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A REVIEW OF THE APPLICATION OF GIS IN BIOMASS AND SOLID WASTE SUPPLY CHAIN OPTIMIZATION: GAPS AND OPPORTUNITIES FOR DEVELOPING NATIONS

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ABSTRACT

The application of Geographical Information Systems (GIS) enhanced modelling techniques in biomass and solid waste supply chain problems is hinged on a common denominator for both systems: the spatial distribution of supply points and variability of resource quantities. Since the sustainability of bioenergy or waste-to-energy projects around these resources will be affected significantly by the cost of supplying them, it is important to optimize decisions around facility location, size and transport routes. GIS is an important tool that can be used to capture the spatial and temporal dynamics of the biomass and waste. It can then be used alone or integrated with other software tools, for strategic and tactical level optimization of biomass and solid waste supply chains. In as much as a lot of progress has been made globally in research and application of GIS enhanced modelling techniques in biomass and solid waste supply chains, developing nations have trailed behind. This explains why spatial and temporal waste or biomass statistics are not readily available in these areas. This paper reviews recent developments in the application of GIS in biomass and solid waste supply chain models, with the ultimate objective of identifying the gaps and opportunities that exist. It is especially biased towards the use of the biomass and waste in renewable or waste to energy schemes- a fast growing field within the green economy.

1. INTRODUCTION

1.1 General background: Waste to energy and bioenergy systems

Waste to energy (WtE) and biomass to bioenergy (BtB) are both significant highlights within global green economy schemes, representing the use of 'renewable' waste and biomass (Kennes, et al., 2016; Vlachos et al., 2008). Recent green initiatives are hinged on the fact that these two resources can be an invaluable substitution for fossil based fuels both in the power and fuels industries since both can be converted into fuels, heat and power using various technologies (Batidzirai et al., 2012; Nkosi & Muzenda, 2014; Pantaleo & Shah, 2013; Pilusa & Muzenda, 2014; Sobrino et al., 2011). Biomass can be thermally or biochemically converted into renewable biofuels, while selected fractions of Municipal Solid Waste (MSW) like tyres, rubber and plastics can also be thermo chemically converted into heavy oils and fuels (Pilusa & Muzenda, 2014; Pradhan & Mbohwa, 2014). Due to the rising awareness and advocacy for a green economy, both fields have registered a significant growth in the past decade. The global Waste to Energy (WtE) market was valued at US$25.32 billion in 2013, having grown by 5.5% from 2012. It has then been projected to grow by a Compound Annual Growth Rate (CAGR) of over 5.5% from 2016, reaching a value of US$40 billion by 2023 (World Energy Council, 2016). The BtB industry is also growing with the follow segmented CAGR projections: 44% for advanced biofuels from 2017-2021; 9.6% for all biofuels (2013-2019); 7% and 8.1% for biomass power generation and biodiesel respectively in 2018 (Sapp, 2014a, 2014b, 2017). The main, common drivers for both are the global lookout to increase Renewable energy sources (RES), rising environmental consciousness, the advent of circular economies, government policies and support through grants, tax credits, incentives and special loans (Sapp, 2017; World Energy Council, 2016).

A significant fraction of the biomass available for energy exploitation is essentially waste- especially agricultural and forestry residues- which then form an intersection with solid waste (SW) (Iakovou et al., 2010). In such WtE ventures, the green economy value is double pronged: comprising

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ameliorating the environmental problem of the waste and deriving useful energy products from it (Pilusa & Muzenda, 2014). According to Gasparatos et al. (2015), the weight of each of these value propositions varies from developing to developed nations; with the latter according a significant weight to climatic and environmental issues, while the former are more interested in socio-economics (Gasparatos et al., 2015). According to Maslow's hierarchy, this is perfectly normal, since developing nations have to meet pressing subsistence needs before thriving for safety and environmental issues (Yawson et al., 2009). Indeed, the potential socio-economic benefits for such WtE or bioenergy ventures can be significant, spanning increased economic development (more income and tax revenues), employment creation, increased national energy security, alternative & cleaner fuels and alleviation of energy poverty in remote/rural communities (Ji & Long, 2016). In light of such potential benefits, optimized management and utilization of MSW and biomass could help developing nations derive more value from these abundant resources in them, tackling both socio-economic and ecological issues in significant ways.

1.2 WtE and BtB supply chain dynamics

Due to the spatial distribution of supply points and variability of quantities for both biomass and SW resources, one of the critical decisions to be made would be site locations and optimal transportation routes (Chalkias & Lasaridi, 2009; Kinoshita et al., 2009; Shi et al., 2008). Beyond the common applications for both resources in renewable energy, an interesting fact to note is the similarity of the supply chain systems around the two feed stocks. A number of authors have concurred that the two major constraints that hamper widespread uptake and dissemination of WtE and bioenergy projects are cost (a function of technical complexities, especially in the conversion technology) and the feedstock supply chain (SC) dynamics (Amundson et al., 2015; Batidzirai et al., 2012; Iakovou et al., 2010; Vlachos et al., 2008). Even though the feed stocks can be cheap, as in the case of MSW, agriculture and forest residues, the total cost for the feedstock supply significantly contributes towards high production costs; ranging from 40-70% (IRENA, 2016; Ji & Long, 2016). This is due to the low energy density of biomass and MSW, the spatial distribution of supply points and variability of resource quantities at those points compared to fossil fuels (Amundson et al., 2015; Iakovou et al., 2010). The sustainability of bioenergy or WtE projects around these resources is therefore affected significantly by the cost of supplying them, making the optimization of supply chain factors like facility location, size and transport routes important considerations (Iakovou et al., 2010). In waste management, the WtE facility can be a direct replacement of landfills, where demographic patterns begin to influence the location of the site, or can be based on the landfills available.

