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# SUSTAINABLE LIGNOCELLULOSIC BIOMASS ECONOMICS AND LOGISTICS FOR BIOFUEL IN MALAYSIA

ChuLee Ong

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**SUSTAINABLE LIGNOCELLULOSIC BIOMASS ECONOMICS AND  
LOGISTICS FOR BIOFUEL IN MALAYSIA**

**BY**

**ONG CHU LEE**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in  
Fulfillment of the Requirement for the Degree of Doctor of Philosophy**

**July 2023**



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**Abstract** of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

**SUSTAINABLE LIGNOCELLULOSIC BIOMASS ECONOMICS AND LOGISTICS FOR BIOFUEL IN MALAYSIA**

By

**ONG CHU LEE**

**July 2023**

**Chair : Jean-Marc RODA, PhD**  
**Institute : Tropical Forestry and Forest Product**

Lignocellulosic biomass is one of the renewable resources to help carbon emissions mitigation and delay peak oil events and transition fossil energy reliance to alternative sustainable energy. In tropical region with high primary productivity, biofuel development was motivated by its abundance of biomass. However, biofuel sustainability is challenged by the context of resource fragmentation and complex landscape structure, this is compromising the feasibility and competitiveness of biorefineries. Hence, this study aims to assess the costs and quantities of feasible biofuel potentials in Peninsular Malaysia while considering the impact of spatial fragmentation as a significant challenge. This involves determining cost and quantity of lignocellulosic biomass wastes in Peninsular Malaysia, identifying ideal location(s) for a biorefinery (biorefineries) and assess the cost and quantity of biofuels that could potentially be produced in Peninsular Malaysia at an optimum scale. Furthermore, the impact of spatial fragmentation on the feasibility of biofuels production is also examine.

Using GRASS GIS, this study simulates the biomass transportation in Peninsular Malaysia and extend the costs and supply into biorefineries using the order of magnitude estimation method. As a result, we obtained biofuel transportation cost curves, least-cost locations, biorefinery cost curves, biorefinery optimal costs and scales based on ten major biomasses and multi-biomass scenarios in Peninsular Malaysia. Quantification of impacts from significant factors were also demonstrated.

Biomass transport costs increases by more than 4 USD/tonne at basis of 1 million tonnes feedstock for every added unit of edge density (fragmentation index). It also increases by more than 6 USD/tonne for every added 100km of average transport distance. Average truck size has a strong nonlinear negative relation with 84 USD/tonne reduction when changing from 3- to 26-tonne trucks. Biorefinery optimal costs also strongly linked to spatial fragmentation, it increases 42 USD/tonne for each unit of edge density. Every 10% increase of moisture content increase optimal cost by 12 USD/tonne. Conversion

technology is as important as fragmentation, parameter-a (represent investment cost and conversion efficiency) at interval of 250 increases optimal cost by 42 USD/tonne. To the author's knowledge, this is the first work that simultaneously address effects of fragmentation with other classical logistical factors to biomass and biorefinery economics in tropical country like Malaysia. It has strong implications for policymakers: the importance of the landscape structure makes a seemingly abundant biomass not viable for biorefineries if too fragmented compared to a much less abundant one, but more concentrated. This is illustrated by the identified feasibility of rice straw and palm pressed fiber (PPF) in contrast of more discussed resources such as empty fruit bunch and oil palm frond. The fermented biofuels produced from rice straw or from PPF are the only biomass source to be systematically cheaper than 97.5% of the crude oil price variability (below 191 USD/tonne).

The total potentials from the two biomasses are between 0.96 to 1.38 million tonnes of annual liquid biofuel which represents 5 to 7% tonne of oil equivalent of Malaysia petrol consumption in a year. This also implies that in tropical countries where the landscape is typically very fragmented, more holistic approach that include landscape variations is needed in selection of supply zone and location, as well as consideration of multi-feedstock for sustainable biorefineries.

Keywords: bioenergy, biomass, biorefinery, feedstock, landscape fragmentation, lignocellulose, residues, supply cost, transport cost, biofuel cost, wastes

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia Sebagai memenuhi keperluan untuk Ijazah Doktor Falsafah

**PELESTARIAN EKONOMI DAN LOGISTIK BIOJISIM  
LIGNOSELLULOSIK UNTUK PENGELUARAN TENAGA-BIO DI MALAYSIA**

Oleh

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**Julai 2023**

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**Institut : Perhutanan Tropika dan Produk Hutan**

Biojisim lignoselulosa ialah salah satu sumber yang boleh diperbaharui untuk membantu pengurangan pelepasan karbon dan menanggukkan kemelesetan punca tenaga fosil dan mengalihkan pergantungan tenaga fosil kepada tenaga lestari alternatif. Di rantauan tropika, dengan produktiviti primer yang tinggi, pembangunan tenaga-bio didorong oleh kesuburan biojisimnya. Walau bagaimanapun, kemampanan tenaga-bio dicabari oleh struktur kepingan sumber-sumber dan struktur geografi yang kompleks, ini menjejaskan kebolehlaksanaan dan daya saing produksi tenaga-bio. Ini merangkumi penentuan kos dan kuantiti sisa biomassa lignoselulosa di Semenanjung Malaysia, mengenal pasti lokasi yang ideal untuk satu atau lebih biorefineri, dan menilai kos dan kuantiti biofuel yang berpotensi dihasilkan di Semenanjung Malaysia pada skala optimum. Selain itu, kesan pecah bahagian ruang terhadap kelayakan pengeluaran biofuel juga dikaji.

Dengan menggunakan GRASS GIS, kajian ini mensimulasikan pengangkutan biomassa di Semenanjung Malaysia dan meluaskan kos dan bekalan ke biorefineri menggunakan kaedah anggaran kadar besaran. Akibatnya, kami memperoleh lengkung kos pengangkutan biofuel, lokasi kos terendah, lengkung kos biorefineri, kos optimum dan skala biorefineri berdasarkan sepuluh biomassa utama dan skenario biomassa pelbagai dalam Semenanjung Malaysia. Kuantifikasi kesan daripada faktor-faktor penting telah ditunjukkan.

Kos pengangkutan biojisim meningkat lebih daripada 4 USD/tan pada asas 1 juta tan bahan mentah untuk setiap unit tambahan 'kepadatan tepi' (indeks kepingan geografi). Ia juga meningkat lebih daripada 6 USD/tan untuk setiap tambahan 100km jarak pengangkutan purata. Purata saiz trak mempunyai hubungan negatif tidak-linear yang kuat dengan pengurangan 84 USD/tan apabila menukar daripada trak 3- kepada 26 tan. Kos optimum kilang tenaga-bio juga berkait kuat dengan 'kepadatan tepi', ia meningkat 42 USD/tan untuk setiap unit 'kepadatan tepi'. Setiap peningkatan 10% kandungan lembapan meningkatkan kos optimum sebanyak 12 USD/tan. Teknologi pemprosesan

tenaga adalah sama kepentingnya dengan indeks kepingan geografi, parameter-a (mewakili kos pelaburan dan kecekapan proses) pada selang 250 meningkatkan kos optimum sebanyak 42 USD/tan. Dalam penaklukan pengetahuan penulis, ini adalah karya pertama yang secara serentaknya menangani kesan kepingan sumber dengan faktor logistik klasik yang lain-lain kepada biojisim dan ekonomi kilang pemprosesan tenaga-bio di negara tropika seperti Malaysia. Ia mempunyai implikasi yang kuat untuk penggubal dasar: kepentingan struktur landskap menjadikan biojisim yang kelihatan banyak tidak mampan untuk produksi tenaga-bio jika terlalu berpecahan berbanding dengan yang kurang banyak, tetapi lebih padat. Ini digambarkan oleh kebolehlaksanaan yang dikenal pasti bagi jerami padi dan sabut mesocarp sawit (PPF) berbanding sumber yang lebih banyak dibincangkan seperti tandan kosong sawit dan pelepah sawit. Tenaga-bio yang diperolehi daripada jerami padi atau daripada PPF adalah satu-satunya sumber biojisim yang secara sistematik lebih murah daripada 97.5% kebolehubahan harga minyak mentah (di bawah 191 USD/tan).

Jumlah potensi daripada kedua-dua biojisim itu adalah antara 0.96 hingga 1.38 juta tan tenaga-bio cecair tahunan yang mewakili 5 hingga 7% tan minyak bersamaan dengan penggunaan petrol Malaysia dalam setahun. Ini juga menyarankan bahawa di negara tropika di mana struktur geografinya sangat berpecah-belah, pendekatan yang lebih holistik dengan merangkumi variasi struktur geografi diperlukan dalam pemilihan zon bekalan dan lokasi, serta pertimbangan berbilang bahan biojisim untuk produksi tenaga-bio yang mampan.

Kata kunci: biotenaga, biojisim, biorefinery, bahan mentah, pemecahan landskap, lignoselulosa, sisa, kos bekalan, kos pengangkutan, kos tenaga, bahan buangan

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I certify that a Thesis Examination Committee has met on 23 March 2023 to conduct the final examination of Ong Chu Lee on her thesis entitled "Sustainable Lignocellulosic Biomass Economics and Logistics for Biofuel in Malaysia" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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## LIST OF ABBREVIATIONS

°c	Degree Celsius
CAPEX	Capital expenditure
CO <sub>2</sub>	Carbon dioxide
DM	Dry matter
ED	Edge density
EFB	Empty fruit bunch
EU	European Union
FAO	Food and Agriculture Organization
FFB	Fresh fruit bunch
FOB	Free On Board
GHG	Greenhouse gas
GIS	Geographic Information System
GRASS	Geographic Resources Analysis Support System
ha	hectare
IEA	International Energy Agency
km	kilometre
m/ha	meter per hectare
MC	Moisture content
MYR	Malaysia Ringgit
NPP	Net primary productivity
OPEX	Operating expenditure
OPF	Oil palm frond
OPT	Oil palm trunk

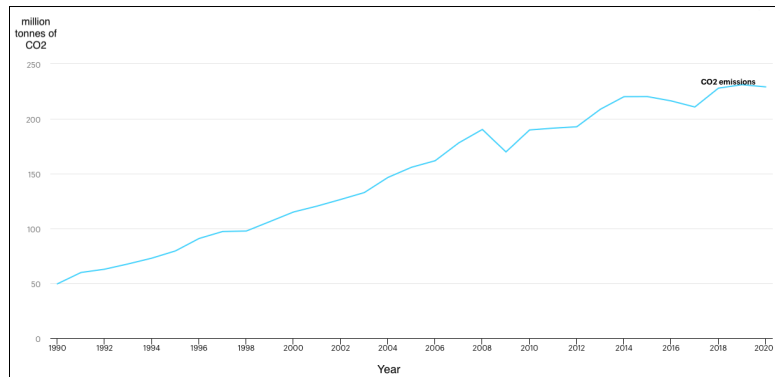
PKS	Palm kernel shell
POME	Palm oil mill effluent
PPF	Palm pressed fibre
RAM	Random-access memory
RBPD	Regional Biomass Processing Depots
U.S.	United States
USD	United States Dollar

# CHAPTER 1

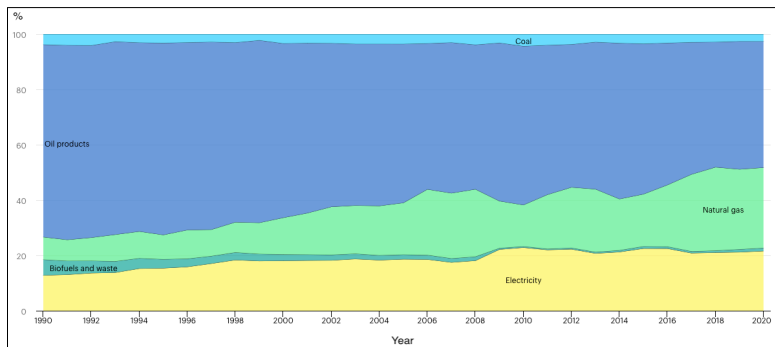
## INTRODUCTION

### 1.1 Background

Climate change is posing unprecedented threats to humanity. These risks include biodiversity loss, global warming, and extreme weather events (OECD, 2012). Transitioning from fossil fuels to renewable energy is at the forefront of mitigating these risks among the available alternatives. However, in Malaysia the major culprit of global warming – carbon dioxide emissions are still on the rise (Figure 1.1); where the nation’s energy consumption is still heavily relying on fossil sources while biofuels and waste sources only composed of 1.1% in Year 2020 (Figure 1.2).



**Figure 1.1: Total CO<sub>2</sub> emissions from energy consumption Malaysia, Year 1990 – 2020**  
(Reproduced from: IEA,2023)



**Figure 1.2: Total final energy consumption by source, Malaysia Year 1990 – 2020**  
(Reproduced from: IEA,2023)

This suggested that there is urgency to accelerate reduction of fossil fuel reliance for climate change mitigation. Among others, biofuel is expected to become one of the major alternative energy to replace fossil energy (Mofijur, Masjuki, Kalam, Ashrafur Rahman, & Mahmudul, 2015). Their renewability and sustainability can insure environmental and sociological services such as energy security, carbon neutrality and rural areas development (Gheewala, Damen & Shi, 2013).

### **1.1.1 Definitions of biofuel**

Biofuels are energies in the form of solid, liquid or gaseous that are derived from renewable sources such as biomass (Demirbas, 2009; Liew, Hassim, & Ng, 2014). Biofuels are classified into four types according to their sources of feedstock (Naik, Goud, Rout, & Dalai, 2010, Demirbas 2011).

The first-generation biofuels also known as ‘conventional biofuels’ are derived from agricultural food crop. Sugar or starchy crops such as corn, wheat, sugar cane and cassava are used to produce bioethanol through microbial fermentation. Oil seed crops such as palm, soybean and rapeseed are used to produce biodiesel through transesterification process which the lipids were reacted with alcohols (Balat, 2011).

The first-generation biofuels involve large scale crop cultivation that heighten inefficiencies and created issues such as competition of arable land and water resources with food crop, increased food prices, land use change and anthropogenic emission (Rajagopal & Zilberman, 2007; Searchinger et. al., 2008; Gehlhar et. al., 2010). This led to advent of newer generations of biofuel or “advanced biofuels” as describe below which could avoid these externalities.

The second-generation biofuels are derived from non-edible plant, solid waste and residue materials. These feedstocks are lignocellulosic biomass from cultivation on marginal land (Izaurrealde & Zhao,2015); agricultural residues, forestry, wood and industrial wastes (Balan, 2014; Mahlia, Ismail, Hossain, Silitonga, & Shamsuddin, 2019; Magda, Szlovák, & Tóth, 2021). Other materials including used cooking oils and municipal solid waste also fall into this category (Azapagic et al., 2017).

The third-generation biofuels are derived from microbes, microalgae, and seaweeds and furthermore the fourth-generation biofuels are derived from genetically modified microalgae (Agrawal, Khatri, & Rathore, 2020).

The following table summarize the feedstock sources, benefits and drawbacks of each generation of biofuels.

**Table 1.1: Feedstocks, benefits and drawbacks of the four generations of biofuel**

Biofuel Generation	Feedstock	Benefit	Drawback
First	<ul style="list-style-type: none"> <li>• Edible crops cultivated on arable land including, <ul style="list-style-type: none"> <li>- Sugar/Starchy crops, i.e., Cassava, corn, wheat, barley, sugar cane, potatoes</li> <li>- Oil seeds, i.e. Rapeseed, Sunflower, Palm oil, Coconut, <i>Jatropha curcas</i>, Soybean</li> <li>- Animal fat</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>• Cost efficient processing <ul style="list-style-type: none"> <li>- due to well-established and simpler technology, does not require intensive pre-treatment (3, 10)</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>• Intensive use on arable land and fresh water <ul style="list-style-type: none"> <li>- led to competition with food resources, raising food price (11)</li> </ul> </li> <li>• Negative in energy balance (2,11)</li> </ul>
Second	<ul style="list-style-type: none"> <li>• Non-edible crops, from waste or cultivated on non-arable land; other organic wastes <ul style="list-style-type: none"> <li>- Lignocellulosic biomass from agricultural and forestry residues, i.e. straw, husk, sawdust; wood chips</li> <li>- Grass, i.e., Kenaf, <i>Miscanthus</i>, <i>Sorghum</i></li> <li>- Organic wastes, i.e., used cooking oil, municipal solid wastes, manure</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>• Potentially to be positive in energy balance (4, 14)</li> <li>• Utilize waste sources thus avoided the food vs fuel conflict (circular economy)</li> </ul>	<ul style="list-style-type: none"> <li>• Limited amounts of biomass</li> <li>• Require extensive pre-treatment, due to complex feedstocks (12)</li> </ul>
Third	Microalgae, macroalgae and microbes	<ul style="list-style-type: none"> <li>- Fast growing organisms in water body utilizing photosynthesis process (sunlight, carbon)</li> <li>- Potentially carbon neutral and positive energy balance (1)</li> <li>- Does not use arable land</li> </ul>	<ul style="list-style-type: none"> <li>- Expensive downstream process where intensive dewatering is required (9, 15)</li> </ul>
Fourth	Genetically modified microalgae	<ul style="list-style-type: none"> <li>- Higher yield with high lipid containing algae due to genetic engineering (6)</li> <li>- Potentially carbon negative through creation of artificial carbon sinks. (5)</li> <li>- No land use change, reduced fresh water use</li> </ul>	<ul style="list-style-type: none"> <li>- High initial investment but economical in the long run. (8)</li> <li>- Higher regulation due to safety issues from environmental risk in case of algae spills (7, 13)</li> </ul>

(Source: (1) Aresta, Dibenedetto & Barberio (2005) ; (2) De Souza, Pacca, De Ávila, & Borges (2010) ; (3) Eggert & Greaker (2014); (4) Eisentraut (2010); (5) El-Sheekh, El-Dalatony, Thakur, Zheng & Salama (2021); (6) Flynn, Mitra, Greenwell & Sui (2013); (7) Gressel, van der Vlugt & Bergmans (2013); (8) Ketzer, Skarka & Rösch (2018); (9) Lee, Cho, Chang & Oh (2017); (10) Naik, Goud, Rout & Dalai (2010); (11) Sims, Taylor, Saddler & Mabee (2008); (12) Sinitsyn & Sinitsyna (2021); (13) Snow & Smith (2012); (14) Wang, Han, Dunn, Cai & Elgowainy (2012) ; (15) Yang, Xu, Zhang, Hu, Sommerfeld & Chen (2011). )

### 1.1.2 Lignocellulosic biomass biorefinery and biofuel conversion pathways

Among the feedstock choices for second-generation biofuels, lignocellulosic biomass is a major input source and it is an abundant resource resultant of its non-edible nature. Unlike crop such as grain, seeds, vegetable and fruit, lumber from forestry that has immediate economic and consumption value at its natural form; lignocellulosic biomass is treated as waste or residues with very low or no economic value unless it can fit into a specific value-added process.

From a biorefinery standpoint, biomass is a broad term that encompasses any organic material with the potential to be transformed into fuels and chemicals. It is a renewable and non-fossil substance from living matter, created through natural or human-driven processes. Biomass is derived from plants, algae, and certain bacteria; which utilize sunlight, CO<sub>2</sub> and water to produce carbohydrates and lipids through the process of photosynthesis. For a lignocellulosic biomass biorefinery, the sources of lignocellulose feedstock are numerous from various fibrous botanical parts ranging from straw, stalk, hull, husk, bagasse, coir, shell, barks, leaves, needles, twigs etc. (Nanda, Rana, Sarangi, Dalai & Kozinski, 2018). A prevalent lignocellulosic biomass biorefinery is pulp and paper mill where after production of main products (paper, fibre board) it also created various by-products (black liquor, saw dust, ash, sludge) and could be further valorize to produce higher value added fuels and chemicals. (Haile et al.,2021; Isaksson, Pettersson, Mahmoudkhani, Åsblad & Berntsson, 2012; Sikarwar, Zhao, Fennell, Shah & Anthony, 2017).

Lignocellulosic biomass consist of three main components, its composition usually made up of about 30-60% cellulose, 20-40% hemicellulose, and 15-25% lignin. The trio are all important components of a plant's cell wall, and they work together to provide structural support and protection. Cellulose is a long chain of glucose units linked together, forming a strong structure. Hemicellulose is a shorter chain of different sugars, including xylose, arabinose, mannose, glucose, galactose, and sugar acids. Lignin is a complex molecule that gives plants their strength and resistance to pests and microbes. Unlike sugary or starchy feedstock (e.g., corn, cassava, sugarcane) in first-generation biofuel, the presence of lignin brings up the need for pre-treatment which increases the processing cost and time. (Nanda, Rana, Sarangi, Dalai & Kozinski, 2018; Rosales-Calderon & Arantes, 2019).

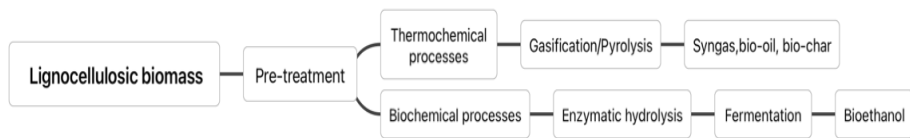
In the pre-treatment stage, biomass undergoes a compaction and decomposition process via chemical (i.e., acid, alkali or ion) or mechanical process aimed at transforming it into an intermediate product suitable for two primary conversion pathways: thermochemical and biochemical technologies. The objective of the pre-treatment stage is to enhance the bulk density and energy density of the biomass (Yan, Acharjee, Coronella & Vasquez, 2009). This involves implementing size reduction and milling processes to improve supply chain efficiency (Hamelinck, Suurs & Faaij, 2005; Lam et al., 2015; Uslu, Faaij & Bergman, 2008). Specifically, prior to thermochemical conversion, the pre-treatment stage focuses on reducing the moisture content of the biomass and enhancing its chemical reactivity (Acharjee, Coronella & Vasquez, 2011; Mosier et al., 2015; Yan, Acharjee, Coronella & Vasquez, 2009). For biochemical conversion, the pre-treatment aims to

delignify the feedstock and breaking down the cell wall of the biomass and release the internal components - cellulose and hemicellulose to latter facilitate the recovery of fermentable sugars (Hendriks & Zeeman, 2009; Rizal et al., 2018).

In the thermochemical conversion pathway, different processes are utilized by applying varying levels of heat and oxygen to the biomass. At temperatures ranging from 250 to 350°C without oxygen, the process known as torrefaction is employed. Torrefaction is considered a pre-treatment method for the thermochemical pathway, resulting in the production of biochar as its main output. Additionally, two other significant thermochemical processes are pyrolysis and gasification. Pyrolysis occurs at higher temperatures (550 to 750°C) in the absence of oxygen, yielding bio-oil as its primary product. Whereas, gasification takes place at even higher temperatures (750 to 1,200°C) with limited oxygen. The primary products of gasification are predominantly syngas, while biochar and bio-oils serve as by-products. (Lee & Lavoie, 2013).

After the pre-treatment stage, the biochemical conversion process involves two main steps: enzymatic hydrolysis and fermentation. Enzymatic hydrolysis use enzymes such as cellulases and hemicellulases to break down chemical bond in cellulose and hemicellulose into simpler sugar molecules. This stage requires careful optimization of enzyme dosage, reaction conditions (pH, temperature), and duration to achieve efficient sugar conversion (Rizal et al., 2018; Zhu & Pan, 2022). In the next step, fermentation, microorganisms like yeast or bacteria consume these sugars and convert them into useful products. The main product that can be obtained from fermentation is ethanol, which can be used as a biofuel. Other products include organic acids and chemicals that can be used in various industries (Lee & Lavoie, 2013; Nanda, Rana, Sarangi, Dalai & Kozinski, 2018).

The following diagram depicts a simple schematic process of the two pathways.



**Figure 1.3: Thermochemical and biochemical biofuel conversion pathway for lignocellulosic biomass**

## 1.2 Problem Statement

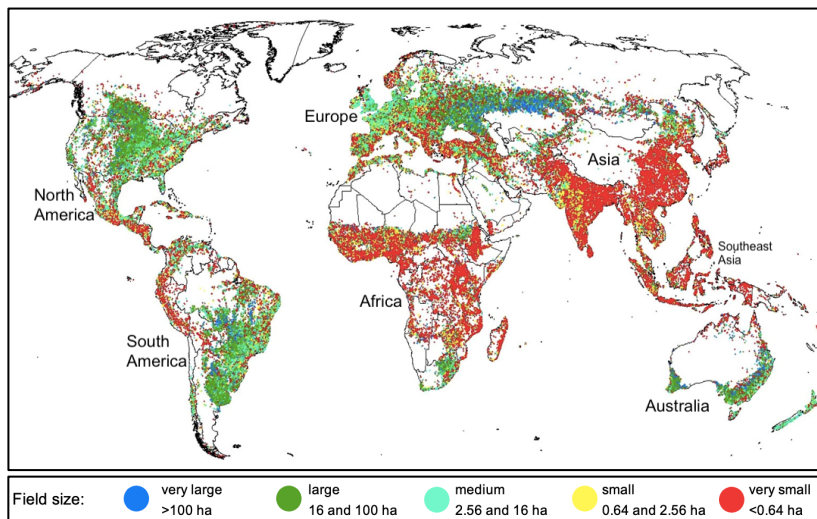
### 1.2.1 Spatial fragmentation hinders biomass accessibility

Malaysia as part of Southeast Asia region is located in the tropical and subtropical climatic zone, it is one of the zones that contains global highest net primary productivity



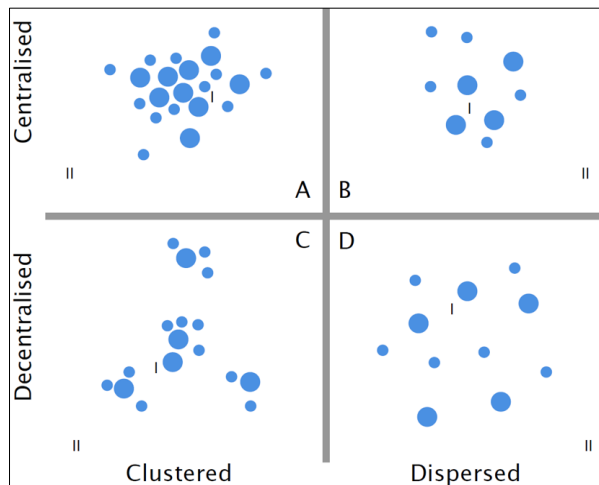
(NPP) (Cramer et al., 1999). NPP is a measure of the amount of energy captured by plants through photosynthesis, minus the energy they consume during respiration (Del Gross et al., 2008). In other words, Southeast Asia is one of the regions around the globe that is experiencing the highest rate of biomass production by photosynthetic organisms. This condition led to prosperous agricultural and forestry industries (de Koninck & Rousseau, 2013). For example, Indonesia, Malaysia and Thailand are the world’s top three producers of palm oil for decades (FAOSTAT, 2021a). Major exporters of woods in the region are Malaysia and Myanmar (FAOSTAT, 2021b). Abundance of lignocellulosic residues are generated from agriculture and forestry industry (Gregg & Smith, 2010; Koopmans, 2005). These resources are underutilized and commonly being disposed through open burning and dumping in the past decades (Carlos & Ba Khang, 2008).

The availability of un-valorized lignocellulosic biomass in the region could provide substantial sustainable biofuel potentials. However, the nature of biofuels production is tied with the biomass feedstock characteristics such as its geographical spatial pattern. This is even more so in Malaysia. As illustrated in Figure 1.1, measures from Lesiv et. al. (2019) shows that half of the field size in Asia (53%) and Africa (50%) are of the category “very small”. In contrast, majority of field size in South America, North America and Australia are categorized as “large” – 44%, 45% and 56% respectively. While in the Europe, majority of the fields are “large” (32%) and “medium” (30%). This implies that the agricultural landscape structure in the region other than Asia and Africa are more centralized. This can provide advantage on ease of access and more efficient logistics for feedstock supply to achieve higher scale economy in biofuel production. Contrarily, the agronomic practices in Southeast Asia are highly fragmented as shown by the mosaic and relatively small size of croplands (Figure 1.1). This phenomenon poses a significant challenge for the region, including Malaysia, in harnessing the potential of lignocellulosic biomass for biofuel production.



**Figure 1.4: Global field size of agricultural area**  
(Reproduced from: Lesiv et. al., 2019)

Differences in spatial patterns play a crucial role in determining the accessibility of biomass. The ease of accessing biomass resources is influenced by variations in their spatial density and distribution. While optimizing the location can improve access by reducing distances, the existing landscape structure largely dictates the overall distances required. For instance, in Figure 1.5, Location-I in the four theoretical spatial patterns aims to optimize access to the circles representing the biomass locations, resulting in reduced total distances. However, in Figure 1.5A, the biomass exhibits a highly centralized and densely clustered spatial pattern, leading to significantly lower overall collection distances compared to other patterns. This is further illustrated by the relative global field size in Figure 1.4. In Southeast Asia, including Malaysia, biomass locations are more dispersed and smaller in size compared to other continents. As a result of spatial fragmentation and varying land use practices, the accessibility of biomass in Southeast Asia including Malaysia varies significantly, impacting the economics of biomass logistics and relative supply costs.



The circles represent locations of biomass. Location-I can access the biomass areas with lower total distance compared to Location-II. Location-I in quadrant-A required less total distance to access compared to other quadrants.

**Figure 1.5: Theoretical spatial pattern of biomass**

(Source: Rodrigue, Comtois, & Slack, 2013)

### 1.2.2 Biomass logistics determine biorefineries' scale economy and sustainability

Studies on biofuel production had found that the logistic variable such as transportation, collection, and storage have substantial impact on its economic feasibility (Iakovou, Karagiannidis, Vlachos, Toka, & Malamakis, 2010). An evaluation showed that there are two significant factors affecting the biorefinery production cost the most, namely conversion efficiency and variations in biomass spatial structure and transportation distance (Gan & Smith, 2011). With technology advancement, conversion technology could reduce its cost by improving the productivity and recovery rate. However, the biomass landscape affects the biorefinery cost externally and have substantial impact on

its profitability. Due to high reliance on biomass feedstock, the major portion of the production cost is stemming from the biomass transportation (Caputo, Palumbo, Pelagagge, & Scacchia, 2005; Kudakasseril Kurian, Raveendran Nair, Hussain, & Vijaya Raghavan, 2013; Reeb, Hays, Venditti, Gonzalez, & Kelley, 2014). Empirically, the cost to deliver the biomass to its facility were ranging from 35% to 50% and it could be more (Allen, Browne, Hunter, Boyd, & Palmer, 1998; Kumar, Sokhansanj, & Flynn, 2006).

This cost constraint presents a challenge to realized biofuel potential in Southeast Asia including Malaysia. On one hand, biorefinery need to expand its capacity to achieve economy of scale or lower unit cost. On the other, biomass transportation cost would increase due to increase of sourcing distance to supply more feedstock input for biorefinery which could lead to diseconomy of scale. Given the context of resource fragmentation in Southeast Asia including Malaysia, the variation in the spatial structure would be vital to determine ideal location, capacity and cost of sustainable biofuel production.

### **1.3 Research objective and scope**

Based on the observations and descriptions in the previous section, the distribution of lignocellulosic biomass in Malaysia exhibits resource fragmentation, primarily attributed by the higher dispersion and smaller sizes of croplands. The objective of this thesis is to conduct a comprehensive assessment of the potential for second-generation biofuel production by examining the logistics involved in utilizing agricultural and wood industry waste for biofuel production. Through the analysis of unique spatial patterns and other relevant characteristics of biomass logistics, a deeper understanding of their economic impact on biofuel production can be obtained. It should be noted that due to limitations in time and resources, the scope of this thesis will be confined to Peninsular Malaysia.

#### **1.3.1 Study Area**

Peninsular Malaysia has 13.21 million hectares of total land area with 43.6% (5.76 million hectares) of forested area (Forestry Department of Peninsular Malaysia, 2018). Another 40.3% are agricultural land consisting 5.32 million hectares in year 2012 (Ministry of Agriculture and Food Industries Malaysia, 2016). Major commodity that could generate copious amount of lignocellulosic biomass includes oil palm, rubber, paddy, sugar cane, coconut and forest (Goh & Lee, 2011; Koopmans, 2005; Milbrandt & Overend, 2008). The oil palm, rubber and paddy took up majority of the cropland (total area in year 2018 – 4.03 million hectares); at 2.73 million hectares, 0.78 million hectares and 0.52 million hectares respectively. Within these three crops, the percentage of smallholder setting is around 31% (Department of Statistics Malaysia, 2021).

### **1.3.2 Research objectives**

In the context of spatial fragmentation, the accessibility and logistics associated with biomass can become complex. Existing studies that assess biofuel potentials in Malaysia without considering logistics and their economic impacts may yield over-optimistic results (Chuah, Wan Azlina, Robiah & Omar, 2006; Tock, Lai, Lee, Tan & Bhatia, 2010; Goh & Lee, 201; Tye, Lee, Wan Abdullah & Leh, 2011; Ng, Lam, Ng, Kamal & Lim, 2012; Aditiya, Chong, Mahlia, Sebayang, Berawi & Nur, 2016). Therefore, this study aims to obtain a comprehensive assessment of the biofuel potential in Peninsular Malaysia by investigating biomass transport and logistics in the context of spatial fragmentation, thus providing a more accurate depiction of the biofuel potential.

The main research objective of this thesis is as follows:

To assess the costs and quantities of feasible biofuel potentials in Peninsular Malaysia while considering the impact of spatial fragmentation as a significant challenge.

A set of sub-objectives were developed to obtain the details and desired findings.

Objective-1: To determine the cost and quantity of lignocellulosic biomass wastes in Peninsular Malaysia.

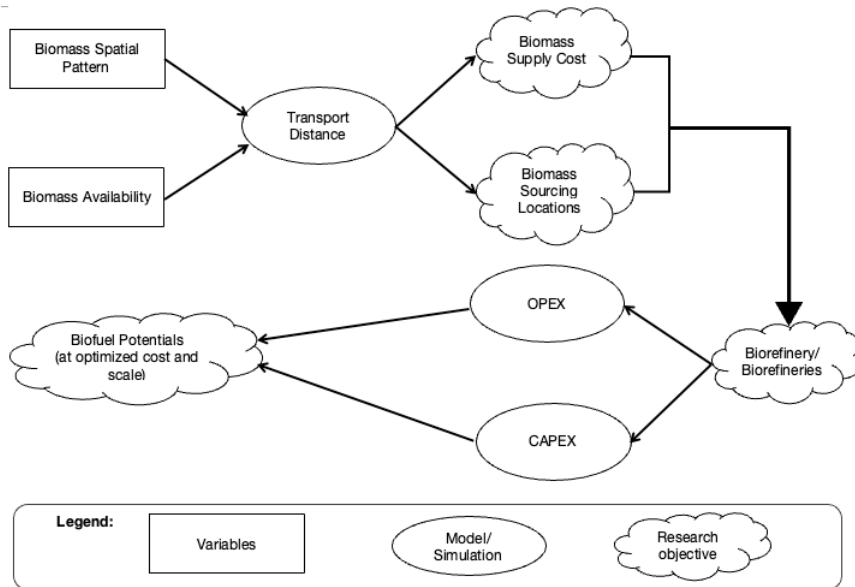
Objective-2: To identify the ideal location(s) for a biorefinery (biorefineries).

Objective-3: To assess the cost and quantity of biofuels that could potentially be produced in Peninsular Malaysia at an optimum scale.

Objective-4: To examine the impact of spatial fragmentation on the feasibility of biofuels production in Peninsular Malaysia.

### **1.4 Theoretical framework and thesis organization**

A theoretical framework (Figure 1.6) was developed based on the research objectives mentioned above to guide the study. Figure 1.6 illustrates the theoretical framework that corresponds to the research objectives.



**Figure 1.6: Theoretical framework diagram corresponding to respective research objectives**

Chapter 1 sets the context by providing an overview of lignocellulosic biomass and biofuels. It emphasizes the issue of spatial fragmentation in Malaysia and its potential impact on sustainable biofuel development. This chapter also outlines the research objectives, delimitations, and the significance of the study.

Chapter 2 presents a review of existing studies on lignocellulosic biomass logistics and supply chains for biofuel production. The review categorizes the research based on decision-making and planning hierarchy. Additionally, it identifies the United States as a dominant country in this field and explores the geographical context and industrial practices in both the United States and Malaysia.

Chapter 3 addresses Objective-1 and Objective-2. As illustrated in Figure 1.6, the relevant variables in the aspect of “Biomass Spatial Pattern” and “Biomass Availability” are gathered. Using Geographic Information System (GIS) as a tool, along with other variables as data inputs, a model is developed to simulate logistics operations. The model generates important interim results such as "Transport Distance", "Biomass Supply Cost" while also identifying the optimal "Biomass Sourcing Locations" for specific biomass types

Chapter 4 focuses on Objective-4 and examines the impact of landscape fragmentation. It explores various relevant biomass characteristics and logistical variables to quantify their effects on "Biomass Supply Cost." This chapter also presents scenarios of different

biomass types in Malaysia in the international market of densified biomass, contributing to the investigation of the supply chain for viable biofuel production.

Chapter 5 introduces a biorefinery cost estimation model. It demonstrates the computation procedures for the "CAPEX" (capital expenditure) of different conversion pathways. The results from Chapter 3, including "Biomass Supply Cost" and "Biomass Sourcing Locations," are used as scenarios for respective lignocellulosic "Biorefineries" in Peninsular Malaysia. These scenarios serve as the basis for "OPEX" (operating expenditure) calculations to determine biofuel production costs. The model also identifies optimal costs and capacities based on these scenarios and considers crude oil prices to assess feasibility and competitiveness, ultimately providing insights into the "Biofuel Potentials" in Peninsular Malaysia.

Finally, Chapter 6 synthesizes the major findings of the study and draws conclusions. It also recommends directions for future research.

## **1.5 Significance of the study**

The biomass landscape in Malaysia is characterized by intricate patterns and fragmentation, which have implications for the cost of biomass transportation, a major factor in feedstock supply and biorefinery operations. The economic impacts resulting from spatial fragmentation specific to Peninsular Malaysia remain largely unknown. Therefore, conducting a thorough study of biomass logistics becomes imperative in order to assess the variations and their significance given that there is abundance of biomass in the nation. By examining these variations, we can gain insights into diverse conditions of feedstock supply conditions and extend our analysis to energy conversion and biofuel production. This will enable a comprehensive assessment of biorefinery feasibility and to present a more accurate and nuanced portrayal of the biofuel potentials within the region.

This research endeavour aims to identify the underlying bottlenecks that hinder the sustainable development of biofuels, ensuring a more robust and pragmatic understanding of the challenges faced. By deepening our comprehension of these factors, we can pave the way for advancements in the field of sustainable biofuels in Malaysia and beyond borders where similar phenomena exist.

## CHAPTER 2

### LITERATURE REVIEW

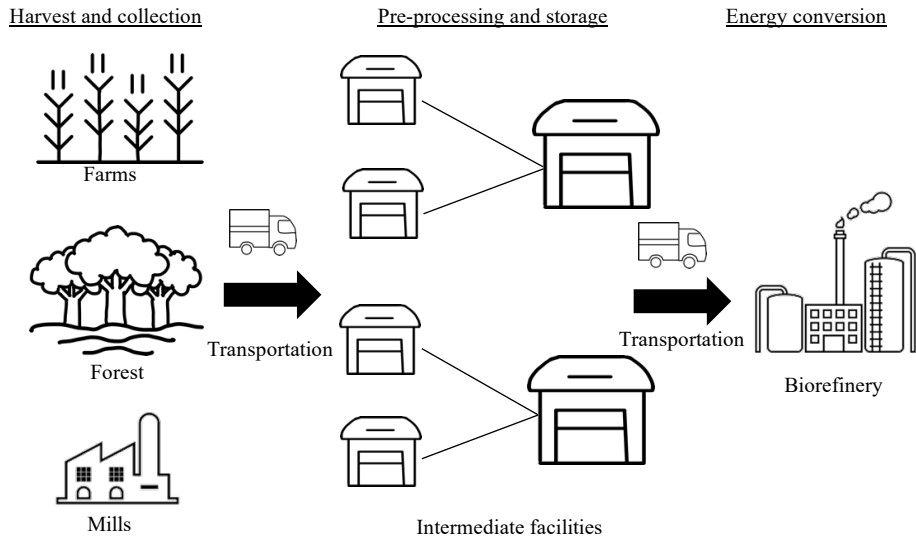
#### Chapter overview

This chapter presents a description of literatures on biomass logistics studies for biofuels. In general, this body of research were divided into management hierarchy including strategic, tactical and operational levels. Next, this work also identified the pioneering country in biomass logistics especially in terms of crop residues – United States. Descriptions and comparisons were then illustrated between the subject country of this thesis – Malaysia and the U.S. to identify research gap and bottlenecks.

#### 2.1 Introduction

Lignocellulosic biomass supply is the origin in biofuels supply chain. A supply chain is constituted by a network of activities for movement of materials, goods, and information (Lummus & Vokurka, 1999). Within the network, biomass logistical and distributional operations served as the major components between stages in the network.

The logistics of biomass feedstock involved several stages including harvest and collection, transportation, storage, pre-processing and energy conversion across various entities and stakeholders (Figure 2.1). In each of the stages, there would be different factors affecting the production system. Factors such as biomass composition and bulk density would affect the pre-processing technology and storage method used and calorific value of biofuel (Allen, Browne, Hunter, Boyd & Palmer, 1998; Svanberg & Halldórsson, 2013). Prior to this, the high reliance on biomass feedstock that are geographically scattered also led to the questions on feedstock supply variations, collection and transport cost minimisation and facility location (Miao, Shastri, Grift, Hansen & Ting, 2011; Young, Zaretzki, Perdue, Guess & Liu, 2011).



**Figure 2.1: Biomass supply chain**

The geographical and climatic conditions could lead to differences in managing biomass resources. It is also the major challenge in biomass logistics and supply chain optimization when the resources are fragmented and when this contradicts with cost efficiency and economy of scale (Sultana & Kumar, 2012; Argo et al., 2013). Due to socio-economic, political and environmental reasons, the geography of biomass in Southeast Asia is more fragmented than other continents (Fritz et al., 2015; Lesiv et al., 2018). This situation could further complicate the biomass logistics management and towards sustainable biofuels.

This review provides an overview of biomass logistics studies which can be categorized into decision hierarchy; including the strategic, tactical and operational levels. Furthermore, to put the geographical differences into context, this review also includes specificities of two countries in their development of biomass logistics for biofuel productions. First, the United States as the top contributor in this body of research and Malaysia as the typical Southeast Asian country with fragmented resources.

## 2.2 Review

### 2.2.1 Levels of biomass logistics studies

Biomass logistics studies could be based on various biomass, localities, scale of study and biofuel products. However, these studies shared a common role which is to provide information for decision-making. Since biomass to biofuel production requires a series of interlinked decisions, we can distinguish the vast body of literature into levels of decision that encompasses strategic, tactical and operational planning.



