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# Two-stage stochastic optimization of sustainable bioethanol supply chain based on demand uncertainty and seasonal availability of biomass

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## ABSTRACT

Bioethanol-blended gasoline fuel is one of the alternatives for reducing $CO_2$ emissions in the transportation sector. Since its production is still dependent on demand fluctuations and feedstock availability, an optimal supply chain design needs to be evaluated. A two-stage stochastic optimization model with mixed-integer linear programming (MILP) was developed for designing the optimal bioethanol supply chain under the constraints of multi-feedstock second-generation biomass based on seasonal availability and demand uncertainty. Two optimization models were implemented. The goal of the first model was to maximize the expected profits of the supply chain based on the optimal combination of biomass type, plant location and biomass-bioethanol pathways. The second extension model focused on maximizing expected profits of the supply chain with the least amount of impact on the environment via the reduction of net emission to result in an optimal supply chain. The validation process was then performed by comparing the stochastic and deterministic models in terms of plant location and operating decisions. The first model was applied to actual data of a Thailand case study involving 26 existing plants and agricultural residue availability. The optimization result illustrates that the stochastic model is 16% more profitable than the deterministic model for all random data sets. Furthermore, the extension model shows that carbon credit can contribute to around 5% of the total profit earned. Thus, the proposed models can address demand uncertainty in supply chain design and can be implemented by policymakers to achieve sustainable bioethanol production.

**Keywords:** biomass to bioethanol; sustainable supply chain; stochastic MILP; second generation biomass

## 1. INTRODUCTION

In order to achieve a net zero scenario, the use of fossil-based energy must be decreased as it produces greenhouse gas (GHG) emissions and increases carbon dioxide ($CO_2$) concentrations in the atmosphere. In theory, burning biofuel for energy should be carbon neutral as the carbon absorbed from the atmosphere by the plant via photosynthesis is returned to the atmosphere during the biofuel-burning process, where the carbon compounds derived from solar energy in the plant will be released as chemical energy. The biofuel-burning process speeds up the return of $CO_2$ to the atmosphere and reduces the time constant in the carbon cycle of vegetation and soil. However, GHG emissions from biofuel are reduced by the amount that would have been released by the fossil energy replaced. The transportation sector is known to be hugely dependent on the use of fossil-based energy and was found to be one of the largest contributors of $CO_2$ emissions in the atmosphere (International Energy Agency [IEA], 2023). Thus, to have an alignment with the net zero scenario, utilizing more sustainable energy is required to reduce GHG emissions; biofuel can be one of the alternatives to solve this issue (Wang et al., 2007).

The transition to cleaner energy will result in the increase of biofuel blends production such as bioethanol blend. In order to ensure a price-competitive and consistent supply of bioethanol to distribution centers, an efficient and reliable supply chain is required to coordinate supply and demand activities to achieve economic goals. However, to design an optimal bioethanol supply chain network, some parameters relating to uncertainty need to be considered, since they could impact production efficiency, flexibility, and operation profitability (Li et al., 2022). Several uncertainties that are possibly involved in the bioethanol supply chain network are biomass supply (Zarei et al., 2022), bioethanol demand (Awudu and Zhang, 2013), prices (Azadeh et al., 2014), policies and regulations, technologies, costs, and yield (Li et al., 2022).

Stochastic programming is the first approach from within the operations research community to deal with uncertainty in mathematical programming-based optimization. When uncertainty is added to a problem, some of the problem's parameters are modeled as a random variable following a probability distribution, which is assumed to be known to the decision maker (Bakker et al., 2020). There are several studies dealing with supply chain modeling by stochastic programming under uncertainties. A stochastic mixed-integer linear programming (MILP) has been developed to optimize a sugar-bioethanol supply chain under demand uncertainty. The model is used to maximize the expected net present value (ENPV) by defining the transportation networks, the truck fleets, the production and storage system, the material flows distributed over the networks and kept in the storage sites (Lima et al., 2023). A two-stage stochastic robust programming model is applied to bioethanol supply chain with various technological conversion choices and biomass uncertainty. The model enables the selection of biorefineries and warehouse capacity, production schedule and inventory, and provides risk-averse solutions that achieve a balance between system economics and robustness (Huang et al., 2024). The supply chain management of carbon dioxide utilization has been done with gas composition and market demand used as uncertainty factors. This supply chain was done by an MILP combined with a risk model to evolve the design to achieve a high probability of more expected profit compared with the target profit (Suchartsunthorn and Siemanond, 2017). The supply chain network of microalga-derived biodiesel using diesel demand as the uncertainty factor has been done with two-stage stochastic MILP, and the results were compared with the deterministic model among regressed demand values (Yu et al., 2020). The model of supply chain management of butyric acid-derived butanol for the South Korea 2030 case scenario with two uncertainties, butyric acid processing and butanol market demand, has been studied. This model was formulated as a two-stage MILP with an objective function of minimizing the total expected cost (Kwon and Han, 2021).

In this work, a stochastic bioethanol supply chain network was designed with multiple feedstock (rice, sugarcane, cassava and palm residues), while the seasonal availability of each biomass was also one of the considerations. This research also considered the uncertainty of bioethanol demand and carbon credits. A two-stage stochastic MILP in general algebraic modeling System (GAMS) software was used to solve the stochastic bioethanol supply chain model wherein the resulting model was then applied to achieve the maximum-profit supply chain using actual data from a published Thailand case study (Jusakulvijit et al., 2021).

## 2. MATERIALS AND METHODS

This paper studies the bioethanol supply chain consisting of three echelons: biomass sources, bioethanol refinery plants, and demand points, as shown in Figure 1. The second-generation type of biomass is denoted as $m$ types. $i$, $j$, and $k$ are expressed as the numbers of harvesting sites, bioethanol plants and demand points, respectively. Each biomass was considered to have different supply capacity at low and high seasons represented by time period, $t$. There was an uncertainty in bioethanol demands that are denoted as $p$ and $s$, which represent the probability distribution and number of scenarios, respectively.

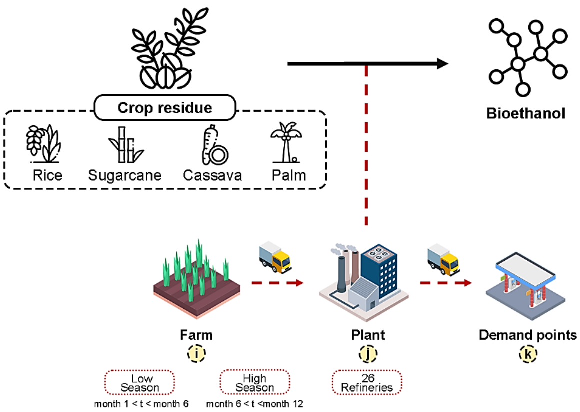


**Figure 1.** Biomass-to-bioethanol supply chain diagram

The objective of this work was to maximize the economic and environmental performances of the multi feedstock bioethanol supply chain by optimizing several decision variables including variable (1) representing the number and location of bioethanol plants; variable (2) representing the amount and types of biomass harvested from each harvesting site; variable (3) representing the yield of ethanol and renewable electricity generated; variable (4) representing the amount of transportation required for biomass to be delivered to the plants and bioethanol to be sent to each demand points; and variable (5) representing the amount of bioethanol sold and unsatisfied bioethanol demand. The commercial optimization software, GAMS, was used to solve the bioethanol supply chain model. The output data of the model, such as the decision variables mentioned above, were determined by GAMS. The overall optimization flowchart of the two-stage stochastic model for optimal decision making is presented in Figure 2.

