Article

Uncertainties in Life Cycle Greenhouse Gas Emissions from Advanced Biomass Feedstock Logistics Supply Chains in Kansas

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Abstract: To meet Energy Independence and Security Act (EISA) cellulosic biofuel mandates, the United States will require an annual domestic supply of about 242 million Mg of biomass by 2022. To improve the feedstock logistics of lignocellulosic biofuels in order to access available biomass resources from areas with varying yields, commodity systems have been proposed and designed to deliver quality-controlled biomass feedstocks at preprocessing "depots". Preprocessing depots densify and stabilize the biomass prior to long-distance transport and delivery to centralized biorefineries. The logistics of biomass commodity supply chains could introduce spatially variable environmental impacts into the biofuel life cycle due to needing to harvest, move, and preprocess biomass from multiple distances that have variable spatial density. This study examines the uncertainty in greenhouse gas (GHG) emissions of corn stover logistics within a bio-ethanol supply chain in the state of Kansas, where sustainable biomass supply varies spatially. Two scenarios were evaluated each having a different number of depots of varying capacity and location within Kansas relative to a central commodity-receiving biorefinery to test GHG emissions uncertainty. The first scenario sited four preprocessing depots evenly across the state of Kansas but within the vicinity of counties having high biomass supply density.

The second scenario located five depots based on the shortest depot-to-biorefinery rail distance and biomass availability. The logistics supply chain consists of corn stover harvest, collection and storage, feedstock transport from field to biomass preprocessing depot, preprocessing depot operations, and commodity transport from the biomass preprocessing depot to the biorefinery. Monte Carlo simulation was used to estimate the spatial uncertainty in the feedstock logistics gate-to-gate sequence. Within the logistics supply chain GHG emissions are most sensitive to the transport of the densified biomass, which introduces the highest variability (0.2–13 g CO_2e/MJ) to life cycle GHG emissions. Moreover, depending upon the biomass availability and its spatial density and surrounding transportation infrastructure (road and rail), logistics can increase the variability in life cycle environmental impacts for lignocellulosic biofuels. Within Kansas, life cycle GHG emissions could range from 24 g CO_2e/MJ to 41 g CO_2e/MJ depending upon the location, size and number of preprocessing depots constructed. However, this range can be minimized through optimizing the siting of preprocessing depots where ample rail infrastructure exists to supply biomass commodity to a regional biorefinery supply system.

1. Introduction

Post-industrialized economies rely on energy for almost all fundamental needs including food production, heat, transportation, manufacturing, and communication. Since the Industrial Revolution, fossil energy resources such as coal, petroleum, and natural gas have become the dominant sources of energy because they are readily accessible and inexpensive. The use of fossil fuels have enabled large-scale industrial development, but growing concerns regarding energy security and the environment, particularly climate change, have inspired the development of mandates for renewable energy from wind, biomass, and solar energy sources. In the United States for example, by 2022, the Energy Independence and Security Act (EISA) of 2007 requires that 61 billion L/year cellulosic ethanol replace petroleum-based transportation fuels. To meet this demand, an estimated 242 million Mg/year of biomass will need to be supplied to biorefineries that can process lignocellulose [1]. Sufficient biomass supply has been identified to meet these requirements through large-scale national assessments [2], and research is on-going concerning the logistics required to cultivate, harvest, transport, and process such large quantities of biomass into fuel. Our study focuses on the supply and logistics chain of the lignocellulosic ethanol produced from corn stover, an agricultural residue.

Biomass supply chains currently use equipment and infrastructure designed for existing agriculture and forest industries. These supply chains are designed to move biomass short distances, store it for limited periods of time, and are constrained in their ability to address biomass quality issues like moisture and ash content. Most widely cited lignocellulosic biorefinery designs [3–6] that utilize agricultural residues (e.g., corn stover) or dedicated energy crops (e.g., switchgrass) for biochemical conversion to alcohol have been designed and priced to take in baled biomass feedstocks, assuming the existing

(conventional) infrastructure. Although these conventional systems are cost-effective in high biomass-yielding areas, such as supplying corn stover in Iowa or forest resources in the Alabama, they are limited in their ability to support and meet long term national biofuels production goals [7]. For example, there are ample biomass resources that would be considered stranded under this model due to having a high transport distance that would result in prohibitive costs. A strong driver for the conventional system is to minimize transportation costs as biomass characteristics make them expensive to handle and transport. Examples of these characteristics include high moisture content, low bulk density, low energy density, high variability, and multiple formats. Richard [8] reviewed the challenges of establishing bioenergy systems from low energy-density biomass resources and discusses different technologies for increasing the energy density of agricultural feedstocks through different preprocessing steps, including pelleting, pyrolysis, and torrefaction. Such densification systems may be more appropriate for thermochemical (e.g., torrefaction and pyrolysis) as opposed to biochemical (pelleting) conversion. One approach to addressing these challenges for biochemical conversion platforms, while also bringing in stranded resources and reducing risk to the biorefinery, is to transition to a commodity-based feedstock supply system, such as that proposed by Idaho National Laboratory (INL) [7]. The commodity system incorporates distributed biomass preprocessing depots located near the point of production. The depots can provide the biorefineries with a quality-controlled biomass supply, which is sourced from a variety of biomass types [9]. Based on the availability of sufficient corn stover in Kansas to meet the biorefinery's capacity (2000 dry metric tons/day based on the work of [6]), the biorefinery could take in corn stover feedstock to meet annual supply. In the commodity system, the variability in feedstock characteristics such as moisture and ash content can be addressed by the local preprocessing depot to therefore supply the biorefinery with a dense, stable, quality controlled feedstock [8].

Most life cycle assessment (LCA) studies of biochemically-derived ethanol from lignocellulose have assumed the conventional model of delivering baled biomass (for agricultural residues or dedicated energy crops/purpose-grown grasses) directly to the lignocellulosic biorefinery [10–14]; however, recent LCA literature has compared conventional and commodity systems. Eranki *et al.* [15] compared the energy inputs and greenhouse gas (GHG) emissions of commodity and conventional systems delivered to a 5000 ton/day centralized biorefinery. The commodity system consists of nine preprocessing depots with a fixed capacity (500 tons/day). The mass fraction of biomass feedstock (corn stover, switchgrass and miscanthus) was varied in order to account for the uncertainty in energy requirements for feedstock production. The study concluded that the commodity system's GHG emissions are about 4% lower, while consuming approximately the same total energy as the conventional system. The study also emphasized that the processing technology was critical to cost-reduction for the commodity system, a point also addressed by Shastri *et al.* [16] and Uria-Martinez *et al.* [17]. Recently, Argo *et al.* [18] evaluated several environmental sustainability impacts (100-year global warming potential (GWP), rainfall (green water) and groundwater through irrigation (blue water) footprints), and costs for advanced logistics designs that employ densification steps for preprocessing agricultural residues and grasses in depots for long-haul transport to centralized biorefineries designed on the biochemical platform. Their results showed that the commodity system reduced both spatial and temporal variability and thus stabilized the cost of the feedstock logistics and supply chain. Egbendewe-Mondzozo *et al.* [19] analyzed the cost and GHG emissions of conventional and commodity

systems practiced in Southwest Michigan. The supply and logistics chain of the commodity system included seven preprocessing depots located in nine counties, and a centralized biorefinery. The authors examined different processing technology in order to evaluate their effects on biofuel production cost and energy inputs. The study concluded that the commodity system reduced the net life cycle GHG emissions; however, the profitability varied with the type of biomass feedstock and processing technology. Ray *et al.* [20] and Hess *et al.* [21] tested the effects of corn stover pellet densification on low- and high-solids pretreatment performance within biochemical conversion systems. The study concluded that pelletizing corn stover did not have a negative impact on pretreatment efficacy. Limited investigation from literature on the effects of densified feedstock on downstream processes suggests there is no adverse impact or possible improvement on pretreatment efficacy [22–24].

