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Multiple Criteria Land Use Analysis

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Abstract

Since the early 1980's, the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA) have been collaborating on expanding FAO's Agro-Ecological Zones (AEZ) Methodology of land resources appraisal by incorporating decision support tools for optimizing the use of land resources. Initially these tools consisted in the application of linear optimization techniques for analyzing land-use scenarios with regard to single objective functions, such as maximizing agricultural production or minimizing the cost of production under specific physical environmental and socio-economic conditions and constraints. Often the specification of a single objective function does not adequately reflect the preferences of decision-makers, which are of a multi-objective nature in many practical problems dealing with resources. Multi-objective optimization approaches address problem definitions and solutions in a more realistic way and have recently been applied by FAO and IIASA in a land resources appraisal study in Kenya. In this study, multi-objective optimization coupled with multi-criteria decision analysis (MCDA) techniques, using the Aspiration–Reservation Based Decision Support (ARBDS) approach, have been used to analyze various land use scenarios, considering simultaneously several objectives such as maximizing revenues from crop and livestock production, maximizing district self-reliance in agricultural production, minimizing costs of production and environmental damages from erosion. The main users of the new tool being developed, which combines AEZ and MCDA, are expected to be natural resources analysts and managers, land-use planners, ecologists, environmentalists, economists at national and regional levels, and agricultural extensionists at the local scale.

Key terms: Agro-Ecological Zone (AEZ) methodology, Integrated Land Use planning and management, Geographic Information System (GIS), Decision Support System (DSS), Multi-Criteria Decision Analysis (MCDA), Aspiration–Reservation Based Decision Support (ARBDS), Linear Programming (LP).

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Introduction

In most developing countries, the socio-economic needs of rapidly increasing populations are the main driving force in the allocation of land resources to various kinds of uses, with food production as the primary land use. In Sub-Saharan Africa, in particular, the population may increase at the rate of 25 million people a year until it reaches 2 billion by the year 2050. This rate of increase will double food requirements in many countries [1]. Heavy population pressure and the related increased competition by different types of land users have emphasized the need for more effective land-use planning and policies. Rational and sustainable land use is an issue of great concern to governments and land users interested in preserving the land resources for the benefit of present and future populations.

Policy-makers and land users face two basic challenges: the need to reverse trends of land degradation in already cultivated areas by improving conditions and re-establishing their level of fertility; and to prevent the degradation of land resources in new development areas through appropriate and just allocation and use of these resources to maintain productivity and minimize soil erosion. In both cases an integrated approach to planning and management of land resources is a key factor in a solution which will ensure that land is allocated to uses providing the greatest sustainable benefit. This principle is anchored in Chapter 10 of UNCED Agenda 21.

As Task Manager for Chapter 10, FAO promotes the integrated planning and management of land resources in cooperation with regional institutions and individual countries as well as land users. Land use decisions should be based on comprehensive and quantified assessments of potentials and development possibilities of the land resources, taking into account the biophysical, environmental and socio-economic factors, as well as the space and time dimensions of sustained land use. Reaching a consensus on land use should be a main objective in the conceptualization of decision support systems (DSS) for sustainable land use. Feasible “real world” solutions are compromise solutions, resulting from trade-offs between various conflicting objectives, thus not maximizing single objectives, but finding an efficient and acceptable balance between the requirements of the *stakeholders in the land* and resources availability. Different kinds of objectives may need to be included, expressing not only economic values of land products but also addressing goals which can not always be expressed in monetary terms such as biodiversity, people’s preferences, equity, or minimizing risk and uncertainty. Decision making in land use also involves the consideration of a number of goals which can not be aggregated into a single criterion to be used as a performance measure for ranking alternatives. Usually models may have to be run a number of times in order to identify a "best", or even acceptable, solution. The elements of a solution are not fixed valued, but are variable or fuzzy within certain ranges determined by resources availability and socio-economic realities. Many options need to be examined to generate the information and knowledge required for these decisions and to quantify and display the trade-offs between conflicting objectives.

This entails the use of multi-criteria optimization techniques; it also requires the interaction of the various stakeholders in the elaboration of decision support systems in order to ensure the relevance and applicability of the systems and also to facilitate their dissemination, acceptance and use. Brinkman [2] has indicated a three-step approach to the conceptualization of DSS for land use as follows:

(1) identification of the degree to which the objective functions of the different actors in the land use allocation process overlap and the ways in which they contrast or may give rise to conflict;

(2) land use optimization on the basis of the various objective functions of the different actors and analysis of the extent to which the different optimization runs lead to similar land use patterns for the area; and

(3) development and application of interactive methods to maximize the extent of consensus in the adopted land use pattern.

The information produced in this process can then form a common basis and tool for arriving at a negotiated solution for any remaining differences. This paper is a revised version of the paper [3] presented at the *First International Conference on Multiple Objective Decision Support Systems for Land, Water and Environmental Management: Concepts, Approaches and Applications*, held 23–28 July 1995, in Honolulu, Hawaii.

