Assessment of herbaceous plant habitats in water-constrained environments: predicting indirect effects with fuzzy logic

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Abstract

Herbaceous plant production plays a key role in determining the function of rangeland ecosystems in the semi-arid and Mediterranean regions. Therefore, assessment of herbaceous plant habitats is important for understanding the ecosystem functioning in these regions and for applied purposes, such as range management and land evaluation. This paper presents a model to assess herbaceous plant habitats in a basaltic stony environment in a Mediterranean region. The model is based on geographic information systems (GIS), remote sensing and fuzzy logic, while four indirect variables, which represent major characteristics of herbaceous habitats, are modeled: rock cover fraction; wetness index (WI); soil depth; and slope orientation (aspect). A linear unmixing model was used to measure rock cover on a per pixel basis using a Landsat TM summer image. The wetness index and local aspect were determined from digital elevation data with 25 m × 25 m pixel resolution, while soil data were gathered in a field survey. The modeling approach adopted here is process-based and assumes that water availability plays a crucial role in determining herbaceous plant production in Mediterranean and semi-arid environments. The model rules are based on fuzzy logic and are written based on the hypothesized water requirements of the herbaceous vegetation. The results show that on a polygon basis there is positive agreement between the model proposed here and previous mapping of the herbaceous habitats carried out in the field using traditional methods. Intrapolgon tests show that the use of a continuous raster data model and fuzzy logic principles provide an added value to traditional mapping. Moreover, herbaceous biomass measurements at two time intervals—mid- and peak winter season—corresponded with the habitat assessment predictions achieved using a new scenario that is proposed in this research. This scenario suggests that rockiness increases herbaceous production on south-facing slopes, while in other slope aspects the rock cover has lower impact on herbaceous growth. Due to its simplicity, the model suggested here can be used by planners and managers, to adjust range activities over large areas. The process-based approach should allow adaptation of the model to other regions more effectively than models that were formulated on a purely empirical basis. The model could also be used to study the relationship between water availability and ecosystem productivity on a regional scale.

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Keywords: Fuzzy logic; GIS; Remote sensing; Habitat; Herbaceous production; Water availability

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Herbaceous plants cover approximately 25% of the global land area, occurring on all continents of the world except Antarctica (FAO, 1990). Herbage production is an important characteristic of savanna and grassland ecological systems as it supports, directly or indirectly, all consumer groups (Tueller, 1988). From the applied point of view, production of herbaceous vegetation is a key management variable for range managers and planners, while knowledge of habitat productivity can aid in land-use designation.

An assessment of habitat productivity can be achieved with actual field measurements of herbaceous biomass. Among the techniques developed for this purpose, there are two commonly used (Whittaker and Marks, 1975). The first—the ‘harvest’ technique—is based on harvesting plants from sample plots and determining their mass. The harvest technique has been implemented in different environments around the world and has proved accurate and reliable (e.g., Ungar et al., 1997). The second—the ‘gas exchange’ technique—is based on the correlation between the gas (especially CO₂) exchange in the atmosphere and the primary production of the ecosystems studied (Wohlfahrt et al., 2000). The main limitation of these two techniques is their resource requirements (time, manpower), which make them impractical for implementation over large areas.

As an alternative to field techniques, the rapidly developing remote sensing methodologies provide useful tools for estimating herbaceous vegetation production. Radar remote sensing models are used for this purpose (e.g., Svoray and Shoshany, 2003) and in cases where the Leaf Area Index (LAI) is less than 2, optical data can also be used, mainly based on the Normalized Difference Vegetation Index (NDVI) frequency analysis (Moreau et al., 2003). However, radar radiative transfer models are site specific in many cases and their application over large areas, on complex, hilly, high rock cover terrain, is particularly difficult. Optical data are limited to a description of the top layer of the vegetation strata because penetration depth is very small.

Although the difficulties involved in both field and remote sensing estimations of biomass over large complex areas might be solved in the future, there is still an inherent problem in their use for the assessment of potential production of herbaceous habitats. Empirical measurements can only represent the actual vegetative production at a given time, under dynamic rainfall and temperature conditions. Therefore, the extent to which observations at a given time could be representative of habitat quality is questionable. This limitation could be solved with a long series of measurements under various conditions, using statistical analysis to provide a temporal average production expected from a given habitat. However, another approach could be process-based modeling that predicts habitat conditions based on cause and effect relationships. Thus, a habitat could be assessed not on the basis of the biomass yielded in a given year but using models of the driving forces that determine production of the herbaceous vegetation in a study area. Austin (1980, 2002) has defined three types of ecological variables that determine vegetation distribution, abundance and quantities: (1) resources; (2) direct variables; and (3) indirect variables. Resources refer to matter and energy consumed by plants, i.e., nutrients, water and light. Direct variables refer to environmental variables that have physical importance but are not consumed (pH, EC, temperature), and indirect variables refer to variables that have no physiological relevance for the species performance (e.g., slope orientation and gradient, soil characteristics and parent material). Resources and direct variables are sometimes closely related to indirect variables or, in some cases, their effect is small and therefore could be replaced by more easily mapped indirect sources.

