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Accounting for uncertainty in eco-efficient agri-food supply chains: A case study for mushroom production planning

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A B S T R A C T

Due to the increasing awareness of climate change, depletion of natural resources, and increasing world population, companies in the agri-food sector need to redesign their existing supply chains and take into account both the economic and environmental impact of their operations. In practice not all the required information is available in advance due to various sources of uncertainty in agri-food supply chains. In this research a multi-objective two-stage stochastic programming model is proposed to analyse and evaluate the economic and environmental impacts to account for uncertainty in agri-food supply chains. A mushroom supply chain in the Netherlands is presented as an illustrative case study. Optimal production planning decisions calculated with a two-stage stochastic programming model are compared with the results of an equivalent deterministic model. The results of the optimizations show that accounting for stochasticity in important model parameters can reduce the difference between expected and realized economic performance by approximately 4% on average. Moreover, this paper demonstrates that including stochastic model parameters can reduce the environmental impact without compromising the current economic performance. Given the assumptions in the setup of the case study and the available information, it is concluded that applying a 2-stage stochastic programming approach for production planning decisions can lead to improved economic and environmental performance in an agri-food supply chain. New findings in real-life case studies are needed to get profound insights and understanding on the impact of uncertainty on production planning decisions in sustainable agri-food supply chains.

1. Introduction

Due to increased exposure in the media about climate change and depletion of natural resources, society is more aware of the environmental impact caused by food production. At the same time it is estimated that by 2050 overall food production must increase by some 70% to feed the increasing world population (Alexandratos and Bruinsma, 2012). To be able to satisfy the needs of future generations, agri-food supply chains must eliminate current inefficiencies and focus on more sustainable production. Eliminating inefficiencies requires decision support tools that account for intrinsic characteristics of food production. Moreover, sustainable agri-food supply chains require more than just the economic validation of a single overriding objective (i.e. profit). Decision support tools for sustainable agri-food supply chains need to simultaneously evaluate economic and environmental performance. Such evaluations require not only the assessment of environmental and economic performance but also the relationship and trade-offs between these conflicting objectives.

Multi-objective optimization is particularly suitable for finding the best compromise between economic and environmental dimensions of sustainability (Chaabane et al., 2011), and for determining eco-efficient solutions, i.e. solutions in which it is not possible to decrease environmental damage unless increasing costs (Quariguasi Frota Neto et al., 2009). In many cases from agri-food supply chains multi-objective optimization models are deterministic, i.e. it is implicitly assumed that all model parameters are known in advance. However, in practice not all the required information for parameterization of production planning models is

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deterministic. Main sources of uncertainty in agri-food supply chains are related to productivity (yields), estimated supply and demand patterns, processing parameters, and prices (Soysal et al., 2012).

Despite the increasing use of quantitative models in sustainable supply chains (Brandenburg and Rebs, 2015), agri-food supply chain models, which include both economic and environmental criteria, rarely consider uncertainty in parameters. It is recognised by Brandenburg et al. (2014) that there is a need for more stochastic models for sustainable supply chains, as the amount of available literature is limited and provides for further research opportunities. Importance of accounting for uncertainty in agri-food supply chain decision support models has been stressed in literature (Ahumada and Villalobos, 2009), but, to the best of our knowledge, there are no studies that quantify the consequences of uncertainty in data on the environmental and economic performance in agri-food supply chains.

This study aims to quantify the impact of accounting for important sources of uncertainty in a decision support model for production planning in an agri-food supply chain. The impact of uncertainty on best environmental, best economic, and other eco-efficient solutions is quantified using a two-stage stochastic programming approach in a multi-objective optimization model. Particularly in agri-food supply chains, many decisions have to be taken in an early stage while yields and demand are often revealed later in the production process. To decompose such multi-phase planning decisions in eco-efficient agri-food supply chain, a multi-objective two-stage stochastic programming model is proposed. An illustrative real-life mushroom supply chain is presented to demonstrate the potential benefits of treating uncertainty for the optimization of production planning decisions. To compare the performance of the generated solutions, a simulation is performed to unravel the different objective values and generated solutions depending on the realization of uncertainty in model parameters.

The paper is structured as follows: Section 2 presents an overview from literature on publications treating uncertainty in food supply chains and on publications treating uncertainty in multi-objective optimization. Section 3 introduces industrial mushroom production. Section 4 describes methods and data, i.e. presents the mathematical model, provides the data for considered case study, and specifies the setup of numerical analysis. Section 5 discusses the results of the model, and section 6 gives the conclusions of the study.

2. Literature review

The data in real-world optimization problems are not exactly known at the time the problem is being solved due to inevitable estimation, measurement and implementation errors (Ben-Tal et al., 2009). Incorporating uncertainty in some parameters of the model may lead to a better representation of the actual problem (Munhoz and Morabito, 2014). Moreover, food production is unique in its complexity, and optimization-based decision support should account for intrinsic characteristics of food production. Food products are particularly characterised by seasonality, yield variability, products' perishability and high fluctuations in demand and prices (Akkerman et al., 2010). Therefore, in agri-food supply chains, not all the required data are known in advance due to various sources of uncertainty, i.e. risks related to the market, fluctuating demand, production yields, and prices. These sources of uncertainty should be taken into account in mathematical models used to support decision making in agri-food supply chains to achieve a better representation of the actual decision making process. Ignoring important sources of uncertainty or using averages to parameterize deterministic models of the agri-food supply chain may lead to calculated production planning decisions, which if implemented, result in lower than expected overall economic and environmental performance.

