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Modelling the impact of climate change risk on bioethanol supply chains

Abstract

The availability of bioethanol, a promising renewable alternative to fossil fuels depends on the supply of biomass produced from agricultural resources. The study attempts a system dynamics modelling approach to explore the implications of greenhouse gas concentration trajectories associated with climate change on bioethanol supply chains. Eight different climate change scenarios are simulated spanning over a 40-year horizon to predict biomass yield and bioethanol availability, by considering first generation (corn) and second generation (switchgrass) ethanol feedstocks. The developed model is used to assess the extent of potential disruptions resulting from global warming. Cascading effect of climate change risk is evident through decreased yield and production, and increased shortages at end customer in the bioethanol supply network. The results indicate that, if climate change risk is not adequately mitigated and current used source of ethanol (corn) continues to be leveraged, the bioethanol availability may decrease by one-fourth by the year 2060. The comparative study encourages exploring the increased use of switchgrass as a sustainable feedstock for renewable energy. Developed insights support identifying effective climate change mitigation policies and sustainable investment decisions for the reduction in carbon emissions.

Keywords: Bioethanol; Climate change; Renewable energy; Supply chain risk; System dynamics

1. Introduction

The demand for reduction in greenhouse gas (GHG) emissions warrants an increased focus on renewable energy sources (Balat and Balat, 2009; Sharma et al., 2013). One of the most promising alternative renewable energy sources is biomass (Mafakheri and Nasiri, 2014; World Energy Council, 2016). Ethanol, also known as bioethanol in commercial terms, is a liquid biofuel that is derived from biomass feedstocks for primary use in the transportation sector (Sharma et al., 2013). USA and Brazil are two leading countries in biomass production, and they account for approximately 80% of liquid biofuel production in the world (World Energy Council, 2016). Bioethanol can be produced from various food crops and non-food lignocellulosic materials (Vohra et al., 2014; Zabed et al., 2017). Therefore, the production of bioenergy from biomass is highly dependent on the supply of crops (Haberl et al., 2010; Kung et al., 2018).

Past research shows that the agriculture sector is facing significant challenges due to the impact of climate change risk (Hatfield et al., 2011; Lobell and Gourdji, 2012). The demand for ethanol as an alternative energy source is continually increasing (Bibi et al., 2017). However, the feedstock used for bioethanol production is threatened due to land-use competition for food versus biomass (Pimentel and Patzek, 2005; Gold and Seuring, 2011), and amplified vulnerability towards expected future climate change.

Future climate change consequences as described by the Intergovernmental Panel on Climate Change (IPCC) predicts significant increases in GHG (IPCC, 2014). It is also expected that this trend will continue throughout future decades, leading to a temperature rise of 1.5 to 2 degrees over the next 30 years. Under this predicted trend, it is plausible that sustainability of feedstocks for bioethanol production would be under severe threat. In this paper, sustainability refers to "*meeting the needs of the present without compromising the ability of future generations to meet their own needs*" (United Nations, 1987). Thus, there is an urgent need to investigate the vulnerability of bioenergy supply chain (SC) to estimate the overall bioenergy availability in the future and develop robust production and investment strategies for similar renewable energy sources. Limited research studies have been attempted to capture the effect of climate change hazards on feedstock availability and biomass production (e.g. Langholtz et al., 2014; Kung et al., 2018). However with growing focus on finding alternate and/or renewable energy sources, such studies are needed. Furthermore, there is an evident lack of empirical studies capturing the impact of different climate change scenarios on the availability of bioethanol (Haberl et al., 2010; Wheeler and von Braun, 2013). Without robust, empirical and comparative studies, it is difficult to predict future and make informed decisions.

This study aims to examine the impact of changing climate risk on bioethanol supply and the cascading effect of this risk along the bioethanol SC network. By investigating the impact of the climate change risk on bioethanol SCs, the study attempts to estimate the overall bioenergy potential for the future. Temperature is one of the critical variables influencing feedstock growth and production (Lobell and Field, 2007; Gunderson et al., 2008; Deryng et al., 2014). Other variables such as precipitation, CO_2 fertilization and feedstock prices (Dimitriadis and Katrakilidis, 2018), also influence the growth rate and production. Key variables influencing the bioenergy industry need to be investigated following a multi-disciplinary, empirical approach (Haberl et al., 2010).

Since bioenergy supply network comprises of multiple stakeholders and includes various dynamic relationships, it can be classified as a complex system (Rentizelas et al., 2009; Awudu and Zhang, 2012) and a systems theory would be an effective way to model such system to understand the interactions under multiple variables better. Adopting System Dynamics (SD) modelling approach will provide a basis for understanding the complex casual loop structure of the bioethanol SC network and simulating the implications of global warming on feedstock yield and bioethanol production over a period of time. Due to its suitability for the identified problem, a SD approach is employed in this paper to explore the implications of climate change risk on bioethanol supply chain over a 40-year horizon (from 2020 to 2060).

The IPCC adopts four greenhouse gas concentration trajectories, also called as *Representative Concentration Pathway* (RCP) (IPCC, 2014). In order to examine possible climate change effects, two extreme future climate pathways provided in the Climate Change 2014 report are considered in order to capture the best- and worst-case situations for the bioethanol supply chain. The first pathway, RCP 2.6, includes moderate climate change risk mitigation activities and thus leading to the lowest increase in the global surface temperature. The second pathway, RCP 8.5, represents a scenario without risk mitigation activities and, therefore, denotes a scenario accompanied by the highest increase in the global surface temperature (IPCC, 2014). Other pathways namely, RCP 4.5 and RCP 6.0 are intermediate to above two and hence not considered in this study.

Corn is a first-generation bioethanol feedstock and widely used crop for bioethanol production in the United States (USDA, 2017; RFA, 2017). About 38% of corn grown in the USA is used to make ethanol, according to the US Agriculture Department. However, corn is often considered as a vulnerable crop to climate change (Deryng et al., 2014). The United States is the biggest global producer of bioethanol; therefore, the data used in this study is primarily derived from sources related to the United States. Switchgrass is the best second generation bioethanol feedstock due to its high yield potential and ease of growth (Zhang et al., 2013). Both corn and switchgrass feedstocks are considered as biomass samples in the study. To achieve defined aim of the research, eight different climate change scenarios are developed (using RCPs) to investigate the levels of different feedstocks and biomass inventories during yield and non-yield periods over a long time duration.

The remainder of the paper is structured as follows. Section 2 provides a background of the problem. Next section provides literature on the biomass supply chain. Section 4 introduces the research methodology. Section 5 presents the proposed SD model and provides the results of the simulation analysis.

Section 6 provides a comprehensive discussion of key findings. Theoretical and practical contributions along with future research directions are summarized in the concluding section.

2. Background

A typical biomass SC consists of the following operational components: feedstock production, pre-treatment & storage, conditioning & processing and conversion to ethanol (Rentizelas et al., 2009; Sharma et al., 2013; Mafakheri and Nasiri, 2014). As soon as the feedstock is harvested, it is transported to a suitable location for storage. Then, biomass is processed and conditioned to facilitate the handling of pellets (Gold and Seuring, 2011). After this stage, biomass is ready to be converted into (bio) ethanol as shown in Figure 1.

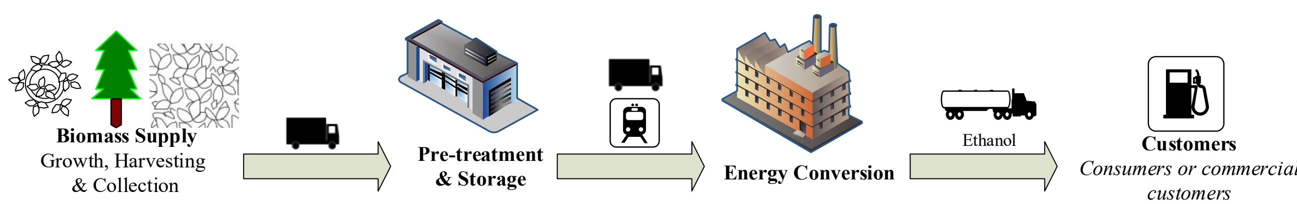


Figure 1. Operational components of a biomass supply chain

The biomass energy sector is affected from various factors such as crop yields, value/energy content of biomass feedstocks, efficiency of conversion of the biomass to useful energy (e.g. energy conversion technologies and processes), and land restrictions on energy crop production (Karmakar and Halder, 2019; Nunes et al., 2020). Understanding the influence of such factors on the supply of biomass feedstocks is helpful for development and commercialization of biomass energy. Climate change is one of the principal exogenous factor influencing supply side disparity in biomass availability (Hatfield et al., 2011; Lobell and Gourdji, 2012; Deryng et al., 2014). The supply and costs of bioethanol feedstocks are affected by the direct and indirect effects of climate change including weather conditions, crop diseases, insect pests, and availability of agricultural land (Ekşioğlu et al., 2009). Climate change may cause various types of uncertainty and disruption in bioethanol SCs including quantity of harvested feedstock yield and cost of raw materials; which, accordingly affects the production amount in bio-refineries, production capacity and logistics activities (Gunderson et al., 2008; Haberl et al., 2010; Awudu and Zhang, 2012; Mafakheri and Nasiri, 2014).

