridge the research gap by analyzing efficiency patterns in pond fisheries, thereby informing policy interventions for sustainable development.

Although North Bengal is primarily agricultural, its extensive land and water resources offer considerable scope for pisciculture expansion. The State Government has introduced training programs to promote scientific fish farming, yet overall production remains modest. Only select areas have adopted intensive practices with high efficiency, while others lag behind, indicating significant variation in yield and operational success across the region.

Two key factors could be contributing to the suboptimal growth in fish output: an inter-regional efficiency gap, where some regions excel while others lag, and an intra-regional efficiency gap, where variations in specialization and intensive practices exist within the same area. In this context, an essential area of study is to study the resource-use efficiency of fish farmers across different pisciculture zones. Such an analysis

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would reveal the extent to which fish farmers have benefited from government schemes aimed at expanding pisciculture. This paper seeks to estimate pond-level technical efficiency (TE) concerning the use of inputs like land, labor, and other resources to maximize potential output. This assessment is crucial to determine whether fish farms are operating at their full productive capacity or if resources are being underutilized, as well as to identify inefficiencies and opportunities for improving individual farm performance.

It deserves to be mentioned that the adaptation of the DEA for the estimation of Technical Efficiency (TE) in the pisciculture sector of North Bengal is still unfolded in the existing literature. Hence, a rising need for conducting a DEA augmented study to investigate the TE in the above-mentioned context, and also to see whether the potential realization of efficiency gain is fundamentally region-specific or region-neutral.

This paper is organized in the following way. Section 2 revisits the existing literature, While Section 3 and 4 describes Data and methodology, and its outcomes respectively. Finally, concluding remarks along with policy prescription has been mentioned in Section 5.

2. LITERATURE REVIEW

India, endowed with extensive inland and marine water resources, engages in both capture and culture fisheries, benefiting from diverse ecosystems ranging from the Himalayas to the Indian Ocean (Aigner & Chu, 1968; Alam *et al*., 2005; Anand, 2013). This biodiversity sustains millions of livelihoods, and as population growth fuels rising need for fish protein, the requirement for sustainable aquatic resource management becomes increasingly urgent (Anjani *et al*., 2005; Das *et al*., 2019). Fisheries play a critical role in India's economy, contributing to nutrition, employment, and income for approximately 16 million fishers and farmers, with millions more involved along the value chain (Anon. Handbook of Fisheries, 2013–14, 2014–15, 2015–16, 2017–18). Over the decades, fish production has risen significantly, transforming the sector into a key contributor to foreign exchange earnings and solidifying India's position as a leading seafood exporter. In 2018–19 alone, marine exports reached 13,92,559 metric tonnes, valued at Rs. 46,589 crore (USD 6.73 billion), largely due to brackish water aquaculture (Anon. Handbook of Fisheries, 2013–14, 2014–15, 2015–16, 2017–18). To address sustainability challenges, initiatives like the Pradhan Mantri Matsya Sampada Yojana (PMMSY) focus on modernizing the sector, improving infrastructure, and encouraging sustainable fishing practices (Cooper & Brand, 2007; Department of Animal Husbandry, Dairying and Fisheries, Ministry of Agriculture & Farmers Welfare, Government of India, 2018–19). Governance of the fisheries sector, characterized by a cooperative federalism approach, involves both central and state governments, with states managing inland fisheries and the central government regulating marine fisheries within the Exclusive Economic Zone (Kirkley *et al*., 1999; Nobuyuki *et al*., 2008; Karthikeyan *et al*., 2019; Nayak & Kumar, 2019). Close collaboration between these entities, alongside active participation from local communities, is essential for ensuring sustainable and responsible fisheries management (Neogi *et al*., 2016).

The available literature on fisheries in North Bengal is quite limited, necessitating the inclusion of studies from broader West Bengal, India, and international sources to understand the region's fisheries sector better. A focused study on the pond fishery in North Bengal is needed to analyze its various operational aspects, such as the economic rationale for the rise of smallholder fish farmers and the effects on the local economy. An essential aspect of this inquiry would be evaluating efficiency, as it is critical to assessing the performance of production units like pond fisheries. Studies on efficiency help to identify the causes of inefficiency, however limited empirical research has been conducted on this topic in North Bengal. For instance, Roy (2008) examined fish fingerling markets in Dakshin Dinajpur, identifying challenges and emphasizing the need for environmental awareness and collective efforts for sustainable fish production and marketing. Saha (2016) highlighted the sustainability challenges in the coastal fisheries sector of West Bengal. Similar studies outside India, like Alam *et al*. (2005) in Bangladesh, showed how age, experience, and farm size influenced economic efficiency in fish farming. Misra & Misra (2014) further applied meta-frontier DEA to fish farms in West Bengal, revealing that farm size, ownership, and experience significantly impacted technical efficiency. Their findings suggested that targeted development strategies could improve overall efficiency in fish farming.

Other studies contribute to this body of knowledge by highlighting efficiency in agriculture and fisheries management across regions. Kundu (2011) focused on the growth of inland fisheries in Dakshin Dinajpur, West Bengal, and suggested measures to address local challenges. Olaniyi (2012) studied fish production in Nigeria, finding that efficient use of labor and fingerlings increased productivity. Hossain *et al*. (2015) analyzed banana farming efficiency in Bangladesh, stressing the importance of education and modern cultivation techniques. Ekramuddin (2017) explored the socio-economic impact of small-scale fish farming in Birbhum, West Bengal, and Majumder (2017) investigated tea-growing efficiency in the region, showing how smallholders could improve their productivity. Similarly, Moges *et al*. (2018) analyzed teff farming efficiency in Ethiopia, finding potential for improvement through better resource use, while Singh & Devi (2020) emphasized the role of investments, education, and credit access in improving carp production efficiency in Manipur. These studies underline the critical importance of efficiency in fisheries and agriculture, making a compelling case for further research on pond fisheries in North Bengal to fill existing knowledge gaps and promote sustainable growth in the region.

While DEA has been extensively adopted to evaluate the technical efficiency of fish farms in other regions (e.g., Alam *et al*., 2005; Misra & Misra, 2014; Moges *et al*., 2018; Chatterjee & Agarwalla, 2024), its application in the context of North Bengal's pond fisheries is scarce. There is a gap in empirical studies that use DEA to analyze the efficiency of pond fisheries in this specific region. This limits the understanding of how efficiently resources like land, labor, and feed are utilized in these smallholder fisheries. Existing DEA studies, such as those by Misra & Misra (2014), focus on broader regional or national scales, but they do not provide insights into the unique socio-economic and ecological characteristics of North Bengal. There is a need for location-specific DEA models that account for the particular environmental and economic conditions of North Bengal's pond fisheries. This would help to develop tailored strategies for improving efficiency in the region.

In conclusion, these studies underscore the economic importance of fisheries, the key factors affecting production efficiency, and the pressing need for sustainable development strategies, particularly in regions such as North Bengal. The proposed research seeks to address existing gaps by investigating the operational dynamics and efficiency of pond fisheries, with the goal of providing valuable insights to guide policy-making and development efforts.

