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Forest health assessment using hyper spectral image and multi-criteria analysis: A case study: Ramsar Forest, North of Iran

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ABSTRACT

The hyperspectral images have so far been widely used to monitor and detect environmental changes in vast areas. The analysis of hyperspectral images provides the spatial distribution (maps) of terrain physical and ecological characteristics. In this study, fuzzy set theory integrated with a decision-making algorithm in a Geographic Information Systems (GIS) was used to map Ramsar forest health. In the fuzzy set theory, all classes must have a certain boundary or grouping. (i.e., fuzzy) and consist of a rule base, membership functions, and an inference procedure. For forest health assessment, NDWI, CRI1, PSRI, PRI, and NDVI indices were used to infer the causative factors of forest health. Spectral indices can provide different methods for identifying vegetation coverings. The results of this study are quite useful in identifying potential forest health, where forest health protection measures can be taken in advance. The results also suggest that the southern and the western aspects of the study area are of "very low to low" forest health. Furthermore, the results introduce the potentiality of multi-criteria analysis integrated with GIS as an effective tool in assessing the fire-prone areas of forests.

1. INTRODUCTION

The majority of the current assessments of forest conditions are limited to ground-based visual evaluation. Although these conventional field assessments are valuable, they do not reveal physiological changes that characterize early stress responses (Sampson et al., 2000). Assessing physiological conditions can indicate productivity and adaptability to environmental stress (Chapin, 1991; Colombo and ParAcker,1999) and may provide an early indication of the decline in stand vigor and productive capacity (Zarco et al, 2002). The applications of hyperspectral imaging to natural resources, vegetation, and surface water, have been widely tested (Mouroni et al, 2013). The spectral signature of vegetation is influenced by the presence of pigments (mainly chlorophyll-a, chlorophyll-b, xanthophylls, and carotenoids), canopy water component, whose content varies depending on the chemical and biological activity and the physical structure of plants as well (Blachborn, 1998; Baret, 1998; Sims and Gamon, 2002). The reflectance spectrum of plants provides information on the degree of senescence, the deterioration of leaf structure, or any diseases and abnormalities that plants may be affected from. [Baret, 1998, Blachborn, 1998, Carter and Miller, 1994). Gamon and Surfus (1999) reported quantitative estimates of chemical content in leaves and canopies using indices derived from spectral reflectance at specific wavelengths. Several important eco-physiological properties can be inferred from these reflectance indices based on the links which exist between chemical content, leaf structure, and function. Thenkabail et al (2002) determined the optimal hyperspectral narrow wavebands, in the visible and near-infrared portion of the spectrum, that best characterize agricultural crop characteristics. Vegetation indices derived from narrow and broad wavebands were used to establish relationships with crop biophysical variables and yield.

Moreover, integration of multi-criteria decision-making (MCDM) methods in a spatial domain provides a novel framework for addressing several environmental problems, such as quantifying "fire risk", "forest health" etc. MCDM methods have been developed to solve conflicting preferences among criteria (Keeney and Raiffa 1976). Rational decision-making requires combining both objective and subjective criteria (Pomerol and Barba-Romero2000), most notably in a

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collaborative participatory framework for which MCDM methods can provide a useful framework (Saaty 1994; Malczewski 2002; Sadiq and Husain 2005). MCDM is believed to be a powerful technique for analysis and prediction. It also provides a rich collection of technique for structuring decision problem and designing, evaluating, and prioritizing alternative decisions (Feizizadeh et al, 2012 and Feizizadeh and Blaschke, 2012a)

Forest health mapping is useful for detecting pest and blight conditions in a forest and is useful for assessing areas of timber harvest. Within the gamut of the current study, a forest health map was generated for the study area by using five different spectral indices in conjunction with a Fuzzy set.

2. METHODOLOGY

2.1. Study Area

Ramsar is the capital city of Ramsar County, Mazandaran Province, Iran. Green coverage of forests contributes to the majority of the city area and is one of the main vegetation hotspots in Iran regarding the volume of the produced trees. These forests are graded from 1 to 3 with an area of 42,894 ha, 32,758 ha, and 52,972 ha respectively. The commercial utilization is 21,202 m^3 (6,505,000 cu ft) and the non-commercial utilization is 32,173 m^3 (4,455,800 cu ft). The Total Annual Precipitation (TAP) of Ramsar is about 1200 mm. The study area is located between the following geo-coordinate: 50° 22' 06"- 50° 59' 31"N 36° 11' 08"- 36° 45' 06" E.