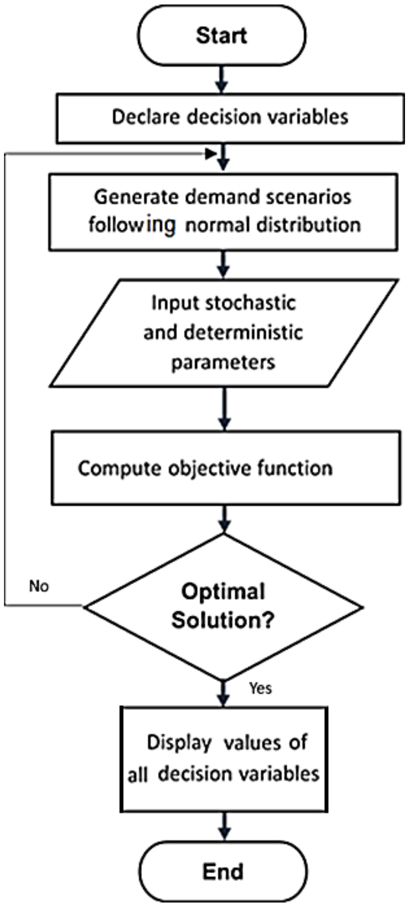


**Figure 2.** The developed optimization algorithm for bioethanol supply chain

## 2.1 Model formulation

The mathematical model of this bioethanol supply chain was formulated in a two-stage stochastic MILP to solve for the optimal amount of mass flow between echelons. It consisted of an objective function and constraints. All continuous decision variables were non-negative, while integer variables were binary.

### 2.1.1 Objective function

The objective was to achieve the maximum expected profit, $E$, by designing an optimum supply chain, which can be obtained by subtracting the expected total cost from the expected revenue. The demand uncertainty following the normal distribution was applied to this model. The objective function is presented below:

$$\begin{aligned} Max\ E\ =\ & \sum_k \sum_t \sum_s P_s\,(PE \cdot sale_{k,t,s} + ETC \cdot sale_{k,t,s}) + \sum_j \sum_t (EP + RETC) \cdot re_{j,t} - \sum_j F_j \cdot b_j \\ & - \sum_j \sum_t PC \cdot w_{j,t} - \sum_m \sum_i \sum_j \sum_t BP_m \cdot xx_{m,i,j,t} - \sum_m \sum_i \sum_j \sum_t DD_{i,j} \cdot TC \cdot xx_{m,i,j,t} \\ & - \sum_j \sum_k \sum_t D_{j,k} \cdot TCE \cdot x_{j,k,t} - \sum_k \sum_t \sum_s P_s \cdot PEN \cdot ud_{k,t,s} \qquad (1) \end{aligned}$$

Equation (1) shows expected profit, $E$, as a function of ten terms: term (1) is the revenue from bioethanol sale; term (2) is the tax credit accrued from the bioethanol production; term (3) is the revenue from renewable electricity generation; term (4) is tax credit resulting from renewable electricity generation; term (5) is the fixed cost of bioethanol refineries; term (6) is the bioethanol production cost; term (7) is the purchasing cost of biomass; term (8) is the transportation cost of biomass; term (9) is the transportation cost of bioethanol; and term (10) is the penalty cost for opportunity loss of bioethanol demand. The demand uncertainty was represented by scenario probability $P_s$. Both the expected revenue and cost from this equation were calculated and represented in \$/day.

### 2.1.2 Constraints

The objective function was subject to the following set of constraints:

$$\sum_{j} xx_{m,i,j,t} \leq Y_{m,i,t} \tag{2}$$

$$\sum_{m}\sum_{i} xx_{m,i,j,t} \cdot \alpha_m = w_{j,t} \tag{3}$$

$$\sum_{m}\sum_{i} xx_{m,i,j,t} \cdot \beta_m = re_{j,t} \tag{4}$$

$$w_{j,t} \leq CAP_j . b_j \tag{5}$$

$$\sum_{k} x_{j,k,t} \leq w_{j,t} \tag{6}$$

$$\sum_{j} x_{j,k,t} + ud_{k,t,s} \geq D_{k,s} \tag{7}$$

$$\sum_{k} x_{j,k,t} \geq sale_{k,t,s} \tag{8}$$

Equation (2) states that the total amount of biomass types, $m$, harvested from site $i$ should not exceed the available amount. Equations (3) and (4) ensure that in the season period of $t$, the cumulative amount of biomass from any types $m$ used by biorefinery $j$ is converted to bioethanol and renewable electricity, respectively. Equation (5) expresses that the amount of bioethanol produced should not exceed the number and capacity of biorefineries. Equation (6) assures that the amount of bioethanol transported according to demand should not exceed the bioethanol produced in biorefinery, $j$, in each season of $t$. Equation (7) ensures that in each season $t$, during scenario $s$, the amount of unfulfilled bioethanol requirement plus the amount of bioethanol transported to demand points, $k$, should be higher than or equal to the bioethanol needs in the demand zones. Equation (8) states that the amount of bioethanol sold in each season $t$, based on scenario $s$, should not exceed the amount of bioethanol transported to demand zone $k$. Table 1 provides a list of notations with their meaning.

## 2.2 The extension model with environmental performance considerations

This part explains an extension of the bioethanol supply chain model formulation combined with the carbon emissions policy to maximize the reduction of greenhouse gas emissions. This model will assess the $CO_2$ emissions from the harvesting of biomass, production of bioethanol, and the transportation that occur in the bioethanol supply chain. The goal of this model was to demonstrate the change in the computational result based on maximum emission reduction, NR, by conducting certain modifications relating to production and transportation decisions such as biomass type selection, amount of production, and amount of feedstock-product transported between nodes.

The extension to the model is presented below:

$$\begin{aligned} NR = RETH \cdot \sum_{j}\sum_{t} w_{j,t} + RRE \cdot \sum_{j}\sum_{t} re_{j,t} - \sum_{m}\sum_{i}\sum_{j}\sum_{t} EHV_m \cdot xx_{m,i,j,t} - \sum_{m}\sum_{i}\sum_{j}\sum_{t} EPP_m \cdot xx_{m,i,j,t} \\ - \sum_{m}\sum_{i}\sum_{j}\sum_{t} DD_{i,j} \cdot ETRB \cdot xx_{m,i,j,t} - \sum_{j}\sum_{k}\sum_{t} D_{j,k} \cdot ETRE \cdot x_{j,k,t} \end{aligned} \tag{9}$$

In Equation (9), NR refers to the reduction of emissions that consists of six terms: term (1) is the reduction in carbon emissions due to the substitution of gasoline with bioethanol; term (2) is the reduction in carbon emissions due to the substitution of fossil-based electricity with bioelectricity; term (3) is the increase of carbon emissions from biomass harvesting; term (4) is the increase in carbon emissions from the process of converting biomass into bioethanol; term (5) is an increase in carbon emissions from biomass transportation; and term (6) is the increase in carbon emissions from bioethanol transportation. All components from Equation (9) were calculated and represented in tons of $CO_2$-equivalent/day.

Next, NR in Equation (9) was converted by multiplying it with the carbon emissions price, as shown in the equation below:

$$CCR = PCO\ .\ NR \tag{10}$$

CCR in Equation (10) refers to the carbon credit obtained from the net reduction of greenhouse gas emissions from bioethanol production. This term is represented in $/day, and the resulting value will be incorporated into Equation (1).

## 2.3 Evaluation

The proposed mathematical problem was implemented using four models which are the deterministic model, with and without environmental performance considerations, and the stochastic model, with and without environmental performance considerations. The deterministic model was applied using the mean of the demand value calculated from historical data, while the stochastic model was conducted under three scenarios (pessimistic, realistic, and optimistic) with different probabilities as shown in Supplementary To evaluate the solutions of each model, 10 hypothetical datasets consisting of 365 days of bioethanol demand were generated. All the datasets were obtained using the random generator function from MS Excel based on the mean and standard deviation of the demand value following normal distribution. The feasibility and profit obtained from the bioethanol of each solution were compared.

