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The Regional Self-Organizing Potential in Sustainable Agriculture

Peter Nijkamp[1]
Katrin Oltmer[2]

[1] *Faculty of Economics and Business Administration, Vrije Universiteit Amsterdam, and Tinbergen Institute,*
[2] *Agricultural Economics Research Institute (LEI), The Hague.*

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Tinbergen Institute Amsterdam
Roetersstraat 31
1018 WB Amsterdam
The Netherlands
Tel.: +31(0)20 551 3500
Fax: +31(0)20 551 3555

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Amsterdam
The Netherlands
Tel.: +31(0)10 408 8900
Fax: +31(0)10 408 9031

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THE REGIONAL SELF-ORGANIZING POTENTIAL IN SUSTAINABLE AGRICULTURE:

AN ANALYSIS OF CO-OPERATIVE AGREEMENTS ON NITRATE POLLUTION BY MEANS OF ROUGH SET METHODS

Peter Nijkamp[a] and Katrin Oltmer[b]

[a]Dept of Spatial Economics
Free University
De Boelelaan 1105
1081 HV Amsterdam
The Netherlands

[b]Agricultural Economics Research Institute (LEI)
Burgemeester Patijnlaan 19
2502 LS The Hague
The Netherlands

Abstract

This study addresses the achievements of cooperative agreements in sustainable agriculture policy. After an economic analysis of multi-actor choice situations, it focuses the attention on the self-organizing potential of regional market parties in order to comply with environmental policy objectives. The empirical application concerns voluntary agreements among farmers in Bavaria regarding intensified efforts to reduce nitrate pollution of drinking water. By means of new variants of artificial intelligence methods based on rough set analysis, a systematic investigation of success factors of such strategies is achieved.

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1. Agriculture in Transition

Agricultural activities do not only meet the needs for food, but play also a critical role in sustainable land use planning. Agri-environmental policy has become a focal point of policy concern and scientific interest (see e.g., Kleijn et al. 2001; Dabbert et al. 1998, or Whitby 2000). For example, the EU Agri-environmental Programmes aim to incorporate environmental values and nature conservation explicitly in agricultural production systems, e.g., through financial incentives and regulatory measures. Clearly, this is not an easy strategy in a competitive sector where productivity is the key to success. Bottlenecks in such a sustainability-oriented strategy are the long time scale of ecosystems development, the interaction with non-agricultural sectors, and the fragmented nature of agricultural production. In applied agri-environmental research much attention has been devoted to the design of environmental pressure-state indicators (such as the implications of pesticide use for food quality and biodiversity). Such information, as well as assessments of the social revenues of environmental policy, are a *sine qua non* for a balanced and structural sustainable development of agriculture, but the large number of actors precludes an unambiguous result (cf. also De Groot et al. 2002). Despite all policy and trade uncertainties, agricultural support policies – especially in Europe – have witnessed a significant transformation from traditional price subsidies to income and environmental subsidies (see e.g. Frandsen et al. 2003). Especially the need for an environmentally-benign agricultural production system has prompted the development of alternative perspectives and strategies for the agricultural sector.

The present paper will illustrate the above mentioned re-orientation in agricultural policy by addressing the issue of agricultural nitrate pollution and subsequent abatement strategies by means of co-operative agreements between farmers and water supply companies. The increased utilisation of manure and of other nitrogen-containing fertilisers in agricultural production in the past decades has caused an increasing nitrate leaching, which may lead to groundwater pollution, eutrophication of surface waters, or pollution of nature areas. We will focus here in particular on nitrate pollution in groundwater used for producing drinking water.

Along with their many negative effects on ecosystems and biodiversity, high nitrate levels in drinking water are assumed to cause two kinds of health problems: the blue baby syndrome (oxygen starvation in bottle-fed babies) and stomach cancer (Hanley 1990; Chowdhury and Lacewell 1996). In order to protect water against the risk of these diseases, the European Commission (EC) in its Drinking Water Directive (established in 1989) and the World Health Organisation have defined a legal maximum threshold of 50 mg per litre (Fuchs 1994). Whereas scientific evidence on the actual existence of a link between excessive nitrate levels and the above mentioned diseases is still controversial, water consumers may indeed favour pure and untouched groundwater as a source of drinking water (Hanley 1990).

The response on the producer side has inter alia been to favour co-operative (voluntary) agreements rather than command-and-control policies, as the first policy strategy may enhance economic efficiency and environmental effectiveness by deploying the specific knowledge base of local stakeholders in the area under consideration, as well as policy flexibility by tailoring environmental policy measures to local conditions. The co-operative agreements investigated in this paper are between water supply companies and farmers in the German state of Bavaria. Water supply companies have to comply with the above mentioned European Drinking Water Directive. Especially in nitrate-sensitive areas with intensive agriculture, water supply companies find it difficult to deliver drinking water with less than 50 mg of nitrate per litre without using technical means to reduce the nitrate content. Whereas blending groundwater from contaminated wells with water from clean wells is a relatively easy option, purification by means of an installation for nitrate removal is a sophisticated technical process involving considerable cost. An important motivation for water supply companies to initiate co-operative agreements with farmers is therefore to avoid the risk of incurring future purification costs (Kuks 1998), which is related to the well-known Coase theorem.

The first objective of this paper is to assess the environmental effectiveness of co-operative agreements in the context of the regional self-organizing potential of farmers. This effectiveness is measured here in terms of the development of the nitrate level in groundwater. The effect of co-operative agreements on groundwater quality is positive if the nitrate level shows a decreasing or, at least, a stabilising trend. We will utilise rough set analysis in order to assess the environmental effectiveness of the co-operative agreements. Rough set analysis is a non-parametric method from artificial intelligence that assists in identifying regularities in classified data and generating so-called decision rules that may be used for policy evaluation and advice.

Rough set analysis is, however, plagued by a combination of methodological issues. The first issue that has not received much attention in applications of rough set analysis to empirical policy assessment deals with the categorisation of the data required for performing a rough set analysis. The second issue is related to the first issue and is concerned with the potential loss of information due to the categorisation of the data. The second objective, therefore, adds to the existing literature on rough set analysis for policy assessment by addressing the two described methodological problems. The subsequent analysis compares a set of three strictly-defined categorisation methods (equal-frequency binning, equal-interval binning and the entropy-based method) and assesses their respective effects on the final results. The comparison between the three methods may be regarded as a sensitivity analysis concerning the categorisation of the data . In order to address the potential loss of information, we compare the results of the rough set analyses based on the three categorisation methods with the results of a specific discrete choice method, viz. probit analysis. In this comparison, we are particularly interested in the direction in which different factors affect the effectiveness of the co-operative agreements, i.e., the development of the nitrate level in groundwater.

This paper is organised as follows. Section 2 reviews some important economic aspects of nitrate pollution. Next, Section 3 extends the discussion on co-operative agreements by providing some empirical examples and descriptions of experiences from the literature, particularly focusing on co-operative agreements between farmers and water supply companies. Section 4 provides a description of the data and influencing factors included in the analysis. Section 5 presents the empirical results. The paper concludes with a discussion and conclusions in Section 6, followed by Annex A presenting a concise description of the methodology of rough set analysis and of the three categorisation methods, and Annex B offering several empirical results.

