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Chapter 7

The Need for Integrated Life Cycle Sustainability Analysis of Biofuel Supply Chains

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Additional information is available at the end of the chapter

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1. Introduction

Climate change has been widely investigated by the scientific community, and its potential impacts are expected to affect the world's economy, ecosystem services, and societal structures within a few decades. To reduce the undesirable consequences of climate change, adaptation and mitigation technologies and policies have to be implemented. Analyzing technological advances to address sustainable development, through integrated systems level methods and approaches, is needed to predict future vulnerability to climate change and continued ecosystem deterioration [1-4]. The incorporation of sustainability notion into all sub-systems of our global society has come into full swing and must be continued to be pursued by any entity, both in private as well as public sectors. However, these challenges require integrative and transdisciplinary computational tools and methods to aid in embedding sustainability goals into corporate and government policy decision making processes [5-8]. United States Environmental Protection Agency (USEPA) has been reshaping its strategies and programs in conjunction with incorporating the triple dimensions of sustainability [9].

In the U.S. bioenergy development, recent innovations in biotechnology, genomics and complexity science have contributed to the renewed interest in converting (ligno) cellulosic biomass to valuable fuels and other bioproducts [10]. The U.S. Department of Agriculture (USDA) and Department of Energy (USDOE) are actively supporting projects to make biofuels and bioproducts economically, socially and environmentally sustainable and viable. U.S. Bioenergy Research Centers work on accelerating genomics-based systems biology research to achieve the transformational breakthroughs in basic science needed for the development of cost-effective technologies to make production of next-generation biofuels from lignocellulose, or plant fiber, commercially viable on a national scale [11]. Figure 1 shows

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the many potential production pathways to biomass hydrocarbons. Features of these alternative pathways include diversity in feedstocks, fuel composition, and byproducts. Integrated decision-making tools are urgently needed to support choices among these alternatives. Developing these tools effectively requires a life-cycle and dynamic perspective. Life Cycle Assessment (LCA) follows internationally accepted methods (ISO 14040 and ISO 14044) and practices to evaluate requirements and impacts of technologies, processes, and products so as to determine their propensity to consume resources and generate pollution.

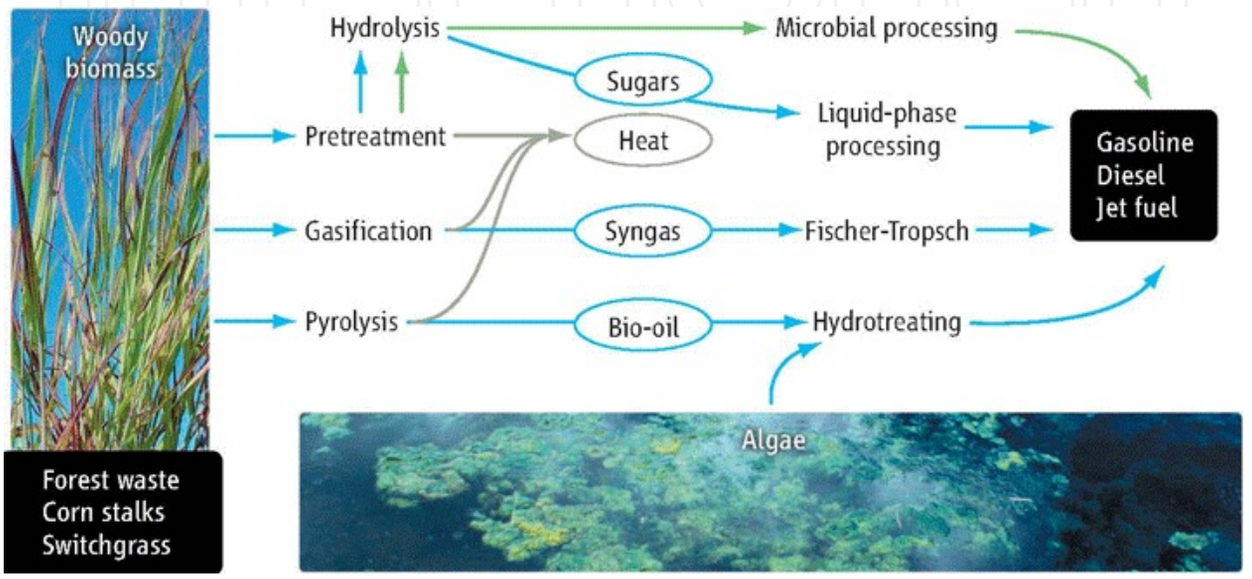


Figure 1. Pathways to biomass hydrocarbons. Reproduced with permission from [10]; published by Science, 2009

