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FOREST BIOMASS SPECIES CATEGORIZATION AND EVALUATION OF THEIR CONDITION AND QUALITY USING AERIAL IMAGES

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Abstract:
In recent years, the effects of climate change have become more intense and the role played by the forest ecosystems and the forest biomass produced, seems to become increasingly important. Forest biomass is a source of large quantities of timber, but also of a great variety of valuable materials, chemicals and biofuels, and therefore, the identification of the species, the categorization of them into tree and non-tree species, the monitoring and assessment of their health status, as well as quality characteristics, where feasible, constitute crucial actions of a plan for the protection and rational management of the forest biomass. In the current work, for the identification and recording of trees and shrub vegetation species, the disease detection and the assessment of the biomass condition and quality in an operationally, time and power cost efficient manner, the use of aerial data is proposed. Specifically, using the abovementioned data, we propose the segmentation of trees and shrubs applying an energy minimization approach and then, assuming that the forest areas and forest biomass quality depends on trees and shrubs vegetation condition, their modelling through the extraction of multi-pyramid textural features through linear dynamical systems. The experimental results presented use images of a forest area in Greece, where fir trees prevail, and reveal the great potential of the proposed methodology.

Key words: *remote sensing; machine learning; separation of vegetation; biomass quality.*

INTRODUCTION

Forests offer countless benefits to humans and the ecosystem, as they contribute to the creation of a sustainable environment, climate stabilization, upgrade of air and water quality, preservation of biodiversity, anti-erosion protection and the production of the valuable resource of woody biomass. Forest biomass consists mainly of wood from trees and shrubs and residues (stem, bark, foliage, branches, stump and roots) and provides the raw materials for the production of innumerable valuable bio-products, such as timber, wood based products, wood pulp, paper, cellulose, hemicelluloses and lignin derivatives, extractives for chemical products, bioplastics etc., as well as in the production of biofuels and energy (Filippou 2014). Due to climate change, combined with the increase in the natural disasters it causes, the gradual reduction of forest land and other factors such as heredity and the fact that the health of the tree is affected by the environmental conditions in which it develops the presence of old, injured, diseased, dead or fallen trees has increased. The occurrence of such incidents in forest areas usually leads to their attack by insects, fungi, bacteria and other xylophagous microorganisms and as a result to the decomposition of wood, bark or foliage and damaging the health of trees by degrading the quality of forest biomass and to more severe cases they die (Voulgaridis 2015). Consequently, monitoring of the health and condition of forest species in real conditions is of great importance in avoiding the loss of biomass due to decomposition and its qualitative degradation by various factors acting in this direction. Generally, the identification and knowledge of the exact forest species, the volume stock, the quality status and characteristics of biomass produced in the forest ecosystem is a critical factor for its rational management, protection and sustainable utilization.

To date, automated forest monitoring methods, as well as algorithms for the identification of infected trees in forest area (that can be used in order to assess the quality of woody biomass) are divided according to their spatial application (Galidaki et al. 2017). Specifically, satellites and their data are used for >10ha - scale analyses, LiDAR (Light Detection and Ranging) technology are used in order to create 3D point clouds in >5ha-scale areas (using airborne systems) and in <1ha-scale areas (using terrestrial or mobile systems) and UAVs equipped with digital, multispectral and hyperspectral image sensors for access to visible and invisible spectrum achieving monitoring of <5ha-scale areas per flight. In contrast with satellite and LiDAR systems, the advantages of UAV systems include the possibility of frequent monitoring, the adaptability to carry various types of sensors, the high intensity of data collection and the low operational costs (Tang and Shao 2015).

