Modeling of biomass supply system by combining computational methods – A review article

Aalto Mika, KC Raghu, Korpinen Olli-Jussi, Karttunen Kalle, Ranta Tapio

DOI: 10.1016/j.apenergy.2019.03.201

Modeling of biomass supply system by combining computational methods –a review article

Mika Aalto*, Raghu KC, Olli-Jussi Korpinen, Kalle Karttunen and Tapio Ranta

School of Energy Systems, LUT University

Lönnrotinkatu 7, 50100 Mikkeli, Finland

** Corresponding author*

ABSTRACT

As computing power increases, more complex computational models are utilized for biomass supply system studies. The paper describes three commonly used modeling methods in this context, geographic information systems, life-cycle assessment, and discrete-time simulation and presents bibliometric analysis of work using these three study methods. Of the 498 publications identified in searches of the Scopus and Web of Science databases, 17 reported on combinations of methods: 10 on life-cycle assessment and geographic information systems, six on joint use of life-cycle assessment and discrete-time simulation, and one on use of geographic information systems jointly with discrete-time simulation. While no articles dealt directly with simultaneous use of all three methods, several acknowledged the potential of this. The authors discuss numerous challenges identified in the review that arise in combining methods, among them computational load, the increasing number of assumptions, guaranteeing coherence between the models used, and the large quantities of data required. Discussion of issues such as the complexity of reporting and the need for standard procedures and terms becomes more critical as repositories bring together research materials, including entire models, from various sources. Efforts to mitigate many of modeling's challenges have involved phase-specific modeling and use of such methods as expressions or uncertainty analysis in place of a complex secondary model. The authors conclude that combining modeling methods offer considerable potential for taking more variables into account; improving the results; and benefiting researchers, decision-makers, and operation managers by producing more reliable information.

Keywords: Biomass, Supply chain, Life cycle assessment, Geographical information system, Agent-based modeling and simulation, Discrete-event simulation

1. INTRODUCTION

Continuing advances in computing power have made it possible to develop larger-scale and more complex computational models that may be utilized in biomass supply chain analyses. These models enable studies that expenses or practical constraints to operations might render impossible to conduct in the real world [1]. Thanks to greater computing power, multiple modeling methods can be applied in combination to study biomass supply systems. Which of the many available modeling methods are employed in a given case depends on the study subject, the tools at hand, and the researchers' expertise. To examine the landscape, bibliometric analysis was conducted to reveal the latest developments in modeling methods' usage. This involved a review of articles reporting on joint use of two or more modeling methods in biomass supply chain analysis.

Researcher interest in modeling as an approach to studying bioenergy systems is evident from the rising number of papers presenting reviews in this field [2–6]. The categorization of modeling methods, which are typically referred to as mathematical models in this domain, varies from one review to the next. These models, described as sets of equations that characterize real-world phenomena [7], were divided into three classes by De Meyer et al. (2014) [2] and by Ghaderi et al. (2016) [6]: the mathematical programming, multi-criteria decision-making, and heuristic approaches. Meanwhile, Sharma et al. (2013) [4] considered four classes of mathematical model: deterministic, stochastic, hybrid, and IT-driven, where they clarified the last of these consists of models that use application software to coordinate and integrate phases in the supply chain on a real-time basis. Wang et al. (2015) [5], in turn, did not enumerate a typology of mathematical models, only distinguishing among models based on geographic information systems (GIS), life-cycle assessment (LCA), crop-growth models, joint use of process models and reaction kinetics, and mathematical models that have been developed specifically to analyze and optimize complex biomass supply systems. Finally, Awudu and Zhang (2012) [3] took a simpler approach by splitting models into only two classes: analytical methods and simulation methods.

In Awudu and Zhang's terms, analytical methods include linear programming, mixed integer linear programming, integer stochastic programming, and other methods that involve "mathematical programming." Mathematical programming optimizes the given system by minimizing or maximizing the values resulting from certain decisions in line with set constraints and objective functions [8]. Since these methods, which many scholars have concluded are popular [2–6], are employed for optimization purposes, they can be seen as a suitable for extended use involving other methods, such as GIS-based methods [2]. Since mathematical programming and combined uses involving it have been extensively reviewed already, these are excluded from consideration here. This paper focuses instead on three methods that are used particularly often in biomass supply system studies – the GIS, LCA, and discrete-time simulation (DTS) approaches, where the last of these encompasses such tools as discrete-event simulation (DES) and agent-based modeling and simulation (ABM). Together, these can cover the spatial, temporal, and environmental aspects of the system under study.

Biomass supply chains display spatial variation with regard to, for instance, the distribution of feedstock-generation locations, the location of the various operations, and long transport distances. Through GIS tools, researchers can assess the effects of these variables on the system. Environmental factors too are important, since, while biomass is generally considered carbon-neutral and its use is often promoted for environmental reasons, the reality may be more complicated. This can be addressed by LCA. Finally, DTS can cover temporal challenges in the system, such as hot-chain issues, supply-and-demand problems, and changes in feedstock availability. Each of the three approaches addresses particular important facets of the system. Since these overlap little, applying multiple methods can yield more comprehensive results, giving practitioners and academics more information and, thereby, greater opportunities to understand system mechanics and the consequences of change in the system.

While particular modeling methods have been presented and reviewed in numerous publications, reviews that consider combinations of methods are far scarcer. Combining different models brings both challenges and advantages, which we attempt to highlight through a systematic review of work that has involved this combined use. We thereby point to possible solutions that address the challenges and confer the benefits, offering orientation for future research. With constantly evolving and increasingly critical bioenergy systems, this study of combining the three modeling methods could be of timely assistance in identifying the potential pitfalls of existing energy systems. Furthermore, a marriage of these approaches may aid in further optimizing the systems from the technical, economic, and environmental perspective alike.

With this strong motivation to investigate past and current trends in combined-method modeling in the context of bioenergy and to present meaningful conclusion to inform future research, we set out to understand the issues of the biomass supply chain and the three modeling methods and conduct bibliometric analysis accordingly, by using headwords to find publications in the Scopus and Web of Science (WoS) databases, these being the largest and best-known scientific databases. We introduce the biomass context and our research methods below. After this, we analyze the findings and review the publications discussing use of two or more modeling methods to study the biomass supply chain. Discussion of bibliometric results and reviews is followed by suggestions for future actions.

1.1. The biomass supply chain

The typical supply chain system is a complicated logistics system composed of multiple activities [9, 10]. The activities in the supply system are discrete processes that are distributed in space. A biomass supply system differs from traditional supply systems in that biomass is collected over vast territories, supply and demand both fluctuate, and the feedstock has to be treated before use [11]. The complexity of the supply chain is evident in nonlinearity and multi-scale behavior, the structure of the system spans several levels, and the system evolves and organizes itself through its functions and structures [12].

Biomass supply system may be divided into specific activities that are needed if biomass is to reach the end-use point from the point of origin. These activities, conceptualized in terms of the main groups shown in Figure 1 [10, 13], are highly interconnected, and decision upstream in the chain affect various activities downstream [10]. Since the various activities change in accordance with the end product required, the raw material available, and the structure of the chain, it can be challenging or even impossible to find the optimal solution.

