Relative Efficiency Analysis of Biomass Agricultural Plants using Data Envelopment Analysis

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Abstract. Renewable energy has recently been a promising interest as a substitute for fossil fuels due to an increasing energy demand as well as a rising concern over the environmental impact of fossil fuel consumption around the globe. Biofuel, in particular, is a type of renewable energy, which can be derived from various biomass types. In this research, we analyze relative efficiencies using Data Envelopment Analysis (DEA) technique from three types of energy-related plants in the Northeastern region of Thailand, which are cassava, sugarcane, and palm. The relative efficiency of each province is further analyzed during 2017 to 2019 for a comparative study. Next, the input criteria are collected including allowable planting area, labor cost, and rainfall amount; whereas the included output criterion is the quantity of harvested product. Our initial analysis using CCR, BBC, and Scale Efficiency (SE) models of DEA provides the baseline of efficient provinces to be benchmarked and directions for improving inefficient provinces, given desired input and output criteria in this study.

Keyword. Relative Efficiency, Data Envelopment Analysis, Biomass, Renewable Energy

1 Introduction and Motivation

Renewable energy, such as biomass, solar, and wind has recently been a promising interest as a substitute for fossil fuels, such as oil and coal, due to an increasing energy demand as well as a rising concern over the environmental impact of fossil fuel consumption around the globe. Many countries have taken a variety of actions through strategic policies aiming at meeting energy needs more securely and sustainably. For example, the United States mandates to have more than 20 billion gallons of biofuel under the Energy Security Act by 2022. The European Union (EU) also aims to achieve 20% of energy from renewable sources by 2020. Also, China issues a long-term development plan of renewable energy aiming to increase the capacity of biomass power generation for 30 million Kilowatt (kW) by 2020 [1-2]. Thailand has also promoted a new economic model towards Industry 4.0 development plan by focusing on 10 targeted, S-curve industries – three of them are agricultural, logistics, and biofuel sectors [3].

Biomass, in particular, can be obtained from several sources including edible crops, non-edible crops, crop residues, forests, and waste. In comparison to fossil fuels, biomass is easy to grow and replace quickly without depleting natural resources. The advantages of using biomass are noted for its ability to be stored and used on demand, clean energy, renewable, and no carbon dioxide side effect. In addition, biomass also has the potential to reduce the dependency on fossil fuels, which are the main source of carbon dioxide release in the atmosphere [4-7].

Biofuel supply chain, in particular, involves a number of stakeholders, including farms providing feedstocks from biomass, pre-processing facilities, transshipment depots, bio-refinery plants, fuel-blending facilities, and demanding points of gas stations. Thus, biomass can be viewed as the upstream of the biofuel supply chain, in which the efficiency evaluation needs to be properly addressed. Fig. 1 illustrates the differences and similarities between traditional industrial and bioenergy supply chain.

In this research, we collect and analyze biomass data of three major feedstock for biofuel in the Northeastern region of Thailand. In particular, energy plants are collected for cassava, sugarcane, and palm during 2017 to 2019. Then, the relative efficiency of each province is further analyzed using Data Envelopment Analysis (DEA) for a comparative study. The input criteria are collected including allowable planting area, labor cost, and rainfall amount; whereas the included output criterion is the quantity of harvested product. Our initial analysis using CCR, BBC, and Scale Efficiency (SE) models of DEA provides the baseline of efficient provinces to be benchmarked and directions for improving inefficient provinces, given desired input and output criteria in this study.