More specifically, remote sensing technologies combined with computer-aided signal and image analysis has become one of the major research subjects in forest health surveillance (Sakari et al. 2015). To this end, numerous approaches for environmental monitoring have been proposed to assist foresters and experts in the disease recognition challenge using expensive and customized multispectral cameras and estimating health indicators features (Brovkina et al. 2018). Furthermore, in order to extract more spectral bands, researchers have exploited the significant role of hyperspectral cameras and Fabry-Pérot interferometer (FPI) technology (Moriya et al. 2017, Nasi et al. 2018). However, all these computer-based methods for forest health surveillance suffer from some limitations. Most of the approaches use ground sensors or require expensive and specialized hardware (e.g. using small Cessna-type aircraft platform), with complex standard protocols for data collection and complex analysis methods (Keenan et al. 2015, Trumbore et al. 2015), limiting their potential eventual widespread use by local authorities, forest agencies and experts. Additionally, the majority of these approaches use near infrared spectroscopy in conjunction with Crop Surface models (CSMs) and estimate vegetation health indices (Brovkina et al. 2018). However, the use of infrared cameras increases significantly the cost of such systems (Barmpoutis et al. 2019). Furthermore, to the best of our knowledge, none of the existing published research work in international bibliography has focused on the assessment or prediction of forest biomass quality and research efforts have not yet been identified to involve UAV data in this direction.

In this paper we present an accurate and affordable approach to identify and separate trees from non-tree (shrubs) vegetation regions and identify their condition and characteristics associated with biomass quality through UAV data in an operationally, time and power cost efficient manner. Specifically, we propose the segmentation of trees applying an energy minimization approach and then, in order to rate the condition of trees and assess the biomass quality we propose and extract multi-pyramid (multi-scale and multi-orientation) textural features using linear dynamical systems.

The proposed real-time, automated method for aerial capturing and assesment of the forest biomass quality is expected to contribute positively to addressing the lack of information and the absence of field measurement results in terms of biomass and wood quality at the stage of standing tree within a forest ecosystem. Developed models would be able to accurately detect the condition of trees using digital camera sensors. To evaluate the efficiency of the proposed methodology, we used a dataset of fifty images, where the fir trees prevail.

OBJECTIVE

The main objective of this research work is to develop a computer-based methodology that will exploit aerial images in order to perform identification and seperation of the forest species between trees and shrub vegetation, evaluation of their health condition, disease detection and finally, assesment of their biomass quality. To this end, we classify the detected trees and shrub vegetation regions in the following classes: I) healthy trees and shrubs vegetation, II) trees or shrub vegetation partially defoliated or decolorized III) infected, fully defoliated and decolorized trees or shrub vegetation. Additionally, assuming that the best biomass products quality is acquired from the healthy trees which do not bear apparent defects or irregularities in appearance (non-uniform colour, absence of top or foliage etc.), we aim to correlate these classes to biomass quality.

MATERIAL, METHOD, EQUIPMENT

To evaluate the efficiency of the proposed methodology, we created a dataset, consisting of 50 forest images containing trees and shrubs. The research was conducted at a part of AUTH university forest in central Greece which consists mainly by fir trees. In this area, the annual average rainfall is 885 mm, while the average annual temperature is 9.6°C. This climate is considered to be Csb according to the Köppen-Geiger climate classification. In this research, the study area covers approximately 200 ha. For the validation of the proposed methodology results, we manually labelled the trees and shrubs vegetation in the images. Field research was carried out in some cases where manual labeling was not considered adequate and clarification was necessary. From the annotation we excluded shrubs and trees that are at the edges of the images and the biggest part of them was not included in them.

Fig. 1.
Dataset image samples including trees and shrubs.

Separation of trees and shrub vegetation

Initially, in order to separate trees and shrub vegetation using an aerial image, an unsupervised energy minimization technique that is based on graph cuts was applied (Kolomogorov and Zabih 2004). In this labeling problem, the image is represented as a graph $G = \langle V, E\rangle$, where V is the set of all nodes and E is the set of all edges connecting adjacent nodes. Nodes and edges correspond to pixels and their adjacency relationship, respectively. The graph also contains two terminal nodes, which are referred to as the source and the sink. The labeling problem is to assign a unique label x_p for each node V, so as to minimize the following energy:

$$E = \sum_{p \in V} C_p(x_p) + \sum_{(p,q)\in E} S_{p,q}(x_p, x_q) \quad (1)$$

where: C_p is the color consistency cost which depends on the label x_p. The $S_{p,q}$ is the smoothing cost between two neighboring pixels (p, q) and it depends on the labels (x_p, x_q). The cost of the cut which partitions the graph into two disjoined subsets, is defined to be the sum of weights of the edges crossing the cut, whereas the minimum cut problem is to find the cut with the minimum cost, that minimizes the energy either globally or locally. The algorithm resulted into the labeling that minimizes the energy of Equation (1) leading to the separation of trees and shrubs. Then, we used the four central moments in order to define accurately the trees and shrubs regions. For the initialization of the algorithm, a k-means approach was adopted for assigning an initial label to each pixel.

