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The impact of environmental uncertainty on the performance of the rice supply chain in the Ayeyarwaddy Region, Myanmar

Thuzar Linn^{1*} and Broos Maenhout² 

* Correspondence: thuzarlinn.eco@gmail.com

¹Department of Agricultural Economics, Yezin Agricultural University, Pyinmana, Myanmar
Full list of author information is available at the end of the article

Abstract

In this paper, we study the relationship between environmental uncertainty and performance in the rice supply chain in the Ayeyarwaddy Region, Myanmar. Efficiency is one of the important performance indicators in both supply chain and agribusiness. In this regard, the objectives of the study are to identify the different sources of uncertainty perceived by the different actors in the supply chain, to measure the rice supply chain efficiency, and to study the impact of the environmental uncertainty on the supply chain efficiency. The data of 215 respondents is collected from the Ayeyarwaddy Region by using a purposive and stratified random sampling method, and we analyze this data via descriptive statistics, an exploratory factor analysis, data envelopment analysis (DEA), and Tobit regression analysis. The scores for the technical, pure, and scale efficiency show a very low performance of the rice supply chain in the Ayeyarwaddy Region resulting from the fact that most of the rice businesses are too small and need to expand their operating size. We found that this global rice supply chain performance is significantly impacted by the planning and control uncertainty and the climate uncertainty. Therefore, mitigation initiatives must be developed such as financial insurance mechanisms and extension services should be widespread. Both aim to improve the impact of the climate adverse conditions and to increase the efficiency of resource utilization in the supply chain. Moreover, the actors should organize themselves in cooperatives such that the scale of operations can be increased and information is captured and shared between different parties in the supply chain. This is crucial to operational control and planning because a higher quality of information input will increase the quality of managerial decision making.

Keywords: Environmental uncertainty, Efficiency performance, Rice supply chain, Myanmar

Introduction

Agriculture plays a major role in Myanmar's society by ensuring food security at community and national levels as well as in the provision of employment and income for a growing population. Agriculture is essential to the domestic economy of Myanmar. In 2014–2015, 22.1% of the gross domestic product resulted from agricultural activities (MOAI 2015a). More than half of the population is directly employed in this sector.

The agricultural sector is considered as one of the major driving forces for economic growth and the heart for improving of social wellbeing (World Bank 2014). Moreover, rice contributes export earnings to the economy of the country and provides food security and poverty reduction in Myanmar. In 2016, the paddy production in Myanmar was ranked seventh among the paddy-producing countries in the world (World Rice Production 2017). Rice is the country's most important agricultural product by far, accounting for about half of all cultivated land. In 2015–16, the sown areas and production of paddy in Myanmar are 7.21 million hectares and 27.16 million metric tons, respectively (MOALI 2016). Most of the household income is earned from rice farming and related activities, especially in major rice growing areas, i.e., the Ayeyarwaddy, Bago, and Sagaing regions in Myanmar. The Ayeyarwaddy Region is the main rice growing area in Myanmar and occupies 25% of Myanmar's rice acreage and the use of farm mechanization in the region is very low with 251 tractors and 83 combined harvesters (AMD 2015).

In most developing countries, governments, development agencies, and private sectors recognize the role of poverty reduction and food security and, as a result, are increasingly investing in agricultural value chains, providing inputs, financing, and other services that support their development. Over the past five decades, food availability has been greatly improved through productivity gains in the agricultural sector (Baldos and Hertel 2014). However, the agricultural sector is currently under increasing pressure, i.e., (i) to be sustainably run, which implies that the sector should be able to meet the needs of the present without compromising the ability of future generations to achieve their own ends, and (ii) to provide food, energy, and industrial resources to satisfy the demand of a rising world population (Yakovleva et al. 2012). At the same time, there is an increasing awareness that uncertainty impacts the sustainability of a value chain and the performance of the entire supply chain and of each of the involved actors. In an agricultural supply chain, uncertainty can emerge either from an internal or an external source in the supply chain. Some sources of uncertainty are different compared to general supply chains, i.e., the perishability of products, variable harvest and production yields, and the huge impact of climate and environmental conditions on upstream and downstream activities (van der Vorst and Beulens 2002; Wijnands and Ondersteijn 2006; Cafiero et al. 2007). Moreover, the operational complexity resulting from uncertainty related to the high variability in consumer demand, production and supply lead times, varying quantity and quality standards of products, trade and buffer stock traceability, etc. expose the chain to severe disruptions (van der Vorst 2000; Dong 2006; Taylor and Fearn 2006).

In Myanmar, in particular, far lower profits are gained from producing rice compared to other countries in Asia (Zorya 2016). The agricultural sector has suffered persistently from insufficient investment in technology transfer, research and extension services, infrastructure development, value chain upgrading, and marketing (IFAD 2017). The Ministry of Agriculture and Irrigation has mapped the principal challenges and strategic objectives in order to further develop and upgrade the rice value chain via investments (MOAI 2015b). According to these challenges and objectives, the rice value chain in Myanmar is not well integrated and efficiency should be improved to increase the market value of rice production and the rice food quality via well-focused investments. However, the Ministry of Agriculture and Irrigation of

Myanmar has expressed its concerns regarding the impact of uncertainty in particular related to the climate, the price volatility, and arising from the unsatisfactory integration of the value chain over the different actors in the chain from rice production to trading and marketing (MOAI 2015b).

In this paper, we study in an explorative manner the sources of environmental uncertainty that impact the rice supply chain performance in the Ayeyarwaddy Region in Myanmar. We learn to understand the challenges the supply chain in the region is dealing with and we can establish priorities. This helps to identify solutions to improve the supply chain operations. To that purpose, we exploit a three-step solution methodology. In a first step, we measure the environmental uncertainty perceived by the various actors in the supply chain. We carried out a questionnaire survey and a statistical analysis to identify the main sources of uncertainty encountered by the different parties in the rice supply chain, i.e., farmers, primary collectors, millers, wholesalers, retailers, and exporters. In a second step, we measure the efficiency performance of the different sample respondents per actor category in the rice supply chain via data envelopment analysis (DEA). In a third step, regression analysis is applied to identify the significant sources of uncertainty that impact the performance of the supply chain.

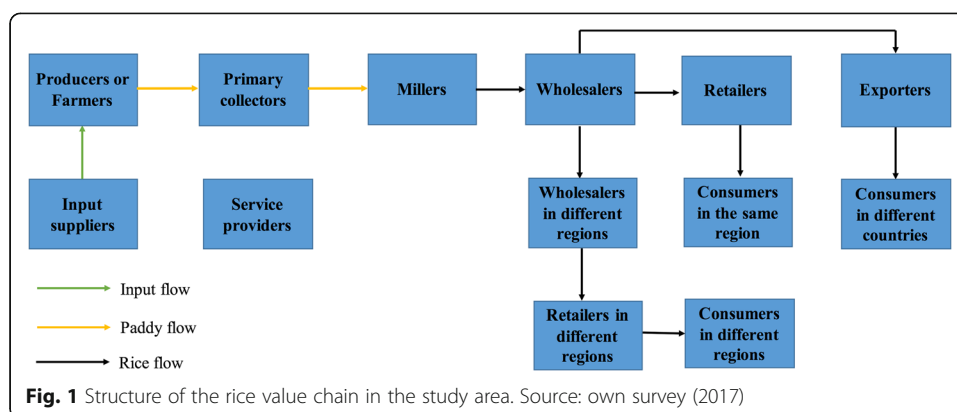
The remainder of the paper is organized as follows. “[Literature review](#)” section reviews the relevant literature on the rice supply chain of Myanmar, the uncertainty in an agricultural supply chain, the relevant indicators to measure the supply chain performance, and in particular the DEA approach, which is used in this study to benchmark the supply chain efficiency. In “[Research methodology](#)” section, the methodology is described to identify the main sources of uncertainty that impact the supply chain efficiency. The findings of our study are revealed in “[Results and discussions](#)” section. First, we present the sources of uncertainty as perceived by the actors in the rice supply chain. Second, we measure the performance of the rice supply chain via DEA. Third, we study the impact of the uncertainty on the supply chain efficiency. A conclusion and some policy recommendations are summarized in “[Conclusion and recommendations](#)” section.

Literature review

The rice value chain in Myanmar

Agricultural value chains involve a sequence of value-adding activities to bring products from the farm to the final consumer. The activities in a value chain link together the inputs from providers, farmers, processors, retailers, and consumers and create relationships that enable the effective functioning of the value chain (Baldos and Hertel 2014). The agricultural supply chain includes all functions such as the input provision, production, post-harvest, storage, processing, marketing and distribution, food service, and consumption for a given agricultural product (Jaffee et al. 2010).

The rice value chain of Myanmar has been studied by Wong and Wai (2013). The structure of the rice value chain in the study area is shown in Fig. 1. The farmers buy inputs such as agrochemicals, machinery, seeds, credit, etc. from the input suppliers for the paddy production. Primary collectors buy the paddy from the farmers with the financial support of millers. The millers buy and mill the paddy to rice. They carry out different activities that add value such as transportation, processing, grading, and



packing. The millers store and distribute rice mainly to wholesalers. Wholesalers deliver rice on their turn to retailers in order to supply the domestic consumers or to exporters who supply consumers in foreign countries.

