ASSESSMENT OF SUSTAINABLE DEVELOPMENT: A NOVEL APPROACH USING FUZZY SET THEORY

A.M.G. CORNELISSEN, J. VAN DEN BERG, W.J. KOOPS, M. GROSSMAN AND H.M.J. UDO

ERIM REPORT SERIES *RESEARCH IN MANAGEMENT*	
ERIM Report Series reference number	ERS-2000-23-LIS
Publication status / version	draft / version April 2000
Number of pages	17
Email address corresponding author	Jvandenberg@few.eur.nl
Address	Erasmus Research Institute of Management (ERIM) Rotterdam School of Management / Faculteit Bedrijfskunde Erasmus Universiteit Rotterdam PoBox 1738 3000 DR Rotterdam, The Netherlands Phone: # 31-(0) 10-408 1182 Fax: # 31-(0) 10-408 9020 Email: info@erim.eur.nl Internet: www.erim.eur.nl

Bibliographic data and classifications of all the ERIM reports are also available on the ERIM website:
www.erim.eur.nl

ERASMUS **R**ESEARCH **I**NSTITUTE OF **M**ANAGEMENT

REPORT SERIES
RESEARCH IN MANAGEMENT

BIBLIOGRAPHIC DATA AND CLASSIFICATIONS		
Abstract	The objective of this paper is to introduce fuzzy set theory and develop fuzzy mathematical models to assess sustainable development based on context-dependent economic, ecological, and societal sustainability indicators. Membership functions are at the core of fuzzy models, and define the degree to which indicators contribute to development. Although a decision-making process regarding sustainable development is subjective, fuzzy set theory links human expectations about development, expressed in linguistic propositions, to numerical data, expressed in measurements of sustainability indicators. In the future, practical implementation of such models will be based on elicitation of expert knowledge to construct a membership function. The fuzzy models developed in this paper provide a novel approach to support decisions regarding sustainable development.	
Library of Congress Classification (LCC)	5001-6182	Business
	5201-5982	Business Science
	QA 76.9	Fuzzy sets
Journal of Economic Literature (JEL)	M	Business Administration and Business Economics
	M 11 R 4	Production Management Transportation Systems
	C 69	Mathematical Methods and Programming : Other
European Business Schools Library Group (EBSLG)	85 A	Business General
	260 K 240 B	Logistics Information Systems Management
	250 B	Fuzzy theory
Gemeenschappelijke Onderwerpsontsluiting (GOO)		
Classification GOO	85.00	Bedrijfskunde, Organisatiekunde: algemeen
	85.34 85.20	Logistiek management Bestuurlijke informatie, informatieverzorging
	31.80	Toepassing van de wiskunde
Keywords GOO	Bedrijfskunde / Bedrijfseconomie	
	Bedrijfsprocessen, logistiek, management informatiesystemen	
	Fuzzy sets, duurzame ontwikkeling	
Free keywords	sustainable development, assessment, fuzzy set theory, agriculture	
Other information		

Assessment of sustainable development: a novel approach using fuzzy set theory

A.M.G. Cornelissen[1, *], J. van den Berg[2], W.J. Koops[1],
M. Grossman[3] and H.M.J. Udo[1]

[1]Animal Production Systems Group, Wageningen Institute of Animal Sciences, Wageningen University and Research Center, P.O. Box 338, 6700 AH Wageningen, the Netherlands.
[2]Department of Computer Science, Faculty of Economics, Erasmus University Rotterdam, P.O. Box 1738, 3000 DR Rotterdam, the Netherlands.
[3]Department of Animal Sciences, University of Illinois, Urbana 61801, USA.
[*]Corresponding author. Telephone: +31 317 484626. Fax: +31 317 485006. E-mail: Ton.Cornelissen@dps.vh.wag-ur.nl
[*]Correspondence address (until June 2000): Ton Cornelissen, University of Illinois, Department of Animal Sciences, 305 Animal Sciences Laboratory, 1207 W. Gregory Drive, Urbana IL 61801, USA. (from June 2000): Ton Cornelissen, Animal Production Systems Group, Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands.

Abstract

The objective of this paper is to introduce fuzzy set theory and develop fuzzy mathematical models to assess sustainable development based on context-dependent economic, ecological, and societal sustainability indicators. Membership functions are at the core of fuzzy models, and define the degree to which indicators contribute to development. Although a decision-making process regarding sustainable development is subjective, fuzzy set theory links human expectations about development, expressed in linguistic propositions, to numerical data, expressed in measurements of sustainability indicators. In the future, practical implementation of such models will be based on elicitation of expert knowledge to construct a membership function. The fuzzy models developed in this paper provide a novel approach to support decisions regarding sustainable development.

Key words: sustainable development, assessment, fuzzy set theory, agriculture

1. Introduction

The impact of "sustainability" on development of national and international policy has increased over the last decade. Sustainability is now a core element of government policies, of university research projects, and of corporate strategies (Spedding, 1995; WRR, 1995; Graaf and Musters, 1998; Mebratu, 1998).

Despite the variety of definitions and interpretations, sustainability consistently means, either explicitly or implicitly, "continuity through time." Rather than referring to continuity *per se,* sustainability associates continuity to *context-dependent* economic, ecological and societal (EES) issues (e.g., Shearman, 1990; Brklacich et al., 1991; Neher, 1992; Heinen, 1994; Clayton and Radcliffe, 1996; Hansen, 1996; Vavra, 1996; Becker, 1997; Giampietro et al., 1997; Mebratu, 1998).

"Agricultural sustainability," which is sustainability in reference to agricultural production systems, invokes concern that in the future, also in the near future, current agricultural activities might endanger the continuity of agricultural production systems (WRR, 1995). This concern is expressed through EES issues, which can range from meeting a need for sufficient, safe, and inexpensive food products to achieving agricultural production practices without undesirable side effects. Possible undesirable side effects include erosion of the soil, nutrient emission to the environment, exhaustion of non-renewable resources, decline of rural communities, and a negative impact on the welfare of animals (e.g., Ikerd, 1993; Stockle et al., 1994; Steinfeld et al., 1997; Kelly, 1998).

Sustainability does not represent the endpoint of a process; rather, it represents the process itself (Shearman, 1990; WRR, 1995). Sustainability implies an ongoing dynamic *development*, driven by human expectations about future opportunities, and is based on present EES issues and information. Sustainability *is* "sustainable development" (Bossel, 1999).

As a consequence of the impact of sustainability on agricultural production systems, a standardized framework to initiate and monitor sustainable development (SD) would have great practical utility (Heinen, 1994; Vavra, 1996; Becker, 1997). Such a framework requires a four-phased methodology to: (1) describe the problem in a defined context, (2) determine context-dependent EES issues, (3) translate EES issues into measurable context-dependent sustainability indicators (SI), and (4) assess the contribution of SI to overall SD. Phases (1) through (3) have been dealt with in the literature (e.g., Verbruggen and Kuik, 1991; Ikerd, 1993; Stockle et al., 1994; Mitchell et al., 1995; Rennings and Wiggering, 1997; Kelly, 1998; Udo and Cornelissen, 1998; Bell and Morse, 1999; Bossel, 1999; Callens and Tyteca, 1999). Phase (4), however, has not been investigated. To assess the contribution of SI to overall SD requires a formal mathematical basis. This paper, therefore, introduces the mathematical theory of fuzzy sets, which enables assessment of overall SD based on the contribution of SI information.

2. Methodology

2.1. Uncertainty regarding sustainable development

To decide upon a mathematical theory to model sustainable development, we must consider the *type of uncertainty* related to SD. Because SD will be assessed using selected SI, this selection determines how much we know about SD, i.e., how much information is available; and how much we do not know about SD, i.e., how much information is missing. Certainty about SD requires complete and consistent information. To reduce the description of SD to a manageable level and to obtain a feasible model, it is necessary to reduce the amount of information. Incomplete information, therefore, is a fundamental characteristic of complex concepts (Klir, 1991; WRR, 1995).

In addition to incompleteness, information regarding SD is inconsistent. Human expectations about future opportunities for agriculture may change over time. If so, EES issues and, consequently, context-dependent SI will change.

Further, SD involves trade-offs among issues that cannot be resolved simultaneously (WRR, 1995). An increasing number of Dutch consumers, for example, object to battery housing systems that interfere with the natural behavior of laying hens. Keeping laying hens in floor housing systems instead of in battery housing, therefore, is a societal issue in the Netherlands. There is a trade-off, however, because floor housing tends to have higher ammonia emissions than battery housing, and high emissions conflict with ecological issues for Dutch agriculture (Groot Koerkamp, 1994).

