Application of fuzzy sets and cognitive maps to incorporate social science scenarios in integrated assessment models

A case study of urbanization in Ujung Pandang, Indonesia

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Received 20 April 1999; revised 17 February 2000

Decision–support systems in the field of integrated water management could benefit considerably from social science knowledge, as many environmental changes are human-induced. Unfortunately the adequate incorporation of qualitative social science concepts in a quantitative modeling framework is not straightforward. The applicability of fuzzy set theory and fuzzy cognitive maps for the integration of qualitative scenarios in a decision–support system was examined for the urbanization of the coastal city of Ujung Pandang, Indonesia. The results indicate that both techniques are useful tools for the design of integrated models based on a combination of concepts from the natural and social sciences.

Keywords: integrated assessment modeling, decision–support systems, fuzzy set theory, fuzzy cognitive maps, scenario analysis

1. Introduction

The scientific literature shows a growing interest of both scientists and policy makers for tools that can support strategic decision making in water management issues [1–4]. The research issue addressed in this paper is how to incorporate social science concepts in integrated assessment models. The influence of migration on the urbanization and waste-water discharge of the city of Ujung Pandang, Southwest Sulawesi, serves as case example to examine the applicability of two different techniques for this purpose.

The coastal region of South-West Sulawesi, Indonesia has been chosen as the study area for a multidisciplinary research program with the aim of formulating a scientific methodology for sustainable coastal-zone management [5]. In the area the rapidly growing coastal city of Ujung Pandang forms a potential threat to nearby marine ecosystems such as coral reefs and seagrass beds. The scientific concepts and data that were gathered in the framework of the research program form the basis for a recently completed rapid assessment model for sustainable coastal-zone management (RaMCo) [6]. Geographical information is combined with a dynamic system model for the ecological, physical and social-economic coastal-zone processes (figure 1). The model can be used to examine the environmental and economic impacts of a number of management measures, such as the construction of a storage lake, fisheries regulations, urban waste-water treatment, and large-scale investments in industry. Quantitative scenarios are used to describe the influence of uncertain future demographic, macro-economic, and hydrological developments on the coastal-zone system.

The consequences of the future urbanization of Ujung Pandang for the municipal drinking water demand and waste-water discharge is one of the themes incorporated in the RaMCo model. In 1995 the city was estimated to have over one million residents [7]. Urban population growth is the result of natural population growth and the permanent settlement of rural migrants in the city. Whereas reliable forecasts are available for the natural population growth rate [7], the long-term development of the migration rate is difficult to predict due to the complex combination of uncertain social-economic, social-cultural and institutional factors that exert a strong influence on migration [8]. Urban economic growth, the future attitude of the municipal authorities to the informal sector and the development of slum areas, or changes in the level of rural education may affect the migration rate in ways that are hard to foresee on the basis of sheer trend extrapolation. By nature these factors pertain to the domain of the social sciences, are subject to considerable uncertainty, and difficult to measure on a quantitative scale. On the other hand, a variety of mathematical techniques are available to describe the direct and indirect environmental consequences of the urbanization of the city.

One of the problems encountered during the design of the RaMCo model was how to incorporate the qualitative concepts for the migration process in the quantitative modeling framework of the model. Graphical model relationships or time functions and differential equations can be

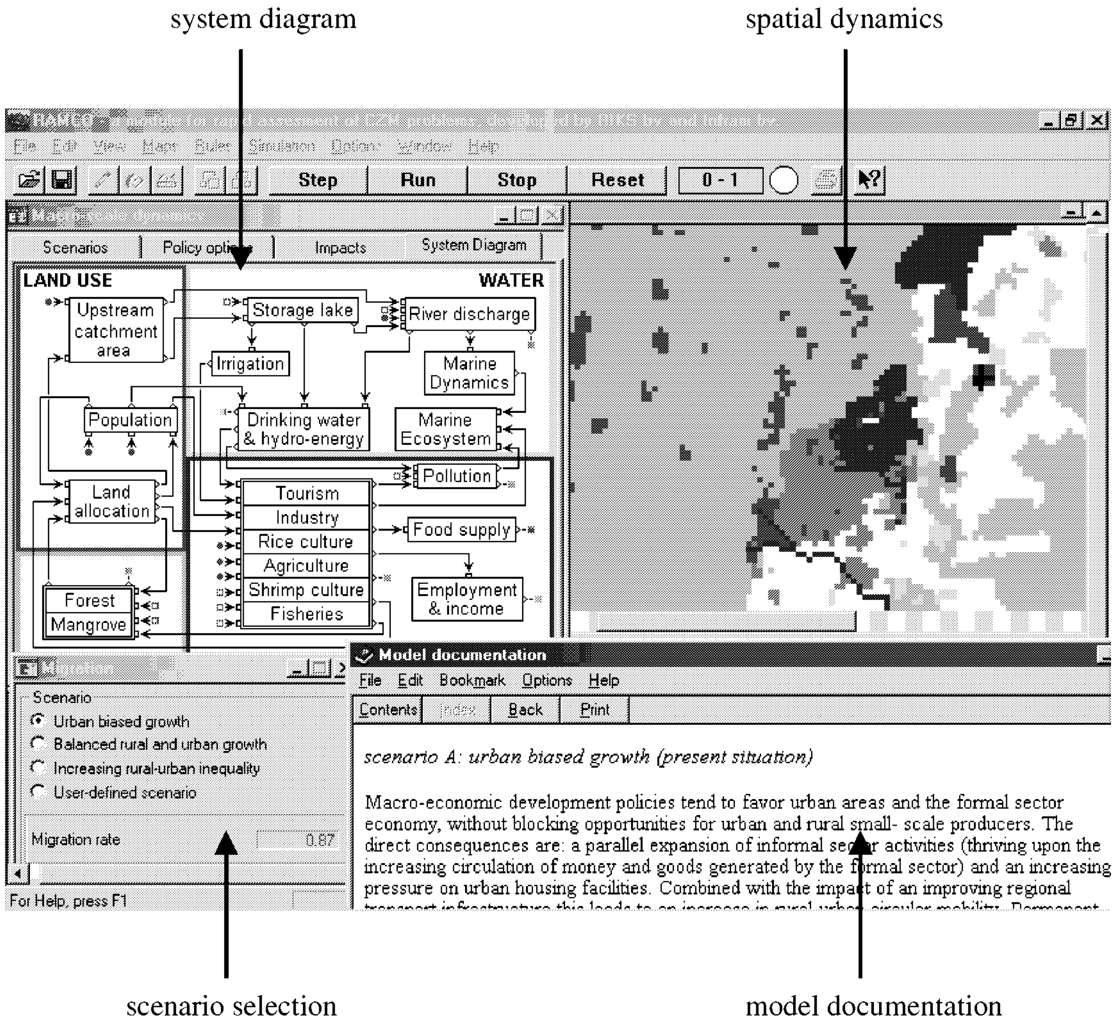

Figure 1. User interface of the RaMCo prototype model.

used to incorporate social processes involving human behavior in simulation models [9–12]. For a number of reasons these approaches are not entirely satisfactory from a social science perspective. In practice the mathematical representation of the issues considered often requires a restriction on the number of variables as well as a reduction of the complexity deemed necessary from the social science perspective. The operationalization of the model variables can be a problem as the required data are often insufficient and model parameters may be difficult to measure on a quantitative scale. This complicates the calibration and validation of the model and the interpretation of the model outcomes. Furthermore, the representation in purely quantitative terms may provide an unjustified sense of model accuracy and forecasting capability that is not in line with the uncertainties present in the real system. In general the finesses of the social science concepts do not permit a representation that is exclusively based on quantitative techniques such as algebraic or differential equations.