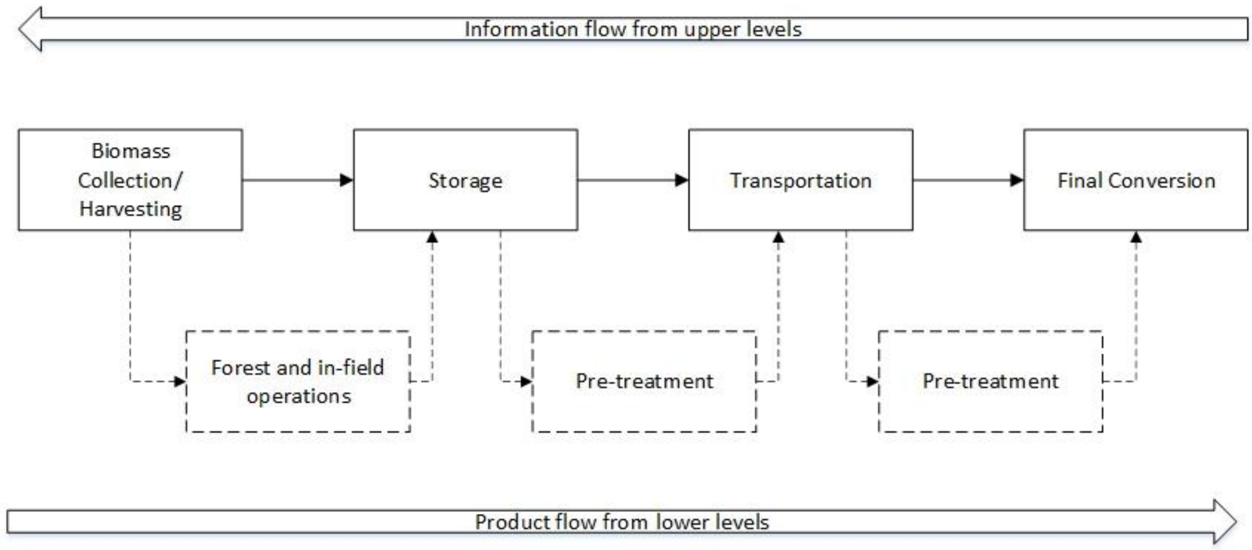

FIGURE 1: A graphical depiction of the main activities in the biomass supply chain.

Because the biomass supply chain is a wide web, such tools as GIS are utilized to study the spatial distribution of the biomass supply. This is important since logistics costs in biomass supply tend to be high [14–16]. With several sources of material and numerous applications being available for biomass processing, the supply system is even more spatially dispersed, creating greater reason to use GIS in studying biomass supply systems [17–19]. In contrast, DTS models focus on the temporal aspect of a biomass supply system. This is important for examining the effect of interconnections and the timeliness of the various logistics elements. Finally, LCA has found popularity as interest has grown in the environmental impact associated with biomass supply, since, for example, biomass used to substitute fossil fuels can have a negative impact. Though biomass is less harmful, on account of its sustainability and the fact that is use reduces gaseous emissions of pollutants [10], dedicating land to biomass may be ecologically harmful and in some scenarios might even compromise food security [20]. Also, transporting biomass feedstock to processing facilities could lead, in some cases, to higher total greenhouse-gas (GHG) emissions than produced by conventional use of fossil fuels [21].

1.2. Geographic information systems

A GIS is a system for the production, management, analysis, and presentation of information that can be localized in a spatial environment. These systems are able to synthesize data from many geospatial information sources for visualization or analysis, as needed (Visual representation by GAO (2012) [22] as Figure 2). The first computer-driven systems of this nature were implemented in the 1960s [23], and since then GIS infrastructure development has been closely connected with the development of computing hardware and software [24]. The 1990s saw the introduction of GIS in research into biomass supply and transportation, where the methods were brought to bear primarily for ascertaining the economic costs of biomass supply logistics [19, 25, 26]. Later, the scope of such studies was extended such that aspects additional to monetary economy – e.g., land-use changes and environmental impacts of biomass-handling – were taken into account [27].

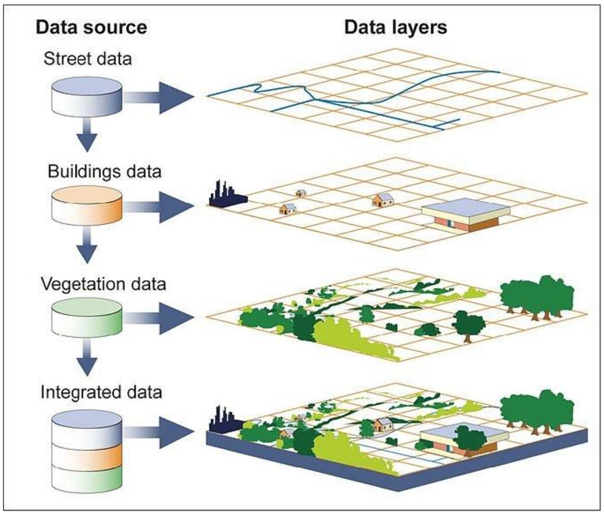

FIGURE 2: A visual representation of incorporating data with GIS approach [22].

One key technological advance in the GIS sphere has been the development of route calculation features, which are important in a logistics context. It was clearly impossible for such algorithms as Dijkstra's shortest path [28] and other work on the vehicle routing problem (VRP) [29], presented in the 1950s, to be widely applied before the processing capacity of standard computers reached a level satisfactory for this. Also, development from command-line programs to applications based on a graphical user interface (GUI) and, later, enhanced cartography obviously increased the attractiveness of GIS in biomass supply studies. Modern GIS applications support several standards for data transfer between external systems, and this compatibility has increased the opportunities for them to be used in parallel or together with other computer-driven study frameworks [21].

1.3. Discrete-time simulation

Dynamic simulations take into account temporal variation, in various ways. System dynamics and ordinary differential equations (ODE) are examples of modeling methods that operate in continuous time, whereas discrete-time simulation uses time steps, with a change in the system represented as occurring only set points in time. The DES and ABM approaches are widely used

DTS methods in logistics studies [30, 31]. It is worth noting that simulation methods, DTS among them, do not by nature include optimization; rather, results from simulation scenarios are compared in pursuit of near-optimal results [30]. Optimization may be part of a comparison phase that involves mathematical programming or heuristic methods.

DES describe the behavior of the complex system under study by considering events in sequential order. In this, the entities are passive objects that travel through blocks in a flowchart [32]. In DES, the system can be thought of as a network of queues and servers [33]. Researchers have improved on DES methods ever since the 1960s, when it was first presented for general-purpose system simulation [34]. ABM is more novel discrete-time simulation method then DES. The novelty of ABM has led to problems with terminology: the literature lacks universally accepted definitions that identify the fundamental concept of ABM and its assumptions [35]. While the first publications referring to a study method that could be classified as ABM were published relatively early, in 1971 [36], the method has developed vastly since then and can still be considered young.

ABM is suited well to describing activities of individuals and how they interact with each other. With regard to biomass, a supply-system agent might be a truck, harvester, biomass processor, or user of biomass. Some have suggested that ABM method is a suitable replacement for DES, even though DES has a large user base and may be better for some study settings [37]. For instance, because individuals make decisions both independently and in interaction with each other, ABM demands more computing power than DES does. In addition, the models tend to take longer to develop in ABM, rendering it a less attractive choice of study method in certain quarters [33].

In both methods of DTS, a modeling expert must create the model, and the modeler should be an expert in the subject under study too, so that the model logic is guaranteed to be valid [38]. This cannot always be achieved, so the model may have to be validated by a separate individual who is an expert in the field being modeled. The two main methods, DES and ABM, possess similarities, with it having been said that all ABM models are a combination of DES and ABM in operations research [37].

1.4. Life-cycle assessment

Life-cycle assessment is a technique developed to assess and address the possible impacts of products or services on the environment. It can be used to identify any opportunities to improve the environmental performance of a product or service at any phase in its life cycle, and it can be used also as a tool for decision-makers' use in strategic planning, decision-making, and product design aimed at improving the environmental performance of said product or service. One way of employing LCA is as a marketing tool, for any product or services, such that consumers can make an informed decision about their choice of product.

LCA is a systematic process that begins with defining the system's boundaries in accordance with the goal of the project. In the second phase an inventory is taken of the process input and outputs that fall within the boundaries delineated. During the impact-assessment phase, the data collected in the inventory phase are correlated with the respective environmental implications that may exist. Finally, in the interpretation phase, the results from assessment of impact are interpreted and discussed, conclusions are formed, and recommendations are made on the basis of the goal set in the first phase. The four major phases of LCA and the steps defined for it are presented graphically in Figure 3 [39].

