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Using pixel and object based IKONOS image analysis for studying decay in silver fir stands

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Abstract. The problem of old silver fir stands decay has appeared in the last decades of the last century with symptoms such as defoliation, wood decay and parasites attacks. The problems in monitoring this phenomenon is that the defoliation and mistletoe attack appear on the crown top, triggering the coronation process - tree develop branches on their lower stem part in order to resist to the defoliation. This reaction makes the attack difficult to notice on aerial or satellite images, due to the reflection of light on the lower branches. The objective of the article is to find a research methodology for identifying and even mapping the mistletoe attack phenomenon at a tree or stand level. For a tree-level analysis, a comparison between the data obtained in a 1 ha sample plot and the data extracted from an IKONOS satellite image has been used. The simple spectral response is less correlated at tree level with the defoliation and mistletoe attacks. We found a very significant correlation in the infrared channel but with low correlation coefficients. Better results have been obtained in a stand-level analysis. In order to improve the separability, the methodology for extracting the remote sensing data did not resume only to the mean spectral response, but we also performed a variability and texture analysis. The obtained correlation coefficients were around 0.7, very significant for the data used in the research. The results obtained with the texture analysis are also related to the biometric characteristics of the stands, mistletoe attacks occurring in stands with a low canopy closure index and is usually accompanied by distorted crowns. The model of forest health analysis should also be tested in similar conditions in order to validate and apply on a large scale inventory.
Keywords: forest health, silver fir, IKONOS, image texture

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Introduction

Sustainable forest management requires a diverse spectrum of forest parameters in order to allow the design of management activities. Among other information, the forest health status is very important due to its high impact on forest development, especially in the general context of climatic change. The forest health parameters are related to the negative factors causing the forest decay phenomena. In most cases, the terrestrial assessment of forest health status requires much efforts in covering relatively wide areas of potential affected stands. Since the early start of remote sensing use, it has been considered as a more efficient solution for forest health inventory: analogical fotogrammetry with different spectral characteristics. It has been used over the past decades in visual photo-interpretation of the tree decay phenomena (Gross 2000). The high spatial resolution and spectral sensitivity of the used spectral channels make these images very appropriate for local studies, that are sometimes descending to tree crown-level analysis, or lower. The forest health assessment on broad scale remained still very costly, due to the local character of the photogrammetric inventory - large area image analysis methods are difficult to apply because of the highly textured images. Satellite remote sensing could fill the gap between the high resolution and high texture of the images, especially if the texture analysis methods are applied (Haralick et al. 1973).

The use of these methods abroad and in Romania led to good results in cases of dead trees or highly defoliated crowns (Jehl 2007, Ciesla 2001), especially in detecting bark beetle infestation hotspots. The research done within the paper is aiming at applying the same methods for identifying and mapping the decay phenomena present in Silver fir (*Abies alba* Mill.) stands in the North-Eastern part of the Eastern Carpathians.

Materials and methods

The study is located within the Vânători Neamț Natural Park, in the North-Eastern part of Romania (Fig. 1). The general aspect of the area is represented by low altitude mountains (<1000 m), with high productivity mixed forest stands with Norway spruce (*Picea abies* (L.) Karst), silver fir (*Abies alba* Mill.) and beech (*Fagus sylvatica* L.). The health problems are encountered in stands with high percentage of silver fir and are affecting especially this species, related to the mistletoe attack on a high percentage of the trees. Two of the symptoms are obvious in silver fir stands: the foliage loss and the mistletoe attacks (*Viscum album*), which are quantifiable by field data collection. These two health status parameters have been correlated with other structural parameters and image characteristics in order to understand the particularities of the stand decay phenomenon and the relation with the satellite sensors capability to capture the differences between various degrees in tree debilitation.

