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Image interpretation for landforms using expert systems and terrain analysis

Al-garni, Abdullah Mohammed, Ph.D.
The Ohio State University, 1992

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IMAGE INTERPRETATION FOR LANDFORMS USING EXPERT SYSTEMS AND TERRAIN ANALYSIS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

Abdullah Mohammed Al-garni, B.S., M.S., M.S.

** * * * **

The Ohio State University

1992

Dissertation Committee:
Anton F. Schenk
Douglas S. Way
Kurt Novak

Approved by
Advisor
Department of Geodetic Science and Surveying
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1992
To My Parents
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VITA

December 31, 1959 .......... Born - Balgarn, Saudi Arabia

1983 .................. B.S., Civil Engineering, King Saud University, Riyadh, Saudi Arabia

1986 .................. M.S., Remote Sensing, Civil Engineering, The Ohio State University, Columbus, Ohio

1991 .................. M.S., Department of Geodetic Science and Surveying, The Ohio State University, Columbus, Ohio

PUBLICATIONS


FIELDS OF STUDY

Major Field: Geodetic Science and Surveying
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CHAPTER I

1 INTRODUCTION

In this chapter a statement of the problem as well as the objectives and organization of this dissertation are given first. The next section provides definition and background about landforms. Finally, a definition of and an introduction to expert systems are presented.

Photo or image interpretation is a process of collecting evidence about features of interest in the image so that their identification can be obtained. Aerial photographs contain raw photographic data. These data, when processed by a human interpreter’s brain, become usable information (Lillesand and Kiefer, 1979). It has been a very long time since image interpretation was employed to identify features on images corresponding to real world objects. However, the heuristic nature of the knowledge needed to conduct image interpretation indicates that the image interpretation process is more than reading gray values of pixels of digital images.

Image interpretation is better conducted on terrain features that possess distinct pattern elements that can contribute to image understanding and, consequently, to image interpretation. For this reason, landforms are selected by this study as terrain features whose pattern elements (explained later) can be systematically studied to form a better understanding about different terrain features and consequently to lead to a full identification of these features. A Landform can be described as ...a terrain feature formed by natural processes, which has a definable composition and range of characteristics that occur whenever that landform
is found (Way, 1978). Also, terrain analysis is defined as ...the systematic study of visual elements relating to the origin, morphologic history, and composition of distinct landscape units that appear in aerial photographs (Way, 1987).

Mainly, image interpretation requires experts who conduct the interpretation process based on logical reasoning and inferences. This requirement contains many obstacles. For instance, experts in image interpretation and terrain analysis are rare, and these few are expensive and sometimes unavailable. Moreover, the nature of the problem of identifying and classifying landforms is subjective. Also, terrain analysis itself requires special skills and training. Finally, terrain analysis is a costly, time-consuming, and labor-intensive process (Way, 1978; Argialas, 1984).

The objective of this study is to build an interactive image interpretation expert system. The main purpose of developing this expert system is to interpret and identify different types of landforms based on terrain analysis. That is, based on an engineer's input (which is guided by the expert system) from available images, the expert system identifies the type of landform under investigation. Accordingly, proper information can be supplied to planners and engineers concerned about site developments in various parts of the world. This knowledge is important in the first stage of developing engineering projects. The developed expert system is called EXpert system for LANdform interpretation using Terrain analysis (EXLANT).

There are two main reasons for studying landforms with the aid of aerial photogrammetry, satellite images, and Artificial Intelligence (AI). The first reason is the fact that landforms include all descriptive aspects of our planet; therefore, any mapping process deals with landforms in one way or another. This makes landforms a fruitful concept for the late vision process of image pyramid (see Figure 1), where vocabulary, terminology, algorithms, and expertise should be developed. In the late vision process the problem is complex (Schenk, 1992); not much work has been done in that respect. A large effort is required to investigate experts' rules
Figure 1: Major Tasks of Digital Photogrammetry From Raw Digital Imagery to An Interpreted Scene (GIS)
(Source: Schenk, 1990- Class Notes)
of thumbs and to furnish the foundations of image understanding. In this research image understanding is viewed as the process of recognizing proper elements for image features that eventually lead to proper identification of the features. The second reason is the fact that landforms lend themselves to site developers as an information source. That is, the identity of the landform, if known, provides essential information to the engineers and planners of projects in civilian and military sectors. The interpretation process, in this case, is usually accomplished by experts in image interpretation who are very knowledgeable in many different fields, such as image interpretation, geography, geology, meteorology, and soil mechanics. However, many countries, such as Saudi Arabia, lack qualified experts in the field of image interpretation; therefore, a substitution for human experts is mandatory.

Since the primary objective of this dissertation is the identification of landforms and the inspection of their engineering suitability, it is essential to explore the nature of this problem. To identify a landform, terrain analysis is the main clue. The problem, however, contains many pattern elements, such as drainage patterns, that could lead to more than one conclusion. Moreover, the pattern elements used in terrain analysis are vague. For instance, these expressions are common during an interpretation session: light tone, medium tone, dark tone, fine drainage, medium drainage, and coarse drainage. In two consultations with one person or with two persons, coarse drainage in one consultation and fine drainage in another may be assigned for the same landform while, in reality, the actual value could be medium drainage. Therefore, the assignment of terrain analysis elements to image attributes is a subjective undertaking.

Due to the previously mentioned problems, this study, unlike other studies, views the problem globally to provide a theoretical basis for introducing AI in order to resolve some of the subjective matters and to weight the elements of image interpretation based on their contributions. Accordingly, in this dissertation
an interactive rule-based expert system (EXLANT) is developed for interpreting landforms. The user is guided by the expert system. The knowledge-base is presented in a frame-based system. EXLANT has three distinguishing properties:

1. The conceptual and theoretical aspects of interpreting landforms are investigated in view of terrain analysis and AI.

2. The expert system has the ability to learn from a teacher.

3. The expert system is easily extendable and capable of many external interfaces.

Finally, the following list precisely points out the purposes and contents of this dissertation. The objectives and contents are:

1. The analysis of the task of interpreting landforms,

2. The development of proper methods for acquiring knowledge from the experts,

3. The development of theoretical bases for landforms' interpretation using terrain analysis and expert systems,

4. The selection of suitable AI search strategies and mapping functions that best fit landform interpretation,

5. The development of recognition and learning agents in the expert system to fulfill current objectives of image interpretation and meet necessary improvements in the future,

6. Writing a computer program that accomplishes the requirements of the developed expert system, which include reporting the identified landform(s) along
with certainty factors and samples of consultation reports about landforms for civil and military sectors, and

7. Testing the expert system by conducting real applications and experiments.

1.1 Landforms and Terrain Analysis

Different topographic features are developed by chemical and physical processes that are occurred at or near the surface of the earth. The study of these features -their origin and their processes- is known as geomorphology (Easterbrook, 1969). The physical site condition is of concern to planners as well as to engineers. Image interpretation based on terrain analysis provides these people with a clear understanding and a complete overview of site conditions. Terrain analysis deals primarily with landforms. Accordingly, land suitability appraisals are based on terrain analysis, classification, and evaluation. Usually, knowledge obtained from landforms' interpretation serves as a basis for further studies in other fields, such as in civil engineering, earth sciences, military activities, and agriculture.

It is a crucial task for engineers and land planners to have a reliable site analysis so that projects can be implemented properly (Ray, 1960; Way, 1978; Avery, 1985; Lueder, 1959). There are many factors and many critical relationships and interrelationships of surface and subsurface terrain conditions that a land planner deals with (Way, 1978). Accordingly, planners need to have accurate and complete information about the site to be developed. Geology, water, soil, vegetation, and minerals are examples of factors that must be considered by planners while evaluating a physical site's condition.

Before constructing an engineering project, a variety of experts must evaluate, plan, and get alternatives for the project under consideration. That is, experts in soil mechanics, geology, geography, photogrammetry, agriculture, and hydrology
should participate in the first stage of the project. Such a variety of experts in this stage of planning is very expensive or may even be unavailable. Having unavailable or insufficient experts could lead to improper planning and could jeopardize a country's economy. Image interpretation is considered, in most cases of applied engineering, as the main required factor in the early stage of a project. Landforms are the main type of land surface that this research made the effort to identify, interpret, and classify. On the one hand, landforms contain all elements necessary for performing image interpretation. These elements, called visual or pattern elements, are elements that provide clues to features' identities. For instance, drainage patterns and erosion are two types of image pattern elements, called image attributes as well. On the other hand, any engineering project is built on a specific landform. If the landform is properly identified, the right assessment and decision about developing a site can be reached.

Since landforms are the common base that all planners or site developers start with, it is essential to elaborate on the term "landforms." In many land classification systems, different definitions for "landforms" can be found. For example, civil engineers, geologists, planners, and landscape architects use the term "landforms," but each group has a concept and a definition different from the other groups for that same term. Every field looks at landforms from the viewpoint of the requirements of that field. In this study the engineering view and definition is of concern and, therefore, is adopted. The definition given by Way, (1978), is the one suitable for the purpose of this study:

Landforms are natural terrain units (including geologic elements and transported or residual soils) that, where developed under similar conditions of climate, weathering, erosion, and mass wasting, will exhibit a predictable range of physical and visual characteristics. Therefore, soils developed from similar parent materials (under similar conditions) are related and have similar engineering properties. Thus specific distinctions can be made among landform units, by which it is possible
to describe unique topography, composition, or structure or to make visual distinction relevant to planning issues and capabilities.

As indicated in the definition above, site studies, evaluation, and interpretation require the analysis and classification of landforms. Another definition is given by Belcher (1948). Belchers’ definition portrays landforms as unique entities (Way, 1978):

The earth’s features may be divided into landforms so that each form presents separate and distinct soil characteristics, topography, rock materials, and groundwater conditions. The recurrence of the landform, regardless of the location, implies a recurrence of basic characteristics of that landform (Belcher, 1948).

This definition also reflects the engineering view regarding landforms. Moreover, these two definitions of landforms include two important issues with which this dissertation is concerned. First, every landform possesses particular visual attributes that distinguish it from other landforms. Second, every landform possesses some physical characteristics based on which the suitability of the landform, for a particular application, can be judged.

There are a number of principles for landform interpretation (Way, 1978). These principles are very important and make landforms a place of multi-purpose applications. Two of the most important principles are that the same landform, regardless of its location, if found under the same approximate environmental conditions, will exhibit similar identifying pattern elements and that each landform has a characteristic range of soil and rock composition (Way, 1978). If the landform is identified, then its suitability for a particular engineering application can be evaluated.

To have suitable terrain analysis, it is essential to find a proper means to distinguish between different types of landforms. There are a few visual elements that a photo interpreter concentrates on in order to draw his/her own conclusions
about site analysis. Drainage pattern, gully characteristics, tone or color aspects, topographic form, land use, vegetation, and a combination of these elements are the most important visual elements. These may be tested carefully so that a proper interpretation can be obtained. Every element should be examined alone, with respect to one another, and with respect to the entire pattern (Way, 1978).

As manual interpretation is accomplished today, the interpretation of the visual elements is based on suggested hypotheses that indicate the site's morphologic units and landforms. Afterwards, these hypothesis are checked against factual knowledge and verified, rejected, or modified if necessary (Way, 1978).

1.2 Expert Systems

In recent years, the field of AI has accomplished great success in many different areas. The realization and development of expert systems is one representative of such success. Expert systems form one of the most important fields of AI (Bowerman and Glover, 1988). An expert system is a knowledge-based program that provides "expert quality" solutions to problems in a specific domain (Luger and Stubblefield, 1989). Expert systems are large, powerful programs designed to replicate and autonomously apply human expertise. In other words, an expert system may be defined as a computer-based system that consists of computer programs designed to use knowledge, facts, and reasoning techniques in order to simulate human problem-solving. Accordingly, expert systems represent and apply factual knowledge for certain areas of expertise to reach a proper solution for particular problems. For example, expert systems can diagnose diseases, prospect for minerals, and configure computer systems at a performance level equal to or better than that of human experts. Expert systems and knowledge-based systems (KB) are viewed as two synonyms (Bowerman, et al., 1988). Some people however, prefer one or the other of these synonyms. For instance, a knowledge-based system
implies a system that may contain information beyond what can be assimilated by an individual expert or group of experts (Bowerman, et al., 1988). In this research, expert system and knowledge-based system are used interchangeably.

Expert system builders seek several goals: to name a few examples, replacing an unavailable or too expensive human expert; coding expertise; saving experts' time; collecting experiences and knowledge from several human experts; or transferring expertise to different locations. A given expert system aims to mimic experts in solving a problem (Adeli, 1988; Martin, et al., 1986; Bowerman, et al., 1988). Therefore, it should be accepted that an expert system could make mistakes just as a human expert could, even though these cases are very rare.

The main components of an expert system are:
1. a set of input data,
2. a set of output data, and
3. a set of modules designed to make necessary manipulations.

Figure 2 represents the general architecture of an expert system (ASCE, 1988). To be more compatible with expert system terminologies, the components of an expert system, formulated above, can be presented in a different way. Three general parts can picture an expert system, namely:
1. the user interface,
2. the knowledge-base (KB), and
3. the inference engine (IE).

The IE is defined as the part of an expert system which is responsible for reasoning strategies. It selects suitable knowledge and facts from the KB which best fit a specific problem under consideration, so that a conclusion is reached. The IE also supports explanations and user interface as well as knowledge acquisition. The reasoning process is achieved by devising proper algorithms and search strategies. These latter usually start at a very coarse knowledge level and end with
Figure 2: A Typical Architecture of an Expert System
Source: ASCE, 1988
very specific solutions. The coarsest level of knowledge, at which little information is available, is known as the initial state space of the problem under consideration. It is the state where, based on available knowledge, some hypotheses about particular goals are developed.

As the name implies, the inference engine performs the inference process. The inference mechanism obtains the solution of a particular problem based on information provided by a user and based on the expert system's KB. The KB, however, has parameters, production rules, and structures which contain a collection of information concerning the KB (these structures are called frames in our case; see PC+ manuals (1988) for more information about frames). Every individual piece of knowledge is represented by a parameter. Another important term is knowledge engineer (KE). A KE is a person who designs or develops expert systems based on the expertise of an expert. The task that a KE performs is to have the knowledge formulated in a suitable way so that other individuals can use it. Production rules can be designed in the form of IF-THEN statements.

Before giving definitions of expert systems from the literature, we must discuss the word expert. Experience and positive performance in a particular field make someone an expert. Paul E. Johnson, a scientist concerned about the behavior of experts, quoted Waterman in 1986:

An expert is a person who, because of training and experience, is able to do things the rest of us cannot; experts are not only proficient but also smooth and efficient in the actions they take. Experts know a great many things and have tricks and caveats for applying what they know to problems and tasks; they are also good at plowing through irrelevant information in order to get at basic issues, and they are good at recognizing problems they face as instances of types with which they are familiar. Underlying the behavior of experts is the body of operative knowledge we termed expertise. It is reasonable to suppose, therefore, that experts are the ones to ask when we wish to present the expertise that makes their behavior possible.
Accordingly, expertise and intelligence are two characteristics that an expert system should maintain. In fact, expert systems are considered a: "vigorous part of the burgeoning field of artificial intelligence" (Edmunds, 1988).

Many definitions of expert system exist today. Bowerman, et al., 1988, define it as follows: "An expert system is a system of software or combined software and hardware capable of competently executing a specific task usually performed by a human expert." Jackson (1986) gave the following definition: "An expert system is a computing system capable of representing and reasoning about some knowledge-rich domain, such as internal medicine or geology, with a view to solving problems and giving advice."

Artificial intelligence (AI) is defined as: "the study of how to make computers do things, which at the moment, people do better" (Rich and Knight, 1991). The problem of image interpretation is quite in compliance with this definition; therefore, image interpretation is an AI problem. There are many other definitions that the reader can be referred to. For instance, from a list of definitions collected from different literatures by Adeli, 1988, the following definition of an expert system is selected: "An interactive computer program incorporated judgement, experience, rules of thumb, intuition, and other expertise to provide knowledge and advice about a variety of tasks, (Gaschnig, et al., 1981)" (Adeli, 1988).

Expert systems are distinguished from traditional programs. Unlike other programs, expert systems deal with issues that are complex and need a considerable amount of human expertise. Also, an expert system differs from a traditional program by its capability of explaining and justifying solutions in terms of speed and reliability as well as in providing convincing reasoning and in delivering rational recommendations. Moreover, expert systems are flexible as opposed to the rigid character of other programs (Edmunds, 1988). Finally, expert systems deal with qualitative model and knowledge bases that are difficult to be defined in
terms of what these data bases may contain (Clancey, 1989). Finally, knowledge acquisition, representation, and quality constitute the most important part of the expert system. There are two entities that are of concern in knowledge representation. First, there are elements that a knowledge engineer wants to presents. These elements are facts concerning a specific problem. Facts or truths are known as the knowledge level in expert systems. The second entity is the symbolic level of knowledge, meaning that truths are defined using proper symbols so that computers can access, manipulate, and process the knowledge by developed programs. Sometimes, knowledge about knowledge is required in expert systems. For instance, dendritic drainage is considered a piece of knowledge for many landforms on earth; the words coarse and fine are two more pieces of knowledge added to the term dendritic so that new knowledge (such as soil types) can be inferred. In expert systems knowledge about knowledge is known as meta-knowledge.
CHAPTER II

2 LITERATURE REVIEW

The value of aerial photographs in the science of image interpretation is not a new concept. During the last stages of World War I and during World War II, image interpretation was a big source for military information, such as inferring troop movements, military installations, and military supplies (Quackenbush, 1960). Since then, the photo interpretation field started to develop and to be used for civilization purposes, such as identifying mines, land cover, and other economic sources (Ray, 1960; Way, 1978; Avery and Berlin, 1985; and Zuidam, 1985). Lately, the idea of employing AI in the field of image interpretation has emerged. This chapter reviews three distinct areas: image interpretation, AI and expert systems, and AI and expert systems in image interpretation.

2.1 Image Interpretation

Information can be extracted from imagery and photography by different interpretation methods. Generally, there are two basic methods (Moffitt, and Mikhail, 1980):

1. Pattern recognition and

2. Pattern interpretation methods.

The first method is based on checking distinct visible features against familiar objects observed before or against a priori prepared list of key identification elements. The second method, pattern interpretation, goes beyond the identification
of features. That is:

Pattern interpretation is broader in scope than pattern recognition. Not only is identification necessary, but analysis by logical deductive reasoning is also required in order to classify and interpret the significance of the pattern and all of its elements. For example, almost anyone can recognize a hill on a photograph. However, to interpret and classify the hill as a kame implies knowledge of its origin and its potential as a source of a sand and gravel for construction purposes (Moffitt and Michail, 1980).

Computer-assisted interpretation can be described as the process of restoration, transformation, and enhancement of images of numerical forms (digital images) so that a further interpretation process can be conducted. This implies comprehensive image processing techniques that are applied to the spectral characteristics (matrix of brightness values of a scene) of images. Figure 3 (Estes, et al., 1983) portrays the general themes of computer-assisted interpretation using image processing techniques. As opposed to computer-assisted techniques, there is a human or visual interpretation, called manual interpretation. It can be described as the process of applying human mental power to evaluate, reason, and inference spatial patterns of a scene. This indicates the training, skills, and expertise that are required for an image interpreter. A new trend for image interpretation emerges, called expert systems. Estes, et al., (1983) stated “Another contemporary trend in image interpretation is the move from numerical decision-theory models (e.g., maximum likelihood and Bayesian) to the more complex heuristic (or exploratory) models in artificial intelligence.” A comparison of image interpretation by human interpreter and by the aid of computers is summarized by Richards (1986); also see table 1.

Even though computer-assisted photo interpretation has evolved recently, human interpretation has been accepted as a standard means for preparing thematic maps during the past few decades. The automation of the interpretation and
Figure 3: General Themes of Computer-Assisted Interpretation
(Source: Estes et al., 1983-Origin Moik, 1980)
classification processes is not a new concept (Grasselli, 1969). Unfortunately, in introducing the computerized techniques for image interpretation, many elements that an interpreter uses proved difficult to model. This has led to an elimination of valuable knowledge from the process of interpretation, which, in turn, results in less reliable interpretation (Myers et al., 1989).

Today, computer-assisted image classification is performed based on statistical methods. For the past twenty years, statistical pattern recognition was fully implemented and utilized for image classification. The main assumption of statistical pattern recognition is that the realization of this method is possible only for a pattern of classes that can be described by a set of numerical measurements (gray values presented usually in vector or matrix forms).

During the past twenty years, pattern recognition based on a statistical approach has been extensively practiced and is now well established (Duda et al., 1973, and Young et al. 1986). This rich experience is completely dependent on the automation of gray values. In the last decade researchers started to realize that image interpretation is more than just reading pixels of digital images. Instead, it involves understanding images and consequently proceeds to image analysis and the identification of features. Clearly, the statistical approach lacks the capability of performing image interpretation (Argialas, 1989 and Bolstad et al., 1991). After two decades of applying gray value methods, it can be concluded that fine tuning and a quick fix of the interpretation problem through purely spectral-based automation is not a promising solution and cannot reduce the reliance on experts for interpretation.

Lately, some interpretation functions such as shapes, location, and relationships have been used to perform simple scene analysis and interpretation. The state-of-the-art of current computer-assisted techniques form incomplete solutions for class interpretation as well. These techniques failed to reach results that are
compatible with those of a human interpreter (Argialas et al., 1990 and Bolstad et al., 1991). Identification of objects, object significance, object relationships, and photo interpretation elements are the main factors needed for proper image interpretation but hardly resolved in current digital image analysis.

Expert systems and their roles in image interpretation receive great interest nowadays (Argialas, 1988; Mintzer, 1989; Bolstad et al., 1991; Ellam et al., 1987). Since AI science and expert systems evolved, it become possible to model and formulate experts' knowledge, which was difficult to modeled a few years ago. Today, a knowledge engineer and qualified field-related specialists (experts) can produce sophisticated expert systems.

In image interpretation, experts are still in great demand to enhance and properly guide digital pattern recognition. In spite of proper handling of some thematic categories, computerized pattern recognition techniques failed to report acceptable results for categories having important elements of spatial context deeply attached to categories' identity (Myers et al., 1989). This weakness of the pure statistical method of pattern recognition forces some researchers to seek different pattern recognition methods that request the human analyst's attendance. Of course, the methods that require a human expert will be successful in obtaining excellent results but not without disadvantages. That is, human experts are both expensive and scarce. As a result, the methods which demand the physical existence of human experts are not feasible.

2.2 AI and Expert Systems

The quality of acquired knowledge about a problem domain influences the quality of the expert system. In the early 1960's most of the works of Computer Information Science (CIS) in AI were games-playing works (Rich and Knight, 1991; and Patten, 1991). The emphasis was on how to improve search theories and bring
about sophisticated inference techniques. These dimensions of emphasis, however, were never found to be fruitful in theory or in practice. It was quite clear that improved inference techniques would never improve the AI systems alone (Rich and Knight, 1991).

Late in the 1960's, fields outside the CIS community started to think of AI to solve some problems in their own fields. MYCIN is a medical expert system that represents a good example of developers from fields other than CIS fields. It was a big evolution in the field of AI, for very impressive and sophisticated expert systems could now be developed at a better achievement and at better standards. Only then did the CIS community start to think about re-evaluating their concepts of concentrating on improving inference techniques alone. For instance, the outside-CIS developers of expert systems used relatively simple inference mechanisms, but they produced better real-world problem-solving systems compared to game-solving systems that have very sophisticated inference engines.

