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Geostatistical approach to spatial analysis of forest damage

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Abstract

Background and Purpose: *Significantly increased forest damage has recently been observed in the Republic of Croatia, as well as increased proportion of unplanned felling in prescribed cuts, which has negative repercussions for sustainable management. The objective of this study was is to explore the possibilities of simple and reliable detection, inventorying (mapping) and monitoring forest health condition by means of color infrared (CIR) imagery and geostatistical methods.*

Materials and Methods: *Four trees (crowns) closest to the point of the raster (100 × 100 m) which was set up in the digital orthophoto for the area, were interpreted in CIR images. Forest damage indicators, mean damage and damage index were calculated for the whole area under observation. The assessment and identification of spatial distribution of these damage indicators were performed using raster point data, from which a random (966 points) and a systematic (445 points) sample were created. The results on forest damage acquired by interpreting CIR images were used for geostatistical analysis. A model of theoretical semivariograms provided parameters which were used for interpolation of both damage indicators with ordinary kriging. Continuous maps of damage degree distribution were then constructed. The results of interpolation were tested with the cross-validation method.*

Results and discussion: *Damage indicator maps are the result of the following: data variability, sampling intensity and method, form of experimental and theoretical semivariograms which were subsequently used to compute kriging matrices, method of selecting a particular semivariogram, assessment accuracy, the choice of interpolation methods (kriging, cokriging, stochastic simulation, inverse distance, etc.). Tree damage generally does not have regular, but rather random spatial distribution. This is why the primary aim in identifying forest damage is to incorporate the whole area of interest into sampling. Sampling intensity should be adapted to the required accuracy and to the time and funds at our disposal.*

Conclusions: *This research relies on the application of CIR aerial photographs and geostatistical tools in spatial analysis of forest damage. Continuous maps of damage indicators acquired with kriging provide a better insight into the spatial distribution of damage than do thematic maps obtained by interpreting CIR aerial imagery on the basis of a systematic sample (the raster method). Integration of interpretation results of CIR aerial images and geostatistical approach ensures a more precise distribution of damage indicators, and consequently, the possibility of better spatial analysis of the occurrence, trends and development of damage in the study area.*

INTRODUCTION

Aerial photographs and satellite imagery have been used to monitor forest condition and identify stand parameters since the mid-twentieth century. These possibilities have since been additionally enhanced by the development of the global positioning system (GPS), the geographic information system (GIS), and geomathematical (neural and geostatistical) tools.

The concept of forest decline relates to the dieback of those trees which are in the prime of their life but for certain reasons die earlier *(1)*. Forest damage inventories are commonly performed by means of terrestrial methods. Remote sensing techniques are considered a powerful tool in the automation and improvement of such inventories because they improve their rationalization. The characteristics of color infrared aerial photographs (CIR) are highly conducive to making inventories of forest vegetation, forests and forest trees in particular *(2, 3, 4, 5)*.

Since aerial photographs are frequently one of the layers within a GIS-investigated area, the results obtained from the interpretation of CIR aerial images are usually presented in the form of thematic maps of spatial damage distribution.

Geostatistics is applied in diverse fields that deal with spatial data analysis. As a special branch of applied statistics, geostatistics describes spatial data (samples) and provides value assessments in unsampled sites. It is based on the concept of regionalized variable (which means that the value of the variable depends on the sampling site). The geostatistical approach assumes that the relationships among the sampling data depend only on their spatial relationship (spatial location), such as distance and direction. For spatially closer samples, the variations are presumably smaller in comparison with spatially more distant samples, as described in the earliest geostatistical studies *(e.g. 6, 7)*. While statistical analyses of spatial data perceive the location value as an external factor, spatial analysis recognizes the location as a feature of, and a logical link, in spatial data interaction. For this reason spatial analysis is a useful tool in the study of natural resources *(8)*.