Due to incomplete and inconsistent information, SD has no well-defined *meaning*. The type of uncertainty regarding an assessment of the contribution of SI to SD, therefore, essentially concerns the *meaning* of SD. In mathematical terms, this type of uncertainty is known as fuzzy uncertainty (Klir and Folger, 1988).

2.2. Probabilistic and fuzzy uncertainty

Probabilistic uncertainty relates to events that have a well-defined, unambiguous meaning. Probability theory is based on classical set theory and on two-valued logic, e.g., true-or-false or yes-or-no statements; probability theory assesses *whether* an event will occur (Batschelet, 1975; Bethea et al., 1985; Kosko, 1992). Because SD cannot be well-defined, it is impossible to assess unambiguously whether development of an agricultural production system is two-valued: sustainable or unsustainable. Two-valued logic, therefore, yields an unsatisfactory conclusion (Klir and Folger, 1988; Fresco and Kroonenberg, 1992; Pelt et al., 1995).

Fuzzy uncertainty, in contrast, relates to events that have no well-defined, unambiguous meaning (Kosko, 1992). Fuzzy set theory is based on multi-valued logic (McNeill and Freiberger, 1993; Pedrycz, 1993; Klir and Yuan, 1995; Zimmermann, 1996). Multi-valued logic enables intermediate assessment between strictly sustainable and strictly unsustainable; i.e., fuzziness describes the *degree* to which an event occurs, not *whether* it occurs (Kosko, 1990; Kosko, 1992). We propose, therefore, that fuzzy set theory offers a formal mathematical framework to assess SD.

2.3. Basic definitions of set theory

Classical set theory is based on two-valued logic. Let the universe of discourse define a set U that consists of elements x ($x \in$ U). If A is a subset of U (A $\subset$ U), then each element x is either a member of A ($x \in$ A) or a nonmember of A ($x \notin$ A). In set theory, "subset" and "event" are interchangeable, i.e., $x \in$ A means that for element x event A has occurred (Hogg and Tanis, 1997). A *characteristic function* μ_A defines an *unambiguous distinction* between members of A and nonmembers of A. Thus, characteristic function μ_A assigns to each x one of two values: $\mu_A(x) = 1$ iff (if and only if) $x \in$ A, or $\mu_A(x) = 0$ iff $x \notin$ A (Figure 1A).

Recall the example of housing systems for laying hens. Let U_{SI} be the universe of discourse for the SI "Ammonia Emission," where x is the amount of ammonia emission (kg NH_3/hen), and let A be the subset "Acceptable" (A $\subset U_{SI}$). Further, assume that the Dutch government determines as acceptable a maximum (threshold) amount of ammonia emission x_T. If $x \leq x_T$, then the amount of ammonia emission is acceptable, so $\mu_A(x) = 1$. If $x > x_T$, however, then the amount of ammonia emission is unacceptable, so $\mu_A(x) = 0$ (Figure 1A).

Classical set theory, therefore, requires a *hard threshold* x_T to determine an unambiguous distinction between acceptable amounts of ammonia emission ($x \leq x_T$) and unacceptable amounts ($x > x_T$). A hard threshold is often unrealistic in practice, however, because two nearly indistinguishable measurements x of SI on either side of x_T will be placed in complementary subsets (Bosserman and Ragade, 1982; George et al., 1997; Silvert, 1997).

Fuzzy set theory, in contrast, is based on multi-valued logic. Analogous to classical set theory, $\tilde{A}$ is a fuzzy subset of U ($\tilde{A} \subset U$), and a *membership function* $\mu_{\tilde{A}}$ defines the partial membership in a set. Transition between membership and nonmembership,

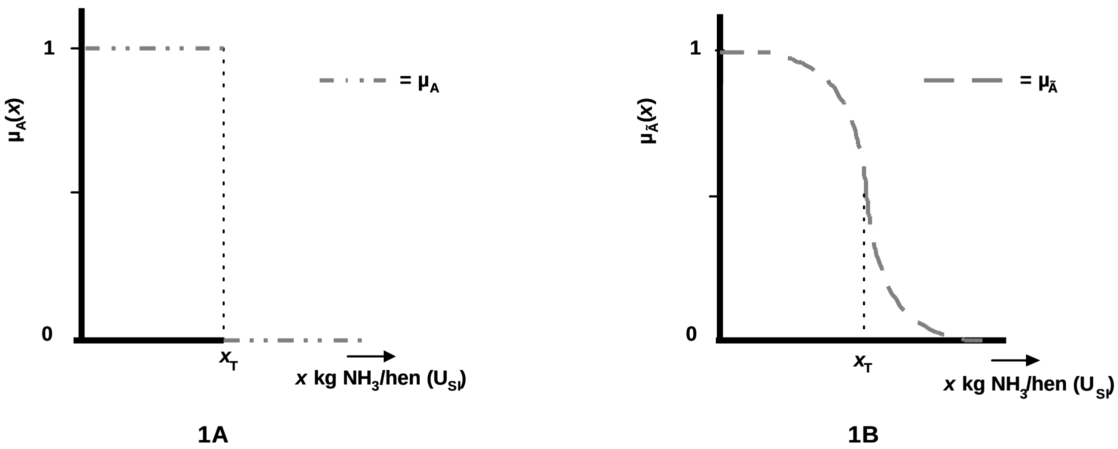

Figure 1

U_{SI} is the universe of discourse for the sustainability indicator "Ammonia Emission," and x is the amount of ammonia emission (kg NH_3/hen): x Î U_{SI}.
(1A) A is the classical subset "Acceptable" (A Ì U_{SI}), and characteristic function m_A defines a hard threshold x_T between acceptable amounts of ammonia emission (x £ x_T) and unacceptable amounts (x > x_T): m_A assigns to each x one of two values: $m_A(x)$ = 1 iff x £ x_T, or $m_A(x)$ = 0 iff x > x_T.
(1B) Ã is the fuzzy subset "Acceptable" (Ã Ì U_{SI}), and membership function $m_{\tilde{A}}$ defines a soft threshold between acceptable amounts of ammonia emission and unacceptable amounts: $m_{\tilde{A}}$ assigns to each x a value $m_{\tilde{A}}(x)$ decreasing from 1 to 0 with increasing x.

therefore, is gradual rather than abrupt. Thus, membership function $\mu_{\tilde{A}}$ assigns to each x a value from 0 through 1, indicating the *degree of membership* $\mu_{\tilde{A}}(x)$ of x in $\tilde{A}$. Membership functions, therefore, are functions that map x from U into the interval [0,1] (Figure 1B).

Recall again the example of housing systems for laying hens, and the universe of discourse for "Ammonia Emission" U_{SI}. Let $\tilde{A}$ be the fuzzy subset "Acceptable" ($\tilde{A} \subset U_{SI}$). Membership function $\mu_{\tilde{A}}$ is assumed to have a nonlinear form, with degree of membership $\mu_{\tilde{A}}(x)$ for ammonia emission decreasing from 1 to 0 with increasing x (Figure 1B).

Fuzzy set theory, therefore, requires a *soft threshold* to determine an intermediate assessment $\mu_{\tilde{A}}(x)$ between acceptable amounts of ammonia emission and unacceptable amounts. A membership function $\mu_{\tilde{A}}$ defines a soft threshold, which enables a smooth and practical assessment of measurements x of SI (Bosserman and Ragade, 1982; George et al., 1997; Silvert, 1997).

2.4. Fuzzy models and linguistic variables

Membership functions are fundamental to fuzzy models, which use such functions to operate “linguistic variables.” In fuzzy set theory, a linguistic variable Ã is characterized by: (1) *base variable* x of Ã, (2) *name* of Ã, (3) *linguistic value* $\tilde{A}_i$ of Ã (i = 1,…,n), and (4) *membership function* $\mu_{\tilde{A}i}$ of $\tilde{A}_i$ (adopted from: Zadeh, 1975a; Zadeh, 1975b; Klir and Yuan, 1995). Characteristics of a linguistic variable are in Figure 2.

Consider the example of housing systems for laying hens. The amount of ammonia emission x, which is a measurement of the SI “Ammonia Emission,” defines U_{SI}; hence, x is the *base variable* of Ã. If the contribution of “Ammonia Emission” to SD is expressed in terms of “Acceptability” of base variable x, then the *name* of Ã is “Acceptability.”