3. DATA AND METHODOLOGY

3.1. Data collection

The present study is based on the primary data composed through a field survey in the districts of Uttar Dinajpur and Dakshin Dinajpur in 2023. Next, two blocks, namely, Raiganj and Hemtabad are selected from Uttar Dinajpur while Balurghat and Gangarampur are selected from Dakshin Dinajpur.

In the next stage, two villages are selected from each of the four blocks chosen in the first stage. The villages, namely, Kantore and Goalpara are selected from Raignaj Block, and the villages, namely, Chainpara and Kothagaram are selected from Hemtabad Block. The villages Ajodhya and Kothagaram are selected from Balurghat block and the villages Kathalhat Hosenpur and Narayanpur are selected from Gangarampur block). The detailed scheme of data collection can be seen from the following figures 1 and 2.

As shown in figure 1 above, from the Raiganj block of Uttar Dinajpur, a total of fifteen samples are collected, a total of seven samples from Kantore village and another eight samples from Goalpara village. From the Hemtabad block of Uttar Dinajpur, a total of fifteen samples were collected of which seven samples were collected from Chainpara village and eight samples were selected from Kothagaram village. Thus, a total of thirty samples were collected from the district of Uttar Dinajpur.

It can also be observed from the above figure that from the Balurghat block of Dakshin Dinajpur, a total of fifteen samples are collected, out of the total, seven samples from Ajodhya village, and the remaining eight samples from Kothagaram village are collected. From the Gangarampur block of Dakshin Dinajpur, a total

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of twenty samples were collected, out of which ten samples were collected from Kathalhat Hosenpur village, and the rest of the ten samples were selected from Narayanpur village. In this way, data were collected from a total of sixty-five pond-owner households residing in eight villages in the two districts under study. The data are collected using a pre-designed structured questionnaire.

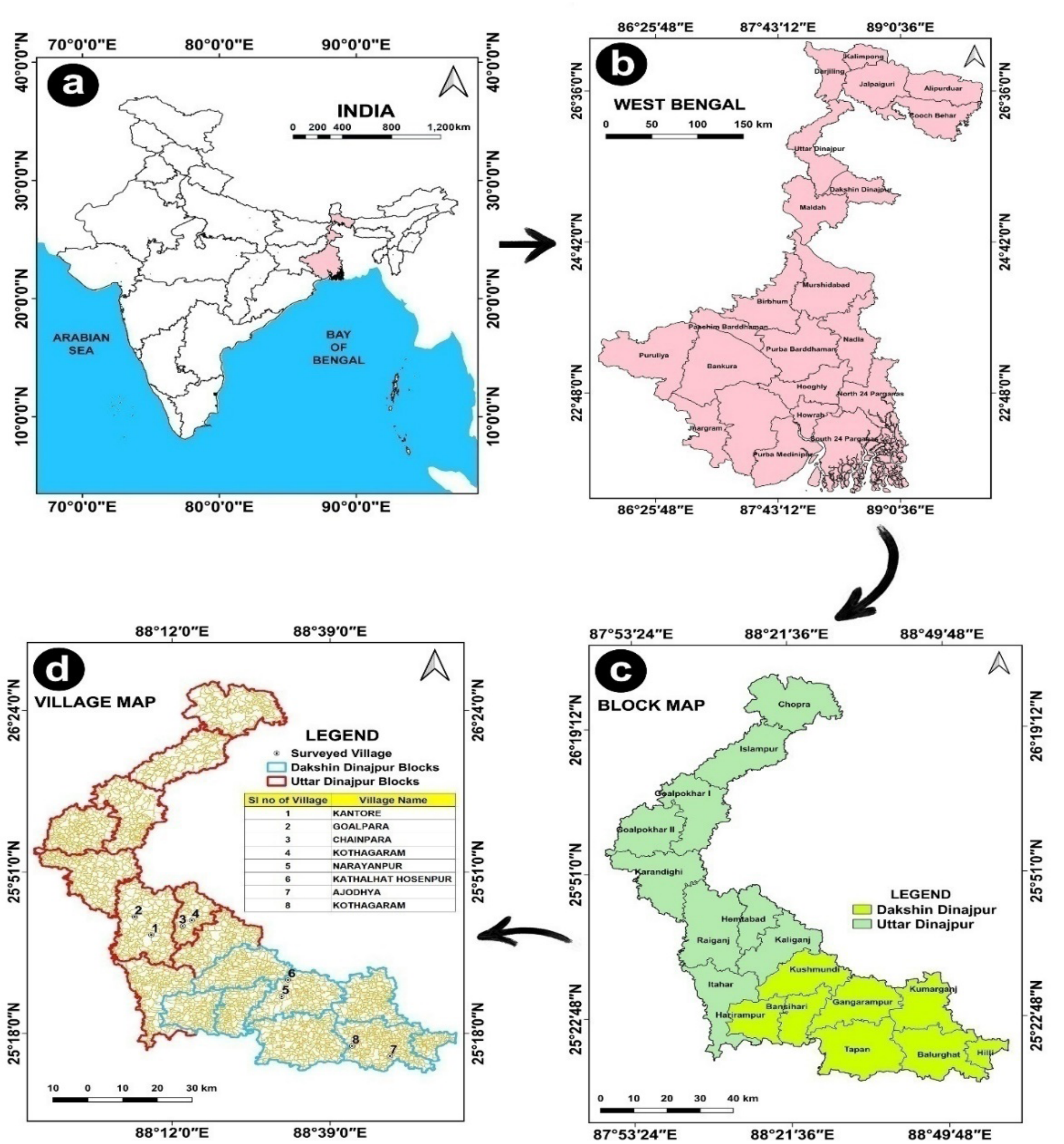

Figure 1. Illustration of Districts and Blocks selection a) India b) West Bengal c) Selection of C.D. blocks d) Selection of villages. Source: author's own elaboration.