1.3 Methodology

This study examines the growing opportunity for GIS application in SW and biomass WtE supply chains for developing regions, keeping the trends in developed regions in perspective. Africa presents itself as an interesting focus case for developing nations by combining high population growth and MSW generation with slow technology (GIS) uptake and low biomass waste utilization (Abarca et el., 2013; Nwosu & Pepple, 2016; Pradhan & Mbohwa, 2014). The specific countries in Africa were then picked based on availability of research reports around GIS applications for bio-energy or MSW waste and they should categorized among the developing countries (Fantom & Serajuddin, 2016). A couple of successful applications from developed nations were also picked in order to draw out a parallels compared to developing regions. Using this criteria, a total of eight studies (four for each case) were carried out in detail. References are made however, briefly to other relevant studies.

The main method used in obtaining data was a desktop survey using google search engines and mainly targeting peer reviewed scholarly articles. To stream line the search, phrases containing 'GIS' along with 'biomass', 'bio-energy' or 'MSW waste' were formulated. The study however, excludes solid sewage waste from both biomass and MSW wastes. The review timeframe is from 2001 to 2018, capturing both historical and state-of-the art trends in the application of GIS.

2. GLOBAL VIEW OF THE APPLICATION OF SC OPTIMIZATION IN BIOMASS AND WTE VENTURES

The complexities associated with the design and planning of bioenergy and WtE SCs have emanated from the associated high costs of handling per unit energy, seasonal and uncertain nature of feedstock supplies, variability of feedstock locations and other factors (Iakovou et al., 2010). These and other reasons have made it imperative to optimize these SCs, with various objectives such as maximizing conversion throughput, maximizing social returns like employment, minimizing GHG emissions and minimizing costs. Despite an equally compelling case for research around feedstock supply chain dynamics and costs, most research has focused on the conversion technologies (Paolucci et al., 2016). There has, however, been a recent upsurge in research around bioenergy and WtE SCs, though the initial focus was the assessment of potential resource volumes, allocation of collection sites and location of production facilities (Iakovou et al., 2010). In MSW management particularly, the initial focus was transport routes for waste and location of landfills rather than energy conversion facilities (Nwosu & Pepple, 2016). However, SC optimization has increasingly been covering a broader scope owing to recent advances in computational tools, subsequent improvements in mathematical models and the realization recent awakening to SC logistic issues as a major bottleneck in most bioenergy and WtE projects, (Ba et al., 2016; Hadidi & Omer, 2017; Pantaleo & Shah, 2013). Still, more research is required to ascertain the viability of bioenergy and WtE projects through SC optimization. Such research outputs could contribute to a significant reduction in the cost of the integrated bioenergy system (Gold & Seuring, 2011; Hombach et al., 2016; Iakovou et al., 2010).

SC optimization literature has generally concurred that supply chain complexities have to be addressed at 3 decision levels: strategic, tactical and operational (De Meyer et al., 2014; Iakovou et al., 2010), (Awudu & Zhang, 2012). These are defined in Table 1, along with the activities normally tagged along these levels.

A number of studies have looked into SC optimization at the different levels demonstrated in table 1. Most of the researches take a Multicriteria decision analysis (MCDA) approach based on many hierarchical attributes or objectives, often conflicting, which are analyzed mathematically to obtain an optimal choice (De Meyer et al., 2014).

In principle, the entire supply chain comprises the production, harvesting or collection of biomass or MSW; transportation; pre-treatment; storage; subsequent conversion to bioenergy (heat, power or fuels) and supply to markets (Ba et al., 2016). Consequently, the other important factor in the SC optimization studies is the part of the supply chain they focus on, as shown in Figure 1. The upstream process includes the generation, pre-treatment and delivery of MSW or biomass in the appropriate form to the conversion facility. The midstream SC covers the bioenergy or WtE conversion facility, while the downstream SC concerns the supply and distribution of the bio-product (heat, power or fuels) to the market (Ba et al., 2016).

Though there has been a push towards integrated SC optimization models that span all the stages and variables within the whole chain to maximize or minimize certain objectives, such models could be complex, requiring a multi-disciplinary approach (Amundson et al., 2015; Nogueira et al., 2017). The conventional practice therefore, has been to separately optimize the upstream and midstream parts, since they jointly represent the largest fraction of costs incurred in the whole SC (Amundson et al., 2015; Batidzirai et al., 2012; Iakovou et al., 2010; Vlachos et al., 2008). The upstream SC optimization is mostly an operations research problem, while the midstream is largely process engineering and associated unit operations.

3. THE ROLE OF GIS MODELLING IN SC OPTIMIZATION

3.1 GIS and its functionalities in the context of SW and biomass supply chains

Recent technological advances in computational tools have presented GIS as an innovative and versatile tool in both SW management and biomass SCs (Hadidi & Omer, 2017; Sufiyan et al., 2015). Consequently, there has been a significant increase in the use of desktop GIS in the last few decades, encouraged by the expansion of PC capabilities and reduction in cost of using them. GIS software vendors have, since, been redesigning their packages to conform to global trends and demands- one such being the green economy (Nwosu & Pepple, 2016).