**Table 1.** List of indices, sets, parameters, and decision variables of the model

| **Sets/Indices** | |
|---|---|
| $i$ | harvesting sites |
| $j$ | bioethanol plants |
| $k$ | demand points |
| $m$ | types of feedstocks |
| $t$ | time period |
| $s$ | demand scenario |
| **Parameters** | |
| $RETC$ | renewable electricity tax credit ($/MWh) |
| $ETC$ | ethanol tax credit ($/liters) |
| $F_j$ | unit fixed cost of plant $j$ ($/day) |
| $PC$ | bioethanol unit production cost ($/liters) |
| $BP_m$ | unit cost of biomass types $m$ ($/tons) |
| $DD_{i,j}$ | distance between harvesting sites $i$ to plants $j$ (km) |
| $D_{j,k}$ | distance between plants $j$ to demand $k$ (km) |
| $TC$ | unit transportation cost of biomass ($/ton-km) |
| $TCE$ | unit transportation cost of bioethanol ($/liter-km) |
| $PE$ | ethanol price ($/liters) |
| $TC$ | unit transportation cost of biomass ($/ton-km) |
| $TCE$ | unit transportation cost of bioethanol ($/liter-km) |
| $PE$ | ethanol price ($/liters) |
| $EP$ | renewable electricity price ($/MWh) |
| $\alpha_m$ | conversion of biomass $m$ to ethanol (liters/tons) |
| $\beta_m$ | conversion of biomass $m$ to renewable electricity (MWh/tons) |
| $Y_{m,i,t}$ | availability of biomass types $m$ in harvesting site $i$ at time period $t$ (tons/day) |
| $P_{k,s}$ | probability at demand $k$ with scenario $s$ |
| $PEN$ | unit penalty cost ($/liter) |
| $CAP_j$ | capacity of plant $j$ (liters/day) |
| $D_{k,s}$ | bioethanol demand in demand point $k$ with scenario $s$ (liters/day) |
| $RETH$ | reduction carbon emission from bioethanol (ton $CO_2$-eq/liter) |
| $RRE$ | reduction carbon emission from renewable electricity (ton $CO_2$-eq/MWh) |
| $EHV_m$ | emission from harvesting biomass type $m$ (ton $CO_2$-eq/ton biomass) |
| $EPP_m$ | emission from converting biomass type $m$ to ethanol (ton $CO_2$-eq/ton biomass) |
| $ETRB$ | carbon emission from biomass transportation (ton $CO_2$-eq/ton-km) |
| $ETRE$ | carbon emission from bioethanol transportation (ton $CO_2$-eq/liter-km) |
| $PCO$ | price of $CO_2$ credit ($/ton $CO_2$-eq) |
| **Decision variable** | |
| $b_j$ | 1 if plants in region $j$ selected |
| $sale_{k,t,s}$ | amount of bioethanol sold in demand $k$ at time period $t$ with scenario $s$ (liters/day) |
| $re_{j,t}$ | renewable electricity generated in plant $j$ at time period $t$ (MWh/day) |
| $w_{j,t}$ | amount of bioethanol produced in plant $j$ at time period $t$ (liters/day) |
| $xx_{m,i,j,t}$ | amount of biomass type $m$ sent from harvesting site $i$ to plant $j$ at time period $t$ (tons/day) |
| $x_{j,k,t}$ | amount of bioethanol sent from plant $j$ to demand $k$ at time period $t$ (liters/day) |
| $ud_{k,t,s}$ | amount of opportunity loss of bioethanol demand in demand $k$ at time period $t$ with scenario $s$ (liters/day) |

# 3. RESULTS AND DISCUSSION

## 3.1 Case study

The supply chain model was applied using actual data of biomass availability ($Y_{m,i,t}$) in Thailand obtained from literature (Jusakulvijit et al., 2021) as shown in Table 2. In general, Thailand is divided into the northern, northeastern, central, and southern regions, as shown in Figure 3. All four regions were set to be biomass resources, wherein each region was considered to have four types of biomass residues consisting of rice, sugarcane, cassava and palm, which are categorized as second-generation biomass. Every type of biomass in each region was considered to have a high and low season supply capacity. The biomass in the high season was assumed to be three times higher than in the low season.

This case study also involved 26 existing bioethanol plants in Thailand that are spread out in the northeastern and central regions, wherein each region assumed to have three scenarios of demand including low, medium, and high demand. The probability distribution of each demand scenario is given in Table S1. All existing plants and their capacity ($CAP_j$) are listed in Table 3. Similar to the biomass resources, the daily amount of bioethanol demand was also separated into four regions. In the optimization of the bioethanol supply chain, the data and parameters were collected from literature, such as cost parameters, product price and tax credit, and emissions parameters, as shown in Table 4. The distance between the echelons ($D_{j,k}$ and $DD_{i,j}$) were measured based on data from Google Maps.

**Table 2.** Second generation biomass availability ($Y_{m,i,t}$) in Thailand

| Biomass | Harvesting site | Biomass residues (ton/day) | |
|---|---|---|---|
| | | High season | Low season |
| Rice | North | 6166.23 | 2055.41 |
| | Northeast | 28321.23 | 9440.41 |
| | Central | 32178.7 | 10726.23 |
| | South | 947.67 | 315.89 |
| Sugarcane | North | 1663.97 | 554.66 |
| | Northeast | 75652.2 | 25217.4 |
| | Central | 75241.23 | 25080.41 |
| | South | 0 | 0 |
| Cassava | North | 1088.84 | 362.94 |
| | Northeast | 39630.41 | 13210.14 |
| | Central | 18436.64 | 6145.55 |
| | South | 0 | 0 |
| Palm | North | 172.4 | 57.46 |
| | Northeast | 5158.56 | 1719.52 |
| | Central | 2616.58 | 872.19 |
| | South | 69738.28 | 23246.1 |

The proposed model was computed using GAMS version 24.2.1 with the CPLEX 12.6 solver on a computer equipped with an AMD Ryzen 7-5800H processor operating at 3.20 *GHz.*

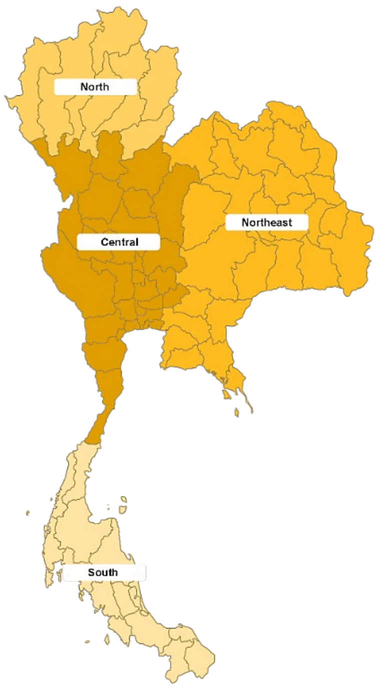


**Figure 3.** Thailand map illustrating the four regions

**Table 3.** Bioethanol plants in Thailand and their production capacity (Jusakulvijit et al., 2021)

| Plant no | Location | Region | Production capacity (Million liters/year) |
|---|---|---|---|
| P1 | Nakhon Sawan | Central | 84.0 |
| P2 | Saraburi | Central | 98.6 |
| P3 | Tak | Central | 84.0 |
| P4 | Kanchanaburi | Central | 73.0 |
| P5 | Kanchanaburi | Central | 109.5 |
| P6 | Suphan Buri | Central | 73.0 |
| P7 | Suphan Buri | Central | 127.8 |
| P8 | Nakhon Pathom | Central | 73.0 |
| P9 | Ratchaburi | Central | 54.8 |
| P10 | Phra Nakhon Si Ayutthaya | Central | 9.1 |
| P11 | Lopburi | Central | 73.0 |
| P12 | Khon Kaen | Northeastern | 54.8 |
| P13 | Nakhon Ratchasima | Northeastern | 73.0 |
| P14 | Kalasin | Northeastern | 84.0 |
| P15 | Kalasin | Northeastern | 116.8 |
| P16 | Chaiyaphum | Northeastern | 182.5 |
| P17 | Sa Kaeo | Northeastern | 54.8 |
| P18 | Chachoengsao | Northeastern | 73.0 |
| P19 | Sa Kaeo | Northeastern | 109.5 |
| P20 | Ubonratchatani | Northeastern | 146.0 |
| P21 | Khon Kaen | Northeastern | 29.2 |
| P22 | Chonburi | Northeastern | 54.8 |
| P23 | Prachinburi | Northeastern | 21.9 |
| P24 | Prachinburi | Northeastern | 182.5 |
| P25 | Nakhon Ratchasima | Northeastern | 124.1 |
| P26 | Chachoengsao | Northeastern | 54.8 |