Multiple Criteria Decision Analysis for Integrated Land Resources Planning and Management in the FAO

Concurrently with the rapid development of information technology in the last decade, FAO, with the collaboration of the International Institute for Applied Systems Analysis (IIASA), has upgraded its Agro-Ecological Zoning (AEZ) Methodology [4], for land resources appraisal which implements the land evaluation approach of FAO's framework for Land Evaluation [5] with DSS tools, including Geographic Information System (GIS) and Linear programming [6].

Linear programming techniques have been used in applying single-criterion optimization models to sets of AEZ/GIS outputs in order to examine alternative regional or district level land use patterns. Such models suggest feasible land use allocation patterns that best satisfy specified single development objectives, e.g., target food production levels, population supporting capacities or rural employment levels.

The traditional methods used to deal with de facto multiple criteria land use problems are based on the idea of converting a multi-criteria problem into a single-criterion one by summing up weighted criteria. This approach has a number of drawbacks as discussed in detail in [7] and [8]. Here only the two main arguments are summarized. First, such an approach does not allow for a user-controlled examination of interesting (for him/her) Pareto-optimal solutions[1]. Second, using weights can be counter-intuitive, as one can find examples in which for certain regions of the efficient frontier increasing the weight for a criterion does not lead to any improvement of the corresponding criterion value.

Currently the FAO AEZ/GIS package is being complemented with recent DSS tools developed at IIASA [9], [7], to deal with multiple criteria decision analysis (MCDA) problems. There is a number of different approaches to multiple criteria decision analysis (see [10] for a review). MCDA techniques are increasingly applied in different areas in agriculture: for instance, food security [11], livestock feed formulation [12], forest management [13], environmental management [14], water resources systems analysis [15], regional water quality management [16]. One of the most successful MCDA methods is the aspiration-led decision support (see [17] for a justification, [18] and [19] for a review). An extension of this method called Aspiration-Reservation Based Decision Support (further on referred to as ARBDS) has been applied to the case study reported in this paper.

The ARBDS Method

From the user's point of view, the critical step of MCDA is generating a part of the Pareto-optimal solution set. Generating the entire Pareto-set is practically impossible. Therefore, most MCDA methods facilitate generation of Pareto-solutions having certain properties. The kinds and combinations of properties are different for every method. The ARBDS uses the most natural way for linking the properties of the Pareto-optimal solutions with the preferences of the decision-maker expressed by aspiration and reservation levels set interactively by the user for each criterion. The ARBDS method provides tools for analyzing Pareto-optimal solutions and generating another set of Pareto-optimal solutions based on these results. Since aspirations are usually not attainable, the decision maker (DM) uses an interactive tool in order to adjust both aspiration and reservation levels until he/she finds a solution which best meets his/her expectations.

The ARBDS method, which has been implemented in the following example, is based on the concept of satisficing behavior (also called bounded rationality), in which the decision maker attempts first to improve the criterion which shows the worst performance [20], [21]). This method has a number of noteworthy advantages over other MCDA methods, as discussed in detail along with a more formal presentation of the ARBDS technique in [22] and [7].

Here we summarize the ARBDS method as a two-stage approach (a more detailed discussion can be found in [23]):

- First, a *core model* is specified and generated. The core model contains only a set of constraints that correspond to logical and physical relations between the variables used in the model. The list of variables in the core model should also include variables that represent potential criteria (goals, performance indices). In the preparatory stage a DM selects out of those variables a set of criteria that will be used for the analysis of the model, and specifies for each criterion its type. In addition to commonly used minimized or maximized criteria one can also use a goal type of criterion (which minimizes a deviation from a given value). There are also techniques that allow for representation of more complicated forms of criteria (like following a trajectory, minimization of a distance, etc.).

[1] Efficient, or Pareto-optimal, solutions are those for which an improvement in the value of one criterion cannot be attained without worsening the value of at least one other criterion.

After the selection of a set of criteria, the DSS performs automatically a series of optimizations in order to compute the *Utopia* point and an approximation of the *Nadir* point[2]. The preparatory stage is finished with computation of the so-called *compromise solution* which corresponds to a problem for which the aspiration and reservation levels are (automatically) set to the Utopia and an approximation[3] of the Nadir points, respectively.

- Second, during an interactive procedure a DM specifies goals and preferences, including values of criteria that he/she wants to achieve and to avoid. The vectors composed of those values are called *aspiration* and *reservation* levels, respectively. These are used to define component achievement functions which are used for selection of a Pareto optimal solution. This is achieved by generation of additional constraints and variables, which are added by the DSS to the *core model* thus forming an optimization problem, whose solution results in a Pareto solution that is nearest (in the sense of a measure defined by the aspiration and reservation levels) to the specified aspiration levels (or uniformly better than these levels, if they are attainable).