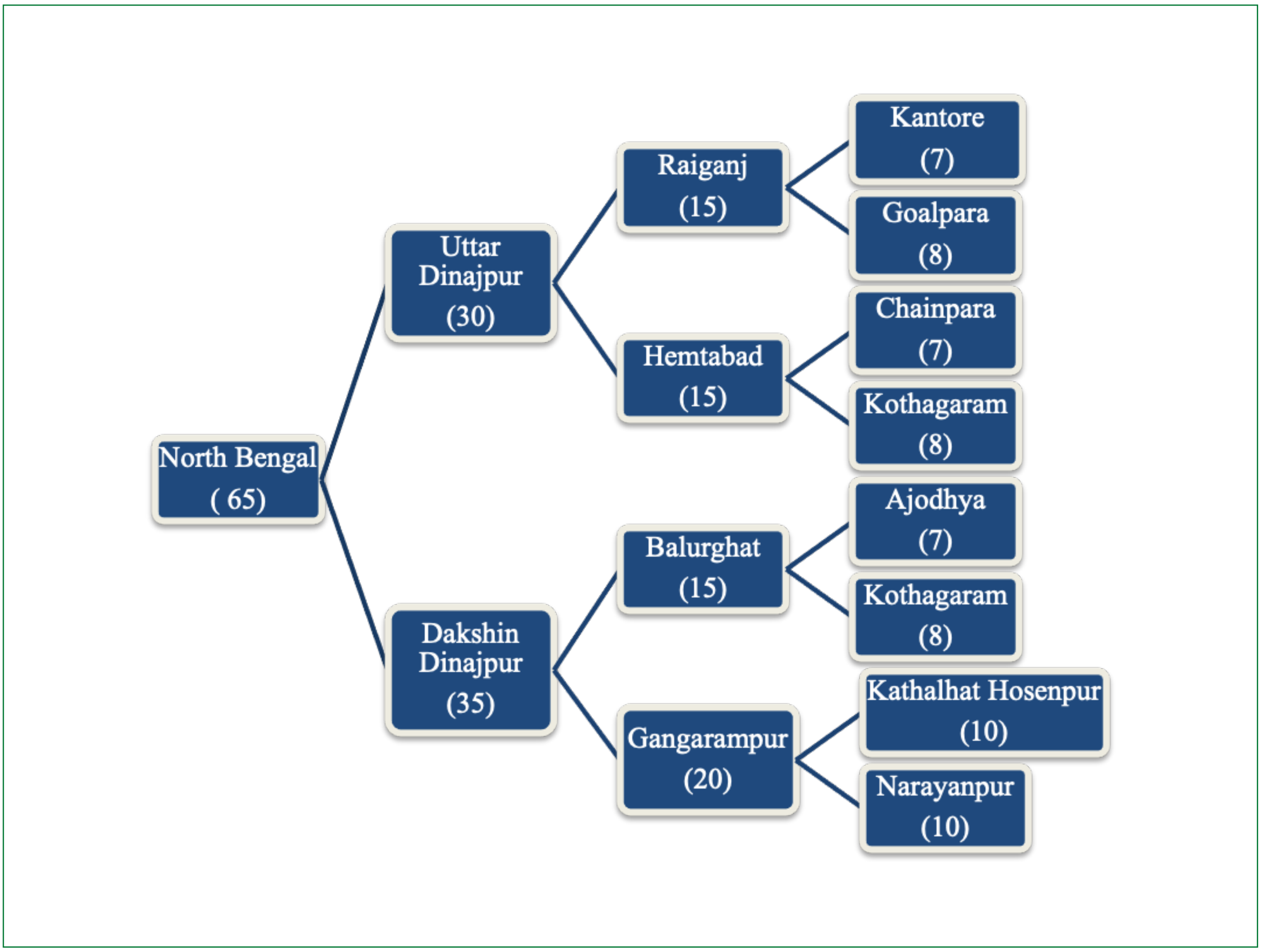

Figure 2. Schematic presentation of data collection. Source: author's own elaboration.

In the selection of districts, the following factors are prioritized:

1. Both districts encompass extensive water bodies, representing nearly half of North Bengal's total impounded water area.
2. Each district has a high density of tanks and ponds.
3. They share a unified agro-climatic zone due to similar soil types, climate conditions, and other environmental features. Their adjacency further facilitates a meaningful comparative analysis.

Fish farmers in these districts cultivate various species, sourced either from fish seeds or fingerlings purchased from the market. Production output is measured as the combined real value of all fish species, rather than individually, due to farmers' general reluctance or limitations in providing species-specific data on seed use or fish composition.

3.2. Analytical framework

This study employs the traditional framework of Data Envelopment Analysis (DEA), specifically using the CCR and BCC models. DEA calculates the production frontier for a group of decision-making units (DMUs) and assesses each unit's relative technical efficiency, differentiating efficient from inefficient DMUs. The 'best practice units,' or those that define the frontier, receive a score of one, while the technical inefficiency of other DMUs is determined by the Euclidean distance of their input-output ratio from this frontier (Charnes *et al*., 1978).

Technical Efficiency (TE) indicates a DMU's capability to maximize output given certain inputs and technology, or to achieve optimal reductions in input quantities with existing input prices and outputs (Farrell, 1957). A high TE score reflects effective resource use, yielding maximum output, whereas a low score implies that resource utilization could be optimized to increase output without additional resources. In this analysis, an input-oriented DEA model is deemed appropriate, as aquaculture farms generally have greater control over inputs than outputs (Sharma *et al*., 1999; Kumar *et al*., 2010). Notably, most previous studies have used an input-oriented DEA to assess the technical efficiency of aquaculture farms. Since input- and output-oriented measures yield identical TE scores, the interpretation remains consistent regardless of the chosen approach (Färe *et al*., 1994; Kumar *et al*., 2004).

The selection of inputs for the DEA model was guided by both theoretical considerations and practical constraints from field data collection. The four inputs, namely, fingerlings, land area, organic manure (cow dung), and labor, represent the most direct, commonly used, and consistently measurable production factors across all sampled pond fisheries. These inputs reflect essential operational components in smallholder aquaculture where formal record-keeping is limited (Agarwalla & Chatterjee, 2024). While variables like feed and veterinary costs are indeed important in commercial aquaculture, their exclusion was based on two key reasons: first, inconsistent reporting and lack of standardized measurement among fish farmers made the data unreliable; and second, many respondents either did not use commercial feed or veterinary services at all, relying instead on organic practices and household labor. Thus, including these variables would have introduced bias or measurement error (Chatterjee & Agarwalla, 2024; Agarwalla & Chatterjee, 2024). The chosen inputs, by contrast, are uniformly used and offer a reliable basis for technical efficiency analysis using DEA.

3.3. Model specification

Consider a scenario where n decision-making units (DMUs) or firms generate m distinct outputs using h various inputs. In this context, Y represents a $(m \times n)$ matrix of outputs, while X is an $(h \times n)$ matrix of inputs. Both matrices collectively encapsulate data for all n firms. The input-oriented Data Envelopment Analysis (DEA) model, employed to determine technical efficiency (TE) under the assumption of constant returns to scale (CRS), can be structured as follows (Esmaeili & Omrani, 2007):

$$\begin{cases} Min\ \theta \\ \text{Subject to } y_i + Y\lambda \geq 0 \\ \theta x_i - X\lambda \geq 0 \\ \lambda \geq 0 \end{cases}$$

This model is applied to each decision-making unit (DMU) or firm within the sample. The term θ_i represents the technical efficiency index of firm i relative to the other firms in the sample, with values ranging from 0 to 1. Here, y_i and x_i denote the output and input vectors of firm i, respectively, while λ is an $(n \times 1)$ vector of constants (or weights). The terms $(Y\lambda)$ and $(X\lambda)$ correspond to the efficient projections onto the frontier. It is to be noted that here a value of θ, that is, $\theta = 1$ signifies that the firm is fully technically efficient. Consequently, $(1 - \theta_i)$ quantifies the proportional reduction in inputs possible for firm without compromising output levels. However, the constant returns to scale (CRS) assumption holds only when firms operate at optimal scale (Coelli *et al*., 2002). If firms are not at optimal scale, using the CRS input-oriented DEA model could lead to technical efficiency (TE) measurements affected by scale efficiencies, thus resulting in inaccurate TE estimates. To address this, Banker *et al*. (1984) proposed the variable returns to scale (VRS) DEA model, which incorporates a convexity constraint into the original model, forming what is known as the BCC model, specified as follows:

$$\begin{cases} Min\ \theta \\ \text{Subject to}, y_i + Y\lambda \geq 0 \\ \theta x_i - X\lambda \geq 0 \\ NI'\lambda = 1 \\ \lambda \geq 0 \end{cases}$$

The newly introduced constraint $NI'\lambda = 1$ represents the variable returns to scale (VRS) condition, where NI is a $(n \times 1)$ vector consisting entirely of ones. This constraint facilitates the comparison of DMUs of similar scale by constructing a convex hull of intersecting planes, allowing for a more precise envelopment of the data. Technical efficiency measures are thereby refined. To estimate three efficiency measures, CRS Technical Efficiency, VRS Technical Efficiency, and Scale Efficiency, the DEAP software package version 2.1 (Coelli, 1997) is employed.

