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FOOD SECURITY AND AGRICULTURAL SUSTAINABILITY

A COMPARATIVE MULTI-COUNTRY ASSESSMENT OF CRITICAL SUCCESS FACTORS

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Abstract

This paper offers an overview of factors that are decisive for productivity increase in the agricultural sector (both farming and agro-food). An attempt is made to explain differences in total factor productivity in agriculture in different countries by means of meta-analysis, in particular, by using rough set theory as a framework for comparative study. The main aim is to derive the drivers of changes in agricultural food production with a view to conditional future predictions of an 'if…then' nature. The empirical application to OECD countries is used to illustrate the potential of this new approach for identifying critical success factors in agriculture with a view to future food security objectives.

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1. The Need for a New Perspective on Food Security and Agricultural Sustainability

Issues related to water, food and land are all concentrated in agriculture which forms a local point in the sustainability and security debate. The agricultural sector is a dynamic economic sector with many conflicting issues. Agriculture has gone through cyclical movements over the past decades. In the late 1960s and early 1970s it was generally expected that agricultural production growth would be unable to keep pace with the rising needs for food by our world population. But during the mid 1970s, world food production grew rapidly, thus reducing the threat of an ever increasing gap between supply and demand. Since the late 1980s however, the optimism was tempered because of the persistent problems of insufficient food supplies in major parts of our world and the environmental and social concerns about intensive farming methods. At present there is a greater recognition of the problem of food security in the medium and long term, inter alia as a result of depletion of natural resources and of environmental and land degradation (see United Nations 1997 for more details). Against these background observations, the notion of sustainable agricultural development in relation to international food security is quickly gaining importance (see also Lancker and Nijkamp 2000, Nijkamp 1999).

The interest in sustainable agricultural development has grown rather rapidly after the United Nations Conference on Environment and Development in Rio de Janeiro (1992), since - in the spirit of the Brundtland Report (1987) - it was recognised that, as a consequence of the intensified use of natural resources and the rise in pollution worldwide, a greater commitment to environmental protection and sustainable development was needed. In the action programme labelled 'Agenda 21', a wide array of policy proposals and plans was laid down. The problem however, is that global recommendations need to be translated at the meso level of economic sectors and regions where different trade-offs may be made between economic efficiency, the need for food security and the fulfilment of sustainability objectives.

Consequently, the general description of sustainable development in the Brundtland Report (see WCED 1987) as a means of meeting the needs of the present without compromising the ability of future generations to meet their own needs is too abstract and too less committing to be of practical use for a balanced agricultural policy (see Nijkamp 1999). The Food and Agricultural Organisation (FAO) of the United Nations has tried to offer a more specific description of sustainable agricultural development as a development path where resource use and environmental management are combined with increased and sustained production, secure livehoods, food security, equity, social stability and people’s participation in the development process. If these conditions are fulfilled, sustainable agricultural development is environmentally non-degrading, technically appropriate, economically viable and socially acceptable, so that a maximum welfare can be achieved through a co-evolutionary strategy focussed on economic, environmental and social objectives and/or constraints on agricultural production, now and in the future (see also Pearce and Atkinson, 1993).

Conflict management (for instance, between productivity rise and land degradation) is at the heart of any sustainability policy (cf. Crane et al. 1996), since there are different interests among policy-makers, among various actors and stakeholders, among population groups affected, among different regions, and even among different generations. In so far as sustainable development does not offer a normative framework for policy evaluation, it is evident that the empirical results of sustainability analysis are of a descriptive nature, or at best, of a "what-if" nature.

As has already been mentioned, in the past decade the issue of sustainable development has gained much importance (see for an overview of the current debate Manusinghe and Shearer 1995). While it began as a policy-oriented and action-based concept to alleviate and solve global environmental change issues, it was increasingly focussed on meso - mainly sectoral - issues, such as sustainable industry, sustainable tourism or sustainable transport (see Van den Bergh 1996). Furthermore, the discussion on sustainable development has shifted towards sub-global spatial units such as sustainable regions or sustainable cities (see Giaoutzi and Nijkamp 1994, and Nijkamp and Perrels 1994). It has also been recognised that the distinction between strong and weak sustainability (see also Pearce and Turner 1990, and Van Pelt 1995) essentially means a spatial substitution between different categories of land use. The question here is whether and where the environmental decay of one area for a certain distinct purpose (e.g., industrialisation) may perhaps be compensated for by enhancing the environmental quality of another area (e.g., a tourist area).

The above observations are clearly exemplified in agriculture; various choice options can be imagined (such as milk production, wheat production, etc.) which cannot be undertaken simultaneously at the same place (see Barnett and Payne 1995). Furthermore, different types of intervention can be envisaged such as intensified land use, the use of pesticides, herbicides, etc. (see Douven 1997 and Simmons 1997). Consequently, the question of whether a certain agricultural land use is sustainable is a complicated one which cannot be easily answered without thorough knowledge of all trade-offs involved. The complexity of the sustainability and security issue is even further enhanced by the existence of different policies in different countries. To measure the performance of such policies is fraught with many difficulties, also because there is no unambiguous measuring rod. In various studies total factor productivity (TFP) is used as a yardstick for the agricultural performance, although it is certainly not the only one.

The above considerations do not only have a local or regional meaning but altogether also lead to global environmental issues which impact on food supply, resource availability and climatological stability (see Cline 1992 and Fankhauser 1995). In a recent survey article by Van Ierland and Klaassen (1996), the authors identify a series of research priorities on socio-economic aspects of land use and climate change, viz. a deeper analysis of:

- agricultural impacts in developing regions;
- influence of climate scenarios on water availability in sensitive areas;
- socio-economic impacts of changes in human health;
- socio-economic impacts of environmentally induced migration;
- impacts of extreme weather events based on risk assessment;
- socio-economic impacts of changes in ecosystems and biodiversity.