During the design of the RaMCo model the aforementioned problems have been addressed in a two-step approach: the formulation of qualitative scenarios for the migration process and the quantification of these scenarios. The scenarios provide a linguistic description of the possible social-cultural, social-economic and institutional factors affecting the net permanent settlement rate. In the RaMCo model a selection can be made out of three different scenarios for the future migration of the population from the surrounding rural region to the city of Ujung Pandang (figure 1).

The formulation of these scenarios is addressed in section 2 and comprises the problem description, a definition of the dependent and independent variables, and a formal description of the scenarios. A causal diagram is used to describe the complex interactions that are assumed to operate between the different variables. In section 3 a brief summary is given of two techniques that can be used to quantify these scenarios. *Fuzzy set theory* can facilitate the description of systems, which are too complex or ill defined to allow for a precise mathematical description [13,14]. The independent variables are translated from the numerical to the qualitative or fuzzy domain (fuzzification). Next a number of conditional rules are formulated that describe how the independent variables affect the permanent settlement rate. With these inference rules the fuzzy output values can be calculated and finally the fuzzy results are translated back to the numerical domain (defuzzification). *Fuzzy cognitive maps* are fuzzy directed causal graphs with feedback [15,16] and may be more suitable if the system state variables are difficult to measure on a quantitative scale. The causal diagram is used to describe the influence between the different state variables. Regardless of the number of variables used, the consequences of the different scenarios can be examined by using simple matrix operations and assuming different initial states for each scenario. In contrast with the fuzzy set approach no quantitative information is needed in principle. The consequences of the different scenarios for the permanent settlement rate have been compared for the two methods. The results are presented in section 4 and are qualitatively consistent. A clear distinction can be observed for the migration rate of the city under the three scenarios. Interesting enough both approaches show a trend breach in the migration rate for one of the three scenarios, which was not explicitly included in the model. Sensitivity analyses were conducted in order to determine the relevance of the different conditional rules for the fuzzy set approach and the assumptions made for the initial state vectors for the cognitive map approach. The advantages and drawbacks of the two methods are discussed in section 5.

2. Formulation of scenarios

An appropriate definition of a scenario is "...a description of the present situation (or an aspect thereof), a description of one or more potential future situations and a description of the path or events that may lead from the present to these future situations..." [17,18]. A scenario should not be interpreted as a prediction of the future. Scenarios can be used to study the robustness of policy decisions under uncertain future social-economic, geophysical, and social-cultural conditions. Management options can be ranked according to the extent the objectives of the decision makers are met [19]. If a particular management option is ranked highest compared to its alternatives under all the scenarios this alternative may be considered robust under changes of external conditions. In principle only a few different scenarios are needed. Preferably the scenarios should be consistent, without contradictory elements, and must differ sufficiently [17,20].

2.1. Problem description

The future domestic water demand and waste water discharge of Ujung Pandang bears social (urbanization), technical (water engineering), and ecological (marine water quality) aspects. The population size of the city is the key determinant of the municipal water usage and the volume of wastewater discharge. In 1992 the households of Ujung Pandang accounted for over 80% of the urban water demand [7]. In 1994 the city was estimated to have around one million inhabitants, while the yearly population growth rate for the period 1980–1990 was 2.9% [7]. The natural population growth rate during this period was estimated to be $1.8\%\,\mathrm{yr}^{-1}$. Hence the net permanent settlement rate must have been $1.1\%\,\mathrm{yr}^{-1}$. The future natural population growth rate can relatively well be predicted on the basis of birth and mortality figures. In view of the uncertainty in the future water demand the key question is how the permanent settlement rate will develop.

2.2. Definition of influence factors and descriptor variables for migration

As suggested by Von Reibnitz [17] a statement of the purpose of the scenarios should precede the formulation of scenarios, the influencing factors, and the descriptors, which are the variables in which the scenarios are expressed. Within the total urban labor force one can distinguish between three worker categories on the basis of their residential status: the permanent residents, commuters and the remainder category of circular migrants (which includes seasonal and temporary workers who have their permanent residence outside the city). In the remainder of this paper we will distinguish between:

- the *permanent settlement* of rural migrants in the city; and
- *circular mobility*, the combination of commuting and circular migration.

The latter category of workers comprises both non-permanent migrants and commuters. For simplicity these will be referred to as non-permanent migrants. The central assumption maintained throughout this paper is that an increase in the circular mobility reduces the permanent settlement rate but not vice versa.

The next step was to identify the relevant social-economic and social-cultural variables that influence the permanent settlement rate. Figure 2 shows the causal relationships between the different independent variables, and the two descriptors; the rate of the permanent settlement and non-permanent migration to Ujung Pandang. The diagram is based on the scenarios that will be discussed in the following paragraph.

As far as the independent variables are concerned a distinction can be made between the *urban pull factors*, urban conditions which exert an attraction on the rural population, and the *rural push factors*, conditions which cause the rural population to migrate to the city. For example, the availability of cheap housing can be a pull factor for permanent settlement. Other pull factors that were considered important are: urban economic growth, the development of the formal and informal sector, the opportunities for skilled and unskilled labor in the city, the availability of cheap urban housing, and the income difference between the rural and urban population. The concept informal sector is widely used among social scientists and economists, and pertains to all the small-scale activities with a high labor and low

