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A novel approach for optimisation of bioenergy supply chain: Integrating mathematical programming, Geographic Information System, and Analytic Hierarchy Process

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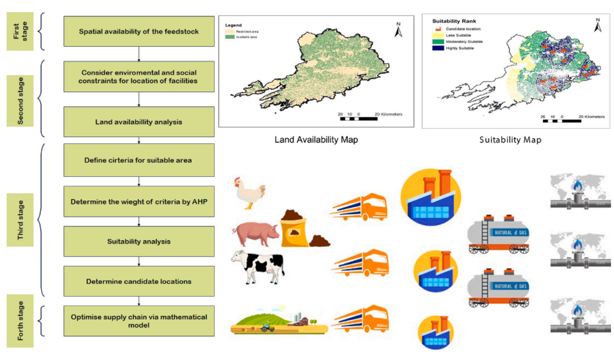
HIGHLIGHTS

- Presents a novel four-stage methodology using GIS, AHP, and mathematical modelling for biorefinery optimisation.
- Develops a mathematical model to reduce supply chain costs and environmental impact.
- Identifies 12% of the study area as highly suitable for biorefineries.
- Provides a framework enhancing bioenergy production efficiency from agricultural waste.
- The proposed method can reduce transportation distances, costs, and GHG emissions.

GRAPHICAL ABSTRACT



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ABSTRACT

The crucial role of sustainable energy in addressing environmental challenges and using agricultural waste for bioenergy supports a circular bioeconomy. This paper presents a four-stage approach to optimise a biorefinery supply chain for Ireland's agricultural waste sector. The spatial availability of agricultural waste was assessed, followed by evaluating land suitability for biorefinery development under economic, environmental, and social constraints. A hybrid method using GIS and AHP was employed to rank suitable areas, and a mathematical model was used for supply chain optimisation. Results showed only 12 % of the study area is highly suitable for biorefineries, with an average transportation distance of 39 km, leading to reduced costs and emissions. The framework's efficiency is highlighted by a transportation cost of only 4 %, compared to 16 % in previous studies. This research fills a gap in bioenergy supply chain management by demonstrating advanced tools for optimising sustainability and site suitability.

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1. Introduction

In order to minimise the global use of fossil fuels, bioenergy resources have been recognised as important participants in worldwide sustainable energy policies (Kasinath et al., 2021). Bioenergy has been listed as one of the greatest energy sources that can boost economic growth, reduce Greenhouse gas (GHG) emissions, increase the employment rate especial in rural sectors, and fulfil the needs of the circular economy (Vadenbo et al., 2018).

Europe's agriculture sector faces a sustainability crisis due to the combined challenges of depleting fossil resources and increasing environmental pressures through waste generation (Matharu et al., 2016). Agricultural waste is readily available and can be valorised for energy generation in a useful manner, which otherwise can lead to environmental pollution and cause health problems (Roudneshin and Sosa, 2024; Ghaderi et al., 2016; Prasad et al., 2020). It also plays a key role in bioenergy generation in the European Union (EU) as it does not compete between energy and food production like the first generation of biomass (Ajanovic & Haas, 2014). Additionally, it is a significant source of renewable energy that can merge the principles of the bioeconomy and circular economy. The circular economy emphasises converting waste into resources to create a sustainable and waste-free environment (Selvaggi and Valenti, 2021; Ranjbari et al., 2022).

Generally, the locations of agricultural waste resources, biorefineries, and demand centres are geographically separated from one another (Delivand et al., 2015). Therefore, transportation between them is inevitable and can cause environmental burdens as well as increase the total supply cost. Moreover, some features of agricultural waste, such as seasonality, sparse distribution, and low bulk density, make the bioenergy supply chain unsustainable (Brahma et al., 2016). Hence, the process of determining potential locations to build a biorefinery is a complicated task that requires a thorough evaluation, especially when dealing with a large geographic zone. The biorefinery locations should be chosen based on different criteria that meet the economic, environmental, and social conditions (Demirbaş, 2001). Thus, selecting optimal locations for biorefinery plants can have a significant effect on the sustainability of the supply chain (Delivand et al., 2015).

Effective supply chain management plays a crucial role in aligning bioenergy supply with demand. In bioenergy systems, geographic distance between agricultural waste sources and biorefineries can significantly impact the costs, carbon emissions, and overall efficiency of the supply chain. By optimising locations for biorefineries and reducing transportation distances, supply chain management enhances the ability to meet bioenergy demand sustainably, with minimal resource waste. This research explores the relationship between location optimisation and demand fulfillment, emphasising that a well-managed bioenergy supply chain can enhance both economic viability and environmental outcomes.

Geographic Information System (GIS) is commonly known as an efficient software tool that can be utilised for the analysis of geographical data associated with biomass locations, supply chains, and the identification of suitable facility locations (Ghaderi et al., 2016). Significant developments in Geographical Information Systems (GIS) have increased the use of this technology to evaluate biomass supply and logistics for bioenergy production worldwide (Selvaggi and Valenti, 2021). A recent literature review on biomass supply chain and planning (Roudneshin and Sosa, 2024; Mottaghi et al., 2022) indicated that only 11 % of published studies have used GIS as decision-support software and benefitted from its potential features, which may be divided into three categories: (a) evaluating biomass quantity and distribution (Singlitico et al., 2018; Brahma et al., 2016), for example Brahma et al. (2016) assessed biomass availability and optimal supply network for an existing biorefinery in India; (b) another popular application of GIS is finding candidate location to establish different types of facilities in a biomass supply chain such as storage, biorefinery, etc. (Jayarathna et al., 2021; Razm et al., 2021), as an instance Franco et al. (2015) used a GIS-based model combining with fuzzy to determine the potential locations for biogas plants in Denmark, (c) some researchers adopted GIS to identify the shortest route between different elements in supply chain (Selvaggi and Valenti, 2021), Selvaggi and Valenti (2021) applied GIS-based methodology to find shortest routes between feedstock resources and biogas plants in order to create the best biomass distribution map.

Also, Multi-criteria decision-making (MCDM) involves addressing decision-making challenges that require the simultaneous assessment of multiple criteria or attributes that often contradict each other (Moattaghi et al., 2021). Incorporating GIS and MCDM is identified as a significant and effective technique for choosing locations for bioenergy facilities (Pepiñá et al., 2013; Delivand et al., 2015). This combination is capable of building a strong decision-support system that considers experts' preferences to make better decisions. However, few studies combined GIS capacities with MCDM techniques (Ghaderi et al., 2016).

The primary objective of this research is to develop a novel, integrated approach to optimize the bioenergy supply chain for agricultural waste in Ireland, with the goal of improving sustainability and reducing costs.

Sarkar et al. (2024) developed a model to identify the optimal quantities for production and distribution, while helping in decisions related to facility location and size, considering various scenarios of supply and demand disruptions (Sarkar et al., 2024). In another study by Singh et al. (2024a), the sustainability and resilience of biodiesel production systems using waste animal fat, focused on production quality improvement and carbon emissions.

The work by Singh et al. (2024b) offers strategic planning for a biodiesel supply chain focused on waste animal fat as a feedstock. A multi-objective optimisation model (MOOM) was developed to design an optimal biodiesel supply chain, addressing decision-making at both the planning and strategic levels. The model aimed to determine the best locations for facilities while optimally allocating resources across the supply chain. Mridha et al. (2023) investigate the joint effects of production quality improvement and carbon emissions in biofuel supply chains. While significant work has been done on bioenergy supply chains, literature lacks geographic considerations for feedstock distribution and facility location optimisation, which are critical aspects of our study. Our research contributes by using **GIS and AHP** to optimise biorefinery locations while minimising transportation distances and costs, enhancing the economic and environmental sustainability of bioenergy supply chains, and few studies have integrated GIS-based spatial analysis with multi-criteria decision-making tools like AHP to optimise the siting of biorefineries based on economic, environmental, and social criteria. Moreover, existing research often neglects the comprehensive optimisation of transportation routes and costs in the supply chain. Therefore, this research contributed to the existing literature review by introducing a four-stage approach that combines Geographic Information System (GIS)-based land suitability analysis and the Analytic Hierarchy Process (AHP) with a mathematical optimisation model. This approach optimises biorefinery site selection by incorporating economic, environmental, and social constraints, ultimately minimising transportation costs and GHG emissions. The proposed methodology advances the field by offering a more comprehensive and practical model for sustainable bioenergy supply chains.

One of the key contributions of this study is the development of a novel, bioenergy-specific optimisation process. The bioenergy supply chain poses unique challenges—such as the geographic dispersion of feedstock, seasonality, and the need for sustainable logistics—that are less relevant in other industries. By incorporating spatial analysis (GIS) and decision-making frameworks (AHP) tailored to these unique characteristics, the methodology offers a specialised solution for optimising the bioenergy supply chain. This ensures a more accurate, sustainable, and economically viable framework for site selection and supply chain management, addressing challenges specific to the sector. Current technologies for bioenergy supply chain optimisation often lack a holistic approach that incorporates both spatial and economic factors simultaneously. Many existing models focus on cost or emissions reduction independently, without a comprehensive multi-criteria framework that considers all relevant factors, such as site suitability and social acceptance.

Additionally, to the best of our knowledge, this is the first study conducted to optimise the agricultural waste supply chain in Ireland. The results of this research contribute to a more efficient and sustainable bioenergy supply chain, offering a systematic and replicable approach for other regions facing similar challenges.

2. Materials and Methods

This paper introduces a novel four-stage approach to optimise the biorefinery supply chain for agricultural waste in Ireland, incorporating advanced spatial analysis, multi-criteria decision-making, and mathematical modelling techniques. Integrating Geographic Information System (GIS) Suitability Land Analysis with the Analytic Hierarchy Process (AHP) provides a comprehensive framework for assessing land availability by considering economic, environmental, and social constraints. Unlike previous studies, this research not only identifies optimal biorefinery locations but also incorporates a mathematical model to minimise the total supply chain cost, taking into account the collection, conversion, and distribution stages. This combined methodology enhances the accuracy and efficiency of site selection and supply chain management. The paper's approach is particularly innovative in its ability to balance localised feedstock availability with regional demand, thereby advancing the field of sustainable bioenergy production.

2.1. Case study

Ireland is one of the highest producers of agricultural waste in Europe (Bedoić et al., 2019). The development of opportunities in the waste sector is vital to have a sustainable Irish bioeconomy (Science and Technology Select Committee, 2014). Within the category of agriculture waste and residues, straw and livestock manure, which are unavoidable wastes, are considered potential resources (SEAI, 2017). Thus, cattle manure, pig manure, poultry litter, and straw are chosen as feedstocks for this study.