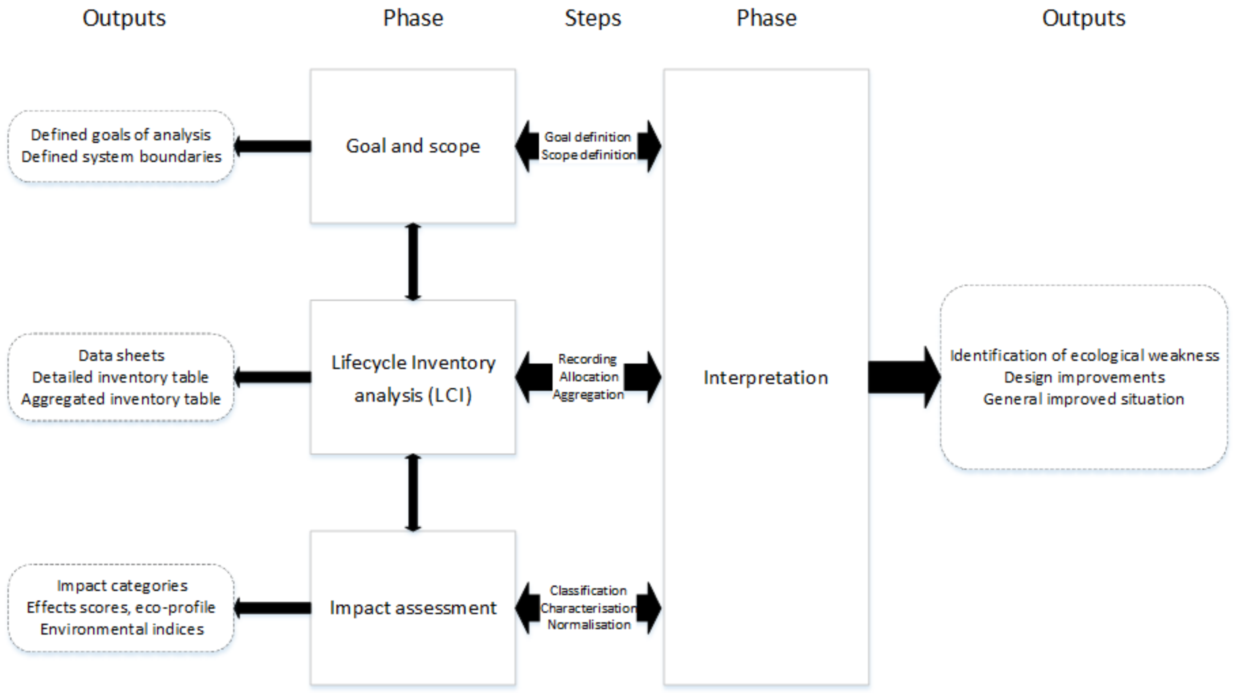

FIGURE 3: The phases of LCA, including the individual steps and outputs.

LCA has been used for estimating consumer products' environmental impact ever since the 1960s, and the International Organization for Standardization (ISO) has been involved in LCA since 1994 [40, 41]. In the context of energy-system analyses, LCA is considered to be among the best methods for identifying environment impacts and opportunities for improvement, although several issues have been acknowledged as strongly influencing the results [42, 43]. Recently, bioenergy has come under scrutiny for its environmental performance in comparison to other green energy sources even though bioenergy does offer clear benefits over traditional fossil fuels such as coal. Accordingly, governments around the world apply various environmental policies that have motivated bioenergy organizations to assess the environmental benefit of their products on dimensions such as reduction of GHG emissions [42].

2. MATERIALS AND METHODS

In our survey of publications that refer to using computation-based methods for biomass supply chain analysis, we queried the Thomson Reuters bibliographic database WoS and Elsevier's Scopus database because the two differ substantially in coverage while both being commonly used for bibliometric analysis [44]. To obtain the most useful result sets, we constructed queries specific to each database and for each of the three modeling methods in turn. Hence, the queries yielded six distinct sets of publications for analysis, with hits from the publication title, keywords, and/or abstract. Sometimes authors use different terms for a given concept or refer to a keyword subclass alone, with the result that their paper might not be found by a query for only the more commonplace term or one relying on main classes alone, such as "biomass." To mitigate this effect, the queries were constructed to include several known general terms for the main class and also subclasses.

To find as many publications as possible addressing biomass supply chain analysis with computational methods, the queries featured three parts, referring to biomass, referring to the supply chain, and referring to the method. For each of these three elements, we used a list of headwords (see Table 1) that were composited with the Boolean operator OR. These three parts were combined with the Boolean operator AND. The headwords feature some use of parentheses, asterisks for wildcard matches, and quotation marks. Quotation marks were used to limit the results to matches for the exact multi-word search phrase rather than permit inclusion of spurious matches based on a single word. The use of asterisks was confined to the end of a word, to allow for several suffixes to be included in the search.

TABLE 1: Headwords of the queries

Description of biomass	Description of Supply chain	Description of method
Biomass	"Supply chain"	**GIS**
Bioenergy	"Supply system"	"Geographical information system"
Biofuel	"supply network"	GIS
Bioethanol		"Spatial analysis"
Biodiesel		"spatial statistic"
biogas		
"Energy wood*"		**LCA**
"Forest fuel"		"Life cycle assessment"
"wood chip*"		LCA
woodchip*		"Life cycle analysis"
"Wood waste"		"Lifecycle assessment"
"Pellet*"		
"Energy Crop*"		**DTS**
"sugarcane"		"Agent-based"
"Agricultural waste"		"Discrete-event"
"Municipal solid waste"		"multi-agent simulation"

WoS and Scopus differ in their syntax for search queries; hence, we needed to build two versions of the query for each of the lists (the full set of queries is presented in the supplementary materials). The queries have brackets so that the search sequence works as intended: it is important for the OR operator to be processed before the AND operator. While the queries do not include document-type restrictions, we included only articles in the results considered, and, to have a better basis for comparison, only those articles published in 2018 or earlier were selected for analysis. The analysis included all the results listed from the queries. Articles addressing use of multiple methods together were found by comparing titles and authors in the list.

3. RESULTS

Of the 498 publications returned via the search queries, Scopus included 312 and WoS included 364 (160 publications were found in both databases). The modeling method for which the most publications were found was LCA, with 335 records. Modeling based on GIS had the second-highest number of hits, with 98 records, of which 10 publications were also on the LCA list and one was on the DTS list. The modeling method for which the fewest publications were found was DTS, with 44 publications, one of which dealt with GIS also and 6 dealt with LCA. No publications on using all three modeling methods were found. The publication counts and their breakdown by modeling method and between the databases are shown in the Venn diagram provided as Figure 4.

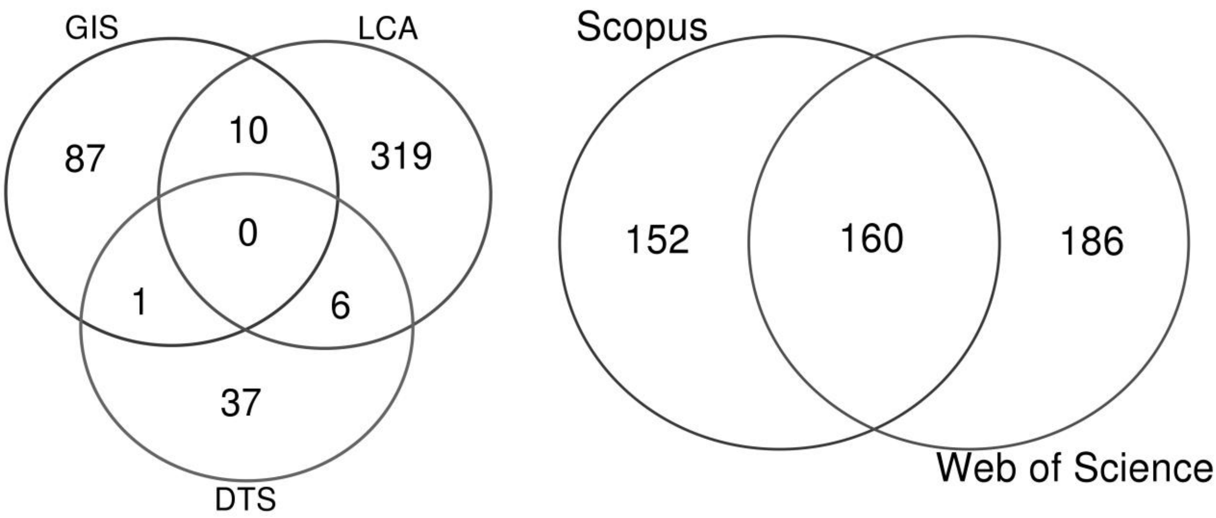

FIGURE 4: A Venn diagram of the publications found.