A study issued by the Ministry of Agriculture and Irrigation (MOAI 2015b) posed that the rice value chain in Myanmar is not well integrated and its efficiency should be improved. The supply chain is fragmented as there are too many different parties in the different stages and too many stages ranging from between the farmer and the end consumer. Compared to the neighboring countries Thailand and Vietnam, the rice value chain in Myanmar is characterized by a less efficient input supply system, a lower farm productivity and profitability, higher milling and export costs, and a lower quality of exported rice (Zorya et al. 2016). As a result, the rice sector is less competitive on the international market.

Uncertainty in supply chains

Many researchers have investigated uncertainty as an important factor affecting supply chain implementation and performance (Bhatnagar and Sohal 2005). According to Miller (1993), uncertainty refers to the unpredictability of environmental or organizational variables that have an impact on corporate performance. Carter et al. (2015) stated that supply chain uncertainty can occur at multiple levels, including the level of individual decision makers, functional departments, organizations, and, ultimately, supply chains. Uncertainty propagates throughout the network and leads to inefficient processing and non-value adding activities (Patil et al. 2012). Throughout the supply chain, agents are faced with different sources of uncertainty which may be exogenous, endogenous, or both (Chaudhuri et al. 2014).

According to Miller (1992), Davis (1993), Prater (2005), and Lee (2002), supply chain uncertainty has been widely recognized as an issue in modern supply chain and logistics. Uncertainties in a supply chain may cause delays, lead to a bottleneck, and may hinder the performance of the entire supply chain. Literature stated that it is important to consider uncertainties to achieve operational excellence and smooth operations in every link of the supply chain since uncertainty cannot be avoided (Wang et al. 2014). Uncertainty factors in the supply chain involve *supply uncertainty* (Davis 1993; Towill et al. 2002; van der Vorst and Beulens 2002; Sawhney 2006; Thongrattana and Jie 2009; Patil et al. 2012; Chaudhuri et al. 2014), *demand uncertainty* (Lee et al. 1997; Lee,

2002; van der Vorst and Beulens 2002; Sun et al., 2009; Thongrattana and Jie 2009; Patil et al. 2012), *process uncertainty* (Ettile and Reza 1992; Miller 1992; Davis 1993; Koh et al. 2002; Towill et al. 2002; van der Vorst and Beulens 2002; Sawhney 2006; Thongrattana and Jie 2009; Patil et al. 2012), *control and planning uncertainty* (Wilding 1998; Geary et al. 2002; Towill et al. 2002; van der Vorst and Beulens 2002; Childerhouse and Towill 2004; Prater 2005; Thongrattana and Jie 2009), *competitor uncertainty* (Ettile and Reza 1992; Miller 1992; Davis 1993; van der Vorst and Beulens 2002; Bhatnagar and Sohal 2005; Paulraj and Chen 2007; Thongrattana and Jie 2009), *government uncertainty* (Miller 1992; van der Vorst and Beulens 2002; Christopher and Peck 2004; Thongrattana and Jie 2009), and *climate uncertainty* (Miller 1992; Christopher and Peck 2004; Kleindorfer and Saad 2005; Thongrattana and Jie 2009). Note that these factors are perceived differently across industries and countries. Cafiero et al. (2007) presented a summary of policies intended to manage risk and uncertainty in the context of a developed economy. They recognize that first the main uncertainty factors should be identified before a strategic policy plan can be developed.

Performance measurement in supply chains

Neely et al. (1991) defined performance measurement as the process of measuring the efficiency and effectiveness of an action. According to Aramyan et al. (2006), Aramyan et al. (2009), Chaowarut et al. (2009), and Shen et al. (2013), performance measurement has gained attention in the agri-food chains and various performance measurements have been used. In marketing and supply chain management literature, supply chain performance is measured via different methods such as activity-based costing, balanced scorecard, economic value added, multi-criteria analysis, life-cycle analysis, data envelopment analysis, and the supply chain operations reference model. Among these methods, data envelopment analysis (DEA) is a powerful analysis model to calculate the efficiency score of the supply chain performance in various sectors. DEA evaluates the involved business units with multiple inputs and outputs and takes qualitative and quantitative measures into account (Shafiee et al. 2014). DEA has been used to measure the supply chain performance in various studies (Liu et al. 2000; Easton et al. 2002; Talluri and Baker 2002; Biehl et al. 2006; Min and Joo 2006; Reiner and Hofmann 2006; Li and Dai 2009; Saranga and Monser 2010; Jalalvand et al. 2011; Liang et al. 2011; Sanei and Mamizadeh-Chatghayeh 2013; Shafiee et al. 2014; Rezaei and Adressi 2015; Shewell and Migiroy 2016) in different application areas, e.g., the shipping industry (Pattanamekar et al. 2011), the pharmaceutical industry (Mishra 2012), the dairy industry (Mor and Sharma 2012), and the vegetable food industry (Lu 2006).

Uncertainty has a major impact on the performance of the supply chain and managerial decisions. van der Vorst and Beulens (2002) pointed out that the literature recognizes that uncertainties in supply, process, and demand have a major impact on the manufacturing function. Thongrattana and Robertson (2008) investigated that periodic rice production losses due to a drought year may create significant problems such as inventory level fluctuations, stock-outs, and unfulfilled customer demand. The findings of Thongrattana and Jie (2009) showed that demand and climate uncertainty lead to a significant decrease in efficiency of the rice milling process in Thailand. The empirical model of Matanda and Schroder (2002) measured uncertainty by means of competitive

intensity and market turbulence and pointed out that these uncertainty measurements had a direct negative impact on the performance. The relationship between uncertainty based on subjective perceptions by the involved decision makers and performance has been widely studied in research areas such as management accounting but also in supply chain management (e.g., Buchko 1994; Flynn et al. 2016; Jusoh 2010; Thongrattana and Robertson 2008; Wong et al., 2011).

Research methodology

In this study, we aim to identify the major sources of uncertainty that impact the performance of the rice supply chain. In this way, directions can be determined to improve the efficiency, i.e., to utilize the scarce resources more efficiently and to adopt the right scale of operations. Efficient farm practices can enhance productivity, the farmers' profit, and the amount of rice marketed, which improve the competitiveness of the rice sector in Myanmar (MOAI 2015b; SAYSAY 2016). To that purpose, we have employed a three-step methodology for which the specific techniques used in each step are explained in the subsections below.

Step 1: Identify the sources of uncertainty perceived by the different actors in the rice supply chain

Different organizational theorists (e.g., Duncan (1972), Hofer and Schendel (1978), Ansoff (1979), Miles (1982), and Rhyne (1985)) established the link between the perceived environmental uncertainty and performance. Organizations must adapt to their environment if they are to remain viable. One of the central issues in this process from the perspective of the decision-making units is coping with uncertainty resulting from environmental factors. The environmental uncertainty and its associated factors are defined in terms of perception of the respondents given the role of individuals in the decision-making process. The research of Duncan (1972) showed that although there are difficulties in getting respondents to verbalize their views of uncertainty, there is a remarkable degree of similarity in the way in which the concept was ultimately defined. Miles et al. (1974) also theorize that managers respond primarily to what they perceive. Strategic action is dependent upon perceptions and interpretations of the environment. In this research, we identify the components of this environmental uncertainty for the entire rice supply chain in Myanmar and identify different degrees of uncertainty as perceived by individuals in decision-making, i.e., the different actors in the rice supply chain, taking their actor role into account. This study is based on the development of a questionnaire and conducting this survey via in-depth and key informant interviews (cf. "Data collection and sampling" section). The results for this questionnaire are checked for its validity and reliability. A factor analysis is applied for measuring the sources of uncertainty and a principal component analysis is applied to reduce the number of variables (cf. "Research method: instrument development and factor analysis" section).

Step 2: Measure the rice supply chain efficiency to assess the supply chain performance

Based on his perception, the decision maker will take the relevant strategic and operational decisions, i.e., he will determine the mix of inputs to maximize his output level and his scale of operations. Hence, we can conclude that from the perception of uncertainty, the decision maker within a company can change the level of efficiency. In order to relate the perceived uncertainty with the efficiency level of the actors, we measure

the efficiency by making use of data envelopment analysis (DEA) (Charnes et al. 1978) (cf. “Research method: data envelopment analysis” section). Using this technique, we can measure the overall technical efficiency, pure technical efficiency, and scale efficiency for all actors in the supply chain, i.e., farmers (production stage), millers (processing stage), and distributors such as wholesalers, retailers, and exporters (distribution stage). The marketed amount of paddy is considered as the output variable. The production, financial, transportation, and storage costs are considered as the input variables in the input-oriented DEA model.