Mckone et al. [1] have identified 7 grand challenges that we must address to enable life cycle assessment (LCA) to effectively evaluate the environmental "footprint" of biofuel alternatives and to support the evolving bioeconomy. According to their work, the grand challenges for applying life cycle assessment to biofuels are:

- Understanding feedstock growers, options, and land use;
- Predicting biofuel production technologies and practices;
- Characterizing tailpipe emissions and their health consequences;
- Incorporating spatial heterogeneity in inventories and assessments;
- Temporal accounting in impact assessments;
- Assessing transitions and end states; and
- Dealing with uncertainty and variability.

The above challenges have already been addressed and analyzed in disaggregated and piecemeal fashion in several papers in various disciplines. *What we really need is to integrate the disparate methodologies systematically and computationally to obtain comprehensive and robust*

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results (i.e. indicators and metrics) which can support decisions and policies in public and private sectors. Thus, our one grand challenge is to synthesize our current results and infer relevant and critical information either to support or not bioeconomy development. Integrated-oriented decision-making frameworks and tools with the support of information and communication technologies (ICT) and cyberinfrastructure are needed to support choices among the competing production pathways and provide information to various stakeholders. For instance, systems modeling (such as the use of DOE's GREET model) is relatively inexpensive to perform prior to physically implementing any experiments in laboratory or pilot scale. Towards developing a decision support system (DSS) tool that accounts for multi-stakeholders' interests in analyzing system's sustainability, this paper aims to highlight and describe the available tools, models and frameworks which can be used to address the 7 challenges identified and explore the possibility of their complementary attributes to result to an integrated system framework for assessing the sustainability implications of further investments in biofuels, bioenergy and bioproducts.

Thus, an in-depth analysis is needed to critically understand the re-emergence of biofuels in conjunction with sustainable development. Most of the research projects on cellulosic biofuels have not given due attention to social acceptability and economic feasibility, besides not considering the competing interests of various stakeholders [2- 3]. The interactions between environmental, social and economic impacts of biorefinery development must be analyzed in a comprehensive and integrated manner to ensure the sustainable development of a bio-industry (such as the increasing interest in "drop-in" biofuels). Concerns related to biomass harvest and its impact on soil erosion, nutrient losses, biodiversity losses, land use changes, water consumption, eutrophication and environmental impacts of auxiliaries inputs must be weighted with the benefits of cellulosic biofuels [2, 12]. Several studies (e.g. [11, 13-15]) have been conducted to identify biomass potential, assess technological efficiency and understand the environmental implications of biofuels. However, a complete and comprehensive evaluation of biofuels supply chain from a holistic and systems perspective has been lacking. Several authors [2-3; 6-8] have argued the need for further research for large scale deployment of second-generation and third generation biomass crops including their effects on land use, biodiversity and hydrology. Technological researches have focused on using cheap and easily available feedstock (e.g. woody biomass, harvest residues, agricultural residues) to advance lignocelluloses feedstock bio-refinery [16 - 17], whereas environmental concerns of biofuels have focused on carbon dioxide emissions only [18]. Though integrated forest products bio-refinery systems may result to additional revenues by producing co-products like biofuels and other biomass based chemicals in addition to the main products [16, 19], uncertainties prevail regarding the capital investments required as well as the social impacts for large-scale production [2-3].

With the above challenges in implementing bioenergy policies while carefully considering stakeholders' interests, dynamic integrated system methodologies are urgently needed to analyze the sustainability of biofuels supply chain and to better understand the overall impacts of introducing (ligno) cellulosic ethanol [5-7; 11] or even to support the development of "drop-in" biofuels.

In the subsequent sections of this paper, we elaborate on how we might support the conduct of integrated sustainability analysis and modeling of biofuel supply chains.

2. Status

2.1. Understanding stakeholders and resource requirements

The future feedstocks for biofuels may come from farms, rangelands, or forests. Because of transportation costs, harvested feedstocks are likely to be stored and processed at small- to intermediate-scale (distributed) facilities. Unlike oil companies and government agencies that have a hierarchical structure for decision-making, the first stages of biomass production might involve hundreds to thousands of decision-makers (stakeholders). Using life cycle perspective approach to influence policies that would alter the behaviors of these distributed decision-makers poses different challenges than when the decision-making authority is more highly concentrated. One expects that feedstock growers utilize land to maximize profits.

