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Diversity and flexibility in sustainable supply chain design

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Diversity and flexibility in sustainable supply chain design

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CHAPTER 1: INTRODUCTION

In many parts of the world, consumers have shown increasing interest in the provenance of their purchases. Where do the things we purchase come from? How are they made? How do those products and processes impact the natural environment that surrounds us? As people have become increasingly aware of the sustainability challenges that our world now faces, many have wondered if the things that we enjoy today could be made or put together in a more sustainable way.

The ideas for this dissertation work grew from that same motivation. Of course, the field of sustainable supply chain management had already decades earlier been founded. But, its development, as of 2014, is understandably incomplete. In my reading, and in others', the nascent field of sustainable supply chain management currently lacks operational principles. Not unlike the motivating consumer's problem, a supply chain practitioner or researcher interested in doing sustainability work is still left to ask: How do I design a sustainable supply chain?

This dissertation begins by taking a cue from the natural environment. Driving between towns in Iowa, past corn field after corn field, I couldn't help but think about how long we've been unwittingly designing our supply chains the way that we do, by growing one crop (corn) at the exclusion of others – and how much different our approach is to supply chain design than what one would observe in a natural ecosystem, like a prairie, or a jungle. At the time, I simply drove on, assuming that we grow corn almost exclusively because that's just cheapest way to do it— and because we thought up this unwitting supply chain design long before anyone really cared about sustainability.

But, could that really be true? Are single-input systems really the cheapest way to do it? If supply chain management is, in large part, the study of the flow of resources and information between firms; and ecology is, in large part, the study of the flow of energy and nutrients between communities of living things, then might one inform the other? Moreover, with such similar conceptual frameworks, I began to doubt that ecologically evolved systems like prairie and jungles would really be poorer stewards of monetary and natural resources than the single-input, inflexible supply chains that we typically design.

This dissertation begins at this conceptual level. By way of an agricultural analogy, chapter two first offers basic ecological reasons to be interested in multi-input systems that more closely resemble natural systems. This ecological diversity is then tied to the operations research literature's notion of *manufacturing flexibility*, and the beginning agricultural analogy is used to illustrate similar dynamics across a variety of other processing industries. From there, we offer the three reasons that this dissertation project envisions multiple input-systems sometimes outperforming single input in terms of logistical costs.

Chapter three begins empirical testing of these ideas in a bioeconomy context. A simulation model was crafted with parameters drawn from real world applications in Iowa, USA. We then tested for the resulting costs when one, two or three crops are used as feedstock. Tests were done under a variety of circumstances, to see when, and if, more diverse, flexible systems were in fact, cost-effective.

Chapter four takes the idea further, to consider how independent, profit-maximizing actors would interact in a diverse/flexible environment. This necessitated proposing new ways to model flexibility interacting across firms, which we do by employing elements of Game Theory and shadow pricing to two inter-linked linear programs.

CHAPTER 2: DIVERSITY AND FLEXIBILITY AS DESIGN PRINCIPLES FOR SUSTAINABLE SUPPLY CHAIN MANAGEMENT

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Abstract

Supply chain management and logistics researchers face a new challenge. In addition to designing supply chains that reduce cost and increase agility, recently, we have also been asked to design systems that also lower a product's environmental burden. To-date, supply chain designers have approached this challenge with scant new design principles specific to the task. This paper endeavors to start filling sustainable supply chain designer's operational toolbox. Specifically, by bridging recent developments in the fields of ecology and operations research, we elucidate a design principle that we call 'diversity/flexibility' and conceptually argue its place as a beginning principle of design in sustainable supply chain management for natural resources.

1. Introduction and Review

Calls for considering the environmental burden of supply chain design come from myriad motivations. First, and most imminently practical, 20% of world energy consumption owes to transportation (Halldórsson and Kovács, 2010), and another 70% to

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advanced manufacturing (Mulhall and Bryson, 2014). As oil and gas resources around the world continue to rise in price and in volatility, the researchers and field logisticians who design supply chains have taken note. In their 2010 Delphi-method based forecasting project, von der Gracht and Darkow found that both researchers and practitioners identified "the problem of energy supply" as the highest probability scenario of 41 projected problems that will beset the logistics industry in 2025 (2010).

There are other more broad-based reasons too. Lieb and Lieb have suggested that their survey of logistics CEOs reveals five key reasons that logistical firms think about the sustainability of their supply chains: "desire to do the right thing; pressure from customers; desire to enhance company image; desire to attract green customers; and competitive pressures" (2010). To this list, Dey, LaGuardia and Srinivasan have added: "brand value; misuse of resources; government intervention; and international standards and regulations" (2011). The management literature has also reminded us that sustainability can be pursued proactively too, as an effective motivator for operational innovation (Nidumolu et al., 2009; Shrivastava, 1995).

Ultimately, then, because all supply chains trace back to the natural resources that sustain them, sustainable supply chain managers see threats to the abundance and/or quality of these critical natural resources as— at least— deserving of their attention. But, how do supply chain designers heed this call? What are the design principles of sustainable chain management? The literature is awash in papers key-worded to sustainability. [Recent reviews can be found in: (Ashby et al., 2012; Carter and Rogers, 2008; Dey et al., 2011; Halldórsson and Kovács, 2010; Hassini et al., 2012; Linton et al., 2007; Winter and Knemeyer, 2013) But, in some opinions (discussed below), actionable principles specific to the designing of sustainable supply chains are still lacking. This paper draws on research from both operations research and ecology to argue for the first time that ‘diversity/flexibility’ stands to become among the first basic principles of design for sustainable supply chain management.

1.2 What is sustainable supply chain management?

To-date, the most widely-cited recent definition of sustainable supply chain management (SSCM) in the research literature comes from Carter and Rogers (2008), who synthesized extant ideas and research to define it as, “the strategic, transparent integration and achievement of an organization’s social, environmental, and economic goals in the systemic coordination of key interorganizational business process for improving the long-term economic performance of the individual company and its supply chains.” This definition, and the many authors who have subsequently employed it, then embrace a dauntingly holistic view of sustainability, suggesting that it encompasses the entire supply chain’s impact on society, the natural environment, and firm profitability. While seemingly overwhelming, this wide-lens definition of SSCM is largely in line with the most famous original definition of general sustainability, the 1987 Brundtland Commission’s report, which called it, “development that meets the needs of the present without compromising the ability of future generations to meet their needs.” (World Commission On Environment and Development, 1987). SSCM research along these lines has grown dramatically over last ten to fifteen years (Linton et al., 2007); and has recently progressed from the classic phases of theory development, [review in (Carter and Rogers, 2008)]; to measure development [review in (Hassini et al., 2012)]; and even new types of supply chain model building [e.g. (Chaabane et al., 2012).

But, in the past half decade, a concurrent clamor for more narrowly focused logistical attention to SSCM suggests that certain ground-level operational insights are lacking. As examples: in their review of SSCM, Winter and Knemeyer (2013) point out that operational model building is the least represented methodology in sustainable supply chain research; Halldórsson and Kovács suggest that all this theory development has left basic questions about distribution strategies and batch-sizing appropriate to sustainable supply chain management un-answered (2010); and Hassini, Surti and Searcy (2012) point out in the conclusion of their review of sustainable supply chain management that matters of pricing between trading partners and inventory management in sustainable supply chain systems have yet to be sufficiently addressed.

Operational questions such as these can be described as 'principles' of sustainable supply chain management. Unlike more heavily researched features of wide-lens sustainable supply chain management —like cultural antecedents, theoretical linkages, or relationships to firm profitability — the basic how-to's of designing sustainable supply chains in specific contexts are a lesser explored territory. In the section that follows, we suggest one new principle, diversity/flexibility, and elucidate its origins and function.

2. Narrow lens SSCM: Biodiversity and the Natural Environment

If, as the review above suggests, one tenant of sustainable supply chain management is environmental stewardship, then design of a sustainable supply chain's input systems ought to reflect that goal. This, of course, requires that, for now, we willingly train our focus on to only the environmental dimension of Carter and Roger's definition. We suggest that this narrowing be entertained for two reasons: (1) it allows us to begin to fill in the absence of on-the-ground, tactical supply chain design principles in

SSCM; and (2) it could be argued that protecting the health and abundance of the natural resources that ultimately feed a supply chain is itself of benefit to both the societies, and the firms that surround it.

Herein, we begin by summarizing insights on sustainable supply chain management drawn from the natural world: the benefits of biodiversity. Evidence of the long-term sustainability benefits of biodiversity abound in the natural world. Natural ecosystems like prairies, rainforests, and jungles have all continued themselves for generations through the cycling and recycling of abundant and balanced communities of diverse plant and animal life. Particularly in the context of industries whose supply chains start in the soil (consider agriculture as a prototype illustration), the mechanisms of biodiversity can clearly begin to inform our supply chain design. But, if we start there, we can go further. Building on ecological and agronomic illustrations, we can meaningfully address design principles for the interface of environmental stewardship and supply chain management across the many industries whose supply chains ultimately source back to raw materials and the natural world. (A complete treatment of ecological diversity is beyond the scope of this paper; but, below we will summarize key mechanisms motivating our research and provide references for further reading.

<u>Nutrient Recycling and Environmental Quality</u>

- Different plant types give and take different qualities from the soil in which they grow. Growing only one plant year after year deprives the soil of the opportunity to restore its health and fertility; while growing a diversity of crops allows soil nutrients to replenish naturally in a process known as “biotic regulation”. Without diversity, soil nutrients must be maintained by chemical fertilizers, which have been known to leak into ground water, rivers and oceans, upsetting the delectate balance of life in those systems. [See: (Gliessman, 1998; Pimentel et al., 1997)]

Natural Pest Control and Environmental Quality

- Every plant type is preyed upon by its own community of noxious and lethal pests. In single input systems, management of these pests is achieved by chemical treatments that can also end up in surrounding waterways. However, decades of research shows that the addition of more crops to a landscape – even incrementally across both space and time – reduces pest pressure and therefore the need for toxic chemical inputs. [For reviews see: (Altieri, 1993; Gliessman, 1998)]

Natural Resiliency

- Ongoing science suggests that a combination of the two effects above, and others, lead to an intuitive result: the "diversity-stability hypothesis", which posits that, ceterus peribus, systems showing a greater variety of plant types recover more effectively from shocks like weather anomalies and toxic events than do less diverse systems, saving the community and the environment at least some of the monetary and environmental costs of remediation [See: (Johnson et al., 1996; Tillman and Downing, 1994)]

Resource Conservation

- Studies that compare production agriculture systems where a diversity of crops is employed against a single crop show the many natural efficiencies of more bio-diverse systems. Diverse cropping systems have been shown to reduce water use, reduce soil erosion, and reduce CO_2 emissions of agricultural production systems in field studies. [See: (Groom et al., 2007; Perlack et al., 2005; Tillman et al., 2006; Williams et al., 2009).]

2.1 From biodiversity to manufacturing flexibility

So, if a sustainable supply chain designer accepts that biodiversity can beget sustainability in a system, how does she begin to implement it? Firstly, what are the conceptual tools from the existing literature that can bridge ecology into her toolbox? And, second, might there be any reason for sustainable supply chain managers to believe that biodiversity might also confer some cost-saving logistical advantages? Profitability is, after all, another dimension of Carter and Roger's definition.

In the operations research literature, the term that describes a system's ability to produce multiple outputs is product flexibility. Product flexibility, has been defined as "The ability to changeover to produce a new (set of) product(s) very economically and quickly (Beach et al. 2000; Browne et al. 1984). Consider in this regard then the bio-diverse ecosystems described above (natural prairies, rainforests, and jungles) to be product flexible. Their inherent design and infrastructure allow them to output a wide abundance of plant and animal life.

But, from the sustainable supply chain manager's perspective, a natural environment's product flexibility is only useful so long as we can make something of that array of products. A similar term in the operations research literature is process flexibility. Process flexibility has been defined as, "The ability to produce a given set of part types, each possibly using different materials in several ways" (Beach et al., 2000; Browne et al., 1984). Consider first then as a beginning illustration the industries described above that draw their feedstock straight from the soil (agriculture, textiles and biorenewables) to be, in some cases, product flexible. Food, as a source of nutrients and energy certainly is so. Some textiles can be made from blends of different plant types by mixing standard cotton-twill denim, as one example, with also hemp and recycled fibers. In bioenergy, conversion technologies like fast pyrolysis have shown the ability to output energy and liquid fuels with a huge variety of different plant-based feedstock (Correll, 2009).

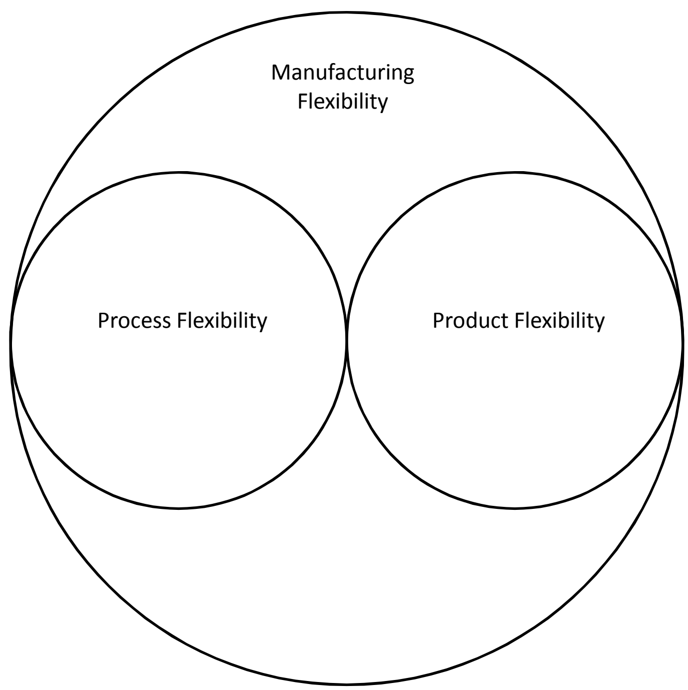

Figure 1: Manufacturing Flexibility, Product Flexibility and Process Flexibility

Both product and process flexibility are sub-sets of a bigger operational concept known as manufacturing flexibility (see figure 1). Sethi and Sethi broadly define manufacturing flexibility as "… adaptability to a wide range of possible environments that it [the system] may encounter. A flexible system must be capable of changing in order to deal with a changing environment" (Sethi and Sethi, 1990). Interestingly, manufacturing flexibility stemmed from a different motivation than the environmental stewardship and sustainability models that we suggest herein. Since its inception in the operations research literature in the 1960s, the concept of manufacturing flexibility and its resulting mathematical models have been employed exclusively in efforts to avoid production costs owing to demand uncertainty (For reviews see (Beach et al., 2000; Fine and Freund, 1990; Karsak and Kuzgunkaya, 2002; Sethi and Sethi, 1990)). From this motivation, a wide variety of other industries have pursued process flexibility. Consider: electricity generation, which seeks to meet quickly shifting demand through mixes of fossil fuel combustion, renewable fuel combustion, wind, and solar power; Petroleum, which uses advanced linear programs to process different grades of crude oil from disparate parts of the world into a standard slate of products; Cement production, which recent research shows cost and environmental benefits from inputting mixes of different heating fuels and raw materials; and metal alloys, where process flexibility models have been recently employed to optimize mixes of different input ores for cost. In the next section we will contribute both to these literature streams, and to developing the operational toolbox of SSCM, by outlining the new propositions of 'diversity/flexibility' in sustainable supply chain design.