2 Related Studies and Method

2.1. Biomass and Bioenergy Supply Chain in Thailand

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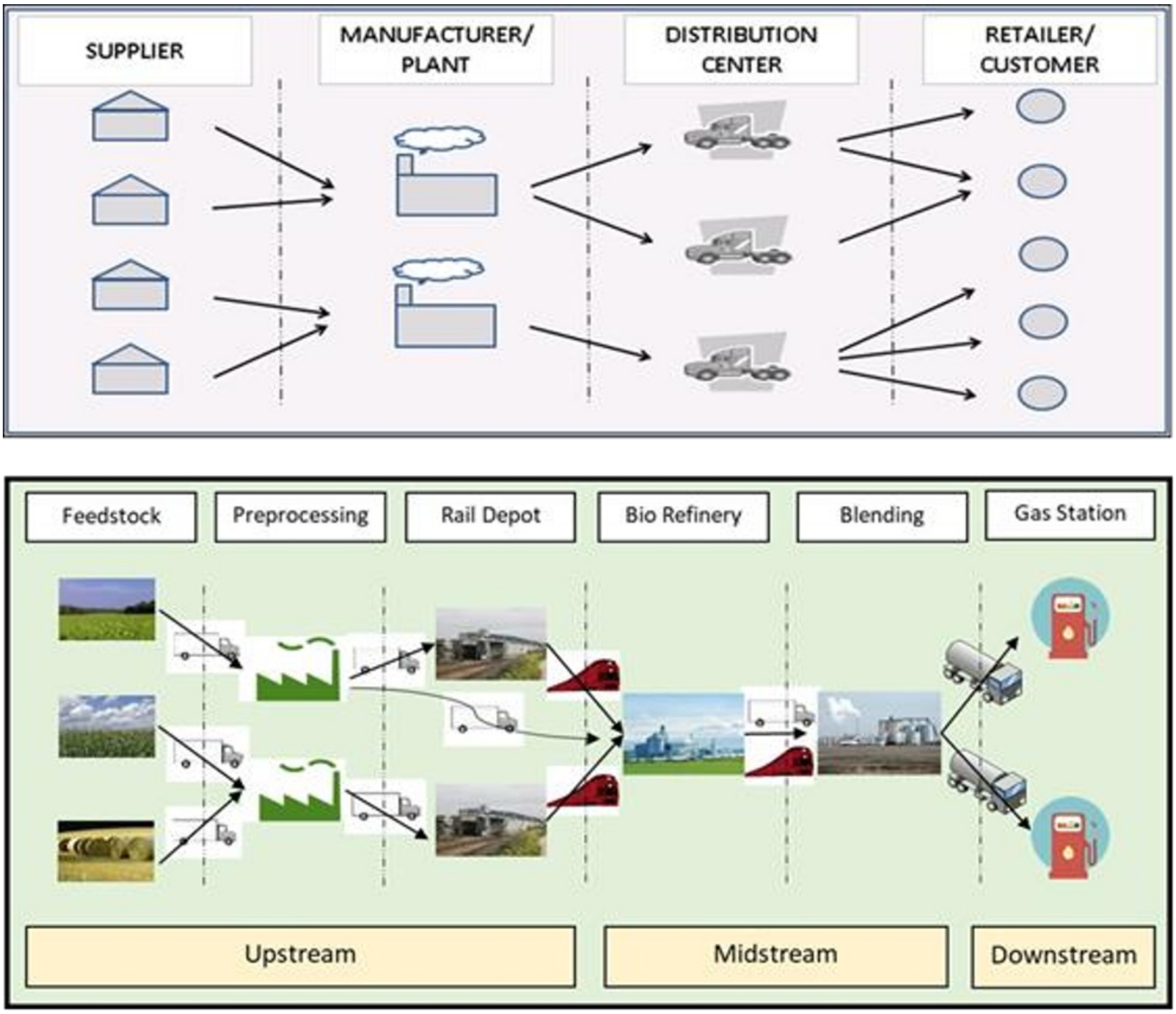

Fig. 1. (Top) Traditional industrial logistics; (Bottom) Bioenergy logistics

Renewable energy has attracted the attention of researchers around the globe for ensuring future energy security and sustainability. Biofuel energy, in particular, is one of the renewable energy that has gained ground in this regard. According to REN21 [5], biofuels employment attracted around 2 million jobs in 2018, in which most of these jobs are in the agricultural supply chain in developing countries, especially in the case of Southeast Asia, including Thailand. REN21 (2019) also estimates annual capacity and production of ethanol production in 2018 and finds that the top five countries are United States, Brazil, China, Canada, and Thailand, respectively. Besides, the top five countries for biodiesel production are United States, Brazil, Indonesia, Germany, and Argentina, respectively. Thus, Thailand also has a high potential to enhance its economics through bioethanol process.

In Thailand, the Department of Alternative Energy Development and Efficiency (DEDE [8]) plays a key role, in which a mission is to promote and support sustainable and worthy energy consumption and production for exporting and domestic use and to build collaborative network for bringing the country into the knowledge based society with sustainable economic stability and social well beings. Two key performance-related projects noted are 1) developing community-based biomass power plants and 2) developing the biomass potential database in Thailand.

In addition, the report by DEDE [9] for Research and development (R&D) studies of renewable energy in Thailand suggests that there are four groups of research studies going on in Thailand – 1) the research on the potential of materials focusing on assessing the overall potential of biomass as raw materials; 2) research on biomass preparation process focusing on finding a way to improve the quality of biomasses, such as chipping, grinding, pelletizing, and humidity reduction; 3) research on electricity and heat production technologies for improving production process and quality of technologies in producing power and heat from biomass; and 4) research on economics and environmental impacts of biomass. The authors also note that most of the research in Thailand falls under group 3 and there is a need to pursue studies in other research areas.