The oldest publications found [45], from 2000, was unique to the Scopus GIS list. The oldest publications for LCA [46] dated from 2004, and by the next year three further articles dealing with LCA were published. The earliest DTS article found [47] was published in 2006. As for articles on use of modeling methods in combination, the earliest one found [48] was from 2009 and addressed joint use of DTS and LCA. The distribution of articles reflects the recent increase in popularity of computational modeling methods, with LCA proving to be the most frequently used modeling method in studies of biomass supply chains as of 2018 (see Figure 5). The breakdown of the publications found features only one article, if any, per year on a combination of methods, apart from 2017 and 2018. For 2017 there were four distinct publications in which a combination of methods was reported upon, and there were six in 2018. Later, upon closer examination, it was noted that three of the publications from 2017 and five from 2018 had been added to the results on the basis of automatically generated keywords.

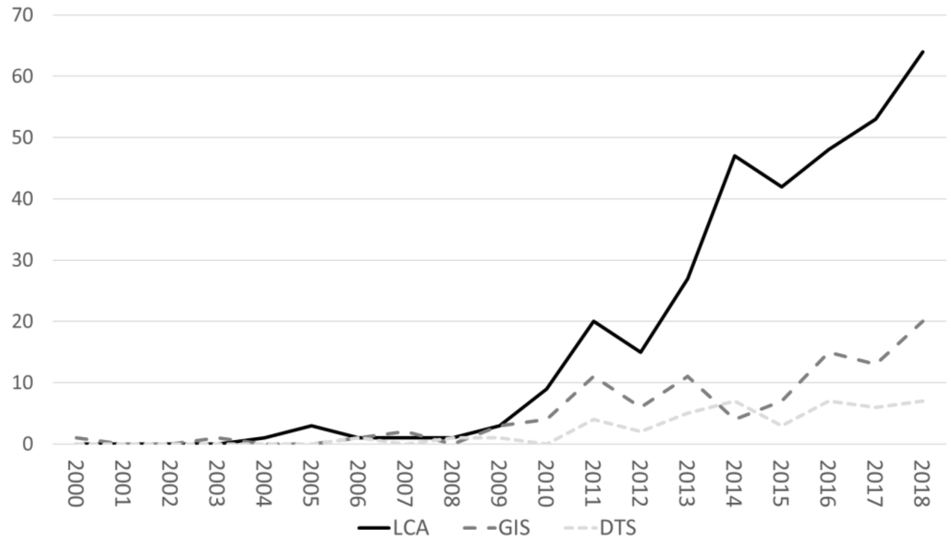

FIGURE 5: The articles found, by year of publication.

The papers found were scattered over 140 journals, although *Journal of Cleaner Production* articles accounted for the largest number of them, 68 publications in all, with LCA publications accounting for the vast majority of these, 54 articles. This journal also ran two of the modeling-method-combining publications [25, 49]. Most publications on GIS modeling came from the journal *Biomass and Bioenergy*, with 15 of the 98 GIS publications found. Finally, the largest number of DTS-based publications came from *Applied Energy*, at six publications. That said, there were 24 LCA articles and 10 GIS publications in that journal, making DTS the least commonly used modeling method in work presented in *Applied Energy*.

As noted above, some of the results were yielded via a set of keywords that the Scopus and WoS service generated themselves rather than author-supplied keywords. As was visible upon later inspection, the auto-generated keywords did not always accurately describe the paper. Also, it is possible that some publications on modeling-based methods or even on combinations thereof were not found, on account of the terms used diverging from the headwords we specified.

4. DISCUSSION

4.1. Approaches combining LCA and GIS

The searches yielded 10 publications with headwords for LCA and GIS in the abstract, title, and/or keyword list. Six of these pieces were found on account of WoS and Scopus adding auto-generated keywords for the papers in question. Some of articles did reported upon a combination of GIS and DTS, rendering these added keywords justified but some cases did not.

That said, Marzullo et al. (2018) [50] studied water ecotoxicity footprints via LCA and GIS. While this 2018 work did involve a combination of the two methods, a keyword denoting biomass was automatically added and supply chains were not considered in this work.

One publication not to refer to GIS was a paper by Chaplin-Kramer et al. (2017) [51], who referred instead to spatial modeling. For this article, they applied it to account for the heterogeneous usage of land and thereby manage the problem that using average values for a region in LCA leads to inaccuracies in determination of the environment effects of the land-use change arising from increased demand. The authors' method supplements certain values from the life-cycle inventory and replaces others, to get the LCA to encompass spatial analysis. They called this method "Land Use Change Improved" LCA, or LUCI -LCA. The results from their case study illustrate considerable differences between conventional LCA and LUCI-LCA, thereby demonstrating the importance of taking into account spatial variation. Their conclusions stress the import of considering spatial elements when conducting land-use change studies and that the results for ecosystem impact must be translated into decision-ready information through predictive, system-scale, robust modeling.

Mirkouei et al. (2017) [52] too did not use any headwords for GIS section in their title, abstract, or keywords, even though GIS was used to analyze transport distances and the spatial distribution of forest biomass. They focused largely on multi-criteria decision-making, using the results as input to LCA involving mobile and stationary refineries in the bio-refinery supply chain. In the background to their work, these authors referred to various quantitative assessment methods, among them GIS, simulation with cost calculations, and operative research. The paper concludes with benefits for decision-makers, a proposed framework, and ideas for further research (including multiyear analysis) along with benefits to society from such work.

Three publications from 2018 did have the LCA keyword added. Furubayashi and Nakata (2018) [53] used GIS to determine transportation paths for estimating emissions from biomass co-firing, but the estimations were from an energy-consumption expressions and no LCA was described in the publication. Santibañez-Aguilar et al. (2018) [54] employed GIS methods to determine viable facility locations for use in the relevant supply chain on the basis of residual biomass. Again, LCA was not used. Finally, Kesharwani et al.'s study (2018) [55], for which keywords for LCA and GIS were generated automatically at database level, did involve employing LCA to study total emissions of the supply chain, but the method as presented does not actually use it (GIS is not mentioned, though the locations of the facilities are in latitude and longitude).

Singlitico et al.'s (2018) paper [56] featured GIS- and LCA-related headwords, but LCA was mentioned only as the next stage in the research. The authors conducted GIS analysis to estimate waste and residue potential in Ireland, but LCA had not yet been implemented.

The oldest paper to be found with regard to LCA and GIS method was by Jäppinen et al. [57]. They analyzed the small-diameter energy wood supply chain in Finland, comparing three distinct supply methods. The authors used GIS material to examine the feedstock availability and transportation network, and LCA was conducted on the basis of the results from GIS analysis – transportation distances and road types were taken as input values for estimation of the GHG emissions of the scenarios studied. Using GIS solves the problem of using average values in small-scale analysis. The authors found that significant GHG reductions in biomass supply could be achieved in regions with poor road networks could be achieved by serving outlying parts of the supply area around a given demand point with transportation by rail from areas near a train loading station in another supply area. This shows the importance of spatial analyses when LCA is being carried out for a biomass supply chain at local scale.

Jäppinen et al. performed another study combining LCA and GIS methods [58]. As with the one described above, GIS was used to analyze feedstock availability and transport networks. This study examined three possible locations for a bio-refinery, with two separate scenarios. This led to larger numbers of results, which were reported via diagrams and vast swaths of numbers accompanied by copious explanation in the body text and in the figure caption and axis labels. The concluding section of the paper emphasizes the need to take into account feedstock combinations that allow for train or marine transportation options.