As the remote sensing methodology books suggest (Lillesand & Kiefer 2000, Franklin 2001, McCoy 2005), every remote sensing forest inventory model has to be based on field measurements and their comparison with the data extracted using remote sensing means. The procedures applied included field inventories in sample plots of 1000 m^2 and one hectare, overlaying the plots on the images, extracting the image parameters corresponding to individual trees and sample plots.

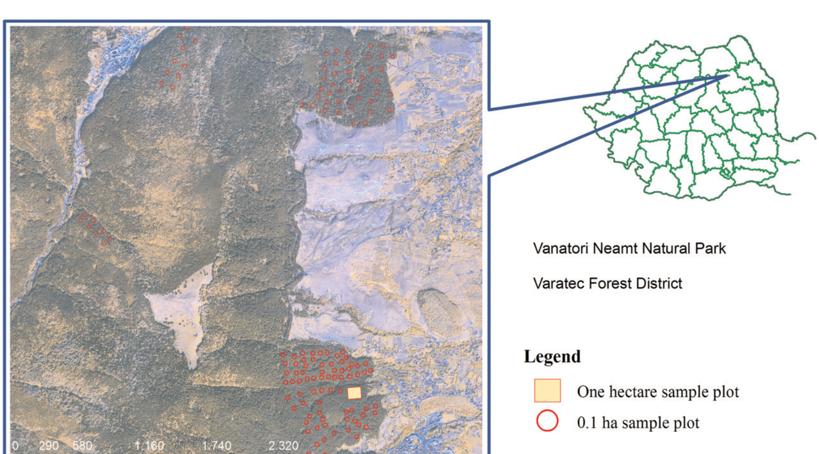

Figure 1 The study area and the location of the sample plots

Field data acquisition

The inventory was conducted at two different spatial scales: a tree-level inventory within a sample plot with an area of one hectare and a stand level inventory by means of 1000 m^2 circular sample plots. The forest stands chosen for the analysis are composed by silver fir and Norway spruce, with a high percentage of the first species, with ages ranging form 100 to 120 years, crown closure index 0.3-0.9. The stands have a wide range of defoliation percentages in the case of the silver fir, responding to the requirements of a representative sampling.

A rectangular network was used for installing the plots in the stands, with approximate position designed on the satellite image, taking also into account the spatial limits of the homogenous portions of the stands. The horizontal position of the center of the plot is measured in the field by means of hand-held GPS, kept in the same position (the center of the plot), in the tracking mode, during the biometric measurement. The final position is the center of the point cloud resulted from consecutive GPS measurements, as an average of single measurements.

We have chosen quantitative and qualitative biometric parameters that would characterize the individual trees and stands, but also the relations between the parameters of the attack and the other tree, and stand characteristics (Table 1). A special attention was given to the horizontal position of the trees in the one ha sample plot as they were overlaid afterwards on the satellite image. To obtain an acceptable accuracy for the georeferencing needed, a total station was used for measurements; the surveying has included also the georeferencing points in the area of the plot in order to use them in the comparison with the IKONOS image. The defoliation degree (percentage) has been determined using standardized images of the crowns on different foliage losses (Műller & Rudolph 1998).

Remote sensing materials

The available remote sensing material for the research is constituted by IKONOS 2 images taken in October 2003 at the request of the Vânători Neamț Natural Park Administration for the entire area of the park. The spatial resolution of the images is 1 m in the panchromatic and 4 m in the other spectral channels (blue, green, red and near infrared). The off-nadir angle of the satellite in the moment of image taking is very low (close to 0°), resulting in a spatially accurate image. While studying coniferous stands, the period of the year when images were taken (October) does not compromise their use for forest health survey purposes.

