energies

MDPI

Article

Two-Phase Approach for Designing Sustainable Biomass Supply Chains for Community-Scale Biomass Power Plants in Thailand

Athipthep Boonman [1,2,3], Suneerat Fukuda [1,2,*], Shubham Tiwari [3] and Florian Kraxner [3]

[1] The Joint Graduate School of Energy and Environment, King Mongkut's University of Technology Thonburi, Bangkok 10140, Thailand; athipthep.boon@kmutt.ac.th
[2] Center of Excellence on Energy Technology and Environment (CEE), Ministry of Higher Education, Science, Research and Innovation (MHESI), Bangkok 10140, Thailand
[3] Agriculture, Forestry, and Ecosystem Services Research Group (AFE), Biodiversity and Natural Resources Programs (BNR), International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, A-2361 Laxenburg, Austria; tiwaris@iiasa.ac.at (S.T.); kraxner@iiasa.ac.at (F.K.)
* Correspondence: suneerat.pip@kmutt.ac.th

Abstract: This study proposes a novel two-phase model framework for designing sustainable biomass supply chains of Community-Scale Biomass Power Plants (CSBPPs) by optimization based on geospatial-based Multi-criteria Decision Making (MCDM), the Analytic Hierarchy Process (AHP) method and the Location–Allocation Model. Phase I involved land suitability criteria prioritization and suitable land area analysis. The location–allocation model was the main tool used in Phase II to identify optimal locations, followed by the analysis of the levelized cost of electricity (LCOE). The model optimized site location based on the availability (remaining) of local crop residues, electricity demand, road networks and other key criteria for power plant development, such as the location of substations and the location of existing power plants. The results show that the estimated total remaining crop residue potential in the EEC region was 2403 kt/year, which can generate approximately 34,156 TJ. The location–allocation model identified the top five locations for CSBPPs. The total required installed capacity of these five locations was approximately 100.23 MW in order to serve the district energy demand by the residential sector of 793.82 million (kWh/year). Assuming direct combustion-steam turbine technology with an installed capacity of 6–10 MW, the average LCOE was found to be in a range of \$0.076 to \$0.081 USD/kWh.

Keywords: distributed energy generation; community-scale biomass power plant; sustainable supply chain; location–allocation model; optimal locations; plant-level levelized cost of electricity

Academic Editor: Alberto Maria Gambelli

Received: 14 November 2024
Revised: 2 January 2025
Accepted: 3 January 2025
Published: 23 January 2025

Citation: Boonman, A.; Fukuda, S.; Tiwari, S.; Kraxner, F. Two-Phase Approach for Designing Sustainable Biomass Supply Chains for Community-Scale Biomass Power Plants in Thailand. *Energies* **2025**, *18*, 520. https://doi.org/10.3390/en18030520

1. Introduction

Thailand's centralized energy system, reliant on fossil fuels and imports, hinders economic security and sustainability [1,2]. Distributed energy resources (DERs) offer a solution, enabling efficient local power generation and community participation. This aligns with Thailand's vision of supporting local economies through community-based energy initiatives [3]. Biomass is considered a sustainable alternative fuel for power generation and serves the purpose of DERs. For a successful and sustainable community-scale biomass power plant (CSBPP) project, a holistic approach considering multi-faceted decision-making criteria ranging from geographical to socio-cultural issues must be taken [4–7]. The availability of biomass resources and securing a stable supply are crucial [2,3,8]. Engaging the local community in biomass supply is a strategic approach to ensure a stable supply of biomass and leverage local acceptance and participation.

Different methods have been used in energy policy-making and sustainable energy management and prioritizing renewable energy key criteria selection. Budak et al. [9] used AHP to evaluate the best renewable energy technology for sustainable energy planning in Turkey. Effatpanah et al. [10] conducted a comparative analysis of five Multi-criteria Decision Making (MCDM) techniques (SAW, TOPSIS, ELECTRE, VIKOR, and COPRAS) for clean energy technologies including biomass, solar, wind, and nuclear solutions. Numerous scientific studies have been conducted, including Multi-criteria Decision Making (MCDM) methods for renewable energy planning and resource allocation [7,11–15] and combined Geographic Information System (GIS) with Analytic Hierarchy Process (AHP) to prioritize renewable energy options [9,16] or for facility site selection [17]. The methods have also been applied to explore the suitability of biomass resources for bioenergy production and power plant location and size determination. Kocoloski et al. [18] investigated the impact of facility size and location on production costs. Perpiñá et al. [19] used GIS for biomass logistics optimization, while Bojić et al. [20] and Höhn et al. [21] focused on power plant location and size determination. Modeling and optimization studies have also been conducted to optimize power plant locations [13,22–25]. Leduc et al. [26] developed an optimization model for forest biomass-based methanol production plants in Sweden, and Comber et al. [27] used GIS-based location–allocation algorithms for community-scale ADs in the UK. Natarajan et al. [28] created maps to determine surplus biomass resources and optimize power plant placement.

Despite these advancements, existing studies still have some limitations. The selection criteria are somehow considered separately from the GIS-based location analysis, and therefore, the resulting locations may not reflect the most suitable candidates. So far, physical factors such as geographical and infrastructural factors are often included as criteria in the location analysis and less socio-economic criteria, which are also important for the sustainability of a project. Lastly, there is a lack of integration of spatial and temporal analysis of feedstock residues, especially for distribution at district levels.

To address some of the gaps mentioned above, this study has developed a two-phase model framework and used it for CSBPPs site selection and LCOE analysis for the EEC region in Thailand as a case study. The proposed mode framework has the following features.

Phase I: Prioritizing critical criteria and developing a comprehensive framework. This study prioritized 13 critical criteria reflecting sustainability for CSBPPs. Combining GIS-based MCDM, AHP techniques, and expert recommendations, area suitability was classified in the EEC region.

Phase 2: Optimizing CSBPPs locations using Location–Allocation Modeling. An optimization model based on the p-median problem was implemented on the ArcGIS Pro 3.0.2 platform to identify optimal CSBPP locations based on the minimum distances between demand locations and CSBPP locations. The constraints of local demand and plant capacity were also applied. Then, the levelized cost of electricity (LCOE) was analyzed for potential CSBPPs. Sensitivity analysis of biomass fuel types was also conducted for future fuel supply management.

The main advantage of conducting the study in two phases over other existing models is that each phase can be flexibly designed based on the objectives, available database, selection criteria, level of complexity and so on. The model can also work in conjunction with other open platforms.

2. Materials and Methods

2.1. The Study Area

The Eastern Economic Corridor (EEC) is a newly developed industrial region situated along Thailand’s eastern seaboard [29,30]. This innovative hub focuses on high-value industries and covers 1.334 million hectares. The study area is located between latitudes 12°20′ and 14°10′ N, and longitudes 100°50′ and 102°00′ E. To assess land suitability for CSBPPs, a geospatial modelling platform was used, incorporating ModelBuilder and the coding toolbox from ArcGIS Pro 3.0.2 platform [31].

2.2. Modeling Framework

Figure 1 presents the model framework, which uses a two-phase approach. Phase-I used the GIS-MCDM and AHP methods. Key criteria considered as constraints included four main criteria groups: geophysical, infrastructural, socioeconomic–cultural, and exclusion. Each criteria group was further divided into sub-criteria, prioritized with expert recommendations. Based on the geospatial dataset and GIS-MCDM and AHP results, area suitability was classified. Within the boundary of highly suitable areas optimized in Phase-I, Phase-II used the network analysis to select the most suitable sites for CSBPPs and LCOE analysis. Constraints included electricity demand, biomass supply availability and other factors such as road networks.