Step 3: Study the impact of uncertainty on supply chain efficiency to understand the challenges of the supply chain

We relate the outcomes of the first two steps in order to identify the most important types of uncertainty, i.e., these that impact the performance of the supply chain significantly. This analysis is performed by a Tobit regression since the dependent variable, i.e., the efficiency of individual actors, is a latent variable and is bounded between 0 and 1. These efficiency scores are censored and the differences are small such that the standard regression technique provides a biased estimate.

Data collection and sampling

Both primary and secondary data are collected for understanding the uncertainty in the rice supply chain in the Kyangin and Myanaung townships in the Ayeyarwaddy Region. A purposive and stratified random sampling method is used for primary data collection (Kong et al, 2015). The stratification of the sample is solely based upon the role of the respondents in the supply chain in order to discern any differences in the types of uncertainty and its impact between different roles in the supply chain. The sample size is calculated for each stratum in direct proportion¹ to the size of the stratum compared to the (finite) population (Table 1) (Judez et al. 2006). As a result, a sample of 130 farmers, 21 primary collectors, 25 millers, 7 wholesalers, 28 retailers, and 4 exporters is

Table 1 Sampled respondents along the rice supply chain in the study area

Actors	Townships	Total population	Sampled respondents
Farmers	Myanaung (Laharpauk village)	399	30
	Myanaung (Htanthonepin village)	327	30
	Kyangin (Kyantaw village)	663	35
	Kyangin (Sonehele village)	630	35
Collectors	Myanaung	105	15
	Kyangin	60	6
Millers	Myanaung	132	18
	Kyangin	80	7
Wholesalers	Myanaung	34	4
	Kyangin	20	3
Retailers	Myanaung	103	20
	Kyangin	61	8
Rice exporters	Yangon	36	4
Total respondents			215

Source: DOA (2017) and MRF (2017)

selected for conducting the face-to-face interviews. A representative sample for each stratum has been constructed. Table 2 shows the socio-economic and demographic characteristics of the respondents, i.e., gender, age, family size, education, working experience, yield, marketed amount of paddy or rice, and farm size. For example, 34.62% of the farms have a small size (≤ 2.02 ha), 37.69% have a medium size (> 2.02 ha and ≤ 4.05 ha), and 27.69% have a large size (> 4.05 ha).

In-depth and key informant interviews are used to interview sample respondents in order to collect primary data (Umberger 2014). The questionnaire uses a 7-point Likert

Table 2 Characteristics of the different actors in the rice supply chain

Items	Unit	Parameters	Farmer	Primary collector	Miller	Wholesaler	Retailer	Exporter
Gender	Number	Male	114 (87.69)	19 (90.48)	23 (92)	5 (71.43)	19 (67.86)	4 (100)
		Female	16 (12.31)	2 (9.52)	2 (8)	2 (28.57)	9 (32.14)	0 (0)
Age	Years	Mean	51	41.60	50.10	46.70	49.90	43
		Min.	27	25	30	41	30	35
		Max.	85	60	66	62	72	50
Family size	Numbers	Mean	4	4	4.40	4	3.60	4
		Min.	2	1	2	2	2	3
		Max.	8	7	8	6	6	6
Education	Schooling years	Mean	6	9	11	12.3	9.9	15
		Min.	2	5	5	6	4	15
		Max.	15	15	15	15	18	15
Work experience	Years	Mean	27	10.80	12.80	13	13.60	13
		Min.	3	1	1	3	1	5
		Max.	54	30	33	24	50	26
Farm size	ha	Mean	3.07	–	–	–	–	–
		Min.	0.40	–	–	–	–	–
		Max.	15.78	–	–	–	–	–
Small farm size	≤ 2.02 ha	Numbers	45 (34.62)	–	–	–	–	–
Medium farm size	> 2.02 ha and ≤ 4.05 ha	Numbers	49 (37.69)	–	–	–	–	–
Large farm size	> 4.05 ha	Numbers	36 (27.69)	–	–	–	–	–
Yield of paddy	kg/ha	Mean	3000.11	–	–	–	–	–
		Min.	516.44	–	–	–	–	–
		Max.	5164.39	–	–	–	–	–
Milling amount	000 kg/day	Mean	–	–	11.99	–	–	–
		Min.	–	–	0.21	–	–	–
		Max.	–	–	59.71	–	–	–
Milling capacity	$< 15,000$ kg/day	Numbers	–	–	19 (76)	–	–	–
	$\geq 15,000$ kg/day	Numbers	–	–	6 (24)	–	–	–
Marketed amount	000 kg/year	Mean	6.50	127.29	1088.17	669.74	25.73	507,500
		Min.	0.29	10.45	12.68	13.46	13.80	60,000
		Max.	31.04	627.00	3793.48	1776.75	189.75	1,700,000

Figures in the parentheses represent percentage
Source: own survey (2017)

scale with end points “1—strongly disagree” and “7—strongly agree” to measure the relevant sources of uncertainty. The questionnaire is constructed based on the literature (cf. Table 3) and includes different sources of uncertainty with respect to the supply, demand, process, planning and control, competitor, government policy, and climate. The questionnaire items are presented in Table 3. Moreover, we collect production, marketing, and financial data to evaluate the supply chain performance. The secondary data originates from various published sources, from government and other organizations, and will be revealed when relevant in discussing the results.

Research method: instrument development and factor analysis

This study measures the uncertainty perceived by the different actors in the supply chain and uses a pilot survey to question the farmers. Some previous studies in the rice or food industry (Thongrattana and Jie 2009; van der Vorst and Beulens 2002; Bran and Bos 2005) used the same pilot study and the Q-sort method to check the validity and reliability. For the statistical analysis, non-parametric statistics are applied using SPSS software because of the 7-point Likert scale used for each item and each factor is composed out of a number of items leading to quasi-normal distributed data (Lewis and Harvey 2001). Descriptive statistics, inferential statistics, and factor analysis are applied to investigate the sources of uncertainty. Scale reliability and scale validity tests are conducted before applying factor analysis (Thongrattana and Jie 2009; van der Vorst and Beulens 2002; Bran and Bos 2005). Factor analysis helps to reduce the dimensionality operating on the notion that measurable and observable variables can be reduced to fewer latent variables, which share a common variance and are unobservable (Bartholomew et al. 2011). The factor analysis is conducted using principal component analysis as a method of extraction. Principal components analysis is used to extract maximum variance from the dataset with each component and thus reducing a large number of variables into a smaller number of components (Tabachnick and Fidell 2007).

Research method: data envelopment analysis

Charnes et al. (1978) originally developed data envelopment analysis (DEA), which is a very powerful service management and benchmarking technique to evaluate nonprofit and public sector organizations. DEA has been widely used to evaluate the firm (i.e., the decision-making unit) performance based on relative efficiency measurements. In this way, this analysis method may contribute to improving the productivity, reducing the costs, and increasing the profit margins. In this study, we consider the technical efficiency to measure the performance of the different actors in the rice supply chain. In the literature, distinction is made between the input-oriented and the output-oriented DEA model to measure the efficiency. The input-oriented DEA model minimizes the inputs keeping the outputs at their current level. The output-oriented DEA model maximizes the outputs, keeping the inputs fixed at their current level (Banker et al. 1984).

Technical efficiency and scale efficiency

Technical efficiency is defined as the ability of a farm to either produce the maximum feasible output from a given bundle of inputs or to produce the given level of output using the minimum amount of inputs (Basanta et al. 2004). The technical efficiency

Table 3 Questionnaire items of uncertainty factors

Uncertainty factors	Concept	Aspects of measurement	Code	Questions to the actors	References
Supply	Supply uncertainty is related to the unpredictability of the delivery of raw or packed materials in time, in the right amount or according to the right specifications. In this study, paddy is supplied from farmers to rice millers, and milled rice from millers to distributors and so on.	Quantity	SU1	Rice quantity from rice producers is unpredictable.	van der Vorst 2000; Li 2002; Paulraj and Chen 2007; Thongrattana and Jie 2009
		Quality	SU2	Rice quality from rice producers is unpredictable.	
		Time	SU3	Rice producers' delivery time is unpredictable.	
Demand	Demand uncertainty is related to uncertainty about customers' requirements as a combination of unpredictability of demand and product variety (van der Vorst 2000). Both the international and domestic demand are considered.	Quantity	DU1	The volume of customer demand is difficult to predict.	Li 2002; Paulraj and Chen 2007; Thongrattana and Jie 2009
		Quality	DU2	Customers' rice preference changes over the year.	
		Time	DU3	The lead time of customer order is unpredictable.	
Process	Process uncertainty is related to the production system, including the uncertain ability to produce adequately a particular product or the uncertain availability of sufficient raw materials (van der Vorst 2000). In this study, the processor refers to any procedure carried out by supply chain members, such as producing, milling, quality control, and packing process.	Quantity	PU1	Yield of production or processing (e.g., producing, milling, packing) can vary.	van der Vorst 2000; Thongrattana and Jie 2009
		Quality	PU2	The quality of rice after processing (e.g., milled, stored) can change.	
		Time	PU3	The throughput time of rice processing can vary.	
Planning and control	Planning and control uncertainty relates to incomplete information about production, inventory and customer demand (van der Vorst 2000).	Quantity	PCU1	Information about stock level of rice and rice production capacity is inaccurate.	van der Vorst 2000; Thongrattana and Jie 2009
		Time	PCU2	Information about stock level of rice and rice production capacity is not on time .	
			PCU3	Information concerning changes to customer orders cannot be distributed on time.	
Competitor	Competitor uncertainty refers to unpredictable actions by competitors in the competitive markets. This is related to reducing their product price, the time	Action	CU1	Competitors' actions are unpredictable.	Li 2002; Thongrattana and Jie 2009
		Domestic market	CU2	Competition in the domestic market is intensifying.	
		International	CU3	Competition is intensified	

