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An integrated intelligent geographic information-based decision support system

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In this paper the integration between geographic information systems, decision support systems, artificial neural networks and knowledge bases has been studied and a developed integrated system is presented. Integration of such tools into one set is highly desirable to achieve reliable decisions based on both mathematical and reasoning models since the nature of many problems require a number of different tools to solve or to draw conclusions. The developed system has been designed specifically for non Geographic Information Systems (GIS) users, and can be used by decision-makers, technical advisers, planners, and researchers. The system has been applied to study one of the major challenging decision making problems facing many countries which is sustainable land use assessment. The developed system has been validated against other available models, expert decisions and ground truth data where it showed a very high degree of agreement. Two case studies have been used to test the overall system performance, and generate different kinds of maps, reports and graphs from which in-depth data analysis was possible. The testing results showed that the system provided a powerful tool to support the user in multi-objective/multi-criteria decision-making process for the different alternatives of land use ranking and selection.

يتم فى هذا البحث تصميم وتنفيذ وتطبيق نظام دعم اتخاذ قرار ذكى متكامل بالمزج بين نظم المعلومات الجغرافية ونظم دعم اتخاذ القرار والشبكات العصبونية الإفتراضية وقواعد المعرفة وذلك بهدف الوصول إلى القرارات عالية الإعتمادية والتى تستنبط من كل من النماذج الرياضية والنماذج السببية حيث أن طبيعة عدد كبير من المشكلات تحتاج إلى عدد من الأدوات المتنوعة للوصول إلى الحل المناسب وقد روعى فى تصميم هذا النظام أن يمكن إستخدامه من قبل هؤلاء ذوى الخبرة المحدودة فى نظم المعلومات الجغرافية أو متخذى القرار أو الإستشاريين أو المخططين أو الباحثين فى المجالات التى تتطلب تكامل هذه الأدوات. وقد تم تطبيق هذا النظام فى أحد أهم الموضوعات الحيوية والتى تواجه العديد من الدول وهو تقييم التوظيف المستدام للأراضى وبخاصة فى المناطق المستصلحة حديثا وقد تم التيقن من كفاءة أداء هذا النظام بمقارنة النتائج التى تم الحصول عليها بتلك المتاحة من النماذج المتوافرة وكذا آراء الخبراء فى هذا المجال بالإضافة إلىالبيانات المتاحة من القياسات الأرضية وتم فى هذا الصدد إختيار حالتين للدراسة حيث أظهر النظام المصمم مقدرته على توفير الدراسات المستفيضة والتحليلية التى تمكن متخذى القرار من بحث جميع الإستراتيجيات المتاحة بكفاءة

Keywords: Intelligent decision support systems, Geographic information systems, Artificial neural networks

1. Introduction

A number of components and their inter-relationships have been studied in order to be able to integrate them altogether to perform the desired functions. The components are Decision Support Systems (DSS), Geographic Information Systems (GIS), Knowledge Base Systems (KBS) and Artificial Neural Networks (ANN).

Also the nature and importance of the application problem has been studied along with the available applicable models. The aim of that study was to decide on which components will fit onto the developed model and to what extent the output will give the desired results.

Two test cases have been studied using the developed system. The two areas are of potential economic value and a number of reclamation projects are planned for them.

1.1. Target system components

DSS are computer-based systems with the objective to enable a decision-maker to devise high quality solutions to what are often only partially formulated problems. A DSS is typically composed of three elements; the database; the model base, and the dialogue base. The database contains the main files of information used in models that are contained in model base. The model base comprises management scenarios and other mathematical models that are used to analyze data. The dialogue base (user interface) typically provides a user-friendly interactive front end to the DSS [1].

A Multiple Objective Decision Support System (MODSS) has been classified as a specific type of systems within the broad family of DSS [2]. The multi objective, multi criteria decision-making process is the most realistic and interesting in land evaluation [3]. It is also sought that integrating the knowledge components in the DSS conceptual framework will considerably increase the expertise embedded in DSS and will improve the capacity for users to enhance this expertise [4].

GIS, which allow for the acquisition, storage, manipulation, analysis, visualization, dissemination of geospatial information are therefore of prime interest to society at large. This implicit definition of a GIS follows the well-known IMAP (Input, Management, Analysis, Presentation) model, but adds the aspect of dissemination of information, because the latter has become a major focus of research, development, and economic activity [5]. The distinct contribution of GIS to decision making lies in the ability of these systems to store and manipulate data based on its spatial location where spatial data is of great importance in a wide range of government and business activities [6]. Promisingly, there are many strategies for coupling GIS with models. Fedra [7] discussed the types of coupling that could be sought between environmental models and GIS, and classified such integration as loose, close, and tight coupling with GIS software.

Spatial Decision Support Systems (SDSS's) are becoming important tools for planning and decision making for environmental management. The SDSS has to combine spatially explicit observational data and simulation of physical processes with a representation that is suited for communication with non-specialists and/or decision-makers. Model based simulation systems provide the mean for scientific analysis of decision scenarios [8]. The most important capability of GIS is to interpret and map data for solving spatial problems. One of the approaches for the analysis of spatial data has focused on artificial intelligence techniques such as knowledge-based systems with GIS [9].

Knowledge must be represented in such a way that allows us to relate facts in a formal representation scheme to facts in the real world. Rule-based systems allow knowledge to be represented as a set of IF-THEN or condition-action rules. Reasoning can be controlled using a forward or backward chaining interpreter [10].

Artificial Neural Networks (ANNs) are simplified models of the central nervous system. A neural network consists of many simple processing units (or neurons) connected together. The behavior of each neuron is very simple, but together a properly connected network of neurons can have sophisticated behavior and be used for complex tasks [10]. They are networks of highly interconnected neural computing elements that have the ability to respond to input stimuli and to learn to adapt to the environment. It is believed by many researchers that neural network models offer the most promising unified approach to building truly intelligent computer systems. ANNs have been shown to be effective as computational processors for various tasks including pattern recognition, classification, data compression, modeling, forecasting, adaptive control, and noise filtering [11]. Neural networks provide a rather different approach to reasoning and learning.

The integration of knowledge base components and neural networks in a system can be explored from their functional and structural relationships in the system. Five integration architectures can be identified as follows [12]:

- *Completely overlapped:* In this architecture, the system has a dual nature. The system optimizes its performance by combining the strengths of the two forms. Depending of the need, it can be presented to the user as a traditional expert system or as a neural network. One form can be converted to the other through inherent translation mechanisms, therefore; only one form needs to be stored.

- *Partially overlapped:* The system exhibits features of both. The two components share some but not all of their own internal variables or data structures. They often communicate through computer internal memory rather than external data files. An expert network augmented with explanation capability is a partially overlapped system.
- *Parallel:* The system works in parallel to solve a common problem. Both can be standalone systems. The two components do not share their own internal variables or data structures. They communicate through their input/output devices, such as data files.
- *Sequential:* A knowledge-based system and neural network operate in sequence to solve a particular problem. Again, both can be stand-alone systems, and they do not share internal variables. The output of one component is passed on to the other for further processing.
- *Embedded:* In this integration, either a knowledge-based component is embedded within a neural network or vice versa. However, this architecture differs from the partially overlapped architecture in that the system's external features are determined by the host component only. It is arguable that many neural networks already use knowledge in specifying their input/output and structures.

1.2. Land use assessment modeling

Land use planning is the systematic assessment of land and water potential alternative uses, along with the economic and social conditions, in order to select and adopt the best land use options. Its purpose is to select and put into practice those land uses that will best meet the needs of the people while safeguarding resources for the future. Land use planning helps decision-makers in such a way that current problems are reduced and specific social, economic and environmental goals are satisfied [13].