The success of the outsiders' expert systems indicated that the inference engine was not the key for success. In fact, super, fancy, and advanced inference techniques add very little to the success of expert systems (Patten, 1991). Instead, sophisticated and precise knowledge was the main reason behind the success. The conclusion was that a relatively simple inference mechanism (for example, backward chaining with depth-first search) could work efficiently as long as enough specific knowledge is provided to guide the system.

As soon as sophisticated, detailed rules were realized to be the key of success for real-world expert systems, a trend of separating inference engine from knowledge evolved (Buchanan, 1989). The knowledge that is built in expert systems is not the knowledge learned in school. Instead, it is the knowledge gained after graduation. This knowledge is known as "Coarse-Grained Knowledge." It is very specific knowledge. On the opposite side, the routinely known or practiced
knowledge, which is gained through general sources such as schools, is termed "Fine-Grained Knowledge." This general knowledge (everywhere known) is not, in most cases, the main motive for developing expert systems (Rich and Knight, 1991; and Patten, 1991). In early stages, however, CIS fields used fine-grained knowledge in developing expert systems. The later success of other fields over CIS fields in developing expert systems was driven by experts who brought about and used coarse-grained knowledge rather than fine-grained knowledge.

Coarse-grained knowledge is written nowhere and, therefore, must be obtained from experts. Accordingly, in the 1970's it was realized that knowledge acquisition from recognized experts should be emphasized rather than impressive inference mechanisms. In the case where experts face poser (strange), problems they go back and check what they have learned to solve the problem. It is in this case of unusual situations where the notion of fine-grained knowledge appears. Expert systems will fail to solve poser problems if they have no access to fine-grained knowledge. Accordingly, current research activities explore how to combine both coarse-grained and fine-grained knowledge and how to make interactions between them (Patten, 1991).

Today, two main types of limitations can be observed in the AI field. These limitations are technical limitations, such as storage problems, and theoretical limitations, such as the general lack of understanding that characterizes the field of AI vis-à-vis the way human minds process knowledge. With the rapid advancement of the hardware technology, the technical limitations become less significant. The theoretical problem is improving slowly, and acceptable approximations to human reasoning are available. Scientific experiments are essential to provide suitable theoretical bases about how human minds process large knowledge bases in a matter of microseconds.

Knowledge in expert systems may be presented in many different ways, such
as frame systems or semantic networks. Frames replace semantic nets for large problems (Fieschi, 1990). Frames can be thought of as records that contain information about attributes, goals, attribute values, and types of expected values for attributes (e.g., single and multiple values). A frame is described as a *collection of attributes (usually called slots) and associated values (and possibly constraints on values) that describe some entity in the world* (Rich and Knight, 1990).

Finally, machine learning is considered an important part of any AI system (Michalski et al., 1983; Kodratoff et al., 1990; Weiss et al., 1991; Laird, 1988; Winson et al., 1986). Machine learning is not a new topic in CIS fields. Rather, it started as early as the 1950's (Patten, 1992). Forsyth and Rada (1986) stated that *machine learning is the key to machine intelligence just as human learning is the key to human intelligence*. Moreover, they summarized the main objectives of learning systems in the following statement: "In practice, learning algorithms attempt to achieve one or more of the following goals:

— provide more accurate solutions,
— cover a wider range of problems,
— obtain answers more economically,
— simplify codified knowledge,"

### 2.3 Expert Systems and Image Interpretation

Expert systems have been used during the last five years in the field of image interpretation very extensively due to the heuristic nature of the problems of interpretation. In 1987 Wharton developed "a spectral-knowledge-based approach for urban land-cover discrimination." This system was ideal, with many assumptions that often cannot be met in real applications.

Some other applications of image interpretation in the favor of engineering applications have been developed. One example is the work by Wang and Newkirk
in 1988. They developed a KB system for the extraction of highway networks. This system was developed using image processing techniques and AI. Interpretation of suburban areas on aerial images was performed based on expert system notions and themes. Nicolon and Gabler (1987) developed “a knowledge-based system for analysis of aerial images” which specialized in the analysis of static, monocular, and panchromatic aerial images to interpret suburban scenes. Airports are another area of applied photogrammetric engineering (APE) where expert systems may be utilized (McKeown et al., 1985). A rule-based system called SPAM was developed for interpreting airports from aerial images (McKeown et al., 1985 and Snook et al., 1987). Agricultural information captured from different sources, such as satellite images, soil models, and experts was manipulated and analyzed by an expert system to provide important consultations regarding crop production and expectations (Hadipriono et al., 1989).

In 1987 an aerial scene analysis system was described by Matsuyama. The system, called SIGMA, is a KB system which utilizes the frame concept of knowledge representation. Details about the development of the SIGMA expert system and a good review of current systems in the field as well can be found in a book by Matsuyama and Hwang (1990). Bolstad and Lillesand (1990) described a classification model for land cover via a rule-based system.

Argialas (1988) developed an expert system to handle the identification of three types of landforms in two different weather conditions. The landforms were sandstone, shale, and limestone, which exist in arid areas or in humid areas. His development was based on a bottom-up approach where the landform to be identified is hypothesized first, and the system starts to collect evidence to accept or reject the hypothesis. The system, named TAX, was developed again in 1989 based on frame modelling.

Many other solutions to the inadequacy of current spectral-based statistical
pattern recognition have been proposed. An integrated manual/digital approach was developed, in which a human analyst has full control over the whole process (Myers et al., 1989). Another trend of handling image interpretation and recognition is the use of neural networks (Hepner et al., 1990; Civco, 1990; and Short, 1991). Today, the concept of fuzzy sets in expert systems for satellite image interpretation is under consideration (Hadipriono et al., 1990; Shine et al., 1985; and Wang, 1990). Recently, neural networks have been introduced to the field of image classification (Hepner et al., 1990). Neural networks can be described as 

...large number of simple, interconnected “processors” (neurons) working in parallel within a network (Hepner et al., 1990). In this dissertation no further discussion is provided for neural networks.

A knowledge-based approach that can make inferences about land use based on interpreted land cover was developed by Gong and Howarth (1990). This work utilizes SPOT multispectral (XS) data for “land cover to land use conversion” using a KB approach. A nice summary and review of expert systems and their applications in image interpretation is given by Argialas (1990). A good summary of current software and hardware tools is presented in that same paper.

Some available knowledge regarding image is not considered in the pure statistical techniques of pattern recognition. As many authors have realized, negligence of such valuable knowledge is a big shortcoming attached to the spectral methods. A pure statistical classification scheme cannot perform standard photo interpretation functions, such as simple description of features and basic identification of objects (Argialas, 1990). In the field of remote sensing, spectral-based methods of land classification have been reported to be inefficient (Bolstad and Lillesand, 1991). It was found that the spectral-based methods do not extract all information which an operator can see on the image. The consequence is a low classification accuracy.
Many non-spectral factors were behind the motivation for creating expert systems for classification. For instance, drainage pattern, topographic forms, weather conditions, and surface association (land use and land cover) are different forms of non-spectral knowledge that can contribute to image understanding and, unfortunately, are not considered by traditional computer-assisted techniques. Middelkoop and Janseen (1991) found it very encouraging and statistically accurate to combine spectral information with ancillary data and knowledge.

Bolstad and Lillesand (1991) developed an expert system for land cover classification. The system is based on data from spectral sources as well as from GIS sources. It is still in its first phase of development. So far, it shows about 18% time delay compared with traditional methods.

The classification of land use has been improved after introducing the expert systems at University of Waterloo (Gong and Howarth, 1991). Gong and Howarth successfully developed a knowledge-based approach to create accurate and reliable land use classes as a part of the traditional approach of land cover/land use classification. Using this new technology, an 85% accuracy was obtained for land cover classes with quite plausible inferences and reasoning offered by the expert system.

A task-driven rule-based system was developed for interpreting linear map features (Schenk and Zilberstein, 1990). This system was an experimental prototype that can interpret contour lines, rivers, streams, and roads appearing on digital topographic maps. OPS5 was the rule-based expert system shell used for the development of the above expert system.

Drainage patterns provide important clues about soils and rocks while performing image interpretation and analysis. For the purpose of drainage pattern analysis, a KB expert system was developed (Hadipriono et al., 1990). In another engineering application (urban area classification), a KB system was developed (Moller-Jenseen, 1990). This KB system was based on utilizing texture and con-
text information to classify urban areas appearing on Landsat-TM imagery. A rule-based image classification system was developed to classify images in urban and non-urban areas (Mehldau et al., 1990). This system was developed with a C-extension.

Nowadays, expert systems are advancing and developing in the field of image interpretation more than ever before. Comparisons between methods of developing expert systems, definitions, and a good overview of these advancements are reported by Argialas and Harlow (1990). In another paper, the authors concluded that incorporating ancillary data with spectral data improves the classification accuracy 4% to 20% compared with the results obtained only from spectral information (Middelkoop et al., 1989, and Middelkoop et al., 1991).

The following table summarizes the advantages and disadvantages of traditional methods (spectral-based techniques) and new methods (expert system-based techniques).

Table 1
Traditional and Computer-Assisted Image Interpretation Methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
</table>
| Traditional Methods | * Well established  
* Commercially available  
* Large part is automated  
* Spectral aspects of images are fully evaluated | * Partial knowledge is used  
* Slow executions  
* Rigid in reporting explicit conclusions  
* Still requires human interventions |
| New Methods      | * Use richer knowledge  
* Flexible in reporting explicit information  
* Human interference can be minimized  
* Easily modified and updated | * Requires more research to have it available commercially  
* Requires theoretical foundations to codify knowledge and expertise |
CHAPTER III

3 KNOWLEDGE ACQUISITION

Knowledge acquisition is by far the most difficult and most important part of developing an expert system (Waterman, 1986; Caudiall, 1990; Adeli, 1988). This stage is time-consuming. Moreover, it is the most critical phase, for it determines the quality and reliability of the expert system. Three important features of knowledge acquisition can influence the quality of the expert system. The features are:

1. the type of acquired knowledge. That is, is the acquired knowledge well defined, and does it possess unique characteristics that can lead to proper conclusions?

2. the spectrum of the acquired knowledge. That is, does the acquired knowledge cover full or partial aspects of the problem?

3. the explicitness of the required knowledge. That is, does the expert express implicit knowledge clearly?

Accordingly, a regular time was set every week with the expert to conduct "photo analysis" during a three-month period for this dissertation.

The person who engineers the knowledge in expert systems is known as the knowledge engineer (KE). Knowledge engineers initiate interactions with qualified experts to acquire proper knowledge for expert systems. This process usually extends for several months. Interviewing the expert, observing him/her while solving real problems in the field, and trying to conceptualize the expert's rules for
solving problems are the main tasks that a knowledge engineer performs at this stage. Besides the experts, there are other knowledge sources, such as textbooks, publications, reports, personal experience, case studies, maps, and empirical data.

In this chapter three important aspects of knowledge acquisition are treated. The first aspect is a description of the role that the landform knowledge plays in building expert systems. Next, methods of acquiring knowledge from experts in landform interpretation are investigated, and new techniques are proposed. The final aspect is the types of knowledge and attributes of landforms that should be considered while acquiring the knowledge from experts and from other sources.

3.1 The Role of Landform Knowledge in Building Expert Systems

Acquiring and formalizing the knowledge from an expert is a challenging task in building expert systems. There are seven important considerations while doing this task (Waterman, 1988):

- On-site observation (while an expert solves real problems in the field) contributes to the faithfulness of the system.

- Detailed discussion is required so that data, knowledge, and procedures followed by the expert in solving a problem can be explored.

- The expert should describe his/her solution to the problem.

- The knowledge engineer must understand and analyze the problem. This means that the KE should prepare techniques that will have the expert state the solution aloud and explain his/her rationale.

- The knowledge engineer should ask the expert for some problems to solve, using the rules acquired from the on-going interaction with the expert. This
interaction will shape and refine the system.

- The knowledge engineer should have the expert examine the system and give his/her feedback.

- Finally, the system should be tested in solving real problems in the field.

All seven factors are interrelated and overlap in many stages of developing the expert system. In developing an expert system, four major phases must be integrated to draw the complete concept of the system. These four phases are, in order, the planning, the analysis, the design, and the construction phases. The first two phases can be regarded as the initial stage of developing the system. This stage is called the conceptual validation phase, in which, having defined the problem and verified it to be one that needs human expertise, knowledge engineers conduct acquisition sessions (Minasi, 1990).

Constructing an expert system means modeling a solution for a specific problem that demands an expert in order for it to be solved in the real world. This implies three integrated factors. One factor is the existence of a problem that can be resolved only by experts. Regarding this factor, the Image Interpretation Using Terrain Analysis (ITA) task is properly accomplished by experts in the field but not by computers at the moment. This is compatible with the AI definition which is given by Rich and Knight (1991). Therefore, landform identification for site evaluation purposes is considered to be an AI problem (Argialas, 1990). The problem of ITA has the property that, while many facts are well documented in different sources, such as books, reports, and maps, the most important knowledge for ITA is written nowhere but in the minds of the experts. This knowledge contains the strategy for approaching the problem under different circumstances. The problem of landform interpretation has been dealt with since 1985, but on a purely experimental basis (Mintzer, et al., 1988). Two parties interact during the
system's development. The first party is the knowledge engineer (the person who engineers the knowledge base and builds the expert system). The second party is the expert whose way and style of problem-solving is modelled. The second factor to be integrated is a human factor—that is, the existence of qualified experts who can solve the problem. The third factor, a human factor as well, is the existence of a KE who is interested in modeling human intelligence in solving the problem. The KE can be the expert or one of the participating experts in the problem-solving with the condition that he/she can develop the system. For precaution and to avoid biases in developing the system, the KE should think about dual participation (as an expert and a KE) in constructing an expert system. The KE, however, plays many roles in developing the system. That is, the KE can participate as a system analyst, an interviewer, and a problem solver.

Knowledge acquisition is a major step that defines the system's requirements. These requirements, in turn, highlight the design stage of developing the system. For instance, collecting the knowledge about different types of landforms triggers the questions "How will the system process this knowledge?" and "What will the system do?" The second question is a conceptual one that adds to the general idea of developing the system. The first question, however, is a design-related question that creates thoughts about search theories and data structuring (e.g., breadth-first, depth-first, best-first, means-ends analysis, heuristic search, and constraints). It is quite clear that the conceptual validation stage and the design stage both overlap and are parallel.

Based on the acquired knowledge as well as the design themes, the knowledge engineer starts to formalize the operational stage of the system by defining the system and its requirements to solve the problem. For instance, the problem of interpreting landform types requires developing many nets that need sophisticated link supports and object supports in order for different nodes to communicate. This
implies the stage of developing semantic nets which are converted incrementally into more structured forms called frames.

3.2 Methods of Knowledge Acquisition

It is commonly agreed that the quality and performance of a system is proportional to the quality and precision of the acquired knowledge rather than the sophistication of the inference engine. It requires months to acquire data due to the difficulty of inventing proper techniques to have the expert think aloud and due to the time required by the expert to treat the general aspects of the problem (Adeli, 1988; Jackson, 1986; Waterman, 1986; Rich and Knight, 1991). Sometimes, experts possess implicit knowledge which is difficult to make explicit. Moreover, complete knowledge does not exist (Chandrasekaran, 1992). Even though experts are the best source for landform knowledge, they cannot provide everything, especially in those situations that are not raised during the development of the system.

There are two main techniques of acquiring data. The first one is the manual method. This is the standard method used today in the field of AI for acquiring knowledge from a domain expert. It is the method of getting information from people to the system. (This method will be discussed in the next paragraph.) The second method is called the automatic method. This method is far from realization nowadays (Patten, 1991). The idea of the second method is to have the system replace the KE. It is thought that the system will acquire the knowledge by direct communication with the expert, with the assumption that the expert may lack the qualification of a KE. The idea here is that the information is obtained and developed by the system. (Due to inapplicability of this method nowadays, it will not be discussed further.)

In this dissertation, the manual method was used to develop EXLANT for landform interpretation. Acquiring landform knowledge from experts is quite dif-
ferent from problem domains in other fields. The main reason for such a special remark is that most problems can be solved without any or with very few visual factors involved in the process. For instance, developing expert systems in business administration or in financial management needs no visual participation, in general. On the other hand, there is no way that an expert system can be developed for landform interpretation unless images of a particular type participate fully in the development. This needs no proof since the acquired knowledge is embedded in the imagery. Landform information (expertise) consists of two parts: the thoughts of the experts (these are used alone in most domain problems) and the materialized visual process (i.e., aerial photographs) that complements the expert's thoughts. This duality has a real impact on the type of technique that should be used to acquire landform knowledge from a domain expert.

This study proposes four integrated techniques for data acquisition. These techniques are:

1. Interviewing the domain expert at different stages before and after practical solutions of some parts of the problem domain.

2. Process tracing (protocol analysis) in which the KE acts as an observer. Process tracing must participate in all works that are achieved by the domain expert.

3. Videotaping the expert while conducting the process of image interpretation. This process is by far the most important one. It allows both the expert and the KE to do their work without any interruption that could alter the expert's natural way of thinking or could make the KE miss some important events while observing the expert. Moreover, this insures that the KE will make a precise analysis of the way the expert behaves, talks, moves, and pauses. For instance, small stops mean that a great deal of searching is
going on, implicitly, in the mind of the expert. Such different behaviors can be brought to the expert’s attention after the session is finished, and the expert can be asked to explain aloud the searching process.

4. Designing specific problems for the expert to solve in cases where certain parts of the problem were unclear to the KE.

3.3 Types of Knowledge and Attributes for Landforms

The types of knowledge required for a specific domain expert system define the attributes of the problem under consideration. To behave knowledgeably, a system should preserve different types of knowledge. Any expert system must have a reasonable answer to the question “What does the system know about a problem domain?” so that the system can be classified as an AI system. Facts about objects are one type of knowledge regarding landforms. For example, sandstone can be viewed as an object that has a dendritic drainage pattern. This pattern is a type of knowledge that is accepted as a fact associated with the landform sandstone. Accordingly, landforms ("objects"), their categories, and their descriptors (visual pattern elements) are essential in any knowledge base which concerns landforms. "Events" are a different type of knowledge about landforms that an AI system must have as well. For instance, geological conditions and weather activities are two cause-and-effect events that should be either reasoned by the system or provided a priori in the knowledge-base of the expert system. A third type of knowledge for landform interpretation is called “performance.” This type of knowledge goes beyond the limits of objects and events. It is the knowledge used by the intelligent part of the system, the inference mechanism, to provide solutions and consultations about landforms and their suitability for a particular application based on processed facts. That is, collections of events and objects are
manipulated and analyzed to provide a new knowledge called performance. For instance, facts about a landform's attributes and weather conditions can be used by the expert system to infer the types of landforms appearing on a particular image. Finally, "meta-knowledge" is defined as the knowledge about what the system knows (see Section 1.2).

This research is intended to combine both fine-grained and coarse-grained knowledge, as recent AI publications recommend (for more details see Chapter 2). "Objects" and some of the "events" previously mentioned are regarded by this study as the fine-grained knowledge. The other part of the "events" and "performance," as well as "meta-knowledge," are coarse-grained knowledge.

It is essential to realize that the acquired terrain knowledge influences the representation methods and the organization of the knowledge base of the expert system. The intelligent basis for landform interpretation is provided by pattern elements or attributes that are obtained from the analysis of single or stereo images. Accordingly, suitable attributes for landforms must be defined. Based on the value of the selected attribute, a particular landform can be defined. Consequently, identification of landforms is the foundation for a proper consultation with civilian or military sectors (Brew et al., 1980).

Landforms' knowledge needs to be carefully prepared in such a way so that they can be structured in an expert system for interpretation and consultation. The first requirement is that a set of attributes for the landforms be defined. This indicates the requirement of creating precise specifications and attribute values based on which the initial states (hypotheses) and expected solution(s) (goals) can be defined (see Section 1.2). Based on these specifications, the expert system is developed using suitable search strategies that best fit the problem under consideration.

Proper analysis of a problem results from a precise set of problem descriptors
upon which a control strategy may be formed on a selective basis. Accordingly, one must acquire suitable criteria for landform interpretation from appropriate sources, such as standard manual interpretation methods that are conducted by recognized experts in terrain analysis. As soon as these criteria are defined, proper algorithms and control strategies can be justified for the expert system. For example, if the initial states and final states of an interpretation problem (landform) are clearly defined, then the number of initial states and the number of goal states form one of the criteria based on which either forward or backward chaining can be used (Rich and Knight, 1991).

The knowledge base that is assembled in EXLANT consists of pattern elements similar to those used by experts in the manual interpretation of landforms. Each set of pattern elements represents terrain analysis descriptors that can define a specific landform and that serve as a reference template to verify hypotheses. A single element has the property parameter or attribute. This attribute (parameter) is assigned yes/no, single, or multiple values. The hypothesis of expected types of landforms is usually instantiated based on a priori knowledge.

Experts and researchers in terrain analysis and image interpretation use pattern elements that contribute to the identity of landforms. The pattern elements include topography, drainage system, gully characteristics, photographic tone, site association, land use, and vegetation character. Each pattern element has its indications, contributions, values, and sub-attributes (e.g., texture). Some of the pattern elements can be based on mono images (Avery et al., 1985).

Following the general guidelines and themes of experts, this study concentrates on five visual attributes and observes them carefully. These attributes are:

1. Landform topography
2. Landform drainage
3. Landform photographic tone

4. Landform association (land use and land cover)

5. Landform erosion (Gullies)

During a four-months period the proposed four techniques of knowledge acquisition were used. A large number of stereo pairs was processed by the expert. The processed models included SPOT images, large scale aerial photographs, and medium-to-small-scale aerial photographs. Many other sources, such as maps, reports, publications, and textbooks, were used to acquire the needed knowledge.

A total of fifty-four stereo models was processed by the expert (Professor Douglas Way, Chair, Department of Landscape Architecture, The Ohio State University). The scale of the images ranges between 1:10,000 and 1:250,000. These models cover different generic landforms, such as sedimentary, igneous, metamorphic, glacial, eolian, and fluvial landforms. The areas covered in the images are located in U.S.A. and Saudi Arabia. After collecting these observations, I closely analyzed them. Chapters 4 and 5 include tabular forms of knowledge and detailed analyses about the observations. Table 2 (Appendix A) includes some symbols (labels or abbreviations of large expressions) and their meanings. Table 3 (Appendix A) contains observations of the topographic attribute values. The observations of the rest of the five classes of landforms attributes are in tables 4 through 7 in Appendix A. Most of the expressions that are included in the KB are unaltered expressions of the expert’s (Way, 1992) publications, reports, or oral conversations.
CHAPTER IV

4 THEORY OF LANDFORM CONCEPTS

Even though the theories of certainty factors are not well established yet in AI (Weichselberger et al., 1990), most of the developed expert systems include some sort of quantitative approach to show the strength of the conclusions reached. Associating a certainty factor with an identified landform determines how accurate the interpretation is. In this chapter a theoretical approach to quantitatively identifying landforms is developed. The chapter opens with remarks about landforms as a problem of logic. Then the relational aspects of landform knowledge are explained. Finally, modeling landform knowledge using probability is presented, and different evaluation functions are developed.