**Table 4.** Value of deterministic parameters

| Input parameter | Value | Reference |
|---|---|---|
| Ethanol price ($/liters) | $PE = 1$ | (GlobalPetrolPrices, 2023) |
| Ethanol tax credit ($/liters) | $TC = 0.066$ | (Osmani and Zhang, 2014) |
| Conversion of biomass $m$ to ethanol (liters/tons) | $\alpha_1 = 146$; $\alpha_2 = 121$; $\alpha_3 = 174$; $\alpha_4 = 85$ | (Osmani and Zhang, 2014); (Palniandy et al., 2017); (Anggono et al., 2019); (Sombatpraiwan et al., 2019); (Muryanto et al., 2015) |
| Conversion of biomass $m$ to renewable electricity (MWh/tons) | $\beta_1 = 0.16$; $\beta_2 = 0.15$; $\beta_3 = 0.2$; $\beta_4 = 0.1$ | Assumption |
| Renewable electricity price ($/MWh) | $EP = 110$ | (BloombergNEF, 2022) |
| Renewable electricity tax credit ($/MWh) | $ETC = 10$ | Assumption |
| Bioethanol unit production cost ($/liters) | $PC = 0.3$ | Assumption |
| Unit cost of biomass types $m$ ($/tons) | $BP_1 = 24$; $BP_2 = 22$; $BP_3 = 20$; $BP_4 = 14$ | (Ishii et al., 2016); (Kent, 2007) |
| Unit transportation cost of biomass ($/ton-km) | $TC = 0.13125$ | (Osmani and Zhang, 2014) |
| Unit transportation cost of bioethanol ($/liter-km) | $TCE = 0.0000281$ | (Osmani and Zhang, 2014) |
| Unit penalty cost ($/liter) | $PEN = 10$ | Assumption |
| Reduction of carbon emission from bioethanol (ton $CO_2$-eq/liter) | $RETH = 0.0015$ | (Osmani and Zhang, 2014) |
| Reduction of carbon emission from renewable electricity (ton $CO_2$-eq/MWh) | $RRE = 0.7$ | (Osmani and Zhang, 2014) |
| Emission from harvesting biomass type $m$ (ton $CO_2$-eq/ton biomass) | $EHV_1 = 0.99$; $EHV_2 = 0.49$; $EHV_3 = 0.03$; $EHV_4 = 2.61$ | (Kawasaki et al., 2015) |
| Emission from converting biomass type $m$ to ethanol (ton $CO_2$-eq/ton biomass) | $EPP_1 = 0.08$; $EPP_2 = 0.07$; $EPP_3 = 0.08$; $EPP_4 = 0.09$ | (Kawasaki et al., 2015) |
| Carbon emission from biomass transportation (ton $CO_2$-eq/ton-km) | $ETRB = 0.000068$ | (Osmani and Zhang, 2014) |
| Carbon emission from bioethanol transportation (ton $CO_2$-eq/liter-km) | $ETRE = 0.00000005$ | (Osmani and Zhang, 2014) |
| Price of $CO_2$ credit ($/ton $CO_2$-eq) | $PCO = 40$ | (Osmani and Zhang, 2014) |

## 3.2 Optimal bioethanol supply chain

The optimal infrastructure configuration and mass flow between nodes for the high-season and low-season biomass supply are shown in Figure 4 and Figure 5, respectively. All 26 existing biorefineries operated in both seasons to satisfy bioethanol demand. During the high season, the only type of biomass utilized to produce bioethanol was the cassava residue, in the amount of 34,979 tons/day, and during the normal season, the production of bioethanol from cassava residue could reach up to 9.4 million liters/day, which far exceeds demands approximated at 4.2–4.5 million liters/day (Jusakulvijit et al., 2021). This reflects the actual situation in Thailand, where cassava is the second major feedstock used to produce bioethanol after molasses (Khanunthong, 2021). In contrast, during the low season, several types of biomass were required to make up for the insufficient supply of feedstock from cassava residue as shown in Table S2, (see supplementary). Rice and sugarcane residues were combined with the cassava residue to satisfy bioethanol demand in the low season of biomass. The amount of each type of biomass used were 15,569 tons/day for the rice residue (41%), 3,159 tons/day for the sugarcane residue (8%), and 19,718 tons/day for the cassava residue (51%), respectively. Palm residue was not utilized as a feedstock due to its low conversion into bioethanol (Polprasert et al., 2021). This result accurately reflects the real situation in Thailand, where palm residue is rarely used as a feedstock for bioethanol production (Khanunthong, 2021). Every type of biomass utilized in both seasons is transported from the northern, northeastern, and central regions of Thailand, and no biomass is transported from the southern region since the location is relatively far from the biorefineries. On the other hand, the bioethanol transported from plant to demand points have the same configuration in both the low and high seasons as shown in Table S3 (see supplementary). This configuration can make daily logistic planning for transporting bioethanol from plants to demand points more simple. In comparison to the stochastic model results, the deterministic model has different bioethanol mass flow from biorefineries to demands, whereas biomass mass flow has the same configuration, as shown in Tables S6 and S7 (see supplementary).

