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Decision Support System for Bioenergy Supply Chain Optimization: A Case Study at Lebak District, Banten Indonesia

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ABSTRACT

This study aims to design a decision support system (DSS) development model in sustainable bioenergy supply chains. Our approach involves 1) identifying the bioenergy supply chain model through determining the spatial potential model of agroindustry area using geographic information system (GIS) and analytical hierarchy process (AHP); 2) determining the optimization model for aggregate production process planning using fuzzy goal programming for bioenergy production to design the biomass inventory level determination model using adaptive neuro-fuzzy inference system (ANFIS) approach; 3) designing the concept of DSS model in bioenergy supply chain. The results showed the identification of the supply chain model from the spatial model of potential agroindustry locations with three regional categories: 19.34% potential, 16.93% not potential, and 63.70% developing. Aggregate planning is appropriate based on three objective functions to be achieved in production planning for determining inventory levels using ANFIS using three input variables and comparing performance with RMSE, MAPE, and R2 inventory levels so that the model can predict inventory levels adaptively. The concept of the DSS Model on the bioenergy supply chain from agricultural centers to users by adding Internet of Things (IoT) technology can increase the effectiveness and efficiency of the bioenergy supply chain. The managerial implications of this research can provide relevant insights for the design and improvement of renewable energy management programs. Utilization of local biomass resources becomes more optimal.

1. INTRODUCTION

The fulfillment of energy consumption needs in Indonesia, 88%, is still very dependent on fossil energy [1]. Energy is a prominent supporter of sustainable development goals. Following the Sustainable Development Goals (SDGs), get clean and affordable energy for everyone [2]. Government regulations regarding the acceleration of development and use of renewable energy through Government Regulations on National Energy Policy (KEN) require efforts to develop the use of energy made from biomass raw materials [3]. Bioenergy contributed 5.9% to the share of the NRE mix in 2020 and is renewable energy made from natural plant waste [4, 5].

Lebak District consists of 28 sub-districts divided into 340 villages and five urban villages. As an agricultural center, Lebak District is geographically located at 105º 25' - 106º 30' East Longitude and 6º 18' - 7º 00' South Latitude. By regional conditions and sufficient land for the growth of rice plants, Lebak District is one of the rice barns with 53,946 hectares of paddy fields and 565,820 tons of rice production. Government Regulation on the National Energy Policy (KEN) is necessary to develop the use of biomass-based energy. Lebak District has land with great potential for developing rice plants and bioenergy raw materials from rice waste in rice husks. Rice husk waste and straw from agricultural products have the potential to become bioenergy for household heating, energy sources for power generation, and industrial products.

It is necessary to manage the bioenergy supply chain to fulfill renewable energy needs to be more optimal. The bioenergy supply chain starts from agricultural centers, collection locations, and distribution to the processing industry into bioenergy and power generation companies. Bioenergy supply chain in Figure 1.

Some of the problems in the bioenergy supply chain include: 1) the bioenergy supply chain model has not been effective and adaptive in terms of the fulfillment of raw materials (biomass) both qualitatively and quantitatively, so it is necessary to map potential bioenergy agroindustry areas to formulate priority regional development strategies. Determination of potential bioenergy agroindustry areas can facilitate the government in taking development strategy policies. 2). Aggregate production planning in the bioenergy product processing industry is currently influential in determining the amount of production and supply of biomass. The company does not have a definite value for a series of objectives, such as limits on the number of goods produced, the maximum or minimum amount of inventory allowed, limits on the availability of working hours, and minimum income with minimum production target constraints that must be achieved, this causes the unclear value of achieving existing objectives to achieve optimal conditions. The importance of making production planning to calculate the optimal amount of production using the fuzzy goal programming method and biomass inventory assessment with the ANFIS approach. 3). The importance of the need for optimal bioenergy supply chain management with a decision support system (DSS) for stakeholders in formulating strategies for developing potential bioenergy agroindustry areas and adaptive inventory management for bioenergy industry players in determining the amount of inventory for aggregate production planning.

This research aims to design a decision support system model for optimizing the rice husk bioenergy supply chain. The study is expected to be a recommendation for policymakers in developing potential bioenergy agroindustry areas and a bioenergy raw material inventory model for aggregate production planning for bioenergy industry players.

Studies on decision support systems in the supply chain have been widely carried out. Model-based decision support system development research can assist operational managers in selecting the most effective SGA alternatives in the Multi-tier supply chain [6]. Research on a new web-based DSS for optimizing hydrogen refueling locations (HRS) and hydrogen supply chain (HSC) resulted in the DSS being effective in solving optimization problems and has the potential to help governments and municipalities plan hydrogen project infrastructure [7]. Lack of data on global and local supply chain disruptions due to natural and human disasters with the proposed DSS effectively generates supplier risk profiles that supply chain managers and practitioners can use to manage the risk of supply chain disruptions more efficiently [8].

Regional and environmental conditions and potentials support agroindustry development in bioenergy, so the need for DSS in the bioenergy supply chain refers to the evaluation and classification of land capabilities for rice-based bioenergy agroindustry. Land evaluation is a performance assessment process land for sustainable development of the bioenergy agroindustry, which includes the implementation and interpretation of surveys and forms of field studies, soil, vegetation, climate, and other land aspects to identify and make comparisons of various land uses that may be developed [9, 10].

Aggregate planning is made to adjust production capabilities in the face of uncertain market demand by optimizing the use of labor and available production equipment to reduce total production costs to a minimum [11, 12]. The goal of aggregate planning is to establish an overall level of output in the short or medium term to deal with fluctuating or uncertain demand [13].

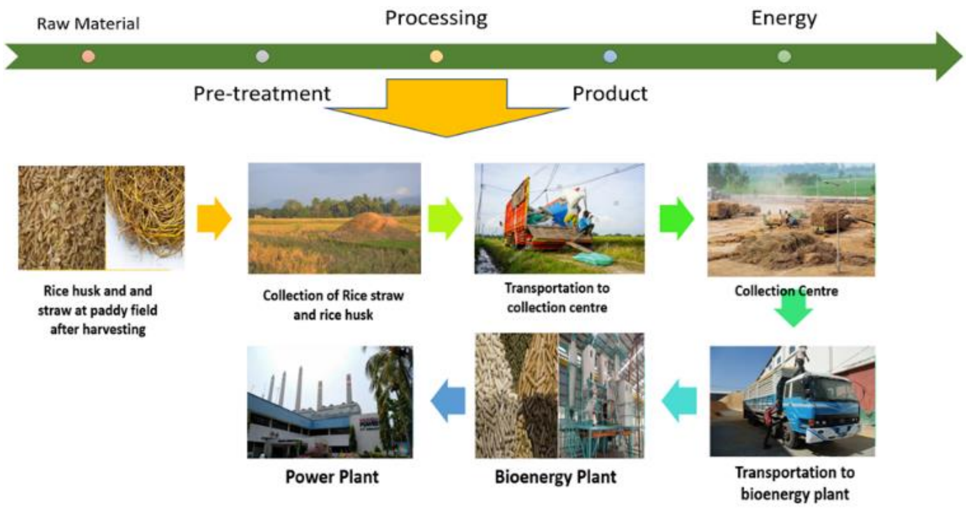

Figure 1. Bioenergy supply chain model

The model is a critical approach in clarifying the understanding of the goal of improving supply efficiency [14]. Optimization of the DSS model in bioenergy supply chains is essential to overcome obstacles and uncertainties that can hinder sustainable and adaptive supply chain development [15].

Based on the previous description, we propose designing a spatial DSS model of GIS data with the addition of Internet of Things (IoT) technology. The DSS Model is a concept that aims to improve the optimization of the rice waste bioenergy supply chain. We add IoT technology to extend the benefits of internet connectivity following the development of Industry 4.0 in the renewable energy sector in a sustainable manner [16, 17]. Implement IoT in the bioenergy supply chain operationally to increase effectiveness and efficiency in determining yield and yield capacity (precious farming) [16, 18].

Determination of the best path of bioenergy distribution to the decision support model for determining agricultural productivity and yield in real-time. In previous studies, DSS have been widely applied to the bioenergy supply chain. In this study, we added that Internet of Things (IoT) technology is expected to improve supply chain performance to be more effective and accurate [19, 20].

2. MATERIAL AND METHODS

2.1 Stages of research

The stages of research as a whole are: 1). We identify bioenergy supply chain models by determining spatial models of bioenergy agroindustry locations. Assessment of biomass inventory model and optimization model of aggregate planning of bioenergy production process. 2) Step 2 of the research is the design of the spatial DSS model concept for determining the amount and productivity of crops for determining the amount of bioenergy raw materials—

determination of biomass inventory model and aggregate planning optimization model of bioenergy production process.