Yeh and Li [14] tested different development scenarios and land consumption parameters, and concluded that planners and government officials can use GIS sustainable land development model as a DSS in areas in the world that are under great pressure of rapid urban growth. The model would be able to suggest areas where future urban development should take place.

Automated Land Evaluation System (ALES) is an empty shell, that is, a framework within which land evaluators are free to generate different models and develop database. This program has a framework where proposed land uses can be described and evaluated in both physical and economic formats. It matches the knowledge base describing the proposed land use and the database where land units are described. ALES does not have any geo-referencing capability, cannot produce maps, and cannot take into account spatial analysis requirements [15].

The MicroLEIS (Microcomputer Land Evaluation Information System) was developed to assist specific types of decision-making faced with specific agro-ecological problem in the Mediterranean region. It has been designed as a knowledge-based approach which incorporates a set of information tools. Each of these tools is directly linked to another, and custom applications can be carried out on wide range of problems related to land productivity and land degradation [16].

Parametric Land Evaluation System (PLES-ARID) is a mathematical model constructed to calculate the land productivity and land suitability. It was designed to simplify and facilitate data processing for users [17].

Agriculture Land Evaluation System for Arid region (ALES-Arid) was designed to estimate land capability and land suitability evaluation, based on the minimum data set concept. The GIS software can read the output for visualization of land capability and suitability maps. This approach is considered as loose coupling with GIS software [18].

2. System design and implementation

The developed system integrates the functionality of geographic Information Systems with Knowledge Base and Decision Support System as described below. The system is composed of the following main components fig. 1:
1. Digital map; 2. Mapping object; 3. Internal database; 4. External database; 5. Knowledge base; 6. Model base; 7. Report generator; 8. Graph generator; 9. Map generator; and 10. User interface.

2.1. System main components

The digital map utilizes the shapefile format developed by ESRI [19] to load, view and query the map. Mapping object is used to provide the most common GIS functions [20]. The system has been designed to include eight GIS functions necessary for GIS users, namely, display a map; zoom and pan throughout a map; identify features; select features based on SQL expressions; label map's features with text; copy and paste maps; virtual database join, and map printing. The Internal database contains the constant parameters that are used for the model base. It contains seven tables to store the neural network models connection weights, in addition to a table to store the constant parameters of the crop water requirements model (crop type, crop index, crop growing period, and crop coefficient value). External database is an MS-Access database file format created inside the project directory to store the input and output data. Fig. 2 shows the external database tables with their inter-relationships.

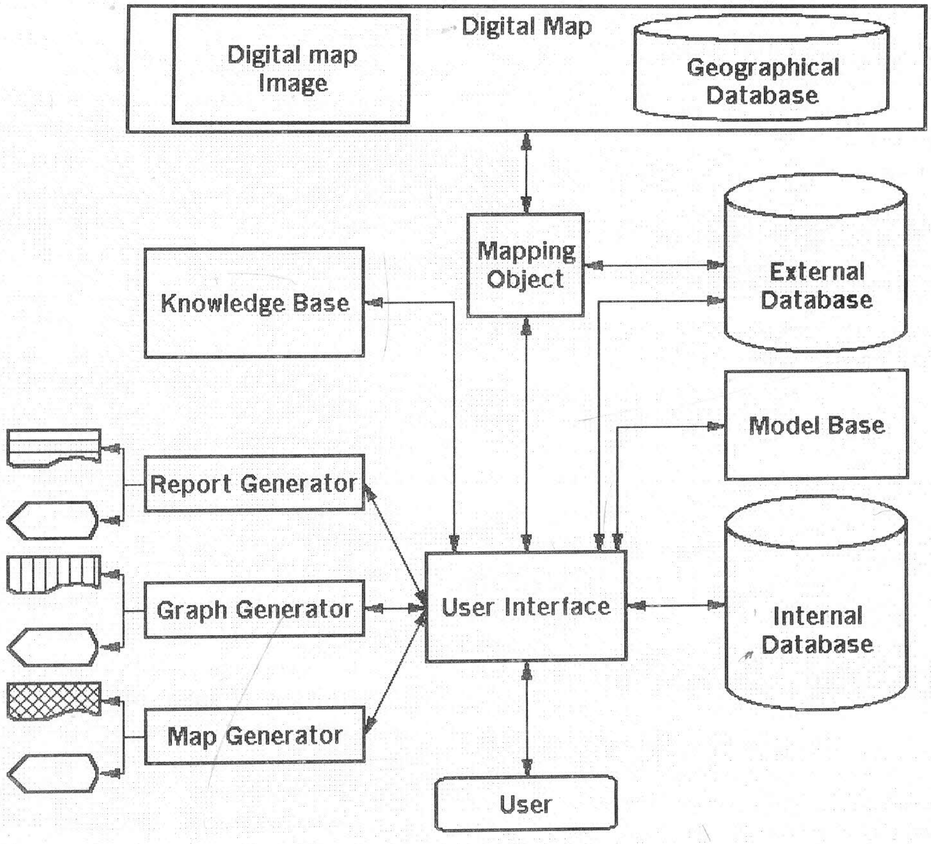


Fig. 1. System architecture.

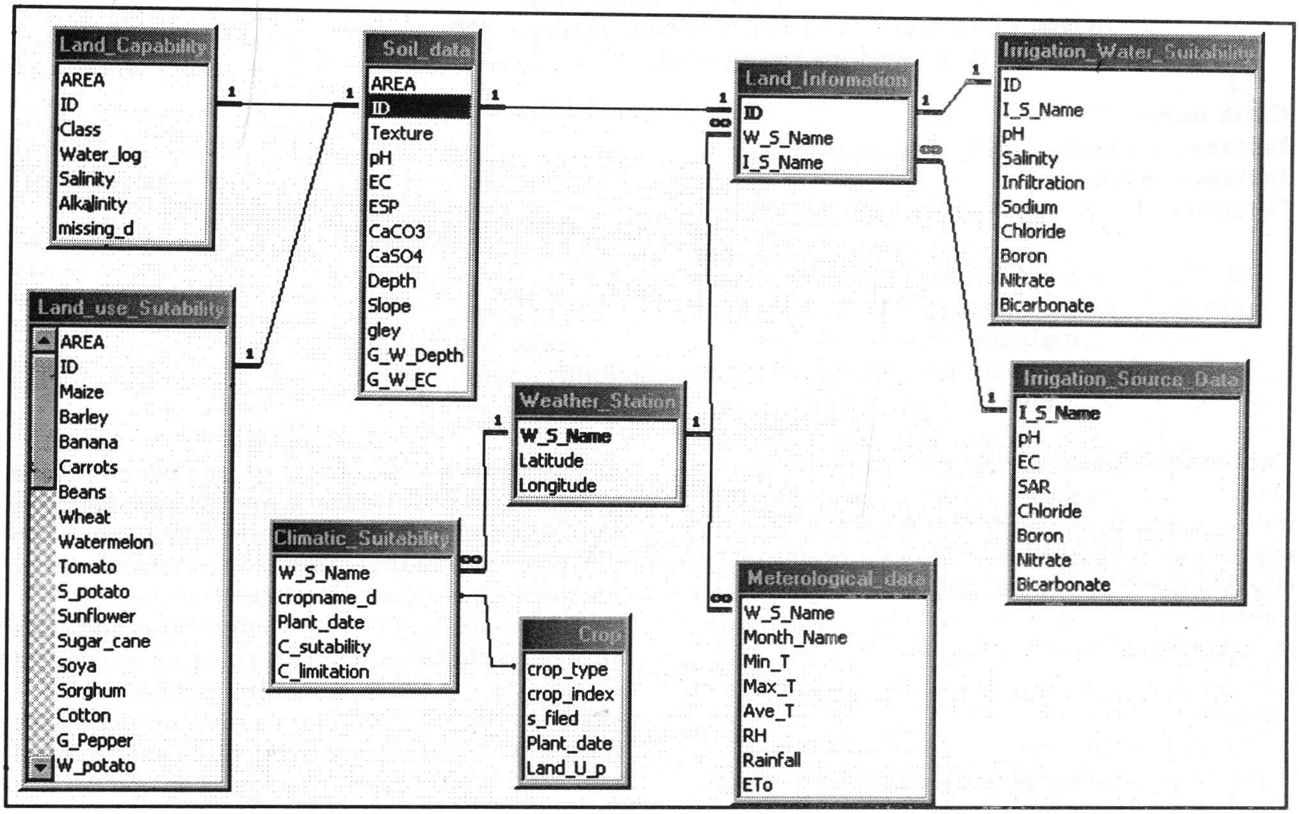


Fig. 2. External database tables and their relationship.