GIS is a sophisticated modern technology used for capturing, storing, displaying, analyzing and manipulating spatial data (Chalkias & Lasaridi, 2011). One key advantage of the platform is that it can combine the spatial datasets with non-spatial quantitative or qualitative data including quality and quantity of the resource, vector and raster data from satellite imagery, digital elevation model data, topographic data and operational environment. The data is then arranged into thematic layers represented by digital maps (Chalkias & Lasaridi, 2009). Quinta-Nova et al. (2017) applaud GIS's embedded capability to provide a Multi Criteria Decision Analysis (MCDA) support based on spatial criteria (Quinta-Nova et al., 2017). In this case, a set of environmental, economic and social criteria is defined, ranked and weighted, either using some logic system or the Analytic Hierarchy Process. (Quinta-Nova et al., 2017) The GIS can then select optimal sites for conversion or landfill sites using the ranked suitability criteria. For both biomass and SW management, objectives usually include minimizing distance, cost of transporting waste or biomass and GHG emissions, while other site related criteria like topography and legal requirements would also need to be factored in (Chalkias & Lasaridi, 2011; Eason & Cremaschi, 2014; You, Graziano, & Snyder, 2012). In some cases, only socio-economic objectives are incorporated to obtain a wide array of potential sites, then some are eliminated based on other logical and legal criteria. Essentially, a GIS model not only acts as a digital data bank for spatial characteristics (e.g. quantities) of waste or biomass, but can manipulate that data at reduced time and cost to give best location and alternatives for processing or storage facility (Sufiyan et al., 2015). Figure 2 exemplifies a stage wise approach to a GIS optimal site selection problem.

In a number of cases, the GIS is integrated with simulation or optimization tools and can either be embedded in the overall program or be a precursor to predetermine the best candidate sites for subsequent SC optimization

TABLE 1: SC decision levels (Charis, Danha, & Muzenda, 2018).

Decision level	Strategic	Tactical	Operational
Description	Long term and usually investment intensive decisions that can be revised after several years.	Address medium term decisions (usually between 6months to 1 year) using guidelines provided by strategic decisions	Address short term decisions (weekly, daily and hourly)
Decision spheres and variables	Conversion facilities- size and technology to be used; biomass supply network design & configuration; facility location; sourcing and procurement (including supply contracts);	Inventory planning & control: How much to harvest/collect and store; selection, timing and place of treatment technology. Fleet management: transport mode, shipment size, routing & scheduling, outsourcing options.	Inventory planning & control: Daily inventory control and planning. Fleet management: vehicle planning and scheduling
Literature	(De Meyer et al., 2014; Iakovou et al., 2010) (Tembo et al., 2018)	(De Meyer et al., 2014; Iakovou et al., 2010) (Awudu & Zhang, 2012)	(De Meyer et al., 2014; Iakovou et al., 2010) (Awudu & Zhang, 2012)

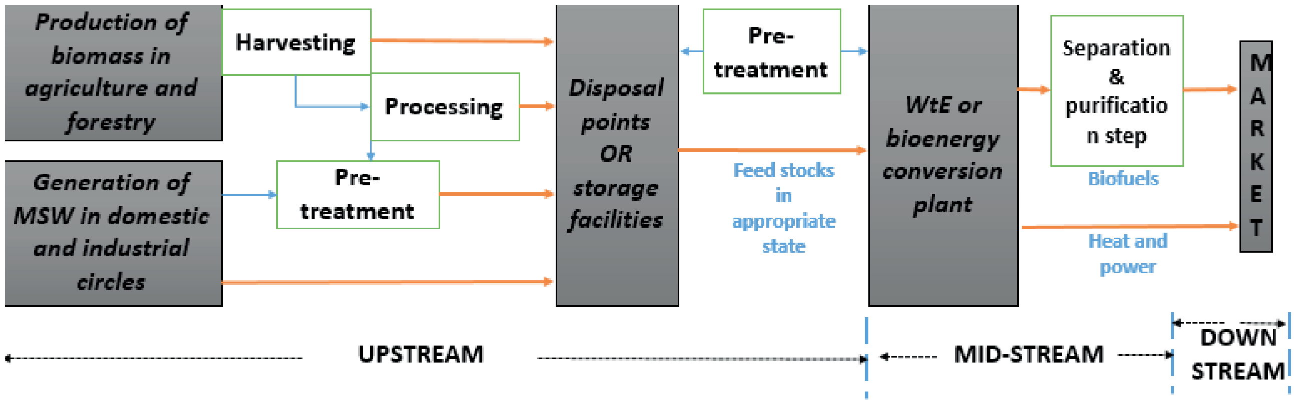

FIGURE 1: WtE and biomass supply chains. Colour filled blocks represent major operation nodes while unfilled blocks represent minor operations. Arrows denote possible transport links.

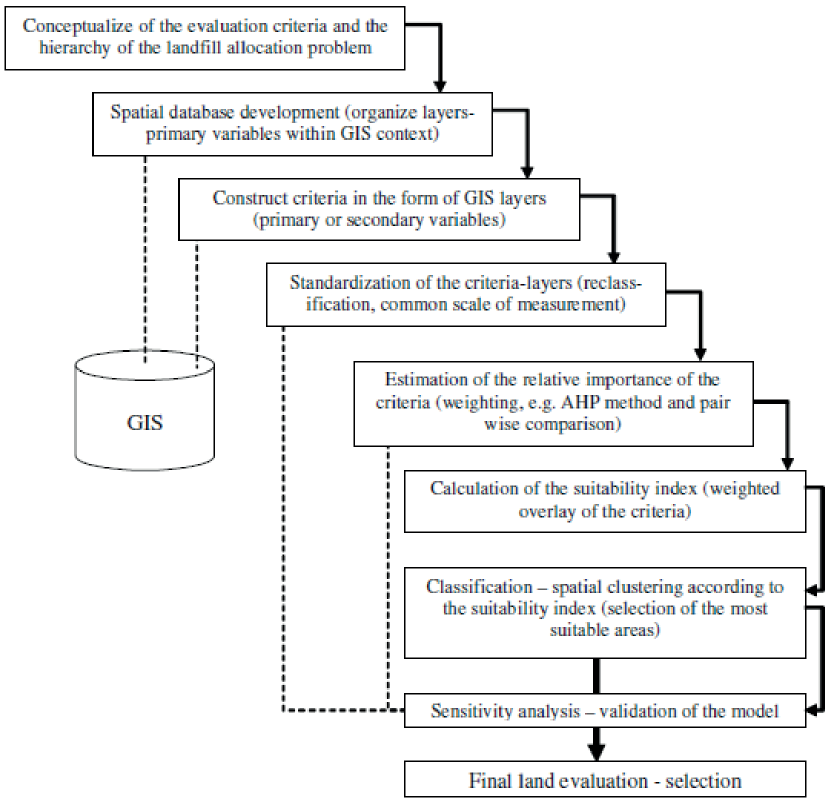

FIGURE 2: Application of GIS for site selection for landfill (also applicable to WtE and bioenergy facilities) (Chalkias & Lasaridi, 2011).

