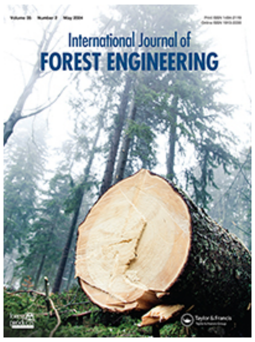


International Journal of Forest Engineering

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tife20

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**To cite this article:** Karin Westlund, Lovisa Engberg Sundström & Lars Eliasson (2024) An optimization and discrete event simulation framework for evaluating delivery performance in Swedish wood supply chains under stochastic weather variations, International Journal of Forest Engineering, 35:2, 326-337, DOI: 10.1080/14942119.2024.2313417

**To link to this article:** https://doi.org/10.1080/14942119.2024.2313417



Published online: 25 Feb 2024.

INTERNATIONAL JOURNAL OF FOREST ENGINEERING
2024, VOL. 35, NO. 2, 326–337
https://doi.org/10.1080/14942119.2024.2313417

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# An optimization and discrete event simulation framework for evaluating delivery performance in Swedish wood supply chains under stochastic weather variations

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**ABSTRACT**
Delivery performance in wood supply chains is affected by carrying capacity on forest roads. Stochastic weather variations affect carrying capacity of roads and accessibility of harvested wood on landings. In Sweden, annual harvest scheduling is usually based on four seasons and road accessibility classes are set to match these seasons. In reality, road accessibility changes depend on weather variations not season. This causes a risk of poor delivery performance. Delivery performance is evaluated using two performance indicators, backorders (orders not delivered on time) and lead time (time from harvesting to delivery to mill). A data-analytic framework, combining optimization and simulation, is proposed to assess and evaluate these performance indicators for the wood supply chain under stochastic weather variations. An optimization model is used to generate a feasible harvest schedule for expected weather. This is thereafter evaluated given various weather scenarios using a discrete-event simulation model. The combination of optimization and discrete-event simulation is used to assess delivery performance over time, and changes in road accessibility caused by weather variation. An expected decrease in road accessibility implies a stable delivery performance, while an unexpected decrease causes a reduced delivery performance.

**ARTICLE HISTORY**
Received 13 June 2023
Accepted 22 January 2024

**KEYWORDS**
Harvest scheduling; discrete-event simulation; optimization; road accessibility; weather variation

## Introduction

Every year, about 74 million m$^3$ under bark (ub) of roundwood is transported from roadside landings along Swedish forest roads. Wood customers, such as pulp and sawmills, are dependent on a smooth flow of wood deliveries to keep production at stable levels over time. Timely delivery of high-quality wood, separated into different products, to these customers is prioritized by forest managers, but uncertainty at several levels in the wood supply chain makes the precise scheduling of deliveries a complex task. One major obstacle is the weather-dependent carrying capacity of forest roads.

Since the carrying capacity of forest roads varies according to weather, it is normally accounted for at an annual planning level. The annual plan consists of a harvest schedule that distributes the stands over the months to ensure that monthly customer demand can be fulfilled. Annual planning must therefore match the volumes of each wood product demanded, while also considering the varying carrying capacity of forest roads to ensure that the roadside landings are accessible at the scheduled time (Rönnqvist et al. 2015). Annual harvest scheduling is currently based on timing the harvesting to time periods of good or sufficient carrying capacity of the roads at roadside landings. For the scheduling, the year is divided into four categorical and coherent seasons, described by an average weather for that season, with each assumed to prevail during one continuous period in the year. For the purpose of road construction and maintenance, a matching classification of road accessibility is in use (Table 1) (Biometria 2021). Harvesting on a site is therefore planned for one of the four seasons, when the road accessibility class on the forest road indicates that the roadside landing is accessible.

In reality, however, accessibility varies stochastically according to the weather. For example, roadside landings along forest roads with carrying capacity "D" are accessible only in times with Frozen Ground. In a winter season warmer than average, some roadside landings in road class "D" may unexpectedly become inaccessible. Increased variability in weather, with greater precipitation and higher temperatures, would increase the variability in the carrying capacity of forest roads. Unexpected inaccessibility causes disruptions in the wood supply chain, since wood can be trapped for a long time until the weather permits transport again. This type of disruption is a main cause of long lead times in the wood supply chain, in turn associated with a high risk of costs for degraded wood quality (Rauch et al. 2022) and delayed deliveries (backorders), the latter implicating delivery penalties or nonpayment of bonuses. In addition, these disruptions usually require expensive rescheduling.

How well the supply chain attains a high level of delivery performance (DP), i.e. delivers the right qualities on time in the right quantity, is a direct effect of whether the scheduled harvesting and transport can be performed when scheduled. Wood deliveries are usually planned at different horizons (D'Amours et al. 2008). In Sweden, tactical and strategic planning involves the selection and scheduling of forest stands to be

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**Table 1.** Assessment of the accessibility of a roadside landing (Boolean values) given its accessibility class and the weather condition. Definitions are based on the classification by Biometria (2021).

| | | Accessibility given weather condition | | | |
|---|---|---|---|---|---|
| Accessibility class | Definition | Frozen Ground | Dry Ground | Raining Period | Thawing Period |
| A (highest) | Accessible full year | True | True | True | True |
| B | Accessible full year except during thawing periods | True | True | True | False |
| C | Accessible full year except during thawing periods and continuous rain periods | True | True | False | False |
| D (lowest) | Accessible only on frozen ground | True | False | False | False |

cut within a one-to-five year period, while operational scheduling spans days, weeks, or months. The boundaries between these horizons are usually not strict; for example, seasonal uncertainty in the annual harvest schedule is, to some extent, handled at an operational level by allowing some adjustments to better comply with prevailing weather conditions (Frisk et al. 2016). A high level of accuracy in the annual plan requires a thorough understanding of accessibility of roadside landings.

The variations in carrying capacity caused by seasonality and weather variations have received attention in the Nordic countries. Lehtonen et al. (2019) discuss how shorter-than-usual periods of frost affect harvesting operations and wood supply in Finland. Jönsson and Lagergren (2017) study the potential of seasonal forecasts for operational planning in forestry and the effect of unfrozen soil, and draw attention to the sensitivity of harvesting operations and truck transports to weather and climate events. The authors also assess the potential of using weather forecasts in the planning of these activities. D'Amours et al. (2008) argue that the effect of seasonality and weather on the stability of the wood supply chain is one of the most important motivations for new and advanced planning methods. Rönnqvist et al. (2015) motivate the use of advance planning of the wood supply chain to accommodate the effect of seasonality and varying weather conditions on the carrying capacity. The authors also address the importance of maintaining high carrying capacity in the road network, referring to different models for optimal road building decisions, such as that described by (Flisberg et al. 2014).