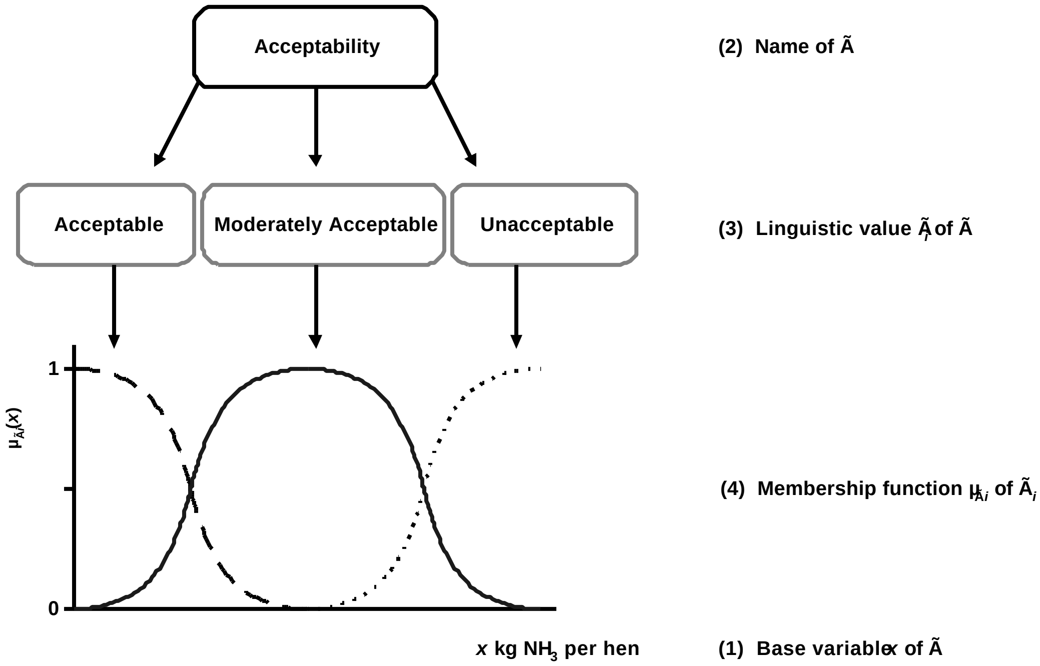

Figure 2

Linguistic variable Ã is characterized by: (1) base variable x of Ã, (2) name of Ã, (3) linguistic value $\tilde{A}_i$ of Ã, and (4) membership function $m_{\tilde{A}i}$ of $\tilde{A}_i$ (based on Zadeh, 1975a; Zadeh, 1975b; Klir and Yuan, 1995).

Three *linguistic values* $\tilde{A}_i$ ($\tilde{A}_1$, $\tilde{A}_2$, and $\tilde{A}_3$) define the contribution of x to SD in linguistic terms (Figure 2): $\tilde{A}_1$ = “Acceptable,” $\tilde{A}_2$ = “Moderately Acceptable,” and $\tilde{A}_3$ = “Unacceptable.” A linguistic value, therefore, is a fuzzy subset of U_{SI} ($\tilde{A}_i \subset U_{SI}$). A *membership function* $\mu_{\tilde{A}i}$ defines each linguistic value $\tilde{A}_i$ by determining to what degree $\mu_{\tilde{A}i}(x)$ a base variable x is “Acceptable,” $\mu_{\tilde{A}1}(x)$; “Moderately Acceptable,” $\mu_{\tilde{A}2}(x)$; or “Unacceptable,” $\mu_{\tilde{A}3}(x)$.

In the standardized framework, human expectations about SD are expressed as EES issues, for which SI provide numerical data. Use of linguistic variables in fuzzy models enables one to link expectations about SD, expressed in linguistic propositions, to numerical data, expressed in measurements of SI (Dubois and Prade, 1998). Use of “Acceptability,” for example, enables one to link the proposition “Ammonia Emission is Acceptable” to amount of ammonia emission (x kg NH_3 per hen).

3. Fuzzy models to assess sustainable development

3.1. Notation

Two fuzzy models are explored to assess SD: one model that applies fuzzy set aggregation operations, and another that applies approximate reasoning. Input for fuzzy models includes m sustainability indicators SI_k ($k = 1,\ldots,m$) and base variable x_k. Associated with each SI_k is a membership function μ_{ik} that defines a linguistic value $\tilde{A}_i$ by mapping x_k into the interval [0,1]. Associating x_k with μ_{ik} results in m degrees of membership $\mu_{ik}(x_k)$. Numerical assessment of SD, μ_{SD}, is the output of a fuzzy model; i.e., μ_{SD} is in the universe of discourse U_{SD} ($\mu_{SD} \in U_{SD}$), which is defined as the interval [0,1].

3.2. Fuzzy model applying fuzzy set aggregation operations

3.2.1. Scheme of fuzzy model

The scheme of a fuzzy model applying *aggregation operations* to assess SD is in Figure 3. Five steps are involved: Step 1 defines model input, sustainability indicator SI_k and base variable x_k; Step 2 defines linguistic variable $\tilde{A}$ and linguistic value $\tilde{A}_i$; Step 3 constructs membership function μ_{ik}; Step 4 computes degree of membership $\mu_{ik}(x_k)$; and Step 5 selects a fuzzy set aggregation operation for $\mu_{ik}(x_k)$ so as to assess model output μ_{SD}.

3.2.2. Selection of aggregation operation

An aggregation operation expresses an attitude toward SD. A meaningful assessment μ_{SD}, therefore, requires careful selection of an aggregation operation (Dubois and Prade, 1988; Munda, 1995; Silvert, 1997).

Assume that Step 2 defines linguistic variable “Acceptability” and linguistic value “Acceptable” ($\tilde{A}_1$). A *conservative* attitude toward SD means that μ_{SD} cannot be larger than the smallest degree of membership $\mu_{11}(x_1),\ldots,\mu_{1m}(x_m)$. In fuzzy set theory, the *standard fuzzy intersection* enables a conservative attitude toward SD by applying the *minimum operator* (Dubois and Prade, 1985; Dubois and Prade, 1988):

$$\mu_{SD} = min[\mu_{11}(x_1),\ldots,\mu_{1m}(x_m)]$$

where *min* denotes the minimum operator. Consequently, if one degree of membership $\mu_{1k}(x_k)$ is 0, then assessment μ_{SD} is 0.

A *liberal* attitude toward SD, in contrast, means that μ_{SD} cannot be smaller than the largest degree of membership $\mu_{11}(x_1),\ldots,\mu_{1m}(x_m)$. In fuzzy set theory, the *standard fuzzy union* enables a liberal attitude toward SD by applying the *maximum operator* (Dubois and Prade, 1985; Dubois and Prade, 1988):

$$\mu_{SD} = max[\mu_{11}(x_1),\ldots,\mu_{1m}(x_m)]$$

where *max* denotes the maximum operator. Consequently, if one degree of membership $\mu_{1k}(x_k)$ is 1, then assessment μ_{SD} is 1.