Table 3 Questionnaire items of uncertainty factors (*Continued*)

Uncertainty factors	Concept	Aspects of measurement	Code	Questions to the actors	References
	to market or the increasing product quality and variety (Li 2002). Uncertainty about competitors' actions in the Myanmar rice industry is considered in both domestic and international markets.	market		in different countries.	
	Government policy	Government policy uncertainty includes the unpredictable set of laws, regulations, administrative procedures, and policies formally sanctioned by the government, which can affect an organizations' profitability (Badri et al. 2000).	Rice	production	GU1
			Rice	Government policies in rice trading (e.g., FTA, tax) directly affecting your firm are unpredictable trading	Javidan 1984; Badri et al. 2000; Bran and Bos 2005; Thongrattana and Jie 2009
GU2	The grantee price from government regulation is unpredictable.				
New government	GU3	New government regulations are introduced unexpectedly.			
Climate	Climate uncertainty is referred to the unpredictable occurrence of serious weather events affecting agricultural lands. These phenomena can lead to rice supply shocks, delays in the time of arrival of paddy to market or transportation disruptions (Curz et al. 2007).	Drought	CLU1	Drought occurrences affecting firms are unpredictable over the year.	Curz et al. 2007; Thongrattana and Jie 2009
			CLU2	The duration of drought is unpredictable over the year.	
		Flooding	CLU3	Flooding occurrences affecting firms are unpredictable over the year.	
			CLU4	The duration of flooding is unpredictable over the year.	

Source: Own compilation based on Thongrattana and Jie (2009)

can be measured under the assumption of *constant returns-to-scale* (CRS), which hypothesizes that the output will change in the same proportion as the inputs are changed (e.g., doubling the inputs will double the output). If the technical efficiency is measured under the assumption of *variable returns-to-scale* (VRS), the production technology is assumed to or decreasing returns to/or decreasing returns to scale

(Kumar and Gulati 2008). The technical efficiency with constant returns-to-scale (TE_{CRS}), which is further referred to as the *overall technical efficiency*, helps to determine inefficiencies due to input/output arrangement as well as the size of operations and is composed out of two components, i.e., the *pure technical efficiency* and the *scale efficiency* (Sharma et al. 1999). The *pure technical efficiency* measure, also called the technical efficiency with variable returns-to-scale (TE_{VRS}), is achieved by estimating the efficient frontier under the assumption of variable returns-to-scale. The pure technical efficiency measures the technical efficiency without considering the scale effect and purely reveals the ability of the business unit to organize its inputs efficiently in the production process. Hence, the *pure technical efficiency* can be used as an index to capture the managerial performance of the decision maker. The ratio of the *overall technical efficiency* vs the *pure technical efficiency* provides the scale efficiency (SE). When the *overall technical efficiency* is equal to the *pure technical efficiency*, this business unit is called a scale-efficient unit. *Scale efficiency* expresses whether a firm is operating at its optimal size. The scale efficiency gives notion of the managerial ability to select the optimal resource input size and scale of production to achieve the expected production level (Kumar and Gulati, 2008). The scale inefficiency may be the result from decreasing returns-to-scale (DRS) and increasing returns-to-scale (IRS). Decreasing returns-to-scale implies that a firm is too large to take full advantage of its scale and has a supra-optimum scale size. In contrast, a firm that is experiencing increasing returns-to-scale is too small for its scale of operations and, thus, operates at sub-optimum scale size. A firm is scale efficient if it operates at constant returns-to-scale (CRS).

Using the DEA model specification, the technical efficiency (TE) score for a given farm n is obtained by solving the following input-oriented LP problem:

Notation

Sets	
I	Set of farms (index i)
J	Set of inputs (index j)
K	Set of outputs (index k)
Parameters	
x_{ij}	The amount of input j used on farm i
x_{nj}	The amount of input j used on farm n
y_{ik}	The amount of output k produced on farm i
y_{nk}	The amount of output k produced on farm n
Decision variables	
λ_i	The nonnegative weights for I farms
θ_n	The technical efficiency of farm n (a scalar ≤ 1)

Mathematical formulation

$$TE_n = \min \theta_n \quad (1)$$

Subject to

$$\sum_{i=1}^I \lambda_i x_{ij} - \theta_n x_{nj} \leq 0 \quad \forall j \quad (2)$$

$$\sum_{i=1}^I \lambda_i y_{ik} - y_{nk} \geq 0 \quad \forall k \quad (3)$$

$$\sum_{i=1}^I \lambda_i = 1 \quad (4)$$

$$\lambda_i \geq 0 \quad (5)$$

The objective function (Eq. 1) of the input-oriented DEA model minimizes the inputs while the outputs are kept at their current levels. If θ_n is equal to 1, the business unit is technically efficient. When θ_n is smaller than 1, the business unit is technically inefficient with the level of inefficiency equal to $1 - TE_n$ (Coelli 1995). Equation (2) is the input constraint formulated for every input j . This constraint stipulates that the input used by farm n , weighted by its efficiency level θ_n , must exceed or be equal to a weighted combination of inputs used by the other farms. Equation (3) is the output constraint formulated for every output k . This constraint stipulates that the output obtained by farm n must be lower than or equal to the weighted combination of outputs obtained by the other farms. Equation (4) sets the sum of all weights given to the other farms is equal to 1 and ensures that the technical efficiency TE_n in Eq. (1) is calculated under the assumption of variable returns-to-scale (VRS) (Coelli 1995). Model (1)–(5) is the formulation proposed by Banker et al. (1984) and calculates the pure technical efficiency ($TE_n = TE_{VRS_n}$). When Eq. (4) is omitted, CRS are assumed and the model reflects the formulation proposed by Charnes et al. 1978 to calculate the overall technical efficiency ($TE_n = TE_{CRS_n}$).

The scale efficiency for farm n (SE_n) can be calculated by the following equation:

$$SE_n = \frac{TE_{CRS_n}}{TE_{VRS_n}} \quad (6)$$

where TE_{CRS_n} is the technical efficiency under CRS assumption for farm n and TE_{VRS_n} is the technical efficiency under VRS assumption for farm n .

Research method: Tobit regression model

The Tobit regression model is used to perform a regression analysis to determine the significant uncertainty factors that hinder the rice production efficiency, which is obtained via DEA. Tobit analysis assumes that the dependent variable has a number of factors clustered at a limiting value, usually zero (Tobin 1958). Hence, the following regression model is employed, i.e.,

$$y_i^* = x_i \beta_i + \mu_i \quad i = 1, 2, \dots, n \quad (7)$$

$$y_i = y_i^* \text{ if } y_i^* < 0 \quad (8)$$

$$y_i = 0, \text{ otherwise} \quad (9)$$

where

$\mu_i \sim N(0, \sigma^2)$ the error term

x_i explanatory variables

- β_i estimated parameter coefficients
- y_i^* a latent variable
- y_i the efficiency scores obtained via the DEA model

Results and discussions

In this section, we present the results of this study using the proposed three-step methodology. “[Uncertainty factors in the rice supply chain](#)” section discusses the environmental uncertainty as perceived by the actors in the rice supply chain and investigates the most important uncertainty factors in the rice supply chain by using factor analysis. In “[Efficiency performance of the rice supply chain](#)” section, we measure the rice supply chain efficiency as a measurement of supply chain performance by applying a DEA approach. In “[The impact of uncertainty on of the rice supply chain performance](#)” section, we determine the impact of uncertainty factors on the supply chain efficiency and determine the major sources of uncertainty by conducting a Tobit regression analysis.