2. Economic Aspects of Nitrate Pollution in Groundwater

Nitrate pollution in groundwater is a negative externality of agricultural production. Water suppliers and farmers use groundwater resources in different ways. Whereas water suppliers take groundwater as input for production, farmers use the groundwater basin as a waste disposal facility. For both of these uses, groundwater is regarded as a common property resource, implying that exclusive property rights are not defined (Siebert 1986). A concept that would properly apply to this particular situation is the Polluter Pays Principle (PPP) advocated by the OECD (1975). The PPP is also included in the European Nitrate Directive that states that "*…the costs of measures necessary to change current practices to reduce nitrate pollution should be borne by agricultural operators*" (European Commission, 2000, p. 41). However, the current distribution of costs and benefits involved in the abatement of nitrate pollution and in the establishment of co-operative agreements between water suppliers and farmers is not consistent with the PPP. Costs for purification and co-operative agreements are borne by water suppliers who, under German legislation, can in turn pass on their costs to the consumer. It has frequently been observed that the farming sector has been exempted from the PPP and has instead been subsidised in order to encourage the adoption of environmentally friendly farming practices for reducing the emissions of harmful substances (Hanley et al. 1998). Clearly, a subsidisation of environmentally friendly farming practices implies the production of positive externalities by farmers, namely the *improvement* of environmental quality.

Two important reasons for this mismatch between theory, claiming that nitrate pollution in groundwater is an external cost, and reality, indicating that the *improvement* of groundwater quality may be regarded as an external benefit, are pointed out by Tobey and Smets (1996). First, there is the problem that the agricultural sector is mainly characterised by non-point source pollution. It is difficult to determine who and what kind of activity has been responsible for which share of the total pollution. Furthermore, the severity of pollution does not depend only on the quantity of the harmful substance applied, but also on the time of application, the type of crop to which it is applied, the method of application and the complexity of the underlying ecosystem, such as the soil type, the climatic circumstances or the hydrological system. Second, there is the aspect of competitiveness. Agriculture is a classical competitive sector with a large number of small producers who cannot influence the producer price. This implies that pollution abatement costs cannot be passed on to the consumer. Competitiveness may hence be affected. Diakosavvas

(1994) shows in a study considering 23 countries and 10 agricultural commodities that a country's net exports tend to fall due to environmental regulation. However, the general literature on international trade does not provide unambiguous evidence of a negative relationship between environmental regulations and competitiveness (Mulatu et al. 2001).

Costs involved in switching to environmentally friendlier farming methods may not only include costs for alternative machinery, additional land, or manure storage facilities, but also for remedying farmers' lack of knowledge of how to apply these methods. Conventional agricultural policy has stimulated farmers to adopt farming methods that intensify production. Total abatement costs may indeed be unbearable for family farms with limited human and financial resources, which are not only subject to environmental policies, but also to ongoing agricultural policy reforms. Co-operative agreements may be a proper instrument for raising farmers' awareness of environmental problems, by directly involving them in the policy process and for assisting farmers in adopting alternative production methods. The following section gives some examples of co-operative agreements.

3. Co-operative Agreements between Farmers and Water Suppliers

Co-operative or voluntary agreements were first established between governmental agencies and the industrial sector in order to reach certain environmental goals, such as the reduction of CO_2-, NO_X-, and SO_2-emission, or the reduction of CFCs in refrigerators and spray cans. The increasing popularity of co-operative agreements as self-organizing arrangements can mainly be ascribed to their communicative and interactive character. Governmental agencies and the polluting industries negotiate for the most appropriate solutions to reach the environmental target, mainly in combination with governmental subsidies for technical innovations (Sunnevåg 2000). Because of the joint responsibility concerning the content of the agreement, the industrial sector is more likely to accept and to be well disposed towards reaching environmental goals. Furthermore, the interactive character creates more flexibility, which in turn provides the opportunity to find cost-effective solutions that are tailored to the local conditions, and reduces the time span between formulation of the policy goal and policy implementation (Segerson and Miceli 1998).

Segerson and Miceli (1998) distinguish between two types of co-operative agreements: the stick approach and the carrot approach. In the stick approach, participation in the co-operative agreement is stimulated by threats to implement more stringent legislation if the environmental target agreed upon is not reached. In the carrot approach, participation is encouraged by incentive payments such as subsidies or cost-sharing programmes for investments in pollution abatement technologies.

There are a number of examples of voluntary environmental agreements between the agricultural sector and governments. One of them is the agri-environmental policy programme of the EU. Another example is the Conservation Reserve Programme in the United States. Voluntary agreements between the agricultural sector and another private sector, such as the drinking water industry, are, however, rare. In fact, direct agreements between farmers and water suppliers are uncommon in all EU Member States. They can mainly be found in Germany and the Netherlands and to a lesser extent in France. Germany, with over 400, has the largest number of agreements. This is more than 80% of the total number of agreements in the EU. However, in Germany, the distribution of co-operative agreements is not well-balanced. They can mainly be found in four of the 16 Bundesländer, viz. North-Rhine Westphalia, Bavaria, Hessen and Lower Saxony (Heinz et al. 2001).

Apparently, a number of factors can promote or hamper the establishment of co-operative agreements between water supply companies and farmers in the EU. An important promoting factor is that drinking water stems from well-contained and compact groundwater resources, e.g., well-determined groundwater protection zones. This limits the spatial dispersion of pollution such that the cause of the pollution can be determined unambiguously. Furthermore, the water supply companies' ability to finance the co-operative agreements, the willingness of the farmers to adopt pollution-reducing practices and public preferences for pure and untreated water are supporting factors for the establishment of co-operative agreements. Important hampering factors are a reliance on command-and-control measures in some countries and a lack of enforcement of environmental legislation in other countries. Moreover, the existence of other local, regional or national agri-environmental programmes in some parts of the EU may crowd out local initiatives from water supply companies (Heinz et al. 2001).

Existing co-operative agreements between farmers and water suppliers cannot strictly be categorised into one of the two types distinguished by Segerson and Miceli. Most of them are a combination of both, which means using background threats of stronger legislation and providing incentive payments for applying environmentally improved practices. In fact, as is pointed out by Wu and Babcock (1999), citing Davies et al., successful voluntary agreements must be based on a proper statutory framework (i.e., background legislation), need to have a clear and measurable environmental target and must provide substantial financial incentives. The importance of financial incentives is also underlined by Anders Norton et al. (1994), who state, referring to conventional wisdom, that farmers would not be willing to voluntarily adopt pollution abatement methods without a subsidy compensating for the costs of these methods and any revenue losses. However, positive incentives need not only be of financial nature. They may also be provided in the form of payments-in-kind, such as technical assistance and teaching programmes or supervised study groups and workshops, where farmers get the opportunity to acquaint themselves with environmentally sound farming methods. An important aspect of organised teaching programmes is that they increase farmers' awareness and understanding of the nitrate problem. Farmers might accept that pollution abatement practices may also increase on-farm environmental quality. In such self-organizing situations, farmers may even be willing to adopt pollution abatement practices without full compensation for costs and revenue losses (Anders Norton et al. 1994).