With regard to biomass and biofuel status in Thailand, according to DEDE [8], Thailand has the target for ethanol production in 2036 to be 11.3 million liters per day. The actual ethanol production, however, is below the target (i.e., 3.51 million liters in 2015, 3.67 in 2016, 3.94 in 2017, and 4.20 in 2018, respectively). Obviously, the trend of ethanol production in Thailand will continuously grow in the future and thus a proper evaluation of biomass efficiency for each agricultural regional area is required. Regarding biomass types in Thailand, studies from DEDE [8] also show the potential of the biomass for varied types of feedstocks with more or less capacity, in which cassava, sugarcane, and palm are among the top potential biomass types.

2.2. Efficiency Study with DEA applications

Multi-Criteria Decision Analysis (MCDM) is a sub-discipline of operations research and management science (OR/MS) that explicitly considers multiple criteria in a decision-making environment and has been used to support decision-makers facing decision and planning problems that a unique optimal solution does not exist and/or decision-maker's preferences are involved. Common methods, specifically, include various tools, such as Analytic Hierarchy Process (AHP), Data Envelopment Analysis (DEA), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Multi-Attribute Utility Theory (MAUT), Multi-Objective Mathematical Programming (MOMP), and Goal Programming (GP). These tools have been applied and extended in a number of applications (e.g., [10-19]).

DEA, particularly, is a Linear Programming (LP) methodology to measure relative efficiency of multiple Decision-Making Units (DMUs) or so-called alternatives when the problem is presented with multiple input and output criteria. After the DEA linear programming model is solved, a particular DMU will be considered efficient if it obtains a score of one, whereas scores that are lesser than one imply relative inefficiency. It is also possible that more than one alternatives are found to be efficient. According to survey study from Liu et al. [20], the DEA literature's size is expected to continue to grow at least double the size of the existing literature. In addition, the DEA method has been applied in various applications [21-22]. We next discuss the three prevalent DEA models commonly used in the literature and the DEAP computer program.

2.2.1 CCR Model

The CCR model was early developed and named after the three researchers (Charnes, Cooper and Rhodes [23] to measure the overall technical efficiency ($TE_{overall}$), in which a Constant Return to Scale (CRS) assumption holds. That is, the CRS assumption holds true when the DMUs are operated under the condition of the optimal size and perfect competition. In particular, equations (1)-(5) present the CCR model of DEA in a linear programming form.

Sets

I: Set of inputs, indexed by i
J: Set of outputs, indexed by j
K: Set of DMUs, indexed by k

Parameters

x_{i,k_0} *: Amount of input data for input i of DMU k*
y_{j,k_0} *: Amount of output data for output j of DMU k*

Decision variables

U_i *: The weight assigned to input i*
V_j *: The weight assigned to output j*

Mathematical model

$$\text{Maximize} \quad TE_{overall} \quad \sum_{j\in J} y_{j,k_0} V_j \tag{1}$$

$$\text{Subject to} \quad \sum_{i\in I} x_{i,k_0} U_i = 1 \tag{2}$$

$$\sum_{j\in J} y_{j,k} V_j - \sum_{i\in I} x_{i,k} U_i \le 0 \quad ;\forall k \in K \tag{3}$$

$$U_i \ge 0 \quad ;\forall i \in I \tag{4}$$

$$V_j \ge 0 \quad ;\forall j \in J \tag{5}$$

2.2.2 BCC Model

The BCC model was later developed by and named after Banker, Charnes, Cooper [24] to measure the pure technical efficiency (TE_{pure}) of DMUs. The BCC model is formulated by extending from the dual model of the primal CCR model, which transforms the primal maximization to dual minimization problem. In contrast to CCR model, the BCC allows DMUs to be operated under imperfect condition and not necessarily at optimal size, which is more practical in real situations. That is, the Variable Return to Scale (VRS) assumption holds for the BCC model of DEA (Equations (6)-(10)), where θ is the relative efficiency and λ_k is the dual decision variable for each DMU.

Mathematical model

$$\text{Minimize} \quad TE_{pure} \quad \theta \tag{6}$$

$$\text{Subject to:} \quad \sum_{k\in K} \lambda_k x_{i,k} \le \theta x_{i,k_0} \quad ;\forall i \in I \tag{7}$$

$$\sum_{k\in K} \lambda_k y_{j,k} \ge y_{j,k_0} \quad ;\forall j \in J \tag{8}$$

$$\sum_{k} \lambda_k = 1 \tag{9}$$

$$\lambda_k \ge 0 \tag{10}$$

2.2.3 SE Model

The SE can be computed to express whether a particular DMU is operating at optimal size (i.e., similar to the CRS assumption) or whether at imperfect condition (i.e., similar to the VRS assumption). That is, if the latter holds true, the value of SE can be used to indicate whether the DMU operates under Increasing Return to Scale (IRS) (i.e., the size is too large) or Decreasing Return to Scale (i.e., the size is too small). In particular, the SE can be computed as a ratio between the relative efficiency obtained from the CCR model and the BCC model as shown in Equation (11).