The application of geostatistics in remote sensing is based on the assumption that the digital number (registered in the image) is a regionalized variable, i.e., it is a variable that presents spatial distribution and spatial variability function defined by the variogram *(9)*. Curran *(10)*, Woodcock *et al. (11, 12)* published the first results in the field of geostatistics application in remote sensing. Initial research was followed by new research activities *(9, 13, 14, 15, 16)*, which stress the usefulness of applying geostatistical methods in remote sensing. Zawadzki *et al. (17)* gave an extensive survey of geostatistical applications in forest ecosystem research by using remote sensing imagery, and divide them into three close fields: (a) specific properties of geostatistical measures of spatial variability, (b) determination of biophysical parameters using semivariograms, and (c) forest classification methods based on spatial information.

The application of geostatistics in forest damage assessment to date can be divided into terrestric, where spatial distribution (assessment) of damage is determined by means of terrestric data (e.g. national forest damage inventories), and assessments performed by means of remote sensing data.

Köhl & Gertner *(18)* applied geostatistics to assess forest damage using the Swiss Forest Damage Inventory data. In their view, the geostatistical approach is highly suited to the description of spatial distribution of forest damage. By comparing the results of inventories made at different time periods, they concluded that the geostatistical approach is useful for epidemiological studies. Franklin *et al. (19)* and Bowers *et al. (20)* used semivariograms acquired from panchromatic (resolution 10 m) and multispectral SPOT HRV images (resolution 20 m) to assess damage in balsam fir (*Abies balsamea*) stands infested by the balsam woolly adelgid (*Adelges piceae*). They concluded that spatial statistics calculated with geostatistical methods complement the data acquired from the spectral sample. As expected, when calculated for the unthinned, in relation to the thinned, stands, as well as for damaged, in relation to undamaged, stands, the semivariograms differ by the curve form, sill, nugget and range. Lévesque & King *(21)* used semivariogram analyses of multispectral and multi-temporal high-resolution aerial imagery (0.25 m, 0.50 m, 1.0 m) to evaluate mixed forest damage at an acid mine site. Pixel sampling by means of near IR band was conducted on the forest canopy scale and tree crown scale in the form of matrices and transects (in two perpendicular directions), whereby omnidirectional and directional semivariograms were calculated. Their research shows the usefulness of semivariogram curve interpretation and statistical analysis in discriminating damage variations of forest structure.

Research is also under way in other forestry fields: entomology *(22)*, production and nutrition *(8)*, pedology *(23)*, analysis of the kriging method in the interpolation of species distribution from ICP plots *(24)*, geostatistical simulation of bark beetle infestation for forest protection purposes (25), forest inventory, stand parameter evaluation and determination of their mutual spatial relationships *(26, 27, 28, 29)*.

Research area includes forests in the northern part (flow) of the River Sava plain, located in Lonjsko Polje Nature Park. These forests are in the management unit »Josip Kozarac«. In terms of ecology and management, the forests of this management unit are highly valuable natural stands of pedunculate oak, narrow-leaved ash and the accompanying species. Significantly higher forest damage has recently been observed in the Republic of Croatia and the study area, and so has a larger proportion of unplanned felling in prescribed cuts, which has negative repercussions for sustainable management. The objective of this study was to explore the possibilities of simple and reliable detection, inventorying (mapping) and monitoring forest health condition by means of CIR imagery and geostatistical methods.

MATERIAL AND METHODS

Four trees (crowns) closest to the point of the raster (100 × 100 m) which was set up in the digital orthophoto (DOP) for the area, were interpreted in CIR images. Forest damage indicators, mean damage (MD) and damage index (DI) were calculated for the whole surveyed area *(30)*.