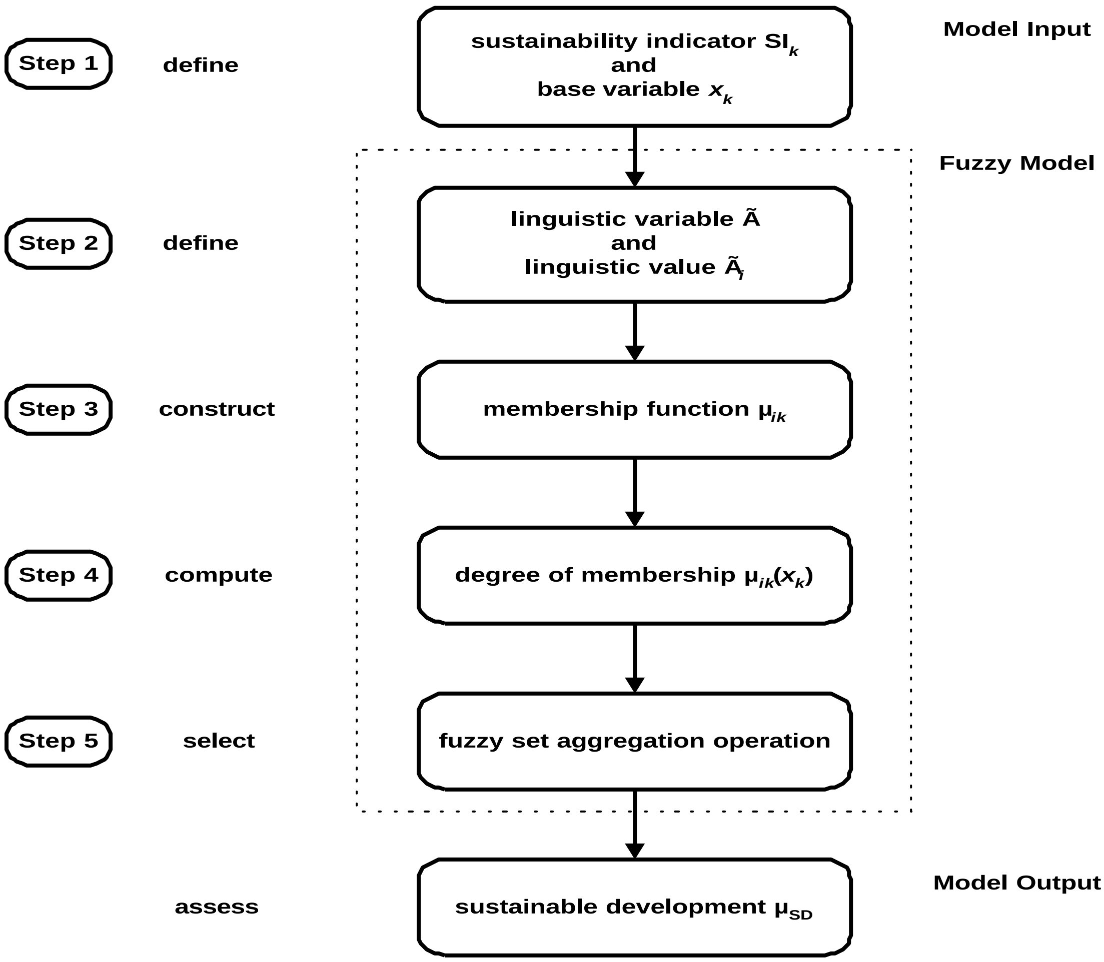

Figure 3
The scheme of a fuzzy model applying fuzzy set aggregation operations to assess the contribution of sustainability indicators (SI) to sustainable development (SD).

In political reality, economic, ecological, and societal issues inevitably will be balanced against each other (Silvert, 1997). *Averaging operations* allow a *degree of compromise* among the *m* degrees of membership $\mu_{11}(x_1),\ldots,\mu_{1m}(x_m)$ and determine a value for μ_{SD} between $min[\mu_{11}(x_1),\ldots,\mu_{1m}(x_m)]$ and $max[\mu_{11}(x_1), \ldots, \mu_{1m}(x_m)]$ (Dubois and Prade, 1985; Dubois and Prade, 1988; Klir and Yuan, 1995; Munda, 1995). In addition, if the *relative importance* of SI_k with respect to SD is considered to be unequal, then it is necessary to weight the contribution of SI_k, e.g., in proportion to its importance (Silvert, 1997).

If α denotes the degree of compromise among *m* degrees of membership and w_k denotes the relative importance of SI_k, then a generalized formulation of weighted averaging operations is

$$\mu_{SD} = \left[\frac{\sum_{k=1}^{m} w_k \mu_{1k}(x_k)^{\alpha}}{\sum_{k=1}^{m} w_k} \right]^{1/\alpha} \qquad (1)$$

where $\alpha > 0$, in this model.

In the special case when the relative importance of each SI_k is equal, equation (1) reduces to

$$\mu_{SD} = \left[\frac{\sum_{k=1}^{m} \mu_{1k}(x_k)^{\alpha}}{m} \right]^{1/\alpha} \qquad (2)$$

Equation (1), generally, includes special cases for specific values of α: (i) if $\alpha \rightarrow -\infty$, then μ_{SD} is the standard fuzzy intersection; (ii) if $\alpha \rightarrow 0$, then μ_{SD} is the geometric mean; (iii) if $\alpha = 1$, then μ_{SD} is the arithmetic mean; and (iv) if $\alpha \rightarrow +\infty$, then μ_{SD} is the standard fuzzy union (Dubois and Prade, 1985).

In the example of housing systems for laying hens, assume SD is to be assessed based on three SI: SI_1 is "Farm Continuity" (x_1, costs per hen), SI_2 is "Ammonia Emission" (x_2, kg NH_3 per hen), and SI_3 is "Total Dust in Air" (x_3, mg per m^3) (de Boer et al., 2000). Further, assume that associating x_k with μ_{1k} results in three degrees of membership $\mu_{11}(x_1) = 0.2$, $\mu_{12}(x_2) = 0.3$, and $\mu_{13}(x_3) = 0.9$.

In Equation (1) the smallest degree of membership determines μ_{SD} to an increasingly lesser extent with increasing degree of compromise α. Using the specific values of α above results in special cases: (i) $\mu_{SD} = 0.2$, (ii) $\mu_{SD} = 0.4$, (iii) $\mu_{SD} = 0.5$, and (iv) $\mu_{SD} = 0.9$.

3.3. Fuzzy model applying approximate reasoning

3.3.1. Scheme of fuzzy model

The scheme of a fuzzy model applying *approximate reasoning* to assess SD is in Figure 4 (on the next page). Six steps are involved: Step 1 defines model input, sustainability indicator SI_k and base variable x_k; Step 2 defines linguistic variable $\tilde{A}$ and n linguistic values $\tilde{A}_i$, and also defines linguistic variable $\tilde{O}$ and q linguistic values $\tilde{O}_p$ ($p = 1,\ldots,q$) regarding assessment μ_{SD}; Step 3 constructs membership function μ_{ik} and $\mu_{\tilde{O}p}$; Step 4 computes degree of membership $\mu_{ik}(x_k)$; Step 5 determines a fuzzy conclusion $\tilde{N}$; and Step 6 draws a numerical assessment μ_{SD}. In approximate reasoning, Step 4 is known as *fuzzification*, Step 5 as *fuzzy inference,* and Step 6 as *defuzzification* (Bezdek, 1993; Klir and Yuan, 1995; Cox, 1998).

3.3.2. Fuzzy rule base

Reasoning is the process of infering a conclusion regarding a problem that cannot be observed directly (viz, SD), from aspects of the problem that can be observed directly (viz, SI) (Bhatnagar and Kanal, 1992). In a fuzzy model applying approximate reasoning, the reasoning process is based on a series of r fuzzy rules R_j ($j = 1,..,r$), which together is refered to as the *fuzzy rule base* of the model. A fuzzy rule presents the contribution of SI_k to SD by way of linguistic *if-then propositions*.

A proposition contains a *premise*, the *if*-part, and a *conclusion*, the *then*-part (Boixader and Godo, 1998; Dubois and Prade, 1998). The premise contains one or more *facts* "SI_k is $\tilde{A}_i$." The conclusion contains a single fact "SD is $\tilde{O}_p$," where linguistic value $\tilde{O}_p$ defines a fuzzy assessment regarding SD ($\tilde{O}_p \subset U_{SD}$). Fuzzy rule R_j, therefore, reads

$$\textit{if } \text{“}SI_k \text{ is } \tilde{A}_i\text{”} \textit{ then } \text{“SD is } \tilde{O}_p\text{”.}$$