To deal with uncertain input parameters in models, a number of approaches can be applied. The most popular approaches include stochastic programming and robust optimization. Stochastic programming models are used to determine production plans that optimize the expected value of an objective function based on numerous scenarios for realizations of uncertain data. Robust optimization models are used to obtain robust production plans that are less risky, immune to infeasibilities, and less sensitive to realizations of uncertain data. The benefits of robust optimization include the fact that exact distributions of uncertain parameters are not necessary, and independently on the number of uncertain parameters the (transformed) model remains computationally tractable. For a detailed description of stochastic programming and robust optimization see Birge and Louveaux (2011) and Ben-Tal et al. (2009), respectively.

In stochastic programming some data parameters are uncertain, and an accurate probability distribution of these parameters is assumed to be available (Birge and Louveaux, 2011). The aim of stochastic programming is to find the best solution depending on the expected value of an objective function. Variations of stochastic programming exist in terms of e.g. number of stages, types of recourses, or the inclusion of probabilistic (chance) constraints. The difficulty of considering continuous distributions is often avoided by introducing a discrete set of (limited) scenarios. However, a large number of scenarios may be necessary to accurately resemble the distributions of parameters, and the more scenarios the harder to solve the considered problem to optimality (Keyvanshokooh et al., 2016).

Stochastic programming and robust optimization approaches are hardly applied in food production context. Pauls-Worm et al. (2014) study lost sales in inventory problems for fresh food products with uncertain and fluctuating demand. A stochastic programming model is developed to find order quantities to meet cycle fill rate service requirements while keeping outdating low. Guan and Philpott (2011) present a production planning problem in dairy industry under uncertain milk supply and formulate a multi-stage stochastic programming model with a linear price-demand curve. Soysal et al. (2015) develop a chance-constrained programming model with demand uncertainty for a multi-period generic inventory routing problem for perishable products with specific attention to environmental considerations. Borodin et al. (2014) propose a stochastic optimization model for the annual harvest scheduling problem of cereal crop production. A chance constrained optimization model is proposed to minimize the risk of crop quality degradation under meteorological uncertainty. Bohle et al. (2010) propose a modified robust optimization approach to solve an agricultural planning problem of wine grape harvesting subject to uncertain labors harvesting productivity. Munhoz and Morabito (2014) apply a robust optimization approach to an aggregate production planning model for frozen orange juice concentrates to minimize total costs with uncertainty in juice acidity parameters. It is observed that stochasticity in production yields, which are highly uncertain in food production, is not considered in the aforementioned studies. Moreover, hardly any of the above mentioned publications take multiple conflicting objectives into account.

Publications treating environmental and economic performance in multi-objective optimization while including uncertainty in parameters in production planning are very scarce. Mirzapour Al-E-Hashem et al. (2013) propose a two-stage stochastic programming model for aggregate production planning with quantity discounts in green supply chain with uncertain demand.

Environmental performance is embedded in the presented model by limiting the greenhouse gas emission from transportation and waste produced to a predetermined level. Radulescu et al. (2009) assume an uncertain amount of pollution emissions per unit of product, and formulate two stochastic programming models for production planning: a maximum expected return problem, and a minimum pollution risk problem. Sazvar et al. (2014) propose a multi-stage stochastic programming model to optimize costs and total GHG emissions for a supply chain with deteriorating products under uncertain demand. Amin and Zhang (2013) investigate the impact of demand and return uncertainties on the closed-loop supply chain network configuration using a multi-objective model. A scenario-based stochastic programming approach is used to minimize costs and an environmental objective. The aforementioned publications apply multi-objective optimization in supply chains under uncertainty. However, none of the studies consider (fast moving) food products.

There are multiple calls in literature reviews for more stochastic models on realistic case studies see e.g. Brandenburg et al. (2014). Notably, most of the papers on eco-efficient supply chains assume all data to be deterministic, and uncertainty is hardly taken into account. Additionally, none of the sources related to food production (e.g. production yields or demand), are included in publications which present decision support models for eco-efficient supply chains. To the best of our knowledge there is a lack of publications considering environmental criteria in multi-objective optimization with uncertain parameters to support production planning decisions in agri-food supply chains. Moreover, the quantified impact of treating uncertainty in optimizing different objectives associated with sustainability is still unclear. This paper contributes to literature by 1) providing a stochastic programming model for a real life sustainable supply chain optimization problem, and 2) quantifying the impact of taking uncertainty into account on environmental and economic performance of an agri-food supply chain.

3. Industrial mushroom production

This section describes an industrial mushroom production (Fig. 1). The described chain is an example of an agri-food supply chain in which crucial decisions need to be made before the actual values of uncertain production and demand parameters reveal. This gives rise to decompose the decision making process into multiple steps, providing therefore a typical example in which multi-stage decision making may have an added value above a commonly applied deterministic approach.

All raw materials are first transported to facilities and then processed industrially in factories that produce growing medium for mushrooms, called substrate. Substrate comprises two layers: compost, and casing soil. Production of compost takes place in multiple phases and total duration of compost production takes a few weeks (Banasik et al., 2017). The final product must be produced just-in-time, because compost cannot be stored for long due to biological processes taking place in the compost inoculated with mycelium.