4. RESULTS

4.1. DEA results

We present below an analysis of DEA results by considering a single data set being consisted of the DMUs of both districts of Uttar Dinajpur and Dakshin Dinajpur. Table 1 illustrates the summary statistics of variables of our interest.

Table 1. Descriptive Statistics of Inputs and Output variables (Uttar Dinajpur + Dakshin Dinajpur).

Variables	Minimum	Maximum	Mean	Std. Dev.
Variable Output (Y)	170.00	74000.00	10031.11	14205.52
Variable Input				
x_1	50.00	375.00	127.54	78.17
x_2	3.00	50.00	9.98	7.53
x_3	500.00	8000.00	2077.47	1171.18
x_4	1.00	7.00	2.94	1.14

Source: author's own derivation based on primary survey.

The descriptive statistics for TE scores for an inputs-oriented BCC-I model are presented below in table 2.

Table 2. Descriptive Statistics for TE Scores.

Statistics (%)	CRS Value (%)	VRS Value (%)	Scale (%)
Minimum TE	1.10	25.00	1.10
Maximum TE	100.00	100.00	100.00
Mean TE	30.39	73.75	37.73
Std. Deviation	37.53	23.42	41.77
Range	98.90	75.00	98.90

Source: author's own derivation based on primary survey.

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The analysis reveals a broad range in technical efficiency (TE) scores, with a minimum of 25 percent and a maximum of 100 per cent. The average TE of the decision-making units (DMUs) is estimated at approximately 74 per cent, reflecting a moderate level of efficiency across the sector. This mean TE score of 74 per cent suggests that, on average, fish farms could reduce input usage by about 27 per cent while maintaining the same level of output. This finding also implies a potential 27 per cent improvement in yield within the sector. In other words, inefficient fish farms could increase their yield by this margin to match the performance of "best practice" farms. The frequency distribution of TE scores is presented in table 3 and figure 3 below.

Table 3. Distribution of Efficiency Score of Fish Farms in North Bengal.

Efficiency Range (%)	Percentage of Fishing Farms		
	Technical Efficiency CRS	Technical Efficiency VRS	Scale Efficiency
Less than 20	58.47	0	58.47
20-40	7.79	9.23	1.54
40-70	4.72	20	3.08
70-80	15.38	27.79	10.77
80-100	4.72	7.79	17.92
"Best Practice farm" (TE/ SE=1)	9.23	35.38	9.23
Total	100	100	100

Source: author's own elaboration.

An analysis of table 3 reveals that approximately 35.38 per cent of fish farms in the sample operate with optimal efficiency, indicating that a significant portion of farms are performing below potential. This presents considerable opportunities to enhance the technical efficiency (TE) levels among fish producers. The table also shows that around 71 percent of decision-making units (DMUs) achieve efficiency scores between 70 and 100 per cent, demonstrating that the expansion of aquaculture in the study area has been largely motivated by substantial efficiency gains and the profit potential this emerging sector offers.

Further examination of table 3 highlights that best practices in aquaculture have not been widely adopted across the sample, resulting in notable variations in TE scores. Discussions with the sample farmers indicated that many were not following recommended schedules for fish farming practices, with a significant number unaware of specific scientific methods. Therefore, to address technical inefficiency in North Bengal's fish farming sector, it is crucial to implement optimal farming practices and effective input management based on the methods of the most efficient farms.

A DMU is considered scale efficient when its operational size is optimal, as any changes in scale would reduce its efficiency. Scale efficiency is determined by dividing overall efficiency by pure technical efficiency. In this study, nine percent of the fish farms are identified as scale-efficient, with a scale efficiency score of one, indicating no further room for improvement in scale efficiency. Seventeen percent of DMUs are close to achieving efficient operation, with efficiency scores of 80 per cent or higher, suggesting they have the potential to reach top efficiency levels. However, 62 per cent of DMUs exhibit scale efficiency below 60 per cent, and 59 per cent operate with scale efficiency under 20 per cent, signaling significant room for improvement.

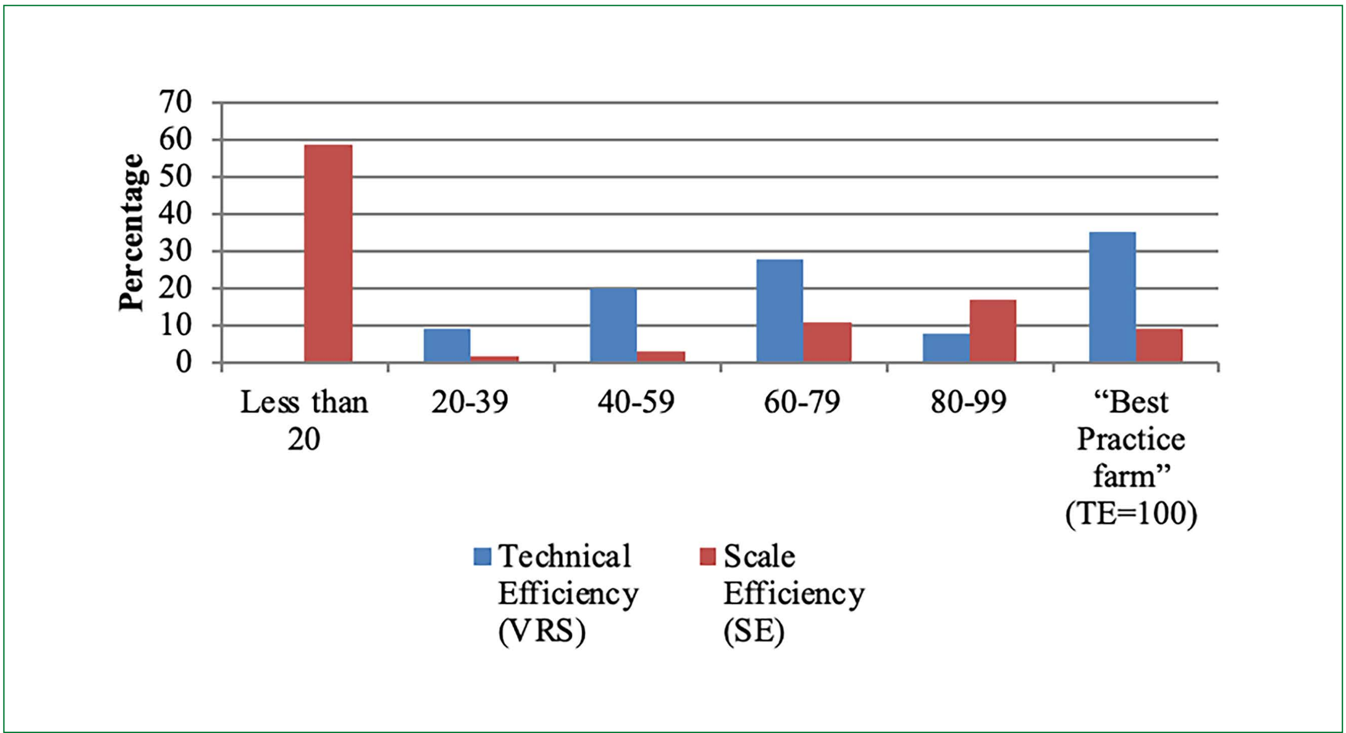

Figure 3. Technical Efficiency (VRS) & Scale Efficiency (SE). Source: drawn by author(s) based primary survey.