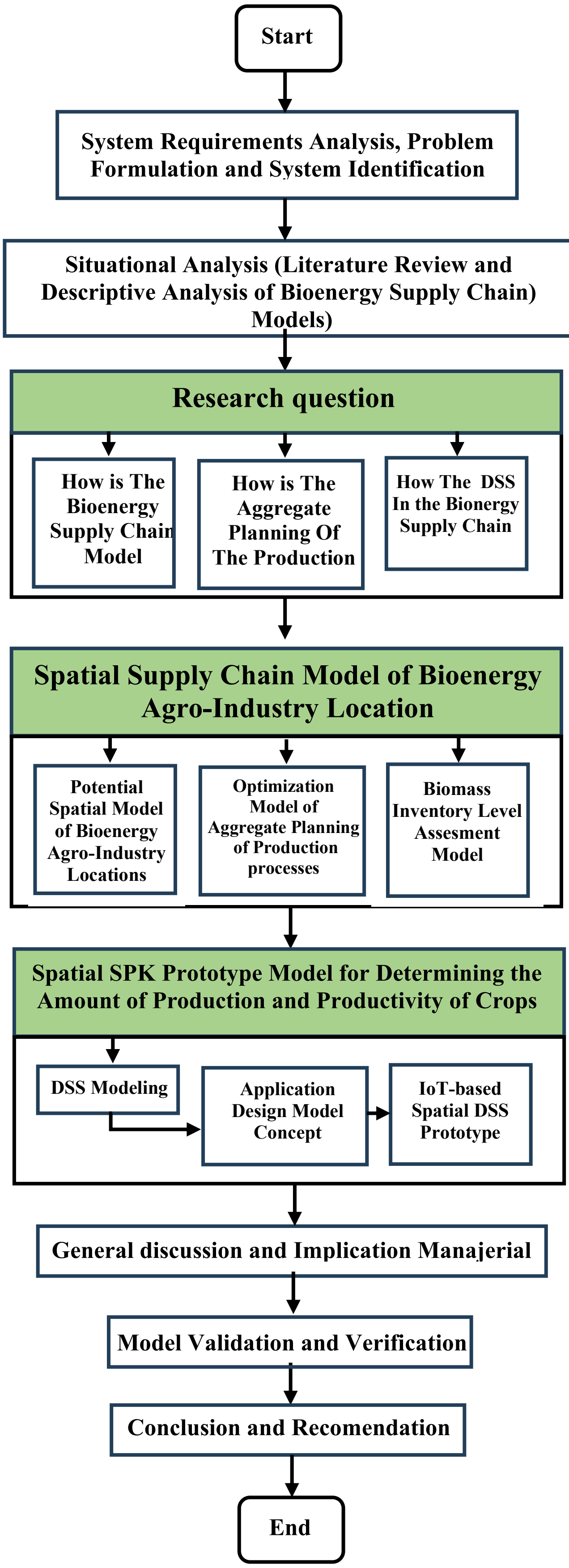

Figure 2. Stages of research

Bioenergy production involves turning organic feedstock (biomass) into energy. Raw material inventory management aims to provide raw materials for efficient production planning consistently and avoiding wastage, supply risk management, cost efficiency, supporting aggregate planning, and raw material quality tracking.

In bioenergy production, aggregate planning with feedstock inventory management is necessary to achieve sustainable, efficient and quality-oriented production and reduce the risks associated with feedstock availability and surplus. The next step is designing a decision support model for optimizing the bioenergy supply chain—the stages of research in Figure 2.

2.2 Data analysis techniques

1. Potential spatial models of bioenergy agroindustry locations using geographical information systems (GIS), namely slope maps, road network maps, river network maps, settlement maps, industrial maps, and rice field area maps. The analytical hierarchy process (AHP) approach creates hierarchies for weighting to map potential level classification results of *bioenergy agroindustry* areas.

AHP is a decision guidance tool used to solve complex choice problems. It utilizes multi-level hierarchical criteria to achieve objectives, criteria, sub-criteria, and alternatives. The stages of quantitative modelling with the AHP method are as follows:

a. Creating a pairwise comparison matrix according to Saaty [21] in Table 1.

Table 1. Pairwise comparison matrix

A	A1	A2	…	An
A1	a11	a22	…	a1n
A2	a21	a22	…	a2n
…..	…	…..	…	…
Am	am1	am2	…	amn

b. The pairwise comparison matrix only fills the value in the upper triangle, and the main diagonal is always worth one because the comparison of criterion a with criterion a results in 1. An intensity of importance comparison is used based on the safety comparison scale to fill the upper triangle value.

c. Normalize the decision matrix by adding each column of the matrix, then each column value in the matrix is divided by the total value of the column. c. Determine the weight of the criteria by averaging the matrix rows in the previous step for several n weights w, namely $w1$, $w2$, ..., wn.

$$w_i = \frac{1}{n}\sum_{j=1}^{n} a_{ij} \qquad (1)$$

d. Determining the consistency level of the pairwise comparison matrix obtained from the previous step. The steps are as follows:

- Determine $\lambda 1$, $\lambda 2$, ..., λn, which is obtained by multiplying the weight of each criterion by the number of columns of the decision matrix in step b.
- Determine the value of λmax with $\lambda max = \lambda 1 + \lambda 2 + \cdots + \lambda n$. λmax is the largest eigenvalue of the matrix of order n.
- Calculate the Consistency Index (CI) as follows:

$$Consistency\ Indeks\left(CI\right)=\frac{\lambda\max-n}{n-1} \quad (2)$$

With n is the number of criteria.

e. Calculate the Consistency Ratio (CR) as follows $CR = CI$ / IR with IR is the Random Index in Table 2.

Table 2. Index random consistency

Matric Size	1	2	3	4	5	6	7	8
IR Value	0	0	0.58	0.90	1.12	1.24	1.32	1.41

If the CR value ≤ 0.1, then the pairwise comparison matrix can be considered consistent.

f. Determining the level of conformity in Eq. (3)

$$X=\sum_{i=1}^{n} wixXi(\sum_{i=1}^{n} wi\ \ x\ \ xi \\ =\frac{Largest\ aggregate\ value-Smallest\ aggregate\ value}{Number\ of\ classes} \quad (3)$$

i = *Ba* – *Bb*
X = aggregate value of potential area mapping score
wi = criterion weight for parameter *i*
wi = subcriteria weight for parameter *i*
Xi = class score on criteria for *ith* parameter
xi = class score on subcriteria for parameter *i*
i = class interval
Ba = upper limit of class
Bb = lower limit of class

Using GIS, spatial-based multi-criteria decision-making modeling will be carried out for bioenergy agroindustry site selection. The GIS analyses and evaluates spatial and non-spatial data sub-criteria to select bioenergy agroindustry locations classified by weight [22]. Determining the location of bioenergy agroindustry needs to consider multi-criteria. The multi-criteria used in this study uses sustainability parameters so that the bioenergy agroindustry can be competitive sustainably. The weighting to classify these parameters using the Analytic Hierarchy Process (AHP), which is recognized to work together with GIS procedures to determine the best location [23]. Combining these approaches is expected to facilitate the modeling of bioenergy agroindustry site selection [24, 25].

The potential map classification is obtained from the classification value of the possible level of the bioenergy agro-industrial area obtained from the classification formula in Table 3.

Table 3. Classification of potential levels of bioenergy agroindustry areas

Interval Value (IV)	Classification
Minimum Value ≤ IV ≤ A * Value	Areas of non-Potential
A* Value < IV ≤ B** Value	Growing areas
IV > Maximum Value	Potential areas

* A Value = Minimum Value + Classification Hose Width
** B Value = A Value + Classification Hose Width

2. Optimization model of bioenergy production aggregate planning with Fuzzy goal programming with multi-criteria decision-making (MCDM) approach.

The fuzzy Goal Programming with Multi-Criteria Decision Making (MCDM) approach is used to overcome decision-making uncertainty involving many criteria or factors. In MCDM, these criteria can have different levels of uncertainty. The following criteria are relevant to implementing Fuzzy Goal Programming with the MCDM approach: 1). Vagueness in Criteria. 2). Qualitative Criteria: 3). Weight of Criteria: 4). Membership Function: 5). Fuzzy Decision Variables: 6). Trade-Off Criteria.

Fuzzy Goal Programming with MCDM is a powerful tool to overcome uncertainty in multi-criteria decision-making. The selection and use of appropriate criteria is critical to ensure that the Fuzzy MCDM model provides relevant and reliable results. Determination of bioenergy inventory model and aggregate planning optimization model of bioenergy production process.

Bioenergy production involves turning organic feedstock (biomass) into energy. Raw material inventory management aims to consistently provide raw materials for efficient production planning and avoiding wastage, supply risk management, cost efficiency, supporting aggregate planning, and raw material quality tracking. In bioenergy production, aggregate planning with feedstock inventory management is necessary to achieve sustainable, efficient and quality-oriented output and reduce the risks associated with feedstock availability and surplus.

Bioenergy inventory assessment model with adaptive neuro-FIS (ANFIS)

The ANFIS structure consists of five (5) layers. Each layer has different nodes. The layer is connected with nodes of the receiver of the previous input signal derived from the output signal of the previous level. The basis of the rule uses Takagi-Sugeno. A typical rule with three input variables and one output in the model is:

Rule i: If X1 be Ai dan X2 be Bi and X3 be Ci so fi = pix1+ qix2+ uiX3+ri

The parameters of the membership function are defined on the learning cycle that can use reverse propagation of hybrid learning algorithms.

