Assessing and modelling catastrophic risk perceptions and attitudes in agriculture: a review

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Abstract

Catastrophic risks result in high losses in agriculture. To cope with such losses farmers need to apply risk management strategies to balance their profits and risks. Therefore risk assessment and risk modelling are important to support farm-level decision-making. This paper (1) reviews the techniques to elicit risk perception and risk attitude, and (2) describes how the simultaneous impact of risk perception and risk attitude could be accounted for in risk programming. Although inherent in catastrophic risks, objective data are sparse and eliciting subjective data is likely to be flawed. The review shows that the negative impact resulting from catastrophes cannot be ignored without compromising the optimal decision.

Additional keywords: catastrophe, farmer, risk attitude, risk modelling, risk perception

Introduction

Farming is typically a risky business (Hardaker *et al.*, 2004). Facing a risk implies the possibility of losing property or income (Pritchet *et al.*, 1996). Farm risks can be of financial and business nature. Financial risk refers to the method of financing. Business risk of a farmer is related to production, personal, price and institutional risk (Hardaker *et al.*, 2004). Particularly, severe business and financial risks or their combinations can constitute a catastrophic risk at farm level.

Generally defined, a catastrophic risk is a low-probability (rare) event leading to major and typically irreversible losses with adverse impact on business results (Chichilnisky, 2000; Vose, 2001). Catastrophic risks in agriculture can cause severe cash flow problems or even result in bankruptcy. For example, livestock farmers can be exposed to epidemic diseases such as foot-and-mouth disease (FMD), bovine spongiform encephalopathy

(BSE) or classical swine fever (CSF), or be injured and not able to continue farming (Huirne *et al.*, 2003; Hartman *et al.*, 2004). In arable farming, potential damage of crops can be caused by extreme meteorological events such as hail, excessive precipitation, drought, storm and frost (Langeveld *et al.*, 2003).

Farmers somehow need to manage catastrophic risks. This can be done by applying risk management strategies, such as insurance, diversification, self-insurance, or forward contracting. In decision analysis, the models should take the farmer's perception of specific risk and risk attitude into account.

Many researchers modelling risk prefer to deal with objective probabilities and impact (e.g., Johnson-Payton *et al.*, 1999; Pradlwarter & Schueller, 1999; Ermoliev *et al.*, 2000a, b; Melnik-Melnikov & Dekhtyaruk, 2000; Bouma *et al.*, 2005). Contrary to this, risk perception is a subjective statement of risk by decision-makers, their degree of belief. Risk perception is more like the mental interpretation of risk, broken down into the chance to be exposed to the content and the magnitude of the risk (Smidts, 1990; Senkondo, 2000; Pennings *et al.*, 2002; Hardaker *et al.*, 2004).

Like risk perception, risk attitude plays an important role in understanding the decision-maker's behaviour. Risk attitude is a personal characteristic and deals with the decision-maker's interpretation of the risk and how much he dislikes the outcomes resulting from the risk (Pennings *et al.*, 2002). According to Dillon & Hardaker (1993), risk attitude is the extent to which a decision-maker seeks to avoid risk (i.e., risk aversion) or prefers to face risk (i.e., risk preference). According to reasonable asset integration assumptions, a farmer would view losses or gains from specific risks as being equivalent to changes in wealth (Hardaker *et al.*, 2004). Therefore, although risk attitude is not affected by specific catastrophic risk, it does affect the decisions to cope with catastrophes.

Many risk modelling studies are devoted only to either objective or subjective (i.e., risk perception) probabilities, whereas the impact of risk attitude is usually omitted from the context (e.g., Johnson-Payton *et al.*, 1999; Pradlwarter & Schueller, 1999; Ermoliev *et al.*, 2000a, b; Melnik-Melnikov & Dekhtyaruk, 2000; Kunreuther *et al.*, 2001; Cummins & Mahul, 2003; Bouma *et al.*, 2005). Examples of studies combining risk perception and risk attitude include Smidts (1990), Pennings (1998) and Senkondo (2000). However, to the best of our knowledge, quantitative modelling studies focusing specifically on agricultural catastrophic risks that combine risk perception and risk attitude are rare and hard to find.

Concerning catastrophic risks, there are some challenging problems with respect to the data. Data on catastrophes, by their nature, are skewed (have a non-symmetric distribution), and major problems are inherent in the proper estimation of low probabilities in the downside tail of their distribution (e.g., Ganderton *et al.*, 2000; Kunreuther *et al.*, 2001; Hardaker *et al.*, 2004). So the properties of tail estimation need to be explicitly accounted for.

This paper reviews the methods of risk perception and risk attitude elicitation (i.e., extraction), and the methods of risk modelling combining risk perception and risk attitude towards the agricultural decisions to cope with catastrophic risks within one framework. The central question is to what extent standard methods are appropriate to accommodate catastrophic risks.

The paper is structured as follows. First, the standard methods of risk perception and specific issues on catastrophic risks are reviewed. In the next section, the subjective expected utility theory with its limitations and risk attitude elicitation techniques are discussed. Then the methods of combining risk perception and risk attitude for catastrophic risk modelling are described. Hail, which is a typical catastrophic risk for a Dutch farmer, is used as an example. The paper concludes with the main findings with respect to the modelling of catastrophic risks.