Based on the authors' initial assessment of potential feedstock in Ireland, County Cork possesses the highest concentration of cattle, accounting for around 26 % of the nation's overall cattle production (CO). Furthermore, County Cork ranks as the second largest producer of pigs and straw (wheat, oat, barley), making up approximately 18 % and 15 % of the country's respective output. Consequently, County Cork was chosen as the focus region for this study due to its abundant feedstock resources (Fig. 1).

In our study, we assume that biorefineries can handle and process all four types of feedstock: pig manure, poultry manure, cattle manure, and straw. This assumption is based on the premise that modern biorefinery technologies are designed to be versatile and adaptable, allowing for the utilisation of various feedstock sources. By assuming a multi-feedstock approach, we acknowledge the potential for biorefineries to optimise their operations by diversifying their feedstock inputs. This approach aligns with resource efficiency and sustainability principles, as it enables the efficient utilisation of agricultural waste streams to produce valuable bioenergy products.

2.1.1. Economic parameters

2.1.1.1. Investment and operational cost. Data for investment and operating costs of biorefinery plants were obtained from a report released by SEAI (SEAI, 2017). This report assesses several models of biogas and biomethane facilities and contains different costs and features of each model. The data is obtained through consultations with stakeholders and supplemented by information from literature review. Investment and operational costs of AD plants of different levels of capacity are reported in Table A1.

2.1.1.2. Transportation cost. Transportation of feedstock can account for 35–50 % of the total cost in the supply chain for biogas production at an AD plant. Optimising transportation distances can significantly reduce these costs. (DEA, 1995; Flotats et al., 2009). In this study, agriculture feedstock moved from supply points to storage facilities and from storage facilities to biorefineries. The transportation cost of bio fertiliser from the AD plants to farms was not considered in the models as it was assumed that farmers would collect this bioproduct. During the

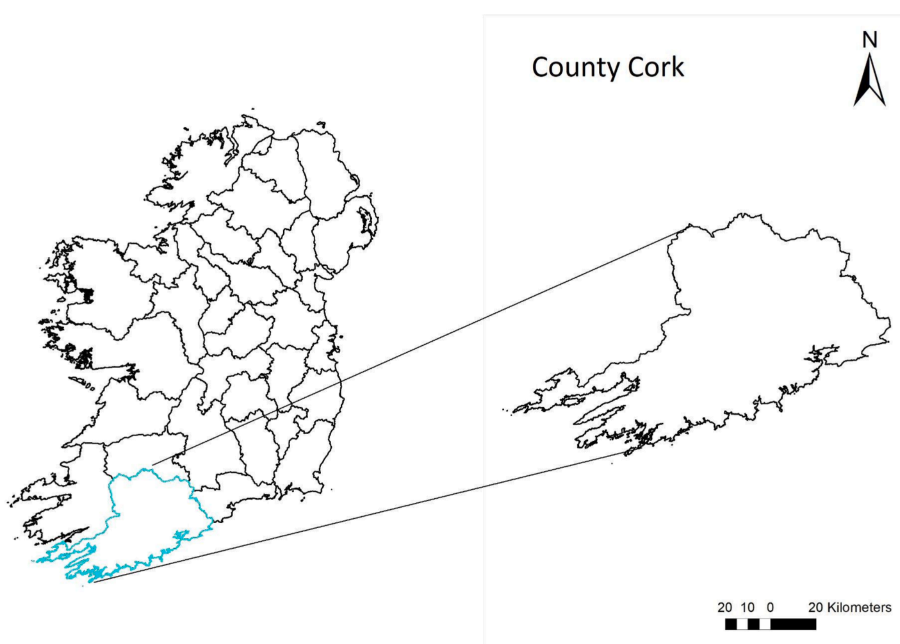


Fig. 1. Map of the study area for bioenergy supply chain optimisation.

study in 2022, the cost of hauling a 30-tonne load within a 10–15 km radius was €100, resulting in a unit transportation cost of €0.33 per tonne per kilometre (obtained in conversations with the AD plant manager, Date: 17/05/2022). The methodology to calculate the distance between feedstock sources and potential facility locations.

For the transportation of biomethane, costs are calculated at €0.009 per cubic meter per kilometre. This estimate is based on the cost of €300 for each load, assuming a travel distance of 7 km and a capacity of 5000 cubic meters per load (obtained in conversations with the AD plant manager, Date: 17/05/2022).

2.1.2. Spatial availability of the feedstock

2.1.2.1. Cattle manure. This study considered both cattle for dairy and meat production. Ireland had circa 6.5 million cattle heads in 2021, with around 5 million heads for meat production and 1.5 million heads for dairy production (CSO, 2023). Cattle manure can have multiple purposes, including being fertiliser, a source of bioenergy, and even a construction material. In some countries, dried cattle manure is considered a high-quality fuel, often mixed with straw and used for cooking. Anaerobic digestion is recognised as a more efficient approach to generating energy from cattle manure (Patsios et al., 2016).

Under the Irish production system, cattle are kept indoors for an average period of 20 weeks (from November to late March); this time is assumed to estimate slurry production for this study. The estimation of the quantity of collectable manure/slurry is based on the amount of time that livestock stays indoors as well as animal numbers and average waste production per animal, which is estimated at 5.08 (t/y/head) (Singh et al., 2010). The cattle number is available by Electoral Divisions (EDs), which are recognised as the smallest administrative area in Ireland; there are 398 electoral divisions in County Cork (CSO, 2023; CSO, 2011). In total, there were 1,103,425 heads of cattle in Cork in 2020, equating to 5,605,399 tonnes of manure (CSO, 2023). The centroid of electoral districts with the greatest number of cattle and, therefore, manure production were considered the location of cattle manure resources as the centroids of EDs were the most detailed available data.

2.1.2.2. Pig manure. Pig manure consists of both faeces and urine excreted by pigs. Typically, manure is composed of 60 % faeces and 40 % urine. The composition of pig manure, like all animal manures, can vary. However, on large farms with animals of different ages, weights, and growth stages, the manure tends to be a mixture from all these animals, resulting in a more stable composition Patsios et al., 2016). There were 1.5 million pigs in Ireland in 2020, and around 19 % of them are in the study area (CSO, 2021). Pig manure is mostly applied to the soil as a fertiliser or used in anaerobic digestion plants to produce biogas. Pig manure is a highly valuable fertiliser due to its high levels of nitrogen, phosphorus, and other minerals besides its organic content. However, there are limitations regarding the direct utilisation of pig manure in planted fields due to the potential presence of substantial levels of harmful pathogens. Therefore, using it as feedstock to produce energy is a more sustainable pathway (Patsios et al., 2016). A total of 10 pig farms with available data were incorporated in this study (EPA, 2021).

2.1.2.3. Poultry manure. Poultry manure is a mixture of manure, urine, feathers, straw or wood, and food residue, and it is collected every 6–8 weeks at poultry farms. In Ireland, it is currently used as mushroom compost or spread on the land as a fertiliser, although the amount that can be applied to the soil should be limited due to Nitrates regulations (SEAI, 2017). In Ireland, around 140 kt of poultry manure was produced from about 13 million poultry per year, and about 60—–100 kt (43 % – 71 %) of this litter was applied for mushroom compost, with the remaining 40 to 80 kt spread on land SEAI (2017). In Ireland, the mushroom industry holds the top position among horticultural sectors, with a value of €119 million (Teagasc, 2023). Around half of the remaining amount (20–40 kt) could be applied as feedstock to produce energy (SEAI, 2017). By assuming 15.5 million poultry in 2019 (CSO, 2023), 167 kt poultry litter was produced, and considering the same amount of litter that is needed for the mushroom compost industry, 67–107 kt litter remained, and 50 % of it, 33.5–53.5 kt can be collected and made available for other utilisations. Therefore, 20–32 % of them are available to convert into energy. A total of 3 poultry facilities with available data in the study area were incorporated as part of this study (EPA, 2021) (Fig. 3).

2.1.2.4. Straw. The cereals cultivated in Ireland consist of wheat, barley, and oats. Cereal crops are harvested across 266,600 ha of land in the country (CSO, 2023). Straw is the major agriculture by-product during the harvesting stage of cereals (Bedoić et al., 2019). Although straw is the highest quantity of agriculture feedstock compared to other types (SEAI, 2003; Singlitico et al., 2018), there are various competing demands for straw, most of which are used for animal bedding and livestock fodder, particularly barley straw. Additionally, wheat straw is commonly used for mushroom compost in Ireland. It was predicted that around 67 % of the potential straw resource would be used by competing (non-energy) demands in 2035 in Ireland (SEAI, 2017). Also, there is a new plan, the Straw Incorporation Measure (SIM), which encourages farmers to chop straw and incorporate it into the soil, and the government gives them a payment to do so. This proposal would use 150,000 t or 40,000 ha of straw (DAFM, 2021). Around 1.2–1.5 million tonnes of straw are produced every year in Ireland (Teagasc, 2021), therefore, this plan would use 10 % of total straw production. Therefore, the available straw for the biorefinery would be 12 % of all straw. Table 1 shows the potential availability of straw in County Cork in 2018.

Corine Landcover 2018 land cover dataset (EPA, 2021) was used to determine the quantities and location of the straw feedstock. The map provided contains various classes that represent different land features. Specifically, Class 211 is defined as non-irrigated arable land used for rainfed agricultural practices, where crops are cultivated and harvested on an annual basis, typically following a crop rotation system. This class also includes areas where crops or crop residues, such as straw, have been collected. Concerning this, the class that closely corresponds to cropland, including straw, was utilised to identify the locations of straw production. Hence, Class 211 from the Corine data was employed to map the straw production sites (Kosztra et al., 2017).

2.2. Assessing land availability

The assessment of available land for the construction of a biorefinery formed the initial step in the location selection process. The location selection of a biorefinery must meet a set of environmental, ecological, and social considerations and constraints that are determined by government guidelines and regulations (Perpiña et al., 2013; Delivand et al., 2015; Zhang et al., 2017; Durmaz and Bilgen, 2020). For example, to reduce the undesirable effects of the biorefinery operations, they should be constructed at a sufficient distance from protected areas, water resources, residential areas, natural parks, Natural Heritage Areas (NHAs), Special Areas of Conservation (SAC), and Special Protection Area (SPA) which are shown in Table 2. The safety distances are applied from the literature review (Perpiña et al., 2013) as there is no specific distance for Ireland. To apply these constraints by ArcGIS, buffer analysis is used to surround environmental and industrial areas at safe distances. Buffer

Table 1
Agriculture waste production in the study area (County Cork).

County	Approximately quantities of biomass available (tonnes/year)			
	Cattle manure	Pig Manure	Chicken manure	Straw (ICT-BIOCHAIN project, n.d.)
Cork	1,821,316.00	121,006.00	1,985.50	150,034.00

Table 2
Constraints considered in locating biorefineries (Perpiña et al., (2013); Durmaz and Bilgen, 2020).