The structure of a DSS that provides the above outlined functions is illustrated in Figure 1. The DSS is composed of a number of modular and portable software tools that are characterized below with a brief description of their functions:

- A Graphical User Interface (GUI), which handles all the interaction with the user. GUI hides the differences between modules of the DSS from the user by providing a uniform way of interaction with all the components of the DSS.
- A problem-specific model generator for generating the core model which represents in the terms of mathematical programming the model for Sustainable Agricultural Development Planning. It is important to stress that the core model includes only physical and logical relations, and not the preferential structure of the DM. A more detailed discussion on core model specification is provided in [7].
- The SAP-tool (described in [23]) which supports specification of user preferences both in terms of aspiration/reservation levels and in terms of fuzzy sets. SAP also provides the user with other means of control over the problem analysis by allowing changing the criteria status, selection of displayed solutions, etc. In terms used in Figure 1 the SAP is used for the definition of *Aspirations*, *Reservations* and for changing the status of *Criteria*. However, the SAP provides more functions than can be outlined in Figure 1.
- The LP-Multi (see [7] for details), a modular tool for handling multiple criteria problems using the methodology outlined above. The resulting Linear Programming (LP) problem is based on the core model and the aspiration and reservation levels which represent the preference structure of a DM.
- HOPDM - a modular LP solver based on Interior Point method (see [25] for details). The solver does not require any interaction with the user.

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[2] Utopia and Nadir points (in the space of criteria) are vectors composed of best and worst values of the criteria in the efficient set.

[3] It can be shown (e.g., see [24]) that computation of a Nadir point for problems with more than two criteria may be very difficult. In our approach the Nadir point plays a minor informative role (it only bounds values of corresponding reservation levels). Therefore there is no justification for spending resources in order to get its better approximation. Hence, we assume as an approximation of Nadir the worst value (obtained during the analysis) of a corresponding criterion.

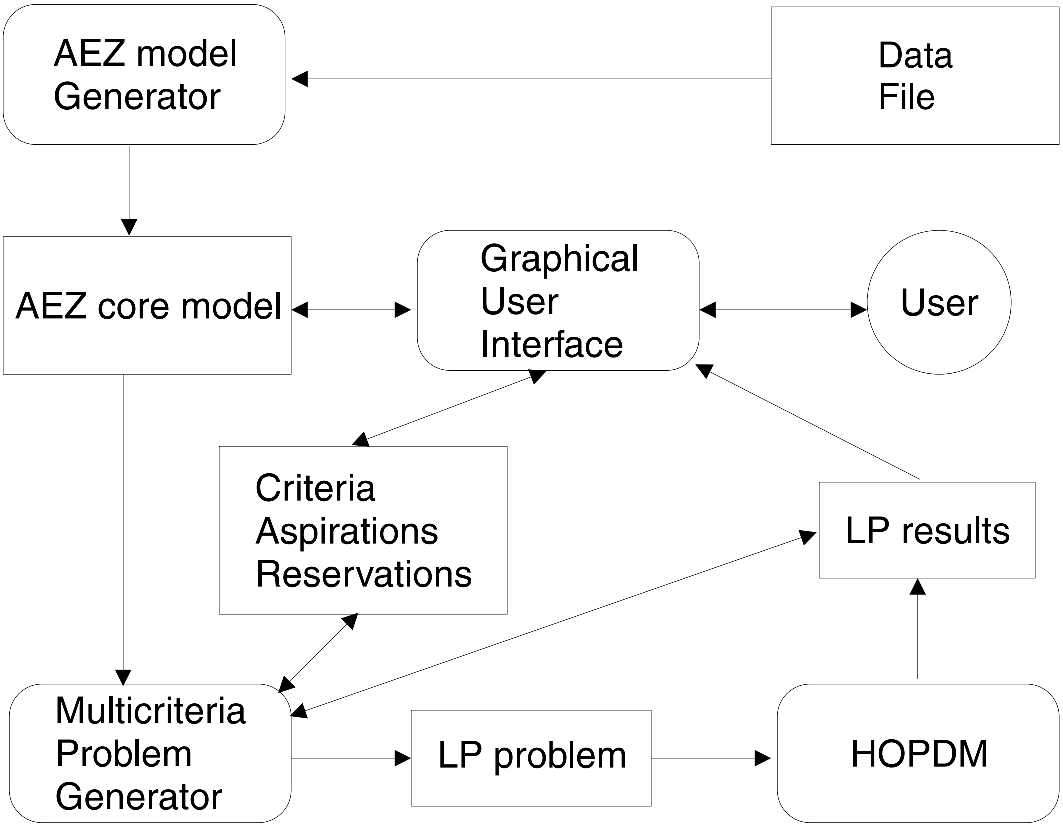

Figure 1. The structure of a Decision Support System for the Sustainable Agricultural Development Planning.

- A data interchange tool LP-DIT described in [9]. This tool provides an easy and efficient way for the definition and modification of LP and MIP problems, as well as the interchange of data between a problem generator, a solver, and software modules which serve for problem modification and solution analysis. LP-DIT is used for the definitions of the core model and the LP problems (the latter defined for each multiple-criterion problem), as well as for the optimization results.

We concentrate our discussion on presenting in more detail the interactive stage of the ARBDS outlined above. The interaction is handled by the SAP tool and can be summarized in the form of the following steps:

Step 1. The DM specifies new aspiration and reservation levels for all criteria. For each stabilized criterion (if any), the DM specifies a corresponding target (desired) value and aspiration and reservation levels for a deviation from the specified target value. Optionally, the DM can specify for each criterion his preferences in terms of fuzzy sets.