Theoretical economic analyses of voluntary agreements in agriculture have been carried out by Segerson and Miceli (1998) and Wu and Babcock (1999). Segerson and Miceli's objective was to find out whether voluntary agreements lead to efficient environmental protection as compared to mandatory legislation. They show that along with background threats and financial incentives, the structure of the bargaining power between the regulator and the firm plays an important role in the agreement about the level of abatement. In particular cases where the regulator has all of the bargaining power, the equilibrium level of abatement under the voluntary agreement might be the first-best level, i.e., higher than the level under mandatory legislation. Wu and Babcock (1999) have analysed the relative efficiency of voluntary programmes compared to mandatory programmes. They point out that important comparative advantages of voluntary programmes are the reduction of enforcement costs and the avoidance of duplicate private effort. As a comparative disadvantage, they mention, that voluntary programmes may involve large government expenditures that may cause deadweight social losses.

The present paper does not attempt to provide a theoretical-mathematical analysis of underlying complex decision processes of these sectors. It focuses instead on an empirical examination of data collected for a number of existing co-operative agreements. The method used in this analysis is based on rough set theory, which is concisely explained in Annex A of this paper.

4. Data and Attributes

The data used in the analysis stem from a survey that was held among water supply companies and municipalities in Bavaria, Germany, about co-operative agreements with farmers in the year 2000.[1] The addresses of the water supply companies and municipalities that offer co-operative agreements to farmers were obtained from the State of Bavaria. The list of addresses contained 139 water supply companies and municipalities. Each of them received a questionnaire, and 75 were returned. However, because of incomplete answers and missing information we used the data of only 40questionnaires. The analysis is hence based on 40 observations. The following gives a description of the attributes that characterise the observations.

Decision attribute:

Development of nitrate content in groundwater

The decision attribute – in fact, the dependent variable - is the development of the nitrate content in groundwater. This attribute is derived from the question in the survey answered by the water supply companies about the effects of the co-operative agreement on drinking water quality. It is categorised into two classes. Class 1 contains all those cases in which, at the time of the survey, the nitrate levels in

[1] The survey was part of the EU research project "Co-operative agreements in agriculture as an instrument to improve the economic efficiency and environmental effectiveness of the European Union water policy" (Heinz et al., 2001).

groundwater show a decreasing or at least stabilising trend, or, in other words, in which the co-operative agreement indicates a positive effect. Class 2 contains the cases that still show increasing nitrate levels and cases where a change in the development of the nitrate level is not yet recognisable, i.e., cases in which the effect of the co-operative agreement is negative.

Condition attributes:

The first set of condition attributes concerns given external features.

1) Year of foundation

Depending on geological conditions, rainwater needs a certain amount of time to percolate through the soil into the groundwater reservoir. Residuals of nitrogen containing substances, such as mineral fertiliser and manure, are transported into the groundwater reservoir by the percolating rainwater. The effects of a policy aiming at the reduction of nitrogen surpluses may hence become visible only after a number of years. The earlier the year of foundation of the co-operative agreement, the more likely a positive policy effect.

2) Total area under contract

The size of the total area under contract is supposed to have a positive relationship with the policy effect. A larger area under contract implies a larger catchment basin where the restrictive measures of the co-operative agreement apply.

3) Land use: arable

Arable land lacks permanent and complete soil cover, which means that residuals of nitrogen containing fertiliser are washed out more easily. A high share of arable land would hence likely be associated with a negative policy effect.

4) Number of participating farmers

This condition attribute may give an indication of whether the number of participating farmers plays a role in the effect of the co-operative agreement.

Next, we will present policy attributes that are related to the contents of the co-operative agreements. Condition attributes 5), 6) and 7) describe the restrictions farmers face when entering into an agreement. The restrictions are ordered according to their severity. It should be mentioned that all co-operative agreements described by the 40 observations include restrictions on the use of mineral fertiliser and liquid manure, such as the amount and time of application. Such restrictions are therefore not explicitly formulated as an attribute. Condition attributes 8) and 9) describe the number of restrictions and the amount of payments, respectively.

5) Restriction 1: set-aside

This restriction implies that farmers are supposed to take (some) land located in the area under consideration out of production. It is the most severe restriction offered by a co-operative agreement. This factor is binarily formulated. It takes 'yes' if the co-operative agreement includes set-asides and 'no' if not.

6) Restriction 2: permanent grassland

This restriction requires farmers to use the land under agreement as permanent grassland. It includes prohibiting the conversion of grassland into arable land and mandating that arable land be converted to grassland. This factor is also binarily formulated. It takes 'yes' if permanent grassland is included as a restriction, and 'no' otherwise.

7) Restriction 3: soil cover

The third restriction imposed on farmers is the maintenance of permanent soil cover. This restriction includes measures such as intercropping or the cultivation of catch crops. It does not prescribe actual changes in agricultural land use, but demands additional effort during the main crop's vegetation period. This attribute is also binary. It takes 'yes' if the co-operative agreement includes soil cover and 'no' otherwise.

8) Number of restrictions

Some co-operative agreements include no other restrictions than the general one on fertilisation. Others include one, two or all of the restrictions described in condition attributes 5), 6) and 7). This attribute hence comprises four different categories: 1 = no extra restriction, 2 (3) (4) = one (two) (three) additional restrictions. This condition attribute may also be regarded as an indicator of the variability or possibility of choices offered by the co-operative agreement. We hypothesise that a combination of more restrictions has a positive influence on the nitrate level in groundwater.

9) Expenses

This factor describes the expenses the water supply company has to bear to support the co-operative agreement. It is measured in expenses per hectare . It also indicates the compensation payments that farmers with land under co-operation receive. It is hypothesised that higher payments induce greater efforts to reduce nitrate leakage.

Table 1: Condition attributes with ranges and expected signs

	Condition attribute	Range	Expected sign
1	Year of foundation	1989 - 2000	-
2	Total area under contract	7 ha - 1500 ha	+
3	Land use: arable land	0 % - 100 %	-
4	Number of participating farmers	1 - 77	?
5	Restriction 1: Set aside	yes/no	+
6	Restriction 2: Permanent grassland	yes/no	+
7	Restriction 3: Soil Cover	yes/no	+
8	Number of restrictions	0 - 3	+
9	Expenses per hectare	51 - 8003 Euro	+

Table 1 summarises the condition attributes, shows their observed ranges of values and indicates their hypothesised association with the development of the nitrate level in groundwater. The sign, shown in the last column of Table 1, indicates the hypothesised direction of the effect, i.e., "+" for a decreasing nitrate level in groundwater (a positive policy effect) and "-" for an increasing nitrate level in groundwater (negative policy effect), for increasing attribute values.