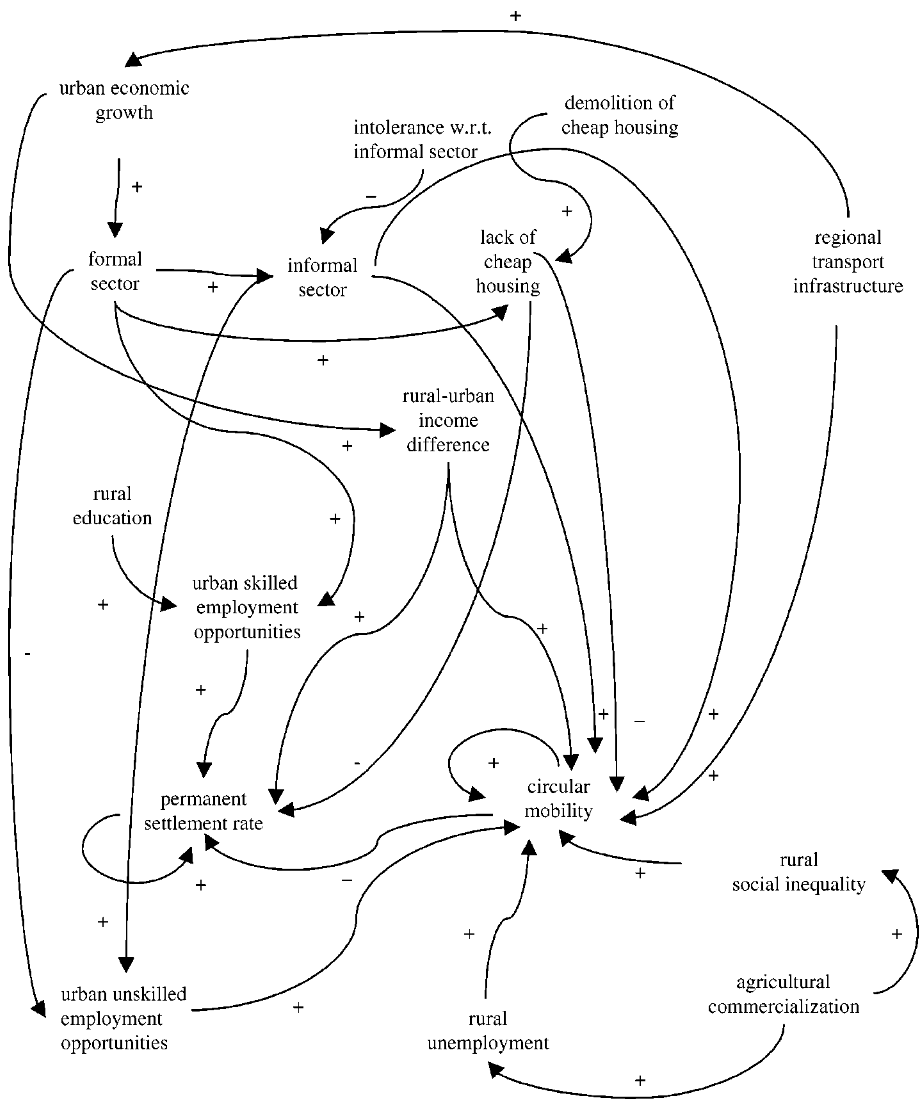

Figure 2. Cognitive map for permanent settlement and circular labor mobility to Ujung Pandang.

capital input. Usually these are performed by unskilled and semi-skilled independent producers or casual workers who act on an informal, i.e., unregistered and unlicensed basis. In Ujung Pandang this includes occupations as diverse as street sellers, market traders, domestic servants, micro-bus drivers, small-scale manufacturers, etc. According to this broad definition 50–60% of the labor force in Ujung Pandang is estimated to be employed in the informal sector economy. The push factors consist of rural social inequality, rural unemployment, the level of rural education, and agricultural commercialization, as these aspects are usually the cause of the expulsion of certain segments of the rural population. Furthermore, the quality of the regional transport infrastructure was considered to be important for the incidence of circular mobility.

Finally, the municipal authorities can indirectly influence the migration rate in two ways: by the demolition of cheap housing and the restriction of economic activities that belong to the informal sector, as it is this sector that absorbs the bulk of the unskilled migrants from rural areas.

2.3. Formulation of scenarios

Three qualitative scenarios were formulated for the urbanization of Ujung Pandang on the basis of the problem formulation and insights gained from field research. Scenario A reflects an extrapolation of the present type of urban development, which is characterized by a bias of urban over rural development. Scenario B represents the sustainable development option, aiming at a rural–urban balance in development opportunities. In scenario C the urban development rate increases and urban economic growth is maximized. As will become clear the three scenarios are based on similar underlying social-economic and social-cultural mechanisms, but differ in the assumptions made for the key driving variables.

2.3.1. Scenario A: urban biased growth (present situation)

Macro-economic development policies tend to favor urban areas and the formal sector economy, without blocking opportunities for urban and rural small-scale producers. The direct consequences are a parallel expansion of informal sector activities (thriving upon the increasing circulation of money and goods generated by the formal sector) and an increasing pressure on urban housing facilities. Combined with the impact of an improving regional transport infrastructure this leads to an increase in rural–urban circular mobility. At a certain point the permanent settlement becomes less important due to the higher costs of living in the city and its replacement by circular mobility.

2.3.2. Scenario B: balanced rural and urban growth (sustainable development option)

Decentralization policies favor the development of rural areas and small service centers (agropolitan development). Urban economic growth declines together with both formal and informal sector employment opportunities, whereas rural employment is improving. This engenders a decrease of circular mobility and, potentially, also of permanent settlement. The latter impact, however, is often off-set by processes of improving rural education and rising overall levels of aspiration, as well as by the advance of agricultural commercialization, thus uprooting both the landless and small peasant-farmers.

2.3.3. Scenario C: increasing rural–urban inequality (maximum modern sector growth)

Maximization of economic growth through large-scale modern sector investments favors the formal sector in large cities at the expense of informal sector opportunities (which are often actively discriminated against by the urban authorities). Urban employment becomes largely inaccessible for unskilled rural workers due to a shrinking informal sector, the demolition of cheap housing and rising educational requirements for formal sector jobs. This engenders a strong decline of circular mobility from rural areas. Permanent settlement, however, might slightly increase due to the increasing rural–urban income difference and increasing urban attraction for skilled labor (from both rural areas and smaller towns).

Combination of the causal assumptions that form the basis for the three scenarios leads to the diagram of figure 2. Depending on the scenario different combinations of variables in the diagram are in effect. In the following section we will examine how the scenarios and diagram can be applied in a quantitative simulation model.

3. Quantification of scenarios

A quantitative description of the urbanization rate is desirable for the planning of the municipal water supply and the modeling of the potential impacts on the marine water quality. Therefore, the three urbanization scenarios must be quantified. We will examine two different techniques for this purpose.

3.1. Fuzzy set theory

In fuzzy set theory a partial truth value in the range [0, 1] can be assigned to variables. This is what distinguishes fuzzy set theory from conventional Boolean logic [16]. The main characteristics of fuzzy set theory are: the use of qualitative, linguistic instead of precise numerical variables, the description of simple relationships between these variables in terms of conditional statements (inference rules), and the characterization of complex relationships in terms of fuzzy algorithms [13]. The design of a fuzzy system comprises four steps, which will be discussed for the example at hand: the translation of the independent variables from the numerical to the fuzzy domain (fuzzification), the formulation of conditional inference rules, the application of these rules to determine the fuzzy output values, and the translation of the output to the numerical domain (defuzzification). The calculations were conducted with the Fuzzy Logic Toolbox provided by MathWorks®.