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_p\left(i\right)-Q_o\left(i\right)\right)^2} \quad (4)$$

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\frac{Q_p\left(i\right)-Q_o\left(i\right)}{Q_o\left(i\right)}\times 100 \quad (5)$$

$$R^2=1-\frac{SS_{res}}{SS_{rot}};where\ SS_{res}=\sum_{i=1}^{n}\left(Q_0\left(i\right)-Q_p\left(i\right)\right)^2; \\ SS_{tot}=\sum_{i=1}^{n}\left(Q_o\left(i\right)-\overline{Q_o\left(i\right)}\right)^2 \quad (6)$$

3. The concept of the DSS model in the bioenergy supply chain with GIS and IoT approach.

Decision support system (DSS): Determination of productivity and yield is used in aggregate planning and assessment of biomass inventory in the form of rice husks and straw in the bioenergy production process in the Lebak district. DSS development design in the Bioenergy supply chain in Figure 3.

Based Figure 3, DSS design with the combination of

Internet of Things (IoT) and Geographic Information System (GIS) technologies can be very beneficial to optimize the bioenergy supply chain from rice husk. This will provide a better understanding of the spatial and real-time aspects of the supply chain, thus enabling smarter and more efficient decision-making for: Real-time supply chain monitoring. Optimal transportation route management, Soil Quality and Environmental Condition Monitoring, Warehouse and Stock Management, Environmental Impact Analysis, Capacity and Infrastructure Planning. The combination of IoT and GIS technology will help improve efficiency and accuracy in the bioenergy supply chain from rice husk. With better data analysis and a deeper understanding of geographical factors, you can make better decisions in supply chain management and maintain sustainable bioenergy production.

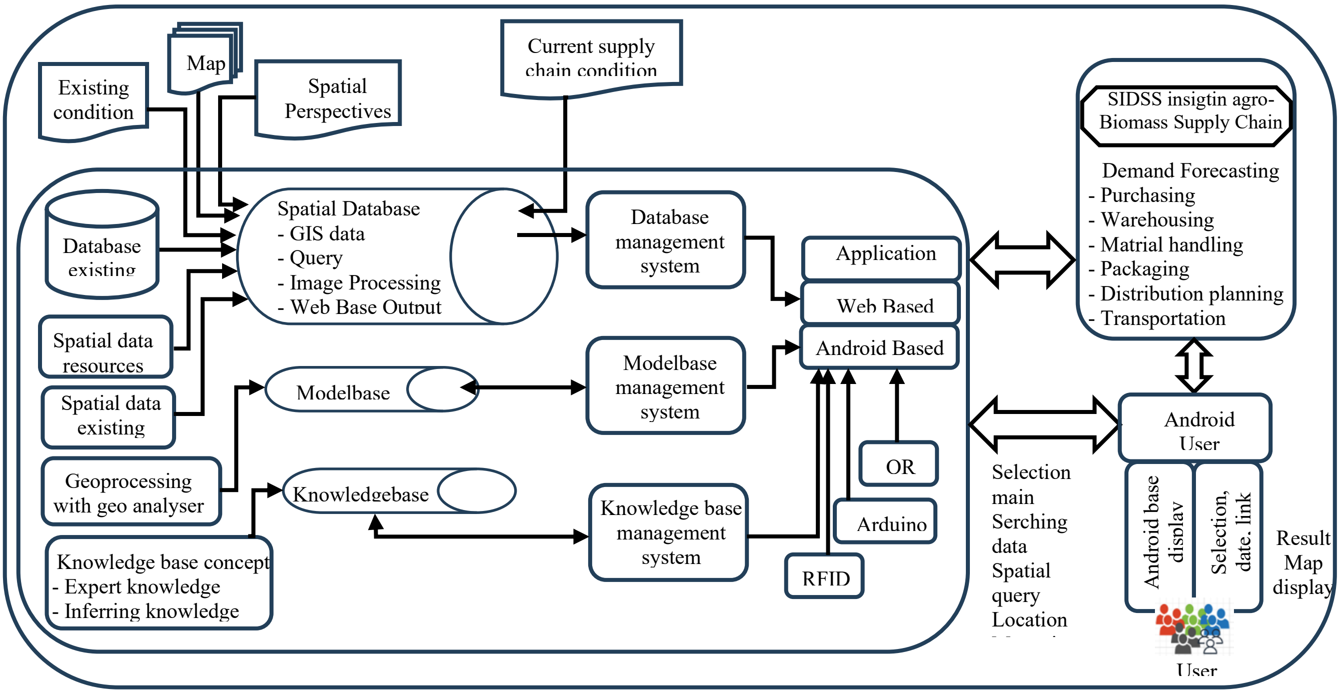

Figure 3. DSS development design in the bioenergy supply chain optimization

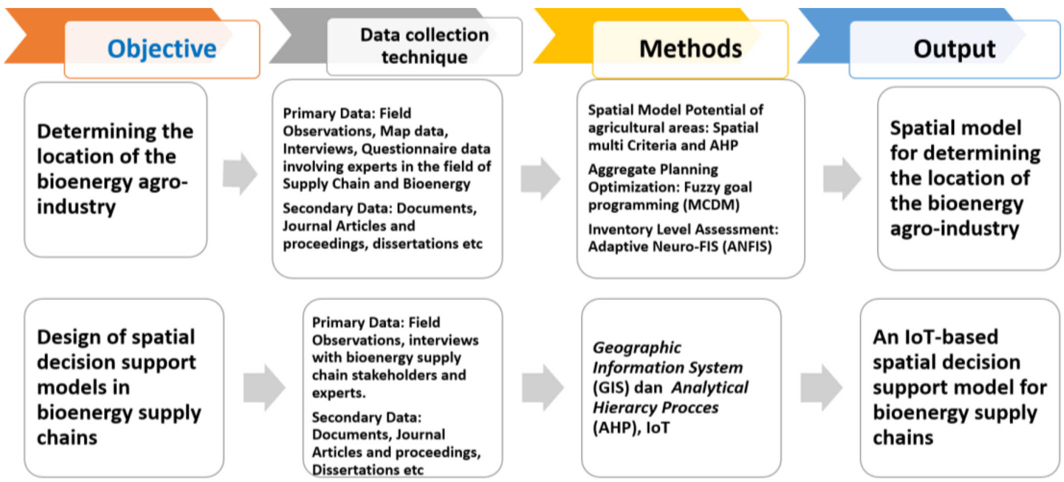

Figure 4. Data collection techniques

2.3 Data collection

This research uses spatial methods using data both qualitatively and quantitatively. Criteria data on the design of potential spatial models of bioenergy agroindustry locations are divided into two criteria: environmental and human. In the adaptive neuro-FIS (ANFIS) approach, the data used were 120 data with training data and as many as 300 data from 3 inputs used, namely the amount of rice production, rainfall level, and yield level that resulted in rice husk inventory levels. Data Collection Techniques in Figure 4.

3. RESULT AND DISCUSSION

3.1 Result

3.1.1 Potential spatial model of bioenergy agroindustry

In this research, the industrial location map is derived from the map of criteria and sub-criteria. The criteria are taken from the literature and validated by experts in Table 4.

Area visual model interpretation of bioenergy agroindustry area was obtained using a combination of land area attribute data and agricultural land overlay on land cover in Lebak

District with satellite data sources used in SPOT-6 and SPOT-7. Map projection to produce bioenergy agroindustry areas through selection and elimination processes and correction of spatial data and attribute data used. The method of modelling the location map of the bioenergy agroindustry in Lebak District began at the digitization and mapping stages. This stage is crucial because it is the basis for the suitability of assessing the potential of agricultural areas.

The suitability factor of the selected bioenergy agro-industrial agricultural area facilitates the mapping process in an integrated manner, showing conditions that are due to naturally occurring events or the influence of human behaviour. Each of these factor conditions is classified based on the degree of suitability for the requirements of the agricultural, agro-industrial, and bioenergy areas. The formulation carries out this mathematical model of measurement of the potential level of the agricultural regions:

$X = E\,\Sigma\, wi\, xi + H\,\Sigma\, vi\, yi$, E states environmental criteria, and H states human standards, to obtain:

$$Xi = 0{,}12\ (0{,}52\ \text{KJT} + 0{,}48\ \text{KJS}) + 0{,}88\ (0{,}19\ \text{KJJ} + 0{,}21\ \text{KJSu} + 0{,}15\ \text{KJP} + 0{,}34\ (0{,}8\ \text{KJPNonSwh} + 0{,}2\ \text{KJPSwh}) + 0{,}1\ \text{KHKH})$$

$$Xi = 0{,}05\ \text{KJT} + 0{,}05\ \text{KJS} + 0{,}16\ \text{KJJ} + 0{,}17\ \text{KJSu} + 0{,}12\ \text{KJP} + 0{,}22\ \text{KJNonSwh} + 0{,}06\ \text{KJSwh} + 0{,}09\ \text{KJKH}$$

Information:

Xi: The potential level of KJT bioenergy agro-industrial rice fields: KJS soil type class score: KJJ slope class score: Distance class score against KJSu road network: Distance class score against KJP river network: Distance class score against settlement location KJPNonKeb: Distance class score against farms that do not have rice fields KJPKeb: Distance class score against the establishment of agro-industrial rice fields that have KJKH rice fields: Class score farm area

The spatial mapping model of the potential area of bioenergy agro-industrial rice fields shows that 63.73% of the bioenergy agro-industrial rice fields in Lebak district are developing agricultural areas with a land area of 163,004.2 hectares, 16.93% are non-potential agricultural areas, and 19.34% are potential agricultural areas in Table 5.

