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Changing the World's Energy Future

Md Mamunur Rahman, Ruby Thuy Nguyen, Liang Lu

Idaho National Laboratory

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Idaho National Laboratory
Idaho Falls, Idaho 83415

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Multi-Level Impacts of Climate Change and Supply Disruption Events on a Potato Supply Chain: An Agent-Based Modeling Approach

Md Mamunur Rahman[1,*], Ruby Nguyen[1], Liang Lu[2]
[1] Idaho National Laboratory, Idaho Falls, ID 83415, USA
[2] University of Idaho, Moscow, ID 83844, USA
*Email: MdMamunur.Rahman@inl.gov

Abstract

Context: The world is experiencing frequent extreme weather events like droughts, snowstorms, and shifting of seasons due to climate change. Increased frequency and severity of these extreme weather events threaten food security because agriculture depends on climate conditions. Impacts of climate change on the agricultural system not only occur at the grower's level, but also cascade to other levels along the supply chain.

Objective: This study aims to quantify a wide range of economic impacts of different extreme climate events on different stages of a food supply chain.

Methods: We chose the potato supply chain in Idaho as a case study. We developed a multi-echelon supply chain simulation model using an agent-based modeling (ABM) approach with five types of agents—farmers, shippers, processors, retailers, and logistics companies. In addition to the business-as-usual (BAU) scenario, we designed two climate-related disruption events—drought and snowstorm. We quantified the heterogeneous impacts at different stages of the supply chain for both fresh and processed potatoes using key performance indicators (KPIs) including revenues, prices, lead times, traded quantities, and food waste quantity.

Results and Conclusion: The impacts of the disruption events are different on different agents in the supply chain for different product categories. The price hike of fresh potatoes is far higher than processed potatoes during disruption events. This price hike makes consumers switch to processed potatoes, which require more fresh potatoes as an input that further reinforces the price hike. However, because processed potatoes have an elastic demand, once their prices go up due to higher input cost, their demand drops. Non-contracted farmers gain additional revenues from the disruption events, whereas contracted farmers incur a loss due to lock-in price and lower than usual harvest.

Significance: The methodology developed in this study could be applied to other food and agricultural supply chains for understanding the vulnerabilities at agent levels due to climate change disruption events. The findings would help develop mitigation strategies or policies to improve the well-being of the overall supply chain.

Keywords: Climate change, Supply disruption, Potato supply chain, Agent-based modeling, Drought, Snowstorm.

1. Introduction

Agricultural systems are susceptible to changing climate conditions. As reported by the World Bank, major potential impacts of climate change on agriculture include long-term water shortages, a higher pressure of disease and pest outbreaks, and losses in agricultural productivity and crop yields (Kurukulasuriya and Rosenthal 2013). A quarter of crop yield variability due to climate change was estimated (Kukal and Irmak 2018) and accompanied by increased pesticide expenditure (Reilly 2002) or further damage from pesticide resistance (Ma et al. 2021).

Changing climate conditions is a subset of environmental variability, which can impact any stage of the food production system/supply chain (SC) from production to storage and processing, distribution, retail and markets, and finally consumption (Davis, Downs, and Gephart 2021). Of the 325 studies reviewed (Davis, Downs, and Gephart 2021), 89% examined impacts at the production stage, 73% only focused on food production, and a mere 6% investigated the impacts between SC steps. A closer look at SC impact studies showed that very few papers focus on the interactions among economic agents (Inoue and Todo 2019; Kumar and Nigmatullin 2011; Otto et al. 2017). Supply disruptions of major agricultural commodities and food inputs including maize (Tigchelaar et al. 2018; Kukal and Irmak 2018), wheat (Fair, Bauch, and Anand 2017), rice (Horie 2019; Wang et al. 2022), other cereals (Kukal and Irmak 2018), potatoes (Ebrahimji 2020), fruits and vegetables (Yaffe-Bellany and Corkery 2020), and dairy and livestock products (Jeffrey and Newburger 2020) were witnessed in recent years, including impacts caused by the COVID-19 pandemic.

Network-based modeling has been used to assess the downstream impacts of food supply shocks (Tamea, Laio, and Ridolfi 2016; Puma et al. 2015; Gephart et al. 2016; Distefano et al. 2018; Inoue and Todo 2019). Countries that are most vulnerable to external disruption events are highly globalized (Tamea, Laio, and Ridolfi 2016), import reliance (Puma et al. 2015; Gephart et al. 2016), have low gross domestic product (GDP) numbers (Distefano et al. 2018), and low strategic reserves (Marchand et al. 2016). Agent-based modeling (ABM) has been used to compare the indirect effects with direct impacts at global (Inoue and Todo 2019; Otto et al. 2017) and local scales (Fernandez-Mena et al. 2020; Lu et al. 2021) and derive adaptation policies. Another common modeling method is system dynamics to study the food SC, with a focus on the logistics and retail sections (Ge et al. 2004; Kumar and Nigmatullin 2011; Song, Goh, and Tan 2021). While it is important to understand the production substitution impact on prices during disruption, there is limited research on this topic, including studies on a general product (Kuypers et al. 2013), seafood (Gephart et al. 2016), and organic agricultural products (Jia 2021).

Understanding the impact of a food SC disruptions from environmental shocks is very crucial for mitigating the risks of food shortage, price hike, and food quality (Davis, Downs, and Gephart 2021). However, different studies measured such impacts differently. Price disruption is the main indicator to evaluate disruption propagation along the SC (Davis, Downs, and Gephart 2021). Beyond prices, supply quantity (Mu, van Asselt, and van der Fels-Klerx 2021), order fulfillment rate (Barroso et al. 2015), supply shortage (Moosavi and Hosseini 2021), and lost sales cost (Gao et al. 2019) have been used as performance metrics. However, a common limitation of these studies is the use of a single metric to quantify the impact of disruptions.

The main research gap remains on capturing three things: (1) the heterogeneous interests of agents along the SC; (2) the substitution effects during disruption events impacting demand and prices; and (3) the multiple metrics to quantify impacts. To fill these research gaps, this paper uses an ABM framework and Idaho's potato SC as a case study to connect the physical aspects, logistics, and market dynamics for five types of agents—farmers, shippers, processors, retailers, and logistics companies —and two product categories—fresh and processed potatoes. We designed two climate-related disruption events—drought and snowstorm—and quantified the heterogeneous impacts at different stages of the SC using multiple key performance indicators (KPIs). This framework exhibits four important aspects of a SC: (1) complexity; (2) dynamic behavior; (3) agent heterogeneity; and (4) agent interactions. Stakeholder decisions are heterogeneous because they have different functions in the SC and constraints to their operations (Lu et al. 2021). The outcome of one agent's behavior affects the next agent along the SC. Downstream agents must plan accordingly if input quantity and prices change. Conversely, upstream agents need to take actions when they get feedback from downstream agents.

This paper makes four main contributions to the literature. First, it analyzes the heterogeneous impact of climate change on various agents along the SC, which is the basis for developing risk management strategies. Second, a wide range of performance metrics have been considered to measure the disruption impacts at different SC stages. Third, sensitivity assessment demonstrates non-linear relationships between disruptions and impacts enabling future research to set thresholds for SC resilience. Finally, substitution effects during disruption events were evaluated dynamically to reveal price hike impact of one commodity on another.

2. Methodology

2.1 The Potato Supply Chain and Model Overview

The potato SC consists of 14 major stakeholders including seed producers, farmers, chemical suppliers, water suppliers/irrigation companies, utility companies/power suppliers, telecommunication service providers, shippers, frozen food companies, dehydrated food companies, logistic companies, rail companies, gas suppliers, retailers, and food services, as shown in Figure 1. Export represents distant consumers and is similar to the retail sector. The farmers can choose to sell potatoes directly to processing companies via annual contracts at agreed-upon prices. Alternatively, they can sell potatoes to the open market using shippers as the middleman. Prices of the open market fluctuate based on seasonal demand and supply. The shippers wash, sort, and package potatoes to deliver to the retail sector or frozen food companies. Because processing companies mostly source potatoes directly from contracted farmers, they only source a small portion of potatoes from the open market when the contracted amount is not sufficient.

In this paper, five core stakeholders were considered—farmers, shippers, frozen food companies (or processing companies), logistics companies, and retailers. The other stakeholders were not considered to model the supply chain (SC) because either their contributions are not substantial enough or not explicit on the SC. For example, the export sector accounted for a small portion of

U.S. potatoes, about 10% in 2018 (Du, Taylor, and Ruhoff 2019), and hence excluded from the model. The Food services sector was not considered because sales to processors accounted for ~70% from 2017 to 2019 (USDA 2020). To simplify product types, only frozen food companies were chosen. The seed producers' productivities are less likely to be affected because their operations are well-controlled in greenhouse settings. Other utility suppliers' (i.e., fertilizer, biocides, and gas suppliers) contributions to the SC are not direct and hence excluded from the model.