$$MD\% = \frac{\sum f_1 \cdot x_1}{\sum f_1} \tag{1}$$

Based on complex arithmetic mean, where tree numbers in different damage degrees act as weights, formula (1) provides the mean damage degree in the observed area (sample), where:

f_1 – the number of trees in i-damage degree

x_1 – i-stage interval centre in the damage degree scale for single trees

x_0=5%; x_1=17.5%; $x_{2.1}$=32.5%; $x_{2.2}$=50%; $x_{3.1}$=70%; $x_{3.2}$=90%; x_4=100%

$$DI\% = \frac{\sum f_{(2-4)}}{\sum f_{(0-4)}} \cdot 100 \tag{2}$$

Damage index (2) shows the percent share of trees in the sample which were classified into the damage degree over 25 %. Damage index can be equated with the category of significantly damaged trees, which is common in terrestric damage assessments. The results of forest damage acquired by interpreting CIR images were used for geostatistical analysis with standard tools. These tools were used in their research by Isaaks & Srivastava *(31),* Goovaerts *(32),* Malvić *(33),* and others. The assessment and identification of spatial distribution of these damage indicators were performed using raster point data, from which a random and a systematic sample were created. Every fourth raster point was used in the random sample, totalling 966 points. The systematic sample is a reduced raster point network (300 × 300 m) containing 445 points in all.

First, semivariogram surface maps were made in order to determine anisotrophy. A semivariogram was used as a measure of spatial dependence between the measured points. Experimental and theoretic semivariograms were then computed. The experimental semivariogram was obtained after multiple testing of lag distances. A model of theoretical semivariograms provided parameters which were used for the interpolation of both damage indicators with ordinary kriging. Continuous maps of damage degree distribution were then constructed. The results of interpolation were tested with the cross-validation method *(34, 35)*. The method is based on excluding a value measured in a selected point and determining a new value in the same point, also taking into consideration the remaining dataset. The procedure was repeated for all locations. The square root of the mean error presented in equation 3 was then calculated,

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[(meas.val(x_i) - ass.val.)\right]^2} \tag{3}$$

where: RMSE = root mean square error (cross-validation) of the selected method, meas. val. = measured value of the selected variable, ass. val. = assessed value of the selected variable.

Three software programmes were used for variogram analyses, mapping with ordinary kriging, and statistical calculations. These are VARIOWIN 2.21 *(36),* SURFER 8.0™ and STATISTICA 7.1™.

RESEARCH RESULTS AND DISCUSSION

Semivariogram surface maps for mean damage and damage index did not indicate the presence of anisotrophy. Figure 1 shows semivariogram surface maps of damage index for the random sample and mean damage for the systematic sample.

Since no anisotrophy was identified, an experimental omnidirectional semivariogram was computed for both damage indicators after testing lag width, i.e., the lag distance of 100 m in the random sample, and 350 m in the systematic sample (Figure 2).

The points of experimental omnidirectional semivariograms grow relatively rapidly; in other words, they

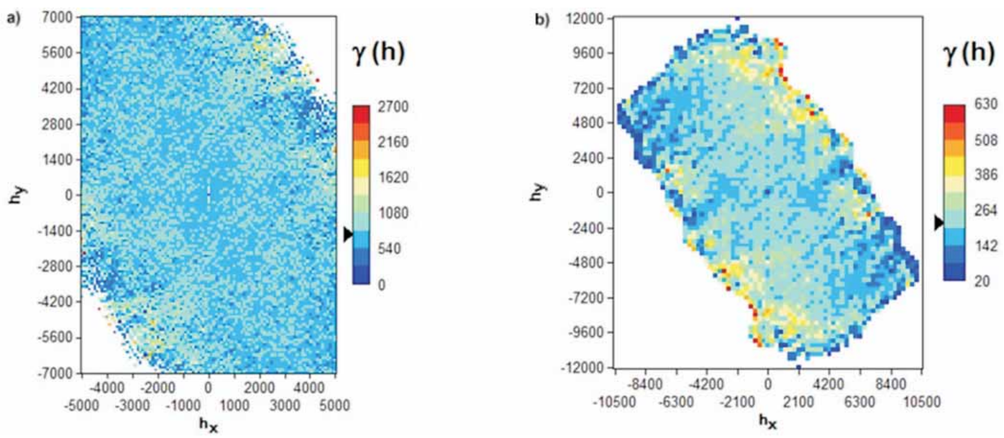

Figure 1. *Semivariogram surface map: a) damage index (random sample), b) mean damage (systematic sample).*