Criteria	Safety distance (m)	Description
Buildings and residential areas	600	Minimum 600 m away from built-up areas
Natural Heritage Areas (NHAs)	500	Minimum 500 m away from these areas
Special Areas of Conservation (SAC)	500	Minimum 500 m away from these areas
Special Protection Area (SPA)	500	At least 500 m away from these areas
Water resources (lake, dams, etc)	3000	At least 3000 m away from water bodies
Roads	100	At least 100 m away from roads
Airports	500	At least 500 m away from airports
Railways	100	At least 100 m away from railways

analysis determines an area around a geographic element, including locations that are within a specific distance of that element, and it is called a buffer or buffer zone in GIS and spatial analysis. Therefore, unavailable and restricted areas were determined by buffer analysis on the map, and then available and environmentally suitable areas were obtained by removing unavailable and unsuitable places with their buffer from the whole land. Then, using analysis and overlay tools, the intersection part of the buffer and available areas are identified.

2.3. Area suitability analysis and Analytical hierarchical process

Spatial suitability analysis is a systematic procedure for evaluating and comparing different areas based on how well they meet a set of chosen criteria. This procedure entails assessing a list of factors, including environmental, social, economic, and spatial considerations, to determine the most suitable sites for a specific activity or development. The final result of a suitability analysis is a ranked range of potential areas that are considered from low to high suitable zones according to the selected criteria. Considering multiple criteria provides a comprehensive understanding of land suitability, which can help land-use planners and decision-makers (ESRO, 2023). This approach also allows for the consideration of multiple criteria and the flexibility to adjust the importance of each criterion in the assessment. This means that certain criteria can be prioritised over others, and the analysis can be based on their certain requirements and purposes (Razm et al., 2021). The steps to conduct a spatial suitability analysis in this study included:

- Determine criteria for considering the suitable areas for building biorefinery and drawing multiple ring buffers around them.
- Define weights for each criterion by AHP as not all of them have the same importance
- Then, the suitability ranking map is generated by using the weighted overlay tool in ArcGIS to overlay and combine different map layers (which represent a different criterion for suitability) with their relative importance/weights that were gained from AHP (Al Garni and Awasthi, 2017). Suitability scores are applied to show the area's suitability rank. They have been categorised into three groups: less suitable areas containing scores 1 to 2, moderately suitable, and highly suitable areas, including scores 3 and 4 to 5, respectively.
- In the final step, unavailable lands produced in the previous section are excluded from the suitability map. This ensures that only available areas are considered for the final suitability map.

2.3.1. Criteria chosen for potential locations

A group of criteria was chosen based on expert consultation, which includes researchers and plant managers in Ireland and literature (Perpiña et al., 2013; Zhang et al., 2017; Jayarathna et al., 2021). The number and characteristics of the criteria and the importance of each were chosen through interviewing experts via questionnaires. The criteria were based on distances and access to agriculture feedstocks, demand points, and roads. Three main criteria for the location of the biorefinery plants were identified:

2.3.1.1. Road accessibility. In a biomass supply chain, transportation is costly. A crucial issue that puts an expense on the supply chain and makes it financially unproductive is connecting biorefineries to the main roads and rail networks. To address this issue, various buffers were utilised around the main roads to concentrate the location of the biorefinery plants within a certain transportation distance (Sultana and Kumar, 2012). Therefore, multiple ring buffers are applied at different spaces (e.g., 2, 4, 5, 6, 10 km) around the roads.

2.3.1.2. Proximity to the feedstock resources. The feedstocks are collected from several agricultural lands, farms, and pig/poultry facilities. The cost of transportation increases if the distances between biorefineries and feedstock suppliers rise (Razm et al., 2021). The method applied multiple ring buffers for various distances (e.g., 5, 10, 20, 30 and 50 km) from the feedstock resources to better access suppliers and reduce the distances between them. The applied buffer values were based on interviewing experts and literature (Razm et al., 2021).

2.3.1.3. Proximity to the demand points. Another significant criterion that was not considered in previous studies is its proximity to the demand point, which can be even more important than other criteria as the transportation of the products might be more complicated and expensive than the transportation of raw materials. In this research, the gas injection point is the demand point where biomethane is transported. Multiple ring buffers for various distances (e.g., 5, 10, 20, 30 and 50 km) from the gas injection point to make better accessibility to demand points and reduce the distances between them.

2.3.2. Analytical Hierarchy process (AHP) method

During spatial suitability analysis, each of the criteria is considered as a map layer and can have a comparative weight to indicate that some criteria have a greater influence than others on the location of the biorefinery (Monteleone and Cammerino, 2012; Delivand et al., 2015). The Analytical Hierarchy Process (AHP) method is applied as a powerful technique to obtain an estimation of weights of the criteria. AHP is a mathematical approach for multi-criteria decision making which was presented by Saaty for the first time (Saaty, 2008). This method divides the problem into several levels for analysis in accordance with a hierarchical framework, and then it gives weight to each criterion at every level. It entails the creation of a decision matrix through pairwise comparisons. To create a matrix for pairwise comparisons, a matrix with n*n dimension, which n is the number of the criteria, is formed. Each element of the matrix demonstrates the preference of one criterion to the

Table 3
Description of the meaning of preference score values (Saaty, 2008).

Importance score of criteria a to b	Description
1	The importance of criteria a and b is the same
3	The importance of criterion a is a little more than criterion b
5	The importance of criterion a is relatively more than criterion b
7	The importance of criterion a is strongly more than criterion b
9	The importance of criterion a is extremely more than criterion b
2, 4, 6, 8	Intermediate scores

other one based on a relative value scale 1 to 9 proposed by (Saaty, 2008), as shown in Table 3. Also, The level of uncertainty that could be caused by the experts is calculated by an indicator known as “consistency ratio” (CR). If this ratio is less than 0.1, this shows the accuracy of the computed weights and the consistency of the created matrix. Otherwise, a revision of the comparison matrix would be required (Saaty, 2008; Ying et al., 2007).

In this study, the AHP method is applied to obtain the weights for each criterion by using the software Expert Choice 11. Expert Choice software is a decision-making software and can be applied to carry out the AHP technique (Expert Choice, 2009).

2.3.3. Combined AHP-GIS to find suitable areas

The process of creating a suitability map involved several steps. Firstly, the criteria layers are converted from polygon to raster format using the polygon to raster conversion tool in ArcGIS. Once in raster format, each layer is reclassified using the reclass spatial analysis tool. This step assigns scores to cells in the digital raster layer based on the specific criteria being considered.

After reclassification, the weighted overlay tool is utilised to combine all the layers into a single raster layer. This tool allows for the assignment of relative weights to each layer, reflecting their importance in the overall suitability assessment. These weights, obtained through the Analytical Hierarchy Process (AHP), highlight the priority of each criterion.

The weighted overlay tool combines their data to generate the final suitability map by overlaying the reclassified layers with their assigned weights. This map represents the overall suitability based on the combined influence of the criteria and their respective weights (Malczewski, 2004; Gorsevski et al., 2012).

The score of each cell in the final map is multiplied by the preference weight, which was obtained through the AHP. All the multiplication is summed up to calculate the overall score of each cell (Malczewski, 2004). The equation below shows the process:

$$C_i = \sum\nolimits_{j=1}^{m} w_j C_{ij}$$

Where Ci is the score of cell i, wj is the weight of criterion j (the criterion chosen by the experts), Cij is the value of cell i in the criterion layer j, and m is the number of criteria considered for suitability analysis (Sultana and Kumar, 2012).

In the next step of the process, a suitability map is generated to classify the study region into different classes based on the level of suitability. These classes range from high to low suitability, indicating more suitable areas.

Once the suitability map is obtained, it is converted into a polygon layer. This means continuous suitability values are transformed into distinct polygons or shapes representing different suitability levels. Finally, unavailable land (from Section 2.2) was removed from the polygon layer. This ensures that only available areas are considered for the final selection. A sensitivity analysis was performed to investigate the impact of different weights for each criterion and its impact on the suitability analysis.

2.4. Mathematical modelling

In the last stage, the potential location is obtained from previous stage. This model aims to minimise the total cost of the supply chain. The supply chain structure comprises multiple levels, including the collection, conversion of feedstock, and distribution to demand centres. Each level is interconnected by various transportation modes for material transfer. Key stages include feedstock collection from agricultural sources, transportation to biorefinery sites, processing into bioenergy products, and distribution to meet demand points. Each component of the network is interconnected, highlighting dependencies and opportunities for optimisation, such as reducing transportation distances and minimising costs. This structural layout supports strategic decision-making for a sustainable and efficient bioenergy supply chain. Table 4 lists the sets, parameters, and variables used in the model. is used as input in the mathematical model to optimise bioenergy supply chain plan.

Objective function:

The objective function is the minimisation of total cost of supply chain, and includes investment cost, agriwaste purchasing cost, feedstock transportation cost, distribution cost, variable and fixed operational cost.

$$\mathbf{MinZ} = \sum_{g,k,u} P_{gk}.I_{ku} + \sum_{a,r,g,l,t} AG_{arglt}.pm_a + \sum_{a,r,g,l,t} AG_{arglt}.ct_{al}.dis_{rgl} + \sum_{g,j,k,d,l,t} X_{jgkldt}.cd_{jl}.dist_{gdl} + \sum_{a,r,f,k,t} AGR_{afgklt}.ov_{ku} + \sum_{a,r,f,k,t} P_{gk}.of_{ku}$$

Investment Cost ($\sum_{g,k,u} P_{gk}.I_{ku}$): Represents the capital investment required to establish biorefineries at locations ’g’ with capacity ’u’. Investment costs are influenced by the choice of facility capacity, which directly impacts construction costs and the feasibility of operations.

Agricultural waste Purchasing Cost ($\sum_{a,r,g,l,t} AG_{arglt}.pm_a$): Reflects the cost of acquiring agricultural waste feedstock. This cost depends on both the volume purchased and the price of agriwaste, which varies geographically and temporally.

Feedstock Transportation Cost ($\sum_{a,r,g,l,t} AG_{arglt}.ct_{al}.dis_{rgl}$): Covers the cost of transporting feedstock from agricultural sources to biorefineries. Transportation cost is a function of the distance and the

Table 4
The sets, parameters, and variables used in the mathematical model.