The results of mapping the location of the bioenergy agroindustry in Lebak District show that the area of agroindustry is at a place of 225,737.32 ha—map of potential bioenergy agroindustry in Lebak district in Figure 5.

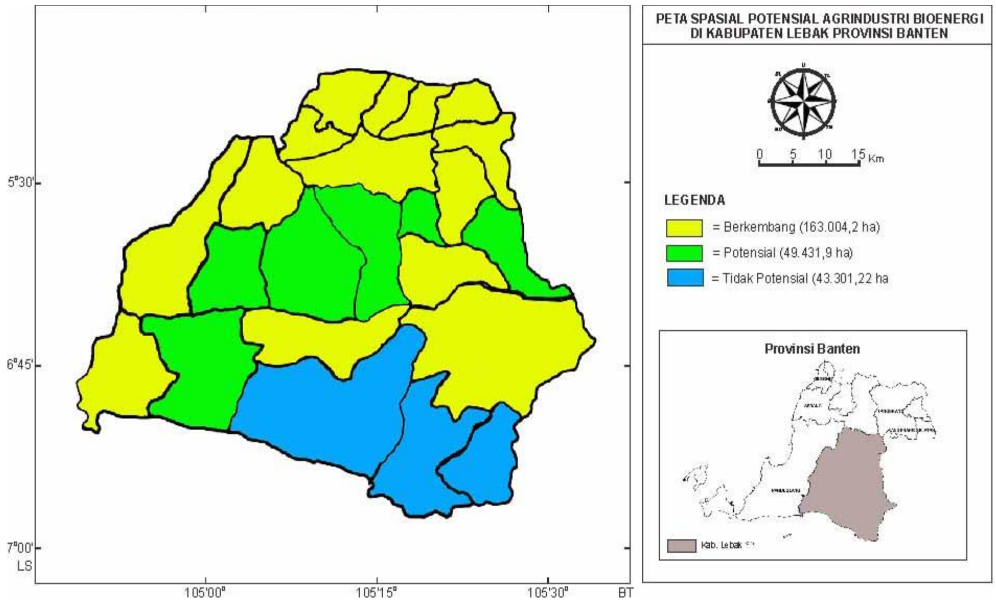

Figure 5. Map of bioenergy agroindustry potential

Table 4. Weight results parameter suitability assessment evaluation criteria and sub-criteria

No	Criteria and Weight	Sub-Criterion	Classification	Class	Weight of Sub-Criteria
1	Economic (0.42003)	Raw Material Availability	Insufficient	≤ hectares	(0.5)
			Sufficient	≥ hectares	
		Proximity to the market	Very suitable	0-1000m	(0.5)
			Retrieved	1001m – 3000m	
			less suitable	3001m - 5000m	
2	Infrastructure (0.31012)	Utilities	Poor	1	(0.5)
			Good	2	
			Very good	3	
		Accessibility	None	0	(0.5)
			there is accessibility	5	
3	Technology (0.11768)	Technology convenience	Inadequate	0	(1)
			adequate	5	
4	Social (0.18094)	human resources	Insufficient	≤ 500 FH farmer	(1)
			Sufficient	≥ 500 FH farmer	
5	Environment	RT/RW			To be intersected

Table 5. A land area with the potential level of agricultural area, agroindustry bioenergy

Classification	Broad (ha)	Propose (%)
Areas of non-Potential	43,301.22	16.93
Growing areas	163,004.20	63.73
Potential areas	49,431.90	19.34
	255,737.32	100

This is supported by Banten provincial regulation number 10 of 2019 concerning the Regional Spatial Plan of Banten Province 2019-2039 (Banten Provincial Government 2018), which shows that the area of agro-industrial agriculture in Lebak district is 256,823 ha. Differences influence insignificant differences in results in analysis periods, concepts and limitations on agricultural sites, data sources and scales, mapping methods, and area coverage. Previous research determined bioenergy agroindustry location by multi-criteria analysis integrated with the GIS model for selecting the best bioenergy agroindustry site candidate [26, 27].

The results of mapping potential bioenergy agroindustry development areas with three categories, namely 63.73% are areas that have the potential to be developed as bioenergy agroindustry areas based on development criteria, 19.34% are areas that have the potential and are developed as bioenergy agroindustry areas and 16.93% are areas that fall into the category of not allowing them to be used as bioenergy agroindustry area development areas. The area's development is directed at creating linkages between the agricultural and bioenergy industries to foster economic activities in the region. The results of the agroindustry area are expected to increase income, expand employment, increase the added value of agricultural waste into bioenergy products and spur the growth of other industries that require raw materials from the agricultural sector and renewable energy.

3.1.2 Optimization model of aggregate planning of bioenergy production with Fuzzy Goal programming approach

A quantitative method approach to aggregate planning to formulate three objectives: minimization of inventory levels, maximization of employee working hours, and minimization of the number of labourers. Constraints on aggregate planning are Production balance constraints, machine capacity constraints X Regular machine hour capacity, and People hour capacity constraints. Formulation of functions, objectives, and constraints in Eqs. (7)-(11).

Multi-objective mathematical modelling in this study combines rice's season and harvest period, accounting for 48 weeks of activity after rice milling. Results are based on the objective programming model in Table 6.

$$= \begin{cases} 1 & if\ G_k(x) \le g_k \\ \dfrac{U_k - G_k(x)}{U_g - g_k} & if\ g_k \le G_k(x) U_k ; k = 1, \dots, m \\ 0 & if\ G_k(x) \ge U_k \end{cases} \tag{7}$$

$$\mu_{Z_k}(x) = \begin{cases} 1 & if\ G_k(x) \ge g_k \\ \dfrac{G_k(x) - L_k}{g_k - L_k} & if\ L_k \le G_k(x) \le g_k ; k = m+1, \dots, n \\ 0 & if\ G_k(x) \le L_k \end{cases} \tag{8}$$

$$\mu_{Z_k}(x) = \begin{cases} 0 & if\ G_k(x) \le L_k \\ \dfrac{G_k(x) - L_k}{g_k - L_k} & if\ L_k \le G_k(x) \le g_k \\ & ; k = n+1, \\ \dfrac{U_k - G_k(x)}{U_k - g_k} & if\ g_k \le G_k(x) \le U_k \\ 0 & if\ G_k(x) \ge U_k \end{cases} \tag{9}$$

$$\begin{aligned} Min\, Z &= P_1 \times \sum_{t=1}^{T} \sum_{i=1}^{N} p_i . D_{it}^{-} \\ &+ P_2 \times \sum_{t=1}^{T} \left(L_t^{+} + L_t^{-} \right) + P_3 \times \sum_{i=1}^{N} \left(C_i^{-} \right) \\ &+ P_4 \times \sum_{t=1}^{T} \left(1.5 R_t^{+} + R_t^{-} \right) + P_5 \times \sum_{t=1}^{T} \sum_{i=1}^{N} C_i . D_{it}^{+} \end{aligned} \tag{10}$$

With Purpose Function:

$$\begin{aligned} & I_{i0} + X_{i1} - D_{i1}^{+} + D_{i1}^{-} = d_{i1}\ \forall i = 1, \dots, M \\ & D_{i,t-1}^{+} - D_{i,t-1}^{-} + X_{it} - D_{it}^{+} + D_{it}^{-} = d_{it}\ \forall i \\ & = 1, \dots, M ; \forall t = 1, \dots, T \end{aligned} \tag{11}$$

Table 6. Results based on the multi-purpose programming model

Months	X_{At}	X_{Bt}	X_{Ct}	X_{Dt}	W_t	L_t^+	L_t^-	R_t^+	R_t^-
1	14	0	0	0	20000	11000	0	0	0
2	42	0	0	8	50000	20000	0	15000	0
3	45	0	0	16	50000	0	0	15000	0
4	32	0	0	0	34839	0	15161	10452	0
5	4	23	7	0	34839	0	0	10452	0
6	11	15	7	7	34839	0	0	10452	0
7	26	18	7	0	42879	8040	0	12864	0
8	12	27	0	0	42879	0	0	6130	0
9	5	0	0	11	42879	0	0	0	24126
10	0	11	4	4	18855	0	24024	5657	0
11	0	5	5	10	18855	0	0	56576	0
12	0	0	3	5	26799	7944	0	0	16799

The forecasting average rate changes with the values of maximum labour requirements are *Tk* = 8,000 and *Tkm* = 40,000, and the correlation rate *r* = 0.3. Validation is carried out by involving experts in the field of bioenergy—forecasting change fluctuations in Figure 6.