### 2.2.1.1 Strategic level

Strategic decisions are decisions that span over long-term time horizons. In cellulosic based biofuels value chain, the high reliance on biomass feedstock requires decision makers to carefully assess the opportunities and cost of adopting the biomass and to capture its dynamics along with the technology and investment involved. The focus of these decisions is to ensure that the value chain is established in a sustainable and economical way.

#### i. Securing feedstock supply

Before venturing into a cellulosic biofuel project, one must understand its local biomass. This would require knowledge about the cost and quantity of the feedstock at the desired locations. In this regard, biomass logistics cost assessments are keys to determine economic feasibility and energy potential in the area (Singh, Panesar, & Sharma, 2008; Kinoshita, Inoue, Iwao, Kagemoto & Yamagata, 2009; Mahmoudi, Sowlati & Sokhansanj, 2009; Mateos & Edeso, 2017). When presented with alternative biomass, it is important to recognize the differences among them and in preparing the biomass; the economics and associated impacts of a feedstock is pivotal to the biorefinery sustainability. Such studies could assist the decision maker to distinguish based on their priority, be it of financial or environmental performance or both. For instance, Huang, Ramaswamy, Al-Dajani, Tschirner & Cairncross (2009) found that the chemical composition of the feedstock determined the amount of ethanol production, among the four alternatives; aspen wood could produce highest amount of ethanol and excess electricity while incurring least water loss but corn stover could produce the cheapest ethanol; switchgrass and hybrid poplar are the in-betweens. Using mathematical programming model, Egbendewe-Mondzozo, Swinton, Izaurralde, Manowitz, & Zhang (2011) simulate the economics and environmental impacts of biomass production. They found that feedstocks from agri-waste have negative impacts on soil quality and increase GHG emissions while perennial grass although more costly they create positive environmental outcomes. Other similar studies also found the nuances between alternative biomass and their relative impact in biofuel production (Noon & Daly, 1996; Tembo, Eppin, & Huhnke, 2003; Kumar, Cameron, & Flynn, 2005; Lu, Withers, Seifkar, Field, Barrett & Herzog, 2015).

The spatial variations of the feedstock land cover are geographically unique. In these circumstances, biofuel investors need to determine the choices of supply zone while fulfilling their desired fuel capacity and demand. Frombo, Minciardi, Robba, Rosso & Sacile (2009) developed a decision support system with GIS that categorized forest biomass into categories of elevation in non-reserved area, account the collection cost and supplies variation to various plant size and investment at a designated location. These combinations of factors determined the suitable plant size and specified the area for feedstock supplies. Thomas, Bond & Hiscock (2013) estimated the amount of feedstock and energy potentials within 25km and 40 km to provide information to policy makers on renewable energy related decisions such as constraints on transportation distances, resource utilization and industry supports. The associated transport distance of the supply zone is an important insight towards sustainability of an energy value chain because it is

the key cost element and major source of GHG emission. Such studies often involved GIS application which allows inclusion and organization of related spatial features such as land cover types, tortuosity factor, elevations and connectivity into the simulation (Ghilardi, Guerrero & Masera, 2007; Rørstad, Trømborg, Bergseng & Solberg, 2010; Sahoo, Mani, Das & Bettinger, 2018).

To cope with inconsistent feedstock supply such as biomass seasonality, researchers tried to implement multi-feedstock sourcing strategy. Several studies had found that compared to single feedstock supplies, the average supply distance could be reduced and has significant cost-saving on transportation in addition capital cost is spread thinner and warehousing need is also lower (Rentizelas, Tatsiopoulos & Tolis, 2009; Maung et al., 2013; Ascenso, D'Amore, Carvalho, & Bezzo, 2018).

## **ii. Facility location and capacity optimization**

Feedstock supply cost is the key input cost in a biorefinery. This cost component is hinge on the availability and geographical distribution of the biomass over the biorefinery lifetime of 20 to 30 years (Stephen et al., 2010). This strategic decision is very much dependent on the accessibility to the input material that includes logistical operations and transportation to a location which the final feedstock delivered cost can be derived. The cost of the feedstock supplies differs according to the quantity of supplies; hence it will also determine the plant size and its associated capital investment. This situation requires cost optimization to find the balance between economy of scale from biorefinery capacity and diseconomy of scale from expanding sourcing distance. For instance, Noon, Zhan & Graham (2002) developed a GIS model to present maps of varying feedstock cost for a number of potential locations. This allowed decision maker to visualize the locations and biomass areas that are feasible for biofuel plants. A GIS tool that is commonly used in such studies is continuous cost surface also known as Euclidean distance, researchers could include the local road network and differentiate the associated transport cost on different kind of access (on-road and off-road) for identification of the most suitable plant location (Möller & Nielsen, 2007; Nepal, Contreras, Lhotka& Stainback, 2014). This tool operates in raster format where the map data are in pixel cells. Other approach in this setting includes resource density measurement, for example Laasasenaho, Lensu, Lauhanen & Rintala (2019) categorize the density of forest biomass to locate biofuel facility in the core supply zone. Vector tool such as route optimization are also applicable, it aims to minimize transport distances and travel time, the energy potentials and locations are then summarized in the form of points, lines and polygons (Khachatryan, Jessup & Casavant, 2009; Laasasenaho, Lensu, Lauhanen & Rintala, 2019). A similar study was also performed with GIS and included a decision ranking tool to rate and shortlist the choices of candidate locations based on biomass density, elevation and logistical and transportation cost (Rodríguez, Gauthier-Maradei & Escalante, 2017).

More factors could be included in deciding the plant location and capacity. Among options of plant locations, factors that affect biomass availability are included to find the best biorefinery plant size. Sahoo, Mani, Das & Bettinger (2018) concerned on impacts of residues removal rate and developed a predictive model that includes elevation, weather, soil type and crop management practice of corn and wheat to find sustainable

capacity for numbers of biorefinery locations in Ohio, United States. Logistical operations would also affect feedstock cost and affect the feasible quantities of supplies and plant size. Stephen et al. (2010) explored the uncertainties of biomass productivity along with several options of logistical configuration to find optimal distance and range of input capacity that could mitigate this supply risk. Policy measures could also affect the choice of locations and capacity. In the case of Sweden, ideal plant location is affected due to carbon tax from the feedstock transportation altering the optimum cost and supplies (Leduc et al., 2010).

### **iii. Supply chain network configuration**

Supply chain network involves decisions of multiple facilities that includes structuring flow of materials and configuration of distribution channel. Since supply chain risk are mostly associated with operational parameters (e.g. distribution and inventory management, supply and demand variability, transportation schedule), the tactical and operational planning became precursor in strategic planning (e.g. number, size and location of facilities) of supply chain network (Borghesi and Gaudenze, 2012; Yue, You & Snyder, 2014; Ho et al., 2015).

Fundamentally, supply chain network configuration is to allocate and optimize resource use through logistic network that consists of biomass sourcing area planning, determining transportation mode and distance; and allocate the supplies to an optimized number of facilities, locations and capacity that encompass warehouses, intermediate processing plants and biorefineries (Gonzales & Searcy, 2017; Morato, Vaezi & Kumar, 2019). One of the methods is to simulate and find optimal mix of feedstock via multiple biomass sourcing and blending technology to increase total output and minimize supply uncertainty and logistics cost of the supply chain network (Roni, Thompson & Hartley, 2019). Supply chain that involved large area and scale of production often involved intricate distribution network from source to end users, optimization model that includes multi-modal transportation and availability of infrastructure could also optimize the supply chain by identifying cost-minimizing routes and combination of transport channels (Ekşioğlu, Li, Zhang, Sokhansanj & Petrolia, 2010; Jeong, Karim, Sieverding & Stone, 2021).

Other than economic sustainability, environmental sustainability is essential in designing biofuel supply chain. Environmental assessment is included in the network configurations studies to suggest improvement to the supply chain. The most used indicator is greenhouse gas (GHG) emissions, other indicators include impacts to the ecosystem such as land use change and water footprint (You & Wang, 2011; Kanzian, Kühmaier, & Erber, 2016; Khoo, Eufrasio-Espinosa, Koh, Sharratt & Isoni, 2019). Furthermore, network design also includes robustness analysis to deal with supply chain related uncertainties such as fluctuations of market demand, seasonal feedstock supply or major disruptions (You & Wang, 2011; Maheshwari, Singla & Shastri, 2017; Ascenso, D'Amore, Carvalho, & Bezzo, 2018; Sy, Ubando, Aviso, & Tan, 2018; Khoo, Eufrasio-Espinosa, Koh, Sharratt & Isoni, 2019). The purpose is to minimize the negative effects from disruptive events through risk identification and assessment followed by measures to monitor and control the risks.

### **2.2.1.2 Tactical and operational level**

Tactical decisions focus on execution planning for medium-term deployment. Operational decisions focus on day-to-day tasks and problems. The common decisions in operational level include scheduling of biomass harvesting, collection and transport demand while tactical management focus on selecting processing methods and technologies for harvest and collection, storage, pre-treatment, transport mode, inventory management and coordination of these operations for production of feedstocks and biofuels.

#### **i. Processing method selection and scheduling for harvesting, storage and pre-treatment**

Other than transportation, logistic operations between biomass source to biorefinery includes harvest and collection, storage, and pre-treatment. Managers need to decide the suitable equipment, machineries and the capacity for these operations. The level of these decisions are between strategic and tactical planning. Some are unchanged and some need to be restructured according to harvesting seasons given the climatic conditions, weather, yield composition, suppliers feedback and other relevant info. Timing the harvest and collection of biomass, scheduling of workforce and subsequent operations are also critical to reduce dry matter loss and minimize the supply chain costs.

To plan the harvesting operation, the manager can determine the demand and cost of harvesting equipment and storage by using yearly number of harvesting days and differences in days between harvesting season (McCullough & Judd, 2012; Aguayo, Sarin., Cundiff, Comer & Clark, 2017). To minimize the logistics cost, it is essential to compare between the alternative harvesting and storage method (Spinelli, Ward, & Owende, 2009; Yu, Larson, English, & Gao, 2011; Brue, Darr, Bergman & Webster, 2015; Sun et al., 2017). Both of these functions can achieve cost-savings through densification of biomass, prevention of material loss and degradation. Furthermore, accounting the GHG emission is also crucial to ensure sustainability of the supply chain since energy demand of harvesting machinery and equipment are substantial (Zhang, Johnson & Wang, 2015).

The pre-treatment process aims to produce standardized semi-finished feedstock with required quality prior to energy conversion at biorefinery. The process involved size reduction, densification or compaction and drying of biomass (Annevelink et al., 2017). The pre-treated biomass could increase cost efficiency by prolonging the biomass shelf life and having higher density thus increasing payload during transportation (Lin et al., 2016). To decide between alternative pre-treatment technology, other than cost and technical efficiency, the manager also need to take into account other operational limitations such as storage capacity, weather condition and equipment maintenance to ensure quality and timeliness of feedstock supplies (Cundiff & Grisso, 2008; Flisberg, Frisk & Rönnqvist, 2012).

## **ii. Transportation planning and scheduling**

Tactical and operational decisions in biomass transportation generally involve transport mode selection, route optimization and scheduling. The biomass can be moved by means of truck, train, pipeline and barge or combination of the above. The selection of transportation modes are subject to the availability of infrastructure. The selection process involves cost and carbon accounting of the transport mode, biomass demand, distance, weather condition or seasonality and timeliness (Kumar, Cameron, J & Flynn, 2005; Jappinen, Korpinen & Ranta, 2013; Jäppinen, Korpinen & Ranta, 2014; Xie, Huang & Eksioğlu, 2014; Balaman, Matopoulos, Wright & Scott, 2016; Zhang, Johnson & Wang, 2016).

In the daily operations, large fleet of trucks is required to deliver biomass from source to terminal or plants. To organize this demand, the manager needs to find optimal route to minimize transport distance and cost (Gracia, Velázquez-Martí & Estornell, 2014), schedule the transport demands (Han & Murphy, 2012; An, 2019) and foresee uncertainties like traffic congestions (Bai, Hwang, Kang & Ouyang, 2011; Jouzdani & Fathian, 2016). Other factors such as road conditions (Jäppinen, Korpinen & Ranta, 2011) and tortuosity factor (Sultana & Kumar, 2014) were also examined to improve accuracy of the simulation for decision making support.

## **iii. Inventory control**

Inventories in biofuel supply chain are biomass feedstock stored in facilities to ensure fulfilment of all year-round biofuels demand. The sufficient amount of inventory is a tactical decision dealing mainly with seasonal biomass availability and variations of biofuel demands. Since biomass feedstock can be perishable and semi-finished goods, the decision-making process involved determining inventory level within multi-stage productions with multi-period supply variations. For instance, Gharaei, Pasandideh & Arshadi Khamsheh (2017) demonstrated a decision support model that fulfilled these criteria using mathematical algorithms to account the stochastic constraints and achieved integrated objective function. Others situation involved more specified inventory management scenarios. Larson, Yu, English, Jensen, Gao & Wang (2015) examined the factors determining storage losses for switchgrass-to-ethanol supply chain and found that amount of dry matter depreciated with time and delivery distance; they coped this with last in, first out method and coordination of delivery schedule and locations. Akhtari, Sowlati, Siller-Benitez & Roeser (2019) found that inventory management is also key to sustainability of biomass supply chain because from operational perspective it incurred cost and emissions from biomass preparation with machineries and transportations. They examined two inventory systems i.e. order-up-to-level and fixed order quantity and found that the first system has better cost and emissions performance.

## **iv. Master Production Planning**

Master production planning involves simultaneously making tactical decisions for multi-stage process in the biomass-to-biofuel supply chain. The decisions would involve production schedule, work force requirement, inventory level and biofuel demand

forecast while considering the production capacities and potential uncertainties. Dunnett, Adjiman & Shah (2007) using state-task-network approach to modelled the monthly tasks and supply variations for creation of biomass delivery operation schedule and anticipate inventory requirement, this led to 5 to 25% cost savings for 20MW bioenergy supply. Awudu & Zhang (2013) tested two simulation models to cope with biofuel supply chain production planning in uncertainties of biofuel demand and price, their scenario analysis showed that application of stochastic model generated more profit than the deterministic model. Sharma, Ingalls, Jones, Huhnke & Khanchi (2013) focused on uncertainties from weather condition to schedule field harvest operation and chose biomass storage method to optimize cost of biomass supply chain.

### **2.2.2 GIS application in biomass logistics and supply chain**

GIS methodology plays a vital role in the field of biomass logistics and supply chain management. Its robust capabilities in collecting, storing, analysing, and visualizing spatial data make it a powerful tool for gaining insights, aiding decision-making, and facilitating planning processes. Within the realm of biomass logistics and supply chain, GIS methodology has been successfully utilized to address critical decisions, including assessing biomass availability, optimizing transport distances, identifying suitable facility locations, and managing the supply chain.

Several noteworthy application examples highlight the versatility of GIS methodology, allowing for the incorporation of key concerns and attributes within the local context. For instance, Zambelli et al. (2012) conducted a study in Italy, considering different forest residue harvesting techniques to estimate the amount of biomass that could be harvested in a specific forest area. They employed open-source GIS software, such as GRASS, PostgreSQL, and PostGIS, utilizing the raster setting to account for important parameters like topography, road conditions, and wood biomass yield. Similarly, Gonzales and Searcy (2017) conducted a study in Texas, USA, where they examined the impact of biomass accessibility on the feasibility of biorefineries. Using a raster-based algorithm, they measured the proximity of biomass to roads and railroads, identifying biomass distribution centroids and estimating the number of biorefineries and hubs that could be located in the region.

Recognizing the significance of geographical distribution and biomass variations, as well as the presence of constraints, some studies focused on optimizing transport and supply chain scenarios. Woo, Acuna, Moroni, Taskhiri & Turner (2018) integrated socio-economic and environmental criteria into the ArcGIS software's raster setting. They delineated areas suitable for building biomass plants, considering factors such as excluding preserved areas and creating buffer zones. Additionally, they employed the p-median location-allocation method to optimize transport routes and minimize biomass supply chain costs for siting biomass plants.

As this review of GIS applications in the biomass logistics and supply chain field demonstrates, the raster setting is more commonly used compared to the vector alternative. The distinction between these settings lies in their data structure and

representation. The raster setting's suitability for handling large-scale analyses and incorporating diverse parameters makes it particularly advantageous in this context.

### **Raster and vector models**

The difference between raster and vector settings stems from their data structures and the way they represent spatial information.

In a raster setting, data is organized into a grid of cells or pixels, where each cell represents a specific area and contains a value or attribute. This data structure is well-suited for continuous or regularly sampled phenomena, such as elevation or temperature data. Raster data is represented as a matrix of rows and columns, and each cell's value represents a measurement or characteristic of the spatial phenomenon at that location. This structure allows for efficient storage and analysis of large-scale data sets, as well as the ability to perform operations like interpolation and overlay analysis (Lloyd,2010; Longley, Goodchild, Maguire & Rhind, 2005).

On the other hand, in a vector setting, spatial features are represented as individual points, lines, or polygons. Each feature has its own set of attributes, and the relationships between features can be defined through topology. This refers to the spatial relationships and connectivity between geographic features. It defines how features are related to each other based on their geometry and position in space. Vector data is based on geometric elements such as points (representing discrete locations), lines (representing linear features), and polygons (representing areas). This data structure is suitable for representing discrete or non-continuous phenomena, such as roads, buildings, or administrative boundaries. Vector data allows for precise spatial representation and analysis, including operations like buffering, intersection, and network analysis (Lloyd,2010; Longley, Goodchild, Maguire & Rhind, 2005).

Raster data is often used when dealing with continuous phenomena that can be measured or sampled at regular intervals, such as elevation or satellite imagery (Bernal, Stephens, Collins, & Battles, 2022). Vector data, on the other hand, is commonly used for representing discrete objects or features with precise boundaries and attributes, such as road networks or land parcels.

In comparison, the raster and vector data have the following advantages and disadvantages over one another (Lloyd,2010; Longley, Goodchild, Maguire & Rhind, 2005; Neteler & Mitasova, 2013).

#### **Advantages of Raster Data:**

1. **Continuous Representation:** Raster data provides a continuous representation of spatial phenomena, allowing for the analysis of phenomena that vary smoothly across space, such as elevation or temperature. This makes raster data suitable for modeling and analyzing continuous processes.

2. **Efficient Storage:** Raster data can be stored efficiently using grid-based structures, where each cell contains a value. This makes it easier to handle and manage large datasets, especially when dealing with extensive spatial coverages or high-resolution imagery.
3. **Spatial Analysis:** Raster data enables various spatial analysis techniques, such as interpolation, overlay analysis, and proximity analysis. These operations are well-suited for raster data because they can be performed on a cell-by-cell basis, allowing for the derivation of new information from the original data.

#### **Disadvantages of Raster Data:**

1. **Loss of Detail:** Raster data, by its nature, represents spatial features as a collection of cells. This can result in a loss of detail, particularly when representing complex geometric shapes or capturing fine-scale features. Raster data may not accurately represent sharp boundaries or intricate shapes.
2. **Large Data Size:** Raster data can consume significant storage space, especially at high resolutions or when working with large study areas. This can pose challenges in terms of data storage, processing speed, and data transfer, particularly in resource-constrained environments.
3. **Generalization:** Raster data is typically aggregated at a certain resolution or cell size, which requires generalization of the original spatial information. This can lead to a loss of precision and introduce uncertainties, especially when analyzing data with varying spatial scales.

#### **Advantages of Vector Data:**

1. **Precise Representation:** Vector data provides a precise representation of spatial features with distinct boundaries and attributes. It can accurately represent points, lines, and polygons, making it suitable for capturing discrete objects like buildings, roads, and administrative boundaries.
2. **Topological Relationships:** Vector data allows for the establishment of topological relationships between spatial features, enabling advanced spatial analysis operations such as network analysis, connectivity analysis, and geometric operations like buffering and intersection.
3. **Compact Data Size:** Vector data tends to have a smaller file size compared to raster data, as it only stores the geometric coordinates and attributes of individual features. This makes it easier to manage, transfer, and store data, particularly when dealing with datasets that primarily consist of discrete features.



### **Disadvantages of Vector Data:**

1. **Discrete Representation:** Vector data represents spatial features as individual points, lines, or polygons, which may not be suitable for representing continuous phenomena or data that varies smoothly across space. It may require additional processing or interpolation to analyse and model continuous processes accurately.
2. **Complex Geometries:** Vector data can become more complex when dealing with intricate geometric shapes, such as irregular boundaries or overlapping features. Handling and processing such complex geometries can be computationally intensive and may require specialized algorithms or tools.
3. **Limited Analysis Techniques:** Some spatial analysis techniques, such as surface analysis or modeling continuous phenomena, are more challenging to perform directly on vector data. Additional steps, such as converting vector data to raster format, may be required to enable certain types of analysis.

When deciding between the raster and vector setting, it becomes apparent that the raster setting offers greater flexibility in designing algorithms that are suitable for specific situations, particularly when dealing with large study areas. This flexibility has been demonstrated in various studies focusing on biomass logistics and supply chain, where different algorithms and methods, such as k-medoid data mining, weighted overlay, and least-cost path analysis, have been employed (Kaundinya, Balachandra, Ravindranath & Ashok, 2013; Lozano-García, Santibañez-Aguilar, Lozano & Flores-Tlacuahuac, 2020; Panichelli & Gnansounou, 2008). Additionally, heuristically designed algorithms have been utilized, this shows that the raster model allows for customization based on specific criteria and situations (Gonzales & Searcy, 2017).

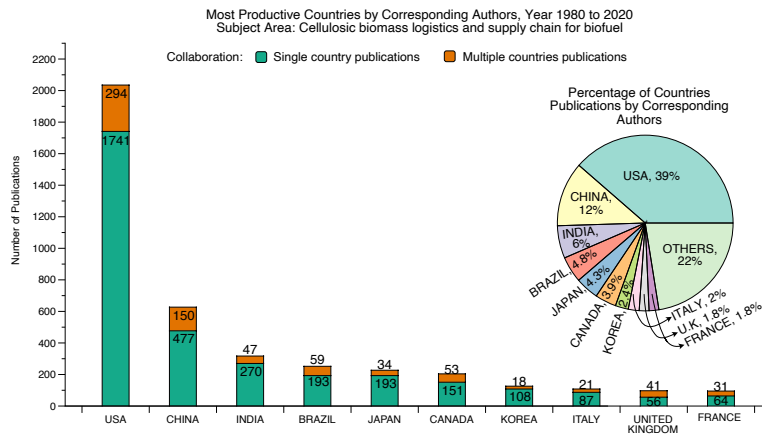
Furthermore, a hybrid approach has been identified, where the vector sector is initially employed to capture map features and serve as a data layer before converting the analysis into the raster setting. Furthermore, higher resolution setting can be set in raster model to maintain the precision in representation and computations (Jappinen, Korpinen & Ranta, 2013). This hybrid procedure minimizes data loss while enabling analysis over large study areas and facilitating iterative processes, such as the continuous cost surface method commonly utilized in biomass supply chain studies (Fiorese & Guariso, 2010; Möller & Nielsen, 2007; Zhang, Johnson & Sutherland, 2011).

By considering these approaches, researchers could leverage the advantages of the raster setting, such as its flexibility and ability to handle large spatial datasets, while also incorporating vector data to preserve important map features. This combination of techniques ensures more accurate and comprehensive analyses in the context of biomass logistics and supply chain management.

## 2.2.3 Geographical differences in biomass logistics study: case of U.S and Malaysia

### 2.2.3.1 Genesis and development of the industrial practices in the U.S

In the literatures of cellulosic biomass logistics for biofuel production, a dominating majority of the studies is led by the United States. The publications from the U.S. alone in the last four decades are more than one-third globally (Figure 2.2). This suggest that the epistemology of this subject area is more developed and comprehensive in the U.S. Hence, this section seeks to understand the development of cellulosic biomass logistics and supply chain for biofuel using U.S based publications.



Notes: This bibliography collection is from SCOPUS database, based on search query in Annex A. Analytics tool: biblioshiny for bibliometrix (Aria & Cuccurullo, 2017). (In the field of cellulosic biomass logistics and supply chain for biofuel. U.S. alone consists of 39% of total worldwide publications.)

**Figure 2.2: Scientific publications by country**  
(Source: This study)

Due to the development of first-generation biofuel, large scale cereal crops production was used to produce biofuel in the U.S. This led to resource competition with food production and environmental issues like land use change and conservation, raising concerns on food security and sustainability (Pimentel et al., 2009). To cope this with more sustainable approach, in the late 90s biofuels' interest started to switch to cellulosic based resources. This switch involved new feedstock cultivation of perennial grass and biomass sourcing from crop residuals.

In the late 90s and 2000s, a series of effort was focusing on biomass economics by determining production cost and supply structure of cellulosic feedstock from various sources such as wood residuals, straws, corn stover and cultivation of switchgrass (Downing & Graham, 1993; Downing & Graham, 1996; Walsh, Ugarte, Slinisky,

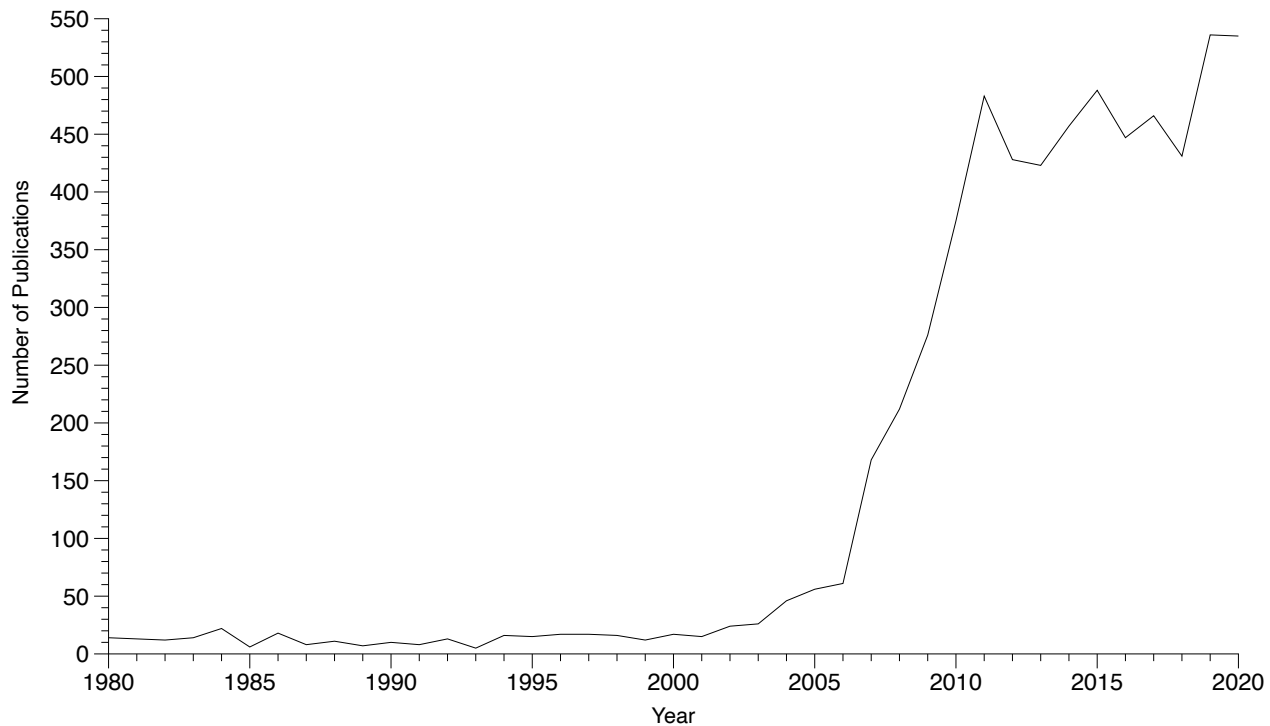
Graham & Ray, 1998; Graham, English & Noon, 2000; Perlack & Turhollow, 2003; Banowetz, Boateng, Steiner, Griffith, Sethi, & El-Nashaar, 2008; Sanderson, & Adler, 2008). Other than finding out cost of producing biomass feedstock, researchers also seek to understand and portrayed the variations of feedstock costs and supplies with geographical distribution, soil and climatic conditions, yields, availability and scale of processing facility in their region and subregions (Walshi, Ugarte, Slinsky, Graham & Ray, 1998; Noon, Zhan, & Graham, 2002; English, Ugarte, Walsh, Hellwinkel, & Menard, 2006; Di Virgilio, Monti, & Venturi, 2007; Walsh, 2008; Scheffran & BenDor, 2009). A switch of resource development and application might create new externalities to the environment and current crop practice. Hence, assessments were performed to foresee the possible impacts. For example, Lal (2009) collated and compared data of crop residues removal and impacts on soil properties, he found that crop residuals removal has negative impacts on soil quality in all climates. He also concluded that cultivation of perennial grass on marginal and degraded soils could restore the land and that these grass are the better option as biofuel feedstock. Meanwhile, others studied the environmental impacts of crop residues extraction and explored the sustainable rate of crop residues removal and ecological management (Cruse & Herndl, 2009; Newman, Kaleita & Laflen, 2010; Wilhelm et al., 2010; Meki et al., 2011; Nafziger, 2011).

One of the advantage from cultivation of perennial grass is that it can overcome seasonal supply of other biomass (Golecha & Gan, 2016a). Other than evaluating production cost and quantities of perennial grass (Epplin, 1996; Turhollow & Sokhansanj, 2007; Khanna, Dhungana & Clifton-Brown, 2008; Larson, Yu, English, Mooney & Wang, 2010), the development also involved research on management of farmers' participation such as their willingness to plant and contracts arrangement (Caldas et al., 2014; Golecha & Gan, 2016b; Fewell, Bergtold & Williams, 2016). Furthermore, feedstock production inevitably involved harvest and collection operations as well as transportation and storage; this led to logistics simulation models (Kumar & Sokhansanj, 2007; Larson, Yu, English, Mooney & Wang, 2010; Ebadian, Sowlati, Sokhansanj, Stumborg & Townley-Smith, 2011; Yu, Larson, English & Gao, 2011) and development of harvesting machinery and methods (Sanderson, Egg & Wiseloge, 1997; Thorsell, Epplin, Huhnke & Taliaferro, 2004; Shastri, Hansen, Rodriguez & Ting, 2010; Mathanker & Hansen, 2013; Brue, Darr, Bergman & Webster, 2015; Tsapekos et al., 2017) that specifically focused on the cellulosic biomass.

In the late 2000s, more focus transitioned to economic feasibility of cellulosic biofuel. This involved costs identification and evaluation that encompass feedstock supplies, capital investment, biofuel production and energy conversion efficiency (Kwiatkowski, McAloon, Taylor & Johnston, 2006; Morrow, 2006; Shapouri & Salassi, 2006; Perrin, Fretes & Sesmero, 2009). Comparisons of biofuel production were also made between applications of alternative feedstock (Vadas, Barnett & Undersander, 2008; Huang, Ramaswamy, Al-Dajani, Tschirner & Cairncross, 2009) and conversion technologies (Woodson & Jablonowski, 2008; Tiffany, Morey & De Kam, 2009; Anex et al., 2010), to find the most viable deployment settings and move towards commercialized production (Chandel, Singh, Chandrasekhar, Rao, & Narasu, 2010). At the same time, the dynamics between feedstock supplies and biorefinery scale effects, its associated impacts and limitations were also explored (Gallagher, Brubaker & Shapouri, 2005; Fike, Parrish, Alwang & Cundiff, 2007; Huang, H.-J., Ramaswamy, Al-Dajani, Tschirner & Cairncross, 2009).

In the last decade, the body of research in cellulosic biofuel logistics and supply chain management was proliferated. The number of publications spiked since 2011 and maintained more than 450 publications per year (Figure 2.3). These publications had evolved into industrial practices in management and operations of biomass and biofuel productions. In the initial stage, it involved making decisions simultaneously on biorefinery or facility location, and associate biomass supply with plant capacity. Subsequently, the focus moved towards more comprehensive supply chain planning, the concept of “Regional Biomass Processing Depots” (RBPDs) (Eranki, Bals & Dale, 2011) were introduced. This is a supply chain concept proposed to overcome limitations of biomass feedstock such as low bulk density, variation in composition and seasonal supplies. The “RBPDs” refers to the network of strategically located facilities that procure, densified and produce standardized intermediate biofuel products. The publications during this period developed more advanced simulation and programming methods that aimed to optimize in ways that are more refined and at the same time encompassing multi-level and networks in the biomass the supply chain. Burgeoning author’s keywords such as “artificial neural network”, multi-criteria decision making”, “multi-objective optimisation”, and “geographic information system” in the niche quadrant of the research themes between year 2011 to 2020 shows the computation models deployed for this development (Figure 2.4).

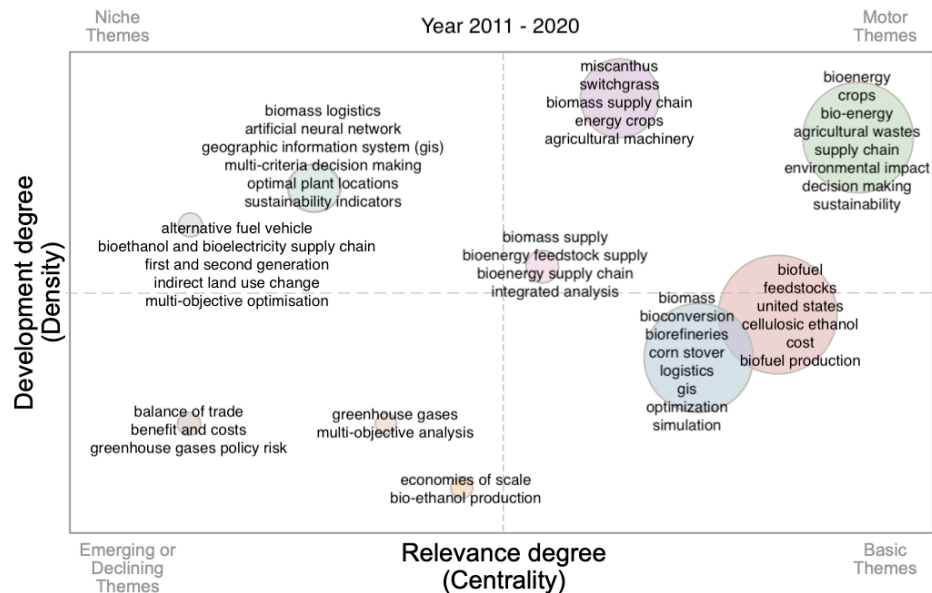
Annual Production of Publications  
(Subject Area: Cellulosic biomass logistics and supply chain for biofuel)



Notes: This bibliography collection is from SCOPUS database, based on search query in Annex A. Analytics tool: biblioshiny for bibliometrix (Aria & Cuccurullo, 2017)

**Figure 2.3: Annual production of publications in the field of cellulosic biomass logistics and supply chain for biofuel**

(Source: This study)



Notes: The bibliography used here is from author’s refined collection, targeted publications in U.S based cellulosic biomass logistics and supply chain for biofuel. The dataset is a subset from collection based on query in Annex A.

Analytics tool: biblioshiny for bibliometrix (Aria & Cuccurullo, 2017).

Interpretation: (1) Motor theme: high centrality and density, indicates developed and essential area of research; (2) Basic theme: high density but low centrality, indicates themes that are general; (3) Niche theme: high centrality but low density, indicates developed and specialized research field; (4) Emerging or declining theme: low centrality and density, indicates either new or fading research fields (Aria & Cuccurullo, 2017; Cobo, Jürgens, Herrero-Solana, Martínez & Herrera-Viedma, 2018).

**Figure 2.4: Thematic Evolution by Author’s Keyword**

(During year 2011 to 2020, various programming and simulation methods for biomass supply chain optimization were developed shown by the niche quadrant. This indicates that biomass supply chain models in the U.S. had become more sophisticated, refined and comprehensive. Source: This study)

### 2.2.3.2 Development of lignocellulosic biomass to biofuel in Malaysia

Interest on biomass to biofuel had been growing in Malaysia since last decade. Researchers are increasing the awareness and showing potentials of biomass valorization in Malaysia for biofuel production (Shuit, Tan, Lee & Kamaruddin, 2009; Goh & Lee, 2011; Asari, Suratman & Jaafar, 2011; Aditiya, et al., 2016).

With tropical climate and as one of the world's top producer of palm oil, lignocellulosic biomass in the country has high primary productivity and with various agronomy crops; biomass availability here is perceived as abundance (Mekhilef, Saidur, Safari & Mustafa, 2011; Ratnasingam, Ramasamy, Wai, Senin & Muttiah, 2015; Shafie, 2016; Yatim, Lin, Lam & Choy, 2017). Majority of the attentions are surrounding on oil palm biomass as the most abundant resource. To date, majority of the research effort are focusing on developing conversion and processing technology using palm-based biomass. For example, identification and comparison of efficient parameters and catalysts for biochemical (Chin, H'ng, Wong, Tey & Paridah, 2010; Yamada et al., 2010; Chin, H'ng, Wong, Tey & Paridah, 2011) and thermochemical (Guangul, Sulaiman & Raghavan, 2012; Abnisa, Arami-Niya, Daud & Sahu, 2013; Abnisa, Arami-Niya, Wan Daud, Sahu & Noor, 2013; Chiew & Shimada, 2013; Ayodele & Cheng, 2016; Pogaku, Hardinge, Vuthaluru & Amir, 2016; Chan, Quitain, Yusup, Uemura, Sasaki, & Kida, 2018) energy conversion pathways and various pre-treatment technology (Shamsuddin & Liew, 2009; Aziz, Morad, Wambeck & Shah, 2011; Chin et al., 2013a; Chin et al., 2013b; Rizal et al., 2018) using palm-based biomasses.

The palm oil industry produced a variety of biomass wastes. Biomass generated from the plantations are oil palm frond (OPF) and oil palm trunk (OPT). OPF were pruned during harvesting and both the OPF and OPT are available during tree felling for replantation. Based on Loh (2017), the yield of OPF and OPT are 10.4 and 74.48 tonnes per hectare respectively. For the planted area in Peninsular Malaysia year 2018 - 2.73 million hectares (Department of Agriculture Malaysia, 2019; Department of Statistics Malaysia, 2021), there would be 28.4 million tonnes of OPF and 203 million tonnes of OPT available. After deducting 50% to leave in the field for soil nutrient maintenance (Onoja, Chandren, Abdul Razak, Mahat, & Wahab, 2019), the total palm biomass from field would be 115.7 million tonnes.

The harvest – fresh fruit bunch (FFB) would be processed in the palm oil refinery; it consists of 21% of palm oil and 7% of palm kernel. Twenty-eight percent from the FFB are liquid waste - palm oil mill effluent (POME). The remaining 44% are solid biomass wastes including 23% of empty fruit bunch (EFB), 6% of palm kernel shell (PKS) and 15% of mesocarp or palm pressed fibre (PPF) (Husain, Zainac, & Abdullah, 2002). In year 2018, Peninsular Malaysia produced 47.6 million tonnes of FFB (Department of Agriculture Malaysia, 2019; Department of Statistics Malaysia, 2021) and this would yield 20.9 million tonnes of solid oil palm biomass. Together with biomass wastes from the field,s for the year 2018 alone the oil palm industry produced a staggering 136.6 million tonnes of lignocellulosic biomass wastes.

The existing practices of handling palm biomass in most cases are left in or return to the plantation for soil maintenance, mulching, and incineration for energy for the milling process (Khalil, Jawaid, Hassan, Paridah & Zaidon, 2012; Onoja, Chandren, Abdul Razak, Mahat & Wahab, 2019). With the biomasses ready on-site, palm oil refineries can generate energy more than what they required and sell the extra to national grid (Lacrosse & Shakya, 2004; Hossain & Jalil, 2017). For instance, palm mesocarp fiber and palm kernel shells are combusted since they are drier and smaller in size (Salleh et al., 2020). After these applications, the palm oil industry would still have plenty of biomass pending to dispose or valorize (Poh, Wu, Lam, Poon & Lim, 2020).

Among which, EFB are relative more bulky with higher moisture and left behind in large quantities. The EFB presented disposable problems to the industry, it requires further processing before an intended application. For example, EFB are not favoured for mulching since it requires backhauling cost to plantations and also will caused nitrogen loss in soil while leaving it at site would lead to sludge leachate pollutions and risks of combustions (Poh, Wu, Lam, Poon & Lim, 2020; Salleh et al., 2020). Due to this, EFB is the most abundant resource and it received the most attention in biomass to biofuel studies. A number of works focused on application of EFB alone, including processing system and parameters for energy, chemical and material productions (Chiew, Iwata & Shimada, 2011; Langé & Pellegrini, 2013; Zahraee, Golroudbary, Shiwakoti, Stasinopoulos & Kraslawski, 2020; Karunakaran, Abd-Talib & Kelly Yong 2020), solid biofuels (Faizal, Jusoh, Rahman, Syahrullail & Latiff, 2016; Sukiran, Kheang, Bakar & May, 2011; Pua, Subari, Ean & Krishnan, 2020; Kamal Baharin et al., 2020) and liquid biofuels (Sukiran, Loh & Bakar, 2018; Lau, Muhammad Syafiq, Nasuha Yahya & Abdul Rasid, 2019).

Other than biomass processing, biomass logistics play a pivotal role in biomass to biofuel supply chain. However, biomass logistics studies are very limited in Malaysia. Only a handful of studies address this issue. A series of rice straw logistics models were developed, these studies focused on the tactical and operational level (Mahlia, Masjuki & Chong, 2013; Shafie, Masjuki & Mahlia, 2014; Shafie, 2016). Tan et al. (2018) included spatial model for biomass logistic cost in biofuel production, however the contextual difference such as fragmented landscape in Malaysia was ignored and applied a distance threshold from the U.S. which is based on large field size and high centrality landscape. Profitable biofuel value chain design that included biomass logistics costs based on EFB was demonstrated by Abdulrazik, Elsholkami, Elkamel & Simon (2017) and Chiew, Iwata & Shimada (2011) using integrated system with palm oil refinery. These successful examples are encouraging however due to their specificity of study area, capacity and single-biomass-based, it does not paint the bigger picture whereby the high spatial fragmentation, unique geographical distribution and characteristics variation of biomasses in Malaysia would lead to high variability in feedstock cost. A number of research highlighted logistics as an issue to the biomass to biofuel industry, and the cost variability in biomass sourcing is a major challenge (Goh & Lee, 2011; Onoja, Chandren, Abdul Razak, Mahat & Wahab, 2019; Salleh et al., 2020). Mohd Idris, Leduc, Yowargana, Hashim & Kraxner (2021) included various biomasses in Malaysia with spatial model to also compute logistics cost for bioenergy productions, but the study focused only on fulfilling policy targets in amount of renewable energy and carbon credit without looking at economic feasibility. To the best knowledge of the author, no one



address the issue of landscape fragmentation in relation to strategic views in biomass logistics and economics.

### **2.3 Discussion and Conclusion**

This literature review first categorized the biomass logistics studies into level of decision and management hierarchy. This is followed by chronically review studies within pioneering country – U.S. and the subject country of the thesis – Malaysia.

