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The search for life beyond Earth through fuzzy expert systems

R. Furfaro[a,*], J.M. Dohm[b,c], W. Fink[d], J. Kargel[b], D. Schulze-Makuch[e], A.G. Fairén[f], A. Palmero-Rodriguez[h], V.R. Baker[b,c], P.T. Ferré[b], T.M. Hare[g], M.A. Tarbell[d], H. Miyamoto[i], G. Komatsu[j]

[a]Aerospace and Mechanical Engineering Department, University of Arizona, Tucson, AZ 85721, USA
[b]Department of Hydrology and Water Resources, University of Arizona, Tucson, AZ 85721, USA
[c]Lunar and Planetary Laboratory, University of Arizona, Tucson, AZ 85721, USA
[d]California Institute of Technology, Visual and Autonomous Exploration Systems Research Laboratory, Division of Physics, Mathematics and Astronomy, Pasadena, CA 91125, USA
[e]Department of Geology, Washington State University, Pullman, WA, USA
[f]NASA Ames Research Center, Space Science and Astrobiology Division, Moffet Field, CA 94035, USA
[g]United States Geologic Survey, Flagstaff, AZ, USA
[h]Department of Earth and Planetary Science, University of Tokyo, Tokyo 113-0033, Japan
[i]Department of Geosystem Engineering, University of Tokyo, Tokyo, Japan
[j]International Research School of Planetary Sciences, Università d'Annunzio, Pescara, Italy

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Abstract

Autonomy will play a key role in future science-driven, tier-scalable robotic planetary reconnaissance to extremely challenging (by existing means), locales on Mars and elsewhere that have the potential to yield significant geological and possibly exobiologic information. The full-scale and optimal deployment of the agents employed by tier-scalable architectures requires the design, implementation, and integration of an intelligent reconnaissance system. Such a system should be designed to enable fully automated and comprehensive characterization of an operational area, as well as to integrate existing information with acquired, "in transit" spatial and temporal sensor data, to identify and home in on prime candidate locales. These may include locales with the greatest potential of containing life.

Founded on the premise that water and energy are key to life, we have designed a fuzzy system that can (1) acquire the appropriate past/present water/energy indicators while the tier-scalable mission architecture is deployed (first layer), and (2) evaluate habitability through a specialized fuzzy knowledge-base of the water and energy information (second layer) acquired in (1). The system has been tested through hypothetical deployments at two hypothesized regions on Mars. The fuzzy-based expert's simulation results corroborate the same conclusions provided by the human expert, and thus highlight the system's potential capability to effectively and autonomously reason as an interdisciplinary scientist in the quest for life. While the approach is demonstrated for Mars, the methodology is general enough to be extended to other planetary bodies. It can be readily modified and updated as our interdisciplinary understanding of planetary environments improves. We believe this work represents a foundational step toward implementing higher-level intelligence in robotic, tier-scalable planetary reconnaissance within and beyond the solar system.

Keywords: Fuzzy logic; Tier-scalable mission autonomy; Astrobiology; Search for life; Robotic planetary exploration; Autonomous planetary reconnaissance

1. Introduction

Even though orbiting spacecraft and ground-based landers and rovers have successfully collected significant data through instrument suites, working hypotheses are yet

*Corresponding author. Tel.: +1 520 3127440; fax: +1 520 6218191.
E-mail address: robertof@email.arizona.edu (R. Furfaro).

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to be confirmed, such as in the case of Mars, whether sites of suspected hydrothermal activity are indeed hydrothermal environments, or whether prime candidate sites of potential life-containing habitability (Dohm et al., 2004) actually contain life. In answering the question of how best to explore planetary environments such as the ancient mountain ranges of Mars that contain complex structure and magnetic signatures (Acuña et al., 1999; Dohm et al., 2001a, b, 2002; Connerney et al., 2005), the expansive martian canyon system of Valles Marineris (Scott and Tanaka, 1986), the putative ocean beneath the ice of Jupiter's moon, Europa (Carr et al., 1998), a scientific mission concept for remote planetary surface and subsurface reconnaissance has been recently devised (Fink et al., 2005a–c, 2006a, b, 2007) to replace the engineering and safety constrained mission designs of the past. This novel mission concept is a paradigm shift from traditional missions that perform either local ground-level reconnaissance via immobile landers or rovers of limited mobility, or global mapping through orbiters, to what is termed *tier-scalable reconnaissance* in scientific missions. The paradigm integrates multi-tier (orbit–atmosphere–surface/subsurface) and multi-agent (orbiter–blimps–rovers–immobile sensors) hierarchical mission architectures to enable unconstrained, science-driven and intelligent planetary exploration (Fig. 1, Fink et al., 2005a).

The full-scale and optimal deployment of agents as part of a tier-scalable mission architecture requires both the integration of design and architecture and the implementation of an intelligent reconnaissance system. Such a system should (1) include software packages that enable fully automated and comprehensive identification, characterization, and quantification of feature information within an operational region (e.g., with the *Automated Geologic Field Analyzer (AGFA)* by Fink et al., 2005d; now *Automated Global Feature Analyzer*, see Fink et al., 2008) with subsequent target prioritization and selection for close-up reexamination (e.g., Fink, 2006c); and (2) integrate existing information with such AGFA-acquired, "in transit" spatial and temporal sensor data to automatically perform smart planetary reconnaissance and identify and home in on prime candidate life-containing targets on planetary bodies.

Our goal is to define the framework for the design of an expert system (intelligent reconnaissance system) to be integrated into the tier-scalable reconnaissance mission architecture and more generally to provide a basis for implementing intelligent algorithms capable of autonomously performing reasoning over data collected during planetary exploration. Here, we propose a fuzzy logic-based expert system capable of simulating the combined approach of a geologist, biologist, and chemist to identify, in one instantiation, prime candidate locales of life-containing potential through tier-scalable reconnaissance, which includes comparative analysis of the spatial and temporal spaceborne-, airborne-, ground-, and subsurface-based observations, i.e., synthesis of stratigraphic, paleotectonic, topographic, geomorphologic, hydrologic, geophysical, geochemical, spectral, and elemental information. As explained in the subsequent sections, the system is designed to acquire a sequence of life-habitat indicators whose values are inferred from the sensor data streaming through the system. The indicators, which are specific to the planet under observation, are the input to the system and are manipulated by the fuzzy rules, which form the core of the knowledge-base, in order to infer new facts. The number and type of indicators vary with the planet being explored. For example, indicators suitable for identifying life-potential locales on Mars may be different than those required by the ice-covered Europa where conditions for life may be drastically dissimilar. The fuzzy logic knowledge-base we are creating for tier-scalable autonomous reconnaissance is based on the geologic mapping-based reconnaissance and related synthesis of information of Mars, but can be modified/revised and updated for other planetary bodies. The intelligent system presented here may be considered a critical part of the "brain" of the tier-scalable reconnaissance mission architecture, though there may be other possible designs and implementations schemes. Importantly, we intend to show the potential of the methodology, leaving an open forum for the community to discuss about what are the appropriate life indicators for different planetary scenarios.

Here, Mars is used as case study to show how the fuzzy logic framework can be employed to design autonomous systems capable of assessing planetary habitability. Starting from the premise that water and energy are key ingredients to life, we devised a two-layer fuzzy system equipped with appropriate knowledge (i.e. rules) as derived from field expertise. The two layers are inherently interconnected: the first layer is comprised of four independent fuzzy systems, each devised to acquire remote and in-situ information and evaluate the potential for past/present water and energy. The second layer is comprised of rules that arrange water and energy (both past and present) in order of importance. For example, if the first layer infers that potentials for past/present water and energy are all high, then the potential for the site to harbor life will be very high. Life-related rules at lower level of importance have been included to provide the system with a comprehensive understanding of Mars habitability for effective and intelligent prediction.

The paper is organized as follows: Section 2 discusses the general problem of designing expert systems for planetary exploration. Section 3 makes a case for using fuzzy logic and provides a review of the subject. In Section 4, the rationale for designing the fuzzy expert is outlined and its implementation is shown in Section 5. Simulations and system testing for two hypothesized martian scenarios are illustrated in Section 6. Conclusions and future efforts are outlined in Section 7.

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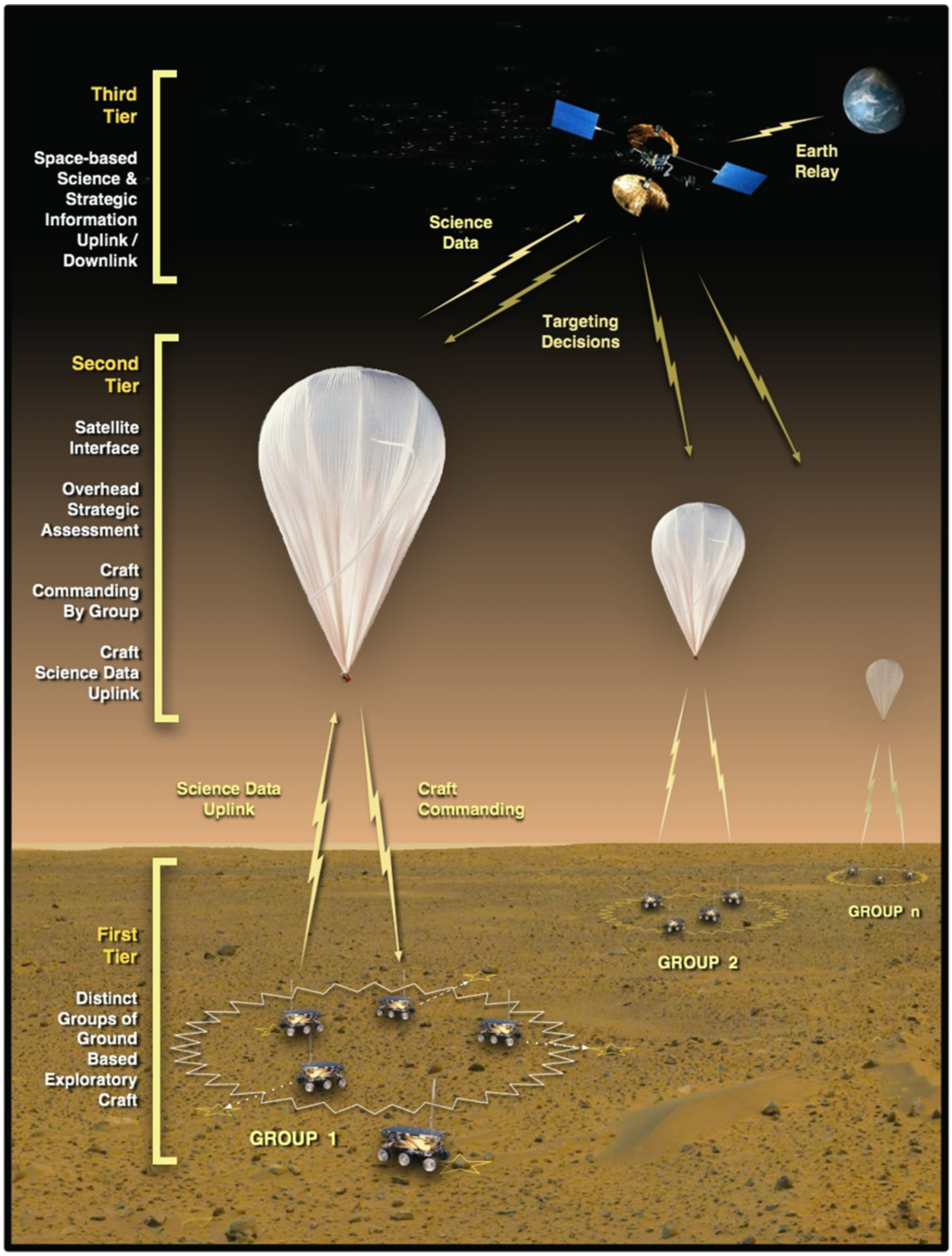

Fig. 1. Schematic illustration of the ''tier-scalable'' mission concept (Fink et al., 2005a). The paradigm integrates multi-tier and multi-agent hierarchical mission architectures to enable unconstrained, science-driven planetary exploration. The depicted three-tier architecture is comprised of: (1) a ground tier composed of multiple miniaturized and expendable agents with complementary sensor suites that can transmit the sensor information back to a main data compilation hub for comparative analysis; (2) an airborne tier comprised of blimps and/or balloons to control and command the surface/subsurface reconnaissance agents; (3) a spaceborne tier comprised of multiple orbiters which command the airborne tier, receive the data transmitted from the airborne- and ground-based agents, and interact with Earth-based systems (Fink et al., 2005a–c, 2006a, b, 2007). This novel paradigm introduces new implications for space exploration, including increased mission safety, mission reliability, and science return, which in turn enable new scenarios for the exploration of various planetary bodies.

2. Expert system design for planetary reconnaissance: problems and solutions

The design of an expert system to assess the potential for habitability (PH) through a tier-scalable reconnaissance approach is a knowledge engineering problem: given the domain-containing input data, find a suitable solution among all possible candidates occurring in the solution space. In our case, ''input data'' consist of information collected via multi-scale and multi-sensor deployment coupled with existing information, while ''solution'' is the answer to the following question: ''What is the potential for a particular locale under investigation to harbor life?''.

If the answer to this question must be given in an automatic fashion, specific field-based knowledge must be implemented on a computer. In defining an expert-system approach to the problem, knowledge is one of the major aspects of the procedure. Knowledge is "condensed information" and for our purposes consists of a set of rules or methods from which it is possible to perform plausible reasoning to obtain new facts, and to formulate new hypotheses while testing existing hypotheses. Generally, the knowledge domain consists of a set of definite rules that can be coded into computer language.