Condition attributes 1), 2), 3), 4) and 9) are continuous variables. These variables need to be classified according to the three categorisation methods described in Annex A, viz. equal-frequency binning, equal-interval binning and entropy-based approach[2]. Table 2 shows the qualitative classes and the ranges of the five condition attributes for all three categorisation methods.

Table 2: Classes and ranges of attributes for three different categorisation methods

Qualitative classes for attributes		**Equal-frequency binning**		**Equal-interval binning**		**Entropy-based categorisation**	
1) Year of foundation	1	1987-1991	(10)	1987-1990	(6)	1987-1989	(3)
	2	1992-1995*	(9)	1991-1993	(10)	1990-1991	(7)
	3	1996-1997*	(11)	1994-1996	(14)	1992-1998	(23)
	4	1998-2000	(10)	1997-2000**	(10)	1999-2000	(7)
2) Total area under contract (ha)	1	< 55	(10)	< 375	(27)	< 9	(1)
	2	60-185	(10)	376-750	(8)	9-59	(9)
	3	187-537	(10)	751-1125	(3)	60-70	(3)
	4	600-1500	(10)	1126-1500	(2)	71-1500	(27)
3) Arable land use (%)	1	0-50	(10)	0-25	(4)	0-45	(8)
	2	51-64	(10)	26-50	(6)	46-50	(2)
	3	65-79	(10)	51-75	(16)	51-92	(26)
	4	80-100	(10)	76-100	(14)	93-100	(4)
4) Number of participating Farmers	1	1-11	(10)	1-19	(22)	1-4	(5)
	2	12-15	(10)	20-38	(10)	5-12	(8)
	3	17-35	(10)	39-58	(3)	13-65	(24)
	4	37-77	(10)	59-77	(5)	66-77	(3)
9) Expenses (Euro per hectare)	1	< 74	(10)	< 219	(27)	< 6	(1)
	2	76-130	(10)	220-444	(9)	6.1-26	(5)
	3	138-253	(10)	445-659	(2)	67-546	(31)
	4	254-2557	(10)	> 660***	(2)	547-2557	(3)

Figures in brackets are the number of observations in a class.
*) In order to keep all observations from 1996 in one class, the class sizes are slightly different.
**) The total range of years of foundation comprises 14 years, such that the years cannot be equally divided across 4 categories. We hence constructed categories comprising 3 and 4 years respectively.
***) 2557 was not taken into account in the determination of the intervals since it would have led to empty classes. It is, however, included in the number of observations for this category.

Table 2 indicates that the class intervals as well as the number of observations in each class differ significantly between the three categorisation methods. By definition, equal-frequency binning results in the most even distribution of observations over the four classes. The other two categorisation methods result in rather unbalanced distributions of the observations across the different classes. The information in the table is illustrated in the following two figures. Figure 1 shows the distribution of the observations across the four classes according to the three categorisation methods. Figure 2 depicts the bin widths of the four categories of the three categorisation methods.

[2] With the help of the agglomerative hierarchical clustering procedure, we determined that four is the most appropriate number of classes for most of the condition variables. Agglomerative hierarchical clustering indicate the stepwise combination of objects into clusters, starting with a situation in which the number of objects is equal to the number of clusters. The optimal number of clusters is determined on the basis of a similarity measure that measures the average cluster distance (for detailed information on clustering procedures, see Hair et al. 1998).

By definition, equal-interval binning results in equal widths of the four categories. This is shown in Figure 2, which indicates that the bin widths differ for equal-frequency binning and the entropy-based method. This is particularly obvious in Panel (b) and (e), in which the fourth category has the widest intervals. It should be noted that the distribution of the observations across the four categories (Figure 1) may influence the *procedure* of the rough set analysis. The influence of differences in bin widths (Figure 2) may become more obvious in the interpretation of the results. The following section shows whether the different categorisation methods do indeed have an influence on the results of the rough set analysis.

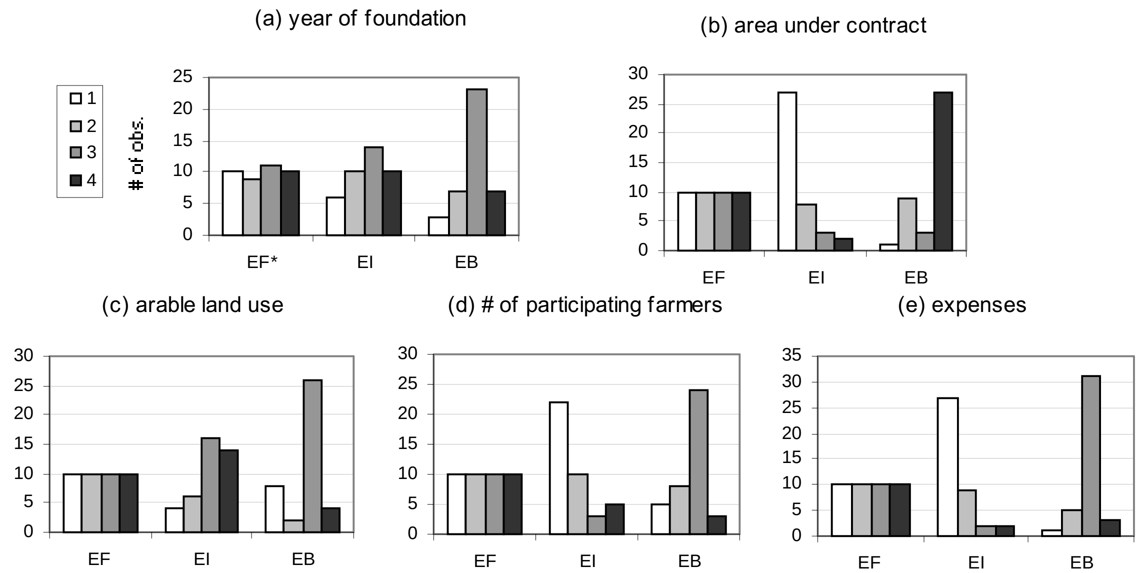

Figure 1: Distribution of the observations across the four classes according to the three categorisation methods (EF: equal-frequency binning (EF*: remind remark*) in Table 2), EI: equal-interval binning, EB: entropy-based method)