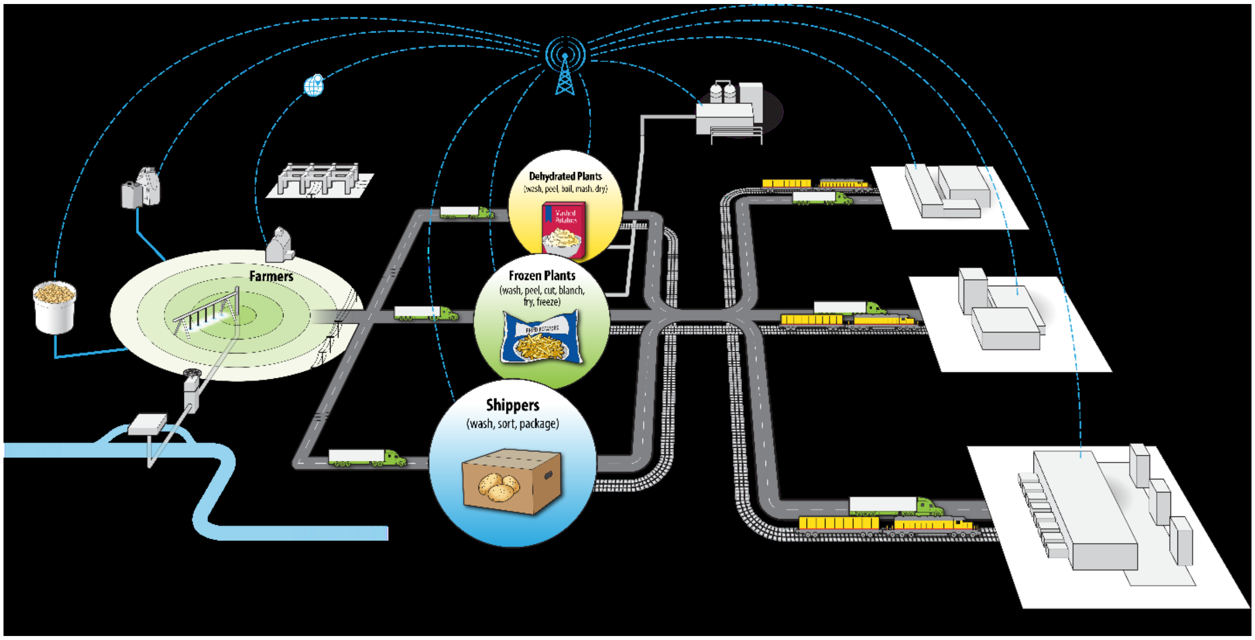


Figure 1: Potato SC stakeholders, supporting infrastructures, and required inputs.

The simulation model was built in AnyLogic Professional 8.7 (AnyLogic 2022), a powerful agent-based simulation modeling software. The software allows users to connect with external databases, import geographic information system (GIS) maps, and write custom codes in Java programming language to model very complex systems (Rahman, Zhou, and Rogers 2019; Rahman, Galvez, and Zhou 2021; Rahman and Zhou 2018). It also allows connecting with the open street map (OSM) database (Haklay and Weber 2008) to import road network data. Moreover, trained machine learning Python models can be integrated with AnyLogic simulation models using the Pypeline library (Tyler 2020). These features meet the modeling needs to develop our SC model. The SC model contains eight farmers, two shippers, two processors, three retailers, and two logistics companies. Each of the logistics companies owns 10 trucks and each shipper owns three in-house vehicles. The time step was one hour, while the time horizon was three years. This time horizon was chosen so that the model can reach equilibrium in the first year after initialization. Disruption events are introduced in the second year and impacts can be observed in the second and third years. The spatial scale was set so that 10 pixels are equivalent to one meter in distance. The geographic information system (GIS) capability of AnyLogic has been utilized to generate the transportation network information of Idaho by linking with the open street map (OSM) server (Haklay and Weber 2008).

Figure 2 shows the conceptual framework of our simulation model and integration with different components. Each of the aforementioned stakeholders was modeled as an agent class in ABM. In addition to the five primary agent classes, the model has a "shipper vehicle" class representing in-house vehicles owned by the shippers, the "semi-truck" class owned by the logistics companies, and the "order" class containing a list of attributes such as order generation date, order quantity, product types, customers, due date, and delivery address. Under each agent class, we defined several state variables to help model the behaviors and actions of the agents. The list of parameters for model initialization are provided in Table S1 of the supporting document along with brief descriptions of the state variables, types, and their sources. The required data to initialize our model came from five separate databases, namely farmer DB, shipper DB, processor DB, logistics company DB, and retailer DB. These databases include information regarding agent attributes like name, longitude, latitude, warehouse capacity, farmland area, number of owned vehicles, contract status, etc. The input data of the databases come from surveys, stakeholder interviews, and publicly available data. A machine learning (ML) model has been integrated into the simulation to project market price dynamics. More descriptions of the ML models are provided in Section 2.3. The target statistics are collected and exported to a CSV file. A Python script is then employed for further analysis and extracting useful information from the exported data.

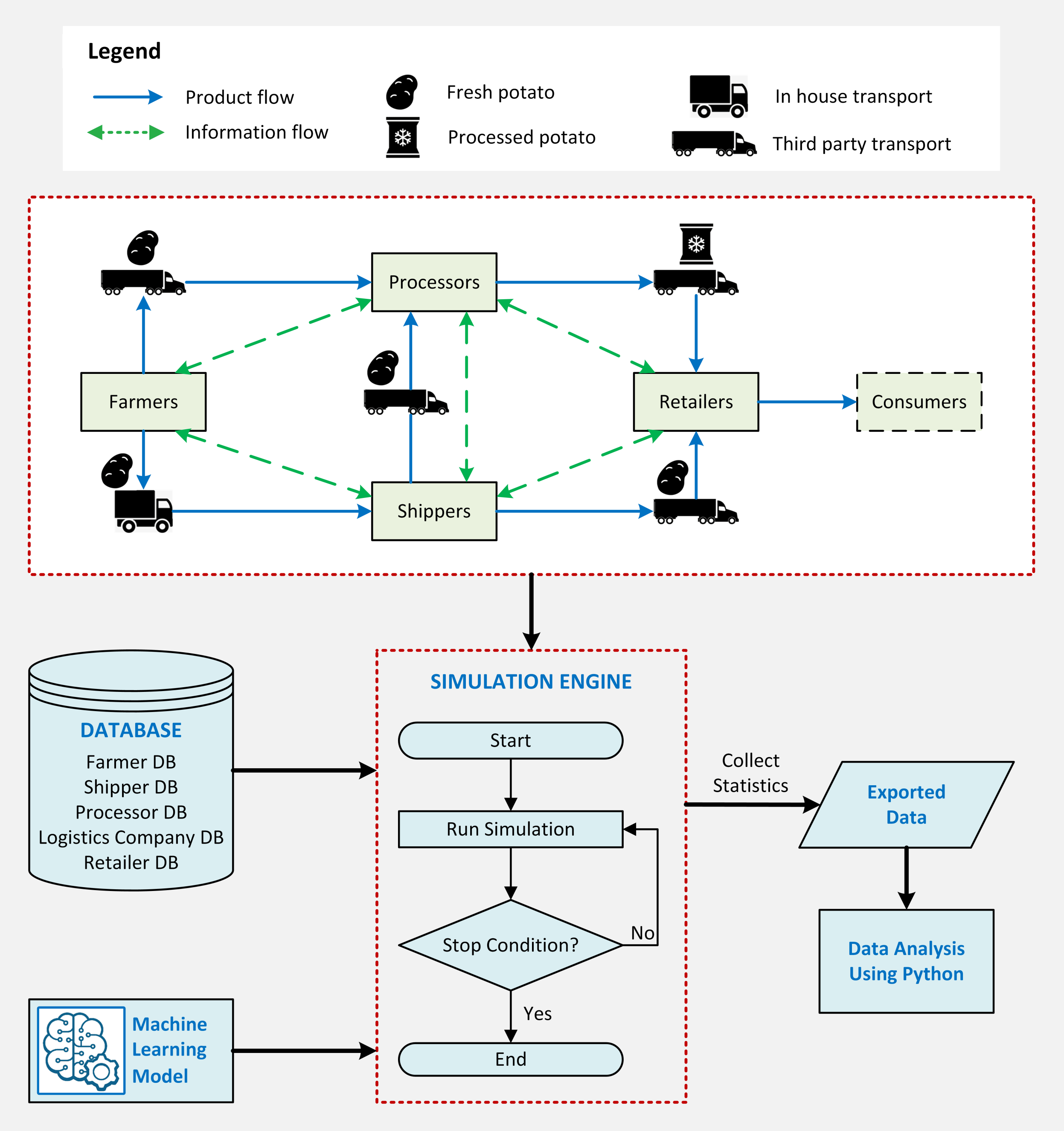


Figure 2: Conceptual framework of the simulation model and integration with different components.