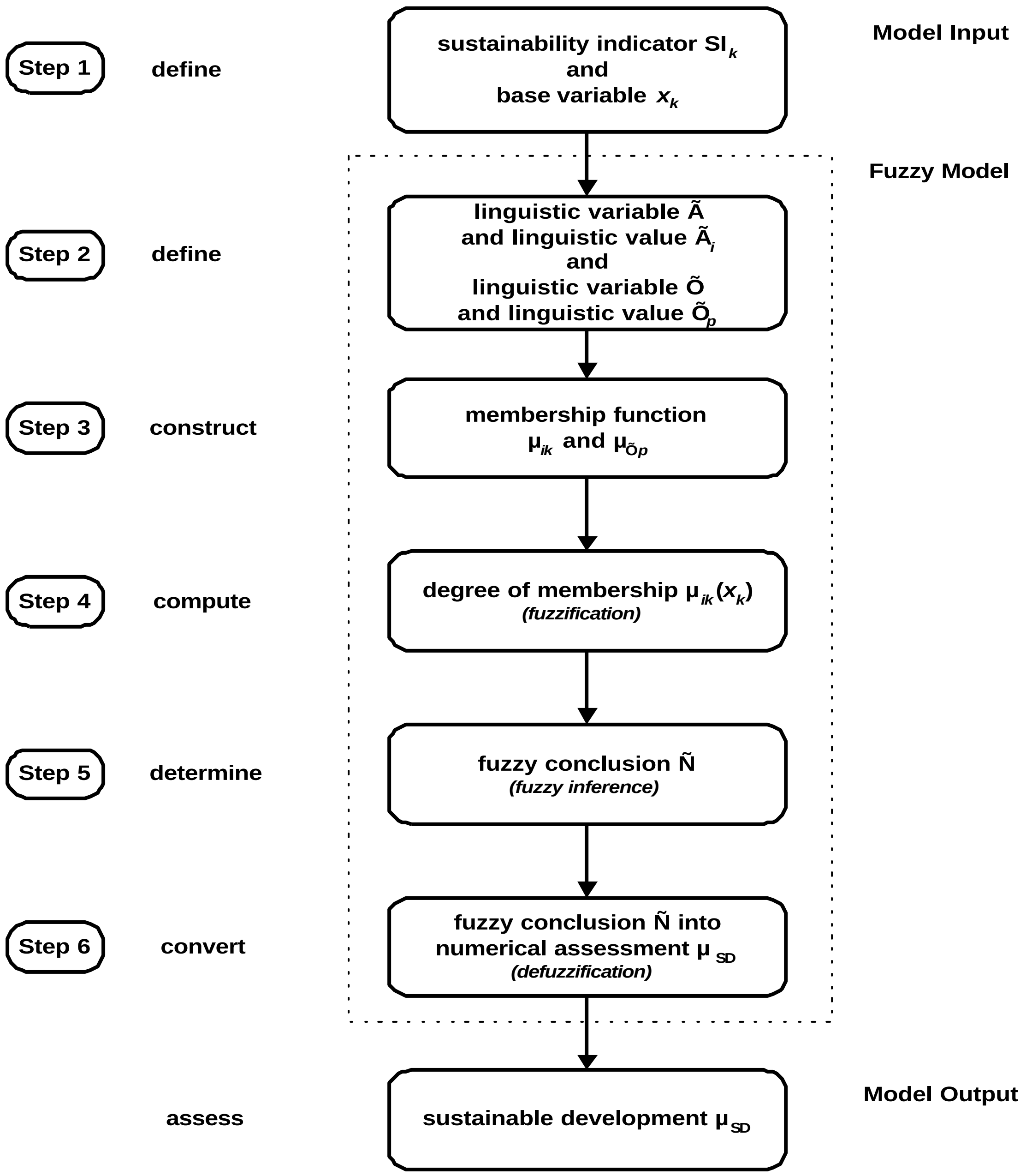

Figure 4
The scheme of a fuzzy model applying approximate reasoning to assess the contribution of sustainability indicators (SI) to sustainable development (SD).

If, for example, SI_k is "Ammonia Emission," $\tilde{A}_i$ is linguistic value "Acceptable," SD is "Sustainable Development," $\tilde{O}$ is linguistic variable "Achievement," and $\tilde{O}_p$ is linguistic value "Very Good," then fuzzy rule R_j reads

if Ammonia Emission is Acceptable *then* Sustainable Development is Very Good.

Recall assessing the SD of housing systems for laying hens: SI_1 is "Farm Continuity" (x_1, costs per hen), SI_2 is "Ammonia Emission" (x_2, kg NH_3 per hen), and SI_3 is "Total Dust in Air" (x_3, mg per m^3). Further, linguistic value $\tilde{A}_1$ is "Acceptable" and $\tilde{A}_2$ is "Unacceptable;" and linguistic value $\tilde{O}_1$ is "Very Good," $\tilde{O}_2$ is "Good," $\tilde{O}_3$ is "Poor," and $\tilde{O}_4$ is "Very Poor." A fuzzy rule base comprising four fuzzy rules could read

R_1 *if* SI_1 is $\tilde{A}_1$ AND SI_2 is $\tilde{A}_1$ AND SI_3 is $\tilde{A}_1$ *then* SD is $\tilde{O}_1$,
R_2 *if* SI_1 is $\tilde{A}_1$ AND SI_2 is $\tilde{A}_1$ AND SI_3 is $\tilde{A}_2$ *then* SD is $\tilde{O}_2$,
R_3 *if* SI_1 is $\tilde{A}_1$ AND SI_2 is $\tilde{A}_2$ AND SI_3 is $\tilde{A}_2$ *then* SD is $\tilde{O}_3$,
R_4 *if* SI_1 is $\tilde{A}_2$ AND SI_2 is $\tilde{A}_2$ AND SI_3 is $\tilde{A}_2$ *then* SD is $\tilde{O}_4$.

where "AND" denotes a *logical connective* (Klir and Yuan, 1995). Rule R_1, for example, reads "*if* Farm Continuity is Acceptable AND Ammonia Emission is Acceptable AND Total Dust in Air is Acceptable *then* Sustainable Development is Very Good." Steps 4 (fuzzification), 5 (fuzzy inference), and 6 (defuzzification) will be illustrated based on the fuzzy rule base above.

3.3.3. Fuzzification

Fuzzification of model input refers to computing the degree of membership $\mu_{ik}(x_k)$. In the example of assessing SD of housing systems for laying hens, fuzzification of SI_1 results in $\mu_{11}(x_1) = 0.2$; of SI_2, $\mu_{12}(x_2) = 0.3$; and of SI_3, $\mu_{13}(x_3) = 0.9$. Further, $\tilde{A}_2$ ("Unacceptable") is the *fuzzy complement* of $\tilde{A}_1$ ("Acceptable"), so that $\mu_{2k}(x_k) = 1 - \mu_{1k}(x_k)$ (Klir and Yuan, 1995): $\mu_{21}(x_1) = 0.8$, $\mu_{22}(x_2) = 0.7$, and $\mu_{23}(x_3) = 0.1$ (Figure 5).

3.3.4. Fuzzy inference

Fuzzy inference is a two-step process: the *implication process* and the *aggregation process* (Yager, 1994; Anonymous, 1998). The implication process defines a fuzzy conclusion $\tilde{N}_j$ for each rule R_j. The aggregation process then defines an overall fuzzy conclusion $\tilde{N}$ for the entire fuzzy rule base.

The implication process first defines a *truth value* τ_j for the premise of the proposition in R_j. If the premise contains a single fact "SI_k is $\tilde{A}_i$," then τ_j is defined by the degree of membership $\mu_{ik}(x_k)$. If the premise contains more than one fact, however, then τ_j is defined by a logical connective (Zadeh, 1975b; Boixader and Godo, 1998).

Consider the example that assesses the SD of housing systems for laying hens. For R_j, the logical connective "AND" defines a fuzzy intersection operator to compute τ_j based on degrees of memberships. Applying the *min*-operator for R_1, for example, results in $\tau_1 = min[0.2, 0.3, 0.9] = 0.2$ (Figure 5).

The implication process then defines how τ_j implies a fuzzy conclusion $\tilde{N}_j$ based on the fact "SD is $\tilde{O}_p$." The operator defined to implement the implication process in R_j modifies membership function $\mu_{\tilde{O}p}$, constructed in Step 3, to the degree specified by τ_j. Applying the *min*-operator for R_1, for example, modifies the membership function $\mu_{\tilde{O}1}$ by truncation at $\tau_1 = 0.2$. The fuzzy conclusion $\tilde{N}_1$ is the *area* under the truncated membership function (Figure 5).