The stochastic nature of accessibility to roadside landings is not currently recognized in the scheduling of forest sites for harvesting. This inadequacy can lead to damaged roads and high restoration costs, as well as inefficiencies in the wood supply chain and low-level DP as a consequence. One major cause of road damage is the use of forest roads for transportation of harvested wood during periods when the carrying capacity is insufficient, which could be the rational choice if the risk of unsatisfactory DP is too high. Forecasting the DP in advance is difficult. Instead, the DP is monitored on a monthly basis and the schedules are subject to change if DP is too low, for example due to deliveries lagging behind, wood on roadside landings being at risk of quality losses, and backorders increasing. How weather variations impact DP has not yet been adequately investigated, despite the indisputable effect of varying accessibility in forest roads. To estimate the DP in advance for an entire planning period given a harvest schedule, simulation tools are needed that can handle the weather and accessibility stochasticity. However, to the best of our knowledge, the literature on such tools is lacking.

### *Delivery performance measures*

Few metrics are available for assessing DP and the effects of road accessibility caused by weather variations. The effect of stochastic weather variations on actual road accessibility in harvest and transport scheduling is at the heart of our evaluation of DP in the wood supply chain. Gunasekaran et al. (2004) proposed that performance measurements should be chosen to enable assessment of the organizational performance of a specific value chain. The definition of DP metrics varies between supply chains depending on their context. Measurement of DP in a forestry wood supply chain requires metrics that describe how operational decisions affect deliveries and the value of the delivered products. Commonly used measures in order-to-delivery value chains address lead time and on-time delivery, in which ordered qualities are delivered on time in the ordered quantities (Forslund et al. 2008). Pound et al. (2014, p. 57) suggest using lead time, defined as the time needed to complete the delivery of a product, and backorders, the quantity of ordered products that are currently late. The authors describe the metrics in the context of supply chains where different buffers are required, including the wood supply chain using roadside landings. Nevertheless, performance in the wood supply chain from a logistics perspective is also discussed and the formulation of measures to evaluate DP.

### *Optimization and discrete-event simulation*

Due to the complexity of the scheduling tasks, research has addressed developing automated systems that support managers at different levels within forestry companies in their decision-making activities. Mathematical optimization is well established in forestry, starting in the late 1960s, and has been used in scheduling since then. Development of tailored optimization models and methods has been rapid in the 21st century (D'Amours et al. 2008; Bredström et al. 2010; Malladi and Sowlati 2017; Acuna et al. 2019; Audy et al. 2022). However, combining optimization and discrete-event simulation (DES) in forestry supply chain applications are rare. Marques et al. 2014) suggest an approach combining optimization and simulation in which uncertainty is handled separately in the simulation model. Jerbi et. al. (2012) combine optimization with simulation to evaluate production and logistics flows between forest product industries with a focus on maximizing profit, where stochasticity in the logistics is included in the DES model. Both studies overlook the fact that optimization contributes to the results of the simulation. Neglecting uncertainties in optimization, providing the result is a prerequisite to

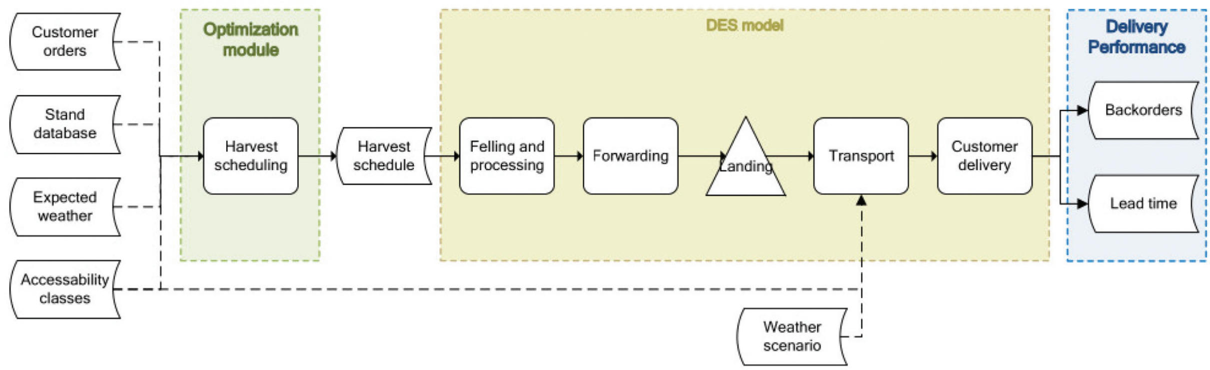


**Figure 1.** Structure of the presented framework.

the simulation, is not a realistic approach, since managers account for uncertainties when drawing up a plan. The stochastic parameter must also be included in the planning or scheduling task. For harvest scheduling, an optimization formulation can be adapted to provide a feasible schedule to match supply, demand, and estimated variations in accessibility of the forest roads. The latter must be included both in the optimization parameters and the DES model.

Different authors have used DES in a variety of ways to analyze the supply of wood products in a real-world setting. Some examples are (Windisch et al. 2015; Eliasson et al. 2017; Gronalt and Rauch 2018) wherein DES is used to model production and logistics in wood chips systems, including both the raw material allocation process and railway terminals for timber. Kogler and Rauch (2018) regard DES as a suitable method for modeling the complexity of supply chains and analyzing the consequences of different actions at operational and tactical levels along the value chain. Although simulation alone is not an optimization tool, a DES model is suitable for evaluating how an optimized delivery plan, adapted to expected weather variations, works. The harvest schedule based on an average weather scenario can be evaluated in the DES model for other types of weather patterns when it comes to transport and actual road accessibility. The DES model can simulate scenarios with weather variations which are different from the weather used in the harvesting schedule, to imitate reality where weather does not follow the expected weather in the original harvesting schedule.