Table 1 Field inventory parameters

Parameter	1 ha sample plot	1000 m^2 sample plot	Instrument:	UNIT	Estimated accuracy
DBH	x	x	Haglof Digitech caliper	cm	± 1 mm
Total height	x	x	Vertex III electronic hypsometer	m	± 0,1 m
Pruned height	x		Vertex III electronic hypsometer	m	± 0,1 m
Crown diameter	x	x	Measuring tape	m	± 0,3 m
The horizontal position	For each tree	For each sample plot	Total station Hand held GPS	m m	± 0,1 m ± 1 m
Defoliation degree	x	x	Standardized images of tree crowns with different defoliation percent (for each specie in the stand)	%	± 10 %
The intensity of mistletoe attack	x	x	Visual estimation of the percent of the mistletoe volume in the affected crown	%	± 15 %

The basic image processing included the subset and mosaic of the images in order to obtain a unitary image. In order to increase the spatial resolution and the contrast for the interpretation, a resolution merge function was performed within the Imagine Professional software (Erdas Imagine Tutorials 2008). The ortho-rectification and spectral correction were done by the satellite programmer, but it has been verified in the analyzed case by using Ground Control Points (GCP).

For the tree-level analysis, the tree crowns were delineated within ArcGIS 9.2 shape file according to the survey work done in the field (Fig. 2). The polygons corresponding to each tree were converted into areas of interest in the ERDAS Imagine Software. The spectral proprieties of each areas were measured as digital numbers (pixel value) for which the program exports the mean value of the pixel, the standard deviation and the covariance matrix. All these parameters are practically used by the program for the supervised classification.

A more complex analysis was performed using specialized software for pixel based (Erdas Imagine 9.2) and object based analysis (eCognition Professional 4.0). The pixel based analysis software allows the measurements of the pixel values (so-called digital numbers) (Saghri et al. 1978, Das 2004), and the supervised classification of remote sensing data. For spectral enhancement the principal component function was performed, using the four spectral channels of the IKONOS image.

A more complex method is the image object based analysis. With this method, the analysis takes into account not only the individual pixel value, but also the spatial variation of this parameter. Practically, the texture is a spatially related feature, with indicators computed on the basis of neighboring pixel values within a co-occurrence matrix (Haralick et al. 1973). The texture analysis software (i.e. eCognition) is used for computing a wide variety of indices that could be correlated with parameters of the reflexive surface (eCognition User Guide, 2004).

The first step in applying textural analysis in this case is the image segmentation, an automatic process that is based on the image texture and also accounts for the values of three user defined parameters: scale parameter, shape factor and the compactness-smoothness index. In case of stand level analysis, the segmentation process was done by taking into account the shape file containing the limits of the analyzed stands.

The values are extracted by exporting the image objects resulted from the image segmentation for each of the polygons delineating in the inventoried stands. For the identification of each row of the database, an ID field of the thematic layer (.shp) was exported along with the texture features. The field ID was neces-

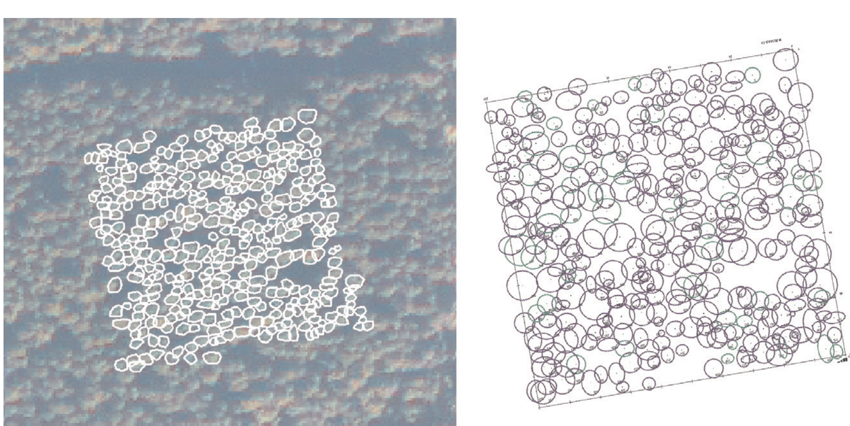

Figure 2 Comparison between ground measured 3D stand profile (right) and the IKONOS 2 satellite image (left)