We found that in the three decades of biomass logistics development in the U.S., majority of the focus transition from resource economics (biomass supply costs, zonings and categorisation of biomass supply areas), development of supply chain design and network to the recent burgeoning mathematical programming and simulations of logistics and supply chain operations and optimization. This transitions encompass first understanding the effects of biomass application in terms of economics and environmental impacts before further planning and optimization of the value chain.

Malaysia development in lignocellulosic based biofuel is around one decade, majority of the studies were developing conversion technology and systems that could suit local climate and biomass. This is important as one of the foundation to biofuel development. The biomass logistics and economics are as important as we witnessed from the U.S., however the perceived resource abundance in the country led to overlook in this aspects. Availability does not permit accessibility, the landscape fragmentation in Malaysia would affect biomass supplies differently and hence impacting the feasibility of biofuel productions.

Furthermore, we observed that other than centrality of land use in the U.S., the crop residues in the country are relatively homogenous in size with existing large-scale mechanized logistics operations. For example, switchgrass and corn stover. Although these biomass supplies were hampered by seasonality, the associated landscape centrality and highly mechanized practices could yield efficiency in biomass logistics. Conversely, Malaysia enjoys all year round production of biomass but we foresee bottlenecks in logistics operations since the flagship biomasses are from oil palm industry and the industry is still relying significantly on importation of labour (Crowley, 2020). Furthermore, the palm-based biomasses come in varieties of size and form, the needs to process variety of biomasses will also requires various efforts and investments in research and development. This further highlights the crucial need to first understand the local biomass economics and their feasibility for sustainable biofuel, which is viable through biomass logistics studies; before expanding substantive investment into diverse alternatives resources.

## CHAPTER 3

### DESIGNING GIS MODEL FOR BIOMASS TRANSPORT COST IN PENINSULAR MALAYSIA <sup>1,2</sup>

#### Chapter overview:

This chapter develop biomass transportation model using GRASS GIS software. The model consists of fine resolution raster workspace in view of landscape fragmentation in the study area. Ten major biomass and several multi-biomass scenarios were explored to illustrate their biomass transport cost curves. On top of least-cost locations identification, their cost and supply variations were also presented.

This chapter integrates the following two articles by restructuring the content of both papers, removing repetition to avoid excessive length and reshaping the content to fit into the thesis structure.

<sup>1</sup> Ong, C. L., Babin, J., Chen, J. T., & Liew, K. (2016). Designing model for biomass transport cost of biofuel refinery in Malaysia. *Proceeding of the Burapha University International Conferences 2016*, 610–621. Retrieved from [www.buuconference.buu.ac.th](http://www.buuconference.buu.ac.th)

<sup>2</sup> Ong, C., Deprés, G., Hollebecq, J.-E., Shaiffudin Hishamudin, M. O., Kamaruddin, N., Anugerah, A. R., ... Roda, J.-M. (2020). Quantifying the effect of landscape structure on transport costs for biorefinery of agricultural and forestry wastes in Malaysia. *GCB Bioenergy*, 12(11), 910–922. <https://doi.org/10.1111/gcbb.12740>

The original published article is reproduced in Appendix A and Appendix D.

#### 3.1 Introduction

Biofuels is expected to become the major alternative energy to replace fossil energy sources (Demirbas, 2008). Their renewability and sustainability insure some environmental and sociological services such as energy security, rural areas development and a lower greenhouse gases emission. These environmental considerations added to the current variability of the oil price leads to an increased interest by the industries, such as the aviation industry.

Southeast Asia including Malaysia is having the fastest growing demand for biofuel, although the expansion of new crops is very limited in the region (Roda et al., 2015). In Malaysia, there are abundance of biomass waste (Tye, 2011), it is estimated that around 168 million tons of biomass are annually wasted (Roda et al., 2015). The availability of these resources can be valorize for biofuel production.

Numerous studies have highlighted the significant impact of logistic variables such as transportation, collection, and storage on the economic feasibility of biofuel production (Iakovou, Karagiannidis, Vlachos, Toka & Malamakis, 2010). The transportation of biomass, in particular, constitutes a major portion of the production cost due to its heavy reliance on feedstock (Caputo, Palumbo, Pelagagge & Scacchia, 2005; Kudakasseril Kurian, Raveendran Nair, Hussain & Vijaya Raghavan, 2013; Reeb, Hays, Venditti, Gonzalez & Kelley, 2014). Cost variations in delivering biomass to the facility are substantial and directly impact total cost of biofuel productions (Allen, Browne, Hunter, Boyd, & Palmer, 1998; Kumar, Sokhansanj & Flynn, 2006). This predicament poses a challenge for biofuel refineries, as the pursuit of economies of scale to reduce production costs necessitates larger quantities of feedstock, leading to increased transportation expenses (Leboreiro & Hilaly, 2011). Therefore, it is crucial to minimize transportation costs by strategically locating biorefineries to optimize feedstock sources in terms of cost and quantity.

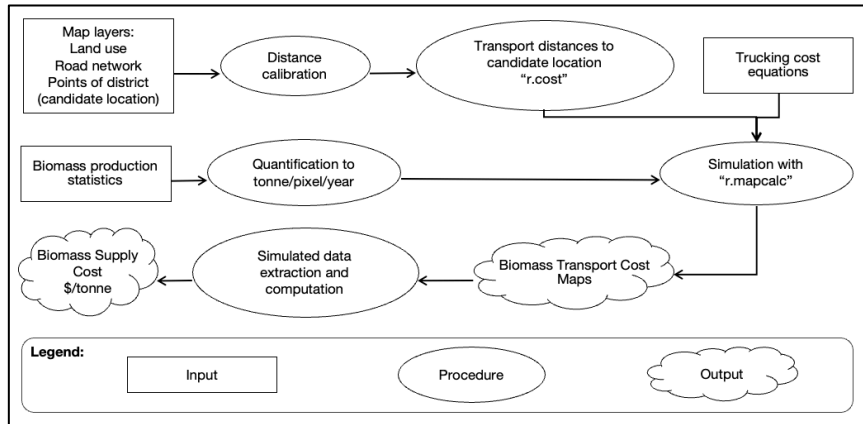
Nevertheless, in Malaysia the complexities arise and affect the accessibilities when spatial structure of the resources differs greatly in terms of centrality and dispersion (Rodrigue Comtois & Slack, 2013) as well as residues production density. To be able to take these factors into account, it was found that GIS (Geospatial Information System) modelling is pertinent to such conundrum and had been used in many related studies. These GIS applications were addressing subjects such as biomass availability assessments (Ranta, 2005; Batzias, Sidoras & Spyrou, 2005; Kinoshita, Inoue, Iwao, Kagemoto & Yamagata, 2009; Viana, Cohen, Lopes & Aranha, 2010), location and cost analysis (Panichelli & Gnansounou, 2008), biomass potentials and environmental impact (Fiorese & Guariso, 2010) and impact of topography features to transportation cost (Sultana & Kumar, 2014). Furthermore, there are spatial models specially proposed for processing facilities network design (Kim, Realff, Lee, Whittaker, & Furtner, 2011), logistics cost evaluation (Graham, English & Noon, 2000; Larson Yu, English, Mooney & Wang, 2010) and decision support system (Voivontas, Assimacopoulos & Koukios, 2001) of bioenergy plant establishment.

Existing studies based in Malaysia are very limited and only founded on selected feedstock and smaller study area (Reeb, Hays, Venditti, Gonzalez & Kelley, 2014; Shafie Masjuki & Mahlia, 2014). To address the lack of information and aiming at minimize the major cost component for biofuel industry in Malaysia, this section would assess the geo-location factor and availability of biomass wastes within the region to develop the transport cost model for biorefineries.

### **3.2 Material and methods**

Peninsular Malaysia is an example of Southeast Asia landscape, with an intricate mosaic of land uses, and contrasted elevations. It comprises 13 million hectares of landmass. We used GRASS GIS (Neteler et al., 2012 & GRASS development Team, 2018) open-source software on a 64GB RAM and 12-core computing station. The workspace was a 10870 by 10822 cells raster (West 99.40538; East 456.987285311424; South 4.95295466447834; North 4.95295466447834), where a pixel is approximately 0.4 hectare (63 x 63 meters). We obtained the land use layers from the Department of

Agriculture Malaysia (2010). Our work considers distances, quantities of biomass, landscape patterns, and costs. The procedures applied are programs in GRASS such as the continuous cost surface method using “r.cost” and map calculator “r.mapcalc”. Figure 3.1 shows the simplified steps in the simulation and computation process for estimations of biomass supply cost in Peninsular Malaysia.



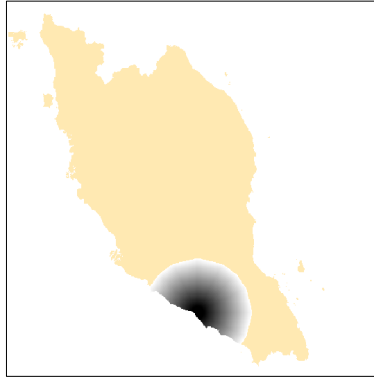
**Figure 3.1: Simplified methodology framework for Biomass Supply Cost**

### 3.2.1 Transport network calibration

Prior to the distance computation, the modelling first started with simulating the movement on the roads and off-roads in GRASS GIS workspace.

#### i. Road calibration

To account travel distance on the paved road, the distance of crossing one pixel of the surface was calculated. GRASS continuous cost surface procedure “r.cost” (Greenberg et al., 2011) tool was used to compute a “friction” coefficient. In the map workspace, thirty-two sets of coordinates were randomly selected to measure their distance and cell counts (Figure 3.2). In addition, the “knight move” option was applied to account the diagonal distance of crossing a pixel. This application improved the accuracy of distance whereby the movements were calculated in 16 directions instead of only 8 directions (Figure 3.3). However, the diagonal distance is longer than the straight-line distance of crossing one cell hence resulting error in the cell counts. To fix this, Equation 3.1 was applied as bias correction in the values of cell count.



**Figure 3.2: Cumulative distance calculated between two coordinates with “r.cost” procedure**



**Figure 3.3: Possible directions to go from one point to another**  
 (– diagonal, vertical or mixed of vertical and horizontal and an example of knight move moving from the centre to point “K”)

**Equation 3.1 Bias adjustment for diagonal movement**

$$Bias = \frac{4\sqrt{2}+12}{16} = 1.1 \tag{3.1}$$

Next, a statistical correlation was performed between the adjusted cell counts and distances of the coordinates. The result indicated that there are 0.0696 kilometres in one pixel (Figure 3.4). The coefficient of determination (R-squared) showed that the data fitted very well and the value of standard error is almost zero. Every pixel appeared to be very similar and were not distorted by the shape of the Earth. This coefficient could be applied to the paved road.

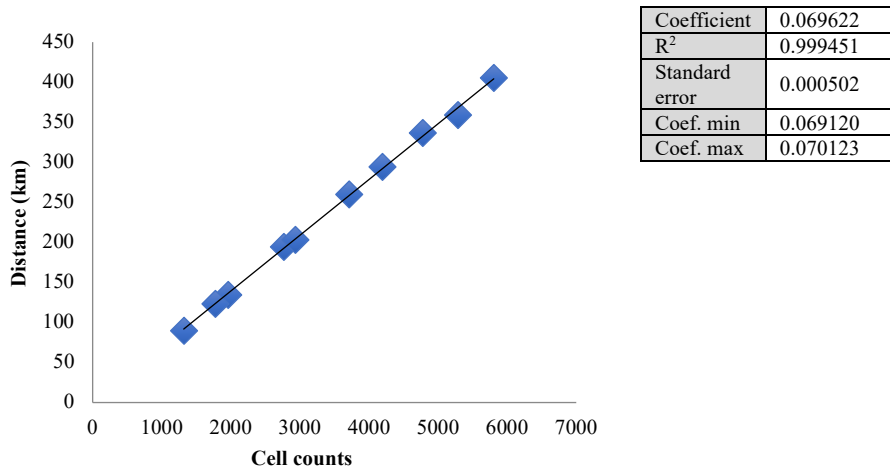


Figure 3.4: Statistical correlation of distances, function of cell counts

## ii. Off-road calibration

To enter the location of cropland and forest in the reality, there are routes that are unpaved. Unlike the road network, these off-road cannot be treated the same because of its tortuosity and roughness.

There were four steps taken in calibrating the off-road

- a. Acquire map area of a typical forest massif without roads
- b. Measure the straight-line or also known as crow-flight distance and travel distance from point of road to point inside the forest massif (Figure 3.5).

The chosen off-road area is the biggest area of forest massif in Malaysia located in natural park or “Taman Negara”. The distance from a point of road (red) to a point inside the forest massif with forest track (blue) were collected using Google maps. Ninety-six sets of point were collected to have a good approximation.

This approach imagined that to enter the forest massif, the driver must travel on the same road until the closest forest track could be found. This way of capturing the higher “friction” traveling on the unpaved road is a good representation of the reality.

- c. Perform statistical correlation between forest tracks distances of Google Map over the straight-line distances (Figure 3.6)

As shown, the standard deviation is much higher than the statistical correlation of road calibration previously. The reason is due to the diversity of forest tracks. For example, some of the tracks were newly established for luxury hotel and some are old and obsolete.

- d. Multiply the tortuosity coefficient with the road calibration coefficient to represent unpaved road “friction” (Equation 3.2)

Equation 3.2 shows the distance to cross each pixel of off-road is 0.145km. This is more than double of the paved road coefficient.

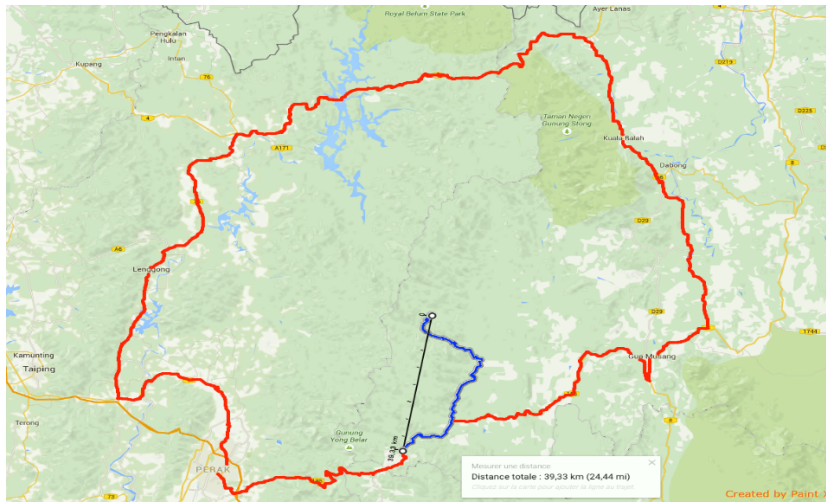


Figure 3.5: Forest massif of Taman Negara from Google Map

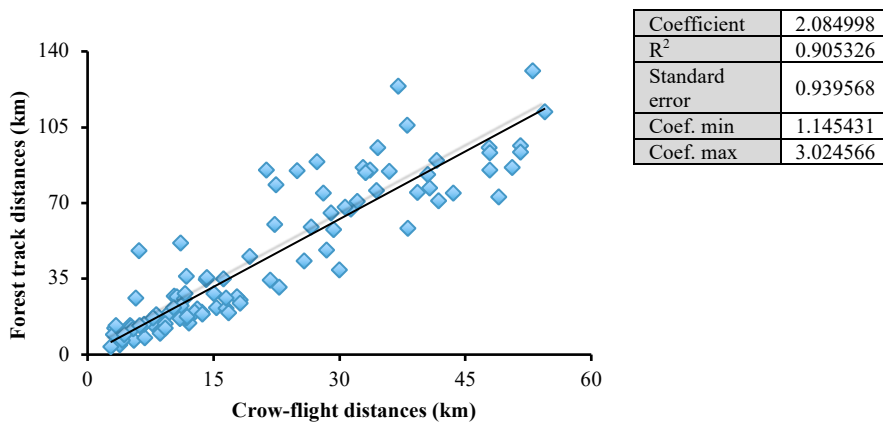


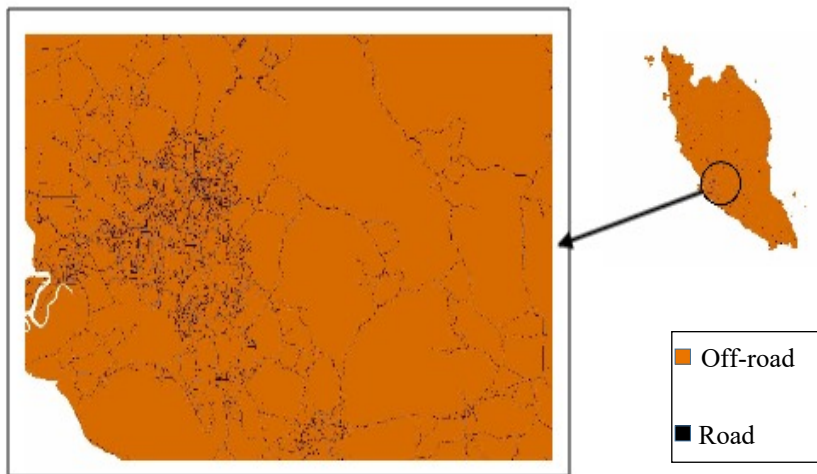
Figure 3.6: Linear regression on forest tracks length function of straight line

Equation 3.2 Friction coefficient for off-road

$$\text{Off-road friction cost} = 2.85 * 0.07 = 0.145 \text{ km} \quad (3.2)$$

### 3.2.2 Transport costs

An effective driving network was obtained from the Malaysia-Singapore association of drivers (Malsingmaps, 2015) and a friction map was created using the coefficient calibrated previously (Figure 3.7). Any location could be a candidate site for biorefineries. To simplify, the possibilities was narrowed down to the vicinity of 89 capitals of Peninsular Malaysia districts (Annex B). The transportation distance maps of the 89 locations was generated with “r.cost” procedure. As an example (Figure 3.8), the city of Kuala Lumpur was set as the destination and the remaining pixels contained continuous values of distance to reach the pixel of the city.

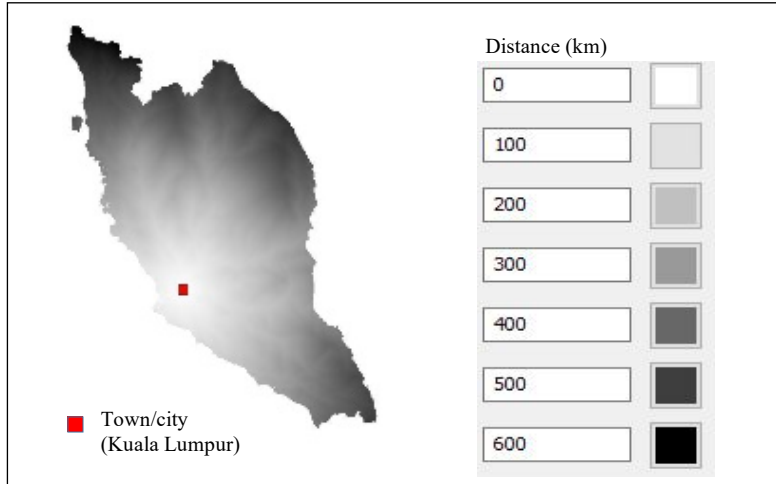


**Summary of Friction coefficient**

Friction	Coefficient	SE	df	R2
Paved-road friction	0.07km/pixel	0.0005	31	0.9989
Off-road tortuosity	2.085km of track/km of crow-flight	0.94	95	0.8188
Off-road friction	$2.085 * 0.07 = 0.145 \text{ km/pixel}$			

**Figure 3.7: Friction map of Peninsular Malaysia**





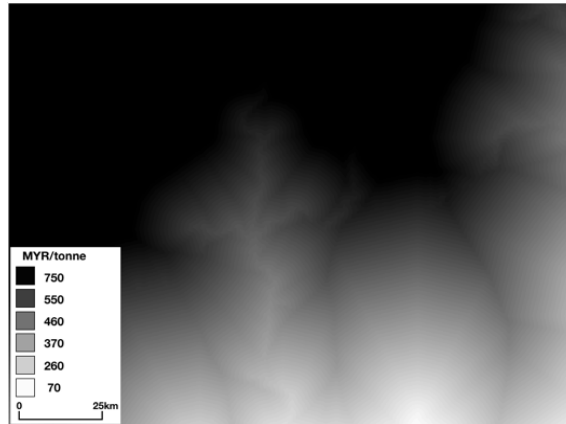
**Figure 3.8: Distance map to Kuala Lumpur from anywhere within the peninsula using “r.cost” procedure**

Using another another GRASS procedure “r.mapcalc” (Mitasova et al., 1995), the Malaysian trucking costs equations were applied to the distance maps. These equations give the trucking cost as a function of transportation distance and tonnage of the truck (Table 3.1; Roda et al., 2012) which we obtained the transport cost maps as illustrated in Figure 3.9. In Figure 3.9, the darker colour is farther and more expensive, but the heterogeneity of the transport network plays a role too; where there is no transportation network the colour is very dark, and where there are various roads, the colour is lighter.

**Table 3.1: Trucking cost equation of 4 sizes in Peninsular Malaysia.**

Truck size (tonnes)	Trucking cost linear equation
1	MYR/tonne = distance (km) x 1.88657771 + 132.004442
3	MYR/tonne = distance (km) x 0.672738734 + 69.0615618
10	MYR/tonne = distance (km) x 0.258860505 + 49.3286760
26	MYR/tonne = distance (km) x 0.193541212 + 39.5358461

Notes: The linear equations are fitted from data collected from logistic companies in Malaysia. (Source: Roda et al., 2012.)



**Figure 3.9: This illustrative raster shows what would be the cost to reach any pixel from a given point (here cost for 1-tonne truck)**

### 3.2.3 Feedstock quantification

We separated feedstocks into primary sources and secondary sources of lignocellulosic biomass (Seixas, 2008). The primary sources are the harvesting biomass potentially available on the field. These biomasses are forest logging wastes, rubberwood logging wastes, oil palm fronds, oil palm trunks, and rice straw (Figure 3.9). The secondary sources are processing residues potentially available at mills (Figure 3.10). These biomasses are rice husk, sawmill and plywood mill waste, empty fruit bunches, and palm pressed fibre. We used the quantities of biomass published for Peninsular Malaysia (Roda et al., 2015, see Table 3.2). To explore the quantities of feedstock available per area in a raster workspace, we created a variable “biomass yield”. For the primary sources, the national average quantity per pixel was quantified. For the secondary sources, the same was applied into average quantity available per mill, or per pixel representing such mill. Table 3.3 shows the steps to derive these values. Malaysia is an equatorial country with limited seasonality. Except for rice which is harvested twice a year, all feedstocks are produced all year long. To simplify, we consider only annual production.

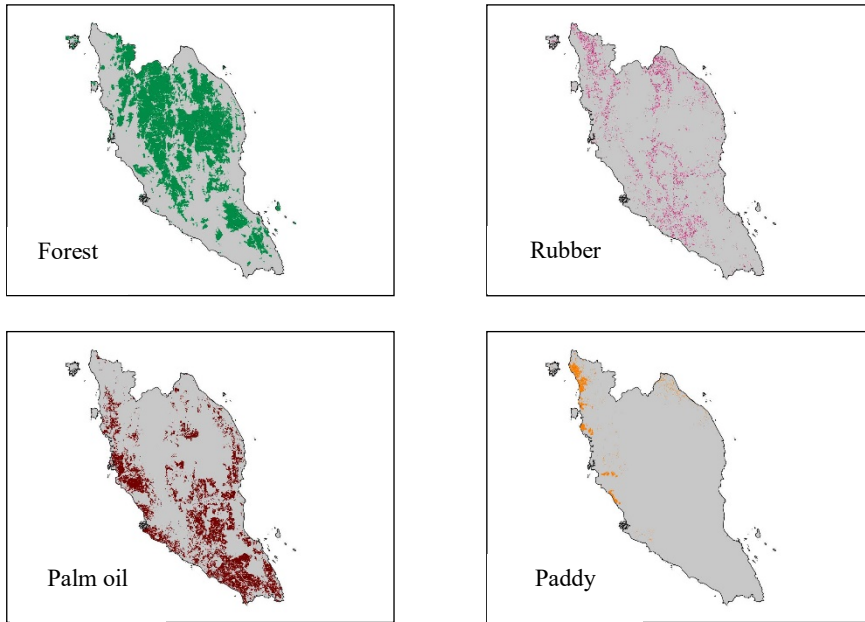
**Table 3.2: Biomass wastes availability in Peninsular Malaysia**

Lignocellulosic biomass wastes	Total biomass availability <sup>(1)</sup>		Local biomass yield
	Min	Max	Tonne/hectare/year (fresh)
	Million tonne/year (fresh)		Tonne/mill/year (fresh)
<b>Primary sources</b>			
Forest logging waste	1.83	2.65	0.44
Oil palm frond		7.12	2.68
Oil palm trunk		17.80	6.7
Rice straw	2.83	4.96	16.45
Rubberwood logging waste	0.20	0.70	0.64
<b>Secondary sources</b>			
Rice husk	0.51	0.67	65,555.56
Empty fruit bunch		9.40	95,918.37
Palm pressed fibre		5.70	58,163.27
Plywood mill waste	0.17	2.49	2,871.75
Saw mill waste	0.97	1.16	840.61

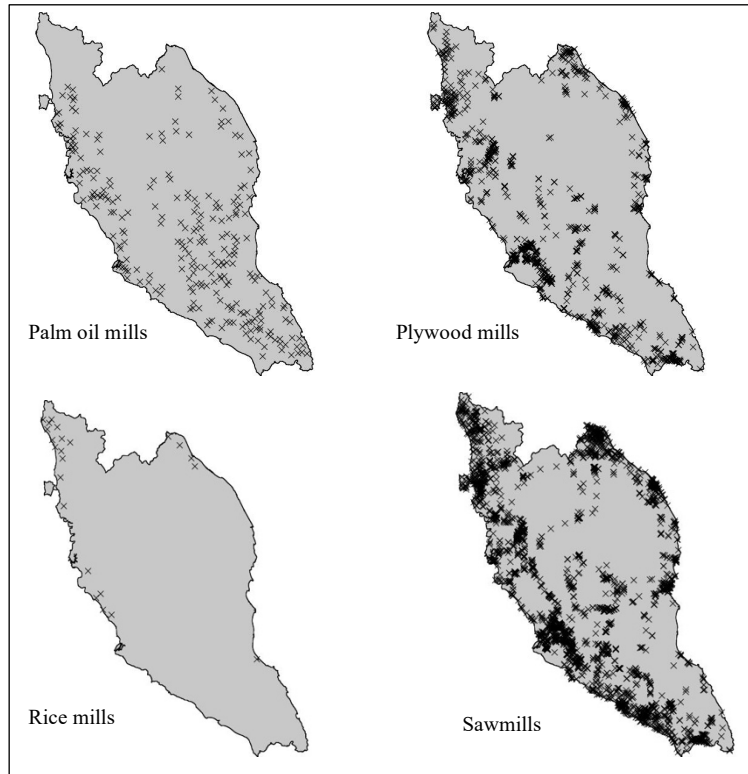
(Source : Roda et.al., 2015)

**Table 3.3: Equations used to quantify biomass waste yield to tonne/pixel/year**

	Equations	Unit
Step 1	Area per pixel = Total land use area of biomass / Total pixel cells of biomass	ha/pixel
Step 2	Average annual waste yield per hectare = Average of annual waste available / Total land use area of biomass	Tonne/ha/year
Step 3	Biomass availability =Average annual waste yield per area × Area of biomass per pixel	Tonne/pixel/year



**Figure 3.10: Land cover of biomass from primary sources**



**Figure 3.11: Distribution of mill locations for biomass from secondary biomass sources**

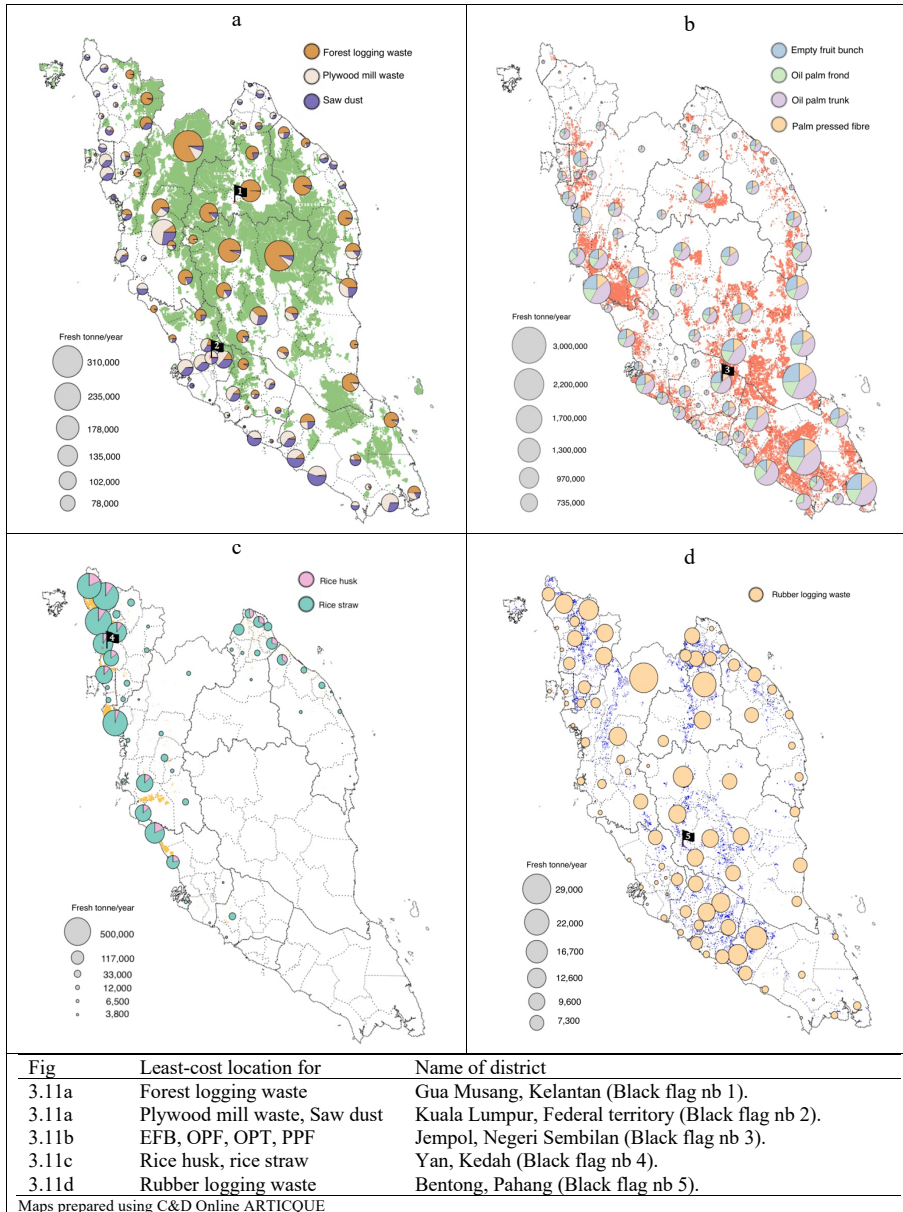
### **3.2.4 Biomass transport simulation and least-cost location**

Transportation of biomass was obtained through the multiplication of transport cost maps with waste density maps. This procedure simulates the truck delivery of biomass contained in each pixel to the potential biorefinery location. Each pixel of the new map contained the biomass transport cost from that pixel to the biorefinery location in MYR/pixel. The sum of the values of each pixel under a given biomass category provides the total biomass transport cost to one specific location. With the GRASS procedure “r. report” (Mitasova et al., 1995), the total biomass transport cost of each biomass to each district was computed. For each biomass, the district with the lowest total transport cost (see Table 3.4) was identified as the best possible biorefinery mill location, and we named it “least-cost location”. Several biomasses coming from the same crop (such as rice biomasses or palm biomasses) share the same least-cost location (Figure 3.12). We also created different sourcing scenarios based on the least-cost locations as illustrated in the latter sections.

**Table 3.4: Total transport cost in ascending order (case of 1-tonne-truck)**

Ranking	Forest logging waste	Total transport cost (RM)	Oil palm frond	Total transport cost (RM)	Oil palm trunk	Total transport cost (RM)
1	Gua Musang, Kelantan	1,042,514,763	Jempol, Negeri Sembilan	4,072,279,119	Jempol, Negeri Sembilan	10,180,697,799
2	Lipis, Pahang	1,048,420,803	Bera, Pahang	4,143,731,418	Bera, Pahang	10,320,090,069
3	Jerantut, Pahang	1,090,309,514	Temerloh, Pahang	4,186,932,473	Temerloh, Pahang	10,430,357,193
\	\	\	\	\	\	\
87	Pontian, Johor	2,090,830,721	Pokok Sena, Kedah	9,402,601,341	Pokok Sena, Kedah	23,456,500,807
88	Kota Tinggi, Johor	2,149,584,684	Padang Terap, Kedah	9,482,998,990	Padang Terap, Kedah	23,656,786,718
89	Johor Bahru, Johor	2,165,627,892	Perlis	9,902,194,132	Perlis	24,702,372,594
Ranking	Rice straw	Total transport cost (RM)	Empty fruit bunch	Total transport cost (RM)	Palm pressed fibre	Total transport cost (RM)
1	Yan, Kedah	1,212,928,564	Jempol, Negeri Sembilan	5,373,412,589	Jempol, Negeri Sembilan	3,258,345,932
2	Seberang Perai Utara, Penang	1,227,147,677	Bera, Pahang	5,398,346,896	Bera, Pahang	3,273,465,671
3	Pendang, Kedah	1,241,641,075	Temerloh, Pahang	5,418,060,413	Temerloh, Pahang	3,285,419,612
\	\	\	\	\	\	\
87	Kulaijaya, Johor	4,479,608,814	Pokok Sena, Kedah	12,087,712,875	Pokok Sena, Kedah	7,329,783,339
88	Johor Bahru, Johor	4,623,433,712	Padang Terap, Kedah	12,194,286,079	Padang Terap, Kedah	7,394,407,516
89	Kota Tinggi, Johor	4,678,043,332	Perlis	12,745,053,599	Perlis	7,728,383,565
Ranking	Rice husk	Total transport cost (RM)	Plywood mill waste	Total transport cost (RM)	Saw mill waste	Total transport cost (RM)
1	Yan, Kedah	268,784,075	Kuala Lumpur, Federal Territories	100,886,601	Kuala Lumpur, Federal Territories	607,529,150
2	Pendang, Kedah	271,325,716	Hulu Langat, Selangor	101,884,580	Hulu Selangor, Selangor	608,607,806
3	Seberang Perai Utara, Penang	271,732,695	Hulu Selangor, Selangor	102,057,176	Hulu Langat, Selangor	611,892,750
\	\	\	\	\	\	\
87	Kulaijaya, Johor	783,390,741	Pokok Sena, Kedah	189,427,625	Pokok Sena, Kedah	1,067,451,840
88	Johor Bahru, Johor	805,652,631	Padang Terap, Kedah	191,517,999	Padang Terap, Kedah	1,079,253,690
89	Kota Tinggi, Johor	809,757,498	Perlis	201,113,455	Perlis	1,135,402,308
Ranking	Rubberwood logging waste	Total transport cost (RM)				
1	Bentong, Pahang	133,034,242				
2	Hulu Selangor, Selangor	133,079,025				
3	Raub, Pahang	133,105,952				
\	\	\				
87	Kulaijaya, Johor	226,718,869				
88	Johor Bahru, Johor	236,413,097				
89	Kota Tinggi, Johor	237,544,760				





**Figure 3.12: Land use, amount of biomass by districts and least-cost locations in Peninsular Malaysia**

### 3.2.5 Simulated-data extraction and computation of biomass transport cost

We created zonal maps based on general transport cost maps of each least-cost location using the GRASS procedure “r.reclass” and each zone categorised by intervals of MYR50. The areas without biomass were nullified with the GRASS procedure “r.null”

and only areas with biomass were accounted. With the GRASS procedure “r.univar” and the zonal map as input, we extracted the sum of biomass transport cost and the sum of biomass tonnage within each zone. An illustrative example of this procedure is presented in Figure 3.13. These data were then calculated with Equation 3.3.

Equation 3.3

$$Biomass\ supply\ cost_{L,B} \left( \frac{MYR}{fresh\ tonne} \right) = \sum_{z=1}^z \left( \frac{BTC_z}{Tonnage_z} \right) \quad (3.3)$$

where,

L denotes the location of the biorefinery

B denotes the types of biomass waste

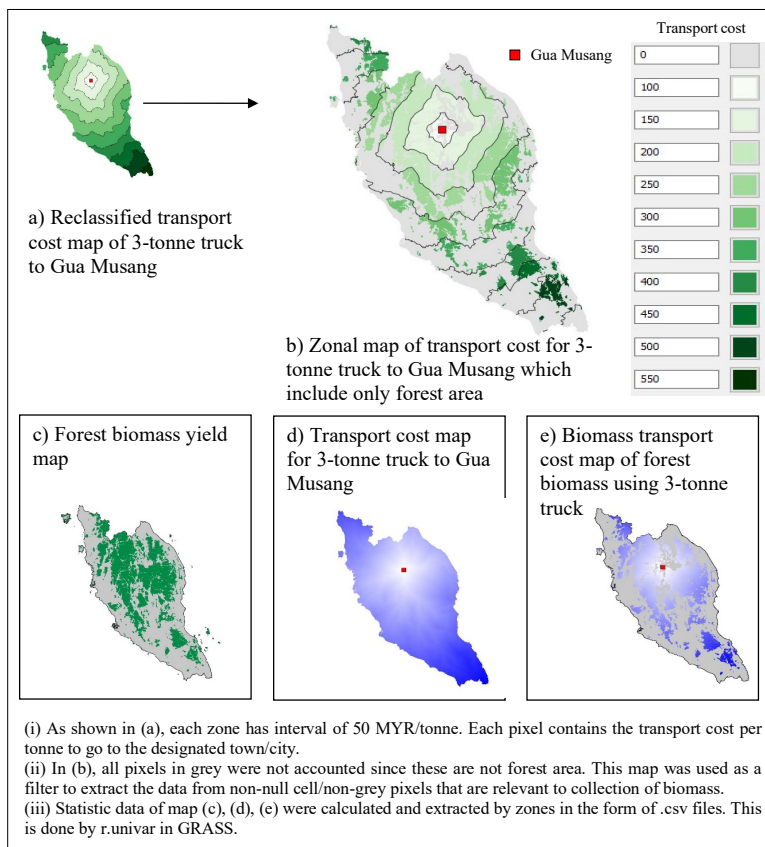
z denotes the number of the zone

BTC denotes biomass transport cost of each zone

Tonnage denotes the amount of biomass waste in each zone

The cost was converted from MYR into USD at the rate of 3.94 MYR/USD (Accountant General’s Department of Malaysia, 2016). The marginal cost curves of the best potential mill location for each biomass category, using 1-tonne trucks and 26-tonne trucks, are established and used in the discussion.





**Figure 3.13: Illustrative example of data extraction - procedures of zonal map and statistical data computation**

### 3.3 Result and discussion

#### 3.3.1 Heterogeneity of lignocellulosic biomass supply cost and structure

From the least cost locations identified (Figure 3.12), we also obtained the biomass supply cost structure. At each least-cost location, the biorefinery could maximize the supply quantity of the biomass and minimize the supply distance and cost. Each biomass has their own unique cost structure which were driven by the spatial structure and biomass yield. In Table 3.5, the supply costs at maximum availability were ranked in ascending order within categories of primary sources, secondary sources and multi-biomass scenarios.

**Table 3.5: Supply cost to transport 100% of biomass residues in Peninsular Malaysia to optimal location for each truck size**

Biomass	Optimal locations	Average availability	1 tonne truck	3 tonne truck	10 tonne truck	26 tonne truck
<b>Primary sources</b>		<b>Million fresh tonne/year</b>	<b>USD/fresh tonne</b>			
Rice straw	Yan, Kedah	3.88	110.09	44.88	23.09	17.94
Oil palm frond (OPF)	Jempol, Negeri Sembilan	7.12	146.34	57.81	28.07	21.66
Oil palm trunk (OPT)		17.80	146.34	57.81	28.07	21.66
Forest logging residues	Gua Musang, Kelantan	2.22	147.27	58.14	28.19	21.76
Rubberwood logging residues	Bentong, Pahang	0.45	356.76	132.85	56.94	43.25
<b>Secondary sources</b>						
Rice husk	Yan, Kedah	0.59	134.85	53.71	26.49	20.48
Empty fruit bunch (EFB)	Jempol, Negeri Sembilan	9.40	146.26	57.78	28.06	21.66
Palm pressed fibre (PPF)		5.70	146.26	57.78	28.06	21.66
Plywood mill residues	Kuala Lumpur, Federal Territory	1.33	151.75	59.74	28.81	22.22
Saw mill residues		1.06	160.33	62.80	29.99	23.10
<b>Multi-biomass scenarios</b>						
Paddy (Rice straw & rice husk)	Yan, Kedah	4.47	119.80	48.35	24.42	18.94
Palm oil (OPF, OPT, EFB, PPF)	Jempol, Negeri Sembilan	40.02	146.32	57.80	28.06	21.66
5 primary biomasses (Rice straw, OPF, OPT, forest & rubber logging residues)	Temerloh, Pahang	30.11	164.06	64.13	30.50	23.48

### 3.3.1.1 Ample biomass supplies from only two crops

It appears that in Peninsular Malaysia, there are two significant biomass for biorefinery. One is rice straw – it is the cheapest biomass but the supply is limited. Secondly, biomass from palm oil industry offer significant quantities but at moderate cost. Refer to Table 3.5, among the primary and secondary wastes; with 1-tonne-truck, rice straw can supply at 110 USD/fresh tonne to Yan, Kedah but the availability is capped at 3.88 million fresh tonne annually. Palm-based biomass are abundant and shared the same least-cost location at Jempol, Negeri Sembilan. Namely the OPT, OPF, EFB and PPF cost 146 USD/fresh tonne at 1-tonne-truck supply at total supplies of 17.8, 7.12, 9.4 and 5.7 million fresh tonnes respectively.