One other important aspect that must be considered is the inference mechanism. Inference can be defined as the process of matching data and knowledge to determine a solution to the problem (i.e., infer new facts and/or map around a problem, ultimately addressing the problem). Knowledge is usually acquired and integrated via the inference mechanism. To implement reasoning over knowledge, a theoretical framework is required (i.e., the need to define the appropriate logic). The selected logic will help determine the chain of matching results created to provide a suitable solution to the problem.

Fig. 2 shows a flow diagram that provides the general architecture of an expert system suitable for the tier-scalable reconnaissance mission concept. The various blocks in the diagram represent the essential ingredients. The knowledge-base contains information acquired via interaction with a field expert required to solve the problem. The database contains information about existing and in-transit acquired facts (i.e., information coming from the sensor after processing coupled with existing information). The inference engine is the place where the inference mechanism for reasoning over knowledge and data is implemented. The results of the inference are provided to the spaceborne command and control module, which selects the course of action based on the inferred information. The latter is usually implemented in the spaceborne tier and distributed through commands sent to the tiers beneath according to a hierarchical scheme. The explanation module is important because it provides explanation about how and why new information has been generated. This module can be interfaced with Earth-based centers where the explanation provided by the reconnaissance system is monitored. The Earth-based center can override the spaceborne control at "any" time (aside from the communication time lag) if there is an error in the inference.

The expert system paradigm defined above is general and requires appropriate design, which includes definition of knowledge, data inputs, and inference mechanisms. In the following, we will focus on the two major parts of the system: knowledge-base and inference. It should be pointed out that different choices of those two ingredients may yield different solutions for the intelligent reconnaissance system. In this regard, we believe that an expert system based on fuzzy logic may be a suitable candidate for

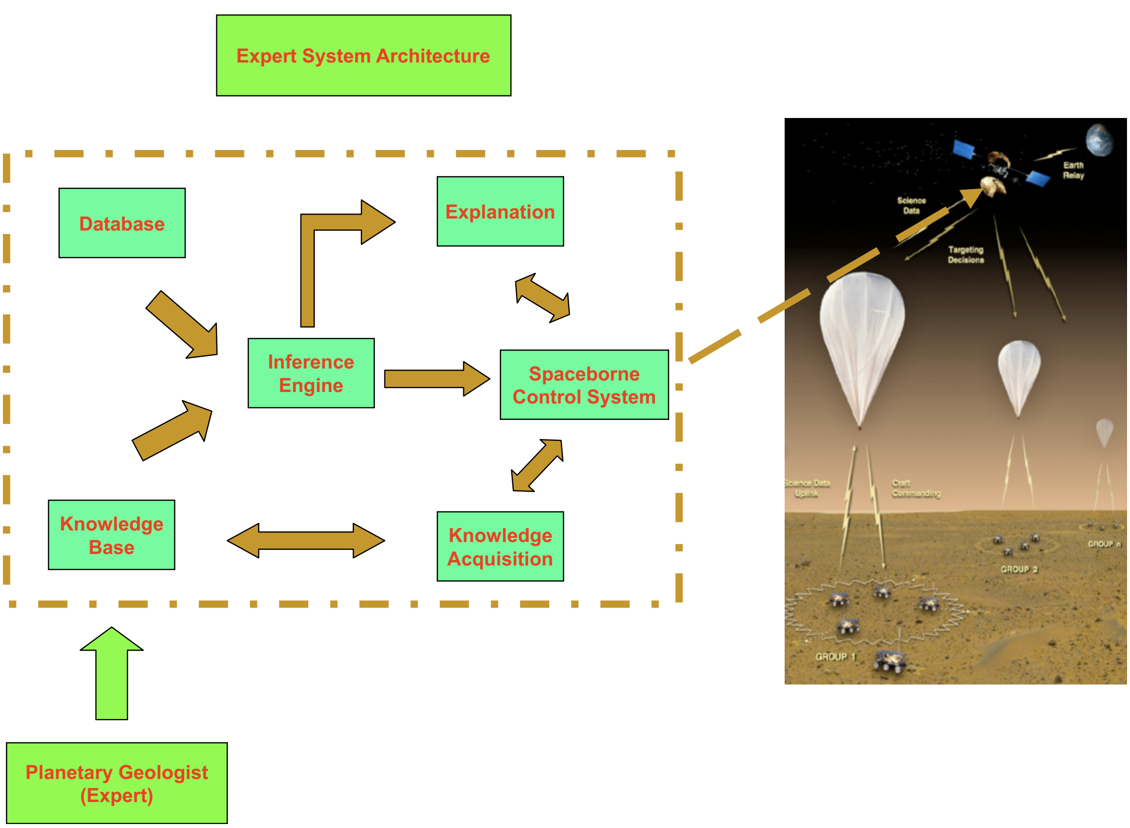

Fig. 2. General architecture of an expert system proposed for tier-scalable mission deployment.

an autonomously operating tier-scalable reconnaissance mission.

3. Fuzzy logic paradigm for autonomous fuzzy expert system design

The proposed system bases its foundation on the concept of fuzzy sets and fuzzy logic as an inference mechanism. In the following, an overview of fuzzy logic concepts, required for an effective system design, is provided for a basic understanding of the subject.

3.1. Why fuzzy logic for planetary exploration?

Planetary exploration is about understanding planetary bodies via remote and in-situ sensing. New discoveries are made using newly acquired data to infer new and unknown facts, as well as to test working hypotheses and to formulate new hypotheses. Formulated working hypotheses become closer to reality when diverse layers of information corroborate the formulated hypothesis (conciliation of diverse information), upping the potential of discovery, especially through interdisciplinary investigation. The tier-scalable reconnaissance missions strategy provides the means to acquire multi-scale and multi-sensor information (e.g., stored in a multi-layer-information system (MLIS), introduced by Fink et al., 2005a–c) that must be appropriately synthesized to evaluate certainty about possible new facts and findings. Nevertheless, general statements such as "the observed site contains life" cannot be stated as true or false, as classical and propositional logics require, until certainty is guaranteed. Unfortunately, global scale measurements might be inconclusive and require the concentration of efforts in a defined area where newly acquired information coupled with existing knowledge gives us clues (but not necessarily certainty) about, for example, presence of water and/or presence of life. Moreover, a statement such as "elevated hydrogen content is indication of an elevated presence of water", although rather general, is a linguistic expression of the common reasoning performed by planetary geologists in analyzing data. The knowledge system of planetary scientists, expressed in such statements, can be incorporated in the knowledge-base of an expert system for automatic reasoning.

The fuzzy logic semantic provides an ideal framework to deal with independent layers of information of varying degrees of confidence such us elevated hydrogen content, low sulfate level, and medium number of sapping channels. The absolute values of the input data can be transformed into fuzzy values and incorporated in rules that deal with concepts/working hypotheses of varying degrees of confidence (depending on the layers of information that are collectively consistent with the hypothesis), typical for planetary exploration. Thus, fuzzy logic provides a powerful framework that can be exploited to design an expert system to be embedded in tier-scalable reconnaissance mission architectures for assessment of the PH.

3.1.1. Deploying fuzzy experts on planetary bodies: Titan, Enceladus and Mars

One of the questions that naturally arise while considering autonomous systems for habitability assessment is how the effectiveness of the system varies as function of the observed planetary body. Indeed, the usefulness of a fuzzy expert system for autonomous interpretation of global and local habitability is influenced by two major and interconnected factors: (1) the ability of the system to acquire and store data and (2) the distance of the observed planet from Earth. Generally speaking, the larger the distance between the deployed observing platform(s) and Earth, the higher is the level of needed autonomy. Consider Titan and Enceladus exploration scenarios. The current Cassini mission has been successful in collecting and sending back to Earth a great deal of information unveiling novel features of these two saturnian satellites. For example, Cassini radar observations and the Huygens descent/landing probe unveiled apparent methane lakes, riverbeds, coastlines (Elachi et al., 2006; Perron et al., 2006) and dunes (Lorenz et al., 2006) on Titan. Enceladus geological activity is under scrutiny as well: closer observations of the saturnian satellite as imaged by Cassini, revealed an interesting world where tectonic activity and cryo-volcanism dominated the satellite geologic history and where geyser-like eruptions continued in real-time during Cassini's exploration (Porco et al., 2006; Kargel, 1995, 2006). Cassini is an orbiting platform equipped with instruments for remote data collection and most of its operations are constrained by instrument resolution and atmospheric effects (Tomasko et al., 2005). Science data are stored in the solid-state recorder (SSR) which has the ability to retain 2 Gigabits of data coming from the 12 on-board instruments. Clearly, data storage becomes a factor since if the collected bits exceed the storage capability, information must be erased. Currently, since the spacecraft is located between 8.2 and 10.2 astronomical units (AU) from Earth, it takes about 68–84 min to communicate with Earth. Real-time communication is impossible and as a matter of fact, it takes 3 h for the system (including human beings) to react to any on-board problem. Limited on-board software can diagnose occurring problems, but if they appear too severe, the spacecraft is put into a safe mode and essentially shut down until human's intervention. Similar approach to fault tolerance caused the Galileo spacecraft at Jupiter to lose nearly half of its data collected at the most interesting close-approach phases. The absence of software capable of autonomous decision-making and control jeopardizes the ability of the system to perform optimal reconnaissance.

Far more problematic than engineering monitoring and fault detection/protection (where the system is nominally known and understood) is the task of autonomous science which consists in autonomously and intelligently discovering key natural phenomena in environments that are neither well known nor understood. These phenomena may be either transient or may be observable for only brief periods. The dynamic nature of some phenomena or the brevity of the observing windows, coupled with concerns for the engineering safety of the spacecraft are two key aspects limiting the ability of current systems to respond to serendipitous discoveries and to modify their observing strategies. More fundamental are the problems of (1) autonomous recognition of what may constitute an important discovery, (2) autonomous prioritization of the discovery relative to other observing and engineering maintenance tasks, (3) the autonomous development of an observing strategy if the phenomenon should be deemed to be important enough to formulate and insert new observations. Current systems are entirely unable to make such decisions. The consequence is that many profoundly important phenomena probably go undiscovered or under-observed. This is a severe handicap when dealing with phenomena that may be difficult to detect due to a transient nature, due to low frequency or low concentration relative to detection thresholds, or due to observability only from special vantages. When the phenomenology is not yet known, and thus is not predictable by traditional means of spacecraft observation, the ability to capture a discovery observation is especially challenging; indeed, some of the things we most search for in the Solar System may be essentially impossible to find with current mission and observing approaches. Is life or fossil detection on distant worlds among these phenomena? We suggest that it may be; thus astrobiology is an important and exceptionally challenging application of the fuzzy logic-based approach to planetary exploration.

In the case of Titan, while we believe that a tier-scalable deployment on the saturnian satellite is the most effective way to explore it (Fink et al., 2006b, 2007), any system equipped with a fuzzy-based expert system for habitability assessment can effectively overcome the limitation imposed by Earth communication delays and data storage. We envision a scenario where a multi-tier system (e.g., orbiter(s) plus blimp(s) plus ground agent(s)) is deployed on Titan. The platforms are equipped with various sensors for in-transit and continuous data acquisition. Despite the fact that the overall amount of data collected during the course of a tier-scalable mission could be extremely large, a fuzzy-based expert system for life assessment and interpretation can effectively retain only data that yields significant findings; thus, the integrated system can concentrate its actions on locales worth of exploration using the platforms and sensors best suited to make the observations.

Such expanded platform/sensor systems may work in the traditional human-controlled mode, but they also may work in a semi-autonomous mode. For example, on Titan, the system might select potentially interesting information-rich sites concentrated around zones of mobile condensed hydrocarbons (e.g., lakes), send signals back to Earth and initiate a human–machine interaction where the humans analyze both system results and explanations (see Fig. 2). Subsequently, humans could command further investigation or alternatively disregard the selected areas. At Enceladus, the system might be designed to look specifically for transient geyser eruptions and geothermal emissions and focus observations on the phenomena deemed most interesting or most suitable for safe observations.

In this paper, we focus on designing a fuzzy system for habitability assessment taking Mars as a case study. Since Mars is an extremely rich and complex environment, our work may serve (a) to illustrate the ideas behind developing such fuzzy expert and (b) to provide a platform for system design and implementation that can be readily tested and verified for consistency on hypothesized and (in the future) real Mars scenarios. Mars is relatively close to Earth and one could argue about the need for such system. Indeed, one could envision two alternative scenarios where (1) one deploys landers and/or rovers in a carefully selected locale (e.g., forth coming Phoenix mission 2008) or (2) one deploys a large number of inexpensive agents looking for life everywhere. Case 1 suffers the classical limitations associated with the relative mobility of the deployed agents and past and present missions (e.g., Pathfinder, Mars Exploration Rovers Spirit and Opportunity) have been unsuccessful in looking for life. For case 2, either if agents are deployed following a tier-scalable scheme or if multiple agents are indiscriminately sent onto the Martian surface, data management becomes a critical factor. As the number of agents increases, the amount of data increases exponentially. Fuzzy experts may be extremely functional in understanding and interpreting the collected data and again, if the semi-automatic mode with human in the loop is preferred, Earth-based fuzzy systems could help humans to perform synthesis of information quickly and effectively. The Mars reconnaissance orbiter (MRO) has been recently inserted into a martian orbit and its on-board instruments are sending an unprecedented amount of data back to Earth. For example, the high resolution imaging science experiment (HiRISE) camera system is expected to send 12 Terabytes over the course of two years (McEwen et al., 2007). Careful human analysis of large datasets is generally problematic and expert systems capable of understanding Martian geology and geochemistry as well as assess locales' habitability may operate from Earth in a quasi real-time mode and be established as an aiding tool to help coordinating the sequence of observations. Therefore, while we believe that the proposed methodology is most effective in tier-scalable architectures, it may be considered as foundational in developing an Earth-based semi-autonomous system for decision making (with humans in the loop). Such a system could help humans coordinating the observing platforms already deployed around/on Mars.