The number of possible inference rules increases rapidly with the number of variables and the number of fuzzy values distinguished for each variable. Therefore, we simplify the analysis by accounting only for the permanent settlement rate, and three variables which are considered to be of dominant influence on the permanent settlement: the growth rate of employment in the informal urban economy, the urban per capita income, and the circular mobility.

3.1.1. Quantitative range of the variables

Although the influence on the permanent settlement rate is described in qualitative terms, quantitative values are required for all the independent variables. The three scenarios differ in the assumptions made by the social scientists for the development of the independent variables over a period of 20 years. An identical initial situation is assumed for the three scenarios. Estimates for the initial values and the numerical range of the variables are based on the literature sources as much as possible. The selected range of the variable should allow for reasonable changes over the simulation period of 20 years. If necessary a symmetric interval around the initial value can be assumed.

Based on the 1995 statistics [21] an initial *per capita income* of 500 US$ per year is assumed. This value was assumed as the lower limit of the range. The upper limit of 2500 US$ was based on the extrapolation of the recent economic growth rate of $9\%\,\mathrm{yr}^{-1}$ over the 20 year period. The present growth rate of the total labor force of the city is roughly estimated to be $3.5\%\,\mathrm{yr}^{-1}$, of which 60% is absorbed by informal sector activities. Therefore, the initial *informal sector employment growth rate* is assumed to be $2\%\,\mathrm{yr}^{-1}$ and range between 0 and $4\%\,\mathrm{yr}^{-1}$. An in-depth study of migration [22] revealed that in 1985 the total labor mobility from three rural communities to the city of Ujung Pandang consisted of 39% permanent settlement and 61% non-permanent migration, including commuters. Based on this distribution and the estimated net yearly rate of permanent settlement in Ujung Pandang of 1.1% the *circular mo-*

bility should be 1.7% per year. However, a sample survey taken in Ujung Pandang during the same study showed that the share of non-permanent migrants among the newcomers was only 45%. This corresponds to a circular mobility of 0.9% yr^{-1}. Therefore, as a conservative estimate the initial circular mobility is assumed to be 1% yr^{-1}. The circular mobility was assumed to range between 0 and 2% yr^{-1}. As mentioned earlier, the initial *permanent settlement rate* is 1.1% yr^{-1}. The maximum urbanization rate of larger Indonesian cities during the period 1980–1990 was estimated to be 6% yr^{-1} [23]. Based on the natural growth rate of 1.8% yr^{-1} [7] the maximum rate of permanent settlement is estimated to be 4% yr^{-1}. Therefore, the permanent settlement rate is assumed to vary in the range between 0 and 4% yr^{-1}.

The assumptions made for the development of the independent variables for each scenario are chosen in qualitative agreement with the descriptions given in section 2. The per capita income in scenario A rises to 1500 US$ $\mathrm{cp}^{-1}\,\mathrm{yr}^{-1}$ over the period of 20 years, whereas the informal employment growth rate increases to 4%. The circular mobility increases to 2%. In scenario B the per capita income increases slightly to 750 US $ $\mathrm{cp}^{-1}\,\mathrm{yr}^{-1}$, whereas the informal sector employment growth rate and circular mobility remain 2 and 1%, respectively. In scenario C the per capita income increases up to 2500 US$ $\mathrm{cp}^{-1}\,\mathrm{yr}^{-1}$, while the informal employment growth rate and circular mobility decrease to 0%.

3.1.2. Fuzzification

The fuzzification of a variable requires a definition of the numerical domain X, the number of fuzzy values to be distinguished, and the choice of the membership functions. The mapping of a variable from the numerical domain X to the fuzzy domain is described by the membership function:

$$x\colon \to \mu_{\mathrm{F}}(x) \in [0, 1]. \tag{1}$$

The fuzzy set is defined by [13]:

$$F = \{(x, \mu_{\mathrm{F}}(x) \mid x \in X\}. \tag{2}$$

The membership functions and fuzzy sets for the three independent variables and the permanent settlement rate are shown in figures 3–6. Three fuzzy values are discerned for each variable. Gaussian membership functions are used for the independent variables whereas trapezoidal membership functions have been chosen for the permanent settlement rate.

3.1.3. Formulation of the inference rules

The next step was to formulate a set of conditional inference rules that reflect the mechanisms underlying the qualitative scenarios. The 27 possible combinations of fuzzy values for the three independent variables are listed in table 1. For each combination the expected impact on the permanent settlement rate is to be estimated. Different rules are in effect for each scenario depending on the dynamic conditions that prevail in the scenario. Not all the

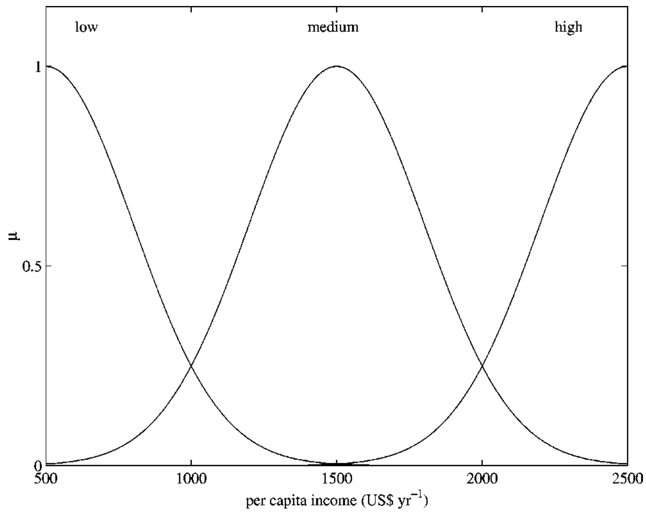

Figure 3. Membership functions for independent variable per capita income.

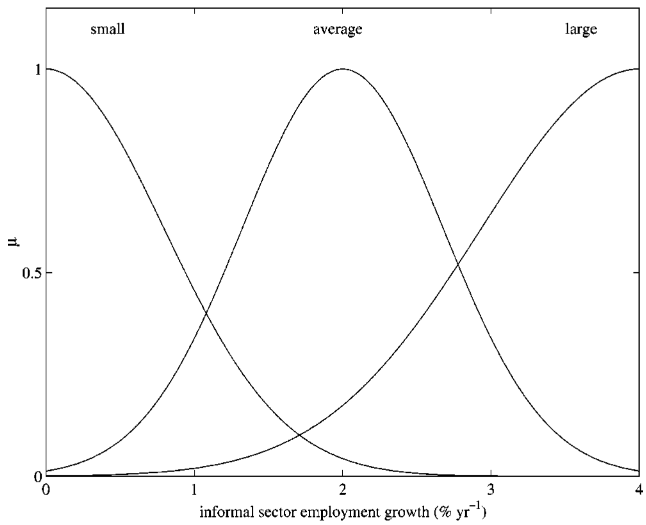

Figure 4. Membership functions for the growth rate of the informal sector employment.