Estimation of trees and shrubs health condition

Having estimated the regions of trees and shurbs vegetation, we aim to evaluate the condition of them based on hidden texture measurements. Initially, aerial images were divided into 20×20 blocks and inspired by the dynamic texture analysis techniques that have been widely used for time and spatially evolving signals, (Dimitropoulos et al. 2018) and textures classification in forestry applications (Barmpoutis 2017, Barmpoutis et al. 2018), we considered each one of these blocks as a spatially evolving multidimensional signal. Moreover, due to the variant heights and orientations of trees and shrubs we use a multi-pyramid modeling method and we create twenty-seven representations in three different scales and nine orientations (Barmpoutis et al. 2019). Thus, we consider each multi-pyramid representation as a multidimensional signal evolving in the spatial domain and model it through the following dynamical systems:

$$x(t+1) = Ax(t) + Bv(t) \quad (2)$$
$$y(t) = \bar{y} + Cx(t) + w(t) \quad (3)$$

where: $A \in \mathcal{R}^{n\times n}$ is the transition matrix of the hidden state and $C \in \mathcal{R}^{d\times n}$ is the mapping matrix of the hidden state to the output of the system. The quantities $w(t)$ and $Bv(t)$ are the measurement and process noise respectively, while $\bar{y}$ is the mean value of observations. The LDS descriptor, $M = (A, C)$, contains both the appearance information of the observation data modeled by C, and its dynamics that are represented by A.

The multidimensional spatial signal can be represented by tensor $Y \in R^{nxnxm}$, where *n* is the size of the examined tree and *m* is equal to the number of *rgb* image channels. For the estimation of the system parameters, we applied a higher order singular value decomposition (Kolda et al. 2009) to decompose the tensor:

$$\boldsymbol{Y} = S \times_1 U_{(1)} \times_2 U_{(2)} \times_3 U_{(3)} \quad (4)$$

where: $S \in R^{n\times n\times m}$ is the core tensor, while $U_{(1)} \in R^{n\times n}$, $U_{(2)} \in R^{n\times n}$ and $U_{(3)} \in R^{m\times m}$ are orthogonal matrices containing the orthonormal vectors spanning the column space of the matrix and $\times_j$ denotes the *j*-mode product between a tensor and a matrix. Given the fact that the choice of matrices A and C is not unique, we consider $C = U_{(3)}$ and $\boldsymbol{X} = S \times_1 U_{(1)} \times_2 U_{(2)}$. Hence, equation (9) can be reformulated as $\boldsymbol{Y} = X \times_3 C \Leftrightarrow Y_{(3)} = CX_{(3)}$ where $Y_{(3)}$ and $X_{(3)}$ indicate the unfolding along the third dimension of tensors $\boldsymbol{Y}$ and $\boldsymbol{X}$, respectively. Thus, the transition matrix A, can be easily computed by using least squares as:

$$A = X_2 X_1^T (X_1 X_1^T)^{-1} \tag{5}$$

where: $X_1 = [x(2), x(3), \dots, x(n)]$ and $X_2 = [x(1), x(2), \dots, x(n-1)]$. After the estimation of the systems parameters, each multi-pyramid tree representation can be described by the $M = (A, C)$. For the representation of each tree through the extracted descriptors, we adopted the Martin distance as a similarity metric. Specifically, we estimate the subspace angles [9] between two descriptors and solve the Lyapunov equation $A^{\intercal}PA - P = -C^{\intercal}C$, where:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}, A = \begin{bmatrix} A_1 & 0 \\ 0 & A_2 \end{bmatrix}, C = [C_1 \quad C_2] \tag{6}$$

The cosine of the subspace angles is calculated by the following formula:

$$cos^2\theta_i = i^{th} eigenvalue(P_{11}^{-1} P_{12} P_{22}^{-1} P_{21}) \tag{7}$$

Then, the Martin distance between M_1 and M_2 is defined as:

$$Martin_{distance}(M_1, M_2) = -ln \prod_i cos^2\theta_i \tag{8}$$

Then, through the definition of K representative codewords, we created a Term Frequency (TF) histogram representation for each tree that corresponds to its extracted representations. Thus, each TF histogram corresponds to an extracted block (Barmpoutis et al. 2018). Finally, for the classification of each blocked, we used an SVM classifier.