Twenty-two land use types (crops) were selected based on Sys et al. [21], taking into consideration the regional experience in the form of production rules to simulate the FAO land suitability classification framework [22] and maximum limitation method, for estimating the suitability class according to the land characteristics for each land use type.

The Knowledge base has been formalized in an object-oriented manner so that, to represent knowledge, the classes, instance variables and instance methods of each class have been defined. The production rules are organized into five groups, namely, land capability classes; environment limitations; land suitability classes; climate according to the metrological data; and irrigation water suitability classes.

As an example, based on the decision process of land capability classification, the following ratings of land characteristics have to be made during the process, namely: soil texture, depth, calcium carbonate status, gypsum status, salinity/alkalinity, drainage and slope ratings.

Rules for each step are treated, and defined as instance methods for the relevant class. Land capability index is determined using the model base. The definition of instance methods with two examples, namely, "Gypsum_rating" and "Capability_class" are as shown below:

Class name: Gypsum_rating
Instance variable: Soil_Gypsum_rating
Instance methods:

```
Determine_Soil_Gypsum_rating( )
    {
       if (Gypsum >= 50) Soil_Gypsum_rating = 30;
       elseif (Gypsum > 25) Soil_Gypsum_rating = 60;
```

```
        elseif (Gypsum > 10 ) Soil_Gypsum_rating = 85;
            elseif ( Gypsum > 0.3 ) Soil_Gypsum_rating = 100;
                else Soil_Gypsum_rating = 90;
    }
```

Class name: Capability_class
Instance variable: Land_capability_class
Instance methods:

```
Determine_Land_capability_class (Capability_index)
   {
    if ( Capability_index > 80 ) Land_capability_class = I;
    elseif ( Capability_index > 60 ) Land_capability_class = II;
        elseif ( Capability_index > 45 ) Land_capability_class = III;
            elseif ( Capability_index > 30 ) Land_capability_class = IV;
                    else Land_capability_class = V;
   }
```

The model base is used to allow users to obtain information about land capability index, crop water requirements, the leaching requirements and land use suitability. The model base subsystem contains four models, namely, land capability [23]; crop water requirements [24]; leaching requirements [25]; and land suitability using artificial neural networks.

In this study each land characteristic is fitted to a neural network structure. Generalized Regression Neural Network (GRNN) and Back Propagation Neural network (BPNN) models have been both studied for possible application. The number of hidden nodes in the BPNN model depends on the complexity of the underlying problem and this has been determined empirically by training the model with different number of hidden nodes. In addition, different combinations of the learning rate (η) and the momentum term (β) were also tried out and the structures that yielded the smallest errors were adopted. For the GRNN model, the number of pattern nodes corresponds to the number of the data samples in the training set. Different values for the smoothing parameter (σ) have been also tried. Table 1 shows the adopted ANN structures along with the learning parameters and training parameters for different land characteristics.

Using rule-based knowledge base alone in land evaluation domain is very difficult to develop because it requires the formulation of a large number of rules (e.g. 924 land suitability rules: 7 Land characteristics x 6 land suitability classes x 22 crops). It has been decided to couple neural network and knowledge base components in a single hybrid subsystem with the goal of building architectures that confer the benefits of both of them (see fig. 3). The land use suitability knowledge base contains only carefully selected 128 rules as suggested by experts. The land use suitability knowledge base tests if it can determine the land use suitability classes from the land characteristics and determine the overall land use suitability class, which will be stored as results in the external database. Otherwise, a message containing the land characteristics and the land use index will be sent to the neural network model to determine the land use suitability class for each land characteristic. The output of the model, will be sent to the overall land suitability class knowledge base to determine the land use suitability class, and will be stored in the external database to support the decision making process. The neural network connection weights are obtained from the internal database.

The report generator was designed to represent a powerful and flexible reporting tool, that enables the user to preview, print, or export the report as a file directly to disk. The Graph generator is used to create graphs to enable the user to preview, print or save the charts. The Map generator represents the visualization technique for results presentation. Fig. 4 illustrates the main components of the graph generator.

Table 1
Neural network model architecture, learning parameters and training performance for different land characteristics

Land charac-teristic	Training data			N.W. model	Network archi-tecture*	Training parameters†			Classification		CCR§ %
	#	Min	Max			η	β	σ	correct	incor-rect	
Slope	222	0	25	BPNN	2-38-1	0.5	0.5	-	175	47	78.8
				GRNN	2-222-2-1	-	-	.001	222	0	100
Texture / structure	462	Very fine clay	Coarse sand	BPNN	2-36-1	0.6	0.5	-	317	145	68.8
				GRNN	2-462-2-1	-	-	.001	462	0	100
Soil depth	206	0	200	BPNN	2-38-1	0.5	0.3	-	103	103	50
				GRNN	2-206-2-1	-	-	.001	206	0	100
Calcium carbonate	297	0	75	BPNN	2-24-1	0.9	0.1	-	196	101	66
				GRNN	2-297-2-1	-	-	.001	297	0	100
Gypsum	191	0	25	BPNN	2-28-1	0.9	0.6	-	125	66	65.4
				GRNN	2-191-2-1	-	-	.001	191	0	100
Salinity	207	0	25	BPNN	2-33-1	0.8	0.1	-	112	95	54.1
				GRNN	2-207-2-1	-	-	.001	207	0	100
Alkalinity	241	0	50	BPNN	2-36-1	0.6	0.7	-	169	72	70.1
				GRNN	2-241-2-1	-	-	.001	241	0	100

*Network architecture: (BPNN: input nodes – hidden nodes – output nodes)
(GRNN: input nodes – pattern nodes – summation nodes – output nodes)
†Training parameters are (η) learning rate (β) momentum term and (σ) smoothing constant.
§ CCR: Correct Classification Rate

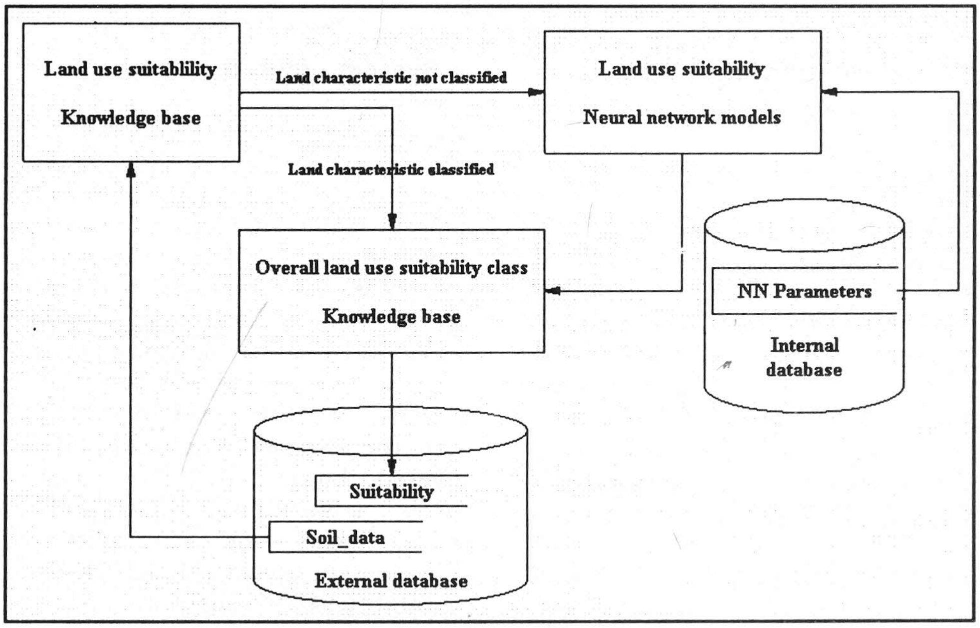


Fig. 3. Coupling neural network models with knowledge base component.