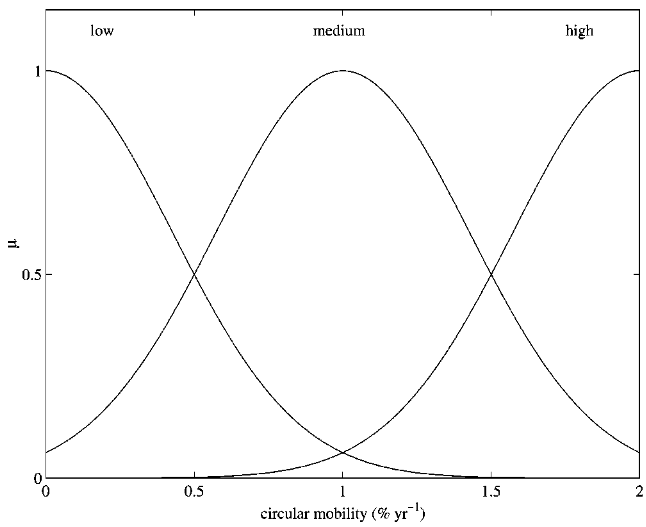

Figure 5. Membership functions for independent variable circular mobility.

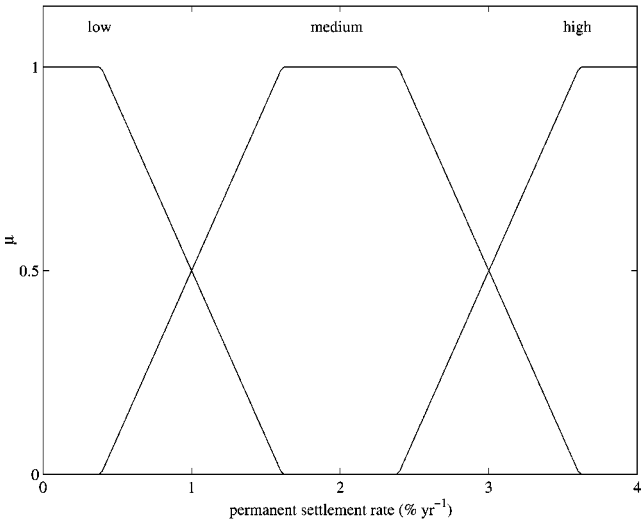

Figure 6. Membership functions for output variable permanent settlement rate.

Table 1
Inference rules for the permanent settlement rate as a result of urban income, employment growth and circular migration rate.

Rule	Urban per capita income	Informal sector employment growth rate	Circular mobility	Permanent settlement rate
1	low	small	low	low
2	low	small	medium	low
3	low	small	high	low
4	low	average	low	medium
5	low	average	medium	low
6	low	average	high	low
7	low	large	low	medium
8	low	large	medium	medium
9	low	large	high	low
10	medium	small	low	medium
11	medium	small	medium	low
12	medium	small	high	low
13	medium	average	low	medium
14	medium	average	medium	low
15	medium	average	high	low
16	medium	large	low	high
17	medium	large	medium	medium
18	medium	large	high	low
19	high	small	low	medium
20	high	small	medium	medium
21	high	small	high	low
22	high	average	low	high
23	high	average	medium	medium
24	high	average	high	low
25	high	large	low	high
26	high	large	medium	medium
27	high	large	high	low

27 inference rules can be derived from the three scenarios, as these correspond only to a subset of the total rule base.

A number of underlying social-economic *guiding principles* were formulated to facilitate the completion of the inference rule base and identify improbable combinations of variable values:

(a) The pull force exerted on the migrants primarily depends on the urban per capita income and the employment opportunities provided by the informal sector economy [23–30]. An explanation is that most rural migrants are poorly educated which confines them to informal sector jobs. Furthermore, the salaries obtained in the urban informal economy usually exceed the rural labor wages.

(b) A positive causal influence exists between the urban per capita income and the informal sector employment due to the growing circulation of currency and goods generated by the formal sector economy.

(c) The positive causal relationship between the per capita income and the informal sector employment changes into a negative one if the urban development reaches a point where the formal sector starts to interfere with the informal sector expansion. Usually this process is amplified by restrictions imposed on the informal sector by the authorities.

(d) The circular mobility tends to increase as the growing urban income and employment opportunities in the city occur simultaneously with a rise in the housing costs and improvement of the regional transport infrastructure.

(e) The circular mobility grows at the cost of permanent settlement as permanent settlement becomes either unnecessary or too expensive.

Now the rule matrix can be completed as follows. If both the urban per capita income and the growth rate of the informal sector employment attain a low value the permanent settlement rate must be low as well, in agreement with principle (a). This leads to rules 1, 2 and 3 (table 1). From principle (e) it follows that the permanent settlement rate must be low if the circular mobility is high, this leads to rules 6, 9, 12, 15, 18, 21, 24 and 27. The remaining rules can be derived by combining principle (a) and (e). For example, rule 4 corresponds to a low urban income and average informal sector employment growth rate. Based on principle (a) the permanent settlement rate for these conditions can only have the value low or medium. Furthermore, the circular mobility rate is low. Principle (e) then implies a medium permanent settlement rate. Similarly rule 5 can be derived, the only difference being that the circular mobility and permanent settlement rate have changed roles.

3.1.4. Application of the inference rules

The calculation of the value for the output variable migration for each combination of numerical values of the two independent variables is a matter of convention [31]. The approach followed here is referred to as Mamdani inference [32] and will be illustrated for an example. Consider inference rule 7 (table 1):

IF (urban per capita income is low) AND (employment growth rate is large) AND (circular mobility is low) THEN (permanent settlement rate is medium).

First the fuzzy value for the *rule antecedent*, which is the condition preceding the THEN statement, must be determined by calculating the corresponding membership functions. The AND operation is implemented by taking the minimum value of the membership values for the three independent values:

$$\mu_{\text{AND}} = \min[\mu_1(x_1), \mu_2(x_2), \mu_3(x_3)], \tag{3}$$

where μ_{AND} is the membership value for the rule antecedent and $\mu_2(x_2)$, for example, is the membership value for a large employment growth rate that corresponds to the numerical value x_2. Note that the result for μ_{AND} is a value in the numerical range [0,1].