The newest paper found for which LCA and GIS headwords were supplied by the authors was published in 2017 by Sánchez-García et al. [25], who used GIS analysis to find the optimal location for a hypothetical power plant and applied LCA to estimate GHG emissions. The case study, set in Spain, involved wood chips produced from eucalyptus stems as the fuel. Three levels of feedstock availability were defined via GIS analysis, which was used also to determine transportation distances. The output values were fed in to LCA to ascertain the GHG emissions of the hypothetical power plant for each of several supply-chain operations. The paper concludes with description of a method that may be used on a smaller scale with more specific data and that demonstrates additional advantages in informing relative spatial and temporal decisions on scale of local demand. The paper also notes a need to consider competing demand points in this kind of study.

It was evident that most studies that combined GIS and LCA have used GIS data in feedstock availability and transportation network analysis and taken these results as input to LCA. An exception to this is the study conducted by Chaplin-Kramer et al. (2017) [51] that improved on joint use of LCA with GIS, to estimate land-use-change-related emissions with higher spatial resolution. This method integrates the two models more than do the others, which only chain methods and translate results between them. Either way, when complicated methods are used and multiple scenarios are analyzed, reporting the results in an easily understandable way grows more challenging.

The authors often note that the information produced by these study methods aids decisions-makers by providing them with new information (e.g., Chaplin-Kramer et al. [51] and Mirkouei et al. [52]).The value of simulation and the need for taking into account temporal variation were mentioned too. The requirements cited for future research includes taking into account multiple demand points, performing multiyear analysis, and accounting for the possibility of other supply sources – such as transportation by railway or waterway. All of these can be incorporated into the study by means of DTS.

Since GIS is a powerful spatial optimization tool that provides the opportunity to include the transportation network in analysis in terms of actual driving distances and real-world locations of the entities under study, it has much to add to LCA studies that are location-specific. Especially in small regional studies, in which spatial variation has a greater impact, GIS improve the results and makes them specific to the region. While tying the result to the given region limits applicability, such specificity is important in decision-making. Articles bring up concern about static results, since the biomass supply chain is highly dynamic, so sensitivity analysis should be conducted to mitigate this. A range of results, with different initial values, can imitate dynamic changes in the system.

4.2. Approaches combining LCA and DTS

Our search queries found six publications with an LCA and a DTS headword in the abstract, title, and/or keyword list. For three of these articles, the LCA keyword was added by WoS or Scopus. One of the publications was by Zhang et al. (2016) [59], study in which a multi-agent simulation was used to study various scenarios for the biomass supply chain. The study did not use LCA, so it is unclear to us why WoS added the corresponding automatically generated keyword. Yazan et al. (2017) [60] used ABM to study production of biogas from manure. While these authors noted the importance of GHG emissions, their description of results refers to neither emissions nor LCA. The last article with an added keyword was piece by Kishita et al. (2017) [49] on using DES to study the effect of the feed-in tariff applied to Japan for the adoption of woody biomass. Since the paper explicitly mentions life-cycle simulation (LCS) and the study did involve LCA, adding the keyword was justified.

Kishita et al. (2017) [49] study used DES for analyzing long-term (20-year) effects, with temporal uncertainties included, for a woody-biomass-fueled power generation plant. They used LCA to study CO_2 emissions, and the ISO 14044 standard was used to specify as the analysis unit the amount of wood consumed per year. The authors listed the advantages and disadvantages of the method. They cited the advantages of providing a narrative storyline via quantitative analysis, aiding in decision-making, and being able to be developed for all ways of converting biomass for energy use. Disadvantages cited were the use of annual averages in the model, omission of the ripple effect of the actions, and utilization of CO_2 emissions alone as indicative of environment aspect. The author noted the importance of the scenario selection also. Since the storyline is created on the basis of the set of scenarios chosen and they are compared only with each other, well-justified selection of scenarios is important.

Although these authors of Kishita et al (2017) [49] did not include an LCA-linked headword in their abstract, title, or keyword list, their work did combine DTS and LCA study methods. The case studied was clearly explained, but that was less true of the combination of methods. For LCS, the authors referenced another study, done by Umeda et al. (2000) [61], and the source of LCA data was identified as one database providing initial values for the simulation. Still, the study shows that

DES and LCA can be applied jointly in scenario-based analysis of the biomass supply chain wherein economic and environmental sustainability are determined.

The earliest article returned from the queries for DTS and LCA combined was published in 2009, on a study conducted by Davis et al. (2009) [48]. They took advantage of similarities between LCA and ABM to integrate LCA into ABM. The paper presents, as proof of principle, a study case investigating bioelectricity production in the Netherlands. Before presenting their proof of principle, the authors go through advantages of integrating LCA into the approach and address the limitations to such integration. The method expands the LCA matrix to provide corresponding values for input that agents use from a database or other agents in the model. Because this expansion makes the matrix larger, inversion of the matrix is computationally expensive. To circumvent this problem, Davis et al. (2009) [48] used an algorithm to perform the inversion and applied simplified LCA to evaluate climate change on the basic emissions.

The model used in the study case dealt with only two scenarios, and the case study was presented superficially. Sensitivity analysis involved running 100 simulations, leading to 100 results, which were examined via bar charts. These results were only a subset of the data gathered from the simulations, and it is noted in the paper that even this subset may be interpreted differently. The authors pointed out, as we do, that current LCA models are linear and ABM could provide spatial differentiation and dynamic aspects. Furthermore, the combination of ABM and LCA could have important implications for uncertainty analysis. Although uncertainty analysis is vital for balanced interpretation of a study, the linear and static nature of LCA creates problems in this regard; however, ABM could provide a solution to this problem, since it is a dynamic tool.

In a paper published by Halog and Manik (2011) [62] proposed a framework to integrate LCA, multi-criteria decision-making, ABM, and system dynamics into a hybrid model. Their report goes through all of this method's advantages and disadvantages, including the benefits conferred by hybrid thinking. Although the framework is described in detail, the authors did not utilize, for example, a case study, so the work is only theoretical in nature. The paper concludes by presenting multiple endeavors (e.g., research at the energy–environment–society nexus, novel energy-productions adaptations, and engaging the public in efforts to understand issues of sustainability and energy) that could be explored via the hybrid model described as the framework.

A 2015 publication featuring headwords related to LCA and DTS was authored by Bichraoui-Draper et al. (2015) [63]. The authors referred to agent-based life-cycle analysis (AB-LCA) for their method that uses ABM to complement LCA. Their method and case study are focused more on LCA. The model was developed as a modular structure, so that it would be easy to expand later. The paper examines the effect of economic, environmental, and social factors for the adoption of switchgrass as a biomass-based fuel. A case study of switchgrass-based ethanol production was used alongside reference values of 1,800 GJ electricity generation from coal or natural gas with use of 10,000 liters of fuel. The model was described in line with the ODD protocol [64], developed specifically for describing agent-based models.

The study presents vast quantities of LCA data via two matrices of figures. This method makes it easy to see how particular attributes affect environment impacts. While the study addressed only CO_2 emissions and did not consider emissions from land use, the authors conclude their paper by presenting extension possibilities – for instance, using GIS methods to consider real-world spatial information, such as yields and transportation distance from farm to refinery.

From the studies introduced above, it can be noted that there is strong motivation for using an LCA– DTS combination to support decision-making. With DTS, researchers gain the ability to compare effects between specific decisions, and LCA indicates the emissions connected with each respective decision. By accounting for temporal variation, DTS gives LCA a more dynamic nature.

Studies of the integration of bioenergy-related LCA and DTS have turned out to be rare. This might be because dynamic simulation is typically employed for decision-making on a certain process or well-bounded system while LCA is popular for considering consequences of life-cycle of product. At the same time, it might be that, since today's LCA modeling is relatively simple and linear in structure, it would be challenging to integrate ABM into LCA.

4.3. Approaches combining GIS and DTS

Kim et al. (2018) [65] wrote the only publication we found on combining GIS and DTS. In 2018, they presented a two-phase simulation method to allocate optimal locations for biomass storage facilities. The first phase used a process-based model, the Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC), to estimate switchgrass yields on the basis of weather and location data, with GIS utilized to achieve this. In the second phase, ABM was applied to take into account dynamic activities in the supply chain. This phase too involved GIS, for estimation of transportation times.