4.2. Source of technical inefficiency

The DEA mechanism provides us crucial information on how inefficient DMUs can be made efficient by diminishing inputs and/or rising outputs. The table 4 provides figures on such input excesses and output shortfalls.

Table 4. Input Excesses and Output Shortfalls of Dinajpur.

DMUs	Inputs				Output Surplus/ Deficit (%)
	Fingerling Surplus/ Deficit (%)	Land Area Surplus/ Deficit (%)	Cow-dung Surplus/ Deficit (%)	Labour Surplus/ Deficit (%)	
1	53.21	47.59	35.54	57.73	0.00
2	47.34	48.23	72.87	70.00	0.00
3	37.79	37.79	47.37	37.70	0.00
4	30.04	30.04	41.89	55.00	0.00
5	21.37	21.37	21.37	34.05	0.00
7	78.94	37.20	37.20	49.17	0.00
7	0.00	35.79	71.32	75.70	0.00
8	0.00	0.00	0.00	0.00	0.00
9	0.00	17.77	79.38	0.00	-242.72
10	0.00	70.00	59.58	48.35	0.00

DMUs	Inputs				Output Surplus/ Deficit (%)
	Fingerling Surplus/ Deficit (%)	Land Area Surplus/ Deficit (%)	Cow-dung Surplus/ Deficit (%)	Labour Surplus/ Deficit (%)	
11	52.41	22.75	22.75	42.82	0.00
12	9.09	9.09	12.30	24.53	0.00
13	57.87	37.39	37.39	37.40	0.00
14	0.00	0.00	0.00	0.00	0.00
15	27.57	17.43	20.73	17.45	0.00
17	0.00	0.00	0.00	0.00	0.00
17	77.77	77.89	77.77	77.75	0.00
18	33.33	70.00	17.77	50.00	-1090.48
19	50.00	28.58	28.57	38.10	-1199.89
20	77.77	53.77	53.78	75.70	0.00
21	49.21	39.78	50.84	75.70	0.00
22	0.00	58.49	59.25	47.18	0.00
23	50.00	75.87	75.87	75.87	0.00
24	77.05	49.78	70.45	74.08	0.00
25	77.77	71.13	73.23	77.75	-12.97
27	0.00	29.17	11.50	0.00	-279.41
27	75.00	75.00	87.33	77.10	0.00
28	75.79	72.14	70.23	74.73	0.00
29	77.74	54.77	49.72	49.70	0.00
30	0.00	0.00	0.00	0.00	0.00
31	50.00	70.00	17.77	50.00	0.00
32	0.00	0.00	0.00	0.00	0.00
33	0.00	0.00	47.22	33.50	-448.15
34	0.00	0.00	0.00	0.00	0.00
35	74.17	37.34	37.35	49.43	0.00
37	20.78	53.01	20.78	20.70	0.00
37	48.44	74.37	48.44	58.37	0.00
38	30.79	53.75	34.98	30.80	0.00
39	0.00	0.00	0.00	0.00	0.00
40	52.99	57.78	40.15	40.15	0.00
41	42.40	19.27	19.27	19.25	0.00

DMUs	Inputs				Output Surplus/ Deficit (%)
	Fingerling Surplus/ Deficit (%)	Land Area Surplus/ Deficit (%)	Cow-dung Surplus/ Deficit (%)	Labour Surplus/ Deficit (%)	
42	0.00	0.00	0.00	0.00	0.00
43	70.54	71.93	49.77	49.75	0.00
44	0.00	0.00	0.00	0.00	0.00
45	0.00	0.00	0.00	25.25	-77.97
47	0.00	29.17	79.27	0.00	-330.00
47	33.33	50.00	0.00	33.33	-1438.47
48	0.00	0.00	47.92	50.00	-218.75
49	77.41	49.80	78.27	49.80	0.00
50	50.00	79.25	73.80	75.83	0.00
51	77.78	48.70	47.92	73.70	0.00
52	49.95	59.78	85.01	49.95	0.00
53	77.78	77.19	77.19	77.20	0.00
54	0.00	55.71	70.22	47.00	0.00
55	33.33	75.80	80.98	33.50	0.00
57	50.00	39.13	39.13	75.43	0.00
57	0.00	0.00	0.00	0.00	0.00
58	0.00	0.00	0.00	0.00	0.00
59	33.33	33.33	77.14	33.50	0.00
60	77.40	49.80	73.48	49.80	0.00
61	77.24	77.24	72.72	77.23	0.00
62	0.00	0.00	0.00	0.00	0.00
63	73.77	54.77	50.00	50.00	0.00
64	33.33	70.72	33.33	33.50	-297.03
65	28.55	28.55	28.55	53.53	0.00

Source: author's own elaboration.

In table 4, there is a total of sixty-five DMUs and among them twelve (i.e., nineteen percent of the total DMUs) are referred to as efficient DMUs, as they lie on the efficient frontier line with zero input excesses and zero output shortfall, and the rest eighty-one percent need to bring close to this efficient frontier line through decreasing inputs and/or increasing outputs. Consider, for example, DMU numbered 45 in the above table. For it, output could be increased by 78 per cent without altering the level of inputs. On the contrary, the input of labour could be reduced by 25 per cent without changing the level of output. Notice that, unlike the input of labour, there is neither any deficit nor any surplus in the utilization of the other three inputs, namely, fingerling, land area, and organic manure. This indicates that there is an optimal utilization of this input by the concerned DMU.