Step 2. The DM can change the status of each criterion. The default (originally defined in the preparatory stage) status can be changed to *stabilized*, or *inactive* or *disregarded*.

Step 3. The DM can analyze criteria values of the solutions computed so far (together with values of aspiration and reservation levels used for each solution).

Step 4. The DM may want to store a currently analyzed solution of the underlying LP or MIP problem for a more detailed analysis (which is typically problem specific).

Step 5. The DM can freely switch between the actions summarized above until he/she decides that his/her preferences are properly represented for the next optimization. Once the optimization is selected, the DSS takes over the control of the program flow. The DSS generates a single-criterion optimization problem whose solution is a Pareto-efficient solution which corresponds to the current preference structure of the DM (see below for details) and executes an appropriate solver, which computes such a solution. The DM regains the control of the program when the solution of the last specified problem is ready and added to the previously obtained solutions.

The steps described above are repeated in order to explore various Pareto-efficient solutions, until a satisfactory solution is found or until the user decides to discontinue the analysis. In either case the analysis can be continued from the last obtained solution at a later time.

All multiple-criteria optimization methods assume that a multi-objective problem is converted into an auxiliary parametric single-objective problem whose solution provides a Pareto-optimal point. The methodological background of the conversion is usually hidden from the user. However we present here its outline for those readers who are interested in the underlying methodology.

Different methods apply different conversions but all commonly known methods can be interpreted (see [7]) in the terms of an Achievement Scalarizing Function. This concept, which was introduced by Wierzbicki (see, e.g., [21], [26]) for the mathematical foundations, interpretations and applications), is very useful for comparing different approaches to multiple-criteria optimization (see [7] for a comparison).

The following form of the Achievement Scalarizing Function is implemented in the DSS reported here:

$$S(q,\ \bar{q},\ \underline{q}) \;=\; \min_{i \in I}\ u_i\ (q_i,\ \bar{q}_i,\ \underline{q}_i) \;+\; \varepsilon \sum_{i \in I} u_i\ (q_i,\ \bar{q}_i,\ \underline{q}_i) \;+\; \varepsilon \sum_{i \in \bar{I}} s_i\ q_i \tag{1}$$

where $\bar{q}_i$ and $\underline{q}_i$ are aspiration and reservation levels for the i-th criterion, I and $\bar{I}$ are sets of indices of active and inactive criteria, respectively, and the scaling coefficients s_i are defined by:

$$s_i \;=\; \frac{\mathrm{sign}(q_i^U - q_i^N)}{\max(1\ ,\ |q_i^U - q_i^N|)} \tag{2}$$

where $\mathrm{sign}(x)$ is a function that returns 1 for non-negative numbers and –1 otherwise.

Component achievement functions $u_i(\cdot)$ are strictly monotone (decreasing for minimized and increasing for maximized criteria, respectively) functions of the objective vector component q_i with values

$$u_i(q_i^U, \cdot\ ) \;=\; 1 + \bar{\beta}, \quad u_i(\bar{q}_i, \cdot\ ) \;=\; 1, \quad u_i(\underline{q}_i, \cdot\ ) \;=\; 0, \quad u_i(q_i^N, \cdot\ ) \;=\; -\bar{\eta} \tag{3}$$

where q_i^U and q_i^N are utopia and approximation of nadir values, respectively; $\bar{\beta}$ and $\bar{\eta}$, are given positive constants, typically equal to 0.1 and 10, respectively.

In order to allow for either specification of only aspiration and reservations levels or for additional specification of preferences (for the criteria values between aspiration and reservation levels) in terms of fuzzy sets the SAP supports specification of the component achievement functions in a more general form than discussed in [26]. Namely, the piece-wise linear functions u_i are defined by segments u_{ji}:

$$u_{ji} = \alpha_{ji} q_i + \beta_{ji}, \quad q_{ji} \le q_i \le q_{j+1,i} \quad j = 1, \ldots, p_i \tag{4}$$

where p_i is a number of segments that define u_{ji}. The coefficients defining the segments are defined indirectly by the user, who specifies aspiration and reservation levels and (optionally) also additional points between those levels (see [7] for details).

Making Land Use Choices in Kenya Districts

The following is an example of the application of the ARBDS method in a district land use case study in Kenya. The basis of this application is a set of GIS-based AEZ land resource inventories of individual districts in Kenya (see [27]). The AEZ land resource inventories combine digitized map overlays that relate to climatic conditions, soil inventory, administrative units and selected properties of present land use, i.e., cash crop zones, forest areas, irrigation schemes, Tsetse infestation and game parks. The digitized data were converted to a grid cell or raster database. Each grid cell represents one square kilometer (100 ha). AEZ computer programs are applied to the district land inventories to analyze land suitability and land productivity including cropping patterns, linkage to livestock and forestry production systems and soil erosion considerations. In this way a land productivity database is generated which contains quantified information on the productivity of all feasible land utilization types for each agro-ecological cell in the districts. The land productivity assessment involves 64 types of food and cash crops, pastures, 31 fuelwood species, and 10 livestock systems. These are grouped into 36 production commodities, including 26 crop and 10 livestock production commodities. This database provides the input to the ARBDS optimization model.