Risk-perception methods

In this chapter the standard direct method, strength of conviction method and specific issues on elicitation of catastrophic-risk perceptions are reviewed. Their main advantages and disadvantages are presented in Table 1 and for each method the implication for the hail example is addressed.

Hail is a typical catastrophic risk on arable Dutch farms, since it occurs very irregularly in time and space and can have a serious adverse impact on the farm business as a result of damage to several crops. In general, crop damage can be categorized into (1) destruction of the entire or part of the crop, resulting in yield losses depending on the percentage of the crops destroyed; (2) mechanical damage to the plants, such as defoliation, breakage or bruising of the stems, and (3) reduced quality of the product, resulting in downgrading and therefore lower prices (Van Asseldonk *et al.*, 2001). Concerning hail, in Dutch agriculture the insurance strategy is very commonly adopted. Dutch insurers have defined spatially separated hail-risk prone locations for field crops, in which premiums are lower for coastal regions than for interior regions. A maximal discount of 65% of the base premium rate can be obtained for coastal regions versus no discount for highly prone locations (Van Asseldonk *et al.*, 2001). The average annual hail insurance premiums for a main crop such as wheat constitute 0.625% of the insured sum. For sugar beet, potato (industry and consumption) and rye this percentage is 1.75, 0.75 and 0.65, respectively (Anon., 1999).

Hail incidence has a low probability but a high negative impact, which can be seen from the annual levels of loss ratio – total indemnities paid plus administration costs divided by total premiums collected – of insurance companies. A loss ratio of 100% means that every euro collected in premiums is offset by a euro in indemnities paid. A loss ratio lower than 100% indicates high profits for the insurer, whereas a loss ratio higher than 100% implies that the indemnities paid are higher than the premiums collected. On average, in the Netherlands the loss ratio of hail insurance for arable farming and horticulture (including bulb growing) is 50–100%, whereas in adverse years with catastrophes it can be above 100%.

Standard methods of risk-perception measurement

There are two standard methods to measure risk perception: (1) the direct method, and (2) the strength of conviction method.

In the *direct method*, risk perception is measured by conducting a survey using a

Table 1. Methods used and their advantages and disadvantages with catastrophic risks.

Method	Advantages	Disadvantages with catastrophe risks	Sources with examples
1. Risk elicitation			
Risk perception elicitation			
Direct method	High descriptive power, generated scale variables.	No probabilities derived.	Smidts (1990); Pennings (1998); Senkondo (2000); Van Asseldonk *et al.* (2002b).
Strength of conviction	Main distributional parameters are derived.	Problems to derive low probabilities.	Smidts (1990); Pennings (1998); Senkondo (2002).
Risk perception of catastrophic risks	Avoids judgemental biases.	Biases still possible.	Weinstein *et al.* (1996); Kunreuther *et al.* (2001).
Risk attitude elicitation and estimation			
Direct method	High descriptive power, generated scale variables.	No risk-attitude coefficients derived.	Smidts (1990); Pennings (1998); Senkondo (2000); Ganderton *et al.* (2000); Van Asseldonk *et al.* (2002).
ELCE [1]	Fifty-fifty chance situations easy to evaluate.	Fifty-fifty chance situations are not relevant.	Smidts (1990); Pennings (1998); Senkondo (2000); Torkamani (2005).
Econometric models	Inferences about degree of aversion are obtained.	Strong assumptions of models, specification errors.	Antle (1989); Bar-Shira *et al.* (1997); Oude Lansink (1999); Gardebroek (2002).
2. Risk modelling			
Stochastic simulation			
MCS [1]	The most commonly used method.	Can underestimate tail of the distribution.	Ermoliev *et al.* (2002a, b); Kobzar (2006).
Latin Hypercube	All segments of the distribution are considered, including a tail.	n.a. [2]	Lien *et al.* (2006); Richardson *et al.* (2006).
Farm risk programming			
QRP [1] and MOTAD [1]	Only mean and variance required.	Only quadratic form of utility function, normality assumptions.	Kobzar (2006); Lien *et al.* (2006).
UEP [1]	Any form of utility function and joint probability distribution.	More sensitive to input data.	Lien & Hardaker (2001); Torkamani (2005); Acs (2006); Kobzar (2006); Flaten & Lien (2007).

[1] ELCE = equally likely certainty equivalent; MCS = Monte Carlo simulation; QRP = quadratic risk programming; MOTAD = minimization of total absolute deviation; UEP = utility-efficient programming.

[2] n.a. = not appropriate.

questionnaire with straightforward questions about risk perception. Studies that were conducted using this method include Smidts (1990), Pennings (1998), Senkondo (2000) and Van Asseldonk *et al.* (2002). Such a questionnaire can include socio-economic and psychological statements, perhaps helping to explain risk perception of farmers. In the example of hail, farmers can place their subjective expected probability of hail incidence on a 7-point Likert scale. In a similar way, questions can be asked about the magnitude of a loss after hail occurs. The direct measurement procedure does not define a subjective absolute probability distribution; instead, it estimates probability and outcomes in relative terms (Smidts, 1990). Nevertheless, this method is useful if it is possible to combine scores on Likert scales with known probabilities.