3.1.2. Fuzzy logic versus alternative AI schemes

Any artificial intelligence (AI) scheme must be able to deal with the major issues arising in knowledge engineering. For example, representation, inference, learning, generalization, explanation and adaptation capabilities must be carefully analyzed and considered when choosing a suitable scheme for habitability assessment. Symbolic AI, fuzzy logic-based and neural networks schemes provide different solutions to the life-searching problem. Neural networks are connectionist systems where knowledge is distributed among various nodes. Thus, neural networks use unstructured knowledge (i.e. they learn by examples, by doing or by analogy), and they are capable of good generalization and adaptation. Conversely, symbolic AI and fuzzy systems provide an effective mean to represent structured knowledge. Moreover, inference is exact in symbolic AI while it is approximate in fuzzy-based and neural network systems. Because of their nature, symbolic AI systems do not deal very well with missing corrupted and inexact data.

When dealing with planetary exploration one of the major problems to be addressed is how to represent uncertain knowledge and uncertain data. Besides fuzzy methods that are inherently capable of dealing with uncertainties, probabilistic methods could be also employed. By relying on the axioms of probability as a mathematical framework, coherent knowledge-bases can be built using (a) data collected in the course of past missions and (b) statistical methods to determine the appropriate conditional probabilities (objective probability). Moreover, conditional probabilities that define beliefs unsupported by data (subjective probability) can be implemented as well. In short, probabilistic methods are based on estimating the posterior probability for a conclusion (defined by a rule) to be accepted as correct. In practice, probabilistic methods cannot deal with ambiguous and contradictory scenarios. Indeed Bayes' theorem fails whenever multiple rules reach different conclusions if a condition is true. Conversely, fuzzy systems can deal with contradictory and ambiguous rules by naturally providing a trade-off during the inference process (rules are fired at the same time). Such scenarios are expected to be found when assessing habitability in complex environment.

At this stage of development, we believe that fuzzy-based systems are an ideal solution to the problem of assessing planetary habitability. In such systems, structured knowledge is directly implemented by intuitive, easy-to-devise, fuzzy rules that can facilitate the interaction between planetary scientists and computing, autonomous machines. The basis of fuzzy logic is the basis for human communication and therefore in unknown and uncertain planetary environments, fuzzy systems will be able to provide good and solid explanation for any autonomous decisions. Planetary experts (e.g., geologists, astrobiologists, cosmochemists) will be required to provide their knowledge and to contribute both in the design and testing phase while working on a common ground with computer and AI engineers.

3.2. Fuzzy logic basics

Fuzzy logic was introduced by Lotfi Zadeh (1965, 1975) as multi-valued logic capable of dealing with intermediate values between traditional, absolute evaluations such as "true or false", "hot or cold", "yes or no", and so on. Fuzzy logic-based systems were born as an alternative to the traditional notion of set membership and the Greek classical logic. One of the famous propositions of the Aristotelian logic is the "law of the excluded middle" according to which any proposition must be either true or false. The semantic meaning of a proposition is usually determined via a truth table. Fuzzy logic allows the possibility of degree of membership to a set, opening the door to a new way of defining knowledge using statements that can be true to a certain degree (the "excluded middle" coming to the forefront). Fuzzy logic is an excellent tool for implementing common sense knowledge on a digital computer. It is based on simple mathematical concepts and is supported by a well-defined logical framework. Moreover, fuzzy logic is tolerant of noisy, imprecise, and faulty data. Fuzzy logic expert systems deal with uncertainty by reasoning over the general understanding of the problem rather than on exactness of the process (e.g., the natural world vs. the confines of a lab-based controlled experiment). Next, we define the basic ingredients and concepts that are required to design a fuzzy expert system for assessing life habitability.

3.3. Fuzzy sets and membership function

The basic ingredient of fuzzy logic design is the simple notion of a fuzzy set (Zadeh, 1965; Dubois and Prade, 1980; Kasabov, 1996). In conventional classical and/or propositional logic, given a set U (called universe of discourse) and a subset A (included in U), any element ξ in U can either belong or not belong to A. Formally, this can be stated defining a function, called membership function, that takes any element ξ in U and assigns either 1 (the element belongs to A) or 0 (the element does not belong to A). In this sense, the set is distinctly constrained since it has well-defined boundaries ("crisp" in Fuzzy Logic terms). A fuzzy set is a set without crisp boundaries, i.e., an element ξ can belong to the set with a certain degree of membership. The fuzziness of the set is translated into a new definition of the membership function, which can now take any value between 0 and 1. If the value of the membership function over ξ is 0 or 1, then the element belongs or does not belong to the set. For any intermediate value, say 0.7, we state that the element ξ belongs to A with a degree of membership of 0.7.

It is clear that fuzzy sets are extensions of ordinary (crisp) sets. Operations between fuzzy sets can be extended in similar fashion. Generally, it is desirable to intersect, unify, and negate fuzzy sets. These operations are allowed by using the logical operators AND, OR, and NOT (see Zadeh, 1988; Kaufmann and Gupta, 1985; Ross, 2004, for a detailed explanation of these operators and how they are applied).

3.4. Fuzzy logic paradigm: fuzzy rules and inference mechanism

The fuzzy logic paradigm is based on the appropriate definition of fuzzy propositions, fuzzy rules, and an inference mechanism, which are built upon the concept of fuzzy sets. Fuzzy propositions are linguistic statements linked by fuzzy connectivities. In general, the statements are not true or false but their truth-value is defined by the membership value associated with the respective fuzzy variable represented in the proposition. The connectivities are the classical logical operators such as AND, OR, and NOT, but they are applied according to the way operations between fuzzy sets are defined (see Zadeh, 1988, 1989). If complex propositions must be evaluated, this can be done by the computation of a new membership function constructed using the operational rules between fuzzy sets.

Fuzzy rules are defined by linguistic statements expressing the expert field knowledge required to infer new facts. The rules express conditional statements, which form the basis of the fuzzy logic knowledge system. A large part of the presented effort is devoted to defining the appropriate rules that condense the methodology employed in approaching the problem of identifying suitable prime candidate sites of high potential for life in planetary environments. Thus, the "field expertise" and "knowledge" of a field geologist will be translated into appropriate rules for a direct implementation of an intelligent fuzzy-based expert system.

Two major classes of rules are commonly used by fuzzy systems: Sugeno-type and Mamdani-type. The Mamdani-type rules (Mamdani and Assilian, 1975; Mamdani, 1977) have the following structure:

IF (α is A) THEN (β is B).

Here, we distinguish between two fuzzy propositions: antecedent or premise (α is A) and consequent or conclusion (β is B). The truth-value of these propositions is defined via their membership functions. A and B are two linguistic values defined by their associated membership function in the universes X (for variable α) and Y (for variable β). For example, in the context of Mars exploration, α could be the number of water-carved valleys present in a region, β is the potential for life habitability, and A and B could be representative of linguistic statements such as "high", "low", etc. The Mamdani-type rules are therefore IF-THEN rules. If many inputs are present, many propositions can be formed and linked using logical operators such as AND and OR. For example, the rules may have more than one antecedent:

IF (α_1 is A_1) AND (α_2 is A_2) ... AND (α_n is A_n)
THEN (β is B).

In general, many rules are required to implement the desired knowledge. In fuzzy logic, the inference mechanism determines the sequence used in firing the rules to obtain the desired solution. In typical settings, the rules are fired at the same time or cyclically. In certain Mamdani-type rules, a confidence factor (CF) can be introduced to deal with uncertainty. In essence, the factor is used to weight the importance of a rule relative to the others. We will see how the confidence factor associated to one rule or to a group of rules will play a key role in planetary settings. In our design, we will focus exclusively on Mamdani-type rules (for more information on Surgeno-type rules see, e.g., Sugeno, 1974, 1985).

The Inference Mechanism is a process of matching the domain with the solution space. In some sense, the process can be seen as given some data X and a set of rules, to infer, through a chain of matching, a new value Y'. This is a key process since new facts are inferred using some plausible reasoning over knowledge and data. In a broader sense, the inference mechanism is defined by specifying an implication operator, a composition rule, and else-links between rules. Examples of else-links are the AND- and OR-link. In the AND-link, two propositions are linked together by the AND operator, which consists of determining a new membership function through the MAX operator (i.e., the new membership function is obtained by comparing the two original functions point-by-point and taking the maximum value). In the OR-link, two propositions are linked via the OR operator, which consists of determining the new membership function via the MIN operator (i.e., the new membership function is obtained by comparing the two original functions point-by-point and taking the minimum value). The implication operator provides a way to perform inference using the rule. The antecedent is linked using AND/OR operators and the result is transformed by the implication operator, which shapes the fuzzy set of the consequent. In practice, the Mamdani inference system (Mamdani and Assilian, 1975) is generally employed, which includes the MIN function, (i.e., the fuzzy set is chopped off to a degree specified by the antecedent) and the PROD (scaling) function (i.e., the fuzzy set is squashed to a degree specified by the antecedent). (For more information see text books such as Ross, 2004.)

Importantly, if many rules are considered, the fuzzy inference mechanism combines the results of all rules to provide the output.

4. Knowledge-base for the fuzzy-expert system: mimicking the scientific/operational approach of a geologist, biologist, and chemist

This section provides the basis for building the knowledge-base required to construct a fuzzy-based expert system capable of autonomously determining the potential exhibited by the planetary locale under observation to harbor life. The knowledge-base construction is not only an attempt to simulate the approach of a geologist, but also an attempt to merge other disciplines with geology such as biology and chemistry, thereby establishing connections between presence of life and/or biosignatures and a specific geological environment. As explained in Section 3.1.1, we focus on Mars, which affords an opportunity to establish the basic methodology that can be eventually extended to other planetary scenarios, and we discuss the rationale that underlies the proposed two-layer fuzzy system.

4.1. Rationale for building the knowledge-base to assess potential for life habitability

In a recent paper (Dohm et al., 2004), a novel approach was proposed for selecting prime candidate sites for future Mars exploration. Indeed, published geological maps portray Mars as an episodically active, dynamic planet with magmatic, tectonic, water/ice, and wind activity in its recorded geologic history. It may still be internally active, which includes local elevated heat flow and potential magmatic-driven activity (Dohm et al., 2001b). In the martian context, a prime candidate site can be defined as a locale that has the greatest potential to yield significant geologic, paoleohydrogeologic, paleoclimatic, and exobiologic information (Dohm et al., 2004). More importantly, in answering the fundamental question of life on Mars, the site should possess the greatest potential for extant and/or fossilized life. In the proposed approach, which has been built upon past efforts (e.g., Greeley and Thomas, 1994), the optimal candidate site is established through a synthesis of all published information, including stratigraphic, topographic, geomorphic, paleotectonic, paloehydrologic, geophysical, thermal, spectral, and elemental data. Based on this approach, Dohm et al. (2004) concluded that the martian Northwestern Slope Valleys (NSVs) region has elevated probability to yield significant geologic, climatic, and possible exobiologic information. The elevated confidence came from compiling layers of information, which jointly and consistently pointed in the direction of the region being a prime candidate for future science-driven exploration.

The geologic approach of synthesizing layers of information from various perspectives, including orbital, airborne, ground, and subsurface, can in principle be used to determine the potential that a specific locale on Mars comprises extant and/or fossilized life. The appropriate synthesis is usually performed by the field expert (i.e., the planetary geologist/biologist/chemist) who collects available information and, using existing field- and remote-based knowledge and expertise, determines and explains if a certain region has the potential for past and/or present life. To the extent possible, the terrestrial geologic approach has been adopted and then adapted to meet the needs and special challenges inherent in producing planetary geologic maps that rely on spacecraft data, lacking ground truth. In the specific case, the approach used to determine the life potential for a certain locale via synthesis of layers of information, requires the field expert to perform comparative analysis among various elements in the field, employing some level of intuition/judgment to establish when certain data collectively indicate that a site yields the highest probability for the presence of life. If the amount and diversity of information is great, this is indeed difficult and time consuming for any geologist/biologist/chemist (e.g., while in transit, maintaining location, synthesizing spatial and temporal information at various scales, and testing and formulating hypotheses, etc.). Moreover, in the context of the tier-scalable reconnaissance mission concept, it is desirable to have an autonomous system that mimics the geologist approach, while readily coupling information gathered from various disciplines such as biology or chemistry. Such a system would provide independent inference over a set of basic rules to establish the level of confidence that a certain region is harboring life. Relying on this foundational approach, we aim at defining a set of independent rules that (a) mimic the layers-of-information-synthesis approach as defined above, and (b) can be directly implemented in the fuzzy expert system paradigm. The key element of the knowledge-base approach is to establish how the search for sites with elevated potential for life can be conducted on the basis of layers of synthesis and comparative analysis of diverse information.

One of the premises is that water is the key to life, and as such, the system that performs tier-scalable reconnaissance must identify, characterize, and quantify past and present water. Water is considered a first-order indicator of life-containing potential (including surface and subsurface water) in the form of solid (ice/rock with interstitial ice), liquid (including brines), and water vapor (e.g., moisture to the surface such as in the case of fog embankment). In the case of the evolution of the Tharsis magmatic complex (Dohm et al., 2006a, in press; Komatsu et al., 2004), geologic information points to an episodically active complex, which includes magmatic-driven floods (including hydrothermal activity), ponding forming water bodies ranging from lakes to oceans, and transient hydrological cycles with possible extensive periods of inactivity (Baker et al., 1991; Fairén et al., 2003). During the pulses of catastrophic activity, does life originate in the subsurface and potentially thrive at the surface, as hypothesized (e.g., Schulze-Makuch et al., 2005b; Fairén et al., 2005)? In the Atacama desert, Chile, there are investigations underway that are indicating promising results that life may have sprung during magmatically and hydrothermally active periods. The history of water on Mars is recorded not only in geomorphological features such as valley networks, but also in sedimentary facies, and as such, a variety of sedimentary rocks are candidates for exobiological investigation (Komatsu and Ori, 2000; Ori et al., 2000). Furthermore, groundwater is a potential habitat for life in the past (Mahaney et al., 2004) and present.