$$\frac{TE_{overall}}{TE_{pure}} \tag{11}$$

2.2.4 DEAP Computer Program

We next discuss the Data Envelopment Analysis Program (DEAP). The program consists of the instruction file, the data file, and the output file; in which the CCR model, the BCC model, and the SE model can be simultaneously computed to obtain relative efficiencies of DMUs of interest. The program is also capable of computing how much the input criteria should be decreased for inefficient DMUs to be efficient (i.e., input-oriented) and how much the output criteria should be increased for inefficient DMUs to be efficient (i.e., output-oriented) for benchmarking purpose. In this research, the computer program DEAP Version 2.1 is used for analyzing related efficiency data.

3 Case Study of Biomass Feedstock and Analysis

3.1. Data Collection

We next discuss the case study of biomass data obtained from the Office of Agricultural Economics (OAE) of Thailand, in which the mission is to provide suggestions for policy development plans related to agricultural trade and international agricultural economic cooperation [25]. In particular, data are chosen from the Northeastern region of Thailand inclusive of 20 provincial areas as follows: A1) Loei, A2) Nong Bua Lamphu, A3) Udon Thani, A4) Nong Khai, A5) Bueng Kan, A6) Sakon Nakhon, A7) Nakhon Phanom, A8) Mukdahan, A9) Yasothon, A10) Amnat Charoen, A11) Ubon Ratchathani, A12) Sisaket, A13) Surin, A14) Buriram, A15) Maha Sarakham, A16) Roi Et, A17) Kalasin, A18) Khon Kaen, A19) Chaiyaphum, and A20) Nakhon Ratchasima (Fig. 1). Next, information is gathered for cassava, sugarcane, and palm during 2017 to 2019 as shown in Tables 1-3, respectively. The input criteria are inclusive of I1) allowable planting area, I2) labor cost, and I3) rainfall amount; whereas the output criterion is the quantity of harvested product for energy crop of O1) cassava, O2) sugarcane, and O3) palm, respectively.