Select literature has examined spatial contributions to life cycle environmental impacts of ethanol from different feedstocks, mainly pertaining to the infrastructure and logistics of moving the product (ethanol fuel) to demand centers. For example, Wakeley *et al.* [25] concluded that at higher production scales, ethanol long-haul transport costs and environmental emissions would decline through use of rail infrastructure to transport due to the majority of supply (in the Midwest) needing to access demand centers (on east and west coasts of the U.S.). Strogen and colleagues evaluated the costs and emissions of bio-ethanol distribution on a larger scale than previously studied, and concluded that annual ethanol production scale critically impacts the average transport distance to end use markets [26]. The authors found that more than 300,000 tons of CO_2e could be avoided if all unnecessary transportation were eliminated. Moreover, Argo *et al.* [18] found that the logistics of the commodity system results in lower production costs than the conventional one when the biorefinery capacities are above 5000 Mg/day. A study by INL acknowledged that the transportation cost savings in the commodity system does not completely offset the costs associated with the pelleting and regrinding at all transport distances. If the benefits of handling and storing pellets are quantified, the transportation cost savings can be increased and thus can balance or exceed the cost of densification. However, the total cost of the commodity supply chain system could be higher than the conventional system due to the addition of preprocessing operations and equipment [16,27]. Our objective is to evaluate the spatial variability of life cycle environmental impacts owing to characteristics along the biomass feedstock supply chain (*i.e.*, from field to depot to biorefinery with intermediate transportation and preprocessing steps) that incur variability as a result of the quantity of biomass harvested, collected, stored, moved, and preprocessed prior to long-distance transport to a centralized biorefinery. Thus, our focus is on identifying processes within the feedstock logistics sequence that introduce the most significant uncertainty in life cycle impact assessment (LCIA). We focus on one LCIA metric, the 100-year GWP applied to a case study of a commodity system design in the state of Kansas (United States) through several configurations for depot location siting, and discuss the relevance to other important environmental impacts within agricultural bioenergy supply systems. Kansas was chosen in INL's 2017 [28] design report as an area that could support a uniform format "depot" supply system design mainly because of resource density (*i.e.*, the presence of sufficient biomass supply) and mix of different feedstocks in different supply regions of the U.S. Our study focuses on Kansas in order to leverage assumptions from INL's 2017 report for the Midwest region, whose supply of corn stover could support depots supplying biomass commodities to a centralized biorefinery; and to demonstrate the depot design where it may likely take place, given resource availability. Our specific objective

in this paper is to evaluate the uncertainty in life cycle GWP of the harvest, collection, storage, preprocessing, and transportation stages with two different configurations of depot size and location, whereby the location, size, and number of depots for a particular feedstock supply system design may incur significant dominance and/or variability to the life cycle GWP.

2. Methods

LCA, following the International Organization for Standardization (ISO) 14040 methods [29], was applied to evaluate environmental aspects of the bio-ethanol logistics and supply chain. Data for the life cycle inventory (LCI) model, which include the energy resources consumed to process corn stover at different scales, were derived using simulations from the Biomass Logistics Model (BLM) developed using Powersim™ at INL (Idaho Falls, ID, USA) [27]. The BLM incorporates information from a number of databases which include all the data related to: (1) the engineering performance data of biomass pre-processing equipment; (2) labor costs; and (3) local tax and regulation data [27]. ArcGIS was employed in this study in order to site the biorefinery and preprocessing depots and define all transportation distances [30]. The spatial data are publicly available on the website of the Aerial Photography & GIS Data for the Professional & Novice (for counties) [31], and the Kansas Data Access & Support Center (DASC) (for railroads and highways) (Lawrence, KS, USA) [32,33]. We use an attributional LCA (aLCA) approach in this study to investigate the spatial variability in LCIA metrics; however, we note the limitations of this approach raised by Andersen [34], who discussed potentially negative environmental impacts resulting from agricultural residue diversion, in that case, bagasse, for biofuel production.

Through a focused analysis of agricultural residue harvest, collection, storage, transport, and preprocessing, this study builds on prior work aimed at understanding and characterizing uncertainties within the life cycle supply chain of lignocellulosic ethanol (bio-ethanol) [13,35,36]. With the exception of a recent study [18], most prior LCA studies of bio-ethanol [10,11,13,14,37] have assumed a conventional harvest and biomass delivery in bale format, resulting in relatively low (approximately 10%) net life cycle GHG emissions [11]. Here, we focus on identifying and characterizing uncertainties in advanced agricultural residue harvest, collection, storage, transport, pre-processing, and delivery operations to bio-ethanol facilities in the U.S. Midwest that arise due to variability in: (1) the sustainable harvest yield, defined as the quantity of corn stover removal set to maintain erosion and soil carbon within tolerable levels [2]; (2) transportation of the agricultural residue to depots that process and densify the biomass; (3) depot facility size, which influences equipment and energy throughput per unit of biomass; and (4) long-distance transport of the densified biomass delivered to the bio-ethanol facility. While we note the significant variability in GHG emissions from feedstock production noted in literature, and in particular the possible risks to loss of soil organic carbon (SOC) with corn stover removal [38,39], here we focus exclusively on uncertainties that could arise due to the spatial variability of corn stover feedstocks available at different spatial densities in the U.S. Midwest.

The commodity system allows lignocellulosic biomass to be traded and supplied to biorefineries in a commodity-format market. A number of preprocessing depots can be located within or around the vicinity of biomass and are deployed to convert a diverse, low-density, perishable feedstock resource into an aerobically stable, dense, uniform-format [9,21]. The preprocessing steps and equipment include:
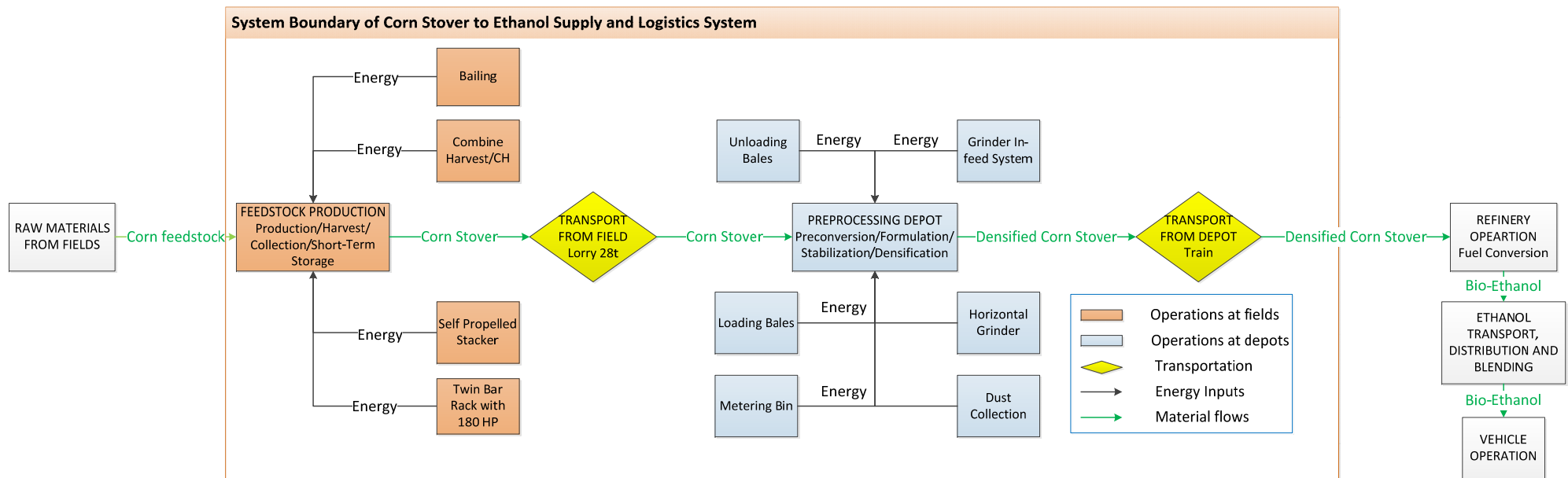
loaders, horizontal grinders, grinder in-feed systems, and dust collection and conveyor systems [7,9]. The energy sources for depot equipment are described in Table S1. A commodity system and depots would likely first appear in areas without enough resources to supply a single biorefinery, requiring resources to be brought in beyond the local area. The incorporation of depots would allow stranded resources to enter the system which would otherwise be economically inaccessible. For this reason, corn stover located in the state of Kansas outside of high yielding areas within the U.S. corn-belt was chosen for analysis.