Having a large number of potential feedstocks with different characteristics in a system of distributed decision-making presents substantial challenges for current LCA approaches because of the vast scope of information needed to address so many alternatives. Multi-criteria decision analysis (MCDA), such as the Analytic Hierarchy Process (AHP), can aid in determining the most critical criteria, variables and indicators to stakeholders, which can represent their conflicting interests with respect to economic, environmental, technological and social dimensions of systems sustainability [4-5, 7-8]. The critical criteria and indicators can be ranked and identified by AHP's eigenvalues, which are calculated from stakeholders' inputs [20].

2.1.1. Multi-criteria Decision Analysis (MCDA) for Stakeholders' analysis

MCDA is a decision support system that is suitable for addressing complex problems featuring high uncertainty, conflicting objectives, different forms of data and information, multiple interests and perspectives, and including complex evolving bio-physical and socio-economic problem [21-26]. MCDA approaches have long been widely applied to economic, social, and industrial systems. An MCDA in general involves *m* alternatives (e.g. bioenergy systems) evaluated on *n* criteria (i.e. sustainability criteria), in which each of *j-th* criteria *C* of *i-th* alternative *A* has performance of *xij*. Each criterion is weighted, and *wj* is the weight of criterion *j*. The grouped (i.e., stakeholders) decision matrix *X* can be expressed as shown on Figure 2.

Wang et al. [27] present a review of MCDA methods to aid in sustainable energy decision making. In their review, the corresponding methods in different stages of multi-criteria decision-making (i.e., criteria selection, weighting, evaluation and final aggregation) are discussed. The criteria are classified into four major aspects: (i) technical (e.g., efficiency, primary energy ratio, etc.), (ii) economic (e.g., investment cost, net present value, etc.), (iii)

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environmental (e.g., CO2 emission, NOx emission), and (iv) social (e.g., social acceptability, job creation, etc.). The weighting methods of the criteria are classified into three categories: (i) subjective weighting (e.g., pair-wise comparison, analytical hierarchy process (AHP), etc.), (ii) objective weighting (entropy method, technique for order preference by similarity to ideal solution, etc.), and (iii) combination method.

	Criteria		c1	c2	⋯	cn
	Weights		w1	w2	⋯	wn
Alternatives	A1	X =	x11	x12	⋯	x1n
	A2		x21	x22	⋯	x2n
	⋮		⋮	⋮	⋱	⋮
	An		xm1	xm2	⋯	xmn

Figure 2. Grouped decision matrix of MCDA

Different MCDA approaches have been applied to support different decisions including environmental and sustainable energy decision making [28-30]. We can use any of MCDA methods to aid stakeholders' analysis to find out the "most critical" criteria, indicators and metrics that represent stakeholders' interests. A combination of AHP and LCA has been used for evaluating environmental performance of pulp and paper manufacturing [31]. Halog [20] and Halog et al [29] proposed the use of analytic hierarchy process (AHP), one of MCDA methods [32-34] in stakeholders' analysis for identifying the critical criteria, indicators and metrics which represent multi-stakeholder's interests. This will provide ranking of different criteria, indicators and metrics which are important holistically. MCDA opens great applicability to support sustainability assessment of existing and emerging multi-attribute systems. For instance, AHP allows stakeholders to weigh different criteria, indicators, and metrics by calculating Eigen values. In biofuels system, where energy efficiency, investment cost, GHG emissions, land use change and social impacts are the most common criteria, MCDA is certainly applicable. Through MCDA, we can focus first on the critical ones that account stakeholder' inputs.

However, the existing life cycle thinking and MCDA methods are considered steady-state methods whereby they provide snapshots of hotspots based on historical data. They do not provide projections or trends in the future. They do not take into account the interactions of different metrics, outputs and parameters over time. To make the results more useful for decision and policy makers, we need to model the dynamic interrelationships of these variables over time. Additionally, we can explore the use of Geographic Information Systems (GIS) to assist spatial analysis when needed.