(He-Lambert et al., 2018; Tan et al., 2014; Woo et al., 2018; Zhang et al., 2016).

A review of the use of GIS in routing optimization shows that this application is more prevalent in SW collection and transport problems rather than biomass SCs (Ahmed, 2006). This is due to the weight placed on collection and transport in SW management as a tactical and operational problem; whereas the bioenergy system (most which are at planning stage), have a bias towards the strategic problem of facility sizing and conversion site selection (Ba et al., 2016; Prins et al., 2015; Shi et al., 2008). Moreover, biomass sites are often in remote spaces where routes are not so many, defeating the purpose of 'route optimization'. With the advent of the green economy, it is also likely that SW management problems will gravitate from the conventional landfill site selection and routing problems to also cover supply chain optimization for WtE plants.

Another interesting point is that the both site and route optimization problems can use tools like ArcGIS, Google Earth, Geographical Positioning Systems (GPS) and Google map for collection of spatial data (Ahmed et al., 2016; Sufiyan et al., 2015). For routing optimization like waste transport and collection it is more imperative to then use ArcGIS Network Analyst or a similar tool like GIS router to analyze and optimize the optimum route. In this case, there is need to supply the road network spatial data for the study area (Chalkias & Lasaridi, 2009). Chalkias & Lasaridi (2009) explain that Network Analyst is an improved optimal path finding algorithm from the classic Dijkstra's algorithm 'which solves the problem of optimal route selection on an undirected, non-negative weighted graph in a reasonable computational time' (Chalkias & Lasaridi, 2009). They present the data flow diagram of their methodology (Figure 3).

3.2 Findings on GIS Applications in MSW and biomass SC optimization

3.2.1 MSW management

Chalkias & Lasaridi (2011) presented a short literature review of two common optimization problems in SW management: Landfill/dumping site optimal location and route optimization. They highlighted that optimal site location of a landfill (applies to a bioenergy or WtE site) is complex, requiring consideration of various technical, environmental, legal and socio-economic constraints (Chalkias & Lasaridi, 2011).Tan et al. (2014) reiterated the increasing complexity and cost of MSW management, especially given the rapid socio-economic development and increased volumes of waste (Tan et al., 2014). Nwosu and Pepple (2016) added that the involvement of so many parameters make the empirical process of selecting such sites complicated, costly and time consuming (Nwosu & Pepple, 2016). The weight of factors to be considered for bioenergy & WtE sites could be similar, however, they may contrast with traditional landfill sites since the latter span more environmental and socio-economic constraints. In their review, Chalkias & Lasaridi (2011) highlighted that in the landfill site evaluation problems in the last few years have used combinations of GIS with fuzzy systems, multicriteria decision analysis (also embedded within GIS suite), analytic hierarchy process and factor spatial analysis, among other integrations (Chalkias & Lasaridi, 2011). Such a flexibility of GIS for integrations, enabling comprehensive spatial analyses, is a major advantage of GIS. Recent GIS applications for both bioenergy/WtE and landfill selections, however, use a 'suitability index' to rank the most suitable sites, rather than binary outputs that would result from the above integrations (Celli et al., 2008; Chalkias & Lasaridi, 2011; Panichelli & Gnansounou, 2008; Voivontas et al., 2001).

Nwosu and Pepple (2016) looked into site selection criteria that meets stipulated standards for dumping sites that includes socio-economics, physical characteristics, and land-use factors in Nigeria (Nwosu & Pepple, 2016). They initially built a spatial database using datasets including road network, topography & geology, GPS co-ordinates for current solid waste dumpsites, land use, water bodies and soil profile of study area. Ultimately, they carried out a spatial analysis using ArcGIS Network Analyst, spanning slope, Euclidean distance, reclassification and weighted overlay analysis. They used the Suitability Analysis Model Builder to identify optimal dumping sites (Nwosu & Pepple, 2016).

Sufiyan et al. (2015) developed a GIS database to monitor trends towards generation and disposal of waste, including preferred dump sites in Nigeria (Sufiyan et al., 2015). The database was meant to inform planning processes in collecting such wastes to reduce aesthetic pollution and curb potential environmental health & pollution problems associated with disposal and burning of the waste. Sufiyan et al. (2015) and Nwosu & Pepple (2016) argued that SW waste accumulation in undesignated places is an acute problem in developing countries due to continued urbanization and the associated increase in consumption and production patterns (Nwosu & Pepple, 2016; Sufiyan et al., 2015). Moreover, the proportion of MSW that has to be disposed is higher in these developing countries due to low recycling and reuse capabilities (Nhubu et al., 2017; Nwosu & Pepple, 2016). As a result, local authorities have not been able to keep up with the disposal of such huge waste volumes, especially in densely populated areas (Ahmed, 2006). Sufiyan et al. (2015) then recommended the use of GIS to determine the spatial & temporal quantities of major illegal dumpsites dotted around such areas them to help in planning, prioritization and mobilizing private and public partnerships in the collection of the SW (Sufiyan et al., 2015).