sary for the correspondence between the data extracted by texture analysis and the data obtained by ground inventory (the image objects are obtained and named automatically). This information was used together with large values of the scale parameter and scale factor in order to obtain stand-level image objects. The reflectance (mean, maximum and minimum pixel values, standard deviations etc.) and texture parameters (Gray Level Co-occurrence Matrix - GLCM, Gray Level Difference Vector - GLDV) were recorded. The extracted values for these parameters were statistically analyzed in order to identify the strongest correlations with the indicators describing the forest health status: the defoliation percent, the basal area of the trees showing some defoliation signs. The program computes the values mentioned above for different directions (0°, 45°, 90°, 135°, all directions), trying to find any axial differences in texture. Given the fact that the naturally regenerated forests do not have significant differences in textures on the mentioned axis, we took further into account only the "all direction" value (Haralick et al. 1973, Haralick 1979, Conner & Harlow 1980).

Statistical analysis of the comparison data

The main statistical methods used are variance, correlation and regression analysis, applied on the sets of data - extracted from terrestrial images and satellite images. Variance analysis was performed in the Anova module of Microsoft Excel 2007; the hypotheses tested are related to the differences between pixel values describing trees with different qualitative characteristics. One of the analysis is based on the assumptions that the trees with different relative positions (Kraft classes) have significantly different pixel values. For the statistical relations showing a sufficiently strong correlation, a regression analysis was performed, using the statistical module of the Microsoft Excel software. To avoid using an averaged variable (average defoliation percentage), a cumulative measure of the decay effect was used - the basal area of the trees with certain defoliation percentage. The basal area was preferred due to the particularities of the attack (Barbu 1991): the highest percentages have been observed in the case of predominant and dominant trees. The levels of damage have been grouped according to the surpassing a prescribed defoliation limit (20, 40 and 60%). The linear regression was applied in the cases of high correlation between texture data and the values of the basal areas in the above mentioned cases.

Results

The analysis of crown defoliation and mistletoe attack follows the aspects detailed in the methods section. The first level of analysis is the tree level, applied to the 1 ha sample plot. Using the pixel values captured within ERDAS Imagine Software, we performed a correlation analysis on the biometric and tree health parameters in the case of 1ha sample plot. The results showed low values of the correlation coefficients in both cases - defoliation and mistletoe attack intensity, although the coefficients are significant if we take into consideration the high degree of freedom (364). The only spectral channel that shows some correlation (0.190***) with the mistletoe attack is the infrared band, known to have a relatively good sensitivity to vegetation status (Fig. 3). Higher correlation coefficients were observed for the relation between the total height and the spectral signatures in some channels, showing that the images are more sensitive to degree of crown enlightenment than the health status or other aspects related to the vigor of the foliage.

In comparison, the stronger correlations were obtained between the attack parameters such as defoliation percent, mistletoe intensity attack and the biometric characteristics: positive correlations with the diameter and height, very significant.

Testing the influence of the relative position of the crown on the pixel value, in different spectral channels, a variance analysis for the pixel values grouped on the Kraft classes of each tree was applied. The impact of the Kraft classes over the pixel values was tested. We found significant differences between the groups of pixel values measured in the near infrared spectral channel (Table 2).

The differences in stand structure are reflected also on the satellite image, in the image texture characteristics of the image corresponding to the inventoried stand. As above mentioned, in the methodology, there were no significant differences between the texture parameter values computed on the four axes, as provided by the calculation algorithm used in the program. The values taken in consideration are the ones offered for "all direction". The selection is important especially if we consider the amount of calculation needed in the computing the gray level co-occurrence matrix (GLCM) and gray level difference vectors (GLDV).