3. Diversity/Flexibility and Logistical Costs

Herein we offer three conceptual propositions to argue that, in addition to protecting the natural environment, diversity/flexibility stands to reduce logistical costs in product-and-process flexible supply chains. Each proposition is elucidated by algebraic statement (lemma) and then brief mathematical proof.

Preliminaries

Consider first, as an illustrative example, any enterprise such as those discussed above, that is process flexible to inputs in a product flexible supply environment. To begin, consider agriculture, textiles and biorenewables, where the firm's core function is to convert plant material into a product. Keep in mind two facts about plants: (1) they live and die (or lie dormant) in seasonal cycles affected by their surrounding weather; and (2) they need to be collected in some time window that begins when they are available for harvest (or, are "ripe"), and that ends before they spoil in the field. Let Ω be a set of days included a time horizon of one year (i.e. $\Omega = [1,2,3\ldots364,A]$), where A is typically 365. Let a single crop's annual harvest window, be given by set $\alpha \subset \Omega$, where cardinality is $a \leq A$ days (i.e. $|\alpha|=a$). Similarly, a second crop's annual harvest window can be given by set $\beta \subset \Omega$, where cardinality is $b \leq A$ (i.e. $|\beta| = b$).

Now widen the lens to consider other analogous examples, electricity generation, petroleum products, concrete production and metal alloys, just to name a few. While the mix of inputs for these industries are not as obviously seasonal in their availability as are plants; plants are nevertheless illustrative. Inputs to each of these additional industries feature seasonal price fluctuations that make them more desirable during certain times of the year, owing to any combination of production cycles, demand cycles, and/or seasonal shipment costs. Moreover, each material must be either collected by the processing firm or its paid agent, not unlike the prototypical agricultural example. Consider then these opportune price points analogous to a plant's "harvest season". Similarly, then let Ω represent any reasonable planning horizon, and have a length of A elements, numbered 1 to A (i.e. $\Omega = [1,2,3\ldots A]$). Let a single input's opportunity window, be given by set $\alpha \subset \Omega$, where cardinality is $a \leq$ A days (i.e. $|\alpha|=a$), and a second input's annual opportunity window be given by set $\beta \subset \Omega$, where cardinality is $b \leq A$ (i.e. $|\beta| = b$). See figure 2.

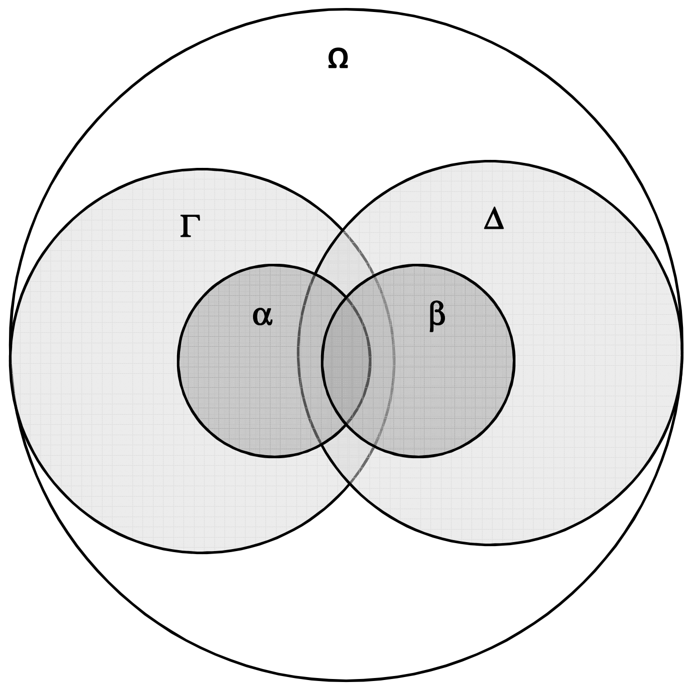

Figure 2: Sets for lemmas One through Three

Capacity utilization

How are the collection machines (like pickers, combines, balers, barges, trucks and mixers) deployed in this illustration system? Basically, the machines go out and collect all the required inputs during that input's opportune collection time (By analogy: during the harvest window). If the industry under consideration uses one input type as feedstock, (say cotton for denim in the American southwest, China, or India; or coal for electricity generation all over the world), the machines go out and collect all the firm's required cotton or coal during the input's opportunity window in that area – the same would be true in application to sugarcane for ethanol in Brazil, or limestone for cement production globally. In practicality then, over the course of one year, the machines work only during the subset of that year that is the single input's opportunity window. A standard measure of annual utilization would then be the fraction of time that the machine is not idle (Hopp, 2008), and could be given as be $U_1 = \frac{a}{A}$. Now, imagine process and product flexibility interacting — that is, that you could make your denim out of cotton and a second crop, like hemp; your ethanol out of mixes of sugarcane and miscanthus; your cement from virgin limestone and recycled tires. The same standard measure of capacity utilization would now be written as $U_2 = \frac{(a+b\ -\ |\alpha \cap \beta|\ )}{A}$, or the opportunity window of the first input, plus the opportunity window of the second input, minus those days common to both sets. Assuming all non-negative values, and $\beta \subsetneq \alpha$, (the opportunity window of the second input is not entirely contained in the set of the first), then algebraically, the utilization of the latter system has to be higher. Lemma one puts this first operational benefit of diversity/flexibility into simple algebraic logic:

Lemma 1: If $A,a,b > 0$ and $\beta \subsetneq \alpha$, then the utilization of a multi-input system U_2 will be higher than of a single input system, U_1.

Proof: Since $\beta \subsetneq \alpha$, we have $a < a+b$ - $|\alpha \cap \beta|$, so that $\frac{a}{A} \leq \frac{a+b-\ |\alpha \cap \beta|}{A}$. Because A,a,b > 0 , this implies that $U_1 < U_2$. ■

Proposition 1: Diversity/Flexibility begets higher capacity utilization and thereby lower logistical costs

Capacity utilization impacts cost in our example firm in the following way. Imagine that a fixed quantity of the required input needs to be covered by these collection machines in one year in order to amass enough material to keep the firm running for the year. Of course, that material must be collected during its opportunity window. Given that each machine can only work, in the single input case, $(\frac{a}{A})$% of the year, lower-capacity-utilization, single opportunity window systems can demand that multiple collection machines be purchased in order to cover the entire required area within the single specified time window. When diversity/flexibility is added to the system, capacity utilization of a single machine is, per Lemma 1, necessarily increased, because a single machine can now work $(\frac{a+b-|\alpha\cap\beta|}{A})$% of the year, meaning that, in some cases, fewer machines need to be purchased, thereby lowering the fixed costs of logistical systems.

However, this algebraic representation leads to an important logical condition when thinking about applying the diversity/flexibility principle. As α and β can be thought of as days in a year, they are necessarily subsets of Ω. In that case, Proposition 1 holds only as long as $\alpha \subsetneq \beta$ (every member of α is not also included in β). By agricultural analogy, this essentially means that Proposition 1 holds only as long as adding crops extends the harvest window (Or, put differently, as long the opportunity window of the additional input is not entirely contained within the first.)

Inventory cost

Revisit our preliminary model at the beginning of the process flexible supply chain. Keeping in mind that, during the course of a year, measured by A, in a single input system, all inbound material comes in during a days (the length of the opportunity window, measured in days), meaning that for a number of days ($A - a$), feedstock must be drawn from stored inventory in order to keep the firm running. Let daily demand for inputs be measured in tons and be given by d. Then the minimum amount of feedstock necessary to ensure year-round operation (assuming no external feedstock sources are available) could be given by $\text{Inv}_1 = A(1 - \frac{a}{A})d$. What then of adding that second input? Inbound material would then be coming in during both α and β, meaning that minimum inventory must be $\text{Inv}_2 = A(1 - \frac{a+b-|\alpha\cap\beta|}{A})d$. Removing the constants, we can see Proposition 2 algebraically:

Lemma 2: If $A,a,b > 0$ and $\beta \subsetneq \alpha$, then, the required inventory of a multi-input system, Inv_2, will be smaller than that of a single input system, Inv_1.

Proof: Since $\beta \subsetneq \alpha$, we have $-a \geq -(a + b - |\alpha\cap\beta|)$, so that, $(1 - \frac{a}{A}) \geq (1 - \frac{a+b-|\alpha\cap\beta|}{A})$. Because $A,a,b > 0$ this implies that $\text{Inv}_1 > \text{Inv}_2$. ■

<u>Proposition 2</u>: Diversity/Flexibility begets smaller required inventories and warehousing

Essentially, more days of inbound material means less days need to draw feedstock from stored inventory. Smaller total inventory size affects logistical costs in the following way: When considering the minimum amount of feedstock necessary to hold on-site in inventory, we are, in essence, considering the required physical space of our inventory facility. Larger facilities beget larger upfront costs in land, construction materials, and sometimes operational costs than do smaller ones. Accordingly, Proposition 2 suggests then that there are logistical costs savings to be captured through diversity/flexibility. With inbound material coming in during more days of the year, the required size of an inventory facility necessarily shrinks. Of course, condition 2 again provides that Lemma 2 only holds true when $\beta \subsetneq \alpha$, meaning that the opportunity windows of the two inputs have to be in some way temporally different.

Transportation and land use

Consider now a slightly more involved situation, where the two inputs' whole life cycles (not just opportunity windows) can be represented by two sets of days which are, again, members of the set of all the days in year, Ω. Let the subset of those days that encompass the entire lifetime of two inputs be Δ and Γ. The amount of land needed for our (denim, ethanol, sweetener, coal mining, wind farming, solar collection…etc) operation could be given by, obviously, the number of hectares needed to collect a year's worth of feedstock, given that input's expected yield over space. Let yield of the first input be Y_1 per hectare, and the second Y_2. Therefore the land area required of a single input system would be given by $\text{Area}_1 = \frac{Ad}{Y_1}$. But, what if two inputs are available on the same area of land? Then what happens to the land requirement? We will find results for the upper and lower bound. In the condition where $\Gamma \cap \Delta = \emptyset$ (the lifetime of the inputs do not intersect at all over the course of one year, so their intersection is an empty set), we can easily see that $\text{Area}_2 = \frac{Ad}{Y_1+Y_2}$.

Lemma 3a: If $A, d, Y_1, Y_2 > 0$ and $\Gamma \cap \Delta = \emptyset$, then the area required for a single input system Area_1 will be larger than that for a multi-input system, Area_2.

Proof: Since $\Gamma \cap \Delta = \emptyset$, we have Area$_1$ = $\frac{Ad}{Y_1}$ and Area2 = $\frac{Ad}{Y_1+Y_2}$. Because $A, d, Y_1, Y_2 > 0$, it follows that Area$_1$ > Area$_2$. ■

But now, consider the more complicated situation wherein the two inputs have overlapping lifetimes (i.e. $\Gamma \cap \Delta \neq \emptyset$). In this case, can logistical – and particularly transportation – efficiencies still be gained? Imagine a single unit of land (say, a hectare) divided in to portions for two inputs. Each input then is given a weight (w_1, w_2) corresponding to the percentage of the land area that it occupies, such that $w_1 + w_2 = 1$. In this case, area of the two input system would be Area$_2$ = $\frac{Ad}{w_1Y_1+w_2Y_2}$. In such a case, the inequality holds only under its own telling condition, $Y_2 > Y_1$.

Lemma 3b: If $A, d, Y_1, Y_2 > 0$, $\Gamma \cap \Delta \neq \emptyset$, $w_1 + w_2 = 1$, and $Y_2 > Y_1$, the area required for a single input system Area$_1$ will be larger than that for a multi-input system, Area$_2$.

Proof: Since $Y_2 > Y_1$ and $A, d, Y_1, Y_2 > 0$, we have $\frac{1}{Y_1} > \frac{1}{w_1Y_1+w_2Y_2}$. Because $w_1 + w_2 = 1$ it follows that Area$_1$ > Area$_2$. ■

<u>Proposition 3:</u> Diversity/Flexibility begets smaller land use, and thereby lower transportation costs.

Lemmas 3a and 3b essentially lay out the logistical benefits of being able to source multiple inputs on the same land in one year. In agriculture, this has long been known in tropical and subsistence agricultures “intercropping”. While a variety of agronomic and ecological advantages of intercropping have already been explored [See

(Collins and Qualset, 1999; Gliessman, 1998) for reviews], herein, we offer a new one: transportation costs. Put simply, 3a says that when you can source two things on one parcel of land instead of one, you will need approximately half as many hectares. As land is inherently un-stackable, the more of it you need, the further out and back you have to travel. 3b adds to this saying that, if the two inputs have overlapping life cycles, the transportation savings can only be realized if the additional input has a higher expected yield over space. Therefore, this type of diversity/flexibility can reduce expenditures on inbound transportation of feedstock in both cases.