2.2 Agent Description

2.2.1 Farmers

There are two major types of farmers—those with contracts and those without contracts. Farmers with contracts sell their potatoes directly to processors at an agreed-upon price, while farmers without contracts sell their potatoes to the shippers in the open market at the current market price. Farmers start preparing their land at least one month prior to planting seed potatoes. Depending on the farmer's geography, they are divided into early, regular, or late growers. Figure 3 presents the timeline of growing potatoes in southern Idaho. The potato planting season starts in early April and goes through mid-May (Idaho Potato Commission 2021). There are primarily four growing stages of potato plants (Fabeiro, Olalla, and de Juan 2001). The first 30 to 40 days after planting seed potatoes are called "plant establishment" (e.g., sprout development, vegetative growth). The next 15 to 20 days are called "tuber initiation" when the tuber starts forming at the stolon tips. The subsequent 45 to 55 days are called "tuber bulking" when the tuber size increases by accumulating water, carbohydrates, and nutrients. The following 20 to 25 days are referred to as "ripening" when the vines turn yellow, lose leaves, die, and tuber growth stops. The harvesting season starts in early September for early growers and in October for late growers (Idaho Potato Commission 2021).

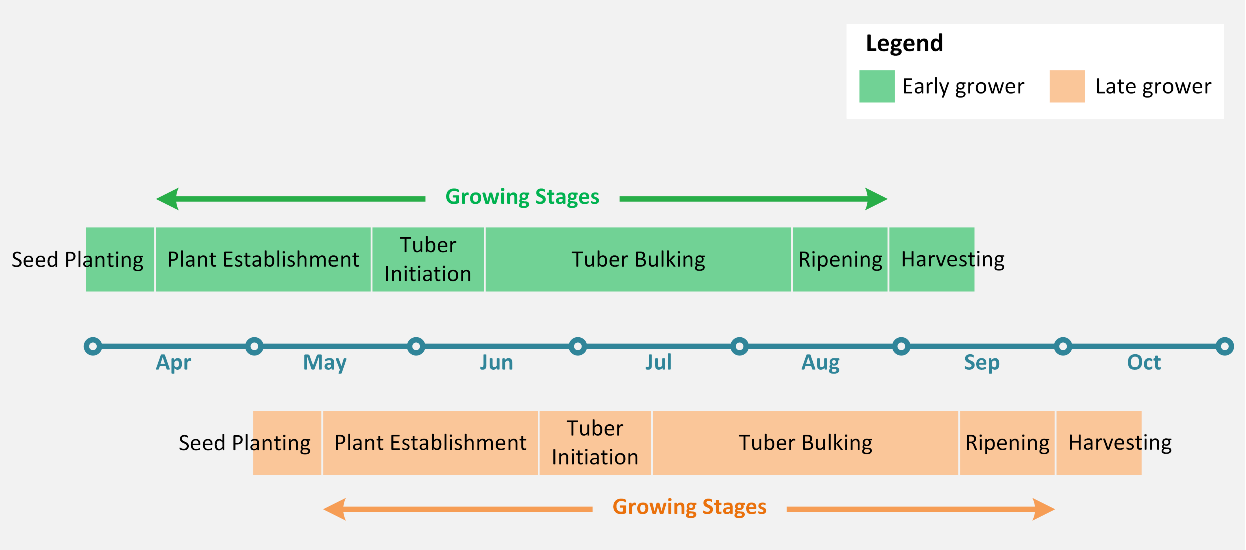


Figure 3: Potato growing timeline in southern Idaho regions.

In our simulation model, we assumed that one-third of the farmers in our model are early growers (primarily located in the southern region), one-third are regular growers (primarily located in the mid-region) who start planting during the last week of April, and the remaining are late growers (located in the northern region). Around one-fourth of the farmers (1,545 acres of farmland) sell their potatoes at the contract price and the rest of the farmers (2,669 acres of farmland) sell their potatoes at the open market price. After harvesting, the potatoes are stored in climate-controlled warehouses until they are sold. The warehouse temperature is maintained between 45 to 50 degrees Fahrenheit (Voss, Baghott, and Timm 2001). The stored potatoes are subject to weight loss over time. To minimize this weight loss, it is recommended to maintain 95% relative humidity in the storage facility (Singh and Ezekiel 2003). The longer the potatoes are stored in warehouses, the more they lose weight (see Figure S2 in the supporting document). We derived a linear regression model, which is shown in Eq. 1, where is the weight loss (in percentage) of the stored potatoes and is the storage duration (in months). The coefficient of determination () of the regression model is 0.975, which is considered satisfactory. We utilized this equation in our simulation model to calculate weight loss over time.

(Eq. 1)

Since the potato is an annual crop, in our simulation model, the injection of fresh potato inventory happens only during the harvesting period. We assumed that the first-in-first-out (FIFO) sequence is applied to orders that farmers receive from processors and shippers. The farmers without contracts sell their stored potatoes on the open market at the current market price. If their unsold potatoes remain at the end of a season, the farmers dispose of the potatoes to make room for the upcoming season's harvest.

2.2.2 Shippers

Shippers act like traders in the SC. They buy fresh potatoes from farmers, and then wash, sort, package, and sell those potatoes to retailers and processors at wholesale price. They do not typically maintain a large inventory and replenish their warehouses frequently. Shippers have their own vehicles to transport potatoes from the farmers' warehouses to theirs. However, they depend on third-party logistics companies to deliver orders to the facilities of processors and retailers. They also follow the FIFO rule to process orders. To place orders with the farmers, they first check their inventory status every 24 hours and only initiate a new order when their inventory level reaches a pre-established reordering point. Next, shippers determine order quantity as the difference between storage warehouse capacity and current inventory level. They create a list of farmers who are eligible to deliver the required quantity at open market price. Finally, they place the order with the farmer closest to their location. Different steps of the order placing algorithm are schematically shown in Figure S3 of the supporting document.

2.2.3 Processors

Processors primarily purchase potatoes from farmers with contracts at an agreed-upon price. When contracted supply is not sufficient, they outsource the rest of the fresh potatoes from shippers at a wholesale price. They follow the steps shown in Figure S3 of the supporting document to initiate and place orders with farmers and shippers. They process the fresh potatoes to produce frozen french fries and sell them to retailers, food service companies, and restaurants. We assumed the production capacity of the processors is 12 to 15 tonnes per day and the weight conversion factor from fresh to processed potatoes is 0.8 (Willersinn et al. 2015).

2.2.4 Retailers

In our model, the retailers sell fresh and processed potatoes to the consumers. The retailers experience seasonal demand variations for fresh potatoes. For example, consumers usually buy more potatoes during November and December because of Thanksgiving and Christmas holidays. On the other hand, the demand variations for processed potatoes due to seasonality are negligible. The retailers continuously review their inventory levels and place orders to the shippers for fresh potatoes and to the processors for processed potatoes following the steps shown in Figure S3 of the supporting document.

2.2.5 Logistics Companies

The logistics companies provide logistics services to transport fresh and processed potatoes from one facility to another using semi-trucks. The semi-trucks follow the actual road network and the corresponding road speeds to transport materials. In our simulation model, the necessary data related to the road network comes from the OSM server (Luxen and Vetter). Figure S1 in the supporting document shows a snapshot of the simulation model in the GIS environment illustrating the movements of the trucks. The trucks contain all the necessary order information including pick-up location, delivery location, order quantity, and so on.

2.3 Price Model

To develop an effective price model, we followed the following two-step approach:

Step 1: We developed a machine learning (ML) model to predict monthly potato prices at the grower level considering yearly trends and seasonality. Here the predictor variables are year and month, and the response variable is the potato price. The monthly potato price data were collected from the U.S. Bureau of Labor Statistics (U.S. Bureau of Labor Statistics 2021) for the periods August 2006 to August 2019. A wide range of state-of-the-art ML algorithms was utilized including support vector regression (SVR) (Awad and Khanna 2015), decision tree (DT) (Myles et al. 2004; Rahman et al. 2019), random forest (RF) (Breiman 2001), and long short-term memory (LSTM) (Greff et al. 2017), which is a variant of the artificial recurrent neural network (RNN). To compare the performances of the ML models, we calculated mean absolute percent errors (MAPEs) and found that the RF algorithm outperformed other models. A detailed description of the model validation technique is discussed in section 2.6. Figure 2 shows the integration of the ML model with the simulation model. We used the Scikit-Learn library (Pedregosa et al. 2011) in Python to train our ML model and the Pypeline library (Tyler 2020) to communicate the trained ML model with the AnyLogic simulation model.