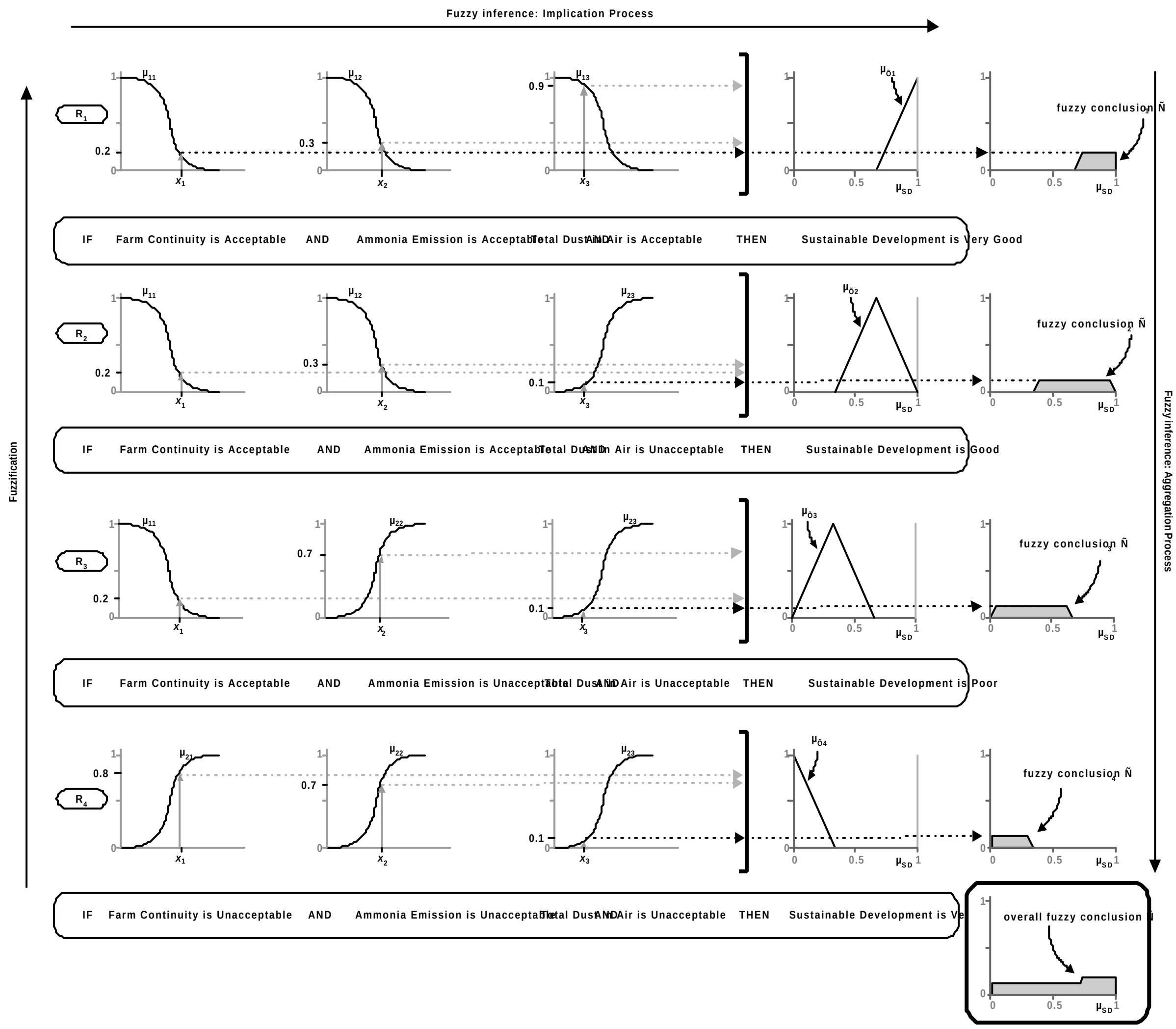

Figure 5

Graphical illustration of a fuzzy model applying approximate reasoning to assess the sustainable development of housing systems for laying hens. A fuzzy rule base comprising four fuzzy if-then rules presents the contribution of three sustainability indicators (Farm Continuity, Ammonia Emission, and Total Dust in Air) to sustainable development. Approximate reasoning starts with fuzzification of model input x_1 (costs per hen), x_2 (kg NH_3 per hen), and x_3 (mg per m^3). Next, fuzzy inference, a two-step process comprising the implication process and the aggregation process, determines an overall fuzzy conclusion $\tilde{N}$ based on fuzzy conclusions $\tilde{N}_1$ through $\tilde{N}_4$ for each rule (based on Anonymous, 1998).

The aggregation process defines an overall fuzzy conclusion $\tilde{N}$ by selecting an operator to aggregate the $\tilde{N}_j$. In a fuzzy rule base, rules are connected by the logical connective “ELSE” (Watanabe et al., 1992). In the example, the fuzzy rule base then reads

R_1	*if* SI_1 is $\tilde{A}_1$ AND SI_2 is $\tilde{A}_1$ AND SI_3 is $\tilde{A}_1$ *then* SD is $\tilde{O}_1$, ELSE
R_2	*if* SI_1 is $\tilde{A}_1$ AND SI_2 is $\tilde{A}_1$ AND SI_3 is $\tilde{A}_2$ *then* SD is $\tilde{O}_2$, ELSE
R_3	*if* SI_1 is $\tilde{A}_1$ AND SI_2 is $\tilde{A}_2$ AND SI_3 is $\tilde{A}_2$ *then* SD is $\tilde{O}_3$, ELSE
R_4	*if* SI_1 is $\tilde{A}_2$ AND SI_2 is $\tilde{A}_2$ AND SI_3 is $\tilde{A}_2$ *then* SD is $\tilde{O}_4$.

Each fuzzy rule above expresses a situation regarding the contribution of three SI to SD. In approximate reasoning, rules R_1 through R_4 are true to a certain degree, as expressed by τ_1 through τ_4, which means that all rules contribute partly to the overall fuzzy conclusion Ñ. If one rule is completely true (e.g., $\tau_1 = 1$), then all other rules must be completely false (i.e., τ_2 through $\tau_4 = 0$) and should not contribute to Ñ. The logical connective "ELSE" is defined, therefore, by the *max*-operator to enable a fuzzy union of $\tilde{N}_j$ (Yager, 1994; Türksen, 1999). The fuzzy conclusion Ñ is the area under the curve (Figure 5).

3.3.5. Defuzzification

Defuzzification converts the fuzzy conclusion Ñ from an area under the curve to a numerical assessment μ_{SD}. Various methods of defuzzification are available (e.g., Filev and Yager, 1991; Yager and Filev, 1993; Bárdossy and Duckstein, 1995; Klir and Yuan, 1995; Dubois and Prade, 1998; Leekwijck and Kerre, 1999). The method used most often is the *center of gravity method*, which defines μ_{SD} as a value that divides the area under the curve into two equal subareas. In the example that assesses SD of housing systems for laying hens, the center of gravity is computed as $\mu_{SD} = 0.6$ (Figure 6).

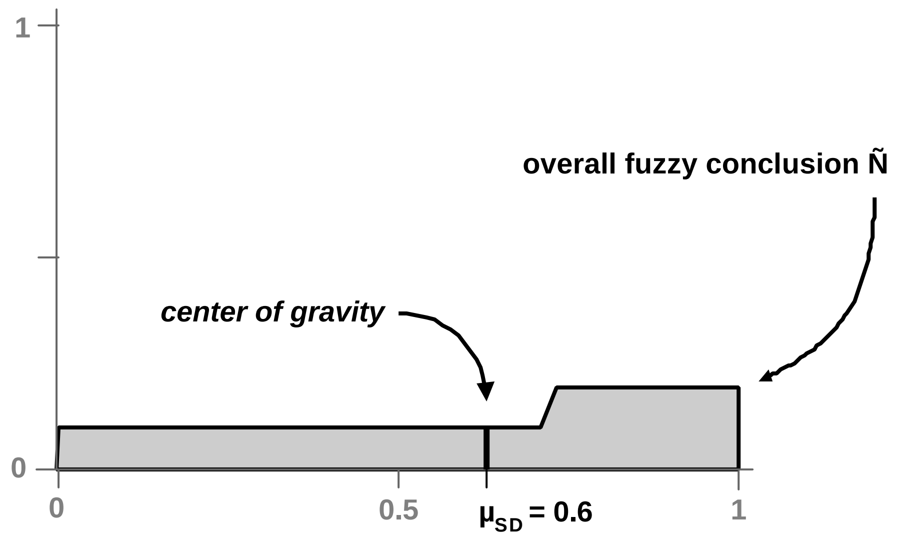

Figure 6

Graphical illustration of defuzzification of the overall fuzzy conclusion Ñ in a fuzzy model applying approximate reasoning to assess the sustainable development of housing systems for laying hens. The center of gravity method divides the area under the curve Ñ into two equal subareas and thus determines μ_{SD}.

4. Discussion

4.1. Fuzzy models to assess sustainable development

The impact of sustainability on agricultural production systems emphasizes the need for a standardized framework to initiate and monitor sustainable development (Shearman, 1990; Hansen, 1996; Becker, 1997). A numerical assessment of SD in such a framework is based on context-dependent economic, ecological, and societal sustainability indicators. The objective of this paper was to introduce fuzzy set theory as a mathematical basis to enable a numerical assessment of SD. For this reason, we developed two fuzzy models: one model that applies fuzzy set aggregation operations and another that applies approximate reasoning. The approach was limited to exploring each model using a hypothetical example of housing systems for laying hens.

The first fuzzy model constitutes a robust application of fuzzy set theory and enables a general approach to human reasoning. Fuzzy set aggregation operations allow a continuum of (political) attitudes toward SD, ranging from conservative to liberal.

The second fuzzy model constitutes a refined application of fuzzy set theory and enables a specific approach to human reasoning. Fuzzy *if-then* rules allow human expectations about SD to be expressed in linguistic propositions that present the contribution of SI to SD. A numerical assessment μ_{SD} can then be "fine-tuned" by selected fuzzy operators used in the approximate reasoning process to draw a conclusion regarding SD. Various fuzzy operators are available to implement fine-tuning of the reasoning process (Klir and Yuan, 1995; Rojas et al., 1999). The choice of operators, therefore, needs careful consideration.