The authors noted that challenges arose during optimization: the computation burden increased, and assumptions were applied in order to reduce it (e.g., considering only three actors in the transportation-cost optimization and decreasing the required optimization performance when a larger number of zones was considered).

The authors concluded that their model achieved realistic locations for biomass storage facilities that accounts for the details of crop growth and supply-chain activities. For finding better locations for storage of biomass, the authors proposed modeling supply-chain activities in more detail and pointed to a need for concrete performance data, for validation of the model.

4.4. Combinations of LCA, GIS, and DTS

Although many combination-related publications conclude that the third method can be used to improving modeling, no work using all three modeling methods could be found. There are many challenges to be overcome for including all three methods. One is that experts in all three methods are needed for developing the model. Co-operation becomes more challenging whenever further participants are added, and costs rise also. Combining methods also creates a need for more assumptions, and increased uncertainties in the model may compromise the validity of the modeling. This challenge is emphasized in that the assumptions have to be compatible across all the methods, and those applied for each method have to be factored in before that method's results are taken as input to another method. To overcome this challenge, much work is needed: interest in developing LCA, GIS, and DTS combination models must increase, and there has to be demand for such integrated models in research and industry alike.

4.5. Combinations of methods in general

It can be noted, from publications on combined modeling methods, that there are numerous challenges in getting two or more modeling methods to work together. Among these are increased computational load, complicated validation of the models, and a need for huge quantities of data.

All modeling methods use different initial data, and combining methods demands large datasets. At the moment, various databases are available that could be used to develop a model that combines the three general modeling methods. Further development of these databases is valuable for the individual methods and for combination methods but also to improve validation of the models. There is a possibility of using assumptions and estimates to reduce the quantities of initial data necessary, but this lowers the accuracy of the model and both increases the importance of validation and complicates conducting it.

Computing power is available in abundance, but optimization of the computing operations still is needed if we are to overcome inordinate requirements when combining the models. This is achievable by improving each of the modeling methods separately and developing different methods to combine methods, finding advantages in particular ways of combining them. Opportunities can be found for using algorithms and well-founded assumptions to lower the computational load.

With all the challenges mentioned above, sometimes combining methods would be ill-advised. In these cases, other ways to add the benefits of the other methods may be examined, such as using stochastic distributions to include uncertainty in the model as Santibañez-Aguilar et al. (2018) [54] did in their study. One example of including emission estimation was supplied by Furubayashi and Nakata (2018) [53], who used mathematical expressions for energy consumption. Expressions of this kind are less demanding of computation power and are easier to use than a complicated model would be.

There are cases wherein combining methods improves a study to such an extent that it is highly advisable, and some integrated methods are not as challenging as others. For example, transportation distances yielded by GIS methods can be produced with ease and then added to DTS or LCA models along with the other initial values. This improves the models by giving them more localized and detailed variables. Adding DTS to a study, in turn, enables including temporal aspects that are important in a dynamic supply system. When combining models, one should consider how detailed all the constituent models have to be. At least the main one should be detailed enough to display proper accuracy, but a supporting model that works in less detail can be reasonable in some circumstances.

Applying one method and chaining it to other modeling methods for the next stage is, as Singlitico et al. (2018) [56] declared in their publication, one way to combine modeling methods. This permits the computation load to be divided, and reporting on the stages' results separately, in two publications, prevents excessively long reports. Thereby, the research might more readily remain coherent.

4.6. Results of the bibliometric analysis

It is easy to see that interest in computational methods is increasing: use of all three methods has risen lately. This development is clearest for LCA, on which we found nine articles published in

2010 and a full 64 in 2018. There are several factors in why more studies are now utilizing computational methods. One reason is the lower-cost and more powerful computing resources now available to researchers. Also, the software that is used in carrying out these studies has advanced and become more user-friendly. While computation-based methods hold great promise, it is particularly important, as their use increases, for the researcher to keep the validation and verification of the method transparent. In this regard, LCA has paved the way: standardized reporting is used in LCA, eliminating black boxes in the studies and rendering reports more comparable throughout the field.

It is worth highlighting that our queries did not find all publications in the field that dealt with combinations of methods. For example, Viana et al. (2010) [66], Karttunen et al. (2013) [67], and Jäppinen et al. [68] made joint use of GIS and DTS methods, but either these publications were not in the databases or the search terms did not match their details. This may well be true of work combining all three methods also. However, because we worked with two large peer-reviewed publication databases and a good-coverage headword list, conclusions can be drawn reliably from the results.

As the most commonly used of the three approaches, LCA has generated solid terminology and reporting practices, for which those using all other methods should strive. Terminology varies greatly with all those methods. Hence, complicated search queries were required for finding most of the publications on them, and any researcher wishing to find publications on a particular method would face the same problem. With novel methods such as computational modeling, some of the terms used are unknown even to experts in the field. While automatic generation of keywords helps to some extent, sometimes a keyword picked out was, as we indeed saw in our work, unjustified. It is authors’ responsibility to make sure their keywords represent the paper correctly. If two modeling methods are used, it is recommendable to mention both in the abstract and include terms referring to both in the keyword list.

This brings us back to the importance of consistent terminology. It would make specifying keywords easier for authors and searchers alike. Kishita et al. (2017) [49] used the term “life cycle simulation,” or “LCS,” to denote all simulation methods. A more precise notion, agent-based life-cycle analyses (AB-LCA), was used by Bichraoui-Draper et al. (2015) [63]. This choice of term focuses on ABM in particular, although LCA is generally associated with life-cycle assessments rather than analyses. Self-explanatory terms such as these two should enter standard public use for all the methods and combinations thereof. When GIS is brought in, the word “spatial” can be added readily to that for the other methods, as Hauscild and Potting (2006) [69] did with the term “Spatial Differentiation in Life Cycle Impact Assessment.” Umbrella terms may also be useful, so long as they are well-established. In this paper, DES and ABM both were referred to as DTS methods to distinguish these from other dynamic simulation methods, such as system dynamics or ODE simulations. Though uniform terminology in the field would be ideal, we recognize that establishing this may take a long time. Hence, alternative approaches to improve communications between modelers and researchers should be considered and developed.

While we did not find publications reporting on use of all three methods in combination, incorporating an additional method into studies was often mentioned in the proposed future research directions. Another common conclusion was that modeling can support decision-makers. This is understandable, since modeling-based methods enable examination of planned and hypothetical entities, thereby giving unique insight into the effects of decisions not yet made. Because all of the methods rely heavily on scenarios and comparative analyses, there are many aspects of the results to report. This may lead to hard-to-follow reporting, which draws attention to the need for devoting greater effort to establishing uniform and systematic reporting for all the individual modeling methods and combination of them. The same thing could be said on reporting on the models themselves, but this has been recognized, and standards and protocols have been developed accordingly. Alongside the ISO standards for LCA [70, 71] that guide authors in reporting on the models and results, ABM has the aforementioned ODD protocol [64] for reporting on the model, although the protocol does not address how the results should be reported. While researchers are waiting for more sophisticated and appropriate instructions for this reporting, it should remain as transparent and precise as possible. Describing the model by referencing previous publications should be avoided, since access to earlier articles describing it may be limited. One option is to describe the model in supplementary material, to keep the paper more concise and focused on the subject of study.

5. CONCLUSIONS

Interest in the use of mathematical computational methods has increased, and this trend only seems to be continuing. A corresponding upsurge can be seen specifically in the use of geographic information systems, life-cycle assessment, and discrete-time simulation for modeling and in applying combination of the associated models. With growing computing power and the need to include more detail and address more extensive subjects of study, the models have gained complexity. These wider study cases and the complex models employed for them must be explained clearly when the results are published. To achieve this, a consistent manner of reporting needs to be established. Also, for greater visibility of the relevant publications, it should be ensured that searches find them via self-evident, uniform methods. It would both facilitate searches and be to the authors' benefit to have coherent terminology in place that is suitable for the various modeling methods. Finally, our work enabled us to conclude that combining the classes of method offers the ability to take more variables into account, thereby improving the results of modeling-based studies. Better results benefit researchers, decision-makers, and operation managers alike, by putting more reliable information at their disposal.