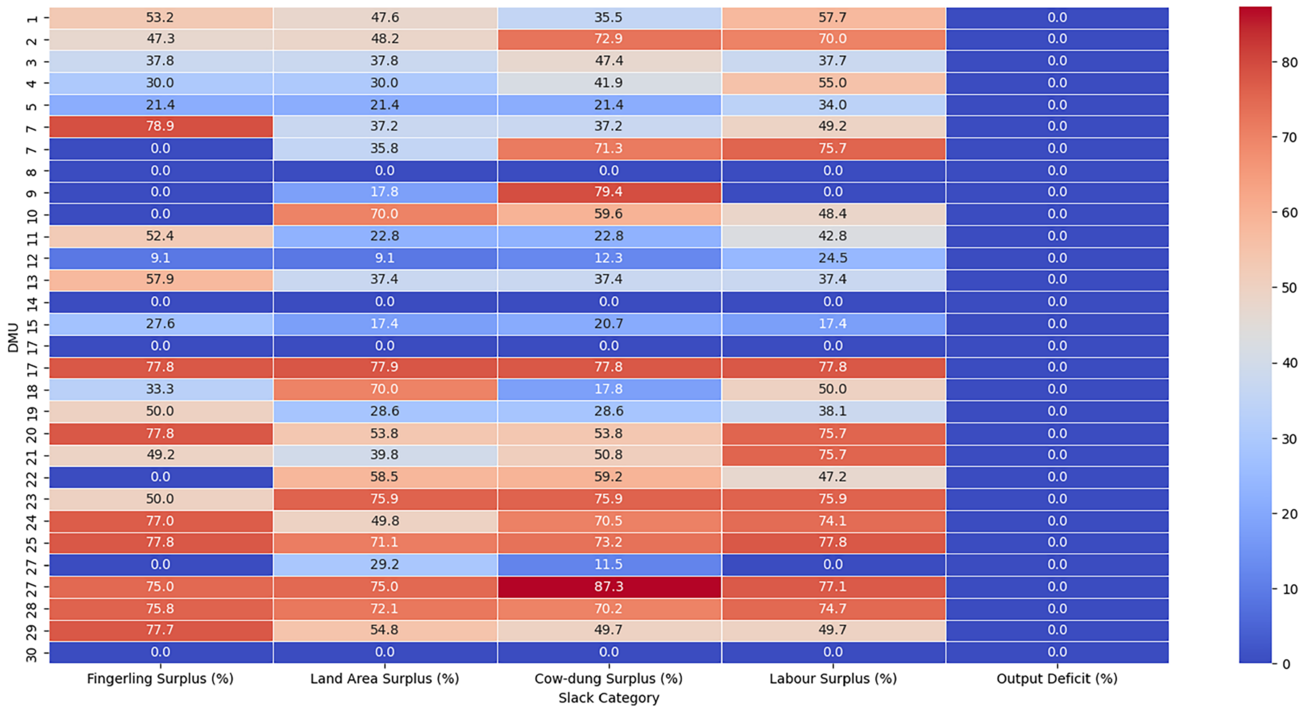

Figure 4. Slack Analysis Heatmap for Uttar Dinajpur District. Source: author's own elaboration.

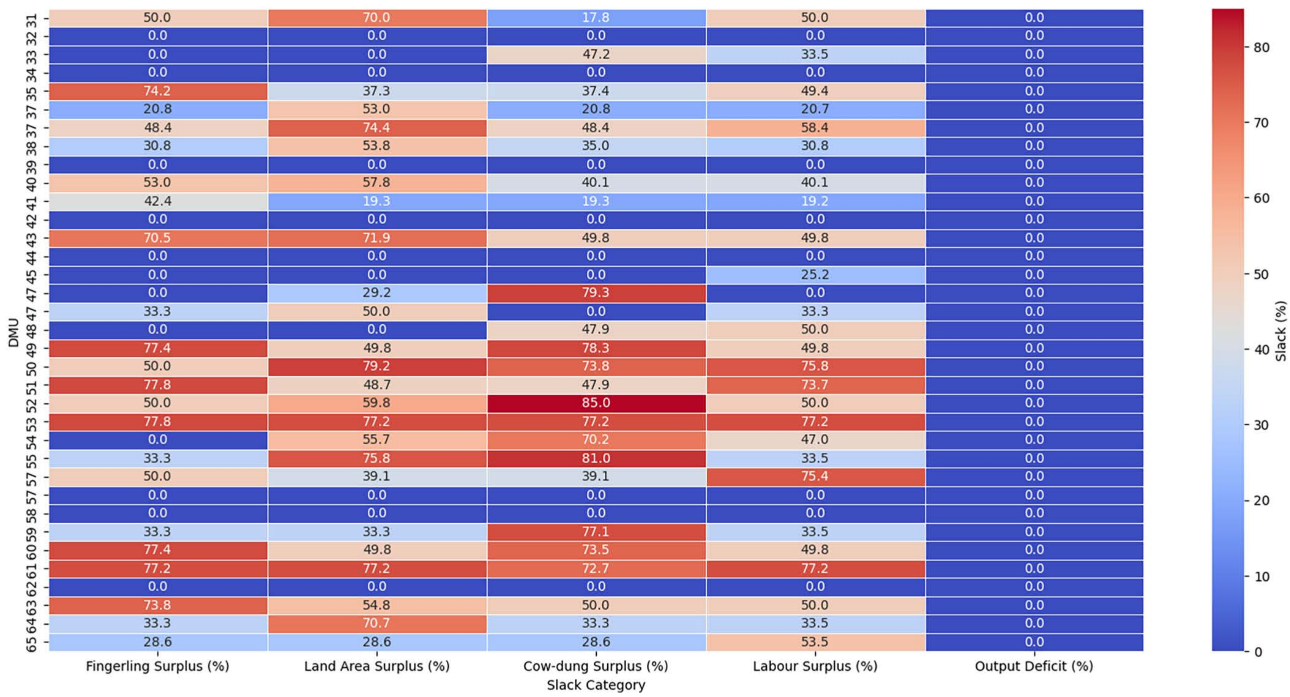

Figure 5. Slack Analysis Heatmap for Dakhsin Dinajpur District. Source: author's own elaboration.

Figures 4 and 5 present heatmaps illustrating the slack values for each decision-making unit (DMU) across the four input categories, namely, fingerlings, land area, cow dung, and labor, as well as the output slack for the districts of Uttar Dinajpur and Dakshin Dinajpur, respectively. These heatmaps help visually identify areas where inefficiencies are concentrated by showing the magnitude of excess input use and shortfall in output across DMUs. In Uttar Dinajpur (figure 4), noticeable inefficiencies are observed particularly in the use of cow dung and fingerlings, with several DMUs displaying slack values exceeding 70 per cent, indicating considerable scope for input optimization. Conversely, Dakshin Dinajpur (figure 5) exhibits a more dispersed pattern of inefficiency, with multiple DMUs showing both moderate and high levels of slack across all input categories. The spatial variation of slack across both districts suggests the presence of intra-regional differences in resource-use efficiency, highlighting the need for targeted technical interventions tailored to local input use patterns.

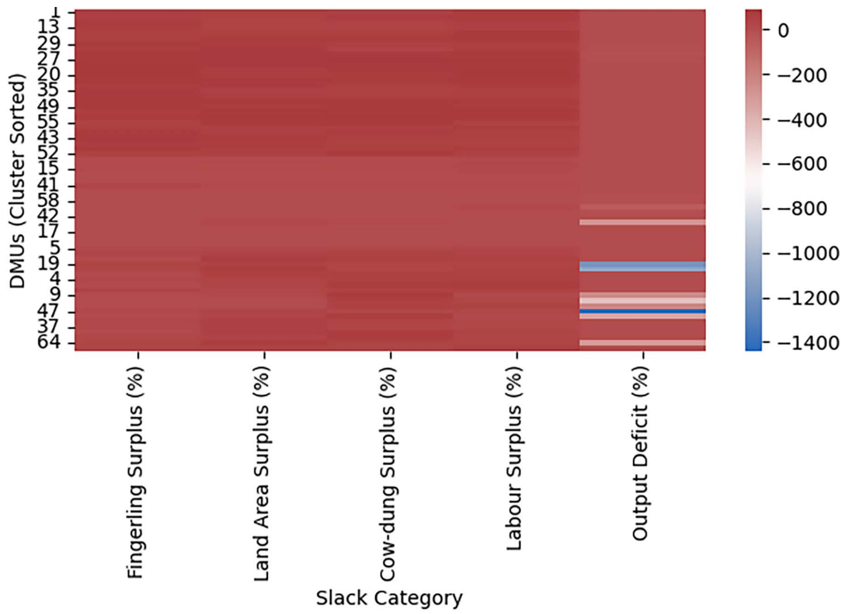

Figure 6. DMU Slack Patterns Clustered. Source: author's own elaboration.