Notably, this is not only a cost savings function, but also a potentially mutualistic benefit with environmental costs, as less land is required to feed the example processing operation. Conceivably, this could leave more land available for conservation. Lemma 3 also requires its own telling condition: when Γ and Δ overlap, Y_2 must be greater than Y_1.

4. Conclusions and Further Work

In this paper, we have endeavored to put forward a new design principle for sustainable supply chain management, particularly by first drawing examples from those industries most connected to the natural world. We have attempted to bridge disparate advancements in operations research and ecology to elucidate what we call 'diversity/flexibility' for the benefit of SSCM. We herein nominated diversity/flexibility for the first time in an effort to begin to fill in the gap of operational insights available to the burgeoning field of sustainable supply chain design.

Drawing from decades of research in ecology, we have suggested diversity/flexibility as a way to learn from the natural world how to build sustainability into our supply chain designs. We have taken the operations research concepts of manufacturing flexibility, product flexibility and process flexibility in a new direction, suggesting for the first time that its natural overlap with biodiversity recommends it as conceptual tool for practicing sustainable supply chain managers and researchers. In so doing, we tied environmental stewardship to profitability in one new design principle, thereby heeding at least two of three calls in Carter and Roger's famous 2008 definition. Of course, we have not explicitly argued the social dimension of the diversity/flexibility principle. However, one could argue that contributing to the health of the ecosystems and firms that surround a society is likely to bring about social benefits as well.

Because this work is mostly conceptual in nature, a wide host of work remains to be done. Firstly, the propositions and lemmas are intended only as starting points, not ending points. We hope to encourage future research on diversity/flexibility in SSCM. Our thinking led us to conditions on each lemma that bear practical implications for field logisticians and researchers. Perhaps further applications and research could lead to new conditions on each lemma that could further inform practical sustainable supply chain design. Second, our own work needs to be empirically tested with realistic parameters across all of the industries discussed herein. Finally, the field of SSCM is larger than just those industries we have imagined. Further thinking could possibly extend these ideas to practical applications beyond the scope of what we have discussed.

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CHAPTER 3: LOGISTICAL SUPPLY CHAIN DESIGN FOR BIOECONOMY APPLICATIONS

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Abstract

This paper propose[5]s and tests novel supply chain designs for bioenergy and biobased products that result in logistical costs savings of 2% to 38%. The proposed supply chain design reduces the costs of (1) purchasing logistical harvesting equipment; (2) operating logistical harvesting equipment; and (3) holding feedstock inventory, by using a multitude of crop types as feedstock, instead of just one, as is common in research and practice today. In so doing, this research challenges the prevalent assumption that monocultures, despite their known environmental concerns, are preferable from a costs perspective. Simulation/optimization is used to test supply chain designs, and then to find the environmental conditions where these new supply chain designs could be most profitably implemented.

1. Introduction

Biorenewable fuels have the potential to offset worldwide carbon and greenhouse gas emissions, develop local economies in rural areas, and enhance energy security in the countries in which they are produced [1]. That has spurred significant public and private interest around the world. By federal mandate in the United States, biorenewable fuels

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production will grow to 36 billion gallons in 2022. Similarly, the European Union has stipulated that the European biorenewable fuels industry grow to meet 10% of its transportation fuel demand by 2020 [2].

The vital role that reducing logistical costs will play in determining the feasibility of a future bioeconomy has been widely published. Hess, Wright and Kenney have suggested that inbound feedstock costs will “largely control the rate at which the industry grows” [3]. Various authors have attributed from 35% to 90% of supply costs for biobased products to logistics under various circumstances [4, 5]. Logistics has thus been pinpointed as a significant cost component and potential obstacle to future development of the bioeconomy [4, 6-8].

Research logisticians have recently been called to: (1) seriously address fuel use and natural resource use [9]; and (2) design smart logistical plans for the profitable development of more sustainable industries [10] . However, mainstream logistics research has only scantly considered supply chain design in the context of many developing sustainable industries, especially biorefining and biobased products (e.g. [11]).

In the US and around the world, supply chains for biorenewable fuels and biobased products are currently being researched and implemented in the seemingly tried-and-true mold of conventional food agriculture — that is, by imagining gigantic swaths of land planted year-after-year to a single, high yielding feedstock crop that surrounds the biorefinery. In both food and biofuel production systems, this, unwitting, supply chain design is referred to broadly as “monoculture”, and is exemplified by modern corn-to-ethanol production in the United States (the world’s largest ethanol producer); sugarcane-to-ethanol systems in Brazil (the world's second largest ethanol producer); and also by researchers' and politicians' visions of advanced switchgrass-to-ethanol facilities that, they argue, will become technically and economically feasible in the next 10 to 15 years.

That the agricultural and biorenewable world has come to embrace monocultural supply chain designs is — like all past — already prologue, and has been well documented from a variety of perspectives [12-14]. Similarly well-documented — although, rarely implemented in modern practice — are the ecological and agronomic reasons to believe that the alternative, more diverse supply chains, that employ a variety of crops on the landscape, could benefit both productivity and environmental stewardship [15-17]. Do business logisticians now have a role to play in this ongoing discussion about changing the future of global agricultural landscapes? This research suggests that we do. The authors suggest that designing supply chains for biobased products that employ multiple crops as feedstock offers distinct logistical cost advantages compared to contemporary practice and research.

In so doing, this research challenges the prevalent assumption that monocultures, despite the problems already researched, are preferable mostly from a costs perspective. The authors suggest that logisticians have a prominent role to play in this discussion. Specifically, the question that this research addresses is: from a logistics and inventory cost perspective, is the traditional monocultural supply chain design the least cost approach given varying environmental circumstances? This paper contributes to the literature by exploring how, and under which conditions, heretofore over-looked savings can arise from using multiple crop types as feedstock instead of only one.

1.2 Previous research

The techno-economic research literature to-date is not without suggestions for supply chain design in the biorenewable context. Recent reviews can be found in [18-20]. In their review, An et. al note the relative absence of strategic thinking about supply chains for biofuels compared to the research attention paid to day-to-day operational issues. While a wealth of papers have been written on techno-economic assessment of facility placement and technology choices, fewer have considered questions of supply chain design. Notable exceptions include Tatsiopoulos and Tolis [21], who compared both centralized and decentralized logistical systems, as well as farmer versus 3rd party carriers for corn stalks in Greece. They found that decentralized systems, where farmers themselves were responsible for trucking, resulted in the lowest possible logistical costs in their case study area. Sokhansanj et al. [22, 23] have evaluated four ways in which switchgrass could be prepared and stored for truck transportation (square bales, round bales, loafing and wet baling). They found that storing the material in roadside loafs, and then grinding it before loading it on to grain trucks was the most cost effective at smaller sizes, but that square baling at the roadside, and then transporting square bales to the refinery on flatbed trucks became more cost competitive as plant size increased. Kanzian et al. [24] used linear programming and GIS to consider setting up intermediate chipping facilities between the forest supplying a biorefinery with woody biomass and an Austrian biorefinery. They found that the intermediate chipping facilities were not cost effective. Fan et al. [25] outlined four archetypal supply chains for cellulosic biofuels and found the most cost effective and environmentally responsible design depended on the size of the facility under consideration.

What has been overlooked in recent imaginations and reviews of supply chain design for biofuels are the potential costs savings of using multiple crops instead of a single one. In Gold's excellent recent review piece, the logistical problems endemic to monocultures are presented; but, the review leaves the emerging evidence that using multiple feedstock crops could provide a solution untouched. Nilsson and Hansson [7] used a discrete event simulation approach to find that a two-crop system offered cost savings in terms of inventory and logistics at one district heating plant in Sweden. Papadopoulos and Katsigiannis used dynamic programming to optimize a biorefinery in Greece, and noted that their optimal solution sets contained multiple types of feedstock coming in to the refinery, not just one [26]. Similarly, in a case study application of their proposed metaheuristic facility citing and plant optimization model in Greece, Rentizelas et al. reported optimal solution sets that used four crops as feedstock instead of only one [8].

What we do not yet know is how robust and generalizable are these emerging findings. Research logisticians have yet to elucidate the mechanisms under which these savings arise, and to investigate under which technological and environmental conditions one could expect to see meaningful logistical savings from multiple feedstock supply chain designs? This is the research gap addressed by this paper.

1.3 Research implications

Because of the projected growth of biorenewable fuels around the world, this potential re-design of supply chains (and thereby very large-scale land use) carries dramatic implications for practitioners and the communities around the world that will be engaged in the bioeconomy. This paper suggests that biorenewable investors and plant operators stand to save up to 38% on the cost of delivered feedstock by re-imagining their supply chains to include multiple crops instead of just one. Companies that seize this opportunity would dramatically re-design agricultural land use around the world and could make the global transition away from fossil fuels more feasible in our lifetimes.

We call the logistical benefits proposed to arise from using multiple feedstock crops ‘the benefits of diversified supply chains’, and present conceptual arguments for their cost savings mechanism in section two. In section three, a simulation/optimization experiment with 81 treatment scenarios is outlined. Each scenario is optimized three times, first as a conventional monoculture, and then again with an increasing number of feedstock crops available. The resulting logistics costs for the first five years of a simulated biorefinery are compared. In section four results are analyzed to see, if, and when, the benefits of diversified supply chains are present and to what extent. Generalizable conclusions are drawn in section five. In section six, known limitations of our study are presented and future work is suggested.

2. Theoretical Motivation

Conceptually, the benefits of diversified supply chains are proposed to manifest in two ways: (1) lower fixed expenditures on logistical harvesting equipment; and (2) lower capital investment in fixed inventory facilities. Each of these savings is argued in turn and presented as a proposition motivating our model.

2.1 Fixed expenditures on logistical capital equipment and the benefits of diversified supply chains

All crops become available for harvest during specific time windows, when they have grown to maturity and are ready for harvesting. This is a function of each plant type’s unique growth patterns. In conventional monocultures, where only one type of crop is grown, gigantic swaths of land demand harvesting at the same time — meaning that multiple harvesting machines are required to service thousands of acres within a single service-time window. On the other hand, if a diversity of plant types were grown, different plant types could become ready for harvest at different times, meaning that a fewer number of machines would be needed to service the same amount of land in one year.

Proposition 1: Expenditures on fixed logistical assets will fall as a greater diversity of crops is added to the feedstock supply area.

2.2 Fixed cost of capital inventory facilities and the benefits of diversified supply chains

When a biorefinery is fed by a single feedstock crop, all inbound material must be received during that crop's single harvestable time window. In practicality, this means that at least one year's worth of feedstock must be held in inventory to keep the biorefinery supplied for daily operation until the single crop's next annual harvest window. This can necessitate large and expensive inventory facilities, where at least one year's worth of inputs must be held on-site. Multiple feedstock types alleviate this burden. Having multiple crop types means having multiple harvest windows throughout the year when inbound feedstock will be received. Staggering these harvest time windows thereby necessarily reduces the minimum amount of feedstock that must be held on-site. In a multi-feedstock scenario, the biorefinery holds only enough inventory to meet supply until the next crop's harvest window, which must be a shorter period of time, as a single year is divided into an increasing number of time windows.

Proposition 2: The maximum inventory held in a year, which determines the minimum size of a storage facility, will fall as a greater diversity of crops is added to the feedstock landscape.

3. Research Methodology

3.1 Simulation and optimization

A simulation/optimization experiment was designed to test propositions one and two under a variety of conditions. We were interested in comparing the total logistical costs incurred when one, two, or three types of crops were employed over a 5-year planning horizon. This use of the optimization method is in-line with Bartolacci et al.'s categorization of optimization for strategic investment planning [27]. The generalized bioprocessor's logistical optimization problem can be formulated as follows.

A bioprocessor requires a fixed number of tons of biomass per year. This demand is assumed to be evenly distributed across every day of the calendar year. Demand can be met in two ways: (1) by baling and collecting biomass from surrounding farms contracted to grow for the bioprocessor; and (2) by purchasing biomass from a spot market.

Collection of biomass from contracted farms takes the following form: Consider that the bioprocessor is surrounded by farmers willing and able to grow a finite set of crops, I = {1,2,3}, where, for instance, 1 = corn stover, 2 = switchgrass and 3 = reed canarygrass. At the beginning of every simulation run, the bioprocessor contracts with farmers for the right to harvest biomass from enough hectares of land to meet annual demands over the planning horizon, given expected yields for each crop type. Let K = {1,2,3,4} be a set of 4 logistical machines, where 1 = balers, 2 = self-propelled loaders, 3 = on-road transports, and 4 = self-propelled un-loaders, which the biorefinery must deploy for collecting crops and transporting biomass. There are both fixed and variable costs associated with each piece of equipment k ∈ K. The fixed cost is given by F_k

(which we chose to approximate with an un-depreciated purchase price because of its clear relevance to practitioners), and the variable cost by C_k (cost per hour of operation).

Purchasing biomass to meet demand takes the following form: Assume that a spot market for biomass is available to the bioprocessor. Purchases on the spot market are measured in tons and given by Θ. This market can deliver biomass of an unspecified crop type to the bioprocessor, but does so at a price premium per ton, given by P. Because this research is addressing only logistical costs, a partial cost accounting approach is employed, wherein the value of P represents a mark-up over the typical cost per delivered ton. (For the purpose of our research questions, it can be assumed that other costs, like the costs to the farmer of growing the crops will be similarly incurred whether the processor harvests themselves, or buys on the spot market, and that these costs are similar across biorefineries). In later sections, we perform a sensitivity analysis on our results with respect to P.

Whether collected or purchased, biomass that is not immediately processed by the bioprocessor accumulates as inventory. The required size of the bioprocessor inventory facility is given by the maximum recorded daily inventory over the simulation. The bioprocessor may or may not choose to hold safety stock (SS) inventory. Our planning horizon, in days, is given by D = {1….d…365a}, where a = 5 (i.e. a 5-year planning horizon).