2.1. Life Cycle Assessment of the Corn Stover to Lignocellulosic Ethanol Logistics and Supply Chain

A LCA model was developed to evaluate uncertainties in GHG emissions for a corn stover-to-ethanol commodity system. A gate-to-gate LCI model was developed followed by LCIA evaluation of the 100-year GWP metric for corn stover feedstock logistics. The feedstock logistics we model in this work fits into a gate-to-gate segment of the full lignocellulosic ethanol life cycle (Figure 1), which refers to the sequence of processes within the life cycle of biomass production, conversion, and in-use consumption. The system boundary for the full life cycle of corn stover-to-ethanol (Figure 1) consists of: (1) feedstock production (*i.e.*, crop production including nutrient replacement and soil GHG emissions); (2) feedstock harvest, collection, and storage; (3) feedstock transport from field to biomass preprocessing depot; (4) preprocessing depot operations; (5) commodity transport from biomass preprocessing depot to biorefinery; (6) biofuel conversion at the biorefinery; (7) ethanol transport, distribution, and blending; and (8) vehicle operation. The functional unit of the analysis is 1 MJ of ethanol. We rely on literatures' estimates for Segments 1, 6, 7, and 8 (see [36,40] for development of the biorefinery model and for discussion of biorefinery inputs, respectively). The assumptions from literature [37] correspond to conventional biomass sourcing with on-site power production and an electricity credit from the Midwest electricity grid mix.

This paper focuses on identifying significant uncertainties in environmental metrics within an advanced logistics configuration of the corn stover-to-ethanol supply chain, which was designed to reduce transportation distance and costs. A single-variable sensitivity analysis was conducted to examine the significance of LCI model parameters for harvesting, transporting from field, preprocessing at the depot and transporting from the depot in the advanced commodity system. Commodity transportation (as baled corn stover or densified biomass) is a function of both transport distance and feedstock density.

Figure 1. Gate-to-gate system boundary for the corn stover commodity feedstock supply and logistics system within the life cycle of bio-ethanol production.
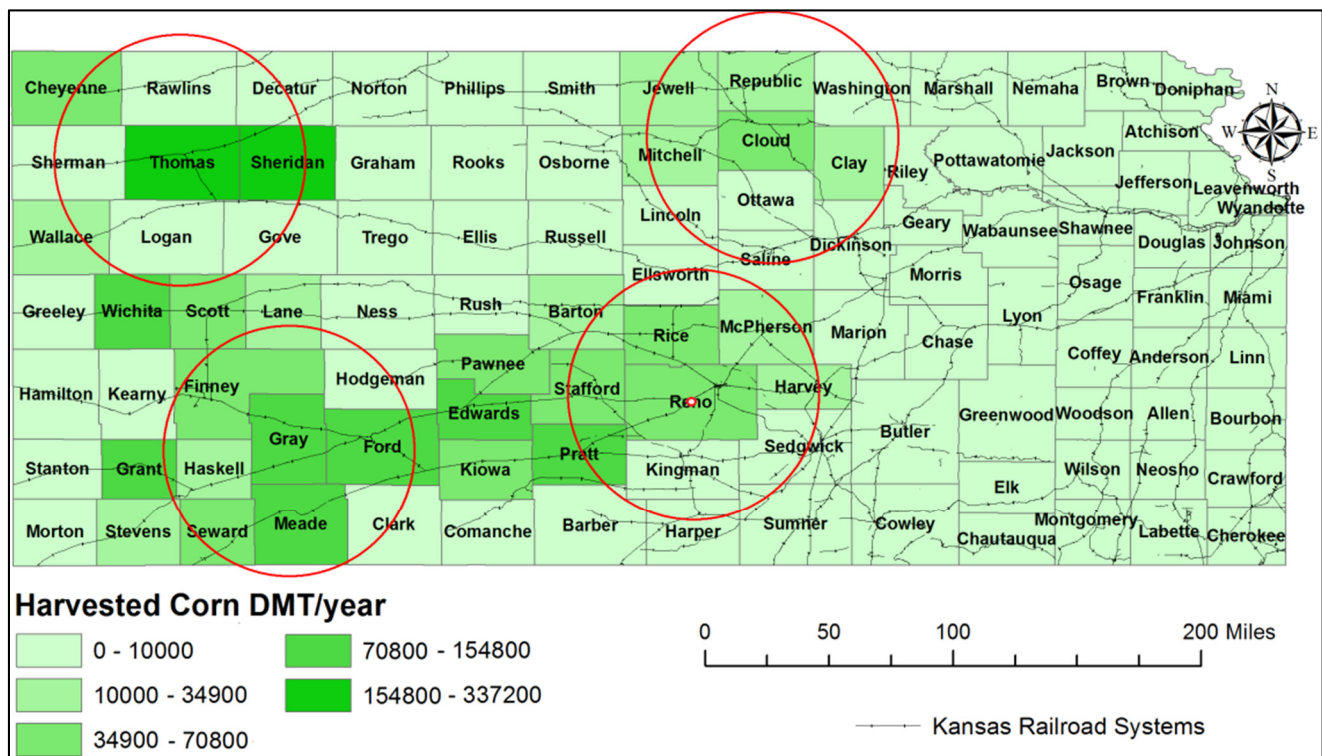
2.2. Data Management and Analysis