Geographic Information Systems (GIS) provide powerful tools for habitat prediction through the modeling of indirect sources (e.g., Store and Kangas, 2001; Franklin, 1998; and for a review see Franklin, 1995) and can replace more expensive empirical methods that are based on measurements of biophysical attributes of the vegetation. However, most of the current models statistically relate the spatial distribution pattern of the vegetation to its present environment (Guisan and Zimmerman, 2000). The variety of statistical techniques is growing including ordinal regressions (Dirnbock and Dullinger, 2004) and logistic regressions (Jelaska et al., 2003), generalized linear model (GLM) and regression trees (Rouget et al., 2001; Franklin, 1998); generalized additive models (GAM–Brown, 1994); Bayesian statistics (Borsuk et al., 2004; Skidmore, 1989); and environmental envelope (Farber and Kadmon, 2003; Busby, 1991).
addition, various classification techniques for mapping vegetation habitats and patterns have been used, such as the maximum likelihood decision rules employed for mapping caribou habitats with satellite data and digital elevation model (DEM) (Hansen et al., 2001) and back propagation neural networks such as applied by Foody (1996) for mapping vegetation patterns. More recent studies (Thuiller et al., 2003) provide a comparative research between GLM, GAM and classification tree analysis. The statistical techniques are very efficient for empirically-based modeling as they are usually based on training sets or prior empirical data/relationships; however they are usually static and probabilistic in nature and there is still a need to develop mechanistic models, without training sets, which will be based on cause and effect scenarios (Guisan and Zimmerman, 2000).

In this paper we propose and test a mechanistic model for the assessment of herbaceous vegetation habitat in a basaltic environment of relatively high rock cover and water constraints. The model is implemented using fuzzy representation, embedded in a GIS. Section 2 below describes the research assumptions and the model developed. Section 3 provides the data and the implementation of the model to the study area. Results are presented in section 4 from three different viewpoints: (1) we show that the input variables are independent; (2) we show the added value of the model upon a field survey; and (3) we show the relationship between direct measurements of herbaceous biomass and the predicted habitats. Finally, section 5 provides a summary and conclusion.

2. Modeling approach and scenarios

In the framework of this study, habitats are assessed based on their potential to produce herbaceous vegetation biomass. We assume that in Mediterranean, semi-arid and other water-constrained environments, water availability plays a crucial role in determining herbaceous vegetation productivity and, therefore, our model is formulated based on the hypothesized water requirements of herbaceous vegetation. This assumption is based on previous studies that have indicated water availability as a prime determinant of herbage biomass in the north of Israel (Henkin et al., 1998) and in other semi-arid environments around the world (e.g., Kumar et al., 2002). The assumption implies that in water-constrained environments the contribution of other resources (light, nutrients) and direct variables (soil chemistry) to the spatial variance of herbage production is relatively small and, therefore, can be added to the model as a secondary component or even neglected. Due to the complexities involved in the measurements and mapping of the above-mentioned resources and direct variables and due to their relatively small effect, they are disregarded within the scope of the current research.