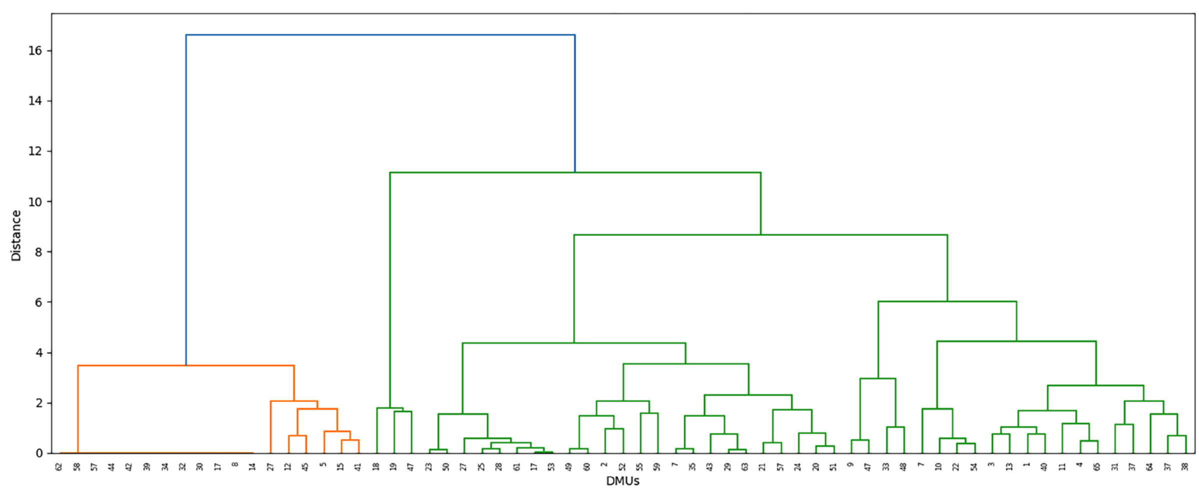

Figure 7. Hierarchical Clustering of DMUs. Source: author's own elaboration.

Figures 6 and 7 explore the grouping of DMUs based on their slack characteristics using clustering techniques. Figure 6 presents a cluster heatmap derived from K-Means clustering, showing how DMUs with similar slack profiles are grouped into distinct clusters. This analysis reveals that certain DMUs systematically underperform due to overuse of specific inputs like organic manure or labor, while others demonstrate near-optimal efficiency. Figure 7 complements this with a hierarchical clustering dendrogram, which provides a tree-like visual of the similarity structure among DMUs. It identifies clusters not only by input inefficiency but also by the degree of deviation from best practices. The hierarchical arrangement shows nested relationships and distances between clusters, revealing which DMUs are closer in performance and which are outliers. Together, these figures help in classifying fish farms into meaningful categories, such as high-potential improvers or consistently efficient operators, and can inform location-specific policy measures or training programs.

Here, table 5 shows the potential average saving of inputs along with the potential average improvement in output.

Table 5. Output Slack and Inputs Slack of Combined Dataset.

Variables	Mean of Combined Dataset
Output slack	542.102
Input Slack	
x_1	12.587
x_2	1.187
x_3	291.722
x_4	0.4

Source: author's own elaboration.

In the above table, the output slack refers to a shortfall of production of output relative to the efficient level and input slack means the excess use of an input relative to the best practice level. The output slack figure in the above table indicates that the average increase in output required for a DMU to become efficient is to the tune of nearly five hundred and fifty percent given the input levels. The inefficient DMUs can also be made efficient through reductions in the usage of inputs while keeping the output level constant. For example, fish fingerling could be reduced by twelve percent to produce the given output level. This input reduction level could be said to be of moderate magnitude. It can be noticed next that there is almost an efficient utilization of input x2 which represents the land area. This seems to indicate the land size neutrality of pond fish farming. However, there seems to be excessive utilization of organic fertilizer (i.e. cow dung) which could be reduced by nearly three hundred percent. Finally, the average reduction in labour input is almost insignificant being less than one percent.

4.3. Robustness checks

Figures 8 and 9 provide a dimensionality-reduced visualization of DMU clustering using two advanced machine learning techniques: Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE), respectively. Figure 8 employs PCA to reduce the multidimensional slack data into two principal components, enabling a clear 2D visualization of the relative positioning of DMUs in terms of their inefficiency profiles. Clusters here are more linearly separable, and DMUs within the same cluster demonstrate similar slack magnitudes and structures. Figure 9, using t-SNE, captures more complex, non-linear relationships in the data and reveals more nuanced local clustering patterns. The tighter and more

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irregular groupings visible in this figure highlight DMUs with shared inefficiency traits, even if they are less distinguishable through linear methods. These visualizations strengthen the analytical framework by reinforcing the consistency of DMU classification across both linear and non-linear lustering strategies and further validate the robustness of the DEA-based efficiency segmentation.

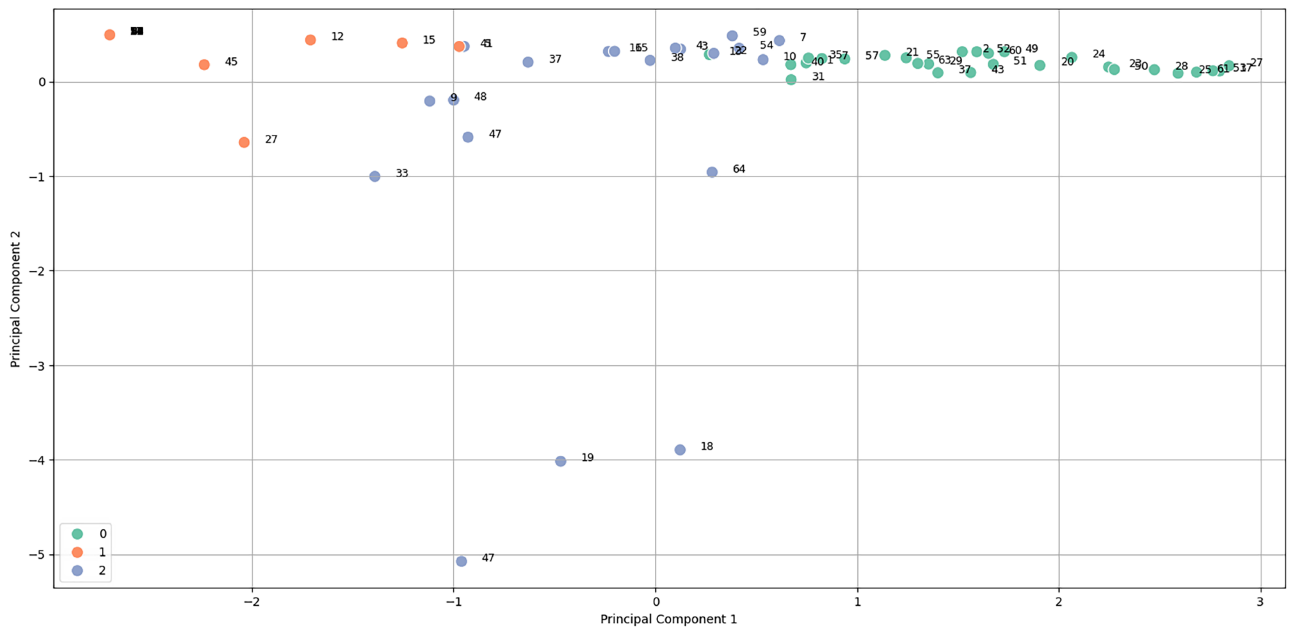

Figure 8. DMU Clustering using Principal Component Analysis. Source: author's own elaboration.