Step 2: In this step, the predicted monthly base potato price in Step 1 is adjusted based on dynamic demand and supply of specific scenarios utilizing Eq. 2 (Nguyen et al. 2021; Lu et al. 2021). In this equation, is the adjusted monthly price of potatoes at the grower level, is the predicted monthly price using the ML model from step 1, is the monthly supply quantity by the growers in the market, is the monthly demand quantity in the market, and is the price elasticity of demand. Our simulation model tracks the growers' cumulative supply amount to the market and simultaneously the cumulative amount of demand the growers experience each month. These monthly supply and demand data are used as inputs in Eq. 2 to predict adjusted monthly potato prices.

(Eq. 2)

We used the epsilon (value of for fresh potatoes (Andreyeva, Long, and Brownell 2010) and for processed potatoes (Katchova, Sheldon, and Miranda 2005). To model the potato price downstream of the SC, we assumed that the price of fresh potatoes is 40% higher at the shipper level and 144.5% higher at the retailer level compared to the farmer's selling price (WGA 2019; Stewart and Hyman 2022). To determine the price of processed potatoes at the processor level, we utilized Eq. 3, where is the price of processed potatoes (USD/tonne) at the processor level, is the fresh potato contract price (USD/tonne), is the quantity of fresh potatoes purchased from the contracted farmers, is the fresh potato price at shipper level (USD/tonne), is the quantity of fresh potatoes purchased from the shippers, is the processing cost of per tonne fresh potatoes, is the profit margin, and is the weight conversion factor from fresh to processed potatoes. The gross profit margin of the food processing company was 20.37% in 2021 (CSI Market 2022).

(Eq. 3)

In our simulation model, if the retailers face a stockout situation of any of the two products – fresh or processed potatoes, consumers can switch their demand from one to another. The quantity of shifted demand of a product depends on price, product share, and some other interrelated substitution parameters. For a detailed description of this product substitution mechanism, the readers are referred to our previous work (Lu et al. 2021).

2.4 Water Requirement for Potato Production

The yield of potatoes greatly depends on proper water management. To establish a relationship between potato yield and water amount, researchers showed that potato yield is a linear function of irrigated water amount applied during the tuber—growth, bulking, and ripening stages (Fabeiro, Olalla, and de Juan 2001). We used the regression model shown in Eq. 4 (Fabeiro, Olalla, and de Juan 2001). Here, , and are the irrigated water amount during growth, bulking, and ripening stages, respectively, and the yield is in kilograms per hectare. The coefficient of determination () of the regression model is 0.993, which means that 99.3% variability of the response variable (yield) can be explained by the model. Therefore, the model has a good fit to establish the relationship between potato yield and water amount.

(Eq. 4)

Irrigation in Idaho comes from both surface water and groundwater. Water allocation is based on the water rights system (Idaho Department of Water Resources 2021). When there is a shortage, a priority date or water right establishment date is used to determine who gets the water. Senior (oldest) water rights holders get to use their allocations before the junior (new) water rights holders. Therefore, when there is not enough water to satisfy all the rights, junior water rights holders do not get water (Idaho Department of Water Resources 2021). Although water right system does allow to transfer unused water rights into a Water Supply Bank for use by others, during drought, those transfers are very unlikely to happen (Elbakidze et al. 2012). Consequently, a drought event directly translates into lower crop yield rather than water market reallocation.

2.5 Performance Metrics

Overall, four categories of performance metrics—revenue, potato price, order delivery lead time, and potato amount sold/purchased/disposed—have been monitored to examine the impacts of different disruption events on different stages of the SC. These performance metrics are widely used in existing literature. For example, see Yang et al. (Yang et al. 2022) for price analysis in agricultural input supply chains, Ash et al. (Ash et al. 2007) for tracking lead time in agricultural systems, and Bellemare et al. (Bellemare et al. 2017) for measuring food waste. The performance metrics have been grouped as shown below:

a) <u>Revenue</u>: Non-contracted farmer revenue, contracted farmer revenue, shipper revenue, processor revenue, retailer revenue from fresh potatoes, retailer revenue from processed potatoes, and logistics company revenue

b) <u>Order lead time (days)</u>: Processor order lead time (LT), retailer order LT (fresh potato), retailer order LT (processed potato)

c) <u>Potato price (USD/tonne)</u>: Fresh potato price, processed potato price

d) <u>Potato amount sold, purchased, and disposed of</u>: Retailer sales (fresh and processed potatoes), contracted farmer sales to processors, open market sales to processors, and amount of disposed of potatoes.

2.6 Model Validation Method

We validated our model against the monthly potato price. Modeling potato prices correctly is extremely important since consumer demand and supplier revenues depend on the potato prices. The simulated price was compared against the actual price to determine the reliability of the model. To validate an ML model, k-fold cross-validation is a common technique (Fushiki 2011; Rahman, Ghasemi, et al. 2021; Rahman et al. 2020). However, the time series potato price data inherited temporal dependency between observations, and this relationship was preserved during the training and testing of our price models. As a result, the rolling window walk-forward validation (RWWFV) technique (Schnaubelt 2019; Żbikowski 2015; Carta et al.) was followed for our time series data.

As shown in Figure 4, the monthly potato price data were divided into 10 years (120 months) for training (Aug 2006 − Jul 2016), and three years (36 months) for testing (Aug 2016 − Jul 2019).

In each iteration, for the month in the testing, we retrained the price model using data from the previous 10 years () to predict result for the month . Absolute percent error (APE) was calculated in each iteration for the test data. After completing all the 36 iterations, the mean value of the APEs was calculated to compute the mean absolute percent error (MAPE).

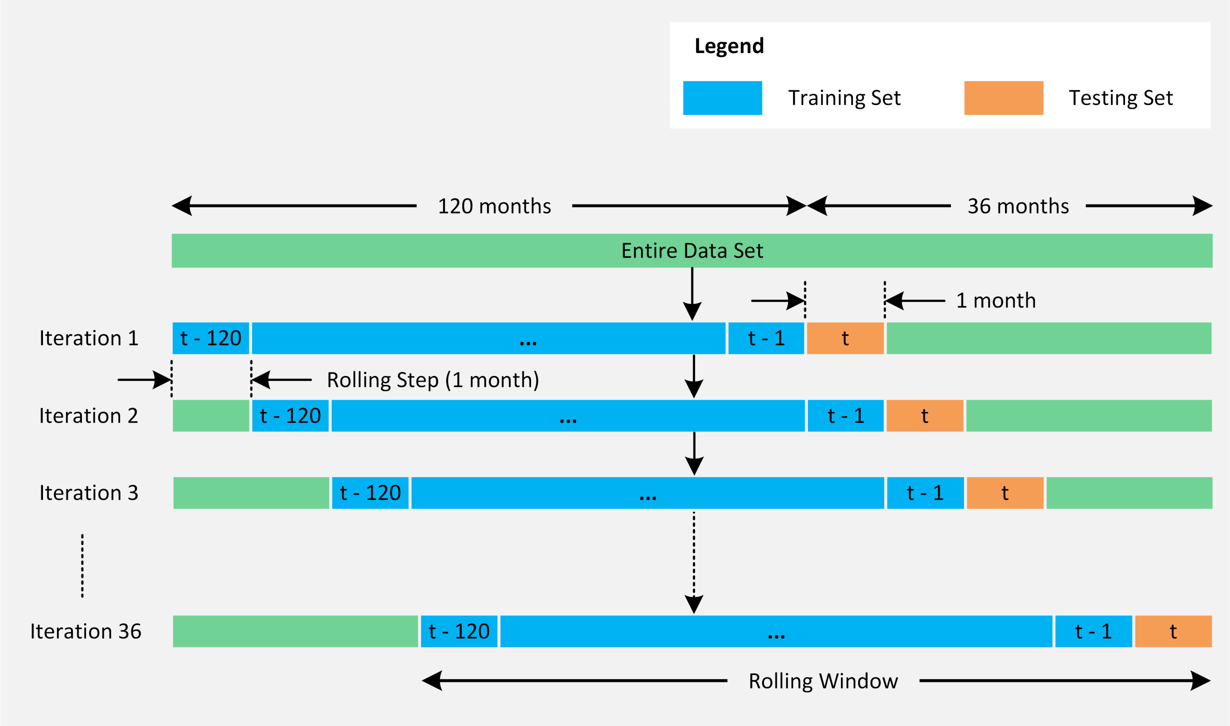


Figure 4: Rolling window walk-forward validation technique. The diagram is not drawn to scale.