Water availability is modeled here using four indirect variables: rock cover fraction; wetness index (WI); soil depth and slope aspect. Spatial variation in soil water content is strongly dependent on topographic conditions through surface and subsurface runoff convergence and dispersion (Moore et al., 1988). Studies (e.g., Chaplot and Walter, 2003) show that lower areas in the catchment are more moist due to the accumulated water reaching these areas through upper and lower runoff flows. Among the topographic variables that play a primary role in surface hydrology, the local slope and catchment area determine the hydraulic gradient and the potential water flux to a given area (Barling et al., 1994). The use of these two variables in conjunction as a wetness index to represent areas of dry and wet conditions was applied successfully by Beven and Kirkby (1979) and later by Burrough et al. (1992). The local aspect represents changes in solar radiation flux, which affects evapotranspiration rates. As a result, in the northern hemisphere, south-facing slopes are commonly less humid than slopes oriented to the north, east or west (Oliphant et al., 2003; Kutiel, 1992). The effect of stone and rock cover on hydrological processes, such as infiltration, runoff generation, evaporation rates and soil moisture content, is well documented (Pérez, 1998; Abrahams and Parsons, 1991; Poesen et al., 1998). Most of the studies show that rock fragments in the topsoil increase water intake rate while decreasing runoff volume. The effect of rock/stone coverage on water regime in the upper part of the soil might be further enhanced in basaltic areas. Recent studies that have explored a basaltic environment in Jordan (Higgitt and Alison, 1999; Allison and Higgitt, 1998) show considerable variation in stone and rock cover, where areas with high rock/stone cover provide small niches of soil with improved water regime. In water-constrained environ-
ments, especially on south-facing slopes that suffer higher evaporation rates, these niches are of major significance for vegetation. Apart from effects of topography and rock cover, soil characteristics such as soil depth, hydraulic conductivity, porosity and preferential flow path may also affect the soil water available for vegetation (Barling et al., 1994). Among these attributes, soil depth has proved to have greater importance for the evaluation of herbaceous vegetation production on arid and semi-arid range soils. McCollie and Hodgkins (1970) have found that herbage production increases as soil depth increases on basaltic bedrock, including three series of basaltic soils with different depths. Similarly, Van Wesemael et al. (2000) have found that the highest rate of infiltration, evaporation and drainage, as well as the lowest rates of overland flow, are typical to shallow soils. van Wesemael et al. have also found that the deeper soils, found on the valley floors, produce a more stable moisture regime than shallower soils, which tend to saturate and dry out quickly. The authors have also established that the water regime caused by varying soil depths affects vegetation: an asymptotic increase in productivity with increasing soil depth.

Modeling the four variables in conjunction may represent the potential for water availability in the study area. However, the weight (importance) of each variable might be different. According to a ‘traditional’ scenario, the wetness index of the microenvironment constitutes the most important factor to represent water availability; second in importance is the rock cover; third is soil depth and finally of the lowest importance.

<table>
<thead>
<tr>
<th></th>
<th>Wetness index</th>
<th>Rock cover</th>
<th>Soil depth</th>
<th>Aspect</th>
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<tbody>
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<td>Avoid aspect</td>
<td>0.57</td>
<td>0.296</td>
<td>0.143</td>
<td>does not participate</td>
</tr>
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<td>0.299</td>
<td>0.97</td>
<td>0.143</td>
<td>&gt;135</td>
</tr>
<tr>
<td>Gradual</td>
<td>0.97</td>
<td>0.396</td>
<td>0.143</td>
<td>&lt;135</td>
</tr>
<tr>
<td>Traditional scenario</td>
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<td>0.3</td>
<td>0.2</td>
<td>0 - 30</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>interval 30</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>interval 150 - 180</td>
</tr>
</tbody>
</table>

Fig. 1. The four different scenarios use for habitat modeling.
is the slope aspect. In another scenario, the hierarchy remains the same but the slope aspect is excluded from the analysis due to the assumption that in a semi-arid environment all slopes suffer from water limitations. Here, we suggest a third scenario, namely the ‘water availability’ scenario, which assumes that on south-facing slopes, where water constraints are most severe, the dominance of the wetness index is lessened. Rocks on the south-facing slopes may act as a shelter from the high evaporation rates and therefore habitats with higher rock cover may provide better conditions for herbaceous vegetation to grow. However, in other slope directions, evaporation is less severe and therefore rock cover would not be of focal importance. Therefore, in the third scenario we suggest that: (1) on south-facing slopes the most important factor is the rock cover, followed by topographic location (wetness index) and soil depth; and (2) on all other slopes, the leading factor is the topographic location, followed by rock cover and soil depth. Since the slope aspect has a crucial role in the ‘water availability’ scenario another question arises: Where is south? Or in other words, does the weight of wetness decreases and rock cover increases gradually with the distance from the south or slope aspect effect is characterized by the nature of a threshold? This question leads to the forth scenario tested here, namely the ‘gradual’ scenario. In this scenario, we gradually increase the weight of the rock cover and decrease the weight of wetness index as the distance from south decrease. The four scenarios and the configuration of weights are illustrated in Fig. 1.

To perform modeling of the above-mentioned scenarios with explicit rules, an approach that can handle cause and effect relationships is required. Among the most flexible modeling techniques is the fuzzy logic that was first proposed by Zadeh (1965) and, since then, has been widely used for ecological modeling of, for example, lake eutrophication (Chen and Mynett, 2003), delineation of agroecozones (Liu and Samal, 2002), spatio-temporal changes of salinity (Metternicht, 2001), and soil mapping (Zhu et al., 2001). Fuzzy logic provides the ability to model in-
exact, imprecise and ambiguous entities, and relationships between different model components (Burrough, 1996). Since the combined effect of the four indirect sources on the production rate of herbaceous vegetation cannot be represented by simple statistical model (Henkin et al., 1998) and since the habitat is an indeterminate geographical entity that is not characterized by a sharply defined boundary, fuzzy logic representation was chosen here as the modeling approach (Fig. 2).