ArcGIS tools were used to identify depot and biorefinery locations and to measure the transport distances within the commodity supply chain. The criteria for location selection consisted of the presence of transportation infrastructure (railroads and road systems) and annual biomass availability (*i.e.*, sustainable harvest yield) in the state of Kansas [2]. Significant factors such as access to water, and availability of utilities and labor were assumed sufficient for the model scenarios constructed. For this study, factors affecting policy such as political districts, voting locations and school systems were not considered. Transportation data, including road and rail networks, and freight and truck stations, were obtained from the Aerial Photography & GIS Data for the Professional & Novice [31] and the DASC [32,33]. Biomass supply data were assumed to correspond to the marginal access (farm-to-gate) cost, which is proportionally related to biomass demand. The US Department of Energy's U.S. Billion-Ton Update Report (BT2) [2] estimates biomass marginal access costs in $5/ton increments. For the counties we consider in Kansas, biomass marginal access costs begin at $40/ton and can be as high as $80/ton depending upon the available supply within each county. Wakeley *et al.* [25] and Argo *et al.* [18] varied biorefinery capacity in their studies in order to examine the range of transportation cost and GHG emissions. In this study, the biorefinery capacity was fixed at 800,000 dry matter tons (DMT)/year. The supply chain was designed to provide 900,000 DMT to account for possible losses due to the converting, handling and transporting processes. We assumed that multiple depots would feed one centralized biorefinery. Given these boundary conditions, a master map was developed joining all transportation and biomass availability data (Figure S1). A radius of 80-km (50-miles) radius is assumed for feedstock transportation from the corn farms to the preprocessing depots. Several tools within ArcGIS were used to identify the geographic boundary of the LCI model. The centroid of each county was identified by using the Spatial Analysis (Feature to Point) tool. The ArcGIS Find Route tool was used to measure the rail distances between two locations based on the available railroad networks. The biomass supply data for each Kansas County were imported to ArcGIS and converted to raster format. The biomass supply data were presented in the master map in order to demonstrate the biomass density and distribution across Kansas. Two depot configurations were considered: (1) equal spatial distance between depots and infrastructure (rail network) availability; and (2) high biomass density and infrastructure (rail network) availability. The rationale for selecting the two configurations was to test the impact that the number of depots and their relative location within a biorefinery supply radius have on life cycle GHG emissions.

2.2.1. Configuration 1: Equal Spatial Distance between Depots and Infrastructure Availability

The first configuration divides the state of Kansas into six equally spaced primary regions: (1) Northwest; (2) North; (3) Northeast; (4) Southeast; (5) South; and (6) Southwest. However, according to resource assessment data from Oak Ridge National Laboratory (ORNL) [2], the counties in Regions 3 and 4 would not supply biomass for ethanol production (Figure S1). Therefore, counties in these regions were eliminated from the scope of analysis. Four depots are located in Regions 1, 2, 5, and 6 within the vicinity of biomass supply of each region. They are also cited close to road and rail transportation infrastructure to take in baled feedstock and export (via long distance) densified biomass

(Figure 2, spatial boundary). Note that the sizing criteria for depots used in this study are different than those used by INL.
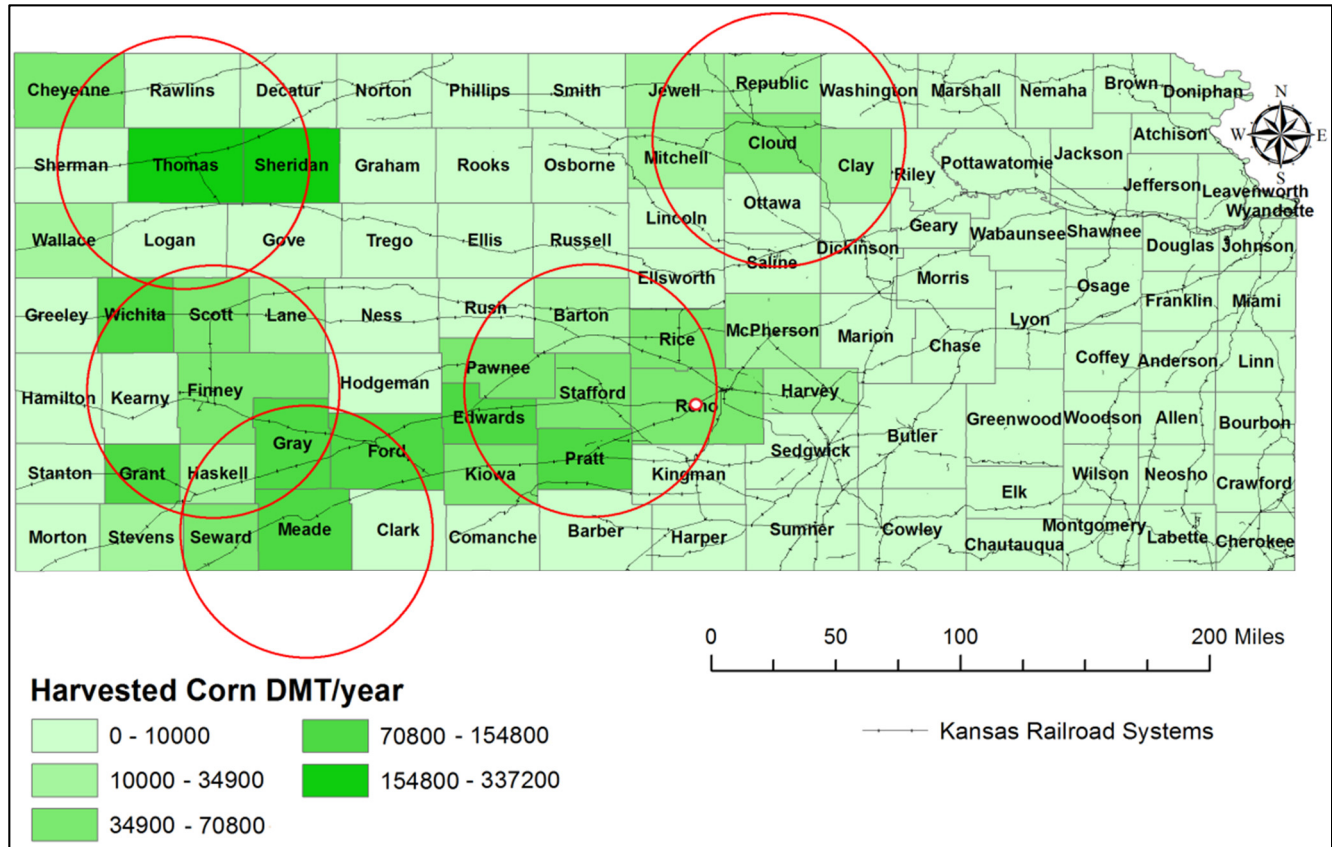
Figure 2. Scenario 1 depot configuration based on equal spatial siting between depots and infrastructure availability. The red circle shows the biomass supply radius. The depots are located at the center of the circle and receive feedstock from counties within an 80-km (50-miles) radius. The red point at the centroid of Reno County corresponds to the location of the biorefinery.

2.2.2. Configuration 2: High Biomass Density and Infrastructure Availability

The second depot configuration places depots according to biomass availability and the shortest railroad distance from the depot to the biorefinery, and is derived from the existing Kansas rail systems (Figure 3) in the central-to-west range of the state. Argo *et al.* [18] assumed in their model that the feedstock was transported from field to depot by semi-truck and from depot to biorefinery by rail given that railcars are capable of carrying a greater volume of goods with the minimal variable cost per mile. Thus, we assumed that distribution by truck is preferred for transport from field to depot, and rail is preferred for long distance transportation from depot to biorefinery. Based on the distribution of biomass and feedstock transport distance from field to depot, five biomass preprocessing depots were located in the state in counties surrounded by dense feedstock supply.