The Model

Bungoma district in Western province of Kenya is used in this example. The district is situated on the slopes and foothills of Mt. Elgon bordering Uganda (district code 801 on Figure 2). The district enjoys good agro-ecological conditions. Presently grown cereal crops include maize, wheat, barley and finger millet. The land productivity assessment shows a total arable land potential of about 200 thousand ha representing over 60 percent of the entire district. About one third of this area is of only marginal quality. There is good potential for cereals, beans and potatoes. In addition, cash crops such as coffee, tea, cotton, pyrethrum and sugar cane can be cultivated.

In the 1989 census, the recorded population in the Bungoma district amounted to 679 thousand people, of which some 525 thousand lived in rural areas. The population in Bungoma is projected to increase to 920 thousand in the year 2000, and to some 1150 thousand in the year 2010. In the past, the growing population density has led to increased fragmentation of holdings. Despite of generally favourable conditions the district is facing increased pressure on its resource base and as a result enhanced intensification of agricultural production will be required to secure future food supplies and adequate incomes.

The core model accepts user specifiable scenario parameters from a control file, reads crop, grassland and fuelwood production potentials by agro-ecological cells from the land

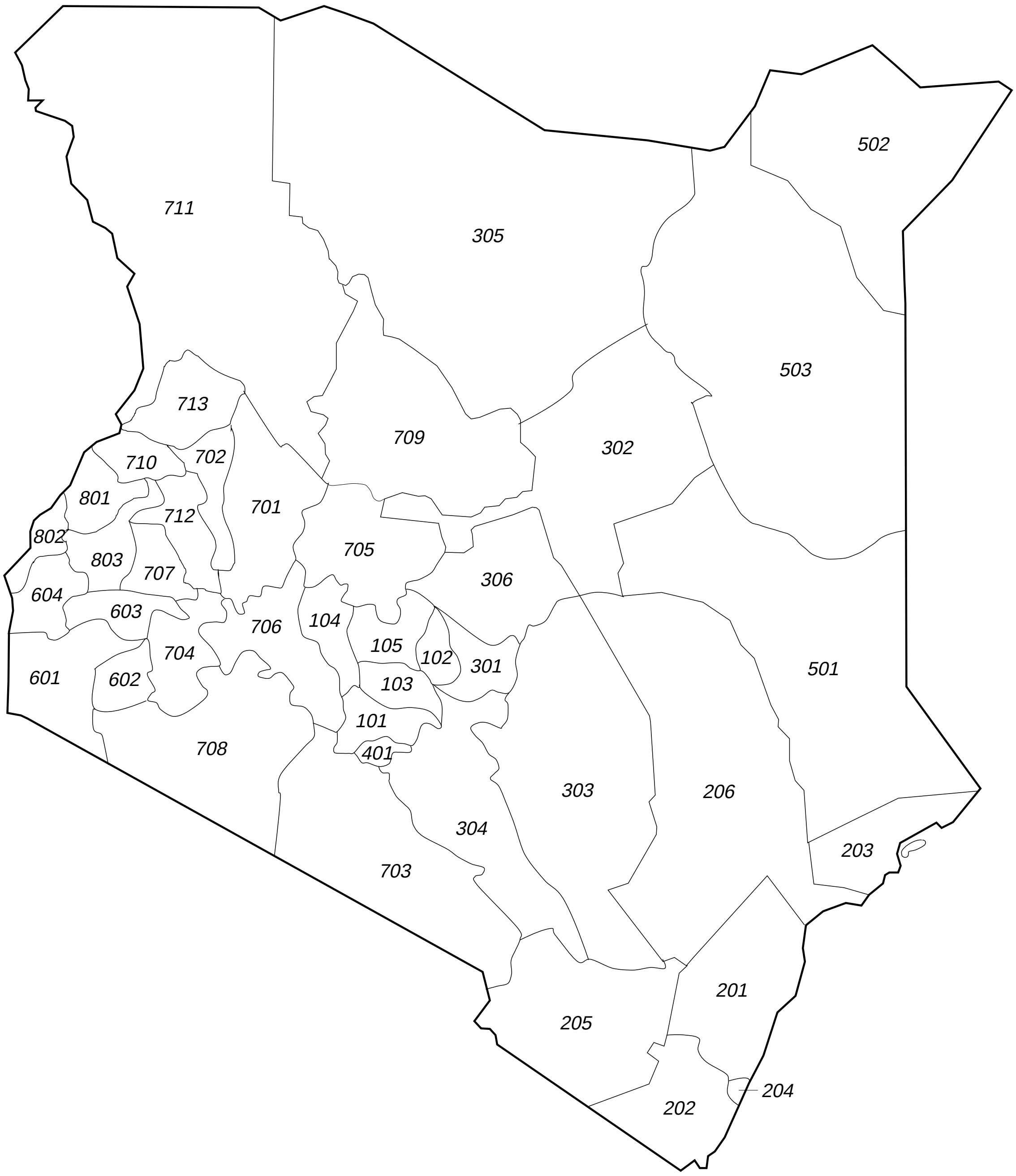

Figure 2. District map of Kenya.

productivity database, reads livestock system related data derived from herd structure models, and determines simultaneously land use by agro-ecological cell as well as supported levels of different livestock systems, feed supplies and utilization by livestock zone and season. The model provides a framework for specifying different types of objectives and kinds of constraints.