In bioethanol SCs, biomass availability and the energy conversion process highly depend upon the nature of raw material (Vohra et al., 2014; Zabed et al., 2017). Biomass-derived ethanol is mainly produced from sugar or starch-rich food crops such as corn, wheat, sugarcane, and sugar beet (Yue et al., 2014). Principally, bioethanol can be divided into three categories depending on the production source (Zabed et al., 2017). First-generation bioethanol is produced from agricultural products that have a high nutritional value such as corn, sugarcane maize, wheat, rice straw, etc. Second generation bioethanol is produced from lignocellulosic non-food crops such as agricultural residues, forestry and wood residues, switchgrass, willow, hybrid poplar, pines, etc. (Sharma et al., 2013; Vohra et al., 2014). Third generation bioethanol is produced from algae (Bibi et al., 2017). The production of bioethanol from first-generation feedstocks is already commercialized, whereas production from second-generation feedstocks is not very popular due to complex conversion processes (Balat and Balat, 2009).

The feedstock, like corn, is typically harvested from September until November (Ekşioğlu et al., 2009). This limited harvesting window, coupled with the year-round demand for bioethanol in the market puts constant pressure on its availability. Additionally, such limited harvesting window leads to hefty storage capacity requirements and logistics inefficiencies (Ba et al., 2016). More recently, the use of corn as a biomass feedstock has received ethical objections, as it is also used as a food source (Ghani et al., 2018). This warrants the investigation of alternative robust and efficient resources for bioethanol production. A promising second-generation ethanol feedstock, switchgrass (Panicum virgatum), is a warm-season perennial grass native to the United States (Kumar and Sokhansanj, 2007; Wright, 2007; Zhang et al., 2013). Although switchgrass has not been adopted on a large scale for bioenergy, it is attracting increased attention due to its tolerance to a broad range of environmental conditions. Switchgrass can grow in a wide range of climatic conditions, soil types and land conditions. Switchgrass can better survive from drought compared to other crops, owing to some morphological and physiological characteristics such as deep and extensive rooting system, pubescent and waxy leaves, water use efficiency and photosynthetic efficiency under drought conditions (Eggemeyer et al., 2009; Zegada-Lizarazu et al., 2012; Liu et al., 2015).

Additionally, the capacity for high yield of switchgrass on relatively poor-quality sites has been demonstrated (Wright, 2007). These factors make switchgrass a resilient feedstock towards expected future climate changes (Langholtz et al., 2014); however, they have not been assessed from the sustainability perspective. It is predicted that switchgrass yield can be doubled through foreseeable research-driven improvements (Kiniry et al., 2008); however, these crops are not commercially viable at the moment (RFA, 2017). As with corn, the optimal harvesting window of switchgrass is limited to the period from September to November.

The literature on biomass SC comprises of studies on the design, modelling and optimization of bio-refinery SC networks (e.g. Sharma et al., 2013; Zhang et al., 2013; Azadeh and Vafa Arani, 2016; Ba et al., 2016, Roni et al., 2017; Li et al., 2017). Some recent studies also focus on the sustainability of these SCs; however, they only consider the effect of bio-energy SCs on the economy, society, and environment (e.g., rate of return of bioenergy investments, reduction of carbon emissions, employment opportunities) (Awudu and Zhang, 2012; Yue et al., 2014; Mafakheri and Nasiri, 2014; Roni et al., 2017). There is evident lack of studies capturing the changes in bioethanol production and utilization due to an increase in climate change or global warming (Xu et al., 2018). The vulnerability of bioethanol production to climate change risk is found to be overlooked in the academic literature. A limited number of studies have examined the relationship between these two areas and discussed the effect of climate change risk on feedstock availability and/or biomass production (e.g. Langholtz et al., 2014; Kung et al., 2018). This study attempts to address this evident research gap.

3. Method and model

3.1. Research methodology

Multiple quantitative methods are followed for supply chain risk modelling ranging from Bayesian modelling, discrete event simulations, bi-objective and stochastic programming (Ghadge et al., 2012; Hosseini et al., 2019). Interestingly, simulation studies have shown strong potential for modelling disruptive risks in supply chains (Ghadge et al., 2013; Sokolov et al., 2016). SD approach followed for this study is based on Systems theory (Sterman, 2000); and involves simulation-based approaches to build models to understand the dynamic behaviour of variables and their interaction over time (Campuzano and Mula, 2011). SD is a computer-based simulation approach for understanding the structure, characteristics and behaviour of complex, dynamic systems under external influences (Davies and Simonovic, 2009; Campuzano and Mula, 2011; Bala et al., 2017). In the SD approach, the problem is identified and defined using available information. Then, the system is conceptualized by designing a causal loop diagram, which is translated into a stock and flow diagram in order to run a computer simulation. The causal loop diagram includes key variables, their interrelationships and feedback structures (Ranganath and Rodrigues, 2008). This system conceptualization phase captures essential variables and their inter-relationships. Positive feedback loops are known as reinforcing loops since they stimulate changes in a system that leads to instability (Bala et al., 2017). Negative loops are known as balancing loops that show goals-seeking behaviour over time (Sterman, 2000).

Stock and flow diagram is a translation of the causal loop diagram into a format which applies to computer simulation (Campuzano and Mula, 2011). The main difference with a causal loop diagram is that the stock and flow diagram distinguish between different types of variables: *stock variables, flow variables and auxiliary variables* (Sterman 2000). Stock (level) variables characterize the system's state at a given time point and are represented as accumulations of differences between inflow and outflow (Mohan and Amit, 2018). Flow variables represent the rate of change in stock variables and are measured over a period of time (Bala et al., 2017). These variables are influenced by auxiliary and constant variables which are parameters within the system (Campuzano and Mula, 2011). As soon as the model is validated and simulated against the chosen policies/decisions, results are analyzed to evaluate outcomes and plan policies.

SD approach has been widely employed; however, its use in the renewable energy or biomass supply chain is very limited. Bantz and Deaton (2006) developed a SD model of the US biodiesel industry to understand the effects of critical variables such as feedstock price and change in government incentives on biodiesel production capacity. Bush et al. (2008) proposed potential commercial availability of the bioenergy market based on a SD approach. Azadeh and Vafa Arani (2016) developed a hybrid approach including a SD and stochastic mixed-integer programming model to optimize biodiesel SC decisions under resource limitations (such as water, land, and technological issues). The study provides multiple inferences associated with biodiesel and biomass demand, production and price; however, it lacks consideration of different scenarios in SD modelling to understand the influence of changes in parameters better. More recently, Vaccaro et al. (2018) applied SD approach to investigate the social, technological, economic, ecological, political and legal factors that affect the sustainability and competitiveness of ethanol production chains using sugar as a source of raw material in Brazil. In their study, changes to climatic factors were considered as a known trend; therefore, it did not lead to a discrimination effect among different simulation scenarios. Implications of climate change on the bioethanol supply over more extended time horizon, modelling and comparing first generation (corn) and second generation (switchgrass) ethanol biomass is novel and has not been addressed in the literature.

In this study, a SD model is developed to investigate the impact of climate change risk on bioethanol SC network. The proposed model is developed and run using Vensim (a commercial simulation software) for a period of 40 years (from 2020 to 2060). Obtaining reliable data beyond this time horizon is extremely difficult due to the high uncertainty of climate change-related events. Thus, data collection was based on a multi-disciplinary review of academic literature and semi-structured interviews with experts from the bioethanol industry. Corn and switchgrass feedstocks are considered for modelling the bioethanol production system under RCP 2.6 and RCP 8.5. Eight different scenarios are modelled to explore the impact of climate change on bioethanol SC network during yield and non-yield periods.