3. Methodology

3.1. The study area and field campaign

The study area is the Korazim Block in the Eastern Galilee, in northern Israel (Fig. 3). Most of the research plots are located in the area of the Karei Deshe experimental range, at longitude 35°35′E; latitude 32°55′N; altitude 80–150 m a.s.l. The topography is hilly with varying rock coverage: from sparse cover...
of little stones to very large and dense boulders with approximately 30% cover (Seligman et al., 1989; Gutman and Seligman, 1979). The soils are variants of brown basaltic protogrumosol (Dan et al., 1970) of variable depths. Patches of soil, up to 100 cm deep, are interspersed between rock outcrops and create varied habitats for herbaceous plants, ranging from small patchy to spersed between rock outcrops and create varied habitats. The area has a Mediterranean climate, characterized by wet and mild winters with respective mean minimum and maximum temperatures of 7°C and 14°C. The average seasonal rainfall is 550 mm, falling mostly in winter (October–April). Summers are dry and hot, with respective mean minimum and maximum temperatures of 19°C and 32°C. The growing season of the herbaceous vegetation is mainly determined by the rainfall distribution. Germination of annuals and regrowth of most perennials occur soon after the first rain (Sternberg et al., 2000). Growth is rather slow during the winter months of December and January, but the vegetation is usually well established by the middle of January. Growth is rapid in spring and peak growth, coinciding with seed set, occurs in March and April. By mid-May, most of the herbaceous vegetation is dry and most seeds have been dispersed. Vegetation is a rich hemicryptophytic grassland (Zohary, 1973) dominated by Hordeum bulbosum L., Echium judaeum L., and annual species (Avena sterilis L., Bromus spp., Trifolium spp., Medicago spp. and many others), some of which are palatable pasture plants (Seligman et al., 1989). Others, including Scolymus maculatus L., Brassica nigra L. Koch. and Echium judaeum L., are palatable for only a short period during the early vegetative phase. The vegetation covers rocky slopes and plateaus that have never been cultivated, as well as stony fields that were cultivated in the past (Noy-Meir et al., 1989).

Two field studies were conducted within the framework of the current research: (1) early March 2003 (main growing phase) and (2) late April 2003 (peak seasonal biomass). A total of 52 plots (30 in March and 22 in April), each 1 ha average size, were used to estimate aboveground biomass with the harvest method. Aboveground biomass was harvested on ten 25 cm × 25 cm quadrats placed at random in the plot. The representation of these plots in the GIS is based on 52 arrays, of nine pixels (a grid of 3 pixels × 3 pixels) each, which spatially correspond to the plots. (Using differential global positioning system (GPS) with 1 m accuracy, it was possible to make geometric adjustments between the sampling design and the array of nine pixels that represent the modeled herbaceous habitats (Fig. 3)).

### 3.2. Rock cover estimates

Landsat TM data, acquired in the summer of 1997 (June 22nd), was used to estimate rock cover in the study area. The image was radiometrically calibrated (TM Channels 1-5 and 7) using the following procedure: the image digital numbers (DN) of all channels were transformed into percent reflectance values using the empirical line method (Smith and Milton, 1999). This was accomplished based on field measurements carried out using the CROPSCAN and FieldSpec radiometers from stable targets: water bodies and highly reflective limestone bare rock areas (Shoshany and Svoray, 2002). The image was geometrically corrected with 0.5 pixel Root Mean Square (RMS) errors, based on 50 ground control points, through a first-order transformation. Reference points were derived from 1:50,000 topographic maps and from points measured in the field using differential GPS.

The rock fraction layer was produced by applying the linear spectral unmixing model. In previous studies this approach has been applied successfully to the reflectance data of, e.g., Viking (Adams and Smith, 1986) and Landsat TM (Shoshany and Svoray, 2002). The hypothesis underlying the unmixing model assumes that the primary component of spectral variation observed in the image is the result of a linear mixture of surface materials. During the summer (as of the first week of May) the herbaceous vegetation in the study area is totally dry (Orshan, 1989). Under these conditions and since there is no woody vegetation in the study plots, it is assumed that during June, the image pixel is composed of rock and bare soil only. This implies that the reflectance data recorded in the image constitutes the outcome of the contribution of these two components only.