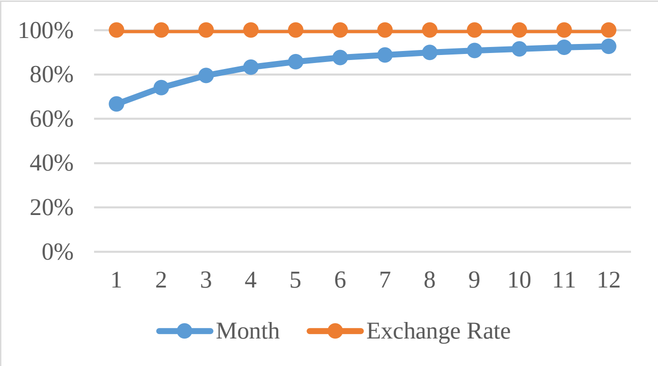

Figure 6. Change fluctuation forecasting

Plan for membership functions 12 months ahead of Active Programming *objectives* based on all three function goals to be achieved. The research was conducted by making a production plan to calculate the optimal amount of production using the fuzzy goal programming method. The result was a decrease in the percentage of production deviations from sales by 9.96%.

Biomass inventory level assessment model with adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a *model-driven data* based on the Takagi-Sugeno inference system. The technique was developed by integrating the principles of fuzzy logic and artificial neural networks to optimize the performance of these two techniques following the fuzzy logic rules of IF-THEN. It can solve nonlinear functions with its ability to learn [28]—parameter Input and output in Table 7.

Table 7. Parameter input and output

Indicator	Classification	Monthly Unit	Parameter
Rainfall (mm)	Light	<600	1, 0, 700
	Keep	700 – 1300	700, 1.000, 1.400
	High	>1400	1.400, 2.000, 2.000
Yield (%)	Low	<3	0, 0, 4
	Moderate	4 – 8	4, 6, 8
	High	9 - 12	8,12,12
Rice Production (Ton)	Low	>700	0, 0, 800.000
	Moderate	800-1400	800.000, 1.200.000, 1.500.000
	High	>1500	1.500.000, 1.880.000, 2.000.000
Rice Husk (Ton)	Low	<120.000	0, 0, 125.000
	Moderate	125.000 - 370.000	125.000, 200.000, 380.000
	High	>380.000	380.000, 400.000, 400.000

The hybrid algorithm is the basis of the ANFIS method, which aims to minimize *errors* and uses the least squares estimator and gradient reduction method to adjust the consequences and parameters of the premise by adapting the connection weight. Three (3) input and output variables are rice husk inventory levels in Figure 7.

ANFIS in the modelling process to produce a model program. At this stage, a set of data is used to prevent the occurrence of a model that fits too well, where the process of building parameters and the ANFIS model is determined at a certain *epoch learning* stage with minimum checking, a set of test data is used to verify the effectiveness and accuracy of the model being trained. ANFIS architecture is in Figure 8.

ANFIS performance is estimated using the measurement values of Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R2). ANFIS performance in Table 8.

Graphic User Interface (GUI) of 3 input indicators in the form of the amount of rice yield (Ton), yield (%), and rainfall (mm) to produce predictions of the number of rice husks produced as supplies for the bioenergy manufacturing process, made with the Matlab application GUI. GUI *assessment* of rice husk inventory levels in Figure 9.

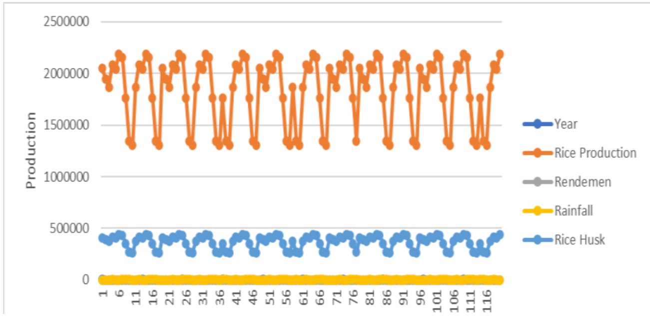

Figure 7. Input and output variables

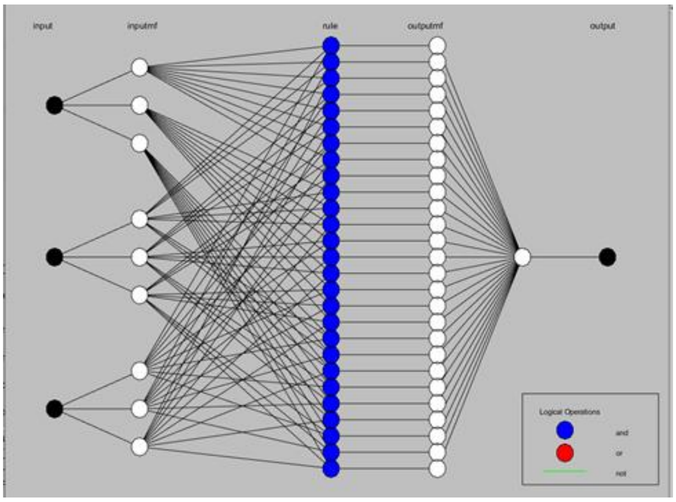

Figure 8. ANFIS structure model

Table 8. RMSE, MAPE, and R^2

	ANFIS
Training RMSE	0.5364
Checking RMSE	0.7781
Linear Regression RMSE (against Checking Data)	0.8506
Training MAPE	9.1810
Checking MAPE	12.3496
Training R^2	0.5953

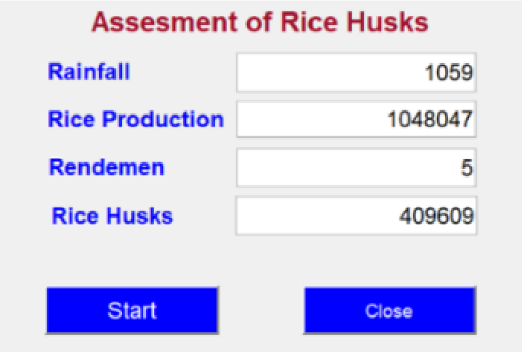

Figure 9. GUI assessment of rice husk inventory level

Following Teerasoponpong's [29] opinion, the approach with the ANFIS method is adaptive enough to be applied in determining the amount of raw material supply with erratic input indicators in small to medium enterprises.

3.1.3 Decision Support System (DSS) concept for bioenergy supply chain optimization

Spatial DSS combines spatial and non-spatial data, analysis, and visualization functions from geographic information systems (GIS). GIS is a *database* used to create, disseminate, store, update, and intelligently analyze and forecast spatial-related information. Tools that help in storing, processing, analyzing, and processing data to present spatial information. IoT-based spatial DSS in the agricultural biomass supply chain consisting of forecasting, demand, purchase transaction processing, warehousing, material handling, distribution, and transportation process planning are all components of the proposed model. DSS prototype design steps in Figure 10.

A layered architecture consisting of 3 layers is proposed in the concept of spatial decision support systems, namely: 1) the acquisition of environmental data is the existing condition on agricultural land or rice fields with consideration of spatial perspectives; 2) data and communication on spatial data sources consisting of soil type, temperature, and rainfall, as well as supplier identity, rice variety type, and supply capacity. *Geoprocessing* consists of map landscapes and segregation with analysis tools, spatial data warehouses consisting of samples from point grids on map landscapes, and data mining based on spatial perspectives using IoT technology; 3) The application layer consists of visualization of spatial data maps containing coordinates (X, Y)—layer architecture in Figure 11.

Figure 11 is the activity stage in developing spatial decision support system layer architecture. In the first layer, data sources at the farmer level are obtained, including the amount of rice harvested, supplier identity, agricultural waste capacity in the form of rice husks and straw, and rice types. The second layer consists of knowledge acquisition, modularization, and representation processes. In comparison, the data warehousing and communication layer presents supporting data for the application layer at the third layer.

Internet of Things (IoT) technology also enables data-driven supply chain systems for bioenergy products, making production and management more timely and cost-effective. Spatial DSS generally collaborates with spatial and non-spatial data, GIS-based analysis, and visualization functions with specific decision domain models in providing alternative decision-making solutions and problem-solving. Developing IoT-based spatial decision support system models involves data mining techniques to assist stakeholders in making better and appropriate decisions for the bioenergy supply chain—design of the DSS model by incorporating IoT technology in Figure 12.

Internet of Things (IoT) technologies can play an important role in bioenergy supply chain optimization by providing better visibility, control, and automation at various stages of bioenergy production, distribution, and use. The role of IoT technologies used in bioenergy supply chain optimization: 1). Biomass Quality Monitoring: IoT sensors can be placed in biomass fields or mills to monitor the biomass feedstock's moisture, temperature, and other qualities. This information can be used to optimize the biomass growth and collection process [30]. 2). Fuel Requirement Prediction: IoT can collect data on the fuel usage of engines used in the bioenergy production [31]. Analyzing this data can help in planning and predicting future fuel requirements [32]. 3). Production Process Monitoring: IoT sensors can be placed on equipment and machinery in bioenergy plants to monitor operational conditions, performance, and required maintenance. This data can be used to identify issues and optimize productivity proactively [33]. 4). Transportation Optimization: IoT can be deployed on vehicles transporting biomass feedstock or bioenergy products. IoT sensors on the vehicle can provide information about its position, speed, and condition, allowing it to plan more efficient routes and reduce fuel wastage. 5). Inventory Management: With the help of IoT sensors, biomass feedstock and bioenergy product inventory can be monitored in real-time. This allows supply chain managers to optimize inventory levels, reduce overstocks, and avoid shortages. 6). Environmental Monitoring: IoT can also be used to monitor the environmental impact of bioenergy production. Sensors placed around production facilities can measure air, water, and soil pollution so that companies can take necessary actions to preserve the environment. 7). Product Quality Prediction: IoT can monitor parameters that affect the quality of bioenergy products, such as moisture, chemical composition, and combustion efficiency. This data can be used to identify changes in product quality before it reaches consumers.