The *strength of conviction method* involves elicitation of several points on the subjective cumulative distribution function. Next a probability distribution function is fitted to these points. From this function the main parameters (mean, median, standard deviation and skewness) can then be derived. The method is indirect, because the measures of central tendency and variation are indirectly derived from the probability distribution function (Smidts, 1990). Examples of studies that used the strength of conviction method include Senkondo (1990), Smidts (1990) and Pennings (1998). For the hail example, the strength of conviction method can be applied by eliciting several points on the subjective cumulative distribution function. However, with only a limited number of points, the probability in the tail of the distribution may be inadequately estimated. If the probability of hail is very low, it is hard to estimate the downside tail of the distribution, as people have problems with interpreting low probabilities (Kunreuther *et al.*, 2001; Kunreuther, 2002). The knowledge of farmers about subjective probability and impact is usually limited. Farmers may overestimate the quality of the data on risk and their ability to perceive risk, and mistake their real exposure to risk. Hence, the evaluation of catastrophic-risk perception from probability distribution by the standard strength of conviction method to elicit probabilities may not be appropriate (Desvousges *et al.*, 1998; Hagihara, 2002).

Specific issues on elicitation of catastrophic risk-perception

Difficulties in risk perception elicitation frequently occur in catastrophe situations, as there is often a lack of data (Ekenberg *et al.*, 2001). When a decision-maker moves from an event with considerable historical and scientific data to one where there is greater uncertainty and ambiguity, there is a much larger degree of discomfort in assessing risk perception (Kunreuther, 2002). But if the number of data increases, subjective probability changes and the degree of conviction concerning the subjective probability are likely to increase too. As a result the value of subjective probability may closely approach the objective probability determined by experts. So if the degree of conviction of the subjective probability is not very high, the subjective probability and the choice based on it may change because of additional data (Hagihara, 2002). As explained in the following, Weinstein *et al.* (1996) and Kunreuther *et al.* (2001) conducted studies where they could handle different psychological biases concerning the elicitation of risk perception of catastrophic risks.

Psychological biases affecting risk perceptions of catastrophic risks

Risk perceptions can be over- or underestimated due to judgmental biases such as availability heuristic, vividness, denial and evaluability.

The *availability heuristic* is the most relevant one for dealing with catastrophe events. Decision-makers estimate the likelihood of an event by the ease with which they can imagine or recall past instances of the event. If the information on an event is conspicuous, many people will tend to overestimate the probability of the event occurring (Kunreuther, 2002). For instance, the farmer's subjective probability of hail incidence typically increases when this event took place recently.

In the decision-making process, *vividness* is a cousin of availability heuristic. Vividness refers to how concrete or imaginable the event is, but occasionally it can have other meanings. Sometimes vividness refers to how emotionally interesting or how exciting something is. Farmers are affected more strongly by vivid information than by pallid, abstract, or statistical information. In this respect vividness can increase the perceived probability of a catastrophe event (Plous, 1993). The power of vivid information is widely appreciated by persuaders. In agriculture it can be an insurance company convincing a farmer that the probability of hail on his farm is high, or that a nearby farmer has already bought a specific type of catastrophe insurance or has already been exposed to a catastrophe event.

Farmers may also tend to *deny* extremely negative outcomes. In this respect farmers will tend to overestimate (is more probable) positive events and underestimate (is less probable) the negative ones (Plous, 1993). Therefore, hail as an example of a negative event can be underestimated.

The notion of *evaluability* is also important for a decision-making process with respect to low probabilities. Most people feel that small numbers can easily be dismissed; only large numbers get their attention (Kunreuther, 2002).

Expressions to improve risk perceptions of catastrophic risks

This subsection deals with ways of how to elicit probabilities for catastrophic risks from farmers, taking into account the psychological biases. For a decision-maker it is usually easier to elicit risk perception for catastrophic risks if the likelihood is depicted in relation to other risks (e.g., the probability of hail is one half of a specific traffic accident probability). It is more reasonable to present the probabilities in a time interval. For instance, for a farmer a probability of hail once every 75 years is more readily imaginable than a probability of 0.013 per year. Weinstein *et al.* (1996) found that expressing the probability of an event as the time interval during which a single event is expected rather than expressing it as a one-year event can affect risk perceptions. It is also evident that the absolute probability in the example would be perceived as a very small number close to zero (Kunreuther, 2002).

Small probabilities will not be readily evaluable by farmers in the absence of context information. Farmers need comparison scenarios that are located on a probability scale and evoke their own feelings about risk. As farmers are provided with increasingly useful context information, the probabilities become more and more evaluable, which results in well-developed risk perceptions (Kunreuther *et al.*, 2001). For easier understanding of a hail probability, a farmer could be provided with additional context information that could include the recent history of hail with its consequences in different regions, probabilities of related risks such as storm, heavy rain, wind speed or temperature.

Subjective expected utility theory

In this chapter, the subjective expected utility (SEU) theory is presented, with a focus on its components: the SEU model, estimation and elicitation of risk-attitude coefficients, forms of utility functions, and stochastic dominance. As in the foregoing, the hail risk of an arable farmer will be used as an example.