Substrate is subsequently delivered to mushroom producers for cultivation. Mushrooms are produced in multiple flushes, i.e. mushroom productive periods between two subsequent (not productive) growth periods of substrate. The same substrate can be cultivated for limited number of flushes due to increasing risks for pests and diseases. Different mushroom sizes are distinguished based on the cap size, which determines the selling price of fresh mushrooms. Each flush is associated with a yield of different sizes of mushrooms and, moreover, each day's yield is associated with a proportion of low quality mushrooms (irregular shape or colour). Typically there is a distinction in selling prices of mushrooms, depending on whether mushrooms are sold within the demand, mushrooms that are sold above the demand (typically sold at an alternative to fresh market, e.g. to sold to processing companies), and low quality mushrooms. After cultivation, the spent mushroom substrate must be disposed. Disposal of spent mushroom substrate is costly due to high transportation volumes.

Mushroom production is intrinsically associated with various sources of uncertainty, including production yields and demand patterns, that considerably complicate decision making. Substrate production facilities must plan their decisions well in advance, while even in perfectly coordinated and collaborative mushroom supply chain, it is unclear how much substrate the industrial production facility should produce to optimize the performance of the complete chain. This is difficult because mushroom producers can adjust their production planning decisions (and as a result also their demand for substrate) as a response to highly fluctuating demand and uncertain yields of mushrooms. The impact of uncertainty and the implications of production planning decisions on environmental and economic performance should be evaluated quantitatively to support effective decision making in practice.

4. Methods and data

To support decision making in a mushroom supply chain a multi-objective model is proposed. The objectives include maximization of economic performance, and minimization of environmental impact. A set of Pareto-efficient solutions (called eco-efficient solutions when considered objectives relate to economic and environmental impact) is derived to provide information on required costs to improve environmental performance. Efficient frontiers ensure finding a solution that compromises the considered economic and environmental criteria and therefore provide valuable information to decision makers. To obtain eco-efficient solutions the ε-constraint method is applied. For a detailed description of this method the reader is referred to Ehrgott (2005).

To treat uncertainty in model parameters, a deterministic model is implemented in which expected values of (uncertain) parameters are used. Next, a two-stage stochastic programming model is implemented. Any two-stage stochastic programming model comprises first, and second stage decision variables. The first stage variables refer to decisions that have to be taken before the actual realization of uncertain parameters is available. After random events have occurred, adjustments can be made by second stage

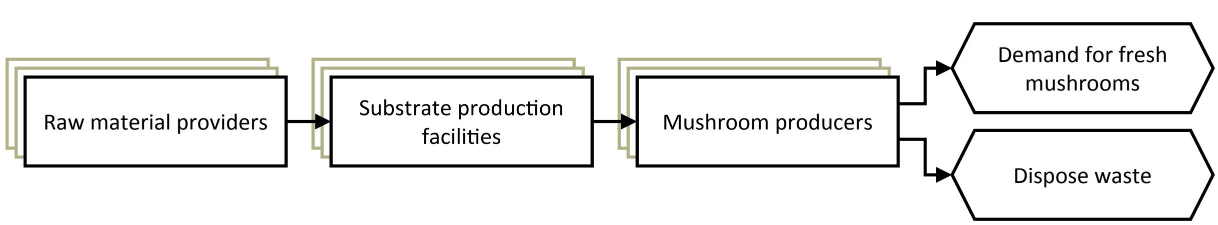

Fig. 1. A mushroom supply chain.

decision variables.

This study follows a common approach to solve the two-stage stochastic programming model by using sample average approximation based on Monte Carlo sampling (Löhndorf, 2016). In this method, the expected value of objective function is approximated by solving the problem for a set of scenarios. A discrete set of scenarios is introduced to avoid the complexity of considering continuous distributions.

In agri-food chains there are situations where infeasibilities are not acceptable, for instance when the demand must be met exactly due to strict periodic delivery contracts with customers, hard restrictions related to quality requirements and safety regulations of perishable products, or in the presence of penalty systems for upper limits on production amounts and the level of environmental impact. In such cases robust optimization is an appropriate approach. Robust optimization provides for solutions that are immune to infeasibilities but are more conservative. However, in the specific case presented in this paper, infeasible solutions are hardly an issue as there are no hard constraints on demand (over and under achievement of demand is allowed at different price levels). Therefore, robust optimization is outside the scope of this study, and two-stage stochastic programming is used in this study to investigate the impact of on decision making and on the optimal solutions.

4.1. Multi-objective linear programming model

The optimization model for an industrial mushroom supply chain supports interrelated production planning and harvesting decisions between different links of the supply chain, and the model is therefore used before the production starts. The purpose of the optimization is two-fold. First, the economic and environmental objectives are optimized to find eco-efficient solutions, which represent the trade-off between economic and environmental criteria. Second, the impact of accounting for uncertainty during the optimization using a two-stage stochastic programming model on all eco-efficient solutions is investigated. The mushroom supply chain is modelled as a single entity, i.e. collaboration between substrate production facilities and mushroom producers is assumed. This implies that the whole supply chain is taken into account, instead of optimizing each link individually. The optimization is relevant, therefore, for each link of the supply chain (i.e. substrate production facilities, and mushroom producers).

In the presented model first stage variables include the amount of substrate produced in each time period (substrate production facilities), and the amount of compost cultivated in each time period (mushroom producers). Second stage variables include the amount of mushrooms sold at each price, size, and period (mushroom producers).