The combination of GIS and AHP methods by adding IoT technology provides convenience for decision-making in data collection and spatial data analysis and storage in the agricultural waste biomass supply chain [34]. Different IoT-based spatial decision support systems concepts are proposed by considering spatial aspects and perspectives. IoT devices and interface modules are included in the mining process in data collection and storage in spatial data warehouses. To overcome the limitations of the GIS perspective in providing a knowledge base, innovative system collaboration with spatial decision support systems is recommended. Furthermore, IoT devices in the form of RFID and QR can be added to spatial decision support systems to facilitate spatial interpretation of data mining. The use of IoT in DSS for bioenergy supply chain optimization enables more informed, responsive, and efficient decision-making [35]. This can result in supply chains that are more efficient, sustainable, and able to adapt to changing conditions in the real world.

DSS for bioenergy supply chain optimization is a powerful tool that combines data integration, modeling, analysis, and decision support capabilities to help stakeholders in the bioenergy sector make informed decisions that improve efficiency, sustainability, and profitability in the bioenergy supply chain [36]. It plays a critical role in advancing the development and adoption of bioenergy as a renewable and sustainable energy source.

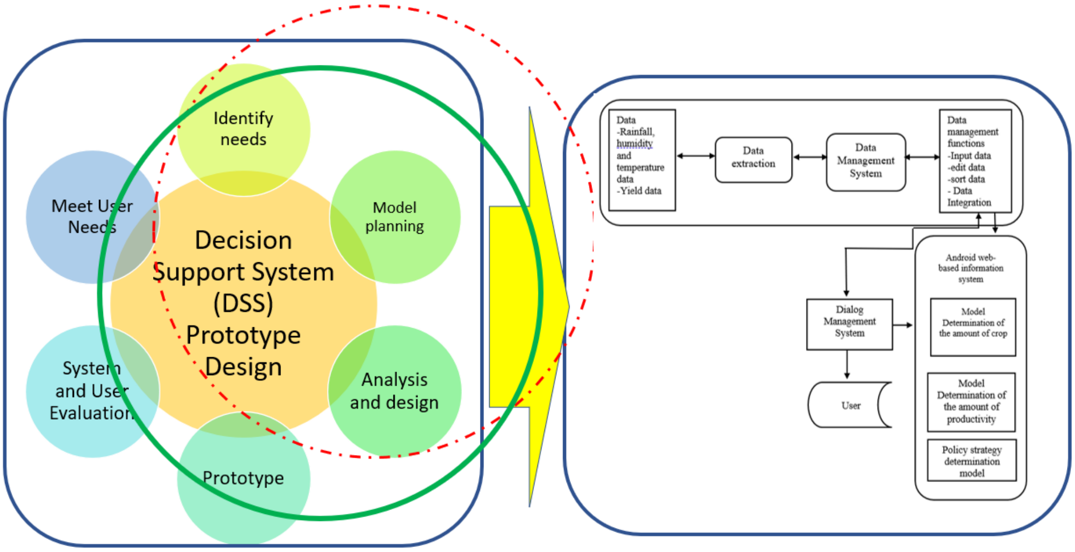

Figure 10. DSS prototype design stages

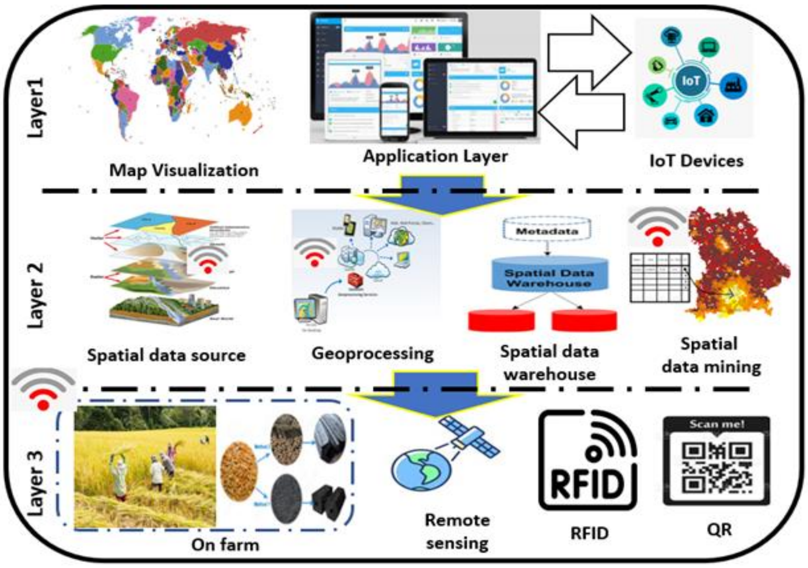

Figure 11. Layer architecture

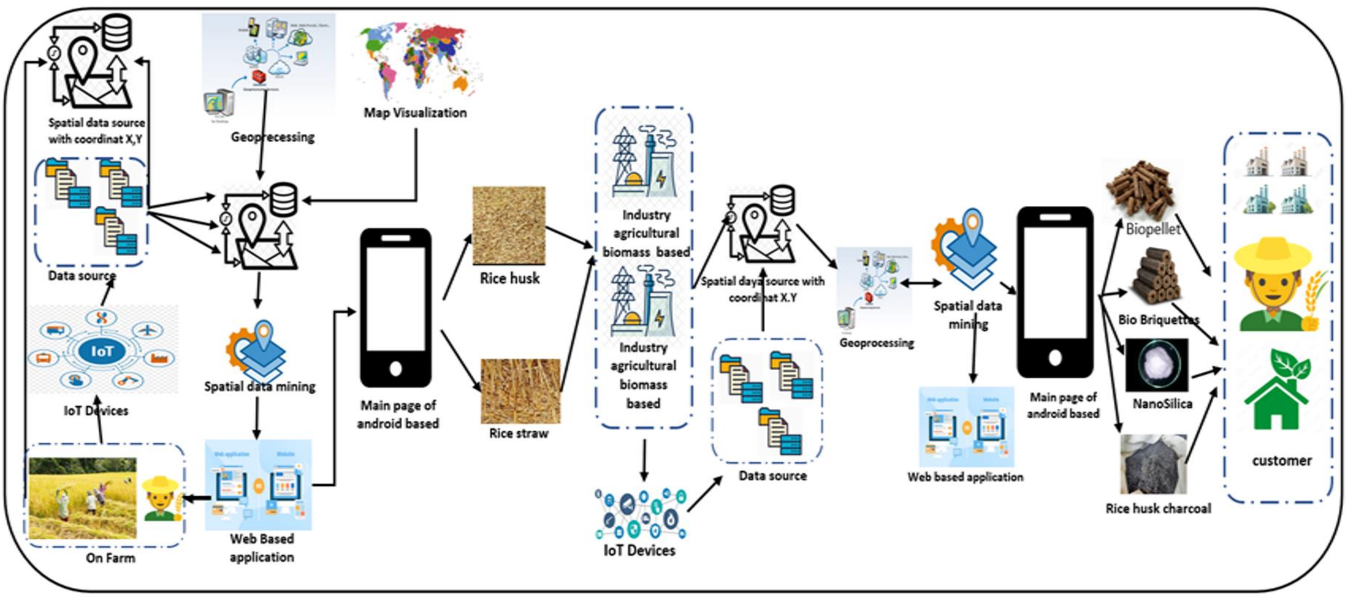

Figure 12. Design a DSS model of the bioenergy supply chain optimization

3.1.4 Validation and verification

Validation is carried out by involving experts in the field of bioenergy supply chain. Experts analyze the results of model solutions and compare them with actual conditions for harvesting in later periods. Model verification and research validation with verification steps ensure the formula and model are correct. FIS and ANFIS model verification provides the lowest error in the model. FIS and ANFIS models are verified by evaluating the performance of FIS and ANFIS modelling. Evaluation of FIS and ANFIS models using RMSE, number of membership functions, number of rules, and error values in training and testing [37]. At the Validation and verification stage, the model involved seven experts from the field of bioenergy and renewable energy, one person from the area of the bioenergy supply chain, two people from government agencies, one expert from the bioenergy industry, one power plant and one expert in the field of information technology (IT). The results of operational validation show from 10 assessment components with an average user value of 38 from the expected value of 50, a comparison value score of 76% is obtained so that the decision support system (DSS) model has been able to meet the system's needs. The model built can be implemented in the field and help decision-makers manage potential areas and sustainably optimize the bioenergy supply chain.

3.1.5 Managerial implications

Our proposed DSS model is expected to provide several benefits: 1). for stakeholders by improving the decision-making process of potential areas of bioenergy agroindustry, the amount of biomass feedstock for bioenergy from the harvest to enable more informed decision-making [38]. 2) Using DSS, bioenergy industry players can increase company profits by optimizing the practice of making better decisions about the company's aggregate capacity and planning and determining the amount of biomass inventory [39]. Use data to determine quotas and quantities of raw materials and production of bioenergy products. Improve the company's reputation to attract more customers and minimize environmental impact. Help increase sustainable promotion of the bioenergy supply chain and industry. DSS can facilitate communication between stakeholders. Help improve the long-term viability of the industry and dependent communities. Contributions for investors and policymakers to the bioenergy industry.