Sets	**Description**
A	Set of Agricultural wastes
R	Set of supply
U	Capacity level of biorefinery
K	Set of technology
J	Set of value-added products
D	Set of demand point
G	Set of potential location for biorefinery
T	Set of time periods
Parameters related to:	**Description**
Costs	
pm_a	Price of biomass a (per tonne)
ct_{al}	Cost of transporting biomass a (€/tonne.km)
cd_{jl}	Cost of transporting product j
of_{ku}	The fixed operation cost of biorefinery with technology and capacity u (€/t)
ov_{ku}	Variable operation cost of biorefinery with technology k and capacity u (€/ton of feedstock)
I_{ku}	Investment cost for installation technology k with capacity u
technology	
β_{ajk}	Conversion rate of biomass a for producing product j by technology k
c_{ku}	Capacity of biorefinery at level u with technology k
distances	
dis_{rfl}	Distances between resources r and biorefinery g (km)
$dista_{gdl}$	Distances between biorefinery g and demand point d (km)
Supply and demand	
AV_{art}	Amount of available biomass a in resource r in period t (ton)
De_{jdt}	Demand for product j at centre d in period t
Variable	**Description**
1. continues variable	
AG_{arglt}	Amount of biomass a in resource r transferred to biorefinery g in period t
Y_{jgkt}	The quantity of bioproduct j produced in biorefinery g with technology k in period t
X_{jgkldt}	The quantity of bioproduct j produced in biorefinery g with technology k transferred to demand point d in period t through transportation mode l
2. binary variable	
P_{guk}	If biorefinery g with technology k and capacity u is to be built, 1; otherwise 0.

transportation rate, making it an essential factor in determining the overall logistics efficiency of the supply chain.

Distribution Cost ($\sum_{g,j,k,d,l,t} X_{jgkldt}.cd_{jl}.dist_{gdl}$): Represents the cost of distributing bioenergy products from biorefineries to demand points. This is influenced by both the distance and the transportation rates for distribution, which are critical for optimising cost efficiency.

Variable and Fixed Operational Costs ($\sum_{a,r,f,k,t} AGR_{afgklt}.ov_{ku} + \sum_{a,r,f,k,t} P_{gk}.of_{ku}$): Include the ongoing expenses related to plant operations, which consist of both fixed and variable components. These costs are directly linked to the facility size and operational technology, affecting overall cost.

Constraints:

Constraints about feedstocks:

the quantity of feedstock type a from resource r should not be more than the available feedstock in that area.

$$\sum_{g,l} AG_{arglt} \leq AV_{art} \forall a, r, t$$

Constraints about production:

This constraint calculates the total amount of bioproduct j is produced from biomass a with the technology k in period t by considering the conversion rate β_{ajk} for each technology.

$$\sum_{d,l} X_{jgkldt} = \sum_{g,l} \beta_{ajk} * AG_{argklt} \forall a, j, k, g, t$$

Constraints about capacities and flows:

ensures that the amount of bioproduct j shipped from each biorefinery g to all demand centers is not more than the amount of the produced in that biorefinery in period t.

$$\sum_{k,d,l} X_{jgkldt} \leq \sum_{g,l} \beta_{ajk} * AG_{argklt} \forall g, j, t$$

Constraints below ensure that maximum 1 biorefinery of all u capacity can be established in every location g.

$$\sum_{u} P_{guk} \leq 1 \forall k, g$$

The amount of biomass shipped to the facilities and biorefinery should be less than the capacity levels of refinery/facilities.

$$\sum_{a,f,l} AGR_{afgklt} \leq \sum_{u} P_{guk} * c_{ku} \forall g, k, t$$

Constraints about demand satisfaction:

This constraint assures that all bioproducts demand is fulfilled in demand points, which means the total bioproduct j that transported form each plant to demand point should be equal or more than demand of the demand point (D_{jt}).

$$\sum_{g,l} X_{jgkldt} \geq De_{jdt} \forall d, j, t$$

Assumptions of the model:

- The bioenergy supply chain is designed with a one-year planning horizon divided into months as some agriculture feedstock is available seasonally.
- Four types of biomass were considered (cattle manure, pig manure, poultry manure, and straw).
- Even though winter wheat is harvested only in July- August, and spring wheat is available in late August till the end of September (Hennessy et al., 2011). There is an available supply throughout the year.
- In Ireland, the cattle are kept indoors for 20 weeks on average (from November to late March) this time is assumed to estimate manure production (Hennessy et al., 2011).
- The biorefineries can have three different capacities in terms of feedstock demand and energy production.
- In the model, the demand for biomethane was set at meeting 1 % of the total biomethane consumption in Cork.

3. Results and discussion

3.1. Result from GIS and AHP stage

The process of mapping available land began with identifying and mapping all restricted units and areas, such as roads, water bodies, and other obstacles, as depicted in Fig. A1. To address environmental constraints, a buffer analysis was conducted (Fig. A2), considering factors and safety distances detailed in Table 2.

Through the utilisation of overlay tools and buffer analysis in ArcGIS, the available and restricted areas were visualised and identified, as illustrated in Fig. 3a.

Out of the 7,500 km2 total area of County Cork, 4,423 km2 is restricted and therefore not accessible. This means that only 41 % of the county's total area, or approximately 3,077 km2, is available for use. As mentioned before, restricted areas include protected lands, water bodies, and other restricted places. The buffer zones around them can play an essential role in preserving natural habitats and ensuring the sustainable use of land (Durmaz and Bilgen, 2020; Delivand et al., 2015).

To find a suitable area among the available lands, this study considered three main categories (proximity to resources, roads, and demand points) and four sub-categories based on experts' opinions (Fig. 2). This can effectively help find optimal locations to minimise transportation movement between different facilities by determining areas close to feedstock resources, demand points, and roads. Ultimately, it can lead to cost reductions and decreased greenhouse gas (GHG) emissions.

Multiple ring buffers for each criterion, i.e., roads, cattle manure, pig manure, poultry manure, demand points, and straw, are shown in Fig. A2. The criteria, sub-criteria, corresponding weights, and consistency ratio are reported in Table 5. Three main categories (proximity to resources, roads, and demand points) and four sub-categories were considered in this research based on experts' opinions, which include researchers and plant managers in Ireland. The proximity to the demand points has the highest weight (0.507) as biomethane transportation would be more difficult, so the expert gave a higher weight to this criterion. Accessibility to roads and proximity to feedstock locations received importance weights of 0.363 and 0.13, respectively. The consistency ratio is 0.02, which is less than 0.1, which demonstrates a high level of consistency and reliability of calculated weights.

Fig. 3b depicts the suitability map, which highlights areas deemed most suitable for building a biorefinery. This procedure is derived from applying the AHP technique and weighted overlay method to assess different areas within County Cork based on multiple criteria. The weighted overlay method involves assigning relative weights to each criterion and then combining and standardising them to obtain a total suitability value (Malczewski, 2004; Gorsevski et al., 2012).

The analysis of the suitability map demonstrated that out of the total area of County Cork, which spans 7500 km2, only 2580 km2 (34 %) were identified as suitable for locating a biorefinery. However, out of this suitable area, only 888 km2 were identified as highly suitable for biorefinery development, which represents approximately 12 % of the study area. These highly suitable areas are predominantly concentrated around the gas injection points or demand points, as the criterion of proximity to demand points held the highest weight in the AHP results.

Fig. 3b shows different categorised lands in the study area based on their suitability for biorefinery development, highlighting the proportion of land ranked as low, moderate, or highly suitable.

As demonstrated in Fig. 3b, most of the study area, approximately 1264 km2, or 17 % of the total area, was moderately suitable for

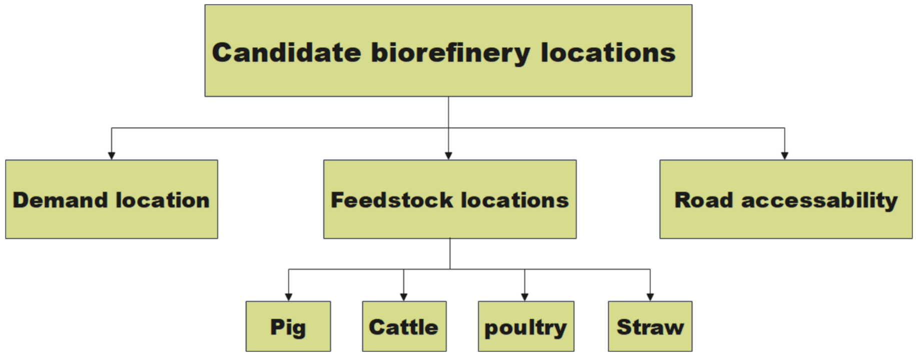


Fig. 2. Criteria considered for land suitability analysis in bioenergy case study (County Cork, Ireland).

biorefinery development. This category includes areas that scored low in proximity to feedstock resources, demand points, and access to roads, which may make them less suitable than highly suitable areas. The results also show that only 6 % of the area is low suitable, which is far away from demand points and resources. By identifying areas that meet economic, environmental, and social criteria, this figure supports strategic site selection for a sustainable bioenergy supply chain.

Furthermore, the results show that about 56 % of feedstock resources are located in highly suitable areas, which accounts for 75 %, 70 %, 67 %, and 40 % of straw resources, pig, chicken, and cow manure production locations. Also, 34 % of feedstock resources are in moderately suitable areas. All three injection points are in a highly suitable area, which can dramatically reduce transportation costs.

Identifying areas that are highly suitable for biorefinery development can help ensure that the establishment of a biorefinery is in the most appropriate location, considering various factors, including environmental impacts and economic and social factors. Identifying low suitable areas for biorefinery development can help avoid potential conflicts with other land uses and minimise negative impacts on the environment.

Finally, ten candidate locations are selected in highly suitable areas to network to minimise transportation costs and environmental effects. Fig. 3c shows these potential locations for building facilities.

As shown in Fig. 3c, all of the highly suitable areas are around the demand points since this criterion has the greatest relative importance (0.507). When the candidate locations are chosen, the distances between agriculture lands, biorefinery candidates, and demand are determined through ArcGIS.

The transportation part of the supply chain is certainly significant as it dramatically impacts costs and environmental issues. In our study, it is observed that the average transportation distance between the feedstock resources and the biorefinery locations was approximately 39 km. This relatively short distance has the potential to yield significant advantages, including lower transportation costs, reduced CO2 emissions, and enhanced environmental compliance. By minimising the distance between feedstock resources and biorefineries, the supply chain can be effectively optimised, resulting in more efficient operations. The reduced transportation distance not only transfers into direct cost savings but also contributes to the sustainability goals of the industry by minimising carbon emissions associated with long-haul transportation, mainly in the context of bioenergy production where biomass resources are usually geographically dispersed.

Around 59 % of County Cork's total area was classified as unavailable. Consequently, only approximately 41 % of the county's area remained available for utilisation. This result shows that preserved areas and their buffers form a significant part of this county. However, only 12 % were recognised as highly suitable for biorefinery development based on three main categories (proximity to resources, roads, and demand points) and four sub-categories. Identifying areas highly suitable for biorefinery development entails a comprehensive consideration of various factors, as revealed through the GIS-AHP analysis. The weighting of criteria, derived from the Analytic Hierarchy Process (AHP), sheds light on the relative importance of different factors in determining the suitability of potential biorefinery locations.