This paper aims to contribute with knowledge of how weather variations impact road accessibility and affect DP in the wood supply chain. A framework combining optimization, simulation and a data-analytic model were used for evaluating DP. First, a feasible harvest schedule was created based on expected weather variations for the scheduled period. Second, the DP for the wood supply chain were systematically evaluated for any weather scenario in a DES model.

The paper is organized as follows. A description of the framework, its current implementation, and its application in a real-world setting is given in the Materials and methods section. The results of applying the framework are presented in the Results section. These results and possible future extensions of the framework are discussed in the Discussion section, which is followed by Conclusions.

## Materials and methods

The framework for evaluating DP presented in this paper covers the generation of a feasible harvest schedule using an optimization model, the simulation of this schedule using a DES model for harvest and transportation operations in a given weather scenario, and the visualization of the simulation output for the evaluation of DP. The focus of the framework is the integration of weather effects on the accessibility of roadside landings. The harvest scheduling module takes an expected weather scenario as input to account for expected changes in accessibility during the planning period. The DES model takes the optimized harvest schedule as input, along with the weather scenario that should be used for simulation. A different weather scenario than the expected can, and should, be used in the DES model. For example, a less probable yet more extreme weather scenario could be used for simulation to evaluate the robustness of the harvest schedule. In the DES model, the weather scenario determines whether the roadside landings are accessible, and the model will only direct trucks to accessible sites.

The structure of the framework and its data dependencies is given in Figure 1. In addition to the weather scenarios, data input to the framework includes customer orders (i.e. demand) and available forest sites and their road accessibility class (stand database). Important concepts or components of the framework – the connection between road accessibility and weather, the generation of harvest schedules, the simulation of a harvest schedule, and the simulation output analysis – are further described in the following subsections.

### *Evaluation of the accessibility of roadside landings from weather*

In Sweden, all forest road segments are assigned an accessibility class (A to D) based on their technical carrying capacity (Biometria 2021). The accessibility class indicates what weather conditions, Frozen ground (FG), Dry ground (DG), Rain period (RP) or Thawing period (TP), can apply for the road segment to enable the transport of fully loaded trucks (Table 1). Applied to roadside landings, the accessibility class equals that of the weakest forest road segment that needs to be traversed between the roadside landing and the mill.

Given a weather scenario with weekly precipitation, temperature, and snow cover and snowmelt data, the road accessibility is determined in this study from the following conditions which are designed to describe the weather conditions FG, DG, TP, and RP:

- Class A-D accessible if Temperature < 1°C and Snow cover ≥10 cm (FG)
- Class A-C accessible if Temperature > 10°C and Precipitation <25 mm (DG)
- Class A accessible if 3°C < Temperature ≤10°C and Snowmelt >3 cm (TP)
- Class A-B accessible if −1°C < Temperature ≤10°C and Precipitation >14 mm (RP), or if none of the above conditions are satisfied

The relationship between the weather conditions and the road accessibility is emphasized in Table 1. In this study, weather data for the years 2015 to 2020 have been retrieved from the weather station in Luleå Kallax Airport in Norrbotten, Sweden, owned by the Swedish Meteorological and Hydrological Institutes (SMHI). The weather during the years 2015–2019 was averaged to create an expected or average weather scenario. The retrieved weather data resulted in the weekly accessibility given in Figure 4.

### Harvest scheduling module

The harvest scheduling module generates a harvest schedule that specifies which forest sites are to be harvested in each month of the one-year planning period. The underlying integer optimization model is formulated so as to find a harvest schedule that results in a monthly production that matches the monthly demand of each wood assortment, while taking the expected accessibility of roadside landings into account. In practice, the expected accessibility is usually determined from a combination of historical weather data and the harvest planner's own experience. In this study, the average weather scenario described in the previous section has been used in the optimization model. The weekly data were recoded into a monthly resolution by selecting the weakest accessibility that occurred in each month.

The model formulation uses the notation $I$ for the set of forest sites, $T$ for the set of time periods (12 months), and $S$ for the set of assortments. The notation $D_{st}$ is used for the total demand (aggregated for all customers) of assortment $s \in S$ in time period $t \in T$, and $V_{is}$ for the estimated harvested volume of assortment $s$ at forest site $i \in I$. The scheduling decision is represented by the binary variable $y_{it}$, equaling 1 if the forest site $i$ is scheduled for harvesting in the time period $t$. The objective function has two components. The first part is the absolute loss function Equation (1)

$$\sum_{t\in T}\sum_{s\in S}\left|\sum_{i\in I} V_{is}y_{it} - D_{st}\right| \tag{1}$$

that penalizes any deviation of the total estimated harvested volume from the demand for each assortment and time period. The second part guides the search toward harvest schedules that comply with the expected accessibility to the roadside landings. This part is defined as (Equation 2)

$$\sum_{t\in T}\sum_{i\in I} A_{it}y_{it} \tag{2}$$

where the parameter $A_{it}$ equals 0 if the roadside landing at forest site $i \in I$ is expected to be accessible in time period $t \in T$, and takes a positive value if otherwise. In other words, the second part of the objective function penalizes the scheduling of a forest site for harvesting in all time periods when the roadside landing likely is inaccessible. The complete optimization model takes the form (Equations 3a-3c)

$$\text{minimize} \sum_{t\in T}\sum_{s\in S}\left|\sum_{i\in I} V_{is}y_{it} - D_{st}\right| + \lambda \sum_{t\in T}\sum_{i\in I} A_{it}y_{it} \tag{3a}$$

$$\text{subject to} \sum_{t\in T} y_{it} \le 1 \quad i \in I \tag{3b}$$

$$y_{it} \in \{0,1\} \quad i \in I, t \in T \tag{3c}$$

where the first set of constraints (Equation 3b) ensures that each forest site is scheduled for harvesting in, at most, one time period. The weighting factor $\lambda$ is used to alter or adjust the balance between the two components of the objective function (Equation 3a).