Model presented in this section has been adapted from Banasik et al. (2017) to include uncertainty into account in important model parameters. The uncertain model parameters include uncertain yields of mushrooms, and uncertain demand. Demand for mushrooms is assumed not to depend on mushroom size. In the presented model, substrate production facilities are aggregated into one, and thus the capacity of the single (aggregated) facility refers to the total capacity of all substrate production facilities. Mushroom producers are also aggregated into a single producer, and thus their growing capacity and demand for mushrooms are combined.

For the mathematical description of the model the following notation is introduced:

Indices	
c	size of mushroom, $c = 1, \ldots, C$
t	time periods, $t = 1, \ldots, T$
a	age of cultivated compost, $a = 1, \ldots, A$
s	scenario number, $s = 1, \ldots, S$
Monetary parameters	
cs_a	variable, labour, and disposal costs of substrate at age a [€/t]
$pl_{c,t}$	selling price of low quality mushrooms size c in period t [€/kg]
$pp_{c,t}$	selling price of mushrooms size c fulfilling the demand in period t [€/kg]
$ps_{c,t}$	selling price of mushrooms size c exceeding the demand in period t [€/kg]
Environmental parameters	
e_p	environmental impact of production per 1 kg of mushrooms
e_w	environmental impact of waste disposal per 1 t of spent substrate
Technical parameters	
cap_fac	capacity of substrate production facility for compost production [t]
cap_gr	capacity of mushroom producer for compost cultivation [t]
$d_{t,s}$	demand for mushrooms in time period t in scenario s [kg]
lq_a	fraction of low quality mushrooms at age a
p_time	processing time of raw materials to produce compost
$pd_{c,t,a,s}$	yield of mushrooms size c in period t at age a in scenario s [kg of mushrooms/t of compost]
Decision variables	
$L_{c,t,s}$	the amount of low quality mushrooms of size c sold in period t in scenario s
$M_{c,t,s}$	the amount of premium quality mushrooms of size c sold in period t in scenario s
$OD_{c,t,s}$	the amount of surplus mushrooms of size c sold in period t in scenario s
$STP_{t,a}$	the amount of compost disposed in time period t at age a
$Z_{t,a}$	the amount of compost cultivated in time period t at age a

The model presented is a two-stage stochastic programming model with S scenarios. The presented model is also used as a deterministic model by considering only one scenario ($S = 1$) and using expected values for the uncertain parameters $pd_{c,t,a,s}$ and $d_{t,s}$.

$$max\left\{OF_{eco} = \frac{1}{S}*\sum_{c,t,s}\left(pp_{c,t}*M_{c,t,s} + ps_{c,t}*OD_{c,t,s} + pl_{c,t}*L_{c,t,s}\right) - \sum_{t,a} cs_a*Z_{t,a}\right\}$$

$$min\left\{OF_{env} = \frac{1}{S}*\sum_{c,t,a,s} pd_{c,t,a,s}*e\_p*Z_{t,a} + \sum_{t,a} e\_w*STP_{t,a}\right\}$$

Subject to:

$$\sum_{k=0}^{p\_time-1} Z_{t-k,a} \leq cap\_fac \quad \forall t,\ a = 1 \tag{1}$$

$$M_{c,t,s} + OD_{c,t,s} \leq \sum_{a}(1 - lq_a)*pd_{c,t,a,s}*Z_{t,a} \quad \forall c, \forall t, \forall s \tag{2}$$

$$L_{c,t,s} = \sum_{a} lq_a*pd_{c,t,a,s}*Z_{t,a} \quad \forall c, \forall t, \forall s \tag{3}$$

$$\sum_{c} M_{c,t,s} \leq d_{t,s} \quad \forall t, \forall s \tag{4}$$

$$\sum_{a} Z_{t,a} \leq cap\_gr \quad \forall t \tag{5}$$

$$Z_{t,a} = Z_{t-1,a-1} - STP_{t-1,a-1} \quad \forall t,\ \forall a | t > 1,\ a > 1 \tag{6}$$

$$STP_{t,a} = Z_{t,a} \quad t = T, \forall a \tag{7}$$

$$STP_{t,a} = Z_{t,a} \quad \forall t, a = A \tag{8}$$

The economic objective (OF_{eco}) maximizes total profit. Total profit comprises (*i*) total revenue, and (*ii*) total costs of substrate cultivation, including the disposal costs. The environmental objective (OF_{env}) minimizes total environmental impact. Environmental impact is associated with (*iii*) cultivation, and (*iv*) spent mushroom substrate disposal.

Constraints (1) ensure compost production capacity at processing level. Constraints (2) and (3) calculate the amount of mushrooms sold at different prices. Constraints (4) guarantee that demand is covered only by premium quality mushrooms. Constraints (5) correspond to periodic capacity at the producer. Constraints (6) are recursive constraints, which entail that the amount of substrate cultivated in a given period is not larger than in the previous period. Restriction (7) and (8) ensure that the mushroom cultivation stops in the last period of the considered planning horizon, and when cultivation has been taking place for the maximal allowed number of days.

4.2. Case study and data

Data presented in this section considers a real-life industrial mushroom supply chain in the Netherlands. The presented data are collected by interviews with industrial partners and collaborating scientists from food processing who quantify the environmental impact in this case study. The data for environmental impact of all processes for the considered case is presented in Zisopoulos et al. (2016).