The subjective expected utility model

The subjective expected utility (SEU) hypothesis states that the utility of a risky prospect is the decision-maker expected utility for that prospect, meaning the weighted average of the utilities of outcomes (Hardaker *et al.*, 2004). If the probabilities of outcomes are discrete, the expected utility model can be formulated in the following way (Smidts, 1990):

$$U(A_i) = \sum_{j=1}^{J} p_i(x_j) \bullet u(x_j) \qquad (1)$$

where
A_i = an alternative from a set of alternatives $A = (A_i;\ i = 1, 2, ..., I)$;
x_j = an outcome from a set of outcomes $X = (x_j;\ j = 1, 2, ..., J)$;
$p_i(x_j)$ = a probability from a set of probabilities $P = (p_i(x_j);\ i = 1, 2, ..., I;\ j = 1, 2, ..., J)$ of outcome x_j with alternative A_i;
$U(A_i)$ = an expected utility of alternative A_i;
$u(x_j)$ = utility function of outcome x_j.

In case of continuous probabilities, the SEU model is formulated as follows:

$$U(A_i) = \int f_i(x) \bullet u(x)dx \qquad (2)$$

where $f_i(x)$ = the probability distribution of outcomes x resulting from choosing of alternative A_i. In the hail example, SEU should focus on the probability distribution of yields, where the hail risk is incorporated in the tail of the probability distribution.

A decision-maker can be risk loving (i.e., risk preferring), risk averse or risk neutral. The risk attitude can be seen from the shape of the expected utility function. This function is concave if a decision-maker is risk averse, convex in case of risk preferring and linear if he is risk neutral. Most farmers are risk averse as decision-makers (Hardaker *et al.*, 2004). As can be seen from the Equations (1) and (2), the SEU model integrates risk perception and risk attitude.

Risk-aversion coefficients

The degree of risk-aversion is measured by the risk-aversion coefficient. The following standard risk-attitude coefficients are used: the *coefficient of absolute risk aversion*, the *coefficient of relative risk aversion*, and the *coefficient of partial risk aversion* (for details see Hardaker *et al.*, 2004). The most relevant is the Arrow–Pratt *absolute risk aversion coefficient, Ra*, which is calculated as follows:

$$Ra = -\frac{U^{(2)}(w)}{U^{(1)}(w)} \tag{3}$$

where
$U^{(2)}(w)$ = the second derivative of the utility function of wealth;
$U^{(1)}(w)$ = the first derivative of the utility function of wealth;
w = the farmer's wealth.

Note that in Equation (3) the outcome term x from Equations (1) and (2) is introduced by term w (wealth). However, other outcome measures such as income can be substituted for wealth (Hardaker *et al.*, 2004).

The second risk-aversion coefficient that is often used in decision analysis is the *relative risk-aversion coefficient, Rr*. The mathematical relationship between Ra and Rr is as follows:

$$Rr = Ra \cdot w$$

Anderson & Dillon (1992) developed a rough classification of decision-makers on the basis of Rr. According to this classification, for a risk averse farmer Rr varies from 0.5 to 4, with the following meanings: 0.5 – hardly risk-averse at all, 1.0 – somewhat risk averse (normal), 2.0 – rather risk averse, 3.0 – very risk averse, and 4.0 – almost paranoid about risk (Hardaker *et al.*, 2004). In decision analysis, Rr is usually taken as a basis for calculating Ra as in Equation (2). Ra and Rr are usually used for the wealth measures of utility function. In case of failure of asset integration assumptions, these coefficients are calculated on the basis of income measure (for details see Hardaker *et al.*, 2004). In decision analysis the *coefficient of partial risk aversion* is rarely used for the measures of gains, losses, or income.

Risk-attitude estimation, elicitation and stochastic dominance

Risk-attitude coefficients can be either elicited or estimated. The following alternatives are described: (1) the direct method, (2) the equally likely certainty equivalent (ELCE) method, and (3) econometric models. The advantages and disadvantages of the three methods are listed in Table 1.

Direct method

Like risk perception, risk attitude can be elicited by a direct method, for example, by straight questions in a questionnaire. The direct measurement procedure, however, does not lead to the estimation of the risk-attitude coefficients. Instead, inferences about risk attitude (aversion) can be derived.

A questionnaire can include socio-economic and psychological Likert statements, characterizing the farmers' risk attitudes (e.g., Smidts, 1990; Pennings, 1998; Senkondo, 2000; Ganderton *et al.*, 2001; Van Asseldonk *et al.*, 2002). In a simple way, risk attitude can be asked as a linear variable measured on a 5-point or 7-point scale (e.g., Ganderton *et al.*, 2001). Some studies elicited the 'relative' risk aversion of a farmer, where a farmer was compared with the average farmers/persons in the group (e.g., Pennings, 1998; Van Asseldonk *et al.*, 2002). The group was asked to state their degree of risk attitude. The questionnaire used several statements on a 5-point or 7-point scale characterizing the risk attitude of a farmer compared with the average farmer in the agricultural sector. They then calculated the average score per farmer and per group. After comparing the individual and the average group scores, farmers were labelled 'less-risk-averse' or 'more-risk-averse'.

Use of econometric models to estimate risk attitude from observed economic behaviour

In the studies by Antle (1989), Bar-Shira *et al.* (1997), Oude Lansink (1999) and Gardebroek (2002), risk attitude in the form of absolute, relative or partial risk aversion coefficient was estimated, using econometric models, from observed economic behaviour based on the assumption that farmers act more or less consistently with the SEU theory. The models are based on assumptions about the nature of the production and decision environment, including the structure of attitudes and perceptions about the associated uncertainty (risks).