Assesment of trees and shrubs vegetation biomass condition and quality

First of all, the presence of old, injured, diseased, attacked, decomposed, dead or fallen trees has been recorded.

Quality characteristics and information of forest species are obtained mainly from the foliage/crown color, crown shape and density. Additionally, potential disease appearance was detected and also the potential absence of a tree part (for example tree top), due to mechanical injuries, disasters or other reasons, corresponding to irregularities and deviation from the normal appearance and growth of the species has been investigated.

RESULTS AND DISCUSSION

In this section, we elaborated an analysis in order to evaluate the efficiency of the proposed algorithm. To this end, we used the dataset, consisting of 50 forest images and involving in total 1548 trees (Barmpoutis et al. 2019) and we calculated the recall and precision rates. In terms of the analysis, recall measures the true positive rates whereas precision measures the number of samples that classified as positive and are actual positive:

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

where: TP is the true positives, FN is the false negatives and FP is the false positives.

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Separation of trees and shrubs vegetation evaluation

The forest species are being examined and categorized into tree and non-tree (shrub) species, mainly taking into account the size of the crown and the height of each species, This categorization is crucial for the proper management and utilization of timber and other forest products (chemicals, biofuels and other innovative biomass products of high added value) that are derived mainly from non-tree biomass. This step could also provide significant information for the evaluation of the timber and non-timber biomass quantities produced.

More specifically, based on the manual annotation of the dataset, we estimated recall and precision on pixel basis in order to evaluate the proposed methodology. In Table 1, the experimental results for the proposed method, in regards to the separation of trees and shrubs, are presented. Specifically, the recall rate for trees is 94.27%, while the precision rate is 93.72%. Additionally, the recall rate for shrubs is 78.17% and the precision rate is 79.79%.

Table 1

Average Recall and Precision rates for separation of trees and shrubs in the dataset, %

	Recall	**Precision**
Trees	94.27%	93.72%
Shrubs	78.17%	79.79%

Fig. 2.
Separation of trees and shrub vegetation.

Estimation of biomass quality based on the health condition of trees and shrubs vegetation

In this subsection, based on the trees and shrub vegetation regions we analyzed the performance of the proposed texture analysis methodology. Specifically, in Table 2 the recall and precision rates for trees and shrubs vegetation in regards to classes I, II and III are shown. As one can easily notice, the proposed methodology achieves better results in the identification of healthy trees in contrast to identification of healthy shrubs vegetation. It can be explained by the fact that the soil that exists and is apparent between the shrubs makes the detection of their condition a challenging task. However, partially defoliated shrubs vegetation regions have more accurately been detected than the partially defoliated trees.

Table 2

Average Recall and Precision rates for separation of trees and shrubs in the dataset, %

	Trees		**Shrubs**	
	Recall	**Precision**	**Recall**	**Precision**
Class I (Green color)	95.12%	81.25%	80.00%	80.00%
Class II (Red color)	94.44%	82.93%	97.50%	91.76%
Class III (Yellow color)	92.72%	95.38%	87.13%	97.78%