3.1.5. Calculation of the output value

In the next step, the fuzzy value of the THEN part of the rule or the *rule consequent* must be determined. This is done by truncating the membership function for the fuzzy output value (medium permanent settlement rate in the case of rule seven) at the value μ_{AND}. The result is a new membership function $\mu_{\text{CONS}}(y)$ for the rule consequent, where y is the value for the permanent settlement rate in the numerical domain. This procedure is repeated for each inference rule, after which the results are aggregated to a single membership function by taking the maximum value of the membership values for the entire set of inference rules:

$$\mu_{\text{OUT}}(y) = \max\left[\mu^i_{\text{CONS}}(y)\right] \quad \forall\, y \in X;\ i = 1, \ldots, 27. \tag{4}$$

The result is a single membership function for the output variable which must now be translated from the fuzzy to the numerical domain (defuzzification) to allow for the integration in a quantitative simulation model. This defuzzification can take place in several ways. Here the migration rate corresponding to the centroid of the output membership function was used.

3.2. Cognitive maps

During team discussions both the specification of the range of variables and the restriction to a few variables posed a problem. For systems which are difficult to describe in terms of measurable, quantitative variables fuzzy cognitive maps may be useful. A fuzzy cognitive map (FCM) is a fuzzy directed causal graph with feedback [15,16]. The causal diagram of figure 2 forms an example of a fuzzy cognitive map for the migration to Ujung Pandang. In a fuzzy cognitive map complex systems are described in terms of a causal diagram consisting of causally linked variables or concepts C_i. The causal edges e_{ij} denote to what extent concept C_i causes concept C_j and take a value in the range [−1, +1]. Together the edges form a causal relation matrix, representing the FCM. Fuzzy cognitive maps provide a tool for quickly modeling complex dynamical feedback systems [33]. The FCM allows experts to draw causal diagrams of the problem at hand and qualitatively study the systems feedback behavior. The elements of the matrix corresponding to the cognitive map for urbanization are given in table 2. A value of −1, 0 or +1 indicates negative causal influence, no causal influence, or positive causal influence, respectively. If desirable, a larger number of different values for the edges can be distinguished. A column vector S consisting of the system variables or concepts describes the state of the system. The three scenarios differ in the assumptions made for the initial state (for example, urban economic growth is "on" or "off"). Starting with state $S(t)$ at time t the new state $S(t+1)$ is obtained by matrix multiplication:

$$S_i(t+1) = \sum_i A_{ij} S_j(t), \tag{5}$$

where A_{ij} represents the causal influence exerted by variable j on variable i. This procedure is repeated until an equilibrium state is obtained or the nature of the state change becomes clear [33]. If necessary, a policy intervention such as the restriction of informal sector activities can be enforced by keeping the corresponding concept value within a specific range [16]. The result is a state vector that consists of integer values for the circular and permanent settlement rate and other concepts. In principle these cannot be interpreted quantitatively. If necessary, quantification can take place by mapping the state concepts from the qualitative domain {−1, 0, 1} to the desired numerical domain of the output value in question.

Table 2
Cognitive map for migration. Only non-zero causal influences are shown.[a]

	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p
a																
b																
c										+						
d			+													
e	–			+												
f		+		+												
g														+		
h														+		
i																
j																
k			+													
l				+					+							
m				–	+											
n																
o					+		+	+		+	+		+		+	–
p						–					+	+			–	+

[a] Notation: a – intolerance with respect to the informal sector, b – demolition of cheap housing, c – urban economic growth, d – formal sector, e – informal sector, f – lack of cheap housing, g – rural social inequality, h – rural unemployment, i – rural education, j – transport infrastructure, k – rural–urban income difference, l – urban skilled employment, m – urban unskilled employment, n – agricultural commercialization, o – circular mobility, p – permanent settlement rate.

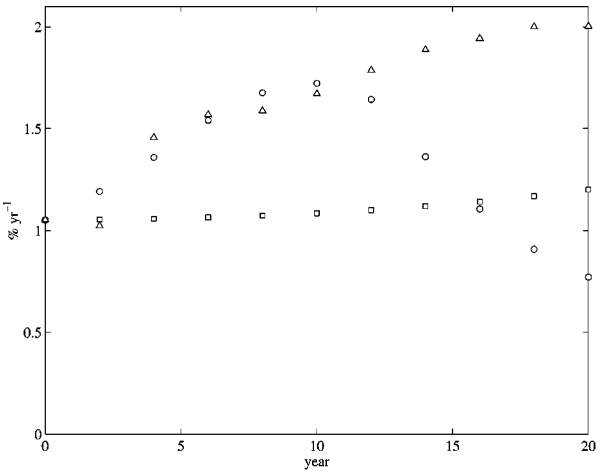

Figure 7. Permanent settlement rate over a period of 20 years for scenarios A (○), B (□) and C (△) based on the complete rule matrix with 27 inference rules.

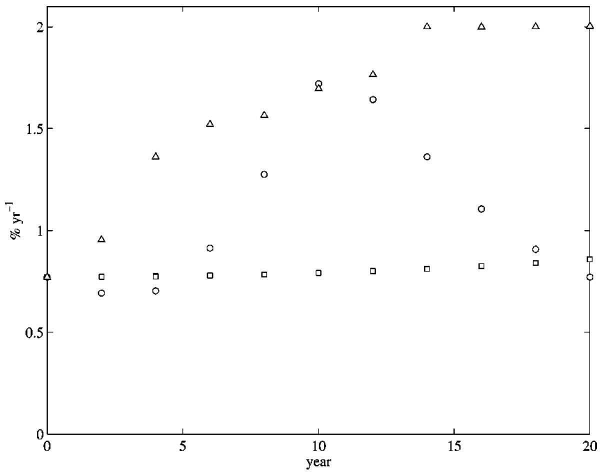

Figure 8. Permanent settlement rate (for scenarios A (○), B (□) and C (△)) obtained without rules 3, 7–12, 16, 21 and 25–27.

4. Results

4.1. Fuzzy set theory

Figure 7 shows the development of the permanent settlement rate over twenty years for the three scenarios. The developments described in the three scenarios are well reproduced, despite of the restriction to three independent variables. In scenario A the permanent settlement rate increases for 10 years and then starts to drop. Although this course of events is also described in the scenario it had not explicitly been included in the inference rule base. Its occurrence is easily understood. Initially the circular mobility and permanent settlement rate increase due the urban income growth and the development of the informal sector. The urban economic growth, however, also leads to an increase in the costs of living, which at a certain point reduces the permanent settlement in favor of circular migration and the result is a trend breach. Scenario B shows the consequences of government intervention in favor of rural development. Although the urban per capita income increases slightly the informal sector growth rate (not its size) remains at a constant, low level due to the restrictive policy, as does the circular mobility. Consequently the rate of permanent settlement in Ujung Pandang remains at its present level. Scenario C, finally, shows what may happen if the urban development takes place at an enhanced rate without government intervention.