4.2. Practical implementation of fuzzy models

Membership functions are at the core of fuzzy models. The membership function is considered to be both the strongest and the weakest point of fuzzy set theory (Munda et al., 1992). It is the strongest, because a membership function defines a soft threshold, which allows a smooth and practical assessment of the contribution of SI to SD, in contrast with a characteristic function, which defines a hard threshold in classical set theory (Bosserman and Ragade, 1982; George et al., 1997; Silvert, 1997). It is the weakest, because the membership function is regarded as too subjective in relation to its construction. In industrial engineering applications of fuzzy set theory, construction of membership functions is realized mostly by trial and error (McNeill and Freiberger, 1993; Bárdossy and Duckstein, 1995; Klir and Yuan, 1995; Zimmerman, 1996). Trial-and-error methods to construct membership functions to assess SD, however, are not possible and are considered unacceptable.

Several studies discuss empirical methods to construct a membership function based on expert knowledge (e.g., Norwich and Türksen, 1984; Chameau and Santamarina, 1987; Santamarina and Chameau, 1987; Türksen, 1991; Bárdossy and Duckstein, 1995; Ruspini et al., 1998; Türksen, 1999). Three aspects regarding use of expert knowledge must be considered in practical implementation of fuzzy models to assess SD: (1) criteria that determine necessary qualifications of experts, (2) proper elicitation of expert knowledge to construct a membership function, and (3) methods to test reliability of a membership function. Reliability of a membership function is also important with regard to verification and validation of the fuzzy model (Chang and Hall, 1992).

4.3. Conclusions

A decision-making process regarding SD is first and foremost a political and, therefore, a subjective issue (Bockstaller et al., 1997; Silvert, 1997; Graaf and Musters, 1998). Although the attitude toward SD might be a subjective one, fuzzy set theory enables a formal mathematical framework to link human expectations about SD, expressed in linguistic propositions, to numerical data, expressed in measurements of SI. The fuzzy models developed in this paper, therefore, provide a novel approach to support decision-making regarding sustainable development.

References

Anonymous, 1998. Fuzzy Logic Toolbox. The Math Works Inc., Natick, MA.

Bárdossy, A., Duckstein, L., 1995. Fuzzy rule-based modeling with applications to geophysical, biological and engineering systems. CRC Press, Boca Raton, FL.

Batschelet, E., 1975. Introduction to Mathematics for Life Scientists. Springer-Verlag, Berlin.

Becker, B., 1997. Sustainability Assessment: A Review of Values, Concepts, and Methodological Approaches. Worldbank-CGIAR, Washington D.C., Issues in Agriculture 10.

Bell, S., Morse, S., 1999. Sustainability Indicators. Measuring the Immeasurable. Earthscan Publications Ltd., London.

Bethea, R.M., Duran, B.S., Boullion, T.L., 1985. Statistical Methods for Engineers and Scientists. Marcel Dekker, Inc., New York.

Bezdek, J.C., 1993. Fuzzy models. What are they, and why? IEEE Trans. Fuzzy Systems 1(1), 1-6.

Bhatnagar, R., Kanal, L.N., 1992. Models of enquiry and formalism for approximate reasoning. In: Zadeh, L.A., Kacprzyk, J. (eds.), Fuzzy Logic for the Management of Uncertainty. John Wiley and Sons Inc., New York.

Bockstaller, C., Girardin, P., Werf, van der, H.M.G., 1997. Use of agro-ecological indicators for the evaluation of farming systems. Europ. J. Agron. 7, 261-270.

Boixader, D., Godo, L., 1998. Fuzzy inference. In: Ruspini, E.H., Bonissone, P.P., Pedrycz, W. (eds.), Handbook of Fuzzy Computation. Institute of Physics Publishing, Philadelphia.

Boer, de, I.J.M., Schweitzer, D.P.N., Cornelissen, A.M.G., 2000. Comparison of egg production systems in the Netherlands for economic, ecological, and societal indicators. In preparation.

Bossel, H., 1999. Indicators for Sustainable Development: Theory, Method, Applications. International Institute for Sustainable Development, Winnipeg.

Bosserman, R.W., Ragade, R.K., 1982. Ecosystem analysis using fuzzy set theory. Ecol. Model. 16, 191-208.

Brklacich, M., Bryant, C.R., Smit, B., 1991. Review and appraisal of concept of sustainable food production systems. Environ. Manag. 15(1), 1-14.

Callens, I., Tyteca, D., 1999. Towards indicators of sustainable development for firms. A productive efficiency perspective. Ecol. Econ. 28, 41-53.

Chameau, J.-L., Santamarina, J.C., 1987. Membership functions I: comparing methods of measurement. Internat. J. Approx. Reasoning 1, 287-301.

Chang, A.M., Hall, L.O., 1992. The validation of fuzzy knowledge-based systems. In: Zadeh, L.A., Kacprzyk, J. (eds.), Fuzzy Logic for the Management of Uncertainty. John Wiley and Sons Inc., New York.

Clayton, M.H., Radcliffe, N.J., 1996. Sustainability. A Systems Approach. Earth Scan Publications Ltd., London.
Cox, E., 1998. The Fuzzy Systems Handbook. AP Professional, Boston.
Dubois, D., Prade, H., 1985. A review of fuzzy set aggregation connectives. Inform. Sci. 36, 85-121.
Dubois, D., Prade, H., 1988. Possibility Theory. An approach to Computerized Processing of Uncertainty. Plenum Press, New York.
Dubois, D., Prade, H., 1998. An introduction to fuzzy systems. Clin. Chim. Acta 270, 3-29.
Filev, D.P., Yager, R.R., 1991. A generalized defuzzification method via Bad Distribution. Internat. J. Intell. Systems 6, 687-697.
Fresco, L.O., Kroonenberg, S.B., 1992. Time and spatial scales in ecological sustainability. Land Use Policy 9, 155-168.
George, R., Srikanth, R., Buckles, B.P., Petry, F.E., 1997. An approach to modelling impreciseness and uncertainty in the Object-Oriented Data Model. In: Dubois, D., Prade, H., Yager, R.R. (eds.), Fuzzy Information Engineering. A Guided Tour of Applications. John Wiley and Sons, Inc., New York.
Giampietro M., Paoletti, M.G., Bukkens, S.G.F., Chunru, H., 1997. Preface. Agric. Ecosyst. Environ. 62, 77-79.
Graaf, de, H.J., Musters, C.J.M., 1998. Opportunities for Sustainable Development. Theory, Methods, and Regional Applications. PhD thesis, Leiden University, the Netherlands.
Groot Koerkamp, P.W.G., 1994. Review on emissions of ammonia from housing systems for laying hens in relation to sources, processes, building design and manure handling. J. Agric. Engng. Res. 59, 73-87.
Hansen, J.W., 1996. Is agricultural sustainability a useful concept?, Agric. Syst. 50, 117-143.
Heinen, J.T., 1994. Emerging, diverging and converging paradigms on sustainable development. Internat. J. Sustain. Dev. World Ecol. 1, 22-33.
Hogg, R.V., Tanis, E.A., 1997. Probability and Statistical Inference. Prentice Hall, Upper Saddle River, NJ.
Ikerd, J.E., 1993. The need for a systems approach to sustainable agriculture. Agric. Ecosyst. Environ. 46:147-160.
Kelly, K.L., 1998. A systems approach to identifying decisive information for sustainable development. Europ. J. Operat. Res. 109, 452-464.
Klir, G.J., 1991. Facets of Systems Science. Plenum Press, New York.
Klir, G.J., Folger, T.A., 1988. Fuzzy Sets, Uncertainty, and Information. Prentice-Hall International Inc., New Jersey.
Klir, G.J., Yuan, B., 1995. Fuzzy Sets and Fuzzy Logic. Theory and Application. Prentice-Hall PTR, New Jersey.
Kosko, B., 1990. Fuzziness vs. probability. Internat. J. General Systems 17, 211-240.
Kosko, B., 1992. Neural Networks and Fuzzy Systems. Prentice-Hall International Inc., New Jersey.
Leekwijck, van, W., Kerre, E.E., 1999. Defuzzification: criteria and classification. Fuzzy Sets and Systems 108, 159-178.
McNeill, D., Freiberger, P., 1993. Fuzzy Logic. Simon and Schuster, New York.
Mebratu, D., 1998. Sustainability and sustainable development: historical and conceptual review. Environ. Impact Assess. Rev. 18, 493-520.