Other biomass supplies are significantly lower in quantity. Forest logging residues can supply about 2 million tonnes per year at cost (147 USD/fresh tonne with 1-tonne-truck) slightly higher than palm-based biomass to Gua Musang, Kelantan. Other resources have negligible availability. For example, rice husk although came with quite competitive cost (135 USD/fresh tonne with 1-tonne-truck) among others, the supplies is only 0.59 million tonne per year. Similarly for rubberwood residues with only 0.45 million fresh tonne annually but with very expensive cost (357 USD/fresh tonne with 1-tonne-truck) although to its optimal location – Bentong, Pahang; due to its highly dispersed geographical structure (see Figure 3.12d). In the case of plywood mill and sawmill residues, both have availability around 1 million tonne per year and optimal location at

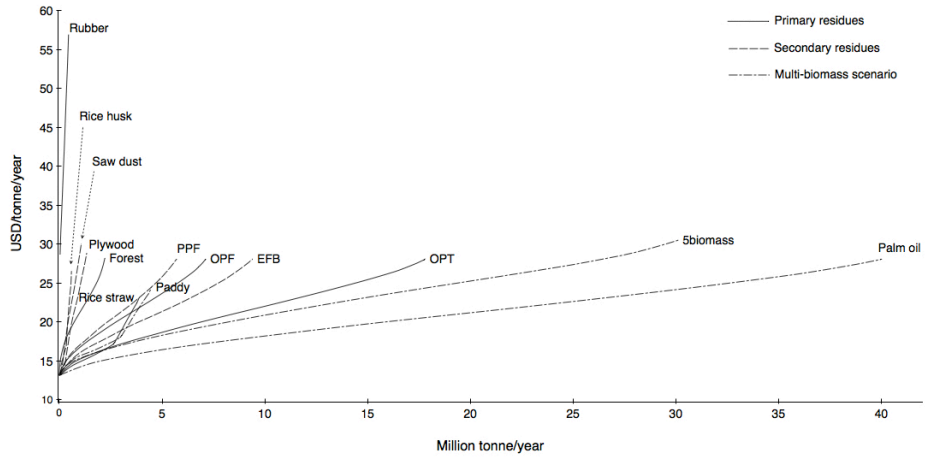
Kuala Lumpur; but the cost (152 & 160 USD/fresh tonne with 1-tonne-truck) were relatively higher than biomass with significant supplies like rice straw and the oil palm biomasses.

### **3.3.1.2 Multi-biomass supplies**

In multi-biomass scenarios, combination of rice straw and rice husk to Yan, Kedah is the cheapest option (120 USD/fresh tonne with 1-tonne truck) among all other scenarios except for rice straw supply alone (110 USD/fresh tonne with 1-tonne truck). This scenario is incurring higher cost than taking rice straw alone without increasing significant quantity at difference of only 0.59 million fresh tonne per year. Combination of four palm-based biomass (OPF, OPT, EFB, PPF) to Jempol, Negeri Sembilan have same per-tonne unit cost with sourcing of each oil palm biomasses alone. This shows a good sourcing strategy as it could increase the supplies to up to 40 million tonnes per year. It allows the biorefinery to obtained more feedstock within the same supply radius. In the 5-primary biomasses scenario to optimal location at Temerloh, Pahang; the supply cost is higher than sourcing of each biomass alone except for rubberwood logging wastes. Furthermore, this combination is dominant by oil palm primary wastes where 83% are OPF and OPT, 11% of rice straw, 6% of forest logging residues and 1% of rubberwood logging wastes. This suggests that the sourcing of different crop to one location in the peninsula is not economic efficient. However, the combined sourcing from single crop is feasible such as the case of palm oil biomass.

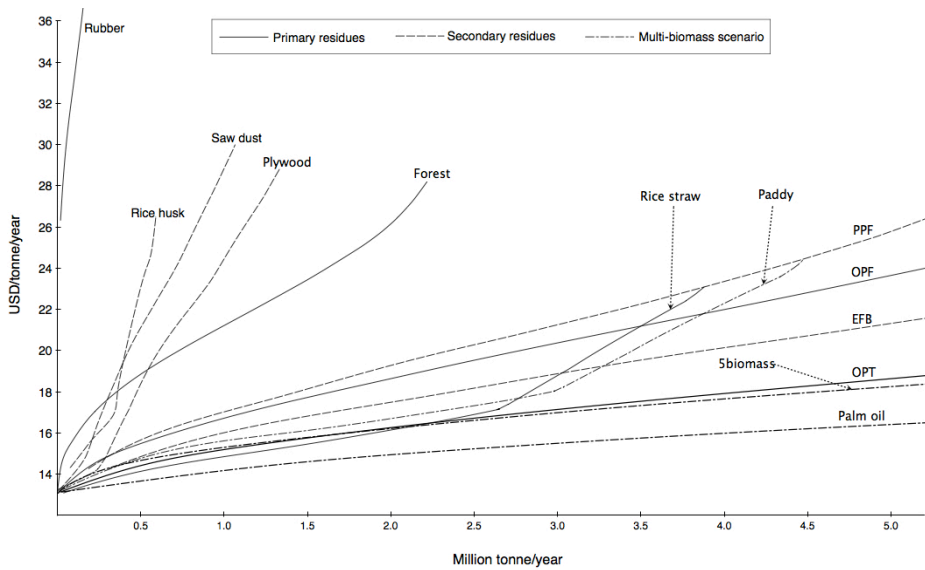
### **3.3.1.3 Biomass supply cost structure varies according to spatial structure**

Figure 3.14 presents the result in the form of supply cost curves. Using 10-tonne-truck supply as example, the supply cost structure are significantly heterogenous. This indicates the effect of the biomass spatial structure. Due to the impact of spatial structure and variations of biomass yield, the economic viability of the biomass varies between each other at different level of availability.



**Figure 3.14: Lignocellulosic biomass supply cost curves (fresh) in Peninsular Malaysia with 10-tonne-truck transport to least-cost locations**

To see the variations, we present the cost curves again with lower threshold at 5 million tonnes limit (Figure 3.15) and presented the cost and supplies at various availability in Table 3.6.



**Figure 3.15: Lignocellulosic biomass in Peninsular Malaysia with 10-tonne-truck supply to optimal locations at below 5 million fresh tonnes per year**

**Table 3.6: Lignocellulosic biomass availability and cost to least-cost location in Peninsular Malaysia with 10-tonne-truck**

Ranking (ascending)	At 2 million fresh tonne/year	USD/fresh tonne p.a.	At 3 million fresh tonne/year	USD/tonne p.a.	At 5 million fresh tonne/year	USD/ fresh tonne p.a.
<b>Single source</b>						
1	Rice straw	16.16	OPT	17.12	OPT	18.64
2	OPT	16.24	Rice straw	18.79	EFB	21.32
3	EFB	17.49	EFB	18.87	OPF	23.66
4	OPF	18.64	OPF	20.37	PPF	25.79
5	PPF	19.27	PPF	21.26	Forest logging residues	N/A
6	Forest logging residues	26.16	Forest logging residues	N/A	Rice straw	N/A
7	Rubberwood logging residues	N/A	Rubberwood logging residues	N/A	Rubberwood logging residues	N/A
8	Rice husk	N/A	Rice husk	N/A	Rice husk	N/A
9	Plywood mill	N/A	Plywood mill	N/A	Plywood mill	N/A
10	Saw mill	N/A	Saw mill	N/A	Saw mill	N/A
<b>Multi-biomass scenario</b>						
1	Palm oil	14.88	Palm oil	15.47	Palm oil	16.40
2	5 biomasses	16.20	5 biomasses	16.96	5 biomasses	18.24
3	Paddy	16.72	Paddy	18.11	Paddy	N/A

At annual supply of 2 million fresh tonne, rice straw is the cheapest biomass at 16.16 USD/fresh tonne with 10-tonne-truck, contributed by its relative geographical concentration in the north of peninsula and high biomass yield at 16.45 fresh tonne-per-hectare. Its supply curve increased steadily up to around 2 – 2.5 million tonnes and later increased steeply (see Figure 3.15). This is due to the centralised and clustered structure of paddy field in the region (see Figure 3.12c), after transporting rice straw in the most concentrated and biggest cluster of paddy fields to Yan, Kedah; the truck needed to travel substantially more distance to get the resources in other smaller clusters and leading to the cost surging steeply. This could be seen at 3 millions fresh tonne availability with 10-tonne-truck, the rice straw supplies had move past the most optimal area and its cost became higher at 18.79 USD /fresh tonne compared to OPT had become the cheapest biomass at 17.12 USD/fresh tonne.

The next economic viable resources are biomass from oil palm. At availability more than 5 million fresh tonnes per year, only biomass from oil palm are available. All the palm-based biomasses have the same cost curvatures where they increased gradually with flatter slope but at different cost level. This is because the oil palm plantations are markedly more ubiquitous and abundant than paddy and rubber plantations (see Figure 3.12); and the palm biomasses also shared the same land cover or least-cost location. Although the forest cover is more centralised than the oil palm plantations but due to very low biomass yield (0.44 fresh tonne-per-hectare) and higher transport cost on the off-roads; the palm-based biomasses incurred less cost than the forest logging wastes. For example, at 2 million tonnes supplies per year with 10-tonne-truck; forest logging wastes cost 24 USD/fresh tonne while OPT, EFB, OPF and PPF cost only 16.2, 17.5, 18.6 and 19.3 USD/fresh tonne respectively. Affected by the biomass yield, the cost at each level of availability for the four major palm-based biomass differ. The OPT seemed to be the cheapest due to its high fresh biomass yield (6.7 fresh tonne-per-hectare), next is the EFB (95,918.37 fresh tonne-per-hectare) are very copious from the palm oil mills and subsequently the OPF (2.68 fresh tonne-per-hectare) and PPF (58,163.27 fresh tonne-per-hectare).

In the multi-biomass scenarios, combination of palm-based biomass appeared as the cheapest option compared to all other alternatives as shown in Figure 3.15 and Table 3.6. With 10-tonne-truck supply, the costs are 14.9, 15.5 and 16.4 USD/fresh tonne at 2 million, 3 million and 5 million fresh tonne annual supplies respectively. The underlying reason could be due to. That the oil palm produces variety of biomasses and they are within the same vicinity. When supply of these resources was grouped, resources are denser within the same sourcing radius. This allows more efficient logistics management and economy of scale.

However, the case is different with combination of paddy biomasses and 5-primary biomasses. From Table 3.6, at 2 million fresh tonnes supply, paddy biomasses cost 0.56 USD/tonne higher compared to rice straw alone. The cost became cheaper at 3 million fresh tonnes supply where the paddy biomasses is 0.99 USD/tonne cheaper than rice straw. This change happened after 2.7 million tonnes supplies. It was due to disproportionate increase of distances over small increase of biomass supplies from the geographical dispersion of resources. At above 2.7 million tonnes, the supplies are from farther paddy fields which are smaller and more scattered. Hence, when combined with

quantities of rice husk after this level of supplies, it increases the quantities within same vicinity and resulted in cheaper cost than rice straw alone.

In the 5-primary biomasses supply scenario, the cost structure is similar to OPT supplies. In this scenario, the supply is dominance by OPT and OPF while others resources have little impact on the cost structure. Given this situation in Peninsular Malaysia, this scenario is inconsequential and negligible compared to scenarios of combination of paddy biomasses and palm-based biomasses.

### **3.4 Conclusion**

The study examined the heterogeneity of lignocellulosic biomass supply cost and structure in Peninsular Malaysia. The results showed that rice straw and biomass from the palm oil industry are the primary sources of biomass for biorefineries. Rice straw is the cheapest but has limited availability, while palm-based biomass offers significant quantities at a moderate cost. Other biomass sources have lower quantities and higher costs. Combining rice straw and rice husk is the cheapest multi-biomass option, while combining palm-based biomasses increases the supply without increasing the cost significantly. The biomass supply cost structure varies based on the spatial structure and biomass yield. Combined oil palm biomasses have lower costs due to their ubiquity and substantial quantity. Overall, combining palm-based biomasses appears promising and potentially cost-effective strategy. Further research and study should be conducted to explore the utilization of various biomass derived from oil palm for multi-feedstock biorefineries, aiming to achieve scale economies. However, it is important to acknowledge the existing technical barriers arising from differences in the chemical composition of these biomasses. By addressing and overcoming these challenges, we can unlock the full potential of palm-based biomass and establish it as a viable and efficient feedstock for biorefinery operations."

## CHAPTER 4

### QUANTIFYING THE EFFECT OF LANDSCAPE STRUCTURE ON TRANSPORT COSTS OF AGRICULTURAL AND FORESTRY WASTES IN MALAYSIA<sup>1</sup>

#### Chapter overview:

This chapter measured the landscape biomass of major biomasses in Peninsular Malaysia. Together with other relevant variables, regression analysis was performed to quantify their impacts to biomass transport cost. Furthermore, the industrial implications were discussed by comparing the biomass transport cost to international biomass pellet price.

The content of this chapter was published in the form of the following peer-reviewed articles in indexed Journals:

<sup>1</sup> Ong, C., Deprés, G., Hollebecq, J.-E., Shaiffudin Hishamudin, M. O., Kamaruddin, N., Anugerah, A. R., ... Roda, J.-M. (2020). Quantifying the effect of landscape structure on transport costs for biorefinery of agricultural and forestry wastes in Malaysia. *GCB Bioenergy*, 12(11), 910–922. <https://doi.org/10.1111/gcbb.12740>

The original published article is reproduced in Apendix D.

#### 4.1 Introduction

In biomass resource assessment and logistics studies, an important metric used to measure biomass attributes is biomass yield density, typically expressed as tonnes per hectare (Golecha & Gan, 2016; Panichelli & Gnansounou, 2008; Van Meerbeek, Muys & Hermy, 2019). This metric quantifies the productivity of biomass and serves as input data for assessing logistics costs. Additionally, it allows for comparisons between choices of biomass to be made and its implication to logistics costs. Research has shown that higher biomass yield density is associated with higher logistics costs, while lower biomass yield density is associated with lower logistics costs (Maung et al., 2013).

However, it is important to note that these comparisons are typically made within the context of homogeneous landscape settings, such as farms where the geographical patterns are similar. In the case of Malaysia, biomass features exhibit significant variation. Chapter one, Figure 1.4 on categories of global field size, it provides evidence that field sizes in Malaysia are predominantly categorized as small and very small, indicating high fragmentation. Together, the fragmentation and unique distribution result in the heterogeneity of biomass supply costs, as depicted in Chapter 3, Figure 3.14.



Furthermore, other apparent differences, such as whether the biomass originates from a field or a mill, production density, and the trajectory of transport distances, contribute to these variations. While spatial patterns do play a role in biomass supply cost variations, they are embedded within the map. Therefore, in this section, our aim is to explicitly consider landscape fragmentation as a variable, alongside other factors, in order to analyse the dynamics between these different factors and quantify their relationship with biomass supply costs. This approach will provide insights into understanding the underlying variations and help in managing scenarios specific to Malaysia. To the best of the author's knowledge, this is the first time that the metric of landscape pattern has been measured to comprehend biomass supply and logistics. Overall, this analysis will contribute to a better understanding of biomass supply costs and logistics by incorporating landscape fragmentation as a key variable, in addition to exploring other factors.

## 4.2 Data and method

### 4.2.1 Landscape metric as spatial fragmentation index

The landscape structure is the arrangement of and relations between the parts or elements of the land mosaic, and can be described through landscape metrics. To investigate the linkages between spatial fragmentation and biomass transport cost, we needed to measure the spatial fragmentation (Rodrigue, Comtois & Slack, 2013) of land cover for biomass waste in Peninsular Malaysia. Many landscape metrics exist (Haines-Young & Chopping, 1996 and Cardille & Turner, 2017). Among these metrics, “edge density”, “patch density”, and the “aggregation index” express various aspects of the spatial fragmentation, respectively expressed by Equation 4.1, 4.2, and 4.3; in Table 4.1 (GRASS Development Team, 2019 and McGarigal, 2012). The metrics for each biomass category was computed, see Table 4.2.

**Table 4.1:** Equations of the selected Landscape Metrics

Equation 4.1: Edge density	
$= \frac{\sum_{k=1}^n e_{ik}}{A} (10000)$	
Unit: meters per hectare	
$k$ = patch type. It refers to the disjointed land areas (or patches) of a biomass category.	
$n$ = number of edge segments of patch type $k$ . It counts the pixels that are recognized as the border of the patches of a biomass category.	
$e_{ik}$ = total edge length (m) in landscape involving patch type $k$ . For a biomass category, $k$ , $e_{ik}$ is the sum of edge length for all the patches of $k$ .	
$A$ = total landscape area (m <sup>2</sup> ). It refers to the land cover of the study area, in our case, Peninsular Malaysia.	
Equation 4.2 Patch density	
$V = \frac{N_{patch}}{A}$ $= \frac{N_{patch}}{A}$	

Units: Number of patches per square kilometre

$N_{patch}$  = number of patches.

It counts the total number of disjointed land area (or patches) for a biomass category.

$A$  = sampling area size.

This refers to our study area – Peninsular Malaysia.

**Table 4.1: Continued**

Equation 4.3 Aggregation index

$$= \begin{cases} \frac{G_i - P_i}{1 - P_i} \text{ for } G_i \geq P_i \\ \frac{G_i - P_i}{1 - P_i} \text{ for } G_i < P_i; P_i \geq .5 \\ \frac{G_i - P_i}{0 - P_i} \text{ for } G_i < P_i; P_i < .5 \end{cases}$$

$$\text{with } G_i = \left( \frac{g_{ii}}{\sum_{k=1}^m g_{ik}} \right)$$

Range:  $-1 \leq \text{Aggregation index} \leq 1$ . $g_{ii}$  = number of like adjacencies between pixels of land cover type  $i$ . $g_{ik}$  = number of adjacencies between pixels of land cover types  $i$  and  $k$ . $(k = \text{unlike cell adjacencies})$ 

Each pixel is referred as a function of its neighbours, with neighbour  $i$  being a pixel of land cover that belongs to the biomass category  $i$ , and neighbour  $k$  being a pixel of land cover that does not belong to the biomass category  $i$ .

 $P_i$  = proportion of the landscape occupied by land cover type (class)  $i$ .

It is the number of pixels for the land cover of the biomass category  $i$  divided by the number of pixels of the study area (Peninsular Malaysia).

The procedure was performed in ‘‘Fragstats 4.2’’ software. It uses double-count method, also known ‘‘Clumpiness index’’.

**Interpretation:**

Edge density & Patch density: a higher value indicates a more fragmented spatial structure.

Aggregation index: The value is expressed in dimensionless unit, from -1 to 1. Approaching to -1 is when the land cover type increasing in disaggregation or each patch is more of an isolated pixel away from each other. Approaching to 1 is the most is when the land cover type increasing aggregation where the patches are more centralized and clustered.

**Table 4.2: Spatial fragmentation metrics for biomass in Peninsular Malaysia**

Category of wastes	Biomass wastes	Spatial fragmentation metrics		
		Edge density (m/Ha)	Patch density (Nb of patches per sq km)	Aggregation index (procedure ‘‘Clumpy’’)
From the Field	Forest logging wastes	3.2705	0.0064	0.9804
	Oil palm frond (OPF)	6.0825	0.0610	0.9434
	Oil palm trunk (OPT)	6.0825	0.0610	0.9434
	Rice straw	1.1346	0.0341	0.9243
	Rubberwood logging wastes	11.7165	2.1068	0.6407
From Mills	Empty fruit bunch (EFB)	0.2822	0.0034	0.6722
	Palm pressed fibre (PPF)	0.2822	0.0034	0.6722
	EFB & PPF	0.2822	0.0034	0.6722
	Plywood & Saw mill	0.3425	0.0261	0.6757
	Plywood mill	0.2990	0.0097	0.6794
	Rice husk	0.2780	0.0018	0.7169
	Saw dust	0.3364	0.0240	0.6725
From Both	OPF & OPT & EFB & PPF	6.0847	0.0618	0.9434
	Rice straw & husk	1.1349	0.0342	0.9243

## 4.2.2 Regression modelling & variables included

We performed a series of regression analyses to understand how to best describe biomass supply costs (variable: Y) at any point of the country, according to different combinations (linear and non-linear) of the factors. These factors are; the transportation distance in km ( $X_1$ ), the truck size in tonne ( $X_2$ ), the yield of biomass wastes in tonne/ha ( $X_3$ ), the spatial fragmentation under the form of edge density of the feedstock in m/ha ( $X_{4a}$ ), or its patch density in number of patches/km<sup>2</sup> ( $X_{4b}$ ), or its aggregation index ( $X_{4c}$ ), and also the categorical origin ( $X_5$ ), of the agricultural or forestry wastes – from field ( $X_{5a}$ ), mill ( $X_{5b}$ ) or both ( $X_{5c}$ ). Nineteen models were analysed and compared (see table 4.3). Their replicable equations are given in methodological annex (Annex C) under the form of R code. These nineteen models are not predictive models which require validation. They are descriptive models meant to explore which structure and combination of variables best describe the observed biomass transportation cost in Peninsular Malaysia. The best way to assess these models is their Akaike information criterion (AIC) and their parsimony. However, in the future other research should ideally validate the generality of their structures by exploring their behaviour in other countries.

**Table 4.3: Evaluation for model selection to describe biomass supply cost**

Group 1: $Y = f(X_1, X_2)$									
Model:	$\beta_1 X_1 + \beta_2 X_2$	Significance			Adj. $R^2$	RSE	df	AIC	
		$\beta_1 X_1$	$\beta_2 X_2$						
M1		$p < 0.001$	$p < 0.001$		0.641	36.95	1218	12274	
Group 2: $Y = f(X_1, \ln(X_2))$									
Model:	$\beta_1 X_1 + \beta_2 \ln(X_2)$	Significance			Adj. $R^2$	RSE	df	AIC	
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$						
M2		$p < 0.001$	$p < 0.001$		0.667	35.60	1218	12183	
Group 3: $Y = f(X_1, \ln(X_2), X_3)$									
Model:	$\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3$	Significance			Adj. $R^2$	RSE	df	AIC	
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$	$\beta_3 X_3$					
M3		$p < 0.001$	$p < 0.001$	$p < 0.001$	0.682	34.81	1217	12129	
Group 4: $Y = f(X_1, \ln(X_2), X_4)$									
Model:		Significance			Adj. $R^2$	RSE	df	AIC	
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$	$\beta_4 X_4$					
M4a	$\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_4 X_{4a}$	$p < 0.001$	$p < 0.001$	$p < 0.001$	0.698	33.89	1217	12063	
M4b	$\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_4 X_{4b}$	$p < 0.001$	$p < 0.001$	$p < 0.001$	0.677	35.08	1217	12148	
M4c	$\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_4 X_{4c}$	$p < 0.001$	$p < 0.001$	$p < 0.001$	0.856	23.44	1217	11164	
Group 5: $Y = f(X_1, \ln(X_2), X_5)$									
Model:	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2)$	Significance			Adj. $R^2$	RSE	df	AIC	
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$	$\beta_0 X_5$					
M5		$p < 0.001$	$p < 0.001$	$p < 0.001$	0.896	19.86	1215	10762	
Group 6: $Y = f(X_1, \ln(X_2), X_3, X_4)$									
Model:		Significance				Adj. $R^2$	RSE	df	AIC
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$	$\beta_3 X_3$	$\beta_4 X_4$				
M6a	$\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3 + \beta_4 X_{4a}$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	0.729	32.11	1216	11933
M6b	$\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3 + \beta_4 X_{4b}$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	0.694	34.11	1216	12080
M6c	$\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3 + \beta_4 X_{4c}$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	0.865	22.69	1216	11085

**Table 4.3: Continued**

Group 7: $Y = f(X_1, \ln(X_2), X_3, X_4, X_5)$										
Model:		Significance					Adj. $R^2$	RSE	df	AIC
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$	$\beta_3 X_3$	$\beta_4 X_4$	$\beta_0 X_5$				
M7a	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3 + \beta_4 X_{4a}$	p<0.001	p<0.001	ns	p<0.001	p<0.001	0.898	19.70	1213	10744
M7b	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3 + \beta_4 X_{4b}$	p<0.001	p<0.001	ns	p<0.01	p<0.001	0.897	19.82	1213	10758
M7c	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3 + \beta_4 X_{4c}$	p<0.001	p<0.001	ns	p<0.05	p<0.001	0.897	19.83	1213	10760

Group 8: $Y = f(X_1, \ln(X_2), \ln(X_3), X_4, X_5)$										
Model:		Significance					Adj. $R^2$	RSE	df	AIC
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$	$\beta_3 \ln(X_3)$	$\beta_4 X_4$	$\beta_0 X_5$				
M8a	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 \ln(X_3) + \beta_4 X_{4a}$	p<0.001	p<0.001	ns	p<0.001	p<0.001	0.898	19.69	1213	10743
M8b	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 \ln(X_3) + \beta_4 X_{4b}$	p<0.001	p<0.001	p<0.1	p<0.05	p<0.001	0.897	19.79	1213	10754
M8c	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 \ln(X_3) + \beta_4 X_{4c}$	p<0.001	p<0.001	p<0.05	p<0.05	p<0.001	0.897	19.80	1213	10756

Group 9: $Y = f(X_1, \ln(X_2), X_4, X_5)$									
Model:		Significance				Adj. $R^2$	RSE	df	AIC
		$\beta_1 X_1$	$\beta_2 \ln(X_2)$	$\beta_4 X_4$	$\beta_0 X_5$				
M9a	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_4 X_{4a}$	p<0.001	p<0.001	p<0.001	p<0.001	0.898	19.69	1214	10742
M9b	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_4 X_{4b}$	p<0.001	p<0.001	p<0.01	p<0.001	0.897	19.81	1214	10756
M9c	$\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_4 X_{4c}$	p<0.001	p<0.001	p<0.05	p<0.001	0.897	19.83	1214	10759

### 4.3 Result

The first category of models (M1, M2, M3, M4a, M4b, M4c, M6a, M6b & M6c) presents low adjusted coefficients of determination below 0.87, and relative standard errors above 22. None of them has simultaneously all the factors (distance, truck size, waste yield, fragmentation, and origin of wastes) in their structure. This suggests that all of these factors have their critical importance in the determination of the supply costs and should be included in the models.

The second category of models (M5, M7a, M7b, M7c, M8a, M8b, M8c, M9a, M9b & M9c) presents higher coefficients of determination and lower relative standard errors. But a number of them are less robust, with non-significant parameters (M7a, M7b, M7c, & M8a), or with less significant parameters (M8b, M8c, M9b, M9c), suggesting that their specific combinations of the factors are not the best representation of the reality.

The two best models are M5 and M9a. M9a = f(Distance, ln(Truck), Edge density, Waste origin) has the highest adjusted coefficient of determination and the lowest relative standard error among these nineteen models. The model M5 have satisfying performances while not describing any aspect of the fragmentation factor: this could mean, according to the rule of parsimony, that this fragmentation factor is not needed to understand the structure of the costs. However, the AIC is lower in the case of M9a. This confirms that the fragmentation factor has critical importance too, and needs to be included and better understood. Thus, the model M9a describes best the structure of the biomass supply costs in Peninsular Malaysia. Table 4.4 provides its details and its reliability.

**Table 4.4: Biomass supply cost as a function of transportation distance, truck size, fragmentation, and waste origin**

Model M9a: USD/fresh tonne = $\beta_0 X_5 + \beta_1 X_1 + \beta_2 \ln(X_2) + \beta_4 X_{4a}$				
Parameter	Coefficient Estimate	SE	t-value	Pr(> t )
X <sub>1</sub> : Transportation distance	0.0678	0.002915	23.274	< 2e-16 ***
ln(X <sub>2</sub> ) : ln(Truck size)	-26.07	0.458950	-56.805	< 2e-16 ***
X <sub>4a</sub> : Fragmentation (Edge density)	1.066	0.228711	4.662	0.00000348 ***
X <sub>5a</sub> : Waste origin_field	63.06	1.974433	31.937	< 2e-16 ***
X <sub>5b</sub> : Waste origin_mill	69.67	1.451147	48.009	< 2e-16 ***
X <sub>5c</sub> : Waste origin_both	62.35	2.027559	30.750	< 2e-16 ***
Significance codes: *** 0.001; ** 0.01; * 0.05; • 0.1				
Residual standard error: 19.69 on 1214 degrees of freedom				
Multiple R-squared: 0.8986		Adjusted R-squared: 0.8981		
F-statistic: 1792 on 6 and 1214 DF, p-value: < 2.2e-16				

We find that the base supply cost is higher for the biomass wastes originating from the mills (69.67 USD/tonne) than for the wastes originating from the fields (63 USD/tonne). This could contradict the intuition because mills produce proportionally much more wastes per hectare. The fact that the mills are relatively small in average, and are scattered all over the territory, is the reason for the counterintuitive finding.

We find also that the fragmentation (edge density) of the resource is extremely costly: a 1 million hectares feedstock would see an increase of 4.16 USD/tonne for every added unit of edge density. With a similar edge density as paddy fields, the field size of such a feedstock would be of 950 hectares in average and have a baseline supply cost of 67.16 USD/tonne. The same feedstock with an edge density similar to palm oil plantations would have field size of 26 hectares in average, inducing a surplus of 20.8 USD/tonne for the supply cost. And with an edge density similar to rubber plantations, field size would be of 7.8 hectares in average, inducing another surplus of 20.8 USD/tonne for the supply cost compared to oil palm plantations.

The supply cost also increases in average by 6.78 USD/tonne for every added 100 km of transportation distance. Conversely and compared to a 1-tonne truck, the supply cost logarithmically decreases according to the tonnage, with -36 USD for a 3-tonne truck, and with -84 USD for a 26-tonne truck.

The scattered nature of the mills increases the supply cost, despite the relatively high concentration of wastes in each mill. This unexpected finding raises the question of whether this model separates correctly the fragmentation from the biomass yield. The categorical variable “waste origin” implicitly contains information on the concentration of biomass yield per hectare since the yields are immensely more concentrated in a mill than in fields. It also contains information on spatial fragmentation since most of the mills are scattered over the territory, which makes them inherently a fragmented source of biomass. The examination of models M7a and M6a which differ from model M9a by only one variable, allows to clarify this point. Model 7a is the same as M9a plus a variable on describing the concentration of biomass yield per hectare. But this variable is not significant (see table 4.3). In model M6a, the categorical waste origin is replaced by the biomass yield (see table 4.5). It reinforces the apparent weight of the fragmentation, which is 3 times more influential on the cost structure. The truck size influence is lower but remains a crucial factor, and the influence of the transportation distance importance is more than double. The yield of biomass, although being significant, induces little supply cost variation. Altogether these results demonstrate that the categorical variable “waste origin” encapsulates relatively few information on the concentration of yield per hectare, and more on fragmentation. However, the regimes of fragmentation of fields and mills are so different, that they are not appropriately described by a single variable, as it is the case in model M6a. They are better described by the categorical variable “waste origin”. The relationships of the fragmentation to the supply costs according to the origin of the wastes would probably yield interesting results with non-linear models, but it is beyond the scope of this paper.

**Table 4.5: Biomass supply cost as a function of transportation distance, truck size, fragmentation, and biomass yield**

Model M6a: USD/fresh tonne = $\beta_1 X_1 + \beta_2 \ln(X_2) + \beta_3 X_3 + \beta_4 X_{4a}$				
Parameter	Coefficient Estimate	SE	t-value	Pr(> t )
$X_1$ : Transportation distance	0.14624175	0.00376956	38.8	< 2e-16 ***
$\ln(X_2)$ : $\ln(\text{Truck size})$	-15.54994379	0.64271174	-24.19	< 2e-16 ***
$X_3$ : Biomass yield	0.00038155	0.00003234	11.8	< 2e-16 ***
$X_{4a}$ : Fragmentation (Edge density)	3.81978851	0.26104091	14.63	< 2e-16 ***
Significance codes: *** 0; ** 0.001; * 0.01; • 0.05	Multiple R-squared: 0.7299,	Adjusted R-squared: 0.729		
Residual standard error: 32.11 on 1216 degrees of freedom	F-statistic: 821.4 on 4 and 1216 DF, p-value: < 2.2e-16			

## 4.4 Analysis and discussion

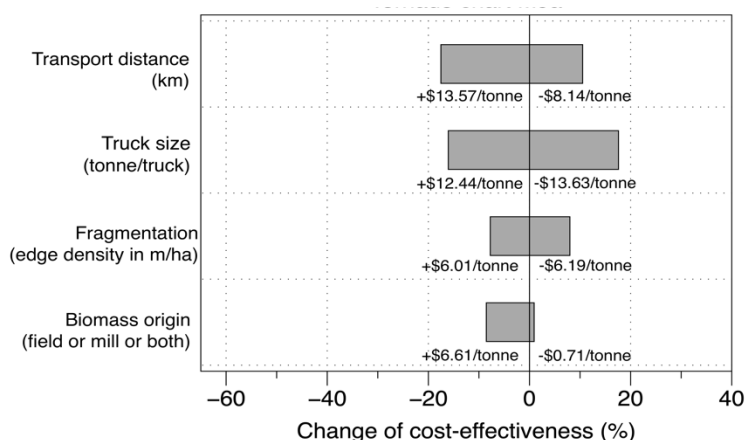
### 4.4.1 Respective impacts of supply cost factors

In a tropical country such as Malaysia, the biomass feedstocks are heterogeneous and fragmented. The increase of biomass supply cost with spatial fragmentation demonstrates that landscape structure can be as much critical for biorefinery economics,

as transport distances are (Tahvanainen & Anttila, 2011; Ghaffariyan, Acuna & Brown, 2013, Vijay et al. 2014 and Reeb et al., 2014). Our results are the first to quantify the direct effect of landscape structure on the transport cost. The fragmentation amplifies the average transportation distance. This consequently amplifies nonlinearly the effects of the size of the fleet trucks. The respective impact of each factor can be measured with the model M9a, and can be visualised by comparing to a base scenario attainable for all feedstocks, of best and worst scenarios; in Table 4.6 and Figure 4.1. The baseline scenario is set at 1 million tonnes of biomass supply because this quantity is commonly available from almost all Malaysian feedstocks. We assign to it the fragmentation of the most common feedstock (oil palm wastes). The most common trucks used for agriculture and biomass transport in West Malaysia are 3-tonne trucks. 26-tonne trucks are uncommon because this kind of trucks cannot reach most of the fields. The best truck scenario is set at 10-tonne truck and the worst with 1-tonne truck. The average distances are computed by GIS for the baseline, best and worst scenarios for 1 million tonnes of supply.

**Table 4.6: Supply scenarios in Peninsular Malaysia**

Parameter	Unit	Scenarios		
		Best	Baseline	Worst
Transport distance	km	180	300	500
Truck size	tonne	10	3	1
Fragmentation (Edge density)	meter/hectare	11.7165	6.0825	0.278
Biomass origin	categories	62.347859	63.056592	69.66853



**Figure 4.1: Impact of the main biomass supply cost factors in Peninsular Malaysia** (The baseline scenario is centered at 0%. The cost-effectiveness increases when biomass supply costs decrease.)

Among all the cost factors, the landscape fragmentation is a heritage of geography, history, and long-term agricultural policies. Biomass entrepreneurs cannot modify this fragmentation, but they can act on the truck size factor. For example, in the US & EU, the trucks used for biomass are always above 20 tonnes (Sosa, McDonnell, 2015; Laitila, Asikainen & Ranta, 2016 and Teter et al., 2017). In Malaysia, 98.5% of businesses are

very small (Department of Statistics Malaysia, 2017) and are extremely small if compared to European standards (Gonzales et al., 2019). In general, 48% of truck traffics are light weighted truck, 33% and 19% are medium and heavy-weighted truck respectively (see Table 4.7 and Ministry of Transport Malaysia, 2019). In the agriculture and forestry sector, the most common trucks are 1-tonne trucks, while 10 to 12-tonne trucks were used only by big mills (Roda et al., 2015).

**Table 4.7: Five years average (2013 - 2017) of truck traffic composition at 14 selected stations**

Light truck	Medium truck	Heavy truck
Below 2 tonnes	2 - 10 tonnes	Above 10 tonnes
48	33	19

(Source: Ministry of Transport Malaysia, 2019)

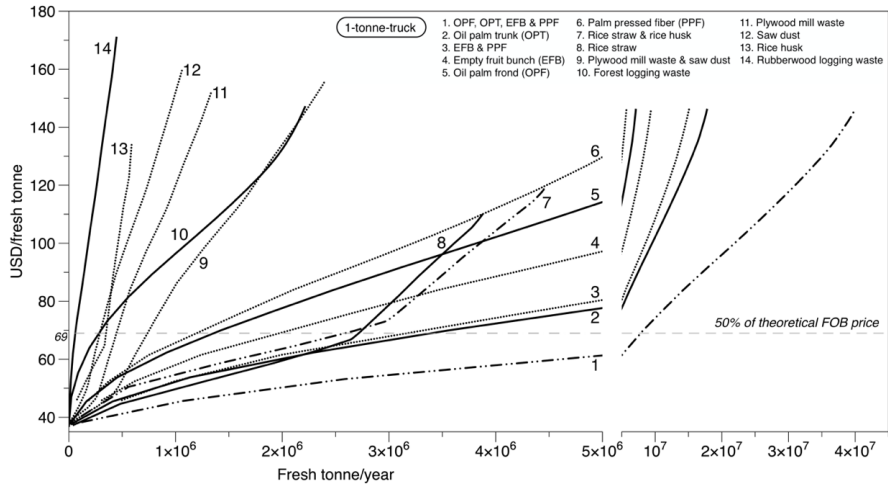
#### 4.4.2 International competitiveness of Malaysian biomass

One criterion in order to assess the feasibility of any industry willing to use Malaysian biomass would be to compare its local cost with the price or cost of biomass available on the international market. For example, we can compare with the feedstock biomass costs in the USA or the densified biomass costs exported by the USA on the international market, Free On Board cost (U.S. Energy Information Administration, 2020). We estimated a theoretical fresh biomass FOB price based on Mani, Sokhansanj and Turhollow (2006) and Mani (2005) as a benchmark for “theoretical FOB price” (FOB export cost – densification cost).

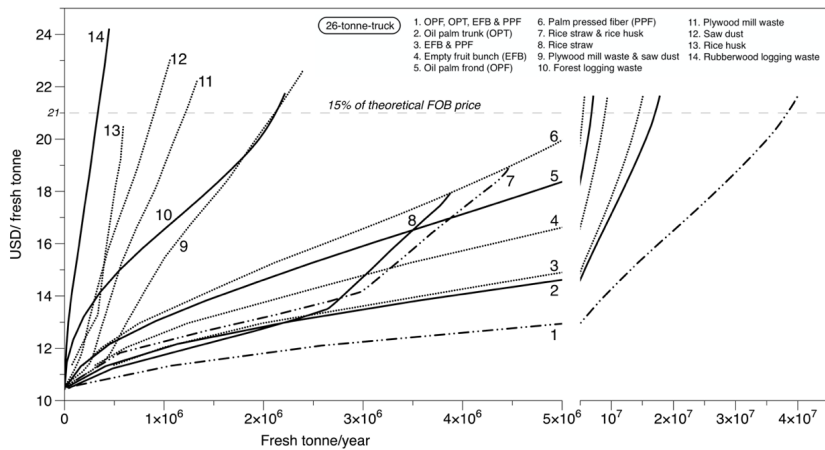
Compared to the marginal cost curves of the best potential mill location for each biomass category (Figures 4.2 & 4.3; Annex D), this kind of competitiveness benchmark discriminates 3 groups of Malaysian feedstocks. These groups are critical for the scale of the possible biorefineries, and for the choice of biofuel technologies. Wastes from plywood and sawmills, forest logging, plywood mills, rubberwood logging, sawdust and rice husk belong to the first group. They could only supply much less than 1 million fresh tonne/year at 50% of the international benchmark if transported with 1-tonne trucks (Figure 4.2). However, they could supply the total of their available wastes if transported with 26-tonne trucks (Figure 4.3). In the case of the forest logging wastes, 26-tonne trucks access to most of the forest tracks is hypothetical in actual Malaysian logistic conditions. The second group is much more competitive. These wastes are Oil Palm Trunks (OPT), Empty Fruit Bunches (EFB), Oil Palm Fronds (OPF), Palm Pressed Fiber (PPF), EFB + PPF, rice straw, and rice straw + rice husk. They could supply from 1.2 to 3.5 million fresh tonnes/year at 50% of the international benchmark with 1-tonne trucks (Figure 4.2), and from 5.4 to 17 million fresh tonnes/year at 15% of the international benchmark with 26-tonne trucks (Figure 4.3). The third group, the simultaneous collection of all lignocellulosic wastes from oil palm plantation or oil palm mills, is extremely competitive. It can supply 8.2 million fresh tonnes/year at 50% of the international benchmark with 1-tonne trucks (about 20% of Malaysian oil palm wastes, Figure 4.2), and 38 million fresh tonnes/year at 15% of the international benchmark with 26-tonne trucks (about 97% of Malaysian oil palm wastes Figure 4.3). The specificity of this third group is that it mixes wastes from the fields and wastes from the mills. It implies



that the mills could be used as collection and pre-treatment point since they are already the collection points of the Fresh Fruit Bunches (FFB). In these conditions, nothing would prevent to add pre-treatment stages in order to dry and densify the biomass prior to further transportation.



**Figure 4.2: Marginal supply cost curves of Malaysian fresh feedstocks – 1-tonne truck, with international benchmark**

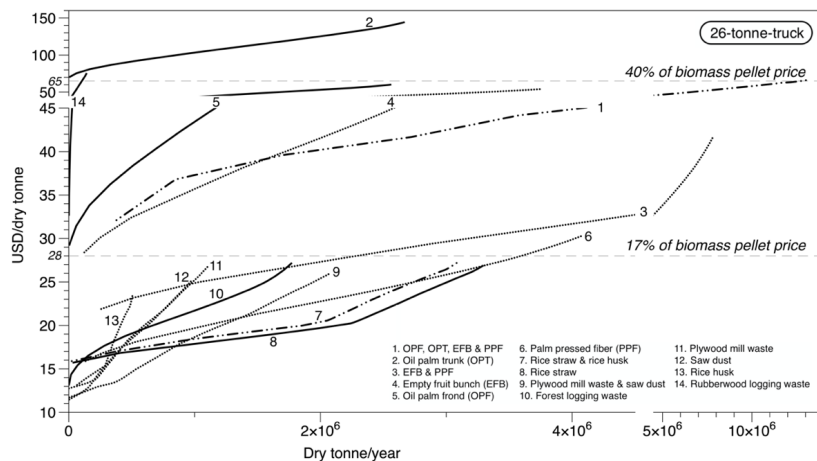


**Figure 4.3: Marginal supply cost curves of Malaysian fresh feedstocks – 26-tonne truck, with international benchmark**

### 4.4.3 Feasibility of consolidation, collection and pre-treatment of the biomass

In the hot and humid Malaysian weather, the actual practice is to transport quickly the biomass in fresh matter, in order to avoid microbial degradation (Salètes, Caliman & Raham, 2004; Hess, Wright & Kenney, 2007; Rentizelas, Tolis & Tatiopoulos, 2009; Chico-Santamarta et al., 2011 and Larson et al., 2015). The low bulk density and the high moisture content (see Annex E) of most of the biomass reduce the profitability of feedstock transportation. Since 26-tonne trucks cannot access many of the tracks within the field (Shafie, Masjuki & Mahlia 2014; Roda et al 2015 and Yusoff, 2019), collection points would be needed for their large-scale use. The exact cost of such facilities is beyond the scope of the present paper, but an approximation of their supply cost can be assessed against international benchmarks (we omit the densification cost in Malaysia). We use international FOB biomass pellet prices (USD162/tonne; U.S. Energy Information Administration, 2020) as a benchmark for the supply of dry feedstocks. We consider only the transportation by 26-tonne trucks that would make sense with densification facilities. Three different dry feedstocks emerge (see Figure 4.4). OPT and rubberwood logging wastes which the fresh feedstocks with the highest water content (Annex E). They form the first group with either very little dry matter available, or most of it above 40% of the international FOB price for pellets. The other oil palm wastes except for PPF (and OPT) form the second group, with most or all of their dry feedstock above 17% of the international benchmark. The remaining wastes form the third group, with 100% (or almost) of the dry feedstock below 17% of the international benchmark. The most remarkable and the cheapest among them are the wastes from plywood and sawmills (0.2 to 0.8 million dry tonnes/year), and rice straw (0.8 to 3.3 million dry tonnes/year).