The question arising is whether it is necessary to complete the full rule matrix because some of the inference rules represent conditions that are improbable from a social-economic perspective. Clearly some of the inference rules in table 1 are in contradiction with one or more of the guiding principles. Obsolete inference rules were identified on the basis of the guiding principles presented in section 3.1. The aim was to determine which minimal set of rules could still reproduce the results of figure 7 and represent the three scenarios. The reduction of the set of inference rules took place as follows. According to principle (a) a low urban income and informal employment growth rate must be accompanied by a low circular mobility rate. This is in contradiction with rule 3, which can therefore be discarded. For similar reasons rules 21 and 25 can be discarded. According to principle (a) and (d) a low informal sector employment growth cannot go together with high circular mobility and vice versa. This is in contradiction with rules 12, 16, 21 and 25. From principle (b) it follows that a low urban income cannot be accompanied by high informal sector growth. Therefore, rules 7, 8 and 9 must be rejected. Principle (b) also implies that a medium urban income and low informal sector growth are incompatible. This is contradicted by rules 10, 11 and 12. Finally, it follows from principle (c) that a high urban income cannot accompany a high informal sector employment growth rate (due to the modernization of the urban economy). Therefore, rules 25 to 27 can be discarded. Figure 8 shows the rate of permanent settlement obtained for the three scenarios with the remaining inference rules. The results agree well with those obtained with the complete rule matrix (figure 7).

Finally, we tried to identify a minimal subset of rules that could reproduce the three scenarios by comparing the quantitative values used for the independent variables with the membership functions (figures 3–6). For example, a per capita income of US$ 500 was assumed, which corresponds to the fuzzy value "low" according to figure 3. Furthermore, the informal sector employment growth rate and circular mobility in the initial situation correspond to the fuzzy values "average" and "medium", respectively. Based on the rule matrix one can conclude that rule 5 reflects the initial situation best. The trend breach of scenario A is best reflected by applying rules 17 and 18 consecutively. For scenario B, the sustainable development option, rule 5, remains in effect. The accelerated increase of the permanent settlement rate for scenario C corresponds to rules 13 and 19. Figure 9 shows the resulting migration rate if only the rules 5, 13, 17, 18 and 19 are included. Qualitatively, the results compare favorably with the migration rate obtained with the complete rule matrix.

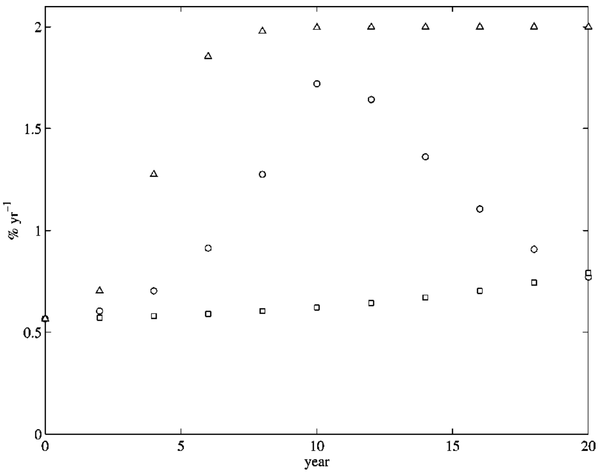

Figure 9. Permanent settlement rate (for scenarios A (○), B (☐) and C (△)) obtained with rules 5, 13, 17, 18 and 19 only.

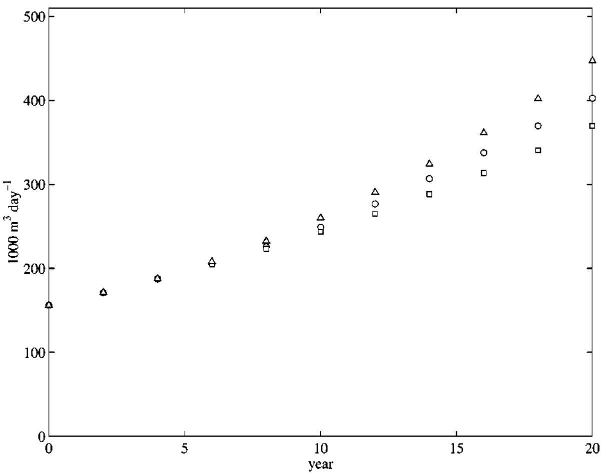

Figure 10. Long-term development of the domestic waste water discharge of Ujung Pandang for the three scenarios (A (○), B (☐) and C (△)) with the full rule matrix. The initial population size is one million capita with a natural population growth rate of 1.8% yr^{-1}. The per capita waste water production increases from 156 to 230 l cp^{-1} day^{-1}.

Although a reduced set of five inference rules could represent the scenarios it is preferable to maintain the complete set of rules for two reasons. First, it is not exactly clear beforehand which rules correspond best to the qualitative scenarios. Second, different assumptions for the independent variables may lead to model indeterminacy. A complete rule matrix is more robust under such changes.

A short description of the three urbanization scenarios and corresponding migration rate has been incorporated in the latest version of the RaMCo simulation model (figure 1). The user of the model can study the consequences for the urban drinking water demand and the discharge of waste water. Figure 10 shows the long-term development of the average daily waste-water discharge for the three migration scenarios obtained with the full set of inference rules. The calculation is based on an initial population size of one million inhabitants with a sustained natural population growth rate of 1.8% yr^{-1} [7]. The per capita daily waste-water discharge of unconnected households is expected to increase from 156 l cp^{-1} day^{-1} in 1992 to 230 l cp^{-1} day^{-1} in 2015 [7]. An indication of the influence of migration on the uncertainty in the future urban waste-water discharge can be obtained from figure 10. Clearly the waste-water discharge is not affected by migration in the mid- and long-term, the difference in treatment capacity required after 20 years between scenario C and scenario B being only 40.000 m^3 day^{-1}, about 10% of the average waste-water volume for the three scenarios.

Table 3
Normalized eigenstate e_1 with non-zero eigenvalue $\lambda_1 = 2$, initial state vectors A_i, B_i and C_i for the three urbanization scenarios and final states A_f, B_f and C_f after five iterations.