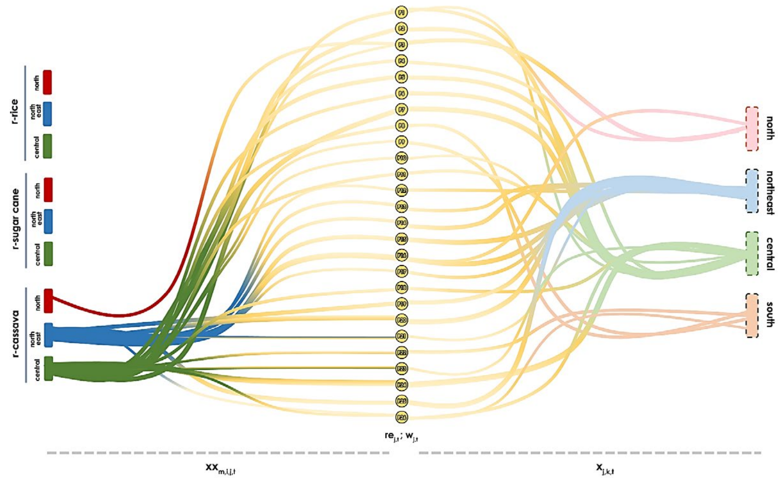


**Figure 4**. Mass flow biomass-bioethanol under the stochastic model (high season)

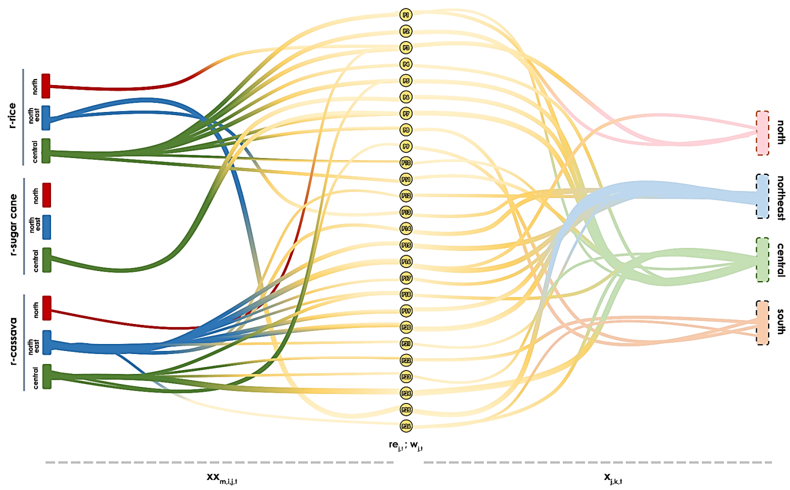


**Figure 5.** Mass flow biomass-bioethanol under the stochastic model (low season)

In order to observe the stochastic model for supply chain network optimization and to handle the uncertainty of demands, results from the stochastic model were compared with those of the deterministic model. Both models computed in a relatively short time (0.062 CPU seconds) with a zero-optimality gap. The profits between the stochastic and deterministic models were compared by applying the solution to the ten sets of random daily data, with a duration of six months for each season and 365 days of demand uncertainty. Table 5 shows a comparison between profits obtained from the stochastic and deterministic models. It illustrates that the optimal stochastic supply chain provides higher profits than the deterministic model, at approximately 16% for all random data sets. The cost distribution is also observed in order to analyze the type of cost that creates differences in profit. Figure 6 reveals that both models have a nearly similar type of cost distribution, except for the penalty cost which is the cost associated with unmet/unsatisfied bioethanol demand in each region. The penalty cost in the deterministic model was almost 270 million USD/year, or 1.8 times higher than the penalty cost in the stochastic model, which was 154 million USD/year. The penalty cost under the deterministic model amounted to approximately 16% of the total cost, whereas in the stochastic model, the penalty cost only made up 10% of the total cost. This was caused by the fixed scenario being applied under the deterministic model wherein only the average number of demands were considered, whereas the stochastic model considered both the below and above average number of demands, resulting in a lower penalty cost.

**Table 5.** Total profit comparison between the stochastic and deterministic models

| Data | Profit ($/year) | | Result (model with the higher profit) |
|---|---|---|---|
| | Stochastic | Deterministic | |
| **Set_1** | 919,260,181.65 | 792,105,890.79 | Stochastic |
| **Set_2** | 933,225,016.76 | 799,985,020.99 | Stochastic |
| **Set_3** | 907,572,157.89 | 781,177,875.79 | Stochastic |
| **Set_4** | 910,050,990.45 | 779,185,845.08 | Stochastic |
| **Set_5** | 923,346,883.66 | 804,012,487.50 | Stochastic |
| **Set_6** | 935,592,494.92 | 808,719,918.03 | Stochastic |
| **Set_7** | 941,553,778.67 | 825,016,757.92 | Stochastic |
| **Set_8** | 923,346,546.67 | 801,026,784.87 | Stochastic |
| **Set_9** | 946,470,914.61 | 823,493,962.68 | Stochastic |
| **Set_10** | 923,421,400.74 | 813,039,976.22 | Stochastic |

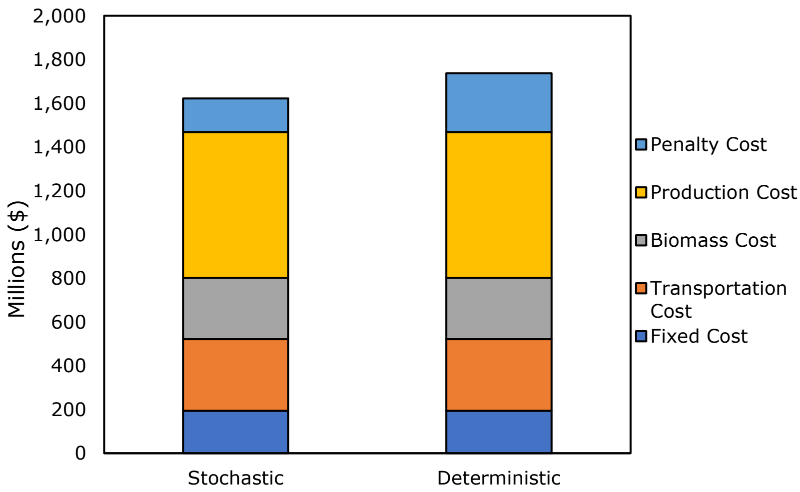


**Figure 6.** Cost distribution of bioethanol supply chain network under the stochastic and deterministic models

The influence of low season duration on revenue was also evaluated. Figure 7 shows that a decrease in revenue was observed when the duration of low season was increased, with a decrease of 7.9%, from 957 to 881 million USD/year. This was caused by the increase in both biomass feedstock and transportation costs during the low season, which if extended, would drive revenue down.

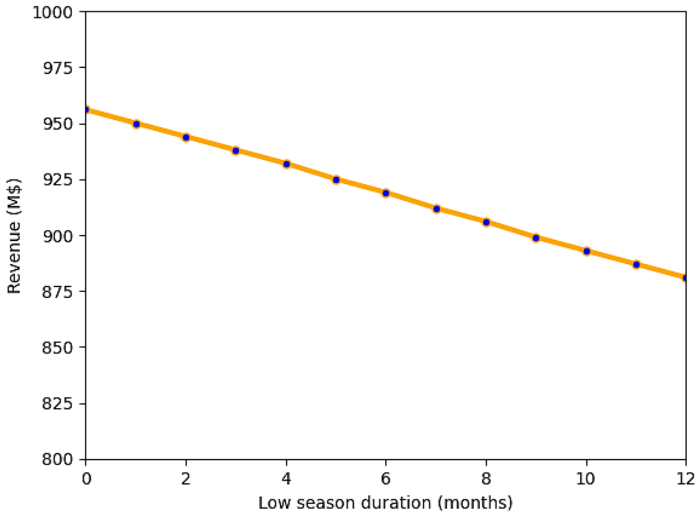


**Figure 7.** Impact of low season duration on revenue

## 3.3 Optimal bioethanol supply chain with environmental performance considerations

The optimal supply chain network configuration with environmental performance considerations is presented in Figure 8 and Figure 9 for high and low seasons, respectively. Similar to the previous high season supply chain configuration, the only type of biomass that was utilized in the high season was the cassava residue, with an amount of 34,979 tons/day. However, there was a difference in the selection of biomass type in low season configurations. The type of biomass used as feedstock in low season was 21,944 tons/day (53%) of sugarcane residue and 19,718 tons/day (47%) of cassava residue as shown in Table S4 (see supplementary) because the emissions generated from the harvesting and production processes of sugarcane and cassava residues are lower than those from rice and palm residues (Kawasaki et al., 2015). Moreover, Table S5 shows that the bioethanols transported to demand points had the same configuration in both the low and high seasons (see supplementary). In comparison with the results from the stochastic model, the deterministic model mostly has different bioethanol mass flows from the biorefineries to demands, while the biomass mass flows from harvesting sites to biorefineries have the same configuration as shown in Tables S8 and S9 (see supplementary).

The net reduction emissions (NR) of stochastic and deterministic models were evaluated and compared with an identical method as in the previous section. As shown in Table 6, the NR of the optimal stochastic model was higher than the NR of the deterministic model for all random data sets. Furthermore, the supply chain model with environmental performance considerations had a higher profit compared to the base model without environmental performance considerations due to the additional revenue from carbon credit given under the former model.

In order to identify the contribution of carbon credit to the total profit, revenues were classified into bioethanol sold, renewable electricity generated, tax credit, and carbon credit. As shown in Figure 10, bioethanol sales made up a major revenue source accounting for 78%, followed by renewable electricity, tax credit, and carbon credit at 11%, 6%, and 5%, respectively. Carbon credit contributed around 58 million USD/year to the total revenue obtained.