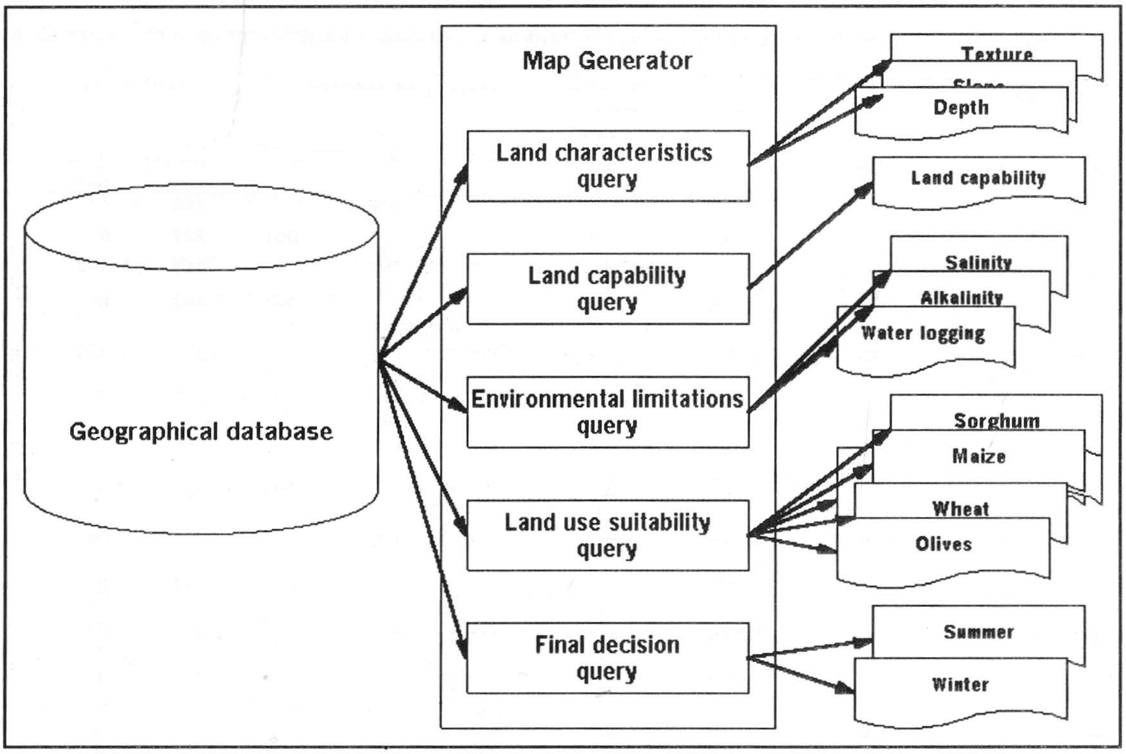


Fig. 4. The types of maps produced by the system.

ıe User interface serves to integrate various ıbsystems as well as to interact with the ser. The button bar contains the necessary nctions to open new projects, open saved ojects or print map functions. It also contains a buttons for zoom-in and zoom-out, full tent, identify, select, and pan map functions.

2. Case studies

The system was tested using two well cumented case studies, yielding different nds of maps, reports and graphs from which -depth data analysis was possible. The digil maps and all the related information and ta are obtained from Yahia [26] for the ıgar Beet area, while the other was obtained om Bahnassy et al. [27] for Fuka-Matrouh ea, Egypt. The Sugar Beet area is located at km southwest of Alexandria city and its ea is about 113,750 feddans and lays proximately between latitudes 30° 45" and ° 55" N and longitudes 29° 30" and 29° 50" Fukah-Matrouh area is located to the west of Matrouh city and lays between latitudes 30° 56" and 31° 35" N and longitudes 27° 25" and 27° 55" E. It is estimated according to Bahnassy et al. [27] to have an area of 2834.55 km^2.

3. System validation

3.1. Knowledge base validation

To evaluate the rule base correctness, the experts provided a set of trial cases (input / expected output). Then, the system used these trial cases as input and the results produced by the system have been compared with the expected outputs initially provided by the experts. The results showed that the accuracy of the rule base reached 100% as compared with the experts' knowledge. The experiment covered land capability classification (643 cases), environment limitation hazard (160 cases), land use suitability (250 cases), climatic suitability (1210 cases), and water suitability (450 cases).

3.2. Crop water requirement model validation

To test the developed crop water requirement model accuracy, the results obtained from the model were compared with those obtained from CropWat model version 4.3.0013 [28] for the same data input. The correlation coefficient for the results obtained from the model and that obtained from CropWat program gave **0.998**.

3.3. Neural network models validation

To examine the ability of the neural network models to predict land suitability classes from land characteristic value for different land uses, they have been tested with a large number of data. The source of the testing datasets was based on the range values for each land characteristic [21]. Each range of the land characteristics (slope, soil depth, calcium carbonate, gypsum, salinity and alkalinity) for the twenty-two land use types was divided into steps of 0.01 according to its lower and upper limits. This has been done to increase the number of testing data elements with that range and to represent values comparable to that of the real world. Table 2 shows neural network testing performance for predicting suitability classes corresponding to land characteristic. The correct classification rate (CCR) [29] of BPNN model ranged from 44.9% to 94.3%; while the GRNN model has a CCR of 100% for all land characteristics and land uses. It has been concluded that the GRNN is more reliable than the BPNN model for predicting the land suitability class at the neural network-testing phase.

4. System application

4.1. Spatial data input

Digital maps have been prepared as inputs for the system in ESRI's shapefile format. The number of polygons is 57 and 213 for the Sugar Beet and the Fuka-Matrouh areas, respectively.

Table 2
Performance testing of the adopted neural network models for different land characteristics

Land characteristic	Testing data			Model	Classification		CCR
	Number	Min.	Max.		correctly	incorrectly	%
Slope (%)	35878	0	25	BPNN	33836	2042	94.3
				GRNN	35878	0	100
Texture/Structure	462	Very fine clay	Coarse sand	BPNN	317	145	68.8
				GRNN	462	0	100
Soil depth (cm)	2326	0	200	BPNN	1045	1281	44.9
				GRNN	2326	0	100
Calcium carbonate (%)	64764	0	75	BPNN	33396	31368	51.6
				GRNN	64764	0	100
Gypsum (%)	22509	0	25	BPNN	14846	7663	66
				GRNN	22509	0	100
Salinity (dS/m)	24493	0	25	BPNN	11395	13098	46.5
				GRNN	24493	0	100
Alkalinity (%)	71023	0	50	BPNN	43074	27949	60.6
				GRNN	71023	0	100

4.2. Attribute data input

Each polygon is assigned a unique internal number (ID) as well as the non-spatial (attribute) data related to it. The non-spatial data contain the soil characteristics, such as texture, exchangeable sodium present, pH, depth, etc., weather station and metrological data, irrigation water characteristics, and other related information. These values are recorded and stored in attribute table in the external database. Fig. 5, shows samples of the data entry of non-spatial data.