The correlation matrix between the parameters analyzed showed very significant correlations, especially in the case of GLCM parameters (Table 3). The highest values were obtained between the health parameters (defoliation percent, basal area of trees with a certain defoliation percent) and the GLCM Correlation Coefficient and the GLDV Contrast Coefficient. The correlation coefficients between the defoliation level and the computed texture parameters range between 0.1 and 0.7 (Table 3). The correlation with the pixel value parameters are relatively low, especially in case of mean pixel value (r<0.4). Higher

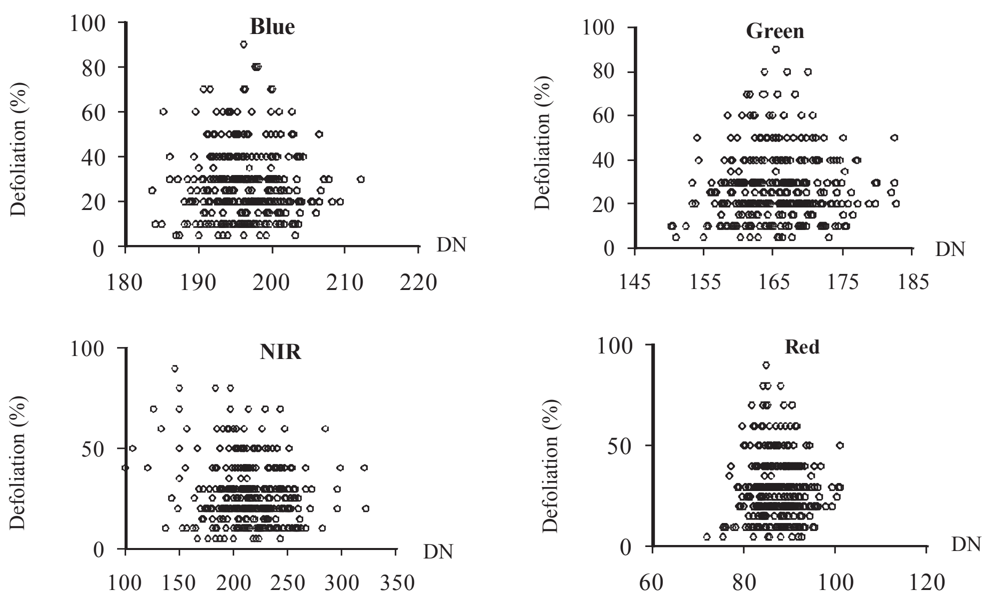

Figure 3 Relation between the average defoliation of the trees within the stand and the GLCM Correlation coefficient (near infrared image)

Table 2 The results of the variance analysis on the hypothesis that the spectral response of the of the silver fir trees is influenced by the crown position of the tree (Kraft classes)

Spectral channel	Average pixel values for each Kraft class				F_{exp}	$F_{t\,0,05}$	$F_{t\,0,01}$	$F_{t\,0,001}$
	I	II	III	IV				
Blue	197.0	196.2	196.4	197.3	0.18303			
Green	166.5	164.8	164.8	166.2	0.85858			
NIR	227.9	215.2	210.2	216.5	4.75086	2.6449	3.8702	5.6111
Panchromatic	151.9	144.9	143.4	148.7	2.30196			
Red	88.1	86.9	86.3	87.7	0.99063			

correlations were obtained in relation to the standard deviations of the pixel values (0.5-0.6), a characteristic that catches better the particularities of the spectral signature variation. The graphic representation of the correlation mentioned above show a linear variation of the bi-dimensional features, easy to model with a linear regression. The correlations are important, especially taking into consideration the relatively low correlation coefficients between the values of the mentioned texture parameters, showing low multicolinearity (correlation between explanatory variables). As mentioned in the methodology, in order to have more reli-

Table 3 Correlation coefficients between the forest health parameters and a part of the texture parameters computed