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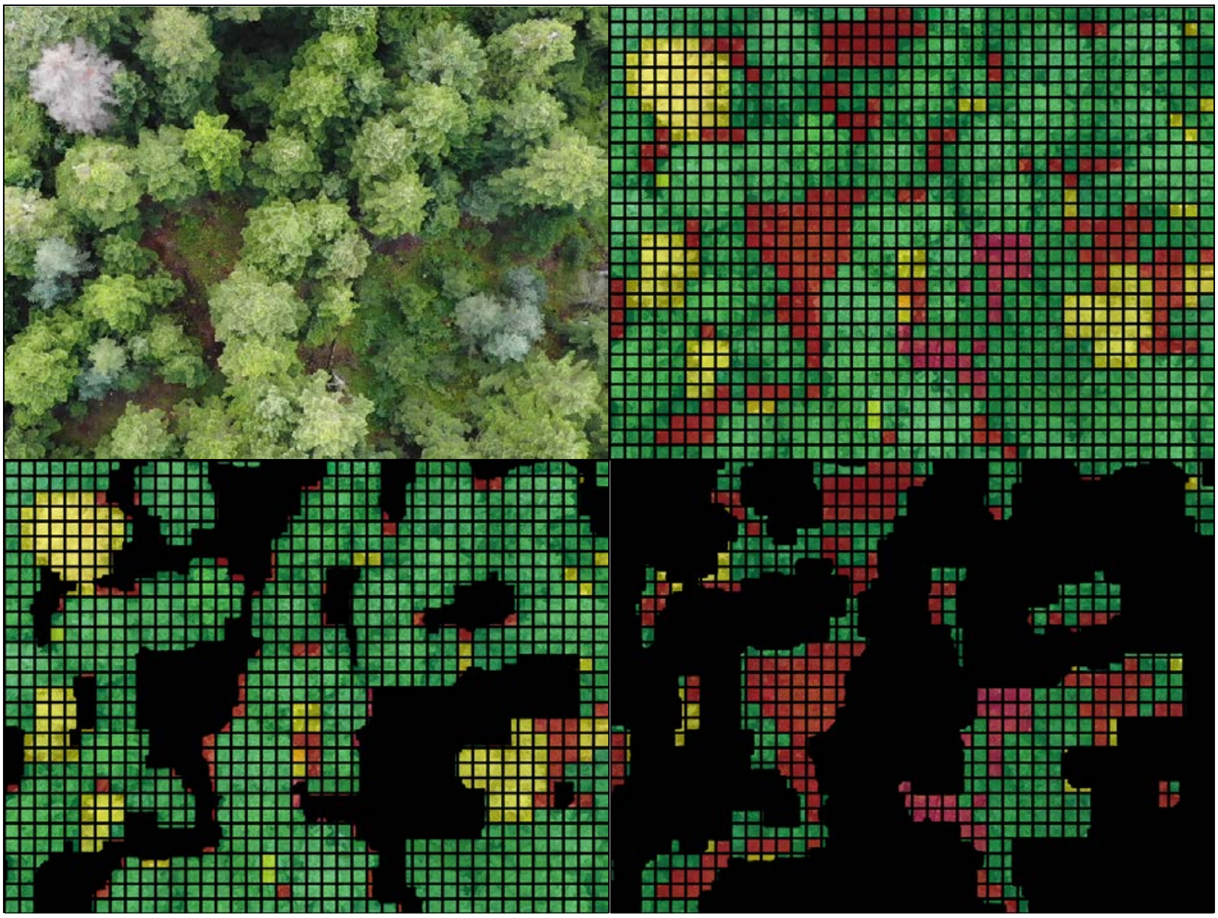

Fig. 3.
Estimation of biomass quality based on the health situation of trees and shrub vegetation.

CONCLUSIONS

In this paper we presented an accurate and affordable approach to detect diseases, estimate trees and shrubs condition and assess their biomass quality through UAV data. Specifically, we proposed the segmentation of trees applying an energy minimization approach and then, the modelling of trees and shrubs vegetation through the extraction of multi-pyramid textural features using linear dynamical systems. The proposed methodology presented satisfing results and it seemed to achieve better results in the identification of healthy trees, compared to the identification of healthy shrubs vegetation.

The research results of the proposed methodology are expected to contribute in the sustainability and the establishment of a rational and supportable management of forest resources, with specifiied focusing on: a) the maintaining of the highest possible quality of timber referring to standing trees, b) The reduction of woody biomass wasting that occurs due to infestations and biological decomposition, and reduction of CO_2 release due to this biomass decomposition and c) the holistic approach of the forest ecosystems management,in order to achieve the protection, conservation and proper utilization of the produced woody biomass.

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