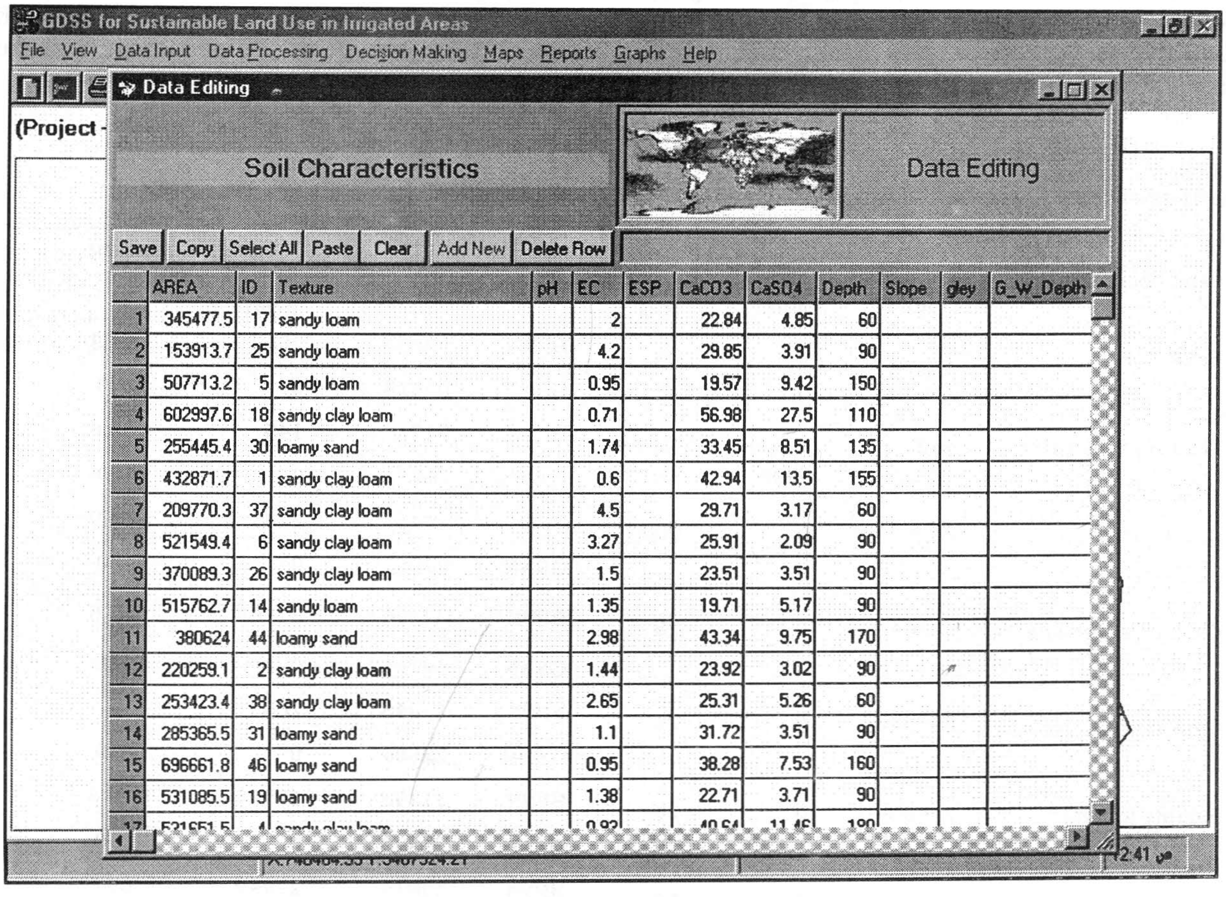
4.3. System output tuning

The system classifies the numeric fields in the external database to create graduated color maps to reflect the status of the soil characteristics. The system allows users to choose the number of classes as in fig. 6-a. When the user clicks the "Start" and "End" color boxes, the system automatically assigns colors to each unique classification fig. 6-b. Fig. 7-a and 7-b show typical query and result panes. Several other features are available to perform standard map functions that are familiar to users of GIS software and easily learned by less-experienced users.

4.4. System produced output

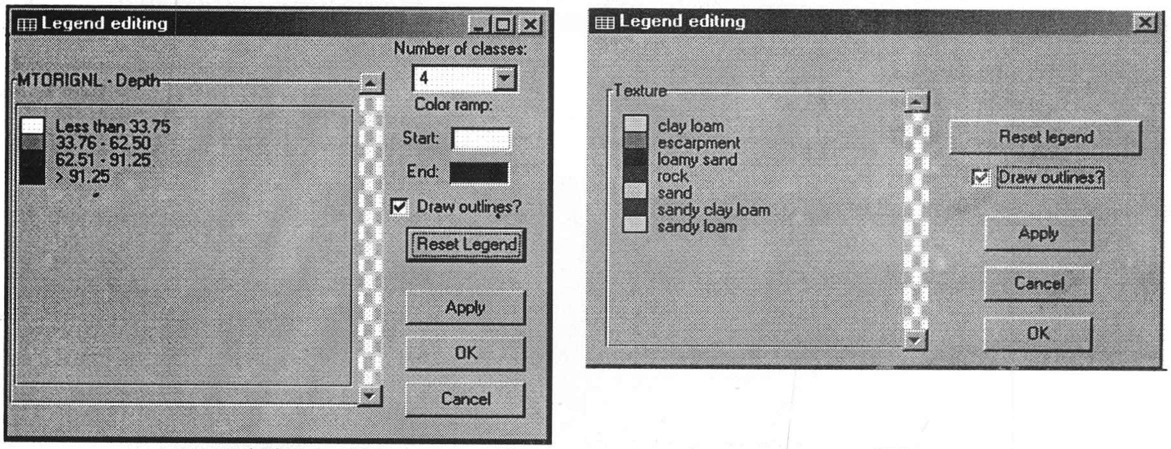
4.4.1. Unprocessed output

The system produces different types of maps from which in-depth data analysis is possible. Fig. 8 and 9 show selected land characteristic output maps for the two study areas visualizing the numeric and textural characteristics. Fig. 8, shows the texture map of Sugar Beet area while fig. 9, shows the soil depth map of Fuka-Matrouh area.



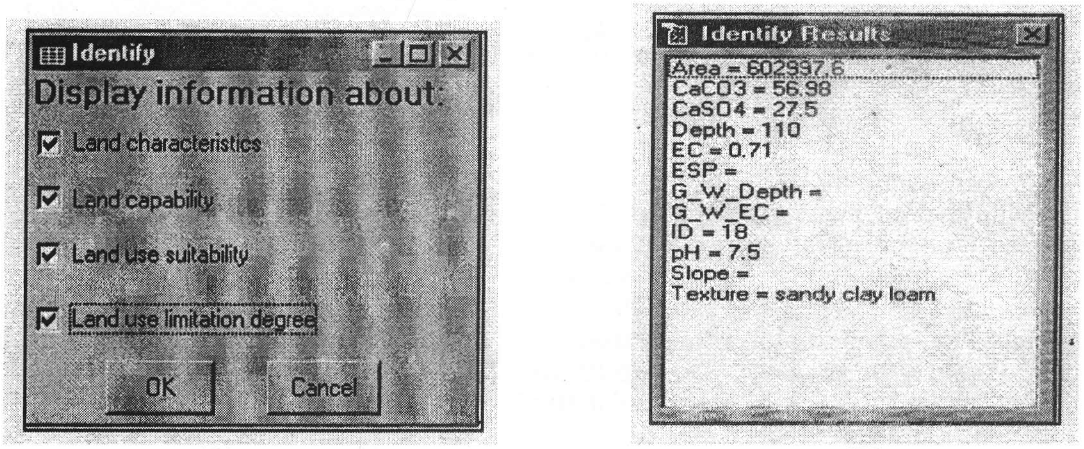
	AREA	ID	Texture	pH	EC	ESP	CaCO3	CaSO4	Depth	Slope	gley	G_W_Depth
1	345477.5	17	sandy loam		2		22.84	4.85	60			
2	153913.7	25	sandy loam		4.2		29.85	3.91	90			
3	507713.2	5	sandy loam		0.95		19.57	9.42	150			
4	602997.6	18	sandy clay loam		0.71		56.98	27.5	110			
5	255445.4	30	loamy sand		1.74		33.45	8.51	135			
6	432871.7	1	sandy clay loam		0.6		42.94	13.5	155			
7	209770.3	37	sandy clay loam		4.5		29.71	3.17	60			
8	521549.4	6	sandy clay loam		3.27		25.91	2.09	90			
9	370089.3	26	sandy clay loam		1.5		23.51	3.51	90			
10	515762.7	14	sandy loam		1.35		19.71	5.17	90			
11	380624	44	loamy sand		2.98		43.34	9.75	170			
12	220259.1	2	sandy clay loam		1.44		23.92	3.02	90			
13	253423.4	38	sandy clay loam		2.65		25.31	5.26	60			
14	285365.5	31	loamy sand		1.1		31.72	3.51	90			
15	696661.8	46	loamy sand		0.95		38.28	7.53	160			
16	531085.5	19	loamy sand		1.38		22.71	3.71	90			