Even experienced analysts assign different statistical values to similar landforms’ attributes. Accordingly, heuristic probability values assigned to landform attributes vary. The individual contribution of attributes to identifying landforms is subjective. For this reason, a scientific approach based on set theory and probability statistics is adopted in this study. This quantitative approach makes the traditional subjective assignment of weights to landform attributes more rigorous.

In employing AI for interpreting landforms based on terrain analysis, the statistical aspects of collecting evidence cannot be ignored. In theory, if a conclusion can be reached regarding the identity of a landform, based on \( n \) pieces of evidence, then collecting \( m \) pieces of evidence (\( n > m \)) indicates incomplete information.

Incomplete information can be resolved on a binary basis. In a binary repre-
sentation, complete information is given a TRUE response, and incomplete information is given a FALSE response. Alternatively, incomplete information can be resolved based on an associative confidence level whereby a value between 0 and 1 is assigned to the reported conclusion. The binary nature of landform identification should be avoided, as explained next.

This study bases the process of image interpretation of landforms on associated probability values. In reality, an image feature, which can be identified based on the ideal properties of that landform, still can be identified based on m properties, but the interpretation will be of a different certainty or level of confidence. For instance, in a small scale image (e.g., 1:250,000), a landform can be identified by most of its pattern elements (four out of five pattern elements), such as morphological aspects, drainage patterns, land-use/land-cover, and photographic tone. The pattern element erosion cannot be detected at such a small scale.

To illustrate the effects of binary representation of conclusions, assume that the above five pattern elements are the required elements for identifying a particular landform. Moreover, assume that all of these elements are equally likely in their contribution to the landform's identity, and that out of these five elements four elements are known. In a binary treatment, the identification process of that landform would report an unknown landform while in an associative confidence treatment, the identification process would report the identity of that particular landform with an 80% confidence level. In the real world, the identity of landforms is usually reached based on partial knowledge. Hence, the TRUE-FALSE method, which is based on complete or incomplete information, should be disregarded. Probability theory is associated with set theories and should be considered in developing random algorithms and generating other related analyses (Cormen et al., 1990). In developing an expert system to identify landforms, the state space of the whole knowledge base was considered as the Universal (U) set that contains
all sample spaces. The $U$ set contains $n$ subsets. Every subset contains its own subsets and eventually its own elements. These elements are regarded as elementary events. An event is a subset of a larger sample space. For instance, Sandstone Frame could be treated as a set containing the events (elements):

- drainage $(D)$,
- morphology $(M)$,
- photographic tone $(T)$,
- erosion $(G)$, and
- land use and land cover $(L)$.

But the Sandstone Frame $(SS)$ itself can be viewed as a subset of a larger sample space or a frame called Sedimentary Rocks Frame $(SR)$, which contains the elements (or subsets):

- sandstone $(SS)$,
- limestone $(LS)$,
- shale $(SH)$,
- flat interbedded $(FI)$, and
- tilted interbedded $(TI)$.

That is:

$$SS = \{D, M, T, G, L\}$$

and

$$SR = \{SS, LS, SH, FI, TI\}.$$ 

Therefore, it can be stated that

$$SS \subset SR.$$ 

It is, however, assumed that all elementary events are mutually exclusive. Therefore, each landform is treated as a separate node. In cases where more resolution is required every generic landform can be given a separate frame. For instance, igneous rocks can have a frame since most landforms of igneous rocks share the
same properties from the standpoint of engineering applications.

4.1 Theory of Developing Evaluation Functions

Basic Theorems and Axioms of Probability

Given a set of attribute values, an evaluation function should be developed to perform the following tasks:

1. Assign probabilities to each attribute according to its contribution to identifying a landform (local),

2. Automatically (or in a parallel process) assign each attribute value to all relevant landforms that share the same value (transition phase),

3. Repeat tasks 1 and 2 until all attribute values, which are selected by the analyst in a particular consultation session, are treated,

4. Accumulate probabilities of evidence values for an individual landform,

5. Instantiate a sort function to order the obtained landforms according to specific criteria,

6. Generate a local test to establish hypotheses,

7. Refine the hypotheses,

8. Report the identities of landforms along with associated confidence or certainty factors, and

9. Repeat steps 1-8 in every consultation session.

The previous section has emphasized the importance of introducing probabilities and set theories to the problem of landform interpretation with expert systems.
This section introduces the theories of probability that are implemented in the expert system. In other words, this section provides a theoretical basis for developing evaluation formulas for interpreting landforms based on AI concepts.

Three axioms (facts) of probability are important to this study. These axioms can be found in any basic text for probability, topology, mathematics, or set theory (e.g., Childress, 1974; DeGroot, 1986; Haeussler et al., 1987; Hogg et al., 1970; Sims, 1976; Hogg et al., 1970). If \{A\} is any event and \(P_r\{A\}\) is the probability of the event \{A\}, the axioms are:

1. Probability of an event is bigger than or equal zero. That is,
   \[ P_r\{A\} \geq 0 \quad \text{for any event } A \] (1)

   (This axiom states that the probability of every event must be non-negative.)

2. If an event is certain to occur it has a probability of one. That is,
   \[ P_r\{A\} = 1 \] (2)

3. Probability of the union of mutually exclusive events equals the sum of the probability of individual events. That is,
   \[ P_r\{A_1 \cup A_2 \ldots \cup A_\infty\} = P_r\{A_1\} + P_r\{A_2\} + \ldots + P_r\{A_\infty\} \] (3)

   for \(A_1, A_2, ..., A_\infty\), which are mutually exclusive events. More general
   \[ P_r\{\bigcup_{i=1}^{\infty} A_i\} = \sum_{i=1}^{\infty} P_r\{A_i\} \] (4)

   where \(P_r\{A\}\) is called the probability of event \(A\) and \(A\) could be a landform attribute value, for example. Accordingly, a probability, as a number \(P_r\{A\}\), is specified for an event in the sample space, provided that the three axioms above are satisfied.
Several related theorems pertain to this research. These theorems are obtained as natural conclusions of the three axioms (DeGroot, 1986). Before these theorems are stated, the following definition, which can be found in most probability text books (e.g., Walpole et al., 1989), is given:

**Definition**: The sum of the weights that are assigned to all elements of an event (a set) $A$ gives the probability of event $A$. Moreover,

$$0 \leq P_r\{A\} \leq 1. \quad (5)$$

In connection with the axioms and the definition mentioned above, the following five theorems are used in this research. These theorems can be found in most basic texts of statistics (Devore et al., 1986; DeGroot, 1986; Walpole et al., 1989).

**Theorem 1** An impossible event must have a zero probability; that is:

$$P_r\{\emptyset\} = 0, \text{ where } \{\emptyset\} \text{ is the empty set.}$$

Accordingly, an impossible event is regarded as a null event $\{\emptyset\}$ with a probability of occurrence at zero. In this study the empty set is defined by a threshold.

**Theorem 2** The probability of an event contained in another event is less than or equal to the probability of the event that contains the other event. That is,

If

$$A \in B \quad (6)$$

then

$$P_r\{A\} \leq P_r\{B\} \quad (7)$$

**Theorem 3** The probability of the complement of an event equals one minus the probability of the event. That is,
Pr{\bar{A}} = 1 - Pr\{A\} \tag{8}

where \( A \) is any event and \( \bar{A} \) is the complement of \( A \).

**Theorem 4** The probability of a union of two events, regardless of whether or not they are mutually exclusive, is as follows:

\[
Pr\{A \cup B\} = Pr\{A\} + Pr\{B\} - Pr\{A \cap B\} \tag{9}
\]

where \( A \) and \( B \) are any two events. Also it follows that:

\[
Pr\{A \cup B\} \leq Pr\{A\} + Pr\{B\}. \tag{10}
\]

**Theorem 5** If \( A, B, \) and \( C \) are any three events, then their union probability is expressed as:

\[
Pr\{A \cup B \cup C\} = \{\delta_1 - \delta_2 + \delta_3\} \tag{11}
\]

where:

\[
\delta_1 = Pr\{A\} + Pr\{B\} + Pr\{C\} \tag{12}
\]

\[
\delta_2 = Pr\{A \cap B\} + Pr\{A \cap C\} + Pr\{B \cap C\} \tag{13}
\]

\[
\delta_3 = Pr\{A \cap B \cap C\}. \tag{14}
\]

Theorem 5 can be generalized to \( n \) events instead of only three. That is, if \( A_1, A_2, \ldots, A_n \) are arbitrary events, then their union probability is expressed as follows:

\[
Pr\{\bigcup_{i=1}^{n} A_i\} = \sum_{i=1}^{n} Pr\{A_i\} - \sum_{i<j} Pr\{A_i \cap A_j\} + \sum_{i<j<k} Pr\{A_i \cap A_j \cap A_k\} + \ldots + (-1)^{n+1} Pr\{A_1 \cap A_2 \cap A_3 \ldots \cap A_n\}. \tag{15}
\]
These theorems and the preceding definition are used in this chapter, where evaluation functions for landform concepts are developed for the purpose of interpreting landforms through images based on terrain analysis.

4.2 Landform Concept as a Problem of Logic

Problems of logic are descriptive in nature. However, they can be treated using set algebraic theories (Childress, 1974). Image interpretation for landform concepts can be categorized as a problem of logic. Landform concepts are descriptive knowledge when viewed from the standpoint of image interpretation. This descriptive knowledge is hard to formalize and structure properly so that computers can access the knowledge and conduct the necessary manipulations. When viewed as a problem of logic, set algebraic theories can be applied to landform concepts. In this section, the landform concept is exposed to three important aspects of logic: logic operators, logic statements, and logic arguments.

The logical representation of knowledge about a landform is the real force behind obtaining inferences about unknown parameters based on collected facts. Mathematicians and philosophers developed formal logic as a calculus of processing facts to reveal some unknown behaviors about certain problems. For example, the following sentence is a major premise in formal logic:

All Sedimentary Rocks Have Drainage.

This sentence can be translated into a mathematical formula as follows:

\[ \forall x. \text{Sedimentary Rocks}(x) \rightarrow \text{Has Drainage}(x), \]  

which reads, for any objects \( x \) in the world, if \( x \) is a sedimentary rock, then \( x \) has drainage. Such a formal representation has the advantage that there is a set of rules (called rules of inference) by which unknown facts can be derived based on the known facts. This is the reference template, by which hypotheses are checked.
against the known facts. For example, let the following fact be added in a data
base to the fact mentioned above about sedimentary rocks:

\[ \forall x. \text{Shale}(x) \rightarrow \text{Sedimentary Rocks}(x), \quad (17) \]

which reads, for any object \( x \) in the world, if \( x \) is shale, then \( x \) is a sedimentary rock. According to equations (16) and equation (17), an inference engine mechanism can recognize that the following fact must be true:

\[ \forall x. \text{Shale}(x) \rightarrow \text{Has Drainage}(x), \quad (18) \]

which reads, all shales have drainage.

Logical representation has the advantage of corresponding to intuitive understand­ing as a natural way of thinking. Also, it combines flexibility in presenting knowledge with precision in conveying the meanings of the expressions. Most importantly, logical representation has a modular property since incremental development of the knowledge base using formal logic can be achieved with the least modification of the knowledge structure. That is, new facts (if known at later stages of developing the system) can be added to the knowledge base and will have no influence on the structure and the behavior of the already existing scheme in the system.

One important concept in logic, which concerns structuring the knowledge of landform concepts, is that of the statement. Set operators can be used to model knowledge by combining simple statements. As counterparts for set operations, there are connectives in logic. For instance, negation, conjunction, and inclusive and exclusive disjunctions are connectives in logic.

To illustrate these connectives as counterparts of set operations, here are some statements about landforms.

1. **Negation** of a statement \( LID \) is the statement not \( LID \).
For example, the negation of the statement

\[ L_{ID} = \text{the landform concept is sandstone}, \]

is the statement

\[ \bar{L}_{ID} = \text{the landform concept is not sandstone}. \]

2. Conjunction of statements \( D, M, \) and \( T \) is the statement \( D \text{ and } M \text{ and } T. \)

For example, the conjunction of the statements

\[ D = \text{the drainage is dendritic}, \]
\[ M = \text{the morphology is flat table rocks, and} \]
\[ L_{ID} = \text{landform identity is sandstone CF 75\%} \]

is the statement

\[ D \cap M \cap L_{ID} = \text{the drainage is dendritic} \]
\[ \text{AND} \]
\[ \text{the morphology is flat table rocks} \]
\[ \text{AND} \]
\[ \text{the landform identity is sandstone CF 75\%}. \]

The conjunction of statements produces compound statements with new knowledge.

3. Inclusive disjunction of two statements \( SS \) and \( LS \) is the statement \( SS \text{ or } LS \text{ or both}. \)

For example, the inclusive disjunction of the statements

\[ SS = \text{the landform is identified as sandstone, and} \]
\[ LS = \text{the landform is identified as limestone} \]
is the statement

\[ SS \cup LS = \text{the landform is identified as sandstone} \]

or

\[ \text{the landform is identified as limestone} \]

\[ \text{or both.} \]

4. **Exclusive disjunction** of two statements \( SS \) and \( LS \) is the statement \( SS \)
   \[ \text{OR} \quad LS \quad \text{But Not Both.} \]

   For example, the exclusive disjunction of the statements
  
   \[ SS = \text{the landform is identified as sandstone, and} \]
   \[ LS = \text{the landform is identified as limestone} \]

   is the statement

   \[ SS \cup LS = \text{the landform is identified as sandstone} \]
   
   or
   
   \[ \text{the landform is identified as limestone} \]
   
   \[ \text{but not both.} \]

Finally, logical *arguments* are the means for knowledge analysis in logic where *premises* and *conclusions* are tested and manipulated. When a list of premises or statements is followed by a single conclusion or a list of conclusions, then the whole process is termed the *logical argument*. Logical arguments are extensions of the principles of set algebra (Childress, 1974). As soon as the logical consequence of a premise is true, the argument is *logically true*. On the other hand, if the logical consequence of a premise is not the desired conclusion, the argument is *logically false*. 
To illustrate logical arguments in landform concepts, let $D, M, L$, and $T$ be a list of landform attributes, and let

\[A = \text{landforms with known } D, M, L, \text{ are assigned more weight than those landforms of known } T \text{ but with unknown } D \text{ and } M,\]

\[SH = T \text{ is known for the landform shale but not for limestone,}\]

\[LS = D \text{ and } M \text{ are known for limestone, and}\]

\[L_{ID} = \text{The landform identity is limestone but not shale.}\]

The statements $A$, $SH$, and $LS$ are the premises of the conclusion reported by the statement $L_{ID}$. As can be seen in the Venn Diagram (Figure 4), since $SH$ is not a subset of $A$ while $LS$ is a subset of $A$, $L_{ID}$ is true, and the whole argument is logically true. In conclusion, arguments, statements, and operators formulate the relational aspects of descriptive knowledge. In the next sections, the type of relational knowledge in landform concepts is discussed.
4.3 Relational Aspects of Descriptive Knowledge

Interpreting landforms is a mental process whereby one collects evidence regarding a particular landform. Every landform on earth can be identified by its unique properties. However, in many cases and for various reasons, a full collection of evidence may not be available. Lack of complete evidence means a necessity of associating a confidence level to the interpreted landforms. This association can be achieved if an evaluation function is developed. Such a function requires theoretical development of mathematical forms through which the relationships between landform concepts and their attributes in the real world can be expressed.

The identification of landforms using expert systems is characterized by three properties. The first property is the descriptive nature of the knowledge associated with landform concepts. That is, the knowledge that can be obtained is categorical in nature. This property calls upon suitable mathematical theories that can structure the knowledge so that computational algorithms can be properly developed. Set theories are promising for this type of problem. The second property is the fact that the landform problem is decomposable into unique units or sub-problems. This implies the applicability of set theory and set algebra. Hence, relational operations for landform concepts can be developed. The third property is that the interpretation process contains hierarchical procedures.

The third property has two consequences for the identification process. First, it confirms the notion of set and subset theory and its applicability to the image interpretation process. Therefore, set theories should be introduced to the identification process. Second, system implementation should be achieved in such a way that the hierarchical property of the problem contributes to the efficiency of the system by developing some constraints to manipulate the necessary parts of the knowledge base and de-activate irrelevant parts.
Three distinct types of correlation or dependency properties can be realized in image interpretation in general and in interpreting landforms in particular:

1. Full correlation or dependency:
   There exist a set or sets of features or landforms that possess the same properties.

2. Partial correlation or partial dependency:
   There exist a set or sets of features or landforms that share some (but not all) properties.

3. Full independence or no correlation:
   There exist a set or sets of features or landforms that have no properties in common.

These three correlation levels are the bases of relational aspects of knowledge about landform concepts. This study introduces three set theories for the interpretation of landforms and consequently for handling the three relational aspects listed above, respectively. These theories are idempotency laws of sets, set intersection theories, and set mutual exclusiveness theories, respectively. These theories are elaborated in the next section.

Mutually exclusive properties of sets are introduced for two reasons. The first reason is to achieve a suitable state space search by partitioning the state space in a coarse-to-fine manner. Set theories are well suited for this purpose. The second reason is to develop a theoretical basis for image interpretation of landforms which are descriptive in nature. Set theory is promising, for it provides a means of introducing probability and statistics into the interpretation process. This new trend will lead to a quantitative way of interpreting landforms in a scientific manner. Image interpretation of landforms contains categorical instances
as opposed to numerical data. In this study, the process of image interpretation is quantified and theorized.

4.4 Modeling Landform Concepts

A set is defined in this research as a concept consisting of a collection of objects or components. Each component in the set is called a member or an element. The word concept fits the purpose of this study better than the word set in some instances; therefore, set and concept are exchangeably used in this dissertation. A concept is an arbitrary node, frame, or parameter, in the state space. The members of the concept are attribute values or unique goals that are attached to a corresponding node or a frame. For instance, frame $F$ can be treated as a concept (a set) concerning landforms in humid regions whose origin is in sedimentary rocks. A subset or a subconcept could be a list of three subframes that treat the landforms sandstone, limestone, and shale. Each subconcept consists of elements, which could be landforms’ attributes (e.g., morphology, drainage, association, photographic tone, and erosion or gullies).

To generalize the theoretical aspects of landform concepts, the following notations are defined:

- {} denotes a set or a concept.
- $\in$ denotes membership and reads “a member of.”
- $\notin$ denotes irrelevant membership and reads “not a member of.”
- $\emptyset$ denotes empty set or empty concept.
- $\subset$ denotes proper subset or proper subconcept and reads “contained in.”
- $\subseteq$ denotes subset or subconcept and reads “contained in.”
- $\supset$ denotes subset or subconcept and reads “contains”
- $|$ denotes a statement or a rule and reads “such that.”
- $\cap$ denotes intersection of sets or concepts.
\( \cup \) denotes union of sets or concepts.

\(-\) denotes a set complement (e.g., \( \bar{A} \) is a complement of \( A \)).

\( \cup \) denotes exclusive union of sets or concepts and reads "exclusive union."

\( \rightarrow \) reads "imply."

The identification of particular sets through other sets is a basic property in set theory, and it is a concern for this study. A set of landform attributes is defined by a set of attribute values, which in turn identify landforms in the real world according to some formulations. That is, landforms' identification and consequent consultations are considered as a sample space with a large number of sample points that are best described by a statement or a rule. For instance, the sample space points that the system contains all static and dynamic conclusions developed in the knowledge base. However, the possible outcome from an individual consultation session will be an activation of only a small random part of the sample space, which is a problem-dependent activation process.

To illustrate the process of set (concept) identification through some other sets (concepts) using set theories, an example is helpful. Suppose that an expert system is developed to treat thirty landforms on earth. This is a large sample space. In a particular image interpretation session, an average of three to five landforms is expected to be found in one image that has image interpretation standards (acceptable scales). To formulate the identification of three landforms (sandstone \( SS \), limestone \( LS \), and shale \( SH \) in humid \( H \) regions, for examples) from the whole hypothesized sample space \( SP \), let the sedimentary rocks' landforms in humid regions be denoted by \( \{S_H\} \). It follows that:

\[
SP = \{S_H | S_H \text{ are a non-cotype sedimentary rock}\}. \quad (19)
\]

This is an expression which states a rule in a set notation. If \( \{A_H\} \) is a set of
attribute values based on which \( \{S_H\} \) can be identified, then:

\[
S_H = \{ A_H | A_H \in S_H \}. \tag{20}
\]

Accordingly, a set \( \{S_H\} \) is identified through the set \( \{A_H\} \). As can be realized from the previous discussion, important set operations and theorems are required for theorizing landform concepts.

As stated previously, landform concepts are of a certain degree of correlation, depending on the overlapping properties of the landform concept. That is, common properties between two or more landform concepts correlates these particular concepts. Set theories can express these correlations in precise mathematical forms. Let \( A, B, \) and \( C \) be three concepts or sets (e.g., a particular landform can be considered as a concept). Three important set relational operations are as follows:

1. Set or Concept Intersections:

\[
A \cap B = \{ y_i | y_i \in A \text{ and } y_i \in B \}. \tag{21}
\]

2. Set or Concept Union:

\[
A \cup B = \{ y_i | y_i \in A \text{ or } y_i \in B \} \tag{22}
\]

3. Set or Concept Difference:

\[
A - B = \{ y_i | y_i \in A \text{ and } y_i \notin B \} \tag{23}
\]

Figure 5 is a Venn diagram showing these operations. Since set operations play an important role in evaluating and analyzing landform concepts, a clear understanding of set terminologies and set operations, as they relate to landform concepts, is essential. For instance, in the list of set notations given previously, the two symbols \( \subset \) and \( \subseteq \) read as contained in. In the operational mode, however, the two notations carry different concepts. A proper subset is different from a subset.
That is, the elements of the left hand set do not equal the elements of the right hand set in the *proper subset* while elements of both sets (both sides) are equal in the *subset*. These relations are essential to landform concepts when the landforms are treated in a universal space, as explained in a later section. For instance, let

\[
S_1 = \{A, B, C\} \text{ and } S_2 = \{A, B, C, D, E\}.
\]

(24)

Even though both sets have some elements in common, they are not equal. That is,

\[
S_1 \neq S_2
\]

(25)

To express the inequality between two sets while, at the same time, they have partial similarity, the relation

\[
S_1 \subset S_2
\]

(26)

is used instead of

\[
S_1 \subseteq S_2.
\]

(27)

This relation is pertinent in the process of interpreting landforms through images. For instance, two landforms may partially share the same elements found in a set

\[
A \cap B, \quad A \cup B, \quad A - B
\]

Figure 5: Set Operations
of attribute values. Also, for any set $S$ the relationships

$$S \subseteq S$$

(28)

and

$$\emptyset \subseteq S$$

(29)

are held. In any other set combinations, if

$$S_1 \subseteq S_2 \text{ and } S_2 \subseteq S_1 \text{ or } S_1 \subseteq S_2, \quad S_2 \subseteq S_3, \quad \text{and } S_1 \subseteq S_3$$

(30)

then a conclusion of equality between these sets is reached. That is,

$$S_1 = S_2 \text{ or } S_1 = S_2 = S_3.$$

(31)

In the real world, there can be found a set of attribute values that are fully shared by more than one landform on earth. As an example, limestone and sandstone are two similar landforms if they exist in arid climates, because both landforms share the same attributes. In such cases, idempotency laws of set are used.