Figure 3. Scenario 2 depot configuration based on biomass density and infrastructure availability. The red circle shows the biomass supply radius. The depots are located at the center of the circle and receive the feedstock from counties within an 80-km (50-miles) radius. The red point at the centroid of Reno County corresponds to the location of the biorefinery.
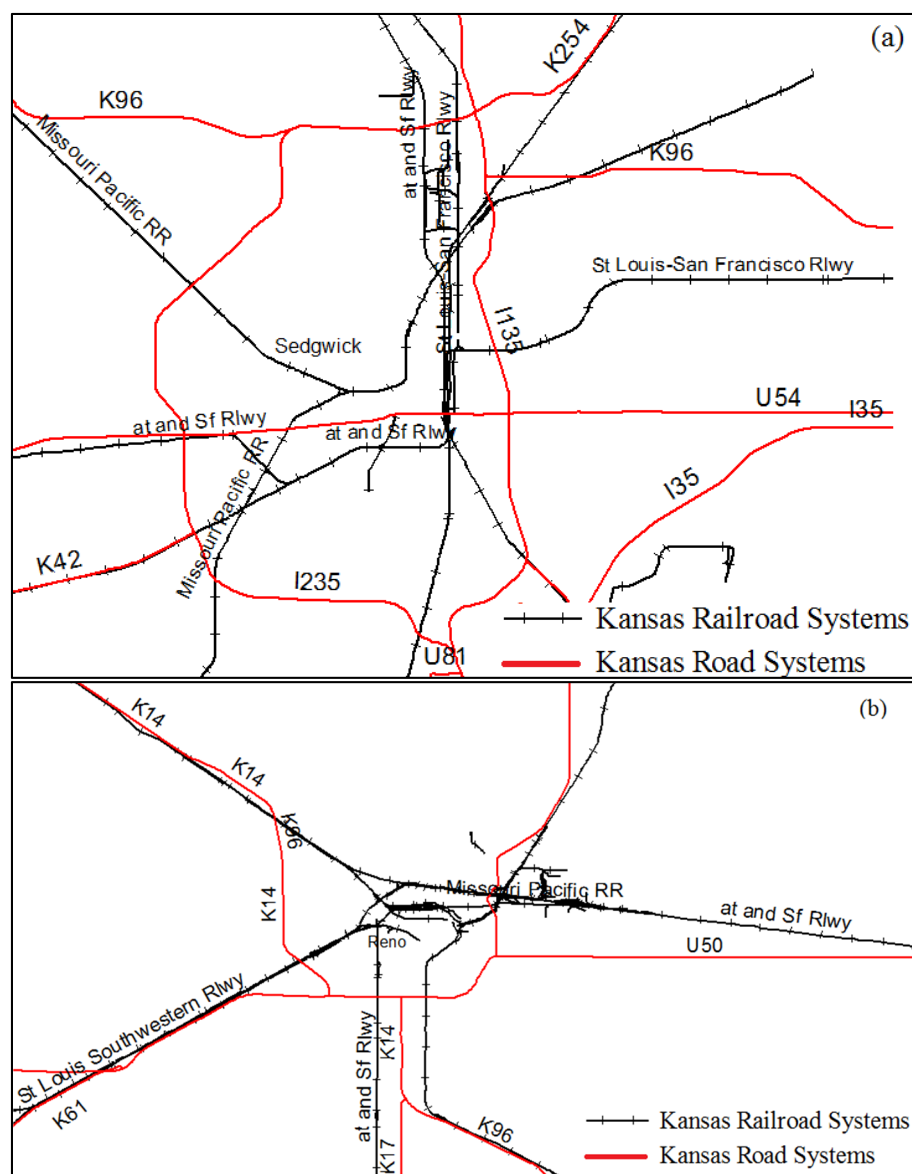

2.2.3. Life Cycle Assessment Modeling Approach

The BLM inventories all equipment and transport modes used to process and move biomass from the field to the biorefinery reactor infeed [29]. The transport distance, specified using ArcGIS software, and the depot capacity were varied and analyzed by the BLM model in order to generate the relative energy consumption from each field supplying feedstock to depot and densified biomass to biorefinery. The cumulative energy consumption in advanced logistics is the product of the normalized energy consumption from the BLM (in gallons of diesel per DMT), which includes a semi-truck (2.88 L) to transport one DMT of biomass and a baler (1.36 L) to compress one DMT of biomass, and the biomass input, which was scaled according to the depot capacity. Energy consumption data were input into the SimaPro V.7.3.3 LCI [41] model in order to compute the life cycle GHG emission. The SimaPro model accounts for all upstream cradle-to-gate inputs of process energy (diesel and electricity). In order to expedite the gate-to-gate LCIA computation for the two scenarios, a Matlab script [42] was written to batch-process the BLM energy and resource data outputs into SimaPro to generate the GHG emissions for the 46 supply counties (See Section S4 for more detail).

2.3. Biorefinery Location

The biorefinery was located in Reno County based on its proximity to road and railway infrastructure. Two counties were identified originally, Sedgewick (Figure 4a) and Reno (Figure 4b), given their location within the state being in areas with high highway and railway access. Reno County was selected based on it having five highways (K14, K17, U50, K61, K96) and four railroads (St. Louis Southwestern, Missouri Pacific and Atchison, Topeka & Santa Fe Railway and Chicago, Rock Island and Pacific Railroad), whereas Sedgewick has nine highways (I235, K96, I135, I35, K15, U54, U81, K42, K254) but a less extensive railway network of three railroads (Missouri Pacific, Chicago Rock Island, Pacific and St. Louis-San Francisco Railway). Thus, the biorefinery was sited in Reno County because of its proximity to the biomass supplying counties and because of its better access to four railroad networks that could facilitate access on energy efficient rail between depots and the biorefinery, thus giving access to all depot locations selected in Scenarios 1 and 2 (Figure S1).

Figure 4. Highway (red) and rail systems (black) of (**a**) Sedgewick County and (**b**) Reno County.

2.4. The Capacity of the Biomass Preprocessing Depots

The available biomass supply in Kansas exceeds the biorefinery feedstock demand of 900,000 DMT/year. The maximum capacity of each preprocessing depot is assumed to be less than 400,000 DMT/year in order to increase the network of the distribution systems. The depot size limitation allows for more depots to be distributed across the state to supply the annual constant corn stover needed for the centralized biorefinery. To be conservative, we set the size of the pre-processing depots based on the local feedstock density within an 80-km (50-miles) radius. A simple mathematical rule was applied to estimate the depot capacity (Tables S2 and S3, and Equation (S1)) and farm supply (Tables S4 and S5, and Equation (S2)) based on the availability of biomass supply. We assumed that neighboring counties would transport biomass to the nearest depot within an 80-km (50-miles) radius. The distance from the depot to the biorefinery is the distance from the centroid of the county with the depot to the centroid of the county with the biorefinery for Scenario 1 (Table 1) and Scenario 2 (Table 2). The sizing criteria for depots used in this study are different than that used by INL.

Table 1. Preprocessing depot capacities and true rail distance from depots to the single biorefinery in Scenario 1. DMT: dry matter ton.

Depot locations	Depot capacity (DMT/year)	Transport rail distance
Thomas	390,000	349
Cloud	50,000	160
Gray	275,000	142
Reno	185,000	14
Total	900,000	665

Table 2. Preprocessing depot capacities and true rail distance from depots to the single biorefinery in Scenario 2.