Hardaker *et al.* (2004) showed two weaknesses of this approach. One is related to the strong assumption that analysts and farmers share the same view of uncertainty farmers can face. It particularly concerns the fact that the probabilities based on historical series of observations of key uncertain phenomena are the same probabilities that farmers use in decision-making. The other one refers to specification errors that can be represented by econometric models. The reality can be far more complex than the assumptions made, and therefore the effects of the specification errors will be rolled into the estimates of risk aversion, making the reliability of results doubtful.

Equally likely certainty equivalent

The equally likely certainty equivalent (ELCE) method is widely used to elicit the utility function of Von Neumann–Morgenstern. Examples of studies that have been conducted (Table 1) include Smidts (1990), Pennings (1998), Senkondo (2000) and Torkamani (2005).

Suppose there is a risky prospect with discrete payoffs x_1, x_2, .. x_m... x_{n-1}, x_n with corresponding probabilities p_1, p_2 ...p_m... p_{n-1}, p_n summing to 1. In using the ELCE method, the first step in dealing with preferences is to find a certainty equivalent (CE) for a hypothetical 50/50 lottery with the best outcome x_n (having a utility of 1) and worst possible outcome x_1 (with a utility of 0) of the decision problem as the two risky consequences. CE is the maximum sure payment, x_m, the farmer would be willing to accept (pay) rather than face the risk (Hardaker *et al.*, 2004); this value is higher than x_1 and lower than x_n. Then the expected utility for the CE of x_m is calculated.

The next step is to find the CE with its corresponding expected utility for other points between x_1 and x_n. Suppose, we then calculate CE for the points between x_1 and x_m. After the CEs between the points x_1 and x_m have been found, the expected utility of this outcome is calculated as a weighted average of utilities for x_1 (which is 0) and x_m (which is known after the first step) and their probabilities of 50%. The CEs and expected utilities for other points can be calculated in the same way. This process of establishing utility points is continued until a sufficient number of CEs is elicited to plot the utility function. For details on the ELCE method see Anderson *et al.* (1977) and Hardaker *et al.* (2004). The advantage of ELCE is that it is based on the ethically neutral probabilities of 0.5 (Smidts, 1990; Hardaker *et al.*, 2004). People find 50/50 risky prospects much easier to conceptualize than prospects with other probability ratios (Hardaker *et al.*, 2004).

In the way presented above, several attempts have been made to elicit utility functions to put SEU hypothesis to work in the analysis of risky alternatives in agriculture. The results were, however, often unconvincing (King & Robison, 1984; Smidts, 1990; Anderson & Hardaker, 2002; Hardaker *et al.*, 2004).

A disadvantage of the expected utility approach is its complexity. The elicitation of CEs and subjective probability distributions is judged as fairly difficult and rather time-consuming, requiring an active role of an interviewer. However, taking into account these limitations, the results obtained may be even more surprising and unconvincing (Smidts, 1990; Hardaker *et al.*, 2004). There is evidence that the functions obtained are vulnerable to interviewer's bias and to bias from the way the questions are framed to elicit CEs (Hardaker *et al.*, 2004).

Concerning catastrophes, one problem arises in the estimation of the worst outcome and the CE between the worst outcome and other points. The simplicity of the method is 50/50 chances, i.e., equally likely outcomes. However, for catastrophic risks with very low probabilities it would be more difficult to assign the states 'there is' and 'there is no' catastrophe hail risk by 50/50 prospects. Morgenstern (1979), one of the founders of standard SEU theory, recognized the limited applicability of expected utility in the elicitation of risk aversion coefficients when probabilities were extremely low (Chichilnisky, 2000; Ganderton *et al.*, 2000; Ekenberg *et al.*, 2001; Kruse & Thompson, 2003).

Forms of utility functions

The utility functions elicited in a way as presented above need to have a mathematical form to derive risk aversion coefficients. However, there are functional forms that are based on the properties of risk aversion. The elicited utility function then can be tested whether it fits the existing functional form.

The most commonly used functional forms are based on the constant absolute risk aversion (CARA) and the constant relative risk aversion (CRRA) properties (Hardaker *et al.*, 2004). The extensively used form in decision analysis is the negative exponential function on the basis of CARA. CARA means that preferences among risky choices are unchanged if all outcomes are multiplied by a positive constant absolute risk-aversion coefficient. The exponential function takes the following form:

$$U = 1 - \exp(-Ra \cdot w);\ Ra > 0,\ w > 0$$

The exponential function has numerical problems for large values of wealth, reason why this function is only applicable if the risky prospect is small compared with the total farm's wealth. In case of a catastrophic risk such as hail, when the risky prospect may result in substantial changes in wealth, CRRA is more applicable. While *Ra* declines as wealth increases (i.e., decreasing absolute risk aversion), it is less probable that *Rr* is affected by changes in wealth. Logarithmic and power utility functions are based on CRRA properties. The power function based on CRRA properties takes the following form:

$$U = \left[\frac{1}{1-Rr}\right] w^{(1-Rr)}, \; w > 0$$

If the relative risk-aversion coefficient equals 1, the power utility function is undefined, so that the logarithmic function should be used, which takes the following form:

$$U = \ln(w), \; w > 0$$

The other commonly used functional forms are expo-power, polynomial-exponential, quadratic and hyperbolic absolute risk aversion (HARA) utility functions (Hardaker *et al.*, 2004; Richardson, 2006). These functional forms are widely used in risk modelling. They will be discussed below.