Based on published geologic, paleohydrologic, and geomorphic information, Mars has been active and water enriched until geologically recent times (Late Amazonian epoch; e.g., Scott and Tanaka, 1986; Scott et al., 1995; Fairén et al., 2008, currently under review). This was recently confirmed through gamma ray and neutron spectrometers (Boynton et al., 2002; Feldman et al., 2002, etc.) to the extent that it could be currently enriched in water in places. In addition, Mars Global Surveyor-, Mars Express-, and Mars Exploration Rovers-based information, which includes the identification of rock materials such as hematite, sulfates, and phyllosilicates, points to histories involving water. Moreover, Mars demonstrates internal heat release, both past and possibly present (e.g., see Dohm et al., 2004, 2006b).

Another first-order indicator for life-containing potential is energy. Voids in the martian subsurface (e.g., Rodriguez et al., 2005, 2006), which are expressed at the surface by a diverse suite of features such as collapsed and broken terrain, referred to as chaotic terrain, may provide suitable habitats for life, but without energy into the system, life may exist in dormant form; once energy is injected into the environment in the form of heat and/or nutrients, then life may spring (e.g., Boston et al., 1992; Boston, 2004; Schulze-Makuch et al., 2005a, b; Fairén et al., 2005). Anything that indicates present energy is extremely important (e.g., elevated heat flow related to the internal heat release of a planet). There are multiple lines of evidence that collectively point to an active Mars (Anderson, 2001; Mitchell and Wilson, 2003; Márquez et al., 2004), and thus there may be heat release to subsurface and surface environments (including associated aquifers). The thermal emission imaging system (THEMIS), an instrument aboard the Mars Odyssey spacecraft, was intended to identify thermal anomalies on Mars related to internal heat release, but has not identified such. One possible explanation is the low resolution of the instrument, or that the heat releases are low grade, and thus exceedingly difficult to identify by remote sensing (Dohm et al., 2006b). The tier-scalable reconnaissance mission paradigm originated by Fink et al. (2005a–c, 2006a, b, 2007) would afford an optimal opportunity to test whether Mars is still active through higher resolution spectroscopy (both multispectral and nuclear) acquired via airborne and field-based reconnaissance (with the advantage of minimizing noise from electromagnetic radiation and atmospheric conditions). Other means of identifying energy, which could be part of a tier-scalable architecture, include heat sensing, seismic, radar sounding, etc.

Our primary objective is to autonomously identify, characterize, and quantify environments that indicate both water and energy (past and present). For example, by identifying a region of heat release with associated near-surface water, the life potential would be at an elevated level. If the presence of water and energy is long-lived, however, then the life potential is even further increased.

These considerations are useful in assessing the utility/importance of the indicators (ranking). We now distinguish between past long-lived water/energy and present water/energy. The simultaneous presence of these four conditions has the highest life potential. For example, if volatiles release from fractures and geologic contacts, a ponding of brines in a topographic low, elevated heat flow, and/or near-surface aquifers are observed, then the probability for life is elevated. If such indications of potential life are coupled with, for example, evidence of past water and energy such as vent structures, lava flows, joints, faults, and rift systems, valleys (including networks), etc., then the life potential is further increased.

Importantly, water alone, though significant, may not be enough. For example, the observation that valley forms such as sapping channels sourcing from fractures, as noted for Mars (e.g., Mouginis-Mark, 1985, 1990), is an indication of past water-related activity, but not necessarily life. The basic indicators for water-related activity (transient and long-lived) are typically geomorphologic, stratigraphic, and topographic. Other indications of past water-related activity include drainage basins, valleys that debouch into basins, stratigraphic sequences (water and rock materials that are deposited into basins), and valley forms (e.g., valley networks, sapping channels). Specifically, if a locale is to be identified as the highest life potential, it must record long-lived, water- and energy-related activity (e.g., ancient-, middle-, and recent-planet magmatic and tectonic activity). Thus, present water and energy coupled with indications of past water and energy has the highest life potential.

The terrestrial- and planetary-based analysis of the relationship between water, energy, and life presented above, allows us to categorize the areas of interest according to past/present water/energy, leading to indicators of life potential. Detecting past AND present water plus past AND present energy is the first order of importance, whereas the second order of importance are areas exhibiting present water AND present energy; a third order of importance are areas with EITHER past and present water OR past and present energy (water and energy separately are at the same level), and a forth order of importance is past water AND past energy.

To implement the above outlined approach in a fuzzy-based expert system, a two-step process is required to connect life to water and energy indicators. First, the expert system acquires water and energy indicators collected via streaming of sensorial data and assesses the past/present water and energy potential of the observed locale. Subsequently, the system reasons over past/present water/energy to extract life-containing potential. Thus, a two-layer fuzzy system is required. The first layer contains knowledge-bases made of rules linking the appropriate water/energy indicators to past/present water and energy potential. For example, if the system detects channels and streamlined bed forms, this is an indication of past aqueous conditions. In addition, if spectral data report high chlorine, sulfates, and evaporites, everything collectively points to past aqueous conditions. The same reasoning can be applied to the indicators of present water and past and present energy.

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The second layer contains a knowledge-base comprised of rules linking past/present water/energy to life-containing potential. The second layer of the expert system reasons over the output of the first layer using rules combining order of importance of past/present water and energy to effectively infer PH of the observed locale. For example, if potential for past/present water and energy is high, the potential for life-containing will be high to the highest degree.

Although the presented analysis outlines the essential approach that considers many lines of evidence and demonstrates the path that must be followed to construct the appropriate knowledge-bases, some extensive work must be done to translate the expert knowledge in appropriate rules that can be implemented on a digital computer (IF-THEN Mamdani-type rules, see Section 3.4). Similar to human experts, fuzzy systems are capable of learning and self-adapting, or being manipulated by humans based on experience. Depending on system performance on Mars, or performance in test simulations on Earth, it might be decided to change some rules or to introduce additional expert systems (e.g., warm vs. cold environmental conditions on Mars; e.g., see Kargel, 2004). The following sections illustrate the details of the process that creates effective knowledge-bases and implements the rules required by the two-layer fuzzy expert system.

5. Building a fuzzy logic expert system for life habitability assessment

Here, we describe in detail the basic structure of the proposed two-layer, fuzzy-logic-based expert system. The life indicators and the proposed set of rules should be foundational and open to revision as our understanding of life on other planetary bodies develops. As such, the approach is generic enough to accommodate any possible modification while still employing the same framework.

Fig. 3 shows a schematic of the proposed multi-layer, fuzzy-logic-based expert system. The system is defined by two layers: according to the deployed multi-tier architecture, data collected by multiple sensors at multiple scales from several vantage points observing an operational area of interest are pre-processed by AGFA-like software (Automated Geologic Field Analyzer by Fink et al., 2005d; now Automated Global Feature Analyzer, see Fink et al., 2007, to be submitted) to extract feature information in the form of numerical values for the respective indicators of interest. The indicators are arranged according to

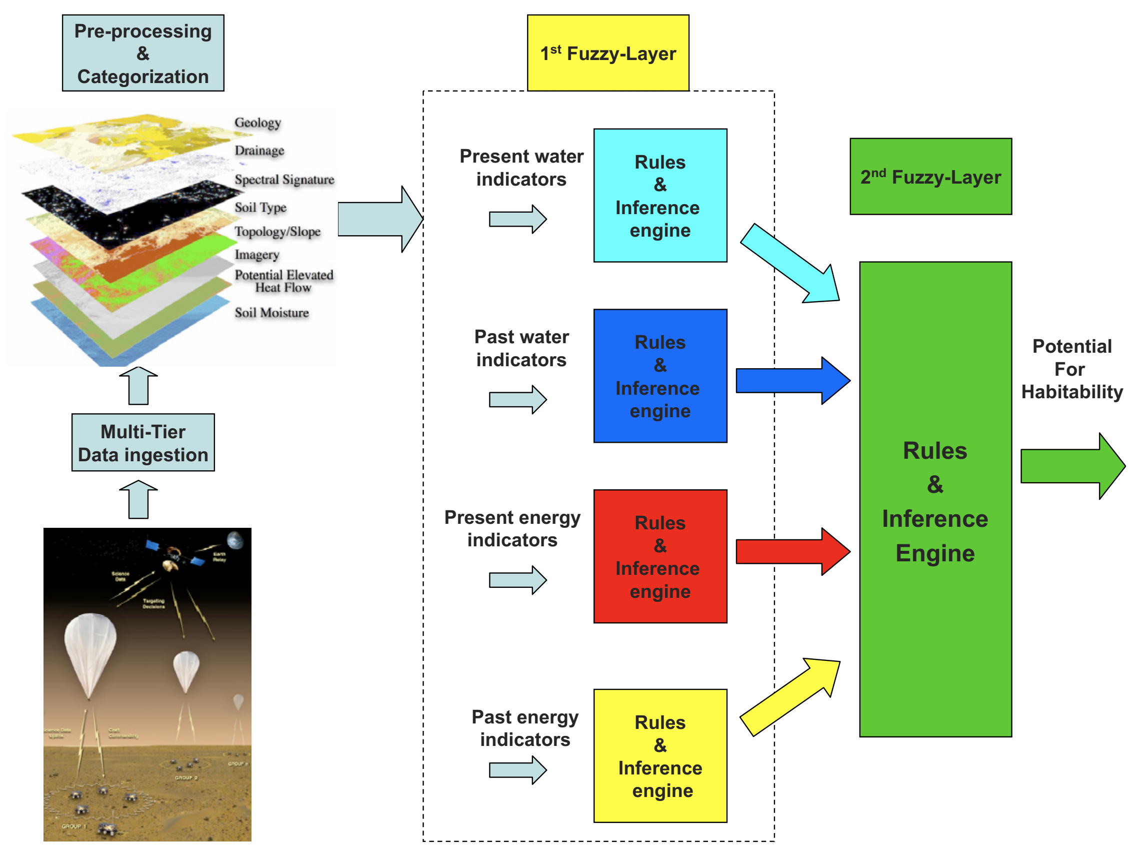

Fig. 3. Schematic of the two-layer fuzzy logic-based expert system for the tier-scalable mission architecture. The illustration shows how an intelligent reconnaissance system can be integrated into the tier-scalable architecture. The "brain" of the system consists of a set of five interconnected fuzzy systems distributed over two layers and operate according to the scheme outlined in the text. Depending on the life-assessment result, the system might order further deployment to the locale (e.g., drill rig that is optimally placed to sample identified near-surface groundwater in a locale of elevated heat flow).

specific categories of scientific interest (e.g., elemental, spectral, geomorphologic, paleohydrologic, topographic, stratigraphic, seismic, paleotectonic, atmospheric, spectral, elemental, etc.) and fed to a set of four independent fuzzy systems that are designed to generate past/present water/energy information. The first layer processes the indicators according to defined fuzzy rules and generates the past/present water and energy potential. The latter is forwarded to the second fuzzy-layer to provide, after appropriate fuzzy inference over a pre-defined set of fuzzy rules, the PH exhibited by the locale under investigation. Next, the rules for both layers are defined.

5.1. First fuzzy-layer: past/present water/energy assessment for life-containing potential

The first layer is defined by four independent fuzzy systems. Each fuzzy system has an embedded knowledge-base composed of a sequence of IF-THEN, Mamdani-type rules. Using the appropriate rules, each fuzzy system independently assesses the present/past water and energy potential.

5.1.1. Fuzzy system #1: present water assessment

The first fuzzy system is designed to acquire indicators of present water at a locale under investigation as signs for potential life. In essence, the first fuzzy system evaluates the presence of water, yielding a parameter (PrW) in the range 0–100, the latter being the maximum possible level. Table 1 shows a set of (intuitive) indicators of the presence of water, and thus relevant to the potential for life. We consider water in all forms (solid, liquid, and vapor/moisture), occurring in the subsurface, on the surface, and in the atmosphere. The mixture of salt and water is also considered (i.e., brines). The confidence factor (varying between 0 and 1) is descriptive of the importance of the indicators relative to each other. Moisture embankment has been considered separately, and when combined with other indicators, is critical to identifying potential life-containing locales.

Table 1
Present water indicators

Present water		
Category	**Indicators**	**Confidence factor**
Elemental/spectral	Surface liquid water (SLW)	1
Elemental/spectral	Surface solid water (SSW)	0.9
Elemental/spectral	Surface brine (SB)	1
Elemental/spectral	Subsurface brine (SSB)	1
Elemental/spectral	Subsurface liquid water (SSLW)	1
Elemental/spectral	Subsurface solid water (SSSW)	0.9
Atmospheric	Atmospheric moisture (AM)	0.9
Atmospheric/spectral	Soil moisture (SM)	0.9
Atmospheric/geomorphology	Embankments moisture (EM)	0.9

The parameters, which are selected to characterize the presence of water on Mars, are the input to the fuzzy system #1 (first layer) to determine the "present water" potential (PrW).

The associated rules are shown in Table 2. The set of IF-THEN, Mamdani-type rules are defined and organized to show the impact of the present water potential on harboring life. In the semantic description of the rules, "H", "M", "L" stand for high, medium, and low, respectively. The rules have been organized in two sets where the indicators have the same confidence factor. The confidence factor weights the importance of the rules associated with the corresponding indicators. Particular care has been taken in defining the lower limit. For example, the locale under observation might show high liquid water content but low solid and atmospheric water (ice and moisture, respectively). In this situation, the locale still exhibits an elevated presence of water. To adapt the rule to this circumstance, the AND connector is utilized for low content, i.e., "present water" is low only if all indicators are low (see Table 2).