The proximity to feedstock locations emerges as a critical factor in the GIS-AHP analysis, with sub-criteria including cattle manure, pig manure, poultry manure, and straw. The allocation of weights to each sub-criterion reflects their significance in the decision-making process. For instance, areas close to abundant sources of cattle manure may be deemed highly suitable for biorefinery development, given the potential for efficient feedstock supply chains. Similarly, areas with access to diverse feedstock sources, such as pig manure, poultry manure, and straw, offer opportunities for biorefineries to optimise their input streams and diversify their product offerings.

Road accessibility is another pivotal criterion, accounting for ease of transportation and logistics. The substantial weight assigned to road accessibility underscores its importance in ensuring the efficient operation of biorefineries. Areas with well-developed road networks facilitate the transportation of feedstock inputs and finished products, reducing transportation costs and enhancing overall supply chain efficiency.

Perhaps the most influential criterion identified through the GIS-AHP analysis is the proximity to demand points. The substantial weight attributed to this criterion underscores its critical role in aligning biorefinery locations with market demand. Areas close to demand centres and gas injection points offer strategic advantages in terms of market access and distribution networks. By situating biorefineries near demand points, stakeholders can minimise transportation distances, reduce carbon emissions, and enhance the economic viability of their operations.

Moreover, the analysis revealed an average minimum transportation distance of 39 km from biorefineries to the demand points. This close proximity further supports the overall efficiency of the supply chain. In a similar study done by Zhang et al., (2017) in Italy, the average transportation distance from supplier to biorefinery was 69 km, which shows a 43 % improvement in minimising the distance when using sustainability analysis.

Hence, the focus on reducing transportation distances and optimising the geographical location of biorefinery demonstrates the methodology's efficiency in achieving cost savings, minimising CO2 emissions, and adhering to environmental regulations. By strategically managing transportation logistics, we can ensure the sustainable success of the supply chain while meeting the requirements of both the industry and the environment, as transportation costs constitute 20 % to 40 % of biomass supply chain costs (Sosa et al., 2015).

3.1.1. *Sensitivity analysis*

To perform sensitivity analysis, various scenarios were taken into account, involving different weights for the criteria, and their overall influence on the land suitability analysis was evaluated. Apart from the

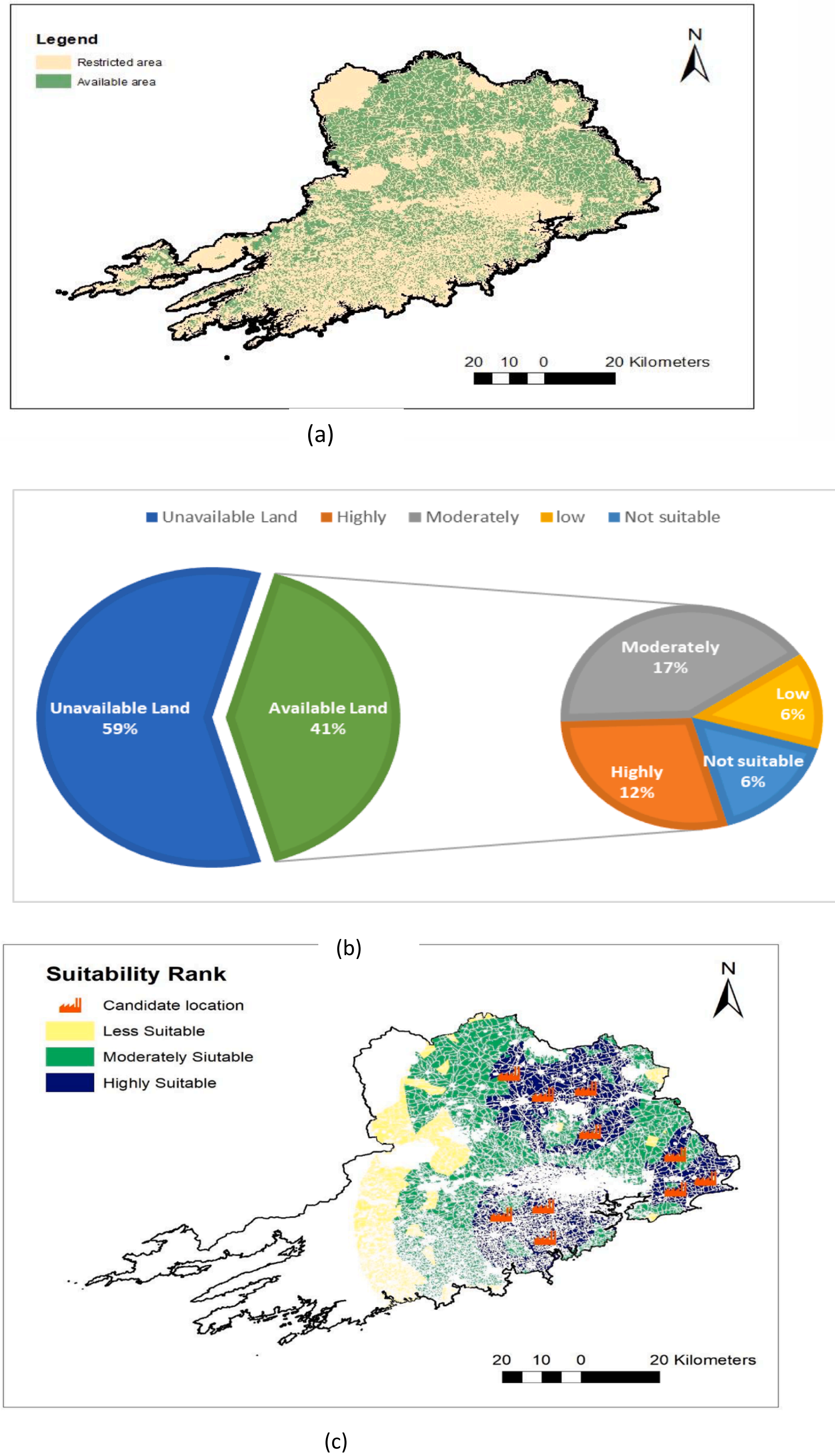


Fig. 3. (a) The restricted and available area of the geographic area for biorefinery location;(b) Distribution of Land Suitability Rankings for Biorefinery Placement; (c) Identification of potential locations for building biorefinery plants on highly suitable lands.

Table 5
Weights of Criteria and Results from the Analytic Hierarchy Process (AHP) Method.

Main criteria	Sub-criteria	Weights	Consistency Ratio (CR)
Proximity to feedstock locations	Cattle manure	0.0325	
	Pig manure	0.0325	
	Poultry manure	0.0325	
	Straw	0.0325	
Road accessibility	–	0.363	
Proximity to Demand points	–	0.507	
CR			0.02

criteria weights determined through the AHP technique, one additional scenario was investigated in this study with equal weights assigned to all criteria. In the equal weights scenario, each criterion was assigned a weight of 16.67 % to disregard their relative importance. This approach represents the most straightforward decision-making method to mitigate risks (Al Garni and Awasthi, 2017).

In the evaluation and ranking of potential locations' equal weight, the total suitable area was slightly reduced by 0.07 % of the research area compared to the results with AHP weights. The results show that the majority of the suitability area is ranked as moderately suitable, the same as the results from AHP, while there is an increase from 41 % to 43 % of the total suitable area for moderately suitable in this scenario. On the other hand, there is a minor decline in areas with highly suitable (from 12 % to 11 %) and low suitable (from 5.7 % to 4.8 %) across the entire study area, as displayed in Fig. A3 and Table 6.

Fig. A4 shows the suitability map for two different scenarios. In the scenario with AHP, the highly suitable areas are concentrated around demand points (gas injection), as this criterion has the highest weight (50.7 %). In the second scenario, the highly suitable areas are focused on the centre of the county, as the weights for all criteria are the same.

Moreover, the results demonstrate that approximately 72 % of the available feedstock resources are concentrated within highly suitable areas, corresponding to 100 % of straw resources, 90 % of pig manure production locations, 67 % of chicken manure production locations, and 60 % of cow manure production locations. Additionally, 23 % of feedstock resources are situated in moderately suitable areas. The percentage of feedstock resources in highly suitable areas in this scenario is more than in the AHP scenario, as the weight of proximity to the feedstock locations was higher than in the first scenario.

Table 6
The proportion of suitability areas across the case study based on different scenarios.

Scenario	Weights for each criterion	Land suitability percentage (%) Highly suitable	Moderately suitable	Low suitable	Not suitable
Weights based on AHP method	Proximity to feedstock locations (Cattle, pig, chicken manure, and straw) = 0.0325 Road accessibility = 0.363 Proximity to Demand points = 0.507	12	18	5.7	6
Equal weights	Proximity to feedstock locations (Cattle, pig, chicken manure, and straw) = 0.166 Road accessibility = 0.166 Proximity to Demand points = 0.166	11	18	4.8	6.7

3.2. Results from mathematical stage

The proposed Mixed Integer Linear Programming (MILP) model, designed to optimise the agricultural waste supply chain. This model execution was facilitated using GAMS (General Algebraic Modeling System) version 24.1. For solving the model, we utilised the CPLEX solver, a robust algorithm capable of handling linear programming, mixed integer programming, and other related challenges. The model, comprising 1,823 constraints and 15,751 variables, was processed on a 1.50 GHz Intel Core i7 processor. The parameters which used in the model such as feedstock price, investment cost, operational cost, conversion rates for each feedstock, etc are in Appendix A section.