Raw materials used for industrial mushroom production include horse manure, chicken manure, straw, gypsum, ammonium sulphate, peat and lime stone. Total duration of compost production in the real-life substrate production facilities is 27 days. The total processing capacity of compost in substrate production facilities over 27 days is limited to 44,415 t. Processed compost and mixed casing soil ingredients are transported to the mushroom producers. Ingredients, processing, transportation, and disposal costs account for 229 €/t of compost.

The total growing capacity of mushroom producers is limited to 51,975 t of compost in each time period. Compost can be cultivated for at most 43 growing days that is equivalent to three flushes of mushrooms, which producers can obtained from cultivation. The yield variations over production cycle for each size of mushrooms (small, medium, large) are presented in Fig. 2. It can be observed, that each subsequent flush of mushrooms is associated with lower yield. Each flush is associated with a given percentage of low quality mushrooms, i.e. the first, second, and third flush, accounts for 5%, 10%, and 20% low quality mushrooms of yield, respectively.

Practitioners emphasize that some of the data are highly uncertain. Despite all measures taken by the substrate production facility to keep the quality of compost standardized, the yield of mushrooms varies. Within this research the data on yields in first, second, and third flush of mushrooms over a period of one year was collected from 22 mushroom producers. Analysis of historical data, confirmed by chi-squared goodness of fit tests, revealed that yield fluctuations in each flush follow a Gaussian distribution with the following parameters: (i) mean yield in the first flush of 192 kg of mushrooms/t of compost and standard deviation of 17 kg of mushrooms/t of compost, (ii) mean yield in the second flush of 109 kg of mushrooms/t of compost and standard deviation of 17 kg of mushrooms/t of compost, and (iii) mean yield in third flush of 48 kg of mushrooms/t of compost with standard deviation of 15 kg of mushrooms/t of compost.

Variable and labour cultivation costs for days 1 up to 31 are 3 €/t of compost per day, and for days 32–43 are 5 €/t of compost per day. Additionally, ingredients, processing, transportation, and disposal costs of spent mushroom compost (229 €/t of compost) are included in variable and labour cultivation costs for the first day of cultivation.

To consider the annual volatility in prices and demand, a time horizon consisting of 365 days is considered (Fig. 3). According to domain experts, the demand can deviate from the expected values following a Gaussian distribution with standard deviation of 10%.

Environmental impact is expressed in this paper by cumulative

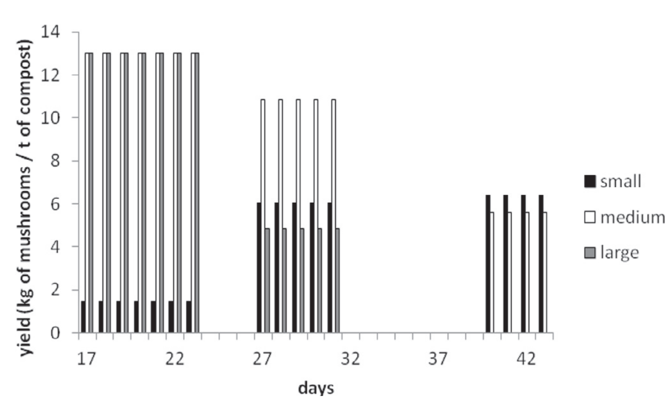

Fig. 2. Expected yield of small, medium and large mushrooms for maximal duration of a single cultivation round (43 days).

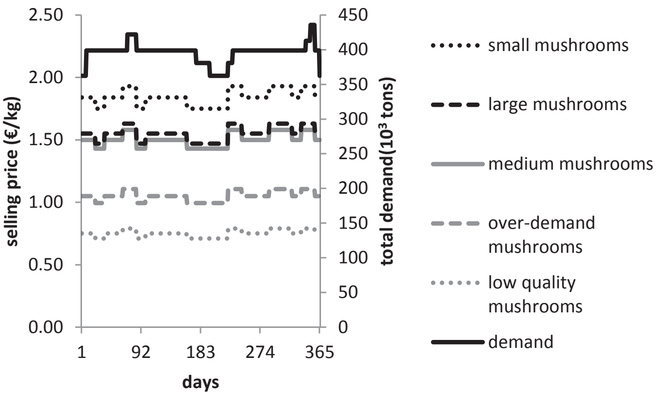

Fig. 3. Fluctuations of mushroom selling prices (primary axis), and expected demand (secondary axis).

exergy losses; an indicator based on exergy analysis. Exergy analysis enables to capture both quantity and quality of energy (Apaiah et al., 2006), and has the potential to quantify the environmental impact in a single unit (MJ). Description of the concept of exergy analysis, as well as the calculation of exergy losses for this case study is presented in Zisopoulos et al. (2016). Exergy losses account for 0.3 MJ/kg of grown mushrooms. Exergy losses associated with waste disposal account for 5959 MJ/t of spent mushroom compost, and include exergy losses due to transportation and waste stream exergy losses (chemical exergy losses).