Depot locations	Depot capacity (DMT/year)	Transport rail distance
Thomas	295,000	349
Finney	190,000	176
Meade	150,000	136
Stafford	220,000	47
Cloud	45,000	160
Total	900,000	868

2.5. Uncertainty Analysis

We use Monte Carlo methods [43,44] to project the range of probable life cycle GWPs for the two scenarios. The gate-to-gate LCIA model developed in SimaPro V.7.3.3 estimates the GHG emissions (GWP) based on the energy resource inputs derived from the BLM. SimaPro GWP output data for each process in the supply chain were best fit to probability distributions using Oracle Crystal Ball Statistical Software (Oracle Corporation, Redwood City, CA, USA) [45] and two distributions for Scenarios 1 and 2, respectively, were aggregated (Figures S2 and S3). With the scenario probability distributions, a Monte Carlo Simulation (1000 iterations) was run to generate stochastic GWP estimates (Table S6, and Figures S2 and S3). The statistical mean, range, and probability

distributions for the stochastic input processes (feedstock harvest, collection and storage, feedstock transport, preprocessing, and commodity transport) are noted in Table S7. This uncertainty analysis procedure was adopted from Venkatesh *et al.* [46], who investigated uncertainties in life cycle GWP of U.S. coal; the authors fit probability distributions to coal model parameter inputs and used Monte Carlo simulation to examine the effect of spatial and temporal variability on life cycle GWP. Finally, we used single-variable sensitivity analysis to determine the relative significance of the four logistics gate-to-gate processes with respect to the final GHG emission given the expected low and high ranges in order to understand the variability within the system boundary and thus evaluate and mitigate potential environmental risks as noted by Venkatesh *et al.* [46].

3. Results and Discussion

3.1. Life Cycle Impact Assessment

The average corn stover-to-ethanol life cycle GHG emissions for the two scenarios we examine in Kansas (Table 3) are 26 g CO_2e/MJ ethanol and 25 g CO_2e/MJ ethanol for Scenarios 1 and 2, respectively, 66% and 63% of the conventional system's life cycle GWP. These average values are 34% and 37% (for Scenarios 1 and 2, respectively) lower than the "conventional system" analog of 39.7 g CO_2e/MJ ethanol (Table 3) taken from literature from Pourhashem *et al.* [37], because of the significantly lower corn stover harvest, collection, storage, preprocessing, and transport from depot to biorefinery sequence estimate that we assume through the BLM model. Review of literature (Table S8) indicated a wide range of results for feedstock harvest, collection, and storage activities within the logistics supply chain of conventional systems. Among the studies reviewed, which presented GWP estimates ranging from 3 g CO2e/MJ [35] to 17.5 g CO2e/MJ [47], aggregate energy input for both collection and harvest were larger than our study findings, suggesting that the GWP for the logistics supply chain will depend on equipment performance, including energy efficiency and age. The equipment and energy inputs for the harvest, collection and storage were detailed in Table S8. The data shows that the energy consumption for feedstock harvest, collection and storage in our study is 58%, 66% and 94% lower than that of Wang *et al.* [35], Larson *et al.* [47] (which Pourhashem *et al.* [37] used), and Eranki *et al.* [15], respectively (Table S8 compares assumptions and energy inputs for our and literature results for feedstock harvest and collection). The GHG emissions of the corn stover harvest, collection, and storage processes for Scenarios 1 and 2 are significantly lower than those suggested in Pourhashem's study [37] as well as work by Larson *et al.* [47], who estimates that corn stover harvest, collection, and storage processes emit 403 kg CO_2e/DMT, which is equivalent to 17.5 g CO_2e/MJ ethanol assuming our fuel conversion assumptions. Other estimates from literature have estimated farm operations for harvesting, collecting, and storing corn stover to be significantly smaller. For example, Wang *et al.* [35] estimate farm operations for the harvest of corn stover for ethanol production to be 3 g CO_2e/MJ. Among the main processes of the supply chain, the transport step from depot to biorefinery contributes the most to the net GHG emissions at 2 g CO_2e/MJ ethanol and 1.5 g CO_2e/MJ ethanol in Scenarios 1 and 2, respectively, but is modest compared to most other life cycle inputs aside from logistics processes. This contribution is estimated as 8% of the net GHG emissions in Scenario 1 and 6% of the net GHG emissions in Scenario 2.

Table 3. Scenarios 1 and 2 weighted average greenhouse gas (GHG) emissions sources and sinks of life cycle components: (1) feedstock production (*i.e.*, crop production including nutrient replacement and soil GHG emissions); (2) feedstock harvest, collection, and storage; (3) feedstock transport from field to biomass preprocessing depot; (4) preprocessing depot operations; (5) commodity transport from biomass preprocessing depot to biorefinery; (6) biofuel conversion at the biorefinery; (7) ethanol transport, distribution, and blending; and (8) vehicle operation. All units in g CO_2e/MJ ethanol.

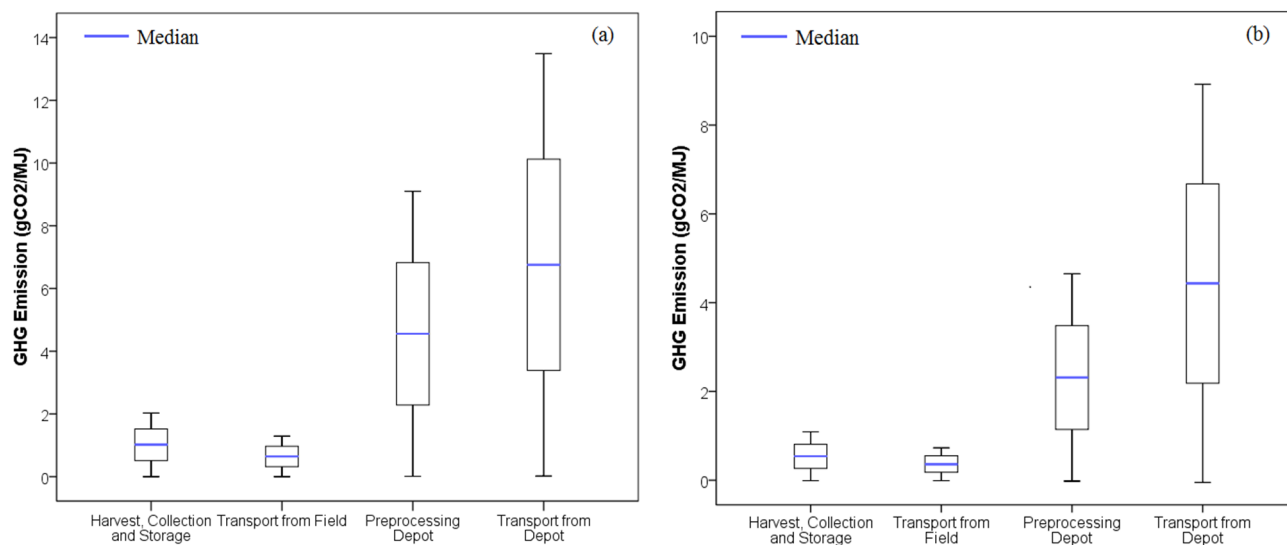| Feedstock production	Scenario 1 commodity system: equal spatial distance between depots and infrastructure availability	Scenario 2 commodity system: high biomass density and infrastructure availability	Conventional system (Pourhashem *et al.* [37])
Harvest, collection, and storage	0.32	0.22	12.8
Nutrient replacement	2.6	2.6	2.6
Total soil N_2O emission	7.4	7.4	7.4
Change in soil carbon	27.3	27.3	27.3
Biogenic carbon	−234	−234	−234
Transport from fields	0.2	0.2	4.4
Preprocessing depot	1.0	0.7	N/A
Transport from depots	2.0	1.5	N/A
Total transport (transport from fields + transport from depots)	2.2	1.7	4.4
Fuel conversion	**Scenario 1 commodity system: equal spatial distance between depots and infrastructure availability**	**Scenario 2 commodity system: high biomass density and infrastructure availability**	**Conventional system (Pourhashem *et al.* [37])**
Pretreatment chemicals	5.7	5.7	5.7
Fermentative CO_2	34	34	34
Boiler	122	122	122
Electricity	−15.6	−15.6	−15.6
Fuel transport & distribution	1.5	1.5	1.5
Ethanol combustion	71	71	71
Net GHG emissions	26	25	39.7