References

[1] Pegden CD, Sadowski RP, Shannon RE. Introduction to Simulation Using SIMAN. 2nd ed. New York, NY, USA: McGraw-Hill, Inc.; 1995.

[2] De Meyer A, Cattrysse D, Rasinmaeki J, Van Orshoven J. Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review. Renew Sustain Energy Rev 2014;31:657–70. doi:10.1016/j.rser.2013.12.036.

[3] Awudu I, Zhang J. Uncertainties and sustainability concepts in biofuel supply chain management: A review. Renew Sustain Energy Rev 2012;16:1359–68. doi:10.1016/j.rser.2011.10.016.

[4] Sharma B, Ingalls RG, Jones CL, Khanchi A. Biomass supply chain design and analysis: Basis, overview, modeling, challenges, and future. Renew Sustain Energy Rev 2013;24:608–27. doi:10.1016/j.rser.2013.03.049.

[5] Wang L, Agyemang SA, Amini H, Shahbazi A. Mathematical modeling of production and biorefinery of energy crops. Renew Sustain Energy Rev 2015;43:530–44. doi:10.1016/j.rser.2014.11.008.

[6] Ghaderi H, Pishvaee MS, Moini A. Biomass supply chain network design: An optimization-oriented review and analysis. Ind Crops Prod 2016;94:972–1000. doi:10.1016/j.indcrop.2016.09.027.

[7] Keramati A, Eldabi T. Supply Chain Integration: Modelling Approach. Res Rev Proc Eur Mediterr Middle East Conf Inf Syst 2011.

[8] Winston WL, Goldberg JB. Operations research: applications and algorithms. Belmont: Thomson Brooks/Cole; 2004.

[9] Rentizelas AA, Tolis AJ, Tatsiopoulos IP. Logistics issues of biomass: The storage problem and the multi-biomass supply chain. Renew Sustain Energy Rev 2009;13:887–94. doi:https://doi.org/10.1016/j.rser.2008.01.003.as

[10] Allen J, Browne M, Hunter A, Boyd J, Palmer H. Logistics management and costs of biomass fuel supply. Int J Phys Distrib Logist Manag 1998;28:463–77. doi:10.1108/09600039810245120.

[11] Zandi Atashbar N, Labadie N, Prins C. Modelling and optimisation of biomass supply chains: a review. Int J Prod Res 2017:1–25.

[12] Surana A, Kumara * S, Greaves M, Raghavan UN. Supply-chain networks: a complex adaptive systems perspective. Int J Prod Res 2005;43:4235–65. doi:10.1080/00207540500142274.

[13] Toka A, Iakovou E, Vlachos D. Biomass supply chain management for energy polygeneration systems. Proc. 1st Olympus Int. Conf. Supply Chain., 2010, p. 1–2.

[14] Gonzales D, Searcy EM, Ekşioĝlu SD. Cost analysis for high-volume and long-haul transportation of densified biomass feedstock. Transp Res Part A Policy Pract 2013;49:48–61. doi:10.1016/j.tra.2013.01.005.

[15] Laitila J, Asikainen A, Ranta T. Cost analysis of transporting forest chips and forest industry by-products with large truck-trailers in Finland. Biomass and Bioenergy 2016;90:252–61. doi:10.1016/j.biombioe.2016.04.011.

[16] Laitila J, Lehtonen E, Ranta T, Anttila P, Rasi S, Asikainen A. Procurement costs of cereal straw and forest chips for biorefining in South-East Finland. Silva Fenn 2016;50. doi:10.14214/sf.1689.

[17] Voivontas D, Assimacopoulos D, Koukios EG. Assessment of biomass potential for power production: a GIS based method. Biomass and Bioenergy 2001;20:101–12. doi:https://doi.org/10.1016/S0961-9534(00)00070-2.

[18] Liang T, Khan MA, Meng Q. Spatial and temporal effects in drying biomass for energy. Biomass and Bioenergy 1996;10:353–60. doi:https://doi.org/10.1016/0961-9534(95)00112-3.

[19] Noon CE, Daly MJ. GIS-based biomass resource assessment with BRAVO. Biomass and Bioenergy 1996;10:101–9. doi:https://doi.org/10.1016/0961-9534(95)00065-8.

[20] Smith P, Haberl H, Popp A, Erb K, Lauk C, Harper R, Tubiello FN, de Siqueira Pinto A, Jafari M, Sohi S, Masera O, Böttcher H, Berndes G, Bustamante M, Ahammad H, Clark H, Dong H, Elsiddig EA, Mbow C, Ravindranath NH, Rice CW, Robledo Abad C, Romanovskaya A, Sperling F, Herrero M, House JI, Rose S. How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals? Glob Chang Biol 2013;19:2285–302. doi:10.1111/gcb.12160.

[21] Jäppinen E, Korpinen O-J, Laitila J, Ranta T. Greenhouse gas emissions of forest bioenergy supply and utilization in Finland. Renew Sustain Energy Rev 2014;29:369–82. doi:10.1016/j.rser.2013.08.101.

[22] GAO. Geospatial information: OMB and Agencies Need to Make Coordination a Priority to Reduce Duplication.(GAO-13-94). 2012.

[23] Chrisman N. Charting the unknown: How computer mapping at Harvard became GIS. Esri Press; 2006.

[24] Tomlinson RF. Thinking about GIS : geographic information system planning for managers 2013.

[25] Sánchez-García S, Athanassiadis D, Martínez-Alonso C, Tolosana E, Majada J, Canga E. A GIS methodology for optimal location of a wood-fired power plant: Quantification of available woodfuel, supply chain costs and GHG emissions. J Clean Prod 2017;157:201–12. doi:10.1016/j.jclepro.2017.04.058.

[26] Zhang F, Johnson DM, Sutherland JW. A GIS-based method for identifying the optimal location for a facility to convert forest biomass to biofuel. Biomass and Bioenergy 2011;35:3951–61.

[27] Malczewski J. GIS-based land-use suitability analysis: a critical overview. Prog Plann 2004;62:3–65.

[28] Dijkstra EW. A note on two problems in connexion with graphs. Numer Math 1959;1:269–71. doi:10.1007/BF01386390.

[29] Dantzig GB, Ramser JH. The Truck Dispatching Problem. Manage Sci 1959;6:80–91. doi:10.1287/mnsc.6.1.80.

[30] Becker M, Wenning B-L, Görg C, Gehrke JD, Lorenz M, Herzog O. Agent-Based And Discrete Event Simulation Of Autonomous Logistic Processes. ECMS 2006 Proc. Ed. by W. Borutzky, A. Orsoni, R. Zobel, vol. 571, ECMS; 2006, p. 566–71. doi:10.7148/2006-0566.

[31] Windisch J, Väätäinen K, Anttila P, Nivala M, Laitila J, Asikainen A, Sikanen L. Discrete-event simulation of an information-based raw material allocation process for increasing the efficiency of an energy wood supply chain. Appl Energy 2015;149:315–25.

[32] Borshchev A, Filippov A. From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools. 22nd Int. Conf. Syst. Dyn. Soc. 25-29 July 2004, 2004, p. 45.

[33] Maidstone R. Discrete event simulation, system dynamics and agent based simulation: Discussion and comparison. 2012, p.1-6.

[34] Gordon G. A General Purpose Systems Simulation Program. Proc. December 12-14, 1961, East. Jt. Comput. Conf. Comput. - Key to Total Syst. Control, New York, NY, USA: ACM; 1961, p. 87–104. doi:10.1145/1460764.1460768.

[35] Schieritz N, Milling PM. Modeling the forest or modeling the trees A comparison of system dynamics and agent-based simulation. Proc. 21st Int. Conf. Syst. Dyn. Soc., 2003.

[36] Schelling TC. Dynamic models of segregation. J Math Sociol 1971;1:143–86.

[37] Siebers P-O, Macal CM, Garnett J, Buxton D, Pidd M. Discrete-event simulation is dead, long live agent-based simulation! J Simul 2010;4:204–10.

[38] Sargent RG. Verification and validation of simulation models. Proc. 2009 Winter Simul. Conf., IEEE; 2009, p. 162–76. doi:10.1109/WSC.2009.5429327.