Some of these concerns are long range and relate to national or international security issues such as soil erosion, chemical poisoning or nuclear waste (see also Daly and Cobb

1990). Others are more directly concerned with the daily quality of life such as water pollution, shortage of food or resources (see Homer-Dixon 1992). Another - increasingly important - issue is the emergence of natural and environmental catastrophes such as floods, landslides, long periods of drought etc. (see United Nations 1997). Events like these are difficult to predict. All such cases provoke the question of how land use (including agriculture) can be used as a vehicle for adaptation or resilience with respect to global change processes.

Sustainable agriculture is indeed concerned with proper soil management and abatement of land degradation, since land (or soil) is basic factor input in this sector. In the history of economic thought, varying attention has been given to land as an economic production factor. A dominant role, for instance, was assigned to land as a basic input to the creation of economic welfare in the period of the Physiocrats. In the neoclassical world, land assumed mainly a functional economic place, as productivity and welfare differences between regions could be explained inter alia by different soil conditions (see also Giaoutzi and Nijkamp 1994). More recently - partly as a result of the emergence of ecological economics - land is regarded having a productive and a consumptive meaning within a sustainable development perspective (see e.g. Van den Bergh 1996). Furthermore, the condition of the soil has a variety of direct and indirect impacts on the quality and resilience of ecosystems impacting on biodiversity, not only locally but also globally (see e.g. Douven 1997). As a consequence of the externalities of soil pollution, we notice that soil management has become an important policy task in many countries. Soil management aims to improve the condition of the soil by actively coping with soil pollution through regulatory and market measures, by mitigating the externalities involved in soil pollution, and by seeking strategic and feasible solutions for clean-up areas (e.g., through brownfield policies).

All such conditions and strategic policies affect agricultural productivity, food security and sustainability, and thus impact upon its growth perspective. In the present paper we will try to map out and explain the differences in growth conditions in the agricultural sector in different countries by applying a recently developed method for comparative meta-analytical research, known as rough set analysis. This method will be outlined in the next section.

2. Rough Set Analysis as a Tool for Meta-Analysis

Meta-analysis is a research tool for comparative research and research synthesis. It has become an established technique in the medical and natural sciences, especially in comparative analysis of (semi-) controlled case study experiments (see, among others Van den Bergh et al. 1997, Glass et al. 1984, Hedges and Olkin 1985 and Petitti 1994) and research synthesis. It has also been used extensively in the social sciences, particularly in experimental psychology, pedagogy, sociology, and more recently in economics (see Matarazzo and Nijkamp 1997; Nijkamp and Baaijens 1999). Meta-analysis tries to synthesise previous research findings or case studies in order to identify common features which might be transferable to other as yet, unexplored cases. The statistics of meta-analysis is, in the meantime, rather well developed. Especially in the case of quantitative case study results, significant progress has been made. In situations of low measurement scales (qualitative, nominal, categorical or ordinal data), meta-analysis deserves to be further developed. In the context of our comparative case study research for the productivity of the agricultural sector we are almost exclusively confronted with 'soft' data, so that standard techniques cannot be utilised. Therefore, we have in our empirical analysis utilised a fairly new method for qualitative classification analysis, known as the rough set theory (see, for details Pawlak 1991, Slowinski 1995 and Van den Bergh et al. 1997).

The main specific problems addressed by rough set theory are:

- representation of uncertain or imprecise knowledge
- evaluation of quality of available information with respect to consistency and presence or absence of repetitive data patterns
- identification and evaluation of data dependencies
- approximate pattern classification
- reasoning with uncertainty
- information-preserving data reduction.

In our study we will use the rough set method as an analytical approach to determine whether there are factors that systematically affect the variation in productivity growth estimates in studies related to agricultural and agro-food sector. In fact, the renewed interest in economic growth and productivity has determined numerous studies aimed at explaining international differences in growth performance as critical success factors for agricultural land use. Although there are various studies focusing on producing meaningful measures of productivity, the empirical problems to make a meaningful comparison of productivity differences have not yet entirely been solved. In addition, there are insurmountable data constraints in producing comparable agricultural productivity measures for an international data set, especially due to the different methods utilised. Consequently, there is a need to develop methodologies and tools which could enhance our understanding of agricultural growth processes and, at the same time, would allow for relatively accurate predictions. Although statistical methods serve the purpose of acquiring new knowledge about the data, they do not provide sufficient insight when there are problems of complex interaction among many interdependent variables. Using rough set approach it is possible to search for hidden regularities in the data-base by deriving some conditional decision rules of "if…then" nature. In the context of our paper rough set analysis may provide a good mix of predictive and knowledge acquisition capabilities for agricultural productivity growth and data analysis.

It should be underlined that rough set analysis uses only internal knowledge and does not rely on prior model assumptions. In other words, rough set analysis uses only the granularity structure of given data, expressed as classes of suitable equivalence relations. Thus the model tries to extract as much information as possible from structural aspects of data, while neglecting other contextual information on attribute domains.

The basis of rough set analysis is formed by a categorical data matrix, coined the **information matrix**, in which qualitative information on attributes or performance values of case studies (objects) is systematically represented. Application of rough set analysis to this data table results in the ability to identify which possible combinations of values of attributes (measured in distinct classes) are compatible with certain ranges of a performance variable. These so-called **decision rules** are then specified as “if… then” statements, based on qualitative (essentially class) information. If certain attributes have a high frequency of occurrence in all decision rules, they tend to exert a dominant influence on the performance indicator characterising the case study concerned and hence may be considered as rather important critical success factors. If an attribute appears in all decision rules, this is the core of the impact system and may therefore be regarded as the dominant critical success factor.