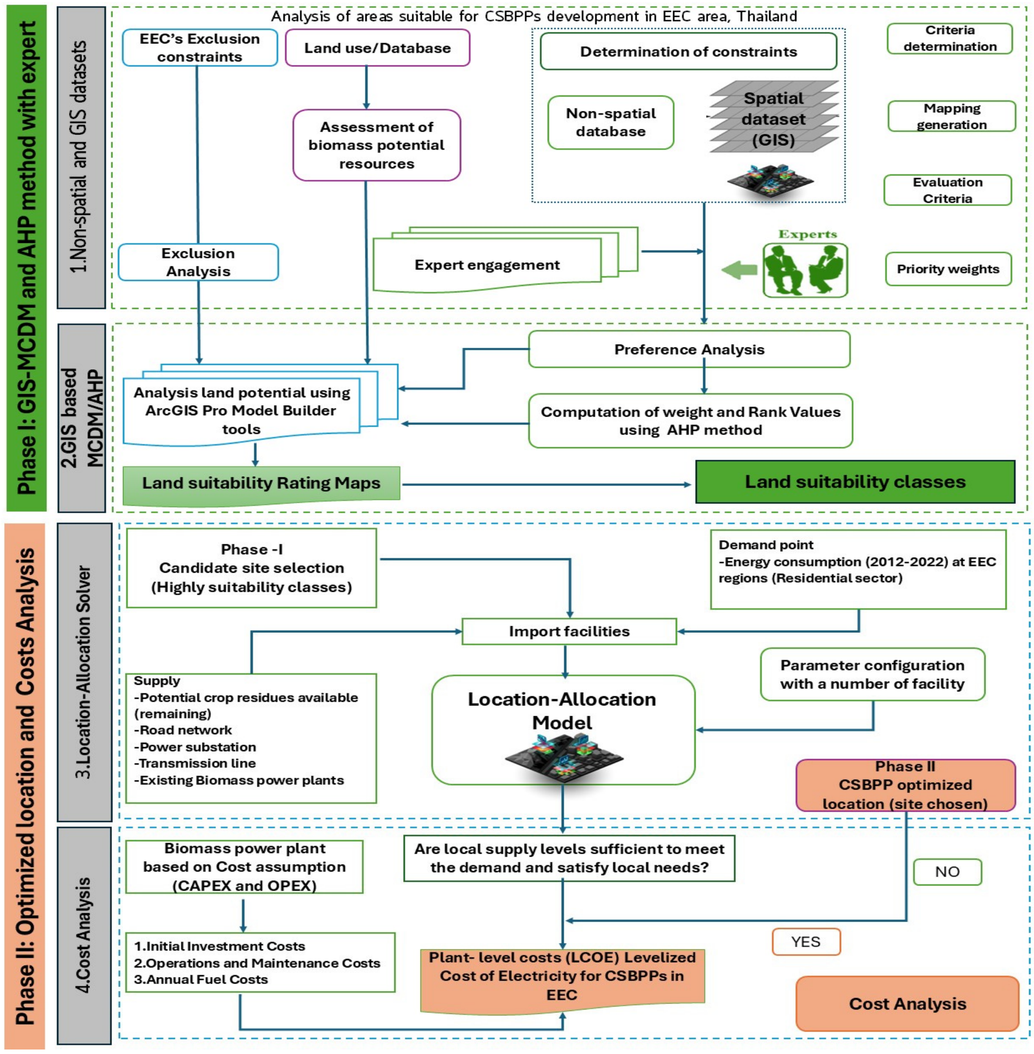


Figure 1. Two-phase CSBPPs location optimization model.

2.3. Input Data and Criteria Assumptions

2.3.1. GIS-MCDM and AHP Method with Expert Recommendation Criteria Assumptions (Phase I)

Parameters or criteria for CSBPPs site selection were initially identified based on Boonman et al. [4], which covered three main dimensions: geophysical, infrastructural, and socioeconomic–cultural with an exclusion zone. Selected experts from multi-stakeholders were invited to evaluate and prioritize the criteria for land suitability assessment. Criteria prioritization was conducted through a questionnaire constructed based on the AHP method. A geospatial database was prepared to convert feature class datasets (points, lines, and polygons) into a raster feature format for automated geospatial-based MCDM and AHP methods. Each dataset was displayed on a 100 m grid cell covering the period from 2019 to 2037, available in both gridded and attribute data formats. A summary of the types and sources of datasets for the main and sub-criteria is presented in Table 1 (Phase I). The selection of CSBPPs suitable sites was determined from the analyzed weight scores given by the experts.

- Geophysical criteria

The geophysical parameters considered included five sub-criteria. Biomass feedstock potential was a crucial factor to ensure a stable supply for the biomass power plant. Water resources were also essential for accessing raw water required in power plant operations. The remaining three sub-criteria focused on land suitability, prioritizing locations within agricultural promotion zones or industrial development zones with appropriate land slopes [32–35].

- Infrastructural criteria

Infrastructure criteria included four sub-criteria. CSBPPs should be located near power lines and substations to minimize grid connection costs. Existing and planned biomass VSPP capacity and location were considered to avoid feedstock competition. Primary and sub-road networks were also evaluated to assess transportation costs for biomass supply [36,37].

- Socio-economic criteria

Socio-economic impact was a key criterion in this study, focusing on three sub-criteria [10,38]. Land suitability for rural community development was determined based on future land use plans. Maintaining appropriate distances between power plants and essential places like schools and hospitals was also considered. Local community participation and public acceptance were crucial for the project's success and benefits. These factors were assessed based on the distance from local communities, which indicated potential for partnerships and local biomass supply.

- Exclusion zone criteria

Exclusion zones, including commercial areas, urban areas, future development sites, and environmentally sensitive areas, were unsuitable for CSBPP construction. Densely populated urban areas, particularly along the eastern coast, forests, and flood-prone regions, were excluded from consideration for new CSBPP development [32,39].

2.3.2. Spatial Optimal Location–Allocation Model Criteria Assumptions (Phase II)

Table 1 (Phase II) summarizes the datasets used for site selection optimization, including highly suitable areas, energy consumption data at the district level, road networks, transmission lines, power substations, potential crop residue availability, and demand location. The specific criteria and their corresponding integer values are detailed in Figure 2a–f.

Table 1. Selection of constraint used, type, and sources of datasets.

Prioritizing Criteria Phase I	Sub-Criteria	Data Format	Sources	Year
1. Geophysical	Biomass feedstock potential	Polygon	LDD [1]/OAE [2]	2019/20
	Waterbody	Polygon	DPT [3]/EECO [4]	2019
	Agricultural promotion zone	Polygon	DPT [3]/EECO [4]	20-year land use plan (2018–2037)
	Industrial development zone	Polygon	DPT [3]/EECO [4]	
	Slope data	Polygon	DEM [5]	2019
2. Infrastructural	Transmission/Distribution power lines	Line	DPT [3]/PEA [6]	2020
	Power substation	Point	DPT [3]/EECO [4]	2019/20
	Existing biomass-VSPP	Point	DPT [3]/EECO [4]	2019/20
	Main road network	Line	DPT [3]/EECO [4]	2019
	Sub road network	Line	DPT [3]/EECO [4]	2019
3. Socioeconomic–cultural	Potential land for rural community development	Polygon	DPT [3]/EECO [4]	20-year land use plan (2018–2037)
	Important locations (Hospitals and Schools)	Point	LDD [1]	2019
	Local community participation and public acceptance	Point	DPT [3]/EECO [4]	2019/20
4. Exclusion zone	Commercial and Urban community area	Polygon	DPT [3]/EECO [4]	
	Future Urban Development	Polygon	DPT [3]/EECO [4]	20-year land use plan (2018–2037)
	Environment protection	Polygon	DPT [3]/EECO [4]	
	Land reform	Polygon	DPT [3]/EECO [4]	
	Forest Preservation	Polygon	DPT [3]/EECO [4]	
	Flood risk area	Polygon	GISTDA [7]	2020
Key Criteria Phase II	**Parameter Assumptions**	**Data Format**	**Sources**	**Year**
A highly suitable location	Candidate site	Point	Generated from the Phase-I study	2020
Main road network	Import facility	Line	DPT [3]/EECO [4]/GISTDA [7]	2019
Power substation and power grid network (22 kV)	Required	Line	DPT [3]/EECO [4]	2022
Energy consumption in the EEC region 10 years average (2012–2022) at the district level	Demand data	Table	PEA [6] and generated	2012–2022
Local community participation point	Demand potential	Point	DPT [3]/EECO [4]	2020
Existing biomass power plants (VSPPs)	Competitor	Point	DEDE [8]	2019
Total potential crop residues (remaining) for energy production	Supply side potential	Point	Generated from the Phase-I study [9]	2019/20