In theory, two sets $A$ and $B$ are mutually exclusive (disjointed) if they have no elements in common. In a universal set $U$, a collection of non-empty sets, $C = \{S_i\}$ forms a partition of the set $U$ if:

1. A pair-wise mutually exclusive property of the sets is maintained. That is,

$$S_i \in C \quad \text{and} \quad S_j \in C \quad i \neq j$$

(32)

and this means

$$S_i \cap S_j = \emptyset$$

(33)

2. The union of the sets constitutes the set $U$. That is,

$$U = \cup_{S_i \in C} S_i.$$

(34)
These properties apply to the landform concepts when the landforms are treated in a local space, as explained later.

The disjoint (mutual exclusiveness) property of sets is also important for landform interpretation. A disjoint property indicates independence between landform attributes and consequently between landform concepts. That is, landform $A$ and landform $B$ are independent if and only if (iff) they constitute two disjointed sets. Another way of expressing disjoint properties of landform concepts (sets) is possible through intersection operations. A landform concept $A$ is independent from a landform concept $B$ iff:

$$A \cap B = \emptyset$$

and, therefore, the two concepts are disjointed. Empty set laws should be considered in developing a confidence interval while interpreting landforms. Empty landform concepts are expressed according to the set laws as follows:

$$A \cap \emptyset = \emptyset$$

and

$$A \cup \emptyset = A.$$  

Fully correlated landform concepts are found while interpreting images. Landform concepts that possess similar attribute values are difficult, if not impossible, to resolve on aerial images (except by a real field check). This full dependency between landform concepts is expressed in set theories by idempotency laws. For instance, let $A$ and $B$ be two similar landforms. If the attribute values for identifying these landforms are:

$$\{M, D, T, G, \text{ and } L\},$$

and if the attribute values of landform $A$ are:

$$M_1, D_1, T_1, G_1, \text{ and } L_1,$$
then, in a set notation:

\[ A = \{ M_1, D_1, T_1, G_1, L_1 \}. \]  \hspace{1cm} (38)

If the attribute values of landform \( B \) are:

\[ M_1, D_1, T_1, G_1, \text{ and } L_1, \]

then, in a set notation:

\[ B = \{ M_1, D_1, T_1, G_1, L_1 \}. \]  \hspace{1cm} (39)

From equation (38) and (39):

\[ A = B. \]  \hspace{1cm} (40)

But the set idempotency laws state that:

\[ A \cap A = A, \]  \hspace{1cm} (41)

and

\[ A \cup A = A. \]  \hspace{1cm} (42)

Then the relationship presented in equation (40) can be expressed according to set idempotency laws as follows: Let

\[ A \in B \text{ and } B \in A. \]  \hspace{1cm} (43)

Then

\[ A \cap B = A = B \]  \hspace{1cm} (44)

and

\[ A \cup B = A = B \]  \hspace{1cm} (45)

and

\[ A \cap B = A \cup B. \]  \hspace{1cm} (46)
Accordingly, whenever idempotent sets are confirmed in a landform consultation session, a field check should be signalled to the analyst or landforms should be reported with equal confidence values.

A partially dependent landform concept is best treated according to intersection theories of sets and subsets as well as the theories of unions. Let $A$ and $B$ be two different landforms, each of which can be identified based on a collection of $v_n$ and $v_k$ pieces of evidence, respectively. Let

$$A = \{v_1, v_2, \ldots, v_n\} \quad (47)$$

and

$$B = \{v_1, v_2, \ldots, v_k\}. \quad (48)$$

If $A$ and $B$ share $j$ pieces of evidence, then

$$A \cap B = \{v_j | v_j \in A \text{ and } v_j \in B\} \quad (49)$$

and a landform concept's identification function $f(L_i)$ is computed as follows:

$$f(L_i) = \begin{cases} 
A & \text{if } \delta < (\bar{A}_s \subset R) < (\bar{B}_s \subset R) \\
B & \text{if } \delta < (\bar{B}_s \subset R) < (\bar{A}_s \subset R) \\
A \text{ and } B & \text{if } \delta < (\bar{A}_s \subset R) = (\bar{B}_s \subset R) \text{ or } \text{if } (A > CL \text{ and } B > CL) 
\end{cases} \quad (50)$$

where $\bar{A}_s$ is a scalable complement of the landform concept $A$, $\bar{B}_s$ is a scalable complement of the landform concept $B$, $R$ is a reference template, $CL$ is certain level that will qualify both landforms, and $\delta$ is a threshold level for accepting a landform's identity.

For more illustrations, $\bar{A}_s$ contains a set of elements that landform $B$ should contain in order for it to be regraded as a set with full information. But for one reason or another this set of elements is not contained in landform $B$. It should
be noticed that the value of $\delta$ considers the combination of both complement and intersection sets that are to be united for a landform's identity. Figure 6 depicts the notions of intersection and complement operations in landforms.

![Set Complement and Intersection](image)

Figure 6: Set Complement and Intersection

As seen in Figure 6, the complement of a concept $A$ is considered as a set that contains all elements, in the defined state space, that do not belong to the concept $A$. In the figure, $A \cap B$ is represented by dots. The defined state space includes everything inside the rectangular shape ($S'$). $\bar{A}$ includes everything in $S$ except the dotted and dashed areas. $\bar{B}$ includes everything in the state space $S$ except the shadowed and dotted areas. The subscript $s$ that is added to $\bar{A}$ and $\bar{B}$ standardizes the logical comparisons expressed in equation 50.

The evaluation functions developed in this study are of different domains and localities. Some evaluation functions are local. That is, there are functions that analyze the attribute's values within the attribute's local space. For instance, the contribution of photographic tone to the identity of the sandstone is computed and compared to all other attribute values that participate in the identity of the sandstone. Other evaluation functions are global and possess transitive properties.
That is, the global evaluation functions analyze every attribute in a landform space (in relation to all other attributes that contribute to a landform’s identity) and, in turn, compare individual attribute values in the $U$ space. For example, individual elements of evidence are assigned to all corresponding landforms and the identity of the landforms are ranked in the global space. For instance, the photographic tone value *white-fringed* is evaluated in the $U$ space. That is, the value *white-fringed* is evaluated in the global space of the landforms as opposed to the local space of only one landform.

Furthermore, every attribute value is classified into $n$ levels according to its quality. That is, a value which is unique in occurrence (it cannot occur in more than one landform) is the most significant value, and the value with the highest occurrence (it occurs $n$ times in $n$ different landforms where $n$ is the maximum frequency in the attribute’s space) is the least significant value. (Attribute frequencies are explained further in later sections.)

4.5 Representative Schemes for Landforms

4.5.1 Local Evaluation Functions

A landform can be described by its attributes. In this research landforms are described by five attributes: topography, drainage, photographic tone, association, and erosion. Further, every attribute is represented by a list of values, each of which describes a particular class of landforms. The main objective of locally evaluating the attributes of the landforms is to qualify values to represent the attributes in a specific space. That is, given an attribute with $n$ values, we want to analyze these values and establish a scheme that can represent the contribution of that particular attribute to identifying landforms.

Local attribute values ($\lambda_i$) vary in their contributions to identifying landforms.
(λᵢ) can be assigned different weights according to their frequency. Let \( \beta \) be the attribute's sample space, each of which contains \( n \) values (λᵢ). Some \( \lambda_i \) occur in the landforms' universal space \( U \) more than once. That is, the same attribute value is found in more than one landform concept. Other \( \lambda_i \) are unique in the space of the universal \( (U) \) set. That is,

\[
\beta = \{\lambda_i | \lambda_i \geq 1\}, \quad i = 1, 2, ..., n. \tag{51}
\]

Every value (λᵢ) has a local contribution to every landform. This contribution ranges between 0 and 1. Accordingly, the local contribution of any value \( \lambda_i \) that does not belong to a landform A equals zero. On the other hand, the local contribution of a \( \lambda_i \) that belongs to a landform B equals \( c \) where \( 0 < c < 1 \). According to axiom 3 of probability, the sum of the probabilities of a sample space must be one. The frequency \( f_i \) of a \( \lambda_i \) in a landform's space indicates the degree of uniqueness of that particular attribute value in the sample space. The frequency \( f_i \) of \( \lambda_i \) is inversely proportional to the quality of the attribute. For instance, in the universal space of landforms, if there exists a total of forty landforms and there exists a \( \lambda_i \) that belongs to all forty landforms, then \( \lambda_i \) has \( f_i = 40 \) and its (λᵢ) quality is zero. This is true since this attribute value offers no contribution to the process of identifying any landform. Accordingly, in this study we used \( f_i \) as a determining factor for assigning individual weights to the attributes. As a basic concept in probability of a finite number of elements of an event, the likelihood of an event's occurrence is evaluated based on the weights (or probability) of the elements, ranging from 0 to 1. Figure 7 shows the relationship between the identity confidence and the frequency range according to the analysis of the observations conducted by this research.

Let \( c_i w \) be a probability coefficient value to be computed, and \( c_i \) be a coefficient which is assigned to individual attribute values in the local space of the
Figure 7: Effects of Attribute Frequency on Landform Identity
attribute. Each $c_i$ is assigned based on the attribute frequency $f_i$ and the total number of global attribute values $\Gamma_i$ in each frequency domain. For example, there could be a total of 22 values for all attributes in the frequency domain 2 (i.e., $f = 2$ and $\Gamma = 22$). The computation of the probabilities is as follows:

$$c_1 w + c_2 w + c_3 w + \ldots + c_n w = 1$$  
$$C w = 1$$  

where

$$C = \sum_{i=1}^{n} c_i$$  
$$c_i = \frac{\Gamma_i}{f_i}.$$  

Then

$$w = \frac{1}{C}.$$  

The individual elements, $\lambda_i$, of every attribute space, $\beta_i$, are observed and assigned to homogenous sets $s_i$ (sets of similar frequency). Every landform in the universal space is assigned five sets ($\beta_i$) of attributes. In a local space, however, every attribute is assigned a different number of values. For instance, for the attribute $\beta_1$ there are different sets of values: $s_1, s_2, \ldots, (s_n$. However, for $\beta_1, s_1$ may have $x$ values while $s_2$ may have $y$ values where $x \neq y$. Each subset $s_i$ is assigned two integer values, $r_i$ and $f_i$. $r_i$ is an integer showing the total number of local attribute values which have the same $f_i$.

$$\beta = \{s_1, s_2, \ldots, s_n\} \quad (57)$$  

where

$$s_1 = \{\lambda_1, \lambda_2, \ldots, \lambda_{k1}\}$$  
$$s_2 = \{\lambda_{k1+1}, \lambda_{k1+2}, \ldots, \lambda_{k2}\}$$  
$$\vdots$$
\( s_n = \{\lambda_{k_n+1}, \lambda_{k_n+2}, \ldots, \lambda_n\}. \)  

All elements of \( s_1 \) have the same \( f_1 \), all elements of \( s_2 \) have the same \( f_2 \), and so on. But the \( f_1 \) of \( s_1 \) is different from the \( f_2 \) of \( s_2 \), different from the \( f_3 \) of \( s_3 \), and so on. Accordingly, an \( s_i \) subset has a total of \( \tau_i \) elements, each occurring exactly \( f_i \) times. For instance, let \textit{tone} be a set with two attribute values, \textit{light} and \textit{dark}, and let each attribute have a frequency domain of 10. Then

\[
\begin{align*}
s_1 &= \{\text{light, dark}\} \quad (59) \\
\lambda_1 &= \text{light} \quad (60) \\
\lambda_2 &= \text{dark} \quad (61) \\
f_1 &= 10 \text{ for each (light, dark)} \quad (62) \\
\tau_1 &= 2. \quad (63)
\end{align*}
\]

This way the attribute space is partitioned into homogenous subsets or levels according to the frequency of the attribute values.

### 4.5.2 Criteria for Global Evaluation Functions

In order to develop a global evaluation function for landform concepts, some assumptions are necessary. Mutual exclusiveness of attributes is assumed, as is the case in reality. For instance, the attribute \textit{drainage} \{\( \beta_1 \)\} is physically disjointed from the attribute \textit{photographic tone} \{\( \beta_2 \)\}. That is, \{\( \beta_1 \)\} and \{\( \beta_2 \)\} are two different entities with no common properties. Another assumption is the ceiling concept of the attributes. That is, the evaluation function should be designed in such a way that a 100% probability of existence of a landform concept is obtained if and only if all evidence is correctly and fully collected with the maximum weight of each attribute value. This optimal value (100%) is the ceiling that should not be exceeded, and the zero value is the floor so that the range of probability is between
0 and 1. Also, the range between 0 and 1 is obtained based on the contribution \( \alpha \) of an individual attribute. These assumptions are necessary for applying the axioms given in section 4.1.

In order to implement mathematical equations to represent local attributes in a global space, three criteria should be considered. First, attribute frequency should be considered as a weighing factor. Second, full coverage of landforms should be maintained in the images. Third, necessary details should be preserved. The second and third criteria contradict each other, so I call them *image interpretation contradictory facts*.

The image interpretation process requires standards so that the optimal identification of features is ultimately reached. One important standard is image scale. It should be selected so that the two contradicting aspects of image interpretation are both satisfied. Full coverage of all pertinent landforms and of their immediate surrounding vicinity demands smaller image scales as long as larger coverage is required. However, detecting some details about certain attributes of landforms, such as erosion features, requires larger image scales as long as more details or micro-features are to be analyzed. Figure 8 is a simple illustration of how experts in landform interpretation view the effects of image scales on image interpretation.

According to the investigation conducted by this study on fifty-four models, an average of three to five landforms can be found in each stereo-pair. The scale ranges from 1:10,000 to 1:250,000. All interpretation sessions that were conducted by the expert on images ranging 1:40,000 to 1:120,000 in scale were optimal in the sense that all landforms and their vicinities had full coverage and all attributes could be observed. Therefore, for image interpretation purposes the image scales should be selected in the range between 1:40,000 and 1:120,000. Coincidently, it was found from the analysis conducted on the observations of this research that contributions of landforms’ attributes to the landforms’ identity is more than 92%
Figure 8: Conflicting Aspects of Image Scale, Evidence Accumulation and Image Interpretation
when \( f \leq 5 \); only less than 8% contributions to the identity of landforms is offered by attributes of \( f > 5 \).

4.5.3 Global Evaluation Function

Theoretically, and practically, only a few elements \( \lambda_i \) of different \( f_i \) can occur at once in one particular landform concept. For instance, if the attribute \( \beta \) is \textit{land use and land cover}, then for one particular landform the attribute values, \( \lambda_i \), can be \textit{barren} or \textit{forested and cultivated}. These particular \( \lambda_i \) are only three values for that hypothesized landform, but in reality there exist about 20 values for the attribute \textit{land use and land cover} amongst which the three values are selected. Each of the three values may be from different \( s_i \) sets, resulting in different levels of values for the attribute’s identity in a local space as well as in a global space. A similar argument is valid for all other types of pattern elements.

Accordingly, an element \( \lambda_i \) in a consultation session should be assigned the probability of its origin set. For instance, if \( P_r\{s_1\} = 0.85 \), then any element from \( s_1 \) should carry this probability. This is valid since the logical operator \textit{OR} will avoid summing the allowable multi-selection of attribute values that are selected by the analyst at a consultation session when more than one element is assigned for the same landform. Another alternative for avoiding accumulations of same origin multi-attributes could be achieved by applying the disjoint properties of sets, which can be visualized in the expert system by treating every landform as a separate node.

So far, an evaluation function for attribute values has been developed (see section 4.5.1; equations 52-56) in order to evaluate the attribute in its local space. In a global sense, a landform concept \( \{E\} \) is a set of elements arbitrarily selected from local spaces and scaled in a landform’s global space according to particular criteria. Accordingly, a global function is developed here to rank the total outcome.
of a particular landform in the universal space of all identified landforms. Assuming
the disjoint properties of local spaces, and considering the previous assumptions
(section 4.5.2), a landform concept \( \{E\} \) is expressed as follows:

\[
E = \{\beta_1, \beta_2, \beta_3, \beta_4, \beta_5\} \quad (64)
\]

\[
\beta_i = \{s_1, s_2, s_3, \ldots, s_n\} \quad (65)
\]

where \( \beta_1, \beta_2, \ldots, \beta_5 \) are mutually exclusive attributes. Using equation 53, the prob­
ability assigned to \( s_i \) is as follows:

\[
Pr\{s_i\} = \frac{w}{f_i}. \quad (66)
\]

Since these attribute values \( (s_i) \) are classified in such a way that they are mutually
exclusive sets, the probability of the attribute can be computed according to axiom
3, as follows:

\[
Pr\{\beta_i\} = Pr\{U_{i=1}^n s_i\}
\]

\[
= \sum_{i=1}^n Pr\{s_i\}
\]

\[
= w \sum_{i=1}^n \frac{\tau_i}{f_i}. \quad (67)
\]

According to previous assumptions, equations 66 and 67 are repeated for every
subset in every \( \beta_i \) until all subsets are treated. Only then is \( \beta_i \) fully accounted for
by a representative value in the global space as follows:

\[
Pr\{\beta_i\} = Pr\{s_1 \cup s_2 \cup \ldots \cup s_n\}. \quad (68)
\]

The next step is to consider all attributes \( \beta_i, \) in the global space, that may con­
tribute to the identity of a landform \( E. \)

\[
Pr\{E_i\} = Pr\{U_{i=1}^n \beta_i\}
\]

\[
= \sum_{i=1}^n Pr\{\beta_i\}. \quad (69)
\]
In identifying landforms, every local attribute contributes to the total evidence. The amount of contribution is \( \alpha_i \) where \( 0 \leq \alpha_i < 1 \). Since \( \beta_i \) represents an attribute in a local space, equation 67 must sum up to \( \alpha_i \) if and only if all events in equation 57 are considered and only if these events actually occurred at once. To simplify, let \( f(R_{ID}) \) be the dependent variable which represents the attribute in a global space, \( w \) be a constant \( k \) in the global space for different levels of attribute values, and \( \frac{w_i}{\alpha_i} = x_i \) be the independent variable. Then equation (66) is modified to:

\[
P_r\{s_i\} = kx_i,
\]

and the local evaluation function (equation 67) is modified to:

\[
P_r\{\beta_i\} = f(R_{ID}) = kx_1 + kx_2 + kx_3 + \ldots + kx_n
\]

\[
f(R_{ID}) = k \sum_{i=1}^{n} x_i = \alpha_i.
\]

At this point of accumulating evidence, the local spaces of attribute values and the global spaces communicate through the transitive property mentioned previously (section 4.4). If all elements of concept \( \{E_i\} \) have optimal attribute values, then \( P_r\{E_i\} = 1 \).

As can be realized by now, the descriptive knowledge found in landform concepts is expressed in mathematical forms according to set theories and statistical aspects associated with different landform concepts. Consequently, we can now model the knowledge of landform concepts in a well-structured way for the purpose of implementing an AI system.

Any expert system should be able to report the reliability of its conclusions and inferences. Therefore, as part of the whole system, there has to be a scientific method of assessing the collected evidence. In the next section, reasons for evaluating the results of the image interpretation obtained by the expert system and methods of crediting the conclusions are presented.
4.6 Correspondence of Dynamic and Reference Templates

The expert system developed in this study contains three main components for landform identification and consultation. These are a reference knowledge template, a dynamic data template, and a matcher inference engine. The dynamic template, a working memory (WM) portion of the system, is activated in a problem-dependent session. This WM template matches a resident memory called a reference template. The reference template is a small fraction of the whole knowledge base that the system contains. Ideally, dynamic and reference templates should match.

There are two main reasons for a lack of full correspondence between dynamic and reference templates. The first reason is human fault, which can be driven by an improper attribute value that the analyst has chosen incorrectly. The second reason is a technical fault, which may be driven by improper photogrammetric systems' products or by the existence of similar features. For instance, attribute values may be degraded by low-quality images that may prevent human eyes from observing important landform attributes. Another example is the effects of image scale on image interpretations where too large-scale images prevent observing large features and general boundaries of landforms, and too small-scale images prevent observing micro-features of landform characteristics.

Each landform concept is assigned a landform identification space \( \{S\} \). The \( \{S\} \) space has two subconcepts, \( \{R\} \) and \( \{D\} \). The subconcept \( \{R\} \) is a reference template matching which contains all elements that are expected to identify the landforms correctly. The subconcept \( \{D\} \) is a dynamic template-matching which contains all evidence that is collected by the analyst during a particular consultation session. If the elements of \( \{D\} \) are correct and complete, then they should have full correspondence with the elements of \( \{R\} \). However, most often
the collected evidence is incomplete or some of the elements are incorrect. This incompleteness leads to a difference or a deviation between the dynamic and the reference templates. This difference, computed after collecting the last possible evidence, is called template deviation.

4.7 Assessment of Template Deviations

To evaluate the actual difference between the identification template matchings (the dynamic and reference templates), a set symmetric difference should be computed. Let the symmetric difference be denoted by $D\Delta R$. Then

$$D\Delta R = \{D - R\} \cup \{R - D\}.$$  \hspace{1cm}(73)

The main objective is to assess the ability of the $\{D \cap R\}$ set to reduce the area occupied by the set $\{D - R\} \cup \{R - D\}$ in the landforms' state space. That is, the larger the area occupied by the intersection of the sets, and the smaller the area occupied by the union of set differences, the better the conclusions reached by the expert system. The concepts of reference and dynamic templates are illustrated in Figure 9. In a full correspondence between the templates of identification, the

Figure 9: Symmetric Difference in Templates of Matching
following is true:

\[
D \Delta R = \{D - R\} \cup \{R - D\} = \emptyset
\]  
(74)

\[
D = R = \{D \cup R\}.
\]  
(75)

This indicates the idempotency property of sets, as previously explained, where a 100% identification confidence is reached. If the relation

\[
D = R = \{D \cup R\}
\]  
(76)

is not held, then the computation of the confidence is different, as illustrated next.

To assess a partial correspondence between templates, let \( S \) be the space of a landform concept that contains the elements of all subsets that treat the identity of that particular landform. In a set notation:

\[
S = \{\{D - R\}, \{R - D\}, \{D \cap R\}\}.
\]  
(77)

This space is dynamic in nature and can be different from one consultation to another. As mentioned above, the space \( S \) consists essentially of the dynamic template set, the reference template set, and their common sets. The dynamic property is caused by the set \( D \), which possesses the following property:

\[
D \begin{cases} 
\subset R & \text{if } D \text{ is a proper subset} \\
\subseteq R & \text{if } D \text{ is an idempotent set.}
\end{cases}
\]  
(78)

There are three possible computational values of the probabilities of identifying landforms according to the two properties imposed by the dynamic template set:

\[
P_r\{S\} = \begin{cases} 
1 & \text{if } D \subseteq R \\
r & \text{if } D \subset R \\
0 & \text{if } D \cap R = \emptyset
\end{cases}
\]  
(79)

where

\[0 < r < 1.\]  
(80)
The value $r$ is the value most likely to be found in the identification process. In fact, if equality is allowed to be associated with the values of $r$ in equation 80, then zero and one (which appeared in equation 79 for $P_r\{S\}$), are inclusive in the range of the values of $r$. If the value of $r$ is defined as the probability of correctly identifying a landform concept and denoted by $P_r\{L_{ID}\}$, then it can be computed as follows:

$$P_r\{L_{ID}\} = \frac{f_{D\cap R}}{f_R}$$

(81)

where $f_{D\cap R}$ is the total outcome of the set $\{D \cap R\}$, and $f_R$ is the total outcome of the set $\{R\}$.