The objective function in Equation 3a is nonlinear due to the absolute value but can be linearized by using standard optimization techniques. These techniques involve the introduction of the two continuous and nonnegative auxiliary variables $u_{st}$ and $l_{st}$ (Equation 4) with additional bounds

$$\text{Missing superscript or subscript argument} u_{st} \ge \sum_{i\in I} V_{is}y_{it} - D_{st} \text{and } l_{st} \ge D_{st} - \sum_{i\in I} V_{is}y_{it}, \tag{4}$$

which allows the transformation of the nonlinear objective function in Equation 3a into the linear expression (Equation 5)

$$\sum_{t\in T}\sum_{s\in S}(u_{st} + l_{st}) + \lambda \sum_{t\in T}\sum_{i\in I} A_{it}y_{it}. \tag{5}$$

The optimization model has been implemented in GLPK (GLPK-GNU Project – Free Software Foundation, FSF 2023), and problem instances are solved using the standalone LP/MIP solver glpsol with a relative MIP gap tolerance of 0.005.

### Simulation model

The DES model was implemented in the ExtendSim software (ExtendSim Simulation Software 2023). The model simulates harvesting (felling, processing, and forwarding) and transportation operations with a sub-hourly resolution given a harvest schedule and a weather scenario. Important to note is that this weather scenario is not necessarily the same as was used to generate the harvest schedule. Schematic illustrations of the harvesting and transportation modules are given in Figures 2 and 3. Figure 2 shows the workflow for a harvest operations team, where the harvester cuts forest sites in the order determined by the harvest schedule and the forwarder transports the harvested

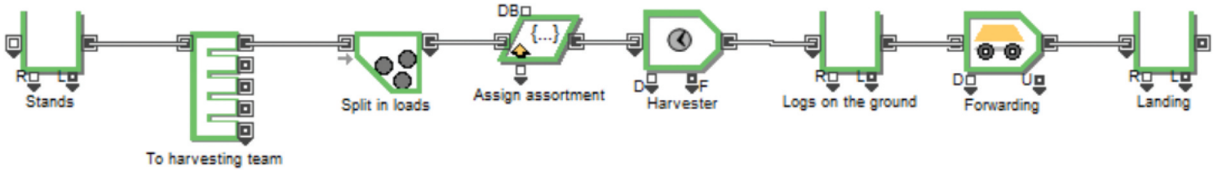


**Figure 2.** Illustration of the harvesting module in the simulation model.

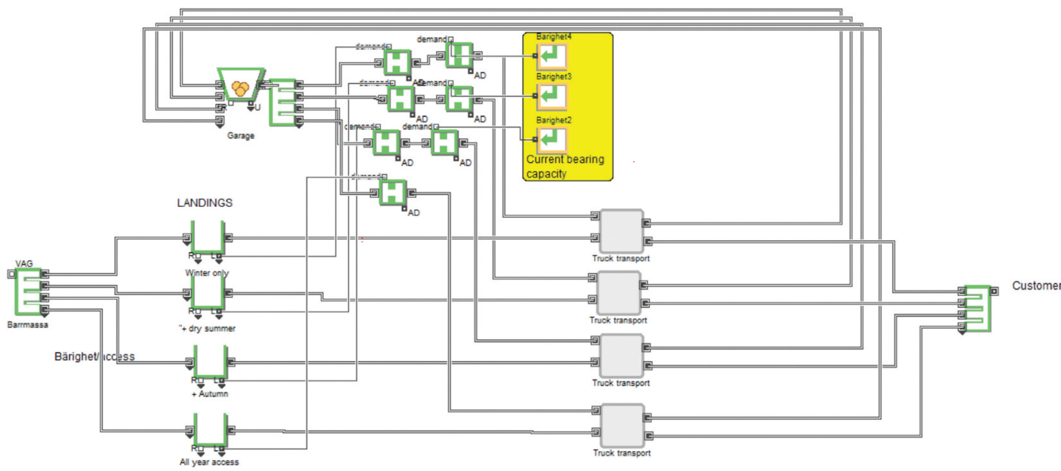


**Figure 3.** The transportation module in the simulation model, illustrated for one assortment.

volumes to the roadside landing. Figure 3 shows the structure of the transportation module for one assortment, in which the accessibility of the roadside landings is evaluated based on the current weather condition prior to the assignment of an available truck to a new delivery. Further details of the two modules are given below.

The harvesting operations are performed on each site by harvesting teams, in the order determined by the pre-optimized harvest schedule. Since the harvest schedule has a monthly resolution, the forest sites scheduled within each month are picked by the simulation model at random. Before harvesting a forest site, the estimated stand volume is converted to a whole number of full truckloads of 40 m$^3$. This facilitates defining all subsequent operations and events by truckload units. The truckloads of wood are then randomly assigned an assortment category based on the estimated assortment proportions of the total stand volume, and forwarded to the roadside landing where they are stored in assortment-specific piles until assigned to a truck. The time required for the harvesting and forwarding operations is calculated using productivity functions (Brunberg et al. 2009; Arlinger et al. 2014) that depend on stand characteristics, such as mean stem volume and mean forwarding distance.

The transportation operations are performed by assortment-specific fleets of trucks in an order determined by a two-level principle. In any given time, the simulation model uses its knowledge about the current weather and the needed road accessible class to assess which of the roadside landings trucks can transport wood from, in accordance with Table 1. At the first level, the principle states that the currently accessible landings should be emptied by a "weakest-first" rule, i.e. with increasing accessibility class (from D to A). At the second level, the principle states that all accessible landings with a lead time of over 2.5 weeks are prioritized over those with a shorter lead time. The aim of the principle is to reflect the overall goal to avoid the downgrading of wood due to excessively long lead times. In general, downgrading of wood begins after three weeks and causes reductions in the wood values, as well as affects the wood flow. To avoid that wood is trapped at inaccessible roadside landings during periods of low carrying capacity is crucial to control the lead times. The time required for transportation is computed using vehicle speed functions (Ranta 2005) and transportation distances. The latter is obtained from the truck routing tool Krönt Vägval (Svenson 2017) applied to the coordinates of all forest sites and customers in the case. Loading and unloading time components are drawn from a log-normal distribution and added to the transportation time in the model.