4.3. Setup of numerical analysis

For the deterministic model the expected (average) values of yield (Fig. 2) and demand (Fig. 3) parameters are used. For the two-stage stochastic programming model 100 scenarios are defined to approximate the probability distribution functions of the yield and demand. For all time periods (t) in each scenario (s), the following four values are drawn from the Gaussian probability distribution functions (with means and standard deviations as given in Section 4.2.): i) the yields in the first flush, ii) the yields in the second flush, iii) the yields in the third flush, and iv) the demand values ($d_{t,s}$). The daily yield of mushroom ($pd_{c,t,a,s}$) depending on mushrooms size (c) at growing age (a) is obtained by dividing the simulated yields per flush in i) − iii) across the productive days and according to the usual ratios in practice for large, medium, and small mushrooms (see Fig. 2). All values are simulated independently.

The deterministic and the two-stage stochastic programming models are optimized with respect to the economic and environmental objectives. The optimal objective function values are further referred to as *expected values* of the deterministic and stochastic model. All models are solved using Xpress-IVE version 7.9.

The eco-efficient solutions for the deterministic problem are obtained by maximizing the economic objective, while varying in ten iterations the allowed level of environmental impact. The same levels of allowed environmental impact were used to derive efficient solutions for the stochastic model.

After obtaining the solutions for each optimization approach, a simulation is performed to benchmark the generated solutions. Uncertain data parameters are simulated for each time period in 1000 scenarios. The optimal values of first stage variables are used to examine the objective function values in the simulation. The results obtained from simulations on the performance of the objective function values are further called *realized values* of the objective functions.

5. Results and discussion

This section presents the optimization results of the deterministic and the stochastic model as discussed in the previous section. The deterministic model consists of 34,675 continuous variables and 18,960 constraints. The two-stage stochastic programming model consists of 359,890 continuous variables and 271,905 constraints. Optimal solutions for economic performance and environmental impact correspond to a specific production plan, i.e. the amount of compost produced on a given day in the substrate production facility, the amount of compost cultivated each day at the mushroom producer, and the amount of mushrooms sold at each price level every day.

5.1. Single objective optimization

According to the results of the deterministic model, compost should be cultivated mostly for two flushes of mushrooms in order to obtain maximal profit. The expected (annual) profit is 65.3×10^6 €, and corresponds to 3.4×10^9 MJ of exergy losses. However, according to the simulation results, the realized value of profit is 3.9% lower than expected (Table 1). The expected profit of the stochastic model turns out to be 1.9% less compared to the expected profit of the deterministic model, but yields 1.8% higher realized profit compared to the realized profit of the deterministic model, corresponding to 1.1×10^6 € more profit for the supply chain on a yearly basis. At the same time 4% more compost is cultivated in the best economic solution obtained for the stochastic model, and therefore this solution is associated with a higher value for exergy losses.

To obtain the best environmental solution, a lower bound on the amount of profit at 90% of the best deterministic solution is introduced. Results show that the best environmental solution mostly refers to three flushes. Decisions on the number of used flushes determine the total amount of cultivated compost, and therefore also the total amount of waste accounting for the majority of environmental impact.

Results show hardly any difference in the environmental performance of expected and realized objective function values (Table 1). The reason is that the amount of waste, which is not associated with uncertainty in our study, accounts for the majority of environmental impact, i.e. 98.7% for the best economic solutions found.

5.2. Multi-objective optimization

The sets of eco-efficient solutions for both models (including the best stochastic solution found for the stochastic model), as well as the objective function values based on simulation, are all presented in Fig. 4. Each point on the efficient frontier corresponds to a specific production plan, and the extreme solutions of the efficient frontier for the deterministic model are summarized in the previous subsection. It is observed that for each efficient frontier the number of flushes used for cultivation change gradually from mostly two for the best economic solutions, to mostly three for the best environmental solution. This entails a lower amount of cultivated compost resulting in lower environmental impact due to less produced waste.

Simulation results show a substantial reduction of the economic performance for the deterministic cases. The expected profits and the realized profits of the deterministic model (D1 and D2 in Fig. 4) differ on average by 4.5%. This shows that not accounting for uncertainty in optimization may lead to considerably lower values of economic performance after the values of uncertain parameters reveal. The difference between the expected and realized profit

Table 1
Summary of best economic and environmental solutions for deterministic and stochastic models as compared to the best economic solution of the deterministic model (shaded cells).

	Profit maximization		Exergy loss minimization	
	Deterministic model	Stochastic model	Deterministic model	Stochastic model
expected (Profit)	100.00 %	98.10 %	90.00 %	90.00 %
realized (Profit)	96.07 %	97.82 %	86.03 %	89.59 %
expected (Exergy loss)	100.00 %	104.25 %	78.28 %	82.96 %
realized (Exergy loss)	100.00 %	104.25 %	78.28 %	82.96 %
Compost produced	100.00 %	104.25 %	78.06 %	82.81 %
2nd flush	98 %	97 %	18 %	45 %
3rd flush	2 %	3 %	82 %	55 %