The GHG emissions from the preprocessing depot contribute 4% and 3% of the net GHG emissions in Scenarios 1 and 2, respectively. This contribution may be low as the logistics design only considered comminution and densification while further processing to address feedstock quality in terms of fuel conversion (moisture, ash, *etc.*) was outside the scope of this paper. The feedstock harvest, collection, and transport from field processes contribute less than 2% of the net GHG emission for both scenarios. The total GHG emissions for transport steps, including transport of biomass from fields and transport of commodity from depots for Scenario 1, is 2.2 g CO_2e/MJ ethanol, which is 50% lower than the GHG emissions of the transport step reported for the conventional case in Pourhashem's paper [37], 4.4 g CO_2e/MJ ethanol; while the GHG emissions from these two transportation steps for Scenario 2, 1.7 g CO_2e/MJ ethanol, is 64% lower than that of the conventional case.

3.2. Uncertainties in Greenhouse Gas Emissions in Corn Stover-to-Ethanol Production

Most LCA studies of agricultural residue-to-biofuel have assumed the conventional logistics system, which consists of a single transportation step from the field to the biorefinery [10,11,13,14,37,48]. These studies indicated that the transport step contributed minimally to the environmental impact of the lignocellulosic ethanol supply chain. For example, Pourhashem's study [37] showed that the transport step contributes approximately 11% to the net life cycle emissions. For the advanced commodity system studied, the transport of densified corn stover from the preprocessing depot to the biorefinery could add significantly to the variability in life cycle GHG emissions for the entire supply chain in both scenarios. Both variability in transportation distance from depot to biorefinery and preprocessing operations at the depot contribute to variation in net GHG emissions from logistics (Figure 5).

Figure 5. Stochastic gate-to-gate logistics GHG emissions over the 90% confidence interval (CI) and interquartile ranges for: (**a**) Scenario 1; and (**b**) Scenario 2. Stochastic estimates based on Monte Carlo simulation (1000 iterations) are presented as box and whisker plots. The top of the box represents the 75th percentile, the middle line represents the median (50th percentile) and the bottom of the box represents the 25th percentile. The whiskers correspond to the 5th and 95th percentiles.
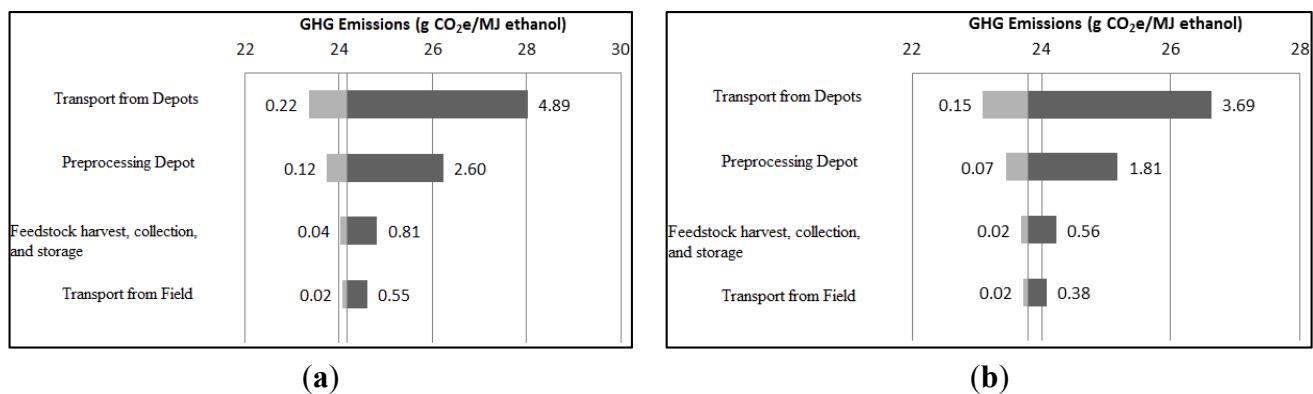

The transportation of densified biomass from the preprocessing depot to the biorefinery introduces the highest uncertainty, ranging from 0.02 g CO_2e/MJ to 13 g CO_2e/MJ ethanol for Scenario 1 (Figure 5a) and from 0.02 g CO_2e/MJ to 9 g CO_2e/MJ ethanol for Scenario 2 (Figure 5b) over the 90% confidence interval (CI). This wide range comes primarily from the variability in transported biomass from each depot and the long, though efficient, transport distance by rail. The transport rail distances range from 14 miles to 349 miles and from 47 miles to 349 miles in Scenarios 1 and 2, respectively (Tables 1 and 2). Scenario 2 has more preprocessing depots distributed around the central biorefinery than Scenario 1, which decreases the size of each depot and thus reduces the feedstock mass being transported per route from the depot to the biorefinery. As a result, the range of uncertainty for logistics in Scenario 2 is smaller than that for Scenario 1. GHG emissions are sensitive to the size of

preprocessing depots. This is evident from the wider range of emissions in both feedstock harvest, collection and storage (0.1–2.3 g CO_2e/MJ ethanol) and preprocessing depot processes (0.02–9.3 g CO_2e/MJ ethanol) (Figure 5a) in Scenario 1, compared to the narrower range of emissions for both feedstock harvest, collection and storage (0.1–1 g CO_2e/MJ) and the preprocessing depot processes (0.2–5 g CO_2e/MJ) in Scenario 2 (Figure 5b). The larger size of the preprocessing depots in Scenario 1 (Tables 1 and 2) raises the upper bounds of cumulative energy consumption in transportation and biomass densification processes. Argo *et al.* [18] also concluded that the commodity system resulted in higher GHG emissions (10%–15%) than the conventional system due to having additional transportation steps. The "transport from field" process shows the least significant impact because the biomass supply radius is limited to 80 km (50-miles).