Tan et al. (2014) synthesized a model that 'preferential-

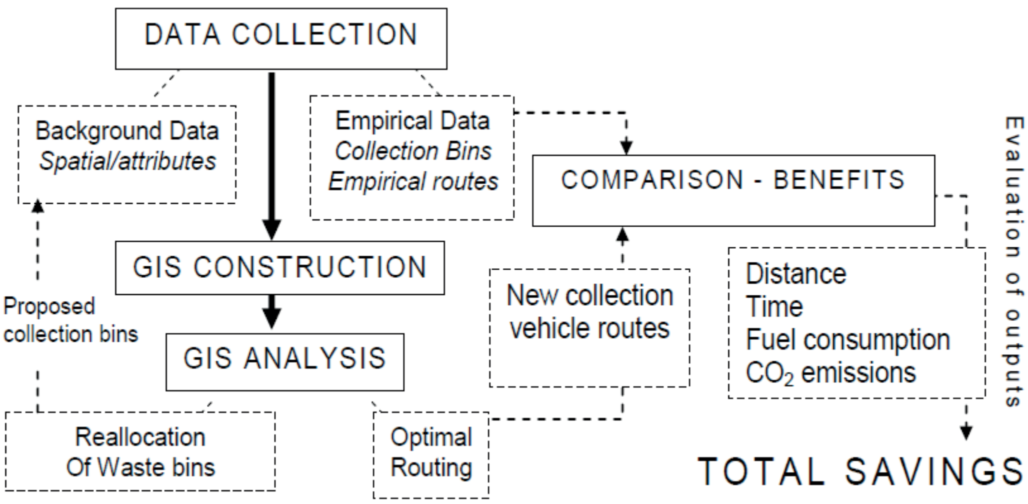

FIGURE 3: Methodology for GIS model for use in optimal route selection (Chalkias & Lasaridi, 2009).

ly utilizes the waste to produce energy to meet the targeted demand with the best mix of WtE technology, types of waste, power plant capacity, location and annual planning of WtE power plant construction' for a Malaysian region in the years 2012-2025 (Tan et al., 2014). They integrated the GIS with a Mathematical model with an overall objective of minimizing the total cost of the WtE strategy. The GIS tool caterered for the location selection for the WtE facility which could either be a combined heat and power (CHP) plant or a Landfill gas (LFG) recovery plant. The suitability criteria comprised maximum driving distance for dump trucks, minimum allowable distances from residential areas, proximity to customers and elevation above sea level. The mathematical model then factored in the technology selection and plant capacity, using cost factors supplied by literature for various technologies and plant sizes (Tan et al., 2014). The objective function for this module was to reduce the cost of producing electricity given constraints of feedstock resources availability, capacity demand, construction lead time and location.

Chalkias & Lasaridi (2009) looked at a route optimization challenge, mainly from a developed nation (Greece) viewpoint (Chalkias & Lasaridi, 2009). They asserted that the sustainable SW waste management paradigm as espoused by the EU waste policy, which requires source separation to recover materials and energy, will require more frugal waste management practices by local authorities (LAs) (Chalkias & Lasaridi, 2009). This is imperative since spatially distributed waste streams like construction and demolition waste, packaging waste, used tyres, biodegradables, electrical and electronic waste have target fractions set for recycling, recovery and landfills. Their research therefore identified GIS as the choice tool for analyzing such a complex spatial problem, where routing optimization can minimize costs. They commented that, although waste sorting is not yet a focus area in developing nations, routing optimization can still deliver value owing to the dense populations and prevalence of open site dumping. The authors then built a model combining spatial/geographical data (road network, location of waste bins, land uses etc.) and non-spatial data; both obtained from analogue maps, on-site data using GPS and digital data from Statistical offices. Chalkias & Lasaridi (2011) obtained an optimal route and bin reallocation model that offers savings in time (3-17%) and distance (5.5-12.5%) compared to the existing route (Chalkias & Lasaridi, 2011).

3.2.2 Biomass to bioenergy (BtB) supply chains

Panichelli and Gnansounou (2008) asserted that the profitability of BtB systems is highly geographically dependent since upstream biomass SC accounts for a significant fraction of total bioenergy costs (Panichelli & Gnansounou, 2008). They pointed out that the key objective is then, how to obtain sufficient biomass quantities above the minimum economic throughput of the bioenergy plant. A number of researchers in biomass SCs have therefore resorted to the use of GIS enhanced tools for optimal facility location at the strategic level and for route optimization at the tactical and operations level (Kinoshita et al., 2009; Voivontas et al., 2001; Zhan et al., 2005).

He-Lambert et al. (2018) combined GIS with a Mixed Integer Linear Programming (MILP) model in a two-stage approach to identify feedstock supply, pre-treatment facilities, and biorefinery locations with high spatial resolution scale to meet the annual biofuel production and demand goal for Tennessee, USA (He-Lambert et al., 2018). The first stage employs the GIS and determines the bio-refinery and feedstock while the second optimizes choice of harvesting options and the location of pre-treatment facilities. They highlighted that the advantage of using GIS only is that one can determine production potential and distribution of available feedstock, optimal biorefinery locations and market distribution routes for the biofuel with no explicit objective functions or resource constraints. There would be limitations however in terms of model replicability, transferability and room to carry out economic analyses and simulations for alternative routes. An integration therefore brings in the GIS advantages and eliminates most limitations (He-Lambert et al., 2018).

Woo et al. (2018) combined GIS with MCA and include a supply chain cost analysis for Tasmania, located in Australia. They argued that a comprehensive SC design that will determine the optimal number, size and location of bioenergy facilities should factor in both economic (especially transport), environmental and socio factors as depicted in Figure 4.