**Table 6.** Net reduction emissions (NR) comparison between the stochastic and deterministic models with environmental performance considerations

| Data | NR (ton $CO_2$-EQ/year) | | Result (model with the higher NR) |
|---|---|---|---|
| | Stochastic | Deterministic | |
| SET_1 | 1,457,007.84 | 1,439,997.51 | Stochastic |
| SET_2 | 1,459,771.22 | 1,441,935.97 | Stochastic |
| SET_3 | 1,462,617.31 | 1,445,710.00 | Stochastic |
| SET_4 | 1,456,070.51 | 1,438,557.17 | Stochastic |
| SET_5 | 1,452,382.31 | 1,438,624.49 | Stochastic |
| SET_6 | 1,459,840.61 | 1,442,868.46 | Stochastic |
| SET_7 | 1,454,489.07 | 1,438,917.91 | Stochastic |
| SET_8 | 1,463,202.36 | 1,446,847.35 | Stochastic |
| SET_9 | 1,465,633.15 | 1,449,189.06 | Stochastic |
| SET_10 | 1,456,742.44 | 1,442,005.67 | Stochastic |

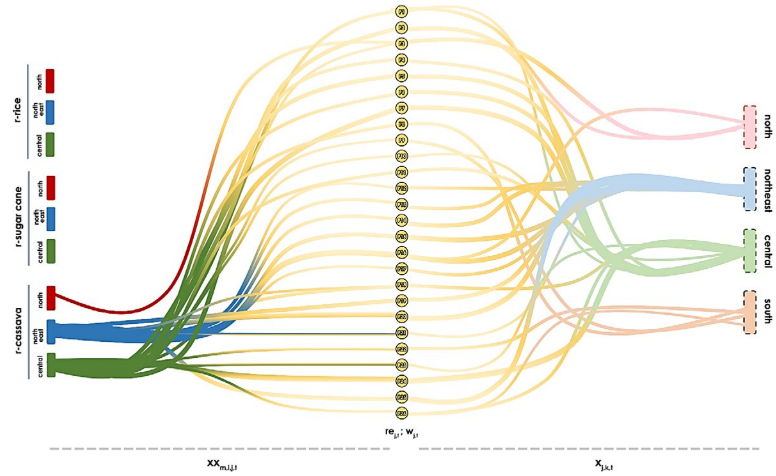


**Figure 8.** Mass flow biomass-bioethanol supply chain with environmental performance considerations (high season)

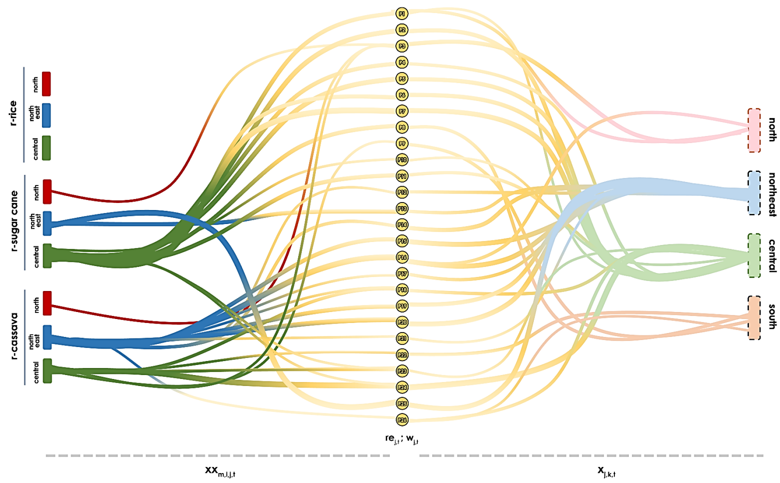


**Figure 9.** Mass flow biomass-bioethanol supply chain with environmental performance considerations (low season)

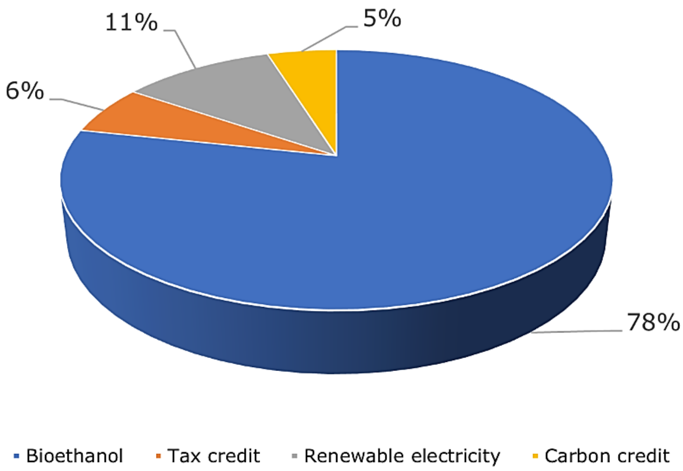


**Figure 10.** Classification of revenue from the bioethanol supply chain with environmental performance considerations

## 4. CONCLUSION

This paper presents the development of a stochastic model that determines the optimal design of a bioethanol supply chain network under the conditions of biomass availability based on season and uncertain bioethanol demand. The objective of this paper was to maximize the expected profit with and without environmental performance considerations. The profit obtained from the stochastic model was compared to the deterministic model, and it was found that the stochastic model gave around 16% more profit than the deterministic model in all ten sets of 365 daily random data of customers' demands. In the high season, cassava residue was utilized to satisfy the bioethanol demand, where sugarcane residue (8%), rice residue (41%), and cassava residue (51%) were combined to satisfy the bioethanol demand during the low season. For the model with environmental performance considerations, the selection of biomass in the low season provided a different result when compared to the base model due to the difference in emissions resulting from the harvesting of the biomass, production process of the bioethanol, and the transportation involved. It was found that selection of the sugarcane residue (53%) combined with the cassava residue (47%) would satisfy the bioethanol demand. Furthermore, carbon credit was found to be one of the revenue contributors, as it made up 5%, or approximately 58 million USD/year, of the total revenue. With an aim towards achieving a more robust model, future research studies must consider other parameters and uncertainty factors, such as biomass availability and/or conversion factors, and incorporate them into the model.

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## SUPPLEMENTARY

**Table S1.** Probability distribution of bioethanol demand realizations for each demand point (assumption based on forecasting (Khanunthong, 2021)

| Demand point (k) | Demand realization/$D_{k,s}$ (liters/day) | | | Probability/ $P_{k,s}$ | | |
|---|---|---|---|---|---|---|
| | Low | Medium | High | Low | Medium | High |
| k1 | 400,000 | 500,000 | 600,000 | 0.25 | 0.50 | 0.25 |
| k2 | 2,300,000 | 2,400,000 | 2,500,000 | 0.30 | 0.40 | 0.30 |
| k3 | 2,300,000 | 2,400,000 | 2,520,000 | 0.35 | 0.35 | 0.30 |
| k4 | 400,000 | 510,000 | 625,000 | 0.30 | 0.50 | 0.20 |

**Table S2.** The amount of biomass transported under the stochastic model without environmental performance considerations (tons/day)

| Biomass | Harvesting site (i) | Biorefinery (j) | High season | Low season |
|---|---|---|---|---|
| Rice | h1 | p3 | 0.00 | 1,143.74 |
| | h2 | p13 | | 1,369.86 |
| | h2 | p25 | | 2,328.77 |
| | h3 | p1 | | 1,576.28 |
| | h3 | p2 | | 1,850.25 |
| | h3 | p4 | | 1,369.86 |
| | h3 | p5 | | 1,869.40 |
| | h3 | p7 | | 1,149.95 |
| | h3 | p8 | | 1,369.86 |
| | h3 | p10 | | 170.76 |
| | h3 | p11 | | 1,369.86 |
| Sugarcane | h3 | p6 | 0.00 | 1,652.89 |
| | h3 | p7 | | 1,506.15 |
| Cassava | h1 | p3 | 1,088.84 | 362.94 |
| | h2 | p12 | 862.86 | 862.86 |
| | h2 | p13 | 1,149.43 | 0.00 |
| | h2 | p14 | 1,322.63 | 1,322.63 |
| | h2 | p15 | 1,839.08 | 1,839.08 |
| | h2 | p16 | 2,873.56 | 2,873.56 |
| | h2 | p17 | 862.86 | 862.86 |
| | h2 | p18 | 0.00 | 103.54 |
| | h2 | p19 | 1,724.14 | 1,724.14 |
| | h2 | p20 | 2,298.85 | 2,298.85 |
| | h2 | p21 | 459.77 | 459.77 |
| | h2 | p25 | 1,954.02 | 0.00 |
| | h2 | p26 | 106.07 | 862.86 |
| | h3 | p1 | 1,322.63 | 0.00 |
| | h3 | p2 | 1,552.51 | 0.00 |
| | h3 | p3 | 233.79 | 0.00 |
| | h3 | p4 | 1,149.43 | 0.00 |
| | h3 | p5 | 1,724.14 | 155.56 |
| | h3 | p6 | 1,149.43 | 0.00 |
| | h3 | p7 | 2,012.28 | 0.00 |
| | h3 | p8 | 1,149.43 | 0.00 |
| | h3 | p9 | 862.86 | 862.86 |
| | h3 | p10 | 143.28 | 0.00 |
| | h3 | p11 | 1,149.43 | 0.00 |
| | h3 | p18 | 1,149.43 | 1,045.88 |
| | h3 | p22 | 862.86 | 862.86 |
| | h3 | p23 | 344.83 | 344.83 |
| | h3 | p24 | 2,873.56 | 2,873.56 |
| | h3 | p26 | 756.78 | 0.00 |