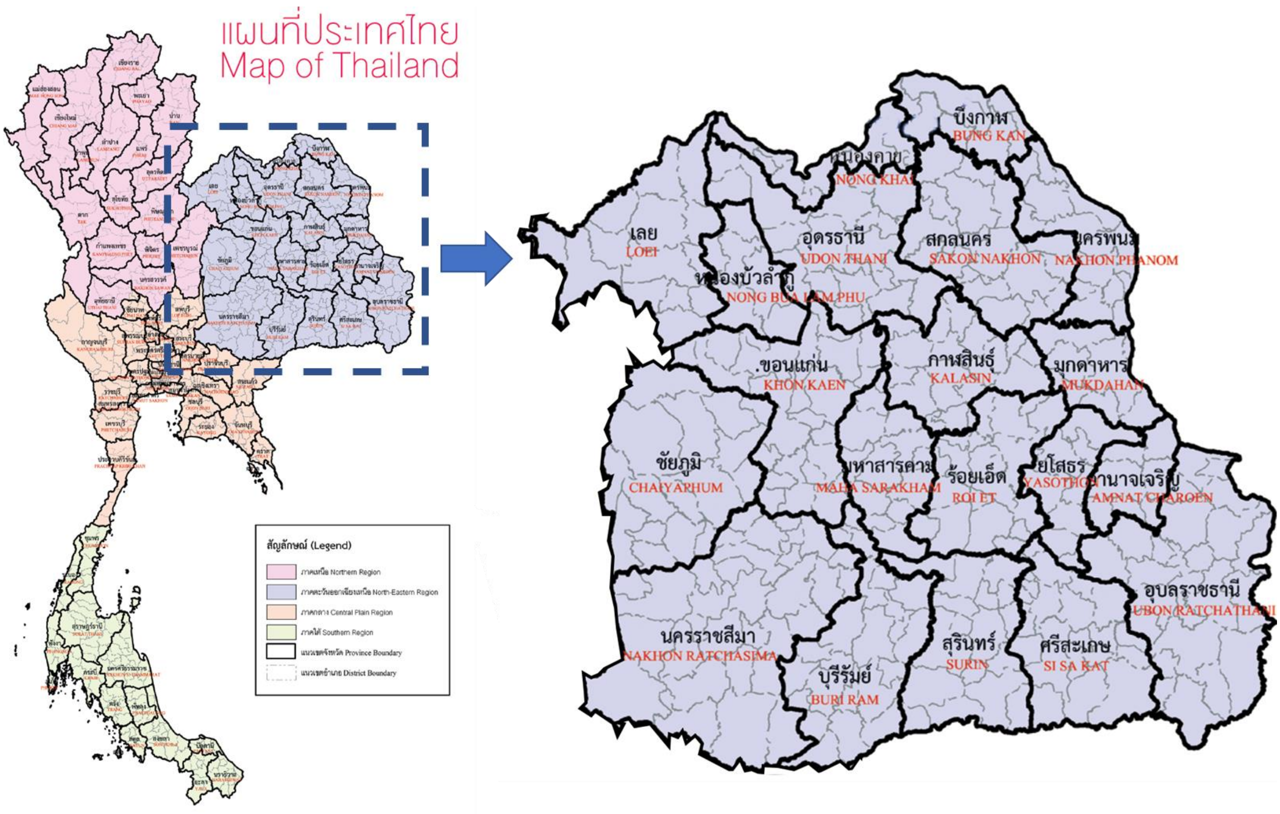

Fig. 2. Case study of the Northeastern region of Thailand (Adapted from [25])

Table 1. Collected data for biomass during 2017 [25]

DMUs	I1 Planting Area Unit (Rai)	I2 Labor Cost Unit (Baht)	I3 Rainfall Unit (mm.)	O1 Cassava Unit (Ton)	O2 Sugarcane Unit (Ton)	O3 Palm Unit (Ton)
A1	617,721	305	1,545	25,574	3,583,762	1,044,323
A2	377,254	305	1,608	3,486	3,725,326	223,764
A3	969,116	305	1,860	26,297	8,343,466	925,753
A4	100,822	305	2,087	23,187	810,936	51,926
A5	29,958	305	1,963	38,080	26,072	24,372
A6	207,176	305	2,369	16,022	845,440	370,380
A7	41,328	305	2,479	5,323	77,698	96,670
A8	361,492	305	2,057	2,702	2,636,511	507,843
A9	175,474	305	1,685	3,390	966,951	334,562
A10	163,373	305	1,720	5,657	833,413	317,478
A11	475,635	305	1,760	21,857	181,485	1,575,033
A12	176,030	305	1,663	7,544	386,678	496,034
A13	323,631	305	1,427	2,881	2,651,375	386,948
A14	445,348	305	1,563	7,343	2,472,410	952,503
A15	289,063	305	1,891	72	1,994,215	383,242
A16	213,411	305	1,691	1,635	1,876,815	176,199
A17	672,759	305	1,714	5,037	5,021,133	875,616
A18	857,249	308	1,561	975	7,587,787	737,716
A19	1,151,083	305	1,136	5,797	7,183,845	1,840,241
A20	2,155,739	308	1,386	10,021	7,893,730	5,514,475

Table 2. Collected data for biomass during 2018 [25]

DMUs	I1 Planting Area Unit (Rai)	I2 Labor Cost Unit (Baht)	I3 Rainfall Unit (mm.)	O1 Cassava Unit (Ton)	O2 Sugarcane Unit (Ton)	O3 Palm Unit (Ton)
A1	372,127	315	1,126	31,827	3,524,287	1,115,774
A2	378,728	310	1,309	5,236	3,663,764	222,125
A3	959,020	315	1,424	30,700	8,204,646	871,482
A4	97,624	320	1,707	25,896	797,524	41,243
A5	31,540	315	1,667	42,774	25,638	20,044
A6	193,094	318	1,735	17,495	831,326	333,302
A7	31,131	315	2,757	6,301	76,397	59,590
A8	356,668	318	1,929	3,508	3,592,793	481,759
A9	172,657	315	1,796	4,364	950,766	319,787
A10	171,582	310	1,804	7,239	819,523	343,245
A11	474,030	320	1,831	27,197	178,420	1,561,688
A12	178,295	310	1,436	9,017	380,201	503,287
A13	324,530	315	1,078	4,523	2,607,745	390,032
A14	446,794	310	792	9,923	2,431,963	969,635
A15	289,968	310	1,225	121	1,960,807	383,371
A16	210,337	315	1,210	2,583	1,845,455	196,194
A17	668,980	318	1,109	6,830	4,936,871	856,325
A18	215,376	320	1,168	2,437	7,460,999	735,135
A19	1,133,900	310	912	7,506	7,063,600	1,787,325
A20	2,073,375	320	1,095	12,489	7,762,504	5,298,895

Table 3. Collected data for biomass during 2019 [25]