2.2. Biofuel production technologies and practices

Much of the variability among LCA results for biofuels arises from lack of knowledge about how biomass production operations and fuel production from biomass will evolve. Many al-

ternatives exist both for production processes and for final products. An important challenge is to understand the energy, biomass, pollutant, and product mass balances of production facilities: To what extent will they be self-sufficient or even net producers of electricity? Will the facilities deliver a single product (fuel) or have multiple product streams (fuel, food, electricity, chemical commodities)? What are their waste products, air emissions, and water demands? A related challenge is accurately predicting scales of future biofuel production. For biofuels, the feedstocks are more dispersed and less dense than petroleum, which will induce biorefineries to be smaller than petroleum refineries. Ultimately, the scale of biorefining will depend on feedstock and production process choices, technological efficiency in converting feedstock to fuel, productivity of local land for feedstock production, and costs associated with feedstock production and transport, and biorefinery construction and operation. Much is unknown about this system at large scale and will remain uncertain until the system is created. Larger biorefineries may economize on refining-related impacts, but will increase transport-related impacts. Biorefinery scale has important ramifications for life-cycle impacts including the nature and the location of impacts. We can use the scenario analysis capability of the methods of agent based modeling (ABM) and system dynamics (SD) to predict potential performance of various biofuel production technologies and practices.

2.2.1. Agent Based Modeling (ABM)

Agent based model is a computer representation of the considered system (e.g. biofuels supply chain) that is comprised of multiple, interacting actors (i.e., stakeholders) [35]. ABM systems possess two distinct properties: (1) the system is composed of interacting agents; and (2) the system exhibits emergent properties, that is, properties arising from the interaction of the agents/stakeholders that cannot be deduced simply by aggregating the properties of the agents [36- 37]. ABM can be used to model the interactions of agents or sub-systems in biofuels supply chain using the metrics, variables and indicators as performance measures. Figure 3 provides schematic illustration of an agent-based system: each of the four circles represents a sub-system of agents (e.g., companies/entities) denoted by small dots and the whole arrows show how agents and sub-system of agents are interacting with each other. Interacting agents and sub-systems, though driven by only a small set of rules which govern their behavior, account for complex system behavior whose emergent dynamic properties cannot be explained by analyzing its component parts [35].

ABM aims to look at global consequences of individual or local interactions in a given geographical (e.g. regional) area. Parker et al [38] have categorized existing literatures on agent-based land use models into five categories—(i) policy analysis and planning; (ii) participatory modeling; (iii) explaining spatial patterns of land use or settlement; (iv) testing social science concepts; and (v) explaining land use functions. Fox et al [39] argue that optimization of supply chain performance is only possible when the impacts of decisions made by one agent onto another agents are understood. A systems model that captures all important interactions among different units of a supply chain would contribute to effective decision making. Julka et al [40] use petroleum refinery integrated supply chain modeler and simulator to mimic a crude refinery's supply chain to develop procurement strategies. Thus,

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ABM can be used to look at the global consequences in developing biofuels supply chain/ network considering the individual interactions of stakeholders across all life cycle stages.