Table 2
Fuzzy rules for fuzzy system #1 (first layer)

Present water fuzzy system: rules	
Indicator and confidence factor	**Rules**
SLW, CF = 1	IF SLW is H THEN PrW is H IF SLW is M THEN PrW is M
SSLW, CF = 1	IF SSLW is H THEN PrW is H IF SSLW is M THEN PrW is M
SB, CF = 1	IF SB is H THEN PrW is H IF SB is M THEN PrW is M
SSB, CF = 1	IF SSB is H THEN PrW is H IF SSB is M THEN PrW is M
Low-rule, CF = 1	IF SLW is L AND SSLW is L AND SB is L…AND SSB is L THEN PrW is L
SSW, CF = 0.9	IF SLW is H THEN PrW is H IF SLW is M THEN PrW is M
SSSW, CF = 0.9	IF SSW is H THEN PrW is H IF SSW is M THEN PrW is M
AM, CF = 0.9	IF SLW is H THEN PrW is H IF SLW is M THEN PrW is M
SM, CF = 0.9	IF SLW is H THEN PrW is H IF SLW is M THEN PrW is M
EM, CF = 0.9	IF SLW is H THEN PrW is H IF SLW is M THEN PrW is M
Low-rule, CF = 0.9	IF SSW is L AND SSSW is L AND AM is L…AND SM is L AND EM is L THEN PrW is L

The rules define the knowledge base required for automatic inference of the present water potential (PrW) Mamdani. The rules structure is fairly intuitive. For example, "IF SLW is H THEN PrW is H (CF = 1)" should be read as "If the surface liquid water is high then the present water potential exhibited by the observed area is high (with the highest confidence)". Each confidence factor group (CF = 1, 0.9) has an associated Low-rule. The latter has been constructed linking water indicators with same confidence factor via the AND connector. The Low-rule reflects the circumstance that potential for water containing is low only if a reconnaissance system observes a concurrent low value for any of the considered present water indicators.

5.1.2. Fuzzy system #2: past water assessment

The second fuzzy system accepts past water indicators as inputs and yields a parameter that assesses the potential for presence of water in the past (PsW). Table 3 shows the major parameters that can be used as indicators of past water-related activity and that are relevant to the possible presence of life at the locale. The indicators are mostly categorized as elemental, spectral, geomorphologic, and topographic. As in the previous case, the indicators are associated with confidence factors that weight the relative impact of the indicators on the potential for past water. The rules, shown in Table 4, are constructed following patterns similar to the previous case, but some variations, due to the nature of the categories, are considered. For example, in defining the rules, the elemental and spectral indicators for past water, generally indicating the chemistry of the observed locale, are not mixed with geomorphologic, topographic, and stratigraphic indicators, which are physical markers of the geologic and paleohydrologic histories of the region. The indicators are organized such that each group possesses the same confidence factor. Each group is evaluated with rules that are based on the level of indicator value (e.g., the higher the indicator value the higher the potential of past water at the locale). Again, "past water" is assumed low if all indicators exhibit low values at the same time, i.e. we used the AND logical connector to implement this condition (see Table 4).

Table 3
Past water indicators

Past water		
Category	**Indicators**	**Confidence factor**
Elemental/spectral	Chlorine (CHL)	1
Elemental/spectral	Sulfates (SU)	1
Elemental/spectral	Hematite (HE)	1
Elemental/spectral	Potassium/thorium (PT)	1
Geomorphology	Valley networks (VN)	0.9
Geomorphology	Sapping channels (SC)	0.9
Geomorphology	Anastomosing patterns (AP)	0.8
Geomorphology	Outflow channels (OC)	0.9
Geomorphology	Poligonal patterns (PP)	0.8
Geomorphology	Alluvial fans (AF)	0.8
Geomorphology	Stream-lined bedforms (SLB)	0.8
Geomorphology	Scarps/terraces (ST)	0.6
Geomorphology	Parallel/concentric ridges (PCR)	0.6
Geomorphology	Summit pits (SP)	0.6
Geomorphology	Pit crater chains (PCC)	0.5
Topographic	Basins (B)	0.6
Topographic	Topographic highs (TH)	0.8
Stratigraphy	Layered stratigraphy (LS)	0.6

The parameters, which are selected to characterize the possible presence of past water on Mars, are the input to the fuzzy system #2 (first layer) to determine the "past water" potential (PsW). The CF values have been established using our long-live experience in studying elemental, geomorphologic, topographic structures of Mars. The indicators list is not intended to be comprehensive but reports the parameters our group believes have the major impact on past water potential.

Table 4
Fuzzy rules for fuzzy system #2 (first layer)

Past water fuzzy system: rules	
Indicator and confidence factor	**Rules**
CHL, CF = 1	IF CHL is H THEN PsW is H IF CHL is M THEN PsW is M
SU, CF = 1	IF SU is H THEN PsW is H IF SU is M THEN PsW is M
HE, CF = 1	IF HE is H THEN PsWI is H IF HE is M THEN PsWIis M
PT, CF = 1	IF PT is H THEN PsW is H IF PT is M THEN PsW is M
Low-rule, CF = 1	IF CHL is L AND SU is L AND HE is L…AND PT is L THEN PsW is L
VN, CF = 0.9	IF VN is H THEN PsW is H IF VN is M THEN PsW is M
SC, CF = 0.9	IF SC is H THEN PsWIis H IF SC is M THEN PsW is M
OC, CF = 0.9	IF OC is H THEN PsW is H IF OC is M THEN PsW is M
Low-rule, CF = 0.9	IF VN is L AND SC is L AND OC is L…THEN PsW is L
AP, CF = 0.8	IF AP is H THEN PsW is H IF AP is M THEN PsW is M
PP, CF = 0.8	IF PP is H THEN PsW is H IF PP is M THEN PsW is M
AF, CF = 0.8	IF AF is H THEN PsW is H IF AF is M THEN PsW is M
SLB, CF = 0.8	IF SLB is H THEN PsW is H IF SLB is M THEN PsW is M
TH, CF = 0.8	IF TH is H THEN PsW is H IF TH is M THEN PsW is M
Low-rule, CF = 0.8	IF AP is L AND PP is L AND AF is L…AND SLB is L AND TH is L THEN PsW is L
ST, CF = 0.6	IF ST is H THEN PsW is H IF ST is M THEN PsW is M
PCR, CF = 0.6	IF PCR is H THEN PsW is H IF PCR is M THEN PsW is M
SP, CF = 0.6	IF SP is H THEN PsW is H IF SP is M THEN PsW is M
B, CF = 0.6	IF B is H THEN PsW is H IF B is M THEN PsW is M
LS, CF = 0.6	IF LS is H THEN PsW is H IF LS is M THEN PsW is M
Low-rule, CF = 0.6	IF ST is L AND PRC is L AND SP is L…AND B is L AND LS is L THEN PsW is L
PCC, CF = 0.5	IF PCC is H THEN PsW is H IF PCC is M THEN PsW is M IF PCC is L THEN PsW is L

The rules define the knowledge base required for automatic inference of the past water potential (PsW). The structure of and the rationale for building the past-water knowledge base is conceptual similar to the other first-layer knowledge base.

5.1.3. Fuzzy system #3: present energy assessment

The third fuzzy system is designed to evaluate the potential for present energy (PrE) via thermal, spectral, atmospheric, and seismic indicators that have a high impact on habitability. The indicators are shown in Table 5. From a life-searching point of view, the fuzzy system must indicate the level of current energy that is fed into the system and that may support life. The tier-scalable exploration architecture should look for locales where thermal anomalies are present due to the internal heat release of the planet, both from manifesting in the ground/subsurface and in the atmosphere. The ground heat anomaly (GHA) and atmospheric heat anomaly (AHA) are defined as the difference between the mean ground and atmospheric temperature of the locale and possible localized thermal spikes. The spectral thermal profile must be processed to filter the thermal signature coming from other possible energy sources, i.e., electromagnetic and radioactive. Thermal inertia and albedo are important parameters indicating the ability of the locale to retain energy. Volatile release might be associated with internal heat release, while seismic events may also record internal activity (e.g., magmatic-driven tectonic activity). The rules are shown in Table 6 and follow the same pattern shown in the previous cases, i.e., the higher the indicator value, the higher the potential for energy to be fed into the locale. The AND logical connector is used for the rules defining the condition that when every indicator is low, the energy present in the system is low.

5.1.4. *Fuzzy system #4: past energy assessment*

The fourth fuzzy system is designed to indicate the potential for energy flowing in the past. The indicators are shown in Table 7, and placed into the ‘‘past energy’’ category based on stratigraphic, paleotectonic, and geomorphologic information. Past energy might have been fed into the region through endogenic-driven injection of magma, Marsquakes, and/or water flow (including hydrothermal activity). The corresponding rules are shown in Table 8. The rules follow the same pattern defined for the previous fuzzy systems based on indicators value (e.g., the higher the indicator value, the greater the potential that energy was flowing into the locale in the past). The indicators are accompanied by confidence factors that weight their relative importance. The AND connector is used in the ‘‘low’’ rule, consistently following the scheme outlined for the other systems.

Table 5
Present energy indicators

Present energy		
Category	**Indicators**	**Confidence factor**
Thermal	Ground Heat Anomaly (temperature spike) GHA	1
Thermal/atmospheric	Atmospheric heat anomaly (temperature spike) AHA	1
Thermal	Thermal inertia (TI)	0.8
Thermal/spectral	Albedo (AL)	0.8
Elemental/Atmospheric	Volatiles (VL)	1
Seismic	Richter number (RN)	1

Energy related indicators are categorized as thermal, spectral elemental and seismic. The selected CF values are not absolute and in the future they can be modified to reflect new acquired knowledge and understanding of present energy mechanisms on Mars.

Table 6
Fuzzy rules for fuzzy system #3 (first layer)

Present energy fuzzy system: rules	
Indicator and confidence factor	**Rules**
GHA, CF = 1	IF GHA is H THEN PrE is H IF GHA is M THEN PrE is M
AHA, CF = 1	IF AHA is H THEN PrE is H IF AHA is M THEN PrE is M
VL, CF = 1	IF VL is H THEN PrE is H IF VL is M THEN PrE is M
RN, CF = 1	IF RN is H THEN PrE is H IF RN is M THEN PrE is M
Low-rule, CF = 1	IF GHA is L AND AHA is L AND VL is L…AND RN is L THEN PrE is L
TI, CF = 0.8	IF TI is H THEN PrE is H IF TI is M THEN PrE is M
AL, CF = 0.8	IF AL is H THEN PrE is H IF AL is M THEN PrE is M
Low-rule, CF = 0.8	IF TI is L AND AL is L THEN PrE is L

The rules define the knowledge base required for automatic inference of the present energy potential (PrE).

Table 7
Past energy indicators

Past energy		
Category	**Indicators**	**Confidence factor**
Stratigraphic	Number of rock types (RT)	0.7
Stratigraphic	Rock Sorting Index (RSI)	0.7
Paleotectonic	Number of Faults (NF)	1
Paleotectonic	Number of Joints (NJ)	0.7
Paleotectonic	Number of intersection between faults (NIF)	1
Paleotectonic/geomorphology	Number of channels connected to faults (NCF)	1
Paleotectonic/geomorphology	Basins (B)	0.7
Paleotectonic/geomorphology	Number of different lava flow in contact (NLC)	1
Paleotectonic/geomorphology	Lava/basaltic material (LBM)	1

Such indicators are categorized as stratigraphic, paleotectonic and geomorphic. Each CF value has been established using our team’s expertise in understanding the impact of the selected indicators on the past energy potential.

5.2. *Second fuzzy layer: water and energy assessment for life-containing potential*

The second fuzzy layer is comprised of one fuzzy system. It accepts four inputs describing, respectively, the potential for past/present water and energy (i.e., the outputs of the above-discussed fuzzy systems forming the first layer), and outputs the PH. Its knowledge-base has been constructed following the rationale outlined in Section 4.1 where water and energy contributions to possible extinct and extant life have been highlighted. Table 9 shows the full set of rules. The rules have been organized by order of importance, which is generally defined by a confidence factor that weights the importance of the rule relative to the others. The confidence factor is selected to have one out of five possible values (e.g., first order: CF = 1, second order: CF = 0.8, etc., see Table 9). There are 13 possible rules which form the backbone of the second fuzzy-layer. Rules number 1 and 2 are of first order of importance. They state that if all the values for past/present water/energy are high (low), the PH is very high (very low). To second order, if the locale under observation exhibits high (low) value of only present water and energy at the same time, the PH is high (low), but the rule is weighted with a lower confidence factor. Decreasing the order of importance further, there are situations where given high (low) potential of past water, or alternatively high (low) potential of past energy, the PH is still high, but the rule is weighted with CF = 0.2, which indicates that the importance of the rule, in our framework, is the lowest possible. The medium condition for the parameters is expressed in rule number 5, where all water and energy indicators are medium. In this case, the PH is medium. The rule is assumed to be of second-order importance.

Importantly, the constructed second-layer knowledge base is directly connected to the experience acquired by our team regarding understanding the connection between life and water/energy indicators. The rules might be modified for various planetary scenarios where the expertise acquired by planetary geologists, astrobiologists, and chemists may require a different set of rules that work better for the particular planetary body under investiga-

Table 8
Fuzzy rules for fuzzy system #4 (first layer)

Past energy fuzzy system: rules	
Indicator and confidence factor	Rules
NF, CF = 1	IF NF is H THEN PsE is H IF NF is M THEN PsE is M
NIF, CF = 1	IF NIF is H THEN PsE is H IF NIF is M THEN PsE is M
NCF, CF = 1	IF NCF is H THEN PsE is H IF NCF is M THEN PsE is M
NLC CF = 1	IF NLC is H THEN PsE is H IF NLC is M THEN PsE is M
LBM, CF = 1	IF LBM is H THEN PsE is H IF LBM is M THEN PsE is M
Low-rule, CF = 1	IF NF is L AND NIF is L AND NCF is L…AND NLC is L AND LBM is L THEN PsE is L
RT, CF = 0.7	IF RT is H THEN PsE is H IF RT is M THEN PsE is M
RSI, CF = 0.7	IF RSI is H THEN PsE is H IF RSI is M THEN PsE is M
NJ, CF = 0.7	IF NJ is H THEN PsE is H IF NJ is M THEN PsE is M
B, CF = 0.7	IF B is H THEN PsE is H IF B is M THEN PsE is M
Low-rule, CF = 0.7	IF RT is L AND RSI is L AND NJ is L…AND B is L THEN PsE is L

The rules define the knowledge base required for automatic inference of the past energy potential (PsE).