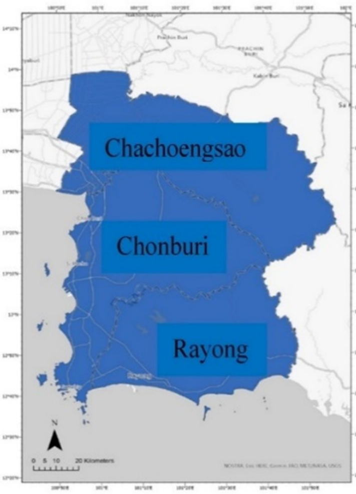
[1] LDD: Land Development Department [33] [2] OAE: Office of Agricultural Economics [34] [3] DPT: Department of Public Works and Town & Country Planning [32] [4] EECO: The Eastern Economic Corridor Office of Thailand [30] [5] DEM: Digital Elevation Model from NASA's Earth Science Data Systems (ESDS) [35] [6] PEA: Provincial Electricity Authority [36] [7] GISTDA: Geo-Informatics and Space Technology Development Agency (Public Organization) [39] [8] DEDEc: Department of Alternative Energy Development and Efficiency [40] [9] DEDEb (ESCAP-guideline for biomass pilot training project handbook, 2020) [38].

- Highly suitable areas

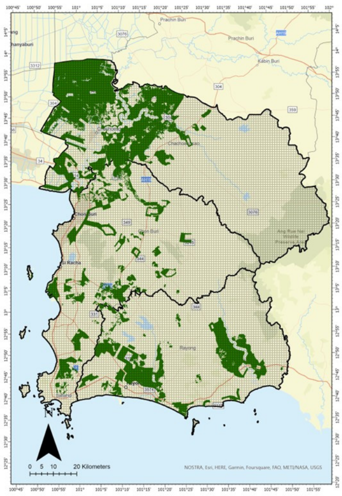
Area suitability was analyzed. Highly suitable areas were identified as illustrated in dark green color (Figure 2b) and was used as the boundary for suitable site selection for CSBPPs.

- Road network, power substation and power grid networks

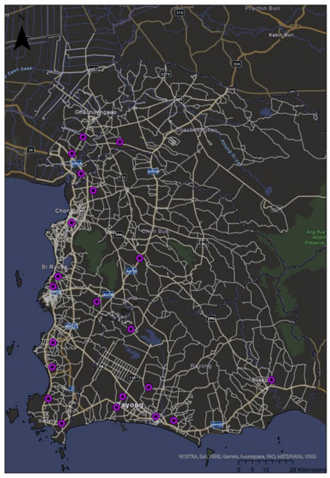
Required facilities were constrained to the following criteria for CSBPPs such as a road network (Figure 2c) or a power grid network (22 kV) with location of power substations identified as red symbols (Figure 2d) [32,36].



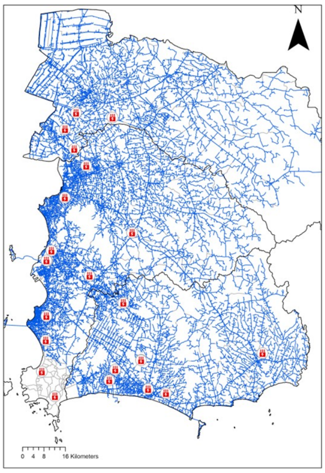
(**a**) EEC regional boundary#



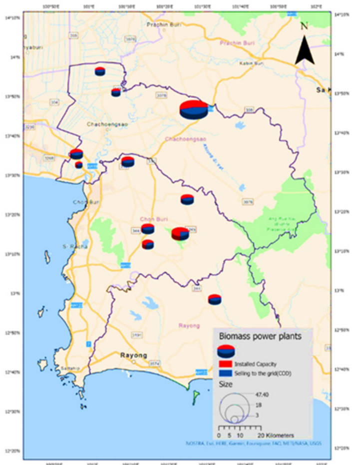
(**b**) Highly suitable area (grided size 1 km × 1 km) (Candidate) #



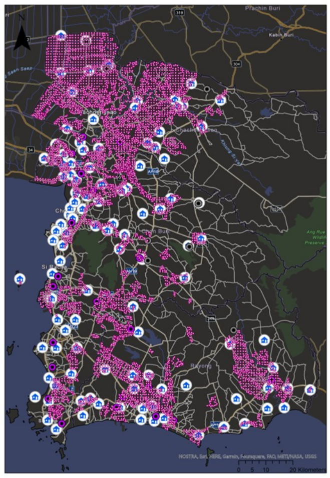
(**c**) Build road network (Required)



(**d**) Power substation and power grid network 22 kV (Required)



(**e**) Existing power plants (VSPPs) (Competitors)



(**f**) Local community participation (demand point)

Figure 2. Spatial layer import facility types and demand point input dataset for the location–allocation model (Source: adapted from Boonman et al. [4], EECO [30], DPT [32], LDD [33], PEA [36]).

- Other spatial data
  (1) A competitor facility pertains to specific types of problems, particularly in addressing market share challenges. This includes the location of existing biomass power plants (VSPPs) within the EEC region categorized by the installed capacity (Figure 2e).
  (2) Candidate point shown in pink color (Figure 2f) represents points of demand or local community participation within highly suitable area, while the facility represented by a symbol indicate locations with district demand potential.
  (3) Once the model solver has determined the optimal locations for the candidate CSBPPs sites, it updates the facility type from candidate to chosen.

2.4. Assessing Spatial and Temporal Variation of Feedstock Supply Availability

This study evaluated the remaining potential of annual crop residues for biomass power production. The parameters and assumptions considered included plantation area, crop productivity, Residue-to-Product Ratio (RPR), and unused fraction. Data on plantation areas and crop productivity were obtained from GIS databases and published studies. Potential feedstock sources included rice (husk and straw), sugarcane, cassava, oil palm, and para rubber tree residues. The spatial and temporal distributions of crop residues are provided in Figures S1–S5 of the Supplementary File.