## Output analysis

DP in a wood supply chain explains how well customer orders are met, in terms of how much of the monthly demand is fully delivered on time and at the right quality according to the suggested metrics. The metrics used for DP evaluation are lead time and backorders per product (assortment). The framework uses the DES model to capture how the schedule meets delivery deadlines for the required product volumes, and how lead time and backorders vary over months over the entire year. Backorders in a month are calculated as the volume of monthly demand for each assortment not delivered by the end of the month. Spruce pulp wood is degraded to conifer wood automatically in the model after a lead time of three weeks, according to Swedish measurement regulations. An increase in backorders indicates a mismatch of demanded product volumes and delivered volumes for that time period,

| Month | Week | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Avg |
|---|---|---|---|---|---|---|---|---|
| Jan | 1 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 2 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 3 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 4 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| Feb | 5 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 6 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 7 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 8 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| Mar | 9 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 10 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 11 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 12 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 13 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| Apr | 14 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 15 | B (RP) | B (RP) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 16 | A (TP) | B (RP) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |
| | 17 | A (TP) | D (FG) | D (FG) | D (FG) | A (TP) | D (FG) | D (FG) |
| May | 18 | A (TP) | B (RP) | A (TP) | D (FG) | A (TP) | A (TP) | A (TP) |
| | 19 | A (TP) | A (TP) | A (TP) | A (TP) | A (TP) | A (TP) | A (TP) |
| | 20 | B (RP) | A (TP) | A (TP) | C (DG) | B (RP) | A (TP) | A (TP) |
| | 21 | B (RP) | A (TP) | A (TP) | C (DG) | B (RP) | B (RP) | A (TP) |
| | 22 | B (RP) | B (RP) | B (RP) | C (DG) | B (RP) | B (RP) | B (RP) |
| Jun | 23 | B (RP) | C (DG) | B (RP) | C (DG) | C (DG) | C (DG) | C (DG) |
| | 24 | B (RP) | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) |
| | 25 | C (DG) | B (RP) | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) |
| | 26 | C (DG) | C (DG) | C (DG) | B (RP) | B (RP) | C (DG) | C (DG) |
| Jul | 27 | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) |
| | 28 | B (RP) | B (RP) | C (DG) | C (DG) | C (DG) | B (RP) | C (DG) |
| | 29 | B (RP) | B (RP) | B (RP) | C (DG) | C (DG) | B (RP) | C (DG) |
| | 30 | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) | B (RP) | C (DG) |
| Aug | 31 | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) | B (RP) | C (DG) |
| | 32 | C (DG) | C (DG) | C (DG) | B (RP) | C (DG) | C (DG) | C (DG) |
| | 33 | C (DG) | C (DG) | C (DG) | B (RP) | B (RP) | C (DG) | C (DG) |
| | 34 | C (DG) | C (DG) | B (RP) | C (DG) | B (RP) | C (DG) | C (DG) |
| | 35 | C (DG) | C (DG) | C (DG) | C (DG) | B (RP) | C (DG) | C (DG) |
| Sep | 36 | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) | C (DG) |
| | 37 | C (DG) | C (DG) | B (RP) | C (DG) | C (DG) | C (DG) | C (DG) |
| | 38 | C (DG) | C (DG) | B (RP) | C (DG) | B (RP) | C (DG) | C (DG) |
| | 39 | B (RP) | C (DG) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) |
| Oct | 40 | C (DG) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) |
| | 41 | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) |
| | 42 | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) |
| | 43 | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) |
| Nov | 44 | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) |
| | 45 | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | A (TP) | B (RP) |
| | 46 | B (RP) | B (RP) | B (RP) | B (RP) | B (RP) | A (TP) | B (RP) |
| | 47 | B (RP) | B (RP) | D (FG) | B (RP) | D (FG) | B (RP) | B (RP) |
| | 48 | B (RP) | B (RP) | D (FG) | B (RP) | D (FG) | B (RP) | D (FG) |
| Dec | 49 | B (RP) | D (FG) | D (FG) | B (RP) | D (FG) | D (FG) | D (FG) |
| | 50 | B (RP) | D (FG) | D (FG) | D (FG) | D (FG) | B (RP) | D (FG) |
| | 51 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | B (RP) | D (FG) |
| | 52 | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) | D (FG) |

**Figure 4.** Weekly weather data for the years between 2015 and 2020 and categorization of weeks into months. The years 2015 and 2018, as well as the average weather (avg), are used as weather scenarios in the application study. Single letter abbreviations A-D are based on the classification by Biometria (2021). Double letter abbreviations refer to frozen ground (FG), dry ground (DG), raining period (RP), and thawing period (TP).

in turn indicating that the schedule is not working. Sufficient wood volumes are not harvested or harvested wood volumes at roadside landings are not accessible. This mismatch in the harvesting scheduling can be captured from the DES model's output data. The average lead time is calculated in the DES model as the average of the total time it takes for a load of 40 m³ to travel from harvesting, via forwarding, roadside landings, and transport to the customers. A major part of the lead time takes place at the roadside landings.

All major forestry activities, from harvesting to delivery, are included in the DES model. The simulation tool allows data to be logged anywhere in the flow, but the focus of this study is to show the possibilities of logging backorders and lead times in the supply chain for follow-up on DP. All lead times, harvesting, forwarding, time in the roadside landing, and transport time are logged and summed to obtain the total lead time for each harvested load. Backorders are measured for each assortment and as a total for each month to monitor the scheduling performance. Unfulfilled product order volumes are registered as the backorder for each month. Both lead time and backorder are measured separately for different wood variants to monitor and measure lead time and backorder of individual product types. Wood quality is dependent on the lead time from harvesting to delivery, which can be also analyzed.

## An application study of the framework

The presented framework has been applied in a study based on real harvesting data from 306 harvested forest sites in northern Sweden and actual weather measurements in the same region. The forest sites are located within an area of 170 × 250 km2. The simulation model was set up with four harvesting teams, each consisting of one harvester and one forwarder, and five wood products: spruce and pine sawlogs, and spruce, conifer, and deciduous pulpwood. While the number of harvesting teams was fixed, the flexibility in the model allowed extra forwarders to be used if the forwarding process was lagging. The two sawlog assortments each had three available trucks, while the three pulpwood assortments each had two, resulting in a total of 12 trucks in the model. The customers were two sawmills who either demanded spruce or pine sawlogs, and two pulp mills who either demanded spruce or conifer and deciduous pulpwood. The total demand (aggregated for all four customers) was specified as constant during the 12 months, resulting in the harvest scheduling module aiming to generate an even flow of each assortment.

A harvest schedule was generated using the harvest scheduling module fed with weather data from the average weather scenario. This schedule was then used to run the simulation model in three weather scenarios: the 2015, 2018, and average weather scenario. The choice of the years 2015 and 2018 was motivated by the fact that these weather scenarios seemed to deviate the most and least, respectively, to the average weather (as can be understood from Figure 4). Three simulations were run for the 2015 and 2018 weather scenarios, and five simulations for the average weather scenario.