Fig. 5. Data entry user interface.



(A) (B)

Fig. 6. Legend editing interface for numeric and textual attributes.



(A) (B)

Fig. 7. Dialogue and results box.

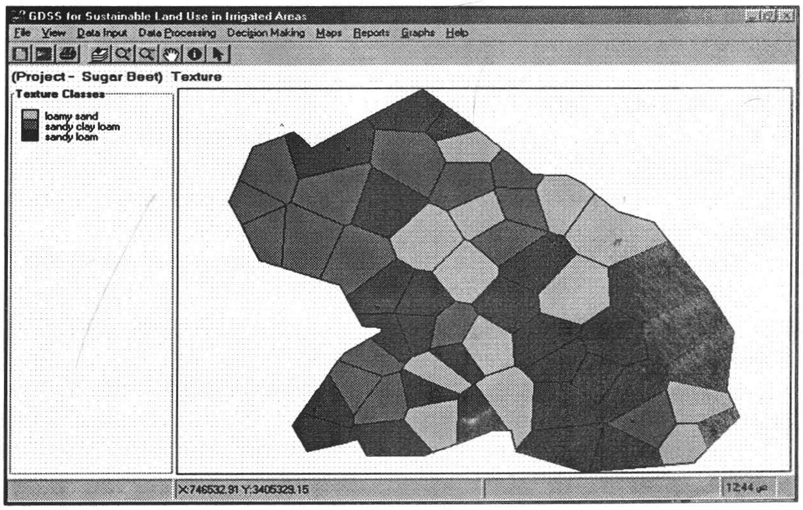


Fig. 8. Texture map of sugar beet area.

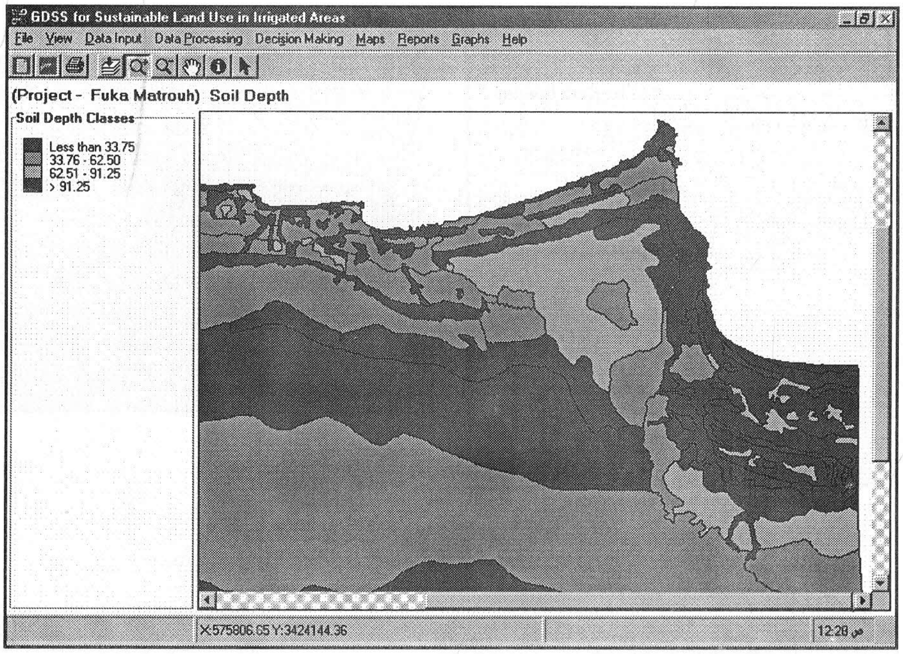


Fig. 9. Soil depth map of Fuka-Matrouh area.

4.4.2. Processed output

The data processing phase in the system estimates land capability and land use suitability for each land unit, climatic suitability for each land use type, and irrigation water suitability for each irrigation source. The system displays the results on a map to allow the user to see distributions, relationships, and trends. Fig. 10 and 11 illustrate the land capability classes of all land units for the two study areas.

The system takes into account 22 land use types when carrying out the land use suitability evaluation. These land use types are grouped into three groups according to the season of growth. These groups are, summer, winter, and permanent as follows:
1. Summer season land use (e.g. Cotton, Green pepper, Maize, Onion, Sorghum, Sunflower, Sweet potato, Watermelon).
2. Winter season land use (e.g. Barley, Beans, Carrots, Soya, Wheat, White potato).
3. Permanent land use (e.g. Alfalfa, Banana, Citrus, Guava, Mango, Olives, Sugar cane).

These land use types are evaluated, and the results reflect the suitability class and type and degree of limitations for each land use. Seven soil limitations are involved, namely, texture (t), salinity (s), calcium carbonate (c), Gypsum (g), depth (d), alkalinity (a), slope (l). The map shows the suitability classes and the degree of limitation after checking the "Limitation type and degree" box in the bottom bar as shown in fig. 12 and 13 showing Land suitability for sorghum in both study areas.

5. Decision support system

5.1. Decision support main interface

Fig. 14, illustrates the decision support interface that can be manipulated by decision-makers. It is designed with the objective to have most important information in one place in a user-friendly manner. It allows selection of spatial polygons from the map, or from the land characteristics tabular form. Then, the land use alternative ranking process extracts the necessary information corresponding to the selected polygon from the external database. The extracted information include land use limitation type and degree; climatic limitation type and degree; land use priority and, in addition, the land use and climatic suitability classes.

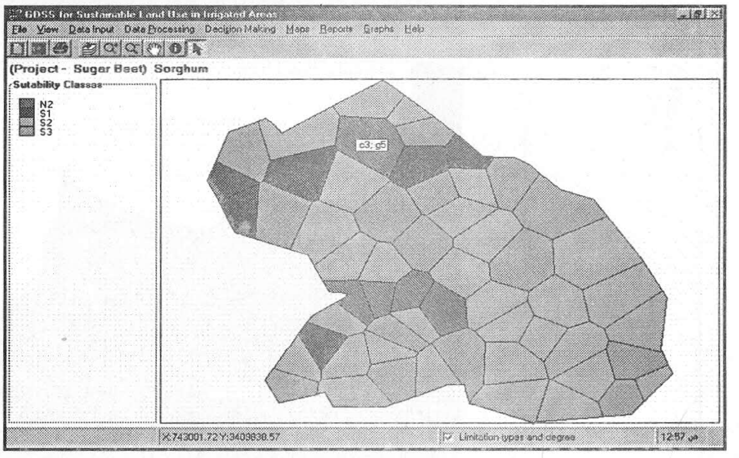


Fig. 10. Land capability map of sugar beet area.