[39] Matthews J, Parr C, Araoye O, McManus M. Environmental Auditing of a Packaging System for Redesign: A Case Study Exploration. J Clean Energy Technol 2014:267–73. doi:10.7763/JOCET.2014.V2.138.

[40] Guinée JB, Heijungs R, Huppes G, Zamagni A, Masoni P, Buonamici R, Ekvall T, Rydberg T. Life Cycle Assessment: Past, Present, and Future. Environ Sci Technol 2011;45:90–6. doi:10.1021/es101316v.

[41] McManus MC, Taylor CM. The changing nature of life cycle assessment. Biomass and Bioenergy 2015;82:13–26. doi:10.1016/j.biombioe.2015.04.024.

[42] Cherubini F, Strømman AH. Life cycle assessment of bioenergy systems: State of the art and future challenges. Bioresour Technol 2011;102:437–51. doi:10.1016/j.biortech.2010.08.010.

[43] Cherubini F, Bird ND, Cowie A, Jungmeier G, Schlamadinger B, Woess-Gallasch S. Energy- and greenhouse gas-based LCA of biofuel and bioenergy systems: Key issues, ranges and recommendations. Resour Conserv Recycl 2009;53:434–47. doi:10.1016/j.resconrec.2009.03.013.

[44] Mongeon P, Paul-Hus A. The journal coverage of Web of Science and Scopus: a comparative analysis. Scientometrics 2016;106:213–28. doi:10.1007/s11192-015-1765-5.

[45] Sørensen B, Meibom P. Global renewable energy scenario. Int J Glob Energy Issues 2000;13:196–276.

[46] Arena U, Mastellone ML, Perugini F, Clift R. Environmental assessment of paper waste management options by means of LCA methodology. Ind Eng Chem Res 2004;43:5702–14.

doi:10.1021/ie049967s.

[47] Sokhansanj S, Kumar A, Turhollow AF. Development and implementation of integrated biomass supply analysis and logistics model (IBSAL). Biomass and Bioenergy 2006;30:838–47. doi:10.1016/j.biombioe.2006.04.004.

[48] Davis C, Nikolić I, Dijkema GPJ. Integration of Life Cycle Assessment Into Agent-Based Modeling. J Ind Ecol 2009;13:306–25. doi:10.1111/j.1530-9290.2009.00122.x.

[49] Kishita Y, Nakatsuka N, Akamatsu F. Scenario analysis for sustainable woody biomass energy businesses: The case study of a Japanese rural community. J Clean Prod 2017;142:1471–85. doi:10.1016/j.jclepro.2016.11.161.

[50] Marzullo R de CM, Matai PHL dos S, Morita DM. New method to calculate water ecotoxicity footprint of products: A contribution to the decision-making process toward sustainability. J Clean Prod 2018;188:888–99. doi:10.1016/J.JCLEPRO.2018.03.307.

[51] Chaplin-Kramer R, Sim S, Hamel P, Bryant B, Noe R, Mueller C, Rigarlsford G, Kulak M, Kowal V, Sharp R, Clavreul J, Price E, Polasky S, Ruckelshaus M, Daily G. Life cycle assessment needs predictive spatial modelling for biodiversity and ecosystem services. Nat Commun 2017;8. doi:10.1038/ncomms15065.

[52] Mirkouei A, Haapala KR, Sessions J, Murthy GS. A mixed biomass-based energy supply chain for enhancing economic and environmental sustainability benefits: A multi-criteria decision making framework. Appl Energy 2017;206:1088–101. doi:10.1016/j.apenergy.2017.09.001.

[53] Furubayashi T, Nakata T. Cost and CO2 reduction of biomass co-firing using waste wood biomass in Tohoku region, Japan. J Clean Prod 2018;174:1044–53. doi:10.1016/J.JCLEPRO.2017.11.041.

[54] Santibañez-Aguilar JE, Flores-Tlacuahuac A, Betancourt-Galvan F, Lozano-García DF, Lozano FJ. Facilities Location for Residual Biomass Production System Using Geographic Information System under Uncertainty. ACS Sustain Chem Eng 2018;6:3331–48. doi:10.1021/acssuschemeng.7b03303.

[55] Kesharwani R, Sun Z, Dagli C. Biofuel supply chain optimal design considering economic, environmental, and societal aspects towards sustainability. Int J Energy Res 2018;42:2169–

98. doi:10.1002/er.4006.

[56] Singlitico A, Goggins J, Monaghan RFD. Evaluation of the potential and geospatial distribution of waste and residues for bio-SNG production: A case study for the Republic of Ireland. Renew Sustain Energy Rev 2018;98:288–301. doi:10.1016/J.RSER.2018.09.032.

[57] Jäppinen E, Korpinen O-J, Ranta T. The Effects of Local Biomass Availability and Possibilities for Truck and Train Transportation on the Greenhouse Gas Emissions of a Small-Diameter Energy Wood Supply Chain. Bioenergy Res 2013;6:166–77. doi:10.1007/s12155-012-9244-9.

[58] Jäppinen E, Korpinen O-J, Ranta T. GHG emissions of forest-biomass supply chains to commercial-scale liquid-biofuel production plants in Finland. GCB Bioenergy 2014;6:290–9. doi:10.1111/gcbb.12048.

[59] Zhang X, Luo K, Tan Q. A feedstock supply model integrating the official organization for China’s biomass generation plants. Energy Policy 2016;97:276–90. doi:10.1016/j.enpol.2016.07.027.

[60] Yazan DM, Fraccascia L, Mes M, Zijm H. Cooperation in manure-based biogas production networks: An agent-based modeling approach. Appl Energy 2018;212:820–33. doi:10.1016/J.APENERGY.2017.12.074.

[61] Umeda Y, Nonomura A, Tomiyama T. Study on Life-cycle Design for the Post Mass Production Paradigm. Artif Intell Eng Des Anal Manuf 2000;14:149–61. doi:10.1017/S0890060400142040.

[62] Halog A, Manik Y. Advancing integrated systems modelling framework for life cycle sustainability assessment. Sustainability 2011;3:469–99. doi:10.3390/su3020469.

[63] Bichraoui-Draper N, Xu M, Miller SA, Guillaume B. Agent-based life cycle assessment for switchgrass-based bioenergy systems. Resour Conserv Recycl 2015;103:171–8. doi:10.1016/j.resconrec.2015.08.003.

[64] Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF. The ODD protocol: A review and first update. Ecol Modell 2010;221:2760–8. doi:10.1016/j.ecolmodel.2010.08.019.

[65] Kim S, Kim S, Kiniry JR. Two-phase simulation-based location-allocation optimization of biomass storage distribution. Simul Model Pract Theory 2018;86:155–68.

doi:10.1016/J.SIMPAT.2018.05.006.

[66] Viana H, Cohen WB, Lopes D, Aranha J. Assessment of forest biomass for use as energy. GIS-based analysis of geographical availability and locations of wood-fired power plants in Portugal. Appl Energy 2010;87:2551–60. doi:10.1016/j.apenergy.2010.02.007.

[67] Karttunen K, Lättilä L, Korpinen O-J, Ranta T, others. Cost-efficiency of intermodal container supply chain for forest chips. Silva Fenn 2013;47:24.

[68] Jäppinen E, Korpinen O-J, Ranta T. Simulation Modelling in Biomass Logistics-Benefits, Challenges and Three Case Studies. 23rd Eur. Biomass Conf. Exhib., New York: ETA-Florence Renewable Energies; 2015. doi:10.5071/23rdEUBCE2015-1CV.3.9.

[69] Hauschild M, Potting J. Spatial Differentiation in Life Cycle Impact Assessment: A decade of method development to increase the environmental realism of LCIA. Int J Life Cycle Assess 2006;11:11–3. doi:10.1065/lca2006.04.005.

[70] SFS-EN ISO 14040. Environmental management - Life cycle assessment - Principles and framework (ISO 14040:2006) 2006.

[71] SFS-EN ISO 14044. Environmental management – Life cycle assessment – Requirements and guidelines (ISO 14044:2006) 2006.