Stochastic dominance

The SEU theory, however, remains the appropriate theory for *prescriptive* assessment of risky choices (Hardaker *et al.*, 2004). To avoid problems with the SEU theory regarding risk attitude elicitation, methods of stochastic dominance have been developed.

Hadar & Russell (1969) were the first to present the concept of first-degree stochastic dominance (FSD). According to FSD, it is possible for decision-makers who prefer more wealth to less wealth, to arrange wealth alternatives with an absolute risk-aversion coefficient on a scale from minus infinity to plus infinity (King & Robison, 1984).

Thereafter, Hanock & Levy (1969) introduced the concept of second-degree stochastic dominance (SSD). Second-degree stochastic dominance assumes that the decision-makers are not risk preferring (i.e., risk neutral and risk averse), so that absolute risk-aversion limits are between zero and plus infinity.

Meyer (1977) introduced stochastic dominance and narrowed risk-aversion levels between a lower and an upper limit. Hardaker *et al.* (2004) applied stochastic efficiency (SERF), providing alternatives in terms of CEs as a measure of risk aversion over a definite range on the basis of the rough classification of relative risk-aversion coefficients of Anderson & Dillon (1992) presented earlier. Several studies have been conducted with SERF assuming this definite range of relative risk-aversion coefficients (e.g., Lien & Hardaker, 2001; Torkamani, 2005; Acs, 2006; Kobzar, 2006). Stochastic efficiency is widely used in risk modelling, as will be shown in the following chapter.

Risk modelling

For applicability of catastrophic-risk modelling, the methods of stochastic simulation and farm-risk programming are reviewed. For details of the advantages and disadvantages see Table 1. Again the example of hail risk is used for applicability in risk modelling.

Stochastic simulation

Stochastic simulation is often applied to generate a sample of outputs recognizing risky inputs (Richardson, 2006). Stochastic models are used to analyse 'what–if' questions about a real system. The method is sufficiently flexible to allow for the incorporation of complex relationships between variables and hence to mimic aspects of complex real systems in agriculture (Hardaker *et al.*, 2004).

A large number of distribution functions can be used for the simulation of inputs. For catastrophic risks such as hail, the distributions are not symmetric around the mean, but skewed (Kruse & Thompson, 2003). The examples of parametric distributions that deal with catastrophes are Poisson, gamma, exponential, negative binomial, Weibull and extreme value distributions (Johnson-Payton *et al.*, 1999; Vose, 2001). Alternatively, besides parametric distributions, also non-parametric distributions can be accommodated for stochastic simulation of catastrophes. One of them is the kernel density estimation (KDE) procedure, where the estimates of the probability at a given point depend on a pre-selected probability density that is specified by different kernel functions and subjective extreme points are added. For details of KDE see Richardson (2004) and Richardson *et al.* (2006).

In complex systems with more than one activity, as in farming, the stochastic dependency is always present. For example, crop yields tend to be positively correlated, as a good year for one crop often suits other crops too, and *vice versa*. Similarly, prices for several kinds of farm products tend to move together, depending on general economic conditions (Hardaker *et al.*, 2004). Ignoring stochastic dependency among risky prospects in farm planning can be seriously misleading. In the modelling of catastrophic risks, the standard approach to accommodate stochastic dependency is the Multivariate Kernel Density Estimation (MKDE) procedure, which is based on historical correlations between yields and prices (Richardson *et al.*, 2006). A more sophisticated approach to account for stochastic dependency is using copula (joint or multivariate distribution) functions. Compared with MKDE, which deals with historical correlation coefficients between variables, the correlation in copulas is a fixed parameter and is specified by the chosen copula function (for details see Venter & Carpenter, 2001). The kernel density estimation (KDE) approach and copulas have a limited use, however, since they are hampered by scarcity of data. The functions need more data points for their justification on a statistical basis, but on the other hand, it is what the decision-maker or expert believes that really counts.

The Monte Carlo Simulation (MCS) is widely used in stochastic simulation studies for the generation of outputs given risky inputs (e.g., Ermoliev *et al.*, 2000a, b; Kobzar, 2006). The risky inputs are specified by a probability distribution function. The number of data points from an input probability distribution function needs to be specified to be able to simulate (generate) outcome values. A number of data points specifying an input distribution is also called a number of *iterations*. Each iteration produces one possible outcome of a system, a so-called *state of nature*. During a simulation, MCS randomly selects data points (values) from probability distributions.

The Monte Carlo Simulation (MCS) is also extensively used for the modelling of catastrophic risks (Ermoliev *et al.*, 2000a, b). However, a possible drawback of the MCS is that it samples a larger percentage of the random values from the area around the mean so that there is a chance that it undersamples the tails of the probability distribution. When the MCS is used it is recommended that a large number of iterations is used to minimize the effect of undersampling the tails. However, if the distribution is highly skewed so that the tail is large, even a very large number of iterations may fail to produce sufficient values in the tail to accurately represent the area of interest (Vose, 2001; Richardson, 2006).