DMUs	I1 Planting Area Unit (Rai)	I2 Labor Cost Unit (Baht)	I3 Rainfall Unit (mm.)	O1 Cassava Unit (Ton)	O2 Sugarcane Unit (Ton)	O3 Palm Unit (Ton)
A1	82,966	320	681	34,657	3,519,084	1,124,470
A2	423,113	315	1,024	5,565	3,832,243	252,398
A3	1,029,612	320	1,286	30,790	8,309,719	950,032
A4	84,622	325	1,545	26,936	798,363	42,509
A5	35,510	320	1,525	46,146	53,982	20,069
A6	208,786	323	1,252	21,398	941,496	332,932
A7	38,375	320	2,111	7,082	115,670	65,623
A8	371,272	323	1,587	4,027	2,638,052	492,214
A9	162,174	320	1,587	4,225	1,052,388	347,932
A10	197,762	315	1,598	6,800	1,021,304	355,759
A11	491,856	325	1,619	27,869	169,503	1,700,045
A12	185,095	315	1,194	9,855	349,185	524,574
A13	328,609	320	1,271	5,923	2,273,529	481,394
A14	488,575	320	1,042	11,813	2,494,540	1,022,085
A15	312,340	315	1,228	120	1,929,941	438,884
A16	227,862	320	1,628	2,695	1,912,407	194,487
A17	721,754	323	1,300	6,813	5,296,986	904,922
A18	894,427	325	1,018	2,406	7,257,231	786,745
A19	1,229,592	315	775	7,078	6,808,992	2,169,264
A20	2,115,752	325	727	12,979	7,277,088	5,325,614

3.2. DEA Analysis and Results

We next analyzed results from the DEAP computer program as shown in Tables 4-6 for data from 2017-2019, respectively. The overall technical efficiency from the CCR model, the pure technical efficiency from the BCC model, and the analysis from the SE model are presented. Provincial DMUs with either IRS (too-large size) or DRS (too-small size) are also analyzed. Regardless, other techniques (i.e., heuristics, simulation) can also be used and integrated to solve the linear programming problem of DEA model as well [26-34].

Table 4. DEA analysis for 2017 data

DMUs	CCR Model ($TE_{overall}$)	BCC Model (TE_{pure})	SE	Type
A1	1.000	1.000	1.000	-
A2	1.000	1.000	1.000	-
A3	1.000	1.000	1.000	-
A4	0.974	1.000	0.974	irs
A5	1.000	1.000	1.000	-
A6	0.833	1.000	0.833	irs
A7	0.870	1.000	0.870	irs
A8	0.973	1.000	0.973	irs
A9	0.943	1.000	0.943	irs
A10	0.925	1.000	0.925	irs
A11	1.000	1.000	1.000	-
A12	0.981	1.000	0.981	irs
A13	1.000	1.000	1.000	-
A14	1.000	1.000	1.000	-
A15	0.919	1.000	0.919	irs
A16	0.963	1.000	0.963	irs
A17	0.976	1.000	0.976	irs
A18	1.000	1.000	1.000	-
A19	1.000	1.000	1.000	-
A20	1.000	1.000	1.000	-

Table 5. DEA analysis for 2018 data

DMUs	CCR Model ($TE_{overall}$)	BCC Model (TE_{pure})	SE	Type
A1	1.000	1.000	1.000	-
A2	0.509	1.000	0.509	irs
A3	1.000	1.000	1.000	-
A4	0.669	0.980	0.683	irs
A5	1.000	1.000	1.000	-
A6	0.561	0.979	0.573	irs
A7	0.679	1.000	0.679	irs
A8	0.499	0.979	0.510	irs
A9	0.554	0.985	0.562	irs
A10	0.608	1.000	0.608	irs
A11	1.000	1.000	1.000	-
A12	0.852	1.000	0.852	irs

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A13	0.431	0.989	0.436	irs
A14	0.778	1.000	0.778	irs
A15	0.404	1.000	0.404	irs
A16	0.292	1.000	0.292	irs
A17	0.686	0.977	0.703	irs
A18	1.000	1.000	1.000	-
A19	1.000	1.000	1.000	-
A20	1.000	1.000	1.000	-

Table 6. DEA analysis for 2019 data

DMUs	CCR Model ($TE_{overall}$)	BCC Model (TE_{pure})	SE	Type
A1	1.000	1.000	1.000	-
A2	0.738	1.000	0.738	irs
A3	1.000	1.000	1.000	-
A4	0.623	0.981	0.635	irs
A5	1.000	1.000	1.000	-
A6	0.523	0.981	0.533	irs
A7	0.225	1.000	0.225	irs
A8	0.527	0.976	0.540	irs
A9	0.282	0.988	0.285	irs
A10	0.273	1.000	0.273	irs
A11	0.887	0.983	0.902	irs
A12	0.397	1.000	0.397	irs
A13	0.477	0.985	0.485	irs
A14	0.560	0.986	0.568	irs
A15	0.417	1.000	0.417	irs
A16	0.450	0.987	0.456	irs
A17	0.800	0.979	0.818	irs
A18	1.000	1.000	1.000	-
A19	1.000	1.000	1.000	-
A20	1.000	1.000	1.000	-