It is very important to differentiate between the sets $\{D - R\}$ and $\{R - D\}$. They are completely different sets, and their functions are completely different as well. The set $\{R - D\}$ is the set that contains the elements that $D$ missed while $\{D - R\}$ contains the elements that were erroneously collected by $D$. Accordingly, $\{D - R\}$ can be the $\{\emptyset\}$ set even if $\{D \cap R\} \neq \{R - D\}$. Inequality which is associated with an empty set indicates that no attribute values are mistakenly collected by the dynamic template matching $D$, but $D$ still does not contain the optimal values for the solution. Non-optimality associated with non-erroneous elements in the dynamic template matching means that part of the evidence that identifies the landform concept under consideration cannot be observed on the images. To avoid confusion between the sets $\{D - R\}$ and $\{R - D\}$, the following modification of landform concept space is helpful:

$$S = \{\{D - R\}, \{R - D\}, \{D \cap R\}\}$$

(82)

$$\bar{R} = \{D - R\}$$

(83)

$$\bar{D} = \{R - D\}$$

(84)

$$I = \{D \cap R\}$$

(85)

$$S = \{\{\bar{R}\}, \{\bar{D}\}, \{I\}\}.$$
Since the reference template is the optimal solution for a particular landform concept, it has a probability of 1. In order to compute the amount by which the dynamic template deviates from the correct conclusion, a simple evaluation function follows:

\[
P_r\{R\} = 1 \quad (87)
\]

\[
P_r\{N_{ev}\} = P_r\{R\} - P_r\{L_{ID}\} = 1 - P_r\{L_{ID}\} = 1 - \left(\frac{f_{DOR}}{f_R}\right) \quad (88)
\]

where \(N_{ev}\) is a set that contains the elements that should participate in identifying a landform but were missed. Equation 88 accounts for the deviations of the obtained solutions from the ideal ones. By now, the basic theories of landform concepts are developed. These theories include the relational aspects of landform knowledge, the statistical probability of landform attributes, and the evaluation functions for accumulating evidence. In the next chapter these theories are implemented in the expert system.
CHAPTER V

5 EXPERT SYSTEM IMPLEMENTATION

Broadly speaking, building expert systems is an incremental process, proceeding from simple to hard tasks. Having developed a simple system (prototype) through acquiring enough data, the knowledge engineer uses this system as a running model to provide the KE with suitable feedback.

One usual problem with incremental building is the paradigm shift. That is, upon reaching a point where the system becomes very slow or where the knowledge-base becomes unmanageable, the KE must redesign the system. This may involve constructing the problem differently or trying different system-building tools. Accordingly, there is a probability of facing some challenging problems that could result in several modifications and changes in the techniques used to build expert systems.

In this study, EXLANT was developed in the following sequence:

1. Identification of the problem
2. Conceptualization and theorization of intended solutions
3. Investigation of tools to formalize knowledge
4. Knowledge acquisition
5. System implementation (prototype system)
   (a) Investigation of search and control strategies
   (b) Knowledge representation (rule and frame representation)
(c) System interfacing

6. System modification (hybrid system)

(a) Gradual expansion of the prototype system

7. System testing

In order to use an expert system to identify landforms that appear on satellite or aerial photographic images, efficient search strategies are required. Different AI techniques and theories are not equally well suited for interpreting landforms. Therefore, one must establish proper theoretical bases for applying AI techniques to the field of image interpretation. Accordingly, expert system solutions to real-world problems should be based on the reasoning of experts who are closely observed while practically solving the problem. However, the integrated solution of any AI problem is not solely based upon experts' knowledge. Rather, the solution is a combination of facts, formulas, common knowledge, and expertise (fine-grained and coarse-grained knowledge as explained in Section 3.3).

One of the most important aspects of expert systems is the search strategy (Patten, 1991; Rich and Knight, 1991; Barr et al., 1982). It is the technique through which the expert system can reach its solutions. Accordingly, selected search strategies could have real impacts on the efficiency and quality of the expert system (Al-garni et al., 1992). "Control strategies in problem solving" was investigated by Chandrasekaran, et al., 1989. After the hardest stage of developing an AI system is complete, namely the stage of knowledge acquisition, the KE must select and organize proper algorithms and methods of search. Successful completion of this stage is the real signal of whether the KE understands the problem or not. During this stage the machine will be instructed to follow closely the experts' ways of attacking the problem.
In this chapter the problem of interpreting landforms based on terrain analysis is analyzed. Then different search strategies are investigated, followed by developing a control strategy that takes into account the technical and theoretical limitations of AI. Finally, a rule-based program that combines the establish-and-refine and ordered state space search strategies is described.

5.1 State Space Search and Control Strategies for ITA

To provide an acceptable state-space search and control strategy for ITA, a conceptual view of the problem should be investigated. There are three general factors based on which a control strategy can be qualified for an ITA problem. The first factor is the nature of the problem, which can be revealed in a careful task analysis. The second factor is the experts' methods of attacking the problem in the real world. The final factor is the intended capacity of the system (scalability). (Most of the contents of sections 5.1-5.7.1 has been presented at the XVII Congress of ISPRS (Al-garni, et al., 1992).)

5.2 A Real-World Human Model for ITA

Before any strategy can be devised for an expert system, a proper task analysis must be performed (Chandrasekaran, 1992, and Patten, 1991). The following paragraphs discuss ITA for the purpose of identifying landforms and deducing their parent materials and characteristics for site analysis and evaluation.

To the question "How did you do it?" an expert may reply "It is easy! Well...I know the answer, but I do not know how I know it." This part of the problem points out the missing links in the chain of the theoretical aspects of AI (Patten, 1991). Also, this part of the puzzle calls for more research and exploration to uncover the high level of intelligence required for introducing AI systems into image interpretations in general.
ITA possesses two important AI properties, namely the decomposability property and the coarse-to-fine property. First, the problem consists of many concepts that can be decomposed, within a general domain, into many subconcepts according to specific criteria (Hoffman, 1989a; Mintzer et al., 1984; Mintzer 1988; Strahler, 1981; Way, 1978; Zuidam, 1985). The other property of the problem is the way the solution is obtained by a human expert. At the beginning the solution is very general; then it is refined until specific conclusions are reached (Way, 1992). This property, called the coarse-to-fine property, is more obvious in relatively difficult (complex terrain) environments. The coarse-to-fine strategy is known in AI fields as the hierarchy classification problem. Figure 10 shows the hierarchical character of the ITA problem. These two properties of the problem are indicative and to a large extent determinative of what control strategies should be devised in expert systems that are to be developed for the ITA problem.

The analysis of processing more than fifty-four stereo models in the field, processed by a recognized expert (Way, 1992), indicated that a human expert analyzes the ITA problem in a logical sequence. Figure 11 shows a human analysis model for the problem. The model consists of five major phases or modules:

1. Adjustment module,

2. Initial settings module,

3. Transition phase module,

4. Hypotheses module, and

5. Verification module.

Many experts do not realize that they reason in this sequence. For instance, experts note the fourth and fifth phases but, often, not the first and third phases.
Figure 10: Hierarchy Classification and Paralellism in Landform Interpretation Using Expert Systems
It is important that the KE recognize this chain of logical analysis. This is essential in qualifying certain state-space search strategies over others for the ITA problem.

\[
\text{Figure 11: ITA Modularity as Processed by Human Experts in the Real World.}
\]

In the real world, an expert is sitting in his office and ready to provide interpretations and consultations for his customers. This is what an expert expects. However, he cannot predict what a customer's image will contain. That is, the expert might work on tens of stereo pairs, each containing different features, different terrain, and different characteristics. Analogously, an AI system for the ITA task should be ready for any type of task within the pre-specified limits of the system. For instance, if the system were developed to identify thirty landforms on earth, it should be able to define any of these landforms at any time without an \textit{a priori} expectation of which landform it will face with the next customer. This ability calls for an engineer to develop a systematic way of ITA that is general enough to cover the whole spectrum of the task.

This dissertation assumes a large system with definite number of goals. Figure 12 illustrates the properties of the task of ITA. The general configuration of the triangle indicates the coarse-to-fine property of the problem while the small squares inside the triangle portray the decomposability of the problem to smaller individual concepts. Depending on the granularity or resolution intended by the system, the reached and verified concept could be a single concept or several concepts. In
Figure 12: ITA with coarse-to-fine concept and decomposition property.
fact, the ITA problem is methodological in nature (Avery and Berlin, 1985) and modular in concept. The modularity of the problem is explained next as a set and subset concept.

5.3 ITA Decomposability Property

Using set theory, let the general concept of the above task be denoted by \( C_g \), and let the first level of the decomposable concepts be a set \( L_1 \) where

\[
L_1 = \{C_{11}, C_{12}, ..., C_{1n}\}
\]

such that \( C_g \supset \{C_{11}, C_{12}, ..., C_{1n}\} \). Then, it is necessary and sufficient for the ITA problem to be decomposable if it has:

1. \( C_g \neq \emptyset \)
2. \( C_g \supset C_{11}, C_{12}, ..., C_{1n} \)
3. \( C_{ij} \cap C_{ik} = \emptyset \), where \( j \neq k \).

Now, let \( C_{11}, C_{12}, ..., C_{1n} \), which were denoted previously by \( L_1 \), present the coarsest level of the concept \( C_g \). Then

\[
L_1 \in C_g.
\]

By the same analogy, \( L_1 \) may be further decomposed. Let

\[
L_2 = \{C_{21}, C_{22}, ..., C_{2k}\}
\]

be the second level of the concept that is filtered from the first level. In a similar fashion:

\[
C_g \supset C_{21}, C_{22}, ..., C_{2k}.
\]

Then the set relations

\[
L_2 \in L_1;
\]

and

\[
C_{21} \cap C_{22} \cap ... \cap C_{2k} = \emptyset,
\]
where $L_2 \neq \emptyset$ are held.

The same decomposition continues for the concept (a concept is a particular consultation goal such as identifying landforms and evaluating their engineering suitability) until $L_g$ is reached, where $L_g$ denotes the resolution level which contains the goal node:

$$L_3 = \{C_{31}, C_{32}, ..., C_{3i}\}$$

$$\vdots$$

$$L_r = \{C_{r1}, C_{r2}, ..., C_{rm}\}$$

$$\vdots$$

$$L_g = \{C_{g1}, C_{g2}, ..., C_{gs}\}$$ (95)

where $g > r > ... > 1$. Then

$$L_g \in L_{g-1} \in ... \in L_1.$$ (96)

Note the qualification factors (attributes of landforms) that an expert uses to move from one level to the other by $Q_1, Q_2, ..., Q_g$. These qualification factors are the criteria based on which subconcepts are derived until the solution is reached. Figure 13 illustrates the filtration concept and the notion of sets and subsets of the ITA problem (see Chapter 4 of this dissertation and Childress, 1974; Kaplansky, 1972; Eisenberg, 1971; and Reed, 1977 for more information about set theory).

The above sets and subsets portray the solution path and should not be confused with the general problem configuration, which may appear quite opposite in a diagram. To illustrate the difference, Figure 14 combines the whole concept, namely the solution path and the general problem configuration. Note the setting of the large triangle as opposed to the settings of the smaller interior triangles. Conceptually, these two triangles are similar in that both have coarser knowledge up and finer knowledge down. The difference, however, is in the final outcome of
Figure 13: The Concept of Sets and Subsets of the ITA Problem.
each. The larger triangle presents the whole spectrum of the problem. That is, all landforms existing on earth that the system may identify are listed at the bottom of the large triangle. In contrast, the smaller triangle presents only those landforms that are of interest and appear on a particular image. Therefore, smaller triangles represent a solution while the larger one represents the whole problem (domain). The individual events represented by the small triangles are eventually summed up to constitute the whole population.

5.4 Search Flow of the Human Model

Based on the previously stated properties of the ITA problem, it is fair to say that in the real world the absolute initial states of the problem are unknown at the first few moments. This general statement immediately implies unknown goals at the initial state space. For instance, an analyst is told to define all existing landforms in a stereoscopic pair of images. Before looking at the pair, the analyst has no way of knowing where to start and what to expect. This momentary vagueness is soon adjusted according to the adjustment module based on some criteria in the very few starting steps of the interpretation processes.

This part of the problem (an unknown hypothesis) calls for an immediate forward tracking of the solution by the expert system (initial setting module). Likewise, the human expert is unconsciously conducting a forward search or tracking at his initial settings and scanning of the problem. As soon as the human expert handles the images and reads them, he narrows the problem and defines his starting points or what is called the initial state-space. Control strategy should be in a close compliance with human search strategies. Accordingly, at this level of discussion, the first conclusion is that the initial search control strategy should be developed to work in a forward-tracking (knowledge-driven) manner.

The next step of the search control strategy conducted by the human expert
is further careful analysis based on well established criteria to prune all irrelevant solutions from the whole space, keeping only the candidate concepts. This middle level of the search can be either forward- or backward-tracking. The tracking method depends on how the expert attacks the problem to decompose it into subconcepts. If he has already developed a broad hypothesis about several subconcepts, then he is doing a temporary backward tracking of this hypothesis in his mind. But if the problem is still too vague, forward tracking may continue because the expert has not yet developed any goal to verify (transition phase module).

The third and last step achieved by the expert is to rank the possible and most promising concepts in the image and to start to verify them one (or several) at a time (hypotheses module). This implies that at this level of the image interpretation process, a hypothesis is clearly defined in the expert's mind. Until the hypothesis is verified or disapproved, the whole process is goal-oriented (or goal-driven). The expert system must follow the human way of attacking the problem and act accordingly. From here on, the rest of the process should use backward tracking for the knowledge search since some goals are developed (verification module). Since there is no absolute forward tracking in AI, it is important to realize that there is a dummy or transitional parameter so that the data-driven search can progress (Chandrasekaran, 1992).

5.5 Qualifications and Implementations of Strategies

Like any other AI problem-solving system, the ITA expert system consists of three main components: a database, a set of operators, and a control strategy. This section and the next three sections investigate the control strategies of expert systems from the viewpoint of image interpretation using terrain analysis.

The basic characteristics that any good control strategy should possess are the ability to maintain a dynamic character (motion) of the state-space and the
ability to provide a systematic behavior to the whole space (Rich, and Knight, 1991; Chandrasekaran, 1990). The mobility of any strategy provides the avenues to eventually reach the solutions to the problem under consideration. On the other hand, the systematic behavior of any strategy prevents the undesirable repeated exploration of useless state-spaces before the solution is reached (Patten, 1991).

The content and the organization of the system's knowledge base are influenced by the selected control strategy. The control strategy of a system becomes obvious in tasks that use operators to modify the problem concepts in a multiple task-domain situation. The ITA problem needs several operator sequences at every level so that the next move is conducted intelligently. This property of the problem exposes two different types of search theories. The first theory is called blind search theory or control strategy (e.g., breadth-first and depth-first search) (Barr et al., 1982; Rich and Knight, 1991). The second theory is called heuristic search theory or strategy (e.g., ordered state-space or best-first search). These theories are illustrated by presenting some examples so that proper conclusions about the suitability of these theories to the ITA problem are reached.

5.6 Blind State-Space Search Strategies

5.6.1 Breadth-First and Depth-First Search Strategies

Breadth-first search strategy expands the concepts (nodes) according to their proximity to the starting node or concept. Arrows can be used as a measure for node proximity. Accordingly, all possible operator sequence of length \( n \) is considered before any sequence of length \( (n + 1) \). In the ITA problem this strategy declines in value as the system's scalability increases. If careful planning is not practiced before developing the expert system, this problem is dangerous, for it may not be obvious at the initial stages of developing the system.
As explained above, expert systems are developed incrementally (Jackson, 1986). That is, system development passes through three phases. The first phase is the prototype development. Most often this phase can use the breadth-first search strategy, which can be of great advantage. The next phase is a transition phase, in which the attributes, parameters, and number of landforms to be treated increase. At this phase the system's slowness becomes evident. In the third phase of development, the hybrid system phase, the problem spectrum is almost completely covered by the system.

Since the number of landforms on earth and their parameters and attributes are so large, a very big knowledge base can be foreseen. This fact makes the breadth-first search strategy unacceptable since its blind behavior causes time and space limitations. The limitations can be visualized by looking at the exponentially expanding nodes in Figure 14. In breadth-first search, if node 23 is an assumed hypothesis in the tree, then this hypothesis cannot be reached until the system searches the whole tree, starting at node 1 on level A through the last hypothesis just before hypothesis 23 on level E. (For basic algorithms for this strategy, the reader is referred to Rich and Knight, 1991, and Barr et al., 1982.)

The depth-first search strategy operates as another blind state-space strategy. It assigns the starting node 0 depth, and from there all other nodes are numbered so that the depth of any node is one more than the depth of its predecessor. Depth-first strategy expands the most recently generated node by following a single path through the state space downward from the starting node until a goal is reached or a dead end is found. Figure 14 illustrates how depth-first search works. Notice here that nodes 1, 2, 5, 9, and 14 are treated in the first processed single path, but in the next alternate path operations start at node 9. The process continues until the hypothesis at node 23 (an assumed goal) is reached. Thus, after the initial state of node 2 and its branches are explored, the search resumes at node 3 and
Resolution Level Increases

Figure 14: Problem Domain Setting vs. Solution Path Settings.
the same process is repeated.

Conceptually, these methods of state-space search are different from human expert methods conducted for an ITA task in the real world. It should be realized, however, that this conclusion is for blind search methods in which no criteria are developed to qualify the promising nodes to be explored amongst the list in every level in the state-space problem. When a set of qualifying criteria is developed for these methods, new and more sophisticated state-space search and control strategies are obtained, which are closer to the human way of reasoning.

5.6.2 Heuristic State-Space Search for ITA

Heuristic control strategy assesses various operator sequences and instantiates the most promising sequence (Barr, and Feigenbaum, 1982). In fact, heuristic search strategies use knowledge specifications (constraints) to direct the search in the state-space of the problem. Based on these criteria and on the nature of the ITA problem, heuristic state-space search and a combination of forward and backward chain reasoning constitute a set of control strategies that meet the conceptual aspects of the ITA problem; therefore, this set is implemented in this study for the ITA problem. This type of search is justified by many facts, some of which were described above and some of which are discussed next.

Representing the knowledge in the expert system according to the logic of the human expert is a prerequisite for developing control and search strategies for the system. This prerequisite stems from two essential factors. First, the expert has to understand the KE's real attempts to model the expert's own expertise, and, as a result, the expert gains the confidence to test and evaluate the system's success based on his/her knowledge and familiarity with the main workings of the system. In relation to this issue, the end user's acceptance of and confidence in the system are more likely to be attained if the knowledge representation and control strategy
schemes approximate the expert's knowledge.

Second, the expert's strategy of representing and controlling the knowledge is a whole package of expertise that an expert system should maintain. In a heuristic search the ingredients of the ITA problem are the initial state, the operators, and the goal states (I.O.G.). The main objective of the KE is to model the control strategy and the logic that the human expert uses when connecting the initial state-space with the goal state-space through appropriate operators.

As can be concluded by now, the blind search of a state-space expands a very large number of nodes before a solution is reached. The reason for that is the arbitrary behavior of expanding the nodes without controlling the search mobility according to the properties of the problem at hand. As a part of the control strategy, the trio (I.O.G.) is assumed to be established. The rest of the control strategy is, then, to develop heuristic information about the ITA problem and to implement a search method which uses this information to effectively search the given space.

5.7 Ordered Establish and Refine Search Algorithm (OERSA)

In this dissertation a heuristic state-space search algorithm that fits the ITA problem is developed. This hybrid search strategy combines the properties of the establish and refine and ordered state-space heuristic search strategies. It is necessary to have a general understanding about what type of heuristic information can be used in searching the space of the ITA problem. This information includes heuristic strategy constraints and can be categorized according to its function into two different categories. The first category is a set of information that qualifies the most promising node to be expanded and which evaluates node successors to generate the best node amongst them. This type of information is used by
the heuristic search strategies to eliminate the blind expansions that characterize breadth-first and depth-first strategies. The second category is a set of information that eliminates irrelevant nodes from the whole space.

The implemented algorithm represents the general idea of the heuristic search methods as compared to the blind search methods. The general concept of the OERSA is that it works globally on the total set of nodes that are not yet expanded, evaluating them to expand the most promising successors or nodes only. The evaluation function \( Q \) is problem dependent. In the ITA problem, the qualification function \( Q \) should be the similarity measure between the current space state node and the goal node (see dynamic and reference templates) instead of the distance or difficulty qualification measure that is used for some other problems. In some instances the \( Q \) function in the ITA problem is developed based on elimination criteria, where refinement is conducted for the established nodes. The OERSA, implemented by this study, is as follows:

1. Start the adjustment module by applying the global qualification function \( Q \) to the ITA space in order to establish the initial state node \( S \) based on weather conditions (humid and dry-hot).

2. Prepare a list in the initial state node \( S \) and evaluate the individual elements in the list according to the \( Q \) function (an evaluation function).

3. If node \( S \) is empty, then report a failure as an indication that no solution exists, and report causes of the failure to obtain a solution.

4. If \( S \) is not empty, then according to the \( Q \) function establish the most promising concept (concept \( i \)) in the node.

5. Call the recognition agent (set of evaluation functions that verify the ID of concepts) and test concept \( i \). If the concept is a goal node, then call the sort
agent, report the proper conclusions, and exit with success.

6. If concept $i$ is not a goal node, then establish successors of concept $i$ and refine each successor node, say concept $k$, using the $Q$ function:

- If concept $k$ is new, then list it among the other unexpanded concepts and give it a pointer to its parent node to trace its path toward the goal concept if found later.

- If concept $k$ is not new, then call the probability function, compare $k$'s current value with the previously calculated one, and make proper substitutions. Refinement based on certainty factors is in effect at this stage of the inference process.

7. Return to step two and continue.

8. Call the learning agent (a set of rules that the system fires in order to learn from a teacher) if certain characteristics are instantiated and particular criteria are met in a specific consultation session.

5.7.1 Advantages and Disadvantages of Different Search Strategies

The human strategy for interpreting landforms is systematic and of clear conceptual blocks. That is, the process is coarse-to-fine, in general, and is knowledge-driven until the initial space states are set; then the rest of the process is a goal-driven verification of the hypothesis. An AI system for the same purpose must closely follow the same general guidelines. It is possible, however, to follow other strategies that could solve the problem but will be characterized by two properties:

1. The expert system will not act according to human methods. This will lead to two conceptual consequences:
(a) The solutions obtained by the expert system will not be optimal.

(b) The system will lack the property adhering in the word expert.

2. The efficiency of the system, both time-wise and storage-wise, may be questionable, especially for large tasks.

We have seen how each type of control strategy (breadth-first and depth-first) behaves, as viewed from an image-interpretation perspective. In reality, both breadth-first and depth-first search methods are characterized by the mobility property that a good strategy maintains. The drawbacks of both, however, are listed here from an AI viewpoint and from the ITA viewpoint as well:

1. The two methods are incompatible with the human way of solving the ITA problem.

2. The depth-first method may be trapped in the state-space and goes through an endless loop.

3. The breadth-first search is characterized by time and space inefficiencies.

4. In both methods, the obtained solutions may be not the optimal solution.

These drawbacks are not necessarily disadvantages for other types of AI problems. For instance, in some other situations the following are advantages of these methods:

1. The depth-first search is fast.

2. The breadth-first search guarantees a solution if one exists.

3. The breadth-first search finds the shortest path to a solution.
On the other hand, for our particular AI problem, the heuristic search is preferable, for this type of control strategy is applicable to the ITA problem. This is true since the number of concepts (concepts of landform identification and evaluation) to be treated is very large and since methods for pruning irrelevant nodes are essential for avoiding the probable “combinatorial explosion” property (exponentially growing nodes). The least important advantage of this search method is the ability to combine the advantages of depth-first search (exploring a minimum number of branches) with the advantages of breadth-first search (avoiding being trapped by a dead end). Most important are the compliance of the heuristic search methods with human reasoning and the intelligence that these methods can provide if proper knowledge about the problem domain is acquired.