Table 9
Second-layer fuzzy knowledge base

Second-layer fuzzy knowledge-base			
Order	Ruler no.	Confidence factor	Rule semantic
First	1	CF = 1	IF PrW is H AND PsW is H AND PrE is H AND PsE is H THEN PH is VH
First	2	CF = 1	IF PrW is L AND PsW is L AND PrE is L AND PsE is L THEN PH is VL
Second	3	CF = 0.8	IF PrW is H AND PrE is H THEN PH is H
Second	4	CF = 0.8	IF PrW is L AND PrE is L THEN PH is L
Second	5	CF = 0.8	IF PrW is M AND PsW is M AND PrE is M AND PsE is M THEN PH is M
Third	6	CF = 0.6	IF PrW is H AND PsW is H THEN PH is H
Third	7	CF = 0.6	IF PrE is H AND PsE is H THEN PH is H
Third	8	CF = 0.6	IF PrW is L AND PsW is L THEN PH is L
Third	9	CF = 0.6	IF PsE is L AND PsL is L THEN PH is L
Fourth	10	CF = 0.4	IF PrW is H OR PrE is H THEN PH is H
Fourth	11	CF = 0.4	IF PrW is L OR PrE is L THEN PH is L
Fifth	12	CF = 0.2	IF PsW is H OR PsE is H THEN PH is H
Fifth	13	CF = 0.2	IF PsW is L OR PsE is L THEN PH is L

The table shows the structure of the fuzzy rules selected to form the backbone of the second-layer fuzzy system Mamdani. The rules are organized in five groups each with decreasing CF factor defining the relative importance of the rule. Each group is coupled with an order of importance depending on the CF value (first order the highest with CF = 1, 5th order the lowest with CF = 0.2). The rules can be read in a very intuitive way. For example, rule number one, "*IF PrW is H AND PsW is H AND PrE is H AND PsE is H THEN PH is VH (CF = 1)*", states that if the content of present water, past water, present energy and past energy is shown to be high (as evaluated by the first fuzzy-layer) then the potential for habitability exhibited by the locale under observation is very high with the highest level of confidence. The order of importance of the rules can be understood by observing that for example regions with high past water and present water content are more important than areas with only high water or energy content.

tion. Similarly, the life indicators may have to change in number and variety, and may have to be custom-tailored to provide the most appropriate information on habitability potential for the locale under investigation. The fuzzy logic framework is general enough to incorporate new expertise into the system without changing its underlying structure.

6. Testing the system on planetary scenarios: two examples

In this Section, we construct and simulate a fuzzy logic expert system based on a simplified version of the above-mentioned knowledge-bases (1) to analyze the behavior of the expert system on reconnaissance-based, hypothesized planetary scenarios, and (2) to demonstrate the potential of the overall approach.

The projected scenario is the following. It is assumed that a tier-scalable reconnaissance mission architecture has been deployed on Mars (Fig. 1): the architecture includes potentially three tiers, i.e., spaceborne, airborne and ground-based, all equipped with multiple agents/sensors to collect sensor data at multiple scales, resolutions, and vantage points. The goal of the mission is to look for signs of life over a large region of Mars. For this simulation, we assume that only nine indicators are available to assess the life potential exhibited by the hypothesized locale under investigation. More specifically, we assume that the gamma ray spectrometer (GRS)-based hydrogen abundance indicates weight percentage of water (Boynton et al., 2002, 2004) in this region. The GRS experience has already shown how gamma ray and neutron spectrometers can be used to map the hydrogen content of an area. Although the knowledge-bases constructed in the previous sections contain a variety of indicators for present water assessment (see Table 1), we assume that the system is able to assess only the relative abundance of hydrogen, which has been interpreted to be related to water in various forms (ice, brine, liquid, moisture, and/or hydrated minerals). Moreover, it is assumed that the system is able to assess abundance of sapping channels, valley networks, and sulfates (in weight percentages) as indicators for past water; heat energy release (thermal spikes/anomalies) and Richter number (i.e. it quantifies the amount of seismic energy released during an earthquake) as indicators for present energy, and number of local faults, volcanoes, and lava flows as indicators for past energy.

The system performs reconnaissance during hypothetical deployments to two martian regions by collecting data en-route (orbiting, hovering, roving, and homing in on) while determining the absolute value of the nine indicators of past/present water and energy (the regions are inferred, though they are not considered unrealistic based on existing geologic, paleohydrologic, geomorphic, geophysical, spectral, and elemental information—e.g., the NSVs regions is hypothesized to approximate region 1, though we do not know whether there is elevated heat flow and groundwater lurking near the surface). Table 10 shows the values of the indicators across the observed regions. Data collected during the hypothetical martian deployments portray a highly interesting region 1: the elemental information is fairly high, with medium-high water content and very high sulfate content. The low number of valley networks is compensated by a high number of sapping channels. Moreover, the area exhibits internal heat release (detected thermal anomalies not attributed to atmospheric and/or electromagnetic radiation) and a high number of faults, lava flows, and volcanoes. During the time of observation, it is assumed that intense seismic activity was recorded. Region 2 is less interesting from a life-potential point of view based on elemental, stratigraphic, paleotectonic, and geomorphologic indicator information: the hypothetical region exhibits low hydrogen abundance interpreted to be low weight percentage of water (based on Boynton et al., 2002, 2004), medium sulfate abundance, low number of faults, minor seismic activity, and medium heat release from the ground. For each of the considered hypothetical regions, the indicators are categorized and fed into the first fuzzy layer to assess the past/present water/energy potential.

6.1. First layer fuzzy system simulation

The four fuzzy systems forming the first fuzzy layer have been designed and implemented using the MATLAB fuzzy logic toolbox, which allowed expeditious modeling/assessing of the fuzzy-design parameters. Fig. 4 shows the conceptual scheme of one of the four first-layer fuzzy systems (i.e., the system capable of assessing past water from the value of the corresponding indicators). Here, the ‘‘past water’’ system is used as an example to show how the parameters have been selected and how the system operates. Initially, the indicators have a crisp value, and they must be fuzzified by a defined membership function. Fig. 5 shows the selected membership functions for the ‘‘past water’’ case. The membership functions, which map

Table 10
Life indicators for two hypothesized martian regions

Life indicators for region #1 and #2: first layer input			
Life indicator	**Category**	**Region #1**	**Region #2**
Hydrogen content	Present water	6% (weight)	2% (weight)
Sapping channels	Past water	3 (number)	1
Valley networks	Past water	10 (number)	1
Sulfates content	Past water	19% (weight)	10% (weight)
Heat release	Present energy	250 (differential)	100 (differential)
Richter number	Present energy	6 (Richter scale)	0.5 (Richter scale)
Local faults	Past energy	7 (number)	2 (number)
Local volcanoes	Past energy	8 (number)	2 (number)
Local lava flows	Past energy	6 (number)	1 (number)

It is assumed that an autonomous tier-scalable system performs reconnaissance over two distinct regions and collects data to derive nine (9) life indicators. The two areas are markedly different with the first region being the place with the richest elemental, geomorphologic, paleotectonic, and thermal features.

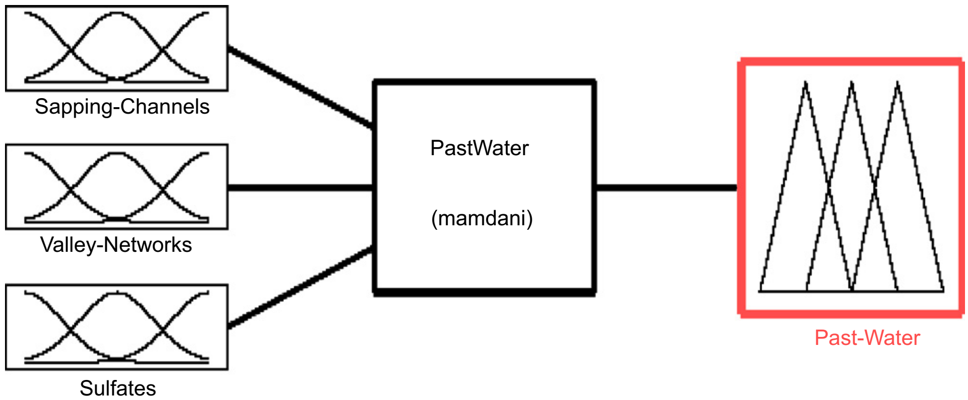

Fig. 4. Conceptual scheme for fuzzy system #2 on the first layer. The system is designed to ingest past water indicators and output the past water potential. In the current simulation, sapping channels, valley networks and sulfates content have been identified to be past water indicators.

the crisp values of the "past water" indicators into truth values, ranging between 0 and 1, are fundamental design parameters of the system. The membership functions quantify our concept of "HIGH", "MEDIUM", and "LOW". For example, a locale containing sulfates in the 0–10% range is characterized as "LOW", 10–16% as "MEDIUM", and values higher than 16% as "HIGH", quantified using a generalized bell curve. The same technique was applied to sapping channels and valley networks. Note that the latter parameter is mapped by the number of networks in terms of order of magnitude ($0 =$ no network, $1 = 10$ networks, $2 = 100$ networks, $3 = 1000$ networks, etc.), again emphasizing that such parameters are open to revision and flexible enough to accommodate changes (one planetary surface may merit a different parameter than another planetary surface). Fig. 5 also shows the membership functions quantifying HIGH, MEDIUM, and LOW for the output for the "past water" fuzzy system. The remaining three fuzzy systems, constituting the backbone of the first layer, have similar membership functions defined for both inputs and outputs, which are appropriately scaled to define HIGH, MEDIUM, and LOW for the corresponding range of the input parameters.

After fuzzification, the inputs are processed by the IF-THEN rules associated with the corresponding fuzzy system. The knowledge-base, established in Sections 5.1.1–5.1.4, has been reduced to accommodate the nine available indicators. Table 11 summarizes the rules for the "past water" fuzzy system included in the first layer. For any of the four first-layer fuzzy systems, the rules are fired concurrently to map out and characterize the potential for past/present water and energy. After fuzzification, if the antecedent of any rule is composed of several parts connected by logical operators (e.g., AND, OR), the fuzzy logical operator is applied to combine the antecedent and provide the support for the rule. Conventional MIN and MAX constructs (see Section 3.4) have been used for AND/OR operators, respectively. Next, the implication method is applied to every rule to appropriately shape the output functions. The MIN implication method was used whenever the support of the rule is employed to cut the output membership function (see Section 3.4). All rules are finally aggregated via summation of all possible reshaped output functions, and the system is defuzzified using the centroid method (i.e., the fuzzy output is defuzzified by computing the centroid of the area under the output membership function).

Figs. 6 and 7 show the overall implication process that yielded the fuzzy-aggregated output and the defuzzified output (crisp number) for the "past water" system in regions 1 and 2, respectively. Interestingly, the past-water characterization, autonomously evaluated by the fuzzy expert system, is different for both regions, since region 1 exhibits high past-water content (80.1/100) whereas region 2 shows a low past-water content (34.8/100). The outputs of the four fuzzy systems (first fuzzy-layer) are reported in Table 12.

6.2. Second layer fuzzy system simulation

The fuzzy system's first layer was designed to provide an assessment of the potential of energy and water both currently present and once existing within the regions. While this information might be used independently by the users via a direct interface with the system, a second layer has been implemented to perform autonomous assessment of the expressed PH in the regions under investigation. Using the knowledge-base established in Section 5.2, and employing similar methods and software outlined in Section 6.1, the second layer fuzzy system was designed and connected to the first layer for rapid streaming of information/assessment.