The bioprocessor problem can be described as the following integer programming problem:

$$Min: \sum_{k \in K}(F_k X_k) + \sum_{k \in K} \sum_{i \in I} \sum_{d \in D}(C_k Y_{k,i}^d) + R(\underset{d \in D}{Max}(\Omega_d)) + P(\sum_{d \in D}\Theta_d) \quad (1)$$

Subject to:

$$\Omega_d = Max\left[\sum_{d=1}^{d} \sum_{i \in I}(Cap_1 Y_{1,i}^d \beta_i) + \sum_{d=1}^{d}\Theta_d - (\frac{Dem}{365})d\, , 0\right] \forall\, d \in D \quad (2)$$

$$\Omega_{d-1} + \sum_{k \in K} \sum_{i \in I}(Cap_1 Y_{1,i}^d \beta_i) + \Theta_d \geq \frac{Dem}{365} + SS\; \forall d \in D \quad (3)$$

$$\Theta_d \geq Max\left[\frac{Dem}{365} - \left(\Omega_{d-1} + \sum_{i \in I} Cap_1\, Y_{1,i}^d \beta_i\right), 0\right] \forall d \in D \quad (4)$$

$$\sum_{i \in I} Cap_1 Y_{1,i}^d \beta_i = \sum_{i \in I} Cap_2 Y_{2,i}^d = \sum_{i \in I} Cap_3 Y_{3,i}^d = \sum_{i \in I} Cap_4\, Y_{4,i}^d \;\; \forall\;\; d \in D \quad (5)$$

$$\sum_{i \in I}(Y_{k,i}^d/10) \leq X_k \forall\; d \in D, k \in K \quad (6)$$

$$\sum_{d=1}^{365a} Cap_1\, Y_{1,i}^d = \alpha_i \;\forall\; i \in I, a = 1,2,3,4,5 \quad (7)$$

$$X_k = integer \;\forall\; k \in K \quad (8)$$

$$X_k \geq 0 \;\forall\; k \in K \quad (9)$$

$$Y_{k,i}^d \geq 0 \;\forall\; d \in D, k \in K, i \in I \quad (10)$$

Where:

X_k — An integer decision variable for the discrete number of pieces of capital equipment of type k to purchase at time 0

$Y_{k,i}^{,d}$ — Hours worked by each type of capital equipment (k), on each crop type i, in day d

β_i — Yield per hectare of crop i, expressed in tons

Ω_d — Inventory held on site, on day d, or the difference between cumulative delivery of biomass and cumulative daily demand up to day d

R — The price per ton of building a storage warehouse ($)

Θ_d — The quantity (tons) of biomass purchased outside of contract on day d.

P	The price of purchasing biomass outside of contract (Θ), per ton ($)
Dem	Annual demand of the biorefinery, in tons
α_i	Hectares of crop i contracted in the given year
Cap_1	The hectare per hour capacity of machine 1 (baler)
Cap_{2-4}	The ton per hour capacities of machines 2 through 4 (loader, truck, un-loader)
SS	Safety stock held by the bioprocessor (tons)

The bioprocessor's objective is to minimize the cost of: purchasing capital equipment; operating the capital equipment over the 5-year planning horizon; constructing and maintaining a storage facility; and purchasing biomass from the spot market to prevent stockouts at the biorefinery (Eq 1). These values, X_1 X_2 X_3 X_4, Y_1 Y_2 Y_3 Y_4, and Θ_d therefore represent independent decision variables in this model. Experiments are conducted to determine their effect on the dependent logistical costs defined in equation (1). Constraint (2) ensures that daily inventory (Ω_d) equals the maximum of either the difference between cumulative delivered biomass plus spot market purchases and cumulative demand (i.e surplus biomass), or 0. Constraint (3) requires that the bioprocessor's daily demand for biomass feedstock is met by either stored inventory, daily delivery of biomass, or a combination thereof. In this design, SS (in constraint 3) was set equal to 0 because we assume the existence of a robust spot market capable of covering any need at any time; so that over the planning horizon, given constant demand, SS would be merely an inventory constant that would not impact this paper's research question. Constraint (4) ensures that spot market purchases occur only when necessary, when cumulative delivery of biomass on that day, minus cumulative demand and inventory, falls short of the daily demand. Constraint (5) provides that all of the feedstock flow sequentially from one machine in the supply chain to the next. Constraint (6) ensures that the amount of machine hours worked in one 10-hour day conforms to the number of machines purchased (X_k) at time 0. Constraint (7) delimits the number of hectares of each crop harvested each year to the amount specified for under contract. Constraints (8), (9) and (10) ensure that only positive integer values of harvesting and logistical equipment are chosen and that they are employed for only non-negative numbers of hours.

3.2 Scenario design and the biobased products supply chain

The optimization was applied to a carefully constructed simulation of a simple biobased products supply chain, based on current, real-world paramaters. Per Evers and Wan [28], simulation was selected for this research because of the following methodological benefits: (1) field experimentation with an actual commercial biorefinery — and, more importantly, the thousands of hectares of agricultural land required to feed it over the planning horizon — would be far too costly and take far too long, especially given the multi-crop treatments of interest, which are not being implemented today; (2) simulation allows observation of the interactions related to large logistical costs in the biobased products supply chain, and freed the authors from incorporating limiting or unfounded assumptions about other components of the system (like farmer psychology, or different equipment depreciation schedules) that do not directly relate to this paper's research question; and (3) certain aspects of the biorenewable system, like crop yields and available work days, are naturally stochastic owing to unpredictable weather patterns.

Development of the simulation conformed to the 8-step guidelines laid out in [29]. Previous engagement with representatives from the bioprocessing industry and farmers, who all expressed personal concern about logistical costs in the bioeconomy, familiarized the authors with the system. As the authors' thinking about logistics and the benefits of diversified supply chains in the biobased product context developed, we pinpointed the costs of: (1) purchasing and operating a logistical fleet and; and (2) building an inventory warehouse, as the key metrics (dependent variables) of interest. Because this research is interested in investigating the logistical benefits that can arise when more types of crops are employed, the number of types of crops used to feed the biorefinery was identified as the key experimental factor (independent variable).

A small and simple biomass supply chain was designed, based on the district heating plant model outlined in [7], wherein a bioprocessor will require 6,000 tons of biomass per year for operation. In the area surrounding the facility, farmers can and/or are willing to grow three types of crops. It is the responsibility of the processor to collect the biomass after it is harvested, bind it into bales for transportation using a “baler”, load those bales on to semi-trucks using a “loader”, deliver the biomass to the processor’s storage facility via on-road trucking, and then un-load the bales. Based on both [31] and private communication with an industry consultant, the cost of holding this inventory was based on a currently popular simple storage yard design, consisting of only purchased and cleared land, spread gravel, and annually replaced tarps. This basic supply chain, which is representative of advanced bioenergy applications, is shown in figure 1.

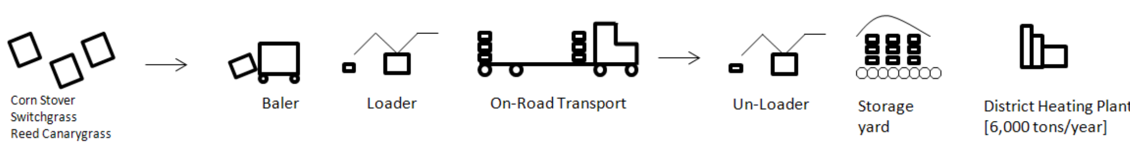

Figure 1: Basic bioproduct logistics.

The capacities and costs of the different pieces of logistical equipment were drawn from ongoing private communications with an industry consultant in 2013 and

2014, as well as recent academic references [30, 31]. These parameters are shown in Appendix A. Data collection also required estimates for crop yield and crop yield variability, as well as the typical range of dates when a crop could be ready for harvest. Three crops were chosen for the simulation: one, for the monoculture, that is already widely grown (corn stover); and two others that have received significant public and research attention as biomass feedstock crops (switchgrass and reed canarygrass). These three crops were also chosen for their known compatibility with the logistical equipment considered by this research. (Corn stover is commonly grown and harvested in the manner described; reed canarygrass was previously modeled with the same system and equipment in [7]; and switchgrass is not physically different enough from reed canarygrass to suggest that the same equipment could not work, at least for this paper's purposes.) Agronomic research literature was searched to find average reported yields, highest recorded yields, lowest recorded yields, and where possible, a measure of variability of a single crop over time [32-37] . Notably, this research rarely reports distributions of yield estimates in a given site. So, per [28], a triangular distribution of mean, high and low yields was employed to represent variability. Finally, consultation with an industry professional suggested that we restrict the amount of time between when a crop becomes available and when it is harvested to between 25 and 35 days, depending on the year, because weather can spoil un-collected biomass. This data is shown in Appendix B.

With the following data and parameters in place, the simulation was built in the Arena © environment, which was chosen for its ease of use and high capability [28], and its successful application to bioenergy systems in previous research [7]. The model was first built without stochasticity, so that the research team could hand calculate model outputs to confirm programming accuracy. Once the research team was confident in its implementation of the simulation model, an industry representative was asked to imagine a scenario similar to one this model could capture, and then asked his professional opinion on what the logistical fleet for such a scenario would look like. His estimates were checked against this model and similar results were found, affording the research team the confidence necessary to begin experimentation.

3.3 Experimental design and analysis

A 3x3x3x3 simulation experiment was designed, wherein the simulation was run with (1) one, two, or three available types of crops; (2) with low, medium or high base yields for each of the crops in the scenario; (3) with low, medium or high yield variability for each of the crops in the scenario; and (4) with three different assumptions (low, medium or high) about the price of biomass on a spot market (P).

Optimization was performed using OptQuest for Arena © software, which uses a metaheuristic solution procedure (tabu search), set by our research team to employ between 2 and 6 replications per trial solution of each simulation run. With tolerance (the convergence criteria for when two solutions are considered equal between two consecutive trial solutions) set at $100, OptQuest typically settled on a solution after approximately 900 runs. With each trial replicated on average four times, this resulted in approximately 291,600 simulations. On a 2.66 GHz quadcore PC with 4GB of memory, the simulation/optimization time per treatment was approximately 30 to 45 minutes, for a total computer run time of roughly 47 hours. Results are shown in tables 1 through 5.

Table 1: Total costs over five years

P = Low			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	$1,163,033	$1,031,683	$1,018,816
		Med	$1,241,595	$1,149,893	$1,021,735
		Low	$1,286,438	$1,049,366	$1,020,041
			High	Med	Low
2 Crops Available	Base Yield	High	$892,833	$953,305	$800,615
		Med	$851,761	$820,889	$810,040
		Low	$978,878	$979,534	$950,894
			High	Med	Low
3 Crops Available	Base Yield	High	$780,750	$781,151	$776,322
		Med	$797,643	$796,087	$790,222
		Low	$930,423	$922,851	$913,834
P = Med			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	$1,165,733	$1,037,083	$1,018,816
		Med	$1,296,822	$1,152,593	$1,036,722
		Low	$1,300,238	$1,049,666	$1,020,041
			High	Med	Low
2 Crops Available	Base Yield	High	$981,606	$953,305	$800,615
		Med	$852,261	$824,685	$810,040
		Low	$981,578	$982,834	$946,686
			High	Med	Low
3 Crops Available	Base Yield	High	$780,750	$781,151	$776,322
		Med	$797,643	$796,662	$790,222
		Low	$930,423	$807,847	$913,834
P= High			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	$1,168,433	$1,042,483	$1,018,816
		Med	$1,319,395	$1,155,293	$1,021,735
		Low	$1,314,038	$1,049,966	$1,020,041
			High	Med	Low
2 Crops Available	Base Yield	High	$847,233	$953,305	$800,615
		Med	$856,761	$824,685	$810,040
		Low	$966,298	$986,134	$950,894
			High	Med	Low
3 Crops Available	Base Yield	High	$780,750	$781,151	$776,322
		Med	$797,643	$796,662	$790,222
		Low	$930,423	$922,851	$913,834

Table 2: Fixed investments in logistics and warehousing

P = Low			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	$813,982	$664,147	$667,570
		Med	$818,063	$800,780	$662,355
		Low	$827,261	$670,846	$662,012
			High	Med	Low
2 Crops Available	Base Yield	High	$536,068	$671,217	$514,711
		Med	$524,980	$520,242	$516,755
		Low	$667,493	$669,033	$662,383
			High	Med	Low
3 Crops Available	Base Yield	High	$521,830	$521,060	$518,491
		Med	$527,052	$523,104	$518,316
		Low	$663,538	$661,760	$657,910
P = Med			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	$812,722	$664,147	$667,577
		Med	$948,473	$800,787	$667,003
		Low	$827,261	$670,846	$662,019
			High	Med	Low
2 Crops Available	Base Yield	High	$677,307	$671,217	$514,711
		Med	$524,287	$521,865	$516,755
		Low	$667,493	$669,040	$658,729
			High	Med	Low
3 Crops Available	Base Yield	High	$521,830	$521,060	$518,498
		Med	$527,052	$520,710	$518,316
		Low	$663,538	$519,072	$657,910
P= High			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	$813,982	$664,147	$667,570
		Med	$827,163	$800,780	$662,355
		Low	$827,261	$670,846	$662,019
			High	Med	Low
2 Crops Available	Base Yield	High	$527,675	$671,224	$514,711
		Med	$524,287	$521,865	$516,755
		Low	$668,403	$669,040	$662,383
			High	Med	Low
3 Crops Available	Base Yield	High	$521,830	$521,060	$518,498
		Med	$527,052	$520,710	$518,316
		Low	$663,538	$661,767	$657,910