Figure 5. Total customer deliveries per month in the three simulated weather scenarios for the assortments pine sawlogs (PS), spruce sawlogs (SS), spruce pulpwood (SP), conifer pulpwood (CP), and deciduous pulpwood (DP). January is affected by the lack of a warm-up period in the simulation run.

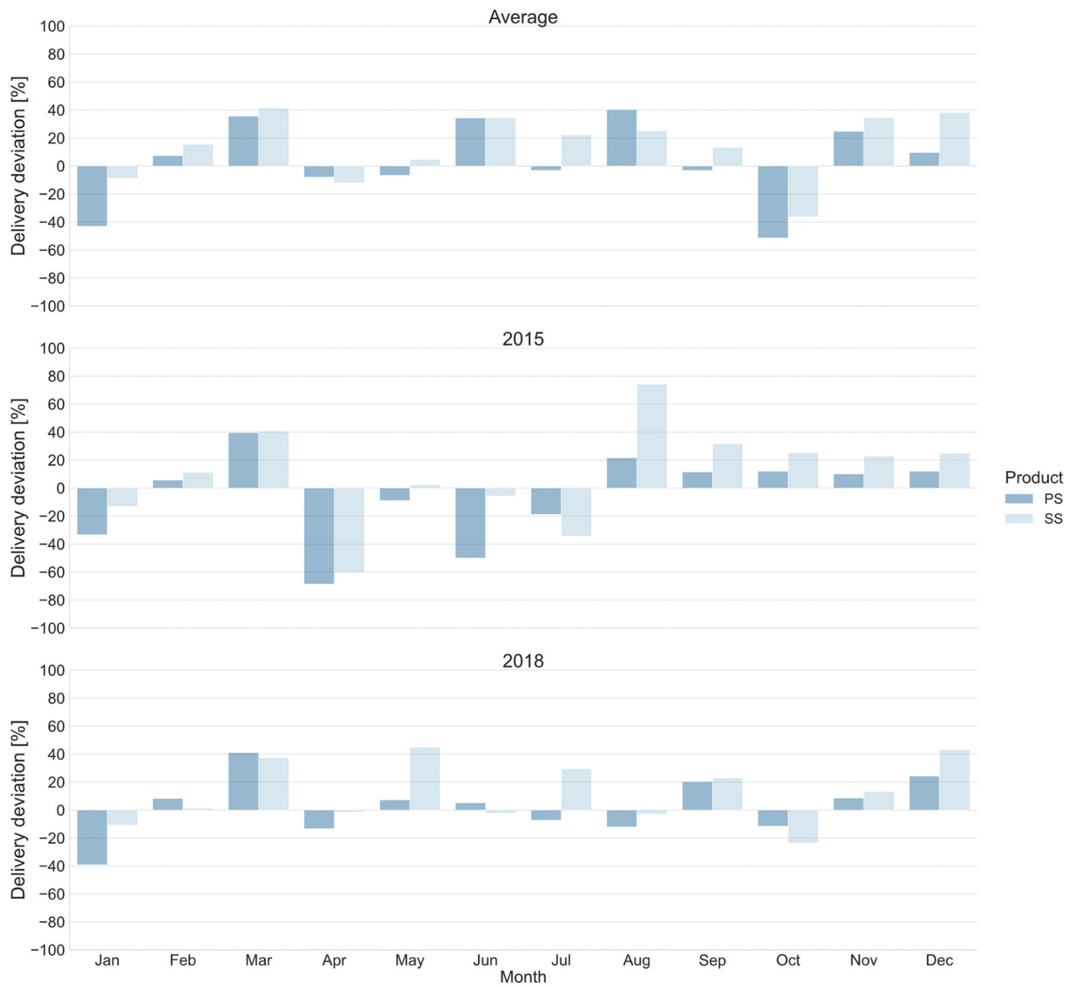


**Figure 6.** Backorders of pine (PS) and spruce (SS) sawlogs per month in the three simulated weather scenarios. January is affected by the lack of a warm-up period in the simulation run.

## Results

The deliveries resulting from simulation and the constant demand of the five assortments are shown in Figure 5. As can be seen, the production of deciduous pulp usually exceeds its small demand and the delivery patterns are mostly stable. This is due to deciduous trees, while a minor product, represent a certain share of the volume at almost all forest sites. To enhance readability in the figures, only pine and spruce sawlogs are shown in Figures 6 and 7. These figures put focus on how the delivery patterns are linked to the weather (i.e. accessibility) fluctuations. Figure 6 shows the monthly deviation in deliveries from the demand, where a negative deviation means that there is a backorder. Figure 7 shows the average lead time per week for delivered products, and the total delivered volumes to customers for which the lead time exceeded 3 weeks are shown in Figure 8. The lack of either a warm-up period during the simulation or initial roadside stocks affected the deliveries during January (Figure 5), which lead to backorders (Figure 6) when the deliveries did not meet the demand. It took about a month before production was in phase with customer deliveries.

In general, the results show that fluctuations in accessibility that correspond to what was expected during scheduling (i.e. that corresponds to the average weather scenario) have less negative impact on the DP than the fluctuations that were not scheduled. This can be seen in Figure 5, where especially in 2015, deliveries during the unexpectedly early and long Thawing Period dropped. Also, in both the 2015 and 2018 scenarios, unexpected Raining Periods during summer caused drops in the delivered volume. In the average weather scenario, however, drops in deliveries during the Thawing and Raining Periods are less pronounced or at least relatively rapidly recover, as these weather effects were expected. Detailed comments on the results are given in the following paragraphs.