Texture parameter	Defoliation	g1	g2	g3
GLCM Homogeneity (blue)	-0,493	0,073	-0,401	-0,478
GLCM Contrast (blue)	-0,592	-0,136	-0,430	-0,477
GLCM Dissimilarity (blue)	-0,581	-0,100	-0,376	-0,455
GLCM Entropy (blue)	0,618	-0,074	0,424	0,518
GLCM Ang 2nd moment (blue)	-0,627	-0,022	-0,486	-0,555
GLCM Mean (blue)	0,088	-0,141	0,077	-0,098
GLCM Homogeneity (green)	-0,428	0,039	-0,291	-0,460
GLCM Contrast (green)	-0,535	-0,299	-0,511	-0,502
GLCM Entropy (green)	0,564	-0,119	0,439	0,483
GLCM Ang 2nd moment (green)	-0,628	0,019	-0,507	-0,546
GLCM Mean (green)	0,007	-0,456	-0,117	-0,221
GLCM Homogeneity (NIR)	0,425	0,150	0,347	0,562
GLCM Contrast (NIR)	-0,553	-0,269	-0,605	-0,626
GLCM Dissimilarity (NIR)	-0,567	-0,236	-0,576	-0,624
GLCM Entropy (NIR)	0,076	-0,294	0,048	0,005
GLCM Ang 2nd moment (NIR)	0,037	0,355	0,069	0,220
GLCM Mean (NIR)	-0,175	0,235	-0,018	-0,251
GLCM Homogeneity (Pan)	0,616	0,034	0,447	0,652
GLCM Contrast (Pan)	-0,609	-0,070	-0,530	-0,603
GLCM Dissimilarity (Pan)	-0,607	-0,058	-0,505	-0,609
GLCM Entropy (Pan)	-0,530	-0,231	-0,401	-0,638
GLCM Ang greennd moment (Pan)	0,585	0,026	0,353	0,636
GLCM Mean (Pan)	-0,248	0,358	0,091	-0,086
GLCM Contrast (red)	-0,513	-0,419	-0,555	-0,512
GLCM Dissimilarity (red)	-0,502	-0,391	-0,548	-0,533
GLCM Entropy (red)	0,564	-0,054	0,471	0,561
GLCM Ang greennd moment (red)	-0,617	-0,047	-0,535	-0,596
GLCM Mean (red)	-0,001	-0,335	0,016	-0,026
GLDV Entropy (blue)	0,573	-0,021	0,458	0,471
GLDV Contrast (blue)	-0,569	-0,136	-0,430	-0,477
GLDV Ang 2nd moment (green)	-0,663	-0,078	-0,563	-0,704
GLDV Contrast (green)	-0,505	-0,299	-0,511	-0,502
GLDV Mean (all dir) (Pan)	-0,595	-0,058	-0,505	-0,609

Note: The significance limits for the correlation coefficients are 0.482 (0.05), 0.606 (0.01) and 0.725 (0.001) able models, the basal area of affected trees was used in the modeling process (Fig. 4).

Basal area and the texture parameters proved to be slightly related, especially for the basal area of highly affected trees (crown defoliation percentage more than 60%). Lower correlations were noticed in the cases of the basal area of trees with defoliation percentage higher than 20 %, with a much larger variability of the data.

The general variation trend is specific for each texture parameter; except for the GLDV Angular 2nd moment. In each case, the variation lines tend to be parallel, fact shown also by the similar slope parameters (explanatory variable regression coefficient).

The texture parameters taken into account are mainly computed on the near infrared and panchromatic spectral channels, showing the high sensitivity of these spectral channels to the changes in vegetation structure. The bidimensional variation charts show a good separation of stands with a relatively high number of intensely affected trees, a separation needed for management decision support.

Discussion

The forest decay process is a complex phenomenon with various implications on ecosystem structure and on the physiological processes that are developing within a forest stand. An accurate analysis should be performed at different levels, due to its different effects. The remote sensing methods are not able to determine the cause of the forest decay process, but only to identify the areas where the symptoms of the phenomenon are manifesting (Franklin 2001).