Table 3: Maximum inventory across scenarios and treatments

P = Low			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	9,426	8,021	8,510
		Med	10,009	7,540	7,765
		Low	11,323	8,978	7,716
			High	Med	Low
2 Crops Available	Base Yield	High	9,724	9,031	6,673
		Med	8,140	7,506	6,965
		Low	8,499	8,719	7,769
			High	Med	Low
3 Crops Available	Base Yield	High	7,690	7,580	7,213
		Med	8,436	7,872	7,188
		Low	7,934	7,680	7,130
P = Med			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	9,246	8,021	8,511
		Med	8,639	7,541	8,429
		Low	11,323	8,978	7,717
			High	Med	Low
2 Crops Available	Base Yield	High	9,901	9,031	6,673
		Med	8,041	7,695	7,670
		Low	8,499	8,720	7,247
			High	Med	Low
3 Crops Available	Base Yield	High	7,690	7,580	7,214
		Med	8,436	7,530	7,791
		Low	7,934	7,296	7,130
P= High			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	9,426	11,440	8,510
		Med	11,309	7,540	7,765
		Low	11,323	8,978	7,717
			High	Med	Low
2 Crops Available	Base Yield	High	8,525	9,032	6,673
		Med	8,041	7,695	6,965
		Low	8,629	8,720	7,769
			High	Med	Low
3 Crops Available	Base Yield	High	7,690	7,580	7,214
		Med	8,436	7,530	7,188
		Low	7,934	7,681	7,130

4. Discussion of Results

4.1 The benefits of diversified supply chains in biobased product systems.

In 81 of 81 treatment scenarios, the combined fixed and variable costs of logistics fell as more crops were introduced to the feedstock landscape, thus evidencing the savings that result from diversified supply chains in the biobased products context. On average, going from one crop to two resulted in savings of 19%. Going from one crop to three saved, on average, 25%. Going from two crops to three showed 7% savings on average. These percentage savings are shown in table 4

Table 4: Savings as a percentage of total logistics costs

	P = $33	Yield Variability				P = $36	Yield Variability			P = $39	Yield Variability			
Crops			High	Med	Low		High	Med	Low		High	Med	Low	
One Vs Two Crops	Base Yield	High	23%	8%	21%	High	16%	8%	21%	High	27%	9%	21%	Average: 19%
		Med	31%	29%	21%	Med	34%	28%	22%	Med	35%	29%	21%	
		Low	24%	7%	7%	Low	25%	6%	7%	Low	26%	6%	7%	
One Vs Three Crops	Base Yield	High	33%	24%	24%	High	33%	25%	24%	High	33%	25%	24%	Average: 25%
		Med	36%	31%	23%	Med	38%	31%	24%	Med	40%	31%	23%	
		Low	28%	12%	10%	Low	28%	23%	10%	Low	29%	12%	10%	
Two Vs Three Crops	Base Yield	High	13%	18%	3%	High	20%	18%	3%	High	8%	18%	3%	Average: 7%
		Med	6%	3%	2%	Med	6%	3%	2%	Med	7%	3%	2%	
		Low	5%	6%	4%	Low	5%	18%	3%	Low	4%	6%	4%	

Costs were also considered on a per delivered ton basis. (Owing to stochasticity of yield programmed in to the simulation model, the exact same tonnage of biomass was not delivered in every model run, which contributed to the additional variability of per ton results.) In 76 of 81 treatment scenarios (89%), adding crops lowered the cost per delivered ton. On average, moving from one to two crops dropped the per ton delivered cost by $7.60; moving from one crop to three crops lowered the per ton delivered cost by $10.07; and moving from two crops to three reduced costs by an additional $2.41 per ton. Those results are shown in table 5.

Table 5: Per ton logistics costs across scenarios and treatments

P = Low			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	\$37.61	\$37.19	\$32.28
		Med	\$42.19	\$39.73	\$33.56
		Low	\$46.40	\$32.75	\$33.66
			High	Med	Low
2 Crops Available	Base Yield	High	\$28.44	\$29.93	\$26.87
		Med	\$30.40	\$26.71	\$27.10
		Low	\$32.25	\$34.43	\$30.89
			High	Med	Low
3 Crops Available	Base Yield	High	\$26.00	\$25.85	\$25.89
		Med	\$25.66	\$26.19	\$26.09
		Low	\$30.28	\$30.45	\$30.99
P = Med			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	\$37.70	\$37.39	\$32.28
		Med	\$43.17	\$39.82	\$32.97
		Low	\$46.90	\$32.51	\$33.66
			High	Med	Low
2 Crops Available	Base Yield	High	\$33.29	\$29.93	\$26.87
		Med	\$30.41	\$26.66	\$27.10
		Low	\$32.34	\$34.54	\$31.48
			High	Med	Low
3 Crops Available	Base Yield	High	\$26.00	\$25.85	\$25.89
		Med	\$25.66	\$26.60	\$26.09
		Low	\$30.28	\$26.98	\$30.99
P= High			Yield Variability		
			High	Med	Low
1 Crop Available	Base Yield	High	\$37.78	\$37.58	\$32.28
		Med	\$44.83	\$39.91	\$33.56
		Low	\$47.39	\$32.77	\$33.66
			High	Med	Low
2 Crops Available	Base Yield	High	\$26.99	\$29.93	\$26.87
		Med	\$30.57	\$27.13	\$27.10
		Low	\$30.97	\$34.66	\$30.89
			High	Med	Low
3 Crops Available	Base Yield	High	\$26.00	\$25.85	\$25.89
		Med	\$25.66	\$26.60	\$26.09
		Low	\$30.28	\$30.45	\$30.99

Next, we investigate the two propositions we suggested as mechanisms for these savings. Then, the sensitivity of these results to different experimental treatments is presented.

4.2 Proposition 1: Capital equipment savings from diversified supply chains

Model output showed evidence for proposition one. In 66 of 81 scenarios (81%), adding crops resulted in smaller fixed investments in logistical fleets and warehousing (table 2). Fixed logistical costs included expenditures on purchasing fleets of balers and loaders, as well as purchasing land, materials and labor for construction of a storage facility for collected biomass. The greatest variation in fixed logistical costs arose from the required number of balers. The number of balers needed to bale all contracted hectares within the 25-35 day time windows fluctuated from four, in mostly high-spot market price, single-crop treatments, down to two in mostly low-spot market price, multi-crop treatments. With the parameters in Appendix A, this alone represents $280,000 in savings, which would account for between 34% and 54% of overall fixed logistical expenditures across all scenarios in this paper.

4.3 Proposition 2: Inventory facility savings from diversified supply chains

Maximum inventory also fell markedly as more crops were introduced to the feedstock landscape. Moving from one to two crops resulted in holding 8% less maximum inventory on average. Moving from one to three resulted in 14% less maximum inventory. Moving from two to three showed an incremental reduction of maximum inventory of 5%. Overall, across all the simulations, maximum inventory values ranged from between 6,673 to 11,323 tons (table 3). Given the authors' decision to consider a relatively low cost storage option, these changes were not especially significant to overall expenditures. (As a reminder, the size of storage facility needed was defined by the simulation's maximum inventory value). The overall range of changes in maximum inventory across all simulations was 4,650 tons, which represented only between 4% and 6% of fixed logistical expenditures across all scenarios in this paper.

Next we consider how the model responded to changes in the treatment parameters (base yield, yield variability, and spot market price).

4.4 Sensitivity to simulation treatments

Across simulation treatments, savings were not equal. Table 6 presents percentage savings across scenarios and experimental treatments with the five highest and lowest values highlighted.

Table 5: Savings as a percentage of total logistics costs (highlighted)

	P = $33		Yield Variability		P = $36		Yield Variability		P = $39		Yield Variability		
Crops			High	Med	Low		High	Med	Low		High	Med	Low	
One Vs Two Crops	Base Yield	High	23%	8%	21%	High	16%	8%	21%	High	27%	9%	21%	Average: 19%
		Med	31%	29%	21%	Med	**34%**	28%	22%	Med	**35%**	29%	21%	
		Low	24%	7%	7%	Low	25%	6%	7%	Low	26%	6%	7%	
One Vs Three Crops	Base Yield	High	33%	24%	24%	High	33%	25%	24%	High	33%	25%	24%	Average: 25%
		Med	**36%**	31%	23%	Med	**38%**	31%	24%	Med	**40%**	31%	23%	
		Low	28%	12%	10%	Low	28%	23%	10%	Low	29%	12%	10%	
Two Vs Three Crops	Base Yield	High	13%	18%	3%	High	20%	18%	3%	High	8%	18%	3%	Average: 7%
		Med	6%	3%	2%	Med	6%	3%	2%	Med	7%	3%	2%	
		Low	5%	6%	4%	Low	5%	18%	3%	Low	4%	6%	4%	

Herein, conclusions can be drawn about which experimental treatments lead to greater logistical savings from diversified supply chains. First, one can certainly see the costs of yield variability being mitigated as more crops were added to the system. Moving from low, to medium, to high yield variability, the logistical savings resulting from diversified supply chains increased, on average, from 13%, to 16%, to 23%. As seen in table 6, the highest resulting percentage savings were all observed in high yield variability experiments. We attribute these savings dynamics to the portfolio-type effect of adding crop types to the landscape. Adding a second and third crop mitigates the cost implications of any one crop dramatically under-yielding (which can result in spot-market purchases), or over-yielding (which can necessitate greater fixed investments in logistical equipment and storage).

Secondly, one can see a general trend wherein higher yielding environments show greater savings from feedstock diversity. These savings range from 12% in low yielding conditions to near 20% in medium and high yielding conditions. As seen in table 6, all of the smallest percentage savings are observed in low yield treatments. We attribute this phenomenon to our selection of crops. When this model added feedstock diversity, it also added dramatically higher-yielding second and third crops (not by design, but because they are among the next imminently viable candidates for future bioeconomy landscapes in the American Midwest). Switchgrass shows roughly four times the per hectare yield of corn stover. Reed canarygrass shows roughly twice the yield of corn stover, per hectare, per cutting. Keeping in mind, then, that in each simulation, a quantity of hectares are contracted according to that scenario's yield expectations, we see that fewer and fewer hectares are needed both as yield expectations increase, and as the number of crops increases. This, in turn, requires fewer logistical machines.

Finally, the price of spot market biomass is rather speculative and merited further analysis and explanation. First, this paper's treatment design considered three values of P ($33/ton, $36/ton and $39/ton), which represents 110%, 120% and 130% of the baseline prices for delivered tons of biomass revealed by the author's early model work. When spot market prices were low, the savings realized from diversified supply chains were lesser than when the spot market price was high. We attribute this to a further reflection of the portfolio effect of diversified supply chains. We note here that spot market purchases were less prevalent in multi-crop scenarios than in single crop ones. Therefore, because single crop systems were compelled to buy on the spot market more frequently than multi-crop systems, increasing the spot market price tended to penalize monocultures.

5. Implications

Increasing from one to two or three crops shows potential for meaningful 2% to 38% savings on logistical costs, which have been previously reported to account for between 35% to 90% of the cost of producing biobased products. These savings could be realized in the short term by the 800 biomass to power plants already operating in European Economic Area; the roughly 100 biomass to power facilities in United States, or any of the many other advanced biomass technology projects around the world capable of processing a diversity of feedstock. The savings shown in this paper suggest that investors and companies that seize this opportunity stand to dramatically change how agricultural landscapes and biorenewable supply chains are designed around the world.

But, the potential savings do not apply equally under all conditions. As formulated in this model, low-yield, low-yield-variability environments showed the weakest of all savings from moving beyond monocultures. The real potential for reaping the logistical benefits of diverse supply chains seems to be in high-yielding, high-yield-variability environments, like flood prone, low elevation areas, or irrigated areas at risk of water contamination or restrictions. This means that field logisticians need to consider their environmental surroundings when designing cost effective supply chains for biorenewable fuels and products.

Because the logistics of biomass account for such large proportions of the overall costs of biobased product production, strategies for reducing logistical costs are important steps to growing the industry in line with public and private objectives. Meeting these ambitious goals for the biobased products industry could result in significant reductions in greenhouse gas and carbon emissions from energy production around the world, and could help in transitioning societies away from fossil fuels.

6. Limitations

From a practical perspective, additional crops — many of which, if suited to that same geographical region will likely share similar harvesting time windows — could offer little-to-no logistical equipment savings over a mono-cropped system. This simulation experiment considers crops that have been considered mainly for the

American Midwest and offer different logistical requirements. Not every region will be hospitable to crops with different logistical patterns.

Also, this study offers only partial cost accounting, both from the farmers' and the bioprocessor's perspectives. We chose to look at only those cost components directly impacted by the logistics of harvesting, transporting and holding different crops. Several detailed cost considerations (like amortization of capital equipment for bioprocessors) have been left out; as have highly variable and as-of-yet speculative costs (such as the price necessary to entice farmers to try growing different crops). In the American Midwest, the predominant monoculture crop can yield two products (corn grain for feed, and corn stover for biomass). This dual use will certainly impact the practicality of our suggestions, and merits further work.

Finally, analysis of our results suggests a meaningful portfolio effect of diversified supply chains, wherein yield of one crop type varies independently from other crop types to beget real logistical cost savings. While we believe this to be representative of many real world situations, there can certainly be yield correlations between crops of different types growing in the same area during the same year. Future researchers could work even more interdisciplinarily with agronomists and plant scientists to effectively model this complex ecological relationship between weather, yield and neighboring plant types.

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Appendix 3.A: Machine capacities, fixed costs and operating costs

Bracket references indicate data source

High Density Baler
Fixed Cost [31]: **$140,000**
Variable Cost [30] : (Labor, Fuel, Twine): $119/hour
CAPACITY [7]:
- Stover: (Yield/12) tons/hour
- Switchgrass: 0.75(Yield/12) tons/hour
- Reed Canary Grass: 0.75(Yield/12) tons/hour

Self-Propelled Loader
Fixed Cost [30]: **$94,000**
Variable Costs (Labor, Fuel) [30]: $69.44/hour
CAPACITY [7]: 0.5 hours to load or unload one truckload (24 bales)

Transportation
Fixed Cost: $0
Variable Costs: $65/hour
CAPACITY [30]: 24 Bales, 13 miles per hour

Storage facility
$7/per ton of capacity. [31]

Cost and capacities adapted from sources noted above and verified in 2013 and 2014 with an independent industry consultant.