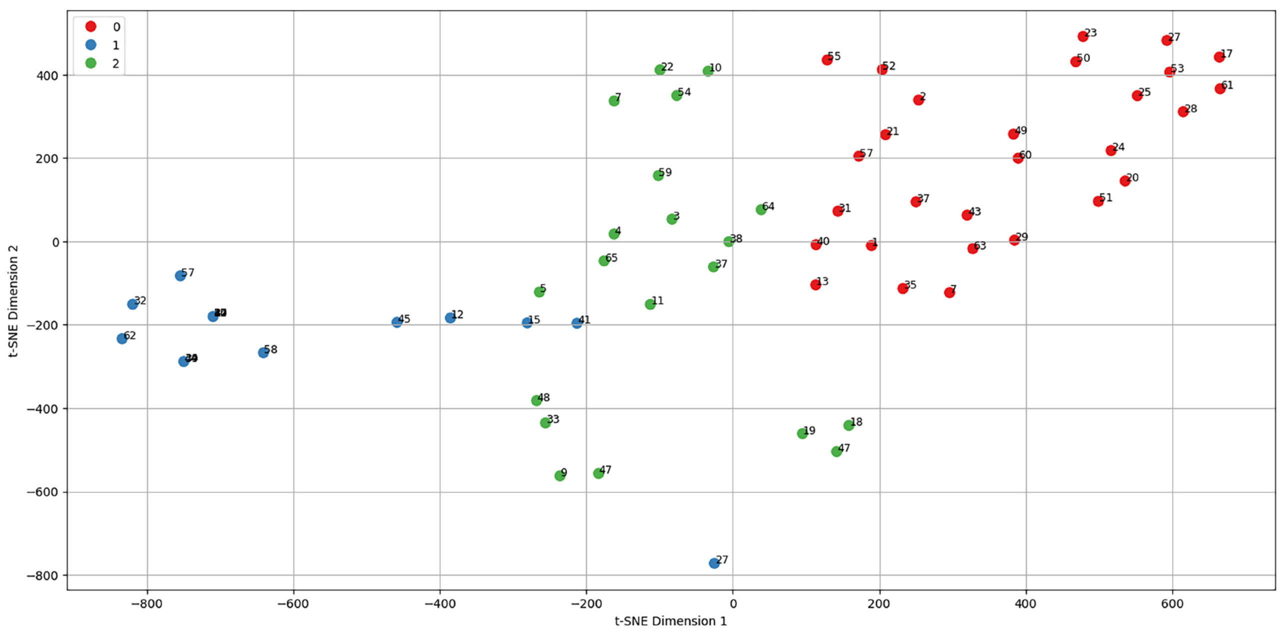

Figure 9. DMU clustering by t-distributed Stochastic Neighbor Embedding. Source: author's own elaboration.

5. DISCUSSION AND CONCLUSIONS

5.1. Summary of findings and discussions

The study highlights that North Bengal, while endowed with rich natural water resources and a substantial base of traditional expertise in aquaculture, has yet to fully realize its potential in pond-based fish farming (Agarwalla & Chatterjee, 2024). Despite the physical and human capital present, aquaculture growth in the region has been hindered by suboptimal productivity and inefficient input use. This discrepancy between actual and potential output reflects both technical gaps and systemic challenges—ranging from lack of scientific training and poor-quality fingerlings to the underutilization of water resources and limited access to institutional support (Chatterjee & Agarwalla, 2024). The evidence suggests that the performance gap is not due to ecological limitations, but rather rooted in the inefficient management of available resources and the absence of coordinated policy action.

The DEA results point to an average technical efficiency of 74% under the BCC model, indicating a potential for 27% improvement in input usage while maintaining current output levels. Over one-third (35.38%) of the fish farms were identified as fully technically efficient, which shows that efficiency gains are possible even within existing environmental and economic constraints. This reinforces the idea that targeted improvements in management practices could significantly raise overall sector productivity. These findings resonate with global trends in semi-intensive aquaculture, especially in Mediterranean contexts. For example, in the Albufera region of Spain, Pérez-Ruiz *et al*. (2021) identified similar inefficiencies due to outdated fertilization methods and suboptimal stocking, despite the presence of suitable ecological conditions. Likewise, De-los-Ríos-Mérida *et al*. (2017) noted that aquaculture systems in Fuente de Piedra suffered from overuse of nutrients and fragmented institutional oversight, which mirrors the issues found in North Bengal's pond systems.

Such cross-regional parallels reinforce the argument that technical inefficiencies in pond culture are not geographically isolated but part of a broader structural pattern in smallholder aquaculture, often tied to dependency on organic inputs, poor integration with extension services, and risk-averse behavior among farmers. Thus, the insights generated from North Bengal are not only locally actionable but also globally relevant. As Sicuro (2024) and Avnimelech (2011) suggest, transitions to sustainable and efficient aquaculture require integrated strategies that combine technical training, input regulation, insurance mechanisms, and capacity-building among producers.

5.2. Policy caveats and recommendations

The implications for policy are immediate and substantial. First, government agencies, particularly the Department of Fisheries, must prioritize region-specific extension services that translate "best practices" from fully efficient farms to those lagging behind. Demonstration farms could serve as knowledge hubs, offering peer-based training and mentorship. Second, input markets, especially those for fingerlings and organic fertilizers, must be regulated to ensure quality and optimize usage. Third, creating insurance mechanisms tailored for small aquaculture units could reduce farmers' risk aversion and encourage innovation and investment in improved techniques. In addition, collaborative public-private partnerships should be explored to facilitate access to affordable technology and capital.

5.3. Study limitations

This study is limited to pond aquaculture systems and does not account for other forms such as cage culture, flow-through systems, or integrated farming. The geographic focus on two districts, namely, Uttar and Dakshin Dinajpur, further narrows the generalizability of the findings to the broader aquaculture landscape of West Bengal or India. Moreover, while DEA captures technical inefficiency, it does not account for allocative or cost efficiency, which are equally important for commercial viability. Future studies could integrate socio-economic dimensions, cost structures, and longitudinal data to capture dynamic changes in efficiency and productivity.

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Responsibilities and conflicts of interest

The authors declare that there are no conflicts of interest regarding the research, authorship, or publication of this article. Author 1 and Author 2 contributed to the conceptualization of the study, literature review, data curation, empirical analysis, and manuscript preparation, while Author 3 was responsible for preparing and analyzing the maps and supporting the interpretation of spatial patterns. All authors reviewed and approved the final manuscript and take full responsibility for its content.

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