Uncertainty factors in the rice supply chain

Descriptive statistics of the uncertain factors in the rice supply chain

Table 4 displays the perceived uncertainty factors in the rice supply chain in the Ayeyarwaddy Region, Myanmar. The actor responses are sub-divided into three groups, i.e.,

Table 4 Descriptive statistics of the uncertain factors in the rice supply chain (N = 215)

Items	Code	Disagree (scale 1–3)	Neutral (scale 4)	Agree (scale 5–7)	Mean	Std. deviation
Supply uncertainty (SU)	SU1	15.82	3.72	80.46	5.66	1.595
	SU2	17.22	2.79	79.99	5.53	1.795
	SU3	17.68	4.19	78.14	5.30	1.776
Demand uncertainty (DU)	DU1	7.91	4.19	87.9	5.79	1.312
	DU2	8.84	4.65	86.51	5.73	1.280
	DU3	4.66	14.42	80.93	5.47	1.126
Process uncertainty (PU)	PU1	8.84	9.30	81.87	5.47	1.314
	PU2	6.06	13.95	80.00	5.50	1.322
	PU3	8.38	14.88	76.75	5.22	1.382
Planning and control uncertainty (PCU)	PCU1	43.71	13.02	43.27	4.12	1.861
	PCU2	36.74	13.02	50.24	4.08	1.840
	PCU3	34.88	13.95	51.17	4.14	1.781
Competitor uncertainty (CU)	CU1	15.82	9.77	74.41	5.17	1.629
	CU2	21.40	10.23	68.37	4.82	1.846
	CU3	21.86	8.84	69.31	4.84	1.818
Government policy uncertainty (GU)	GU1	14.88	8.37	76.74	5.40	1.745
	GU2	12.56	9.77	77.68	5.44	1.642
	GU3	24.18	13.95	61.85	4.84	1.792
Climate uncertainty (CLU)	CLU1	10.70	4.65	84.64	5.80	1.504
	CLU2	12.56	4.65	82.79	5.73	1.598
	CLU3	7.91	3.26	88.84	6.00	1.365
	CLU4	8.38	3.72	87.91	6.00	1.399

Source: own data (2017) and SPSS

“Disagree” (scale 1–3), “Neutral” (scale 4), and “Agree” (scale 5–7) for the 7-point Likert scale. According to Table 4, the rice supply chain actors agree on average on all the uncertainty items since all averages are higher than 4. Hence, the actors in the rice supply chain encounter the different types of uncertainty observed in the literature. There are, however, significant differences in the uncertainty perception between different individuals per questionnaire item ($p = 0.000$ for each item). The item “information about stock level of rice and rice production capacity is not on time” (PCU2) related to the planning and control uncertainty has the lowest mean value of 4.08. The highest mean perceived uncertainty is observed for the items “the flooding occurrence affecting firms are unpredictable each year” (CLU3) and “the duration of the flooding is unpredictable over the years” (CLU4) related to the climate uncertainty. This is in contrast to the study of Thongrattana and Jie (2009), which observed a higher uncertainty for government policy.

Relevant uncertainty factors

According to the results of the principal component analysis (cf. Table 5), 74.65% of the overall variance in the observed variables can be explained by all uncertainty factors together listed in Table 3. Climate uncertainty explains the largest part of the overall variance (14.86%) followed by planning and control uncertainty (12.30%) and competitor uncertainty (10.88%). The findings of this study are clear evidence that the actors in the rice supply chain in the Ayeyarwaddy Region in Myanmar face a high level of climate, planning and control, and competitor uncertainty. Our findings confirm the results of Thongrattana and Jie (2009), Miller (1993), and Lewis and Harvey (2001) showing the impact of the planning and control, competitor’s behavior, government policy, and climate uncertainty on the rice supply chain.

The unpredictable climate is an essential component because it affects the agricultural and socio-economic system both directly and indirectly, especially in developing countries. The agricultural system of the developing countries is mostly dependent on rainfall because of the lack of technological adaptations (Darwin et al. 1995; Ogallo et al. 2000).

The second important component is planning and control uncertainty referring to the unavailability of on time and accurate production and inventory information. This results from the fact that information technology is not appropriately implemented in the rice industry of Myanmar. The importance of acquiring appropriate information is self-evident. The collection of appropriate information about the customer demand, sales forecasts order status, inventory levels, capacity availability, lead times, and quality is critical to the effective functioning of a supply chain. Timely information dissemination affects a supply chain’s ability to cope with uncertainty and faster transmission is better for supply chain members in satisfying both their own differentiated goals and the supply chain’s interdependent goals. The result is consistent with the findings of Mason-Jones and Towill (1998). They indicated the importance of planning and control uncertainty in the rice supply chain, which is concerned with the capability of an organization to use information flow and decisions to transform customer orders into a production plan and raw material requirements.

The high level of unpredictability of competitor’s behavior results from the severe competition for the retailers on the domestic markets and the intensive competition

Table 5 Structure of rotated component matrix for the rice supply chain (N = 215)

Types of uncertainty	Code	Component						
		1	2	3	4	5	6	7
Climate uncertainty (CLU)	CLU3	0.890						
	CLU2	0.889						
	CLU4	0.887						
	CLU1	0.830						
Planning and control uncertainty (PCU)	PCU2		0.953					
	PCU3		0.950					
	PCU1		0.833					
Competitor uncertainty (CU)	CU2			0.952				
	CU3			0.944				
	CU1			0.668				
Government policy uncertainty (GU)	GU1				0.825			
	GU3				0.800			
	GU2				0.758			
Process uncertainty (PU)	PU2					0.824		
	PU1					0.771		
	PU3					0.714		
Supply uncertainty (SU)	SU1						0.840	
	SU2						0.808	
	SU3						0.678	
Demand uncertainty (DU)	DU2							0.832
	DU3							0.727
	DU1							0.700
Eigen value		3.270	2.706	2.393	2.085	2.004	1.989	1.978
% of variance		14.864	12.298	10.879	9.478	9.108	9.039	8.989
Cumulative % of variance		14.864	27.161	38.041	47.519	56.627	65.667	74.656

Extraction method: principal component analysis

Before we conduct a principal component analysis or factor analysis, we must verify if the necessary conditions are fulfilled:

To measure the *scale reliability*, we calculate the correlation matrix of the 22 uncertainty factors and the determinant.

Since the determinant is different from zero, the factor analysis may be completed. Moreover, in order to measure scale reliability of the questionnaire, Cronbach's alpha is used (Bryman 2003; Haire et al. 1995). The value of Cronbach's alpha is accepted for an exploratory study if it exceeds 0.7 (Nunnally 1967). The Cronbach's alpha of these scales ranges from 0.710 to 0.922. No items are deleted in the analysis

The *scale validity* is measured by the Kaiser-Meyer-Olkin Measure (KMO) and Bartlett's Test. The result for the Kaiser-Meyer-Olkin Measure (KMO) is acceptable since it is larger than 0.6 (Kaiser 1974), and Bartlett's Test is highly significant at $p < 0.000$. Scale validity indicates the construct is able to measure accurately the concept under study (Haire et al. 1995)

The *construct validity* is measured by explanatory factory analysis (EFA) (Haire et al. 1995). All components have Eigenvalues larger than 1, which confirms the construct validity

Rotation method: varimax with Kaiser normalization

Source: own data (2017) and SPSS

with other rice production countries, which introduce rice at a low price. The perceived high uncertainty in the government policy gives proof that the government policy in developing countries is turbulent and unpredictable (Badri et al. 2000).

Comparisons of uncertainty perception among the rice supply chain actors

In this section, we investigate the relevance of the uncertainty factors for each of the supply chain actors since different parties may encounter different types of uncertainty.

The results of the descriptive and comparison analysis are carried out using a non-parametric Kruskal-Wallis test.²

The exporters perceive significantly lower supply uncertainty with respect to the quantity delivered by producers ($\alpha = 0.05$) and the delivery time ($\alpha = 0.1$) because of aggregation effects and the fact that exporters typically carry out different roles in the rice supply chain, i.e., farming, milling, and wholesaling. The wholesalers perceive a significantly higher demand and supply uncertainty because of their distributor role in the supply chain. They find it very difficult to predict the customer demand ($\alpha = 0.05$) because of the complexity of the sales network with many retailers and wholesalers. The higher supply uncertainty is related to the unpredictable quantity supplied and delivery time. Farmers perceive a significantly lower competitor uncertainty since they are more aware of their competitors' actions ($\alpha = 0.05$). Farmers witness easily other farmers' strategies applied in their paddy fields within the same village and they even share knowledge about their production techniques. An analysis of the uncertainty resulting from the government actions between different parties reveals that wholesalers suffer from the high volatility in the grantee price ($\alpha = 0.05$). Moreover, exporters encounter significantly less uncertainty resulting from the unexpected introduction of new government regulations compared to other actors ($\alpha = 0.01$) as they are operating on the international market. For the other types of uncertainty (i.e., the processing uncertainty, the planning and control uncertainty, and the climate uncertainty), there are no significant differences between the different actors.