3.2. Development of the SD model

In this section, a SD model is developed to investigate the behaviour of a bioethanol SC under multiple scenarios. Figure 2 represents the causal loop diagram of the bioethanol SC system developed based on the authors' understanding of the bioethanol industry and literature-driven key influencing variables. The SD model incorporates different variables such as yield rate and ethanol inventory, ethanol demand and safety stock, etc. to simulate the dynamic interactions between different stages of a bioethanol SC network. The arrows represent the causal relationships among different variables. All of the variables are related to at least one variable; therefore, each variable is related either directly or indirectly. Positive and negative relationships between different variables are depicted by '+' and '-' signs respectively.

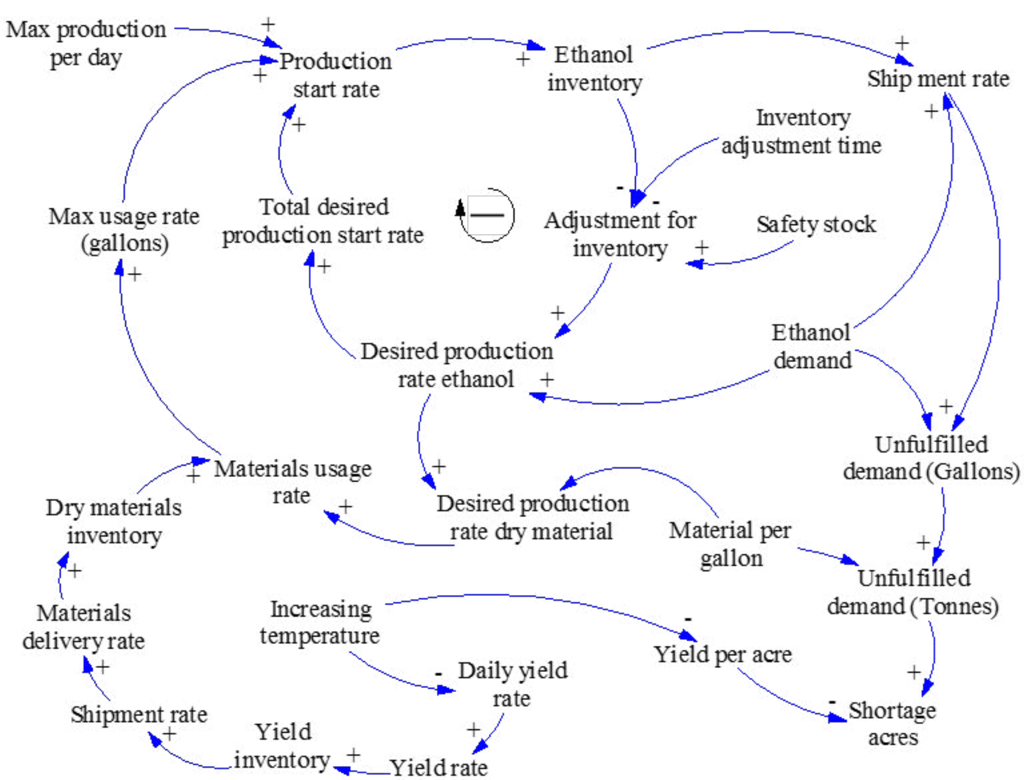


Figure 2. Causal loop diagram of bioethanol supply chain

For instance, an increase in yield rate leads to an increase in yield inventory. The mutual relationship is therefore expressed with a '+' sign. Similarly, an increase in temperature level leads to a decrease in daily biomass yield; the mutual relationship is therefore expressed with '-' sign. The performance of the system depends on which of the loop(s) is/are dominant. Systems are stable if negative loops dominate them; however, positive loops tend to lead to instability irrespective of the initial situation (Campuzano and Mula, 2011). Since the causal loop diagram shown in Figure 2 consists of one negative feedback loop, the system is considered to be in a stable situation. Climate change (increasing temperature) is considered as an exogenous variable in this model, as it is not affected by other variables of the bioethanol production system.

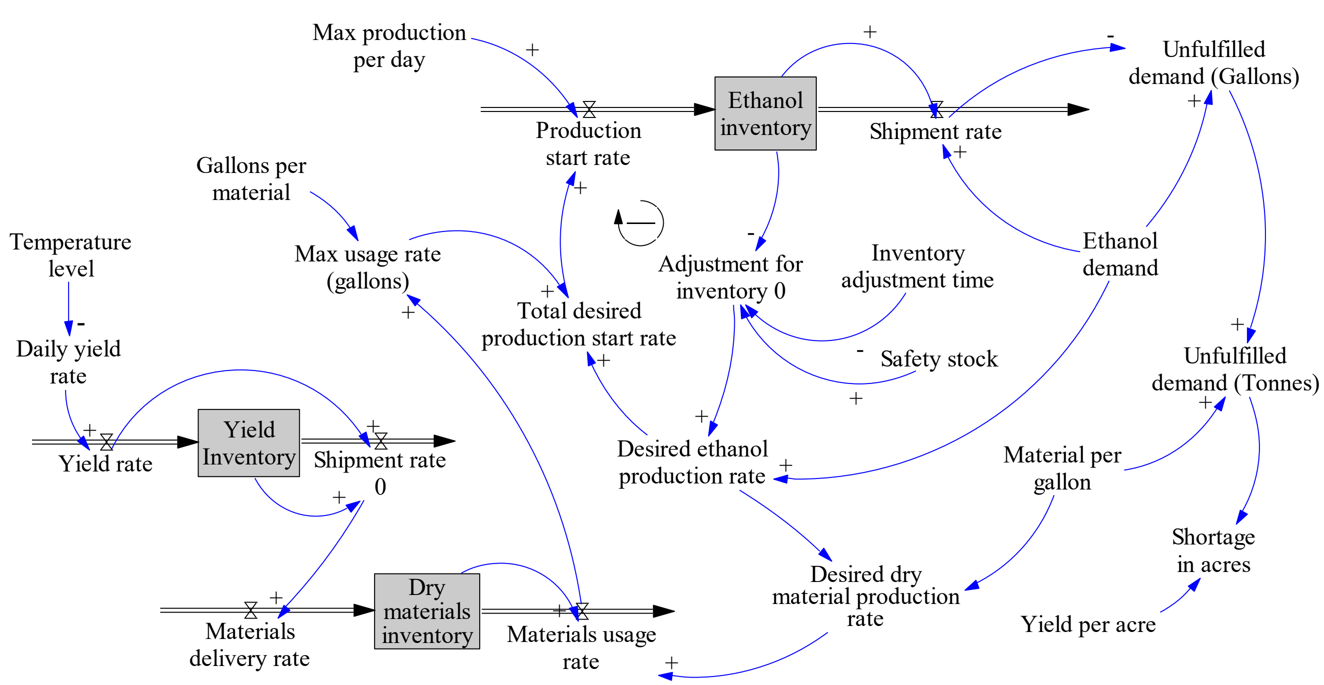


Figure 3. Stock and flow diagram of bioethanol supply chain

The causal loop diagram is then converted into the stock and flow diagram as shown in Figure 3 with identified stock, flow and auxiliary variables. Since the study focuses on inventory levels, the model is broken down into three different echelons: yield inventory, dry materials inventory and ethanol inventory. As shown in Figure 3, the yield inventory comprises of two rate variables: *yield rate* and *shipment rate*; and an auxiliary variable *daily yield*. *Daily yield* input occurs based on the changes in the global *temperature level* for the selected climate change scenario. The *daily yield* determines the *yield rate*. The *shipment rate* is determined by the *yield rate* and cannot be higher than the current level of *yield* *inventory*. The value of *shipment rate* determines the outflow of materials and, therefore, the *materials delivery rate*. *Yield inventory,* equal to the difference between *yield rate* and *shipment rate,* is constrained to be non-negative.