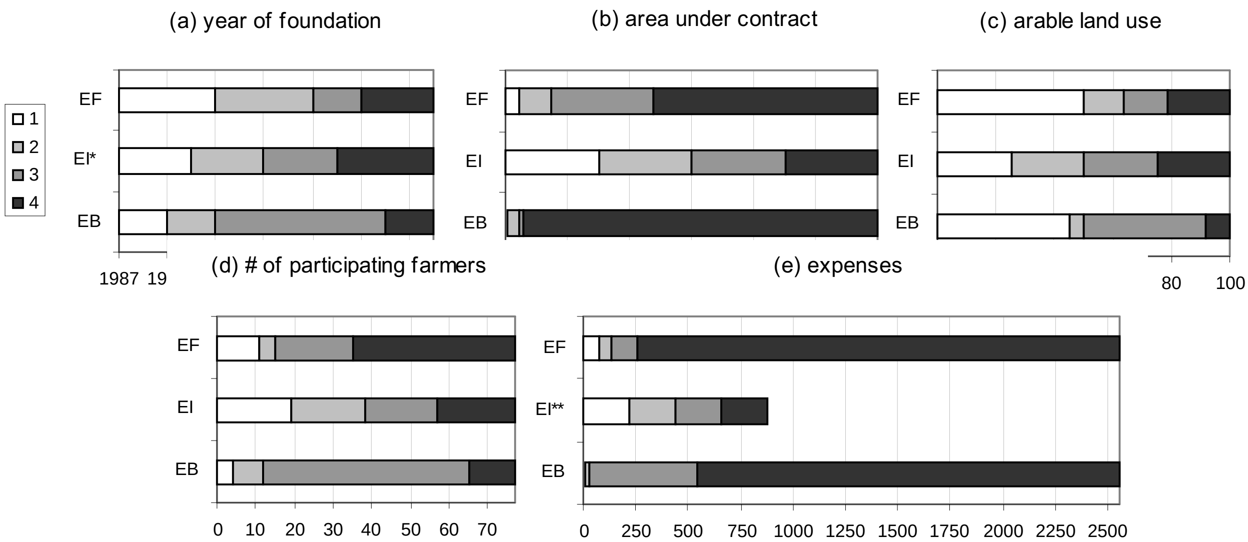

Figure 2: Bin widths of the three categorisation methods (EF: equal-frequency binning, EI: equal-interval binning (EI*/** remind remark *)/**) in Table 2), EB: entropy-based method)

5. Interpretation of the Results

The first question to be answered is whether all the information about the 40 observations given by the nine condition attributes is necessary for a consistent ('if-then') decision algorithm. This procedure refers to the component of attribute reduction described in Annex A, which results in the identification of minimal sets or reducts. Minimal sets contain no redundant information. They represent a reduced set of attributes that provide the same classification quality of the decision attribute as the original set of condition attributes. Nijkamp (2000) points out that a theoretically perfect solution would occur if the attribute reduction results in only one minimal set. The reason for this is that the fewer possibilities for minimal sets, the higher the 'predictive power' of the information (Pawlak 1991).

The attribute reduction based on the three categorisation methods identifies different numbers of minimal sets. On the basis of equal-frequency binning, 11 minimal sets, including either 4 or 5 condition attributes, can be found. The attribute reduction on the basis of equal-interval binning and the entropy-based method results in only 2 minimal sets, each with 4 and 5 or 7 condition attributes respectively. Considering the aforementioned notion about the number of minimal sets, it can be concluded that, on the basis of the data considered in this analysis , equal-interval binning and the entropy-based method lead to a more satisfactory attribute reduction than equal-frequency binning. In other words, the former two categorisation methods seem to have greater predictive power with regard to the considered information than the latter one. The actual minimal sets are given in Annex B.

One interesting and informative way of representing the minimal sets is a frequency table that shows the frequencies with which the different condition attributes appear in the minimal sets. The frequency of appearance gives an indication of the importance of some of the condition attributes relative to others. The frequency table is shown in Table 3.

Table 3: Frequency of appearance of condition attributes in minimal sets

Condition attribute	Equal-frequency binning *frequency*		Equal-interval binning *frequency*		Entropy-based categorisation *frequency*	
	#	%	#	%	#	%
1) Year of foundation	11	100	2	100	2	100
2) Area under contract	6	54.55	--	--	--	--
3) Arable land use	6	54.55	2	100	2	100
4) Number of part. farmers	8	72.73	2	100	2	100
5) Restriction 1: set aside	2	18.18	--	--	1	50
6) Restriction 2: perm. grassland	5	45.45	1	50	1	50
7) Restriction 3: soil cover	3	27.27	--	--	1	50
8) Number of restrictions	5	45.45	1	50	1	50
9) Expenses	4	36.36	--	--	2	100

Table 3 shows that the relative frequency of appearance of the different condition attributes varies between the three categorisation methods. As defined in Annex A, condition attributes that appear in all minimal sets (i.e., a frequency of 100%) are the cores, which have the most explanatory power relative to the other condition variables. The condition attribute 'year of foundation' appears to be a core attribute in all three categorisation methods. It can thus be considered important for the classification of the decision attribute, i.e., the development of the nitrate level in groundwater, and it may give an indication of the environmental success of co-operative agreements over the long/short term. Along with 'year of foundation', the condition variables 'arable land use' and 'number of participating farmers' are identified as cores for equal-interval binning and the entropy-based method. Furthermore, it is interesting to note that only one policy attribute[3] is identified as a core, namely 'expenses per hectare' in the entropy-based method. Additionally, all other policy attributes seem to be relatively less important than the remaining condition attributes in all three categorisation methods.

In order to answer the first objective of this paper, the determination of the environmental effectiveness of the co-operative agreement, we have to look at the direction in which the condition attributes influence the development of the nitrate level in groundwater. The direction of the impact can be derived on the basis of the decision rules in the form of "if-then" statements. The rule induction based on equal-frequency binning, equal-interval binning and the entropy-based method results in 16, 18, and 15 decision rules, respectively. It must, however, be noted that not all decision rules are of equal quality and hence equally important and reliable. A parameter that indicates the quality of the decision rules is their *strength*. Some generated decision rules have a very low strength, which implies that they are only supported by a small number of observations. In Table 4, we report only those decision rules that have a strength greater than 4, implying that the rules are based on at least 4 observations. Table 4 reports the actual ranges of the categories instead of their labels.

When investigating the decision rules, it is important to consider the *combination* of attributes in the rules. The decision rules that include 'year of foundation' do not always show unambiguous results. Regarding 'year of foundation' individually, one might conclude that the actual value of this condition attribute does not seem to matter since a positive development of the nitrate level in groundwater appears over the whole range of possible foundation years. However, in combination with the other attributes, the differences in year of foundation lead to some interesting results. From a theoretical point of view, earlier years of foundation should more likely result in positive developments of the nitrate level in groundwater. Rule a1 says that recently established co-operative agreements may lead to positive developments of the nitrate level if the agreement includes the restriction 'permanent grassland'. Rule a3 says that co-operative agreements established less than ten years ago also have a positive effect on groundwater quality if an additional restriction, soil cover, is included in the agreement. The implication of these two rules are supported by Rule b2, which says that recently established co-operative agreements have a positive influence on groundwater quality if the agreements include two additional restrictions,

[3] As defined in Section 4, the policy attributes are condition attributes 5) - 9).