All the remaining wastes form the third group, with 100% (or almost) of the dry feedstock below 17% of the international benchmark. The most remarkable and the cheapest among them are the wastes from plywood and sawmills (0.2 to 0.8 million dry tonnes/year), and rice straw (0.8 to 3.3 million dry tonnes/year).



**Figure 4.4: Marginal supply cost curves of Malaysian dry feedstocks – 26-tonne truck, with international benchmark**

#### **4.4.4 Policy implications**

Altogether these considerations have strong implications for policymakers: the importance of the landscape structure may make a seemingly abundant biomass not viable for biorefineries if too fragmented, while a much less abundant one, but more concentrated may be viable. This first implies that with proper supply chain management and location optimisation, Peninsular Malaysia biomass could supply a competitive biofuel industry. There are enough quantities to sustain small or medium mono-feedstock industries if their location is carefully chosen. This also means that biomass studies in Malaysia and countries with similar conditions should consider the design and location of collection consolidation and pre-processing, and hubs to connect small and medium stakeholders with bigger ones. The overall results of this study have also shown that large multi-feedstock industries can be economically viable. This means that in Malaysia and other tropical countries where the landscape is typically very fragmented, multi-crops feedstocks could be considered for sustainable biorefineries. It poses new technological and economic implications, but these are beyond the scope of the present paper.

#### **4.5 Conclusion**

Fragmentation of the landscape is costly in tropical countries with complex mosaics of land uses, such as Malaysia. The feedstock cost increases by more than 4 USD/tonne for every added unit of edge density. In comparison, it increases by more than 6 USD/tonne, but by every 100 km of added average transport distance. These natural drawbacks could be offset by organising better logistic chains. From a fleet of 1-tonne trucks, the cost decreases by -36 USD/tonne if using 3-tonne trucks, and down to -84 USD/tonne if using 26-tonne trucks. But most of the biorefinery technologies and solutions for agricultural and forestry wastes were developed in the rather uniform plains of North Europe and North America. Our results mean that these technologies and solutions cannot be just transferred to tropical countries with complex landscape mosaics. We demonstrated here how the landscape structure, through the concept of fragmentation, is a major determinant of biomass economics under the tropics. For policy-makers, counter-intuitive situations may arise, such as seemingly abundant biomasses may be less profitable if too fragmented, while much less abundant but more concentrated biomasses may be more efficient. There may be other situations where multi-crop biomass strategies are more profitable than relying on too fragmented feedstocks. The concept of landscape fragmentation has been mostly used in ecology, for edge effects and other phenomenon. But our results suggest that fragmentation of the landscape probably influence the economics of many activities dealing with agriculture and forest resources, too. Methodologically, it would be interesting to develop fragmentation metrics specifically designed to capture economic aspects. Conceptually, it would also be interesting to explore how multifactorial dynamics, such as deforestation, are linked to pre-existing fragmentation and change it.

## CHAPTER 5

### FEASIBILITY OF LIGNOCELLULOSIC BIOREFINERY IN THE CONTEXT OF LANDSCAPE FRAGMENTATION AND CRUDE OIL PRICE: CASE OF MALAYSIA

#### Chapter overview:

This chapter develop biorefinery cost estimation model in a two-stage approach. The order of magnitude method was adopted to compute capital expenditure of various conversion pathways and later incorporate with operational expenditure that consists of biomass transport cost and other relevant variables. The biorefinery cost curves and optimum cost and scale were derived. Putting into context, the impact of spatial fragmentation and biomass natures to optimum cost were quantified and feasibility of biofuels were assessed by comparing to crude oil price.

#### 5.1 Introduction

The challenge of lignocellulosic biorefineries is the see-saw effect between scale of economy and diseconomy of scale from feedstock supplies (Kumar, Cameron & Flynn, 2003; Larasati, Liu & Epplin, 2012; Liu & Bao, 2019) due to sourcing distance and various biomass characteristics such as geographical distribution, moisture content, yield and bulk density (Caputo, Palumbo, Pelagagge & Scacchia, 2005; Huang, Ramaswamy, Al-Dajani, Tschirner & Cairncross, 2009). This implies that the optimum scale of biorefineries is unique to the biomass feedstock and that the landscape pattern of the biomass could be pivotal to sustainable biofuel.

As a typical Southeast Asia country, Malaysia consists of very fragmented tropical landscape (Fritz et al., 2015; Lesiv et al., 2018). Biomasses in the region have very different supply cost structure due to their heterogeneity (Ong et al., 2020), consequently despite abundance certain biomass might not be economical for biorefinery. Yet, the biofuel production costs are hinge on the choice of biomass. This raises questions on feasibility of biorefineries, the comparative differences among choices of biomass and their respective optimum cost and biofuel potentials.

Lignocellulosic biomass is also one of the renewable resources to delay peak oil events and paves ways towards alternative fuels. As an alternative energy to fossil fuel, studies had found that biofuel profitability is affected by fossil fuel price (Chiu, Hsu, Ho & Chen, 2016; Maghyereh & Sweidan, 2020). There are substitution effects between these two choices of commodity (Chang & Su 2010; Pacini & Silveira, 2011; Anderson, 2012). Hence, this could compromise cellulosic biofuel development when the profitability is temporal and subject to volatility of fossil fuel price (Ghodduzi 2017; Markel, Sims & English, 2018).

In this context, in addition to overcoming biomass heterogeneity; sustainable cellulosic biorefineries are also required to optimize their cost and scale in order to compete and replace conventional fossil fuel energy. In the past, most of the studies compared price of biofuel among choices of conversion technologies and biomass (Egbenkewe-Mondzozo, Swinton, Izaurrealde, Manowitz & Zhang, 2011; Li, Larsson, Thorin, Dahlquist & Yu, 2015; Brigagão, de Queiroz Fernandes Araújo, de Medeiros, Mikulcic & Duic, 2019). Yet very limited study relates crude oil price with biorefinery profitability. For instance, the price of biofuels were compared with price of gasoline by Kennedy & Ahamad (2007) and Slade, Bauen & Shah (2009) to assess commercial feasibility of biofuel in their region but without taking into account the volatility of fossil fuel prices.

As quoted from Kim & Dale (2015): “All biomass is local”, in spite of achieving biorefinery optimization; the feasibility of biorefinery would still subject to the local context of the biomass. Given the unique landscape patterns and natures of biomass in Malaysia, optimization of biomass application for biorefinery also need to be assess in terms of fossil fuel price. To address these issues, this chapter focuses on deriving biofuel production costs unique to the biomass. The design of biorefinery cost estimation model while simultaneously incorporate unique biomass transportation cost curves into it were demonstrated. Furthermore, the optimized cost and scale of biorefineries based on each biomass are compared with crude oil price and the impacts of relevant factors to optimum costs are also quantified. To the best knowledge of the author, this is the first work that simultaneously address biorefinery optimization in relation of landscape fragmentation, natures of biomass and historical crude oil price.

## 5.2 Material and method

### 5.2.1 Actualization of data

This study assessed economic competitiveness of biorefineries in Peninsular Malaysia by expanding the simulation of biomass supply cost (Ong et al., 2020) to biorefinery production cost. We first collected data for capital expenditure (CAPEX) of commercial scale biorefineries (Figure 5.1a). These data were based in different years and located in United States Gulf Coast area. To actualize the historical data into a common year and locality of our study, we applied the following equations (Table 5.1) using details and procedures shown in Annex F and G. We actualized the data into year 2015 and locality of Southeast Asia.

**Table 5.1: Equations to actualize CAPEX data**

<b>Equation 5.1</b>
Cost actualization: $Cost\ in\ year\ A = Cost\ in\ year\ B \times \frac{Cost\ index\ in\ year\ A}{Cost\ index\ year\ B}$
<b>Equation 5.2</b>
Location factor: $Cost\ of\ plant\ in\ location = cost\ of\ plant\ on\ USGC \times LF_A$ where $LF_A = location\ factor\ for\ location\ A\ relative\ to\ USGC\ basis.$

(Source: Towler & Sinnott 2013)

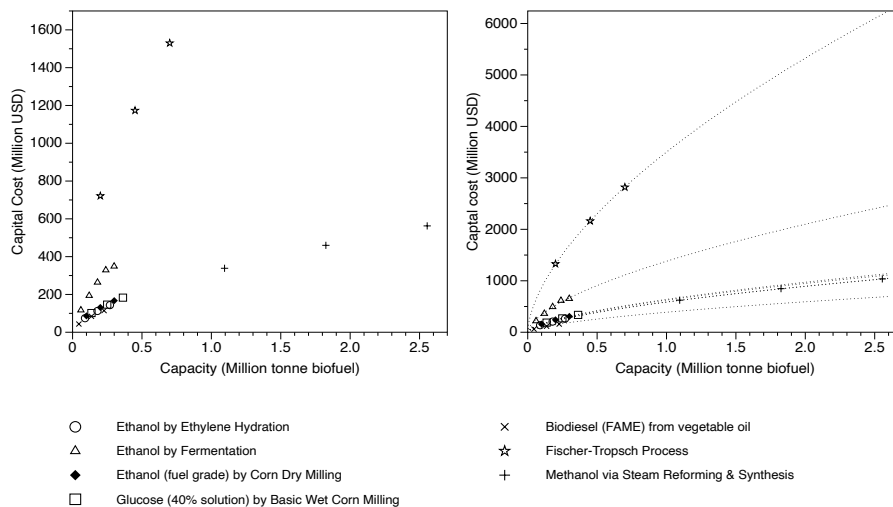
## 5.2.2 CAPEX Models

These data were fed into a non-linear regression analysis using R software to obtain CAPEX models of various biofuel pathways. This method is widely applied in chemical industry using the equation shown in Table 5.2 known as the cost curve method or order of magnitude estimates (Towler & Sinnott, 2013). The models were simulated in Figure 5.1b based on the parameters derived in Table 5.2.

**Table 5.2: Estimation models for capital expenditure of various conversion process**

CAPEX Model: $C = aS^n$					
Process or Variables		Coefficient Estimate	SE	t-value	Pr(> t )
(1) Ethanol by Ethylene Hydration	○	a1: 585.7	23.49	24.93	1.27e-13 ***
(2) Ethanol by Fermentation	△	a2: 1380	24.41	56.52	< 2e-16 ***
(3) Ethanol (fuel grade) by Corn Dry Milling	◆	a3: 639.2	22.20	28.79	1.52e-14 ***
(4) Glucose (40% solution) by Basic Wet Corn Milling	□	a4: 623.6	19.37	32.19	2.93e-15 ***
(5) Biodiesel (FAME) from Vegetable Oil	×	a5: 389.3	26.65	14.61	2.82e-10 ***
(6) Fischer-Tropsch Process	☆	a6: 3502	22.42	156.22	< 2e-16 ***
(7) Methanol via Steam Reforming & Synthesis	+	a7: 588.5	6.36	92.51	< 2e-16 ***
Correlating exponent	<i>n</i>	0.6051	0.0081	74.86	< 2e-16 ***
Significance codes: *** 0; ** 0.001; * 0.01; • 0.05		Residual standard error: 13.77 on 15 degrees of freedom			
Number of iterations to convergence: 8		Achieved convergence tolerance: 7.97e-07			
R-squared: 0.9997245					
<i>C</i> : capital cost		<i>a</i> : coefficient of the process		<i>S</i> : capacity or quantity	
				<i>n</i> : correlating exponent	

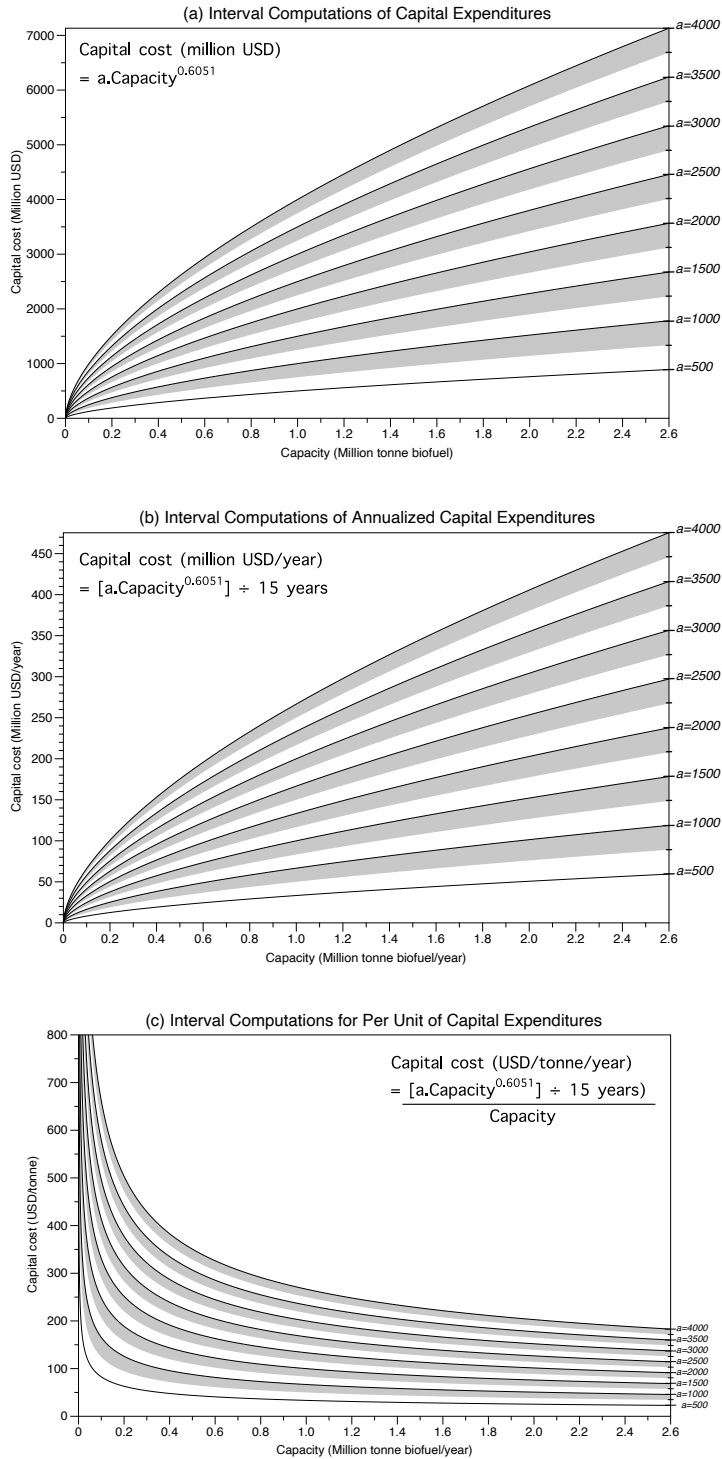
(a) Capital Expenditure for commercial plant of various pathways (b) Actualized CAPEX and CAPEX cost curve simulation



### 5.2.3 Biofuel production cost simulation

To derive biofuel production cost, we first assume the intended product are liquid biofuels and we would simulate both biochemical and thermochemical biorefinery. From Table 5.2, we observed that Process (2), (3) and (4) are fermented biofuel with coefficient estimate  $a_2=1380$ ,  $a_3=639.2$  and  $a_4=623.6$ . Based on these parameters, we rounded up to assume that values of parameter-a for fermentation processes range from  $a=500$  to  $a=1500$ . We used Fischer-Tropsch process as a typical representation of thermochemical process. Based on the coefficient estimates  $a_6=3502$ . We assumed that the values of parameter-a for Fischer-Tropsch process would range from  $a=3000$  to  $a=4000$ .

Based on the assumptions of CAPEX models above, we rearranged the equation of CAPEX estimation model to obtain the per unit CAPEX in USD/tonne of biofuel using interval computations. The interval value applied was 250 between the range of parameter-a for fermentation processes and Fischer-Tropsch process with 15 years biorefinery life span. This process is illustrated in Figure 5.2.



**Figure 5.2: Illustration of procedures and equations in interval computations of CAPEX**



(By varying the parameter-a representing two major conversion pathways, from a=500 to 1500 for fermentation process and a=3000 to 4000 for Fischer-Tropsch process. The rearranged equations of capital expenditure yield capital cost curves in per-unit-basis – USD/tonne/year.)

For the operation expenditures (OPEX), we assumed arbitrarily that biomass transport cost of 26-tonne-truck supplies to optimized location from previous study (Ong et al., 2020) would be 80% of total OPEX to adapt to the context of resource fragmentation in Peninsular Malaysia. The remaining 20% of the OPEX would be other variable cost. Ten major lignocellulosic biomass in Peninsular Malaysia were included in this simulation, including empty fruit bunch (EFB), palm pressed fibre (PPF), oil palm frond (OPF), oil palm trunk (OPT), rice straw, rice husk, forest logging wastes, rubber logging wastes, plywood mill wastes and sawdust. In MS Excel, we synchronized the capacity of the biorefinery based on biomass in dry matter basis (Annex E) using Equation 5.3 and also applied the biofuel recovery rate (Annex H) corresponding to the two representative liquid biofuel pathways. We then applied the synchronized biorefinery capacity based on respective biomass availability following the interval computations procedure mentioned (Figure 5.2) to obtain the per unit CAPEX in USD/tonne of biofuel/year. We computed OPEX in USD/tonne of biofuel with Equation 5.4 and total biofuel production cost in USD/tonne of biofuel/year with Equation 5.5. The process of obtaining the biorefineries production costs in Peninsular Malaysia is simplified into a schematic diagram in Figure

<b>Equation 5.3</b>	$\text{Synchronized Capacity} = (\text{Fresh matter supply} \times \text{DM}) \div R$
<b>Equation 5.4</b>	$\text{OPEX} = \left( \frac{\text{BTC}}{0.8} \div \text{DM} \right) \times R$
<b>Equation 5.5</b>	$\text{Biofuel production cost (USD/tonne/year)} = \text{CAPEX (USD/tonne/year)} + \text{OPEX (USD/tonne/year)}$

OPEX: Operating expenditure (USD/tonne of biofuel/year)

BTC\*: Biomass transport cost (USD/fresh tonne/year)

Synchronized Capacity (S): Biofuel output capacity based on local biomass supplies (tonne of biofuel/year)

Fresh matter supply\*: Biomass supplies in fresh tonne/year

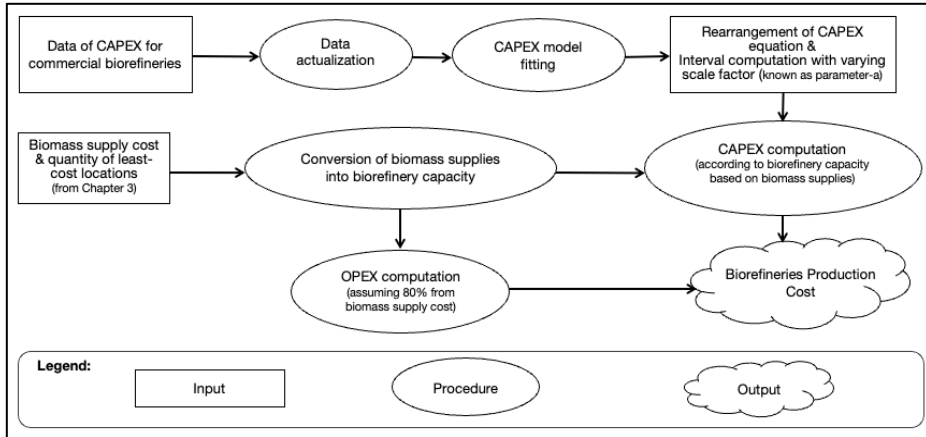
DM\*\*: Dry matter content of biomass (%)

R\*\*\*: Biofuel recovery factor – the ratio of biomass for 1 tonne of biofuel

(\*Source: Ong et al. (2020), Ong & Roda (2020))

\*\* Annex E

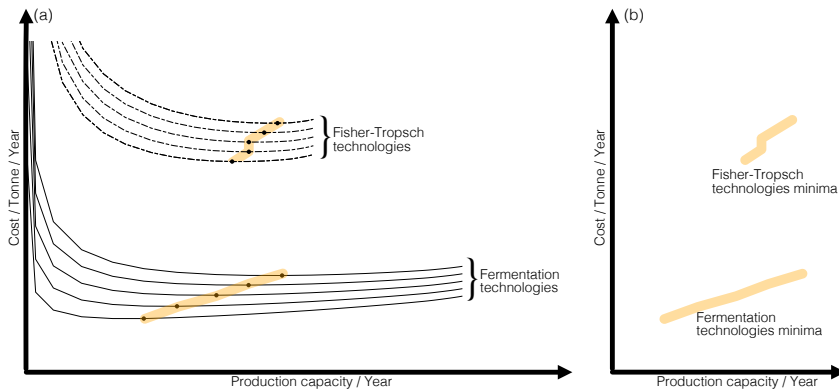
\*\*\*Annex H



**Figure 5.3: Schematic diagram illustrating process of biorefineries production costs**

### 5.2.4 Identification of optimal cost & scale

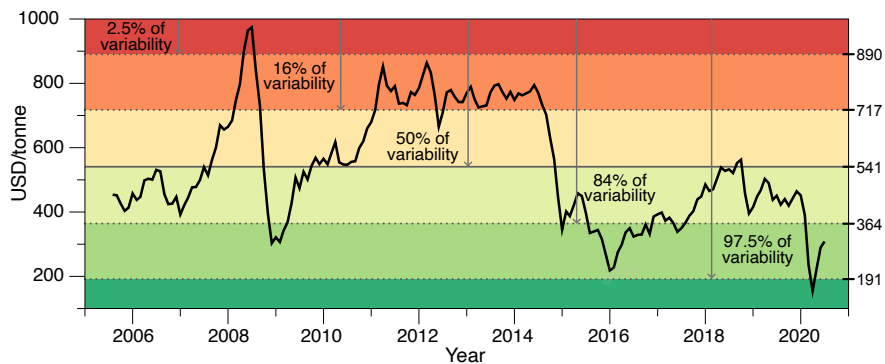
For each biomass we produced five production cost curves for both fermentation and Fischer-Tropsch conversion process. We then identified the minimum per unit production cost along each curve. This is where the capacity of biorefinery is optimal or known as an economy of scale. Figure 5.4 illustrates the identification of optimum points. These points would be compared to the past fifteen years of historical crude oil price.



**Figure 5.4: Illustration example: economy of scale identification and optimal points extraction**

## 5.2.5 Establishing variability of crude oil price over time using empirical rule

We collected data on crude oil prices in the past fifteen years from August-2005 to July-2020 and converted the prices into common unit of metric tonne using the specified conversion rate to match the measurement unit of this study (British Petroleum, n.d.; World Bank, 2020). We wanted to capture the variability of crude oil price over the last 15 years. This was done by regressing the data around its mean. We made a linear model regressing over its intercept in R software. Based on the 68-95 empirical rule (Bandyopadhyay & Cherry, 2011), we computed the crude oil price limits at one and two standard deviation. The R code and the results were presented in Annex I. We then translated the percentage of probability distribution into a chart for ease of comparison (Figure 5.5) and renamed the limits as percentage of variability.



**Figure 5.5: Fifteen years of crude oil price variability (August-2005 to July-2020) and its probability distribution limits**

(e.g. a price at USD150/tonne is lower than crude oil price in 97.5% of the cases)

(Source: BP p.l.c (n.d.); World Bank (2020))

## 5.3 Result and analysis

### 5.3.1 Optimized biofuel production cost of each biomass in Peninsular Malaysia

The biofuel production costs curves were obtained and the minimum cost along each curve is identified as optimum point or commonly known as economy of scale (Figure 5.6). In Table 5.3, the values of the optimized cost and capacity are presented. These values present a more realistic biofuel potentials in Peninsular Malaysia where economics of both biomass supplies and biorefinery were taken into account.

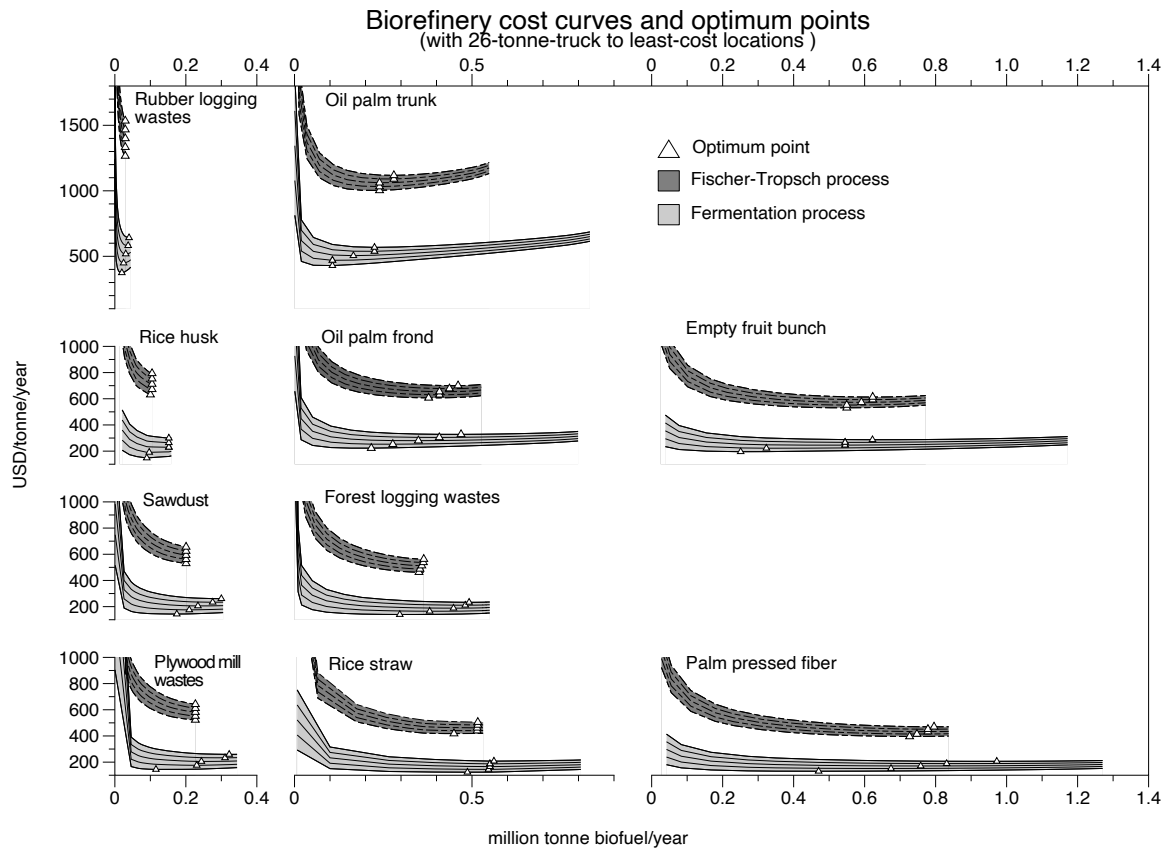
We find the biomass that could yield the largest optimized biofuel potential is palm pressed fiber (PPF) and followed by rice straw and empty fruit bunch (EFB) at annual biofuel capacity of 0.5 million tonne and above. With fermentation process, PPF

biorefinery optimized between 0.47 to 0.97 million tonne biofuel per year at 130 to 206 USD/tonne. With Fischer-Tropsch process, PPF biorefinery achieved optimum at 0.73 to 0.8 million tonne biofuel per year at 396 to 470 USD/tonne. Rice straw biorefinery of fermentation process has similar cost as PPF biorefinery at 123 to 208 USD/tonne but with lower optimized scale range between 0.49 to 0.56 million tonne biofuel per year. Rice straw biorefinery of Fischer-Tropsch process costs higher than the PPF biorefinery, it optimized at 0.45 to 0.52 million tonne biofuel per year at 418 to 505 USD/tonne. In case of EFB biorefinery, although it can optimized at annual potential more than 0.5 million tonne, however its costs are approximately 20% to 60% higher than rice straw and PPF. With fermentation process, EFB biorefinery optimized at between 0.25 to 0.6 million tonne biofuel per year at 196 to 287 USD/tonne and; with Fischer-Tropsch process optimized at between 0.55 to 0.62 million tonne per year at 531 to 613 USD/tonne.

The biomass that could yield moderate optimized biofuel potentials are forest logging wastes and oil palm frond (OPF). Biofuel from forest logging wastes are cheaper than the OPF biorefinery. It costs 140 to 233 USD/tonne for optimized scale between 0.3 to 0.49 million tonne per year with fermentation process and; 463 to 563 USD/tonne for optimized scale between 0.35 to 0.36 million tonne per year with Fischer-Tropsch process. OPF biorefinery cost about 40% to 60% higher than forest logging wastes with fermentation process. It optimized at between 223 to 321 USD/tonne for 0.22 to 0.47 million tonne biofuel per year. With Fischer-Tropsch process, OPF biorefinery costs 24% to 31% higher than forest logging wastes. The optimized costs are between 607 to 701 USD/tonne for 0.38 to 0.46 million tonne biofuel per year.

Biorefinery with small biofuel potential are offer by plywood mill wastes, sawdust and oil palm trunk (OPT). The biorefinery costs of plywood mill wastes and sawdust are very similar. With fermentation process, biorefinery of plywood mill wastes achieved optimum between 145 to 259 USD/tonne for 0.12 to 0.32 million tonne biofuel per year and; biorefinery of sawdust achieved optimum between 143 to 260 USD/tonne for 0.17 to 0.3 million tonne biofuel per year. With Fischer-Tropsch process, biorefinery of plywood mill wastes achieved optimum between 522 to 642 USD/tonne for 0.23 million tonne biofuel per year and; biorefinery of sawdust achieved optimum between 530 to 656 USD/tonne for 0.2 million tonne biofuel per year. The OPF biorefinery is relatively more costly compare to the plywood mill wastes and saw dust, it costs approximately one to two times higher with fermentation process and 74% to 92 % higher with Fischer-Tropsch process. The OPT optimums are between 429 to 563 USD/tonne for 0.11 to 0.23 million tonne biofuel per year using fermentation process and between 1003 to 1118 USD/tonne for 0.24 to 0.28 million tonne biofuel per year using Fischer-Tropsch process.

Biorefinery with very small potentials are from rice husk and rubber logging wastes. The optimum costs of rice husk biorefinery range from 148 to 300 USD/tonne for 0.09 to 0.15 million tonne per year of fermented biofuel and 632 to 794 USD/tonne for 0.1 million tonne per year of Fischer-Tropsch biofuel. Rubber logging wastes supply very expensive biofuel, it offers optimized cost of 375 to 642 USD/tonne for only 0.02 to 0.04 million tonne per year of fermented biofuel and 1266 to 1534 USD/tonne for only 0.03 million tonne per year of Fischer-Tropsch biofuel.



**Figure 5.6: Production cost curves of fermentation and Fischer-Tropsch process for 10 major biomass in Peninsular Malaysia**

**Table 5.3: Biofuel production cost at optimized scale for each biomass**

Technology:	Fermentation process					Fischer-Tropsch process				
Parameter:	a=500	a=750	a=1000	a=1250	a=1500	a=3000	a=3250	a=3500	a=3750	a=4000
Biomass	USD/tonne biofuel million tonne/year					USD/tonne biofuel million tonne/year				
<b>Large biofuel potential (above 0.5 million tonne/year)</b>										
Rice straw	123.2	144.5	165.7	186.8	207.8	418.1	440.4	462.1	483.7	505.4
	0.49	0.55	0.55	0.55	0.56	0.45	0.51	0.51	0.52	0.52
PPF	130.6	151.5	170.7	188.9	206.3	395.9	414.7	433.3	451.7	470.0
	0.47	0.67	0.76	0.83	0.97	0.73	0.75	0.78	0.78	0.8
EFB	195.6	222.2	245.7	266.9	287.2	530.9	552.0	572.7	593.3	613.4
	0.25	0.32	0.54	0.54	0.62	0.55	0.55	0.59	0.62	0.62
<b>Moderate biofuel potential (below 0.5 million tonne/year)</b>										
Forest logging wastes	139.9	165.0	188.3	210.9	233.0	463.0	488.2	513.3	538.2	563.0
	0.3	0.38	0.45	0.48	0.49	0.35	0.35	0.36	0.36	0.36
OPF	222.8	252.8	279.8	304.6	328.1	606.7	630.6	654.3	677.5	700.6
	0.22	0.28	0.35	0.41	0.47	0.38	0.41	0.41	0.44	0.46
<b>Small biofuel potential (below 0.3 million tonne/year)</b>										
Plywood mill wastes	144.6	176.0	205.2	233.1	259.4	522.3	552.2	582.1	612.1	642.0
	0.12	0.23	0.24	0.31	0.32	0.23	0.23	0.23	0.23	0.23
Sawdust	143.4	175.3	205.6	233.8	260.9	530.4	561.8	593.3	624.7	656.1
	0.17	0.21	0.23	0.28	0.3	0.2	0.2	0.2	0.2	0.2
OPT	429.2	469.6	505.1	538.3	568.3	1003.1	1032.4	1061.7	1090.4	1117.9
	0.11	0.11	0.17	0.23	0.23	0.24	0.24	0.24	0.28	0.28
<b>Very small biofuel potential (below 0.15 million tonne/year)</b>										
Rice husk	147.9	190.8	229.4	264.5	299.6	631.5	672.2	712.8	753.4	794.1
	0.09	0.1	0.15	0.15	0.15	0.1	0.1	0.1	0.1	0.1
Rubber logging wastes	374.5	448.7; 0.02	518.1	581.7	641.8	1265.9	1333.0	1400.1	1467.2	1534.3
	0.02		0.03	0.04	0.04	0.03	0.03	0.03	0.03	0.03

### 5.3.2 Feasibility of biofuel feedstock in comparison with crude oil price

Putting into the context of fuel commodity market, we combined the optimal points of each biorefinery and crude oil price variability together (Figure 5.7). We find that fermented biofuels produced from rice straw or from palm pressed fibre are the only biomass source to be systematically cheaper than 97.5% of the crude oil price variability.

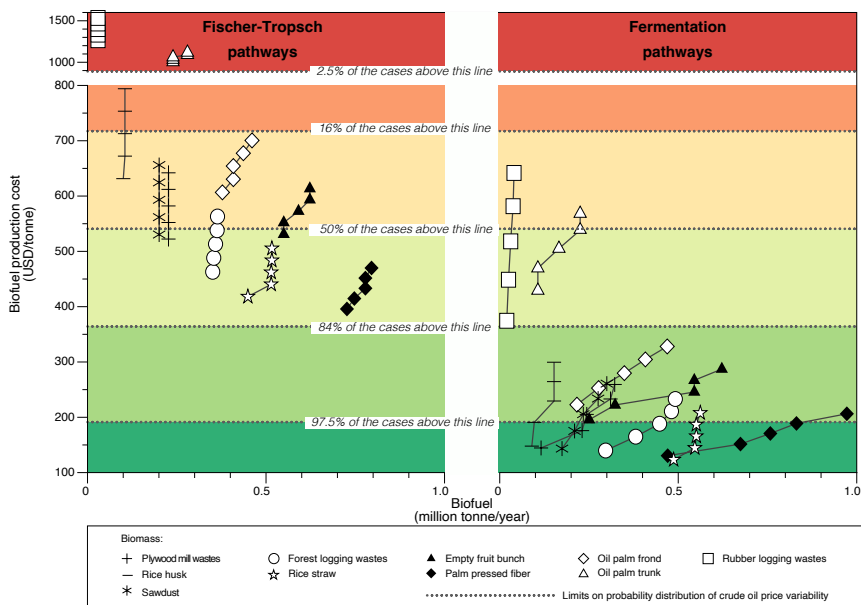
The biorefinery of rice straw and palm pressed fibre (PPF) could produce liquid biofuel most competitively at lowest optimal cost for largest amount of output. With Fischer-Tropsch process, optimized rice straw and PPF biorefinery produce biofuel at cost lower than crude oil price in 50% of the cases (less than USD541/tonne). At this possibility, the annual optimized are between 0.45 to 0.52 million tonne with rice straw and between 0.73 to 0.80 million tonne with PPF. This is more efficient with the fermentation process. The cost is much cheaper at a level lower than crude oil price in 97.5% of the cases (less than USD191/tonne). At this possibility, the annual optimized biofuel output are between 0.49 to 0.55 million tonne with rice straw and between 0.47 to 0.83 million tonne with PPF.

The opposite extremes are biorefinery of oil palm trunk (OPT) and rubber logging wastes. Their optimized cost and scale are expensive and small. For Fischer-Tropsch biofuel, they are higher than crude oil price in 97.5% of the cases (above USD890/tonne) at annual output between 0.24 to 0.28 million tonne with OPT and 0.03 million tonne with rubber logging wastes. For fermented biofuel, they are lower than crude oil price in only 16% of the cases (less than USD717/tonne). The optimum scale consists of annual output between 0.11 to 0.23 million tonne with OPT and between 0.02 to 0.04 million tonne with rubber logging wastes.

Three biomass could optimize at significant quantity of output but at cost higher than biorefinery of rice straw and PPF. These biomass are oil palm frond (OPF), empty fruit bunch (EFB) and forest logging wastes. With Fischer-Tropsch process, biorefinery of OPF and EFB optimized at cost lower than crude oil price in only 16% of the cases (less than USD717/tonne). They optimize at annual biofuel capacity between 0.38 to 0.46 million tonne and between 0.55 to 0.62 million tonne respectively. Forest logging wastes with Fischer-Tropsch process optimized at cost lower than crude oil price in 50% of the cases (less than USD541/tonne) with annual biofuel between 0.35 to 0.36 million tonne. With fermentation technology, they optimized at cost lower than crude oil price in 84% of the cases (less than USD364/tonne). The optimized fermented biofuel from OPF is between 0.22 to 0.47 million tonne, from EFB is between 0.25 to 0.62 million tonne and from forest logging wastes is between 0.30 to 0.49 million tonne.

The remaining biomass are also between the two extremes mentioned above. The biorefinery of rice husk, plywood mill wastes and sawdust could only produce small amount of biofuel due to their limited biomass availability. With Fischer-Tropsch technology, rice husk biorefinery optimized at cost lower than crude oil price in only 2.5% of the cases (less than USD890/tonne) with annual biofuel of 0.1 million tonne only. Plywood mill wastes or sawdust biorefinery of Fischer-Tropsch process optimized at cost

lower than crude oil price in only 16% of the cases (less than USD717/tonne). They optimized at annual biofuel of 0.23 million tonne and 0.20 million tonne respectively. In case of fermentation biorefinery, they optimized at cost lower than crude oil price in 84% of the cases (less than USD364/tonne). The annual optimized production from rice husk are between 0.09 to 0.15 million tonne, from plywood mill wastes are between 0.12 to 0.32 million tonne and from sawdust are between 0.17 to 0.30 million tonne.



**Figure 5.7: Optimal cost and scale of various biomass resources in Peninsular Malaysia and crude oil price variability in percentage of probability density**

### 5.3.3 Impact quantification of biomass natures on optimum biorefinery cost

To examine and quantify the impacts of the biomass natures to optimal biorefinery cost, we ran a multiple regression analysis. The optimal biorefineries cost were regressed over landscape fragmentation - edge density (ED), moisture content (MC) of the biomass and parameter-a that represent conversion technologies (Table 5.4).

**Table 5.4: Multiple regression analysis of optimal biorefinery cost**

Cost of Optimal scale (USD/tonne) ~ Edge Density + Moisture Content + Parameter-a				
Variables	Coefficient estimate	SE	t-value	Pr(> t )
Intercept	-67.98720	35.04253	-1.940	0.0553 •
Edge density	41.94829	5.20969	8.052	2.21e-12 ***
Moisture content	1.22781	0.74532	1.647	0.1028
Parameter-a	0.16807	0.01055	15.93	< 2e-16 ***

Signif. codes: \*\*\* 0; \*\* 0.001; \* 0.01; • 0.05  
Residual standard error: 137.1 on 96 degrees of freedom  
Multiple R-squared: 0.8146, Adjusted R-squared: 0.8088  
F-statistic: 140.6 on 3 and 96 DF, p-value: < 2.2e-16



For the 10 major biomasses types available in Malaysia, the biorefinery technology factor (parameter-a) is the most significant factor of the biofuel cost. All the variables are significant in the model except 'moisture content' but we interpreted that 'moisture content' is as important. This is because the optimal cost is a point in each cost curve where the minimum is achieved but the 'moisture content' exists along the entire cost curve.

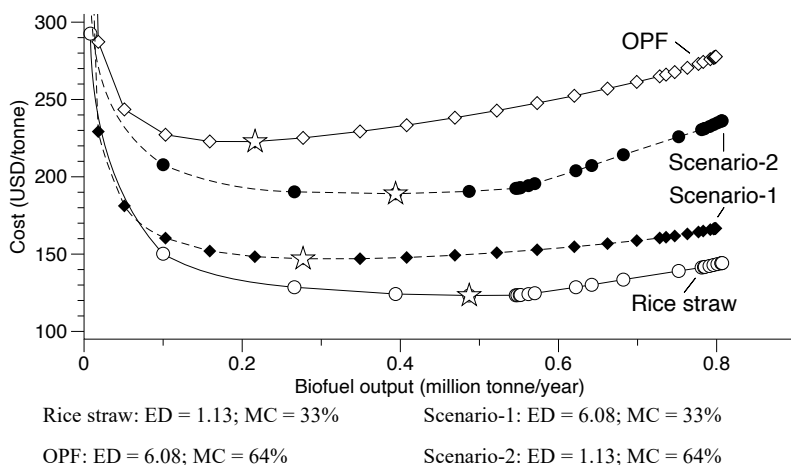
For instance, the two extremes of biorefinery costing – rice straw and PPF are the most competitive feedstock for biorefinery and in contrast rubber logging wastes and OPT are the costliest resources. These resources have opposite attributes in terms of landscape fragmentation and moisture content (Annex J). Rice straw has the most concentrated landscape pattern (ED = 1.13 metre/ha) and PPF is significantly lower in moisture content (28%). Contrarily, OPT has the highest moisture content (85%) and similarly for rubber logging wastes (68%), it also has the most fragmented spatial pattern (ED = 11.7 meter/ha). Based on these examples, we observed that the effects of moisture content exists and with landscape fragmentation, their effects amplify each other creating more impacts on the optimum costs.

Furthermore, the model also indicates a good coefficient of determination at around 80%. To conclude, we find that in a tropical country such as Malaysia; one unit of landscape fragmentation increases the biorefinery optimal cost by 42 USD/tonne, a switch of conversion pathway on parameter-a at interval of 250 increases the optimal cost similarly by 42 USD/tonne and 10% of moisture content increase the optimal cost by 12 USD/tonne.