The spectral unmixing model creates fraction images for a set of class spectral signatures. The input signatures are assumed to represent spectrally pure classes ('endmembers')—rock and bare soil in our case. A typical spectral unmixing model can be expressed by Eq. 1 (from Adams and Smith, 1986):

\[
Ref_b = f_{1b}EM_{1b} + f_{2b}EM_{2b} + \epsilon_b
\]

\(Ref_b\) = fractional rock cover
\(f_{1b}\) = fraction of rock endmember
\(f_{2b}\) = fraction of bare soil endmember
\(EM_{1b}\) = reflectance of rock endmember
\(EM_{2b}\) = reflectance of bare soil endmember
\(\epsilon_b\) = random errors
where $R_{	ext{ref}}$ is the spectral reflectance of an image pixel for band $b$, $f_n$ is the fraction of endmember; $EM_n$ is the image endmember for each band; and $e$ is the residuals and noise component.

Twenty-two plots of soil and rock endmembers were delineated based on visual interpretation of the orthophoto and were also validated in the field to make sure that they are indeed pure. The soil in the study area is partially covered with dry vegetation in June, and therefore its endmember spectra are not of pure soil but a signature that represents the combined reflectance of the two surface covers. Since the separation of dry vegetation and soil minerals is beyond the scope of the current research, we have not made an attempt to separate the two.

Fig. 4 shows the significant differences between the spectral signatures of the rock and soil endmembers of the study area. The error bars on each curve on the graph represent the confidence interval calculated for the 22 plots at each spectral band. The plots show that the spectral signatures of the soil and rock differ significantly as no spectral mixture is found in any of the TM bands. The significant difference between the spectral signatures enables us to apply Eq. (2).

$$R_{	ext{ref}} = f_{	ext{soil}}EM_{	ext{soil}} + f_{	ext{rock}}EM_{	ext{rock}}(b) + e$$

where $R_{	ext{ref}}$ is the spectral reflectance of an image pixel for bands 1–5 and 7 of the available TM image; $f_{	ext{soil}}$ and $f_{	ext{rock}}$ are the fractions of soil and rock, respectively; $EM_{	ext{soil}}$ and $EM_{	ext{rock}}$ are the image endmembers for each band; and $e$ is the noise component.

The results of the rock cover fractions were validated against quantitative assessments of rock cover fractions estimated from ground photography using a visual interpretation. On each of the 22 different sites, three ground photographs were taken, 66 in all. The photographs were scanned and digitized to dissociate between rock and soil cover, based on a visual interpretation analysis. The relative cover of each of the components was then calculated for each photograph averaged for each site. The predicted and observed rock cover fractions were correlated using a regression analysis and show a significant linear correlation ($R^2 = 0.78, n = 22$; Fig. 5).

3.3. Topographic attributes

The wetness index ($WI$) was calculated using Eq. 3 (Barling et al., 1994) from a 25 m × 25 m digital elevation model (DEM) of the Geological Survey of Israel.

$$WI = \log \left( \frac{A_{\text{si}}}{\tan \beta} \right)$$

where $A_{\text{si}}$ is the specific catchment area (the upslope contributing area) and $\tan \beta$ is the tangent of the slope angle of the surface. The output aspect layer was recorded within the range of $0^\circ$–$360^\circ$ as the default option of the software. According to the research assumption the key information is the effect of radiation flux, which is more dense on south-facing slopes, and therefore the aspect layer was encoded according to the distance from the north where $0$ represents north.
Soil depth data was derived from a detailed soil map (1:20,000) presented by Dan et al. (1964). The method used to measure soil characteristics and to extrapolate the measurements from soil cores to an areal extent is based on a well-established methodology (Dan and Koyumdjinski, 1963). However, it is important to note that the soil survey methodology includes delineation of mapping units with similar soil characteristics from aerial photography followed by extensive field validation. Soil depth was measured on all soil cores that were taken from the soil surface of the parent material. Soil depth values were categorized by Dan et al. (1970) into five groups with significant pedologic implications: 0–20 cm (very shallow); 21–45 cm (shallow); 46–75 cm (medium); 76–100 cm (deep); and >101 cm (very deep). For the purpose of the current study, the maps (seven charts) were scanned and corrected geometrically using six ground control points per chart, located at the intersection between longitude and latitude lines at the corners of each map. The root mean square error was, in all cases, smaller than one pixel. Finally, we combined the seven charts to create a single layer of soil attributes that covers the entire study area. We then digitized the contour lines of the soil groups and, for the uniformity of the data models, converted the vector polygons into a raster format with pixels recoded by the soil depth data.

3.5. Fuzzy modelling

3.5.1. Statistical correlation between the indirect variables

The integration of the four indirect variables (Fig. 7) in a fuzzy model requires testing first if the spatial distribution pattern of any of the indirect variables depends on the other indirect variable. For this purpose, we have used two statistical tests:

1. Pearson’s product moment coefficient of correlation. This test provides a measure of both direction and strength of the relationship between two continuous variables (i.e., in our case between wetness index, slope aspect and rock cover);
2. The combined use of student’s t-test and F test to examine if there is a difference between the mean and variance of the wetness index, aspect and rock cover within the different groups of soil depths (i.e., soil groups). This test helps to reject the hypothesis that there is a pattern of specific attributes of the latter variables and the soil groups.