The *dry materials* echelon has two rate variables: *materials delivery rate* and *materials usage rate,* as well as two auxiliary variables: *shipment rate* and *desired dry material production rate.* The *materials delivery rate* is based on *shipment rate* and, thus, equals to this rate. The *materials usage rate* is based on the *desired dry material production rate*, and cannot be lower than the current inventory level. *Dry materials inventory* equals to the difference between these two rates, accumulates over time and is constrained to be non-negative. Additionally, the *production start rate* is constrained by two variables; the *maximum production per day* and the *maximum usage rate (gallons)*. *Maximum production per day* is a function of the *maximum capacity of the refinery*, whereas *the maximum usage rate (gallons)* occurs from the *materials usage rate.* The *materials usage rate* is a function of the *desired dry material production rate* that arises from *the desired ethanol production rate* and *material per gallon.*

The stock variable *ethanol inventory* consists of two rate variables: *production start rate* and *shipment rate,* and a range of auxiliary variables. For *ethanol inventory*, the number of tonnes harvested is fixed, implying that no adjustment in order to complement the inventory could be made. In order to show shortages of ethanol arising from different climate scenarios, *unfulfilled demand (gallons)* is expressed with the difference in *ethanol demand* and *shipment rate*. *Ethanol demand* is assumed as known and constant. *Unfilled demand (tonnes)* variable represents the shortage of ethanol in tonnes of biomass. This variable is then divided by *yield per acre* to show the ethanol shortage in terms of *shortage in acres*.

3.3. Simulation scenarios

Collecting appropriate primary data was challenging from a financial and durational perspective for this research. Hence, internationally acknowledged climate change data from various published academic papers and industry reports were utilized for the investigation. Climate effects are conventionally measured in terms of temperature, precipitation and CO_2 requirements (Lobell and Gourdji, 2012; Kimball, 1983). However, measurements used for calculating precipitation and CO_2 requirements are criticized and considered unreliable since test conditions are not equal in different regions (Long et al., 2006). Besides, this study aims to predict the future global state of the bioethanol industry under the influence of climate change risk. Temperature level is a key and reliable factor affecting crop growth and biomass feedstock availability.

Various conditions and parameters are employed in the SD model to provide a more realistic picture of bioethanol SCs. Table 1 provides base simulation conditions required to run the model. The global surface temperature variations are considered over a 40-year horizon with 2020 representing the base year. A year is further divided into two periods to examine the state of bioethanol shortage during yield and non-yield periods.

Table 1: Simulation conditions

Condition	**Decision**
Climate measurement	Temperature (C^o)
Crops	Corn/Switchgrass
Time path	40 years between 2020 and 2060
Steps in time	10 years
Periods per year	2 periods (P1: harvesting & P2: non-harvesting)
Climate change scenarios	RCP 2.6 and RCP 8.5
Region	Central part of North America

Eight scenarios are analyzed in the simulation model as shown in Table 2. P1 represents the harvesting period and consists of three months. P2 represents the non-harvesting period for both crops and covers nine months. As explained earlier, RCP 2.6 and RCP 8.5 are two extreme pathways associated with climate change. Combination of feedstocks, periods and RCPs are used to assess the impact of climate change risk on bioethanol SCs. First four scenarios capture the impact of two extreme climate change pathways during yield and non-yield period for corn. Remaining four scenarios capture similar impact for switchgrass.

Table 2. Summary of simulation scenarios

Simulation scenario no.	**Feedstock type**	**Period (P1: yield P2: non-yield)**	**Climate change pathway**
1	Corn	P1	RCP 2.6
2	Corn	P1	RCP 8.5
3	Corn	P2	RCP 2.6
4	Corn	P2	RCP 8.5

5	Switchgrass	P1	RCP 2.6
6	Switchgrass	P1	RCP 8.5
7	Switchgrass	P2	RCP 2.6
8	Switchgrass	P2	RCP 8.5

3.4. Parameters

The proposed SD model incorporates various decision variables and parameters related to the bioethanol supply chain. The model parameters and their input values are provided in Table 3. The values of maximum production per day and gallons of ethanol per ton of biomass are adapted from the literature (details provided below). The values of other input variables were decided by a team of three academic researchers from the renewable energy field, in consultation with two bioethanol industry experts. The gathered input data set was verified by benchmarking them with the relevant literature. For modelling purposes, it is assumed that the total agricultural area is 256,000 acres (400 Sq. miles) in the central part of North America. The mean yield per hectare is 11.6 Mg/ha for switchgrass (Gunderson et al., 2008) and 11 Mg/ha for corn (Deryng et al., 2014). The amount of ethanol (in gallons) produced from one ton of biomass is identified as 75 gallons/ton for both feedstock types (Patzek, 2010; Tembo et al., 2003). Future demand for corn and switchgrass-based ethanol is calculated considering average ethanol demand per day (281,500 gallons/day).

Furthermore, full yield during the harvesting period is considered for bioethanol production. It is understood that human-influenced considerations (e.g. food consumption, food wastage, use for animal feed) are likely to influence the availability of raw material for bioethanol production; however, such considerations are difficult to model. Such reasonable assumptions are acceptable and are evident in past research in food/agricultural supply chain modelling (e.g. Kucukvar and Samadi, 2015; Jonkman et al., 2017). The inventory adjustment time is set to two days. The initial value of ethanol inventory is assumed to be equal to the safety stock level, which is set to two days of demand and therefore, equals 563,000 gallons of ethanol on average.

Table 3. Summary of input data

Variable	Value	Reference(s)
Max. production per day	~111,000 tonnes of biomass	Tembo et al. (2003); Chokshi et al. (2016); Ren et al. (2017)
Mean yield per hectare	~11.6 Mg/ha for switchgrass	Gunderson et al. (2008); Springer (2017)
	~11 Mg/ha for corn	Deryng et al. (2014); Jacques et al. (2018)
Gallons of ethanol per ton of biomass	~75 gallons/ ton	Patzek (2010); Tembo et al. (2003); Huang et al. (2018)
Ethanol demand (average)	~281,500 gallons/day	RFA (2019)
Material per gallon	~0,013 tonnes/gallon	RFA (2019)
Safety stock (average)	~563,000 gallons	Expert consultation
Inventory adjustment time	2 days	Expert consultation
Production days per month	26 days	Assumption

For corn, Deryng et al. (2014) applied a global crop model to quantify the impact of future temperature on corn yield. Figure 4 (a) shows the percentage decrease in corn yield under two RCPs based on their study. Under RCP 8.5, the expected decrease in corn yield reaches nearly to 24% in 2060. Under RCP 2.6, the expected decrease in corn yield stays below 5%. The effects of temperature on switchgrass yield are based on Gunderson et al. (2008). Figure 4(b) represents the percentage decrease in switchgrass yield based on their estimations. Under the RCP 8.5, the decrease in switchgrass yield is expected to increase to approximately 13% in 2060. This is considerably higher than the expected decrease under RCP 2.6, which stays below 4%. These two data sets are used to calculate the temperature-effected daily yields over the selected time horizon.

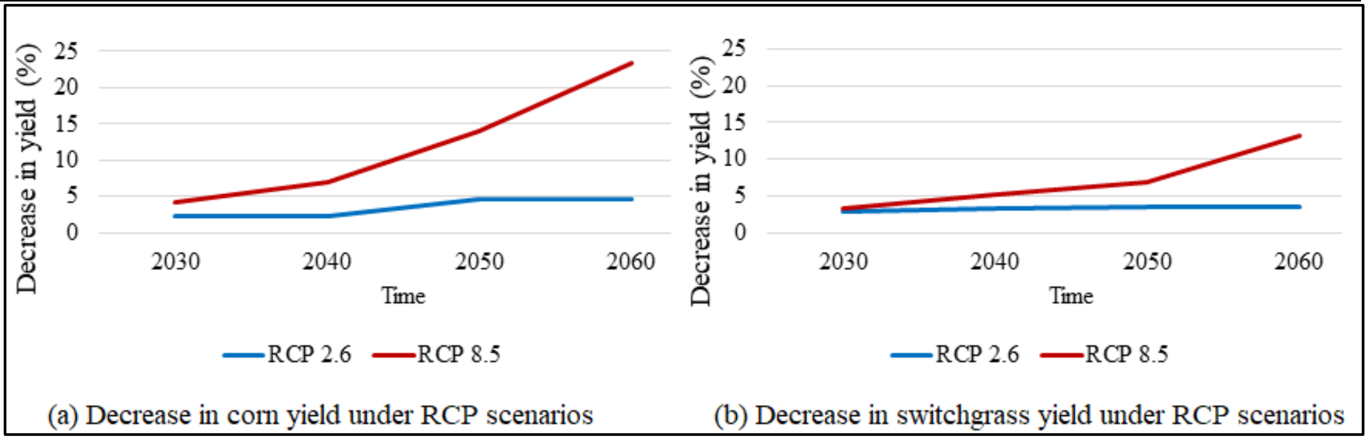


Figure 4. Percentage decrease in corn and switchgrass yields over time

(Adapted from Deryng et al., 2014 and Gunderson et al. 2008)