One way of capturing the downside tail of the distribution is using the Latin Hypercube simulation procedure. Latin Hypercube simulation is a later version of the MCS. Compared with the MCS the procedure significantly reduces the number of iterations. Latin Hypercube segments the distribution into a number of intervals and makes sure that at least one value is randomly selected from each interval. The number of intervals therefore equals the number of iterations, and in this respect this simulation technique ensures that all areas of the probability distribution are considered for simulation (Richardson, 2006). The examples of the simulation studies on the basis of Latin Hypercube sampling include Lien *et al.* (2006) and Richardson *et al.* (2006).

Stochastic efficiency

In stochastic simulation models of catastrophic risks, risk perception and risk attitude can be incorporated by the stochastic efficiency (SERF) method. The advantage of this method is that all types of utility function forms can be assumed. As stated before, SERF is applicable if risk-attitude coefficients (preferences) are unknown so that the whole range of relative risk-aversion coefficients developed by Anderson & Dillon (1992) is used. For each level of risk aversion a CE is then calculated. If the number of decisions is limited, CEs provide discrete alternatives so that a strategy with the highest CE over a range of risk-aversion coefficients dominates other strategies. Stochastic efficiency with respect to a function can be used for simple discrete examples, such as bearing hail risks by the farmers themselves or transferring the risk by purchasing insurance with basic options instead.

However, in case of more complex decisions or when the decisions are not discrete (i.e., allocation of several crops), stochastic models based on SERF have their limitations. The method will be more appropriate for simple insurance decisions, but will not account for the fact that once the decision to insure is made, it will affect other decisions such as a change in the production plan. The complex decisions can be modelled much better with farm-risk programming that uses the same range of relative-risk aversion coefficients as developed by Anderson & Dillon (1992).

Farm-risk programming

Contrary to stochastic simulation models, risk-programming methods are used to optimize an objective function subject to a set of constraints at farm level. Usually a set of activities is optimized to maximize/minimize the objective function. The outputs from stochastic simulation models can be used as inputs in farm-risk programming (i.e., yield or net-farm income per 1 of 500 possible states of nature with equal probability). Methods of risk programming that are often applied to deal with risk perception (or probabilities and impact) and risk attitude (a range of risk-aversion coefficients developed by Anderson & Dillon (1992)) are (1) utility-efficient programming (Hardaker *et al.*, 2004), (2) quadratic risk programming (Markowitz, 1952; Freund; 1956), and (3) minimization of total absolute deviation (Hazell, 1971). Suppose a farmer has a hail risk and operates with the three crops wheat, potato and sugar beet, the available land has to be optimally allocated to each of these crops.

Utility-efficient programming

The aim of utility-efficient programming (UEP) is to maximize the expected utility of a risky prospect. It operates with all functional forms presented above, and therefore can handle changes in wealth by power utility function that is applicable to catastrophic risks. Utility-efficient programming is highly applicable in risk programming and includes examples such as Lien & Hardaker (2001), Torkamani (2005), Acs (2006), Kobzar (2006) and Flaten & Lien (2007). The UEP model is formulated in the following way (Hardaker *et al.*, 2004):

$$\text{Maximize } \mathrm{E}[U] = pU(z, R),$$
$$\text{subject to } Ax \leq b \text{ and } Cx - Iz = U(z, R)$$

where
$\mathrm{E}[U]$ = expected utility;
p = the probability of each state of nature;
$U(z, R)$ = a vector of utilities of farm goal variables by state of nature with risk-attitude level R;
R = coefficient of absolute or relative risk aversion;
A = a vector of technical-economical coefficients per activity;
x = a vector of activities, $x \geq 0$;
b = a vector of available resources (constraints);
C = a vector of state of nature matrix of activity incomes;
I = an identity matrix;
z = a vector of farm goal variables by state of nature.

The risk perceptions for UEP can be imposed by any type of parametric and non-parametric distribution considered in a subsection of stochastic simulation. The catastrophic risks can easily be accommodated by adding states of nature (for instance, generated by simulation) with very low probabilities. In the example of the arable farmers with three crops, the stochastic dependency between yield and prices on the basis of

MKDE or copula function can easily be incorporated in UEP.

Suppose the farm data are limited and contain only 10 years of observations without catastrophe events. Considering parametric or non-parametric distribution assumptions with imposed extremes (catastrophe events), the data can be extended to more observations. Taking into account that hail can have a different impact, the generated states of nature would contain different combinations of probability and impact of hail.

With a limited number of states of nature, without consideration of distribution assumptions to simulate the data, the additional risk perceptions of extreme cases could also be obtained from experts or elicited from farmers and then added to the UEP model. Stochastic dependency can then easily be incorporated into the UEP model to minimize the risk of hail. Because wheat is more prone to hail than potato and sugar beet, the portfolio approach can be used to diversify the mix of activities by allocating more land to crops that are not prone to hail.

Quadratic risk programming and minimization of total absolute deviation

Quadratic risk programming (QRP) combines probabilities and preferences to generate a set of farm plans lying on the efficient frontier of expected income and its variance (Hardaker *et al.*, 2004). Quadratic risk programming aims to maximize the expected income and minimize the variance (risk) of expected income. Examples of QRP studies are Lien (2002) and Kobzar (2006). All equations of UEP, except for the goal function, are applicable to QRP.