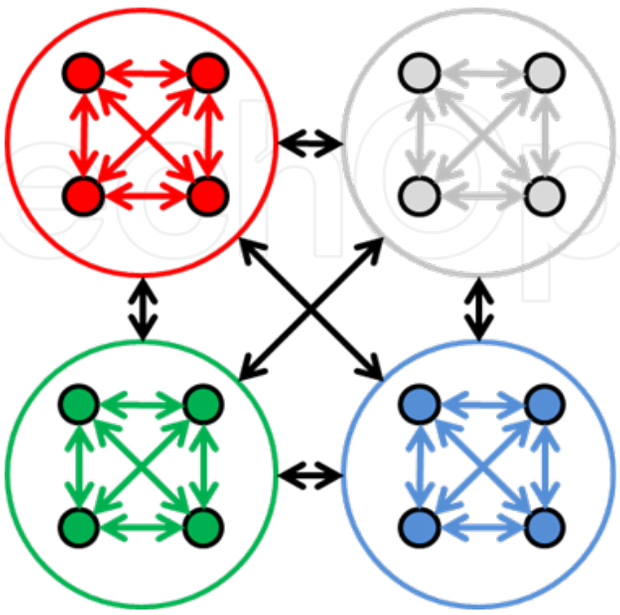


Figure 3. Illustration of an agent-based system

2.2.2. System Dynamics (SD)

SD is a well-established systems perspective/complexity science method which is originally developed by Jay Forrester at MIT [41- 42]. This has been applied in different corporate, industrial and government decisions worldwide which have the intention of modeling and understanding the interrelationships (i.e., feedbacks) of variables, indicators and metrics over time. This has been useful in modeling the interrelationships between or among subsystems which are linked by variables and aids to see how their interlinkages will produce specific overall system behavior. Before using appropriate modeling software package, it is important to draw causal loop diagrams. A causal loop diagram is a visual representation of the feedback loops in a system whereby the stocks and flows (i.e., involving different variables, parameters, indicators) are connected by either positive and negative loops. A stock (e.g., biomass, GHG, revenue, unemployment) is the term for any entity in the system that accumulates or depletes over time. A flow is the rate of change in a stock. A flow changes the rate of accumulation of the stock. The real power of system dynamics is utilized through simulation and in showing the inter-linkages between micro-, meso-, and macro-systems. SD involves computational modeling for framing, understanding, and discussing complex issues and problems [43-45]. It is recognized that the structure of any emerging system—the many circular, interlocking, sometimes time-delayed relationships among its components—is often just as important in determining its behavior as the individual components themselves. There are often properties of the whole which cannot be found among the properties-of-the-elements. The feedback loops as well as the use of stocks and flows can represent and

model the critical sustainability variables, indicators, and metrics to describe how seemingly simple sub-systems display baffling nonlinearity for the whole system [46]. The modeling can be developed by sub-dividing the whole system into sub-models but we need to remember that they are interconnected by variable, parameter or a metric [4, 47]. Through SD we can create a prototype dynamic system model for the system being considered.

In SD, a system is modeled mathematically in a nonlinear, first-order differential (or integral) equation such as:

$$\frac{d}{dt}x(t) = f\left(x,\ p\right) \tag{1}$$

where x is a vector of levels (stocks or state variables), p is a set of parameters, and f is a nonlinear vector-valued function. Simulation of such systems is accomplished by partitioning simulated time into discrete intervals of length dt and stepping the system through time one dt at a time.

SD typically goes further and utilizes simulation to study the behavior of systems and the impacts of alternative policies [44-46]. Running "*What If*" simulations or scenarios to test certain energy and environmental policies on a prototype system model can greatly aid in understanding how an emerging system potentially evolves over time. Similar to MCDA and ABM methods, SD has been applied in a wide range of areas, for example population, ecological and economic systems, which usually interact with each other. SD has been used in the sustainability assessment of technologies in the Canadian Oil Sands Industry [4, 47] as well as in bioethanol production in Canada [48]. SD models have recently been developed in some biofuels studies. Riley et al [49] use SD model to describe the U.S. DOE biomass program. Bush et al [50] and Sheehan [51] explore the potential market penetration scenarios for first generation bio-fuels in the United States. Scheffran and BenDor [52] investigate interaction between economic conditions and land competition between different crops. Franco et al [53] use SD to understand the difficulties in fulfilling government requirements for biofuels blending and to evaluate the effect of different government policies in the production of ethanol and biodiesel.

Once a system model is validated, the procedural steps can be done iteratively depending on the scenario defined. This will also provide information about the trends of important variables over time which will give us insights and guidance on what decisions and policies to take. Eventually, this modeling procedure can support the selection and implementation of sustainable biofuel systems.

2.3. Characterizing emissions and their health consequences

LCAs of transportation fuel systems report that the fuel combustion stage makes the largest contributions to pollutant emissions and associated disease burdens. Credible and reliable impact estimates for biofuel combustion are needed. Another aspect of LCA's tailpipe challenge is the need for accurate emission factors for future fleets that cover a range of fuel alternatives and vehicle technologies. Enormous technological progress has been made in

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controlling motor vehicle emissions, and there is strong momentum for continuing progress. In what ways and to what extent will shifts from petroleum-based fuels to biofuels affect the combustion-phase emissions of air pollutants? One historical approach to answer similar questions has been to conduct laboratory-based emissions testing. However, this approach is relatively expensive and lacks reliability for characterizing fleet-wide emissions from real drivers on real roads, and so is unlikely to provide accurate information in a timely manner. An alternative approach, used in LCA tools such as GREET [27] which assumes that vehicle emissions meet federal and state emissions standards regardless of the fuel used, and that emissions targets are the best estimate of what will happen in future years.

Since the concept of sustainability insinuates temporal and spatial connotations, it is important that variables, indicators, metrics and parameters representing stakeholders' interests are modeled over time within a geographical location, which can be done using dynamic system modeling.