In the tree-level analysis, the high local variability of the IKONOS images surpasses the influence of the health status on the spectral response. As shown in the variance analysis (Table 2), the relative position of the crown is influencing the pixel values corresponding to each crown. The differences in spectral reflectance are explicable if we take into account the method of tree top identification mentioned in the literature - by determining the local maximum of the spectral response (Larsen 1997, Korpella et al. 2006).

The most sensitive channel of the IKONOS image is the near infrared, as shown also by the analysis of the histogram of pixel value distribution for the image taken in this spectral channel. Usually, a high variability in the histogram shows good sensitivity of the sensor to the diversity of the active reflection surfaces in

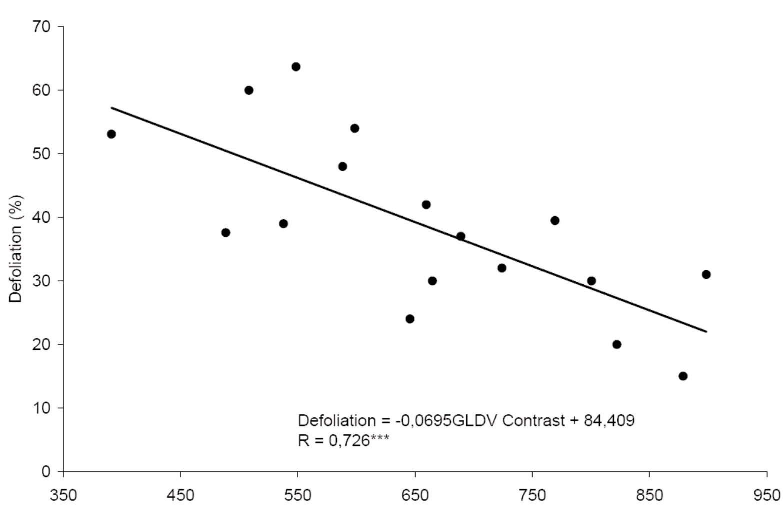

Figure 4 The relation between the average defoliation of the trees within the stand and the GLDV con trast (near infrared image)

the study area (Lillesand & Kiefer 2000, Tso & Mather 2001) (data not shown).

Taking into account the variability and texture parameters of the images corresponding to the affected stands yield better results than the simple pixel based analysis. An interesting fact, noticeable on the graphics, it is the direction of variation. For example, in case of standard deviations, the variation of the defoliation percent is directly proportional, meaning that the defoliation percent increases with the variability of the pixel values. In other cases represented by the GLCM and GLDV texture features, the higher is the average defoliation percent - the higher is the correlation and the lower is the contrast coefficient. This could be explained by the fact that the standard deviation characterizes the whole set of data (the entire statistic population) and it is being affected by extreme values (values that are very distant due to the high variability of the IKONOS image). On the other hand, the texture parameters take into account the local variation of the pixel value within a matrix containing data from neighboring pixels and offering a more accurate image and a more accurate quantification of the texture variations. In this context someone can notice a high correlation coefficient between the defoliation degree and the maximum values of the pixels in each image object. The information is important, but the characteristics mentioned have less stability than the parameters characterizing the pixel value distribution on the entire image object (in certain situations some objects with high spectral reflectance found on the ground - rocks, disseminated broadleaved tree species - could induce very high pixel values). The minimum pixel value is not significantly correlated with the defoliation. As usually observed (Franklin 2001), minimum values are mostly resulting from the gap or shadow areas (data not shown).

The use of the basal area of trees with a certain defoliation percentage offer results that are easier to interpret due to the cumulative character of the data. The strong correlations between the texture parameters and the basal area of the trees with more than 60% foliage loss is important in identifying the trees with a high intensity of the decay phenomenon. These are, practically, the stands that require immediate measures of control, by extracting the affected trees and completing the natural regeneration (the affected silver fir stands have low regeneration capability)(Barbu 1991). From a statistical point of view, we can notice that the variability of the basal area of the affected trees tends to decrease with the increase of the limit set in the computation - the lowest variability is observed in the of trees with more than 60% defoliation, meaning that it can be used as a stable indicator of silver fir stands in respect to remote sensing means. The using of higher limits (70, 80%) showed less representativity of the defoliation process and much lower correlations (data not shown).