Table 4: Decision rules from rough set analysis

	I F									THEN	
Rule	Year of foundation	Total area under contract	Arable land use	Number of participating farmers	Restriction1: Set aside	Restriction2: Permanent grassland	Restriction 3: Soil cover	Number of Restrictions	Expenses (Euro/hectare)	Development of nitrate level	Strength
a) Equal-frequency binning											
a1	98-00					yes				pos.	5
a2	87-91						no			pos.	7
a3	92-95	80-100					yes			pos.	4
a4	96-97							0		neg.	4
b) Equal-interval binning											
b1	87-90						no			pos.	4
b2	97-00							2		pos.	4
b3			0-25							pos.	4
b4								2	<219	pos.	6
b5	94-96							0		neg.	4
c) Entropy-based method											
c1		71-1500						2		pos.	7
c2	90-91									pos.	7
c3									6.1-26	pos.	5
c4		9-59				yes				pos.	4
c5			0-45							pos.	8
c6	92-99							0	67-546	neg.	6

though these have not been explicitly determined. Rule a2 implies that co-operative agreements that have been in operation the longest lead to improvements in the groundwater quality even if the additional restriction on soil cover is not included in the agreement. This interpretation of Rule a2 coincides with that of Rule b1 and, to some extent, also with that of Rule c2. Furthermore, Rules a4, b5 and c6 all indicate that co-operative agreements established less than ten years ago and without any additional restrictions do not positively influence groundwater quality.

Regarding the percentage of arable land use, another conclusion can be drawn from the decision rules. Rules b3 and c5 indicate that lower percentages of arable land use (<25% and <45%, respectively) have a potentially positive relationship with the development of the groundwater quality. This result is in accordance with the hypothesised situation explained in Section 4. Another interesting result revealed by Rules b4, c3 and c6 is that higher payments do not necessarily lead to positive developments in groundwater quality (higher payments are supposed to induce greater efforts on part of farmers). However, on the basis of the results presented here, it is too early to conclude that money does not matter for stimulating environmentally sound farming methods. Finally, the decision rules (a3, c1 and c4) do not lead to any unambiguous conclusion about the potential effect of the total area under contract on the development of nitrate levels in groundwater.

Another way of presenting and interpreting the results of the rule induction is to consider each condition attribute individually. Here, the individual condition attributes are counted according to the value at which they appear in the decision rules. In this case, all decision rules are taken into account, not just the ones with strengths greater than 4. The results are shown in Table 5.

Table 5: Frequency of appearance of condition attribute values in the decision rules

Equal-frequency binning			**equal-interval binning**			**entropy-based method**		
1) year of foundation								
	pos.	neg.		pos.	neg.		pos.	neg.
87-91	8	-	87-90	4	-	87-89	1	-
92-95	4	2	91-93	5	3	90-91	7	-
96-97	-	3	94-96	2	7	92-99	1	7
98-00	-	-	97-00	5	2	99-00	3	-
2) total area under contract								
	pos.	neg.		pos.	neg.		pos.	neg.
< 55	3	2	< 375	-	-	< 9	-	-
60-185	4	2	376-750	-	3	9-59	5	-
187-537	5	4	751-1125	-	1	60-70	-	-
600-1500	4	4	1126-1500	-	-	71-1500	7	-
3) arable land use								
	pos.	neg.		pos.	neg.		pos.	neg.
0-50	2	-	0-25	4	-	0-45	8	-
51-64	2	2	26-50	-	-	46-50	-	2
65-79	2	2	51-75	4	2	51-92	1	4
80-100	-	2	76-100	2	1	93-100	-	1
4) number of participating farmers								
	pos.	neg.		pos.	neg.		pos.	neg.
1-11	-	-	1-19	2	5	1-4	-	3
12-15	3	-	20-38	2	3	5-12	-	-
17-35	3	-	39-58	-	-	13-65	1	2
37-77	-	-	59-77	2	1	66-77	3	-
5) restriction1: set aside								
	pos.	neg.		pos.	neg.		pos.	neg.
Yes	-	2	yes	-	-	yes	-	-
No	3	2	no	-	-	no	-	-
6) restriction 2: permanent grassland								
	pos.	neg.		pos.	neg.		pos.	neg.
Yes	5	-	yes	-	-	yes	4	-
No	2	-	no	-	6	no	1	-
7) restriction 3: soil cover								
	pos.	neg.		pos.	neg.		pos.	neg.
Yes	4	-	yes	2	1	yes	-	-
No	7	-	no	4	-	no	-	-
8) number of restrictions								
	pos.	neg.		pos.	neg.		pos.	neg.
0	-	4	0	-	-	0	-	6
1	-	2	1	2	2	1	1	2
2	5	-	2	10	-	2	7	-
3	-	-	3	-	-	3	-	1
9) expenses per hectare								
	pos.	neg.		pos.	neg.		pos.	neg.
<74	2	2	<219	2	4	<6	-	-
76-130	-	-	220-444	-	-	6.1-26	5	1
138-253	-	-	445-659	-	-	67-546	1	7
254-2557	-	-	660-2557	2	1	547-2557	-	-

Table 5 can be interpreted as follows. Consider the condition attribute ‘year of foundation’ for the equal-frequency binning method. Eight (four) observations appearing in the decision rules describe a situation in which a co-operative agreement established between 1987 and 1991 (1992 and 1995) is associated with a positive development in groundwater quality. The situation in which a co-operative agreement is associated with a negative development in groundwater quality can be derived accordingly. Regarding the ‘positive’ situations in comparison with the ‘negative’ situations, it may be concluded that under equal-frequency binning, the condition variable ‘year of foundation’ indicates that longer established co-operative agreements are more likely to be associated with positive developments in groundwater quality. However, a comparison between the three categorisation methods shows that this result does not appear with all methods. Whereas under the entropy-based method, the results approach those given from equal-frequency binning, the results generated with equal-interval binning are very different from those of the other two methods. The same is true for condition attributes 2), 4), 5), 7) and 9). Approximately conforming results from the three categorisation methods can be observed for condition attributes ‘arable land use’, ‘restriction 2: permanent grassland’ and ‘number of restrictions’.

The results for ‘arable land use’ indicate a tendency to associate lower shares of arable land in total agricultural land with positive developments in the groundwater quality. Regarding the attribute ‘restriction 2: permanent grassland’, it may be concluded that a co-operative agreement including this restriction is more likely to have a positive effect on groundwater quality. Finally, concerning the attribute ‘number of restrictions’, it seems that a larger number of restrictions is advisable in order to obtain a positive effect on groundwater quality. The results of the three latter indicators confirm the hypothesised relationships given in Section 4.

Finally, in order to gain insight into the potential loss of information that results from the categorisation of the data, we want to compare the results of the rough set analysis with those of a standard discrete choice method, viz. probit analysis. The results of the probit analysis are shown in Table 6.

Table 6: Results of the probit model

	variable*	**Coefficient**	**p-value**
	Constant	113.424	0.459
1	year of foundation	-0.056	0.464
2	total area under agreement	-0.002	0.108
3	arable land use	-0.012	0.379
4	participating farmers	0.050	0.057
6	restriction 2: perm. grassland	1.693	0.127
7	restriction 3: soil cover	1.186	0.214
8	number of restrictions	-0.885	0.228
9	expenses per hectare	0.000	0.938
Likelihood ratio test		*12.622*	*0.126*
Number of observations: 40			

*) Because of near-collinearity between the constant and the variable ‘restriction 1: set aside’, we had to exclude this variable from the analysis, which prevents us from comparing it with the results obtained in the rough set analysis.