Appendix 3.B: Base yields, yield variability and schedules for scenarios 1 through 81

	HARVEST	YIELD (Mg/HA)			VARIABILITY (Mg)		
	Start Date	High Yield	Med	Low	High	Med	Low
Crop 1 **Corn Stover**	Oct 7 To Oct 31	4.39	3.62	3.09	2.12	1.49	0.72
Crop 2 **Switchgrass**	Oct 8 To Nov 15	16.2	13.5	11.0	8.4	5.4	2.4
Crop 3 **Reed Canarygrass**	1: 3 -20 June 2: 1 -19 Sept	9.02	6.5	4.3	2.2	1.5	0.7

Appendix 3.B References:
[32 – 37]

CHAPTER 4: BIORENEWABLE FUELS AT THE INTERSECTION OF PRODUCT AND PROCESS FLEXIBILITY: A NOVEL MODELING APPROACH AND APPLICATION

Modified from a paper accepted by the *International Journal of Production Economics 150 (2014), 1-8.*

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Abstract

In recent years, governments, industry and academia have all invested increasing amounts of time, effort and resources into the production of biorenewable fuels. This interest owes, among other reasons, to our planet's growing demand for energy, depletion of fossil fuel resources and the negative effect of drilling for and burning fossil fuels on the health of our eco-systems and atmospheric chemistry. However, research suggests that biorenewable fuels have the potential to cause environmental and social calamities of their own – especially when produced in the same ways and at the expense of conventional food production. This paper proposes novel supply chains and land use plans for advanced biorenewable fuels which are measured for cost and environmental impact. A two-stage Stackelberg leader-follower mathematical optimization model is proposed. The model uses a series of integrated and sequenced linear programs to optimize the benefits of leveraging biodiversity for the production of advanced biorenewable fuels. Numerical experiments with our model show statistically significant cost, land use and environmental improvements on the order of 10% to 25%. Because

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the model captures two types of flexibilities (product and process) interfacing across firms, implications are drawn for production systems in other industries where distinct flexibilities meet and environmental impacts are critical.

1. Introduction

In both energy and agriculture, several changes are occurring at once: (1) Global supplies of fossil fuel are rising in price, and plausibly scarcity, as worldwide demand continues to grow; (2) industry and governments are investing heavily in alternative energies, one of the more popular being "biofuels"; (3) meanwhile, agricultural production in the developed world has become highly centralized and homogenized, commanding much larger swaths of land, employing larger fleets of equipment and generating negative environmental externalities, all of which has lead scientists, journalists, and the public to; (4) increasingly cast critical eyes towards biofuels' potential to offset fossil fuel use without causing environmental and social calamities of their own. This research sits itself at the confluence of these four troubling, and seemingly disparate, developments. This paper proposes a way that advanced biofuels can be produced more efficiently and more sustainably, with optimized supply chains that capitalize on biodiversity in order to reduce land usage, environmental degradation, and overall costs of biofuels production. Our approach entails a unique application of operations research (OR) techniques to uncover the benefits of leveraging natural biodiversity in production systems for alternative fuels.

The production system under consideration (the farmer-bioprocessor dyad) and our mathematical model of it bears broader research implications too. We frame the farmer as a supplier (in this case of plant feedstock), who is *product flexible*, meaning

"The ability to changeover to produce a new (set of) product(s) very economically and quickly" (Beach et al., 2000; Browne et al., 1984). Herein, product flexibility denotes the ability of the farmer-supplier to produce different crop types from year to year. The buyer in this dyad is the bioprocessor, who purchases from farmer-suppliers feedstock for conversion into biorenewable fuels. We frame the bioprocessor-buyer as a *process flexible*, meaning "The ability to produce a given set of part types, each possibly using different materials, in several ways" (Beach, 2000; Browne, 1984). Herein, process flexibility denotes the bioprocessor's ability to convert any of the farmer-suppliers' crop types into biofuels. This process flexibility is unique to emerging advanced biorenewable fuel technology.

Production researchers have been increasingly interested in flexible manufacturing problems since the 1970s, when computer-controlled process automation and Japanese-style production systems began to be implemented across a wide variety of industries (Fine and Freund, 1990; Karsak and Kuzgunkaya, 2002). Over the years, this journal has published several modeling approaches to flexible manufacturing problems, including: Kumar (1995), who proposed finance literature's 'options theory' as a better way evaluate investments in expansion flexibility than traditional Net Present Value calculations; Gertosio, Mebarki and Dussauchoy (2000), who suggested multi-layered discrete event simulation as a decision making tool for analyzing how different control systems and physical production systems interact under manufacturing flexibility; Karsak and Kuzgunkaya (2002), who proposed fuzzy multiple objective programming as a fitting methodology for evaluating the worth of flexible systems, because it uniquely incorporates both strategic and economic benefits, whereas classical analytical modeling considers only the latter; Tseng (2004), who employed elements of game theory to investigate under what types of competitive environments investments in more expensive flexible systems pay off and found that increased competition reduces firms' incentive to invest in expensive flexible technologies; and Francas, Löhndorf and Minner (2011), who optimized two types of flexibility, labor and machine, in a single-firm production system using a two-stage stochastic programming approach.

In the research literature reviewed above, each type of flexibility has traditionally been considered either in isolation, or as it interfaces with another type of flexibility in a single firm. Examples of the latter include: Chod and Rudi (2005), who used a Stackelberg model to consider resource flexibility and "responsive pricing" in a single production system; Iravani, Kolfal and Van Oyen (2012), who modeled one firm's tradeoffs between process flexibility and inventory flexibility; and (Francas et al., 2011). In their recent review of supply chain flexibility, Jayant and Ghagra (2013) noted that more attention should be paid to inter-organizational flexibility in order to realistically depict real-world supply chains. Proposing an approach to modeling real-world circumstances of different types of flexibilities intersecting across firm boundaries is this paper's broader contribution to research. For practitioners, this approach also has merit in the classic sense of game-theoretic models: it allows one player (supplier or buyer) with a distinct flexibility to predict the moves of their partners (who have different flexibilities) under a variety of scenarios. Over time, however, it is possible that cooperatives of biomass processors and farmers could jointly own and operate both biorefineries and their surrounding farms, and then use the model presented in this paper to find optimal management strategies. Similarly, third-party service providers working in-between growing biorefineries and farming operations could use the model presented herein to discover appropriate price incentives for lowering overall logistical costs and protecting the natural environment.

The paper continues as follows. Section two gives further background to the problems above. Section three presents our proposed solution to the issues presented in sections one and two. Section four presents our mathematical formulation of a biodiverse biofuel supply chain, modeled as a Stackelberg leader-follower optimization based on a sequenced series of two basic types of integrated linear programs. In section five we analyze the results of simulation runs on our model. Section six presents implications for biofuels producers, as well manufacturing flexibility research, and limitations and suggestions for further work.

2. Problem Background

2.1 Fossil fuels

Today's world faces the potential for serious energy shortages in the near-term, owing in part to: (1) our own profligate consumption of available energy sources over the last 200 years, and (2) the mounting environmental costs associated with supplying raw material for different energy conversion technologies. During the advent of coal and steam power in the 19th century, energy use by humans increased 10-fold (McNeil, 2000) The development of oil and natural gas resources in the 20th century exacerbated this withdrawal ten times over. Environmental historian J.R. McNeil calculates that humans have expended more energy since 1900 than in all of preceding human history combined (McNeil, 2000). Future consumption is projected by many to grow even faster (EIA, 2010; UN, 2007). Documented affects of growth in population and energy use over the last 200 years include: depletion of economically accessible fossil fuel resources, changing atmospheric chemistry and climate, degradation of ecosystem services, contamination of freshwater, despoilment of soils, and diminishment of global plant and animal biodiversity (Costanza et al., 2007; Hall et al., 2003).

2.2 The bioeconomy solution

For these reasons, and others, governments have become increasingly interested in transforming agricultural crops into fuel and/or other products that, today, are typically made from crude oil. These "biorenewable fuels" are defined as fuels made from plant material, living or recently deceased (Brown, 2003). By federal mandate in the United States, biorenewable fuels production will grow to 36 billion gallons in 2022. Similarly, the European Union has stipulated that the European biorenewable fuels industry grow to meet 10% of its transportation fuel demand by 2020 (Robbins, 2011).

But, in the US and in Europe, biorenewable fuels are being produced in accordance with the tenants of conventional modern food agriculture – that is, by planting gigantic swaths year-after-year to single, high yielding crops that demand significant chemical and fertilizer treatments, as well as large fleets of specialized machines to harvest and transport them. This practice is referred to broadly as "monoculture". For example, in the largest ethanol producing state in the world's largest ethanol producing country, Iowa, USA, 90% of the available cropland has been devoted to only 2 crops for the past 20 years. In recent years, this land has been increasingly devoted to only corn. Fully one-third of that corn output now goes to making corn-based ethanol. In the world's second-largest producer, Brazil, ethanol is made from similarly large monocropped tracts of sugarcane.

2.3 Growing criticisms of the bioeconomy

The rise of monocropping as a standard practice in commercial agriculture is attributed by agricultural and technical historians to the substitution of capital for labor following demographic shifts in the post WWII era (Anderson, 2009; Rasumussen, 1982). But, while economically expedient, monocropping begets several negative environmental externalities, including soil erosion, water pollution and release of carbon stored naturally in soils. As land around the world has been increasingly dedicated to monocropping for biofuels production, scientists have focused renewed attention on biofuels' potential to exacerbate these problems (Foley et al., 2005). For example, Searchinger et al (2008) forecast that increases in corn-based ethanol production around the world could double global greenhouse gas emissions over 30 years, as perennial native lands are converted to large fields of high-input mono-cropped annual corn. Similarly, Stone et al (2010) predicted that to meet the US Federal biorenewable mandates with corn production alone would demand a 6-fold increase America's agricultural water use. (For a further review of biofuels' promise and problems, see also *Nature* 474/7352). Finally, the UN special ambassador on food has called it a "crime against humanity" to dedicate such large swaths of agricultural land to corn production for biofuels, while millions still go hungry around the world (Ferret, 2009).

2.4 Advanced biorenewable fuels and the environment

Advanced biorenewable processing technologies present the opportunity to convert heterogeneous mixes of crop feedstock into a single end product, which we refer to as biofuels' *process flexibility*. Ecological and agronomic research suggests that employing mixes of crops and alternatives to the conventional monocultures in these new process flexible systems could alleviate some of the growing environmental concerns surrounding biofuels. Perlack (2005), Tillman (2006) and Groom (2007) observe that alternatives to monoculture biofuel production systems including mixes of prairie grasses, trees and municipal waste reduce $C0_2$ emissions. Williams (2009) has documented how new alternatives to the monoculture system reduce water use in biofuels systems. Tillman (2006) and Groom (2007) show how alternatives and feedstock mixes can reduce soil erosion compared to monoculture systems. But while this research shows the environmental benefits of transforming biofuels production systems, it is not yet clear how to operationalize these advantages for practitioners. This paper endeavors to bridge this gap.

2.5 Biodiversity and logistics in the advanced bioeconomy

We offer three reasons why, when biorenewable processing technologies are 'process flexible' – meaning that they can convert a variety of different plant materials into common end products – optimized diverse landscapes may outperform modern conventional monocultures in terms of logistical costs of production, as well as environmental footprint. First, different plants naturally give and take different things from the environment in which they grow. In the case of nutrients, some plants naturally deposit fertilizers such as nitrogen, while others deplete it (Pimentel et al., 1997). Replacing nitrogen as a synthetic fertilizer is a significant cost of corn production - and a major source of water pollution for conventional agriculture. These production costs can be alleviated by incorporating nitrogen fixing plants on the landscape over time. Second, because biomass was recently living plant material, it is naturally full of air and water – which are useless to biorefineries and very expensive to move owing to air's bulk and water's weight. Arranging denser biomass sources further away from the biorefinery, and bulkier biomass closer, can reduce transportation cost by maximizing the efficiency of truck transport on longer trips. Finally, all crops become available for harvest during specific time windows, when they are ripe for harvesting. In conventional monocultures, where only one type of crop is grown, gigantic swaths of land become ripe at the same time – meaning that multiple harvesting machines are required to service thousands of acres within a single service-time window. On the other hand, if a diversity of plants were grown, different plant types could become ready for harvest at different times, meaning that a fewer number of machines would be needed to service the same number of acres in one year.

But, while the potential environmental and logistical cost savings benefits of these production systems are conceptually clear, how real-world multi-actor supply chains can transition to them is not. The costs and benefits of these new flexible systems will accrue to different actors in the supply chain as a result of the different decisions that they and their trading partners make. Also, even though there are benefits to both sides of interfacing their flexibilities, it is likely that in practice each side will seek to maximize only their own objectives. Practitioners and researchers need a way to consider the production system as a whole, where two different flexibilities meet – either for the purpose of joint optimization, third-party optimization, or to simply predict and to analyze the moves of their trading partners for scenario analysis. Our work presents a mathematical model that allows for simulation and optimization of these new systems over time.

3. Modeling Product and Process Flexibility in BioEconomy Landscapes

To frame the presentation of the mathematical model, we first describe a conceptual picture of the relationship between farms and biorefineries in our model and the systems that are optimized. This conceptual framing of the biorenewables industry was based on discussions with both farmers and bioprocessing industry representatives. That system is shown in Figure 1.

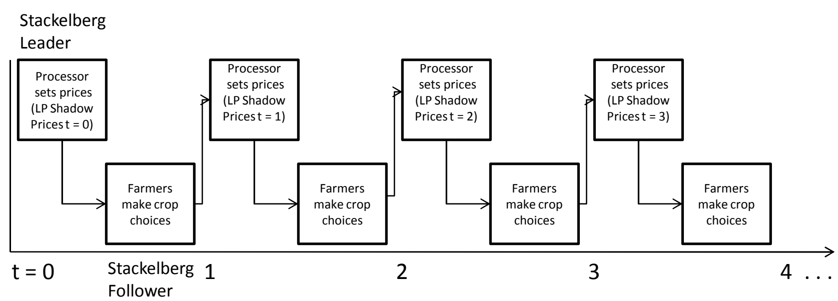

Figure 1: Conceptual Model

In this model, farm businesses are managed by independent actors (farmers), who make their own decisions regarding which crops to grow on the land that they farm. That is, the farmers are product flexible, meaning that they can readily change their output between time periods. In this sense, product flexibility is applied in the conventional sense, as defined in and recently studied in (Goyal and Netessine, 2005), save for: (1) the time frame, which makes product decisions on an annual time scale owing to the natural growing season of plants; (2) their product decisions are influenced by their downstream buyers between time periods; and (3) their product decisions directly impact the environmental and logistical costs of the entire supply chain.