These tests were implemented on six very large sample areas, which together constitute 56% of the total area (Fig. 8).

3.5.2. Model implementation

A general fuzzy system is composed of three primary elements: a membership function, fuzzy production rules and fuzzy sets. A fuzzy set (A) could be defined as in Eq. (4) (Burrough et al., 1992):

$$A = \{ x, \mu_A(x) \} \text{ for each } x \in X$$

where $X = \{x\}$ is a finite set of points and $\mu_A(x)$ a membership function of $X$ in $A$. The membership function of a set determines the degree of membership of $x$ in $A$. Scientific literature provides numerous membership functions, including, for example, linear, trapezoidal, sigmoid and cosine functions (for a review of fuzzy membership functions see the study by Robinson, 2003). In the current research we have tried several
types of membership functions; the sigmoidal function described by Eastman (1997) and Urbanski (1999) in the form of Eq. (5) proved most appropriate to our purposes, based on a visual interpretation analysis of the results.

\[ \mu_A = \cos^2 \left( \frac{x - P_{\text{min}}}{P_{\text{max}} - P_{\text{min}}} \right) \left( \frac{\pi}{2} \right) \]

where \( P_{\text{max}} \) and \( P_{\text{min}} \) are the maximum and minimum threshold values, while \( \mu_A = 0 \) for \( x \leq P_{\text{min}} \) and \( \mu_A = 1 \) for \( x \geq P_{\text{max}} \). The layers that represent the four variables were recoded based on their contribution to the water availability, and thus \( P_{\text{min}} \) and \( P_{\text{max}} \) were specified as minimum and maximum values of the layer histogram of each of the variables (Fig. 9). The joint membership function (JMF) integrates the effect of the four variables using fuzzy production rules that usually
take the form of conditional (‘if–then’) rules. There are several ways to perform a JMF and we have used the convex combination operation (Burrough et al., 1992) in the form of Eq. (6):

$$JMF = \lambda_1 \mu_{A_1} + \lambda_2 \mu_{A_2} + \cdots + \lambda_4 \mu_{A_4},$$  

(6)

where JMF is a joint membership function for several fuzzy sets, $\mu$ are the membership functions, $A_1, \ldots, A_4$ are the four variables studied here and $\lambda_1, \ldots, \lambda_4$ are the weights for each variable (Baja et al., 2002). Based on the membership grades and the patterns that were produced by the JMFs, fuzzy sets are defined.

The outcome of Eq. (6) is a new fuzzy set, the membership function of which is the weighted sum of the membership functions of the four sets. The weights $\lambda_1, \ldots, \lambda_4$ are of major importance, as their size determines the extent of each membership function’s contribution (indirect variable) to the final set (the integrated assessment of the herbaceous habitat). The weights consequently represent a hierarchy of the variable’s contributions to the JMF and, hence, each variable’s value in the final predictive model. Each configuration of weights in the JMF was defined as a scenario (of the four scenarios that were described in Section 2) that conceptualizes the effect of the indirect variables on water availability conditions in each pixel and thus on the production of herbaceous plant biomass.

4. Results and discussion

4.1. Relations between input variables

In Pearson $r$, two variables are proportional to each other positively when $r = 1$, and negatively when $r = -1$. The results in Table 1 show that $r$, in all cases, is closer to 0 than to 1 or $-1$. Therefore, we can assume that the three indirect continuous variables selected here are independent of each other. The large dimensions of the sample plots strengthen the validity of the results that can be explained as follows. The wetness index is designed to represent the combined effect of flow accumulation and slope decline and therefore does not depend on the slope orientation (aspect). However, the relationship between topographic attributes and rock cover is less straightforward. It would be reasonable to claim that slope decline and aspect might affect the rock cover spatial distribution pattern due to, for example, relatively high erosion rates in sharp topography that expose more rocks on steep slopes. Similarly, south-facing slopes may cause a decrease in aggregate stability and therefore yield higher erosion rates (Kutiel, 1992). Evidence for the effect of topography on rock cover spatial distribution is provided by e.g., Poesen et al. (1998) and Cantfield et al. (2001). These authors have studied the movement of sediments in watersheds and show a strong effect mainly of slope decline but also of slope orientation on the spatial variation of rock cover. In the study area, probably due to the fact that many of the rock fragments are very large boulders, the effect...
Table 1
The correlation between the three continuous variables: wetness index, rock cover, and slope orientation

<table>
<thead>
<tr>
<th>Wetness_1</th>
<th>Rock_1</th>
<th>Rock_2</th>
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<th>Rock_4</th>
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</tbody>
</table>

Fig. 9. Frequencies of the membership functions of the four layers.
of topography on the rock fragments’ movement and on soil erosion is much more limited and therefore no direct relationship has been observed.