In another integration case, Zhang et al. (2016) combined GIS with simulation and optimization tools where GIS was a precursor to select candidate biofuel facility locations using factors like accessibility to biomass, railway/road transport network, labour availability and proximity to water bodies. The resulting candidates were then used as inputs for the simulations and optimization tools where the former would then be used to track flows within a given SC network, while the latter determines the optimal SC network in terms of various costs (Zhang et al., 2016).

Koikai (2008) used GIS in siting analysis to identify potential locations for bioethanol processing plants using first-generation feed stocks in a Kenyan province (Koikai, 2008). The author first defined and logically ranked the suitability factors for the plants, including proximity to maize farms; access to major highways/roads or railways and access to utilities like water and electricity. Using acquired geo-referenced data, the author then produced vector maps representing suitability profiles for various sites according to each of the suitability factors. All the vector data was then converted to raster, reclassified then compared for suitability analysis using ArcGIS Spatial Analyst. The result was a map of several potential biofuels processing sites in several towns, which could be used by relevant stakeholders in Kenya, considering other factors (Koikai, 2008).

Kinoshita et al. (2009) came up with a GIS database for a spatial evaluation of forest biomass usage. The database model would reveal usage patterns and serve as an information repository for future decisions (Kinoshita et al., 2009). Kanzial et al. (2009) integrated GIS and Multi Integer Linear Programming to model optimal material flows and subsequent plant production costs for different demand scenarios and supply options. They also demonstrated the differences between direct flow and flow via storage

(Kanzian et al., 2009). Panichelli and Gnansounou (2008) developed a methodology that integrates a GIS system with a biomass allocation algorithm to select suitable bioenergy facilities (Panichelli & Gnansounou, 2008). Their model appealed as different from most facility site location problems since it considered a scenario where these sites could compete for the scarce biomass resource. Papadopoulos and Katsigiannis (2002) developed a GIS tool to locate a conversion facility considering economic sustainability (Papadopoulos & Katsigiannis, 2002).

4. OPPORTUNITIES FOR DEVELOPING NATIONS: CASE OF AFRICA

Figure 5 illustrates that the uptake of GIS technologies is still very low for developing regions like South America and Africa. It also shows that the biggest end user is the government, mostly for demographic purposes, followed by the natural resources field. Moreover, the largest leap in market share by 2025 is also reflected by natural resources, where biomass occupies a very significant role. Since

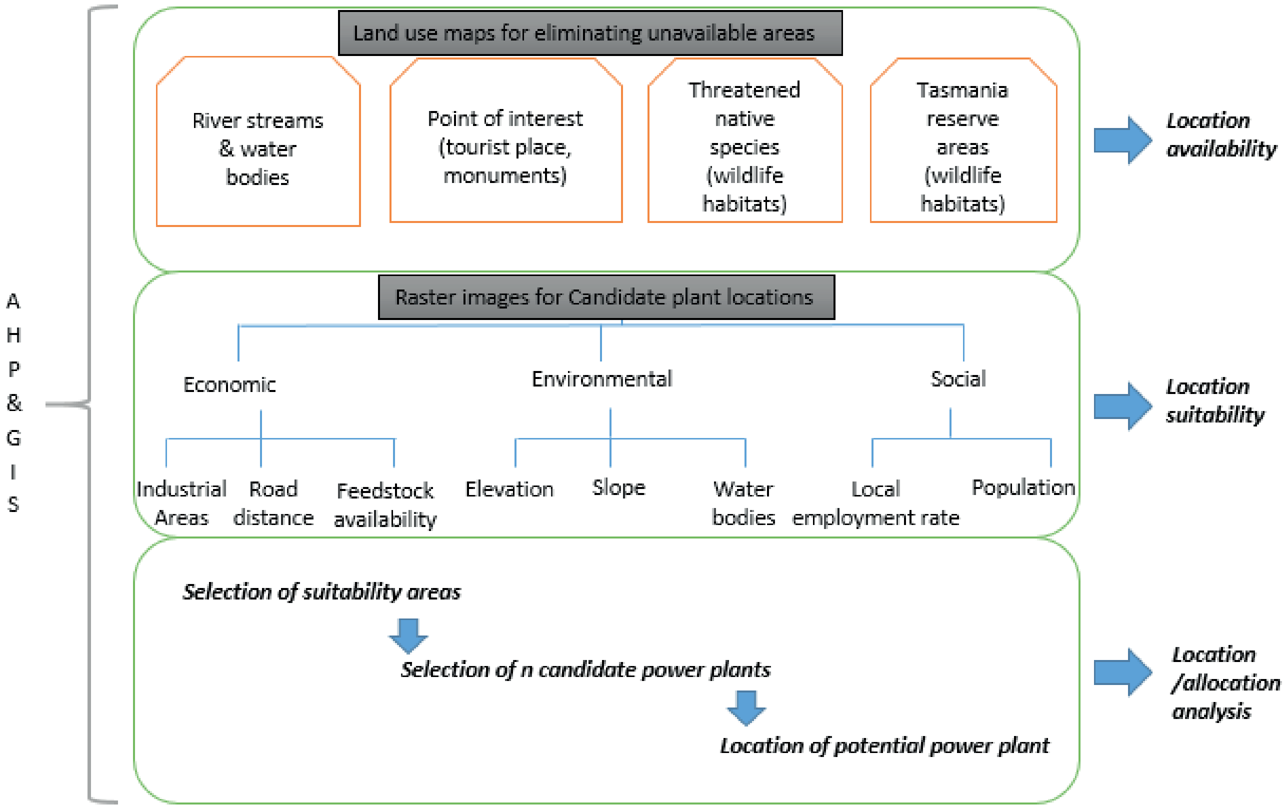

FIGURE 4: GIS methodology for selection of optimal facility sites, adapted from (Woo et al., 2018).