The assumption necessary to validate the use of QRP is that the utility function is quadratic or the distribution of total net revenue is normal. QRP is applicable only for CARA utility function, and will not work with a power utility function that is appropriate for catastrophic risks. The distribution of revenue varies and is not always normal – in agriculture the returns from individual activities are often skewed (Hardaker *et al.*, 2004). Due to the normality assumptions, the QRP model cannot be used for catastrophic risks (Ermoliev *et al.*, 2000a, b), as will be shown below.

A normal distribution is defined by two parameters: mean and standard deviation. Suppose that a farmer has wheat with an average yield of 10,000 kg per ha and a standard deviation of 2000 kg per ha. Based on these parameters a normal distribution is simulated. Assuming a normal distribution the probability that the wheat yield will be lower than 5000 kg per ha is 0.05%. Suppose wheat is more risky so that the standard deviation in a normal distribution changed to 2500 kg, then the probability that the yield is lower than 5000 kg will be 2.2%. From this example it can be seen that a down-side tail can have different densities, depending on the level of the standard deviation.

To be able to decide whether a distribution is normal, at least 20 observations are required. The results will be misleading if the data are sparse and it is hard to obtain more than 10 observations (including catastrophes) under the same economic policy, management regime, farm programme or trade policy (Richardson, 2006). Misspecification of the standard deviation as one of the main distribution parameters can seriously hamper the applicability of QRP for incorporation in the downside tail.

The minimization of total absolute deviation (MOTAD) method is an extension of QRP. It attempts to find linear approximations of QRP and has been developed to handle non-linear functions. The structure of the MOTAD model is the same as that of

QRP, except for one aspect. Instead of minimizing the variance of income, it minimizes the mean absolute deviation of income. We shall not discuss the structure of this model. For details see Hardaker *et al.* (2004). For the same reasons as presented for QRP, MOTAD cannot be considered for effective modelling of catastrophic risks such as hail.

Concluding remarks

This paper reviews the methods of assessing risk perception and risk attitude and of modelling risk on the basis of indicators with the aim to generate an appropriate method to support decision-making of the farmer when facing catastrophic risks.

Risk perception

The data on catastrophes are skewed and deal with low probabilities, so that one of the main problems discussed concerns the risk-perception elicitation of catastrophic risks. The standard strength of conviction method to elicit risk perception is not applicable to catastrophes if one deals with a limited number of points to estimate, resulting in a possible underestimation of the downside tail. But even if a tail were included in the questionnaires, people would have problems with interpreting low probabilities due to different psychological biases. To avoid such biases, techniques of a better representation of probabilities, partly derived from a direct method of risk-perception elicitation, can be applied.

Risk attitude

Subjective expected utility (SEU) remains the main theory to incorporate risk attitude in the models. The most important method, equally likely certainty equivalent (ELCE), was shown not to be applicable to elicitation of risk-attitude coefficients. The main limitation was that it is hard to assume 50/50 chances, and then to divide 50% into 50/50 chances and so on for approaching very low probabilities. Besides catastrophic risks, in many studies applying ELCE the results obtained are unconvincing due to interviewer's bias and bias from framing the questions. Alternatively, risk attitude was proposed to be estimated by econometric models. However, in these models specification errors play a role, which makes the estimates of risk aversion doubtful.

As long as there are problems with obtaining the exact value of risk-attitude coefficients, the differences between portfolio values could be assumed by methods of stochastic dominance, in particular by applying stochastic efficiency (SERF). In the case of farmers, the relative risk aversion levels can be taken from the classification of Anderson & Dillon (1992). Concerning the catastrophic risks, after a catastrophe occurs the level of risk aversion can change, implying changes in wealth position. So it would be easier to assume different levels of risk aversion rather than one specific value.

Risk modelling

Stochastic simulation and farm-risk programming are reviewed as methods of risk modelling. Stochastic simulation was shown to deal with parametric and non-parametric distribution assumptions that have proved to be successful in dealing with the downside tail of the distribution. In complex systems, stochastic dependency can easily be incorporated, simulating historical or assumed patterns of dependencies. Concerning a method of sampling catastrophe data for modelling, a Latin Hypercube sampling technique can be used instead of the Monte Carlo Simulation (MCS). Stochastic simulation based on the Latin Hypercube sampling can be assumed with different types of skewed distributions to capture the downside tail. If the number of decisions is limited, they could be compared in terms of SERF. However, in case of more complex decisions, stochastic simulation has a limited applicability, so that the methods of farm-risk programming, seeking an optimal solution given a set of constraints, will be more appropriate. However, for accounting all possible realizations of the inputs, the input variables can be simulated first with the Latin Hypercube simulation and used further in farm-risk programming.

Three methods of farm-risk programming were reviewed: quadratic risk programming (QRP), minimization of total absolute deviation (MOTAD) and utility-efficient programming (UEP). QRP and MOTAD are shown not to be applicable to catastrophic risks, because they assume normality and deal only with quadratic utility functions. The power utility function, which incorporates changes in wealth, is shown to be more applicable. For this purpose the UEP, which handles any function form, including power utility function, can be applied. Furthermore, all advantages of stochastic simulation to capture the downside tail of the distribution can be incorporated in UEP as states of nature.

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