To conclude this section, any control strategy must maintain the motion and systematic property for the state-space strategy. For the ITA problem a hybrid control strategy that fits the conceptual aspects of the problem and maintains the AI aspects is recommended and implemented by this study. The proposed control strategy consists of a heuristic state-space search strategy along with a combination of forward and backward chaining. Finally, a close look at the brute-force state-space search strategies (called blind strategies in AI), heuristic state-space search strategies, and theories of chaining can provide great clues to the success of expert systems in the ITA problem. Since this dissertation concentrates on the conceptual aspects of the problem, there is no attempt to provide recommendations for particular algorithms. However, on the conceptual level we recommend heuristic state-space strategies for the ITA problem. There are many different ways of selecting from a variety of algorithms for a heuristic state-space search. Popular algorithms, such as generate-and-test, hill climbing, best-first search, problem reduction, and means-ends analysis, can be investigated for the ITA tasks.
5.8 Observations of Attributes

In this study, both numerical and categorical data are used. The categorical data, however, are more extensively used, as the nature of the problem requires. Any record of data, be it numerical or categorical, is referred to as an observation, or set of observations. For instance, collected evidence and clues to identify a landform are considered to be observations.

In order to implement the previously developed theories in the expert system for landform interpretation and consultation, there has to be a way to develop a scientific means for observing landforms' attributes. This task is complicated due to the fact that a landform's attributes are descriptive in nature. Analysis of observations indicates that a large portion of identification confusions can be clarified by the expert as soon as the topographic and drainage attributes of most landforms are defined.

In this study, close analysis of these two attributes (topography and drainage) indicated that their effectiveness in landform identification is mainly due to their low redundancy (frequency) in the universal space of the landforms. However, this conclusion of effectiveness on the part of these attributes is difficult to justify by numerical entities without subjective guessing that could be questionable in many situations. It was then decided to develop a more scientific and theoretical approach to the whole spectrum of landform attributes in the universal space of the landforms, as was explained in Chapter four.

A comprehensive observation for an average of seventy landforms was conducted for every landform attribute (for instance, drainage). These observations were acquired by observing the expert while he processed more than fifty-four stereo models and by reading reports, books, and publications. A careful analysis of these observation led to the recognition of a broad spectrum of frequencies for
landform attributes as they were assigned to different landforms. Accordingly, high frequency (occurrence of the same attribute in more than one landform), unique frequency, and zero frequency for a large sample space of landform concepts were obtained. This knowledge opened the door to quantitatively evaluating the descriptive aspects of landform concepts. Consequently, the development of a probability value for every landform attribute was achieved, and a scientific analysis of the global contribution of individual attributes to individual landforms was theorized. (See Chapter four.)

Topographic features of landforms are observed. The observations are listed in Table 10. In a similar fashion, Tables 11 through 14 (Appendix A) contain the observations that were obtained for the rest of the five main attributes based on which a landform's identity can be obtained through image interpretation. In each table, the name of the attribute, its values, the frequency of these values, and the associated landforms are presented. Associated landforms are coded with a few English letters; these symbols are decoded in table 4. Table 2 is a summary of homogeneous observations, grouped in separate sets according to their frequencies. In Table 2, rows present local space sets, and columns present global space sets. For instance, the set

\{41, 23, 15, 12, 8\}

listed in column 2 in Table 2 is a homogeneous set that has a frequency \(f = 1\) and represents the following set of attributes:

\{\text{topography, drainage, photographic tone, land use and land cover, and erosion}\},

respectively. A similar argument is valid for those attributes with \(f = 2, f = 3,\) and so on. In a local space, however, every attribute contains a set of values with different frequencies. For instance, the topographic attribute in its local space forms the following set:

\{41, 6, 1, 2, 0\}. 
This applies to all other attributes in their local spaces. Finally, the last column and the last rows in Table 2 are the probability values of landforms’ attributes in both local and global spaces. These probabilities are computed according to the previously developed theories (equations 66, 67, and 69). Table 2 represents the probability table that gives specific weights to each attribute in the global space, based on which the following evidence-accumulation function is developed:

\[ f(L_{ID}) = aM + bD + cT + dL + eG \]  \hspace{1cm} (97)

where the coefficients \( a, b, c, d, \) and \( e \) are computed by using equations developed in Chapter four. \( M, D, T, L, \) and \( G \) stand for the values of morphology, drainage, photographic tone, association (land use and land cover), and erosion, respectively.

Table 2

<table>
<thead>
<tr>
<th>Attributes</th>
<th>( f_1 )</th>
<th>( f_2 )</th>
<th>( f_3 )</th>
<th>( f_4 )</th>
<th>( f_5 )</th>
<th>( f_6 )</th>
<th>( f_10 )</th>
<th>( f_11 )</th>
<th>( f_12 )</th>
<th>( f_14 )</th>
<th>( f_17 )</th>
<th>( f_21 )</th>
<th>Total</th>
<th>Local Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>41</td>
<td>6</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>D</td>
<td>23</td>
<td>6</td>
<td>3</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>T</td>
<td>15</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>L</td>
<td>12</td>
<td>3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>G</td>
<td>8</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>99</td>
<td>22</td>
<td>11</td>
<td>7</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Global Prob. x 10^{-2}</td>
<td>8495</td>
<td>944</td>
<td>315</td>
<td>150</td>
<td>17</td>
<td>29</td>
<td>17</td>
<td>8</td>
<td>7</td>
<td>6</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>
5.9 Automation of Knowledge Abstraction

Landform attributes constitute relational aspects of landform knowledge. For instance, an attribute with $f = 2$ indicates a relation between two landforms caused by that particular attribute. In order to investigate all landforms that share the same attribute, there has to be a strategy by which the investigation can be conducted. If the investigation task is designed to be conducted sequentially by the expert system, then a time-consuming investigation process can be expected. The time-consuming process proportionally increases as the expert system becomes larger, and the performance of the system will be degraded. For this reason, an automatic distribution strategy is developed in this study. This strategy, explained next, can be defined as a parallel problem-solving strategy.

Let $f(A_v)$ be an attribute value selected by the analyst, and $P_{ev}(L_{ID})$ be partial evidence of a landform’s identity. Then

$$f(A_v) \rightarrow P_{ev}(L_{ID})_i, \quad i = 1, 2, ..., n.$$  \hspace{1cm} (98)

The value $f(A_v)$ is assigned simultaneously to all landforms that share the same value and exist in the universal space of the landforms. That is,

$$f_1(A_v) \rightarrow P_{ev}(L_{ID})_i = P_r\{\beta_1\},$$

$$f_2(A_v) \rightarrow P_{ev}(L_{ID})_i = P_r\{\beta_2\},$$

$$\vdots$$

$$f_n(A_v) \rightarrow P_{ev}(L_{ID})_i = P_r\{\beta_n\}.$$  \hspace{1cm} (99)

Figure 15 shows the assignment process. After the assignment of each attribute value to all relevant landforms, the global evaluation function starts accumulating and evaluating evidence for every landform, as explained next.
Figure 15: Automation of Knowledge Abstraction
Let $T_{ev}(LID) \) be the total evidence used to identify a landform. Then

$$
T_{ev}(LID)_1 = \sum_{i=1}^{n} P_{evi}(LID)_1 = P_r \{ E_1 \} 
$$

$$
T_{ev}(LID)_2 = \sum_{i=1}^{n} P_{evi}(LID)_2 = P_r \{ E_2 \} 
$$

$$
\vdots
$$

$$
T_{ev}(LID)_n = \sum_{i=1}^{n} P_{evi}(LID)_n = P_r \{ E_n \}. \tag{100}
$$

Next, the expert system instantiates a sorting function that will evaluate the landforms' identities and sort them according to their optimality. Then the expert system tests the criteria for accepting and reporting the identities of the landforms. If the requirements are fulfilled, then the expert system will reveal the identities along with the confidence levels for each identity, and will proceed to the next phase of the consultation session.

5.10 Landform Interpretation

After a careful investigation of proper tools (see Maloney et al., 1988 for details) and after considering all limitations and sources of this research, EXLANT was implemented on a personal computer (PC), a 386 IBM compatible with 4MB memory, 25MH, 120MB hard disk, and VGA color monitor. The expert system contains a knowledge base in a frame-system representation with about one thousand rules. The tools used to build the expert system is the Personal Consultant Plus, Texas Instruments. Figure 16 portrays the general configuration of the system. This hybrid system can handle most of landforms on our planet. Moreover, the system can be expanded to treat many other landforms. Figure 17 shows the general classification scheme of landforms in the real world. There are six generic classes of landforms (Way, 1978):

1. Sedimentary Rocks,
Figure 16: General Configuration of The Developed Expert System.

Figure 17: General Landform Classification
2. Igneous Rocks,

3. Metamorphic Rocks,

4. Set of Eolian Landforms,

5. Set of Fluvial Landforms, and


EXLANT deals with all generic classes. For instance, the first generic class covers about 75% of the earth's surface. This class contains ten main landforms, which are covered by the expert system. Figure 18 shows the general configuration of six of these landforms. These landforms are:

1. Sandstone Landform in Humid Environments,

2. Shale Landform in Humid Environments,

3. Limestone Landform in Humid Environments,

4. Flat Interbedded Landform in Humid Environments,

5. Tilted Interbedded Landform in Humid Environments,

6. Sandstone Landform in Arid Environments,

7. Shale Landform in Arid Environments,

8. Limestone Landform in Arid Environments,

9. Flat Interbedded Landform in Arid Environments, and

10. Tilted Interbedded Landform in Arid Environments.
Figure 18: General Photo Analysis for One Generic Class
Based on landform attribute values, the firing process of proper rules allows suitable frames to be accessed automatically. Figures 19 and 20 show a small portion of a possible process in which proper frames and nodes are accessed automatically based on the collected evidence.

5.11 Learning Aspects of EXLANT

As stated in the literature review (Forsyth et al., 1986), one or more of the following goals are attempted by any developed learning mechanism:

1. Obtaining more accurate results,

2. Dealing with a larger spectrum of problems,

3. Reaching the conclusions efficiently and economically, and

4. Coding system knowledge in easier and simpler techniques.

EXLANT explicitly or implicitly, the last three goals mentioned above. The process of automatically abstracting data (section 5.9) provides an economical way of covering a wide range of landform concepts. Similarly, the OERSA algorithm implicitly prunes irrelevant nodes from the search space to economize and accelerate the process of obtaining the answers. In this section, however, a new mechanism and learning algorithm is developed to cover the first goal stated in the above list.

The learning mechanism, an important part of an AI system, should have the ability to communicate with the system's I/O (input/output) and to criticize the performance of the system. Included in the learning system is the provision of locating the source of the degradation of the system, and, in turn, the provision of improving and curing this problem.

Template deviations represent a matching mechanism that can compare the reference (ideal) template with the dynamic (actual performance) template. Tem-
Figure 19: Sample of Processing Landforms
Figure 20: THE Process of Figure 19 Continues
plate deviations represent a critical agent that makes the necessary comparisons and passes the output to the ideal teacher (experts in image interpretation and terrain analysis). Hence, the teacher provides the correct criteria to the learner (machine). Consequently, the learner makes the necessary adjustment and updates the knowledge base. Figure 21 shows the major components of a typical learning system (Forsyth et al., 1986).

The expert system (EXLANT) provides two "intelligent" responses to the user. First, the system warns the user if he/she has missed important attributes. That is, in any consultation session if the user has missed one or more of the attributes of the landforms, the expert system notes this missing event(s) and informs the user at the end of the consultation session that he has missed this or these attributes. Also, the system warns the user about the negative effects on evidence accumulation if an attribute value is missing. The other "intelligent" response by the system is related to the first one. There is a high probability that the user is not satisfied with the attribute's values, and, therefore, that he/she skipped them intentionally. In this case the system will try to learn from the user if he is a qualified teacher. That is, the system will ask the user if there are values for the missing attributes that do not appear in the multi-selection screen of the attribute. If the user responds positively, then the expert system will instantiate a process through which the human can teach the system.

As a general outline, the user will be asked, first, if he/she wants to teach the system something new. If a positive response is obtained, then the system will ask for the user's qualifications. This includes a small test that a non-expert human is expected not to pass. If the user is proved to be an expert, then he/she will be asked to review the records existing in the universal space of the expert system. There will be one of two possibilities. First, the value is not in the universal space, and the expert will add it to the data base. Consequently, the system will
Figure 21: A Typical Learning System
After Forsyth, R. et. al., 1986
call all probability functions in the system to update the data base and adjust the attribute values. The second possibility is that the value is contained in the record, and teaching will be denied by the system.

The main objective of the learning mechanism here is to assess and modify the behavior of the system if the reported results do not satisfy the teacher. The learning algorithm developed in this study is as follows:

1. Process a normal consultation session \((CS_i)\).

2. Assess template deviations \((D\Delta R)\), report missing attributes \(m_i\), and confirm the user's acknowledgement of being an expert and being unsatisfied with skipped values; if there are no missing attributes or if the user does not acknowledge the missing attributes, go back to step 1; otherwise continue.

3. Open a protection \((P_i)\) and a teaching \((T_i)\) session.

4. If \(P_i = 0\), report failure and go back to step 1; otherwise continue.

5. Conduct an investigation session \((IS_i)\). If \(IS_i = 0\), report failure and go back to step 1; otherwise continue.

6. Modify all necessary records and go back to step 1 to update the system.

7. Repeat steps 1-6 as required.

5.12 System Testing and Experimenting

An expert system should be tested as soon as a simple prototype version of the system is developed (Edmunds, 1988). The testing and improvement process continue until the system is ready to be distributed to the end users. The final testing, however, should be conducted by the expert and the knowledge engineer under variety of real applications to insure that the system is working properly.
EXLANT has been tested under four different circumstances:

1. random selection of ideal landforms,

2. full spectrum of the landforms contained in the KB (debugging purposes),

3. incremental testing of expert’s choices of inputs, and

4. landforms’ interpretation by the expert and by the system.

In the first case, six landforms from six different origins under different climate conditions were tested. The ideal attribute values were input to the system, one landform at a consultation session. The identity of landforms was reported correctly by the system based on the ideal input.

The second test was conducted under two assumptions:

- all landforms appear in one image and all are required to be interpreted by the expert system, and

- all attributes are well defined and correctly fed into the system by the user.

In this test the system reported all landforms. The results obtained by the expert system were checked against some standards (texts and publications of the expert, Way; publications of Mintzer, 1984 and 1988; text of Zuidam, 1985; and publications of Argialas, 1985-1990; Denny et al., 1968) and were found to be very accurate.

The third and fourth tests were conducted by the expert and the knowledge engineer. In the third test few simple landforms were input by the expert at the beginning. At the end of every consultation session, when the conclusions of the system were correct the expert input more complicated problems. Some of the landforms that the expert tested are landforms that students of terrain
analysis consider difficult to interpret. At the end of this test, a nonsense input was intentionally given by the expert to the system to see if unacceptable conclusions would be reported. Indeed, the obtained results reflected the input knowledge. In general, the system is working properly.

The last test was conducted by the expert by filing photo-analysis formats (Table 15, Appendix A). The formats included five attributes for every landform and the values of each attribute. The identity for every landform was \textit{a priori} reported by the expert in the format. The same attributes were input to the system by the knowledge engineer. The results of both the expert and the expert system were compared. Table 3 contains a sample of the conducted test on four landforms. The rest of the tested landforms are in Table 16 in Appendix A. The conclusions obtained by the expert system were very accurate for all landforms that the system was designed to handle. As can be seen in the table, the second and the sixth landforms were not included in the system (N/A).
<table>
<thead>
<tr>
<th>Landform #</th>
<th>Attributes of Landforms</th>
<th>Values of Attributes As Assigned by the Expert</th>
<th>Landform ID As Given by the Expert</th>
<th>Landform ID As Given by the System</th>
</tr>
</thead>
</table>
CHAPTER VI

6 Conclusions and Future Research

The late vision process in the pyramid of digital photogrammetry (Figure 1) requires collective efforts to contribute to image understanding. However, not much work has been done in this regard. Image interpretation can provide a suitable foundation for the late vision process. This, however, entails two prerequisites:

• Proper theories should be developed to model knowledge and expertise that current computer-assisted methods have not been able yet to model (non-spectral knowledge of image features).

• Expert systems should be introduced to the field of digital photogrammetry since they are the tools that can flexibly model non-spectral entities.

To start the foundation of image understanding there have to be suitable image features already accredited in the field of image interpretation. That is, image features which possess distinct characteristics should be used.

This dissertation has selected proper image features and has introduced the expert system to the image interpretation process. Landforms found to represent one comprehensive image feature can provide a broad spectrum of information for the interpretation process. A basic quantitative method of landform interpretation was established by this research. Then an expert system (EXLANT) was developed to interpret landforms based on the established methods. The system was tested carefully and approved by an expert. Many tests indicated that the system is working properly and as expected.
The aim of this study was to interpret landforms via expert systems. The developed expert system can interpret major landforms found on the earth’s surface. A sample consultation for engineering purposes, such as the suitability of a landform for constructing highways, septic tanks, and large foundations and for investigating soil characteristics, was included in the system for one landform (sandstone). Moreover, a learning mechanism was developed for updating the knowledge base through an interactive dialogue with qualified experts. The expert system still can be modified and extended for many other purposes, such as simulating military movements over different topographic surfaces.

Even though the developed expert system is working properly and is covering a wide range of landform identities, there are several aspects that need further research and close investigations. For instance, the assembled knowledge is based on the assumption that landforms are units of clear boundaries. In the real world, however, there are:

1. Layered landforms,

2. Transitional boundaries between two or more adjacent landforms, and

3. Complex features and a combination of mixed landforms.

These three issues need more investigation. Also, a research on individual generic landforms is required. For instance, sedimentary rocks can be investigated for detailed information (e.g., geological information) so that high resolution (granularity) expert systems can be developed.

A second issue worth mentioning here is that of the users’ skill. That is, an investigation should be conducted to determine what level of knowledge and training is required for someone who will use the system. As a rule of thumb, three to seven days of training (training in basic terminologies of terrain analysis
and image interpretation) can give a fair background for a user (Way, 1992). This, however, requires research to determine the degree of training required as well as the most effective ways of training. For instance, a research of the possibility of computerizing the training process can be conducted as one option for training methodologies. Moreover, coupling AI (e.g., expert systems) with pattern recognition is an important area of research that needs further investigation. Finally, certainty factors (see Section 4.1) used in expert systems are controversial issues in AI as well as in fields using expert systems. Until a solid base is attained in this regard, the numbers used for certainty factors should be viewed as guidelines for the range of accuracies of obtained conclusions. For instance, the following terms can replace the exact certainty numbers: very high, high, medium, fair, poor and very poor.

Many extended features and improvements for the system can be accomplished in the future. For instance, a recognition agent can be included in the system so that unique values and special features can be treated separately to accelerate the process of determining the identity of landforms. In the same recognition agent, techniques for varying weights based on special features and image scale can be developed. It is important to research the geometrical aspects that will indicate the location of the identified landforms in the image frame and in the object space as well. That is, theoretical bases for relations between spatial entities and knowledge embedded in images need more research so that new tools for image processing may be developed to communicate properly and easily with expert systems. Advanced learning mechanism can be developed within the expert system to provide new rules that treat newly obtained knowledge. Finally, a dictionary for landform terminologies with unified scientific terms should be considered in the future.
REFERENCES


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The Ohio State University. Report No. ERC/NSM-88-45.


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Appendix A

Future research may concern a unified dictionary for terrain analysis terminologies and indicative knowledge. Such a dictionary will help coding the knowledge of earth surface features for further use in expert systems. This would contribute to standardizing image interpretation for landforms. This Appendix contains a list of tables that have been used in building this expert system. Observed attribute values for each pattern element are listed in Tables 5 through 9, along with the corresponding landforms.

Further analysis of these attributes is detailed in Tables 10 through 14. More observations on the frequency of the attribute values are contained in these tables. These observations are used while coding the knowledge of the current expert system. Mainly, frequencies were helpful in associating certainty factors to reported conclusions. Again, these observations can be used in future research to add more sophisticated features of this expert system. For instance, there could be a separate frame in the expert system to deal with unique features.

Finally, testing expert system has been explained in section 5.12. Table 15 shows a format designed by this study for the purpose of testing the system. The sequence of filling this format is as follows:

1. Values of attributes are assigned by the expert in column 3 of the table.

2. Landform identities are revealed by the expert based on his knowledge and experience (column 4).

3. Values in column 3 are input into and processed by the expert system.
4. Column 5 is completed based on the conclusions that the expert system reports. Columns 4 and 5 are compared.