The main issue here is to analyze potential population supporting capacity of the district under various land use scenarios, considering simultaneously several objectives such as maximizing revenues from crop and livestock production, maximizing food output, maximizing district self-reliance in agricultural production, and minimizing environmental damages from erosion. Population supporting capacity, as defined here, relates the maximum potential of soil and climatic resources to produce food energy and protein, at a given level of technology. An intermediate level of input/technology is considered in this example (see also [28]).

The multiple objective program includes the following criterion functions:

1. maximize food output (weighted sum of food energy and protein available for human beings after conversion and processing into food commodities; criterion Food_avg);
2. maximize net revenue (criterion Net_rev);
3. minimize production costs (criterion Cost_min);
4. maximize gross value of output (criterion Tot_rev);
5. minimize arable land use (weight of 1 assigned to crops and fuelwood species and 0.1 to grassland; criterion Arable);
6. minimize area harvested (criterion Harvest);
7. maximize food output in bad years (as in 1, but evaluated for climatic conditions in bad years; criterion Food_min);
8. minimize total erosion (total soil loss over all land units; criterion Eros_tot);
9. maximize self-sufficiency ratio (minimum of the individual commodity group self-sufficiency ratios, i.e., target demand over production achieved; criterion SSR_v);
10. minimize erosion (largest soil loss per ha occurring in any used land unit; criterion Eros_max).

The core model is defined in terms of three groups of decision variables which, respectively, determine optimal land use, livestock numbers supported, and optimal allocation of feed supplies to different livestock systems:

(a) the land use shares, i.e., the share X_{kj} of agro-ecological cell *j* allocated to a cropping, grassland or fuelwood activity *k*;

(b) the number of animal units L_{sz} of livestock system *s* kept in zone *z*, and

(c) the feed ration f_{ihtsz} of feed item *h* from crop *i* allocated to livestock system *s* in period *t* in zone *z*. These variables form the columns of the constraint matrix, the core model activity set.

For example, the mathematical formulation of objective 7 (i.e., maximize level of self-sufficiency by commodity group) is:

$$\max_{X_{kj}, L_s, f_{ihts}} Z = \min_g \lambda_g \tag{5}$$

where λ_g represents the level of self-sufficiency in product group *g*.

The constraints that can be specified in the core model relate to preferred demand baskets, crop specific production targets, risk aversion, economic constraints, land use by individual crop and crop group, crop mix, input use, quality of human diet, environmental conditions, seasonal feed demand-supply balances, feed quality, and distribution of livestock systems.

The AEZ core model has been analyzed using the methodology and the DSS described above. The discussion presented here is based on results obtained for a subset of 7 (out of 10). Objectives listed above under 1, 2, 5, 7, 8, 9 and 10 have been selected.

Table 1: Results of ARBDS Analysis for Bungoma District.

Bungoma	Food_avg	Net_rev	Arable	Food_min	Eros_tot	SSR_v	Eros_max	SSR
Food_avg	1197.2	1082.6	165.4	969.7	3206.9	1204.0	112.8	96.3
Net_rev	931.1	1316.6	126.4	717.9	2622.1	1000.0	85.4	80.0
Arable	742.6	789.2	96.2	548.4	1875.3	1000.0	85.4	80.0
Food_min	1139.3	1071.2	161.1	1010.5	3256.5	1066.7	148.4	85.3
Eros_tot	773.0	792.5	105.8	598.6	1164.9	1000.0	29.1	80.0
SSR_v	905.6	1044.5	157.3	654.3	3527.0	1337.8	227.8	107.0
Eros_max	746.8	783.0	121.0	574.9	1837.6	1000.0	12.2	80.0
MCD-A	1027.1	1075.5	127.5	813.6	2232.1	1184.7	73.8	94.8
MCD-B	1091.1	1045.1	162.6	873.2	2986.6	1246.2	31.8	99.7
MCD-C	1075.0	1040.5	161.5	855.6	3082.6	1256.8	34.2	100.5
MCD-D	1084.6	1044.9	163.1	869.0	2949.9	1243.2	30.2	99.5
MCD-E	1077.0	1009.8	151.3	858.4	2559.2	1247.5	34.5	99.8

The results of an illustrative analysis for Bungoma district are given in Table 1. The first 7 rows of the table contain the criteria values obtained from solutions where each criterion is optimized separately in successive single-criterion optimization runs (step 1). The diagonal elements of the matrix represent the Utopia values for the 7 criteria (i.e. 1197.2, 1316.6, 96.2, 1010.5, 1164.9, 1337.8, 12.2). The Nadir values are found by taking the lowest values in the columns of the criteria to be maximized (i.e. Food_avg = 742.6, Net_rev = 783.0, Food_min = 548.4, SSR_v = 1000.0) and the highest values of the columns of the criteria to be minimized (i.e. Arable = 165.4, Eros_tot = 3527.0, Eros_max = 227.8).