A biorefinery (or its agent) purchases from its surrounding farmers the right to harvest acres of farmland with the biorefinery's own specialized equipment. Biorefineries are process flexible, meaning that they can convert any of the farmer's feedstock outputs into biofuel. In this sense, process flexibility is employed herein along the lines defined and recently studied in (Graves and Tomlin, 2003; He et al., 2012; Iravani et al., 2012), save for that the shadow prices revealed by their optimizations are passed upstream to their suppliers in our model, and that their environmental impact is measured, and entirely determined by their suppliers' decisions.

Costs of planting and growing crops accrue to the farmers. Costs of harvesting and transporting crops accrue to the biorefinery. This price that a biorefinery will pay for an acre of a given crop is announced by the biorefinery to the farmers annually ahead of the growing season in order to entice farmers to grow the most economically expedient mix of crops in the lowest cost spatial arrangement for the biorefinery. Farmers weigh the prices for each crop on offer from biorefineries against the prices on offer from other conventional markets. (Herein we call crops that can be partitioned for sale to both biorefineries and conventional markets "dual use", because part of the crop goes to biorefineries and part to conventional markets, while the farmer gets paid for both – more on this in section 4.1). Spatially, the land surrounding the biorefinery can be divided into discrete sub-areas (e.g. concentric rings surrounding the biorefinery).

The prices that biorefineries will pay for a given crop in a given area and farmers' responses to those prices are calculated as follows: Initially, a biorefinery is assumed to be surrounded by a crop landscape that is determined exogenously by the surrounding farmers (likely, but not necessarily, the conventional regional monoculture). In its first year, the biorefinery meets its annual biomass throughput requirement by contracting for and harvesting the requisite quantity of biomass from surrounding farms at a pre-set base price per expected ton. We call this "basepay". This base price represents the initial price that the biorefinery offers for biomass after collecting input from the farmers, and is assumed to be attractive enough for them to produce sufficient biomass of at least one variety for the first year of the biorefinery's operations. The initial harvest plan for the biorefinery is determined by a cost-minimizing mixed integer linear program. Shadow prices for potential alternative crops in each of the discrete spatial areas that surround the biorefinery are then empirically derived from this first LP. The shadow price for each crop in each sub-area is then added to the base price for that sub-area to determine the maximum possible price premiums that the biorefinery will announce for the next growing season.

The farmers' planting decisions in the surrounding area are modeled, in aggregate, as a profit-maximizing network flow linear programming problem, where the prices that biorefineries announce for the coming growing season represent revenues, and the costs of growing different crops in different sequences over time represent the costs of production. The network flow formulation allows us to capture how costs and environmental measures change based on prior years' land use, per Detlefsen's contribution of this technique to conventional agricultural modeling in 2007 (Detlefsen and Jensen, 2007). To this approach, we add arc parameters relevant to biofuels production as well as environmental quality measures (in this case, soil erosion), which allows us to keep track of our proposed system's environmental performance.

4. General Mathematical Model

Our model consists of an integrated sequence of two basic types of linear programs interacting over time. First, the biorefinery seeks to minimize the cost of collecting a requisite amount of biomass every year ("the Biorefinery model"). Second, farmers seek to maximize their profit each year by choosing which crops to grow, given the price incentives offered by the biorefinery ("the Farmers' Model"). The price incentives that biorefineries offer are calculated annually by empirically deriving shadow prices for crop availability in the biorefinery model, based on the previous year's cropping plan that resulted from the farmer's model (see Figure 2).

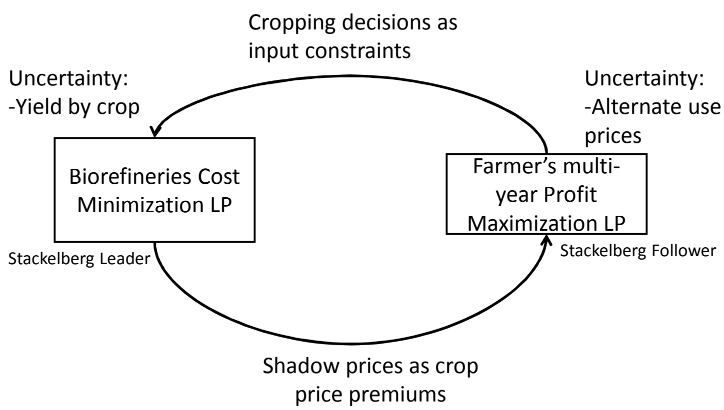

Figure 2: Two-Stage Model Development

4.1 Generalized biorefinery model

Consider a biorefinery facility serving a finite set of spatial areas $R = \{1, 2, \ldots, r, \ldots\}$ surrounding the facility. Let $I = \{1, 2, \ldots, i, \ldots\}$ be the finite set of crops that can be planted in R, and $T = \{1, 2, \ldots, t, \ldots\}$ be the set of time periods observed in one year (e.g., weeks, months, or quarters). Also let $K = \{1, 2, \ldots, k, \ldots\}$ be the finite set of "equipment mixes" (number of harvesting machines and transportation vehicles) which the biorefinery can choose to deploy for harvesting crops and transporting them in a given year. There are both fixed and variable costs associated with each equipment mix $k \in K$. The fixed cost is given by F_k (cost per year), and the variable cost by C_{ikr} (cost per harvested acre in each subregion).

Our Biorefinery model is expressed as a mixed-integer linear program as:

$$\text{minimize} \sum_{k\in K} F_k\theta_k + \sum_{i\in I}\sum_{t\in T}\sum_{k\in K}\sum_{r\in R} C_{ikr} X_{itkr} \tag{1}$$

Subject to: $$\theta_k \in \{0,1\} \quad \forall \quad k \in K \tag{2}$$

$$\sum_{k\in K}\theta_k = 1 \tag{3}$$

$$0 \le X_{itkr} \le Q\theta_k \quad \forall \quad i\in I, t\in T, k\in K, r\in R \tag{4}$$

$$\sum_{r\in R}\sum_{i\in I} X_{itkr} - \theta_k Cap_k \le 0 \quad \forall \quad k\in K, t\in T \tag{5}$$

$$\sum_{t\in T}\sum_{k\in K} X_{itkr} - \theta_k Crop_{irt} \le 0 \quad \forall \quad i\in I, r\in R \tag{6}$$

$$\sum_{i\in I}\sum_{t\in T}\sum_{k\in K}\sum_{r\in R} Y_{it} X_{itkr} \ge REQ \tag{7}$$

where θ_k is a binary variable indicating the equipment deployment decision (1 if equipment mix k is chosen, 0 otherwise), and X_{itkr} is a continuous decision variable indicating the acres of crop i to be harvested by using equipment mix k in spatial area r at time t. Cap_k, $Crop_{irt}$, and REQ denote the harvesting (and transporting) capacity of equipment mix k (per time period), the total availability of crop i during the planning year (which is determined by the farmer model output of the previous year), and the required annual biomass quantity for the biorefinery, respectively. Y_{it} represents the yield per acre of crop type i at time t measured in tons. "Q" is any arbitrarily large number.

The refinery's objective is to minimize the cost of harvesting and transporting the amount of biomass needed to meet their annual throughput requirement. Constraints (2) and (3) jointly ensure that only one equipment mix is chosen for each year and forces X to be 0 when $\theta = 0$. Constraints (4) specify both the lower and upper bounds of X_{itkr}. Constraints (5) mandate that the harvesting performed in each time period does not exceed the maximum machine fleet's capacity per time period. Constraints (6) require that the total harvesting performed in each spatial area for each crop type does not exceed the available (harvestable) amounts grown by farmers, while constraint (7) makes certain that the total harvested biomass is at least as large as the annual biomass requirement.

Except for the first year (year 0) the shadow prices are calculated annually for constraints (6) for all *i* and *r*, which are then input into the farmers' model. (Notice that since the cost of transportation varies from one spatial area *r* to the next because of the varying distance between the refinery and *r*, the shadow price is unique to each *r*.) Since the shadow prices for mixed-integer programs cannot be calculated in a standard way, we empirically derive them by re-solving the biorefinery model m times, where $m = |I| \times |R|$ represents the number of crop availability constraints (6). Specifically, for each of m crops we first re-solve the model after increasing the right-hand-side of (6) (crop availability) by one unit (acre), and then compare the resulting objective value with the original objective value for that year to derive a shadow price. While in theory the amount of land devoted to a certain crop can be increased by a value smaller than one acre, in practice farmers will adjust the land size only in increments of one acre. This condition implies that the shadow price derived by our method is consistent with the concept of average shadow price that is widely used in the mixed-integer programming literature (e.g. (Crema, 1995; Liao et al., 2009; Mukherjee and Chatterjee, 2006)

4.2 Generalized farmers' model

The Farmers' model is shown in Figure 3, which seeks to maximize the aggregate farmer profit over a finite planning horizon.

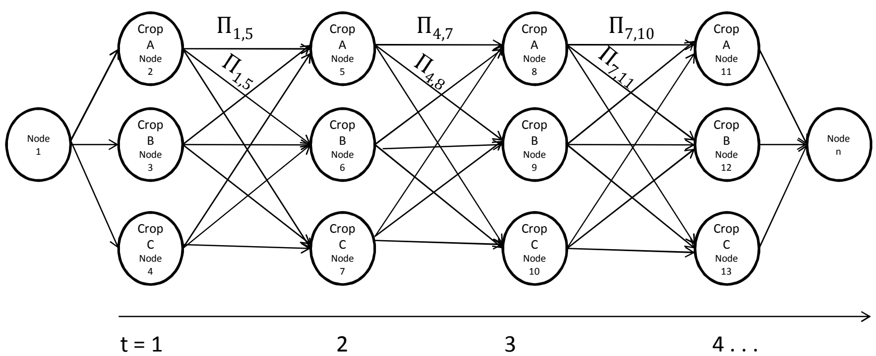

Figure 3: Farmers' Model

Let $G = \{N, L\}$ be a graph representing the crop choices to make for the farmer model, where $N = \{1, 2, \ldots, n\}$ is the finite set of nodes and L is the set of edges connecting the nodes. The expected annual profit of farmers for moving from node a to node b is denoted π_{ab}. The farmer model can be expressed as a capacitated network-flow model (the well-known transshipment model) as follows:

$$\text{maximize} \sum_{a\in N\setminus\{n\}} \sum_{b\in N\setminus\{1\}} \pi_{ab} z_{ab} \tag{8}$$

Subject to: $$0 \le z_{ab} \le Cap_{ab} \quad \forall\ a\in N\setminus\{n\}, b\in N\setminus\{1\}, a\neq b \tag{9}$$

$$\sum_{b\in N\setminus\{1\}} z_{ab} = Acres \quad \text{for } a=1 \tag{10}$$

$$\sum_{a\in N\setminus\{n\}} z_{ab} = Acres \quad \text{for } b=n \tag{11}$$

$$\sum_{h\in N\setminus\{a\}} z_{ha} = \sum_{b\in N\setminus\{a\}} z_{ab} \quad \forall\ a\in N\setminus\{1,n\} \tag{12}$$

where z_{ab} is a continuous decision variable indicating the crop allocation, Cap_{ab} is a constant indicating the arc capacity, and *Acres* is the total acres of land available to the farmers (assumed to be time invariant). Both the costs of production and environmental metrics are attached to the arcs, to capture how growing crops in different sequences changes the costs of production and environmental ramifications.

The objective is to maximize the profit for each discrete spatial area r (note that, because each r is assigned its own set of shadow prices in the biorefinery model, the farmer model must be solved for each r). Constraints (9) specify both the non-negativity and arc-capacity constraints, while constraints (10)-(12) jointly specify the network flow constraints. The arc capacity constraints can be used to control the sequence of crop planting such that the model could respect a "do not follow list" (which specifies the crops whose production cannot follow those of certain other crops), and a "consistency list" (which specifies the crops which, once planted in a given area, must be grown in the land for multiple years consecutively), which allows the model to capture the reality of annually planted crops, and perennial crops, which stay on the land for multiple years.

π_{ab} of the objective function is calculated by the following formula:

$$\pi_{ab} = BasePay + ShadowPrice_b + DualUse_b - Cost_{ab} \tag{13}$$

Where *BasePay* is a constant representing the price floor (per ton) for biomass paid by the biorefinery to the farmer, regardless of crop choice. $ShadowPrice_b$ is the shadow price for having an additional unit of the crop indicated by node *b* as calculated in the biorefinery model. $DualUse_b$ is a stochastic variable showing the value of a dual use of the crop (e.g., sale of corn as grain as well as sale of the corn plant's stover to the biorefinery) indicated by node *b* (at the time of solving the farmer model). $Cost_{ab}$ is the cost associated with growing the crop indicated by node *b* one year after growing the crop indicated by node *a* on the same land. Note that we do not include the environmental costs in Cost_{ab} because it represents the cost for the environment, and not for the farmers. However, we use this environmental cost as a performance measure later in the empirical section, where we test the effectiveness of our approach.

5. Numerical Experiment

In this section we conduct a numerical experiment to test the effectiveness of our approach. Specifically, we address the following questions: First, can an optimized mix of crops reduce supply costs for a biorefinery? Second, what will happen to farm profits under our proposed regime? Third, how would optimized biodiverse feedstock landscapes impact the amount of land required to supply a biorefinery, as well as the environmental footprint of that land use?