Tables 3 and 16 contain a total of ten landforms that have been processed by the expert and by the system for testing purposes.
Table 4
Coding and Decoding Landform Features
for Interpretation Purposes

<table>
<thead>
<tr>
<th>Feature Coding</th>
<th>Decoding for Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>-H,-A</td>
<td>Humid and Arid, respectively</td>
</tr>
<tr>
<td>C,M,F</td>
<td>Coarse, Medium, and Fine, respectively</td>
</tr>
<tr>
<td>M</td>
<td>Morphology or Topography</td>
</tr>
<tr>
<td>D</td>
<td>Drainage</td>
</tr>
<tr>
<td>T</td>
<td>Photographic Tone</td>
</tr>
<tr>
<td>L</td>
<td>Land Use and Land Cover</td>
</tr>
<tr>
<td>G</td>
<td>Gully or Erosion</td>
</tr>
<tr>
<td>SS</td>
<td>Sandstone</td>
</tr>
<tr>
<td>SH</td>
<td>Shale</td>
</tr>
<tr>
<td>LS</td>
<td>Limestone</td>
</tr>
<tr>
<td>FISRK</td>
<td>Flat Interbedded Sedimentary Rocks, Thick</td>
</tr>
<tr>
<td>FISRN</td>
<td>Flat Interbedded Sedimentary Rocks, Thin</td>
</tr>
<tr>
<td>TISR</td>
<td>Tilted Interbedded Sedimentary Rocks</td>
</tr>
<tr>
<td>DLT</td>
<td>Dolomite</td>
</tr>
<tr>
<td>IGLM</td>
<td>Intrusive Granite, Large Masses</td>
</tr>
<tr>
<td>IGLD</td>
<td>Intrusive Granite, Linear Dikes</td>
</tr>
<tr>
<td>EXVF</td>
<td>Extrusive Volcanic Forms</td>
</tr>
<tr>
<td>EXBF</td>
<td>Extrusive Basaltic Flows</td>
</tr>
<tr>
<td>EXIGR</td>
<td>Extrusive Interbedded Igneous Rocks</td>
</tr>
<tr>
<td>EXT</td>
<td>Extrusive Tuff</td>
</tr>
<tr>
<td>TYK</td>
<td>Till, Young Thick</td>
</tr>
<tr>
<td>TOK</td>
<td>Till, Old Thick</td>
</tr>
<tr>
<td>TYN</td>
<td>Till, Young Thin</td>
</tr>
<tr>
<td>TON</td>
<td>Till, Old Thin</td>
</tr>
<tr>
<td>Em</td>
<td>End Moraine</td>
</tr>
<tr>
<td>DLN</td>
<td>Drumlin</td>
</tr>
<tr>
<td>OTPT</td>
<td>Outwash Pitted</td>
</tr>
<tr>
<td>OTVT</td>
<td>Outwash Valley Terrain</td>
</tr>
<tr>
<td>SLB</td>
<td>Sandy Lake Beds</td>
</tr>
<tr>
<td>OTP</td>
<td>Outwash Plain</td>
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Table 4 Continued

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<th>Decoding for Interpretation</th>
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<td>BSD</td>
<td>Beach Sand Dunes</td>
</tr>
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<td>Traverse Sand Dunes</td>
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<tr>
<td>STSD</td>
<td>Star-Shaped Sand Dunes</td>
</tr>
<tr>
<td>BRSD</td>
<td>Barchan Sand Dunes</td>
</tr>
<tr>
<td>WDSD</td>
<td>Wind-Drift Sand Dunes</td>
</tr>
<tr>
<td>LGSD</td>
<td>Longitudinal Sand Dunes</td>
</tr>
<tr>
<td>DYL</td>
<td>Deep Young Loess</td>
</tr>
<tr>
<td>DCL</td>
<td>Dissected (Old) Loess</td>
</tr>
<tr>
<td>MFP</td>
<td>Meander Flood Plains</td>
</tr>
<tr>
<td>CFP</td>
<td>Covered Flood Plains</td>
</tr>
<tr>
<td>TFP</td>
<td>Terraced Flood Plains</td>
</tr>
<tr>
<td>CALVM</td>
<td>Continental Alluvium Forms</td>
</tr>
<tr>
<td>FALVM</td>
<td>Fans, Alluvium Forms</td>
</tr>
<tr>
<td>VFALVM</td>
<td>Valley Fill, Alluvium Forms</td>
</tr>
<tr>
<td>PLAYAS</td>
<td>Lake Beds</td>
</tr>
<tr>
<td>ORDP</td>
<td>Organic Depressions</td>
</tr>
<tr>
<td>YCP</td>
<td>Young Coastal Plains</td>
</tr>
<tr>
<td>OCP</td>
<td>Old Coastal Plains</td>
</tr>
<tr>
<td>SBR</td>
<td>Sand Beach Ridges</td>
</tr>
<tr>
<td>GBR</td>
<td>Gravel Beach Ridges</td>
</tr>
<tr>
<td>MATF</td>
<td>Marsh Tidal Flats</td>
</tr>
<tr>
<td>MUTF</td>
<td>Mud Tidal Flats</td>
</tr>
<tr>
<td>STF</td>
<td>Sand Tidal Flats</td>
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Table 5

Topographic Attribute Observations

<table>
<thead>
<tr>
<th>Topographic Value</th>
<th>Associated Landforms</th>
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</thead>
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<tr>
<td>Massive Steep Slopes</td>
<td>SS-H</td>
</tr>
<tr>
<td>Flat Table Rocks</td>
<td>SS-A; LS-A</td>
</tr>
<tr>
<td>Soft Hills</td>
<td>SH-A</td>
</tr>
<tr>
<td>Steep Rounded Hills</td>
<td>SH-H; SCHIST-H</td>
</tr>
<tr>
<td>Karst Topography</td>
<td>LS-H</td>
</tr>
<tr>
<td>Hill and Valley</td>
<td>DLT-H</td>
</tr>
<tr>
<td>Terraced Hillside</td>
<td>FISRK-H; FISRK-A; EXIGR</td>
</tr>
<tr>
<td>Uniform Slopes</td>
<td>FISRN-H</td>
</tr>
<tr>
<td>Minor Terraces</td>
<td>FISRN-A</td>
</tr>
<tr>
<td>Saw-Toothed Ridges</td>
<td>TISR-A</td>
</tr>
<tr>
<td>Bold, Dome-Like Hills</td>
<td>IGLMH</td>
</tr>
<tr>
<td>A-Shaped Hills</td>
<td>IGLM-A</td>
</tr>
<tr>
<td>Narrow Linear Ridges</td>
<td>IGLD-H,A</td>
</tr>
<tr>
<td>Cinder Cones</td>
<td>EXVF</td>
</tr>
<tr>
<td>Level Plains</td>
<td>EXBF</td>
</tr>
<tr>
<td>Sharp-Ridged Hills</td>
<td>EXT</td>
</tr>
<tr>
<td>Many Sharp Ridges</td>
<td>SLATE-H</td>
</tr>
<tr>
<td>Parallel Lamination</td>
<td>SCHIST-A</td>
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<tr>
<td>Steep Parallel Ridges</td>
<td>GNEISS-H,A; TISR-H</td>
</tr>
<tr>
<td>Flat Plains</td>
<td>TYK; OTPN; SLB; CLB</td>
</tr>
<tr>
<td>Dissected Plateaus</td>
<td>TOK</td>
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<tr>
<td>Rock-Controlled</td>
<td>TYN; TON</td>
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<tr>
<td>Undulating to Rugged</td>
<td>EM</td>
</tr>
<tr>
<td>Drumlinshaped</td>
<td>DLN</td>
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<td>Snakelike Ridges</td>
<td>ESKER</td>
</tr>
<tr>
<td>Cone</td>
<td>KAME</td>
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<tr>
<td>Ridged Hills</td>
<td>KAME</td>
</tr>
<tr>
<td>Pitted Plains</td>
<td>OTPT</td>
</tr>
<tr>
<td>Flat Valley Bottom</td>
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</tr>
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<td>Hummocky</td>
<td>BSD</td>
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<tr>
<td>Crescent Downwind</td>
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<td>Crescent Upward</td>
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### Table 5 Continued

<table>
<thead>
<tr>
<th>Topographic Value</th>
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<td>Rugged Steep Hills</td>
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<td>Parallel Smooth Hills</td>
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<td>Flat Depressions</td>
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<td>OCP</td>
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<td>Sharp Parallel Ridges</td>
<td>GBR</td>
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<tr>
<td>Parallel Ridges Which Are Perpendicular to Winds</td>
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</tr>
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Table 6

Drainage Attribute Observations

<table>
<thead>
<tr>
<th>DRAINAGE VALUE</th>
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<tr>
<td>DENDRITIC C</td>
<td>SS-H</td>
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<td>ANGULAR DENDRITIC M-F</td>
<td>SS-A; LS-A; GNEISS-H,A</td>
</tr>
<tr>
<td>DENDRITIC M-F</td>
<td>SH-H; FINSRK-A; OCP</td>
</tr>
<tr>
<td>DENDRITIC F</td>
<td>SH-A; FISRN-A; EXT</td>
</tr>
<tr>
<td>ANGULAR DENDRITIC M</td>
<td>DLT-H</td>
</tr>
<tr>
<td>DENDRITIC M-C</td>
<td>FISRK-H</td>
</tr>
<tr>
<td>DENDRITIC M</td>
<td>FISRN-H; TOK</td>
</tr>
<tr>
<td>TRILLS M</td>
<td>TISR-H</td>
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<td>TRILLS F</td>
<td>TISR-A</td>
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<tr>
<td>DENDRITIC CURVED ENDS M</td>
<td>IGLM-H</td>
</tr>
<tr>
<td>DENDRITIC CURVED ENDS F</td>
<td>IGLM-H</td>
</tr>
<tr>
<td>RADIAL C-F</td>
<td>EXVF</td>
</tr>
<tr>
<td>REGIONAL PARALLEL</td>
<td>EXBF</td>
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<tr>
<td>PARALLEL DENDRITIC</td>
<td>EXIGR</td>
</tr>
<tr>
<td>RECTANGULAR F</td>
<td>SLATE-H</td>
</tr>
<tr>
<td>RECTANGULAR M-F</td>
<td>SCHIST-H; SCHIST-A</td>
</tr>
<tr>
<td>DERANGED</td>
<td>TYK; EM</td>
</tr>
<tr>
<td>ROCK-CONTROLLED</td>
<td>TYN; TON</td>
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<td>INTERNAL CHANNEL SCARS</td>
<td>OTPN</td>
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<td>INTERNAL AND DITCHES</td>
<td>SLB</td>
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<td>BROAD MEANDERS</td>
<td>CLB; MFB</td>
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<td>PINNATE TO DENDRITIC F</td>
<td>DYL</td>
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<td>PINNATE F</td>
<td>DCL</td>
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<td>FLOOD PLAIN FEATURES</td>
<td>CFP</td>
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<td>NUMEROUS CHANNELS</td>
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<td>NONE TO DENDRITIC</td>
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<tr>
<th>DRAINAGE VALUE</th>
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<td>PARALLEL TO DENDRITIC</td>
<td>YCP</td>
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<td>MATF; MUTF</td>
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<td>TIDAL PARALLEL</td>
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<td></td>
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<td>IGLD-H,A; DLN; ESKER;</td>
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<td>KAME; BSD; TSD; BRSD;</td>
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<td></td>
<td>WDSD; STSD; PLAYAS</td>
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Table 7

Observations of Photographic Tone Attribute

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<th>PHOTOGRAPHIC TONE VALUE</th>
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<td>LIGHT-BANDED</td>
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<td>SH-H</td>
</tr>
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<td>LS-H; TYK; YCP</td>
</tr>
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<td>UNIFORM LIGHT</td>
<td>GNEISS-H,A; DYL; OCP</td>
</tr>
<tr>
<td>LIGHT GRAY</td>
<td>DLT-H; TYN; DLN; FALVM</td>
</tr>
<tr>
<td>SUBDUED BANDS</td>
<td>FISRK-H</td>
</tr>
<tr>
<td>MEDIUM GRAY</td>
<td>FISRN-H</td>
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## Land Use & Land Cover Attribute Observations

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<td>MARSH GRASS</td>
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Table 9

Erosion or Gully Attribute Observations

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<td>DITCHES</td>
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Table 10
Topographic Attribute Observations and Analysis

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**TOTAL = 50**
Table 11
Drainage Attribute Observations and Analysis

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Table 12

Photographic Tone Attribute Observations and Analysis

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<td>MFP; CFP</td>
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</tr>
<tr>
<td>LIGHT TO MIXED</td>
<td>DELTAS</td>
<td>1</td>
</tr>
<tr>
<td>LIGHT TO SCRAMBLED</td>
<td>PLAYAS</td>
<td>1</td>
</tr>
<tr>
<td>DARK TO LIGHT</td>
<td>ORDP</td>
<td>1</td>
</tr>
<tr>
<td>VARIED</td>
<td>MATF; MUTF</td>
<td>2</td>
</tr>
<tr>
<td>BRIGHT</td>
<td>BSD; TSD; LGSD; WDS; STSD</td>
<td>6</td>
</tr>
<tr>
<td>BANDED</td>
<td>FISRK-A; TIRSK-A; EXIGR; SCHIST-A</td>
<td>4</td>
</tr>
<tr>
<td>LIGHT</td>
<td>SS-H; LS-A; IGLD-H,A; ESKER; KAME; OTPN; OTPT; OTVT; BSD; TSD; LGSD; BRSD; WDS; STSD; TFP; SBR; GBR</td>
<td>17</td>
</tr>
</tbody>
</table>

TOTAL = 28

68
### Table 13

Land Use & Land Cover Attribute Observations and Analysis

<table>
<thead>
<tr>
<th>LAND USE &amp; LAND COVER VALUE</th>
<th>ASSOCIATED LANDFORMS</th>
<th>FREQUENCY</th>
</tr>
</thead>
<tbody>
<tr>
<td>FORESTED</td>
<td>SS-H; TYN; EM; DLN</td>
<td>4</td>
</tr>
<tr>
<td>BADLANDS</td>
<td>SH-A</td>
<td>1</td>
</tr>
<tr>
<td>FORESTED AND CULTIVATED</td>
<td>TISR-H; IGLM-H</td>
<td>2</td>
</tr>
<tr>
<td>BARREN, GRASS COVER</td>
<td>IGLM-A; SCHIST-A</td>
<td>2</td>
</tr>
<tr>
<td>BARREN, NATURAL COVER</td>
<td>EXVF</td>
<td>1</td>
</tr>
<tr>
<td>CULTIVATED, GRIDDED</td>
<td>TYK</td>
<td>1</td>
</tr>
<tr>
<td>DEVELOPED</td>
<td>DELTAS</td>
<td>1</td>
</tr>
<tr>
<td>SCATTERED SCRUB AND GRASS</td>
<td>FALVM</td>
<td>1</td>
</tr>
<tr>
<td>GRAIN</td>
<td>CALVM</td>
<td>1</td>
</tr>
<tr>
<td>BARREN TO CULTIVATED</td>
<td>PLAYAS</td>
<td>1</td>
</tr>
<tr>
<td>VEGETATED TO CULTIVATED</td>
<td>ORDP</td>
<td>1</td>
</tr>
<tr>
<td>FORESTED, SOME AGRICULTURE</td>
<td>OCP</td>
<td>1</td>
</tr>
<tr>
<td>NATURAL COVER TO CULTIVATED</td>
<td>SBR; GBR</td>
<td>2</td>
</tr>
<tr>
<td>MARSH GRASS</td>
<td>MATF</td>
<td>1</td>
</tr>
<tr>
<td>LITTLE VEGETATION</td>
<td>MUTF</td>
<td>1</td>
</tr>
<tr>
<td>NONE</td>
<td>STF</td>
<td>1</td>
</tr>
<tr>
<td>CULTIVATED AND FORESTED</td>
<td>DLT-H; FISRK-H; DLN; TIRK; TYN; TON; EM; YCP; FISRN-H; SCHIST-H</td>
<td>10</td>
</tr>
<tr>
<td>CULTIVATED</td>
<td>SH-H; EXIGR; OTPN; LS-H; OTVT; SLB; CLB; OTPT; DYL; VFALVM; EXBF; MFP; CFP; TFP;</td>
<td>14</td>
</tr>
<tr>
<td>BARREN</td>
<td>SS-A; SH-A; LS-A; TS-D FISRK-A; FISRN-A; BSD; EXPF; TISR-A; STSD</td>
<td>13</td>
</tr>
<tr>
<td>NATURAL COVER</td>
<td>IGLD-H,A; EXIGR; STSD; EXT; SLATE-H,A; LGSD; GNEISS-H,A; ESKER; KAME; OTPN; OTPT; MFP; CFP; TFP; WDSD; BRSD; TSD; BSD; DCL; OTVT; DELTAS; VFALVM; CALVM</td>
<td>23</td>
</tr>
<tr>
<td><strong>TOTAL = 20</strong></td>
<td></td>
<td>82</td>
</tr>
</tbody>
</table>
Table 14

Erosion or Gully Attribute Observations and Analysis

<table>
<thead>
<tr>
<th>EROSION OR GULLY</th>
<th>ASSOCIATED LANDFORMS</th>
<th>FREQUENCY</th>
</tr>
</thead>
<tbody>
<tr>
<td>FEW V-SHAPED</td>
<td>SS-H; KAME; OTPT</td>
<td>3</td>
</tr>
<tr>
<td>STEEP-SIDED</td>
<td>SH-A</td>
<td>1</td>
</tr>
<tr>
<td>WHITE-FRINGED</td>
<td>LS-H</td>
<td>1</td>
</tr>
<tr>
<td>VARIED TO FEW</td>
<td>FISRK-A</td>
<td>1</td>
</tr>
<tr>
<td>U-SHAPED</td>
<td>IGLM-H; TFP; OCP</td>
<td>3</td>
</tr>
<tr>
<td>SHORT PARALLEL</td>
<td>SLATE-H,A</td>
<td>1</td>
</tr>
<tr>
<td>PARALLEL U-SHAPED</td>
<td>SCHIST-H</td>
<td>1</td>
</tr>
<tr>
<td>FEW PARALLEL U-SHAPED</td>
<td>SCHIST-A</td>
<td>1</td>
</tr>
<tr>
<td>FEW U-SHAPED</td>
<td>GNEISS-H,A; CALVM</td>
<td>2</td>
</tr>
<tr>
<td>FEW TO SOFT</td>
<td>TYK</td>
<td>1</td>
</tr>
<tr>
<td>BOX-SHAPED</td>
<td>TOK; DYL; DCL</td>
<td>3</td>
</tr>
<tr>
<td>NONE TO FEW</td>
<td>DLN</td>
<td>1</td>
</tr>
<tr>
<td>DITCHES</td>
<td>CLB; ORDP</td>
<td>2</td>
</tr>
<tr>
<td>V-SHAPED</td>
<td>TFP; OCP; SBR; GBR</td>
<td>4</td>
</tr>
<tr>
<td>FEW TO NONE</td>
<td>SS-A; FISRN-A;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LS-A; IGLM-A</td>
<td>4</td>
</tr>
<tr>
<td>SOFT U-SHAPED</td>
<td>SH-H; FISRN-H;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>DLT-H; EXBF; YCP</td>
<td>5</td>
</tr>
<tr>
<td>VARIED</td>
<td>FISRK-H; TISR-H;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TISR-A; EXVF;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EXIGR; EXT; TON</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TYN; EM; MFP; CFP</td>
<td>11</td>
</tr>
<tr>
<td>NONE</td>
<td>IGLD-H,A; ESKER;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OTPN; OTVT; SLB;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STSD; LGSD; WDS; DRS; DLTAS; FALVM;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>VFALVM; PLAYAS;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ORDP; SBR; GBR;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MATF; MUTF; STF</td>
<td>21</td>
</tr>
<tr>
<td>TOTAL = 18</td>
<td></td>
<td>67</td>
</tr>
</tbody>
</table>
Table 15

Designed Formats for Testing the Expert System

<table>
<thead>
<tr>
<th>Landform #</th>
<th>Attributes of Landforms</th>
<th>Values of Attributes As Assigned by the Expert</th>
<th>Landform ID As Given by The Expert</th>
<th>Landform ID As Given by The System</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Topography Drainage</td>
<td>a.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>b.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>c.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>d.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>e.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>Topography Drainage</td>
<td>a.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>b.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>c.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>d.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>e.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>Topography Drainage</td>
<td>a.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>b.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>c.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>d.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>e.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>Topography Drainage</td>
<td>a.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>b.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>c.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>d.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>e.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>Topography Drainage</td>
<td>a.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>b.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>c.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>d.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>e.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 16

Testing the Expert System

<table>
<thead>
<tr>
<th>Landform #</th>
<th>Attributes of Landforms</th>
<th>Values of Attributes As Assigned by the Expert</th>
<th>Landform ID As Given by The Expert</th>
<th>Landform ID As Given by The System</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.</td>
<td>Topography</td>
<td>a. Level (Flat) Plains Terraced</td>
<td>Basalt without Cinder Cones in Arid Climate</td>
<td>Basalt</td>
</tr>
<tr>
<td></td>
<td>Drainage</td>
<td>b. Regional Parallel Coarse</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>c. Dark Flow Marks Complex</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>d. Natural Cover (Cultivated or Barren)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>e. None (U-Shaped)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>Topography</td>
<td>a. Flat Gentle Undulating</td>
<td>Till Plains in Humid Climate</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Drainage</td>
<td>b. Deranged Internal</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>c. Mottled White-Fringed Gullies</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>d. Cultivated</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>e. None</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>Topography</td>
<td>a. Hummocky - Small Hills Cones or Ridged Hills</td>
<td>Kames in Humid Climate</td>
<td>Kames</td>
</tr>
<tr>
<td></td>
<td>Drainage</td>
<td>b. None (Internal)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>c. Light</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>d. Natural Cover</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>e. None Few V-Shaped</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>Topography</td>
<td>a. Karst (Undulating)</td>
<td>Limestone (Karst) in Humid Climate</td>
<td>Limestone</td>
</tr>
<tr>
<td></td>
<td>Drainage</td>
<td>b. Internal</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Photo. Tone</td>
<td>c. Mottled</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Association</td>
<td>d. Cultivated</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>e. Few Sag &amp; Swale (White-Fringed)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 16 Continued

<table>
<thead>
<tr>
<th>Landform #</th>
<th>Attributes of Landforms</th>
<th>Values of Attributes As Assigned by the Expert</th>
<th>Landform ID As Given by The Expert</th>
<th>Landform ID As Given by The System</th>
</tr>
</thead>
<tbody>
<tr>
<td>9. Topography</td>
<td>a. Badlands (Steep Rounded Hills)</td>
<td>Shale in Arid Climate</td>
<td>Shale</td>
<td></td>
</tr>
<tr>
<td>Drainage</td>
<td>b. Dendritic Fine-textured</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Photo. Tone</td>
<td>c. Light Some Banding</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Association</td>
<td>d. Natural Cover (Badlands)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Erosion</td>
<td>e. Steep Sided (U) Gullies</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Topography</td>
<td>a. Bold Flat-topped Hills Massive Steep Side Slopes</td>
<td>Sandstone in Humid Climate</td>
<td>Sandstone</td>
<td></td>
</tr>
<tr>
<td>Drainage</td>
<td>b. Rectangular-Coarse Angular (Dendritic Coarse)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Photo. Tone</td>
<td>c. Light</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Association</td>
<td>d. Forested</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Erosion</td>
<td>e. Few-None V-Shaped</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix B

This appendix contains four main illustrations about the expert system.

1. Several screens show the environment of the system.

2. A few pages show a small part of the main program. The program contains about one thousand rules.

3. One complete consultation session is given. This includes the final report about the identity of the landform and its engineering suitability.

4. The help facility is demonstrated. Some help screens contain a graphical interface facility.
SYSTEM ENVIRONMENT
Figure 22: Sample of Screens Showing System Environment
Review:

- The Relative Location Of The Interpretation
- Treat Landforms Existed In Humid Region
- Landform MORPHOLOGY of the location
- A priori Probability of Contribution
- Drainage existed in the region
- A priori Probability of Contribution
- Photographic Tone of The Landform
- Land Use and Land Cover Aspects

1. Use arrow key or first letter of item to position the cursor.
2. Select all applicable responses.
3. After making selections, press ENTER to continue.
Figure 22 Continued

Landforms' Interpretation and Site Analysis

Activities:
CONSULT
DEVELOP
BUILD

Commands:
PRINT KB
SAVE KB
NEW KB
LISP
VIEW DIRECTORY
CHANGE DIRECTORY
DISPLAY FILE
INVOKE DOS
HELP OFF
FIND
EXIT

Print this knowledge base listing.

Activities:
CONSULT
DEVELOP
BUILD

Run a consultation with this knowledge base. Press F1 for help.