Concept	e_1	A_i	B_i	C_i	A_f	B_f	C_f
a	0	0	0	1	0	0	0
b	0	0	0	1	0	0	0
c	0	1	−1	1	0	0	0
d	0	0	0	0	0	0	0
e	0	0	0	0	0	0	0
f	0	0	0	0	0	0	0
g	0	0	0	0	0	0	0
h	0	0	−1	0	0	0	0
i	0	0	1	0	0	0	0
j	0	1	0	0	0	0	0
k	0	1	0	1	0	0	0
l	0	0	0	0	0	0	0
m	0	0	0	−1	0	0	0
n	0	0	1	0	0	0	0
o	$1/\sqrt{2}$	0	0	0	10	−5	−9
p	$-1/\sqrt{2}$	0	0	0	−9	5	9

4.2. Cognitive maps

The initial state vectors assumed for the three scenarios are given in table 3. The initial values for the state concepts were chosen in correspondence with the description given in the scenario. For example, in scenario A three processes that drive the described development can be discerned: macro-economic development, improved regional transport infrastructure, and the higher costs of living. Therefore, the concepts urban economic growth, transport infrastructure, and rural–urban income difference were given the value +1. Although the development of the formal and informal sector economy and pressure exerted on the housing facilities are also mentioned in scenario A these are the indirect consequences of the causal relationships listed in table 2. Therefore, the corresponding concepts were given the value zero for the state vector. A zero initial value was also given to the state concepts that were not mentioned at all in the scenario. The states obtained after five iterations and development of the concepts for the circular and permanent settlement rate are shown in tables 3–4. Qualitatively the results agree well with the three scenarios. A trend breach is again observed for scenario A: the permanent settlement rate first increases slightly and then drops as the circular migration takes over. In scenario B the permanent settlement rate increases less rapidly than is

Table 4
Change of the circular and permanent settlement rate for the three scenarios.

Circular migration rate	t_0	t_0+1	t_0+2	t_0+3	t_0+4	t_0+5
Scenario A	0	2	2	3	5	10
Scenario B	0	−1	0	−1	−3	−5
Scenario C	0	0	−1	−3	−4	−9
Permanent settlement rate						
Scenario A	0	1	0	−1	−4	−9
Scenario B	0	0	1	1	2	5
Scenario C	0	1	1	2	5	9

the case for scenario C, which is in agreement with the results shown in figure 7. The interesting thing is that the fuzzy cognitive map allows switching from one scenario to another by modifying the initial state. Changing the initial state vectors reveals that the state changes are sensitive for the assumptions made for the initial states. For example, the trend breach for scenario A disappears if the concept for "urban–rural income difference" in the initial state for scenario A is given the value 0 in stead of $+1$.

In principle equation (5) forms an eigenvalue problem. An eigenvalue $|\lambda| \leqslant 1$ would point to a stable state of the system. The matrix that corresponds to the cognitive map of table 2 has only two independent eigenstates, one of which has an eigenvalue $\lambda = 2$. The other eigenstate has a zero eigenvalue. The eigenstate with non-zero eigenvalue is shown in table 3. A more complex cognitive map with more causal relationships could result in more independent eigenstates and more different scenario outcomes.

5. Discussion

Based on a case example two approaches for the application of social-science scenarios in quantitative simulation models, fuzzy sets and fuzzy cognitive maps, have been examined. Although the two techniques are clearly different a comparison can be made of their usefulness for the integration of social-science concepts in a quantitative modeling framework.

As was pointed out by Tessem and Davidsen [14] fuzzy set theory can be a useful alternative for conventional methods to incorporate qualitative concepts in simulation models, such as the table functions provided in some simulation packages. Fuzzy set theory provides quantitative results that can be used directly in a simulation model. When fuzzy set theory is applied the contribution of the social scientists consists of the identification of the independent variables and realistic quantitative input scenarios, the formulation of qualitative scenarios for the influence of the independent variables on the variable of interest, and the formulation of the inference rules. The results clearly show the trend breach anticipated in scenario A, although the inference rule base in itself does not explicitly account for the sudden drop in the permanent settlement rate. In general models of social processes have characteristics in favor of the application of fuzzy set theory: qualitative expert knowledge, dependency of influence variables, non-linearity of system relationships, and the absence of adequate mathematical models. The combination of qualitative scenarios and fuzzy sets forms a particularly useful and elegant supplement to the tools for modeling integrated systems. The scenarios reflect the uncertainty present in complex social systems, whereas the fuzzification allows for the integration in a quantitative model framework.

The advantages of fuzzy cognitive maps have also come to the fore: implicit expert knowledge of complex social systems can be made explicit, feedback behavior becomes clear, no mathematical concepts are required except for simple matrix algebra, and the model can be as complex as desirable without complicating the calculations [33,34]. In case cognitive maps are used the contribution of the social scientists comprises the identification of the independent variables, the design of the causal relationship matrix, and the identification of the initial state vectors for each scenario. Although the outcomes can in principle only be interpreted qualitatively the trend breach for scenario A appeared here as well.

The obvious question arising is whether the migration scenarios cannot be obtained in a more straightforward way, for example by assuming different percentages for the migration rate. This would imply that the underlying social-economic mechanisms were to be largely ignored, however, with the loss of critical details such as the mentioned trend breach. In the past attempts have been made to follow a conventional mathematical approach to model social processes [9,11,12]. These simulation models suffer from the operationalization problem [11], which means that the model parameters are often not measurable, and calibration difficult or even impossible. Moreover, the presentation of quantitative results may provide a false sense of model precision and predictability. In contrast, fuzzy sets and fuzzy cognitive maps allow for a more elegant and adequate description of the complex relationships between key model variables and the influencing factors that exist in social systems.

A few potential obstacles that can be encountered during the analysis must be mentioned. Appropriate and unambiguous working definitions for the social-economic variables had to be formulated. The estimation of a quantitative range for the variables and the restriction to a small number of variables necessary for the fuzzy set approach may complicate the satisfactory representation of social science concepts. A lack of sufficient and reliable quantitative data can hinder the estimation of the default values and ranges of the model variables. In that case the application of cognitive maps may be more appropriate. The distinction between causes and effects or direct and indirect causal influences was not always immediately obvious, but could be clarified by means of the causal diagram of figure 2.

A number of methodological improvements are envisaged. For the fuzzy set approach the number of independent variables can be increased. So far only causal weights of value −1, 0 or +1 have been used in the fuzzy cognitive map. The use of weights in the complete range [−1, +1] allows for a more refined representation of the specified scenarios. The results indicate that the two methods can be applied to a variety of different problems. The choice between fuzzy sets and fuzzy cognitive maps should primarily be based on the degree of quantitative knowledge of the system to be described. In the near future our research will focus on the application of fuzzy sets and cognitive maps in different areas where social-science concepts are important, such as the fishing effort and rural land–use cover change. Our general conclusion is that both techniques are worth further examination and allow for a more direct involvement of the social sciences in the design of integrated assessment models.

Acknowledgements

This research has been funded by the Netherlands Foundation for the Advancement of Tropical Research (WOTRO) in the framework of research program W.01.60. The authors wish to thank C.B. Vreugdenhil and D.C.M. Augustijn for discussions on earlier manuscripts.

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