## **5.4 Discussion**

### **5.4.1 Landscape fragmentation and moisture content amplify costliness of biorefinery**

We created biorefinery costing with scenarios of landscape fragmentation and moisture content based on the attributes of rice straw and OPF. These two resources have the same total annual availability of dry matter at around 2.6 million tonnes but varies in landscape fragmentation and moisture content. This allows us to observe the dynamics of the two significant biomass attributes on optimal biorefinery cost (Figure 5.8).



☆ Optimum ED: Edge density (meter/hectare) MC: Moisture content

Note: Edge density (meter/hectare) is higher when the landscape pattern is more fragmented and vice versa.

**Figure 5.8: Biorefinery costing for rice straw, OPF and pseudo-biomass**

Assuming that rice straw is the base line, in Figure 5.7 rice straw biorefinery achieved optimal cost at 123 USD/tonne and 0.49 million tonnes of biofuel per year. Scenario-1 represents a resource with higher landscape fragmentation and same moisture content as rice straw. This situation increases the cost curve to a higher position due to increase in supply cost incurred by higher transport distance from the landscape fragmentation. This shifted the optimal cost to a higher cost level but lower economy of scale - 19% of optimal cost increment to 147 USD/tonne and 43% reduction of optimal scale to 0.28 million tonne biofuel per year.

Compared rice straw to scenario-2, landscape fragmentation remains the same but moisture content has increased. Within the same supply distance, the density of dry matter per area had reduced hence reducing the quantity supplied per unit of distance and increases the total distance travelled and supply cost. Subsequently, the optimal cost increased by 53% to 189 USD/tonne and the optimal scale reduced by 19% to 0.39 million tonne per year.

Lastly, both landscape fragmentation and moisture content are higher when comparing OPF with rice straw. Both effects as described above would amplify the feedstock supply cost. The increments of biorefinery cost expand significantly as shown by the cost curve shifted to the highest level. The optimal point shifted to 223 USD/tonne with amplification of 81% in cost increment and optimal scale reduced by 56% to 0.22 million tonne per year.

From the point of view of industrial stakeholders and policy makers, the decision-making process often involve projection of a desired scale or selected technology and subject to one or a few feedstocks with availability (Langè & Pellegrini, 2013; Crawford et al.,

2016; Malek, Hasanuzzaman, Rahim & Al Turki, 2017; Mustafa, Calay & Mustafa, 2017). However, our findings suggest that feedstock selection could not rely on merely resource abundant. In tropical country with complex landscape pattern and high relative humidity, landscape fragmentation and moisture content could greatly affect competitiveness and feasibility of the biorefinery. It also implies that intermediary operations such as biomass consolidation and densification centres are needed to diminish the effects of landscape fragmentation and moisture content. The design of the intermediaries needs to adapt to the distinct groups of biomasses taking into account the spatial pattern, size of supply zone and location to minimize its cost. Furthermore, to avoid amplification effects from landscape fragmentation and moisture content, mobile machinery or methods that could perform preliminary drying and densification of biomass at source prior to transportation could significantly improve optimum biorefinery cost and scale.

#### **5.4.2 Abundant biomass does not permit competitive biofuels**

The most abundant biomass should be the main resource for a competitive and sustainable biorefinery (Chuah, Wan Azlina, Robiah & Omar, 2006; Shuit, Tan, Lee & Kamaruddin, 2009; Aditiya et al., 2016), but this is not what we found. Instead, we see that the most abundant biomasses, that are also the most discussed in the literature as candidates for biofuels in Malaysia (Goh & Lee, 2010; Derman, Abdulla, Marbawi & Sabullah, 2018) produce more expensive liquid biofuels. For example, EFB, OPF and OPT received more attention as biorefinery feedstock are more expensive than rice straw and PPF.

Usually biofuels (especially fermentation liquid biofuels) are not expected to be competitive with fossil fuels (Lynd et al., 2017). From our study, in Peninsular Malaysia alone; a total of 0.96 to 1.38 million tonnes of liquid biofuel from rice straw and PPF fermentation could be very competitively produced. This represents 5 to 7% tonne of oil equivalent of Malaysia petrol consumption in a year (Eurostat, 2005; Suruhanjaya Tenaga, 2020). It would be a major step for emissions reduction in a country that historically was a fossil fuel producer (Muhammed, 1986; Rahim & Liwan, 2012).

The quantification of biorefinery production costs, in relation to the landscape structure and categories of feedstock, is not only innovative, but it is also critical for tropical countries with high resource fragmentation such as Malaysia. In these countries less abundant and less fragmented resources may have more potential for sustainable and competitive biofuels than the flagship resources. Sustainability of biorefinery depends on its regional specificities (Kim & Dale, 2015), understanding the impacts of resource fragmentation and biomass nature are critical for the competitiveness of biofuels, it is also critical as supplementary incomes for the small farmers that is a characteristic of Southeast Asia (Gheewala, Damen & Shi, 2013). These supplementary incomes can be a way for them to reduce the practice of agricultural burning that often end up in catastrophic fires in the region (Fox, 2000; Rosmiza et al, 2014).

## 5.5 Conclusion

Our work highlighted the importance of landscape structure and biomass natures in tropical context compared to abundance of resources. We find that fermented biofuels produced from rice straw or from palm pressed fibre are the only to be systematically cheaper than 97.5% of the crude oil price variability. Landscape fragmentation (edge density) and moisture content play directly on the optimum cost of biofuels, they amplify each other. In a tropical country such as Malaysia, one unit of landscape fragmentation increases the biofuel cost by 42 USD/tonne, and 10% of moisture content increase the biofuel cost by 12 USD/tonne. These effects are as significant as the investment or energy conversion pathway indicated by the effect of parameter-a, at interval of 250 it increases the optimal cost by 42 USD/tonne similarly to effect of landscape fragmentation.

We also illustrated the dynamics of how landscape structure and biomass moisture content plays on optimal scale of biorefinery. This shows that resource abundance permits a pool of supplies but not feasibility of biomass and biorefinery. Significant biomass natures in tropical context such as spatial fragmentation and moisture content could greatly increase operating cost and diminish feasibility of biorefinery. In addition, technology efficiency allows more output per unit of investment. For example, our work demonstrated the fermentation technology with higher energy recovery rate and lower investment cost can achieve higher optimum scale at lower cost compared to Fischer-Tropsch pathway. The optimums of biorefinery are mainly determined by these three factors.

In a typical tropical country with abundant of lignocellulosic biomass, it is vital to address feedstock selection in a more holistic approach. This work demonstrate Malaysia as an example, due to landscape fragmentation, less abundant and less fragmented resources may have more potential for sustainable and competitive biofuels than the flagship resources. This also highlighted that the perceived abundance of resource led to overlooking of resource fragmentation. Industry players and policy makers could add a different perspective in developing biofuel industry, deeper understanding of the specifics and the dynamics of biomass within the supply zone is needed to assess feasibility of energy projects than merely the availability. Future study that focus on delineate and cluster the regional resources by geographical patterns, density and costs could help further clarify these obstacles in such landscape. Well planned and customized biomass consolidation centres, method and mobile machinery that could improve bulk density of biomass are also useful to overcome resource fragmentation.

## CHAPTER 6

### SYNTHESIS AND CONCLUSION

#### 6.1 Introduction

One of the motivations of biomass valorization to biofuels in Southeast Asia is driven by resource abundance due to their high primary productivity in the tropical climate. However, Malaysia as an example of such agriculture landscape consists of high resource fragmentation. The biomass transport cost is a major cost component for feedstock supply and biofuel production. However, due to spatial variability and heterogeneity of biomass, these resources would yield very different biomass supply costs to biorefinery. As a result, this would incur different impacts on economics of biorefinery and feasibility of biofuel production.

With the context of spatial fragmentation, this dissertation studies the variations of biomass transport cost and expand it to biorefinery costing and optimizations. This works also address the impacts of spatial fragmentation, explored other variables that have significant impacts to feedstock supply and biofuel production and quantified them. Given the industrial context, scenarios were also established to assess possible implications.

#### 6.2 Major findings

##### 6.2.1 Biomass transport costs and least-cost locations

In this work, we simulate biomass transport cost using GIS raster model with fine resolution at 0.4 hectare (63 x 63 meter) for each cell. The purpose is to capture field size that are small in the context of spatial fragmentation. Based on minimum total transportation cost, we narrowed down six least-cost locations for fresh biomass transportation in Peninsular Malaysia.

These locations are Yan, Kedah for rice straw and rice husk. Gua Musang, Kelantan for forest logging wastes. Bentong, Pahang for rubberwood logging wastes. Jempol, Negeri Sembilan for palm-based biomass namely, oil palm trunk (OPT), oil palm frond (OPF), empty fruit bunch (EFB) and palm pressed fiber (PPF).

We also identified four biomasses that could provide ample fresh supplies at more than 5 million tonnes annually. These biomasses are from oil palm industry. With a moderate truck size of 10-tonne-truck supplies, from 2 to 5 million fresh tonne per year; OPT costs 16.2 to 18.6 USD/tonne, EFB costs 17.5 to 21.3 USD/tonne, OPF costs 18.6 to 23.7 USD/tonne and PPF costs 19.3 to 25.8 USD/tonne. If these four biomasses are combined

for multi-feedstock scenario the cost of 2 to 5 million fresh tonne could be reduce to 14.9 to 16.4 USD/tonne.

Two other alternatives were identified to supply significant amount at around 2 million fresh tonnes annually. With 10-tonne-truck supply, forest logging wastes costs 26 USD/tonne for 2 million fresh supplies. Rice straw could supply 2 to 3 million fresh tonne at 16.2 to 18.8 USD/tonne.

## **6.2.2 Biofuel potentials and costs**

With the order of magnitude estimation method, capital expenditure of various energy conversion pathways was computed and incorporated with dry matter availability, biomass transport cost and other variable cost to obtain biofuel production costs curves. The optimum costs or economy of scale where the minimum cost occurred along each curve are derived.

Among the ten major biomasses, we find that PPF offer the most cost competitive and largest biofuel potential from fermentation pathway, at cost ranging from 130.6 to 206.3 USD/tonne yielding 0.47 to 0.97 million tonnes biofuel per year. This is followed by rice straw, it offers fermented biofuel at cost between 123.2 to 207.8 to yield 0.49 to 0.56 million tonnes per year. EFB could also offer fermented annual biofuel potential up to 0.5 million tonnes and beyond, however the optimum costs are more expensive at varying optimum scales. At cost between 195.6 to 287.2 USD/tonne, the optimum scale varies between 0.25 to 0.62 million tonnes per year.

Other two biomass that could offer moderate biofuel potentials are forest logging wastes and OPF. Forest logging wastes offer more cost-efficient fermented biofuel potentials, ranging from 140 to 233 USD/tonne could yield 0.3 to 0.49 million tonnes biofuel per year. OPF offer 0.22 to 0.47 annual fermented biofuels at cost between 223 to 328 USD/tonne.

Contrary to OPT fresh biomass supplies being the most ample and cheap, its biofuel potential is relatively small and expensive. Due to high moisture content (85%), OPT could yield only 0.11 to 0.23 million tonnes of fermented biofuel annually at costs between 429 to 568 USD/tonne. Other two biomass could offer similar amount of fermented biofuels at cheaper cost. Plywood mill wastes could offer 0.12 to 0.32 million tonnes per year at 145 to 259 USD/tonne and sawdust could offer 0.17 to 0.3 million tonnes per year at 143 to 261 USD/tonne. The remaining biomass including rice husk and rubber logging wastes could offer only very little biofuel production at below 0.15 million tonnes per year.

### **6.2.3 Feasibility of feedstock supplies and biofuel productions**

The feasibility of biomass supplies and biofuel productions were assessed by putting into context of international commodity markets. In comparison to biomass pellet price, a theoretical fresh biomass FOB (free on board) price was established by excluding the estimated biomass densification cost. Small truck transportation for example 1-tonne-truck would make only one biomass sourcing scenario (multi-feedstock from OPF, OPT, EFB and PPF) supply at below 50% of theoretical fresh biomass FOB price. With 26-tonne-truck transport, 93 % of total availability of the ten biomasses could supply fresh biomass at below 15% of theoretical fresh biomass FOB price. Extending the comparison, we converted the fresh biomass transport cost to dry matter basis (USD/dry tonne). We found that PPF, rice straw, rice husk, plywood mill wastes, sawdust, forest logging wastes and 50% of combination of PPF and EFB have competitive cost at below 17% of FOB biomass pellet price.

The optimum biorefinery costs were also put into the context of crude oil price given their substitution effect. We find that fermented biofuels produced from rice straw or from PPF are the only biomass source to be systematically cheaper than 97.5% of the crude oil price variability (below 191 USD/tonne). This total potentials from the two biomasses are between 0.96 to 1.38 million tonnes of annual liquid biofuel which represents 5 to 7% tonne of oil equivalent of Malaysia petrol consumption in a year. Realizing this potential could significantly increase carbon neutrality of the country.

From the findings above, we observed that the biomass that are less abundant i.e., PPF and rice straw are more feasible and competitive compared to biomasses that were perceived as abundant such as OPF, OPT and EFB. Furthermore, larger truck size could give aggregation effect to biomass supplies reducing total transport distance and increase their cost competitiveness.

### **6.2.4 Impacts of spatial fragmentation and other significant factors**

Regression analyses were performed to quantified the impacts of spatial fragmentation and other relevant variables to biomass transport cost and biorefinery optimum costs. We find that spatial fragmentation amplifies the effect of other variables on costliness of biomass transportation and biorefinery optimum costs.

In the case of biomass transport costs, transportation distance, truck size, spatial fragmentation (edge density) and waste origins significantly impact the cost. Given the context in Malaysia, a 1 million hectares feedstock would increase of 4.16 USD/tonne for every added unit of edge density. With a similar edge density as paddy fields, the field size of such a feedstock would be of 950 hectares in average and have a baseline supply cost of 67.16 USD/tonne based on its waste origin. The same feedstock with an edge density similar to palm oil plantations would have field size of 26 hectares in average, inducing a surplus of 20.8 USD/tonne for the supply cost. And with an edge density similar to rubber plantations, field size would be of 7.8 hectares in average,

inducing another surplus of 20.8 USD/tonne for the supply cost compared to oil palm plantations. In addition, the supply cost also increases in average by 6.78 USD/tonne for every added 100 km of transportation distance. Only one variables – truck size could decrease biomass transport cost, compared to a 1-tonne truck, the supply cost logarithmically decreases according to the tonnage, with -36 USD for a 3-tonne truck, and with -84 USD for a 26-tonne truck.

In the case of biorefinery optimal costs, we find that edge density (ED), moisture content (MC) and parameter-a have significant impacts. one unit of edge density increases the biorefinery optimal cost by 42 USD/tonne, a switch of conversion pathway on parameter-a (represent investment cost and conversion efficiency) at interval of 250 increases the optimal cost similarly by 42 USD/tonne and 10% of moisture content increase the optimal cost by 12 USD/tonne. Furthermore, a scenario of biomasses with same dry matter availability also demonstrated amplification effects of spatial fragmentation and moisture content. At baseline scenario – case of rice straw, ED=1.13 and MC=33%; a switch to higher ED=6.08 and MC remain the same increase optimum cost by 19% and reduce optimal scale by 43%. A switch to higher MC=64% and ED remain the same increase optimum cost by 53% with optimal scale reduced by 19%. When both of factors increase - case of OPF; ED=6.08 and MC=64%, the changes drastically increase optimum cost by 81% and reduction in optimal scale by 56%.

This implies that in tropical country with complex landscape pattern and high relative humidity, landscape fragmentation and moisture content could greatly affect competitiveness and feasibility of the biorefinery. Understanding regional specificities is equally important as developing efficient technology pathways, deeper understanding of the variations of biomass within the supply zone is needed to assess feasibility of energy projects than merely the availability for policy makers and industry players to develop sustainable biofuels.

### **6.3 Policy implications and future studies**

This study had identified several constraints in biomass logistics and their implications for feasible sustainable biofuels. These constraints include landscape fragmentation, transport load size, smallholder settings, and moisture content of biomass. Landscape fragmentation, along with higher moisture content in biomass, amplifies the effects on transport distances and costs. To address this, the establishment of consolidation centers can help reduce overall transport distance.

Future studies can focus on delineating biomass availability into zones of different geographical density. This approach would assist policymakers in managing resource utilization and competition. Zones with higher resource density could consider the application of conversion technology with higher scale factors, while zones with lower resource density may benefit from conversion technology with lower scale factors. Another implication pertains to the competitive use of biomass resources. As biomass can be utilized for various purposes, opportunity costs and trade-offs arise. When biomass is used for other products within an area, it reduces the availability and



geographical density of feedstock for biorefineries, negatively impacting their feasibility to achieve economies of scale. Strategic planning and incentives are therefore necessary to redirect biomass applications towards biofuel production.

Additionally, limitations exist in increasing truck sizes due to the prevalence of smallholder ownership structures in the agriculture and forestry sectors. Lighter truck sizes are commonly used in Malaysia, leading to inefficiencies in biomass transportation. This situation is reminiscent of the "last mile logistics" challenges faced in the business-to-consumer (B2C) e-commerce industry, where issues such as "fragmentation of deliveries" and "shipment size and homogeneity" arise (Olsson, Hellström & Pålsson, 2019). In the case of biomass logistics, these challenges manifest at the beginning of the value chain, with geographical dispersion and variations in bulk density. Drawing from successful approaches in the B2C arena, future studies could explore digital platforms and sharing economy models in utilizing transportation capacity to help smallholders schedule and consolidate delivery demands. This could enable the use of larger truck sizes, ultimately reducing transport costs.

#### **6.4 Conclusion**

In conclusion, this study has examined the constraints and implications of biomass logistics for the development of sustainable biofuels. The research focused on the context of spatial fragmentation in Malaysia, where high resource fragmentation poses challenges to biomass transport costs and biofuel production feasibility. By simulating biomass transport costs using a GIS raster model and considering various variables, the study identified least-cost locations for fresh biomass transportation in Peninsular Malaysia.

The analysis revealed that four biomasses from the oil palm industry, namely oil palm trunk (OPT), oil palm frond (OPF), empty fruit bunch (EFB), and palm pressed fiber (PPF), could provide ample supplies of biomass feedstock. Combining these four biomasses in a multi-feedstock scenario could potentially reduce the supply cost, highlighting the potential for cost optimization through biomass diversification. Additionally, PPF and rice straw were identified as alternative biomass sources with the cheapest biofuel potentials.

Furthermore, the study assessed the feasibility of feedstock supplies and biofuel production by comparing fresh biomass transport costs to theoretical FOB prices. The results showed that larger truck sizes could significantly increase the cost competitiveness of biomass supplies. Moreover, fermented biofuels produced from rice straw and PPF were found to be systematically cheaper than the majority of crude oil price variability, offering substantial biofuel potential and contributing to the country's carbon neutrality goals.

The research also quantified the impacts of spatial fragmentation and other significant factors on biomass transport costs and biorefinery optimal costs. Spatial fragmentation was found to amplify the effect of variables on costliness, emphasizing the need to consider regional specificities when assessing the feasibility of bioenergy projects. Moreover, landscape fragmentation and moisture content were identified as crucial factors influencing the competitiveness and feasibility of biorefineries in tropical countries.

Based on the findings, the study suggests several policy implications and areas for future research. Policy efforts should focus on managing resource utilization and competition by delineating biomass availability into zones of different geographical density. Strategic planning and incentives are necessary to redirect biomass applications towards biofuel production, considering the trade-offs and opportunity costs associated with competing uses of biomass resources.

Furthermore, the study highlights the limitations of increasing truck sizes in biomass transportation due to the prevalence of smallholder ownership structures. Drawing on successful approaches in the B2C e-commerce industry, future studies could explore digital platforms and sharing economy models to optimize transportation capacity and consolidate delivery demands. Such initiatives would enable the use of larger truck sizes, ultimately reducing transport costs and improving the efficiency of biomass logistics.

Overall, this research provides valuable insights into the constraints, opportunities, and policy implications of biomass logistics for the development of sustainable biofuels. By addressing spatial fragmentation, optimizing biomass supply chains, and considering regional specificities, it is possible to enhance the feasibility and competitiveness of biofuel production, contributing to a more sustainable and carbon-neutral energy future.

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## ANNEXES

### Annex A: Search query on Scopus database for biomass logistics studies

Search terms:  
 TITLE-ABS-KEY ( (cellulosic) AND (biomass OR feedstock) AND NOT (algae) AND (logistic OR transport) AND (biofuel OR biorefinery OR bioenergy) ) AND (EXCLUDE (SUBJAREA , "PHYS") OR EXCLUDE (SUBJAREA , "MEDI") OR EXCLUDE (SUBJAREA , "PHAR") OR EXCLUDE (SUBJAREA , "HEAL") OR EXCLUDE ( SUBJAREA , "NEUR") OR EXCLUDE (SUBJAREA , "NURS") OR EXCLUDE (SUBJAREA , "VETE") OR EXCLUDE ( SUBJAREA , "PSYC") OR EXCLUDE ( SUBJAREA , "Undefined" ) ) AND ( EXCLUDE (PUBYEAR , 1979) OR EXCLUDE ( PUBYEAR , 1978 ) OR EXCLUDE (PUBYEAR , 1977) OR EXCLUDE ( PUBYEAR , 1976 ) OR EXCLUDE ( PUBYEAR , 1975) OR EXCLUDE ( PUBYEAR , 1974) OR EXCLUDE ( PUBYEAR , 2022) OR EXCLUDE ( PUBYEAR , 2021 ) )

Database: Scopus  
 Result: 6224 documents  
 File: scopus\_compile\_1980-2020.bib  
 Retrieved on: 5 Dec 2021  
 Publication years = 1980 to 2020;  
 Excluded Subject Areas: Medicine; Pharmacology, Toxicology and Pharmaceutics; Health Professions; Neuroscience; Veterinary; Nursing; Psychology; Undefined.

### Annex B: Coordinates for biorefinery locations using representative points of district in Peninsular Malaysia

No	States	Districts	Longitude (x)	Latitude (y)
1	Johor	Johor Bahru	103.741359	1.492659
2	Johor	Batu Pahat	102.928834	1.849442
3	Johor	Kluang	103.318464	2.030068
4	Johor	Kulaijaya	103.606034	1.658267
5	Johor	Muar	102.584872	2.063052
6	Johor	Kota Tinggi	103.899227	1.729375
7	Johor	Segamat	102.820754	2.50346
8	Johor	Pontian	103.387859	1.485561
9	Johor	Ledang	102.53871	2.268446
10	Johor	Mersing	103.836115	2.430917
11	Kedah	Kuala Petani (Sungai Petani)	100.372989	6.119775
12	Kedah	Kota Setar (Alor Setar)	100.353977	6.096953
13	Kedah	Kulim	100.555337	5.371742
14	Kedah	Kubang Pasu	100.40416	6.036246
15	Kedah	Baling	100.916814	5.675547
16	Kedah	Pendang	100.477339	5.993039
17	Kedah	Yan	100.372658	5.79495
18	Kedah	Sik	100.743021	5.818345
19	Kedah	Padang Terap	100.611034	6.256764
20	Kedah	Pokok Sena	100.519358	6.167317
21	Kedah	Bandar Baharu	100.495534	5.131163
22	Kelantan	Kota Bharu	102.277684	6.116785
23	Kelantan	Pasir Mas	102.142782	6.042412
24	Kelantan	Tumpat	102.169372	6.199069
25	Kelantan	Bachok	102.397185	6.069586
26	Kelantan	Tanah Merah	102.147077	5.808887

27	Kelantan	Pasir Puteh	102.407741	5.836163
28	Kelantan	Kuala Krai	102.201851	5.530813
29	Kelantan	Machang	102.215387	5.767933
30	Kelantan	Gua Musang	101.968178	4.884279
31	Kelantan	Jeli	101.843151	5.700699
32	Kelantan	Lojing	101.433164	4.596792
33	Melaka	Melaka Tengah	102.250087	2.189594
34	Melaka	Alor Gajah	102.211561	2.382211
35	Melaka	Jasin	102.430923	2.311337
36	Negeri Sembilan	Seremban	101.937824	2.725889
37	Negeri Sembilan	Jempol	102.405454	2.896577
38	Negeri Sembilan	Port Dickson	101.796293	2.52254
39	Negeri Sembilan	Tampin	102.231194	2.472971
40	Negeri Sembilan	Kuala Pilah	102.248872	2.740474
41	Negeri Sembilan	Rembau	102.092986	2.590525
42	Negeri Sembilan	Jelebu	102.07191	2.941072
43	Pahang	Kuantan	103.220183	3.763386
44	Pahang	Temerloh	102.416348	3.448649
45	Pahang	Bentong	101.910353	3.522168
46	Pahang	Maran	102.779065	3.58338
47	Pahang	Rompin	103.486211	2.794459
48	Pahang	Pekan	103.389545	3.492095
49	Pahang	Bera	102.453864	3.270526
50	Pahang	Raub	101.857465	3.793532
51	Pahang	Jerantut	102.362038	3.937395
52	Pahang	Lipis	102.054126	4.179605
53	Pahang	Cameron Highlands	101.380144	4.47212
54	Penang	Timur Laut Pulau Pinang	100.329761	5.414921
55	Penang	Seberang Perai Tengah	100.451794	5.353468
56	Penang	Seberang Perai Utara	100.435548	5.514834
57	Penang	Barat Daya Pulau Pinang	100.235897	5.351903
58	Penang	Seberang Perai Selatan	100.49213	5.195837
59	Perak	Kinta	101.154737	4.626261
60	Perak	Larut Matang	100.674703	4.81939
61	Perak	Selama	100.69346	5.218462
62	Perak	Manjung	100.709787	4.402249
63	Perak	Hilir Perak	101.023037	4.020928
64	Perak	Kerian	100.485468	5.12605
65	Perak	Batang Padang	101.25927	4.197468
66	Perak	Kuala Kangsar	100.942045	4.773595
67	Perak	Perak Tengah	100.955429	4.363003
68	Perak	Hulu Perak	101.1238	5.429428
69	Perak	Kampar	101.153653	4.308504
70	Perlis	Perlis	100.204769	6.444913
71	Selangor	Petaling	101.535967	3.184624
72	Selangor	Hulu Langat	101.815673	3.113117
73	Selangor	Klang	101.445562	3.044917
74	Selangor	Gombak	101.560332	3.339222
75	Selangor	Kuala Langat	101.49507	2.803828
76	Selangor	Sepang	101.750527	2.691369
77	Selangor	Kuala Selangor	101.249762	3.340184
78	Selangor	Hulu Selangor	101.658312	3.560105
79	Selangor	Sabak Bernam	100.990592	3.678777
80	Terengganu	Kuala Terengganu	103.137014	5.329624
81	Terengganu	Kemaman	103.363802	4.233836
82	Terengganu	Dungun	103.415586	4.754876
83	Terengganu	Besut	102.552378	5.829012
84	Terengganu	Marang	103.204944	5.207711
85	Terengganu	Hulu Terengganu	103.008937	5.073042
86	Terengganu	Setiu	102.825218	5.443798
87	Terengganu	Kuala Nerus	103.047216	5.367864
88	Federal Territories	Kuala Lumpur	101.686855	3.139003
89	Federal Territories	Putrajaya	101.696445	2.926361

## Annex C: Methodological annex

```
## R code for the models M1 to M9c
# Y = Biomass supply Y in the manuscript (USD/fresh tonne)
# X1 = Distance (kilometre)
# X2 = Truck (capacity of the truck in tonne)
# X3 = Biomass yield (fresh tonne/hectare)
# X4a = Edge density (metre/hectare)
# X4b = Patch density (number of patches/square kilometre)
# X4c = Aggregation index (ratio)
# X5 = Waste origin (it is a categorical variable that either take the value of
“field” – X5a, “mill” – X5b, or “both” – X5c)

library(lm)
M1 <- lm(Y ~ 0+(X1 + X2), data=Dataset)
M2 <- lm(Y ~ 0+((X1 + log(X2))), data=Dataset)
M3 <- lm(Y ~ 0+(X1 + log(X2) + X3 ), data=Dataset)
M4a <- lm(Y ~ 0+(X1 + log(X2) + X4a), data=Dataset)
M4b <- lm(Y ~ 0+(X1 + log(X2) + X4b), data=Dataset)
M4c <- lm(Y ~ 0+(X1 + log(X2) + X4c), data=Dataset)
M5 <- lm(Y ~ 0+(X1 + log(X2) + X5), data=Dataset)
M6a <- lm(Y ~ 0+(X1 + log(X2) + X3 + X4a), data=Dataset)
M6b <- lm(Y ~ 0+(X1 + log(X2) + X3 + X4b), data=Dataset)
M6c <- lm(Y ~ 0+(X1 + log(X2) + X3 + X4c), data=Dataset)
M7a <- lm(Y ~ 0+(X1 + log(X2) + X3 + X5 + X4a), data=Dataset)
M7b <- lm(Y ~ 0+(X1 + log(X2) + X3 + X5 + X4b), data=Dataset)
M7c <- lm(Y ~ 0+(X1 + log(X2) + X3 + X5 + X4c), data=Dataset)
M8a <- lm(Y ~ 0+(X1 + log(X2) + log(X3 ) + X5 + X4a), data=Dataset)
M8b <- lm(Y ~ 0+(X1 + log(X2) + log(X3 ) + X5 + X4b), data=Dataset)
M8c <- lm(Y ~ 0+(X1 + log(X2) + log(X3 ) + X5 + X4c), data=Dataset)
M9a <- lm(Y ~ 0+(X1 + log(X2) + X5 + X4a), data=Dataset)
M9b <- lm(Y ~ 0+(X1 + log(X2) + X5 + X4b), data=Dataset)
M9c <- lm(Y ~ 0+(X1 + log(X2) + X5 + X4c), data=Dataset)
```

## Annex D: Accessibility of fresh biomass in Peninsular Malaysia

Benchmarked costs:	*50% of FOB price (USD69 /fT)		* 15% of FOB price (USD21 /fT)	
	1T truck		26T truck	
	Quantity (million fresh tonne)	% of total availability	Quantity (million fresh tonne)	% of total availability
Rice straw	2.74	71	3.88	100
Rice husk	0.36	61	0.59	100
Rice straw + husk	2.67	60	4.47	100
Forest logging wastes	0.35	16	2.13	96
OPF	1.42	20	6.92	97
OPT	3.55	20	17.00	95
OPF + OPT + EFB + PPF	8.20	20	38.15	95
PPF	1.22	21	5.42	95
EFB	2.01	21	8.93	95
EFB + PPF	3.23	21	14.35	95
Plywood wastes	0.45	34	1.22	92
Plywood wastes + Saw dust	0.74	31	2.16	90
Saw dust	0.32	30	0.88	83
Rubber logging wastes	0.04	8	0.34	77

## Annex E: Moisture content of biomass wastes

Biomass	Average weight of moisture content	
	%	
Rice straw <sup>(1)</sup>	33.3	
Rice husk <sup>(2)</sup>	13.5	
Rice straw & rice husk <sup>(1 &amp; 2)</sup>	33.2	
Forest logging wastes <sup>(3)</sup>	20.0	
Oil palm frond (OPF) <sup>(4)</sup>	64.0	
Oil palm trunk (OPT) <sup>(4)</sup>	85	
OPF, OPT, EFB, PPF <sup>(4)</sup>	67.3	
Palm pressed fibre (PPF) <sup>(4)</sup>	28.5	
Empty fruit bunch (EFB) <sup>(4)</sup>	60.0	
EFB & PPF <sup>(4)</sup>	48.1	
Plywood mill wastes <sup>(5)</sup>	17.0	
Plywood mill & Sawmill <sup>(5 &amp; 6)</sup>	13.1	
Saw dust <sup>(6)</sup>	8.2	
Rubberwood logging wastes <sup>(7)</sup>	68	

(Source: (1) Chen, Pen, Yu & Hwang (2011); (2) Shafie, Mahlia, TMasjuki & Ahmad-Yazid (2012); (3) McKendry (2002); (4) Elbersen, Meesters, & Bakker (2013); (5) Aydin, Colakoglu, Colak, & Demirkir (2006); (6) Miskam, Zainal & Yusof (2009); (7) Sik, Choo, Zakaria, Ahmad, Yusoff & Chia (2010).)

## Annex F : Annual CEPCI indices

Year	Chemical Engineering Plant Cost Index (CEPCI)
2008	575.4
2009	521.9
2010	550.8
2011	585.7
2012	584.6
2013	567.3
2014	576.1
2015	556.8

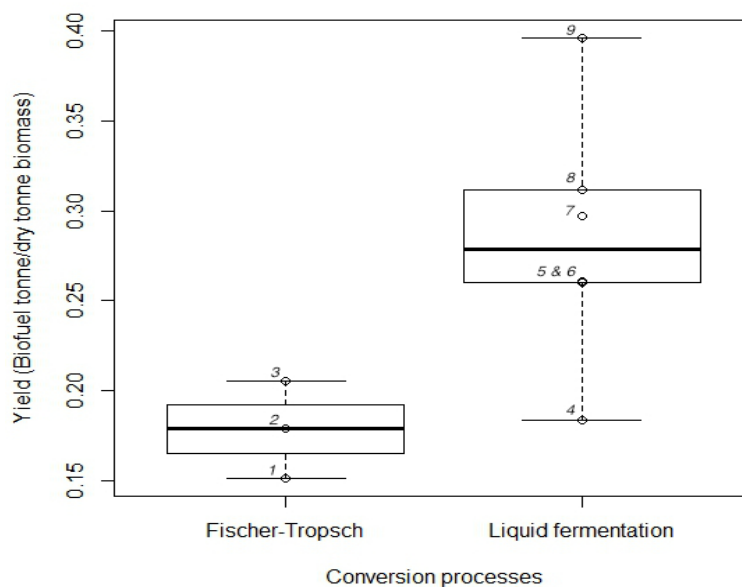
(Source: The Chemical Engineering Plant Cost Index (2018))

## Annex G: Data & calculation of Location factor

Currency exchange rate		Location factor Year 2003 Southeast Asia	1.12
Year 2003	3.8000		
Year 2015	3.9399		
Calculations: Location factor for Malaysia Year 2015 $= 1.12 \times (3.9399/3.8)$ $= 1.16$			

(Source: Towler & Sinnott (2013); Accountant General's Department of Malaysia (2016).)

## Annex H: Liquid biofuel yield based on two major conversion processes



(Source:

(1) Prins, Ptasinski & Janssen (2005)

(2), (4), (6), (7) & (9) Broust, Girard, & Van de Steene (2013)

(3)\* & (8)\* AMIC (2016).

(5) Humbird et al. (2011)

\*Ratios applied in the study.)

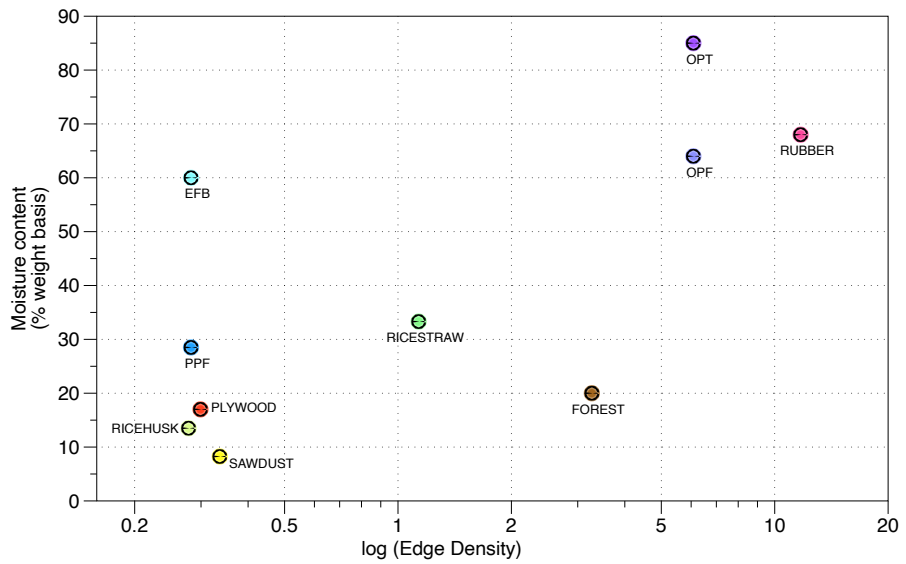
## Annex I: R code to establish variability of crude oil prices

```
> LinearModel.2 <- lm(USD.metric.tonne ~ I(Month*0), data=Dataset)
> summary(LinearModel.2)
Call:
lm(formula = USD.metric.tonne ~ I(Month * 0), data = Dataset)
Residuals:
    Min     1Q   Median     3Q      Max
-386.53 -137.48  -37.62  188.27  433.05
Coefficients: (1 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  540.78      13.16   41.09 <2e-16 ***
I(Month * 0)    NA           NA     NA     NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 176.6 on 179 degrees of freedom
(24 observations deleted due to missingness)

> #Calculate R-Squared LinearModel.2
> 1-(deviance(LinearModel.2)/sum((Dataset$USD.metric.tonne-
mean(Dataset$USD.metric.tonne))^2))
[1] 0

> predict(LinearModel.2, newdata = new.dat, interval = 'prediction', level=0.95) #
for 95% confidence
      fit   lwr   upr
1 540.7792 191.3652 890.1931
> predict(LinearModel.2, newdata = new.dat, interval = 'prediction', level=0.68) #
for 68% confidence
      fit   lwr   upr
1 540.7792 364.1996 717.3587
> #Calculate R-Squared LinearModel.2
> 1-(deviance(LinearModel.2)/sum((Dataset$USD.metric.tonne-
mean(Dataset$USD.metric.tonne))^2))
[1] 0
```

## Annex J: Distribution of biomass moisture content (%) and landscape fragmentation in edge density



(Adapted from: Ong et al. 2020)



## APPENDICES

### Appendix A



Available online at [www.buuconference.buu.ac.th](http://www.buuconference.buu.ac.th)

The 5<sup>th</sup> Burapha University International Conference 2016

*"Harmonization of Knowledge towards the Betterment of Society"*

HUO-050-41



## Designing model for biomass transport cost of biofuel refinery in Malaysia

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### Abstract

The fast-growing energy demand in Southeast Asia and price volatility of fossil fuel is driving the industries such as aviation sector to replace with alternative fuel. Currently, the focus of biofuel is to valorize residues resources as feedstock. In Malaysia, it is estimated around 168 million tons of biomass wasted annually. These resources are greatly useful for biofuel production. Nevertheless, the major barrier is the transportation of these biomass residues due to the geographically dispersed distribution. Using GRASS GIS as tool, this study aims to develop transport cost model to assess feedstock availability and location for biofuel refinery in Malaysia. The study found that there is no cost-efficient location to use multi-biomass sourcing strategy in Malaysia. To optimise production cost of biofuel refinery, multi-plant approach is more strategic given that two locations were found able to access significant amount of biomass residues at reasonable supply cost with annual availability up to 21.7 million tons. These resources include rice stalk and oil palm trunk. This model can be used to estimate biomass supply cost and quantity to aid decision making on location and capacity of biofuel refinery establishment in Malaysia.

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*Keywords:* biofuel; transport cost; modelling; logistic; GIS; bio-refinery; location; Southeast Asia; Malaysia.

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## **1. Introduction**

Biofuels is expected to become the major alternative energy to replace fossil energy sources (Valencia, 2014). Their renewability and sustainability insure some environmental and sociological services such as energy security, rural areas development and a lower greenhouse gases emission. These environmental considerations added to the current variability of the oil price leads to an increased interest by the industries, such as the aviation industry.

Southeast Asia is having the fastest growing demand for biofuel, although the expansion of new crops is very limited in the region (Roda et al., 2015). In Malaysia, there are abundance of biomass waste (Tye, 2011), it is estimated that around 168 million tons of biomass are annually wasted (Rodaet al., 2015). The availability of these resources can be valorize for biofuel production.

Studies about bioenergy production had found that the logistic variable such as transportation, collection, and storage have substantial impact on its economic feasibility (Iakovou et al., 2010). Due to high reliance to biomass feedstock, the major portion of the production cost is stemming from the biomass transportation (Caputo 2005; Kudakasseril et al, 2013 & Reeb et al., 2014). The cost to deliver the biomass to its facility can range from 35% to 50% or more (Allen et. al. 1998 & Kumar et. al. 2006). This issue had posed a dilemma for biofuel refinery, although economies of scale can lead to reduction of production cost, however this will demand more bulks of feedstock which require greater haulage and directly increase the transportation cost (Leboreiro 2011). Thus, it is vital to minimize the transportation cost. To achieve this, the bio-refinery should be placed at the location where it can access the sources at optimized cost and quantity.

Nevertheless, in Malaysia the complexities arise and affect the accessibilities when spatial structure of the resources differs greatly in terms of centrality and dispersion (Rodrigue 2013) as well as residues production density. To be able to take these factors into account, it was found that GIS (Geospatial Information System) modelling is pertinent to such conundrum and had been used in many related studies. These GIS applications were addressing subjects such as biomass availability assessments (Ranta, 2005; Batzias et al. 2005; Kinoshita et al. 2009 & Viana et al. 2010), location and cost analysis (Panichelli 2008), biomass potentials and environmental impact (Fiorese 2010) and impact of topography features to transportation cost (Sultana 2014). Furthermore, there are spatial models specially proposed for processing facilities network design (Kim et al. 2011), logistics cost evaluation (Graham et al. 2000, Larson et al. 2010) and decision support system (Voivontas et al. 2001) of bioenergy plant establishment.

Existing studies based in Malaysia are very limited and only founded on selected feedstock and location (Reeb et al., 2014 & Shafie et al., 2014). To address the lack of information and aiming to minimize major cost for biofuel industry in Malaysia, this study will assess the geo-location factor and availability of biomass residues within the region to develop the transport cost model for biorefinery plant.

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line.
2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (GRASS GIS Manual).

## 2. Material and method

This study aims to construct and apply a computation method for biomass transport cost for biofuel refinery through road transport network. The biomass resources focused in the study are primary residues from four major biomass sources in Malaysia including logging residues from forest, oil palm trunk (OPT) from palm oil plantations, rice stalk from paddy field and rubber wood logging residues from rubber plantations. Within the context, the study intends to identify ideal bio-fuel refinery location utilizing these resources in Peninsular Malaysia with cost-effectiveness perspective.

This methodology is developed through the following four phases with *GRASS GIS* program as the tool.

### 2.1 Study area and potential sites

The study area is the Peninsular Malaysia which constitute around 13 million hectare of land masses between Andaman Sea and South China Sea. The area of the land is divided into “pixels” where each side of the pixel square is approximately 63 meter. The candidates for selection of biofuel refinery sites are town/city from 89 districts in the peninsula.

### 2.2 Travel distances & transport cost simulation

From previous study (Deprés & Roda, 2015), the distance coefficient was calibrated through regression & *GRASS* tool where within each pixel of road contains 0.07 km (kilometre) and off-road<sup>1</sup>=0.14 km. These coefficients are embedded into each pixel on the peninsula map as friction map and is used as the base layer to calculate distances between different geographic locations as shown in Figure 1.