Table 6 shows that most of the estimated coefficients of the explanatory variables are insignificant. This result is, however, not surprising, considering the relatively low number of observations (degrees of freedom) for a probit model. The only coefficient that is significant at a 10-percent level belongs to the variable 'number of participating farmers'. Coefficients that approach the 10-percent significance level belong to the variables 'total area under agreement' and 'restriction 2: permanent grassland'. The condition attribute 'number of participating farmers' in the rough set analysis has been identified as a core attribute for equal-interval binning and the entropy-based method (see Table 3). In the minimal sets based on equal-frequency binning, this attribute appears with a frequency of 73 percent, i.e., it may also be considered important for the classification of the decision attribute. Concerning the relative importance of the variable/attribute 'number of participating farmers', the results of the rough set analysis and of the probit analysis are similar. This attribute does not appear in any of the decision rules with strengths greater than 4. The condition attributes 'total area under agreement' and 'restriction 2: permanent grassland' are not identified as core attributes in the rough set analysis. On the other hand, other variables that appear to be important in the rough set analysis ('year of foundation' and 'arable land use') do not yield significant results in the probit analysis.

Clearly, the relatively low number of observations in the probit model may cause us expect that the coefficients will have low significance levels. However, it is still interesting to investigate the direction of the effects in the probit model and whether they correspond to the results of the rough set analysis.[4] For this exercise, we compare the results of the probit analysis with the information provided in Table 5. Table 7 gives an indication of the extent to which the direction of the effects generated by the two types of analyses correspond.

Table 7: Correspondence between results of the rough set analysis and the probit model

	attribute/variable*	**equal-frequency**	**equal-interval**	**entropy-based**
1	year of foundation	+	+/-	+
2	area under contract	+	-	-
3	arable land use	+	+/-	+
4	participating farmers	+/-	+/-	+
6	Restriction 2: perm. Grassland	+	+	+
7	Restriction 3: soil cover	-	-	+/-
8	number of restrictions	-	-	-
9	expenses per hectare	+/-	-	-

*) Remind that we could not include attribute 5 'restriction 1: set aside' in the probit model

Legend:

+ : corresponds well (both analyses show the same direction of the effect)
+/- : comparison not possible because information in Table 6.5 does not show a clear direction of the effect
- : does not correspond (the two analyses show different directions of the effect)

[4] Note that the coefficients of the probit analysis do not show the marginal effects of the variables, but only the direction of the effect.

A first inspection of Table 7 shows that the rough set results based on equal-frequency binning and the entropy-based method correspond better to the results of the probit analysis than the rough set results based on equal-interval binning. It is striking that only one attribute/variable, i.e., 'restriction 2: permanent grassland', exhibits corresponding results for all three categorisation methods. The attributes 'year of foundation' and 'arable land use' show corresponding results for two of the three categorisation methods.

Next, we address the second methodological issue in rough set analysis viz. the potential loss of information. On the basis of our data and assuming that the probit analysis exploits the data better, since it makes use of the whole range of data, the following results are found. Of the variables that are (nearly) significant at a 10-percent level ('number of participating farmers', 'total area under agreement' and 'restriction 2: permanent grassland') only 'restriction 2: permanent grassland' shows unambiguously corresponding results for all three categorisation methods. For the attribute 'number of participating farmers', only the result based on the entropy-based method corresponds to that of the probit analysis. On the basis of the other two categorisation methods, no clear direction of the effect can be determined. For the attribute 'total area under agreement', only the result based on equal-frequency binning corresponds with that of the probit analysis. Furthermore, the results based on equal-interval binning most often do not show a clear direction of the effect. To summarise, it seems that the categorisation of the data in the rough set analysis leads to a loss of information, which becomes particularly obvious in the results based on equal-interval binning. Given the loss of information, the results are largely consistent.

6. Discussion and Conclusions

The present paper has dealt with two objectives. The first objective was to assess the environmental effectiveness of co-operative agreements by means of rough set analysis. The second objective was to contribute to the existing literature on rough set analysis for policy assessment by addressing two methodological issues, namely, the influence of different categorisation methods on the final results and the potential loss of information due to the categorisation of the data. Let us first concentrate on the second objective. Rough set analysis is an alternative tool for analysing categorised data. Although rough set analysis does not lead to the determination of strong statistical relationships, it may be able to determine factors that lead to certain values of a variable under consideration, in this case the positive or negative development of the nitrate level in groundwater. Rough set analysis hence goes beyond a simple narrative description of the data, but is less rigorous than pure statistical analysis.

On the basis of the data analysed in this paper, different methods of data categorisation appear to influence the results of the rough set analysis. It must be emphasised that the 'safest' method of data categorisation is on the basis of predetermined, theoretical grounds. This condition is, however, not always given, so that other categorisation frameworks need to be applied. The three different categorisation methods investigated in this analysis (equal-frequency binning, equal-interval binning and the entropy-based method) lead to different numbers of minimal sets, which theoretically implies differences in the information's predictive power. However, although the rule induction based on the three different categorisation methods leads to different numbers of decision rules with strengths greater than 4 and to different combinations of condition attributes within the rules, it does not generate contradictory results between the rules based on the three methods. Regarding the frequency of appearance of the individual condition attributes in all decision rules, the rough set analyses based on the three categorisation methods do not show corresponding results for all condition attributes.

In comparing the rough set results with the results of the probit analysis, it appears that the rough set results based on equal-frequency binning (the entropy-based method) correspond to a lesser (stronger) extent to the results of the probit analysis. Assuming that the probit analysis better exploits the data since it includes all individual observations, it seems that categorising the data in the rough set analysis leads to a loss of information. It furthermore appears that, on the basis of the data analysed, equal-interval binning seems to entail the greatest loss of information.

With respect to the first objective, the following conclusion may be drawn on the basis of the data investigated in our study . A result that appears equally strong for all three rough set analyses based on the three categorisation methods as well as the probit analysis indicates a positive relationship between the attribute/variable 'restriction 2: permanent grassland' and the development of groundwater quality. The results from the decision rule induction of the rough set analysis show that this attribute seems to be particularly important in combination with the attribute 'year of foundation', which appears to be an important attribute for the determination of the development of the nitrate content of groundwater. 'Year of foundation' is identified as a core attribute in all minimal sets and it appears most frequently in the generated decision rules. Our interpretation of the decision rules regarding 'year of foundation' leads to the following conclusion about the potential long/short-term impacts of co-operative agreements. Co-operative agreements that were established ten to fifteen years ago seem to have a positive influence on groundwater quality even without any additional restrictions but the general ones on fertiliser use, such as the amount and time of application. Furthermore, if the agreements include additional restrictions such as 'permanent grassland' or 'soil cover', they may have a positive effect on groundwater quality even in the shorter term, i.e., over less than ten or even five years. However, the rules explicitly point out that without any additional restrictions, a short-term beneficial effect from the co-operative agreements is very unlikely. Another attribute/variable that shows an equally strong effect on the results based on two of the three categorisation methods and the probit analysis is 'arable land use'. The results indicate that smaller shares of arable land use with respect to total agricultural land use are more likely to lead to decreasing nitrate levels in groundwater, which is in accordance with the hypothesised relationship.