In winter under Frozen Ground circumstances, deliveries fluctuate from week to week (Figure 5) yet with no backorders with respect to the total monthly demand (Figure 6) and with an overall short lead time (Figure 7). When the Thawing Periods arrive, the deliveries drop in the average weather and 2015 scenarios. In the 2018 scenario, the Thawing Period is short with no notable effect on the deliveries. Backorders occur in April in all scenarios, with a different magnitude and length depending on the length of the Thawing Period. The boundaries between different weather situations varied between years, and as harvesting operations were performed according to the plan for expected weather, this affected deliveries. In 2018, the drop in deliveries during the Thawing Period for the sawlog assortments started just before the actual Thawing

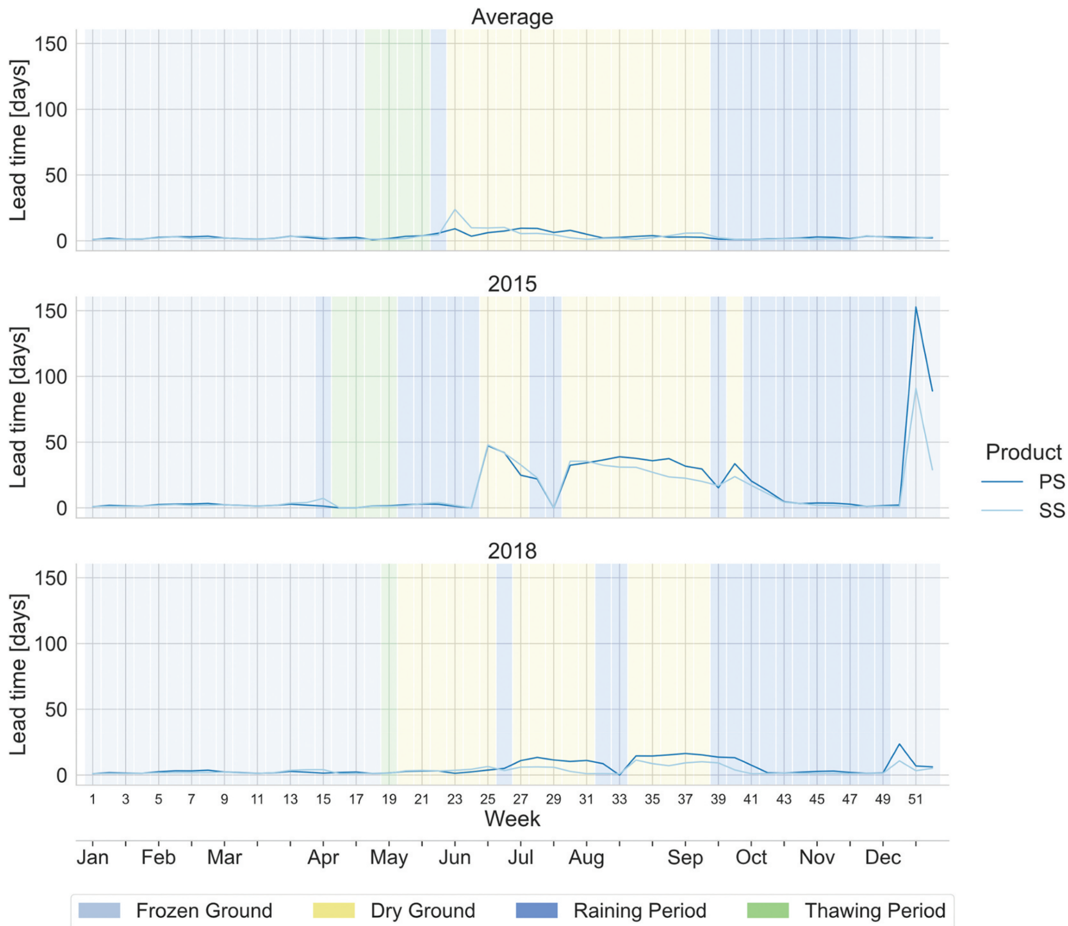


**Figure 7.** Lead times of pine (PS) and spruce (SS) sawlogs per month in the three simulated weather scenarios. January is affected by the lack of a warm-up period in the simulation run.

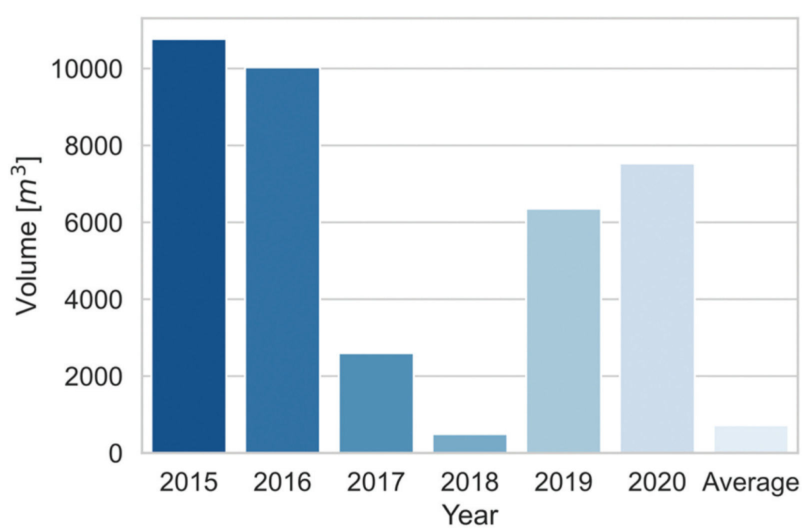


**Figure 8.** Delivered volumes of all products with lead time exceeding 3 weeks. "Average" refers to the average weather scenario defined in Figure 4.

Period given from the weather used in the simulation run. In 2015, the Thawing Period started in April, which can be seen from the pattern in Figures 5 and 6, and the spring conditions continued in mid-May, requiring road class B and A until mid-June, when class B was required. This pattern with a prolonged spring causes backorders from May to June, when in a more normal year, spring backorders are restored in the same period, and there is not enough capacity to fulfil backorders from early spring, drastically increasing backorders in June.

In summer, Dry Periods are usually interrupted by shorter Raining Periods (Figure 4). In the average weather scenario, however, the Dry Period remains uninterrupted throughout the summer months which enables the drop in deliveries during the Thawing Period to be recovered, which can be seen from the deliveries in Figure 6. In 2015 and 2018, deliveries therefore drop during the interrupting (and unexpected) Raining Periods. In 2015 with varying weather, even though it is summer deliveries will be lagging for a long time into the summer period before the backlog is recovered. A long Thawing and Raining Period from spring to summer affects deliveries even during the Dry Period, which can be seen from the backorders in 2015 in Figure 6. In 2018, the effects of the short delivery drops caused by the rain in July and August can also be seen, where delivery deviation for pine sawlogs is negative despite the summer season. The Dry Period in mid- to the end of summer makes the roads dry, so the trucks can reach the roadside landings, and backorders are compensated when autumn starts in September.