3.2 Discussion

A potential spatial model of the bioenergy agroindustry area with a possible map results in three (3) locations, namely potential, developing, and non-potential, to create regional regions to encourage the growth of the bioenergy agroindustry sector. Developing potential bioenergy agroindustry areas can encourage the bioenergy industry sector to be more focused and integrated and provide optimal use results for regions and supply chains [40]. The basic development concepts include efficiency, spatial planning, and environment, which refers to sustainability [41]. Regional development is also a driver for the effectiveness of bioenergy supply chains [42]. The efficiency aspect is one of the factors for developing potential areas.

Through potential development to increase additional income for farmers and create jobs in the bioenergy sector, investors will get adequate industrial activity locations. For stakeholders, especially local governments, developing agro-industrial areas will improve infrastructure facilities and infrastructure [43]. From the environmental aspect, developing potential regions in the bioenergy agroindustry will improve regional ecological quality more thoroughly. This study proposes a bioenergy supply chain model that considers efficiency and optimization—the bioenergy supply chain model in Figure 13.

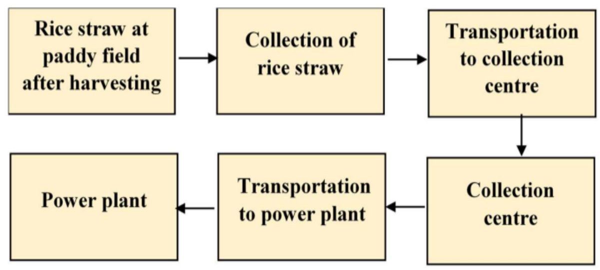

Figure 13. Proposed model of bioenergy supply chain

The biomass inventory assessment model as bioenergy raw material with the ANFIS approach provides rice waste biomass needs—a hybrid system combining artificial neural networks' capabilities and fuzzy logic. The ANFIS system is used as a training process and prediction process. The Least Square Estimator (LSE) method is used for forward feed learning and steepest descent for feedback and applying Takagi Sugeno 1st order fuzzy inference as the basis for fuzzy inference reasoning rules in prediction. The test results with a learning rate of 0.000001 produced the smallest MAPE value of 9.1210%. The accuracy level of comparison of actual data with ANFIS network output, the average MAPE value created was 12.3196% so that the ANFIS method can be applied in predicting the amount of bioenergy raw material inventory.

Design model (DSS) in the bioenergy supply chain to determine crop quantity and productivity. The bioenergy supply chain starts from agricultural centres from spatial data sources in the form of spatial map data by considering environmental and human aspects as system users and increasing added value [44]. The design of the DSS is applied to accommodate users' needs in obtaining information for decision-making [45, 46]. DSS is expected to be able to contribute to the actors involved in the bioenergy supply chain, namely farmers, bioenergy industry owners, stakeholders, and stakeholders [47]. We propose adding IoT technology to DSS to increase the effectiveness and flexibility of DSS from bioenergy supply chains that have not been widely implemented in developing countries in improving decision-making in bioenergy supply chains. The application of IoT technology in the bioenergy supply chain can help reduce costs, improve efficiency, and minimize environmental impacts, while improving the sustainability of bioenergy production.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusion

The design of the DSS model on the bioenergy supply chain optimization in Lebak district resulted in a potential spatial model of the bioenergy agroindustry with the results of mapping potential areas of 19.34% or an area of 49,431.90 ha, developing 63.73% or 163,004.20 ha and not possible 16.93% or covering an area of 43,301.22 ha. The optimization model of aggregate planning of the bioenergy production process is appropriate based on three objectives to be achieved in production planning with the results of the raw material inventory (biomass) assessment based on three input variables quite adaptive applied to the production process in the bioenergy industry.

Biomass inventory level assessment models help estimate accurate inventory levels and implement sustainable raw material supplies. The implication of the research results of aggregate planning in the production process of biomass inventory model values in optimizing bioenergy operations and production is a petting strategy in the bioenergy industry to maximize production, reduce costs and ensure sufficient feedstock availability.

The DSS design concept in the bioenergy supply chain is expected to improve supply chain performance by adding Internet of Things (IoT) technology ranging from agricultural centres to consumer bioenergy users.

4.2 Recommendation

The proposed DSS can provide solutions for stakeholders, namely the government as a policy maker as a projection of optimal bioenergy supply chain management policy development strategies. For the bioenergy industry, the proposed DSS can be a formulation in strategy prioritization and aggregate planning development through an inventory management model. With good collaboration between policy makers and industry players, the implementation of decision support systems for bioenergy supply chain optimization can become more effective, efficient and sustainable, which in turn will support the development of the bioenergy sector as a whole. Future research can include elements of quantity, capacity and cost into the DSS model

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REFERENCES

[1] National Energy Council. (2019). Indonesia energy outlook 2019. https://www.ptonline.com/articles/how-to-get-better-mfi-results.

[2] Fatimah, Y.A., Govindan, K., Murniningsih, R., Setiawan, A. (2020). Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: A case study of Indonesia. Journal of Cleaner Production, 269: 122263. https://doi.org/10.1016/j.jclepro.2020.122263

[3] P. R. Indonesia. (2014). “PP no 78 tahun 2014,” no. 2.

[4] Peluang, T., Bioenergi, P. (2016). Struktur lokakarya dan para peserta pemangku kepentingan.

[5] Santika, W.G., Anisuzzaman, M., Simsek, Y., Bahri, P.A., Shafiullah, G.M., Urmee, T. (2020). Implications of the sustainable development goals on national energy demand: The case of Indonesia. Energy, 196: 117100. https://doi.org/10.1016/j.energy.2020.117100

[6] Jamalnia, A., Gong, Y., Govindan, K., Bourlakis, M., Mangla, S.K. (2023). A decision support system for selection and risk management of sustainability governance approaches in multi-tier supply chain. International Journal of Production Economics, 264: 108960. https://doi.org/10.1016/j.ijpe.2023.108960

[7] Ryu, H., Lee, D., Shin, J., Song, M., Lee, S., Kim, H., Kim, B.I. (2023). A web-based decision support system (DSS) for hydrogen refueling station location and supply chain optimization. International Journal of Hydrogen Energy, 48(93): 36223-36239. https://doi.org/10.1016/j.ijhydene.2023.06.064

[8] Ali, S.M., Bari, A.M., Rifat, A.A.M., Alharbi, M., Choudhary, S., Luthra, S. (2022). Modelling supply chain disruption analytics under insufficient data: A decision support system based on Bayesian hierarchical approach. International Journal of Information Management Data Insights, 2(2): 100121. https://doi.org/10.1016/j.jjimei.2022.100121

[9] Parsa, I.M., Dirgahayu, D., Harini, S. (2019). Pengembangan metode klasifikasi lahan sawah berbasis indeks citra landsat multiwaktu. Jurnal Penginderaan Jauh Dan Pengolahan Data Citra Digital, 16(1): 35-44. http://doi.org/10.30536/j.pjpdcd.2019.v16.a3076

[10] Costa, F.R., Ribeiro, C.A.A.S., Marcatti, G.E., et al. (2020). GIS applied to location of bioenergy plants in tropical agricultural areas. Renewable Energy, 153: 911-918. https://doi.org/10.1016/j.renene.2020.01.050

[11] Jamalnia, A., Yang, J.B., Feili, A., Xu, D.L., Jamali, G. (2019). Aggregate production planning under uncertainty: A comprehensive literature survey and future research directions. The International Journal of Advanced Manufacturing Technology, 102: 159-181. https://doi.org/10.1007/s00170-018-3151-y

[12] Akhtari, S., Sowlati, T. (2020). Hybrid optimization-simulation for integrated planning of bioenergy and biofuel supply chains. Applied Energy, 259: 114124. https://doi.org/10.1016/j.apenergy.2019.114124

[13] Das, U.C., Mishra, A.K. (2019). Production and Operation Management. 5th Edition. Directorate of Distance & Continuing Education.