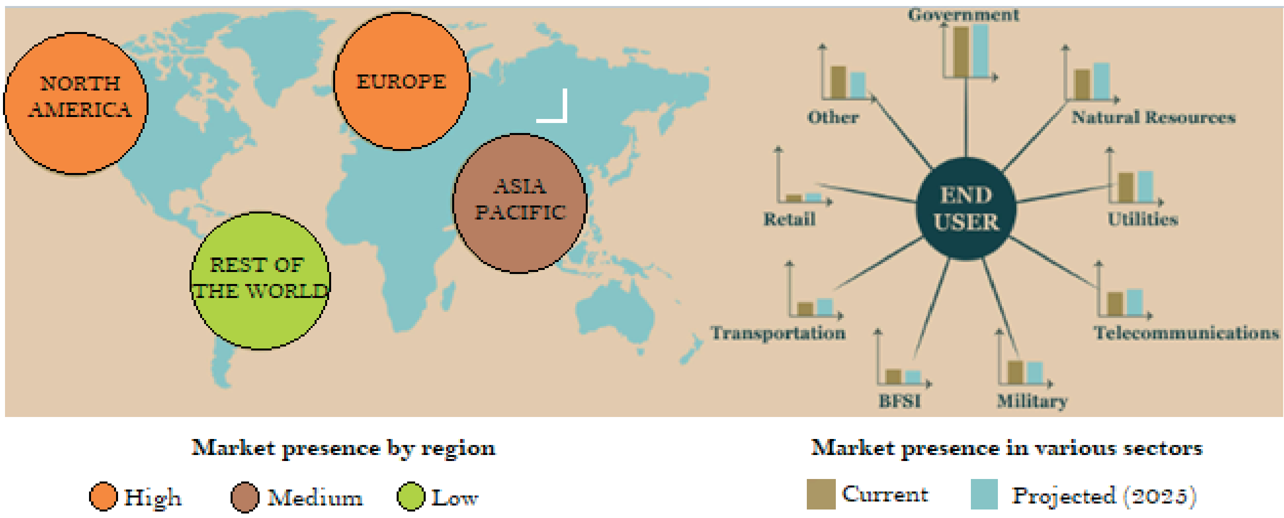

FIGURE 5: Uptake of GIS by various markets and prospects for growth (www.inkwoodresearch.com).

the optimal use of natural resources is increasingly becoming topical, it will be imminent that GIS will soon take centre stage in the planning and allocation of these resources.

On the other hand, most developing regions have experienced a recent rapid urban growth. In the case of Africa mass urbanization since the 1960s resulted in the congestion of areas surrounding major cities and towns, resulting in the increased generation of waste (Matheri et al., 2016; Sufiyan et al., 2015). In the slum areas of some cities, the problem has degenerated into open dumping of SW. Given the booming populations and high urbanization rates in such developing regions, coupled with severe infrastructure and economic constraints, local authorities in these nations should consider optimal management using GIS tools. Integrated GIS technology has been recognized as one of the most promising approaches to automate the process of planning and management of waste management, WtE and bioenergy SC systems (Celli et al., 2008; Chalkias & Lasaridi, 2011; Panichelli & Gnansounou, 2008). Clearly the need for cost-effectiveness cannot be restricted to developed countries for complex segregated waste collection, treatment and recovery. A better opportunity in the green economy, beyond conventional landfill site location, would be planning and location of WtE and pre-treatment sites. These can be a good basis for comprehensive spatial databases revealing demographic data and waste disposal habits (Sufiyan et al., 2015). GIS tools would therefore help developing nations quantify the spatial and temporal characteristics of waste and plan economically for WtE sites.

Africa in particular, along with other developing countries, also boasts of a large inventory of unutilized biomass due to expansive agricultural and forestry land and growing populations. The Stecher, Brosowski, & Thrän (2013), in an International Renewable Energy Agency (IRENA) report, stipulated that bioenergy is a strategic asset in the future of Africa, especially in the light of the fact that it comprises 50% of Africa's total primary energy supply (TPES)(Figure 6) and more than 60% of Sub Saharan Africa (SSA)'s TPES (Stecher et al., 2013). Jingura et.al (2017) remarked that 'biomass is by far the most important renewable resource in SSA'(Jingura & Kamusoko, 2017). Estimates on Africa's collective biomass potential are wide and varied, being classified largely as energy crops, forestry biomass (plantations) then residues and organic waste. The estimates for 2020 are shown in Table 2.

Evidently, the reason why southern Africa would have such a high percentage share of biomass and waste (especially residues) is due to a relatively high abundance of land for energy and food crops, a relatively stable and conducive climate, a thriving agro-forestry industry and a fast growing population rate (Batidzirai et al., 2012; Stecher et al., 2013; Von Maltitz & Setzkorn, 2013). Such fast expanding demographics lay a demand for increased agricultural and forestry products and consequently, the residues accumulated from the activities (Gasparatos et al., 2015; Von Maltitz & Setzkorn, 2013),(Pradhan & Mbohwa, 2014). Given the spatial and temporal distribution of such residues, coupled with global trends, policies and technology advances that are supporting bioenergy, it is imminent that GIS will be widely adopted in the near future for spatial quantification and analyses.

While there is definitely an increase in waste due to population booms in developing nations, developed ones will also experience an increase in variety and possibly, quantities due to better lifestyles (Tan et al., 2014). Regardless of quantities of MSW, the major distinction between the developing and developed nations is the policies framework and legislation, which give developing nations pressure to com-

TABLE 2: Estimates on Africa's collective biomass potential.