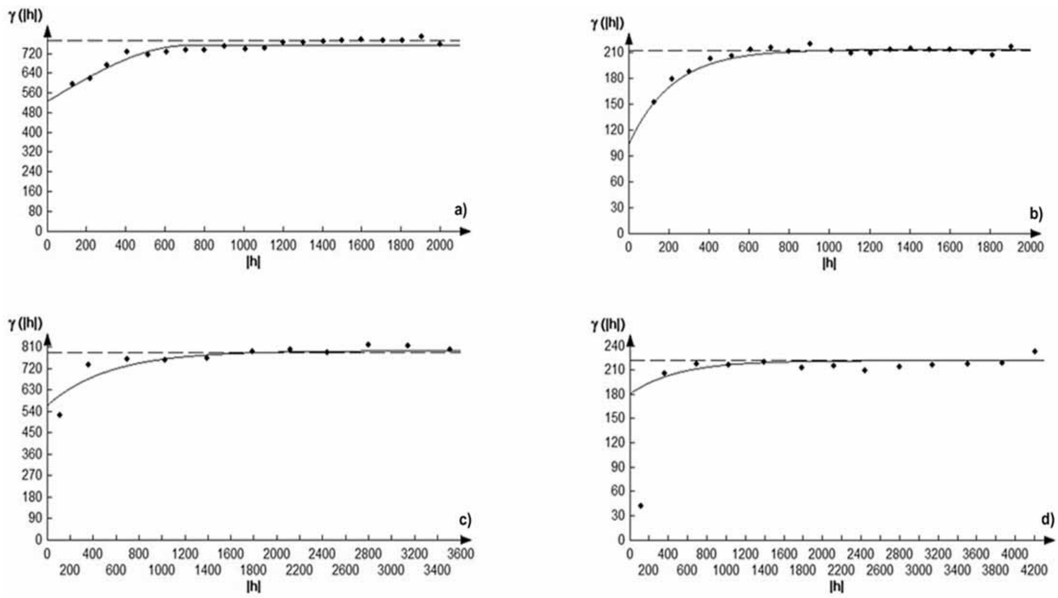

Figure 2. *Experimental and theoretical omnidirectional semivariograms of damage index (a – random sample, c – systematic sample) and mean damage (b – random sample, d – systematic sample).*

show a high nugget effect. They may, nevertheless, be considered reliable because they contain a large number of paired data. Experimental semivariograms were approximated with theoretical curves (Figure 2) whose models and semivariogram parameters are presented in Table 1.

All theoretical semivariograms contain a relatively high nugget effect; expressed in percentages, it is a minimum of about 50% of the sill. The nugget share in the total variance is the lowest in the random sample of mean damage, but is also lower in the random sample in comparison with the systematic sample in general. The nugget primarily indicates large and sudden differences (changes) in the values of close samples (variability), or estimation errors in any raster point. The nugget is generally equalized and is related directly to the points (evaluations) which are closer to the origin of the semivariogram. In general, the lower width of the semivariogram class (lag) results in experimental semivariograms with fewer oscillations. This allows for the construction of a more reliable theoretical semivariogram, which also enables better nugget determination. For this reason, the nugget effect is higher in the systematic sample which has a greater width of the semivariogram class. Therefore, higher nuggets result in a less reliable assessment in the points in which there are no measurements. Consequently, a random sample with a lower nugget effect has better index and mean damage evaluations (Table 1, Figure 2). For both damage indicators, the range is bigger than the sampling interval.

A bigger range has been calculated for the damage index, so this damage indicator has better spatial correlation in relation to mean damage. In case that the range is smaller than the sampling interval, the solution should be sought in a larger number of samples at smaller distances, or, if this fails, the assessment methods should be changed *(29)*. The range (spatial autocorrelation) for the damage index and mean damage was higher in the systematic sample. Actually, due to larger distances between the points (300 × 300 m), this sample had a lower number of assessments, and consequently, lower data variability. On the other hand, the use of systematic sample data with fewer assessments and a higher nugget effect in the interpolation (mapping) of damage index and mean damage with the kriging method results in poorer assessment (Figure 5) in comparison with continuous maps of random sample with a larger number of assessments. Therefore, the range value (size) is the result of data variability and distances between

TABLE 1

Values of theoretical semivariograms for damage indicators.