2.5. Optimizing CSBPPs Site Selection: A Location–Allocation Modeling Approach

Geospatial tools can be used to spatially indicate community-scale biomass power plants facility location. Network analysis can be involved in finding origin and destination points. In the context of CSBPPs, highly suitable areas are origin points, while local communities are destination points. The goal is to maximize accessibility by locating CSBPPs to serve as many communities as possible. This can be framed as a general planning problem, where multiple facilities (CSBPPs) are located and allocated to nearby demand points (communities) for efficient service delivery [31,40,41]. Unlike a sequential approach, where sites are selected one by one, the simultaneous location of multiple CSBPPs is crucial for minimizing transportation costs

Location–allocation modelling provides a valuable tool for complex decision-making processes. By incorporating prioritizing criteria based on both qualitative and quantitative data, this approach optimizes facility locations [25,40–44]. The objective is to minimize the overall distance between facilities potential (x, y, coordinate of feedstock supply) and demand points. The *p*-median problem type, as a common location–allocation model, aims to find the optimal locations for a given number of facilities to minimize the total weighted distance between demand points and facilities. While traditional spider plots visualize facility and allocation decisions, they lack information on demand and allocation quantities. To address this, GIS offers the potential to mitigate errors and uncertainties, enabling a more comprehensive understanding of the problem. Traditionally used for warehouse location optimization, location–allocation models can also be applied to public facilities like CSBPPs, which minimize impedance (travel distance) and ensure equitable access for communities.

The following notation for this study is the metric weighted distance for the location–allocation minimized weighted impedance (*p*-Median) problem type [31,41–44]. The goal is to allocate several CSBPPs to minimize the overall weighted distance between these facilities and the demand points they serve. We assume that each demand point was allocated to the nearest CSBPPs. Consider the following notation for applied the problem in this study, the mathematical representation of the *p*-Median problem is developed according to the mentioned indices, parameters, and decision variables [41]:

$$\mathrm{i} = \text{index of demand point } (1, 2, \ldots, \mathrm{n})$$

$$\mathrm{j} = \text{index of CSBPPs potential site } (1, 2, \ldots, \mathrm{m})$$

$$d_{ij} = \text{shortest distance from demand point } i \text{to potential CSBPPs site } j$$

$$\mathrm{a_i} = \text{amount of demand in point } i$$

$$p \ = \ \text{number of CSBPPS sites to be located}$$

$$Y_{\mathrm{j}} = \text{number} \begin{cases} 1 \\ 0 \end{cases} \text{if CSBPPs at site j is located } (1) \text{ and otherwise } (0)$$

$$X_{\text{ij}} = \text{number} \begin{cases} 1 \\ 0 \end{cases} \text{if demand } i \text{is served by CSBPPs site j } (1) \text{ and otherwise } (0)$$

This condition, given the binary requirement for the Y_j variables, ensures that exactly p of the Y_j variables will equal one. Note that any number of CSBPP site locations can be considered, depending on budgetary limitations or a range of potential sites. These functions and inequalities can be combined to formulate the following location–allocation problem:

$$Minimize \sum_{i=1}^{n} \sum_{j=1}^{m} a_i d_{ij} X_{ij} \tag{1}$$

Subject to:

$$\sum_{j=1}^{m} X_{ij} = 1 \tag{2}$$

$$X_{ij} \leq Y_j \text{ for each } i = 1, 2, \ldots, n \text{ and } j = 1, 2, \ldots, m \text{ for each } i = 1, 2, \ldots, n \tag{3}$$

$$\sum_{j=1}^{m} Y_j = p \tag{4}$$

$$X_j = \{0, 1\} \text{ for each } j = 1, 2, \ldots, m \tag{5}$$

$$X_{ij} = \{0, 1\} \text{ for each } j = 1, 2, \ldots, n \text{ and } j = 1, 2, \ldots, m$$

The goal (1) is to minimize the total weighted assignment distance. Constraint (2) requires each demand point i to be served by a CSBPPs site. Constraint (3) restricts allocations for a given demand i to only sites j that have been chosen for residential community sites. Given the minimization goal and constraints (2) and (3), each demand can be distributed to its nearest CSBPPs. Constraint (4) specifies the selection of p sites for CSBPPs placement.

Finally, binary requirements are imposed in constraints (5). Note that it is only necessary to keep the binary properties on the Y_j variables when solving this problem in practice. Since each demand point must be allocated exactly once and is restricted to assign to only those sites that have been selected for a CSBPPs candidate site, the goal function ensures that demand point assignments will be made entirely to the closest CSBPPs site, if there is a single closest CSBPPs. An assignment variable for a given demand may be functional in an optimal solution only when there is a variable accordingly for the closest located CSBPPs to that demand community location. This model is adapted from the classic facility location problem, as presented by ReVelle and Swain [43], Rosing et al. [44], with adopted from Church and Wang [41].

Figure 3 presents the Phase-II simulation-based optimized location model used in the study. The selection of sites for an ideal multi-site layout was performed simultaneously rather than individually. It is constrained by a domain of values, which is referenced by the integer value in parentheses in the following list:

- Potential site selection (1) is a candidate of a CSBPP site or a facility location potential that is a part of the solution.
- Required (2) is a required of CSBPPs or a facility that is essential to the solution.
- Competitor (3) is a competitor facility location specific to the target demand share problem types. It is an existing biomass power plant site that will competitively reduce duplicate demand within the problem domain.

- Chosen (4) is the CSBPP site that was once determined by the location–allocation solver as a candidate facility for the solution.

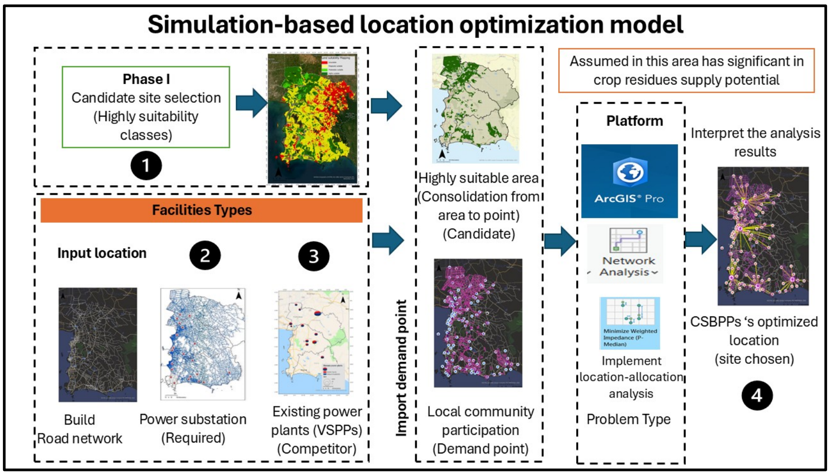


Figure 3. Phase-II simulation-based location optimization model used in the study.

2.6. Cost Analysis and Assumptions for Calculation

Levelized Cost of Energy (LCOE) is a common metric used to compare different power generation technologies. Essentially, LCOE represents the price at which energy must be sold to recover all costs associated with a technology over its lifetime [38,45,46]. The LCOE was calculated as shown in Equation (6).

$$\mathrm{LCOE} = \sum_{t=1}^{n} \frac{\frac{I_t + M_t + F_t}{(1+r)^t}}{\frac{E^t}{(1+r)^t}} \tag{6}$$

where, I_t is investment expenditures in year t (including financing) of investment,

M_t is operations, maintenance and expenditures in year t,

f_t is fuel expenditures in year t,

E_t is the sum of all electricity generated in year t,

r is the discount rate of the project,

n is life of the system.