Fig. 8 shows the second layer schematic. Each of the four inputs is fuzzified using a set of membership functions quantifying the relation between input crisp values and corresponding degree of truth for linguistic terms such as HIGH, MEDIUM and LOW. Fig. 9 shows the employed input membership functions. Fig. 10 also shows the membership functions that have been used to quantify the output. VERY HIGH and VERY LOW statements were also included in the characterization process. The

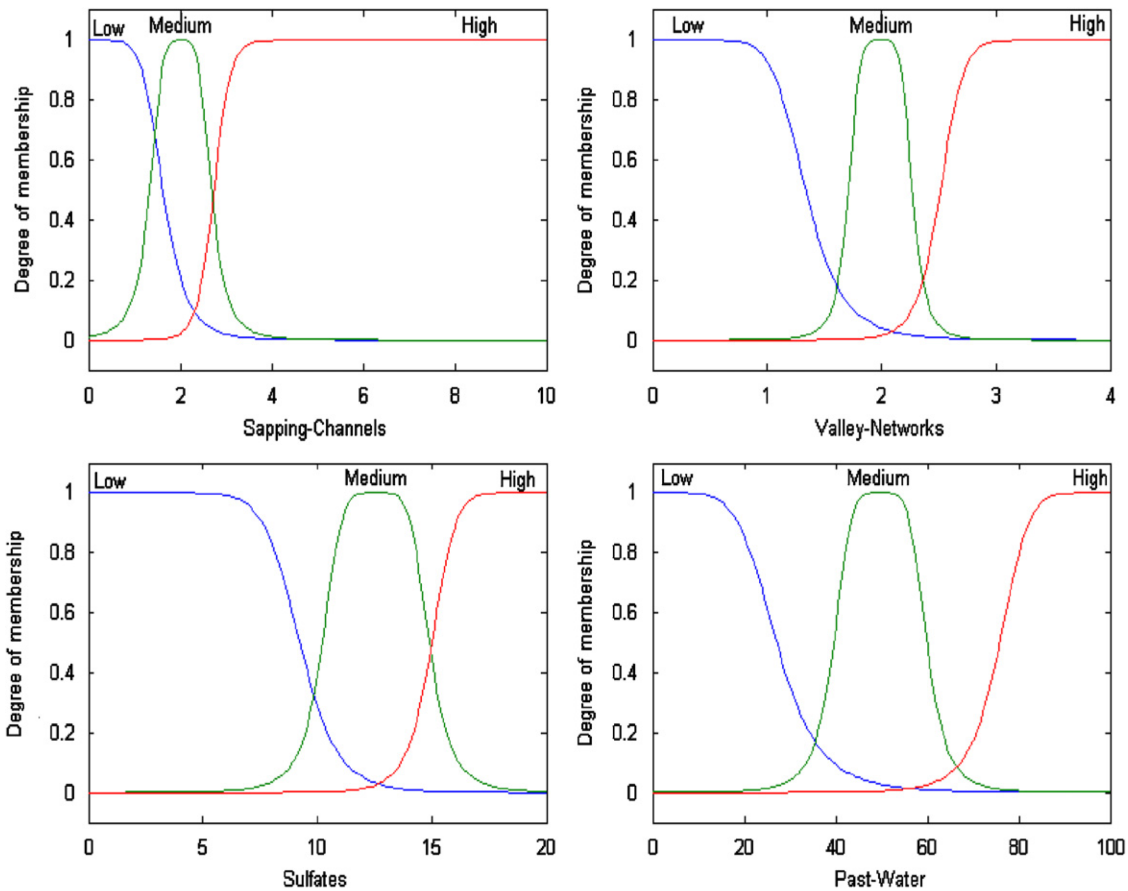

Fig. 5. Membership functions for fuzzy system #2 (Past water, first-layer). The four panels show the selected membership functions for three inputs (sapping channels, valley networks and sulfates) and one output (past water potential). For each of the input-output parameters, the "Low", "Medium" and "High" functions have been established using a generalized bell curve. While the shapes are defined by selecting the function-type, additional considerations and team's experience in working with the input indicators were required to select a suitable parametric form.

Table 11
Fuzzy rules summary for the fuzzy system #2 (past water, first layer) employed in the simulation

Sapping channel	Valley networks	Sulfates	Past water	Connector	CF	Rule no.
		H	H	None	1	1
		M	M	None	1	2
H			H	None	0.9	3
M			M	None	0.9	4
	H		H	None	0.9	5
	M		M	None	0.9	6
L	L	L	L	AND	1	7

The extended past-water fuzzy knowledge base (Table 4) has been modified and adapted to operate with the three available inputs (i.e. sapping channels, valley networks and sulfates). Seven (7) rules are required to operate the system. The rules are presented in a convenient and synthetic form. For example the first row show two H (under sulfates and past water), no connector, and confidence factor equal to 1. The rule should be read as follow: "IF Sulfates content is High THEN Past Water Potential is High (with the highest confidence factor of 1)". Because of the reduced number of input parameters we decided to implement one cumulative Low-rule (rule #7) which states that if all the past water indicators are low then past water potential is low.

generalized bell curve was employed for any of the possible functions. After fuzzification, the system follows a procedure analogous to the one described for the "past water" case. Table 13 reports a symbolic version of the rules employed by the system already defined in Table 9. The rules are implemented in terms of IF-THEN statements and inference is performed using the MIN implication method (see Section 3.4). Defuzzification is accomplished using the centroid method (see Section 6.1). The simulation results are reported in Table 14. Figs. 10 and 11 show how the system operates to assess the potential for life habitability. Fuzzification, rule evaluation, implication,

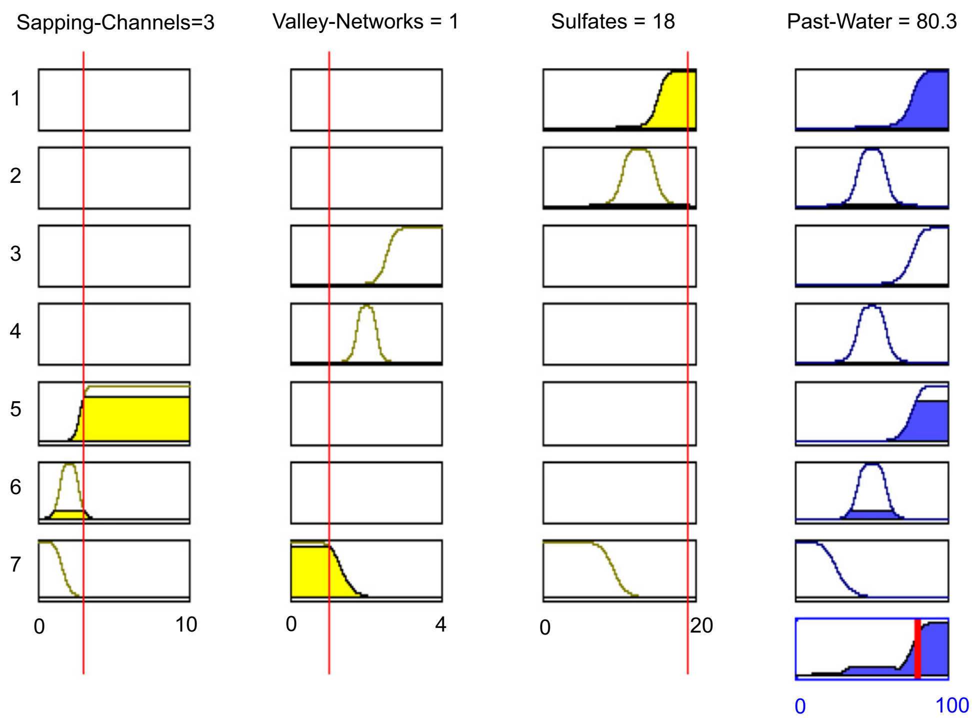

Fig. 6. Fuzzy rules interpretation process for past-water fuzzy system (first-layer) as applied to region #1. The figure illustrates how the overall rule interpretation/implication operates. Each row represents one rule, according to the scheme presented in Table 11. The values for the input parameters are reported at the top of each column. First, the "crisp" input values are processed by the rules using the appropriate membership function (i.e. every fuzzy rule is resolved in the antecedent where the input values are fuzzified into a number between 0 and 1, see yellow regions in the panels belonging to the first three columns). The latter value is generally called "degree of support for the rule". Subsequently, fuzzy operators (AND/OR) are applied if the antecedent is composed of multiple parts (see rule #7). In the next step, implication is applied by taking the degree of support for the rule and using it to shape the past water membership function (blue regions under the past water columns). Finally, the shaped membership functions for the output are aggregated (see bottom-right blue panel), the area computed and its centroid defined to be the output crisp value (defuzzyfication). Past water potential for region #1 is evaluated to be 80.1/100.

and aggregation are reported to show the step-by-step procedure as explained above.

6.3. Discussion of the simulation results

The simulations were aimed at designing two interconnected fuzzy layers to mimic the operations of the proposed fuzzy logic-based expert system for tier-scalable reconnaissance. The overall system was tested on hypothetical scenarios based on the assumption that real-time streaming data were converted into the absolute value of a limited number of indicators available to the system for proper habitability assessment. It is clear from the reported data (i.e., the values of the indicators for the observed regions) that region 1 is a potential candidate locale for further exploration/deployment. The system confirms the human prediction. In fact, the system exhibits high levels of geomorphologic, thermal, elemental, spectral, and paleotectonic information that collectively points toward a high life potential. Based on the fuzzy assessment, the intelligent system will transmit the results to the central navigation and control system of the tier-scalable reconnaissance mission architecture, which will define a new plan of action and send the appropriate commands for further deployment. For example, based on the fuzzy expert system results, further ground deployment of more agents may be ordered to collect higher resolution data that in turn may yield additional proof for life existence. In the region 2 scenario, the system assesses a low PH, and therefore, the fuzzy expert will inform the central navigation and control system not to consider the area as a candidate for further investigation. In fact, the life indicators of region 2 do not collectively describe a locale of elevated life potential. Water and energy indicators are generally low and the fuzzy logic expert system corroborates the same conclusions as provided by the human expert.

Importantly, the design and simulation of the two-layer fuzzy expert system have been accomplished through proof-of-concept. Design parameters have been chosen to show the basic ideas underlying the approach required to successfully design and implement an intelligent system suitable for the integration into a tier-scalable reconnaissance mission architecture. For example, particular membership functions, implication methods, and defuzzifications were selected to complete the design, while realizing that other alternatives are available (e.g., Gaussian membership functions, singleton method for defuzzification, etc., see also Ross, 2004). These parameters can be

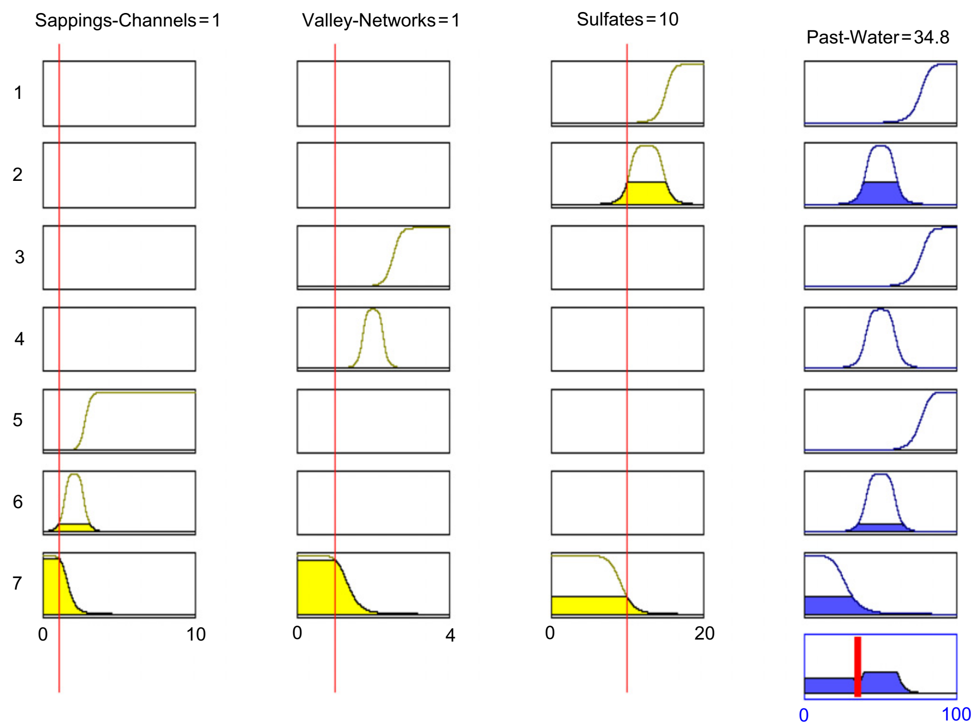

Fig. 7. Fuzzy rules interpretation process for past-water fuzzy system (first-layer) as applied to region #2. The overall rule interpretation and implication methodology is applied to the second region of interest to determine its past water potential. The fuzzy system ingests the three reported input values and output 34.8/100 as assessment of the past water potential.

Table 12
Fuzzy first-layer output

First-layer fuzzy systems: outputs		
First-layer fuzzy systems	Output region #1	Output region #2
Present water potential (PrW)	57.7/100	15.5/100
Past water potential (PsW)	80.3/100	34.8/100
Present energy potential (PrE)	77.9/100	51.1/100
Past energy potential (PsE)	86.4/100	40.9/100

The observed life indicators are categorized as past/present water and energy indicators and fed to the four independent fuzzy systems for past/present water and energy potential assessment. The table reports the results for the two hypothesized regions.

generally changed to tune the system and improve performance. Indeed, a full-scale fuzzy expert system design (including all "known" (to date) life-containing indicators) requires trade studies on the parameters and a multiple-iteration approach to converge to the optimal system design. Nevertheless, the performed design/simulation lays the foundation for and outlines the basic structure of an autonomous, intelligent expert system that may be integrated into tier-scalable reconnaissance mission architectures.

7. Conclusions, implications, and future efforts

If there is any chance of finding life beyond Earth, as well as testing overarching theories concerning the evolution of planetary bodies (e.g., GEOMARS proposed by Baker et al., 2007, Superplume book), a paradigm shift in planetary exploration is required. The novel tier-scalable reconnaissance mission paradigm of Fink et al. (2005a–c, 2006a, b, 2007) will fundamentally change the way current missions are conducted by allowing less constrained, science-driven planetary exploration via deployment of a multi-tier system of sensor platforms (yielding spaceborne, airborne, surface, and subsurface perspectives), approximating the approach of a geologist/biologist/chemist. "Autonomy" is a key factor in achieving the desired success in future planetary reconnaissance (i.e., detecting, characterizing, and homing in on features of special interest, including transient events). Here, a fuzzy expert system is proposed and described to autonomously identify locales with the greatest PH. This system may serve as the part of a multi-tier architecture that elaborates newly acquired information, compiles it with existing information, and performs comparative analysis of the compiled spatial and temporal information while in-transit.