The entire price dataset (Aug 2006 − Jul 2019) considered in our study contained 156 observations. It is not uncommon to apply ML models to datasets with similar sample sizes (Patrício et al. 2018; Khozeimeh et al. 2017). The famous ML benchmark “Iris” and “Wine” datasets contain only 150 and 178 observations, respectively (Fisher 1936; Aeberhard, Coomans, and de Vel 1994). Moreover, Figure 5 shows a great agreement between the predicted and actual potato prices with only 4.83% MAPE. Therefore, it can be said that the application of ML models in our study is well justified.

From our stakeholder interviews, we also collected data on order frequencies by shippers and processors, the percentage of potatoes processors outsource from the contracted farmers and open market, etc. We compared our simulated output with these actual data for the baseline model verification and validation purposes.

2.7 Simulation Replications

Due to the stochastic nature of the simulation model, the value of the performance metrics changes with the random seed number. To address this stochasticity, we estimated the errors of the corresponding performance metrics utilizing Eq. 5 (Rahman, Zhou, et al. 2021; Rahman, Jahan, and Zhou 2020), where is the error as a fraction of the sample mean, is the number of simulation replications, is the critical value of the student's t-distribution, is the level of significance, is the sample standard deviation, and is the sample mean.

(Eq. 5)

In AnyLogic, we created a Monte Carlo experiment to run our model iteratively by varying the random seed number. Table 1 summarizes the percentage of error of different performance metrics under different scenarios. As shown in Table 1, we had to run the simulation 100 times to bring the error under 5% for the metric "disposed potato amount" in the business-as-usual (BAU) scenario. For the rest of the metrics, 50 iterations were sufficient to obtain an error below 5%.

Table 1: Number of runs and the corresponding errors of the performance metrics for different scenarios.

Performance metrics	**No. of runs**	**Error**		
		BAU	**Drought**	**Bad weather**
Farmer (without contract) revenue	50	3.29%	4.76%	3.41%
Farmer (with contract) revenue	50	1.04%	3.70%	3.82%
Shipper revenue	50	2.44%	4.91%	2.67%
Processor revenue	50	2.20%	4.30%	2.33%
Retailer revenue (fresh potato)	50	0.31%	0.96%	0.58%
Retailer revenue (processed potato)	50	2.17%	4.24%	2.31%
Shipper revenue without purchase cost	50	2.44%	4.91%	2.67%
Processor revenue without purchase cost	50	2.38%	4.61%	2.45%
Retailer revenue without purchase cost (fresh potato)	50	0.84%	1.51%	0.98%
Retailer revenue without purchase cost (processed potato)	50	2.24%	4.27%	2.39%
Logistics company revenue	50	1.69%	3.35%	2.20%
Disposed potato amount	100	4.67%	0.00%	0.00%
Harvested amount	50	0.00%	1.38%	0.66%
Retailer order amount (fresh potato)	50	0.47%	1.31%	0.65%
Shipper order LT	50	0.97%	1.30%	4.12%
Processor order LT	50	0.42%	0.64%	0.86%
Retailer order LT (fresh potato)	50	0.89%	0.88%	0.87%
Retailer order LT (processed potato)	50	0.63%	0.82%	0.63%

Fresh potato price	50	0.00%	2.11%	0.99%
Processed potato price	50	0.54%	2.08%	1.16%
Retailer sales (fresh potato)	50	0.31%	1.20%	0.57%
Retailer sales (processed potato)	50	2.18%	4.42%	2.93%
Processor potato from contract	50	1.04%	4.88%	3.83%
Processor potato from open market	50	4.85%	4.70%	4.60%

3. Supply Disruption Scenarios

There are potentially many events for which the potato SC can get impacted. Some of the events might impact only one agent group while others might impact several agent groups. Since the agent groups of the SC are interconnected, there is an adverse ripple effect on the overall SC for failures at any stage. In our simulation model, we have designed the following events and measured the impacts at different stages of the SC, as shown in Table 2.

Table 2: Summary of two supply disruption scenarios.

Scenario	Disruption event description	Duration/timing	Directly impacted stakeholders	Direct impacts
1	Severe drought, only 50% of required water for irrigation is available. The contract price between farmers and processors increases by 20%.	Growing season (May 3rd week to August 2nd week)	Farmers	- Reduced yield
2	Extreme weather, early frost or snow. The affected farmers lose 30% of the harvest. The speed of the delivery vehicles reduces by half.	Early October for 1 week	-Farmers -Logistic companies	- Harvest loss - Delayed delivery

3.1 Drought

During the growing season of potatoes, proper irrigation is extremely important. Due to global climate change, various parts of the world are experiencing frequent droughts. In our simulation model, we designed a drought event during the growing season for potatoes from the third week of May 2018 to the second week of August 2018. This event has a negative impact on potato production, and hence, on the market supply. We assumed that all farmers will be impacted due to the drought event and the water supply would be 50% of the regular amount required for potato production. In reality, because of the water rights system, senior water rights holders still have full water supply whereas junior water rights holders might not get enough water. But overall, the percentage of affected irrigated areas is proportional to that of water availability.

Because of this water allocation system and constraints during a water shortage, farmers cannot grow more potatoes given a fixed amount of farmland. In addition, the relationships between processing companies and contracted farmers are strong and they are locked up in the same number of contracts over time. The only change is that contract prices will be adjusted to a higher price to compensate for supply reduction.

3.2 Extreme Weather

Weather plays an important role to produce potatoes. Favorable weather condition helps farmers to get a better yield. On the other hand, bad weather like early frost could cause a 30% harvest loss (Foerster 2019). Moreover, when there is frost in the lower elevations, heavy snow occurs in the higher elevations and disrupts the transportation network badly and lengthen the transportation time among facilities. Consequently, there would be an adverse effect on the potato supply in the market. In our model, we have designed an inclement weather event (early frost) during early October 2018 with a one-week duration and investigated the consequences on different performance metrics.

4. Results and Discussion

4.1 Business-As-Usual Model Validation

Figure 5 shows the monthly open market simulated price versus the observed price of fresh potatoes for our entire simulation period, August 2016 to July 2019. The monthly observed price of fresh potatoes at the farmer level has been collected from the U.S. Bureau of Labor Statistics (U.S. Bureau of Labor Statistics 2021), which shows our price model has captured the seasonality and linear trend well. The calculated MAPE is 4.83%. Therefore, it can be said that our simulated price with the help of our ML model is in great agreement with the actual monthly observed price.

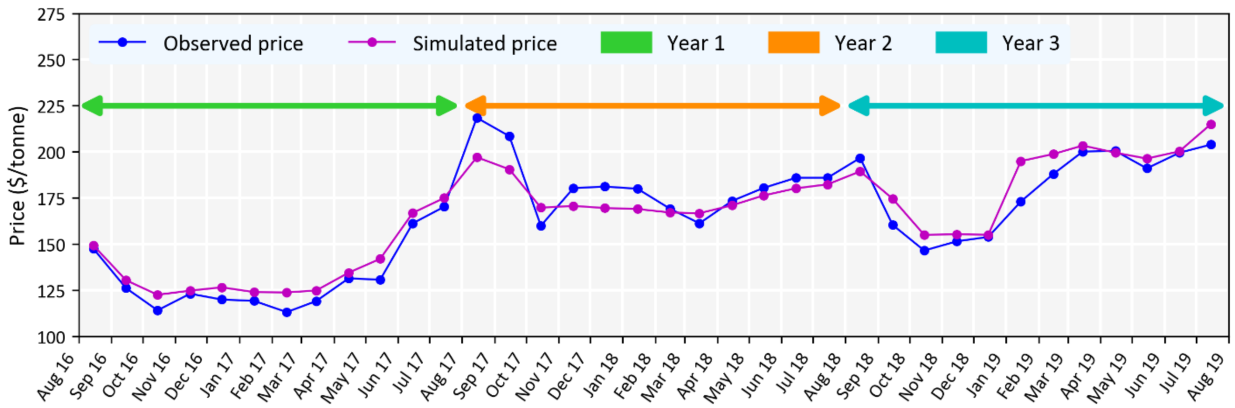


Figure 5: Simulated versus observed price.