In this study, only direct combustion-steam turbine technology with a capacity of 6–10 MW was assumed for CSBPPs since it is the most common technology to convert biomass to electricity in Thailand and worldwide. The popular adoption of this technology is due to its simplicity, cost effectiveness, and flexibility [38,47,48]. Combustion stoker-fired systems can work best with raw material biomass fuels that have up to 60% of moisture. The capacity of 6–10 MW is reasonable for a community scale, which is a trade-off between the fuel supply collection and the economy of scale. Some salient specifications of the technology used, the investment costs related to it, percentages of taxes, depreciation, etc., and cost-specific characteristics are summarized in Table 2. The assumptions were based on a 10 MW CSBPP using para rubber wood as feedstock. The cost analysis includes capital expenditure (CAPEX), operational expenditure (OPEX), and biomass fuel costs. The resulting LCOE is expressed in USD per kWh.

Table 2. Inputs for cost-specific characteristics of selected CSBPPs.

Parameter [38,49–51]	Units	Values
Debt ratio	%	30
Interest rate (MLR)	%	6
Repayment Terms	Year	7
Plant capacity	MWe	10
Initial investment costs	Million USD/MWe	11–20
Variable O & M Cost/year	USD/Year	461,960
Total operation expense cost (fixed O&M cost including labor)	USD/Year	676,588
Total biomass fuel cost (logistics + fuel price + processing) [1]	USD/tonne	38
Biomass Fuel required (Direct combustion)	tonne/MWh	1.5
Biomass fuel-specific consumption	MWh/tonne	0.667
Biomass fuel consumption	tonne/Year	118,741
Total biomass fuel cost (BFC × 1320) based on para rubber [1]	USD/Year	4,478,218
Discount Rate	%	10
VSPP operation hour	h/year	7920
Operation day	Day/Year	330
Plant load factor	%	75
Annual energy production	kWh/Year	79,200,000
Salvage	%	10
Land cost [2]	Million USD/Rai	0.02–0.07
Land required	Hectare (ha)	8
O&M growth rate	%/Year	10
Inflation rate [3]	%/Year	2.2
Project lifetime	Year	20

[1] Woodchip was assumed at 38 USD/tonne (or 1320 THB/tonne) and 1.5 tonne/MWh for direct combustion [2] The Treasury department (Rayong provinces 2000 THB/square wah), Chon Buri provinces 6000 THB/square wah, Chachoengsao provinces 3500 THB/square wah; https://assessprice.treasury.go.th/ (accessed on 25 May 2021) [52] [3] Ministry of Commerce (Inflation rate average: 2.2% in 2023) FPO (Fiscal Policy Office). Annual Report; 2021. https://www.fpo.go.th/main/AboutUs/AnnualReport/17999.aspx#2021 (accessed on 14 March 2023) [51].

3. Results and Discussion

3.1. Crop Residues Remaining Potential in the EEC Regions

The annual gross crop residue potential for use as energy feedstocks in the EEC regions was estimated from feedstock characteristics based on the existing studies [4,31,35,53,54]. As presented in Table 3, total crop residue remaining potential in the EEC region is estimated to be 2403 kt/year, with sugarcane residues (1767 kt/year) being the highest priority feedstock, followed by residues from rice (276 kt/year), oil palm (203 kt/year), cassava (133 kt/year) and para rubber (24 kt/year). The total energy potential from these crop residues is approximately 34,156 TJ.

3.2. Top Five Optimal Site Locations of CSBPPs Candidates

Based on the location–allocation modelling approach discussed in Section 2.5, Figure 4 presents the top five candidate locations for CSBPPs, including (1) Mueang Rayong (Rayong), (2) Mueang Klaeng (Rayong), (3) Chom Thian (Chonburi), (4) Ban Bueng (Chonburi), and (5) Mueang Chachoengsao (Chachoengsao). The total required installed capacity of these five locations was approximately 100.23 MW in order to serve the district energy demand by the residential sector of 793.82 million (kWh/year) [52].

Table 3. Gross crop residue (remaining) potential for the EEC region based on the year 2019/20.

Crop	Total Crop Production (kt) [1]	Residues Types [1]	Crop Residues Remaining (kt, Dry Matter) [2]	Available Energy Potential (TJ) [3]
Sugarcane	17,090	Tops and leaves	1767	27,360
Palm	432	Palm trunk	200	1511
		Palm fronds and leaves	3	5
1st Crop rice	412	Rice straw	129	1591
2nd Crop rice	468	Rice straw	147	1808
Cassava	1580	Cassava trunk	98	1532
		Cassava rhizome	35	190
Para rubber	103	Rubber tree root	24	159
Gross crop residue (remaining) potential			2403	34,156

[1] Total of crop production in the EEC area data source (e.g., statistical information such as annual crop production or annual production of the primary production (ton) and yield (ton/ha) from OAE, 2019 [34], spatial land use information from LDD, 2020 [33]. [2] Total of potential crop residues (remaining) available for energy production (the year 2019/20) was calculated based on five crop residue types, which also included sugarcane (leaves and tops), oil palm (palm trunk), rice (1st and 2nd crop—rice husk and straw), cassava (cassava waste and rhizome), and para rubber (para rubber root). Crop residue (remaining) potential was calculated based on residues to product ratio (RPR) to the main product (%), harvesting coefficient (%) and unused fraction of residues (%). Information was obtained from Energy for Environment Foundation (EforE) [54]; DEDEb and ESCEP-guideline for biomass pilot training project handbook, 2020) [38]; DEDEc, 2014 [53] [3] Energy potential available = amount of biomass residue available (dry weight)× LHV × conversion factor; Conversion factor MJ ×11,700,000 kWh × (efficiency 20%)/(42,120,000 MJ 24 h/day × 330 day/year) [38,53].

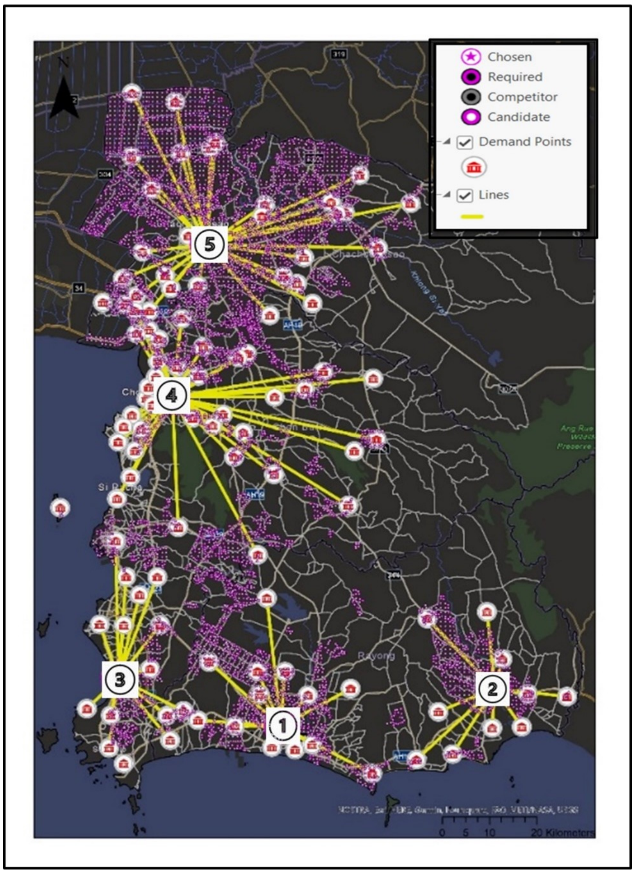


Figure 4. Optimal locations of top five CSBPP sites from location–allocation model.

3.3. Selection of Optimal Installed Capacity and Technology

The Thai government has launched a pilot project to generate a total of 150 MW of power. This project involves constructing biomass power plants with a capacity of less than 6 MW and biogas power plants with a capacity of less than 3 MW [2,3]. While the initial target for biomass power plants was 6 MW, it is also worth considering a capacity of beyond 6 MW but not more than 10 MW due to the expected benefit from better efficiency. Therefore, this study covered CSBPPs with installed capacities between 6 and 10 MWe using direct combustion (steam turbine) technology. The resulting characteristics of the five CSBPP candidate sites are shown in Table 4.