The last five rows of Table 1 contain the criteria values resulting from a session of interactive multicriteria analysis involving 5 iterations (step 2). The user interacts with the software tool through successive screens displaying graphs of the criterion values and preferences, using mouse clicks to make the desired changes in values of decision variables (see Figure 3 for a screen sample).

Solution MCD-A represents the compromise solution automatically determined by the system on the basis of the Utopia point and an approximation of the Nadir point. By inspection, we conclude that solution MCD-A allows for too high soil losses in some land units (criterion Eros_max) and, perhaps, puts too much emphasis on minimizing arable land use (criterion Arable). Also, the level of district self-sufficiency in solution MCD-A is less than desired. We use the SAP tool to modify the aspiration and reservation level for these criteria and obtain

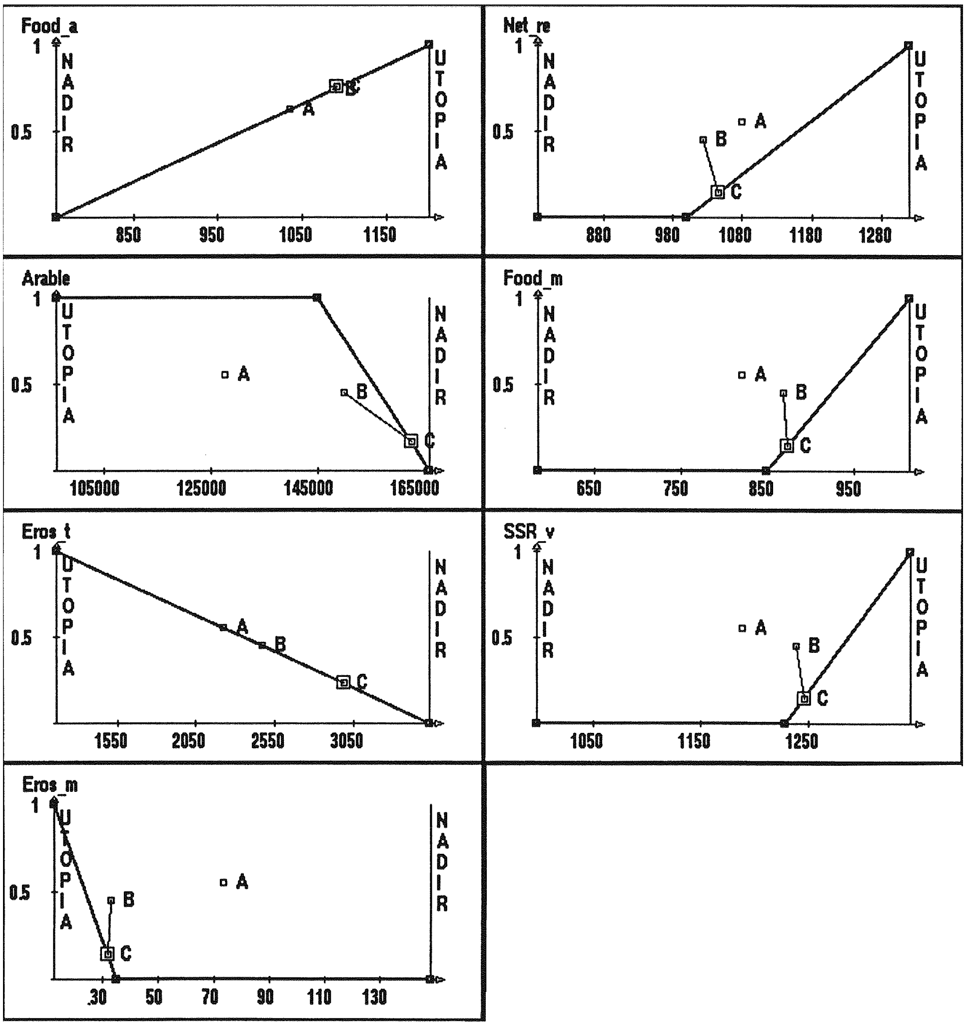

Figure 3. Sample screen display from SAP-tool [23].

solution MCD-B. We iteratively adapt the aspiration levels for different criteria and generate a sequence of Pareto-optimal solutions MCD-C to MCD-E. Generally the increase in arable land use required to achieve higher food production and self-sufficiency ratios leads to higher total erosion; food production, economic return and food security in terms of guaranteed minimum production in bad years and maximum erosion vary within narrow ranges and seem to stabilize. Table 2 contains the acreages of the various crop commodities involved in the production. Table 3 shows, for aggregated groups of commodities, including livestock products, the respective food supplies and commodity group self-sufficiency ratios.

Given that the solutions produce self-sufficiency rates for all aggregate commodities above the 80% minimum limit which was established for the scenarios, the MCD-C solution appears to be a good choice as it represents the relatively "best" optimal combination of values of the decision variables.