Efficiency performance of the rice supply chain

Descriptive statistics of the variables

In this section, we investigate the supply chain efficiency to measure the supply chain performance. We measure the overall technical efficiency, pure technical efficiency, and scale efficiency for the entire supply chain, i.e., farmers (production stage), millers (processing stage), and distributors such as wholesalers, retailers, and exporters (distribution stage) are comprised in the analysis. In this section, we do not consider the primary collectors because they do not have any input resources and all primary collectors receive the same fee from the millers for buying paddy. A summary of the values of the key variables used in the DEA model is presented in Tables 6, 7, and 8. We consider the marketed amount of paddy as the output variable. The production, financial,

Table 6 Descriptive statistics of the output and input variables of the rice farmers ($N = 130$)

Variables	Unit	Mean	Minimum	Maximum	Std. deviation
Output variable					
Marketed amount	000' kg	6.50	0.29	31.04	5.98
Input variables					
Production cost (total)					
Material cost	MMK/kg	58.38	12.89	287.08	38.84
Family labor cost	MMK/kg	54.46	2.83	218.99	35.38
Hired labor cost	MMK/kg	89.72	3.87	359.99	51.50
Financial cost	MMK/kg	7.41	2.43	32.35	4.18

Note: we assumed 1USD = 1350 MMK

Source: own survey (2017)

Table 7 Descriptive statistics of the output and input variables of the rice millers ($N = 25$)

Variables	Unit	Mean	Minimum	Maximum	Std. deviation
Output variable					
Marketed amount	000' kg	1088.17	12.68	3793.48	1132.99
Input variables					
Production cost	MMK/kg	5.66	0.53	32.79	8.66
Financial cost	MMK/kg	5.14	2.31	14.74	2.48
Transportation cost	MMK/kg	21.44	9.08	36.84	8.66
Storage cost	MMK/kg	6.28	3.06	11.22	2.77

Note: we assumed 1 USD = 1350 MMK

Source: own survey (2017)

transportation, and storage costs are considered as the input variables in the input-oriented DEA model. The average marketed amount of paddy per year for the farmers is 6500 kg. The hired labor cost for farmers (on average 89.72 MMK/kg) is far higher compared to the other costs. The mean marketed amount of rice per year for the millers is 1088.17 thousand kilograms and ranges from 12.68 to 3793.48 thousand kilograms (cf. Table 7). The transportation cost (on average 21.44 MMK/kg) embodies the highest cost for the millers. The distributors deliver 52,189.97 thousand kilograms of rice on average with a range between 1.38 thousand kilograms and 1,700,000 thousand kilograms (cf. Table 8). The transportation cost (on average 6.94 MMK/kg) is slightly higher than the other costs for distributors.

Technical efficiency and scale efficiency

Table 9 displays the results derived from the DEA model (1)–(5) and the scale efficiency (cf. Eq. (6)) for the different actors and the global rice supply chain. The overall technical efficiency of the farmers equals on average 0.225 and ranges between 0.002 and 1. Hence, the technical efficiency of farmers can be increased by 77.5% on average. The farmers do not efficiently manage their input costs. They do not obtain the maximal possible output given their input costs. According to the results, only a small percentage (2.31%) obtains a high overall technical efficiency level (0.91 to 1.00). Ten percent of the farmers achieve an acceptable technical efficiency level (range 0.51–0.90). Most of the farmers (87.70%) have an inferior technical efficiency level smaller than or equal to 0.5. Hence, most of the farmers are inefficient and are unable to produce the maximum potential output given their inputs. The mean pure technical

Table 8 Descriptive statistics of the output and input variables of the rice distributors ($N = 39$)

Variables	Unit	Mean	Minimum	Maximum	Std. deviation
Output variable					
Marketed amount	000' kg	52,189.97	1.38	1,700,000.00	273,008.49
Input variables					
Production cost	MMK/kg	2.21	0.00	24.00	6.76
Financial cost	MMK/kg	5.62	0.87	27.78	7.51
Transportation cost	MMK/kg	6.94	2.04	13.78	2.60
Storage cost	MMK/kg	1.92	0.94	9.00	1.96

Note: we assumed 1 USD = 1350 MMK

Source: own survey (2017)

Table 9 Percentage distribution of the technical and scale efficiency index for the actors and the global rice supply chain

Efficiency level	Farmers (N = 130)			Millers (N = 25)			Distributors (N = 39)			Global supply chain (N = 194)		
	TE _{CRS} (%)	TE _{VRS} (%)	SE (%)	TE _{CRS} (%)	TE _{VRS} (%)	SE (%)	TE _{CRS} (%)	TE _{VRS} (%)	SE (%)	TE _{CRS} (%)	TE _{VRS} (%)	SE (%)
0.00–0.10	39.23	0.00	19.23	24.00	0.00	20.00	79.49	0.00	71.79	45.36	0.00	29.90
0.11–0.20	22.31	3.85	24.62	24.00	0.00	12.00	7.69	0.00	10.26	19.59	2.58	20.10
0.21–0.30	13.08	3.08	13.85	0.00	0.00	16.00	0.00	2.56	2.56	8.76	2.58	11.86
0.31–0.40	8.46	4.62	10.00	12.00	0.00	8.00	5.13	5.13	2.56	8.25	4.12	8.25
0.41–0.50	4.62	13.08	6.15	0.00	4.00	0.00	0.00	0.00	5.13	3.09	9.28	5.15
0.51–0.60	5.38	30.77	8.46	12.00	8.00	12.00	0.00	0.00	0.00	5.15	21.65	7.22
0.61–0.70	2.31	16.92	6.15	4.00	12.00	4.00	0.00	12.82	0.00	2.06	15.46	4.64
0.71–0.80	2.31	10.77	3.85	4.00	4.00	4.00	0.00	20.51	0.00	2.06	11.86	3.09
0.81–0.90	0.00	6.15	3.85	0.00	8.00	4.00	2.56	17.95	2.56	0.52	8.76	3.61
0.91–1.00	2.31	10.77	3.85	20.00	64.00	20.00	5.13	41.03	5.13	5.15	23.71	6.19
Mean	0.225	0.610	0.332	0.413	0.873	0.455	0.125	0.820	0.145	0.229	0.686	0.310
Minimum	0.002	0.109	0.014	0.008	0.485	0.009	0.001	0.290	0.001	0.001	0.109	0.001
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
IRS			98.46%			84.00%			94.87%			95.88%
DRS			0.00%			0.00%			0.00%			0.00%
CRS			1.54%			16.00%			5.13%			4.12%

Source: own survey (2017) and DEAP 2.1

efficiency is 0.610 and the mean scale efficiency is 0.332. The mean scale efficiency is lower than the mean pure technical efficiency, which implies that rice farms should improve firstly the allocation of their input costs to achieve a better pure technical efficiency and then try to improve their operational scale to upgrade the scale efficiency in order to boost the overall technical efficiency. No less than 98.46% of the farms have increasing returns-to-scale (IRS), i.e., if these farms can expand their production scale, they should be able to improve the overall operational efficiency. Only 1.54% of the farmers have constant returns to scale (CRS) which means these farmers operate in the desired scale and there is no need for any improvement.

The millers have on average a technical efficiency of 41.3%. About 20% of the millers reach a high technical efficiency score between 0.91 and 1. Twenty percent of the millers have an acceptable overall technical efficiency score between 0.51 and 0.90 and 60% of the millers have an efficiency level smaller than or equal to 0.5. The average pure technical efficiency (0.873) is larger than the average scale efficiency (0.455) for this processing stage. Hence, millers can reduce their operating input costs to improve their pure technical efficiency and expand their scale of operations in order to enhance the overall efficiency. The mean overall technical, pure technical, and scale efficiency scores of this study are lower than those of the millers in Thailand and Taiwan (Wongkeawchan et al. 2004). About 84% of all millers have increasing IRS, which indicates that they are able to improve their overall operational efficiency if they can expand their production scale. Another 16% of the millers are in the stage of CRS. These firms do not have to upgrade the scale of their firm.

The overall technical efficiency of the distributors is on average 0.125 which implies that most distributors have a huge improvement potential. Only 7.69% of the distributors reach a high overall technical efficiency level ranging from 0.81 to 1.00. The majority of the distributors (92.31%), however, obtain an efficiency score smaller than or equal to 0.5. The mean pure technical efficiency is 0.820 and is much larger than the scale efficiency (0.145). The distributors should try to improve the efficient use of the inputs and then adjust their scale of operations. The majority of the distributors (94.87%) have increasing IRS, which suggests that most distributors need to upgrade the scale of their organization.

The technical efficiency amounts 0.229 on average for the global rice supply chain, which is low. This value shows a large improvement potential of 77.1%. The majority of the actors (85.05%) have an overall technical efficiency level smaller than or equal to 0.5. The mean pure technical efficiency is only 0.686 due to the inappropriate management of the inputs. The mean scale efficiency is 0.310, which is very low due to the fact that most actors are operating in a smaller-than-optimal scale. The majority of the supply chain actors (95.88%) have increasing IRS, suggesting they would improve their efficiency if they can expand their production scale. Only 4.12% of the supply chain actors operate conform to their optimal scale.