As illustrated in Table 4, provincial DMUs that operate with an efficient condition (i.e., the score for relative efficiency of 1) and with the optimal size (i.e., the score for SE of 1) during 2017 and should be considered the benchmark units are A1, A2, A3, A5, A11, A13, A14, A18, A19, and A20. In addition, data analyzed for 2018 (Table 5) show that efficient DMUs with optimal sizes are A1, A3, A5, A11, A18, A19, and A20. Next, based on the 2019 data obtained in Table 6, efficient DMUs with optimal sizes are found to be A1, A3, A5, A18, A19, and A20, respectively.

Clearly, an operation for some provincial DMUs fluctuates during 2017-2019, whereas certain provincial DMUs can operate with all efficient conditions for three years. Additionally, the IRS condition for certain provincial DMUs suggest that scale inefficiency exists, in which the size is considered too large when comparing to other DMUs. These analyzed results are also categorized for CCR model, BCC model, and SE model across all progressive years to illustrate the trend with respect to time as shown in Figs 2-4, respectively.

3.3. Discussion

Analyzed results from the CCR model, the BCC model, and the SE model obtained earlier suggest that A1) Loei, A3) Udon Thani, A5) Bueng Kan, A18) Khon Kaen, A19) Chaiyaphum, and A20) Nakhon Ratchasima are efficient across three years from 2017 to 2019. This is due to that the analyzed relative efficiency scores are shown to be 1.00 for three consecutive years in Figs 3-5. Overall, these efficient provinces are found to utilize lesser inputs (e.g., planting area, labor cost, rainfall) and/or obtain higher outputs (e.g., tons of products) when comparing to other peers. Thus, these provinces have been operated with efficient condition, in which they should be further used as a benchmark DMUs for other provinces.

In addition, other provinces operated at inefficient condition can consider whether a particular input criterion should be decreased with a fixed output requirement or a particular output criterion can be increased under a fixed input.