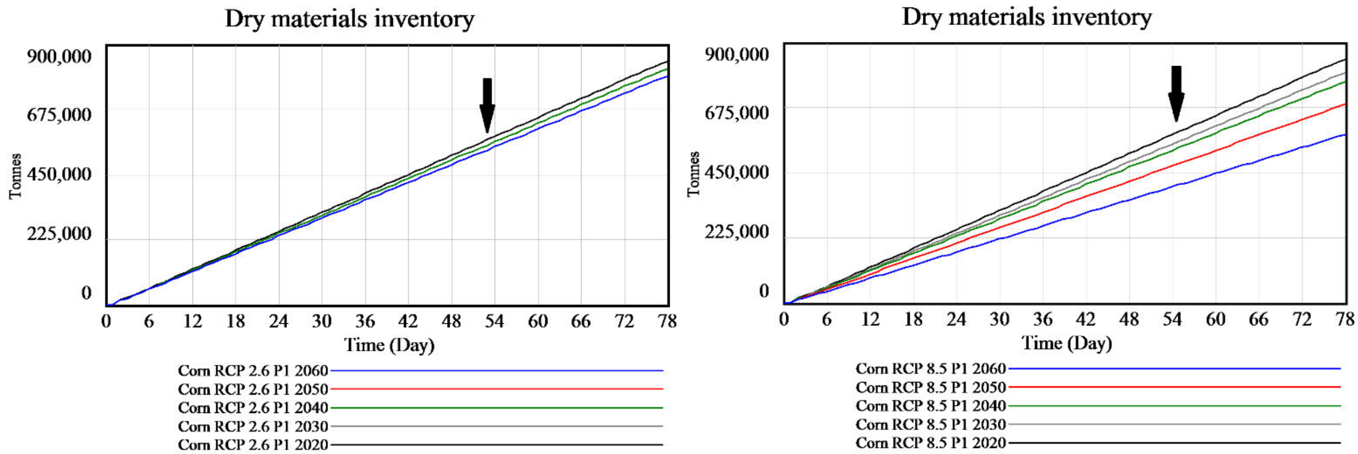
4. Analysis

Eight different scenarios were analyzed to investigate the level of biomass and ethanol inventories and ethanol shortages for the yield and non-yield period under RCP 2.6 and RCP 8.5 for both feedstocks. The results are presented in terms of dry materials inventory, ethanol inventory and unfilled demand of ethanol for all scenarios. The *dry materials inventory* levels for P1 and *ethanol inventory levels* and *unfilled demand* amounts for P2 are also captured. Additional results on the yield inventory levels in harvesting periods and dry material inventory levels in non-harvesting periods are provided in Appendix; Figure A.1 and Figure A.2.

4.1. Corn-based ethanol

Results for scenarios 1 and 2: Corn, P1, RCP 2.6 & RCP 8.5

Scenarios 1 and 2 are based on the production of ethanol from corn and investigate the changes in the variables during the yield period (P1). Figures 5 (a) and (b) show the *dry materials inventory* levels for corn during the yield period under RCP 2.6 and RCP 8.5, respectively. Since the yield period consists of three months and every month has 26 operational days, the period equals to 78 days. Due to the yield period, dry material inventory level shows an increasing trend. However, corn production shows a decreasing trend with the increase in temperature driven by climate change. A significant difference in the inventory level is observed between 2020 and 2060 under RCP 8.5.

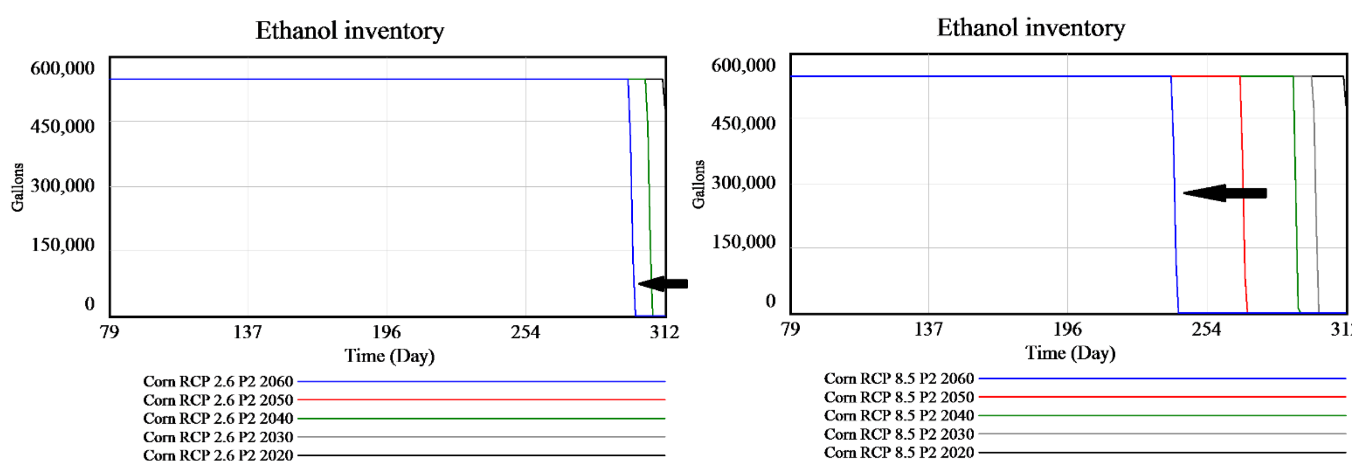


(a) Scenario 1 **(b)** Scenario 2

Figure 5. Dry materials inventory levels for corn during the yield period

Results for scenarios 3 and 4: Corn, P2, RCP 2.6 & RCP 8.5

Different to previous scenarios, scenarios 3 and 4 examine the changes in the bioethanol SC during the non-yield period (P2) under climate change. P2 period represents the remaining time of the year and represents 234 days (nine months with 26 production days per month). Since this period does not cover the harvesting period, the yield inventory is 0, and dry material inventory level decreases to 0 overtime. Appendix Figure A.2 shows the dry material inventory levels during non-yield periods. The year 2020 is the base year; therefore, the dry material inventory levels decrease to 0 in day 312 for this year.



(a) Scenario 3 **(b)** Scenario 4

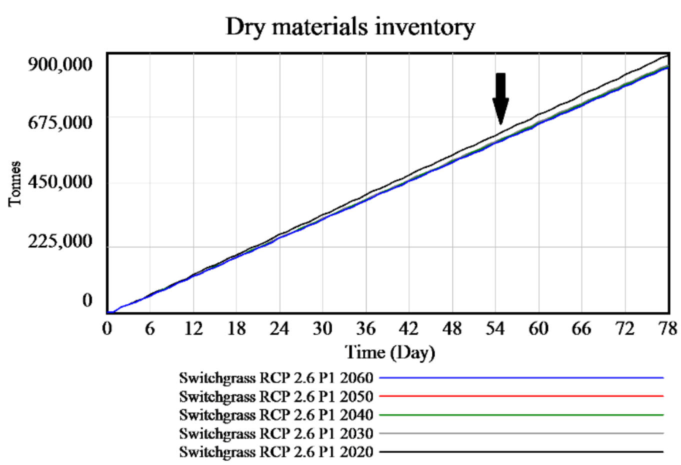
Figure 6. Ethanol inventory levels during the non-yield period for corn

A considerable amount of difference is observed between dry material inventory levels in 2020 and 2060 at RCP 8.5. Figure 6 represents the ethanol inventory levels during non-yield periods for corn. The shortages occur for every scenario in P2, except the base year 2020.