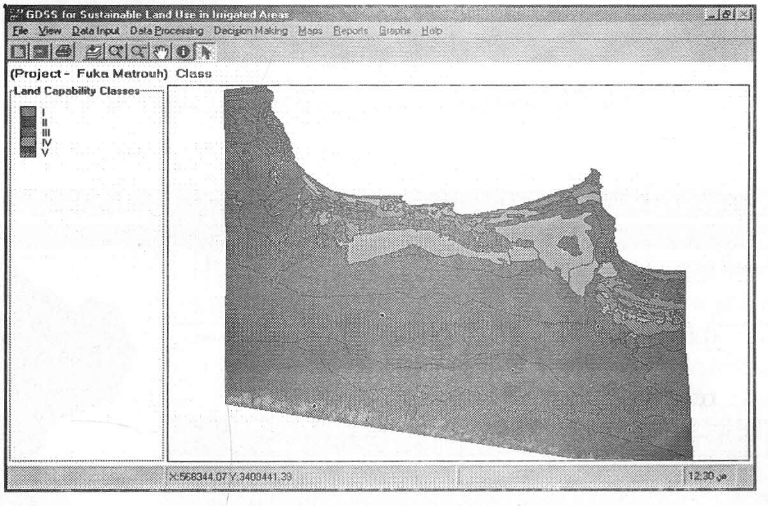


Fig. 11. land capability map of Fuka-Matrouh area.

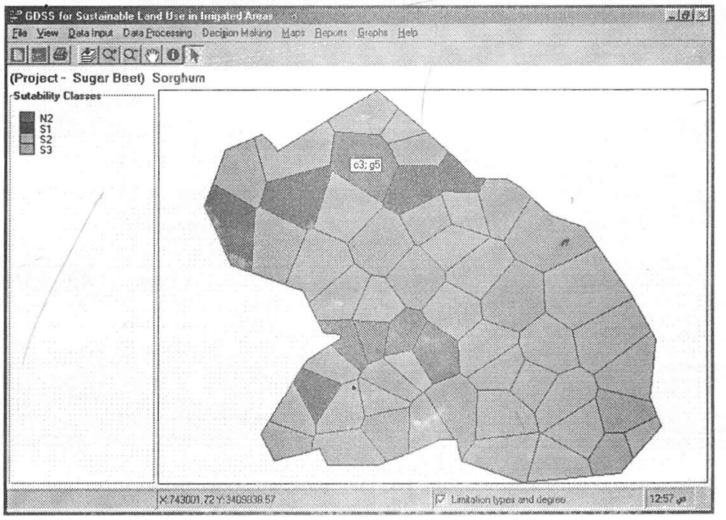


Fig. 12. Land suitability for sorghum in Sugar Beet area.

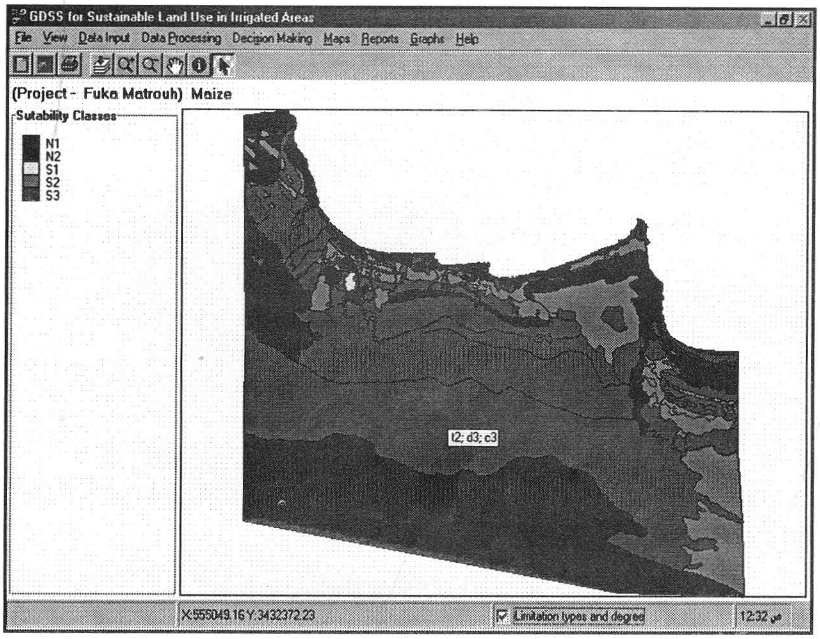


Fig.13. Land suitability for sorghum in Fuka-Matrouh area.

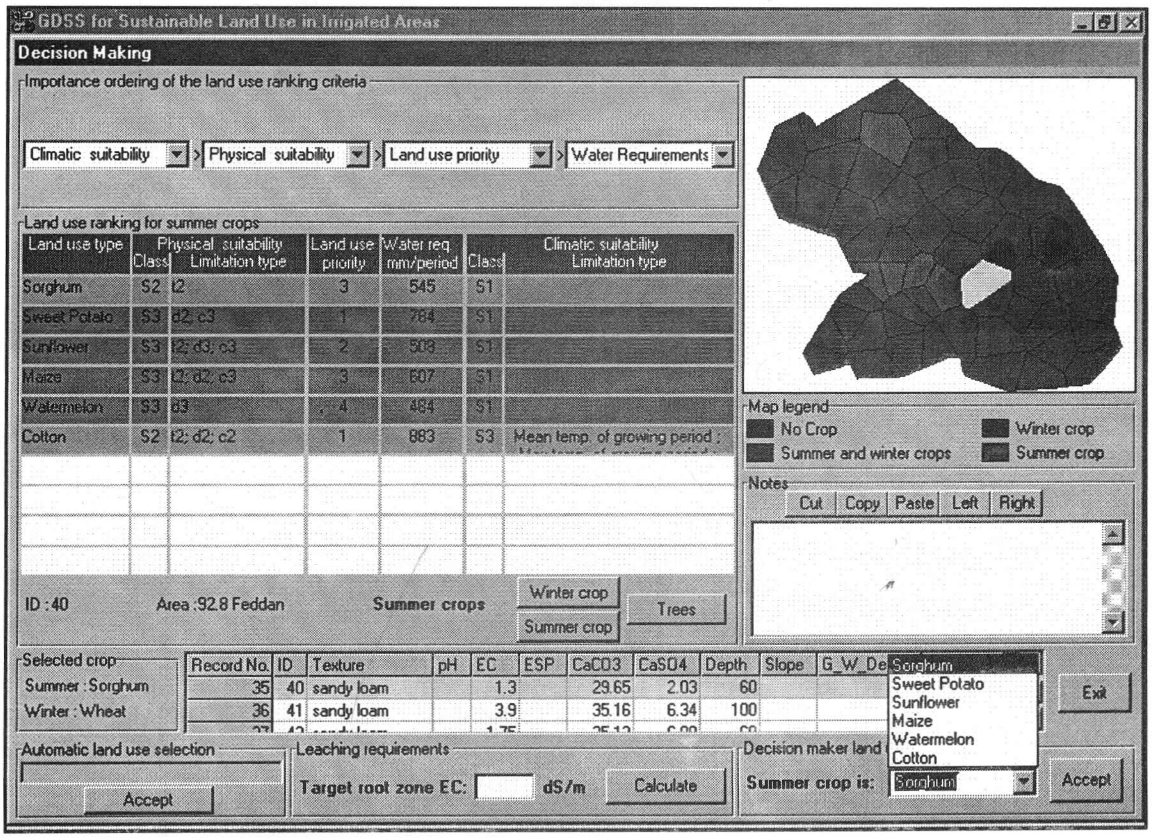


Fig. 14. Decision support main interface.