Mitchel, G., May, A., McDonald, A., 1995. PICABUE: a methodological framework for the development of indicators of sustainable development. Internat. J. Sustain. Dev. World Ecol. 2, 104-123.

Munda, G., 1995. Multicriteria Evaluation in a Fuzzy Environment. Theory and Applications in Ecological Economics. Physica-Verlag, Heidelberg.

Munda, G., Nijkamp, P., Rietveld, P., 1992. Multicriteria Evaluation and Fuzzy Set Theory: Applications in Planning for Sustainability. Free University, Amsterdam, Research-Memorandum 1992-68.

Neher, D., 1992. Ecological sustainability in agricultural systems: definition and measurement. In: Olson, R.K. (ed.), Integrating Sustainable Agriculture, Ecology, and Environmental Policy. Haworth Press Inc., London.

Norwich, A.M., Türksen, I.B., 1984. A model for the measurement of membership and the consequences of its empirical implementation. Fuzzy Sets and Systems 12, 1-25.

Pedrycz, W., 1993. Fuzzy Control and Fuzzy Systems. Research Studies Press Ltd., Taunton, UK.

Pelt, van, M.J.F., Kuyvenhoven, A., Nijkamp, P., 1995. Environmental sustainability: issues of definition and measurement. Internat. J. Environ. Pollut. 5(2/3), 204-223.

Renning, K., Wiggering, H., 1997. Step towards indicators of sustainable development: linking economic and ecological concepts. Ecol. Econ. 20, 25-36.

Rojas, I., Ortega, J., Pelayo, F.J., Prieto, A., 1999. Statistical analysis of the main parameters in the fuzzy inference process. Fuzzy Sets and Systems 102, 157-173.

Ruspini, E.H., Bonissone, P.P., Pedrycz, W., 1998. Handbook of Fuzzy Computation. Institute of Physics Publishing, Philadelphia.

Santamarina, J.C., Chameau, J.-L., 1987. Membership functions II: trends in fuzziness and implications. Internat. J. Approx. Reasoning 1, 303-317.

Shearman, R., 1990. The meaning and ethics of sustainability. Environ. Manag. 14(1), 1-8.

Silvert, W., 1997. Ecological impact classification with fuzzy sets. Ecol. Modelling 96, 1-10.

Spedding, C.R.W., 1995. Sustainability in animal production systems. J. Anim. Sci. 61, 1-8.

Steinfeld, H., De Haan, C., Blackburn, H., 1997. Livestock-Environment Interactions, Issues and Options. FAO-Worldbank, Rome.

Stockle, C.O., Papendick, R.I., Saxton, K.E., Campbell, G.S., Evert, van, F.K., 1994. A framework for evaluating the sustainability of agricultural production systems. Americ. J. Altern. Agric. 9(1/2), 45-50.

Türksen, I.B., 1991. Measurement of membership functions and their acquisition. Fuzzy Sets and Systems 40, 5-38.

Türksen, I.B., 1999. Type I and Type II fuzzy system modeling. Fuzzy Sets and Systems 106, 11-34.

Udo, H.M.J, Cornelissen, A.M.G., 1998. Livestock in resource-poor farming systems. Agric. Outlook 27(4), 237-242.

Vavra, M., 1996. Sustainability of animal production systems: an ecological perspective. J. Anim. Sci. 74(6), 1418-1423.

Verbruggen, H., Kuik, O., 1991. Indicators of sustainable development: an overview. In: Kuik, O., Verbruggen, H. (eds.), In Search of Indicators of Sustainable Development. Kluwer, Dordrecht.
Watanabe, H., Symon, J., Detloff, W.D., Yount, K.E., 1992. VLSI fuzzy chip and inference accelerator board systems. In: Zadeh, L.A., Kacprzyk, J. (eds.), Fuzzy logic for the management of uncertainty. John Wiley and Sons Inc., New York.
WRR, 1995. Sustained Risks: A Lasting Phenomenon. Sdu Uitgeverij, The Hague, Reports to the government 44.
Yager, R.R., 1994. Aggregation operators and fuzzy systems modeling. Fuzzy Sets and Systems, 129-145.
Yager, R.R., Filev, D.P., 1993. On the issue of defuzzification and selection based on a fuzzy set. Fuzzy Sets and Systems 55, 255-271.
Zadeh, L.A., 1975a. The concept of a linguistic variable and its application to approximate reasoning-I. Inform. Sci. 8, 199-249.
Zadeh, L.A., 1975b. The concept of a linguistic variable and its application to approximate reasoning-II. Inform. Sci. 8, 301-357.
Zimmermann, H.-J., 1996. Fuzzy Set Theory and its Applications. Kluwer Academic Publishers, Boston.

ERASMUS **R**ESEARCH **I**NSTITUTE OF **M**ANAGEMENT

REPORT SERIES
RESEARCH IN MANAGEMENT

Publications in the Report Series Research* in Management

Impact of the Employee Communication and Perceived External Prestige on Organizational Identification
Ale Smidts, Cees B.M. van Riel & Ad Th.H. Pruyn
ERS-2000-01-MKT

Critical Complexities, from marginal paradigms to learning networks
Slawomir Magala
ERS-2000-02-ORG

Forecasting Market Shares from Models for Sales
Dennis Fok & Philip Hans Franses
ERS-2000-03-MKT

A Greedy Heuristic for a Three-Level Multi-Period Single-Sourcing Problem
H. Edwin Romeijn & Dolores Romero Morales
ERS-2000-04-LIS

Integer Constraints for Train Series Connections
Rob A. Zuidwijk & Leo G. Kroon
ERS-2000-05-LIS

Competitive Exception Learning Using Fuzzy Frequency Distribution
W-M. van den Bergh & J. van den Berg
ERS-2000-06-LIS

Start-Up Capital: Differences Between Male and Female Entrepreneurs, 'Does Gender Matter?'
Ingrid Verheul & Roy Thurik
ERS-2000-07-STR

The Effect of Relational Constructs on Relationship Performance: Does Duration Matter?
Peter C. Verhoef, Philip Hans Franses & Janny C. Hoekstra
ERS-2000-08-MKT

Marketing Cooperatives and Financial Structure: a Transaction Costs Economics Analysis
George W.J. Hendrikse & Cees P. Veerman
ERS-2000-09-ORG

---

* ERIM Research Programs:
LIS Business Processes, Logistics and Information Systems
ORG Organizing for Performance
MKT Decision Making in Marketing Management
F&A Financial Decision Making and Accounting
STR Strategic Renewal and the Dynamics of Firms, Networks and Industries

A Marketing Co-operative as a System of Attributes: A case study of VTN/The Greenery International BV,
Jos Bijman, George Hendrikse & Cees Veerman
ERS-2000-10-ORG

Evaluating Style Analysis
Frans A. De Roon, Theo E. Nijman & Jenke R. Ter Horst
ERS-2000-11-F&A

From Skews to a Skewed-t: Modelling option-implied returns by a skewed Student-t
Cyriel de Jong & Ronald Huisman
ERS-2000-12-F&A

Marketing Co-operatives: An Incomplete Contracting Perspective
George W.J. Hendrikse & Cees P. Veerman
ERS-2000-13– ORG

Models and Algorithms for Integration of Vehicle and Crew Scheduling
Richard Freling, Dennis Huisman & Albert P.M. Wagelmans
ERS-2000-14-LIS

Ownership Structure in Agrifood Chains: The Marketing Cooperative
George W.J. Hendrikse & W.J.J. (Jos) Bijman
ERS-2000-15-ORG

Managing Knowledge in a Distributed Decision Making Context: The Way Forward for Decision Support Systems
Sajda Qureshi & Vlatka Hlupic
ERS-2000-16-LIS

Organizational Change and Vested Interests
George W.J. Hendrikse
ERS-2000-17-ORG

Strategies, Uncertainty and Performance of Small Business Startups
Marco van Gelderen, Michael Frese & Roy Thurik
ERS-2000-18-STR

Creation of Managerial Capabilities through Managerial Knowledge Integration: a Competence-Based Perspective
Frans A.J. van den Bosch & Raymond van Wijk
ERS-2000-19-STR

Adaptiveness in Virtual Teams: Organisational Challenges and Research Direction
Sajda Qureshi & Doug Vogel
ERS-2000-20-LIS

Currency Hedging for International Stock Portfolios: A General Approach
Frans A. de Roon, Theo E. Nijman & Bas J.M. Werker
ERS-2000-21-F&A

Transition Processes towards Internal Networks: Differential Paces of Change and Effects on Knowledge Flows at Rabobank Group
Raymond A. van Wijk & Frans A.J. van den Bosch
ERS-2000-22-STR