**Table S3.** The amount of bioethanol transported to satisfy demands under the stochastic model without environmental performance considerations (liters/day)

| Biorefinery (j) | Demand point (k) | High season | Low season |
|---|---|---|---|
| p1 | s1 | 155,753 | 155,753 |
| p1 | s3 | 74,384 | 74,384 |
| p2 | s3 | 270,137 | 270,137 |
| p3 | s1 | 230,137 | 230,137 |
| p4 | s3 | 200,000 | 200,000 |
| p5 | s3 | 300,000 | 300,000 |
| p6 | s3 | 200,000 | 200,000 |
| p7 | s3 | 350,137 | 350,137 |
| p8 | s4 | 200,000 | 200,000 |
| p9 | s4 | 150,137 | 150,137 |
| p10 | s3 | 24,931 | 24,931 |
| p11 | s3 | 200,000 | 200,000 |
| p12 | s2 | 150,137 | 150,137 |
| p13 | s2 | 200,000 | 200,000 |
| p14 | s2 | 230,137 | 230,137 |
| p15 | s2 | 320,000 | 320,000 |
| p16 | s1 | 170,411 | 170,411 |
| p16 | s2 | 329,589 | 329,589 |
| p17 | s2 | 150,137 | 150,137 |
| p18 | s3 | 200,000 | 200,000 |
| p19 | s2 | 300,000 | 300,000 |
| p20 | s2 | 400,000 | 400,000 |
| p21 | s2 | 80,000 | 80,000 |
| p22 | s4 | 150,137 | 150,137 |
| p23 | s3 | 60,000 | 60,000 |
| p24 | s3 | 500,000 | 500,000 |
| p25 | s2 | 340,000 | 340,000 |
| p26 | s3 | 140,411 | 140,411 |
| p26 | s4 | 9,726 | 9,726 |

**Table S4**. The amount of biomass transported under the stochastic model with environmental performance considerations (tons/day)

| Biomass | Harvesting site (i) | Biorefinery (j) | High season | Low season |
|---|---|---|---|---|
| Sugarcane | h1 | p3 | 0.00 | 554.66 |
| | h2 | p13 | | 1,652.89 |
| | h2 | p25 | | 2,809.92 |
| | h3 | p1 | | 1,901.96 |
| | h3 | p2 | | 2,232.54 |
| | h3 | p4 | | 1,652.89 |
| | h3 | p5 | | 2,479.34 |
| | h3 | p6 | | 1,652.89 |
| | h3 | p7 | | 2,893.69 |
| | h3 | p8 | | 1,652.89 |
| | h3 | p10 | | 206.04 |
| | h3 | p11 | | 1,652.89 |
| | h3 | p23 | | 495.87 |
| | h3 | p24 | | 105.81 |
| Cassava | h1 | p3 | 1,088.84 | 362.94 |
| | h2 | p12 | 862.86 | 862.86 |
| | h2 | p13 | 1,149.43 | 0.00 |
| | h2 | p14 | 1,322.63 | 1,322.63 |
| | h2 | p15 | 1,839.08 | 1,839.08 |
| | h2 | p16 | 2,873.56 | 2,873.56 |
| | h2 | p17 | 862.86 | 862.86 |
| | h2 | p18 | 106.07 | 103.54 |
| | h2 | p19 | 1,724.14 | 1724.14 |
| | h2 | p20 | 2,298.85 | 2,298.85 |
| | h2 | p21 | 459.77 | 459.77 |
| | h2 | p25 | 1,954.02 | 0.00 |
| | h2 | p26 | 0.00 | 862.86 |
| | h3 | p1 | 1,322.63 | 0.00 |
| | h3 | p2 | 1,552.51 | 0.00 |
| | h3 | p3 | 233.79 | 573.97 |
| | h3 | p4 | 1,149.43 | 0.00 |
| | h3 | p5 | 1,724.14 | 0.00 |
| | h3 | p6 | 1,149.43 | 0.00 |
| | h3 | p7 | 2,012.28 | 0.00 |
| | h3 | p8 | 1,149.43 | 0.00 |
| | h3 | p9 | 862.86 | 862.86 |
| | h3 | p10 | 143.28 | 0.00 |
| | h3 | p11 | 1,149.43 | 0.00 |
| | h3 | p18 | 1,043.35 | 1,045.88 |
| | h3 | p22 | 862.86 | 862.86 |
| | h3 | p23 | 344.83 | 0.00 |
| | h3 | p24 | 2,873.56 | 2,799.98 |
| | h3 | p26 | 862.86 | 0.00 |

**Table S5**. The amount of bioethanol transported to satisfy demands under the stochastic model with environmental performance considerations (liters/day)

| Biorefinery (j) | Demand Point (k) | High Season | Low Season |
|---|---|---|---|
| p1 | s1 | 155,753 | 155,753 |
| p1 | s3 | 74,384 | 74,384 |
| p2 | s3 | 270,137 | 270,137 |
| p3 | s1 | 230,137 | 230,137 |
| p4 | s3 | 200,000 | 200,000 |
| p5 | s3 | 300,000 | 300,000 |
| p6 | s3 | 200,000 | 200,000 |
| p7 | s3 | 350,137 | 350,137 |
| p8 | s4 | 200,000 | 200,000 |
| p9 | s4 | 150,137 | 150,137 |
| p10 | s3 | 24,931 | 24,931 |
| p11 | s3 | 200,000 | 200,000 |
| p12 | s2 | 150,137 | 150,137 |
| p13 | s2 | 200,000 | 200,000 |
| p14 | s2 | 230,137 | 230,137 |
| p15 | s2 | 320,000 | 320,000 |
| p16 | s1 | 170,411 | 170,411 |
| p16 | s2 | 329,589 | 329,589 |
| p17 | s2 | 150,137 | 150,137 |
| p18 | s3 | 200,000 | 200,000 |
| p19 | s2 | 300,000 | 300,000 |
| p20 | s2 | 400,000 | 400,000 |
| p21 | s2 | 80,000 | 80,000 |
| p22 | s4 | 150,137 | 150,137 |
| p23 | s3 | 60,000 | 60,000 |
| p24 | s3 | 500,000 | 500,000 |
| p25 | s2 | 340,000 | 340,000 |
| p26 | s3 | 140,411 | 140,411 |
| p26 | s4 | 9,726 | 9,726 |