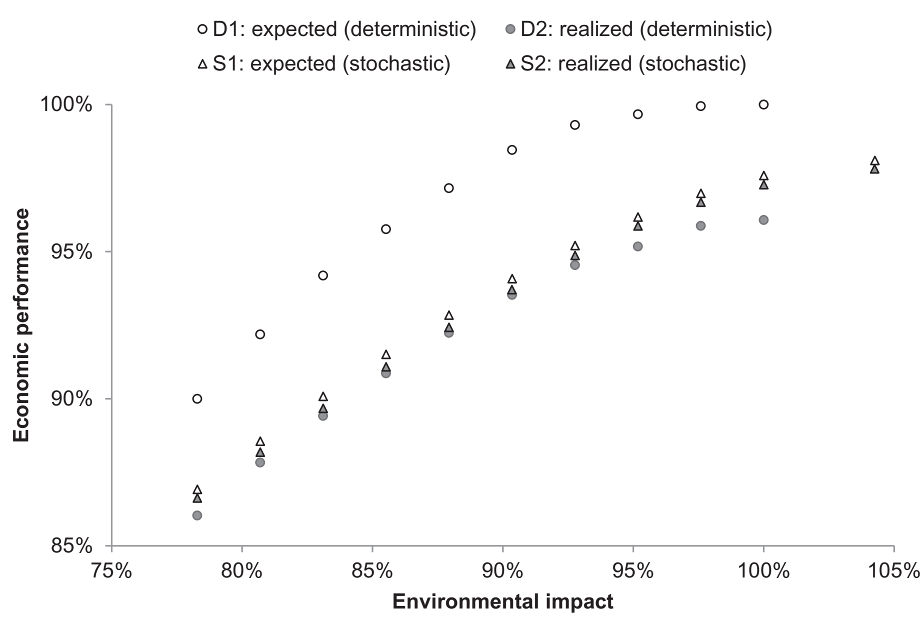

Fig. 4. Eco-efficient solutions for deterministic and stochastic models.

values obtained with stochastic model (S1 and S2) is on average only 0.3%. It is found that accounting for uncertainty leads to more realistic results, where the solutions of the model are on average much closer to the realized (i.e. after uncertainty reveals) optimal solutions. This clearly shows that accounting for the main sources of uncertainty in agri-food supply chain optimization models is important and leads to a better representation of the actual decision problem.

The ten best environmental solutions of D2 and S2 are considered to compare the solutions obtained from the deterministic and stochastic model. The analysis shows that each deterministic solution can be improved by including uncertainty in optimization. The maximum difference between solutions is 1.2%, the minimum difference is 0.2%, and the average difference is 0.5%, which corresponds to over 0.3×10^6 € more profit for the supply chain on a yearly basis. At the same time it can be observed that accounting for uncertainty amounts up to 5% reduction in environmental impact (i.e. by moving from the best economic solution D2 left until reaching S2 in Fig. 4).

Eco-efficient solutions allow to quantify the costs associated with improvement of environmental impact. Based on the results in Fig. 4, it can be calculated that e.g. the environmental impact of the best economic solution obtained with stochastic programming can be improved by 9% at the expense of 2% decrease in total profit.

In the presented model, uncertainty in technical model parameters is considered, i.e. uncertainty in yield, and demand parameters. Future research should account also for stochasticity in environmental model parameters (i.e. uncertain environmental impact associated with production), and economic model parameters (e.g. uncertainty related to selling prices). It will be interesting to explore the impact of uncertain environmental and economic parameters on the reliability of solutions obtained in optimization.

6. Conclusions

Food production is intrinsically associated with various sources of uncertainty, including production yields and demand patterns. The effect of changes in model parameters is often analysed with sensitivity analysis, which provide ex-post optimality analysis of uncertain model parameters. In these analyses the focus is on evaluating the sensitivity of an optimal solution to the value of specific (uncertain) parameters. This provides confidence on the optimal solution of the model. In sensitivity analysis, however, uncertainty is not included explicitly in the optimization phase. This may lead to production planning decisions, which, if implemented, result in lower than expected overall economic and environmental performance. Commonly in agri-food supply chains there exists a substantial time lag between production decisions and the revealed uncertainty of (production) parameters. The decomposition of decisions into multiple stages can have an added advantage above commonly applied deterministic approaches in which all decisions are optimized at the beginning of the planning horizon i.e. based on expected values for uncertain parameters. In contrast to a deterministic approach, n-stage stochastic programming partly allows to “postpone” decision making and to anticipate in an early stage of the planning horizon on different outcomes of future uncertainties. This paper clearly shows that a multi-objective two-stage stochastic programming model has added value above the deterministic model.

Numerical results of the presented industrial mushroom supply chain case study show that using expected (deterministic) parameter values in optimization leads to an overestimated (4.5% on average) economic performance that will hardly be realized in practice. It is found that accounting for the main uncertain model parameters i.e. yield and demand, leads to more realistic results, where the economic performance is overestimated only 0.3% on average. Accounting for stochasticity in important model parameters reduces the difference between expected and realized performance substantially, as compared to a model in which expected values of parameters are used in optimization. It is concluded that the set of eco-efficient solutions obtained with the stochastic model provides a more accurate representation of the trade-off between conflicting environmental and economic objectives. Moreover, it is found that including stochastic model parameters in optimization contributes to 5% reduction of the environmental impact (at the same level for economic performance). This paper concludes that it is important to account for the main sources of uncertainty in optimizing production planning decisions in sustainable supply chains, as it leads to substantial improvements, both in environmental and economic performance of a supply chain.

Future case based research is needed to confirm the finding on superiority on multi-stage decision making over deterministic approach in general. It will be interesting to explore which uncertain parameters play a crucial role in other real-life cases, and to examine the impact of other realistic probability distribution functions for those uncertain model parameters. Future research should also investigate a scenario in which different links of a chain do not cooperate and make production planning decisions in such an uncertain environment while optimizing their own (single link of a supply chain) objectives. It should then be investigated how the benefits obtained from collaboration and from treating uncertainty in optimization should be distributed between different links of an agri-food supply chain.