Table 2: Total Harvested Areas (ha) by Crop Commodity

Commodity	MCD-A	MCD-B	MCD-C	MCD-D	MCD-E
Barley	20043	18489	19026	17737	18683
Maize	73497	88369	89031	88124	89017
Oats	0	0	0	0	0
Rice	3623	6306	6314	6294	6040
Sorghum	2766	3776	3776	3776	3776
Wheat	0	59	163	136	64
Beans	32732	38113	37877	38515	37291
Pigeon pea	1876	1409	1552	1314	1566
Cassava	3527	5410	5291	5270	5319
Sweet potato	0	1847	2141	2151	2127
White potato	627	1823	2117	1776	1236
Banana	7774	10090	10204	10042	9987
Sugarcane	5831	17673	15833	18345	10522
Total	152296	193364	193327	193481	185629

Table 3: Food and Fuelwood Supplies (tonnes) and Self-sufficiency Ratios by Commodity Group

	MCDA		MCD-B		MCD-C		MCD-D		MCD-E	
Commodity	**Supply**	**%SSR**	**Supply**	**%SSR**	**Supply**	**%SSR**	**Supply**	**%SSR**	**Supply**	**%SSR**
Cereals	124871	95	131345	100	132458	101	131031	100	131487	100
Pulses	12308	95	12947	100	13057	101	12916	100	12961	100
Roots	46598	95	47996	100	48404	101	47882	100	48035	100
Sugar	16061	95	40311	238	35920	212	41756	246	24328	144
Bananas *)	43646	47	45910	50	46300	50	45801	50	45960	50
Fuelwood	43646	95	45910	100	46300	101	45800	100	45959	100
Meat	10126	95	10651	100	10742	101	10626	100	10663	100
Milk	109912	157	69691	100	70284	101	69525	100	69767	100
Eggs	873	95	918	100	926	101	916	100	919	100

*)Since banana represents the only fruit crop in the AEZ assessment contributing to this group commodity, the self-sufficiency requirement was relaxed.

Conclusion

As the above example illustrates linking multi-objective methods of optimization with GIS land resources databases provides a powerful DSS tool in land use decision-making support. “Hard” constraints and the sequential analysis of a set of single-criterion solutions, as is necessary in single-criterion optimization, are replaced by interactive specification of the decision makers’ preferences. Moreover, the simplicity and flexibility of the approach help the user, during the process of decision-making, to better understand the decision situation. The ARBDS approach is interactive and fast, so that the development of some dozen solutions does not require more than perhaps a few hours for an experienced user with a good understanding of the problem. The user does not need to be a person experienced in sensitivity analysis and scenario generation techniques which are necessary for the analysis based on the single-criterion approach. However, the detailed evaluation of a large number of solutions obtained in ARBDS can be more problematic and much more time-consuming than the evaluation of a much smaller number of solutions typically analyzed by single-criterion optimization. On the other hand, the analysis of a large number of solutions corresponding to different areas of the Pareto-efficient set provides a more complete understanding of the problem. Solutions which are close to each other, as obtained in the Bungoma case, can appear confusing at first to the decision maker. The SAP tool provides an option for analysing the history of solutions which eases the problem of selecting of solutions. However, this part of the interaction could benefit from further improvements. Many users also have difficulty evaluating more than 3 criteria visually and quickly. Special techniques are provided by SAP to facilitate an evaluation. This can be done by sequential selection of groups of criteria that are investigated more closely while the remaining criteria are either inactive (i.e., they do not enter the function (1)) or their values are stabilized around a desired (as selected for each criterion by the user) target value.

The ARBDS method can also be used for a more detailed model analysis in two ways that have not been applied so far in the case study reported in this paper. The first one is called soft simulation. This is an extension of the traditional simulation allowing to combine multi-criteria analysis with (soft) setting of values of selected variables. Secondly, ARBDS allows for treatment of a group of constraints as so-called soft constraints, i.e., constraints that can be violated up to a certain (interactively controlled by the user) bound. Both techniques are discussed in more detail in [7].

To avoid a possible misleading conclusion, namely that the usage of this DSS package may replace a real decision maker, it should be stressed that the system is designed to help a decision maker to concentrate on real decision making while the program takes care of the cumbersome computations involved in the analysis of scenarios and provides information that serves the analysis of the consequences of different options and alternatives. The user needs to define the various scenarios of interest, changing his/her preferences and priorities when learning interactively about the consequences of possible decisions. Röling [29] has explored the limitation of focusing exclusively on building scenarios on the basis of interactive MCDA, without paying attention to human decision-making in developing and applying those scenarios.

There are a number of constraints to overcome for the successful application of such DSS systems in land use decisions in developing countries. In many of these countries, lack of data and poor data quality remain serious drawbacks to the application of computer based systems of land resources management. Lack of trained personnel to apply the systems in solving practical problems is another constraint, which often causes the available systems to be underutilized and sometimes not to be used at all. In terms of computer technology there is the need to adapt the ARBDS software, which currently requires at least a powerful workstation to run, to the type of PC platforms generally in use in developing countries.

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