**Table S6.** The amount of biomass transported under the deterministic model without environmental performance considerations (tons/day)

| Biomass | Harvesting site (i) | Biorefinery (j) | High season | Low season |
|---|---|---|---|---|
| Rice | h1 | p3 | 0.00 | 1,143.74 |
| | h2 | p13 | | 1,369.86 |
| | h2 | p25 | | 2,328.77 |
| | h3 | p1 | | 1,576.28 |
| | h3 | p2 | | 1,850.25 |
| | h3 | p4 | | 1,369.86 |
| | h3 | p5 | | 1,869.40 |
| | h3 | p7 | | 1,149.95 |
| | h3 | p8 | | 1,369.86 |
| | h3 | p10 | | 170.76 |
| | h3 | p11 | | 1,369.86 |
| Sugarcane | h3 | p6 | 0.00 | 1,652.89 |
| | h3 | p7 | | 1,506.15 |
| Cassava | h1 | p3 | 1,088.84 | 362.94 |
| | h2 | p12 | 862.86 | 862.86 |
| | h2 | p13 | 1,149.43 | 0.00 |
| | h2 | p14 | 1,322.63 | 1,322.63 |
| | h2 | p15 | 1,839.08 | 1,839.08 |
| | h2 | p16 | 2,873.56 | 2,873.56 |
| | h2 | p17 | 862.85 | 862.86 |
| | h2 | p18 | 0.00 | 103.54 |
| | h2 | p19 | 1,724.14 | 1,724.14 |
| | h2 | p20 | 2,298.85 | 2,298.85 |
| | h2 | p21 | 459.77 | 459.77 |
| | h2 | p25 | 1,954.02 | 0.00 |
| | h2 | p26 | 106.07 | 862.86 |
| | h3 | p1 | 1,322.63 | 0.00 |
| | h3 | p2 | 1,552.51 | 0.00 |
| | h3 | p3 | 233.79 | 0.00 |
| | h3 | p4 | 1,149.43 | 0.00 |
| | h3 | p5 | 1,724.14 | 155.56 |
| | h3 | p6 | 1,149.43 | 0.00 |
| | h3 | p7 | 2,012.28 | 0.00 |
| | h3 | p8 | 1,149.43 | 0.00 |
| | h3 | p9 | 862.86 | 862.86 |
| | h3 | p10 | 143.28 | 0.00 |
| | h3 | p11 | 1,149.43 | 0.00 |
| | h3 | p18 | 1,149.43 | 1,045.88 |
| | h3 | p22 | 862.86 | 862.86 |
| | h3 | p23 | 344.83 | 344.83 |
| | h3 | p24 | 2,873.56 | 2,873.56 |
| | h3 | p26 | 756.78 | 0.00 |

**Table S7.** The amount of bioethanol transported to satisfy demands under the deterministic model without environmental performance considerations (liters/day)

| Biorefinery (j) | Demand point (k) | High season | Low season |
|---|---|---|---|
| p1 | s1 | 230,137 | 230,137 |
| p2 | s3 | 270,137 | 270,137 |
| p3 | s1 | 230,137 | 230,137 |
| p4 | s3 | 200,000 | 200,000 |
| p5 | s3 | 300,000 | 300,000 |
| p6 | s3 | 200,000 | 200,000 |
| p7 | s3 | 350,137 | 350,137 |
| p8 | s4 | 200,000 | 200,000 |
| p9 | s4 | 150,137 | 150,137 |
| p10 | s3 | 24,931 | 24,931 |
| p11 | s3 | 200,000 | 200,000 |
| p12 | s2 | 150,137 | 150,137 |
| p13 | s2 | 200,000 | 200,000 |
| p14 | s2 | 230,137 | 230,137 |
| p15 | s2 | 320,000 | 320,000 |
| p16 | s1 | 39,726 | 39,726 |
| p16 | s2 | 460,274 | 460,274 |
| p17 | s2 | 150,137 | 150,137 |
| p18 | s3 | 200,000 | 200,000 |
| p19 | s2 | 300,000 | 300,000 |
| p20 | s2 | 400,000 | 400,000 |
| p21 | s2 | 80,000 | 80,000 |
| p22 | s3 | 274 | 274 |
| p22 | s4 | 149,863 | 149,863 |
| p23 | s3 | 60,000 | 60,000 |
| p24 | s3 | 500,000 | 500,000 |
| p25 | s2 | 340,000 | 340,000 |
| p26 | s3 | 150,137 | 150,137 |

**Table S8**. The amount of biomass transported under the deterministic model with environmental performance considerations (tons/day)

| Biomass | Harvesting site (i) | Biorefinery (j) | High season | Low season |
|---|---|---|---|---|
| Sugarcane | h1 | p3 | 0.00 | 554.66 |
| | h2 | p13 | | 1,652.89 |
| | h2 | p25 | | 2,809.92 |
| | h3 | p1 | | 1,901.96 |
| | h3 | p2 | | 2,232.54 |
| | h3 | p4 | | 1,652.89 |
| | h3 | p5 | | 2,479.34 |
| | h3 | p6 | | 1,652.89 |
| | h3 | p7 | | 2,893.69 |
| | h3 | p8 | | 1,652.89 |
| | h3 | p10 | | 206.04 |
| | h3 | p11 | | 1,652.89 |
| | h3 | p11 | | 1,652.89 |
| | h3 | p23 | | 495.87 |
| | h3 | p24 | | 105.81 |
| Cassava | h1 | p3 | 1,088.84 | 362.94 |
| | h2 | p12 | 862.86 | 862.86 |
| | h2 | p13 | 1,149.43 | 0.00 |
| | h2 | p14 | 1,322.63 | 1,322.63 |
| | h2 | p15 | 1,839.08 | 1,839.08 |
| | h2 | p16 | 2,873.56 | 2,873.56 |
| | h2 | p17 | 862.86 | 862.86 |
| | h2 | p18 | 106.07 | 103.54 |
| | h2 | p19 | 1,724.14 | 1,724.14 |
| | h2 | p20 | 2,298.85 | 2,298.85 |
| | h2 | p21 | 459.77 | 459.77 |
| | h2 | p25 | 1,954.02 | 0.00 |
| | h2 | p26 | 0.00 | 862.86 |
| | h3 | p1 | 1,322.63 | 0.00 |
| | h3 | p2 | 1,552.51 | 0.00 |
| | h3 | p3 | 233.79 | 573.97 |
| | h3 | p4 | 1,149.43 | 0.00 |
| | h3 | p5 | 1,724.14 | 0.00 |
| | h3 | p6 | 1,149.43 | 0.00 |
| | h3 | p7 | 2,012.28 | 0.00 |
| | h3 | p8 | 1,149.43 | 0.00 |
| | h3 | p9 | 862.86 | 862.86 |
| | h3 | p10 | 143.28 | 0.00 |
| | h3 | p11 | 1,149.43 | 0.00 |
| | h3 | p18 | 1,043.35 | 1,045.88 |
| | h3 | p22 | 862.86 | 862.86 |
| | h3 | p23 | 344.83 | 0.00 |
| | h3 | p24 | 2,873.56 | 2,799.98 |
| | h3 | p26 | 862.86 | 0.00 |

**Table S9.** The amount of bioethanol transported to satisfy demands under the deterministic model with environmental performance considerations (liters/day)

| Biorefinery (j) | Demand point (k) | High season | Low season |
|---|---|---|---|
| p1 | s1 | 230,137 | 230,137 |
| p2 | s3 | 270,137 | 270,137 |
| p3 | s1 | 230,137 | 230,137 |
| p4 | s3 | 200,000 | 200,000 |
| p5 | s3 | 300,000 | 300,000 |
| p6 | s3 | 200,000 | 200,000 |
| p7 | s3 | 350,137 | 350,137 |
| p8 | s4 | 200,000 | 200,000 |
| p9 | s4 | 150,137 | 150,137 |
| p10 | s3 | 24,931 | 24,931 |
| p11 | s3 | 200,000 | 200,000 |
| p12 | s2 | 150,137 | 150,137 |
| p13 | s2 | 200,000 | 200,000 |
| p14 | s2 | 230,137 | 230,137 |
| p15 | s2 | 320,000 | 320,000 |
| p16 | s1 | 39,726 | 39,726 |
| p16 | s2 | 460,274 | 460,274 |
| p17 | s2 | 150,137 | 150,137 |
| p18 | s3 | 200,000 | 200,000 |
| p19 | s2 | 300,000 | 300,000 |
| p20 | s2 | 400,000 | 400,000 |
| p21 | s2 | 80,000 | 80,000 |
| p22 | s3 | 274 | 274 |
| p22 | s4 | 149,863 | 149,863 |
| p23 | s3 | 60,000 | 60,000 |
| p24 | s3 | 500,000 | 500,000 |
| p25 | s2 | 340,000 | 340,000 |
| p26 | s3 | 150,137 | 150,137 |