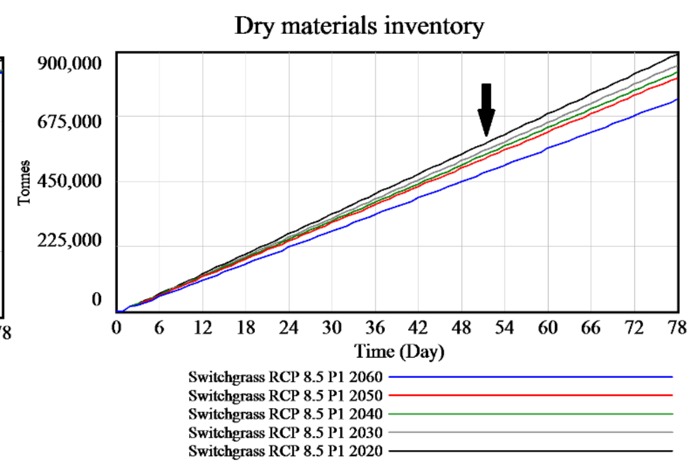
4.2. Switchgrass-based ethanol

Results for scenarios 5 and 6: Switchgrass, P1, RCP 2.6 & RCP 8.5

Scenarios 5 and 6 are based on the production of ethanol from switchgrass and investigate changes in variables during the yield period (P1). Figures 7 (a) and (b) show *dry materials inventory* levels for switchgrass during the yield period under RCP 2.6 and RCP 8.5, respectively. Both graphs show similar trends like corn for the dry material inventory levels. However, a more significant level of decrease was observed in the case of corn, especially under RCP 8.5.



(a) Scenario 5



(b) Scenario 6

Figure 7. Dry materials inventory levels for switchgrass during the yield period

Results for scenarios 7 and 8: Switchgrass, P2, RCP 2.6 & RCP 8.5

Scenarios 7 and 8 examine the non-harvesting period for switchgrass; therefore, the yield value variable is equal to 0. For both RCPs, the *dry materials inventory* decreases to 0 overtime. This is expected since there is no feedstock yield in this period and, therefore, only an outflow rate occurs in the P2 period. Figure 8 represents the *ethanol inventory* levels during non-yield periods for switchgrass. Ethanol shortages are observed in each scenario except the base year 2020. In both climate change conditions, lower levels of ethanol shortages are observed in the switchgrass case, when compared with the corn case.

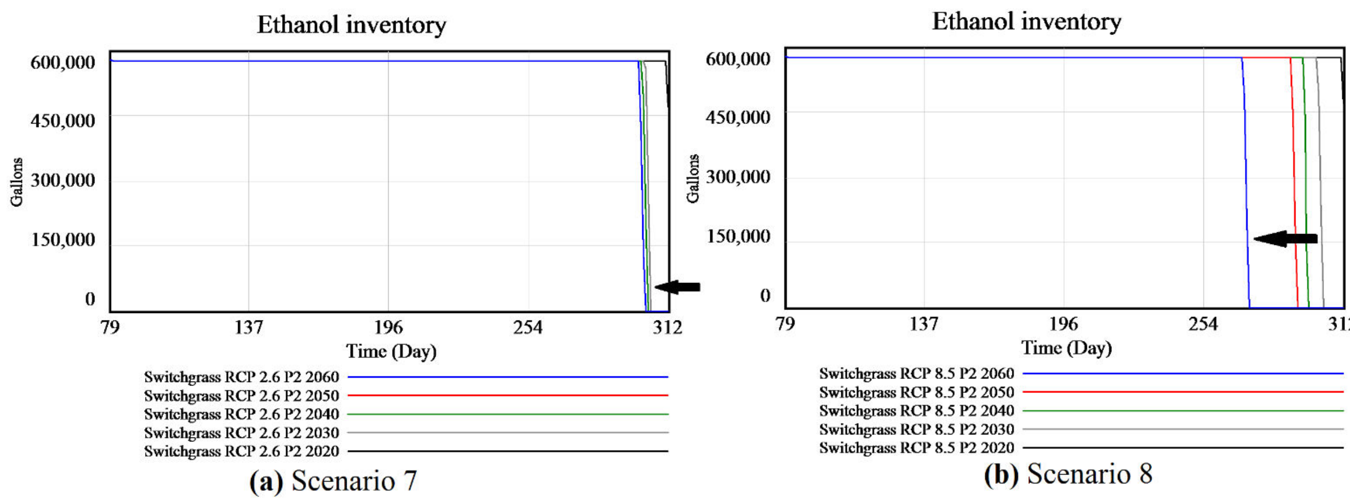


Figure 8. Ethanol inventory levels during the non-yield period for switchgrass

4.3. Comparison of unfilled demand based on feedstock type and climate change

The changes in the unfilled demand in gallons are represented in Figure 9 for four scenarios covering the non-yield periods. Figures 9 (a) and (b) represent the unfilled demand level for corn, and (c) and (d) show the unfilled demand level for switchgrass for RCP 2.6 and RCP 8.5 respectively.

The decrease in dry material inventory levels during yield periods (P1) are represented in percentage compared to the base year, 2020. The amount of unfilled demand in the percentage of the annual ethanol demand is also presented. The results in both cases show that the bioethanol SCs using corn as the primary ethanol feedstock are more vulnerable to increase in the temperature. However, when the temperature increase is 0.80 C° and lower, bioethanol production for switchgrass is more affected than bioethanol production for corn (RCP 2.6 scenario, until 2050). Thus, a decrease in dry material inventory is observed above this temperature level.

Shortages occurring under RCP 8.5 climate change scenario increasingly rise over the years and reach approximately to 23% in corn-based ethanol production and 13% in switchgrass-based ethanol production. Under both climate change scenarios, ethanol shortages in corn-based production are higher than the switchgrass-based production. Besides, shortages in ethanol from switchgrass show a moderate increase and therefore are considered as less sensitive to temperature change.