Fig. 4a displays the optimal biorefinery locations and their processing capacities as determined by the MILP model, identifying eight small facilities (capacity = 1) and one large facility (capacity = 3). The decision to establish a greater number of small facilities versus fewer larger ones is driven by several critical factors:

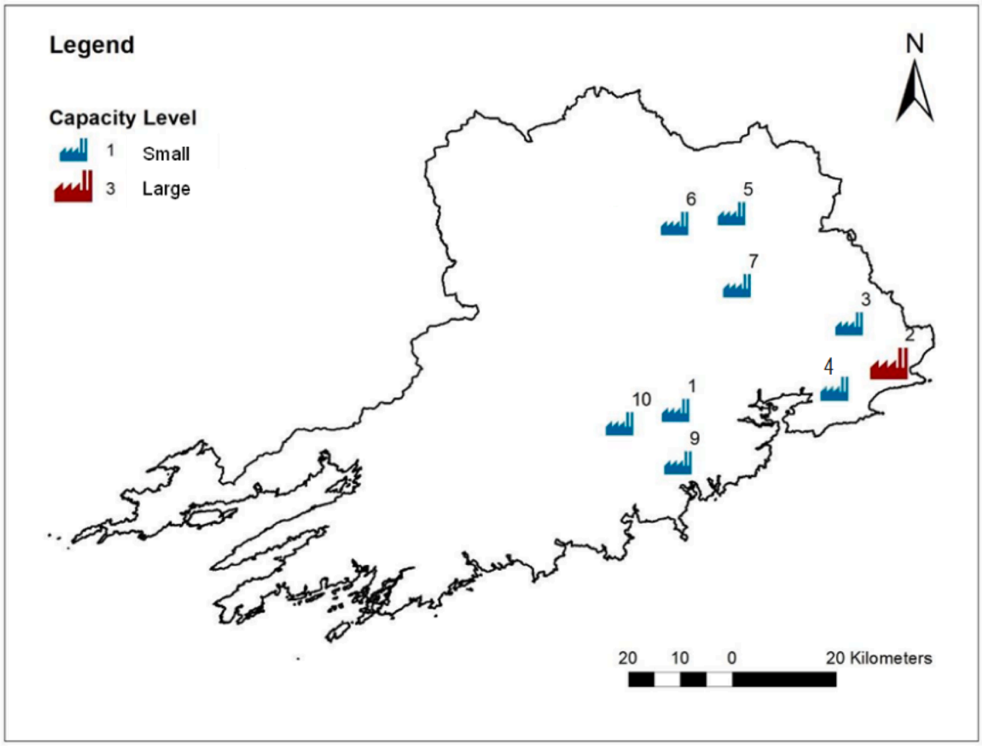
Economic Feasibility: Small facilities generally have lower construction and operational costs compared to larger ones, making them a financially viable option for distributed locations. The model shows that by selecting small facilities, the initial investment can be spread across different sites, reducing financial risk and making it feasible to operate in diverse locations.

Reduced Transportation Costs: By dispersing small biorefineries across the region, the average transportation distance from feedstock sources to processing plants is minimized, effectively reducing logistics costs and the carbon footprint of transporting raw materials. This is particularly important in a bioenergy supply chain where transportation costs are a major component of overall expenses.

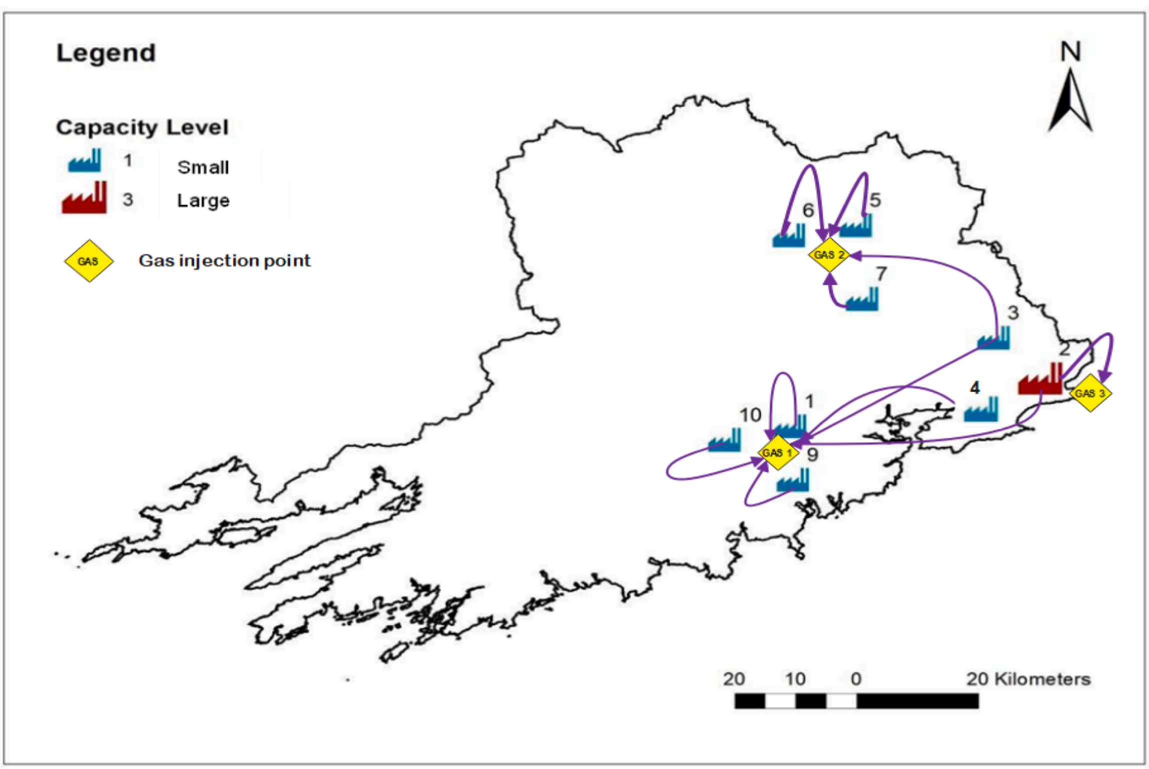
Flexibility and Adaptability: Small facilities provide increased flexibility in adjusting to seasonal variations in feedstock availability. This allows the supply chain to better handle fluctuations in local feedstock production, ensuring consistent processing capabilities across regions. This is a strategic approach to managing supply chain risks associated with feedstock shortages or changes in local supply conditions.

Fig. 4b provides a detailed visualisation of the flow between biorefineries and demand points within the region, illustrating the network of supply chain operations. The map shows a mix of small and large biorefineries, marked with blue and red icons, respectively, indicating a strategic decision to balance the benefits of both small and large facilities. Small biorefineries offer flexibility and lower startup costs, while large biorefineries can capitalise on economies of scale.

The yellow diamond symbols indicate gas injection points strategically placed within the region. These points are crucial for integrating biogas into the existing gas grid, ensuring a reliable supply to meet demand. The arrows represent the transportation routes between biorefineries and demand points. The distribution of biorefineries across the region ensures coverage of all major demand areas. This setup minimises the distance between feedstock sources, biorefineries, and demand points, which is essential for maintaining the cost-effectiveness and efficiency of the supply chain. The presence of multiple small biorefineries, particularly in areas with dense feedstock supplies, highlights a methodology aimed at reducing feedstock transportation costs and leveraging local resources. The larger biorefineries are positioned to serve areas with higher demand, ensuring that the supply can meet the regional requirements efficiently.



(a)



(b)

Fig. 4. (a) Optimal biorefinery locations and capacities determined by the MILP model; (b) The mapped flow of bioenergy products between biorefineries and demand points.

The selection of plant capacities, with a preference for small and large plants while excluding medium-sized ones, indicates a strategic approach to maximise flexibility and cost-effectiveness. Small plants can adapt quickly to variations in feedstock availability, while large plants benefit from operational efficiencies.

Fig. 4b provides a detailed visualisation of the flow between biorefineries and demand points within the region. The map includes various biorefineries, both small (blue icons) and large (red icons), as well as gas injection points (yellow diamond symbols). Each numbered plant is strategically connected to specific gas injection points and demand areas.

This figure illustrates the transport routes between optimally located biorefineries and demand points, providing insight into the logistics of bioenergy distribution. Optimising these flows reduces transportation distances, leading to cost savings and reduced greenhouse gas emissions.

Fig. 5 presents a detailed cost analysis for each component of the bioenergy supply chain, including transportation, feedstock supply, construction, and production. Understanding the cost distribution across activities enables targeted cost reduction strategies to enhance the economic sustainability of the bioenergy supply chain. The majority of the cost, 81 %, is attributed to construction. Production costs account for 15 % of the total, while transportation costs contribute 4 %. The supply costs represent the smallest portion, at just 1 %. This distribution highlights the significant investment required for construction in the supply chain. Notably, the small portion of transportation costs—only 4 % compared to 16 % in previous studies such as Rabbani et al. (2020)—underscores the efficiency of the methodology used to identify optimal locations, effectively reducing transportation expenses.

Additionally, we conducted a practical feasibility assessment by cross-referencing selected biorefinery locations with regional infrastructure and land-use policies, confirming that the proposed locations are implementable in a real-world scenario. Benchmark testing with smaller datasets showed consistent results, further validating the robustness of the optimisation algorithm.

3.2.1. Sensitivity analysis

Sensitivity analysis is a vital tool for predicting the outcome changes in a model in response to variations in its input parameters. This analytical approach is essential for testing the robustness of findings and providing stakeholders with a clear understanding of key drivers and their impacts on the supply chain. It helps identify which parameters are the most influential, guiding targeted strategies to enhance system resilience and efficiency.

By adjusting specific inputs such as feedstock price, and availability, this analysis reveals which factors are most sensitive and guides stakeholders in prioritising strategic adjustments.

- Feedstock price: This parameter is crucial as it directly influences the cost-effectiveness of bioenergy production. Changes in feedstock prices can result from market trends, policy changes, or agricultural yields, all of which affect the overall profitability and viability of bioenergy projects.
- Availability of Feedstock: This reflects the supply-side risks, including seasonal variations, crop yields, and logistical constraints. Understanding how changes in feedstock availability impact the supply chain helps in planning for buffer capacities and risk management strategies.

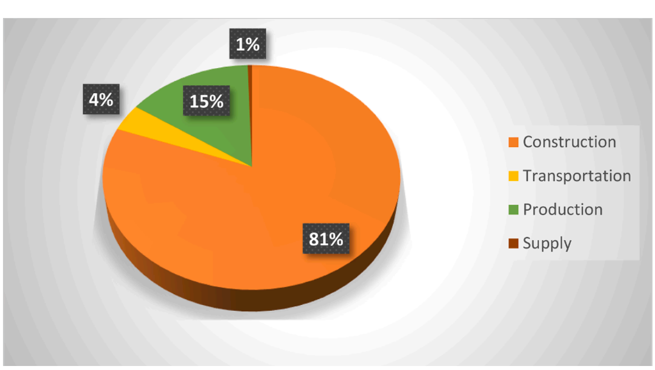


Fig. 5. Cost breakdown of supply chain activities for bioenergy production.

All of these parameter are changed by ± 20 % (±10 %, ±20 %) during the analysis (Hombach et al., 2016) Moreover, the ± 20 % variation in parameters reflects a reasonable range for assessing potential changes in the market and operational conditions, as outlined by the SEAI report (SEAI, 2017). This range is used to model the economic impact of increased competition for feedstocks and variations in material costs, which are significant factors in the bioenergy sector. This approach ensures that the model captures realistic fluctuations and provides a robust assessment of potential financial and operational risks.

The results of sensitivity analysis for each parameter and scenario analysis are as follows:

Feedstock price.

The price of feedstock is shown in Table A3. Straw is estimated to cost about 20 euros for a square bale 8x4x3 m (Mailey, 2023). Each bale of this size weighs about 400 kg, so the cost of straw per tonne would be around 50 euros. The plant manager inquired about the price of poultry litter during a visit to the AD plant. Poultry litter might be available at zero cost due to several reasons, including the fact that it is often considered a waste product by poultry farms and may be given away for free to avoid disposal costs. Additionally, poultry farms may have agreements with biorefineries to supply litter at no charge in exchange for waste management services.