Formally, we may define a rough set as a set for which it is uncertain in advance which objects belong precisely to that set, although it is in principle possible to identify all objects which may belong to the set at hand. Rough set theory assumes the existence of a finite set of objects for which some information is known in terms of factual (qualitative or numerical) knowledge on a class of attributes (features, characteristics). These attributes may be used to define **equivalence** relationships for these objects, so that an observer can classify objects into distinct equivalence classes. Objects in the same equivalence class are - on the basis of these features concerned - **indiscernible**. In the event of multiple attributes, each attribute is associated with a different equivalence relationship. The intersection of multiple equivalence relationships is called the indiscernibility relationship with respect to the attributes concerned. This intersection generates a family of equivalence classes that is a more precise classification of the objects than that based on a single equivalence relationship. The family of equivalence classes that is generated by the intersection of all equivalence relationships is called the family of elementary sets. The classification of objects, as given by the elementary sets, is the most precise classification possible on the basis of the available information.

Two concepts are important: lower and upper approximation of a set. The lower approximation is composed of all elementary sets, which are known with certainty to belong to the subset of interest, whereas the upper approximation is a description of objects, which possibly belong to the subset concerned.

Next, we introduce the concept of a **reduct**. A reduct is a subset of the set of all attributes with the following characteristic: adding another attribute to a reduct does not lead to a more accurate classification of objects (i.e., more granules), while elimination of an attribute from a reduct does lead to a less accurate classification of objects (i.e., less granules).

Finally, the **core** of a set is the class of all indispensable equivalence relationships. An attribute is indispensable if the classification of the objects becomes less precise when that attribute is not taken into account (given the fact that all attributes have been considered until then). The core may be an empty set and is, in general, not a reduct. An indispensable element occurs in all reducts. The core is essentially the intersection of all reducts.

Based on the previous concepts, rough set theory is now able to specify various "if… then" decision rules. For specifying such decision rules, it is useful to represent our prior knowledge of reality by means of a decision table. A decision table is a matrix that contains the values of the attributes of all objects. In a decision table the attributes may be partitioned into condition (background) and decision (response) attributes. A decision rule is then an implication relationship between the description of the condition attributes and that of a decision attribute. Such a rule may be *exact* or *approximate*. A rule is exact, if the combination of the values of the condition attributes in that rule implies only one single combination of the values of the decision attributes, while an approximate rule only states that more than one combination of values of the decision attributes corresponds to the same values of the condition attributes. Decision rules may thus be expressed as conditional statements (“if… then”).

An object *supports* a decision rule if its description is matching both the condition part and the decision part of the rule. Each decision rule is characterised by its *strength*, defined as the number of objects covered by the rule. For further details we refer to Pawlak (1991), Slowinski (1993), Van den Bergh et al. (1997), Matarazzo and Nijkamp (1997), Baaijens and Nijkamp (1998) and Button and Nijkamp (1998). Rough set analysis will now be applied as a technical method for comparing growth rates in agriculture in different countries. Since growth is directly related to security and sustainability, it is important to identify the drivers of productivity rise. Meta-analysis is an excellent tool for comparative research synthesis in this context. This issue will be empirically treated in Section 3.

3. Application

3.1 Introduction

There has been a resurgence of interest in the determinants of growth directed both at isolating factors responsible for differences in growth performance and accounting for spatial growth patterns in relation to sustainable land use and maintenance of secure food supplies. During the late seventies to early eighties most industrialised countries experienced largely many productive fluctuations and a slowdown in productivity. As a result, a large body of literature was developed to provide explanations for these fluctuations. In particular, we observed in that period a concern about the apparent paradox of a slowdown in productivity growth in a context of a rapid development of new technologies. We will offer first some background information on the development in OECD countries.

Agricultural production in OECD countries grew steadily over the last two decades. De facto, it seems that productivity growth has played an important role in output growth in agriculture. Output growth can be attributed to technology, scale or efficiency resource use rather than to an increase of input use. Agricultural adjustment has been occurring primarily in the input mix - intermediate input, land, capital and labour – rather than in total input. Only in few countries (i.e. Ireland, the Netherlands Canada and Greece) the input use has shown a growth.

Over the last 20 years the principal features of input change were the following:

- a significant increase in quantities of intermediate inputs (animal feeds, seeds, fertiliser, pesticides, animal products energy, maintenance, repairs and other services) and capital used; the increase of the volume of intermediate consumption is mainly attributable to a higher use of feed concentrates in most OECD countries, particularly where animal production increased most rapidly. With the exception of Austria, Belgium, Luxembourg, Denmark, Japan and Sweden, the use of fertilisers has increased.

- a rapid decline in labour input for all countries at an average annual rate of slightly over 2 %. The largest decline was in Spain, followed by Denmark, Finland and Austria. The rate of decline was less than 2 per cent in Australia, The Netherlands, Canada, the UK, Ireland, and Greece.
- a slight reduction in land input, but less than 1% per year. In Canada and Greece land use increased by slightly over 1 % per year. Land use remained essentially unchanged in Switzerland and the UK, which implies that most changes in production over the previous two decades in the OECD countries examined were associated with increases or decreases in intensity of land use rather than changes in the farmland.

An international comparison of productivity levels (OECD 1995) shows that partial and total agricultural productivity has been larger than the corresponding economic productivity as a whole.

In contrast to various studies on productivity for the farm sector of OECD countries, there are only a few studies on productivity for the agro-food sector. Our objective is to gather information already available in this field and, after having collected this information, to use it for further comparative analysis. Table 1 summarises some of the results of studies on productivity from the literature for the agro-food sector found in an OECD study (OECD 1995). These studies refer only to a set of selected OECD countries and the measure employed changes from the single factor measure (e.g. labour productivity) to total factor productivity (TFP), thereby making a cross-country comparison rather difficult (see Tables 1 and 2).

Despite differences in methodology and in results, these studies suggest that productivity growth in agro-food industries has been much less than that of the primary agricultural sector. Although these analyses provide useful information, they are subject to important limitations. For example, almost all of them use highly aggregate data and may therefore be unsuitable for assessing effects of different support policies, which in almost all cases are likely to be commodity-specific. At an aggregate level, productivity may increase or decrease because of diversification among sub-sectors. In spite of these limitations, the procedure adopted in the next section permits us to explore the data from these previous studies as a *primary analysis* in order to select the existing information. The results obtained can then be utilised in a *secondary analysis*, *which* is a re-analysis of data that had been previously used.