The results of the combined $F$ and student $t$-tests (Table 2) show that in most cases, the distribution of wetness levels, rock cover and aspect values does not differ significantly between the five soil depth groups. In other words, soils of different depths are found in regions with similar wetness, aspect and rock cover conditions. The soil data used here was mapped on the regional scale, based on the interpolation of soil profiles and field reconnaissance (Dan and Singer, 1973; Dan J. Personal communication). Therefore, differences in soil depth are related to variations in soil formations. The soil formations evolved depending on the six variables in the clorpt model (Jenny, 1941) and thus their typical depth values depend on a combination of long term processes of all clorpt variables rather than a direct dependency on the three variables tested here.

The results presented in this section suggest that the four variables are not directly dependant and thus, their contribution to the water availability assessment in each pixel should be quantified separately.

4.2. A comparison with a traditional map

In order to compare the modeling results achieved here with a previous habitat map which was produced by field techniques applied to a limited part of the study...
Table 2
The correlation between the distribution of wetness index, slope orientation and rock cover values within the different soil groups

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Rock</th>
<th>Wetness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P-value</td>
<td>P-variances</td>
</tr>
<tr>
<td>0–20 cm vs. 20–45 cm</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>0–20 cm vs. 45–75 cm</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>0–20 cm vs. 75–100 cm</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>20–45 cm vs. 45–75 cm</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>20–45 cm vs. 75–100 cm</td>
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<tr>
<td>20–45 cm vs. &gt;100 cm</td>
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<td>45–75 cm vs. 75–100 cm</td>
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<td>45–75 cm vs. &gt;100 cm</td>
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<td>***</td>
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<tr>
<td>75–100 cm vs. &gt;100 cm</td>
<td>***</td>
<td>***</td>
</tr>
</tbody>
</table>

NS: not significant.

* P-value < 0.05.
** P-value < 0.01.
*** P-value < 0.001.

area (Gutman and Seligman, 1985), we ran the fuzzy model through a scenario that is based on the assumptions made by Gutman and Seligman. This enabled us to test the added value expected from the use of fuzzy techniques with raster data, as opposed to a more generalized visual interpretation analysis. The traditional scenario considers two variables: slope decline and rock cover, while the habitats are divided in the map of Gutman and Seligman into six quality groups. Areas of steep slopes and high rock cover are classified as lower quality habitats and vice versa. Since the topography is of higher importance according to the Gutman and Seligman scenario, the weights given to the JMF are 0.65 for slope decline and 0.35 for rock cover.

A visual interpretation of Fig. 10 suggests that there is, in general, an agreement between the two maps. However, the variability within the plots, illustrated by the fuzzy classified habitat map, impedes any attempt to compare the models on a quantitative basis (by using some measure of central tendency). This can be illustrated through polygons, such as 14, identified in both models as low quality habitat. Due to the variability in topography within the polygon, its JMF could not be averaged to a meaningful habitat value. Similarly, polygons 6 and 8 are habitats of low quality but they also include cells with better habitat conditions. This can be better illustrated by the boundary between polygon 7 (high quality habitat) and polygon 8 (low quality habitat)—a boundary that represents a threshold where the habitat quality changes along one particular line from high to low quality. By nature, the spatial variation of the habitats occurs in a more graduated and continuous fashion, due to the fact that their quality is dictated by topographic changes, which are continuous in nature, and due to the fact that cover does not change on a sharp line. On the other hand, Fig. 10 shows isolated high or low JMF grades that represent discontinuity with their environment. These extreme values are mainly an outcome of extreme changes in the rock cover, which is not a continuous phenomenon but a result of local effects. This combination of continuous shifting in quality with ‘hot spots’, resulting from changes in rock cover, demonstrates the more flexible representation that the fuzzy logic can provide of nature in general and the herbaceous vegetation habitats of the study area in particular.

4.3. Habitat assessments

According to the four scenarios, mean JMF values were calculated for the 52 plots that are described in the last paragraph of Section 3.1. The results represent the habitat quality per plot on a continuous scale. The mean JMF values were regressed against the mean biomass values of each plot.

The relationship between the JMF values resulting from the ‘water availability’ scenario and the measured herbaceous biomass is linear, positive and relatively strong in both tests (Fig. 11). The correlation coefficients are relatively high: 0.71 and 0.72 for March and
April respectively and the $P$ values are significant on both dates. A test of the contribution of each indirect variable separately shows that neither is of unique importance; the contribution of each of the variables separately was inadequate to explain the spatial variance of the herbaceous biomass. Fig. 12 illustrates the poor correlation between the variables and the measured biomass. The wetness index that appears to have the strongest relationship exhibits relatively poor Rs with 0.4 and 0.16 for March and April respectively. Rock cover, aspect and soil depth separately shows even less correlation.