Table 4. Location of selected CSBPPs facilities and their required installed capacities.

Location No.	Name of Location	Total Installed Capacity Required for Each Location (MWe)
I	Mueang, Rayong	37.76
II	Meang Klaeng, Rayong	13.93
III	Chom Thian, Chonburi	17.33
IV	Ban Bueng, Chonburi	12.78
V	Mueang Chachoengsao	18.43
		100.23

3.4. Levelized Cost of Electricity (LCOE) of CSBPPs

Table 5 summarizes the main contributors to LCOE and the estimated LCOE for CSBPPs at the top five sites (power plant clusters), based on rubber woodchip as fuel. The smaller the plant size in the cluster, the higher the operational cost.

Table 5. LCOE of CSBPPs from the top five optimal sites.

Power Plant Site (ID)	Units	6858 (I)	5897 (II)	5651 (III)	4258 (IV)	3316 (V)
Installed capacity required	(MWe)	37.76	13.93	17.33	12.78	18.43
CAPEX	(Million USD/site)	43.15	15.92	19.81	14.61	21.06
OPEX	(Million USD/year)	2.71	1.35	1.35	0.68	1.35
Annual fuel costs	(Million USD/year)	16.91	6.24	7.76	5.72	8.25
Annual electricity output	(Million kWh/year)	299.06	110.33	137.25	101.22	145.97
LCOE	(USD/kWh)	0.085	0.089	0.086	0.090	0.085

Note: Levelized Cost of Electricity (LCOE) is calculated based on 10 MWe of CSBPPs using para rubber wood as feedstock, and the following assumptions are included [2,3,38,49,50]. (1) Capital Cost: \$20 million USD/MWe (This represents the initial investment cost of the plant) [2,3,38,49]. (2) Operations and Maintenance (O&M) Costs: \$0.68 million USD/year (This cost applies to a 10 MWe plant and scales based on the number of plants) [38]. (3) Biomass Fuel Cost: \$38 USD/ton (This range reflects the cost of biomass delivered to the plant) [direct interview, [2,3,38]. (4) Biomass Fuel Consumption: 0.667 kWh/USD (This indicates the amount of electricity generated per unit cost of biomass) [38]. (5) Operating Hours: 7920 h per year (This assumes operation for 330 days, calculated for a 10 MWe plant) [38,49] (6) Additional information, including data from stakeholder interviews and literature reviews, was used to refine the calculations [38,49–51].

To conduct the sensitivity analysis, the LCOE was also estimated based on the cost of different biomass fuel types and the results are illustrated in Figure 5. It is worth noting that in this calculation, per unit fuel cost was assumed not to vary with transportation distance or processing costs in order to reflect the competitive nature of the biomass supply business. The range of the LCOE across five candidate locations was the lowest for sugarcane leaves and tops (\$0.067–\$0.072 USD/kWh) and the highest for rubber tree root (\$0.085–\$0.090 USD/kWh). The results clearly indicate that the management of fuel supply, both amount and cost, is an important key parameter to ensure the sustainability of the CSBPP project and to minimize LCOE. When planning a CSBPP project, the seasonal availability of biomass, as shown in Figures S1–S5 in the Supplementary File, should be taken into consideration.

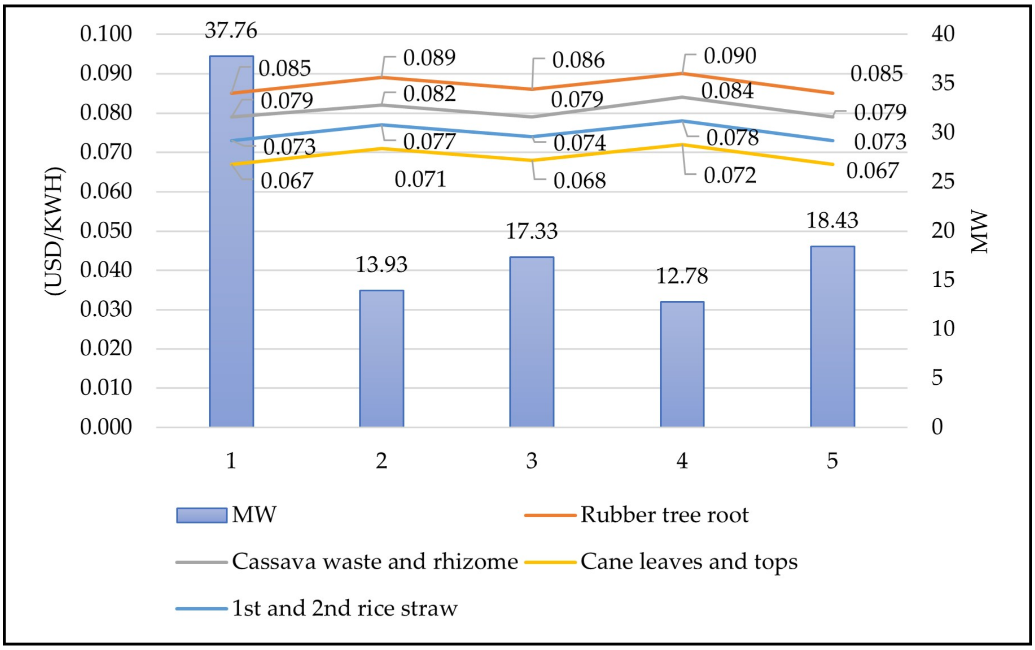


Figure 5. LCOEs varied by the cost of different biomass fuel types.

4. Conclusions

In this study, the optimal site locations for Community-Scale Biomass Power Plants (CSBPPs) in the EEC region of Thailand and their respective LCOEs were obtained using a two-phase model by optimization based on geospatial-based MCDM and AHP method followed by the location–allocation Model. Phase I involved biomass residue supply assessment, land suitability criteria prioritization and suitable land area analysis. The highly suitable land area from Phase I was then used as one of the important inputs for the location–allocation model in Phase II. The optimal locations of CSBPPs were selected based on the availability (remaining) of local crop residues, electricity demand, road network and other key criteria for power plant development, such as the location of substations and the location of existing power plants.

The results show that the estimated total remaining crop residue potential in the EEC region was 2403 kt/year, with sugarcane residues being the highest priority feedstock, followed by residues from rice, oil palm, cassava, and para rubber, and the total energy potential from these crop residues was approximately 34,156 TJ. Five optimal locations for CSBPPs were identified, including Thap Ma (Rayong), Thang Kwian (Rayong), Na Chom Thian (Chonburi), Na Pa (Chonburi), and Bang Tin Pet (Chachoengsao). The total required installed capacity of these five locations was approximately 100.23 MW in order to serve the district energy demand by the residential sector of 793.82 million (kWh/year).

Assuming direct combustion-steam turbine technology with an installed capacity of 6–10 MW, the average LCOE was found to be in a range of $0.076 to $0.081 USD/kWh. The sensitivity analysis clearly indicates that the management of fuel supply, both amount and cost, is an important key parameter to ensure sustainability of the CSBPP project and to minimize LCOE. When planning a CSBPP project, the seasonal availability of biomass should be taken into consideration.