Our aim is now to apply the rough set approach in order to identify predictive rules from results of previous studies. In particular, we seek for strong rules, which may reflect repetitive patterns occurring in the data. The strong rules mirror potentially interesting data patterns and regularities.

3.2 Analysis of the database

In this section a rough set analysis of the data given in Tables 1 and 2 will be performed. This is done by initially classifying the outcomes of all variables by presenting a codification for all attributes and the decision variable (i.e., total factor productivity and average percentage change, respectively). All attributes and their values are listed below. We will utilise the condition attributes and decision variables as given in Tables 1 and 2. The domains of these attributes have been coded in Tables 3 and 4. Table 5 and 6 offer a presentation of the results for the case studies examined, and these tables can be treated as a knowledge information system in which *a1*, *a2*, *a3*, *a4* and *a5* are the condition attributes and *D* represents the decision attributes.

Our problem that we will discuss can be then analysed in two different steps:

1) reduction of knowledge
2) checking the consistency of this knowledge.

Reduction of knowledge consists of releasing all dispensable condition attributes and condition attribute values from the table. Practically, we have to check whether it is possible to eliminate some of the elementary condition attributes in Tables 5 and 6. To this end we computed the quality and the accuracy of the classification, and the core in Table 7 - the set of all indispensable values - of the information system. The core in our example consists of attributes A1, A2, A3, A4 (country, sector, method used and starting point of the studies selected), while in the farm sector it is composed by the attributes A1, A2, A3, A4, A5. This means that it is not possible to eliminate these attributes without disturbing the ability of the system to classify objects, i.e. to make accurate predictions of the drivers. As mentioned already before, insight into the engines of productivity growth allows us to identify in our empirical application the driving forces and limitations of sustainable agriculture and food security.

Consistent knowledge development in our application is intended to discover a functional or causal dependency between the condition attributes on the one hand, and the total factor productivity and the average of change in productivity growth on the agro-food sector respectively on the other. Therefore, we now move on to the analysis of the observed data describing the set of studies selected, in order to obtain a classification decision algorithm. From a decision table a set of decision rules can be derived. The rules are logical statements ("if…then") which represent the relationship between the description of objects and their assignment to particular classes. The set of decision rules for all decision classes is called a decision algorithm.

Table 1 Studies of productivity growth in the farm sector of the OECD countries

N.	*Country*	*Input*	*Output*	***Time period***	***TFP***
1	Australia	- 0.1	1.1	1971 – 81	1.2
2	Australia	- 0.1	1.9	1971 – 90	2.0
3	Australia	- 0.1	2.5	1981 – 90	2.6
4	Canada	- 1.06	1.17	1962 – 70	2.2
5	Canada	0.01	2.37	1962 – 78	2.4
6	Canada	1.05	3.57	1970 – 78	2.5
7	Canada	- 0.4	2.6	1962 – 71	3.0
8	Canada	2.4	0.2	1962 – 90	2.1
9	Canada	1.4	2.6	1971 – 81	1.1
10	Canada	1.9	- 0.5	1981 – 90	2.4
11	Switzerland	- 1.2	1.1	1973 – 81	2.3
12	Switzerland	- 1.1	0.9	1973 – 88	2.1
13	Switzerland	- 1.1	0.0	1981 – 88	1.9
14	U.S.	0.88	1.85	1953 – 57	2.72
15	U.S.	0.25	2.92	1957 – 60	2.70
16	U.S.	0.24	1.90	1960 – 69	2.65
17	U.S.	0.68	1.06	1969 – 73	1.30
18	U.S.	0.72	2.75	1973 – 79	2.02
19	U.S.	0.50	2.20	1973 – 88	1.70
20	U.S.	0.08	1.21	1962 – 70	1.13
21	U.S.	0.31	1.72	1962 – 78	1.41
22	U.S.	0.55	2.22	1970 – 78	1.67
23	U.S.	0.14	1.66	1950 – 60	1.52
24	U.S.	0.17	1.76	1950 – 82	1.57
25	U.S.	0.05	0.84	1960 – 70	0.79
26	U.S.	0.34	2.60	1970 – 82	2.26
27	Germany	-0.3	1.6	1967 – 87	2.0
28	France	0.1	2.3	1967 – 87	2.2
29	The Netherlands	1.4	4.0	1967 – 87	2.6
30	Belgium	-0.2	1.8	1967 – 87	2.0
31	Luxembourg	-1.9	1.8	1967 – 87	2.8
32	U.K.	-0.2	1.6	1967 – 87	1.9
33	Ireland	0.8	2.6	1967 – 87	1.7
34	Italy	0.8	1.8	1974 – 87	2.7
35	Denmark	0.7	2.6	1974 – 87	1.9
36	Germany	-0.4	1.3	1973 – 89	1.7
37	France	-0.5	1.9	1973 – 89	2.4
38	Italy	-0.6	1.7	1973 – 89	2.3
39	The Netherlands	0.4	3.1	1973 – 89	1.7
40	Belgium/ Luxembourg	0.0	1.2	1973 – 89	1.2
41	U.K.	-0.2	1.5	1973 – 89	1.7
42	Ireland	0.9	2.3	1973 – 89	1.4
43	Denmark	-0.1	2.3	1973 – 89	2.5
44	Germany	0.0	1.7	1965 – 85	1.4
45	France	0.1	1.8	1965 – 85	1.6
46	Italy	-0.6	1.6	1965 – 85	2.2
47	The Netherlands	2.6	4.2	1965 – 85	1.5
48	Belgium/ Luxembourg	0.0	2.2	1965 – 85	1.7
49	U.K.	-0.3	2.2	1965 – 85	2.2
50	Ireland	0.9	2.9	1965 – 85	1.7
51	Denmark	-0.1	1.5	1965 – 85	1.6
52	The Netherlands	1.4	3.6	1950 – 60	2.2
53	The Netherlands	0.1	3.8	1960 – 70	3.7
54	The Netherlands	1.1	4.4	1970 – 80	3.3
55	The Netherlands	-0.5	2.4	1980 – 88	2.9
56	The Netherlands	0.6	3.6	1950 – 88	3.0