Single variable sensitivity analysis was conducted to identify significant parameters in the logistics segment of the life cycle (Figure 6). The results confirm the significance of transporting the densified biomass in both scenarios. The transportation of densified biomass from depot to biorefniery can impose a variation in GHG emissions of more than 20% from the average (Table 3) for Scenario 1 (Figure 6a) and Scenario 2 (Figure 6b), whereas all of the other parameters may cause life cycle GHG emissions to vary by up to 10% (Figure 6) above the average.
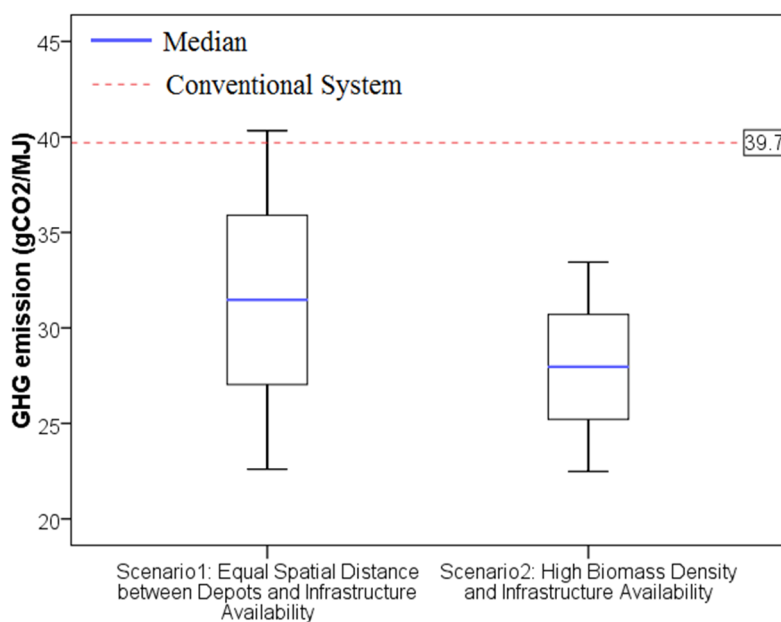
Figure 6. Sensitivity analysis of processes: feedstock harvest, collection, and storage; transport from field; preprocessing depot; and transport from depot to biorefinery on life cycle GHG emissions for: (**a**) Scenario 1; and (**b**) Scenario 2. The tornado diagram shows that GHG emissions (measured as global warming potential (GWP)) are most sensitive to the transport from depot (top process) and least sensitive to transport from field (bottom process). An increase in GHG emissions sensitivity is shown in 50% gray; and a decrease in GHG emissions sensitivity is shown in 30% gray.

(**a**)   (**b**)

The calculated 90% CI shows that the GHG emissions in Scenario 1 can be higher by at least 3.4 g CO_2e/MJ, and by as much as 3.6 g CO_2e/MJ compared to Scenario 2 GHG emissions (see Tables S9 and S10 for further information on the paired-samples *T*-test). The uncertainty in life cycle GHG emission varies from 24 g CO_2e/MJ to 41 g CO_2e/MJ in Scenario 1 and from 24 g CO_2e/MJ to 33 g CO_2e/MJ in Scenario 2 (Figure 7). Only the upper bound of Scenario 1 could cause the biorefinery to fall out of compliance with the U.S. Federal Renewable Fuel Standard Program (RFS2) [49] barring any deviation in all other life cycle inputs that we assume to be fixed do not vary significantly. For example, Pourhashem *et al.* [37] found that soil carbon loss, if not managed, can add significantly

to uncertain and positive GHG emissions, and electricity crediting (a negative GHG emission in most lignocellulosic ethanol life cycle studies) is also uncertain when a biorefinery co-produces electricity to sell to the regional electricity grid because of uncertainties in the displacement of marginal electricity supply [36]. Both of these factors could increase the life cycle GHG emission range above the RFS2 compliance level. Under these circumstances, uncertainty in logistics inputs would add further to the uncertainty of meeting RFS2; however, for the most part, the efficiency gained by densification of the biomass improves life cycle GHG emissions and offers a means of overcoming potentially "stranded" biomass supply. The wider range in Scenario 1 primarily results from the greater uncertainty in the "transport from depot" and the "preprocessing depot" processes while the other two operations contribute much less (Figure 5).

Figure 7. Stochastic life cycle GHG emission results from Monte Carlo simulations for two depot scenarios for the corn stover-to-ethanol logistics and supply chain. The GHG emission for the conventional biorefinery case was obtained from literature [37]. Stochastic estimates based on MC simulation are presented as box and whisker plots. The top of the box represents the 75th percentile, the middle line represents the median (50th percentile) and the bottom of the box represents the 25th percentile. The whiskers correspond to the 5th and 95th percentiles.

Compared to the life cycle GHG emissions of the average conventional case, 39.7 g CO₂e/MJ [37], the GHG emissions at the 90th percentile in Scenario 2 falls under the GHG emission of the conventional case while it is ~1 g CO₂e/MJ higher than the conventional case in Scenario 1. This finding suggests that equally spacing depots across the state of Kansas can possibly surpass GHG emissions of the conventional case, albeit by a small margin.

4. Conclusions

This study examines the variability in life cycle GHG emissions of a bio-ethanol feedstock logistics supply chain in Kansas, specifically examining uncertainties in advanced commodity systems that are

found to mitigate risks associated with weather, pests, and disease [18,27]. In this study, the uncertainty in agricultural residue (corn stover) logistics was examined by testing the location siting and sizing of pre-processing depots in two different but plausible supply chain configurations in the state of Kansas. In Scenario 1, the depots were equally spaced and sited within the vicinity of counties that have high biomass supply density. In Scenario 2, the depot siting was leveraged to consider the shortest rail transport distance to a centralized biorefinery while considering the vicinity of high biomass supply counties. The stochastic results show that the GHG emissions for Scenario 1 have a wider variability and higher mean emissions (See Table S9) than those of Scenario 2. This result illustrates the benefit of locating preprocessing depots in the vicinity of direct railroad lines to the biorefinery since rail transportation has the least environmental impacts and lowest costs [27]. It demonstrates that we expect to find a range of environmental impacts (in this case, GHG emissions) depending upon the quantity of biomass moved and upon the distance from biomass-supplying farms to preprocessing depots and from depots to biorefinery central facilities. Other environmental LCIA metrics that depend on energy consumption are expected to follow the variability trend exhibited by GHG emissions.

The depot-to-biorefinery transportation segment makes the largest contribution to life cycle GHG emissions from logistics and to life cycle GHG uncertainty for both scenarios. This suggests that the transport distance and the volume of transported commodity from depots are the significant parameters for supply regions like Kansas that have sufficient biomass supply in a feedstock commodity supply chain. Results may be quite different in regions that have many stranded biomass resources that need to be transported a long distance and collected at smaller centralized depots, the siting of which could depend on the presence of both road and rail infrastructure. Results also suggest that the uncertainty in GHG emissions of the depot-to-biorefinery and the pre-processing depot processes declines with increasing number of depots in a region. Future uncertainty analysis for feedstock logistics should focus on improving some of the model boundary settings, particularly the feedstock supply radius and the depot sizing method. The variability in the field-to-depot stage is minimized because the feedstock supply is limited to the region within an 80-km (50-miles) radius and thus the transport distance is assumed to be uniform. However, restricting the feedstock collection radius may impose a limitation in meeting biofuels production as noted by Argo *et al.* [18]. Therefore, future work should consider a larger biomass supply radius. In our study, the depot capacity was simply determined based on the feedstock supply ratio; however, a more precise optimizing of depot capacity could be used to test its significance on uncertainty in logistics chains that may require multiple stranded supply locations using a variety of lignocellulosic sources needed to fit a biorefinery's annual supply wheel.

Supplementary Materials

Supplementary materials can be accessed at: http://www.mdpi.com/1996-1073/7/11/7125/s1.

Acknowledgments

Author Contributions

The concept for this research was conceived by Sabrina Spatari. Spatial data management, data processing and interpretation, and manuscript preparation was completed by Long Nguyen, Kara G. Cafferty, Sabrina Spatari, and Erin M. Searcy. All authors contributed to the editing and reviewing of this document.

Conflicts of Interest

The authors declare no conflict of interest.

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