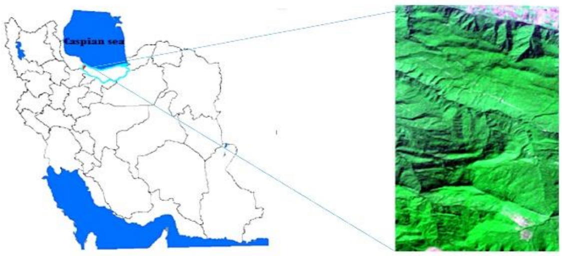

Figure 1. The geographic location of Ramsar Forest in North of Iran

The methodology of the current study consists of three different components: (1), A Fuzzy Inference System for forest health (2), Fuzzy Degree Membership Functions, (3) Performing Scenarios.

2.2. Fuzzy Inference System for Forest Health

Fuzzy logic is a human Knowledge embodying tool through operational algorithms. Several intelligent Systems have been developed globally for forest health assessment on an annual basis (Yan and Yang, 2001) and also for the estimation of risk due to natural hazards (Iliadis et al., 2005). According to fuzzy Algebra, every element of the universe may belong to any fuzzy set (FS) with a degree of membership that varies from 0 to 1 (Ilidias et al, 2009). We used NDWI, CRI1, PSRI, PRI, and NDVI indices for evaluating forest health in the study area.

2.2.1. Canopy Water Content

Water content is an important quantity of vegetation because higher water content indicates healthier vegetation that is likely to grow faster and be more fire-resistant (Penules et al, 1992). Plants of different species inherently contain different amounts of water based on their leaf geometry, canopy architecture, and water requirements. Among plants of one species, there is still significant variation, depending upon leaf thickness, water availability, and plant health. Water features center around the 970 nm and 1190 nm of the microwave spectrum and can be readily measured from hyperspectral sensors. However, they cannot be sampled by multispectral sensors.

2.2.2. NDWI (Normalized Difference Water Index)

NDWI is sensitive to variations in vegetation canopy water content because reflectance at 857 nm and 1241 nm has similar but slightly different liquid water absorption properties. The scattering of light by vegetation canopies enhances the weak liquid water absorption at 1241 nm. Applications of NDWI include forest canopy stress analysis, leaf area index studies in densely foliated vegetation, plant productivity modeling, and fire susceptibility studies (Gao, 1995). NDWI is defined by the following equation:

$$NDWI = \frac{857-1241}{857+1241} \qquad \text{Equation1}$$

2.2.3. Leaf Pigments

There are three main categories of leaf pigments in plants: chlorophyll, carotenoids, and anthocyanin. These pigments are critical to the function and health of vegetation. Vegetation with a high concentration of chlorophyll is generally very healthy. Conversely, carotenoids and anthocyanin often appear in higher concentrations in less healthy vegetation (Gitelson et al, 2002). The main pigments involved in photosynthesis are chlorophylls and carotenoids. One of the structural characteristics of carotenoids is their ability to absorb visible light: p delocalized electrons suffer a photo-induced transformation through which a single state (s2) is produced, then energy is efficiently transferred to chlorophyll (CHL) to form singlet CHL with slightly higher energy (Delgado et al, 2000). In this study, NDVI and CRI1 were used to evaluate chlorophylls and carotenoids.

The Carotenoid Reflectance Index 1 (CRI1) and NDVI are defined as follow:

$$CRI1 = \frac{1}{510} - \frac{1}{550} \qquad \text{Equation 2}$$

$$NDVI = \frac{800-670}{800+670} \quad \text{Equation 3}$$

2.2.4. Dry or Senescent Carbon

Senescence marks the final phase of a leaf's development thereby launching degradation processes integral to the recycling and redistribution of the leaf's nutrients. Plant growth regulators, reproduction, cellular differentiation, and hormone levels are internal factors that influence senescence (Thomas and Stoddart 1980; Smart 1994) In this study, the Plant Senescence Reflectance Index (PSRI) was utilized to assess the Dry or Senescent Carbon status.

PSRI is designed to maximize the sensitivity of the index to the ratio of bulk carotenoids (for example, alpha-carotene and beta-carotene) to chlorophyll. An increase in PSRI indicates increased canopy stress (carotenoid pigment), the onset of canopy senescence, and plant fruit ripening. PSRI is defined by the following equation:

$$PSRI = \frac{680-500}{750} \quad \text{Equation 4}$$

2.2.5. Light Use Efficiency

Light use efficiency is highly related to carbon uptake efficiency and vegetative growth rates and is somewhat related to fractional absorption of photosynthetically active radiation (FAPAR). Light use Vegetation Indices (VI's) use reflectance measurements in the visible spectrum to take advantage of relationships between different pigment types to assess the overall light use efficiency of the vegetation (Gamon et al, 1997). In this study for Light use efficiency assessment, The Photochemical Reflectance Index (PRI) index was used.