2.4. Incorporating spatial heterogeneity in integrated assessment

A key challenge for integrated sustainability assessment of biofuels is to rationally select appropriate spatial scales for different impact categories without adding unnecessary complexity and data management challenges. Though methods such as LCA can address net changes across large geographical areas, it must also address how the impacts will be experienced at local or regional scales. Accurate assessments must not only capture spatial variation at appropriate scales (from global to farm-level), but also provide a process to aggregate spatial variability into impact metrics that can be applied at all geographical scales. We can use geographic information system (GIS) to support regionalized LCA. GIS has a powerful analytical ability to assess data spatially. It stores different layers of information. GIS is a tool that links location and attribute information to enable a person to visualize patterns, relationships, and trends for different parameters of a system. Previous literature and organizational reports have suggested using GIS as a tool to link the aspatial data with spatial data [54-56]. This offers at least two important contributions to the modeling of land use changes impacts on biodiversity and ecosystem goods and services caused by biofuels production. It permits analysis of spatially explicit datasets of land use and land cover, which can be used in the assessment of the areas affected by increased land occupation. It also offers an understanding of land use dynamics. The insight can aid in the predictions of land use changes caused by increased demand for biofuels [57].

2.5. Temporal accounting in integrated sustainability assessment

Similar to spatial resolution when conducting integrated sustainability analysis, selecting appropriate time scales poses challenges for biofuels system modeling efforts. Time allocations are important for comparing impacts, yet the time distribution of impacts is rarely made clear in studies such as LCAs. Many factors in systems analysis vary significantly in time. Therefore, time-based assumptions must be clearly noted and evaluated. Among the "moving targets" are population distributions, technology options, regulatory requirements, and the degree of biofuel penetration in the overall energy mix. Moreover, the inputs one

uses in integrated sustainability assessments to characterize biomass and fuel production technologies as well as transportation infrastructure must capture how these systems are evolving. Different natural time scales associated with different impacts pose challenges for effective comparisons among climate-change, human health, and water use consequences. The impacts of GHG emissions are distributed over decades using integrated assessment models and are commonly discounted. Assumptions about the rate of discounting influence judgments about the relative importance of current year versus future year emissions. Similarly, impacts on water resources and soil can play out over decades. We can use dynamic system modeling and simulation.

2.6. Assessing transitions and end states in sustainability analysis

Both advocates and critics of biofuels often focus on a restricted set of scenarios that appear to reinforce their *a priori* beliefs about how biofuel production and use might function [1]. Even accomplished practitioners of LCA tend to focus attention on system end-states (related to backcasting), i.e., what biofuel production and use will be likely 20 or 30 years from now, when a proposed combination of fuels and vehicles has matured and is thoroughly deployed. This perspective ignores potentially important effects that accrue during the transition phase; the impacts from building new infrastructure, new vehicles, and integrating a new fuel into a mature and, in many respects, inelastic transportation system. This can be addressed using dynamic system modeling and simulation or agent based modeling as discussed above.

To account for transitions, LCA requires much collaboration between economists and systems engineers to address what happens during the transition phase when large-scale changes occur in many components of a complex, market driven, technological system. For example, one of many key issues is whether fuel changes will affect the performance and lifetime of vehicles or the infrastructure transporting that fuel in ways that significantly increase climate forcing, water, health, and other externalities during transition. Technology investments are needed, and these activities could cause GHG emissions to rise in the near-term as part of a longer-term effort to attain a more carbon-efficient end state. In addressing transitions, there should be recognition that emerging technologies could profoundly change the assumptions that underlie biofuel LCAs. This issue makes clear the need to support life cycle thinking methods for building scenarios from which one should learn, rather than as a tool designed to make firm predictions.

2.6.1. Scenario development and analysis for policy planning and making

Forecasting, foresighting and backcasting are approaches used for policy planning and making. These scenario development approaches have their benefits and shortfalls. Backcasting involves working backwards from a particular desired future end-point or set of goals (i.e., sustainable society) to the present state, in order to determine the physical feasibility of that future and the policy measures that would be required to reach the state [58-60]. This helps in analyzing alternative futures response to present situation and deals with problems in a different way rather than extrapolating present scenario into the future (forecasting) [61-64].