Damage indicator	Model	Nugget	Range	Sill
Damage index (Random sample)	Spherical	530 (70,01%)	714	757
Mean damage (Random sample)	Exponential	104 (48,37%)	645	215
Damage index (Systematic sample)	Exponential	569 (71,30%)	1615	798
Mean damage (Systematic sample)	Exponential	182 (81,61%)	1492	223

the points of assessment. For this reason, the description of variables (index and mean damage) and processes (damage degrees) depend on sampling intensity, i.e. the sampling scale. The parameters (model, sill, range) in Table 1 were used to compute the kriging matrices, or in other words, weight coefficients appertaining to the measuring data. In this way, a spatial distribution map of damage index and mean damage was obtained with ordinary kriging (Figure 5). Damage assessment with the kriging method was tested with cross-validation. The root mean square error was used as a numerical measure of assessment accuracy (Table 2).

The root mean square errors calculated with the cross-validation procedure (Table 2), as well as statistical indicators (Figure 3) show that the assessment of damage index and mean damage, i.e. interpolation with kriging, is a more acceptable method for random sample data. Both sampling approaches show high correspondence with statistical values of visual assessment, mean damage and damage index in CIR aerial photographs. For this reason, both these sampling methods are applicable for the assessment of average (basic) forest damage indicators. Note should be made of the fact that statistical indicators in the random sample differ slightly from the systematic sample which has half the number of assessments. This gives the latter precedence over the former from the aspect of efficiency.

Due to the fact that a GIS model has been made for the study area, it was possible to spatially visualize the

TABLE 2

Cross-validation results of damage index and mean damage.

Sample	Random		Systematic	
Damage indicator	DI	MD	DI	MD
RMSE	29.13	14.26	30.39	15.28