The proposed system has been conceived specifically with the goal of mimicking the approach of a planetary geologist, while coupling the expertise of a terrestrial biologist or chemist. The system assesses and evaluates the life-containing potential of a locale through utilization of all possible clues coming from collecting multiple layers of information, which may include elemental, spectral, atmospheric, geophysical, hydrologic, geomorphologic,

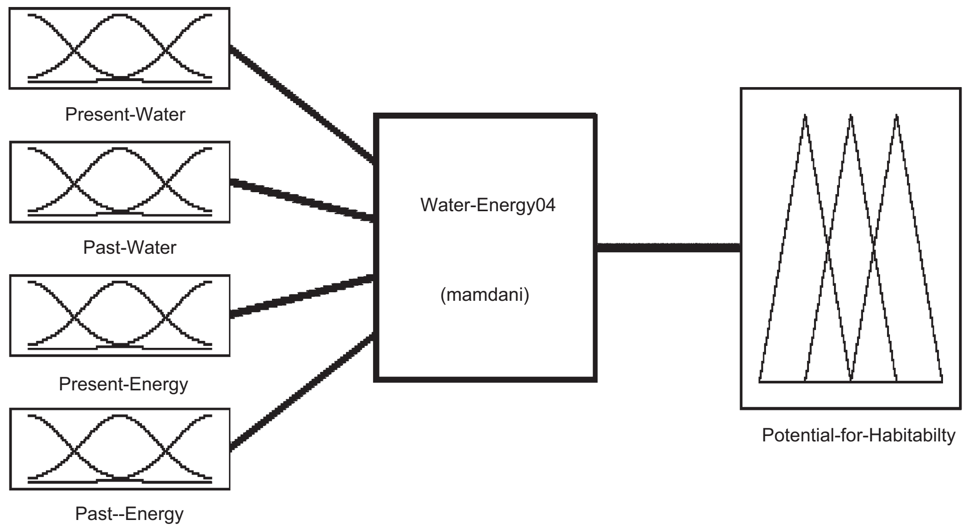

Fig. 8. Conceptual scheme for the second-layer fuzzy system. The system accepts four inputs (present water, past water, present energy and past energy potential) and output the potential for habitability (PH).

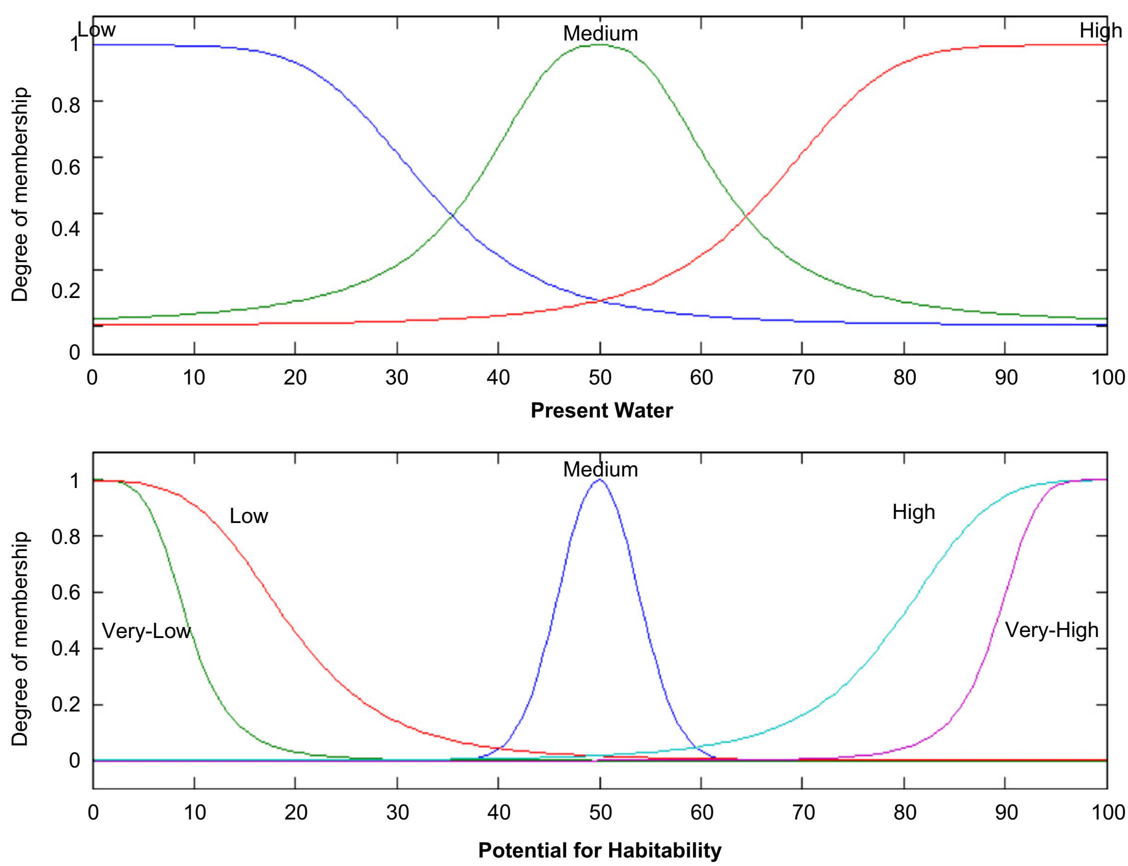

Fig. 9. Membership functions (MFs) employed for the second-layer fuzzy system. The top panel shows the MFs used for one of the input parameters (PrW, range between 0 and 100). Low, medium and high have been implemented using the generalized bell curve. The other input potentials have been associated with membership functions with identical structure. The bottom panel illustrates the MFs associated with the output parameter (PH). In addition to the standard "High", "Medium" and "Low", two extra MFs have been considered to introduce the "Very High" and "Very Low" statements.

stratigraphic, topographic, and paleotectonic information. The compiled information must be interpreted to characterize life potential.

In order to effectively design an intelligent system that can autonomously execute the desired task to look for life, the knowledge-base that condenses the multidisciplinary

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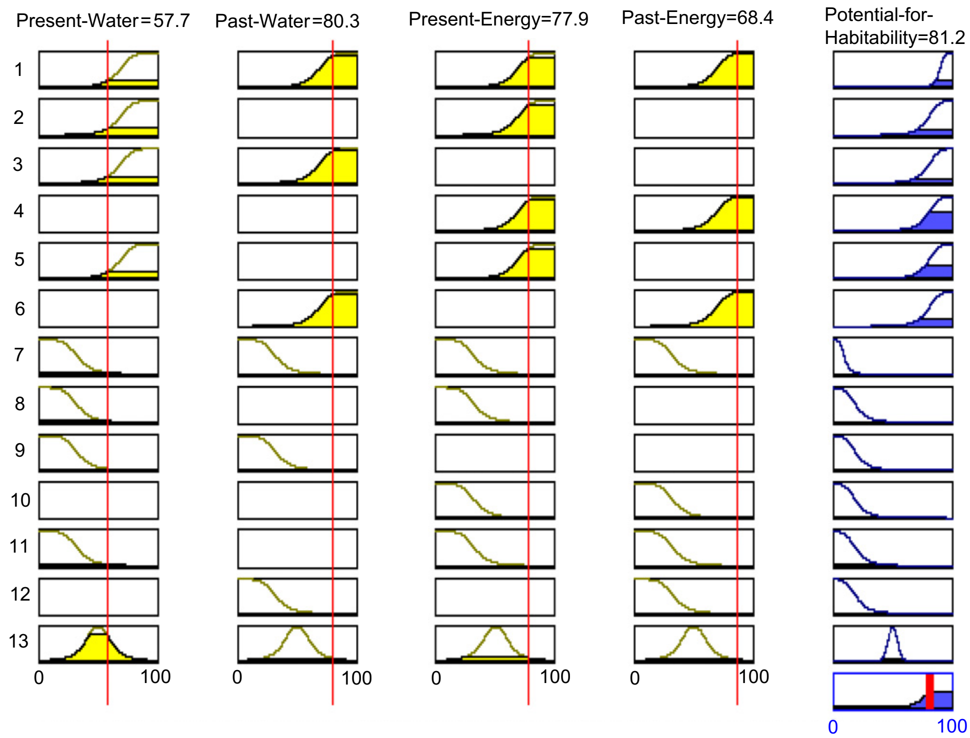

Fig. 10. Fuzzy rules interpretation process for the second-layer fuzzy system as applied to region #1. The figure illustrates how the overall rules interpretation/implication operates. The fuzzy knowledge-base is comprised of 13 rules, which are operated concurrently. The fuzzy rule interpretation and implication method has been already explained (see Fig. 6). The second-layer system proceeds in similar fashion using the same mechanism to evaluate PLH.

Table 13
Fuzzy rules summary for the second-layer fuzzy system employed in the simulation

PrW	PsW	PrE	PsE	PH	Connect	CF	Rule no.
H	H	H	H	VH	AND	1	1
L	L	L	L	VL	AND	1	2
H		H		H	AND	0.8	3
L		L		L	AND	0.8	4
M	M	M	M	M	AND	0.8	5
H	H			H	AND	0.6	6
		H	H	H	AND	0.6	7
L	L			L	AND	0.6	8
		L	L	L	AND	0.6	9
H		H		H	OR	0.4	10
L		L			OR	0.4	11
	H		H	H	OR	0.2	12
	L		L	L	OR	0.2	13

The extended version the fuzzy knowledge base is reported in Table 9.

expertise must be defined and constructed. The fuzzy logic framework provides a way to translate expertise (including both practical and theoretical knowledge) into simple rules that can be understood by a digital computer. The main goal of this paper was to lay the foundation for a fuzzy knowledge-base that can be constructed and implemented in a digital form to autonomously evaluate the PH of the locale under investigation through tier-scalable reconnaissance. Hypothetical deployments to two different regions of Mars were examples for demonstrating proof-of-concept and for showing how fuzzy-based rules can be implemented to characterize life-containing potential. For hypothesized martian scenarios the system autonomously reached the same conclusions as a field expert, showing self-consistency.

It is important to stress that the presented approach is an essential part of the basic foundation currently built by our team of what we think can be the most effective way to perform planetary exploration in the future. Fuzzy logic, applied to tier-scalable reconnaissance mission architectures, can effectively provide the intelligence that is required for autonomous less constrained and science-driven planetary reconnaissance. The fuzzy logic expert system is shown to be flexible enough to accommodate any finite number of indicators and rules. This foundational work on autonomy for tier-scalable reconnaissance missions could initiate an open forum (likened to a field camp for geologists) for the entire planetary science community as well as for any other scientific community (e.g., Math, Engineering, Biology, Chemistry, Physics, Geology, Hydrology) interested in space exploration, to discuss the role of the indicators, the number of indicators, the most appropriate rules that should be used to search for life, or any other objective on planetary bodies. As shown in the

Table 14
Second-layer fuzzy system simulation results

Fuzzy expert system potential for life habitability assessment				
	Input region #1	PH region #1	Input region #2	PH region #2
Present water	57.7/100	81.2/100	15.5/100	24.6/100
Past water	80.3/100		34.8/100	
Present energy	77.9/100		51.1/100	
Past energy	86.4/100		40.9/100	

The table shows the input values presented to the second-layer fuzzy system for region #1 and region #2 and the output of the system for both scenarios. The table shows that region #1 is the area with the highest potential for habitability and therefore a region worth of further deployment/investigation.

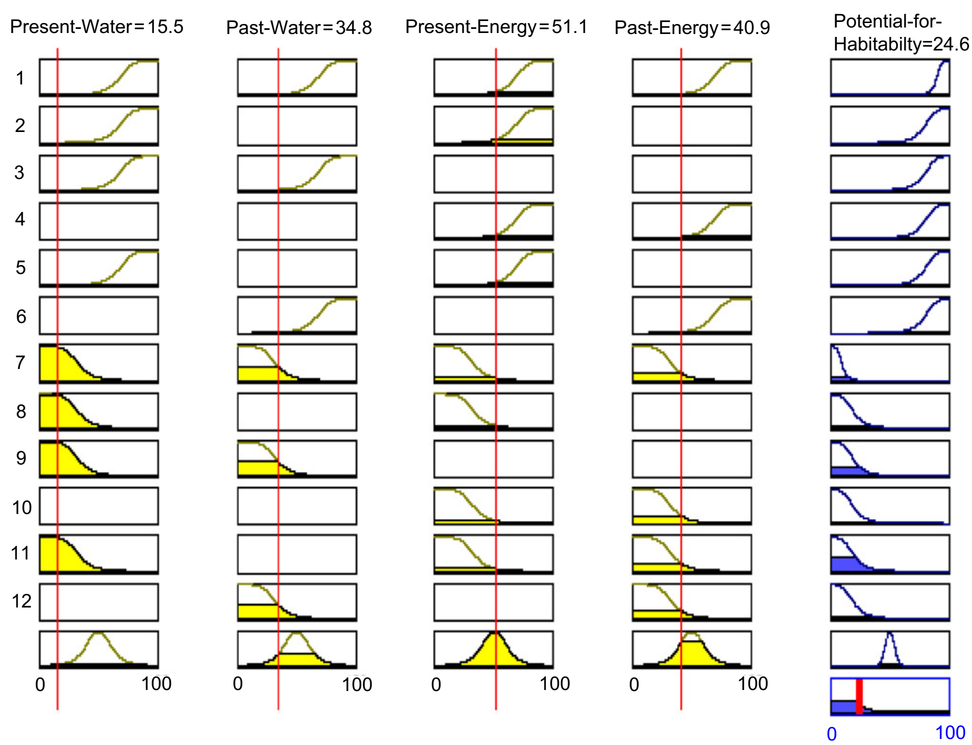

Fig. 11. Fuzzy rules interpretation process for the second-layer fuzzy system as applied to region #2. The figure illustrates how the overall rules interpretation/implication operates (see Fig. 6 for details about the rule interpretation and implication method).

above sections, the system is modular, i.e., is constructed using a sequence of interconnected fuzzy systems and therefore has the flexibility to add and delete elements depending on the goal to be achieved. Future challenges will therefore include the extension of the concept to multiple real-world planetary scenarios to confirm and test working hypotheses, to review and evaluate the rules and indicators to tailor-fit to various planetary bodies, as well as to implement the designed software in tier-scalable Earth-based deployed hardware to test the effectiveness of the system in selected environments on Earth. The latter will be a critical step to promote the transition of tier-scalable reconnaissance architectures from a concept to an operational system for autonomous planetary reconnaissance.

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