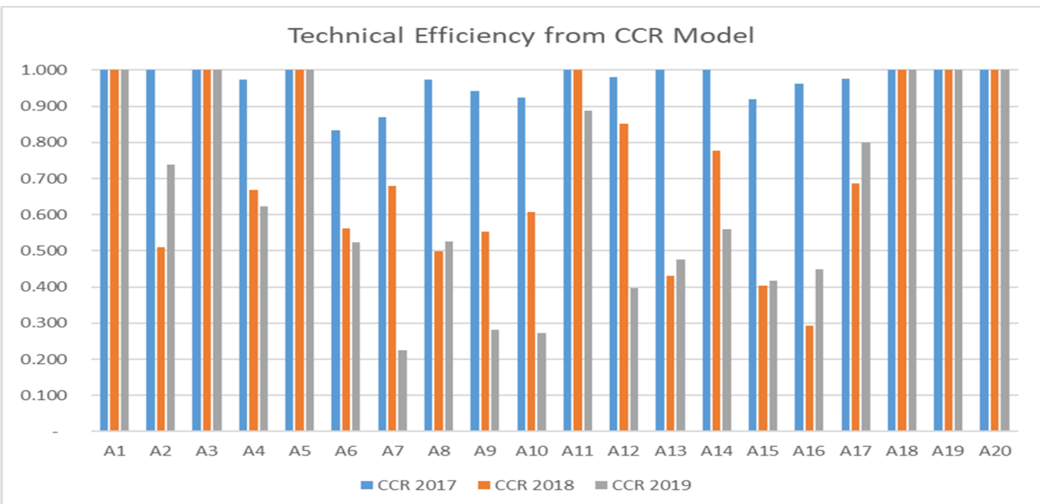

Fig. 3. Trend of CCR model's technical efficiency from 2017-2019

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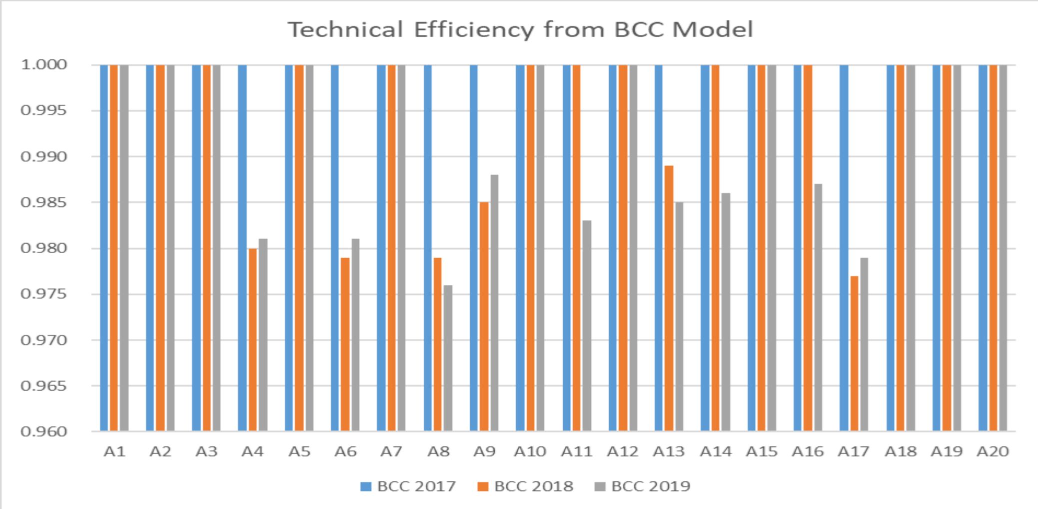

Fig. 4. Trend of BCC model's technical efficiency from 2017-2019

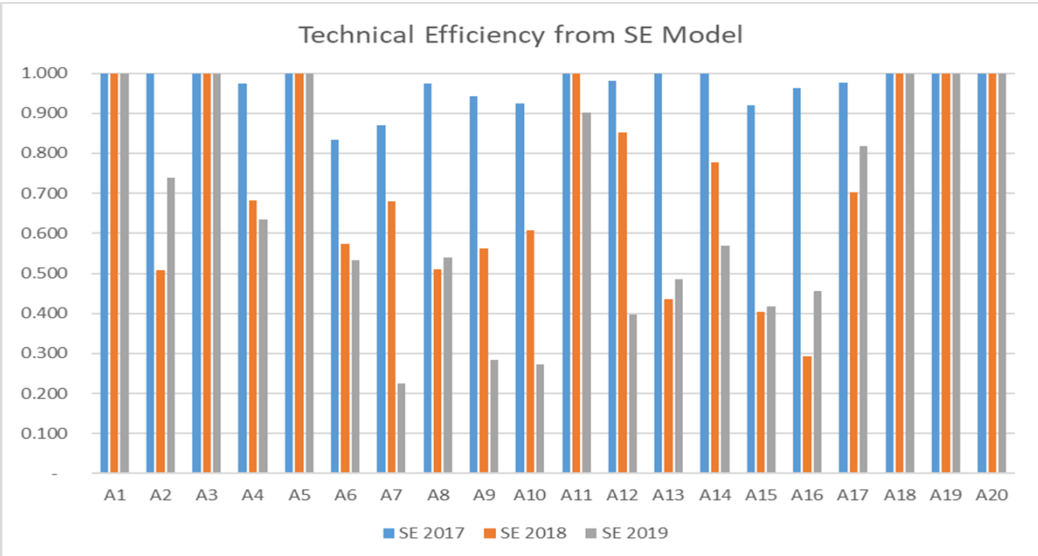

Fig. 5. Trend of SE model from 2017-2019

4 Conclusion and Future Research

Biomass represents a significant source of biofuel, which is a type of renewable energy getting attention from many countries nowadays. In this research, biomass data of three major feedstocks for biofuel in the Northeastern region of Thailand were collected and analyzed using DEA to analyze each provincial efficiency. The input criteria of allowable planting area, labor cost, and rainfall amount as well as the output criterion of the quantity of harvested product were, in particular, collected for the top energy crops of cassava, sugarcane, and palm during 2017 to 2019. Accordingly, the relative efficiency of each provincial alternative was analyzed using DEA analysis of CCR model, BCC model, and SE model, respectively.

Analyzed results showed that, among 20 provinces of the Northeastern region of Thailand, there were six provinces that operated efficiently under the selective criteria. These provinces were found to be Loei, Udon Thani, Bueng Kan, Khon Kaen, Chaiyaphum, and Nakhon Ratchasima, respectively. Thus, these efficient provinces could be further used as benchmark DMUs for other provinces. Regardless, it is important to note that the analyzed results are dependent on selected criteria for inputs and outputs, in which the caution should be noted.

Directions for future research of this study include 1) expanding the case study for other regional areas in Thailand for further comparative study, 2) exploring other types of crops related to energy feedstock, 3) investigating other time spans for different years or with other time units, such as monthly basis, and 4) assessing other criteria types inclusive of both inputs and outputs. That is, other economic aspects can be further included for the input criteria. In addition, outputs concerning the sustainability index can also be enhanced. Additionally, we note that this study is the first phase of our research framework to investigate the upstream process of the bioenergy supply chain. That is, the results obtained from this study will be used as input for further supply chain modelling study.

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