For further use in research, the parameters that had the highest values of the correlation coefficient can become a criterion for the image classification process in texture analysis software. Within this process, one must consider using a high scale parameter in order to apply the method at the same spatial scale (the model is designed in the conditions of entire stands or homogeneous portion of a stand). The image objects having certain defoliation percentage can be used as training areas for the classification process within the methods offered by the program - the nearest neighbor method and the maximum likelihood membership function.

These estimations of the defoliation degree are sometimes considered subjective due to the visual interpretation. For improving the accuracy someone can find in the literature ground and photo interpretation keys for different species and defoliation degrees (Műller & Rudolph 1998, Gross et al. 2000), keys used in the terrestrial data collection. In the usual inventory works, five classes of the defoliation are used in accordance with the growth losses caused by the defoliation (Giurgiu 1979), with more accurate determination. In this case, foliage loss percentages were used because of the continuous character of the values and more divers possibilities of statistical processing and interpretations (Horodnic 2003).

Conclusions

The multilevel analysis of the images against field data has revealed the following conclusions.

The simple pixel based analysis is not sufficient for the characterization of the Silver fir decay phenomena.

The variation in spectral response is correlated more to the position of the crown than to the parameters of crown health (on IKONOS images).

The stand level analysis could offer more detailed information about the phenomenon, especially if the pixel value spatial variations are taken into account.

Strong correlations have been noticed between the defoliation percentage and the GLCM - GLDV parameters.

Texture based classification can offer good accuracy for the Silver fir stands health if using representative training areas.

The correlation analysis applied on the data regarding the silver fir defoliation and the texture feature extracted for the whole stand is necessary prior to the image classification, especially if using texture features in the process. This is important because otherwise the only possibility to verify the classification is the accuracy matrix, which involves an important effort. Besides that, the computation of the GLCM and GLDV require a high computational power and sometimes a relatively long period of time. Taking into account that sometimes one must try even hundreds of classification types and, in case of texture analysis software, a diversity of multiresolution segmentation parameters is much more efficient to identify the optimum spectral combination and the type of relations between the health parameters and the analyzed features.

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Annex: The regression parameters for the relations between the basal area of silver fir trees with more than 60 % foliage loss

Regression Statistics – correlation between g3 and GLDV Ang, 2nd moment

R	0.703703	Standard Error	3.800967		
R Square	0.495198	Observations	17		
Adjusted R Square	0.461545				
ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	212.5877	212.5877	14.714649	0.00162
Residual	15	216.71026	14.447351		
Total	16	429.29796			
	Coefficients	*Standard Error*	*t Stat*	*P-value*	
Intercept	356.9099	91.367734	3.9063012	0.0014031	
GLDV Ang, 2nd moment	-1348.502	351.54143	-3.8359678	0.0016197	

Regression Statistics – correlation between g3 and GLCM Entropy

R	0.637714	Standard Error	4.120774		
R Square	0.406679	Observations	17		
Adjusted R Square	0.367124				
ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	174.58632	174.58632	10.28141	0.005885
Residual	15	254.71164	16.980776		
Total	16	429.29796			
	Coefficients	*Standard Error*	*t Stat*	*P-value*	
Intercept	158.8684	47.547096	3.3412849	0.0044644	
GLCM Entropy	-15.966	4.9793163	-3.2064637	0.0058854	

Regression Statistics – correlation between g3 and GLCM Homogeneity

R	0.706187	Standard Error	3.787762		
R Square	0.4987	Observations	17		
Adjusted R Square	0.46528				
ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	214.09087	214.09087	14.922199	0.001533
Residual	15	215.20709	14.347139		
Total	16	429.29796			