PRI is a reflectance measurement that is sensitive to changes in carotenoid pigments in live foliage (Penuelas et al, 1992). Carotenoid pigments are indicative of photosynthetic light use efficiency, or the rate of carbon dioxide uptake by foliage per unit energy absorbed. PRI is defined by the following equation:

$$PRI = \frac{531-570}{531+570} \quad \text{Equation 5}$$

2.3. Fuzzy Degree Membership Functions

There is no optimal method for choosing the most appropriated Fuzzy Membership Functions (FMFs) and their respective parameters; these are generally selected according to the preference of the decision-makers (Feizizadeh et al, 2013). In this respect, the sigmoidal membership function was used (Fig.3). The Fuzzy Membership tool reclassifies or transforms the input data to a 0 to 1 scale based on the possibility of being a member of a specified set. 0 is assigned to those locations that are not a member of the specified set, 1 is assigned to those values that are a member of the specified set, and the entire range of possibilities between 0 and 1 are assigned to some level of possible membership (the larger the number, the greater the possibility) (Zadeh, 1968).

2.4. Sigmoidal Membership Function

The Sigmoidal ("s-shaped") Membership function is perhaps the most commonly used function in Fuzzy Set theory. It is produced using a cosine function. In use, FUZZY requires the positions (along the X-axis) of 4 points governing the shape of the curve (Zadeh, 1968).

2.5. Performing Scenarios

By linking environmental factors and efficient forestry, GIS can perform as a tool for operational and practical monitoring of forest health assessment and management. As a planning tool, it may also play an important role in forest and land-use studies in a broader sense (Jaiswal et al. 2001).

2.6. Defining membership function

In this study, the Sigmoidal function was used as a membership function and layer overlay was done in the GIS environment. On account of the optimal wizard availability issue for defining the Sigmoidal membership function in GIS, the authors utilized coding. (Fig.4)

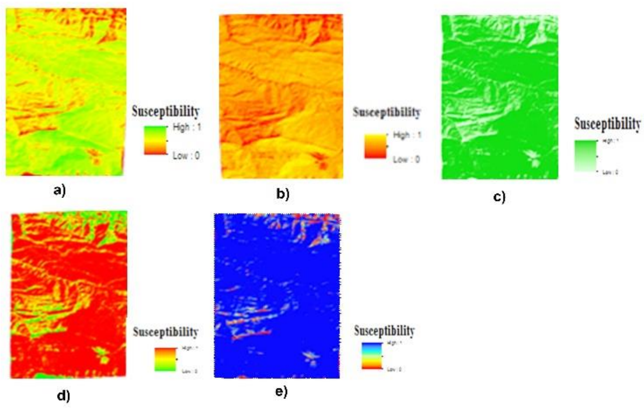

Figure 2. Parameters Susceptibility Maps: *WBI (a), CRI1 (b), NDVI (c), PSRI (d), and PRI (e).*

3. Results and discussion

The locations with at least a 0.5 or greater suitability for all the criteria were satisfied for this study thus the Fuzzy AND function was used. The forest health map (Fig 5) suggests that the southern and western aspects in the study area are of "very low to low" forest health while the other aspects belong to "medium to very high" health zones. Determination of the fuzzy membership boundaries was implemented according to the opinions of four experts.

The results underline a highly dynamic and spatial nature of forest health in the study area. Results also indicate that it is essential to improve our understanding of the causative factors of forest health to manage forest health as well as to prioritize the related measures.

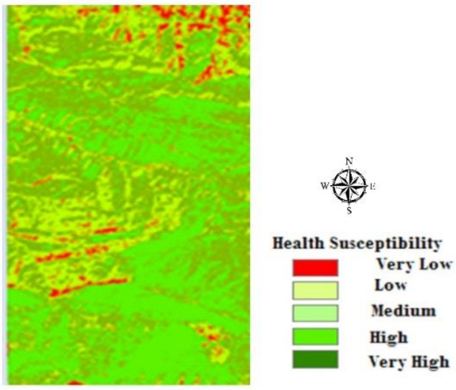

Figure 3. Forest Health Susceptibility Map

4. CONCLUSION

In this study, Ramsar forest health was quantified in terms of canopy water component, carotenoid and chlorophyll pigments in plant foliage, plant senescence, and photochemical reflectance. To address the "fuzziness" in the spatial dataset and also to include the subjective judgments in the modeling process, a fuzzy analytical hierarchy approach in GIS was utilized to assess the fire risk in the study area. Results are quite useful in delineating potential "forest health" zones at a district level. The findings of the current study can be used as a strategic planning tool. They may also be applied to assess the health susceptibility of any vegetation coverage.

Overall, the findings of this study demonstrate the potential of GIS technology, Multi-criteria Decision Making (MCDM), and its viability for the assessment of forest health by integrating objective as well as subjective data in a Fuzzy Logic.

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