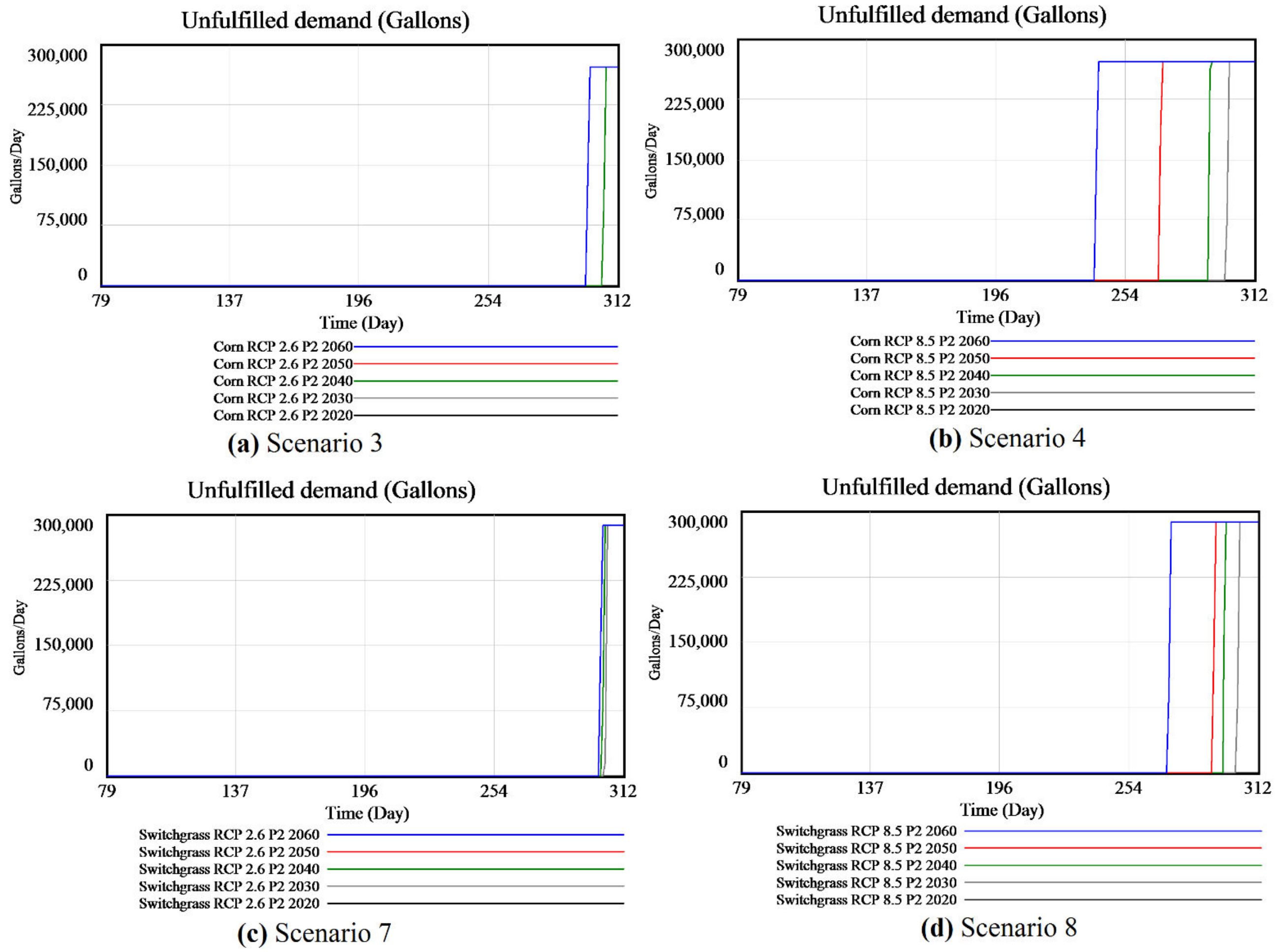


Figure 9. Unfilled demand (in gallons) during the non-yield period for both feedstock types

4.4. Best and worst-case

In order to further clarify the impact of developed RCP scenarios and the choice of crops on bioethanol availability, a comparison between the best and worst-case scenario is presented in Figure 10. The RCP 2.6 switchgrass scenario is selected as the best case because the ethanol shortage level increases only up to 3.37% by 2060. The RCP 8.5 corn scenario is selected as the worst case because the ethanol shortage has the highest levels reaching up to 23%.

The comparison shows a significant difference in the supply of bioethanol between these two scenarios. While the unfilled demand in the base case is approximately three million gallons of ethanol in 2060, it reaches 19.5 million gallons of ethanol in the worst-case scenario. Both scenarios show that in both cases a decrease is expected in bioethanol supply due to the adverse impact of climate change on biomass feedstock availability.

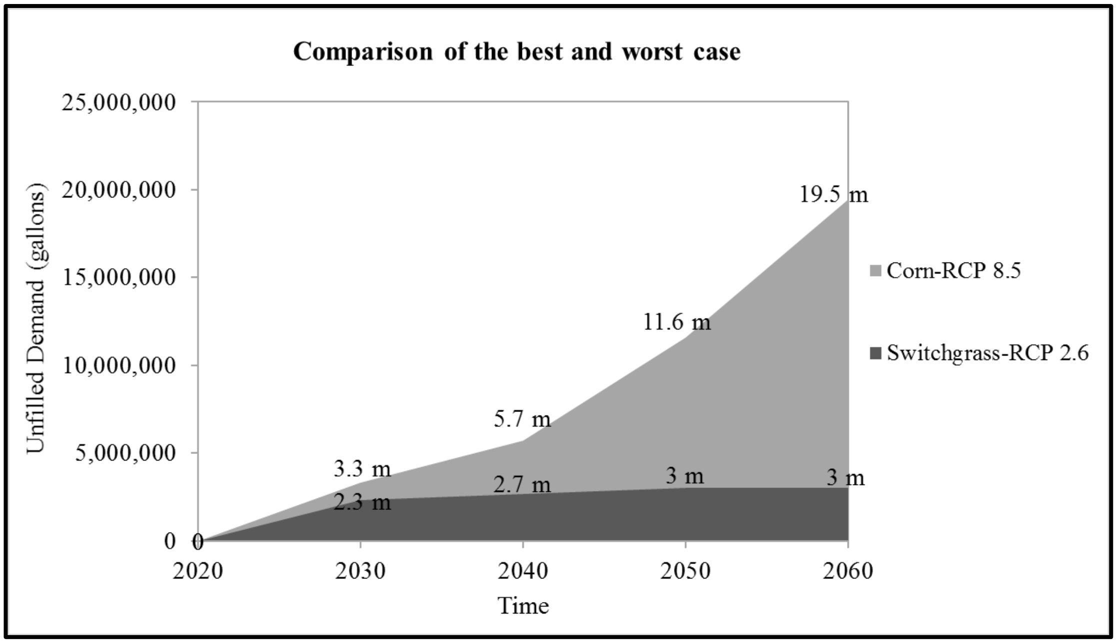


Figure 10. Comparison of the best and worst scenarios

5. Conclusion

5.1. Discussion

The study employed a SD approach to examine the impact of changing climate on bioethanol supply and the propagating effect of the climate change risk along the bioethanol supply chain network. Agricultural feedstock production, production in bio-refinery, delivery, and bioethanol demand layers of the bioethanol SC were considered in the developed model. The bioethanol SC is modelled under two different RCPs, spanning over a 40-year horizon from 2020 to 2060. Both, a first-generation (corn) and second generation (switchgrass) feedstocks were examined in the analysis for a comparison of the vulnerability of the two production networks. The impact of climate change risk was explored, both during the yield/harvesting period (P1) and non-yield/non-harvesting period (P2) to capture the changes in inventory levels at different stages of the bioethanol SC network. Multiple scenarios were examined for corn and switchgrass-based ethanol yield, production and availability during harvesting and non-harvesting periods of a year.

Climate change is a significant global risk that has a high impact on biomass feedstock availability. The study showed that predicted climate change is likely to affect the growth of feedstocks for bioethanol production. According to Kung et al. (2018), under a small climate-induced crop yield change, net bioenergy production will not change a lot, while land use and agricultural resource allocation could vary considerably. This study proves otherwise, as there is enough support to show that climate change is invariably going to affect crop yield and thus production and availability. Some of the findings made in this study compliment past studies (e.g. Deryng et al., 2014; Langholtz et al., 2014), supporting with the validation. However, these studies either focus on single feedstock or generic climate change situations, thus making this study unique. A longitudinal study exploring implications of climate change on the bioethanol SC, particularly considering and comparing first generation (corn) and second generation (switchgrass) ethanol biomass is missing.

Furthermore, the impacts of climate change on different levels of bioethanol SC network has not been addressed in the past. This study contributes to these research gaps by employing a SD model to understand the causal relationships in a bioethanol SC under different climate change scenarios. The ripple effect of the climate change risk is evident through decreased yield and production, and increased shortages at end customer in the bioethanol production network. This cascading impact is observed across bioethanol SC from raw material suppliers to bioethanol manufacturers to end-consumers, in terms of reduced availability and SC performance (Ojha et al., 2018).

The empirical study reinforces that the future supply of one of the most promising alternative renewable energy types, bioethanol, is under threat due to the accelerating adverse impact of global warming. The shortage of bioethanol in 2060 is expected to be 23% of the annual ethanol demand under the RCP 8.5 and 4.3% of the annual demand under RCP 2.6 for corn. A comparison of the best- and worst-case scenarios helps to strengthen the urge for both climate mitigation and the use of switchgrass as a preferred feedstock. The study also reveals that the effect of the RCP 8.5 is much worse than the effect of RCP 2.6 on the yield of both corn and switchgrass crops; thus, demanding strong risk mitigation actions to control increasing global temperatures. Following a systems theory, the study analyzed the differences in the estimated bioethanol shortages up to the year 2060, raising critical issues associated with the sustainability of selected renewable energy sources.

In the global context, the net effect of global warming on overall biomass availability may change slightly depending upon geographical climate patterns. Regional and local climate change impacts may lead to variations in the distribution of suitable areas for switchgrass planting; however, it is hard to foresee these variations as the impact of climate change is quite heterogeneous across different regions of the world. Notably, the impact of climate change on the distribution of water around the planet is a critical issue. As the planet warms, it is expected that the number of records will increase for dry and wet weather as well as extreme events such as droughts and floods. Hence, energy policies should be developed by considering regional differences and challenges.