The spatial decision support tools and location optimization model based on the ArcGIS Pro platform developed in this study can be applied to other regions facing similar challenges. However, modification or selection of the main and sub-criteria to align with specific geophysical conditions, other local contexts, and community priorities will be necessary to achieve a suitable location for the CSBPP facility.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/en18030520/s1, Figures S1–S5: Spatial and temporal information of biomass potential resources based on feedstock supply types in five potential locations. Figure S6 Spatial layer import facility types and demand point input dataset for the Location-Allocation model. Table S1. Inputs for cost-specific characteristics of selected CSBPPs.

Author Contributions: Conceptualization, A.B. and S.F.; methodology, S.T. and F.K.; validation, S.T. and F.K.; formal analysis, A.B. and S.F.; investigation, A.B. and S.F.; writing—original draft preparation, A.B., S.F., S.T. and F.K.; writing—review and editing, S.F. and S.T.; visualization, S.F., S.T. and F.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Petchra Pra Jom Klao PhD Research Scholarship, grant number (46/2563) by King Mongkut's University of Technology Thonburi (KMUTT) and the Center of Excellence on Energy Technology and Environment (CEE), Ministry of Higher Education, Science, Research and Innovation (MHESI) for the financial support provided to perform this study.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Acknowledgments: The authors highly appreciate contributions from Jompob Waewsak, Kanchit Ngamsanroaj, Agapol Junpen and Sylvain Leduc for comments and guidance on methodology and result analysis.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Van der Schoor, T.; Scholtens, B. Power to the people: Local community initiatives and the transition to sustainable energy. *Renew. Sustain. Energy Rev.* **2015**, *43*, 666–675. [CrossRef]
2. DEDEa (Department of Alternative Energy Development and Efficiency). The Alternative Energy Development Plan (AEDP 2018–2037). 2018. Available online: https://policy.asiapacificenergy.org/sites/default/files/Alternative%20Energy%20Development%20Plan%202018-2037%20(AEDP%202018)(TH).pdf (accessed on 14 February 2023).
3. EPPO (Energy Policy and Planning office). Thailand's Power Development Plan (PDP) 2018-2037 (Revision 1). 2020. Available online: https://www.eppo.go.th/images/Infromation_service/public_relations/PDP2018/PDP2018Rev1.pdf (accessed on 20 February 2020).
4. Boonman, A.; Fukuda, S.; Junpen, A.; Waewsak, J.; Ngamsanroaj, K.; Petchprayoon, P. Site suitability assessment for community-scale biomass power plant (CSBPPs) development in the Eastern Economic Corridor (EEC) region using the MCDM and AHP method based on geospatial modeling platform. In Proceedings of the 8th International Conference on Sustainable Energy and Environment (SEE 2022): The Road to Net-Zero: Energy Transition Challenges and Solutions conference, Bangkok, Thailand, 7–9 November 2022.
5. Aragonés-Beltrán, P.; Chaparro-González, F.; Pastor-Ferrando, J.-P.; Pla-Rubio, A. An AHP (Analytic Hierarchy Process)/ANP (Analytic Network Process)-based multi-criteria decision approach for the selection of solar-thermal power plant investment projects. *Energy* **2014**, *66*, 222–238. [CrossRef]
6. Ghosh, S.; Chakraborty, T.; Saha, S.; Majumder, M.; Pal, M. Development of the location suitability index for wave energy production by ANN and MCDM techniques. *Renew. Sustain. Energy Rev.* **2016**, *59*, 1017–1028. [CrossRef]
7. Greening, L.A.; Bernow, S. Design of coordinated energy and environmental policies: Use of multi-criteria decision-making. *Energy Policy* **2004**, *32*, 721–735. [CrossRef]
8. Raychaudhuri, A.; Ghosh, S.K. Biomass Supply Chain in Asian and European Countries. *Procedia Environ. Sci.* **2016**, *35*, 914–924. [CrossRef]
9. Budak, G.; Chen, X.; Celik, S.; Ozturk, B. A systematic approach for assessment of renewable energy using analytic hierarchy process. *Energy Sustain. Soc.* **2019**, *9*, 37. [CrossRef]
10. Effatpanah, S.K.; Ahmadi, M.H.; Aungkulanon, P.; Maleki, A.; Sadeghzadeh, M.; Sharifpur, M.; Chen, L. Comparative Analysis of Five Widely-Used Multi-Criteria Decision-Making Methods to Evaluate Clean Energy Technologies: A Case Study. *Sustainability* **2022**, *14*, 1403. [CrossRef]
11. Zhang, F.; Johnson, D.M.; Sutherland, J.W. A GIS-based method for identifying the optimal location for a facility to convert forest biomass to biofuel. *Biomass Bioenergy* **2011**, *35*, 3951–3961. [CrossRef]
12. Healey, N.C.; Irmak, A.; Hubbard, H.G.; Lenters, J.D. Environmental variables controlling site suitability for corn-based ethanol production in Nebraska. *Biomass Bioenergy* **2011**, *35*, 2852–2860. [CrossRef]