Source: OECD, 1995

Table 2 Studies of productivity growth in the agro-food sectors of the OECD countries

N.	***Country***	***Sector coverage***	***Method***	***Time period***	***Average % change***
1	Canada	Food	Index number	1961-86	0.37
2	Canada	Beverage	Index number	1961-86	0.56
3	Canada	Manufacturing	Index number	1961-86	1.40
4	Canada	Food and Beverage	Index number	1962-85	0.40
5	Canada	Manufacture	Index number	1962-85	0.80
6	Canada	Food and Beverage	Econometric cost function	1961-82	0.10
7	Canada	Food and beverage	Econometric production function	1961-82	0.36
8	Canada	Food	Econometric cost function	1961-79	0.47
9	Canada	Food and Beverage	Index number	1962-77	0.35
10	Canada	Food and Beverage	Econometric cost function	1962-75	-0.20
11	Australia	Food, Beverage and Tobacco	Econometric production function	1976-90	0.67
12	UK	Food	Input-output	1954-63	1.70
13	UK	Food	Input-output	1968-74	1.14
14	UK	Agriculture	Input-output	1979-84	-1.19
15	UK	Agriculture	Input-output	1954-63	1.84
16	UK	Agriculture	Input-output	1968-74	0.84
17	UK	Agriculture	Input-output	1979-84	1.13
18	UK	Food	Econometric production function	1979-86	3.90
19	UK	Drink	Econometric production function	1979-86	7.60
20	UK	Manufacturing	Econometric production function	1979-86	3.70
21	US	Food	Index number	1958-82	0.28
22	US	Food	Index number	1958-72	0.28
23	US	Food	Index number	1972-82	0.29
24	Australia	Food, Beverage and Tobacco	Cobb-Douglas production function	1976-90	0.40
25	US	Food	Index number	1950-77	0.007
26	US	Food	Index number	1950-72	0.074
27	US	Food	Index number	1972-77	-0.418
28	Italy	Food	Solow's growth accounting method	1960-85	2.73
29	Canada	Food	Solow's growth accounting method	1960-85	1.10
30	Germany	Food	Solow's growth accounting method	1960-85	2.46
31	UK	Food	Solow's growth accounting method	1960-85	5.34
32	US	Food	Solow's growth accounting method	1960-85	2.31
33	Japan	Food	Solow's growth accounting method	1960-85	2.85
34	Italy	Food	Labour productivity	1970-80	5.1
35	Italy	Food	Labour productivity	1953-63	4.6
36	Australia	Food	Labour productivity	1980-85	1.11
37	Austria	Food	Labour productivity	1980-85	1.18
38	Belgium	Food	Labour productivity	1980-85	1.32
39	Canada	Food	Labour productivity	1980-85	1.17
40	Denmark	Food	Labour productivity	1980-85	1.10
41	Finland	Food	Labour productivity	1980-85	1.10
42	France	Food	Labour productivity	1980-85	1.02
43	Germany	Food	Labour productivity	1980-85	1.18
44	Ireland	Food	Labour productivity	1980-85	1.46
45	Italy	Food	Labour productivity	1980-85	1.08
46	Japan	Food	Labour productivity	1980-85	1.02
47	Netherlands	Food	Labour productivity	1980-85	1.25
48	Norway	Food	Labour productivity	1980-85	0.65
49	Sweden	Food	Labour productivity	1980-85	1.06
50	UK	Food	Labour productivity	1980-85	1.30

Source: OECD, 1995

Table 3 Codification of variables of studies related to the farm sector

Condition attributes		Code
A 1 – Country	Canada, Australia, and USA	1
	Large European countries: UK, Germany, Italy, and France	2
	Small European countries: Denmark, Finland, Netherlands, Sweden, Norway, and Belgium	3
A2 – Input	Less than - 0,5	1
	Between - 0,4 and - 0,1	2
	Between 0,0 and 0,4	3
	Between 0,5 and 0,9	4
	More than 1,0	5
A3 – Output	Less than 1,5	1
	Between 1,6 and 2,5	2
	More than 2,5	3
Time Period		
A4 - *Starting point*	Before 1960	1
	1970	2
	1980	3
A5 - *Length*	10 years	1
	20 years	2
	30 years	3
D – *Decision variable*		
Total Factor Productivity		
	Less than 1,5	1
	Between 1,6 and 2,5	2
	More than 2,5	3

Table 4 Codification of variables of studies related to the agro-food sector

Condition attributes		Code
A1 – Country	Canada, Australia, and USA	1
	Large European countries: UK, Germany, Italy, and France	2
	Japan	3
	Small European countries: Denmark, Finland, Netherlands, Sweden, Norway, and Belgium	4
A 2 – Sector coverage	Food	1
	Beverages	2
	Manufacturing	3
	Food and beverages	4
	Food, beverages and tobacco	5
	Agriculture	6
A 3 – Method used	Index number	1
	Econometric cost function	2
	Econometric production function	3
	Input-output	4
	Cobb-Douglas production function	5
	Solow growth accounting method	6
	Labour productivity	7
Time Period *A 4 – Starting point*	1950	1
	1960	2
	1970	3
	1980	4
A 5 - Length	10 years	1
	20 years	2
	30 years	3
D –*Decision variables*		
Average percentage change		
	Less than 1%	1
	Between 1% and 2%	2
	More than 2%	3

Table 5 Information system of the studies related to the farm sector after codification