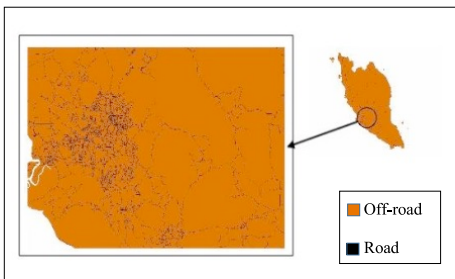


Figure 1. Friction map

Using *r.cost* tool in *GRASS*, the cumulative distance map can be created. As shown in Figure 2 one of the pixel is regards as the destination and the remaining pixels are containing continuous values of distance to reach the pixel of district.

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line. 2. Raster map is is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (GRASS GIS Manual).

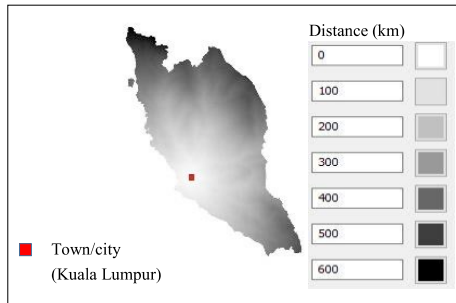


Figure 2. Distance map layer of city in district of Kuala Lumpur

Using a set of transport cost linear equation from previous study (Roda,2015) in Table 1 the distance map layer is used to create 4 sets of transport cost map layers for the 89 town/city. The distance map layer is insert into the *GRASS GIS* calculator – *r.mapcalc* according to the equation and produce a new layer of transport cost map. For example, as shown in Figure 3.

Table 1. Transport cost equation for 4 types of truck

Truck size (tons)	Transport cost linear equation
1	MYR/ton = distance (km) x 1.88657771 + 132.004442
3	MYR/ton = distance (km) x 0.672738734 + 69.0615618
10	MYR/ton = distance (km) x 0.258860505 + 49.3286760
26	MYR/ton = distance (km) x 0.193541212 + 39.5358461

Notes: The linear equation is approximated with regression using data collected from logistic companies in Malaysia.  
Source: Roda, 2015.

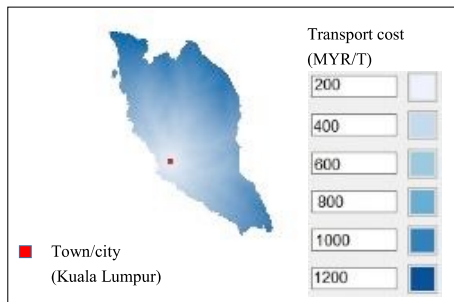


Figure 3. Transport cost map layer for Kuala Lumpur using 1-ton truck

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line. 2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (*GRASS GIS Manual*).

### 2.3 Biomass residues production and biomass transport cost

The sources of feedstock included in the study are biomass residues from forest and major crop of Malaysia agriculture industry. The annual residues production of these biomass is listed in Table 2. Prior to biomass transport cost (BTC) computation, these residues are quantified into production density based on area of pixel. The equations for the calculation are as below and the residues production density is in Table 2. Using *r.mapcalc*, the area of forest, palm oil, paddy and rubber are attributed with the residues production density by multiplying the biomass map with the residues production density. The geographical distribution of each biomass is illustrated in Figure 4.

- Area per pixel ( $m^2/pixel$ ) = Total area of crop ( $m^2$ )/Total pixels of crop
- Residues production per area ( $ton/ m^2/year$ ) = Annual residues production per year/ Area per pixel
- Residues production density ( $ton/pixel/year$ ) = Residues production per area \* Area per pixel

Table 2. Annual residues production from four major primary sources in Peninsular Malaysia

Annual biomass residues production	Fresh matter (Million ton/year)	Residues production density (ton/year/pixel)
Logging (Forest)	1.83	0.14333
Oil palm trunk (Palm oil)	17.80	2.69823
Rice stalk (Paddy)	3.90	6.60222
Logging (Rubber)	0.45	0.25819
Total	23.98	-

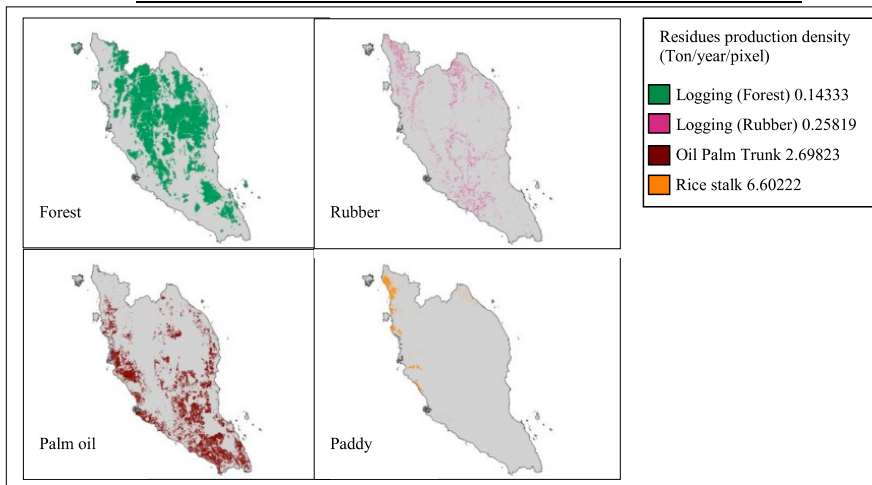


Figure 4. 4 biomass residues density maps

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line. 2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (GRASS GIS Manual).

With biomass residues density map layers in Figure 4, each layer are multiplied with the 4 sets of transport cost map using *r.mapcalc*. Subsequently, BTC map layer as shown in Figure 5 is obtained as the result of:

- Biomass transport cost (MYR/*n* ton) = Residues production density (ton/year/pixel) x Transport cost (MYR/ton) where *n* is the residues production density for each crop.

Each pixel of the BTC map contain MYR/*n* ton of transporting the biomass residues to the designated town/city.

### 2.3.1 Multi-biomass transport cost

In addition to BTC based on each single source, the possibilities of multi-biomass supply is also explored in the study. To calculate the BTC for multi-biomass, the four biomass residue density maps in Figure 4 are combined together using *r.patch* in *GRASS*, the output is as shown in Figure 6. The multi-biomass transport cost for each town/city is then computed using the procedures described in Section 2.3.

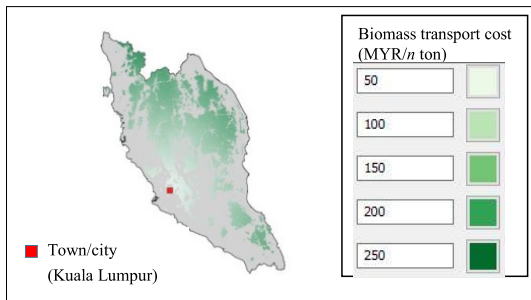


Figure 5. Biomass transport cost map of 1-ton truck to Kuala Lumpur

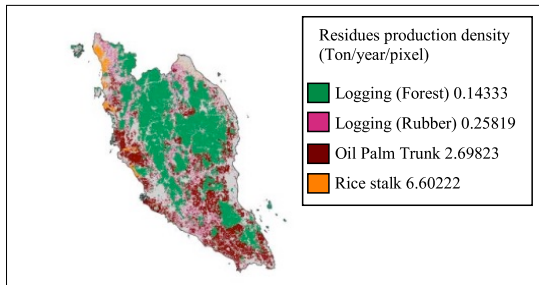


Figure 6. Multi-biomass map

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line.
2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (GRASS GIS Manual).

#### 2.4 Data extraction and sites selection

With the steps performed in previous sections, a database is created containing sets of map for further exploration. Firstly, the sum of BTC and multi-BTC maps for each town/city are collected. This is done by *r.univar* - a tool that calculate statistics from non-null cells of raster<sup>2</sup> map. The city/town which have the minimum sum of BTC are identified. In the cost-effectiveness perspective, the identified city/town are the optimal location for transporting the particular biomass, as shown in Figure 7.

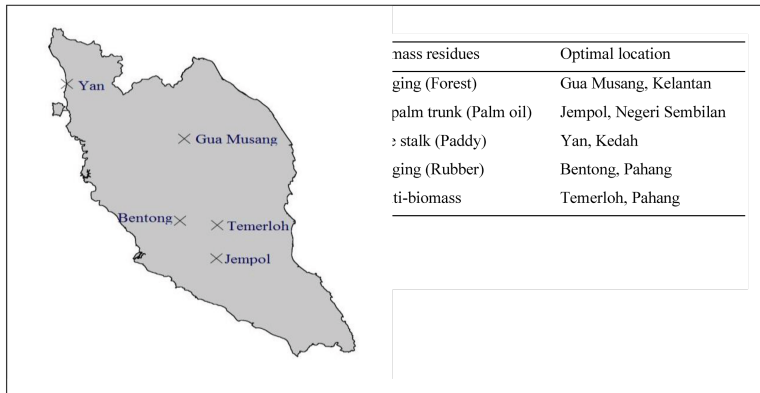


Figure 7. Optimal location for biomass & multi-biomass

To further study the location and strategy for biofuel refinery sites, the data of transportation cost and biomass availability need to be further scrutinized. In order to extract and organize the data, several steps are done in *GRASS*. Firstly, the transport cost map layers of the 5 optimal locations are categorized into zone by interval of MYR50. This can be done with *r.reclass*. As only location with biomass are considered as pixels of origin, the reclassified transport cost map layers are treated in *r.mapcalc* to include only area with biomass. These layers are acting as the zonal maps to read and compute the statistics data of their corresponding maps of transport cost, biomass transport cost and biomass residues density. The analogy of the zonal map is illustrated in Figure 8.

With the data collected using *r.univar*, cumulative unit cost (CUC) for each optimal location of biomass are calculated with the equation below. The CUC is used as indicator for comparison and examine zone by zone using scatterplot to explore the feasibility of biofuel refinery location.

$$Cumulative\ unit\ cost_{L,B}(MYR/T) = \sum_{i=1}^z \left( \frac{BTC_{L,B}}{Tonnage_B} \right)$$

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line. 2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (GRASS GIS Manual).

where,  
 L denotes location of the optimal site  
 B denotes type of biomass residues  
 z denotes number of zone  
 BTC denotes biomass transport cost of each zone  
 Tonnage denotes the tons of biomass residues of each zone

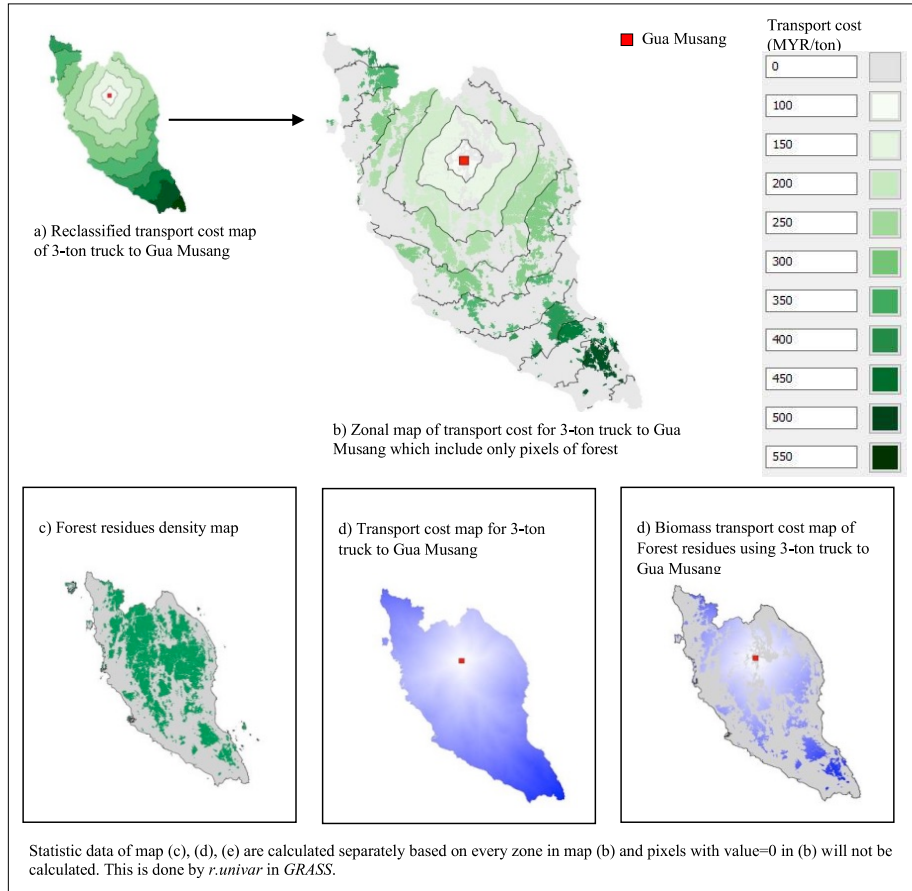


Figure 8. Analogy of zonal map and statistical data computation

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line. 2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (*GRASS GIS Manual*).



### 3. Result and discussion

The following graph in Figure 9 shows an overview of CUC for each optimal location with its corresponding biomass using 1-ton truck. With MYR250/ton as the threshold, rubber residues to Bentong have the least biomass availability of only 0.037 million tons (milT), followed by forest residues to Gua Musang at 0.16 milT, multi-biomass at 1.8 milT to Temerloh, oil palm trunk (OPT) to Jempol at 2.3 milT and all paddy residues at 3.9 milT can be transported within MYR250/ton. Based on the ranking, forest and rubber residues are expensive to transport and with little availability thus not the suitable feedstock for bio-refinery in peninsula.

Furthermore, the biomass availability for three remaining options is organize in following Table 3. Paddy residues to Yan appear to have cheapest transport cost contributed by geographically concentrated location of paddy field in the peninsula and high residues production density. OPT have the advantage of highest residues availability at up to 17.8 milT, to utilize OPT larger truck size can be used to enjoy the economy of scale.

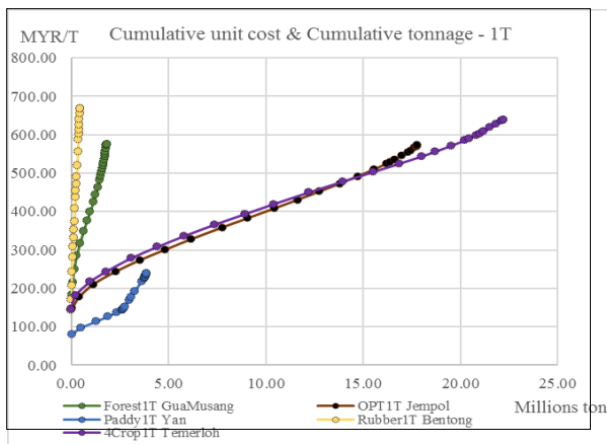


Figure 9. Cumulative unit cost and tonnage for each optimal location

Table 3. Cumulative unit cost to transport 100% of biomass residues to optimal location

Biomass residues	Optimal location	1-ton truck (MYR/ton)	3-ton truck (MYR/ton)	10-ton truck (MYR/ton)	26-ton truck (MYR/ton)
Rice stalk (Paddy)	Yan	238.60	97.28	50.05	38.89
Oil palm trunk (Palm oil)	Jempol	571.95	225.94	109.69	84.67
Multi-biomass	Temerloh	639.19	249.92	118.92	91.57

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line. 2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (GRASS GIS Manual).

Multi-biomass is more expensive and complex, to further explore multi-feedstock strategy Yan is used as the location for comparison as it has the potential to use multi-biomass given the advantage of high residues production density. From statistic data collected using *r.univar*, the tonnage of each zone and average transport cost of each zone is plotted in graph as shown in Figure 10.

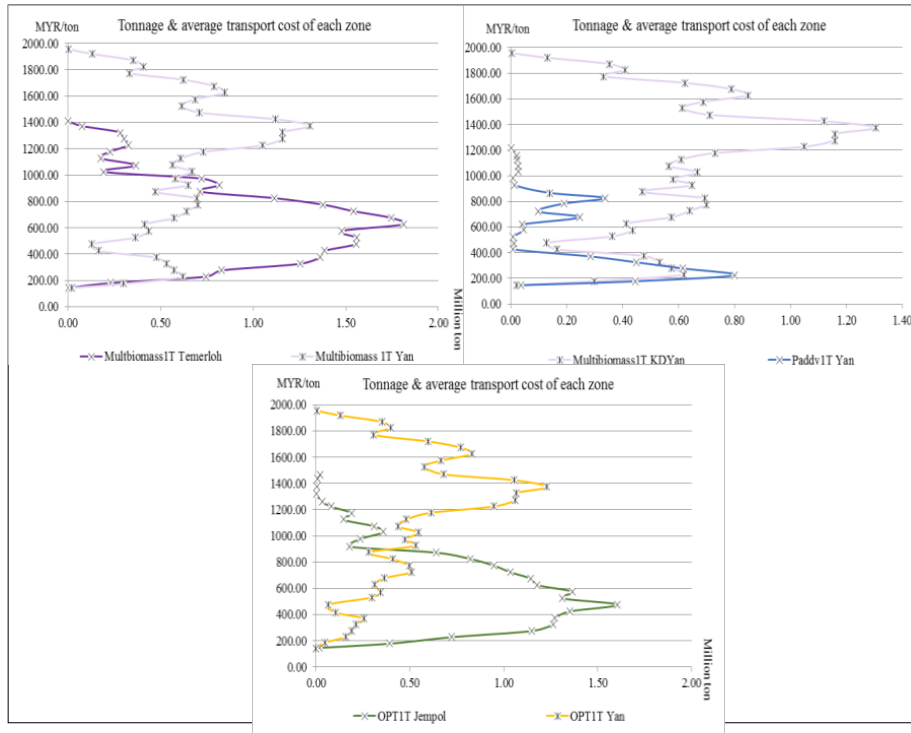


Figure 10. Residues tonnage and average transport cost of each zone for 1-ton truck

From Figure 10, it can be seen that the accessibility for multi-biomass in Temerloh, rice stalk in Yan and OPT in Jempol have consistent pattern where the tonnage consistently increases at first few zone before it goes erratic. This is because the optimal location is situated in location surrounded with the particular biomass. Furthermore, graph of multi-biomass to Yan and OPT to Yan are sharing same pattern. This is because OPT comprise 74% of total biomass. Although Temerloh have the lowest transport cost to get multi-biomass, it is actually not the best place as the cost is mainly attributed by cost of OPT.

1. Off-road refers to forest massif without road. The coefficient 0.14 km is the result of regression between distance from road points to points inside massif and direct line. 2. Raster map is a data layer consisting of a gridded array of cells. It has a certain number of rows and columns, with a data point (or null value indicator) in each cell (GRASS GIS Manual).

#### **4. Conclusion**

From the findings in Section 3, paddy residues and OPT appears to be the most accessible primary residues for biofuel refinery with significant quantities and reasonable cost. The former have the advantage of high residues production density and concentrated geographical distribution, the latter have the advantage of abundance quantities. Forest and rubber have little biomass availability and are not economical to transport. Moreover, the finding also suggests that there is no best location to transport multi-biomass. This result recommends to use multi-plant strategy optimizing paddy residues and OPT with each plant focus on using its most accessible resources.

The result also shows that the location of biorefinery have vast impact on accessibility to biomass and the transportation cost. Using this model, the feasible size of input capacity and major operating cost for biorefinery location can be estimated. This is very useful to logistics planning, cost-efficiency management and vitality of biorefinery facilities establishment in Malaysia. Further study will include more criteria such as sustainability, socio-political factor, energy conversion factor, bulk density and to take into account secondary biomass residues for more detailed analysis.

#### **Acknowledgements**

The authors would like to express sincere gratitude to Airbus Group-AMIC for funding this research and to CIRAD for providing supervisory supports.

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## Appendix B

# Cost Analysis and GIS-Modelling for the Production of Biofuel from Lignocellulosic Biomass in Biorefineries in Peninsular Malaysia

Brenna Jia Tian Chen<sup>1,2,3</sup>, Chu Lee Ong<sup>1,2\*</sup> and Juliette Babin<sup>4</sup>

The global production of aviation fuel, particularly Kerosene Jet A-1, has a market presence of 302.8 billionlitres per year, of which Malaysia consumes up to 3 billion litres per year. The pressure from increasing fuel demand and commitment to reducing CO<sub>2</sub> emissions has led to the use of biofuels as possible alternatives. Malaysia possesses a relative abundance of lignocellulosic biomass residues and thus, has much potential in biofuel development. In this work, Geospatial Information System analysis was used to obtain the geo-location biomass supply cost and was then simulated with non-linear cost estimation modeling for biorefinery production. The spatial analysis suggested that paddy and oil palm trunk could offer significant feedstock volumes at reasonable costs while biomass to fuel conversion pathways comparison showed that an "alcohol to jet" route was more feasible among all the alternatives. The simulation results indicated that the production cost of a bioethanol refinery had high variability due to the geographical heterogeneity of the lignocellulosic biomass resources. At the optimal location of paddy residues, utilising rice stalks was substantially cost-efficient compared to other biomass. The lowest range of relative production cost was achieved at RM359.11 – RM726.41/million tonnes per annum at an input capacity of 1.28 – 2.63 million tonnes. Conversely, using oil palm trunks in the same location gave a much more expensive relative production cost of RM472.23 – RM986.63/million tonnes yearly with only 0.40 – 1.03 million tonnes of input capacity. This model was able to suggest location strategies and cost estimations for biorefineries in Peninsular Malaysia. It is hence, useful as a decision and policy making tool for the implementation of biorefineries for aviation uses.

**Key words:** Sustainable, biomass, biorefinery, Geospatial Information System, information processing, computation analysis, Technology, aviation, economy of scale, biofuel, transport cost, modelling, logistics, location, Southeast Asia, Malaysia

### INTRODUCTION

The global production of aviation fuel, particularly Kerosene Jet A-1 has a market presence of 80 billion gallons, or 302.8 billion litres per year. In the United States alone, 83.3 billion litres of aviation fuel per year is refined (Davidson *et al.* 2014). Of this, 12% is used in the military and 88% is used in commercial flights, with North America having the highest rate of consumption of ca. 102 billion litres. Asia and Russia combined has a fuel consumption of ca. 61.2 billion litres (IATA 2011). Malaysia itself consumes up to 3 billion litres of kerosene jet fuel per year, which accounts for only close to 0.01% of the global aviation usage (US DOE 2016). Countries such as Malaysia, with its high biodiversity due to its equatorial climate, boasts a large potential to develop and produce alternative fuels

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for its transportation industry. Currently, the aviation industry contributes to around 2% or 705 million tonnes (of 36 billion tonnes) of global man-made CO<sub>2</sub> emissions. On top of this, it has been forecasted that the aviation industry will double in terms of air traffic in the next 15 years. Aviation associations such as the International Air Transport Association (IATA) has committed to a set of standards as follows:

- Improve fuel efficiency by 1.5% annually, on average, from 2009 to 2020
- Achieve carbon neutral growth (CNG) from 2020
- Reduce net emissions of CO<sub>2</sub> by 50% by 2050, from 2005 levels.

These however, create opportunities and speed up the development of "green" fuel (also known as biofuel) as an alternative solution. Malaysia, with an estimated 168 million tonnes of biomass waste annually, has great potential in biofuel production.

## MATERIALS AND METHODS

The study was a combination of two methods. One of the methods used GRASS GIS to perform spatial analysis with data containing land use information acquired by satellite. Massive parallel computing algorithms were performed in a high performance computing station to simultaneously process agronomic, economic and geographic information for 117 million spatial units. Each unit was a quasi-square of approximately 63 metres wide. With statistical programming and a nonlinear modelling cost curve method, the biofuel production data from literature and industrial reports were combined with the geo-location biomass supply costs derived from spatial analysis to simulate the cost estimation modelling for biorefinery plants.

## RESULTS AND DISCUSSION

Taking into account the spatial location and residue production density of forests and crops in Peninsular Malaysia, each biomass source has its own optimal location with respective supply cost structures. Two sources of biomass residues offer the cheapest supplies for biorefineries in Peninsular Malaysia using 1-tonne-truck supplying.

- Paddy residues with an annual availability of 3.9 million tonnes and supply costs culminating at RM430.25/tonne at its optimal location - Yan, Kedah.
- Oil palm trunks with an annual availability of 17.8 million tonnes and maximum supply costs culminating at RM571.95/tonne at its optimal location - Jempol, Negeri Sembilan.

Other resources such as forest and rubber primary residues were limited (1.8 & 0.45 million tonnes respectively) with high maximum supply costs. Multicrop-sourcing (primary residues of forest, paddy, rubber and oil palm trunk) had a total availability at 22.2 million tonnes per year with a maximum supply cost of RM639.19/tonne at the optimal location - Temerloh, Pahang. However, the major quantities of multicrop-sourcing were from oil palm trunks (74%) and paddy residues (16%). This suggested that having a single bio-refinery with multicrop-sourcing was not feasible in Peninsular Malaysia. With a multi-plant strategy at its optimal location, each crop source allowed an optimal refinery location with cheaper supply costs. This implied that several biorefinery plants could be considered for Peninsular Malaysia.

While there are several means of biomass conversion and fuel upgrading pathways, only a handful of these are able to handle lignocellulosic or carbohydrate-based feeds. Two pathways that have been gaining traction for such feeds are the "Direct Sugar to Hydrocarbon" and "Alcohol to Jet" routes. The highlighted feedstock from the study, both paddy and oil palm trunks could be fed into either of these process to yield a certifiable drop in kerosene grade fuel.

Preliminary studies on the production costs of biorefineries suggested that an "Alcohol to Jet" route was a feasible option for the process of biofuel production in Malaysia. The cost of producing bio-alcohols such as bioethanol is established in literature and commercial operations. Thus, this study used this pathway as the means to compute the production cost of biorefinery plants.

Results from the spatial analysis were simulated with a cost estimation model to produce biorefinery production costs using a 1-tonne-truck supply cost scenario, and rice stalks and oil palm trunks as biomass feedstock at their optimal locations. The computation showed that the production cost of the biorefineries had high variability corresponding to the mill locations due to the geographical heterogeneity of the lignocellulosic biomass resources.

- At the optimal location of paddy residues, utilising rice stalks were substantially more cost-efficient compared to utilising other biomass. It achieved the lowest range of relative production cost at RM359.11 – RM726.41/million tonnes per annum at an input capacity of 1.28 – 2.63 million tonnes. Conversely, using oil palm trunks in the same location gave a much more expensive relative production cost at RM472.23 – RM986.63/million tonnes yearly with only 0.40 – 1.03 million tonnes of input capacity.
- At the optimal location of oil palm trunks utilising oil palm trunks, a lower cost range of relative production cost at RM370.53 – RM690.93/million tonne annually at an input capacity of 1.13 – 4.82 million tonnes was achieved. Using rice stalks at the same location was significantly inefficient at the relative production cost of RM775.94 – RM1466.18/million tonnes annually with only 0.05 – 0.78 million tonnes of input capacity.

In the case of a biorefinery location at Yan, Kedah; the relatively optimal costs to use rice stalks was between an input capacity of 0.48 to 3.88 million tonnes at costs ranging from RM368.92 – RM999.63/million tonnes and RM603.44 – RM881.26/million tonnes. On the other hand, using oil palm trunks at Yan, the relatively optimal costs ranged between an input capacity of 0.21 to 2.86 million tonnes at costs ranging from RM486.23 – RM1365.61/million tonnes and RM732.19 – RM1045.37/million tonnes. The mill size beyond this capacity was too costly.

The high variability in the production costs stemmed from the location of the mill due to the geographical heterogeneity of the biomass resources. This showed that the location factor was the main determinant of the viability and capacity of biorefinery plants in Peninsular Malaysia.

Table 1. Supply costs of the transport of 100% biomass residues to optimal locations

Biomass residues	Optimal location	1 tonne truck (RM/ton/year)	3 tonne truck (RM/ton/year)	10 tonne truck (RM/ton/year)	26 tonne truck (RM/ton/year)
Logging (Forest)	Gua Musang	575.59	227.24	110.19	85.04
Logging (Rubber)	Raub	319.35	260.55	58.84	45.27
Oil palm trunk (Palm oil)	Jempol	571.95	225.94	109.69	84.67
Rice stalk (Paddy)	Yan	430.25	97.28	50.05	38.89
Multi-biomass	Temerloh	639.19	249.92	118.92	91.57

Table 2. Relative production costs at minimum point in different locations

Biomass and location	Relative Production Cost at Minimum Point			
	Lower Bound (LB)	Upper Bound (UB)	Capacity of LB	Capacity of UB
	RM/Mil ton/year	RM/Mil ton/year	Mil ton/year	Mil ton/year
Paddy@Yan*	359.11	726.41	1.28	2.63
OPT@Yan*	472.23	986.63	0.40	1.03
OPT@Jempol*	370.53	690.93	1.13	4.82
Paddy@Jempol	775.94	1466.18	0.05	0.78

\*optimal location

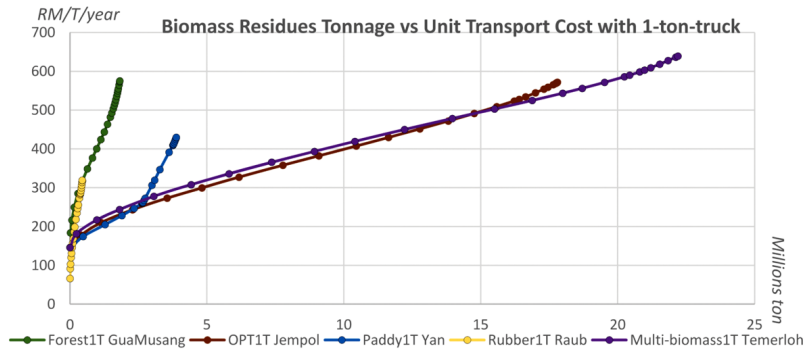


Figure 1. Supply costs and tonnage to each optimal location with a 1-ton-truck



Biomass residues	Optimal location
Logging (Forest)	Gua Musang, Kelantan
Oil palm trunk (Palm oil)	Jempol, Negeri Sembilan
Rice stalk (Paddy)	Yan, Kedah
Logging (Rubber)	Raub, Pahang
Multi-biomass	Temerloh, Pahang

Figure 2. Optimal locations for each biomass & multi-biomass

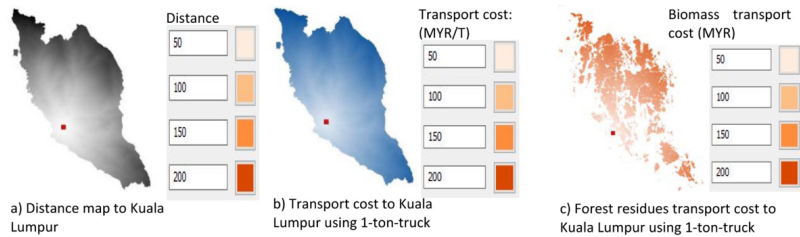


Figure 3. Examples of travel distance, transport costs and biomass transport costs maps



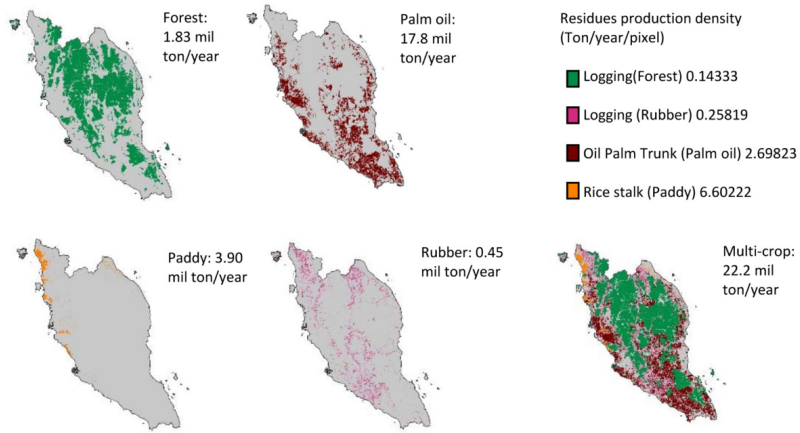


Figure 4. Annual biomass residues production and density

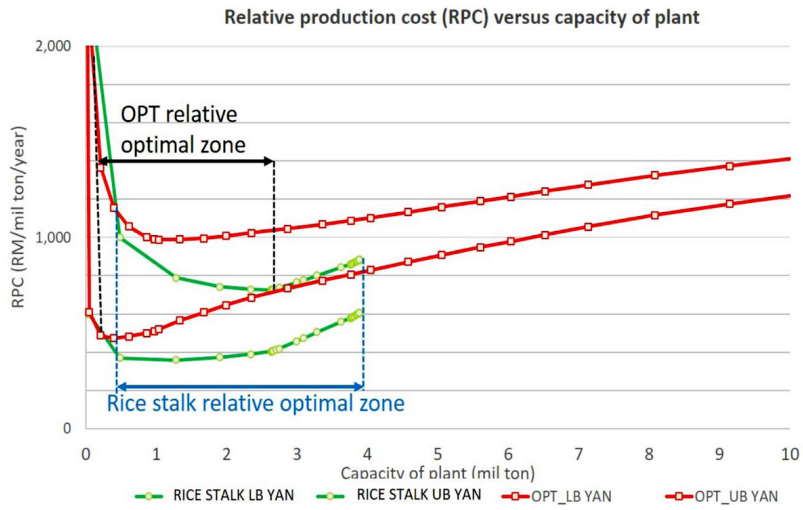


Figure 5. Relative production costs (RPC) versus the capacity of biorefinery plants at the optimal location of paddy residues

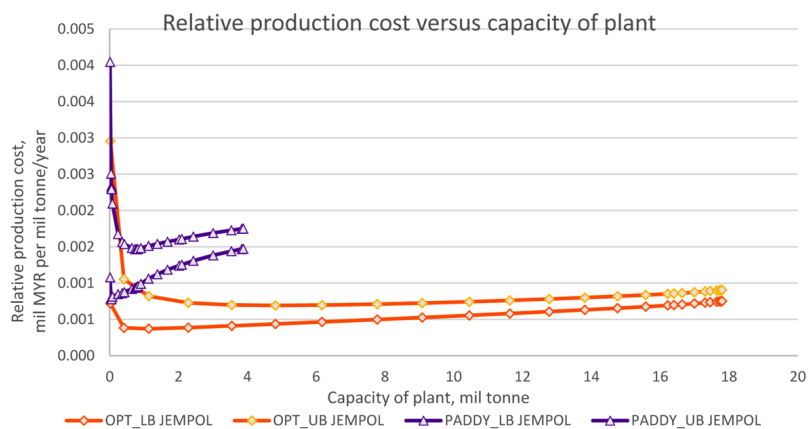


Figure 6. Relative production costs (RPC) versus the capacity of biorefinery plants at the optimal location of oil palm trunks

### CONCLUSIONS

The model could estimate the production cost curves of biorefineries in different scenarios. The data indicated that the geographical structure of the biomass resources in Peninsular Malaysia was the main factor in deciding the optimal location of the biorefinery plants. Based on the simulation method used, the location strategy, input capacity and production cost range of the biorefineries could be derived. This method is useful as a decision and policy making tool for the implementation of biorefineries for aviation uses.

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## Appendix C

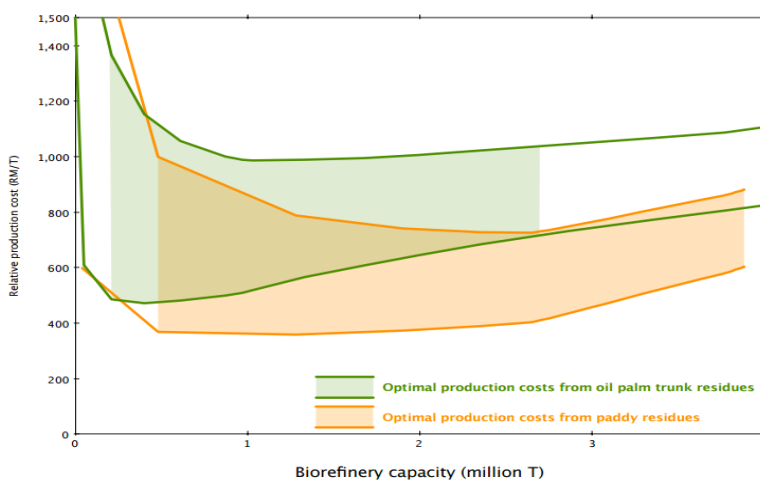
### Box C- 5 Cost Estimation of Biorefinery Plant in Peninsular Malaysia 2

In this case study, cost curve method is used to estimate the capital cost of a biorefinery plant. Location of plant is assumed to be in Yan, Kedah with paddy and oil palm trunk (OPT) as its respective feedstock.



*\*Assumption: Feedstock cost comprised of 80% of the total operating cost*

With the estimation of capital cost of plant, operational cost is obtained as well as the relative production cost of plant. Results were plotted as shown in Figure C-15 below:



**Figure C- 14** Optimal production costs from oil pal trunk residues and paddy residues

Initial finding suggested that paddy is highly available in Yan, Kedah as compared to OPT. Result above visualised the optimal production cost of biorefinery plant in single location with two different feedstocks. When paddy is used as the feedstock, with the capacity of plant in the range of optimal production cost from paddy, it gives a better promising production cost. This is because production cost of plant is highly dependent on the location factor. Economy of scale will be achieved if the biorefinery plant located at an optimal location with high availability of specified feedstock. It is concluded that high variability of production cost in Peninsular Malaysia is corresponding to the location of the biorefinery plant due to geographical heterogeneity of biomass feedstocks.

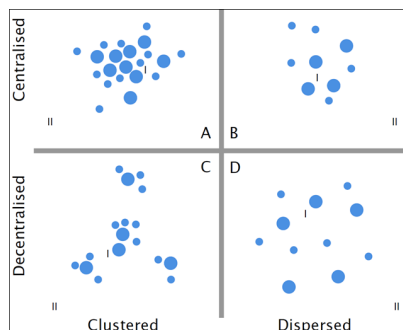
Source: Chen, J.T., Ong, C.L, Roda, J.M., Centre of Excellence of Biomass Valorization for Aviation, CIRAD-UPM-AMIC (2016)

This report presents the economic potential using 2,000t/d forest and oil palm plantation biomass (OPF and OPT) as the feedstock for power generation with main focus on electricity production. The proposed technology is a 27MW capacity direct combustion system with a 76% efficiency comprising of a pre-treatment drying system, fluidised bed boilers for conversion of biomass to heat and steam, and generation of electricity through extraction-condensing turbine. The biomass feedstock with an assumed calorific value of 15.82MJ/kg with 16% moisture content (dry basis) (Fiseha *et al.*, 2012). The direct combustion technology has a 30-year plant life with investment cost of USD900/kW and USD1050/kW for boiler and turbine respectively. The process, costing and financing information are presented in Table C-14. The costing information was obtained through personal interview with a local biomass-to-power industry stakeholder while the financing data are adopted from NREL report (Humbird *et al.*, 2012).

### Box C- 6 Location factor for biofuel plant

Biomass valorisation had been recognised as sources for renewable energy in recent decades. Aiming at utilising biomass residues can avoid food price competition and land uses change. Nevertheless, the major cost factor of biomass supplies lies in the transportation.

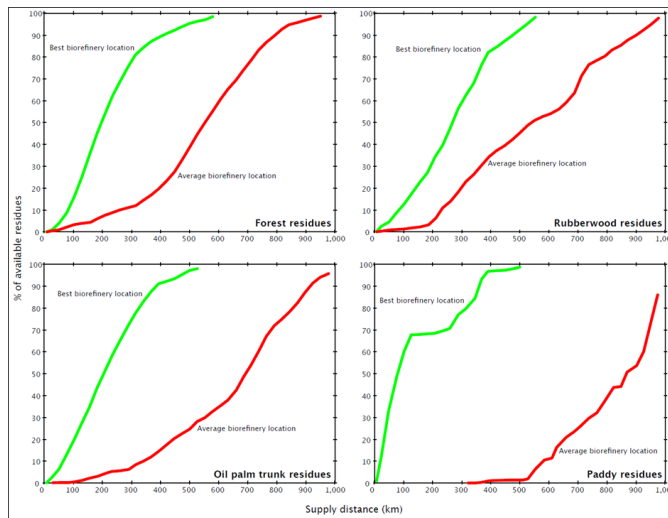
The geographical heterogeneity of biomass is illustrated in Figure C-19. Each type of biomass has different spatial structure varying on the level of centrality and dispersion. Depending of the point of mill location, the accessibility to a particular resource will differ greatly and will significantly impact the transportation cost. In each diagram, Location I can access more biomass areas with less distances compare to Location II. The more distances are required; the transportation cost would be incurred.



**Figure C- 18** Spatial structure of biomass resources (Rodrigue, 2013)

With Euclidean distance computation and taking into account the road network in Peninsular Malaysia, the accessibility to forest, palm oil, paddy and rubber are shown in Figure 2. In each graph, the best biorefinery location is the lowest cost location to access the particular biomass. Contrary, the average location will require higher cost to get less biomass compare to the best location. The best biorefinery location can access more numbers of biomass area with less distances. In case of forest and palm oil, their spatial structures follow the patterns in Figure C-19 (a) and (b) respectively. The accessibility curves of both show that the number of biomass area are reached at accelerating rate from point of origin before its climax. For paddy, its structure follows Figure C-19 (c). Its accessibility takes a terrace-like curve. The paddy area can be access at rapid rate for the first cluster and more distances are required prior to reach next clusters, as shown by the plateau before the subsequent slope. Lastly, the

spatial distribution of rubberwood residues is very scattered. Its accessibility graph always increases steeply, implying that every rubber area required a distinct amount of distances to reach.



**Figure C- 19** Accessibility to biomass from ideal locations and KLIA

The geographical variability of each biomass resources will affect its supply cost structure very differently. This suggests that the location factor has substantial impact on viability of biorefinery plant. It is vital to evaluate carefully the location to establish biofuel plant.

Source:

Adapted from Chu Lee Ong, Juliette Babin, Jia Tian Chena & Jean-Marc Roda. (2016) Designing model for biomass transport cost of biofuel refinery in Malaysia. Unpublished.

References:

Rodrigue, J.P., Comtois, C. and Slack, B., 2013. The geography of transport systems. Routledge. pp.191.