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Annex A. Methodological Framework: Rough Set Analysis

Rough set analysis is a multidimensional classification method for categorical data. As will be explained in Subsection A.1, there are two combined methodological issues inherent in rough set analysis. The first issue is concerned with the categorisation of the data required for performing a rough set analysis and the second deals with the loss of information that results from the categorisation. Subsection A.2 considers the issue of categorisation and describes the three categorisation methods used in the rough set analysis deployed in this paper.

A.1 Description of rough set analysis

Understanding the functioning of rough set analysis requires the clarification of a number of terms (Pawlak 1991; Van den Bergh et al. 1997; Baaijens and Nijkamp 2000). Broadly speaking, rough set analysis consists of three major components: 1) sorting, 2) attribute reduction and 3) derivation of decision rules. First, the sorting procedure can concisely be described as follows. The observations or cases to be sorted form a finite set of objects (x), called universe U. Each object is characterised and identified by a finite set of attributes Q, with the attributes q taking on different values in their domain. The data referring to the objects and attributes are ordered in an *information table*. Objects can also be described in terms of any subset of attributes $P \subseteq Q$. Objects that are described with the same attribute or subset of attributes are called *P-indiscernible*, meaning that they fall into the same class (the *equivalence* class) with respect to the attributes concerned, i.e., they can no longer be distinguished by different attribute values. The equivalence classes are also called *P-elementary sets*, which is the most precise classification possible, on the basis of the available information.

Second, attribute reduction refers to the elimination of redundant information, which means retrieving a minimal set of attributes R that supplies the same quality of classification as the original set of attributes P. The minimal sets of attributes R are called *reducts*. The most important characteristic of a reduct is that additional attributes do not lead to a more accurate classification of the objects, whereas the elimination of an attribute does lead to a less accurate classification. It is important to note that an information table can have more than one reduct. The intersection of all reducts, or, in other words, an attribute that appears in all minimal sets is defined as the *core*. The core contains the attributes that are most important in the information table and that are most relevant for the classification of the objects.

Third, the derivation of decision rules requires the partitioning of the attributes into decision and condition attributes. A decision attribute is a single attribute that reflects the phenomenon to be studied. In fact, the decision attribute is analogous to the dependent variable and the condition attribute to the independent variables in standard regression analysis. It is, however, important to mention that the relationship between the decision attribute and the condition attribute is not the same as those between the dependent and the independent variables within a regression framework. Whereas the estimated relationship between a dependent and an independent variable indicates a potential causal relationship between two variables, the relationship between a decision and a condition attribute indicates the frequency at which a certain category of the decision attribute occurs in certain categories of the decision attributes. Decision rules may more accurately be described as conditional statements that are expressed in the form of “if-then” statements. Decision rules may either be exact or approximate. An exact rule declares that a particular combination of categories of the condition attributes results in only one particular category of the decision attribute. An approximate rule states that a particular combination of categories of the condition attributes implies more than one category of the decision attribute. The quality of the decision rule is indicated by its *strength*. The strength of a rule represents the number of observations or cases that are in accordance with that rule. Decision rules are the most relevant part of rough set analysis, because they indicate the direction in which the investigated condition variables impact the condition variable.

The following subsection is concerned with the categorisation of the data required to perform a rough set analysis.

A.2 Categorisation of the data

The categorisation of data implies the transformation of quantitative, continuous data into categorical information. The process of transforming a continuous variable into a finite number of intervals is called discretisation, and it is regarded as one of the most problematic issues in taxonomic experiments (Van den Bergh et al. 1997). The most popular criticism of discretisation concerns the loss of information involved.[5] The categorisation of a continuous variable is not considered problematic if the discretisation occurs on the basis of underlying theoretical factors. Unfortunately, this condition is not fulfilled in many cases. The categorisation of data is also called binning. Accordingly, categories are also called bins.

In most of the previously performed rough set analyses in economics, the categorisation was performed in a rather ad hoc manner, which means by visually inspecting the data and dividing them into more or less equally-sized categories. A point of concern with this type of categorisation is that it does not take into account

[5] Kohavi and Sahami (1996) point out that discretisation may also be viewed as a form of knowledge discovery, since it may be able to reveal critical values in a continuous domain. This, however, requires that predetermined critical values exist, which is rather uncommon in the economic sciences.

the effect of the determined bin widths and intervals on the final result. In the rough set analysis in this paper, we apply three different strictly defined categorisation methods and compare them with respect to their influence on the final results. . The three different categorisation methods are a) equal-frequency binning, b) equal-interval binning and c) the entropy-based method. These methods can be briefly described as follows.

a) Equal-frequency binning

Categorisation according to equal-frequency binning implies an even distribution of the attribute values over a predetermined number of bins. This type of binning is also known as histogram equalisation (Witten and Frank 2000).

b) Equal-interval binning

In this categorisation method, the bin widths are equalised. The whole range of attribute values is divided by the number of bins, so that equal bin widths can be constructed. The attribute values are then sorted into the respective bins.

c) Entropy-based method

Entropy-based methods create classes with the lowest possible level of entropy, i.e., classes that group the most similar data together, so that the data are represented in the most compact and organised way. In the analysis in this chapter, entropy-based categorisation is carried out by the rough set software package ROSE II (Predki et al. 1998; Predkim and Wilk 1999), which incorporates entropy-based discretisation methods.

The literature on categorisation methods and data mining describes equal-frequency and equal-interval binning as naïve discretisation methods, since these methods may aggravate the problem of information loss. Entropy-based categorisation methods have been proven to be more reliable (Kohavi and Sahami 1996; Fayyad and Irani 1993). However, especially in the case of relatively small data sets with a limited number of observations, the entropy-based methods often result in a very uneven distribution of observations across the different categories, which in turn may influence the results of the rough set analysis. Section 4 of this paper has given an overview of actual bin widths and bin sizes from the three different categorisation techniques, while Section 5 has described the rough set results.

Appendix B. Minimal Sets in Rough Set Analysis

The following minimal sets are found in our rough set analysis.

a) Minimal sets (reducts) based on equal-frequency binning

1: {perm grassland, soil cover, year, area, farmers}
2: {set aside, number of restrictions, year, area, farmers}
3: {soil cover, number of restrictions, year, area, farmers}
4: {set aside, perm grassland, year, area, arable}
5: {perm grassland, year, area, arable, expenses}

6: {number of restrictions, year, area, arable}
7: {perm grassland, year, arable, farmers}
8: {number of restrictions, year, arable, farmers}
9: {perm grassland, soil cover, year, expenses, farmers}
10: {number of restriction, year, expenses, farmers}
11: {year, arable, expenses, farmers}

b) Minimal sets based on equal-interval binning

1: {perm grassland, year, arable, farmers}
2: {number of restrictions, year, arable, farmers}

c) Minimal sets based on the entropy based method

1: {year, arable, set aside, perm grassland, soil cover, expenses, farmers}
2: {year, arable, expenses, farmers, number of restrictions

This information has been used in the interpretation of our findings in Sections 4 and 5.