Objects	*A1*	*A2*	*A3*	*A4*	*A5*	*D*
1	1	2	1	2	1	1
2	1	2	2	2	2	2
3	1	2	2	3	1	3
4	1	1	1	1	1	2
5	1	3	2	1	2	2
6	1	5	3	2	1	3
7	1	2	3	1	1	3
8	1	5	1	1	3	2
9	1	5	3	2	1	1
10	1	5	1	3	1	2
11	3	1	1	2	1	2
12	3	1	1	2	1	2
13	3	1	1	3	1	2
14	1	4	2	1	1	3
15	1	3	3	1	1	3
16	1	3	2	1	1	3
17	1	4	1	2	1	1
18	1	4	3	2	1	2
19	1	4	2	2	1	2
20	1	3	1	1	1	1
21	1	3	2	1	1	1
22	1	4	2	2	1	2
23	1	3	2	1	1	1
24	1	3	2	1	3	1
25	1	3	1	1	1	1
26	1	3	3	2	1	2
27	2	2	3	1	1	3
28	2	3	2	1	2	2
29	3	5	3	1	2	3
30	3	2	2	1	2	2
31	3	1	2	1	2	3
32	2	2	2	1	2	2
33	3	4	3	1	2	2
34	2	4	2	2	1	3
35	3	4	3	2	1	2
36	2	2	1	2	2	2
37	2	1	2	2	2	2
38	2	1	2	2	2	2
39	3	3	3	2	2	2
40	3	3	1	2	2	1
41	2	2	1	2	2	2
42	3	4	2	2	2	1
43	3	2	2	2	2	2
44	2	2	2	1	1	2
45	2	3	2	1	2	2
46	2	1	2	1	2	2
47	3	5	3	1	2	1
48	3	3	2	1	2	2
49	2	2	2	1	2	2
50	3	4	3	1	2	2
51	3	2	1	1	2	2
52	3	3	3	2	1	2
53	3	3	3	1	1	3
54	3	5	3	2	1	3
55	3	1	2	3	1	3
56	3	4	3	1	3	3

Table 6 Information system of the studies related to the agro-food sector after the codification

Objects	A1	A2	*A3*	A4	A5	*D*
1	1	1	1	2	3	1
2	1	2	1	2	3	1
3	1	3	1	2	3	2
4	1	4	1	2	3	1
5	1	3	1	2	3	1
6	1	4	2	2	3	1
7	1	4	3	2	3	1
8	1	1	2	2	2	1
9	1	4	1	2	2	1
10	1	4	2	2	2	1
11	1	5	3	3	2	1
12	2	1	4	1	1	2
13	2	1	4	2	1	2
14	2	6	4	3	1	1
15	2	6	4	1	1	2
16	2	6	4	2	1	1
17	2	6	4	3	1	2
18	2	1	3	3	1	4
19	2	2	3	3	1	4
20	2	3	3	3	1	4
21	1	1	1	1	3	1
22	1	1	1	1	2	1
23	1	1	1	3	2	1
24	1	5	5	3	2	1
25	1	1	1	1	3	1
26	1	1	1	1	3	1
27	1	1	1	3	1	1
28	2	1	6	2	3	3
29	1	1	6	2	3	2
30	2	1	6	2	3	3
31	2	1	6	2	3	4
32	1	1	6	2	3	3
33	3	1	6	2	3	3
34	2	1	7	3	2	4
35	2	1	7	1	2	4
36	1	1	7	4	1	2
37	4	1	7	4	1	2
38	4	1	7	4	1	2
39	1	1	7	4	1	2
40	4	1	7	4	1	2
41	4	1	7	4	1	2
42	2	1	7	4	1	2
43	2	1	7	4	1	2
44	4	1	7	4	1	2
45	2	1	7	4	1	2
46	3	1	7	4	1	2
47	4	1	7	4	1	2
48	4	1	7	4	1	1
49	4	1	7	4	1	2
50	2	1	7	4	1	2

Table 7 Accuracy and quality of classification of the decision variable for the farm sector

Class of decision dependent variable	Accuracy of approximation	Lower approximation Number of objects	Upper approximation Number of objects
1	0.500	7	14
2	1.000	31	31
3	0.611	11	18
Accuracy of approximation : 0.777 Quality of the approximation : 0.875 Core of attributes : A1, A2 , A3, A4, A5			

Table 8 Accuracy and quality of classification of the decision variable for agro-food sector

Class of decision dependent variable	Accuracy of approximation	Lower approximation Number of objects	Upper approximation Number of objects
1	0.5862	17	29
2	0.4167	10	24
3	0.1667	1	6
4	0.6250	5	8
Accuracy of classification : 0.4925 Quality of classification : 0.6600 Core of attributes : A1 , A 2, A 3, A4			

We will proceed by deriving some lessons based on learning principles. Recently research in machine learning, as an area of artificial intelligence, has been intensified. Particularly in similarity-based learning systems, learning is based on establishing similarities between positive examples, which represent the same concept (class), and dissimilarities between positive and negative examples, representing other concepts. Similarity-based learning is also called empirical learning in order to emphasise the fact that it is based on the act of inducing underlying knowledge from empirical data. Thus the task is to include all positive examples from the concept in the description of the concept and to exclude the complementary set containing all negative examples from the description. This experiment is of course critical for forecasting.

In the rough set experiment presented in this paper a rule induction system called learning from examples (LERS) was first used. LERS uses an approach to an inconsistent data set based on rough sets. First, LERS checks the input data for consistency. If data are inconsistent, for every class two sets are computed: a lower and upper approximation for each class, i.e. decision attributes. Rules are then induced separately from both sets. Rules induced from lower approximation are called *certain* rules and from upper approximation are called *possible* rules. The terminology introduced in Gzymala-Busse (1988) is based on the following observation: if a case is a member of the lower approximation of the class, it is a certain member of the class. Similarly, if a case is a member of the upper approximation, then it is only a possible member of the class. This means that the system induces a set of sufficient rules completely describing every class, although only some attribute pairs are involved in the rules concerned.

The intriguing question is now how to use the rules set for classification of new cases on total factor productivity and productivity growth in the agro-food sector of OECD countries. For example, how to use these two rules sets for classification of new studies, and which rule induction system may be useful in the selection choice of individual studies for the analysis by means of a minimal description of a class.