For model analysis, we designed a simulation-based numerical experiment. The two-stage model described in sections three and four was calibrated to conditions representative of the current environment in Iowa, USA. This calibration included consulting with industry representatives and farmers to find realistic crop choices and price scenarios, as well as reviewing agronomic and agricultural economics literature to find parameter values for crops' yields and costs of production and the costs of harvesting and transportation.

We assume the following: A small-scale advanced biorefinery will need 150,000 tons of biomass per year to operate and is introduced into an agricultural landscape dominated by a corn monoculture. Two other crops are candidates for this environment and the refinery's conversion technology: switchgrass, a perennial grass which can be harvested in either late Summer or Fall; and sweet sorghum, a very high yielding, but costly, variety of sorghum that is harvested in the Fall. Our model divides each year into quarters and considers a 5-year planning horizon. Spatially, our model considers land divided into three concentric rings of 10-mile radii that surround the biorefinery, where 75% of the land is assumed to be cropland. Yields and costs of production for these crops are shown in Table 1. [A complete data set is available from the authors upon request.] The market price of corn grain (a dual use revenue stream), and yields of all crops were treated as stochastic variables that changed randomly from year-to-year within the five-year planning horizon.

Table 1: Representative yields and costs assumptions for numerical experiment

Base Yields and Costs	Yield		Production Cost ($/acre)		
	Grain (bu/acre)	Stover (tons/acre)	Establishment	Perennial maintenance	Harvest /Transportation Cost
Corn	150	2	$432.43		19.3
Switchgrass		3.5	359.94	207.86	15.83
Sweet Sorghum		7	309.58		352.82

[a]Sweet sorghum includes a charge for drying the crop
[b]In the complete data set, yields and costs are adjusted based on land use in the previous year (farmer model) and spatial area in which the crop is grown (biorefinery model). Full data set is available upon request.

We present two experiment scenarios for analysis. In the first, price conditions exemplary of the current environment were used. The price for corn's dual use was stochastic between $4 and $8 per bushel. *BasePay* was set to $50 per ton. The second experimental scenario considers a situation where biofuels, and thereby biomass, are relatively more lucrative. In the second scenario, the *DualUse* price was narrowed and lowered to between $4 and $6 per bushel and *Basepay* was increased to $65 per ton. Results for key performance measures are presented as follows: baseline results for each scenario are calculated based on meeting the biorefinery's requirements with an all corn (monoculture) landscape. These results are compared to the optimized biodiverse landscape, wherein the biorefinery can use the price premiums presented in Section 4 to give incentives to farmers to grow different crops in different areas. These results are presented in Tables 2, 3 and 4 and Figure 3.

For each randomly generated instance, 66 integrated and sequenced linear programs are solved (51 biorefinery models and 15 farmer models). For analysis, we solved 500 instances per experiment, resulting in 33,000 LPs. Numerical experiments were implemented using Microsoft Visual Basic.NET along with IBM CPLEX optimization software. On a 2.66 GHz quadcore PC with 4GB of memory, the run time per experiment was approximately 15 minutes.

Table 2 **Average Annual Results**

	Scenario 1 (n = 500)		**Scenario 2 (n = 500)**	
	Baseline	Optimized	Baseline	Optimized
Biorefinery Cost	12,014,355	8,677,097	14,264,355	10,035,833
Farm Profit	1,773,650,242	2,041,859,434	1,398,804,803	1,976,872,218
Acres Harvested	25,000	20,302	25,000	18,946
Soil Erosion	4,060,826	3,769,997	4,060,825	3,572,146

Table 3 **Comparing Optimized to Baseline results in each Scenario**
(Results normalized to baseline results for each scenario)

	Scenario 1 (n = 500)		**Scenario 2 (n = 500)**	
	Baseline	**Optimized**	**Baseline**	**Optimized**
Biorefinery Cost	1	0.72	1	0.7
Farm Profit	1	1.15	1	1.41
Acres Harvested	1	0.81	1	0.76
Soil Erosion	1	0.93	1	0.88

Table 4 **Statistical Significance**

	Scenario 1 (n = 500)			**Scenario 2 (n = 500)**		
	Mean (normalized)	**t-statistic**	**p value**	**Mean (normalized)**	**t-value**	**p value**
Biorefinery Cost	0.72	-133.943	<0.001	0.7	-158.388	<0.001
Farm Profit	1.15	14.776	<0.001	1.41	25.195	<0.001
Acres Harvested	0.81	-67.125	<0.001	0.76	-79.3777	<0.001
Soil Erosion	0.93	-18.004	<0.001	0.88	-26.271	<0.001

1-sided p-value comparing scenario baseline to scenario optimization
All means normalized to each scenario's baseline values.

5. Results

Table 2 shows comparisons of mean values for four key measures of the numerical experiment: (1) overall biorefinery cost of harvest and transport; (2) overall farm profit; (3) total acres harvested for the biorefinery; and (4) landscape soil erosion. Table 3 shows all measures normalized to each scenario's monoculture baseline model for convenient comparison. In Table 4, P-values and t-statistics for a t-test comparing the means of the optimized runs and the baseline scenarios show that the optimized results are significantly different. For every performance measure, the p-value returned <0.001. For biorefinery cost and overall farm profit, this result is intuitive, because both measures were included as objective functions in the two-stage model. It was theoretically impossible that optimization could result in higher cost for the biorefinery or lower overall farm profit. P values <0.001 were also found for comparisons of soil erosion and total land use, which were not included in either of the two basic model type's objective functions, indicating strongly significant improvements in both measures as a result of our optimization.

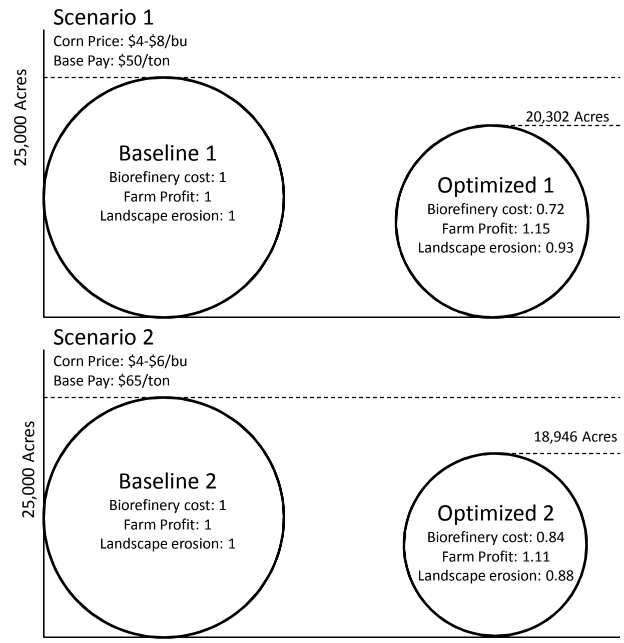

Figure 4: Numerical Experiment Results

These magnitudes and directions of improvements are illustrated in Figure 4. In Figure 4, circle size represents the total area of land required to supply the biorefinery under each scenario. All other measures are again normalized to the monoculture baseline for each scenario one for comparison purposes. In both scenarios, biorefinery cost falls (28% and 16% respectively) as the refinery draws from a smaller radius of cropland and employs less machinery per year for harvest and transportation at different harvest times. Farm profit increases as farmers capitalize on both basepay as well as dual use revenue streams from corn grain when the price of corn is high. Soil erosion falls in our optimized model, but not at the same rate as land use, indicating that farmers are substituting both the low erosion perennial crop switchgrass, as well as the more highly erosive sorghum, on the landscape for the initial corn monoculture over time.

Comparisons across the two scenarios are also revealing, and show a robustness of our model to varying parameters. Recall that in scenario two, the dual use revenue stream is lowered and basepay is increased compared to scenario one, representing a situation where biofuels, and thereby biomass, are relatively more lucrative. As intuition would suggest, this results in farmers planting more crops exclusively for biomass. Our results show that as these higher yielding specialty crops are planted, the total number of acres harvested for the biorefinery decreases compared to the baseline and the scenario one optimization. However, the overall costs to the biorefinery increase and overall farm profitability decreases compared to the scenario one optimization, as biorefineries pay out a higher base price and farmers draw less revenue from dual use. Overall, when comparing a conventional monoculture baseline production plan with our proposed flexible optimization, we find significant improvements in each of the four performance measures, all on the order of 10% to 25%.

6. User Implementation

At this point, we pause to consider how practitioners in this industry (biorenewables) could use our results and our model. First, our results indicate that both dyad partners stand to realize cost of production and environmental benefits by engaging their own flexibilities (product or process) with their trading partner's corresponding flexibility. In this context, both farmers and bioprocessors stand to benefit from linking biodiversity (product flexibility) with omnivorous technology (process flexibility).

Of course, in contemporary real-world application, farmers and biorefineries (suppliers and buyers) need not necessarily work together to jointly optimize a system. Each actor is likely to be more interested in maximizing only their own returns.

However, our model need not be used by both parties in order to be useful. In the short-term, the model presented in this paper can be used by practitioners in the classic Stakleberg, game-theoretic sense: by one player to predict what his or her trading partner will do under different scenarios.

However, we are also envisioning a longer-term future, where the environmental and logistical cost benefits that result from linking biodiversity and process flexibility can be realized by either vertically integrated biorefineries, or by a potential third-party intermediary working in-between farmers and biorefineries. The emerging biorenewables industry may be particularly suited to the former because of the large number of first-generation ethanol plans which are already owned by their surrounding farmers. Equally plausible over the long-term are third-party logistics provider for the bioeconomy, who aggregate farmers' feedstock and then sell it in large quantities to biorefineries owing to the significant portion of total costs that result from transportation and storage of biomass.

7. Implications and Limitations

We present a way that advanced biofuels could be produced more cost effectively and with improved environmentally sustainability, while also reducing the amount of land taken out of food production or conservation. Our two-stage approach respects that biorefiners and their farmer suppliers are separate profit maximizing actors and provides a framework for both parties to leverage the natural cost savings and environmental benefits of biodiversity interactively. For the broader research community, our work suggests both the importance of considering multiple types of flexibility interfacing – as they are bound to do as both the biorenewable industry grows, and other types of processors seek to minimize their environmental footprint – and, a novel, but practical, way to do it.

Numerical experimentation calibrated to contemporary conditions in Iowa, USA suggest that this approach shows merit in a real-world context. When comparing the conventional monoculture approach typically employed today to our optimized process flexible plans, costs of harvest and transport, as well as acres devoted to biofuels production and soil erosion fell, while overall farm profitability rose – all with statistical significance and on the order of 10% to 25%.

This research is, however, still speculative in that advanced process flexible biofuel technologies are not yet commercially widespread. (However, applicable projects do exist, including Dynamotive's fast pyrolysis bio-oil facility in Canada, the POET bioethanol facility in the U.S., the roughly 800 biomass to power plants operating in the European Economic area, as well as the 100 similar plants in the United States.) We hope that further work will include deeper techno-economic analysis of the costs and benefits of the systems envisioned in this paper. Also, as ongoing research makes more data available about water use and carbon sequestration resulting from alternative crops and crop sequences like the ones included in our model, even more environmental ramifications of improved production systems could be considered.

Finally, we hope this work will motivate further work into studying the interface of different types of manufacturing flexibility in research and in practice. As producers increasingly scrutinize the environmental and logistical costs of their systems across partner firm boundaries, we hope that our modeling approach will be applied to different industries where different flexibilities interface and different supply chain-level environmental and social consequences are measured.

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CHAPTER 5: GENERAL CONCLUSIONS AND FURTHER WORK

General conclusions

Sustainability has become an increasingly relevant issue for both supply chain management researchers, and practitioners. In this dissertation, we attempted to offer a few new practical insights in to how sustainable supply chains could be designed. These insights were first gleaned from casual observation of the differences between how resources flow and are stored in naturally evolved systems, and how resources are designed to flow and be stored in the modern supply chains that we design.

Chapter two laid out the conceptual beginnings of our research. We presented a brief overview of the ecological benefits of diversity, and then tied the ecological notion of diversity to the operations research literature's notion of manufacturing flexibility. The logistical cost savings that arise from diverse/flexible supply chain designs were proposed to manifest in three ways: (1) lower expenditures on capital equipment; (2) smaller fixed investment in inventory facilities; and (3) lower transportation costs. Each of these notions was presented, and then briefly argued, algebraically.

Chapter three began empirical testing. We built a simulation/optimization model of a bioeconomy instillation with parameters calibrated to the current environment in Iowa, USA. We were especially interested in seeing how logistical costs responded to the addition of second, and third inputs (crops) to the process flexible system. We found evidence for meaningful logistical savings (2%-38%), as well as evidence supporting the first two propositions laid out in chapter two. In most cases, adding multiple inputs reduced both fixed expenditures on logistical equipment and inventory facilities. These savings were found to be most pronounced in high-yield, high-yield-variability treatment scenarios.

Chapter 4 provided further empirical testing, and also dealt with the reality of the dyadic product/process flexible supply chain. A new simulation/optimization model was built in a different software environment than in chapter three. This more sophisticated numerical experiment allowed product flexible suppliers and process flexible buyers to interact, iteratively over time by using elements of game theory and a series of integrated and sequenced linear programs. We found similar logistical cost savings to what we did in chapter three's experiment (10%-25%), as well as evidence for chapter's two's propositions one and three.

Further work

This work was obviously limited by both our own imaginations, and our resources. We hope that further work will find new ways to contribute to both. Firstly, in terms of resources, data concerning different input's, and mixes of inputs' environmental measures (like $C0_2$ emissions, or water use) could be included in further analysis of the simulation/optimizations that we presented in chapters three and four.

But, the bigger opportunity is likely in terms of imagination. We have empirically tested these ideas in the biorenewables context. Surely, there are more industries (some of which are described in chapter two) where this work could be replicated to find boundary conditions, and new applications.

But, perhaps the biggest opportunity for further work comes from taking more supply chain design cues from the natural environment. In this, we feel we have only begun to draw lessons from the intersection of ecology and supply chain design. Surely, at the confluence of these historically disparate research streams are other new design principles and propositions to be uncovered and tested similar to the way we did in this work.

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