Frames:
CONSULT-D
FRAME2B
FRAME2A
FRAME1

Frame for Engineering and Military Consultations
Figure 22 Continued

Landforms' Interpretation and Site Analysis

Frames:

FRAME2A

FRAME1

FRAME2B

Frames:

CONSULT-D
FRAME2B
FRAME2A
FRAME1

Commands:
ADD
ERASE
MOVE
FIND
RENAME
TREE ON
BROWSE
QUIT

Add a new frame to this knowledge base
Landforms' Interpretation and Site Analysis

Frame: FRAME2A

**PROPERTIES**

<table>
<thead>
<tr>
<th>FRAME2A-PARMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRAME2A-RULES</td>
</tr>
</tbody>
</table>

**Note:**

Select the Group type to add to this frame:

**RULE-GROUP**

Add a new parameter or rule group to this frame

---

**Purpose or description of the frame.**

- **FRAME2A**
  - **TRANSLATION**: Treats Landforms Existed In Humid Regions
  - **DISPLAYRESULTS**: SCORING-H BEST-LANDFORM-H RING-H
  - **PROMPT1ST**: "Do You Want to Instantiate Frame2a?" :LINE "If Yes Please WAIT for Few Moments"
  - **IDENTIFIER**: "FRAME2A-"
  - **G Promt1ST**: "message2"
PARTS OF THE MAIN PROGRAM
Figure 23: Small Sample of The Main Rule-Based Program
Figure 23 Continued

---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE217 RULE198)
USED-BY :: (RULE536 RULE537)

LH611
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE267 RULE268)

LH613
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE530 RULE531)

LH614
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE532 RULE533)

LH615
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE534 RULE535)

LH616
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE536 RULE537)

LH618
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE540 RULE541)

LH619
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE542 RULE543)

LH620
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE544 RULE545)

LH67
---
TYPE :: SINGLEVALUED
UPDATED-BY :: (RULE218 RULE198)
USED-BY :: (RULE259 RULE260)

LH68
RULE016

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
  (SAME FRAME MORPHOLOGY-H UNIFORM-SLOPES))
ACTION :: (DO-ALL
  (SET-VALUE TEST 38.5)
  (CONCLUDE FRAME CELLS-H
   (VALUE-OF TEST) TALLY 100)
  (CONCLUDE FRAME MH54
   (VALUE-OF TEST) TALLY 100))

RULE017

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
  (SAME FRAME MORPHOLOGY-H PARALLEL-RIDGES))
ACTION :: (DO-ALL
  (SET-VALUE TEST 38.5)
  (CONCLUDE FRAME CELLS-H
   (VALUE-OF TEST) TALLY 100)
  (CONCLUDE FRAME MH65
   (VALUE-OF TEST) TALLY 100))

RULE018

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
  (SAME FRAME DRAINAGE-H DENDRITIC-COARSE))
ACTION :: (DO-ALL
  (SET-VALUE TEST 23.4)
  (CONCLUDE FRAME CELLS-H
   (VALUE-OF TEST) TALLY 100)
  (CONCLUDE FRAME DH11
   (VALUE-OF TEST) TALLY 100))

RULE019

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
  (SAME FRAME DRAINAGE-H DENDRITIC-MEDIUM))
ACTION :: (DO-ALL
  (SET-VALUE TEST 23.4)
  (CONCLUDE FRAME CELLS-H
   (VALUE-OF TEST) TALLY 100)
  (CONCLUDE FRAME DH24
   (VALUE-OF TEST) TALLY 100))

RULE020

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
  (SAME FRAME DRAINAGE-H DENDRITIC-MEDIUM-TO-FINE))
ACTION :: (DO-ALL
  (SET-VALUE TEST 23.4)
  (CONCLUDE FRAME CELLS-H
   (VALUE-OF TEST) TALLY 100)
  (CONCLUDE FRAME DH32
RULE025

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(KNOWN FRAME DRAINAGE-H)
(KNOWN FRAME PHOTOGRAPHIC-TONE-H)
(KNOWN FRAME LAND-USE-AND-LAND-COVER-H)
(KNOWN FRAME EROSION-H))
ACTION :: (DO-ALL
(set-value CFR-SH
(plus
(plus
(plus
(val1 FRAME SH-HMA)
(val1 FRAME SH-HDA))
(val1 FRAME SH-HTA))
(val1 FRAME SH-HLA))
(val1 FRAME SH-HGA)))
(conclude frame SH-H
(value-of CFR-SH) tally 100))

RULE026

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(KNOWN FRAME DRAINAGE-H)
(KNOWN FRAME PHOTOGRAPHIC-TONE-H)
(KNOWN FRAME LAND-USE-AND-LAND-COVER-H)
(KNOWN FRAME EROSION-H))
ACTION :: (DO-ALL
(set-value CFR-LS
(plus
(plus
(plus
(val1 FRAME LS-HMA)
(val1 FRAME LS-HDA))
(val1 FRAME LS-HTA))
(val1 FRAME LS-HLA))
(val1 FRAME LS-HGA)))
(conclude frame LS-H
(value-of CFR-LS) tally 100))

RULE027

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(KNOWN FRAME DRAINAGE-H)
(KNOWN FRAME PHOTOGRAPHIC-TONE-H)
(KNOWN FRAME LAND-USE-AND-LAND-COVER-H)
(KNOWN FRAME EROSION-H))
ACTION :: (DO-ALL
(set-value CFR-FI
RULE028

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
               (KNOWN FRAME MORPHOLOGY-H)
               (KNOWN FRAME DRAINAGE-H)
               (KNOWN FRAME PHOTOGRAPHIC-TONE-H)
               (KNOWN FRAME LAND-USE-AND-LAND-COVER-H)
               (KNOWN FRAME EROSION-H))
ACTION :: (DO-ALL
            (CONCLUDE FRAME DUMMY1 "At Least One Parameter Existed In The Root Frame Should be Mentioned in The Subframe So That An Instantiation And Correct Tracing are Correctly Done" TALLY 100)
            (SET-VALUE CFR-TI
               (PLUS
                (PLUS
                (PLUS
                (VAL1 FRAME TI-HMA)
                (VAL1 FRAME TI-HDA))
                (VAL1 FRAME TI-HTA))
                (VAL1 FRAME TI-HLA))
                (VAL1 FRAME TI-HGA)))
            (CONCLUDE FRAME TI-H
               (VALUE-OF CFR-TI) TALLY 100))
RULE029

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
               (GREATERP*
                (VAL1 FRAME SS-H) 99))
ACTION :: (DO-ALL
            (SET-VALUE CFR-SS
               (DIFFERENCE 100 0.6))
            (CONCLUDE FRAME SCORING-H "SANDSTONE-SEDIMENTARY ROCKS WITH CERTAINTY FACTOR ------------------------" TALLY
               (VALUE-OF CFR-SS))
            (CONCLUDE FRAME COUNT-90 SS90 TALLY 100))
RULE030

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
               (GREATERP*
                (VAL1 FRAME SH-H) 99))
ACTION :: (DO-ALL
RULE031

subject :: frame2a-rules
premise :: ($and
(greaterp*
(val1 frame ls-h) 99))
action :: (do-all
(set-value cfr-ls
(difference 100 0.6))
(conclude frame scoring-h "limestone-sedimentary rocks with
certainty factor ----------------->" tally
(value-of cfr-ls))
(conclude frame count-90 ls90 tally 100))

RULE032

subject :: frame2a-rules
premise :: ($and
(greaterp*
(val1 frame fi-h) 99))
action :: (do-all
(set-value cfr-fi
(difference 100 0.6))
(conclude frame scoring-h "flat-interbedded sedimentary rocks
with certainty factor------------>" tally
(value-of cfr-fi))
(conclude frame count-90 fi90 tally 100))

RULE033

subject :: frame2a-rules
premise :: ($and
(greaterp*
(val1 frame ti-h) 99))
action :: (do-all
(set-value cfr-ti
(difference 100 0.6))
(conclude frame scoring-h "tilted-interbedded sedimentary
rocks with certainty factor------->" tally
(value-of cfr-ti))
(conclude frame count-90 ti90 tally 100))

RULE034

subject :: frame2a-rules
premise :: ($and
(lesseq*
(val1 frame ss-h) 99))
action :: (do-all
(conclude frame scoring-h "sandstone-sedimentary rocks with
certainty factor----------------->" tally
(value-of cfr-ss))
(conclude frame count-65 ss65 tally 100))
Figure 23 Continued

PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(GREAT EQ*
(VALL FRAME MH99) 38.5))
ACTION :: (DO-ALL
(CONCLUDE FRAME VOLCANIC-HMA 38.5 TALLY 100))

RULE228
SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(LESSP*
(VALL FRAME MH1010) 38.5))
ACTION :: (DO-ALL
(CONCLUDE FRAME VOLCANIC-HMA 0 TALLY 100))

RULE229
SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(GREAT EQ*
(VALL FRAME MH1010) 38.5))
ACTION :: (DO-ALL
(CONCLUDE FRAME VOLCANIC-HMA 0 TALLY 100))

RULE230
SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(GREAT Eq*
(VALL FRAME MH811) 38.5))
ACTION :: (DO-ALL
(CONCLUDE FRAME GRANITE-DIKES-HMA 38.5 TALLY 100))

RULE231
SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(GREAT EQ*
(VALL FRAME MH811) 38.5))
ACTION :: (DO-ALL
(CONCLUDE FRAME GRANITE-DIKES-HMA 0 TALLY 100))

RULE232
SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME MORPHOLOGY-H)
(LESSP*
(VALL FRAME MH811) 38.5))
ACTION :: (DO-ALL
(CONCLUDE FRAME GRANITE-DIKES-HMA 0 TALLY 100))

RULE233
SUBJECT :: FRAME2A-RULES
Figure 23 Continued

RULE 234

SUBJECT :: FRAME2A-RULES
PREMISE :: ($\text{AND}$
\begin{itemize}
  \item (KNOWN FRAME DRAINAGE-H)
  \item (LESSEP* (VAL1 FRAME DH76) 23.4))
\end{itemize}

ACTION :: (DO-ALL (CONCLUDE FRAME GRANITE-MASSES-HDA 0 TALLY 100))

RULE 235

SUBJECT :: FRAME2A-RULES
PREMISE :: ($\text{AND}$
\begin{itemize}
  \item (KNOWN FRAME DRAINAGE-H)
  \item (GREATEREQ* (VAL1 FRAME DH117) 23.4))
\end{itemize}

ACTION :: (DO-ALL (CONCLUDE FRAME GRANITE-MASSES-HDA 23.4 TALLY 100))

RULE 236

SUBJECT :: FRAME2A-RULES
PREMISE :: ($\text{AND}$
\begin{itemize}
  \item (KNOWN FRAME DRAINAGE-H)
  \item (LESSEP* (VAL1 FRAME DH117) 23.4))
\end{itemize}

ACTION :: (DO-ALL (CONCLUDE FRAME EXT-INT-HDA 23.4 TALLY 100))

RULE 237

SUBJECT :: FRAME2A-RULES
PREMISE :: ($\text{AND}$
\begin{itemize}
  \item (KNOWN FRAME DRAINAGE-H)
  \item (LESSEP* (VAL1 FRAME DH88) 23.4))
\end{itemize}

ACTION :: (DO-ALL (CONCLUDE FRAME EXT-TUFF-HDA 0 TALLY 100))

RULE 238

SUBJECT :: FRAME2A-RULES
PREMISE :: ($\text{AND}$
\begin{itemize}
  \item (KNOWN FRAME DRAINAGE-H)
  \item (GREATEREQ* (VAL1 FRAME DH88) 23.4))
\end{itemize}

ACTION :: (DO-ALL (CONCLUDE FRAME EXT-TUFF-HDA 23.4 TALLY 100))

RULE 239

SUBJECT :: FRAME2A-RULES
Figure 23 Continued

(ACTION :: (DO-ALL
   (CONCLUDE FRAME BEST-LANDFORM-H "EXTRUSIVE-TUFF (IGNEOUS ROCKS)" with Certainty Factor =" TALLY (VALUE-OF CFR-TFF))

RULE440

SUBJECT :: FRAME2A-RULES

PREMISE :: ($AND
   (KNOWN FRAME SCORING-H)
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME EXT-INT-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME EXT-TUFF-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME BASALTIC-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME GRANITE-M-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME GRANITE-DKS-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME LS-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME SH-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME SS-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME TI-H))
   (GREATEQ* (VAL1 FRAME FI-H)
      (VAL1 FRAME VOLCANIC-H)))
   (GREATEQ*
Figure 23 Continued

(VALL FRAME FI-H)
(VALL FRAME SCHIST-H))
(GREATEQ*
(VALL FRAME FI-H)
(VALL FRAME SLATE-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME GNEISS-H))
(GREATEQ*
(VALL FRAME FI-H)
(VALL FRAME BEACH-SD-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME STAR-SD-H))
(GREATEQ*
(VALL FRAME FI-H)
(VALL FRAME YOUNG-DEEP-LOESS-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME OLD-DISSECTED-LOESS-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME MEANDER-FLOOD-PLAIN-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME TERRACES-FLOOD-PLAIN-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME DELTA-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME DRUMLIN-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME ESKER-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME KAME-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME ALLUVIAL-FAN-H))
(GREATEQ*
(VALL FRAME FI-H
(VALL FRAME YOUNG-COASTAL-PLAIN-H)))

ACTION :: (DO-ALL
(CONCLUDE FRAME BEST-LANDFORM-H "FLAT-INTERBEDDED
SEDIMENTARY ROCKS=" with Certainty Factor =" TALLY
(VALUE-OF CFR-FI)))

RULE441

SUBJECT :: FRAME2A-RULES
PREMISE :: ($AND
(KNOWN FRAME SCORING-H)
(GREATEQ*
(VALL FRAME GRANITE-M-H
(VALL FRAME EXT-INT-H))
(GREATEQ*
(VALL FRAME GRANITE-M-H
(VALL FRAME EXT-TUFF-H)))
CONSULTATION SESSION
Expert System for Landforms Interpretations and Consultation
The Ohio State University
Department of Geodetic Science and Surveying-Photogrammetry

Figure 24: Screens Showing A full Consultation Session
**Landforms' Interpretation and Site Analysis**

Select the Suitable Topo-Forms That Describe the Area In The Image:

1. Use arrow key or first letter of item to position the cursor.
2. Select all applicable responses.
3. After making selections, press ENTER to continue.

---

**Legend:**

1. Coarse Dendritic
2. Medium Dendritic
3. Fine Dendritic
4. Angular Dendritic
For Land Use and Land Cover Aspect, Select the Items That Best Describe This Area:


1. Use arrow key or first letter of item to position the cursor.
2. Select all applicable responses.
3. After making selections, press ENTER to continue.

Select The Item(s) That Best Describe the Area:

| Yes    | BRIGHT | COMPLEX | GRAY | LIGHT | LIGHT-BANTED | DOTTLED | MOTTLED-TO-DULL | DULL | SUBDUL-BANDS | MEDIUM-COLOR | FAINT-BANDING | UNIFORM-COLOR | DARK-BANDS | BAND | DARK-COLOR | UNIFORM-LIGHT-COLOR | LIGHT | UNIFORM-LIGHT-COLOR | LIGHT-UNIFORM |

1. Use arrow key or first letter of item to position the cursor.
2. Select all applicable responses.
3. After making selections, press ENTER to continue.
Here is the list of the identified landforms using SHOW command:

<table>
<thead>
<tr>
<th>LANDFORM</th>
<th>CF</th>
</tr>
</thead>
<tbody>
<tr>
<td>SANDSTONE-SEDIMENTARY ROCKS WITH CERTAINTY FACTOR</td>
<td>91</td>
</tr>
<tr>
<td>LIMESTONE-SEDIMENTARY ROCKS WITH CERTAINTY FACTOR</td>
<td>74</td>
</tr>
<tr>
<td>SHALE-SEDIMENTARY ROCKS WITH CERTAINTY FACTOR</td>
<td>29</td>
</tr>
<tr>
<td>GREWISI-METAMORPHIC ROCKS WITH CERTAINTY FACTOR</td>
<td>23</td>
</tr>
<tr>
<td>FLAT-INTERBEDDED SEDIMENTARY ROCKS WITH CERTAINTY FACTOR</td>
<td>21</td>
</tr>
<tr>
<td>EXTRUSIVE-BASALTIC IGNEOUS ROCKS WITH CERTAINTY FACTOR</td>
<td>12</td>
</tr>
<tr>
<td>STAR-SAND-DUNES ROCKS WITH CERTAINTY FACTOR</td>
<td>12</td>
</tr>
<tr>
<td>BENCH-SAND-DUNES ROCKS WITH CERTAINTY FACTOR</td>
<td>12</td>
</tr>
<tr>
<td>TILTED-INTERBEDDED SEDIMENTARY ROCKS WITH CERTAINTY FACTOR</td>
<td>12</td>
</tr>
<tr>
<td>GRANITE-LARGE MASS: IGNEOUS ROCKS WITH CERTAINTY FACTOR</td>
<td>8</td>
</tr>
<tr>
<td>GRANITE-LINEAR DYES: IGNEOUS ROCKS WITH CERTAINTY FACTOR</td>
<td>8</td>
</tr>
<tr>
<td>EXTRUSIVE-INTERBEDDED IGNEOUS ROCKS WITH CERTAINTY FACTOR</td>
<td>8</td>
</tr>
<tr>
<td>EXTRUSIVE-TUFF IGNEOUS ROCKS WITH CERTAINTY FACTOR</td>
<td>8</td>
</tr>
<tr>
<td>EXTRUSIVE-DIABASE IGNEOUS ROCKS WITH CERTAINTY FACTOR</td>
<td>8</td>
</tr>
<tr>
<td>SLATE-METAMORPHIC ROCKS WITH CERTAINTY FACTOR</td>
<td>8</td>
</tr>
</tbody>
</table>

---

Select From The List The Erosion Characters Observed In The Area:

- BH3E2
- FEU-V-SHAPED
- SOFT-U-SHAPED
- WHITE-FRINGED
- U-SHAPED
- NANE
- PARALLEL-U-SHAPED
- SHORT-PARALLEL
- FEU-U-SHAPED
- TUM-U-SHAPED
- BED-SHAPED
- U-SHAPED
- FEU-TO-NONE

1. Use arrow key or first letter of item to position the cursor.
2. Select all applicable responses.
3. After making selections, press ENTER to continue.
Landforms' interpretation and Site Analysis

Conclusions:

A list of the identified landforms reported by SCORDING-D is as follows:

This is a list of the identified landforms along with the certainty factors:

---

Here the list starts-----------------------------------

Sandstone-sedimentary rocks with certainty factor → (91%) (91%)
Limestone-sedimentary rocks with certainty factor → (74%) (74%)
Shale-sedimentary rocks with certainty factor → (23%) (23%)
Gneiss-metaigneous rocks with certainty factor → (21%) (21%)
Flat-interbedded sedimentary rocks, with certainty factor → (14%) (14%)

Accordingly, the most probable landform observed on the image is as follows:

Sandstone------------------------------------------------with certainty factor = (91%)

Press ENTER to get a small reminder about the location of the investigated area.

---

End - press ENTER to continue.
Conclusions:

Sandstones include thin soils, rugged topography, steep slopes, and massive bedrocks. These characteristics, and some other properties such as permeability and broad plateaus, make sandstone areas:

1. Difficult to excavate for heavy duty engineering projects.
2. Costly developed for engineering projects due to the requirements of power shovels and drilling equipments as well as blasting and removal.

More - press ENTER to continue.
Conclusions:
1. Difficult to excavate for heavy duty engineering projects.
2. Costly developed for engineering projects due to the requirements of power shovels and drilling equipments as well as blasting and removal,
3. Unsuitable for sewage disposals due to its permeability that could lead to contaminating ground water resources,
4. Suitable, assuming area of large plateau, for engineering foundations due to its high load-bearing capacity. Spread and foot or column footing foundations are commonly used in sandstone areas rather than pier foundations.
5. Excellent construction materials if it contains aggregate, building stones, fine surface materials,
6. Difficult for highway constructions but difficulties may be reduced by:
   a. minimizing grading by following major valleys, ridges, and plateaus,
   b. minimizing heavy equipment requirements, massive fills, valleys transecting simply by minimizing cut

More - press ENTER to continue.

Conclusions:
4. Suitable, assuming area of large plateau, for engineering foundations due to its high load-bearing capacity. Spread and foot or column footing foundations are commonly used in sandstone areas rather than pier foundations.
5. Excellent construction materials if it contains aggregate, building stones, fine surface materials,
6. Difficult for highway constructions but difficulties may be reduced by:
   a. minimizing grading by following major valleys, ridges, and plateaus,
   b. minimizing heavy equipment requirements, massive fills, valleys transecting simply by minimizing cut

7. Potential for seepage problems in case of large water reservoirs or dams. It requires qualified geologist and engineer to study and investigate dam sites carefully.

End - press ENTER to continue.
HELP FACILITY
Figure 25: Help Facility, Graphics Interface, and Learning Environments
Select the weather condition that applies to this region:

**Help:**

Expected climate condition is either dry or humid. There are, however, some landforms that could be the same in arid or humid weather. In this case, the system can trace the solution from any of the two environments.

**End - press ENTER to continue.**

1. Use arrow key or first letter of item to position the cursor.
2. Press ENTER to continue.
Figure 25 Continued

Landforms' Interpretation and Site Analysis

As Can be Seen In The Sketch
There Are Five Possible Spots
(Regions) On The Image Where
Your Area of Interest Could Be.
Please Select The Proper Region
That You Want To Investigate:

- REGION-1
- REGION-2
- REGION-3
- REGION-4
- REGION-5

1. Use arrow key or first letter of item to position the cursor.
2. Press ENTER to continue.

Do You Want to Instantiate Frame2A?
If Yes Please Wait for Few Moments

- YES
- NO

1. Use arrow key or first letter of item to position the cursor.
2. Press ENTER to continue.
Figure 25 Continued

Landforms' Interpretation and Site Analysis

You Have Missed Some Interpretation Attributes.
Are You Intentionally Doing So?

YES
NO

1. Use arrow key or first letter of item to position the cursor.
2. press ENTER to continue.

Landforms' Interpretation and Site Analysis

Do You Really Want To Change The Data-Base?

YES
NO

1. Use arrow key or first letter of item to position the cursor.
2. press ENTER to continue.
Figure 25 Continued

**Landforms' Interpretation and Site Analysis**

<table>
<thead>
<tr>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMAGE-INTERPRETER</td>
<td>TERRAIN-ANALYST</td>
</tr>
</tbody>
</table>

1. Use arrow key to indicate your degree of certainty.
2. To select one item, with 100% certainty, press CTRL-right arrow.
3. After making selections, press ENTER to continue.

**Landforms' Interpretation and Site Analysis**

**WARNING:**

This Expert System Has Been Developed Based On A Highly Qualified Research, A PH.D. Dissertation. Its is Recommended that This System is not Altered Unless A Human Expert In Image Interpretation and Terrain Analysis Agrees. Changing The System's Contents May Lead To Improper Conclusions. The Person who Wants to Make Some Changes Is Responsible For The Consequences. The Contents Of This Expert System Is Closely Following The Experience, Publications, and Books Of The Expert, Professor Douglas S. Way; The Ohio State Univesity. Please Consult The Dissertation of The Knowledge Engineer, Abdullah M. Al-garni, The Ohio State University.

Do You Want to Proceed ?

YES

NO

1. Use arrow key or first letter of item to position the cursor.
2. press ENTER to continue.
Figure 25 Continued

陆地形态的解释和场地分析

由于您对结论不满意，请阅读以下内容，然后选择合适的项目。此专家系统具有以下标准：

1. 形态学的权重 = 38.5 %
2. 排水的权重 = 23.4 %
3. 色调的权重 = 16.9 %
4. 关联的权重 = 12.1 %
5. 窪（侵蚀）的权重 = 9.3 %

选择您有异议的项目，从以下列表中选择：

是
1. THE-FIRST-CRITERIA

1. 使用箭头键或项目的第一字母来定位光标。
2. 选择所有适用的响应。
3. 在选择了后，按 ENTER 继续。

陆地形态的解释和场地分析

框：FRAME2A

PROPERTIES
FRAME2A-PARMS
FRAME2A-RULES

命令：
ADD
ERASE
QUIT

添加一个新的参数或规则组到这个帧