The values of the investigated parameters fluctuated by ± 20 % during the analysis (Hombach et al., 2016; SEAI, 2017). According to a report from SEAI, as the market for bioenergy feedstocks expands, heightened competition for waste feedstocks changes prices by 20 % (SEAI, 2017).

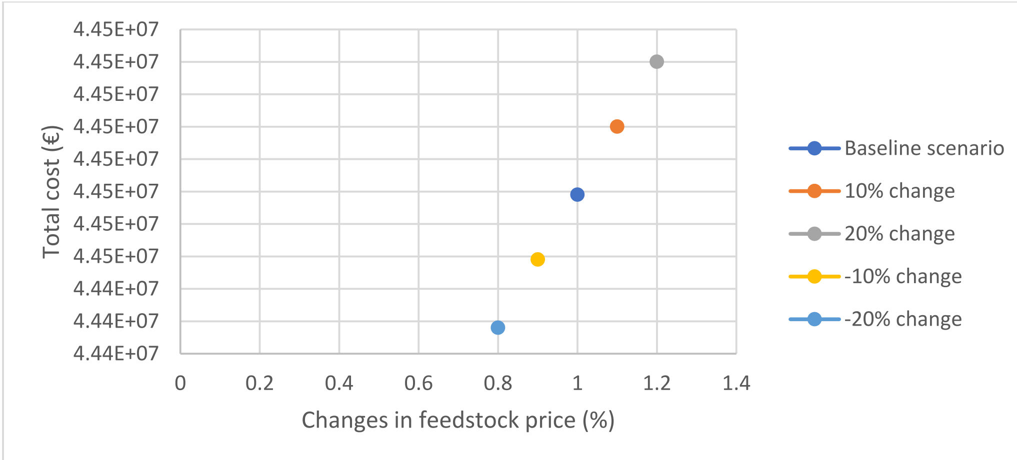
By increasing the feedstock price by 20 %, the share of straw decreased by 60 tonnes, and the share of pig manure increased by 775 tonnes. Therefore model preferred to select cheaper feedstock by increasing the price.

Fig. 6 indicates a direct relationship between the feedstock price and the total supply chain design cost. For example, a 20 % increase or decrease in the feedstock price can result in a €41,000 change in the total supply chain cost. This significant variation underscores the sensitivity of the supply chain to feedstock prices, emphasising the need for careful price management and consideration in policy-making. Providing these specific figures helps illustrate the economic implications and aids in more informed decision-making.

Changes in the availability of feedstock.

The availability of feedstock is one of the factors that can have high uncertainty for several reasons, such as changes in policies (Renewable Energy Directive, Climate Action Plan, etc), feedstock applications, number of livestock, etc (European Union, 2023). In this regard, the total availability of feedstock is varied by ± 20 % to evaluate the impact of this parameter on the whole supply chain design performance.

Fig. 6 illustrates that an increase in feedstock availability can improve economic performance, which means the total cost would decrease by increasing the amount of feedstock availability. This improvement occurs primarily because more feedstock becomes available closer to the biorefineries, reducing transportation costs. When feedstock is more readily available nearby, the distance over which it needs to be transported decreases, leading to lower fuel and logistics expenses. Additionally, increased availability of low-cost or zero-cost feedstocks means that the biorefineries can rely more on these economic inputs, further reducing overall costs. This dual effect of decreased transportation costs and increased use of inexpensive feedstock is crucial to clarify, as it underscores the importance of feedstock



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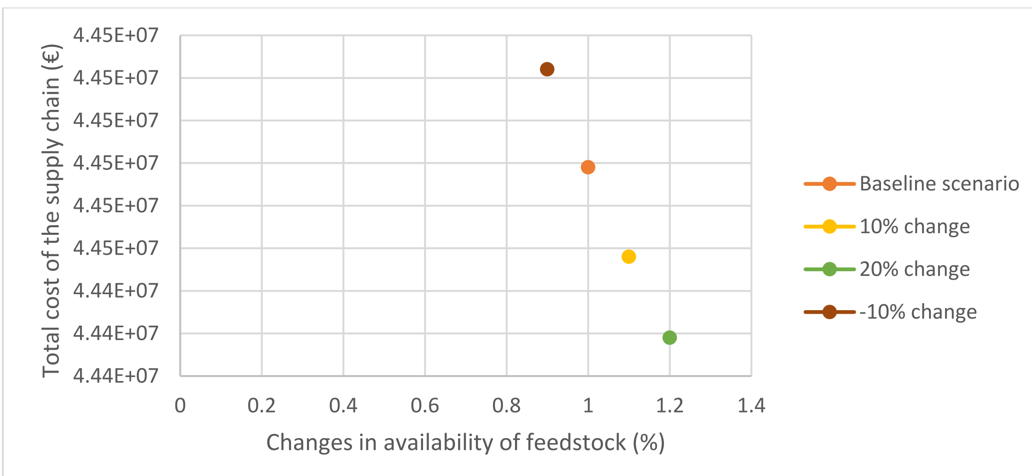

(b)

Fig. 6. (a) The impact of feedstocks' price on the supply chain total cost; (b) The impact of feedstock availability on the total cost of the supply chain.

availability in optimising the supply chain and enhancing economic performance.

4. Conclusion

This study presented a comprehensive approach to optimising the biorefinery supply chain for agricultural waste in Ireland using a four-stage methodology incorporating GIS, AHP, and a mathematical model. The results show that 12 % of the study area is suitable for biorefineries, with an average transportation distance of 39 km, reducing costs, emissions, and improving compliance. The hybrid system of small and large biorefineries balances local feedstock availability with regional demand. This research offers a scalable framework for assessing site suitability and supports agricultural waste's role in a sustainable, circular bioeconomy.

CRediT authorship contribution statement

Maryam Roudneshin: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Amanda Sosa:** Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

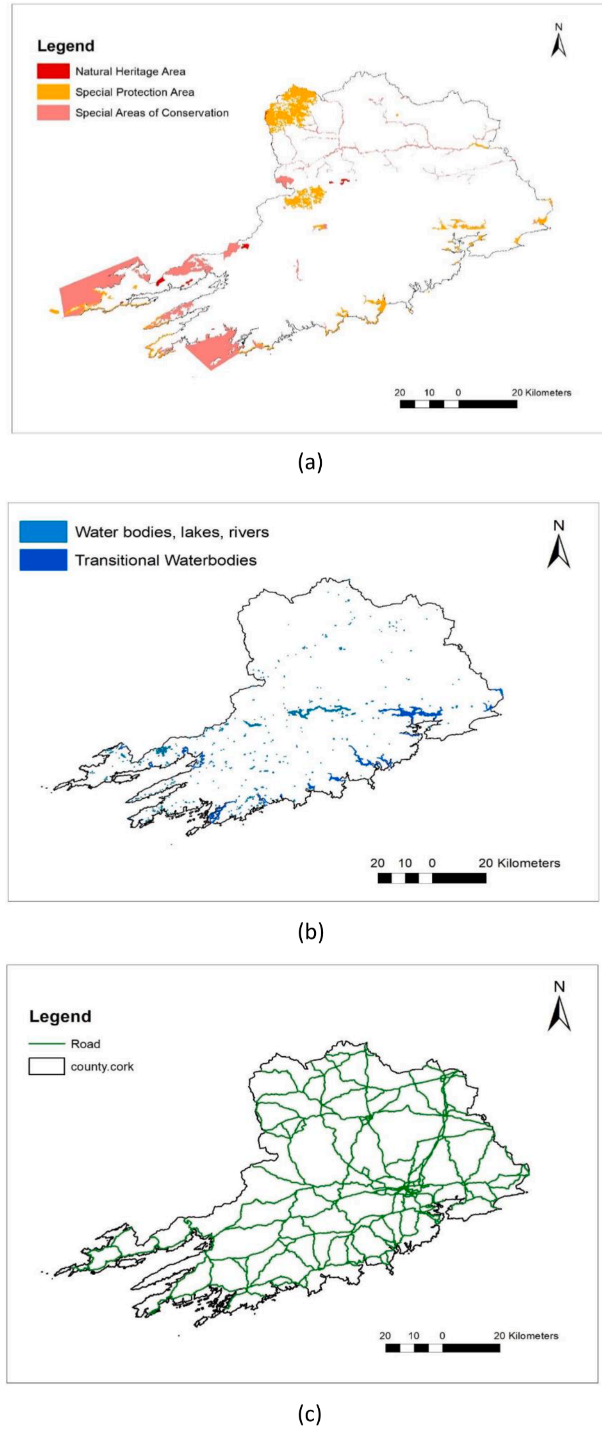

Fig. A1. Different constraints for building biorefineries: (a) Natural Heritage Areas, Special Areas of Conservation, and Special Protection Areas of County Cork; (b) Water bodies, lakes, and rivers of County Cork; (c) National roads map of County Cork manure; (e) demand points; (f) straw.