Besides, we compared the number of orders placed by shippers and processors collected from our simulation model with the data attained from our stakeholder engagement meetings. In practice, on average, shippers place orders twice a week and processors place orders once a week. According to the statistics obtained from our simulation model, the average number of weekly orders placed by shippers and processors are 2.04 and 1.05, respectively. Therefore, the statistics agree with the actual data. Also, according to our stakeholder engagement, on average, processors source 80% of the fresh potatoes from the contract farmers and the remainder from shippers. Simulation output showed that processors sourced 76.4% of fresh potatoes from the contract farmers and the remainder from shippers. This statistic is also quite close to the actual value.

4.2 Impact of Drought on Potato Price

Figure 6 displays the time plot of potato prices for BAU and drought event scenarios for a base run. The red shaded area shows the drought event timing during the growing season of the second year. As a result, the second year's yield received the impact according to Eq. 4. Because of poor yield, the supply of potatoes during the third year dropped as compared to the BAU scenario. Therefore, the price of fresh and processed potatoes increased significantly during the third year. The price hike started at the upstream of the supply chain, from the grower level. Growers supplied less quantity of potatoes due to poor yield. Consequently, the price of potatoes increased (as per Eq. 2) due to the gap between demand and supply at the open market. As a chain effect, the downstream of the supply chain experienced high potato prices as explained in section 2.3.

At grower level, the third-year average price of fresh potatoes was $315.2 per tonne with the drought as compared to the BAU average price of $186.5 per tonne. On average, the price hike was 69.0% due to drought. Since fresh potato demand is inelastic, the consumer demand stays consistent irrespective of price hike. Consequently, the price increased gradually and continued until the next harvest season. On the other hand, the average price of processed potatoes increased from $495.6 to $602.1 per tonne resulting in a 21.5% price hike. The price of processed potatoes increased sharply during initial periods because of increased processed potato demand due to substitution and increased input fresh potato cost. Since the demand of a processed potato is elastic, consumers buy less during a price hike. Therefore, during later periods of the third year, the price dropped slightly because of less consumer demand and reached a steady state.

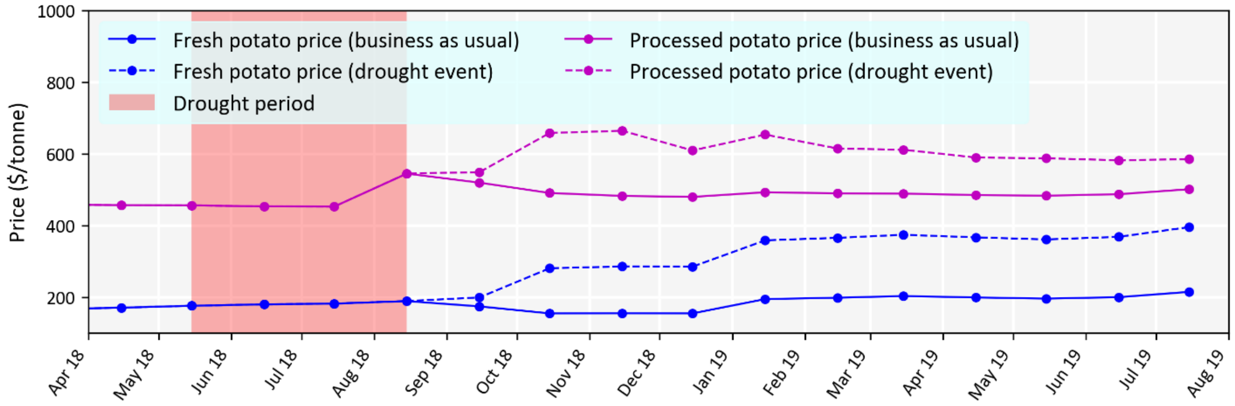


Figure 6: Impact of drought event on fresh potato price.

4.3 Impact of Bad Weather on Potato Price

Figure 7 demonstrates the time plot of BAU and early frost event for a base run. The red shaded area denotes the actual timing of the event during October 2018, the third year of the simulation. As a result, later growers who planned to harvest in October 2018 faced harvest loss due to this early frost. We assumed that the affected farmers lost 30% of their regular potato yield. Due to the harvest loss of one-third of the farmers, the third-year supply of potatoes drops as compared to the BAU scenario. According to the plot, on average, the price of fresh potatoes increased by 20.2% from $180.5 to $224.1 per tonne, while the price of processed potatoes increased by 4.2% from $495.6 to $516.45 per tonne. Similar explanation provided in Section 4.2 based on demand elasticity is applicable here as well.

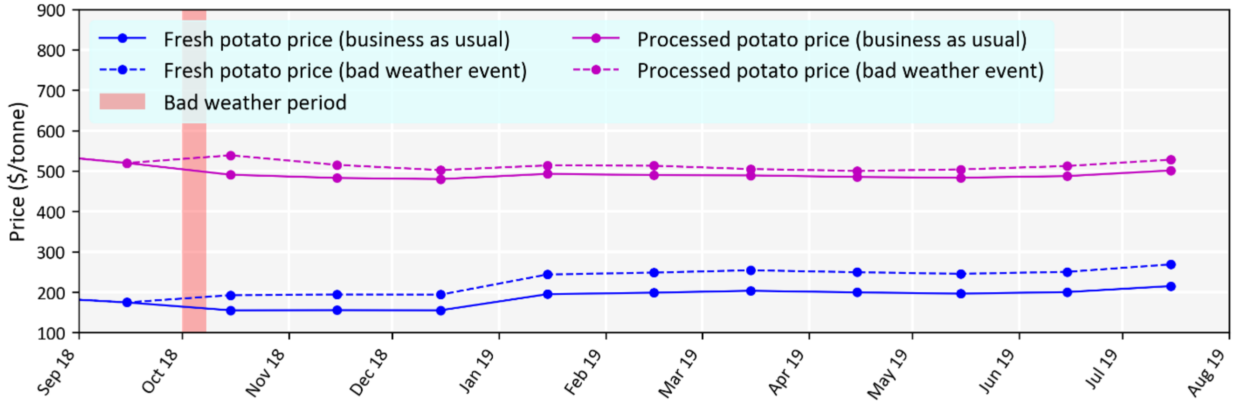


Figure 7: Impact of bad weather (early frost) event on potato price.

4.4 Overall Impacts of Disruption Events on Performance Metrics

Figure 8, Figure 9, and Figure 10 summarize overall comparisons of the disruption events (e.g., drought, early frost) on different performance metrics. The timings of the disruption events have been designed so that the impacts are observed primarily during the third year of the simulation period. All the statistics, except the order delivery lead times, are collected for the third year for comparison purposes. The order delivery lead times are collected for the duration of the bad weather event. The green horizontal bars denote the BAU scenario, the yellow bars denote the drought event scenario, and the blue bars denote the early frost event scenario.

According to Figure 8, the drought event severely impacted the harvest amount, 31.6% less harvest as compared to the BAU scenario. On the other hand, the early frost event caused harvest loss to late growers and resulted in 10.8% overall harvest loss as compared to the BAU scenario. Subsequently, the price of both fresh and processed potatoes increased due to the decreased supply. It is important to note that the price of processed potatoes did not increase as much as fresh potatoes. This is consistent with the demand elasticity estimates by Richards and Kaiser (Richards and Kaiser 2017). Since the demand for processed potatoes is almost 4.5 times more elastic than fresh potatoes, the demand from consumers for processed potatoes is very sensitive to price as compared to fresh potatoes. Therefore, the system reaches the equilibrium state with a high price for fresh potatoes and a comparatively lower price for processed potatoes during disruption events. In addition, when demand for processed potatoes increases at the retailer's end, demand for fresh potatoes automatically increases for processors to meet the product demand. This is another reason for the relatively higher price hike of fresh potatoes. It is also evident from the plot that retailers experienced a relatively sharp sales decline of processed potatoes as compared to fresh potatoes. Processors become more dependent on the open market for outsourcing fresh potatoes because of disruption events. In the BAU scenario, processors source 76.4% fresh potatoes from the contracted farmers at the contract price and the remaining 23.6% from the open market at market price. They sourced almost 6% and 2% more potatoes from the open market during drought and early frost scenarios, respectively.

Figure 8: Impact of disruption events on potato prices, harvests, and traded amounts.