The impact of uncertainty on of the rice supply chain performance

In this section, we examine if the identified environmental uncertainty factors impact the operational efficiency based on a Tobit regression model as suggested by Coelli and Basttese (1996). To that purpose, the Tobit model is applied to regress the efficiency scores on the uncertainty factors since the efficiencies vary from 0 to 1. The Tobit regression analysis is conducted in Eviews 9. The dependent variables are the efficiency scores, i.e., the overall technical efficiency, the pure technical efficiency, and the scale efficiency. The independent variables are the seven sources of uncertainty factors, i.e., supply, demand, process, planning and control, competitive, government policy, and climate uncertainty. Table 10 describes the summary statistics of the uncertainty factors. This analysis is performed for the farmers (production stage), the millers (processing stage), the distributors, i.e., the wholesalers, retailers, and exporters (distribution stage), and the entire supply chain. The results of the Tobit regression analysis for the

Table 10 Descriptive statistics of uncertainty variables of the supply chain

Variables	Unit	Farmers (N = 130)		Millers (N = 25)		Distributors (N = 39)		Global supply chain (N = 194)	
		Mean	Range	Mean	Range	Mean	Range	Mean	Range
Supply uncertainty (SU)	Number	5.59	1–7	5.64	2–7	5.54	1–7	5.59	1–7
Demand uncertainty (DU)	Number	5.58	2–7	5.84	2–7	5.87	1–7	5.67	1–7
Process uncertainty (PU)	Number	5.72	2–7	5.80	3–7	5.59	3–7	5.70	2–7
Planning and control uncertainty (PCU)	Number	4.06	1–6	4.00	3–5	4.14	2–5	4.07	1–7
Competitive uncertainty (CU)	Number	4.63	1–7	5.24	2–7	5.26	2–7	4.84	1–7
Government uncertainty (GU)	Number	5.05	1–7	5.48	2–7	5.69	1–7	5.3	1–7
Climate uncertainty (CLU)	Number	5.92	2–7	6.04	2–7	6.03	1–7	5.95	1–7

Source: own survey (2017)

farmers are presented in Table 11. The Tobit regression coefficients indicate the directional relationship between efficiency and the independent variables.

Table 10 reveals that the planning and control uncertainty has a negative and significant impact on all efficiency measures of the farmers. The overall technical, pure technical, and scale efficiency is reduced when the uncertainty in planning and control increases. Information is crucial to operational planning and control. The higher the quality of information input, the higher the quality of managerial decision making (Gorry and Morton 1989). In-depth interviews learned that the most efficient farmers use information to wait for a higher paddy price and increase their stock level capacity. In this way, these farmers do not have to sell their paddy at a lower price immediately after harvesting. The climate uncertainty has a negative and significant impact on the overall technical efficiency and pure technical efficiency. The technical efficiency of the farms decreases significantly as a result from the high climate uncertainty. This study confirms the result of Masud et al. (2012). The effects of uncertain climate conditions on rice production lead to large inefficiencies and as a result a significant amount of paddy is lost. In order to reduce the climate uncertainty, the farmers can use different types of mitigation strategies. The most efficient farmers change proactively their sowing time to overcome the uneven rain at the harvest time and use cushions to prevent rain to impact the paddy harvest piles when harvesting, threshing, drying, and transporting the paddy. These best practices related to cultivation and post-harvesting techniques and climate mitigation strategies together with the knowledge transfer of new technologies should be widespread via better extension services (Naswem et al. 2016). Moreover, crop insurance is potentially a very effective climate mitigation strategy for the farmers in the study area that can be ensured by the government or private partners. By spreading risk, this strategy can buffer the financial implications of unexpected crop failure following climate uncertainty and may change the decision-making behavior of farms and improve their efficiency level. According to Di Falco et al. (2014), Olivier and Charles (2010), and Ambarawati et al. (2018), agricultural or crop insurance has been an important tool at the farm level in different agricultural supply chains to mitigate the climate or natural disaster uncertainty and has also been implemented in many developing countries including India and Thailand. However, the financing parties should be aware of the fact that that farm and market characteristics have different impacts on the participation of farmers to insurance programs. If policymakers intend to use subsidized crop insurance, they should be concerned with the socio-economic factors such as education and farm size that lead a farmer to adopt insurance and to remain insured (Sherrick et al. 2004; Santeramo et al. 2016). Further, the government and private partners are responsible to secure the availability of high-quality production inputs (seeds, fertilizers, chemicals). Early maturing, drought-resistant and flood-resistant varieties of rice should be made available to farmers to enable them to cope with the vagaries of the climate (Naswem et al. 2016; Santeramo et al. 2016).

The efficient operation of millers is hampered significantly by process uncertainty for all types of efficiency measures (cf. Table 11). This result confirms the study of Thongrattana (2012), Childerhouse and Towill (2004), Bhatnagar and Sohal (2005), van der Vorst (2000), and Davis (1993). In-depth interviews learned that the most efficient millers in the study area manage this type of uncertainty in a reactive manner by hiring skillful mechanics to repair their broken machines immediately. A proactive, more

Table 11 Results of Tobit regression coefficients for all different actors and the global supply chain

Independent variables	Farmers (N = 130)			Millers (N = 25)			Distributors (N = 39)			Global supply chain (N = 194)		
	TE-CRS	TE-VRS	SE	TE-CRS	TE-VRS	SE	TE-CRS	TE-VRS	SE	TE-CRS	TE-VRS	SE
Constant	0.9696*** (0.1508)	1.0383*** (0.1483)	1.0949*** (0.1847)	2.0561*** (0.4420)	1.6660*** (0.3301)	1.6607*** (0.4275)	1.3543*** (0.2428)	1.1184*** (0.2252)	1.3112*** (0.2560)	1.1305*** (0.1346)	0.8348*** (0.1344)	1.2432*** (0.1526)
Supply uncertainty	-0.0195 (0.0133)	-0.0151 (0.0131)	-0.0224 (0.0163)	0.0469 (0.0346)	0.0218 (-) (0.0573)	0.0439 (0.0312)	0.0072 (0.0204)	0.0311 (0.0189)	-0.0073 (0.0215)	-0.0034 (0.0123)	-0.0008 (0.0121)	-0.0060 (0.0140)
Demand uncertainty	-0.0279 (0.0173)	0.0027 (0.0171)	-0.0276 (0.0212)	-0.0063 (0.0408)	-0.0573 (0.0352)	-0.0449 (0.0456)	-0.1026*** (0.0379)	-0.0715** (0.0351)	-0.0887** (0.0399)	-0.0220 (0.0169)	0.0168 (0.0157)	-0.0203 (0.0191)
Processing uncertainty	0.0082 (0.0186)	0.0022 (0.0183)	0.0109 (0.0228)	-0.1940*** (0.0697)	-0.1276*** (0.0541)	-0.1658** (0.0701)	0.0610 (0.0320)	0.0255 (0.0297)	0.0584 (0.0338)	-0.0072 (0.0174)	-0.0074 (0.0168)	-0.0015 (0.0197)
Planning and control uncertainty	-0.0435*** (0.0104)	-0.0244** (0.0102)	-0.0516*** (0.0127)	-0.0585*** (0.0188)	-0.2553*** (0.0153)	-0.0711*** (0.0198)	-0.0103 (0.0208)	0.0104 (0.0193)	-0.0045 (0.0219)	-0.0421*** (0.0097)	-0.0161 (0.0095)	-0.0497*** (0.0110)
Competitive uncertainty	-0.0115 (0.0104)	-0.0112 (0.0103)	-0.0118 (0.0128)	0.0056 (0.0272)	0.0270 (0.0224)	0.0127 (0.0290)	-0.0052 (0.0263)	-0.0356 (0.0244)	0.0058 (0.0277)	-0.0123 (0.0103)	0.0049 (0.0100)	-0.0152 (0.0117)
Government policy uncertainty	-0.0167 (0.0120)	0.0112 (0.0118)	-0.0297 (0.0147)	-0.0392 (0.0381)	0.0052 (0.0305)	-0.0518 (0.0395)	-0.0142 (0.0289)	0.0210 (0.0258)	-0.0238 (0.0294)	-0.0095 (0.0118)	0.0049 (0.0111)	-0.0228 (0.0133)
Climate uncertainty	-0.0374*** (0.0142)	-0.0478*** (0.0139)	-0.0240 (0.0174)	-0.0999*** (0.0406)	0.0151 (0.0315)	-0.0860** (0.0408)	-0.1417*** (0.0289)	-0.0285 (0.0268)	-0.1339*** (0.0305)	-0.0738*** (0.0135)	-0.0287*** (0.0129)	-0.0644*** (0.0153)
LR test	36.5817***	19.9360***	31.5090***	35.1754***	11.2776	32.1591***	29.9492***	9.3101	27.6637***	60.9329***	14.2274***	55.1842***

Dependent variables are TE-CRS index, TE-VRS index and SE index

Note: figures in the parentheses are standard error

** significant at 5% level and *** significant at 1% level

Source: own survey (2017) and Eviews 9

preferred approach to mitigate this process uncertainty is to install labor flexibility and machine flexibility, i.e., multi-skilled workers are trained and/or general purpose machines, equipment, and technologies are implemented to increase the process flexibility (Miller 1992; Sawhney 2006; Ulrich 1995). Moreover, the planning and control uncertainty has a negative and significant impact on the overall technical efficiency and the scale efficiency of the rice millers. The most efficient millers have sufficient storage capacity to meet the changes in customer orders. To prevent the deterioration of the rice quality during the storage time, the millers check the rice quality on a regular basis. The availability of a computer-based information system, shared between different supply chain partners, may provide real-time and accurate information and transparency and will reduce the planning and control uncertainty along the supply chain (Prater, 2005). The climate uncertainty has also a significant and negative impact on the overall technical efficiency and scale efficiency of the millers. Climate uncertainty may cause a rice shortage and inferior rice quality. In order to reduce the uncertainty and to improve their efficiency, the millers perform a quality inspection and adapt their price according to the rice quality. In addition, because of extreme weather conditions, the transportation of paddy (from the farmers) or rice (toward the customers) is impeded because of road destructions leading to customer delays. Paddy and rice reserves help to reduce these negative effects resulting from climate conditions. However, the efficiency of millers is significantly reduced as they cannot distribute the processed rice on time. The government needs to invest in the existing road infrastructure in collaboration with the private sector to increase the access to the markets and avoid inefficiencies in transport and logistics (Linn and Maenhout 2019).