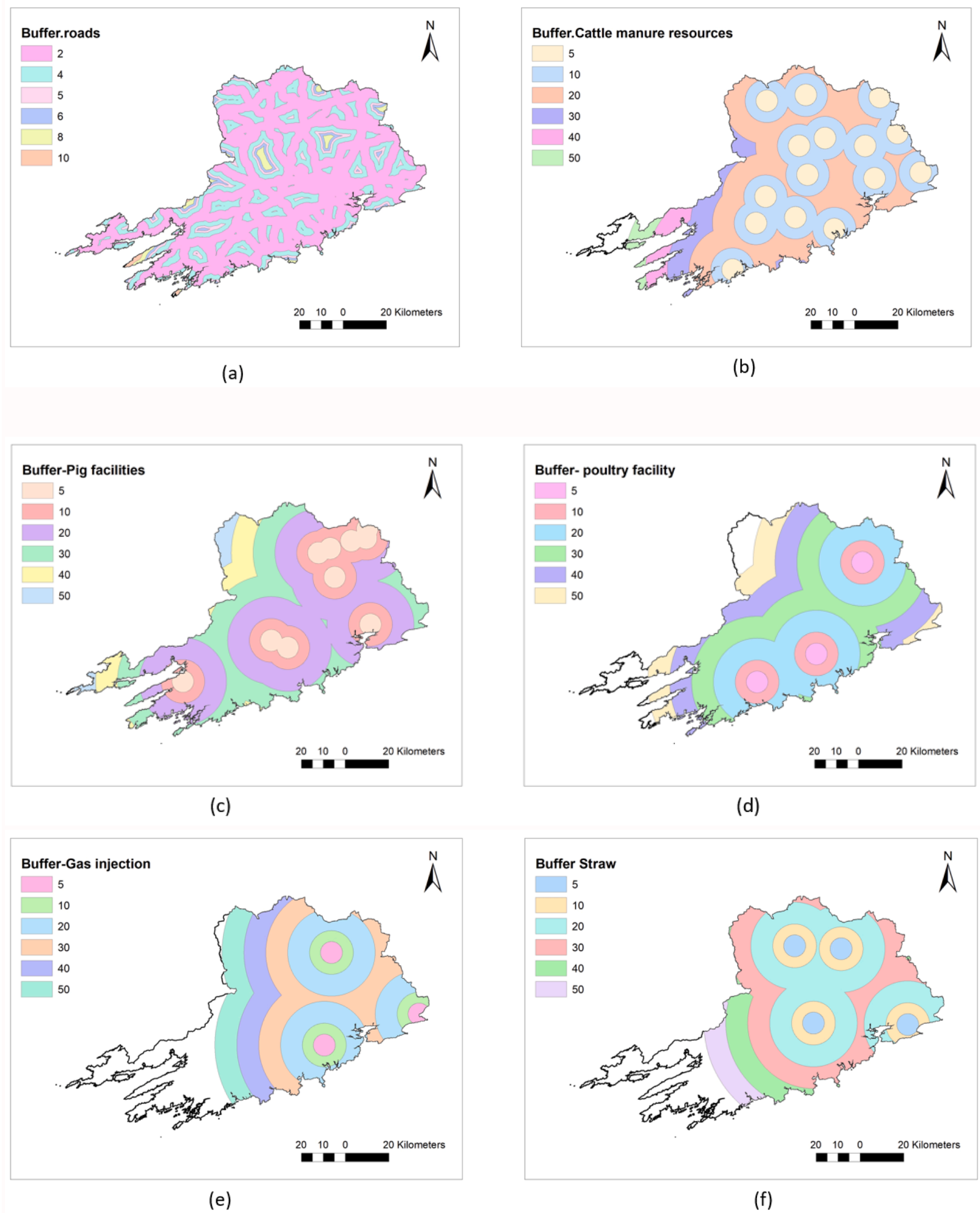

Fig. A2. Multiple ring buffers for (a) roads; (b) cattle manure; (c) pig manure; (d) poultry

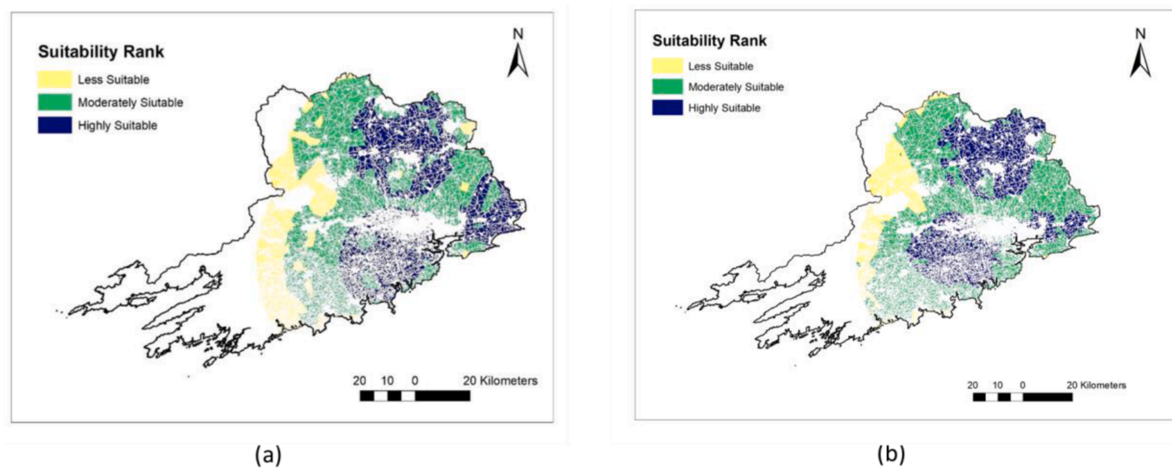

Fig. A3. Land suitability map based on (a) AHP weights and (b) equal weights.

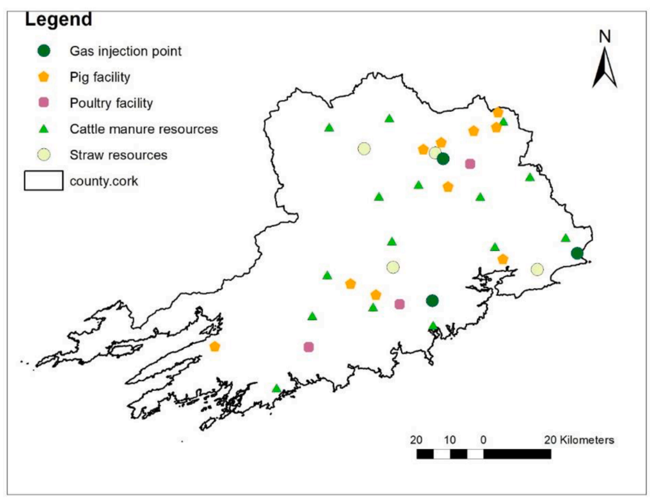

Fig. A4. Distribution of agricultural feedstock resources in county cork.

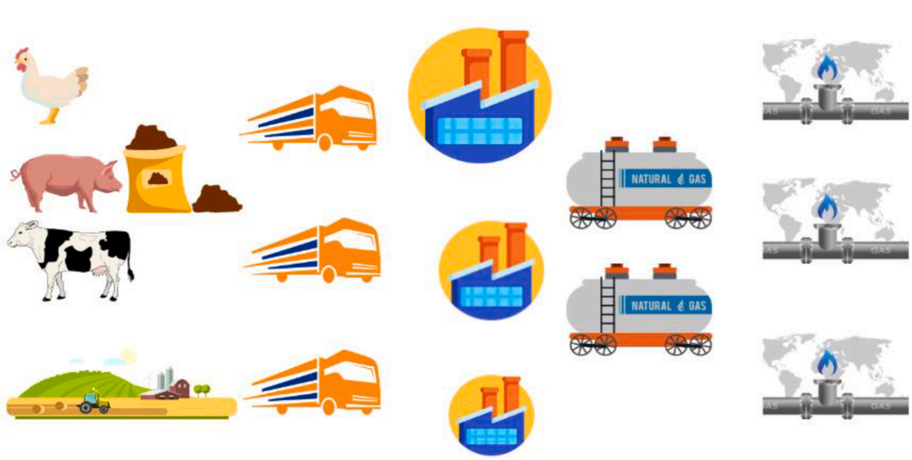

Fig. A5. The structure of bioenergy supply chain network.

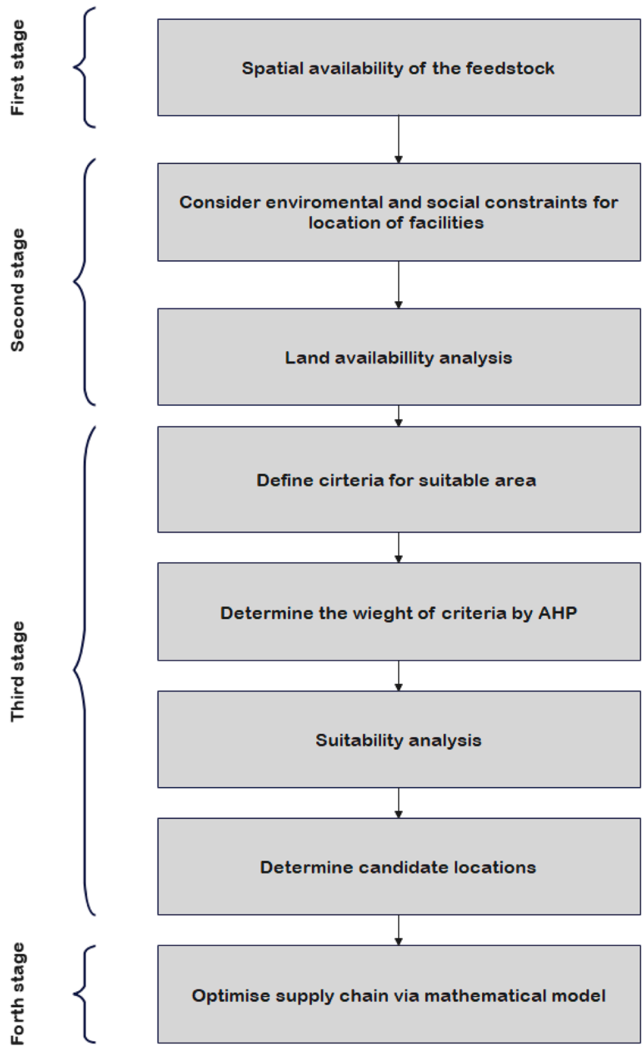

Fig. A6. Four-Stage methodology flowchart for optimising bioenergy supply network design

Table A1
Investment and operational cost of different capacity (SEAI, 2017).

Technology	Capacity	Feedstock required (tonnes/year)	Investment cost (€)	Operational cost (€/month)
AD	1,130 kWth (small)	13,000	1,923,000	28,000
	2000 kWth (medium)	25,600	12,152,000	108,250
	7000 kWth (large)	90,400	20,047,000	321,500

Table A2
The conversion rate for different agriculture feedstock (NNFCC, 2017).

Biomass	Conversion rate (m^3/tonne) for biogas
Cattle manure	25
Pig manure	25
Poultry manure	100
Straw	324

Table A3
Feedstock price.

Feedstock	Price (euro/t)	Reference
Cattle manure	1.85	SEAI, 2017
Pig manure	1.85	SEAI, 2017
Poultry litter	0	Interview with Expert
Straw	50	(Farmers Journal, 2023)

Table A4
Sources of map used in the study.

Data (shapefile)	Description	Resource
Natural Heritage Areas (NHAs)		npws.ie
Special Areas of conservation (SAC)		npws.ie
Special Protection Area (SPA)		npws.ie
natural	Natural features	OpenStreetMap Data
Roads	Roads, tracks, paths,…	OpenStreetMap Data
Railways	Railway, subways, light rail, trams, …	OpenStreetMap Data
waterways (line)	Rivers, canals, streams, drain, …	OpenStreetMap Data
water bodies (polygon)	Lakes, reservoir, wetland…	OpenStreetMap Data
County division		www.townlands.ie
Points of interest(places)	Public facilities such as government offices, post offices, police, Hospitals, pharmacies, … Culture, Leisure, Restaurants, pubs, cafes, Hotel, motels, and other places to stay the night, Supermarkets, bakeries, … Banks and ATMs, Tourist information, sights, museums, Miscellaneous points of interest	OpenStreetMap Data
Buildings	Building outlines	OpenStreetMap Data
Land use	Forests, residential areas, industrial areas, Agricultural land (areas where crops are grown), grass, …	OpenStreetMap Data

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