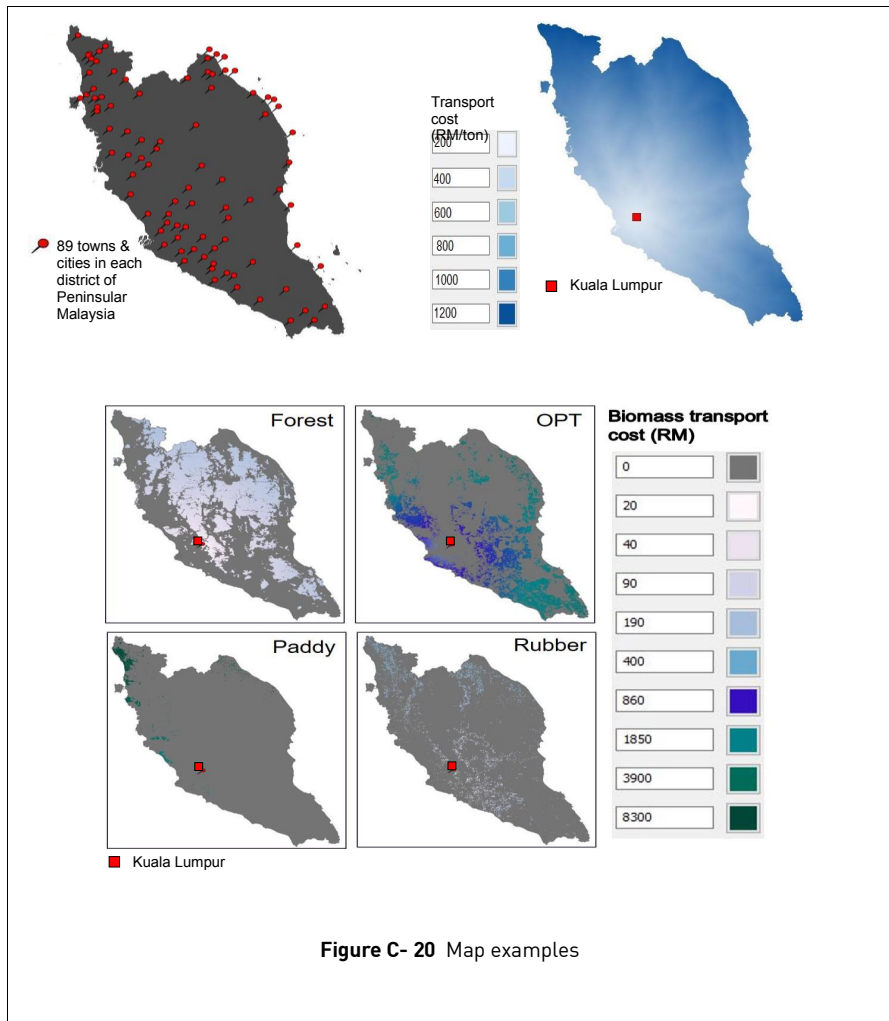


Figure C- 20 Map examples



## Appendix D

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ORIGINAL RESEARCH



# Quantifying the effect of landscape structure on transport costs for biorefinery of agricultural and forestry wastes in Malaysia

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### Abstract

In the context of climate change, sustainable biorefinery helps to mitigate carbon emissions. This paper examines how landscape structure metrics allow us to better understand the economics of agricultural and forestry wastes transportation. To verify that the landscape structure plays a significant role, we quantify the fragmentation of various lignocellulosic feedstock in Malaysia, as a typical tropical country. Fragmentation is compared with the variations of truck size, transport distance, and biomass nature. We use GRASS GIS to develop a series of transport cost maps, to quantify feedstocks, to run various biomass transport simulations, optimize locations of potential biorefineries, and to compute landscape structure metrics. We find that the cost of 1 million tonnes feedstock increases by more than 4 USD/tonne for every added unit of edge density (fragmentation index). It also increases by more than 6 USD/tonne for every added 100 km of average transportation. The average truck size has also a strong nonlinear relation to the cost with –84 USD/tonne when changing from 3- to 26-tonne trucks. To our knowledge, this is the first paper to address simultaneously fragmentation with the other classical logistic factors in a tropical country like Malaysia. It has strong implications for policymakers: the importance of the landscape structure makes a seemingly abundant biomass not viable for biorefineries if too fragmented compared to a much less abundant one, but more concentrated. It also implies that in tropical countries where the landscape is typically very fragmented, multi-crop feedstocks could be considered for sustainable biorefineries.

### KEYWORDS

bioenergy, biomass, biorefinery, feedstock, landscape fragmentation, lignocellulose, residues, supply cost, transport cost, wastes

## 1 | INTRODUCTION

Sustainable biofuels and alternative fuels and energies may help to fight climate change, by mitigating CO<sub>2</sub> emissions.

When based on agricultural and forest biomass, their economics depend on the landscape structure of the feedstocks. Logistics and transport costs are particularly important for the supply costs of bioenergy feedstocks. The industrial location of

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biorefineries, their size, and economies of scale are critical. For second-generation biofuels, lignocellulosic wastes may come from forests and fields or processing units. The sourcing strategy is then also a critical point. The economy of second-generation biofuels is therefore a multifactorial question. Since Graham et al. (1997) and until very recently (Lee, Hashim, Lim, & Taib, 2019; Morato, Vaezi, & Kumar, 2019), a lot of papers tackled a few factors together through modelling or optimization with GIS. Almost all papers discuss various concepts of transportation distance, feedstock yield, and feedstock density or bulk volume. Perpiñá et al. (2009) were the first to discuss also sourcing strategies from multiple feedstocks, and Singh, Panesar, and Sharma (2010) were the first to discuss truck size. Only Gan and Smith (2011) and Torquati, Marino, Venanzi, Porceddu, and Chiorri (2016) address the resource fragmentation, where a resource is scattered throughout the landscape, and into many fragments. Our paper is the first to address simultaneously all these factors and to attempt to quantify the respective influences of resource fragmentation, and classical logistic factors such as biorefinery mill location, truck size, multi or single feedstock sourcing, yield density, and transportation distance.

In all the literature, only a minority of papers also address the same questions in tropical conditions: India (Singh, Panesar, & Sharma, 2008; Singh et al., 2010), Brazil (Uslu, Faaij, & Bergman, 2008), Mozambique (van der Hilst & Faaij, 2012), Malaysia (Lee et al., 2019), and Bolivia (Morato et al., 2019). Tropical conditions are very important to consider for second-generation biofuels, because of the high primary productivity of the vegetation under these latitudes. Yet, many tropical landscapes are very fragmented, especially in Southeast Asia (Fritz et al., 2015; Lesiv et al., 2018; Samberg, Gerber, Ramankutty, Herrero, & West, 2016). Our paper is also the first to explore the question of the spatial fragmentation in a tropical context, and in Southeast Asia.

A few works explore biomass economics in Malaysia, especially regarding location optimization (Chen, Ong, & Babin, 2017; Salleh, Gunawan, Zulkarnain, Shamsuddin, & Abdullah, 2019; Shafie, Othman, & Hami, 2020). Tan et al. (2018) optimize the location in Malaysia with assumptions that follow an American technical report. A few others study the potential of Malaysia for biomass energy (Griffin, Michalek, Matthews, & Hassan, 2014; Ozturk et al., 2017; Suzuki, Tsuji, Shirai, Hassan, & Osaki, 2017). None of these papers explore the question of fragmentation.

## 2 | MATERIALS AND METHODS

Peninsular Malaysia is an example of Southeast Asia landscape, with an intricate mosaic of land uses, and contrasted elevations. It comprises 13 million hectares of landmass. We used GRASS GIS (GRASS Development Team, 2018;

Neteler, Bowman, Landa, & Metz, 2012) open-source software on a 64GB RAM and 12-core computing station. The workspace was a 10,870 by 10,822 cell raster, where a pixel is approximately 0.4 ha ( $63 \times 63$  m). We obtained the land use layers from the Department of Agriculture Malaysia (2010). Our work considers distances, quantities of biomass, landscape patterns, and costs. CO<sub>2</sub> emissions are not considered directly other than through transport distances and costs.

### 2.1 | Transport costs

We obtained the effective driving network from the Malaysia–Singapore association of drivers (Malsingmaps, 2015). Any location could be a candidate site for biorefineries. But we simplified the possibilities by narrowing to the vicinity of 89 capitals of Peninsular Malaysia districts. We computed 89 transportation distance maps to the potential biorefinery locations. We computed them with GRASS continuous cost surface procedure 'r.cost' (Greenberg, Rueda, Hestir, Santos, & Ustin, 2011). This procedure uses a 'friction' coefficient. On the paved road network, we calibrated it with the distances obtained from the Malaysia Singapore association of drivers. We used a different friction for the pixels outside the paved road. We calibrated it from 96 samples, where we measured the distance of real mud tracks with Google maps tools (Samimi, Rahimi, Amini, & Jamshidi, 2019). We then identified a statistical correlation between crow-flight distance and track distances. We derived the off-road friction coefficient from it, and we applied it for all off-road transports in the workspace (Table 1). We used another GRASS procedure 'r.mapcalc' (Mitasova et al., 1995) to apply Malaysian transport costs equations to the distance maps. These equations give the transport cost as a function of transportation distance and tonnage of the truck (Table 2; Roda et al., 2012) which we obtained the transport cost maps as illustrated by Figure 1. In Figure 1, the darker colour is farther and more expensive, but the heterogeneity of the transport network plays a role too; where there is no transportation network the colour is very dark, and where there are various roads, the colour is lighter.

### 2.2 | Feedstock quantification

We separated feedstocks into primary sources and secondary sources of lignocellulosic biomass (Seixas, 2008). The primary sources are the harvesting biomass potentially available on the field. These biomasses are forest logging wastes, rubberwood logging wastes, oil palm fronds (OPF), oil palm trunks (OPT), and rice straw. The secondary sources are processing residues potentially available at mills. These biomasses are rice husk, sawmill and plywood mill waste, empty

TABLE 1 Friction coefficients

Friction	Coefficient	SE	df	R <sup>2</sup>
Paved-road friction	0.07 km/pixel	0.0005	31	.9989
Off-road tortuosity	2.085 km of track/km of crow-flight	0.94	95	.8188
Off-road friction	2.085 × 0.07 = 0.145 km/pixel			

Note: The paved road friction is the ratio between the real-life road distance and the distance computed from the pixelized road. We computed this ratio with statistical correlation between the official road distance of Malaysia and our GIS workspace.

The off-road friction is the ratio between the real-life distances on off-road tracks and the crow-flight distance, computed from the pixel distances (knight's move algorithm). The ratio is obtained from a real sample of forest tracks where we measured the real tortuosity and real distances for 96 tracks.

TABLE 2 Trucking cost equation of four sizes in Peninsular Malaysia

Truck size (tonnes)	Transport cost linear equation
1	MYR/tonne = distance (km) × 1.88657771 + 132.004442
3	MYR/tonne = distance (km) × 0.672738734 + 69.0615618
10	MYR/tonne = distance (km) × 0.258860505 + 49.3286760
26	MYR/tonne = distance (km) × 0.193541212 + 39.5358461

Note: The linear equations are fitted from data collected from logistic companies in Malaysia.

Source: Roda et al. (2012).

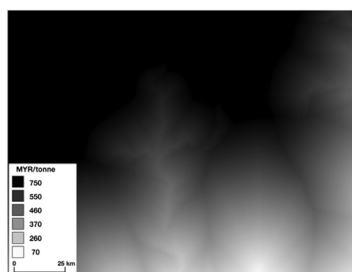


FIGURE 1 This illustrative raster shows what would be the cost to reach any pixel from a given point (here cost for 1-tonne truck)

fruit bunches (EFB), and palm pressed fibre (PPF). We used the quantities of biomass published for Peninsular Malaysia (Roda et al., 2015; see Table 3). To explore the quantities of feedstock available per area in a raster workspace, we created a variable 'biomass yield'. For the primary sources, the national average quantity per pixel was quantified. For the

TABLE 3 Biomass wastes availability in Peninsular Malaysia

Lignocellulosic biomass wastes	Total biomass availability <sup>a</sup>		Local biomass yield
	Min	Max	Tonne ha <sup>-1</sup> year <sup>-1</sup>
Primary sources			
Forest logging waste	1.83	2.65	0.44
Oil palm frond	7.12*		2.68
Oil palm trunk	17.80*		6.7
Rice straw	2.83	4.96	16.45
Rubberwood logging waste	0.20	0.70	0.64
Secondary sources			
Rice husk	0.51	0.67	65,555.56
Empty fruit bunch	9.40*		95,918.37
Palm pressed fibre	5.70*		58,163.27
Plywood mill waste	0.17	2.49	2,871.75
Saw mill waste	0.97	1.16	840.61

<sup>a</sup>Probable quantity.

<sup>b</sup>Source: Roda et al. (2015).

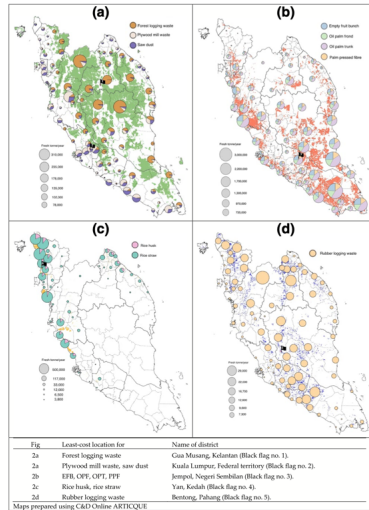
secondary sources, the same was applied into average quantity available per mill, or per pixel representing such mill. Table 4 shows the steps to derive these values. Malaysia is an equatorial country with limited seasonality. Except for rice which is harvested twice a year, all feedstocks are produced all year long. To simplify, we consider only annual production.

### 2.3 | Biomass transport simulation and least-cost location

Transportation of biomass was obtained through the multiplication of transport cost maps with waste density maps. This

**TABLE 4** Equations used to quantify biomass waste yield to tonne pixel<sup>-1</sup> year<sup>-1</sup>

	Equations	Unit
Step 1	Area per pixel = Total land use area of biomass/Total pixel cells of biomass	ha/pixel
Step 2	Average annual waste yield per hectare = Average of annual waste available/Total land use area of biomass	Tonne ha <sup>-1</sup> year <sup>-1</sup>
Step 3	Biomass availability = Average annual waste yield per area × Area of biomass per pixel	Tonne pixel <sup>-1</sup> year <sup>-1</sup>



**FIGURE 2** Land use, amount of biomass by districts, and least-cost locations in Peninsular Malaysia

procedure simulates the truck delivery of biomass contained in each pixel to the potential biorefinery location. Each pixel of the new map contained the biomass transport cost from that pixel to the biorefinery location in MYR/pixel. The sum of the values of each pixel under a given biomass category provides the total biomass transport cost to one specific location. With the GRASS procedure 'r.report' (Mitasova et al., 1995), the total biomass transport cost of each biomass to each district was computed. For each biomass, the district with the lowest total transport cost was identified as the best possible biorefinery mill location, and we named it 'least-cost location'. Several biomasses coming from the same crop (such as rice biomasses or palm biomasses) share the same least-cost location (Figure 2). We also created different sourcing

scenarios based on the least-cost locations as illustrated in the discussion.

## 2.4 | Data extraction and quantification of biomass transport cost

We created zonal maps based on general transport cost maps of each least-cost location using the GRASS procedure 'r.reclass' and each zone categorized by intervals of MYR50. The areas without biomass were nullified with the GRASS procedure 'r.null' and only areas with biomass were accounted. With the GRASS procedure 'r.univar' and the zonal map as inputs, we extracted the sum of biomass transport cost and the sum of biomass tonnage within each zone. These data were then calculated using Equation (1):

$$\text{Biomass supply cost}_{L,B} = \frac{\text{MYR}}{\text{fresh tonne}} = \sum_{z=1}^z \frac{\text{BTC}_z}{\text{Tonnage}_z} \quad (1)$$

where L denotes the location of the biorefinery, B denotes the types of biomass waste, z denotes the number of the zone, BTC denotes biomass transport cost of each zone and Tonnage denotes the amount of biomass waste in each zone.

The cost was converted from MYR into USD at the rate of 3.94 MYR/USD (Accountant General's Department of Malaysia, 2016). The marginal cost curves of the best potential mill location for each biomass category, using 1- and 26-tonne trucks, are established and used in the discussion.

## 2.5 | Landscape structure metric as spatial fragmentation index

The landscape structure is the arrangement of and relations between the parts or elements of the land mosaic, and can be described through landscape metrics. To investigate the linkages between spatial fragmentation and biomass transport cost, we needed to measure the spatial fragmentation (Rodrigue, Comtois, & Slack, 2013)

**TABLE 5** Equations of the selected landscape metrics

<p>Edge density = <math>\frac{\sum_k e_{ik}}{A}</math> (10,000) (2)</p>	<p><math>k</math> = patch type. It refers to the disjointed land areas (or patches) of a biomass category.  <math>n</math> = number of edge segments of patch type <math>k</math>. The edge segments are the pixels recognized as the border of the patches of a biomass category.  <math>e_{ik}</math> = total edge length (m) in landscape involving patch type <math>k</math>. For a biomass category, <math>k</math>, <math>e_{ik}</math> is the sum of edge length for all the patches of <math>k</math>.  <math>A</math> = total landscape area (m<sup>2</sup>). It refers to the land cover of the study area, in our case, Peninsular Malaysia.                      Unit: metres per hectare</p>
<p>Patch density = <math>\frac{N_{\text{patch}}}{A}</math> (3)</p>	<p><math>N_{\text{patch}}</math> = number of patches. It counts the total number of disjointed land area (or patches) for a biomass category.  <math>A</math> = sampling area size. This refers to our study area – Peninsular Malaysia.                      Units: Number of patches per square kilometre</p>
<p>Aggregation index = <math>\begin{cases} \frac{G_i - P_i}{1 - P_i} &amp; \text{for } G_i \geq P_i \\ \frac{G_i - P_i}{1 - P_i} &amp; \text{for } G_i &lt; P_i; P_i \geq 5 \\ \frac{G_i - P_i}{0 - P_i} &amp; \text{for } G_i &lt; P_i; P_i &lt; 5 \end{cases}</math> (4)                      with <math>G_i = \left( \frac{g_{ii}}{\sum_{k=1}^n g_{ik}} \right)</math></p>	<p>Procedure: double-count method ‘Clumpy’ from software ‘Fragstats 4.2’.  <math>g_{ii}</math> = number of like adjacencies (joins) between pixels of land cover type (class) <math>i</math>.  <math>g_{ik}</math> = number of adjacencies (joins) between pixels of land cover types (classes) <math>i</math> and <math>k</math>. (<math>k</math> = unlike cell adjacencies)                      Each pixel is referred as a function of its neighbours, with neighbour <math>i</math> being a pixel of land cover that belongs to the biomass category <math>i</math>, and neighbour <math>k</math> being a pixel of land cover that does not belong to the biomass category <math>i</math>.  <math>P_i</math> = proportion of the landscape occupied by land cover type (class) <math>i</math>. It is the number of pixels for land cover of the biomass category <math>i</math> divided by the number of pixels of the study area (Peninsular Malaysia).                      Range: <math>-1 \leq</math> Aggregation index <math>\leq 1</math>.</p>

Note: Interpretation: Edge density and Patch density: a higher value indicates a more fragmented spatial structure. Aggregation index: The value is expressed in dimension-less unit, from -1 to 1. -1 is the most disaggregated state where each patch is one isolated pixel, and 1 is the most aggregated state where there is only one patch grouping all pixels of a biomass category.

**TABLE 6** Spatial fragmentation metrics for biomass in Peninsular Malaysia

Category of wastes	Biomass wastes	Spatial fragmentation metrics		
		Edge density (m/ha)	Patch density (no. of patches per sq km)	Aggregation index (procedure ‘Clumpy’)
From the field	Forest logging wastes	3.2705	0.0064	0.9804
	Oil palm frond (OPF)	6.0825	0.0610	0.9434
	Oil palm trunk (OPT)	6.0825	0.0610	0.9434
	Rice straw	1.1346	0.0341	0.9243
From mills	Rubberwood logging wastes	11.7165	2.1068	0.6407
	Empty fruit bunch (EFB)	0.2822	0.0034	0.6722
	Palm pressed fibre (PPF)	0.2822	0.0034	0.6722
	EFB and PPF	0.2822	0.0034	0.6722
	Plywood and Saw mill	0.3425	0.0261	0.6757
	Plywood mill	0.2990	0.0097	0.6794
	Rice husk	0.2780	0.0018	0.7169
From both	Saw dust	0.3364	0.0240	0.6725
	OPF & OPT and EFB & PPF	6.0847	0.0618	0.9434
	Rice straw and husk	1.1349	0.0342	0.9243

of land cover for biomass waste in Peninsular Malaysia. Many landscape metrics exist (Cardille & Turner, 2017; Haines-Young & Chopping, 1996). Among these metrics, ‘edge density’, ‘patch density’, and the ‘aggregation index’ express various aspects of the spatial fragmentation, respectively, expressed by Equations (2), (3), and (4) in Table 5 (GRASS Development Team, 2019; McGarigal, Cushman, & Ene, 2012). The metrics for each biomass category was computed (see Table 6).

### 2.6 | Regression modelling and variables included

We performed a series of regression analyses to understand how to best describe biomass supply costs at any point of the country, according to different combinations (linear and nonlinear) of the factors. These factors are the transportation distance in km ( $\Delta$ ), the truck size in tonne ( $\theta$ ), the yield of wastes in tonne/ha ( $\xi$ ), the spatial fragmentation under the form of edge density of the feedstock in m/ha ( $\alpha$ ), or its patch density in number of patches/km<sup>2</sup> ( $\beta$ ), or its aggregation index ( $\gamma$ ), and also the categorical origin of the agricultural or forestry wastes ( $\omega$ ). In all, 19 models were analysed and compared (see Table 7). Their replicable equations are given in methodological annex (Annex A) under the form of R code. These 19 models are not predictive models which require validation. They are descriptive models meant to explore which structure and combination of variables best describe the observed biomass transportation cost in Peninsular Malaysia. The best way to assess these models is their Akaike information criterion (AIC) and their parsimony. However, in the future, other research should ideally validate the generality of their structures by exploring their behaviour in other countries.

### 3 | RESULTS

The first group of models (M1, M2, M3, M4a, M4b, M4c, M6a, M6b, and M6c) presents low adjusted coefficients of determination below 0.87, and relative standard errors above 22. None of them has simultaneously all the factors (distance, truck size, waste yield, fragmentation, and origin of wastes) in their structure. This suggests that all of these factors have their critical importance in the determination of the supply costs and should be included in the models.

The second group of models (M5, M7a, M7b, M7c, M8a, M8b, M8c, M9a, M9b, and M9c) presents higher coefficients of determination and lower relative standard errors. But a number of them are less robust, with non-significant parameters (M7a, M7b, M7c, and M8a), or with less significant parameters (M8b, M8c, M9b, and M9c), suggesting that their specific combinations of the factors are not the best representation of the reality.

The two best models are M5 and M9a. M9a = f(Distance, ln(Truck), Edge density, Waste origin) has the highest adjusted coefficient of determination and the lowest relative standard error among these 19 models. The model M5 has satisfying performances while not describing any aspect of the fragmentation factor: this could mean, according to the

TABLE 7 Model selection to describe biomass supply cost

Model	$\Delta$	$\theta$	$\ln(\theta)$	$\xi$	$\ln(\xi)$	$\alpha$	$\beta$	$\gamma$	$\omega$	Adj. R <sup>2</sup>	RSE	df	AIC
M1	$\Delta, \theta$	0	0							.641	36.95	1,218	12,274
M2	$\Delta, \ln(\theta)$	0	0							.667	35.60	1,218	12,183
M3	$\Delta, \ln(\theta), \xi$	0	0	0						.682	34.81	1,217	12,129
M4a	$\Delta, \ln(\theta), \alpha$	0	0			0				.698	33.89	1,217	12,063
M4b	$\Delta, \ln(\theta), \beta$	0	0				0			.677	35.08	1,217	12,148
M4c	$\Delta, \ln(\theta), \gamma$	0	0					0		.856	23.44	1,217	11,164
M5	$\Delta, \ln(\theta), \omega$	0	0						0	.896	19.86	1,215	10,762
M6a	$\Delta, \ln(\theta), \xi, \alpha$	0	0	0		0				.729	32.11	1,216	11,933
M6b	$\Delta, \ln(\theta), \xi, \beta$	0	0	0			0			.694	34.11	1,216	12,080
M6c	$\Delta, \ln(\theta), \xi, \gamma$	0	0	0				0		.865	22.69	1,216	11,085
M7a	$\Delta, \ln(\theta), \xi, \alpha, \omega$	0	0	ns		0			0	.898	19.70	1,213	10,744
M7b	$\Delta, \ln(\theta), \xi, \beta, \omega$	0	0	ns			0.001		0	.897	19.82	1,213	10,758
M7c	$\Delta, \ln(\theta), \xi, \gamma, \omega$	0	0	ns				0.01	0	.897	19.83	1,213	10,760
M8a	$\Delta, \ln(\theta), \ln(\xi), \alpha$	0	0		ns	0			0	.898	19.69	1,213	10,743
M8b	$\Delta, \ln(\theta), \ln(\xi), \beta$	0	0		0.005		0.01		0	.897	19.79	1,213	10,754
M8c	$\Delta, \ln(\theta), \ln(\xi), \gamma$	0	0		0.01			0.01	0	.897	19.80	1,213	10,756
M9a	$\Delta, \ln(\theta), \alpha, \omega$	0	0			0			0	.898	19.69	1,214	10,742
M9b	$\Delta, \ln(\theta), \beta, \omega$	0	0				0.001		0	.897	19.81	1,214	10,756
M9c	$\Delta, \ln(\theta), \gamma, \omega$	0	0					0.01	0	.897	19.83	1,214	10,759

Note:  $\Delta$ , distance;  $\theta$ , truck;  $\xi$ , biomass yield;  $\alpha$ , edge density;  $\beta$ , patch density;  $\gamma$ , aggregation index;  $\omega$ , waste origin; it is a categorical variable that either take the value of 'field', 'mill', or 'both'. ns, non-significant.

rule of parsimony, that this fragmentation factor is not needed to understand the structure of the costs. However, the AIC is lower in the case of M9a. This confirms that the fragmentation factor has critical importance too, and needs to be included and better understood. Thus, the model M9a describes best the structure of the biomass supply costs in Peninsular Malaysia. Table 8 provides its details and its reliability.

We find that the base supply cost is higher for the biomass wastes originating from the mills (69.67 USD/tonne) than for the wastes originating from the fields (63 USD/tonne). This could contradict the intuition because mills produce proportionally much more wastes per hectare. The fact that the mills are relatively small in average, and are scattered all over the territory, is the reason for the counterintuitive finding.

We find also that the fragmentation (edge density) of the resource is extremely costly: A 1 million hectare feedstock would see an increase of 4.16 USD/tonne for every added unit of edge density. With a similar edge density as paddy fields, the field size of such a feedstock would be of 950 ha in average and have a baseline supply cost of 67.16 USD/tonne.

**TABLE 8** Biomass supply cost as a function of transportation distance, truck size, fragmentation, and waste origin

Model M9a: USD/fresh tonne = $\Delta + \ln(\theta) + \alpha + \omega$				
Parameter	Coefficient estimate	SE	t value	Pr(> t )
$\Delta$ : Transportation distance	0.0678	0.002915	23.274	<2e-16***
$\ln(\theta)$ : $\ln(\text{truck size})$	-26.07	0.458950	-56.805	<2e-16***
$\alpha$ : Fragmentation (edge density)	1.066	0.228711	4.662	0.0000348***
$\omega$ : Waste origin_field	63.06	1.974433	31.937	<2e-16***
$\omega$ : Waste origin_mill	69.67	1.451147	48.009	<2e-16***
$\omega$ : Waste origin_both	62.35	2.027559	30.750	<2e-16***

Note: Residual SE: 19.69 on 1,214 df.

Multiple  $R^2$ : .8986, Adjusted  $R^2$ : .8981.

F statistic: 1,792 on 6 and 1,214 df,  $p < 2.2e-16$ .

Significance codes: \*\*\*0; \*\*0.001; \*0.01.

**TABLE 9** Biomass supply cost as a function of transportation distance, truck size, fragmentation, and biomass yield

Model M6a: USD/fresh tonne = $\Delta + \ln(\theta) + \alpha + \xi$				
Parameter	Coefficient estimate	SE	t value	Pr(> t )
$\Delta$ : Transportation distance	0.14624175	0.00376956	38.8	<2e-16***
$\ln(\theta)$ : $\ln(\text{truck size})$	-15.54994379	0.64271174	-24.19	<2e-16***
$\alpha$ : Fragmentation (edge density)	3.81978851	0.26104091	14.63	<2e-16***
$\xi$ : Biomass yield	0.00038155	0.00003234	11.8	<2e-16***

Note: Residual SE: 32.11 on 1,216 df.

Multiple  $R^2$ : .7299, Adjusted  $R^2$ : .729

F-statistic: 821.4 on 4 and 1,216 df,  $p < 2.2e-16$ .

Significance codes: \*\*\*0; \*\*0.001; \*0.01.

The same feedstock with an edge density similar to palm oil plantations would have field size of 26 ha in average, inducing a surplus of 20.8 USD/tonne for the supply cost. And with an edge density similar to rubber plantations, field size would be of 7.8 ha in average, inducing another surplus of 20.8 USD/tonne for the supply cost compared to oil palm plantations.

The supply cost also increases in average by 6.78 USD/tonne for every added 100 km of transportation distance. Conversely and compared to a 1-tonne truck, the supply cost logarithmically decreases according to the tonnage, with -36 USD for a 3-tonne truck, and with -84 USD for a 26-tonne truck.

The scattered nature of the mills increases the supply cost, despite the relatively high concentration of wastes in each mill. This unexpected finding raises the question of whether this model separates correctly the fragmentation from the biomass yield. The categorical variable 'waste origin' implicitly contains information on the concentration of biomass yield per hectare since the yields are immensely more concentrated in a mill than in fields. It also contains information on spatial fragmentation since most of the mills are scattered over the territory, which makes them



inherently a fragmented source of biomass. The examination of models M7a and M6a which differ from model M9a by only one variable, allows to clarify this point. Model 7a is the same as M9a plus a variable on describing the concentration of biomass yield per hectare. But this variable is not significant (see Table 7). In model M6a, the categorical waste origin is replaced by the biomass yield (see Table 9). It reinforces the apparent weight of the fragmentation, which is three times more influential on the cost structure. The truck size influence is lower but remains a crucial factor, and the influence of the transportation distance importance is more than double. The yield of biomass, although being significant, induces little supply cost variation. Altogether these results demonstrate that the categorical variable 'waste origin' encapsulates relatively few information on the concentration of yield per hectare, and more on fragmentation. However, the regimes of fragmentation of fields and mills are so different that they are not appropriately described by a single variable, as it is the case in model M6a. They are better described by the categorical variable 'waste origin'. The relationships of the fragmentation to the supply costs according to the origin of the wastes would probably yield interesting results with nonlinear models, but it is beyond the scope of this paper.

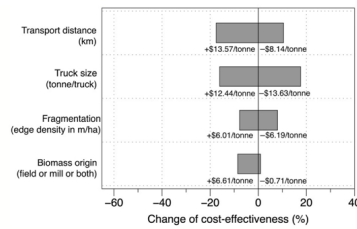
## 4 | DISCUSSION

### 4.1 | Respective impacts of supply cost factors

In a tropical country such as Malaysia, the biomass feedstocks are heterogeneous and fragmented. The increase in biomass supply cost with spatial fragmentation demonstrates that landscape structure can be as much critical for biorefinery economics, as transport distances are (Ghaffariyan, Acuna, & Brown, 2013; Reeb, Hays, Venditti, Gonzalez, & Kelley, 2014; Tahvanainen & Anttila, 2011; Vijay Ramamurthi, Cristina Fernandes, Sieverts Nielsen, & Pedro Nunes, 2014). Our results are the first to quantify the direct effect of landscape structure on the transport cost. The fragmentation amplifies the average transportation distance. This consequently amplifies nonlinearly the effects of the size of the fleet trucks. The respective impact of each factor can be measured with the model M9a, and can be visualized by comparing to a base scenario attainable for all feedstocks, of best and worst scenarios, in

Table 10 and Figure 3. The baseline scenario is set at 1 million tonnes of biomass supply because this quantity is commonly available from almost all Malaysian feedstocks. We assign to it the fragmentation of the most common feedstock (oil palm wastes). The most common trucks used for agriculture and biomass transport in West Malaysia are 3-tonne trucks. 26-tonne trucks are uncommon because this kind of trucks cannot reach most of the fields. The best truck scenario is set at 10-tonne truck and the worst with 1-tonne truck. The average distances are computed by GIS for the baseline, best and worst scenarios for 1 million tonnes of supply.

Among all the cost factors, the landscape fragmentation is a heritage of geography, history, and long-term agricultural policies. Biomass entrepreneurs cannot modify this fragmentation, but they can act on the truck size factor. For example, in the United States & EU, the trucks used for biomass are always above 20 tonnes (Laitila, Asikainen, & Ranta, 2016; Sosa & McDonnell, 2015; Teter et al., 2017). In Malaysia, 98.5% of businesses are very small (Department of Statistics Malaysia, 2017) and are extremely small if compared to European standards (Gonzales, Hommes, & Mirmulstein, 2019). In general, 48% of truck traffics are light-weighted truck, 33% and 19% are medium and heavy-weighted truck respectively (see Table 11; Ministry of Transport Malaysia, 2019). In the agriculture and forestry sector, the most common trucks are 1-tonne trucks, while 10- to 12-tonne trucks were used only by big mills (Roda et al., 2015).



**FIGURE 3** Impact of the main biomass supply cost factors in Peninsular Malaysia. The baseline scenario is centred at 0%. The cost-effectiveness increases when biomass supply costs decrease

Parameter	Unit	Scenarios		
		Best	Baseline	Worst
Transport distance	km	180	300	500
Truck size	tonne	10	3	1
Fragmentation (edge density)	m/ha	11.7165	6.0825	0.278
Biomass origin	categories	62.347859	63.056592	69.66853

**TABLE 10** Supply scenarios in Peninsular Malaysia



**TABLE 11** Five-year average (2013–2017) of truck traffic composition at 14 selected stations

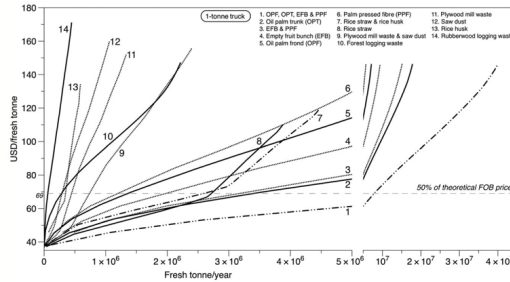
Light truck	Medium truck	Heavy truck
Below 2 tonnes	2–10 tonnes	Above 10 tonnes
48	33	19

Source: Ministry of Transport Malaysia (2019).

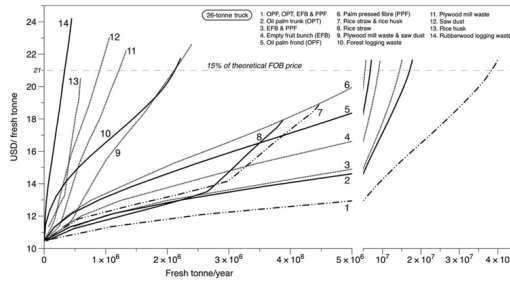
**4.2 | International competitiveness of Malaysian biomass**

One criterion to assess the feasibility of any industry willing to use Malaysian biomass would be to compare its local cost with the price or cost of biomass available on the international market. For example, we can compare with the feedstock biomass costs in the United States or the densified biomass costs exported by the United States on the international market, Free On Board cost (U.S. Energy Information Administration, 2020). We estimated a theoretical fresh biomass FOB price based on Mani, Sokhansanj, and Turhollow (2006) and Mani (2005) as a benchmark for ‘theoretical FOB price’ (FOB export cost – densification cost).

Compared to the marginal cost curves of the best potential mill location for each biomass category (Figures 4 and 5; Annex B), this kind of competitiveness benchmark discriminates three groups of Malaysian feedstocks. These groups are critical for the scale of the possible biorefineries, and for the choice of biofuel technologies. Wastes from plywood and sawmills, forest logging, plywood mills, rubberwood logging, sawdust, and rice husk belong to the first group. They could only supply much less than 1 million fresh tonne/year at 50% of the international benchmark if transported with 1-tonne trucks (Figure 4). However, they could supply the total of their available wastes if transported with 26-tonne trucks (Figure 5). In the case of the forest logging wastes, 26-tonne trucks access to most of the forest tracks is hypothetical in actual Malaysian logistic conditions. The second group is much more competitive. These wastes are OPT, EFB, OPF, PPF, EFB + PPF, rice straw, and rice straw + rice husk. They could supply from 1.2 to 3.5 million fresh tonnes/year at 50% of the international benchmark with 1-tonne trucks (Figure 4), and from 5.4 to 17 million fresh tonnes/year at 15% of the international benchmark with 26-tonne trucks (Figure 5). The third



**FIGURE 4** Marginal supply cost curves of Malaysian fresh feedstocks: 1-tonne truck, with international benchmark



**FIGURE 5** Marginal supply cost curves of Malaysian fresh feedstocks: 26-tonne truck, with international benchmark

group, the simultaneous collection of all lignocellulosic wastes from oil palm plantation or oil palm mills, is extremely competitive. It can supply 8.2 million fresh tonnes/year at 50% of the international benchmark with 1-tonne trucks (about 20% of Malaysian oil palm wastes, Figure 4), and 38 million fresh tonnes/year at 15% of the international benchmark with 26-tonne trucks (about 97% of Malaysian oil palm wastes Figure 5). The specificity of this third group is that it mixes wastes from the fields and wastes from the mills. It implies that the mills could be used as collection and pre-treatment point since they are already the collection points of the Fresh Fruit Bunches. In these conditions, nothing would prevent to add pre-treatment stages to dry and densify the biomass prior to further transportation.

#### 4.3 | Feasibility of consolidation, collection, and pre-treatment of the biomass

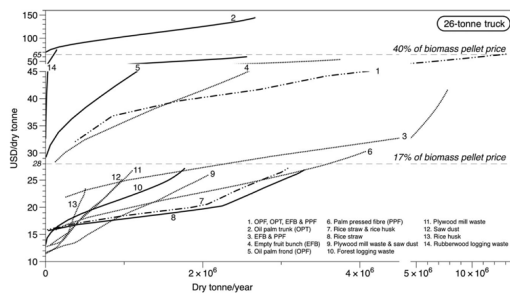
In the hot and humid Malaysian weather, the actual practice is to transport quickly the biomass in fresh matter, to avoid microbial degradation (Chico-Santamarta et al., 2011; Hess, Wright, & Kenney, 2007; Larson et al., 2015; Rentizelas, Tolis, & Tatsiopoulos, 2009; Salètes, Caliman, & Raham, 2004). The low bulk density and the high moisture content (see Annex C) of most of the biomass reduce the profitability of feedstock transportation. Since 26-tonne trucks cannot access many of the tracks within the field (Roda et al., 2015; Shafie, Masjuki, & Mahlia, 2014; Yusoff, 2019), collection points would be needed for their large-scale use. The exact cost of such facilities is beyond the scope of the present paper, but an approximation of their supply cost can be assessed against international benchmarks (we omit the densification cost in Malaysia). We use international FOB biomass pellet prices (USD162/tonne; U.S. Energy Information Administration, 2020) as a benchmark for the supply of dry feedstocks. We consider only the transportation by 26-tonne

trucks that would make sense with densification facilities. Three different dry feedstocks emerge (see Figure 6). OPT and rubberwood logging wastes which the fresh feedstocks with the highest water content (Annex C). They form the first group with either very little dry matter available or most of it above 40% of the international FOB price for pellets. The other oil palm wastes except for PPF (and OPT) form the second group, with most or all of their dry feedstock above 17% of the international benchmark.

All the remaining wastes form the third group, with 100% (or almost) of the dry feedstock below 17% of the international benchmark. The most remarkable and the cheapest among them are the wastes from plywood and sawmills (0.2–0.8 million dry tonnes/year), and rice straw (0.8–3.3 million dry tonnes/year).

#### 4.4 | Policy implications

Altogether, these considerations have strong implications for policymakers: the importance of the landscape structure may make a seemingly abundant biomass not viable for biorefineries if too fragmented, while a much less abundant one, but more concentrated may be viable. This first implies that with proper supply chain management and location optimization, Peninsular Malaysia biomass could supply a competitive bio-fuel industry. There are enough quantities to sustain small or medium mono-feedstock industries if their location is carefully chosen. This also means that biomass studies in Malaysia and countries with similar conditions should consider the design and location of collection consolidation and pre-processing, and hubs to connect small and medium stakeholders with bigger ones. The overall results of this study have also shown that large multi-feedstock industries can be economically viable. This means that in Malaysia and other tropical countries where the landscape is typically very fragmented, multi-crop feedstocks could be considered for sustainable biorefineries. It



**FIGURE 6** Marginal supply cost curves of Malaysian dry feedstocks: 26-tonne truck, with international benchmark

poses new technological and economic implications, but these are beyond the scope of the present paper.

## 5 | CONCLUSION

Fragmentation of the landscape is costly in tropical countries with complex mosaics of land uses, such as Malaysia. The feedstock cost increases by more than 4 USD/tonne for every added unit of edge density. In comparison, it increases by more than 6 USD/tonne, but by every 100 km of added average transport distance. These natural drawbacks could be offset by organizing better logistic chains. From a fleet of 1-tonne trucks, the cost decreases by –36 USD/tonne if using 3-tonne trucks, and down to –84 USD/tonne if using 26-tonne trucks. But most of the biorefinery technologies and solutions for agricultural and forestry wastes were developed in the rather uniform plains of North Europe and North America. Our results mean that these technologies and solutions cannot be just transferred to tropical countries with complex landscape mosaics. We demonstrated here how the landscape structure, through the concept of fragmentation, is a major determinant of biomass economics under the tropics. For policymakers, counterintuitive situations may arise, such as seemingly abundant biomasses may be less profitable if too fragmented while much less abundant but more concentrated biomasses may be more efficient. There may be other situations where multi-crop biomass strategies are more profitable than relying on too fragmented feedstocks. The concept of landscape fragmentation has been mostly used in ecology, for edge effects and other phenomenon. But our results suggest that fragmentation of the landscape probably influences the economics of many activities dealing with agriculture and forest resources, too. Methodologically, it would be interesting to develop fragmentation metrics specifically designed to capture economic aspects. Conceptually, it would also be interesting to explore how multifactorial dynamics, such as deforestation, are linked to pre-existing fragmentation and change it.

## ACKNOWLEDGEMENT

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## AUTHORS' CONTRIBUTIONS

C.O. and G.D. designed, planned and carried out the GIS model and simulation. J.-E.H. designed template for data extraction and collation. C.O. and J.-M.R. performed the statistical modelling, analytic calculations, interpretation of the results and co-wrote the manuscript. J.-E.H., M.O.S.H., N.K., A.R.A., and A.N.A.M. provided feedback and helped shape

the research, analysis, and manuscript. J.-M.R. conceived the original idea, verified the models and simulations, and was in charge of overall direction and planning.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in CIRAD Dataverse at <https://dataverse.cirad.fr/dataset.xhtml?persistentId=doi:10.18167/DVN1/IQO4L6>.

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#### SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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Prior her completion of Master Science degree in Economics at UPM, she had worked in several industries encompassing manufacturing, banking, tertiary education and government agency. She had gained experiences in supply chain management, sales and marketing, training and teaching. During her time as a graduate student studying subject areas within Bioresource Management at Institute of Tropical Forestry and Forest Products, UPM; she had further equipped her research expertise encompassing economic evaluation, statistical modelling, data visualization, spatial and GIS analysis in the field of resource and environmental economics, resource and logistics management and quantitative economics.

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