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Backcasting makes it clear that addressing sustainability concerns requires a paradigm shift from business-as-usual attitudes. On the other hand, industries and organizations use forecasting technique as a data analysis methodology to develop future scenarios from existing information. Forecasting enables decision makers to identify reasonable estimates of various current activities. Using forecasting approach, managers and decision makers can tweak and calibrate their operations at the appropriate time in order to maximize benefits. Forecasting assists in preventing losses by taking in all relevant information and making proper judgment decisions [63]. Moreover, foresighting can be distinguished from forecasting. Forecasting is the passive attempt to diagnose or predict future events. Foresighting aims to actively change or create the future by linking it to the present. Thus, the major difference between foresighting and forecasting is that in forecasting the conclusions for today are missing. There are four major applications of foresighting: (1) assessing possible consequences of actions, (2) anticipating problems before they occur, (3) considering the present implications of possible future events; and (4) envisioning desired aspects of future societies. Foresighting which is a tool for 'decision-shaping' rather than 'decision-making' offers many benefits including: engaging policy-makers and experts in actively planning for the future; identifying potential problems early; verifying expectations and examining trends; bringing people together to create a suitable future; strengthening existing networks,; and educating the public on urgent future-related issues. It could have a positive impact on sustainable technology policy by providing a means for analyzing its broader social and economic implications.

By considering different scenarios (starting from business-as-usual to different plausible scenarios in the future (either through foresighting or backcasting), we can generate different results for our system performance measures and identify a few critical alternative systems or scenarios to be strongly considered for developing sustainable decision, policy, technology, systems, intervention, etc. Again, this is with the assumption that we can gather good quality data. We can also perform sensitivity and uncertainty analyses to improve the robustness of integrated sustainability analysis results.

2.6.2. Uncertainty and variability analysis for robust sustainability assessment

Addressing uncertainty is a major hurdle, not only for biofuels LCA, but for other integrated system modeling efforts as well. Many sources of uncertainty and variability, both inherent and epistemic, are encountered in climate-change, human-health, environmental, and economic impact assessments. Some of the uncertainties and variabilities cannot be reduced with current knowledge (i.e., through improvements in data collection or model formulation) because of their spatial and temporal scale and complexity. Effective policies are possible, but such policies must explicitly take into account uncertainty. Among those commenting on how to formally address uncertainty in impact assessments, it has been established that there are “levels” of sophistication in addressing uncertainty. In its recommendations for addressing uncertainty in risk assessment, the International Program on Chemical Safety proposed four levels, ranging from the use of default assumptions to sophisticated probabilistic assessment [1]:

- Level 0: Default assumptions; single value of result;
- Level 1: Qualitative but systematic identification and characterization of uncertainties;
- Level 2: Quantitative evaluation of uncertainty making use of bounding values, interval analysis, and sensitivity analysis; and
- Level 3: Probabilistic assessments with single or multiple outcome distributions reflecting uncertainty and variability.

Furthermore, Baumgartner [65] argued that assessing environmental and social impacts is associated with uncertainties caused by applied assessment tools, definition of assessment objectives, system boundaries of assessment and data quality. There are various ways to deal with data and model uncertainties when conducting system modeling and simulation [6, 66]. Uncertainties and variabilities come from a large number of variables and parameters considered, assumptions made, and the spatial and temporal variability in parameters or sources [67-69]. The latest LCA, MCDA, and system dynamics software packages include statistical tools to support uncertainty and sensitivity analyses. Uncertainty analysis aids to show if the model's general pattern of behavior is strongly influenced by changes in critical parameters. For system dynamics, the usual method is to perform a sensitivity analysis of the model whereby a collection of simulated experiments is performed [70]. This is done by choosing parameters, metrics and indicators that are judged to be sensitive, changing their values and then re-running the simulation model. If there is a drastic response in the results, this can show a lack of robustness in the system model. For ABM, the goal is to check whether the model addresses the right problem and provides accurate information about the system being modeled [71]. Additionally, Miller [72] proposes to use computer-based Active Nonlinear Tests (ANTs) that are capable of performing multivariate sensitivity analysis, model breaking and validation, extreme cases, and policy discovery. ANTs search across sets of parameter values and are capable of detecting important non-linear relationships among the parameters—relationships that typically go unnoticed using standard techniques [73]. Besides the probabilistic approach in handling uncertainty, fuzzy mathematics, Monte Carlo simulation, etc. can be used to address imprecision [30]. As we confront uncertainty and variability, we need to separate the "doable" and "knowable" from assumptions that are conditional components of the integrated and life cycle sustainability assessments. An informative system perspective assessment should sort out the data gaps that can be addressed with modest effort from those that would require a major undertaking. All integrated assessment efforts require tools, such as sensitivity analysis, variance propagation methods, and decision/event trees for tracking the impact of data quality and model uncertainty through all components of an assessment. A strong challenge for integrated assessments in addressing uncertainty is to provide and track metrics of data quality with respect to how data were acquired (measurements, assumptions, expert judgment, etc.), to what extent the data have been validated or corroborated, and how well the data capture technological, spatial, and temporal variations. This can be best facilitated by capitalizing cyberinfrastructure such as web-based data mining techniques.