During the autumn months under Raining Period circumstances, deliveries start to drop. In 2015 the Dry Period lasted longer in the autumn (Figure 5) which improves the DP with no backorders (Figure 6) in comparison to the other two scenarios. When the period with Frozen Ground starts, assortments with large drops in deliveries can start to catch up again at the end of November–December when the roads with accessibility class D allow transports, which is not possible for the rest of the year. In all three cases, delivery deviation varies. For instance, pine sawlogs varied from an overproduction of 40% in March 2015 to 69% backorders in April 2015, and spruce had a backlog of 63% in April but an overproduction of 63% in August. For an expected and coherent decrease in accessibility, the wood supply to customers is more stable, as opposed to an unexpected decrease in accessibility which causes larger backorders.

The effects of spring weather can also be seen on average lead time in Figure 7. In 2015, when the Thawing Period was extended, there was an increase in wood that had been lying more than seven weeks during the spring and summer months. Such lead times can negatively impact wood quality. When a drier period starts and more roadside landings become accessible, the lead time starts to decrease. In 2015 and 2018, when a Raining Period starts in late summer, wood was trapped in roadside landings again, which can be seen in Figure 7 when the lead time increased in weeks 28 and 32, respectively. At the end of 2015, lead times increase sharply. This is a result from high stocks at roadside landings, accumulated during April to July, which suddenly become accessible during the Frozen Ground period. In the average weather scenario, since the same weather scenario was used for both harvest scheduling and simulation, lead times are in general shorter.

## Discussion

This study is designed to formulate a framework to assess how DP is affected by varying road accessibility. The framework presented covers the construction of an optimized harvest schedule and the simulation of the execution of this schedule in a chosen weather scenario, enabling the evaluation of the DP obtained for the optimized schedule when subjected to weather-dependent variations in road accessibility. A definition of DP in the given wood supply context is suggested, that involves measures of monthly backorders and harvest-to-delivery lead times. The framework is applied to a real-world case to examine how the different components of the DP respond to realistic variations in road accessibility. The results, consisting of visualizations of the DP obtained for one optimized schedule in different weather scenarios, indicate a vulnerability of the supply chain to variations in weather with an overall weaker DP in scenarios of larger weather fluctuations. This is in line with the discussion on the effects of seasonality in forestry operations planning in Rönnqvist et al. (2015) and D'Amours et al. (2008). However, more importantly, the results indicate that the framework allows to measure this vulnerability.

The contribution of this study mainly lies in the concepts of using a wood supply simulation model to assess the output of a harvest scheduling optimization model in aspects that are not easily captured in the objective functions. Since it is in the nature of a framework to be defined by its structure rather than through the definitions of its individual parts, the optimization and simulations models have been given less focus. The primary goal of the currently implemented models is to encompass fundamental functionality, and further development is needed to conduct more complex analyses. Awareness of the correspondence between the simulation model and the actual wood supply chain is particularly important for the validity of conclusions drawn using the framework. Development of the simulation model should therefore focus on the transport planning functionality, for example by expanding the "two-level principle" to a more advanced prioritization between the roadside landings. In this study, however, the simulation model was designed with a slight overcapacity of transport resources, making it less vulnerable to the chosen prioritization. The simulation model could also be extended to include other types of variations, such as deviations from the expected demand or harvest outcome. As to the optimization model, the simplifications made have little effect on the validity of the framework but could have the more negative impact on the efficiency (with respect to DP) of the optimized harvest schedule. It should be noted that the framework can easily work with other types of optimization or DES models.

A future extension of the framework is the inclusion of a feedback loop that connects the simulation output with the harvest scheduling module. Such a feedback loop would facilitate improving the robustness of the initially optimized harvest schedule with respect to unexpected variations in road accessibility. Another possible extension is the inclusion of a re-scheduling event in the simulation model. This could allow to adapt, in regular intervals or as needed, the harvest schedule to the current situation, improving the DP for the remaining months. Re-scheduling by manual adjustments is already in use by forest operation managers to handle unexpected changes in the wood supply chain. A re-scheduling possibility in the simulation model would support the development of methods for efficient re-scheduling with respect to the expected DP.

To develop this framework into a decision support tool, the perspective of the intended decision maker needs to be included. For example, the simulation output, which has the characteristics of multiple time series, needs to be carefully condensed and cleverly visualized to facilitate the assessment of the DP and ensure high usability of the tool. While the monthly resolution currently used is to reflect that wood deliveries traditionally are evaluated at the end of the month, a higher resolution could be applied to support a more detailed analysis of the DP.

## Conclusions

The optimization-simulation data-analytic framework showed the relationship between road accessibility and DP, and how unexpected weather periods influence backorders and lead time negatively. The range of possible fluctuations from one month to another was shown, from large backorders to overproduction the following month. Figures 5–7 clearly show the variations in deliveries and backorders even though the pre-optimized harvest schedule accounted for weather variations. All three simulated cases show backorders to some extent. In general, backorders start to occur during the Thawing Period, when there is lower accessibility in the road network. Truck transport strives to cope with the lagging deliveries during late spring and summer, but in August-September can be in balance or overdeliver when stored products, harvested during spring, are picked up and finally delivered far later than scheduled. In autumn, when the Raining Period starts, deliveries are better matched to demand. The amount of rain in autumn, when winter and better accessibility conditions start, and the amount of spring backorders transported during summer, affect the number of backorders at the end of the year. It is apparent that road accessibility had a direct causal link to DP, lead times and backorders in the DES model. Although this study does not aim to give solutions on how to improve DP, clear trends were shown of periods when scheduling can be improved just by using the framework and the evaluation of backorders and lead times. This study set out to develop a framework to evaluate DP under varying weather conditions. The framework can be used to separate weather patterns in the optimization, and the simulation therefore provides opportunities to evaluate how different harvest scheduling decisions affect DP. The framework will also increase understanding of the robustness of different harvest schedules in relation to variations in weather conditions.

## Acknowledgements

The authors thank Professor Amos Ng for valuable discussions on how to improve the paper.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Funding

This research was supported by Vinnova, the Swedish Innovation Agency, through the framework of the ERA-NET Transport Flagship Call 2017 for Sustainable Logistics and Supply Chains.

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