Energy Crops	Forestry biomass	Residues (forestry & agriculture) and waste
Up to 13,900PJ/yr (IEA, 2010)	1 billion tonnes annually (~9.4PJ/yr) (Cudjoe et al., 2015)	Just above 0.4billion tonnes per annum (Cudjoe et al., 2015)

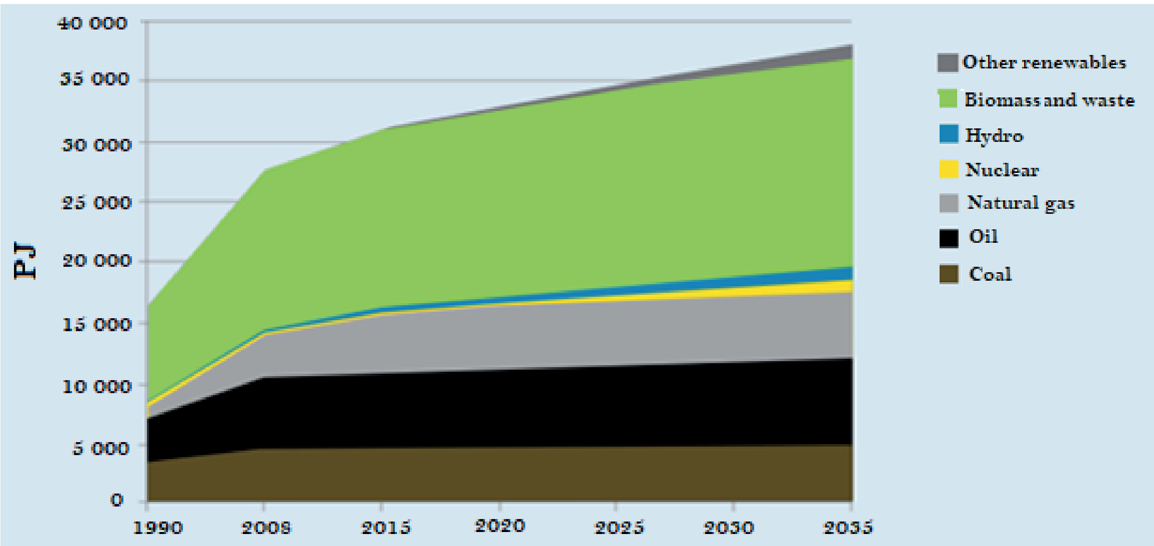

FIGURE 6: Total Primary energy demand for energy sources in Africa (IEA 2010.

ply in efficient ways (Sapp, 2017; World Energy Council, 2016). Chalkias and Lasaridi (2009)'s account of the waste collection and sorting highlighted the EU waste policy that requires source separation and recovery of materials and energy (Chalkias & Lasaridi, 2009). Although waste sorting is not yet a focus area in developing nations, routing optimization can still deliver value owing to the dense populations and prevalence of open site dumping (Chalkias & Lasaridi, 2009). Tan et al (2014)'s model for a developing nation (Malaysia), on the other hand, remains quite instructive in selecting the right mix of WtE technologies using various objectives, when there are limited resources (Tan et al., 2014). In this case, the WtE technologies could also include pyrolysis and gasification alternatives, not only LFG and CHP.

For BtB ventures, it is interesting to note that though not prevalent, cases of unutilized timber residues exist in developed nations as exemplified by the Tasmania, Australia case (Woo et al., 2018). Koikai (2008)'s study is a classic case of the use of GIS alone to identify all candidate biofuels processing sites by ranking according to certain suitability factors in Kenya (Koikai, 2008). Woo et al (2018), however, gave a good example of an even more comprehensive model integrated with simulation and optimization tools to meet various other constraints and objectives, which can only be expressed mathematically (Woo et al., 2018). Moreover, the simulation tool can display results for various scenarios and when expressed graphically, it could be a better marketing tool in developing nations, where more rigour is require to break the ground and convince stakeholders. However, limitations in creating such a robust model may exist in terms of expertise and in some cases, inadequate computational resources in developing nations. This could be solved by having collaborations of researchers in developing nations with those in developed nations for skills transfer and sharing of robust resources. It will also be interesting to note that GIS models as depicted in Figure 4 and the mathematical superstructure will also vary between developing and developed nations due to differences in policies, legislation and socio-economic values or norms.

5. CONCLUSIONS

The review reveals a convergence of various issues like rapid population growth in developing nations, agriculture and forestry growth, advances in computational capabilities and increased policy support for renewable energy schemes. All these constitute a good breeding ground for the application of GIS in creating and analyzing spatial databases with associated, relevant non-spatial attributes. There is indeed a strong case for WtE, bioenergy and improved SW management ventures owing to the wide array of potential socio-economic benefits that could be reaped from them. Given the low energy density of waste and biomass compared to fossil fuels, spatial distribution of supply points and variability of resource quantities, GIS becomes a tool of choice in the optimization of landfill/WtE/bioenergy facility size, site location and routes. In developing nations, where the SW resource has been fast becoming a nuisance and biomass is very abundant, the opportunity for the application of GIS is vast and virgin. An accurate, well conceptualized and built model as exemplified by studies in this review can result in time and cost savings both at the planning and implementation stages. This study also shows that integrations of GIS with other mathematical optimization tools or simulations cover for the former's inability to also optimize on size and technology choice when there are resource constraints. It is also clear that all these SC models will be affected by the differences in policies and legislation between developed and developing nations and the latter may be affected by computational, human and software resources availability. This might warrant an in depth inquiry into the causes of slow uptake of such academic tools like GIS in developing nations to establish the weight of socio-economic or political factors. Perhaps, the bigger gap in literature is on models that will combine the upstream SC, midstream conversion and downstream distribution modules and be able to simulate various scenarios of plant location (determined using GIS), size and technology choice in one package. However, as Charis et al. discuss, such models would require a larger investment in time, a multidisciplinary approach and substantially bigger computational capacities (Charis et al., 2018).

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