The other three scenarios did not correspond well with the herbaceous biomass measurements (Fig. 11). In all cases the correlation between the JMF values and the herbaceous vegetation biomass was lower than the correlation achieved with the ‘water availability’ scenario. However, the results show a clear difference between the two time sets. In March, the ‘gradual’ and ‘avoid aspect’ scenarios provide a positive pattern, yet with non-significant $P$-value, consequentially providing relationships that are suspected to be meaningless. The ‘hierarchical’ scenario shows a positive relationship for March, but low coefficient correlation. In April the results of the ‘gradual’ and ‘avoid aspect’ scenarios are meaningless and the ‘hierarchical’ scenario shows significant results. The reason for this could be that due to the fact that these scenarios do not consider
the effect of rocks on the herbaceous vegetation on the south-facing slopes, the effect of slope is masked in both cases. Thus, when we add the effect of slope without considering the rocks in the ‘hierarchical’ scenario, the results display even lower correlation with biomass than in the ‘avoid aspect’ scenario where the effect of south-facing slopes is avoided. Fig. 11 also shows that a consideration of the rock as a shelter, the importance of which gradually fades from south-facing slopes to north-facing slopes, is also a cause of error since constraints of water prevail only on the south-facing slopes. This implies that a threshold characterizes the difference between north- and south-facing slopes, while east- and west-facing slopes apparently do not experience the effect gradually. This phenomenon is enhanced later in the growing season, when more rainwater is available and the influence of rockiness on south-facing slopes cannot be ignored. Thus, the effect of aspect is represented to a very small extent in the ‘hierarchical’ scenario but the results of the three other scenarios are much poorer with the later test.

The ‘water-availability’ scenario was applied to create herbaceous habitat map to the entire Korazim Block (Fig. 13). In order to facilitate meaningful visual interpretation of the map, we de-fuzzed the JMF into six groups of habitat quality. The map shows that built-up areas already occupy large parts of high quality habi-
Still, some high quality habitats survived as open areas and can be used. Maps, such as Fig. 13, could be used as an infrastructure for applied purposes, such as range management, fire prevention and land-use planning systems. In addition, it could provide a research tool for the evaluation of land development and degradation according to climate change scenarios and studies of herd grazing habits.

5. Conclusion

The importance of model development for habitat assessment has been indicated by Guisan and Zimmerman (2000): ‘The quantification of such species-environment relationships represents the core of predictive geographical modeling in ecology.’ In water-constraint environments, reliable models for habitat assessment are even more necessary as climatic factors increase the heterogeneity and complexity caused by the indirect variables. Therefore, mechanistic modeling provides a challenge for modelers of habitat assessment as it contributes to an understanding that is more generalized and process-based.

A mechanistic model for habitat prediction in a water-constrained environment is presented here. The model is developed using flexible fuzzy representation within a data-rich and spatially explicit GIS framework. The use of indirect variables that can be measured over large areas without special difficulties and the simplicity of the techniques used here make the model suitable for application to other water constraint environments. These characteristics give the model an advantage over traditional methods, particularly when studying large regions, the latter being expensive and usually impractical. The model approach suggested here has also proved to strengthen the ecological information provided in a traditional map by means of more detailed and continuous representation of the habitat. Compared to existing statistical models (such as those presented in Section 1), our model provides habitat prediction based on generalized rules and expert knowledge, which is not based on the relationship, defined when using a specific training set. In that sense our model helps to bridge the gap between generality and accuracy in predictions. Therefore it is recommended to be used in different water constraint environment where expert knowledge can assist in better adaptation through different scenarios. Being spatially-explicit, our model is also complementary to climatic envelop models such as Farber and Kadmon (2003) that are focused on large scale analysis which is based on empirical observations and considers the effect of temperature and rainfall on vegetation characteristics.

An understanding of the effect of the indirect variables on the water availability—and thus herbaceous production—has also proved useful in this research, providing positive correspondence between the ‘water availability’ scenario and herbaceous biomass measurements, while other scenarios fail to present reliable predictions. This result suggests that since the study
area is Mediterranean with ~550 mm irrigation per annum, slopes that are not facing south suffer less severe water limitation while the rock coverage improves water regime on north-facing slopes. In that sense, the Korazim Block, characterized by a hilly terrain with varying rock/stone coverage and water availability constraints, demonstrates the difficulties involved in the use of empirical and analytical approaches for habitat assessment in complex ecosystems.

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