13. Akgul, O.; Zamboni, A.; Bezzo, F.; Shah, N.; Papageorgiou, L.G. Optimization-Based Approaches for Bioethanol Supply Chains. *Ind. Eng. Chem. Res.* **2011**, *50*, 4927–4938. [CrossRef]
14. Shi, X.; Elmore, A.; Li, X.; Gorence, N.J.; Jin, H.; Zhang, X.; Wang, F. Using spatial information technologies to select sites for biomass power plants: A case study in Guangdong Province, China. *Biomass Bioenergy* **2008**, *32*, 35–43. [CrossRef]
15. Rotaris, L.; Giansoldati, M.; Scorrano, M. The slow uptake of electric cars in Italy and Slovenia. Evidence from a stated-preference survey and the role of knowledge and environmental awareness. *Transp. Res. Part A Policy Pract.* **2021**, *144*, 1–18. [CrossRef]
16. Ahmad, S.; Tahar, R.M. Selection of renewable energy sources for sustainable development of electricity generation system using analytic hierarchy process: A case of Malaysia. *Renew. Energy* **2014**, *63*, 458–466. [CrossRef]
17. Ma, J.; Scott, N.R.; DeGloria, S.D.; Lembo, A.J. Siting analysis of farm-based centralized anaerobic digester systems for distributed generation using GIS. *Biomass Bioenergy* **2005**, *28*, 591–600. [CrossRef]
18. Kocoloski, M.; Griffin, W.; Matthews, H. Impacts of facility size and location decisions on ethanol production cost. *Energy Policy.* **2011**, *39*, 47–56. [CrossRef]
19. Perpiña, C.; Martínez-Llario, J.C.; Pérez-Navarro, Á. Multicriteria assessment in GIS environments for siting biomass plants. *Land Use Policy* **2013**, *31*, 326–335. [CrossRef]
20. Bojić, S.; Đatkov, Đ.; Brcanov, D.; Georgijević, M.; Martinov, M. Location allocation of solid biomass power plants: Case study of Vojvodina. *Renew. Sustain. Energy Rev.* **2013**, *26*, 769–775. [CrossRef]
21. Höhn, J.; Lehtonen, E.; Rasi, S.; Rintala, J. A Geographical Information System (GIS) based methodology for determination of potential biomasses and sites for biogas plants in southern Finland. *Appl. Energy* **2014**, *113*, 1–10. [CrossRef]
22. An, H.; Wilhelm, W.E.; Searcy, S.W. A mathematical model to design a lignocellulosic biofuel supply chain system with a case study based on a region in Central Texas. *Bioresour. Technol.* **2011**, *102*, 7860–7870. [CrossRef]
23. Kim, J.; Realff, M.J.; Lee, J.H. Optimal design and global sensitivity analysis of biomass supply chain networks for biofuels under uncertainty. *Comput. Chem. Eng.* **2011**, *35*, 1738–1751. [CrossRef]
24. Leduc, S.; Starfelt, F.; Dotzauer, E.; Kindermann, G.; McCallum, I.; Obersteiner, M.; Lundgren, J. Optimal location of lignocellulosic ethanol refineries with polygeneration in Sweden. *Energy* **2010**, *35*, 2709–2716. [CrossRef]
25. Natarajan, K.; Leduc, S.; Pelkonen, P.; Tomppo, E.; Dotzauer, E. Optimal Locations for Methanol and CHP Production in Eastern Finland. *Biomass Bioenergy* **2012**, *5*, 412–423. [CrossRef]
26. Leduc, S.; Lundgren, J.; Franklin, O.; Dotzauer, E. Location of a biomass based methanol production plant: A dynamic problem in northern Sweden. *Appl. Energy.* **2010**, *87*, 68–75. [CrossRef]
27. Comber, A.; Dickie, J.; Jarvis, C.; Phillips, M.; Tansey, K. Locating bioenergy facilities using a modified GIS-based location–allocation-algorithm: Considering the spatial distribution of resource supply. *Appl. Energy* **2015**, *154*, 309–316. [CrossRef]
28. Natarajan, K.; Latva-Käyrä, P.; Zyadin, A.; Pelkonen, P. New methodological approach for biomass resource assessment in India using GIS application and land use/land cover (LULC) maps. *Renew. Sustain. Energy Rev.* **2016**, *63*, 256–268. [CrossRef]
29. BOI (Thailand Board of Investment), Thailand's Eastern Economic Corridor (EEC). The Special Economic Zone (SEZ) for the Future of ASEAN. 2016. Available online: https://www.boi.go.th/en/Policy_EEC (accessed on 2 February 2020).
30. [EECO] Overall Land Use Plan. Eastern Economic Corridor Office of Thailand. Agriculture and Cooperatives. 2020. Available online: https://eeco.or.th/th/overall-land-use-plan (accessed on 15 May 2021).
31. ESRI (Environmental Systems Research Institute). *ArcGIS Pro Software*, license 3.0.2; ESRI: Redlands, CA, USA, 2020.
32. DPT (Department of Public Works and Town & Country Planning). *GIS Data in Land Use Plan (2037) Data for The Eastern Economic Corridor (EEC) 20-Year*; The Eastern Economic Corridor Office of Thailand (EECO): Bangkok, Thailand, 2020.
33. LDD (Land Development Department). *Land Use (GIS Databased) in the Year 2019/2020*; Ministry of Agriculture and Cooperatives: Bangkok, Thailand, 2020.
34. OAE (Office of Agricultural Economics). *Agricultural Statistics of Thailand fiscal year 2019*; Ministry of Agriculture and Cooperatives: Bangkok, Thailand, 2019.
35. DEM. Digital Elevation Model from NASA's Earth Science Data Systems (ESDS) Program. Available online: https://www.earthdata.nasa.gov/esds (accessed on 18 February 2023).
36. PEA (Provincial Electricity Authority). *Transmission Lines and Distribution Power Lines (115 kV/22kV) in Digital File for The Eastern Economic Corridor (EEC)*; Ministry of Interior: Bangkok, Thailand, 2022.
37. Digital Based Mapping and Cloud-Based Mapping and Geo-Database Platform (Network Analyis) from ArcGIS Pro 3.3.2. Software License. Available online: https://pro.arcgis.com/en/pro-app/latest/help/analysis/networks/network-analyst-tutorials.htm (accessed on 20 February 2023).
38. DEDEb (Department of Alternative Energy Development and Efficiency); ESCAP (The United Nations Economic and Social Commission for Asia and the Pacific). Pilot Training on Power and Heat Generation from Biomass Under the Project "Building Capacity of ASEAN Countries in Biomass Energy Development through Local Capacity Development". In *Handbook for Pilot Training*; Department of Alternative Energy Development and Efficiency: Bangkok, Thailand, 2020; pp. 2–16.

39. GISTDA (Geo-Informatics and Space Technology Development Agency (Public Organization)). *Flood Risk Area*; GISTDA: Bangkok, Thailand, 2020.
40. Spatial Optimization Approach (Location-Allocation Model) Based on ArcGIS Pro Platform. 2021. Available online: https://pro.arcgis.com/en/pro-app/latest/tool-reference/network-analyst/make-location-allocation-analysis-layer.htm (accessed on 20 February 2023).
41. Church, R.L.; Wang, S. Solving the p-median problem on regular and lattice networks. *Comput. Oper. Res.* **2020**, *123*, 105057. [CrossRef]
42. Clar, G. *Guiding Investments in Place-Based Development. Priority Setting in Regional Innovation Strategies, Seville*; European Commission: Brussels, Belgium, 2018; JRC112689.
43. ReVelle, C.S.; Swain, R.W. Central facilities location. *Geogr. Anal.* **1970**, *2*, 30–42. [CrossRef]
44. Rosing, K.E.; ReVelle, C.S.; Rosing-Vogelaar, H. The p-median and its linear programming relaxation: An approach to large problems. *J. Oper. Res. Soc.* **1979**, *30*, 815–823. [CrossRef]
45. Ueckerdt, F.; Hirth, L.; Luderer, G.; Edenhofer, O. System LCOE: What are the costs of variable renewables? *Energy* **2013**, *63*, 61–75. [CrossRef]
46. IRENA, International Renewable Energy Agency. Renewable Power Generation Costs in 2022. Abu Dhabi, 2022. Available online: https://www.irena.org/Publications/2023/Aug/Renewable-Power-Generation-Costs-in-2022 (accessed on 25 May 2021).
47. Vis, M.W.; van den Berg, D. Harmonization of Biomass Resource Assessments, Volume I. Best Practices and Methods Handbook. BEE 2010 (Biomass Energy Europe). 2010. Available online: https://www.ifeu.de/fileadmin/uploads/BEE-Best-Practices-and-methods-handbook8d4c.pdf (accessed on 15 February 2023).
48. Richard, F.; Kevin, T. *Efficient and Low Emission Stoker Fired Biomass Boiler Technology in Today's Marketplace*; Technical Publication; Babcock Power Environmental Inc.: Marlborough, MA, USA, 2007. Available online: https://www.babcockpower.com/wp-content/uploads/2018/02/efficient-and-low-emission-stoker-fired-biomass-boiler-technology-in-todays-marketplace.pdf (accessed on 20 May 2022).
49. International Finance Corporation; World Bank Group. Converting Biomass to Energy. In *A Guide for Developers and Investors*; International Finance Corporation: Washington, DC, USA, 2017.
50. EEC Land Cost. The Treasury Department. Available online: https://assessprice.treasury.go.th/ (accessed on 25 May 2021).
51. Annual Report 2021: Ministry of Commerce (Inflation Rate Average: 2.2% in 2023) FPO (Fiscal Policy Office). Available online: https://www.fpo.go.th/main/About-Us/AnnualReport/15728.aspx (accessed on 14 March 2023).
52. PEA (Provincial Electricity Authority). *The 10-Year Average Residential for Energy Consumption (in MWh) Between 2012 and 2022 Data for The Eastern Economic Corridor (EEC)*; Ministry of Interior: Bangkok, Thailand, 2022.
53. DEDEc (Department of Alternative Energy Development and Efficiency). Biomass Potential Database System in Thailand. 2014. Available online: https://gis.dede.go.th/module/map/index.aspx (accessed on 25 February 2023).
54. EforE (Energy for Environment Foundation). General biomass data, Bangkok. *Biomass Energy Artic.* **2002**, *1*, 2–38.