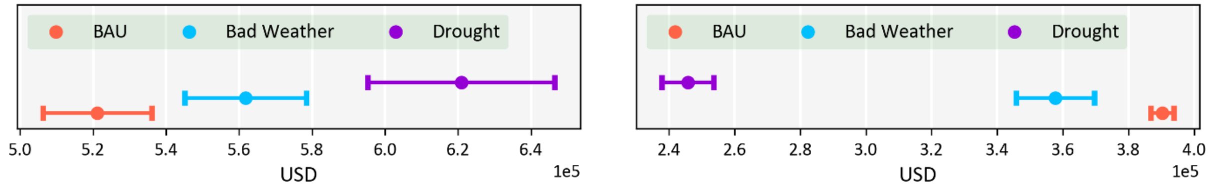
We can observe some interesting outcomes in Figure 9. The farmers with contracts lost a significant amount of revenue because of the disruption event. Since these farmers had to sell their potatoes at an agreed-upon price, the farmers lost revenue primarily because of harvest loss. On the other hand, although farmers without contracts experienced harvest loss during the disruption events, their losses were compensated by higher selling prices. The result is consistent with Ligon (Ligon 2003) who proved that when farmers produce under a contract, there is an important balance between risk and incentives. Non-contract farmers did not produce under any contract and took the risk of losing revenue in case of bad market price due to overproduction. They received the reward by selling their potatoes at a very high price during the disruption events. On the other hand, retailers and processors lost revenue due to the disruption events when selling processed potatoes. There are two potential reasons. First, they experienced significantly fewer sales due to reduced consumer demand for processed potatoes. Consumers purchased 42.5% and 6.6% less processed potatoes during drought, and early frost, respectively. Second, the price hike of processed potatoes was not enough to recoup their losses. For example, during drought, the price of processed potatoes increased by 20.9% only, while the price of fresh potatoes increased by 78.2%. Since consumers were less sensitive to the fresh potato price increase, shippers and retailers earned comparatively more revenue by selling fresh potatoes than in the BAU scenario. Overall, logistics companies lost revenue during the disruption events since they transported fewer orders as compared to the BAU scenario. This result agrees with what Hu et al. observed (Hu et al. 2021).

Figure 9: Impact of disruption events on the revenue of different stakeholders.

Figure 10 displays the impact of a snowstorm on order delivery lead times. Due to closure and poor accessibility to roads, processors and retailers experience longer delivery lead times as compared to the BAU scenario delivery lead times. We did not include the drought scenario in this plot because there is no impact of drought on the performance of a delivery truck.

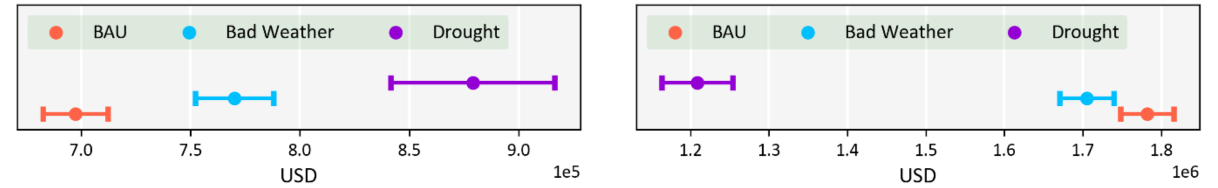
Figure 10: Impact of snowstorm on order delivery lead times

Figure 11 exhibits 95% confidence interval plots of some important performance metrics. In the figure, the overlapping confidence intervals are not statistically significant, while the mean values of the metrics related to revenue and traded amount are statistically different for all three scenarios—BAU, bad weather, and drought. However, the order delivery lead times for drought event is not statistically different from the BAU scenario because the drought event does not have any impact on the delivery trucks or the transportation network. On the other hand, the bad weather (early frost) affected the transportation network and increase order delivery time. Therefore, the order lead times are statistically lengthier than the BAU scenario for this case.



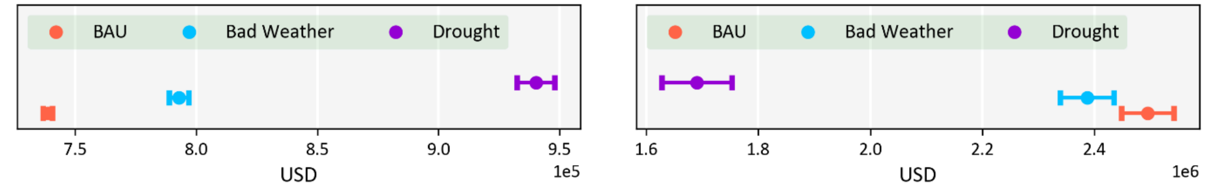
(a) Farmer (without contract) revenue

(b) Farmer (with contract) revenue



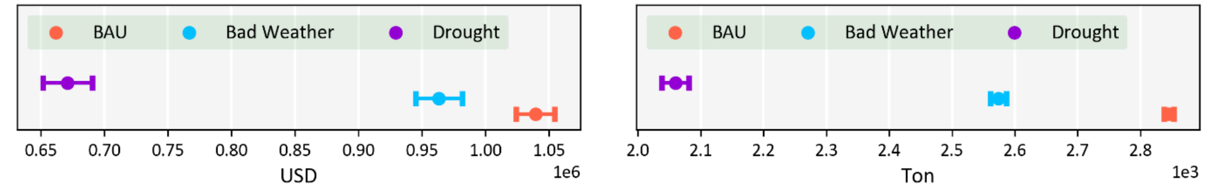
(c) Shipper revenue

(d) Processor revenue



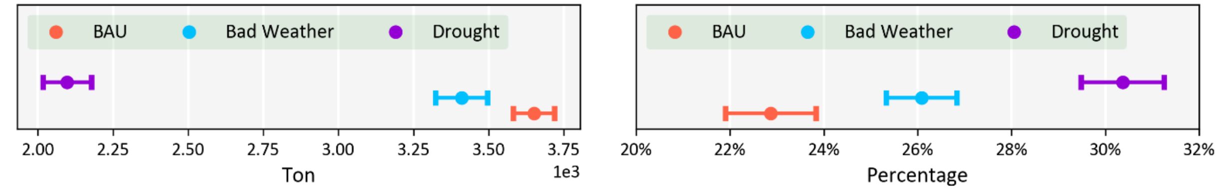
(e) Retailer revenue (fresh potato)

(f) Retailer revenue (processed potato)



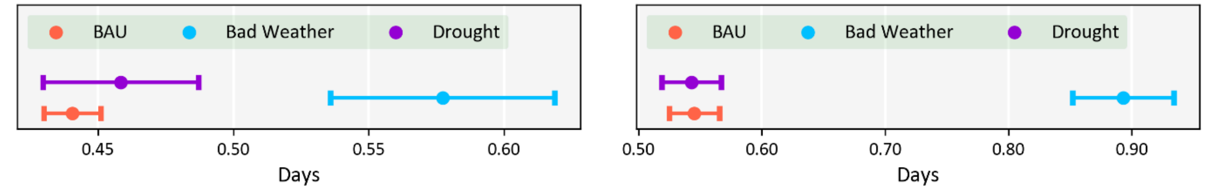
(g) Logistics company revenue

(h) Retailer sales (fresh potato)



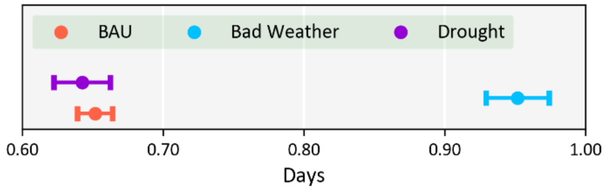
(i) Retailer sales (processed potato)

(j) Outsourced potato from open market by processors



(k) Processor order delivery LT

(l) Retailer order delivery LT (fresh potato)



(m) Retailer order delivery LT (processed potato)

Figure 11: 95% confidence interval plot for different scenarios.

4.5 Sensitivity Analysis

Figure 12 displays sensitivity analysis by showing the change of different parameters and the corresponding impacts on the relevant performance metrics in tornado plots. On a tornado plot, the higher the position of a metric along the vertical axis, the higher the sensitivity.

Figure 12(a) shows the impacts on performance metrics if the water shortage increases or decreases by 10% as compared to the baseline drought scenario where the farmers experience a 50% water shortage. As per the plot, due to higher water shortage, the yield gets impacted and farmers harvest 8.7% fewer potatoes. Consequently, the price of fresh and processed potatoes increases by 15.8% and 8.2%, respectively. Due to higher prices, consumers purchase less compared to their regular amount, and hence, the retailers experience declines in sales by 7.0% and 18.7% for fresh and processed potatoes, respectively. On the other hand, if the water shortage decreases by 10%, farmers harvest 9.5% more, the fresh potato price decreases by 13.4% and the processed potato price decreases by 4.2%. Due to the lower prices, consumers purchase more, and therefore, sales of retailers rise by 7.7% and 11.0% for fresh and processed potatoes, respectively.