The discovered rules contain the guideline we should follow to select new studies. The basic aim is to retrieve knowledge by observing previous studies; this recorded knowledge can be used for the generation of a reduced algorithm, so that it is possible to classify further studies on the total factor productivity of the farm sector and the productivity growth of the agro-food sector.

3.3 Results

The final step of our data analysis is the identification of a classification algorithm, which permits us to make predictions on the basis of the accumulated knowledge in new situations. Here we have used a classification related to the construction of a classification algorithm that, on the basis of the current knowledge, can be applied to a number of cases to classify objects previously unseen. Each new object in the future can then be assigned to a class belonging to a predefined set of classes on the basis of observed values of suitable chosen attributes (features).

The algorithm may also be used for the classification of new objects. It must be noticed that not all decision rules are equally important or reliable. Some rules are formulated by using information about a larger number of objects than other rules. This difference of importance in derived rules can be described by an additional parameter for each rule. Different parameters can be used to quantify the *quality of the rules* generated. In our case study we found respectively 23 exact rules and 3 approximate rules for the studies on Total Factor Productivity and 13 exact rules and 5 approximate rules for the change in productivity in the agro-food sector. As many rules are based on a few observations only, the granularity of the system seems too high. In fact, not all the rules discovered by the system were of high quality, although these rules reflected true properties of the available data. In order to test the significance of the rules in our case, we used *strength* as a method to simplify a decision table and to select a few rules. In particular, for the farm sector we selected rules 1, 5 and 17 and for the agro-food sector rule 1, 3, 6, 12 and 14 (See Appendix 1 and 2). The selected rules discovered for the studies related respectively to the farm sector and to the agro-food sector are the following.

Farm Sector
Class 1
If (output = less than 1.0) and (input = between 0.0 and 0.4), then TFP is less than 1.5
Class 2
If (length = 20 years) and (country = large European counties), then TFP is between 1.6 and 2.5
Class 3
If (length = 10 years) and (output = more than 2.5) and (starting point = before 1980) then TFP is more than 2.5

Agro-Food Sector

Class 1
If (method used = index number) and (sector coverage = food), then average percentage of change is less than 1%
If (country = Canada, Australia, and USA) and (length = 20 years), then average percentage of change is less than 1%
Class 2
If (starting point =1980) and (country = Large European Counties), then average percentage of change is between 1% and 2%
Class 4
If (country = Large European Counties) and (method = econometric production function), then average percentage of change is more than 2%

Approximate rule
If (country = Small European Countries), then average percentage of change can be less than 1.5 or between 1.6 and 2.5.

Regarding the studies related to the change in Total Factor Productivity in the farm sector, we notice that the first rule describes a clear repetitive relationship between the two attributes input and output. More precisely, independently of the countries and the time period considered, a low rate of TFP will be found when the use of input falls between 0.0 and 1.0 and the output is less than 1.0. The second rule describes a relationship between years of length considered in the studies and the Large European Countries. This rule suggests that when the studies selected analyse a length of time of 20 years in the United Kingdom, France, Italy and Germany, the change in TFP increases between 1.6 and 2.5. Finally, a high rate of TFP was found, when the studies considered as a starting point of the analysis the year 1980 for a length of time of 10 years and when the outputs obtained have been higher than 2.5.

Regarding the studies related to the average change in productivity growth for the agro-food industry, two strong decision rules were obtained. According to the first rule, if we would like to classify a study in the agro-food field and if the attribute sector analysed is food and beverages, we can expect the average change to be rather low, since that sector comprises approximately less than 1% of the productivity growth. Similar results can be obtained when the countries considered are Canada Australia and USA and when the length of time is about 20 years.

With regard to class 2, which is related to an average growth falling in between 1% and 2%, the attributes to be considered together in further studies are related to the large European countries (UK, Germany, Italy and France) and the year 1980 as the starting point of the analysis. A higher percentage of change in growth (more than 2%) is found, when we consider the attributes Japan and the Solow growth accounting method. More burdensome is the case of the approximate rule. The strength of a rule has a particular meaning for the non-deterministic decision rules. In this case, if the *strength* of one category is higher than the *strength* of other categories occurring in the non-deterministic rule, one can conclude that according to this rule, the object considered most likely belongs to the strongest category. In our example of a non-deterministic rule, since only one object supports class 1, we have assumed that they are not significant enough at the end to offer a solid prediction for future studies, so that we may expect that the change of growth of the agro-food sector in small European countries falls in the class between 1% and 2% .

5. Conclusion

The present paper has offered an introduction into the use of meta-analysis for security and sustainability policy. Particular attention has been given to the potential of the rough set approach in case of soft information on driving forces of productivity growth. The numerical application demonstrated that this new approach is able to identify interesting patterns in qualitative data, which may explain the performance of policies in different countries. An important issue to be developed in the future research is the question of generalisation or transferability of findings from quantitative information. In this context, also alternative classification methods may have to be considered, such as discriminant analysis or data envelopment analysis.

The focus of the paper has been on total factor productivity in the agricultural sector and the change in productivity in the agro-food sector, i.e. productivity in the resources in agricultural production. There are several important reasons for considering agricultural productivity: sustainable land use, food supply and security, growth aspects, agricultural labour migration, farmers' income and more. We used the concept of total factor productivity regardless of the method used in its computation in the underlying case study. Our interest has been focused mainly on the comparison of changes in inputs and outputs and the regularities in the relationship between them, so that the results are valuable in predicting the response in future agricultural experiments or policies. Recently, the use of the concept of Total Factor Productivity as a critical factor in the process of economic growth has become a matter of controversy. A particular critique of productivity points at the measurement gains in product quality, while an environmental critique points at the measurement of the costs of growth. Despite its limitation, the rough set approach has provided a consistent framework for organising and interpreting data on agricultural growth measurement and prediction. Clearly, much more solid empirical research is necessary, but the present effort clarifies already the central position of agricultural sustainability and food security in global policy platforms.