The results of the Tobit regression analysis for the rice distributors are also presented in Table 11. The demand uncertainty has a negative and significant impact on all efficiency measures, i.e., a higher demand uncertainty can significantly lower the efficiency. The demand uncertainty arises from the complexity of the sales network in the distribution system, i.e., many retailers and wholesalers involved in the rice supply chain and the unpredictable domestic and international demand and product variety. As a result of the demand uncertainty, the rice distributors have difficulties to organize their operations efficiently, i.e., to use the right input resource mix and to operate at the right scale. In order to reduce this uncertainty, the most efficient distributor parties have maintained multiple suppliers, which will guarantee availability to improve supply flexibility to be able to meet the necessities of their customers. According to Tang and Tomlin (2008), flexible procurement contracts can provide supply flexibility, ensure stability for the supplier, and help the buyer respond to demand fluctuations. The climate uncertainty also has a negative and significant impact on the overall technical efficiency and scale efficiency of the distributors. Accurate weather information may help them to better organize the rice distribution to other regions and to foreign countries.

Finally, we discuss the results of Tobit regression analysis for the global rice supply chain (cf. Table 11). Previous results revealed that the different actors in different stages of the rice supply chain face different types of uncertainty, each related to their role in the rice supply chain. However, we observe that global supply chain is principally impacted by the planning and control uncertainty and the climate uncertainty, which were mainly observed as relevant sources of uncertainty in the early stages of the global rice supply chain and resonates throughout the entire supply chain. The planning and

control uncertainty has a negative and significant impact on the overall technical efficiency and scale efficiency, i.e., a higher uncertainty in planning and control leads to a decrease in the efficiency of the supply chain. Prater (2005) recognizes that sharing a computerized information system between supply chain partners enables a better and faster information flow and will reduce the planning and control uncertainty along the supply chain. In this regard, the Myanmar Rice Federation (MRF) encourages actors to establish cooperatives by organizing trainings, meetings, and conferences. Setting up collaborations enables the integration of the supply chain members, i.e., all members of the chain “acts as one,” will lead to reductions in process, supply, demand, and control uncertainty (Simangunsong et al. 2012). The climate uncertainty negatively impacts the overall and pure technical efficiency of the global rice supply chain. This result is consistent with the finding of Nyamah et al. (2017) but does not confirm the result of Thongrattana (2012). According to Kleindorfer and Saad (2005), Tang (2006), and Ritchie and Brindley (2007), insurance is one of the most common strategies for mitigating uncertainty or risk, and hence lessens the severity of disruptions such as natural disasters or weather-related events on supply chain activities.

Conclusion and recommendations

Conclusion

In this study, we determined the major sources of environmental uncertainty impacting the rice supply chain in the Ayeyarwaddy Region, Myanmar. There are different types of actors in the rice value chain, i.e., farmers, rice millers, wholesalers, retailers, and exporters, and we investigate how uncertainty affects the decision-making performance of these actors. To that purpose, we applied a three-step methodology. First, we have conducted an empirical survey and applied an exploratory factor analysis to identify the sources of uncertainty perceived by the different actors in the rice supply chain. The environmental uncertainty and its associated factors are defined in terms of perception of the respondents given the role of individuals in the decision-making process. All the seven considered uncertainty factors are present; however, the climate uncertainty is the most important factor in the rice supply chain followed by planning and control uncertainty and competitor uncertainty. Second, we measure the rice supply chain efficiency to assess the supply chain performance using data envelopment analysis (DEA). Based on his perception, the decision maker will take relevant strategic and operational decisions, i.e., he will determine the mix of inputs to maximize his output level and his scale of operations. The mean performance of the entire rice supply chain is characterized by a low overall technical efficiency score, which is especially caused by the very low scale efficiency for all actors. Therefore, the majority of the business units need to expand their operating size. Moreover, their market knowledge and the method to collect accurate market information should be improved to reduce their input costs. Third, we study the significance of the impact of the identified sources of uncertainty on the supply chain efficiency to find the most important types of uncertainty. Each type of actor suffers from specific uncertainty sources related to their role in the supply chain. Farmers face climate uncertainty and uncertainty in planning and control. The millers in particular suffer significantly from processing uncertainty. Distributors face the adverse effect of demand uncertainty. The climate uncertainty and planning and

control uncertainty, which are both in particular present in the early production stages of the supply chain, have a negative and significant impact on the different types of efficiency leading to the poor performance of the entire supply chain.

Recommendations

The described sources of uncertainty highlight the array of key issues that must be resolved to upgrade the performance of the rice supply chain. The observed low operational efficiency of the studied rice supply chain shows that the actors do not make use of resources in the best possible way and can significantly improve the way their limited resources are allocated. To that purpose, uncertainty should be mitigated, especially the uncertainty regarding the climate and the planning and control. However, priorities should be set to accomplish a feasible and gradual progress to improve the competitiveness of the rice sector in Myanmar. Future research should give more insights in each of the proposed mitigation strategies and their actual impact on the rice supply chain in Myanmar.

First, public awareness of the impact of climate conditions on the agricultural production systems deserves priority consideration and mitigating technologies must be developed, which will require increased public and private investment. An appropriate financial insurance mechanism should be implemented by the government and private partners for all rice supply chain actors and in particular for the farmers taking the socio-demographic characteristics of the farmers into account. Further research should indicate the most suitable insurance program (e.g., a weather-based or area-based crop insurance program). In this way, the actors and especially the farmers should be better able to use their resources more efficiently to maximize their output level as a result of the reduced level of uncertainty.

Second, farmers should have a better knowledge of cultivation and post-harvesting techniques, climate risk mitigation strategies, and new technologies via more efficient and widespread extension services. Accurate weather forecasts are crucial for farmers to organize their activities in a proactive manner. The Department of Agriculture and the Department of Meteorology should educate the farmers how to effectively use this information for their agricultural activities. Moreover, farmers should learn how to deal with adverse climate conditions. Best practices such as switching cultivating time, using early maturing and flood resistant rice varieties, improved land management, e.g., erosion control and soil protection, etc. should be widespread practices among the farmers in the region. Moreover, in order to establish a secure transportation system, the government should design and provide standard roads, rail, and other infrastructure.

Third, farmers and other roles in the supply chain should organize themselves in cooperatives, which imply a horizontal and vertical integration in the supply chain. In the era of intense global trade, it is essential for firms to exploit the benefits associated with sharing supply chain information to improve the supply chain performance. Moreover, the majority of the current rice companies in the supply chain are too small and via setting up cooperatives they will expand their size. In this way, the bargaining power of actors on the national and international market will increase and price fluctuations will be less volatile and more accurate market information will be obtained. These collaborations support the installment of computerized information sharing systems and

decision support systems, which will reduce planning and control uncertainty and supply and demand uncertainty. In this way, they have more accurate information allowing better forecasts and they will be able to react more efficiently to disruptions in the supply chain. In addition, best practices will be more widespread among different actors, which will further increase the efficiency as actors will improve their decision-making skills. The strategic relationships between supply chain actors, i.e., building linkages and sustaining a long-term partnership, would increase the value transferred between entities in the supply chain and would decrease costs.

Endnotes

¹This is based on the equation of Yamane (1967), i.e., $n = \frac{N}{1+N(e^2)}$ where N is the population, e^2 is the standard error and n is the sample size.

²To compare the results between different actors, we apply the non-parametric Kruskal-Wallis test to find significant differences.

Acknowledgements

No acknowledgements.

Funding

We acknowledge the support for the doctoral research project funding by the Lotus Plus Project, Erasmus Mundus Program (Action-2).

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Authors' contributions

TL collected, analyzed, and interpreted the data. BM supervised the research and was the major contributor in writing the manuscript. All authors read and approved the final manuscript.

Ethics approval and consent to participate

The author accepts the ethics approval and consent to participate.

Competing interests

All authors declare: no support from any organization for the submitted work, no financial relationships with any organizations that might have an interest in the submitted work, and no other relationships or activities that could appear to have influenced the submitted work.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Author details

¹Department of Agricultural Economics, Yezin Agricultural University, Pyinmana, Myanmar. ²Faculty of Economics and Business Administration, Ghent University, Tweeckerkenstraat 2, 9000 Gent, Belgium.

Received: 12 July 2018 Accepted: 7 May 2019

Published online: 03 June 2019

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