Figure 12(b) illustrates the impacts on KPIs if the harvest loss increases or decreases by 10% as compared to the baseline early frost scenario of 30% harvest loss. As per the plot, due to 10% additional harvest loss, the price of fresh and processed potato increases and retailers sell fewer potatoes due to less consumer demand. On the contrary, if the harvest loss is 10% less, the impacts on the KPIs are opposite.

Figure 12(c) displays the sensitivity of contract prices between processors and farmers on relevant KPIs. When the contract price increases by 10% as compared to the baseline drought scenario, farmers with contracts receive 5.8% additional revenue. Since processor purchase cost increases, the price of processed potatoes increases. Consumer demand for processed potatoes decreases, and consequently, retailers sell 4.1% less processed potatoes. As a result, retailers and processors receive 3.1% and 2.8% less revenue, respectively. It should be noted that, for all three plots, the shapes of the tornado plots are not symmetrical along the vertical axis. Therefore, the relationships among the input parameters and the output KPIs are not linear.

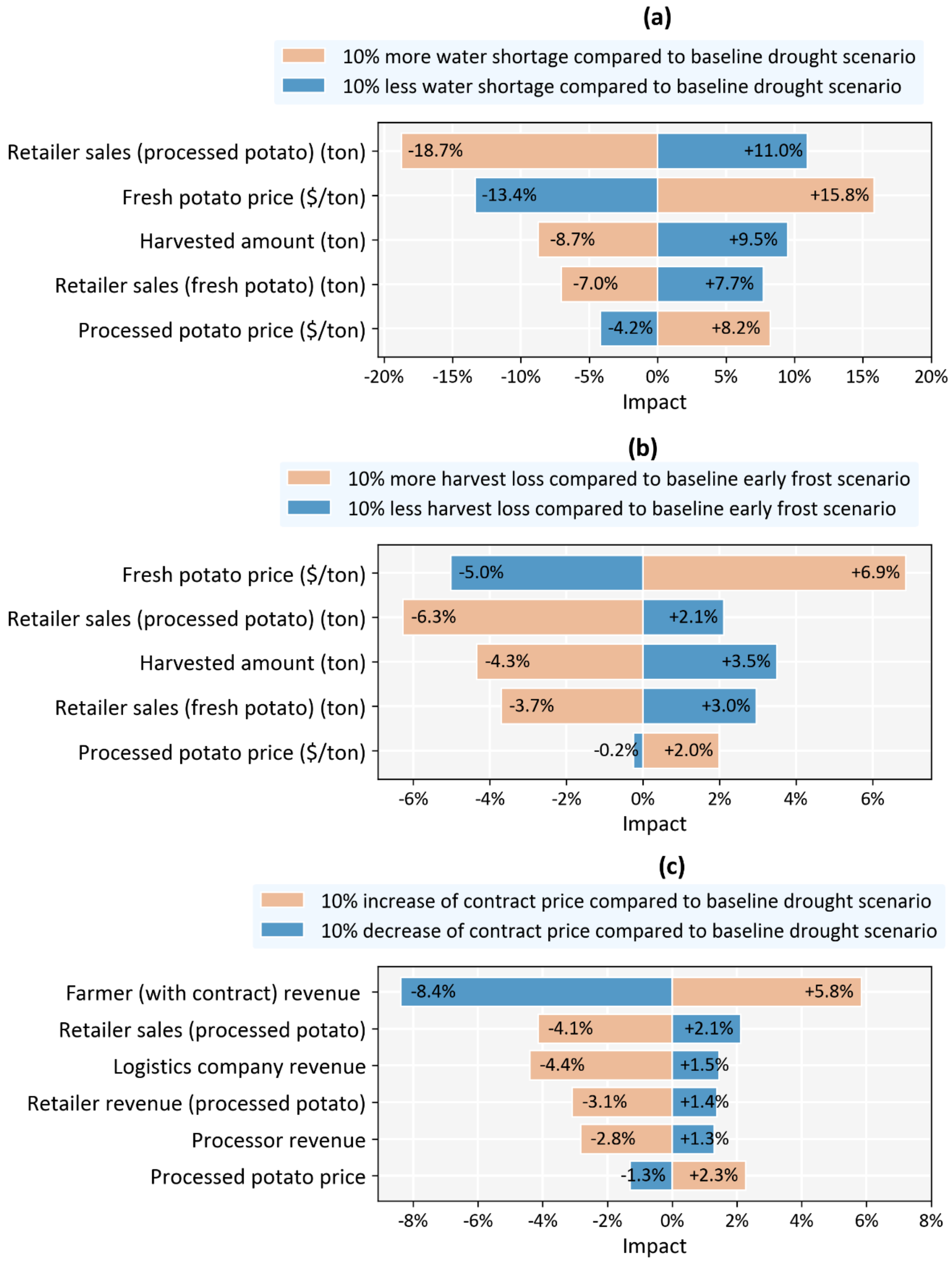


Figure 12: Tornado plots for sensitivity analysis. (a) Impact of irrigation water shortage due to drought. (b) Impact of harvest loss due to early frost. (c) Impact of contract price rise between farmers and processors during drought.

4.6 Limitations and Future Directions

The following limitations of this study should be noted for future research opportunities:

- Agent-based models are computationally intensive (Rand and Rust 2011; Tang et al. 2011; Bernhardt 2007). Our model considered a limited number of agents, although the developed simulation framework can be applied for large-scale simulations. In the future, we plan to utilize high-performance computing (HPC) for the development of a large-scale simulation model.
- This study investigated two climate change-related disruption events, but potentially other events like flood, temperature increases, shifting of seasons, change of rainfall patterns, and degradation of soil health can be studied as well.
- The change in timing of the disruption events has not been investigated in this study because the emphasis was on quantifying the most significant impacts. A previous study (Lu et al. 2021) shows that the impacts of a disruption event on the agricultural SC can be different depending on the timing of the event.
- We modeled the rational behavior of consumers during disruption according to the relationship between prices and demand via the price elasticity of demand. However, it is not uncommon to see irrational behavior during disruption events such as "panic purchase" or "hoarding behavior" (Wang and Na 2020) when consumers anticipate supply shortage beyond the short-term. With this behavior, consumers would buy more irrespective of price hike.
- Remote sensing (RS) from satellites or unmanned aerial vehicles (UAVs) can provide useful data associated with climate change impacts on temperature, groundwater, soil moisture, and water salinity (Khanal et al. 2020; Mulla 2013; Maes and Steppe 2019; Jung et al. 2021). For future research scope, we plan to integrate RS in our model to simulate more scenarios in different geographic regions for a robust and comprehensive analysis.
- A survey on the contracting question for the farmers on uncertainty context could be also useful as our simulation results rely on accurately estimating the share of contract farmers. Such a survey could potentially improve the precision of our simulation results in terms of market equilibrium prices and quantities.

5. Conclusions

In this study, an agent-based simulation model of Idaho's potato SC was developed that includes five different agent types ranging from farmers to retailers. The substitution effect among two commodities on price was also investigated. We leveraged the capabilities of ML by integrating a price mechanism into our simulation. The performance of the ML-powered simulation model is promising to emulate the actual price dynamics with minimum error. In addition to the BAU scenario, two climate change-related disruptions—drought and early frost have been modeled. The heterogeneous impacts at different stages of the SC in terms of revenues, prices, lead times, traded quantities, and food wastes have been quantified. The key findings from the experiments can be summarized as follows:

- The impacts of the disruption events were different on different agents in the SC for different product categories.
- The price hike of fresh potatoes was much higher than processed potatoes during the disruption events. For example, during drought, the price of fresh potatoes increased by 78.2% while the price of processed potatoes increased by 20.9% only.
- During disruption events, agents dealing with processed potatoes were affected more in terms of total revenues compared to the agents dealing with fresh potatoes. For instance, processors and retailers lost revenues for processed potatoes. In contrast, non-contracted farmers, shippers, and retailers did not face the loss from fresh potatoes because of higher market price.
- Contracted farmers lost a significant amount of revenues during disruptions since their selling price was fixed. On the other hand, non-contracted farmers made 19.1% and 7.8% more revenues during drought and bad weather events, respectively. Though they harvested less, they were able to sell their potatoes at a very high price.
- The bad weather event caused 31% to 64% higher delivery lead times, while there was no impact from drought.
- Sensitivity analysis showed that impacts of the severity of the disruptions on different performance metrics are not linear.

The methodology developed in this study could potentially be applied to other food and agricultural SCs for understanding the vulnerabilities at agent levels due to climate change disruptions. The findings would help develop mitigation strategies and adopt policies to improve the well-being of the overall SC.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at
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