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References

Ahumada, O., Villalobos, J.R., 2009. Application of planning models in the agri-food supply chain: a review. Eur. J. Oper. Res. 196, 1–20.
Akkerman, R., Farahani, P., Grunow, M., 2010. Quality, safety and sustainability in food distribution: a review of quantitative operations management approaches and challenges. Spectrum 32, 863–904.
Alexandratos, N., Bruinsma, J., 2012. World Agriculture towards 2030/2050: the 2012 Revision. FAO, Rome. ESA Working Paper No. 12-03.
Amin, S.H., Zhang, G., 2013. A multi-objective facility location model for closed-loop supply chain network under uncertain demand and return. Appl. Math. Model. 37, 4165–4176.
Apaiah, R.K., Linnemann, A.R., van der Kooi, H.J., 2006. Exergy analysis: a tool to study the sustainability of food supply chains. Food Res. Int. 39, 1–11.
Banasik, A., Kanellopoulos, A., Claassen, G.D.H., Bloemhof-Ruwaard, J.M., van der Vorst, J.G.A.J., 2017. Closing loops in agricultural supply chains using multi-objective optimization: a case study of an industrial mushroom supply chain. Int. J. Prod. Econ. 183 (Part B), 409–420.
Ben-Tal, A., El Ghaoui, L., Nemirovski, A., 2009. Robust Optimization. Princeton University Press, Princeton, NJ.
Birge, J.R., Louveaux, F., 2011. Introduction to Stochastic Programming. Springer, New York, NY.
Bohle, C., Maturana, S., Vera, J., 2010. A robust optimization approach to wine grape harvesting scheduling. Eur. J. Oper. Res. 200, 245–252.
Borodin, V., Bourtembourg, J., Hnaien, F., Labadie, N., 2014. A quality risk management problem: case of annual crop harvest scheduling. Int. J. Prod. Res. 52, 2682–2695.
Brandenburg, M., Govindan, K., Sarkis, J., Seuring, S., 2014. Quantitative models for sustainable supply chain management: developments and directions. Eur. J. Oper. Res. 233, 299–312.
Brandenburg, M., Rebs, T., 2015. Sustainable supply chain management: a modeling perspective. Ann. Oper. Res. 229, 213–252.
Chaabane, A., Ramudhin, A., Paquet, M., 2011. Designing supply chains with sustainability considerations. Prod. Plann. Contr. 22, 727–741.
Ehrgott, M., 2005. Multicriteria Optimization, second ed. Springer, Berlin, Germany.
Guan, Z., Philpott, A.B., 2011. A multistage stochastic programming model for the New Zealand dairy industry. Int. J. Prod. Econ. 134, 289–299.
Keyvanshokooh, E., Ryan, S.M., Kabir, E., 2016. Hybrid robust and stochastic optimization for closed-loop supply chain network design using accelerated Benders decomposition. Eur. J. Oper. Res. 249, 76–92.
Löhndorf, N., 2016. An empirical analysis of scenario generation methods for stochastic optimization. Eur. J. Oper. Res. 255, 121–132.
Mirzapour Al-E-Hashem, S.M.J., Baboli, A., Sazvar, Z., 2013. A stochastic aggregate production planning model in a green supply chain: considering flexible lead times, nonlinear purchase and shortage cost functions. Eur. J. Oper. Res. 230, 26–41.
Munhoz, J.R., Morabito, R., 2014. Optimization approaches to support decision making in the production planning of a citrus company: a Brazilian case study. Comput. Electron. Agric. 107, 45–57.
Pauls-Worm, K.G.J., Hendrix, E.M.T., Alcoba, A.G., Haijema, R., 2014. Order quantities for perishable inventory control with non-stationary demand and a fill rate constraint. Int. J. Prod. Econ. 181, 238–246.
Quariguasi Frota Neto, J., Walther, G., Bloemhof, J., van Nunen, J., Spengler, T., 2009. A methodology for assessing eco-efficiency in logistics networks. Eur. J. Oper. Res. 193, 670–682.
Radulescu, M., Radulescu, S., Radulescu, C.Z., 2009. Sustainable production technologies which take into account environmental constraints. Eur. J. Oper. Res. 193, 730–740.
Sazvar, Z., Al-E-Hashem, S.M.J.M., Baboli, A., Jokar, M.R.A., 2014. A bi-objective stochastic programming model for a centralized green supply chain with deteriorating products. Int. J. Prod. Econ. 150, 140–154.
Soysal, M., Bloemhof-Ruwaard, J.M., Haijema, R., van der Vorst, J.G.A.J., 2015. Modeling an Inventory Routing Problem for perishable products with environmental considerations and demand uncertainty. Int. J. Prod. Econ. 164, 118–133.
Soysal, M., Bloemhof-Ruwaard, J.M., Meuwissen, M.P.M., van der Vorst, J.G.A.J., 2012. A review on quantitative models for sustainable food logistics management. Int. J. Food Syst. Dynam. 3 (2), 136–155.
Zisopoulos, F.K., Becerra Ramírez, H.A., van der Goot, A.J., Boom, R.M., 2016. A resource efficiency assessment of the industrial mushroom production chain: the influence of data variability. J. Clean. Prod. 126, 394–408.