Also the system estimates the crop water requirement for each land use alternative. The objective of displaying these information all at once is to give the decision-maker a clear view about the limitation of each alternative. Each land use alternative is evaluated and analyzed in relation to others in terms of a pre-specified decision rule.

Since ranking depends upon the decision-making preferences with respect to the importance of the evaluation criteria, the system allows the user to change the importance order to reflect the main objectives and the orientations of the decision-maker. For example, if the main objective is to select the land use type which has low water requirement, the criteria importance order will be *climatic suitability* > *physical suitability* > *crop water requirement* > *land use priority.*

There are many different scenarios that can be generated according to the decision maker objectives and the system allows the user to select the best alternative manually by the decision maker or automatically by the system for each polygon. The user can then annotate the selected polygon with his own decisions or comments. This text comments may reflect advices, i.e. the type of management, leaching requirement,..etc.

5.2. Report generator

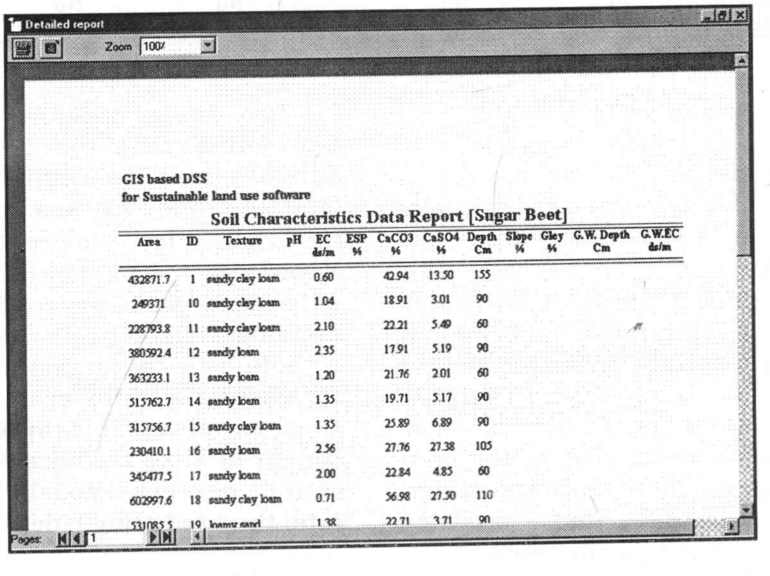
The report generator provides access to the external database using the system's built-in SQL statements. The system creates several types of reports to summarize the information and data that were collected from the external database. The system enables the user to preview, print, export and save the report (fig. 15).

5.3. Graph generator

Fig. 16 illustrates a sample graph that has been generated by the system. The system displays the chart data in a tabular form below the chart to allow the user to make a better decision.

5.4. Comparison with other land evaluation systems

Table 3 provides a review of the most important features in the developed system as compared to other existing systems. It is evident that this system achieves the integration of geographical information systems, and intelligent decision support systems employing knowledge base and artificial neural network models.



GIS based DSS
for Sustainable land use software

Soil Characteristics Data Report [Sugar Beet]

Area	ID	Texture	pH	EC ds/m	ESP %	CaCO3 %	CaSO4 %	Depth Cm	Slope %	Gley %	G.W. Depth Cm	G.W.EC ds/m
432871.7	1	sandy clay loam		0.60		42.94	13.50	155				
249371	10	sandy clay loam		1.04		18.91	3.01	90				
228793.8	11	sandy clay loam		2.10		22.21	5.49	60				
380592.4	12	sandy loam		2.35		17.91	5.19	90				
363233.1	13	sandy loam		1.20		21.76	2.01	60				
515762.7	14	sandy loam		1.35		19.71	5.17	90				
315756.7	15	sandy clay loam		1.35		25.89	6.89	90				
230410.1	16	sandy loam		2.56		27.76	27.38	105				
345477.5	17	sandy loam		2.00		22.84	4.85	60				
602997.6	18	sandy clay loam		0.71		56.98	27.50	110				
531085.5	19	loamy sand		1.38		22.71	3.71	90				

Fig. 15. Layout of a sample soil characteristics report for Sugar Beet area.

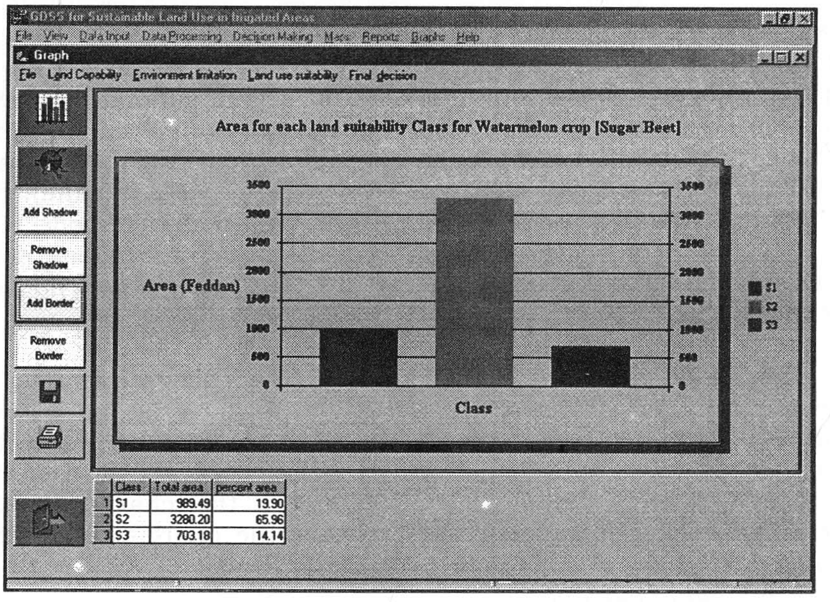


Fig. 16. The graph generator user interface.

Table 3
Summary of the main features of the referenced systems

Feature	ALES[15]	MicroLEIS[16]	PLES-ARID[17]	ALES-Arid[18]	Developed system
Map integration	No	No	No	No	Yes
GIS functionality	No	No	No	No	Yes
GIS integration	Yes	Yes	Yes	Yes	Yes
Knowledge base (KB)	Yes	Yes	Yes	Yes	Yes
KB user customization	Yes	No	No	No	No
Neural network support	No	No	No	No	Yes
Estimate water suitability	No	No	Yes	Yes	Yes
Crop water requirement	No	No	No	No	Yes
Economic suitability	Yes	No	No	No	No

6. Conclusions

The developed system is an integrated model for helping decision-makers to make better decisions on sustainable land use alternatives, using multi-objective/multi-criteria decision-making process. It integrates the functionality of geographic information systems, knowledge bases, artificial neural network models and decision support systems. It is modular in design so new functionality can be easily added to the core application. This approach to software design makes upgrades simple and provides expandability as user requirements grow.

Two neural network models were tested and found that the GRNN model is more suitable than the BPNN model for predicting land suitability classes from land characteristic value for different land uses. The Knowledge base-neural network hybrid subsystem was designed with the goals of building architectures that confer the benefits of both rule base and neural processing to represent the land evaluation expertise in a single system. This approach also has the benefit of easy modification by retraining the neural network models with updated data sets, thus reducing rule base reconstruction.

The system provides a user-friendly interface for organizing, storing, retrieving, displaying and maintaining data. It is targeted towards users who may have only the basic skills in dealing with GIS and DSS software. It also contains built-in queries to provide immediate information in multiple format to support the decision making process. This format can be in tabular reports, graphs, or maps.

The system components have been validated against well documented cases. It showed a profound performance at all stages. Also, the final integration has been compared with well known land evaluation software. It is evident from table 3 that the system has the advantages of being equipped with Map integration, GIS functionality, Neural network support, and built in crop water requirement analysis. However, the system lacks KB user customization and economic analysis tools.

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