Given vulnerability associated with the use of corn as a feedstock, the study encourages exploring increased use of switchgrass as a sustainable feedstock for future use of bioethanol. Recent studies (e.g. Bibi et al., 2017; Xu et al., 2018) support the promotion of other second-generation (e.g. sugar, cassava) and third-generation (e.g. algae) bioethanol due to the rapid enhancement in production technologies in these fields and the growing food security concern. Several researchers have proved the resiliency of switchgrass to drought, owing to its deep rooting characteristics (Wright, 2007; Eggemeyer et al., 2009; Langholtz et al., 2014). However, more comprehensive research studies considering the diverse impacts of climate change such as precipitation and CO_2 fertilization are needed before making investments decisions in this emerging area. In all, the progress towards the commercialization of bioethanol production from second and third-generation feedstocks seems necessary under growing threat of climate change.

5.2. Implications

The study provides some implications for research and practice. The results of the study provide useful practical insights for governments, bioethanol producers and farmers in terms of bioethanol SC network design and risk-management processes to make bioethanol SCs resilient to the direct and indirect effects of climate change risk. For policymakers, the study provides useful insights into setting reliable targets for a shift towards renewable energy sources. The findings may also be useful in making investment decisions associated with bioethanol production. Corn is one of the primary feedstocks in bioethanol production in the world; however, the results indicate that bioethanol production from corn is under severe threat due to climate change. First-generation ethanol feedstocks are under significant pressure from the food shortage perspective (RFA, 2017); hence, in order to keep the bioethanol sector viable, future development of second and third-generation ethanol feedstocks should be explored.

Holistic research supports developing possible strategies for producing renewable sources of energy. Findings can be used for the development of effective risk mitigation and prevention policies to sustain in an uncertain environment. Although there is a lack of consensus on bioethanol policies and strategies of countries, worldwide governments have acknowledged bioethanol as an increasingly important source of future energy. The research can support United Nations Commission on Sustainable Development (CSD) and other partners such as IPCC, United Nations Environment Programme (UNEP) and United Nations Framework Convention on Climate Change (UNFCCC) in developing comprehensive frameworks for renewable energy development following insights established from this study. In general, the research also contributes to increased attention to the impacts of climate change risk on supply chains and the broader ecosystem (Ghadge et al., 2020). By exploring multiple scenarios, the study provides a holistic picture of bioethanol supply and demand for the next 40 years. Such crucial findings can support in developing sustainable schemes to overcome the depleting supply of fossil fuels and meet future energy demand.

5.3. Limitations and future research

Like any other research, the study has few limitations. This study only considered temperature as a critical external variable and did not take into account the effect of precipitation and CO_2 fertilization due to lack of reliable data for the selected region. The bioenergy industry is also affected by several other factors including feedstock prices, policies/regulations, food versus biofuel debate, changing seasons and extreme weather events that disrupt agricultural lands. Owing to the environmental challenges related to the use of fossil fuels, there is a considerable research effort on high-yield feedstocks and biomass conversion technologies. However, due to the complex nature of bioethanol SC network, some of the variables may not be considered in the development of our model. Therefore, the simulation results should be interpreted by considering the effect of such variables and technical conversion efficiency. Future research can consider such unaccounted multiple exogenous variables to capture the impact on biomass and bioethanol. It should be also be noted that, besides the advancement in biomass power generation, there have been recent technological innovations for reducing fuel consumption, especially in the automotive and aviation industries. Due to the long-term simulation period, technological progress in bioethanol production and consumption should not be omitted while defining new policies.

The study also has a limitation in the availability of primary data; however, reliable information sources available in the literature were used to bring robustness to findings. As a future research avenue, model parameters can be identified by performing semi-structured interviews with experts in the bioethanol industry, which may help in providing a global perspective on the study of this nature. Further empirical investigations may be useful for validating the findings made in this study. Potential of developing third-generation feedstock for bioethanol sustainability is another avenue for future research.

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Appendix

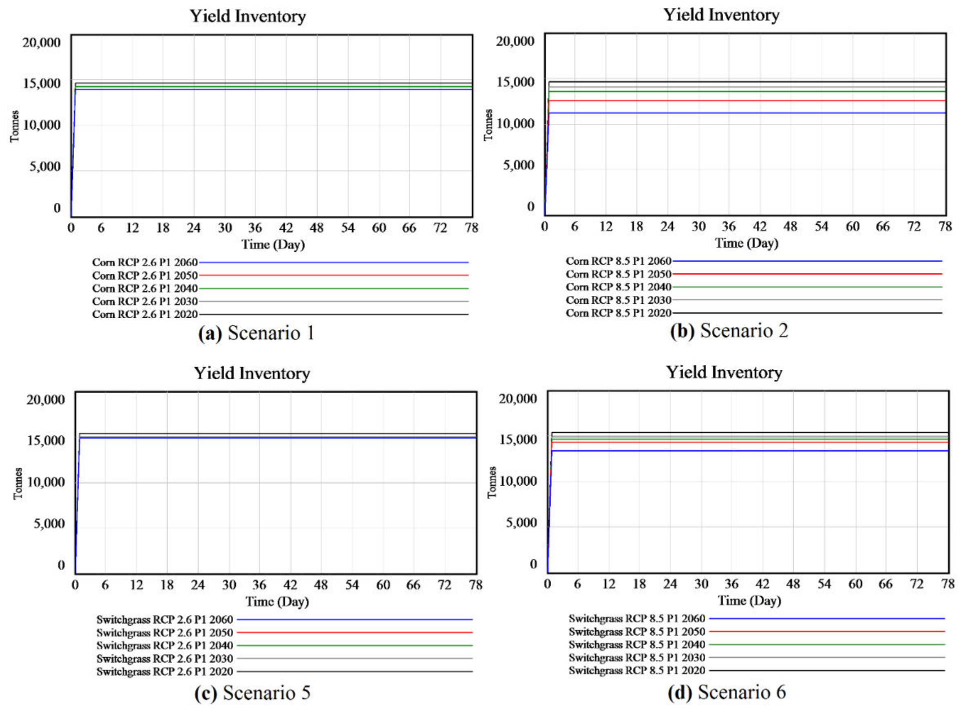

Figure A.1. Yield inventory levels in different scenarios for the yield period

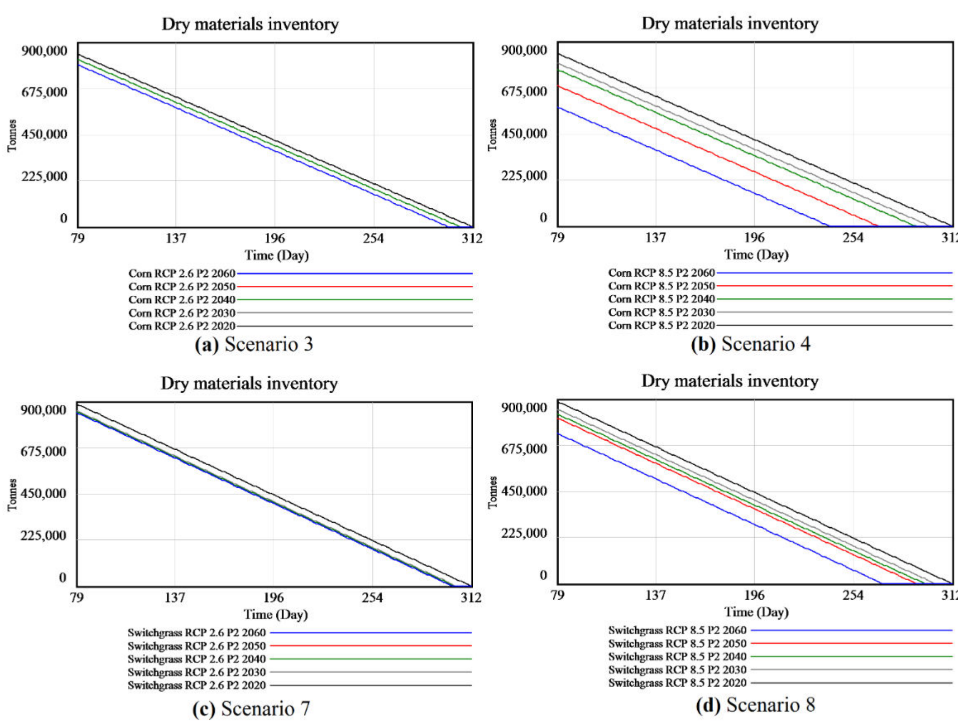

Figure A.2. Dry material inventory levels in different scenarios for the non-yield period

Modelling the impact of climate change risk on bioethanol supply chains

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