[14] Wang, S., Yin, C., Jiao, J., Yang, X., Shi, B., Richel, A. (2022). StrawFeed model: An integrated model of straw feedstock supply chain for bioenergy in China. Resources, Conservation and Recycling, 185: 106439. https://doi.org/10.1016/j.resconrec.2022.106439

[15] De Meyer, A., Cattrysse, D., Rasinmäki, J., Van Orshoven, J. (2014). Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review. Renewable and Sustainable Energy Reviews, 31: 657-670. https://doi.org/10.1016/j.rser.2013.12.036

[16] Mastrocinque, E., Ramírez, F.J., Honrubia-Escribano, A., Pham, D.T. (2022). Industry 4.0 enabling sustainable supply chain development in the renewable energy sector: A multi-criteria intelligent approach. Technological Forecasting and Social Change, 182: 121813. https://doi.org/10.1016/j.techfore.2022.121813

[17] Ghobakhloo, M., Fathi, M. (2021). Industry 4.0 and opportunities for energy sustainability. Journal of Cleaner Production, 295: 126427. https://doi.org/10.1016/j.jclepro.2021.126427

[18] Tao, W., Zhao, L., Wang, G., Liang, R. (2021). Review of the internet of things communication technologies in

smart agriculture and challenges. Computers and Electronics in Agriculture, 189: 106352. https://doi.org/10.1016/j.compag.2021.106352
[19] Nunes, L.J.R., Causer, T.P., Ciolkosz, D. (2020). Biomass for energy: A review on supply chain management models. Renewable and Sustainable Energy Reviews, 120: 109658. https://doi.org/10.1016/j.rser.2019.109658
[20] Van Holsbeeck, S., Srivastava, S.K. (2020). Feasibility of locating biomass-to-bioenergy conversion facilities using spatial information technologies: A case study on forest biomass in Queensland, Australia. Biomass and Bioenergy, 139: 105620. https://doi.org/10.1016/j.biombioe.2020.105620
[21] Saaty, T.L. (1993). Decision Making for Leaders, Analytic Hierarchy Process for Decision Making in Complex Situations. Jakarta PT. Pustaka Binaman Press.
[22] Romero-Ramos, J.A., Gil, J.D., Cardemil, J.M., Escobar, R.A., Arias, I., Pérez-García, M. (2023). A GIS-AHP approach for determining the potential of solar energy to meet the thermal demand in southeastern Spain productive enclaves. Renewable and Sustainable Energy Reviews, 176: 113205. https://doi.org/10.1016/j.rser.2023.113205
[23] Zhang, X., Fan, D. (2022). Carbon emission quota allocation of high energy consumption industries in undeveloped areas–A case study of Inner Mongolia Autonomous Region. Heliyon, 8(11): e11241. https://doi.org/10.1016/j.heliyon.2022.e11241
[24] Teniwut, W., Marimin, M., Djatna, T. (2019). GIS-Based multi-criteria decision making model for site selection of seaweed farming information centre: A lesson from small islands, Indonesia. Decision Science Letters, 8(2): 137-150. http://doi.org/10.5267/j.dsl.2018.8.001
[25] Kan, M., Partigoc, F., Gultekin, I., Arisoy, R.Z., Kaya, Y., Gultekin, S., Sahin, M., Aydogan, S., Ozdemir, F., Taner, A. (2018). Economical aspects of conservation agriculture (Zero Tillage-Direct Seeding) system in Turkey. Fresenius Environmental Bulletin, 27(5): 3332-3341.
[26] Shrestha, R.R., Acharya, A., Karmacharya, N., Sapkota, M., Paudyal, B., Basnet, P., Timilsina, S., Shakya, H.D. (2022). Application of AHP and GIS for optimal solar site identification in Madhesh Province, Nepal. International Journal of the Analytic Hierarchy Process, 14(3). https://doi.org/10.13033/ijahp.v14i3.986
[27] Woo, H., Acuna, M., Moroni, M., Taskhiri, M.S., Turner, P. (2018). Optimizing the location of biomass energy facilities by integrating Multi-Criteria Analysis (MCA) and Geographical Information Systems (GIS). Forests, 9(10): 585. https://doi.org/10.3390/f9100585
[28] Vasileva-Stojanovska, T., Vasileva, M., Malinovski, T., Trajkovik, V. (2015). An ANFIS model of quality of experience prediction in education. Applied Soft Computing, 34: 129-138. https://doi.org/10.1016/j.asoc.2015.04.047
[29] Teerasoponpong, S., Sopadang, A. (2022). Decision support system for adaptive sourcing and inventory management in small-and medium-sized enterprises. Robotics and Computer-Integrated Manufacturing, 73: 102226. https://doi.org/10.1016/j.rcim.2021.102226
[30] Zahraee, S.M., Shiwakoti, N., Stasinopoulos, P. (2022). Agricultural biomass supply chain resilience: COVID-19 outbreak vs. sustainability compliance, technological change, uncertainties, and policies. Cleaner Logistics and Supply Chain, 4: 100049. https://doi.org/10.1016/j.clscn.2022.100049
[31] Wang, L.J. (2014). Sustainability of Bioenergy Systems. Sustain. Boca Raton. CRC Press. https://doi.org/10.1201/b16764
[32] Tan, W.C., Sidhu, M.S. (2022). Review of RFID and IoT integration in supply chain management. Operations Research Perspectives, 9: 100229. https://doi.org/10.1016/j.orp.2022.100229
[33] Culaba, A.B., Mayol, A.P., San Juan, J.L.G., Ubando, A.T., Bandala, A.A., Concepcion II, R.S., Alipio, M., Chen, W., Show, P.L., Chang, J.S. (2023). Design of biorefineries towards carbon neutrality: A critical review. Bioresource technology, 369: 128256. https://doi.org/10.1016/j.biortech.2022.128256
[34] Nguyen, H.T.G., Lyttek, E., Lal, P., Wieczerak, T., Luong, T. (2022). Evaluating loblolly pine bioenergy development potential using AHP integrated weighted overlay and network optimization in Virginia, USA. Trees, Forests and People, 8: 100271. https://doi.org/10.1016/j.tfp.2022.100271
[35] Maraveas, C., Piromalis, D., Arvanitis, K.G., Bartzanas, T., Loukatos, D. (2022). Applications of IoT for optimized greenhouse environment and resources management. Computers and Electronics in Agriculture, 198: 106993. https://doi.org/10.1016/j.compag.2022.106993
[36] Razik, A.H.A., Khor, C.S., Elkamel, A. (2019). A model-based approach for biomass-to-bioproducts supply Chain network planning optimization. Food and Bioproducts Processing, 118: 293-305. https://doi.org/10.1016/j.fbp.2019.10.001
[37] Sargent, R.G. (2010). Verification and validation of simulation models. In Proceedings of the 2010 Winter Simulation Conference, Baltimore, MD, USA, pp. 3212-3219. https://doi.org/10.1109/WSC.2010.5679166
[38] Loy, A.C.M., Kong, K.G.H., Lim, J.Y., How, B.S. (2023). Frontier of digitalization in Biomass-to-X supply chain: Opportunity or threats? Journal of Bioresources and Bioproducts, 8(2): 101-107. https://doi.org/10.1016/j.jobab.2023.03.001
[39] Ahmadi, L., Kannangara, M., Bensebaa, F. (2020). Cost-effectiveness of small scale biomass supply chain and bioenergy production systems in carbon credit markets: A life cycle perspective. Sustainable Energy Technologies and Assessments, 37: 100627. https://doi.org/10.1016/j.seta.2019.100627
[40] Primmer, E., Varumo, L., Krause, T., Orsi, F., Geneletti, D., Brogaard, S., Aukes, E., Ciolli, M., Grossmann, C., Hernández-Morcillo, M., Kister, J., Kluvánková, T., Loft, L., Maier, C., Meyer, C., Schleyer, C., Spacek, M., Mann, C. (2021). Mapping Europe's institutional landscape for forest ecosystem service provision, innovations and governance. Ecosystem Services, 47: 101225. https://doi.org/10.1016/j.ecoser.2020.101225
[41] Yalew, A.W. (2022). The Ethiopian energy sector and its implications for the SDGs and modeling. Renewable and Sustainable Energy Transition, 2: 100018. https://doi.org/10.1016/j.rset.2022.100018
[42] Yan, B., Yan, J., Li, Y., Qin, Y., Yang, L. (2021). Spatial distribution of biogas potential, utilization ratio and development potential of biogas from agricultural waste in China. Journal of Cleaner Production, 292: 126077.

https://doi.org/10.1016/j.jclepro.2021.126077

[43] Beriro, D., Nathanail, J., Salazar, J., Kingdon, A., Marchant, A., Richardson, S., Gillet, A., Rautenberg, S., Hammond, E., Beardmore, J., Moore, T., Angus, P., Waldron, J., Rodrigues, L., Nathanail, P. (2022). A decision support system to assess the feasibility of onshore renewable energy infrastructure. Renewable and Sustainable Energy Reviews, 168: 112771. https://doi.org/10.1016/j.rser.2022.112771

[44] Helo, P., Rouzafzoon, J. (2023). An agent-based simulation and logistics optimization model for managing uncertain demand in forest supply chains. Supply Chain Analytics, 4: 100042. https://doi.org/10.1016/j.sca.2023.100042

[45] Baruah, D., Baruah, D. C. (2021). Decision support system based planning of biomass gasification system for decentralised energy generation. Renewable Energy Focus, 38: 22-35. https://doi.org/10.1016/j.ref.2021.05.002

[46] Vlachokostas, C., Achillas, C., Diamantis, V., Michailidou, A.V., Baginetas, K., Aidonis, D. (2021). Supporting decision making to achieve circularity via a biodegradable waste-to-bioenergy and compost facility. Journal of Environmental Management, 285: 112215. https://doi.org/10.1016/j.jenvman.2021.112215

[47] Tauro, R., Rangel, R., Suárez, R., Caballero, J.L., Anaya-Merchant, C., Salinas-Melgoza, M., Guzmán, H., Ghilardi, A. (2021). An integrated user-friendly web-based spatial platform for bioenergy planning. Biomass and Bioenergy, 145: 105939. https://doi.org/10.1016/j.biombioe.2020.105939