Appendix I Decision Rules Farm Sector

FARM SECTOR

Rule 1. (A3 = 1) & (A2 = 3) => (D1=1); [3][{20,25,40},{},{}]
Rule 2. (A1 = 1) & (A3 = 1) & (A4 = 2) => (D1=1); [2] [{1,17},{},{}]
Rule 3. (A3 = 2) & (A5 = 3) => (D1=1); [1] [{24},{},{}]
Rule 4. (A2 = 4) & (A4 = 2) & (A5 = 2) => (D1=1); [1] [{42},{},{}]
Rule 5. (A5 = 2) & (A1 = 2) => (D1=2);[9] [{},{28,32,36,37,38,41,45,46,49},{}]
Rule 6. (A5 = 2) & (A4 = 1) & (A2 = 4) => (D1=2); [2] [{},{33,50},{}]
Rule 7. (A4 = 2) & (A1 = 1) & (A3 = 2) => (D1=2); [3] [{},{2,19,22},{}]
Rule 8. (A4 = 2) & (A2 = 1) => (D1=2);[4] [{},{11,12,37,38},{}]
Rule 9. (A1 = 3) & (A2 = 2) => (D1=2);[3] [{},{30,43,51},{}]
Rule 10. (A5 = 1) & (A3 = 3) & (A2 = 4) => (D1=2); [2] [{},{18,35},{}]
Rule 11. (A3 = 1) & (A4 = 3) => (D1=2); [2] [{},{10,13},{}]
Rule 12. (A2 = 3) & (A3 = 3) & (A4 = 2) => (D1=2); [3] [{},{26,39,52},{}]
Rule 13. (A3 = 1) & (A5 = 3) => (D1=2); [1] [{},{8},{}]
Rule 14. (A4 = 1) & (A2 = 3) & (A5 = 2) => (D1=2); [4] [{},{5,28,45,48},{}]
Rule 15. (A4 = 1) & (A5 = 1) & (A2 = 1) => (D1=2); [1] [{},{4},{}]
Rule 16. (A1 = 2) & (A2 = 2) & (A3 = 2) => (D1=2); [3] [{},{32,44,49},{}]
Rule 17. (A5 = 1) & (A3 = 3) & (A4 = 1) => (D1=3); [4] [{},{},{7,15,27,53}]
Rule 18. (A3 = 2) & (A4 = 3) => (D1=3); [2] [{},{},{3,55}]
Rule 19. (A2 = 4) & (A1 = 2) => (D1=3); [1] [{},{},{34}]
Rule 20. (A1 = 3) & (A5 = 3) => (D1=3); [1] [{},{},{56}]
Rule 21. (A1 = 3) & (A2 = 5) & (A4 = 2) => (D1=3); [1] [{},{},{54}]
Rule 22. (A3 = 2) & (A2 = 1) & (A1 = 3) => (D1=3); [2] [{},{},{31,55}]
Rule 23. (A2 = 4) & (A1 = 1) & (A4 = 1) => (D1=3); [1] [{},{},{14}]

Approximate rules

Rule 24. (A5 = 1) & (A2 = 3) & (A3 = 2) => (D1=1) OR (D1=3); [3] [{21,23},{},{16}]
Rule 25. (A2 = 5) & (A5 = 2) => (D1=1) OR (D1=3); [2] [{47},{},{29}]
Rule 26. (A2 = 5) & (A3 = 3) & (A1 = 1) => (D1=1) OR (D1=3); [2] [{9},{},{6}]

Appendix 2 Decision Rules Agro-food Sector

AGRO-FOOD SECTOR

Rule 1. (A3 = 1) & (A2 = 1) => (D1=1); [7] [{1,21,22,23,25,26,27},{},{},{}]
Rule 2. (A2 = 4) => (D1=1); [5] [{4,6,7,9,10},{},{},{}]
Rule 3. (A1 = 1) & (A5 = 2) => (D1=1); [7] [{8,9,10,11,22,23,24},{},{},{}]
Rule 4. (A4 = 2) & (A2 = 2) => (D1=1); [1] [{2},{},{},{}]
Rule 5. (A2 = 6) & (A4 = 2) => (D1=1); [1] [{16},{},{},{}]
Rule 6. (A4 = 4) & (A1 = 2) => (D1=2); [4] [{},{42,43,45,50},{},{}]
Rule 7. (A4 = 4) & (A1 = 1) => (D1=2); [2] [{},{36,39},{},{}]
Rule 8. (A5 = 1) & (A4 = 1) => (D1=2); [2] [{},{12,15},{},{}]
Rule 9. (A5 = 1) & (A1 = 3) => (D1=2); [1] [{},{46},{},{}]
Rule 10. (A3 = 4) & (A2 = 1) => (D1=2); [2] [{},{12,13},{},{}]
Rule 11. (A1 = 3) & (A3 = 6) => (D1=3); [1] [{},{},{33},{}]
Rule 12. (A1 = 2) & (A3 = 3) => (D1=4); [3] [{},{},{},{18,19,20}]
Rule 13. (A5 = 2) & (A3 = 7) => (D1=4); [2] [{},{},{},{34,35}]

Approximate rules

Rule 14. (A1 = 4) => (D1=1) OR (D1=2); [8] [{48},{37,38,40,41,44,47,49},{},{}]
Rule 15. (A2 = 3) & (A3 = 1) => (D1=1) OR (D1=2); [2] [{5},{3},{},{}]
Rule 16. (A2 = 6) & (A4 = 3) => (D1=1) OR (D1=2); [2] [{14},{17},{},{}]
Rule 17. (A3 = 6) & (A1 = 2) => (D1=3) OR (D1=4); [3] [{},{},{28,30},{31}]
Rule 18. (A3 = 6) & (A1 = 1) => (D1=2) OR (D1=3); [2] [{},{29},{32},{}]

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