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3. Conclusions and discussion

Confronting the seven grand challenges, as argued by McKone et al [1], means recognizing some issues that have not been well articulated among practitioners of integrated sustainability assessment. In particular, a good balance must be attained between the needs of technology momentum and adaptive decision making. Most importantly, we must recognize that integrated assessment is an adaptive and ongoing process and not just a product. Technology momentum refers to the difficulties encountered in backing away from fixed costs (financial, institutional, and environmental) that have been sunk into one alternative pathway. Adaptive decision-making refers to learning by doing, recognizing that commodity costs and impacts can diminish as a system scales up. For biofuels we need technology momentum, but we must simultaneously maintain options for adaptive decision-making. These can be handled by the system-based approaches proposed in this paper which are being currently applied to wood-derived biofuels.

Although life cycle thinking methods can provide insights on options with the lowest impacts, results are often burdened by uncertainty such that they become more informative as technologies are deployed, making it difficult to apply life cycle thinking methods during the early phases of a major technology shift. One example is the important decision that must be confronted in a transition to (ligno) cellulosic biofuels; what end-product should be targeted among choices such as alcohols, alkanes, or a specific chemical compound such as dimethyl furan? This type of decision hinges on issues of timing, technical feasibility, and competitive advantage.

More collaboration and dialogue between basic scientists and sustainability practitioners is important for incorporating system thinking concepts into early phases of technology evaluation. Overall, approaches are needed to create more cross-talking among all members of the biofuel enterprise, which could be implemented at web-based level. Ideally, efforts toward developing the science and technology of biofuels will be continuously informed by those who are expert in integrated sustainability assessment. In this way, the biofuels community has the best opportunity to attain the overarching sustainability goals they seek. In integrated assessment of biofuels, one must recognize that no large-scale industrial product can be developed in isolation. Natural resource systems such as food, energy, water, and land are all intimately interconnected and thus integrated dynamic system modeling and analysis is absolutely needed.

To confront the uncertainty associated with sustainability analysis of biofuels combined with the irreducibility of many uncertainties, planners and policy makers must consider their role in managing uncertainty as well as managing impacts. Managing uncertainty requires addressing different aspects of the overall decision making process in the context of uncertainty. For example, decisions must be made to allocate resources among (i) investments to collect, store, and manage information; (ii) investments to improve the knowledge base (i.e., to generate new knowledge); (iii) formalization of the processes used to collect,

use, and process information; (iv) formalization of processes to evaluate and communicate uncertainty; and (v) adjustment of the risk assessment process to mitigate the practical impact of the uncertainty on the analysis process. These tasks can be facilitated with the support of ICT and cyberinfrastructure.

Barriers to integrated sustainability assessments will be similar to environmental LCA (such as many stakeholders want a final answer), to be "cleared for takeoff, with no call-backs. These stakeholders view these assessments as a final exam; pass it and you are done being concerned with impacts and can proceed to technology deployment. This conceptualization serves to highlight the flaws in our thinking in sustainable technology development and commercialization. As McKone et al [1] pointed out this shortsighted perspective will fail to take advantage the true power of integrated and life cycle sustainability assessments. At its best, integrated sustainability assessment contributes to an ongoing process that organizes both information and the process of prioritizing information needs. These are opportunities for sustainability practitioners to focus attention and effort on making integrated, system perspective assessments more useful to decision makers. Integrated and life cycle sustainability analysis methods can co-evolve with a technology and provide the basis for adaptive planning. Decision makers who work in real time and often cannot wait for precise results must recognize that integrated sustainability assessment can provide valuable insights but it is not necessarily a "truth generating machine". Effective integrated and life cycle sustainability assessments can guide and inform decisions, but they cannot replace the wisdom, balance, and responsibility exhibited by effective decision-makers.

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