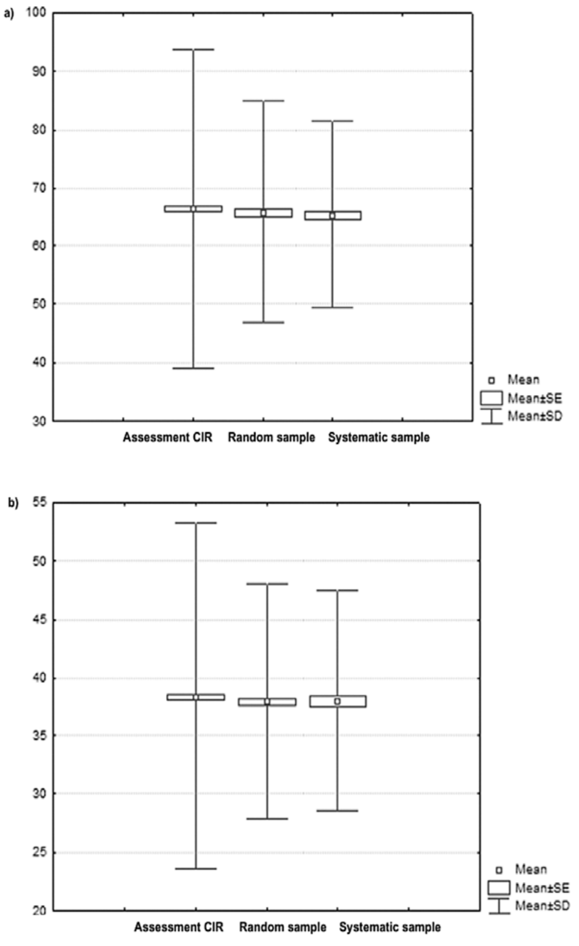

Figure 3. *Box & Whisker diagram of damage index (a) and mean damage (b).*

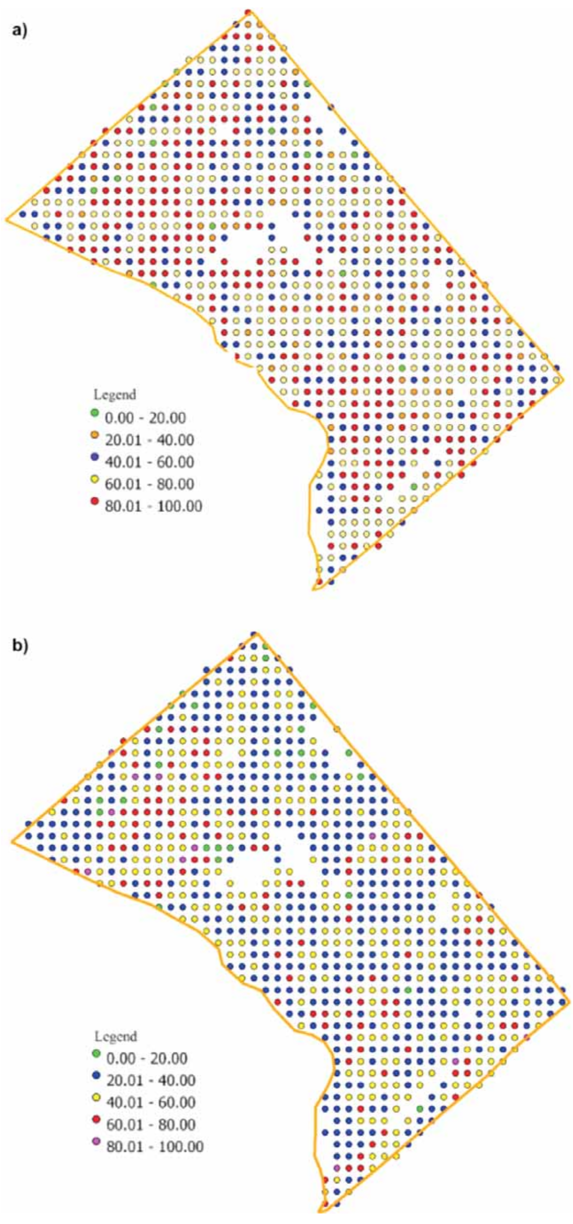

Figure 4. *Results of visual assessment from CIR aerial photographs: (a) damage index and (b) mean damage.*

obtained data. Actually, for the estimation of a regionalized variable at locations where no data were taken, it is important to know whether sample data are representative for the target point or target area. The representativeness can be tested by the use of a GIS. To perform such tests, values of a certain parameter in the sample area are taken from thematic map or grid layer *(37)*. For this reason, continuous maps acquired with the ordinary kriging technique (Figure 5) were compared with thematic maps of spatial distribution of damage indicators acquired with the interpretation of CIR aerial imagery (Figure 4).

Figure 4 presents the results of visual assessment (raster method) of damage index and mean damage from CIR aerial images (a part of the study area). There is striking overlap between spatial distribution of visual assessment results and continuous maps (Figure 5) of certain index degrees and mean damage. In this respect, continuous maps of damage indicators obtained by using random sample data have priority. The user has a larger amount of information on spatial distribution of damage index and mean damage and on their respective degrees. In order to compare and validate continuous maps, areas of particular damage degrees obtained from random sample data were vectorized.

In terms of damage index, the areas were delineated into three categories: (>80%), (60–80%) and (40–60%). The points with lower damage degrees (20–40%) were either rare or were predominantly distributed on an individual basis (>20%). In terms of mean damage, the areas were also vectorised into three categories: (60–80%), (40–60%), and (20–40%). The share of the remaining two damage degrees relate to individual points.

In the process of vectorization, i.e. visual interpretation of assessment results (raster method), it is not possible to take into account the impact of the value of the surrounding points. It is rather difficult to determine the boundaries between damage degrees with vectorization, but also the effect (range) of a particular point in space. This is why there are some differences between visual delineation and the obtained maps of forest damage.

Since it is almost impossible to reliably interpret spatial distribution of damage index and mean damage (as

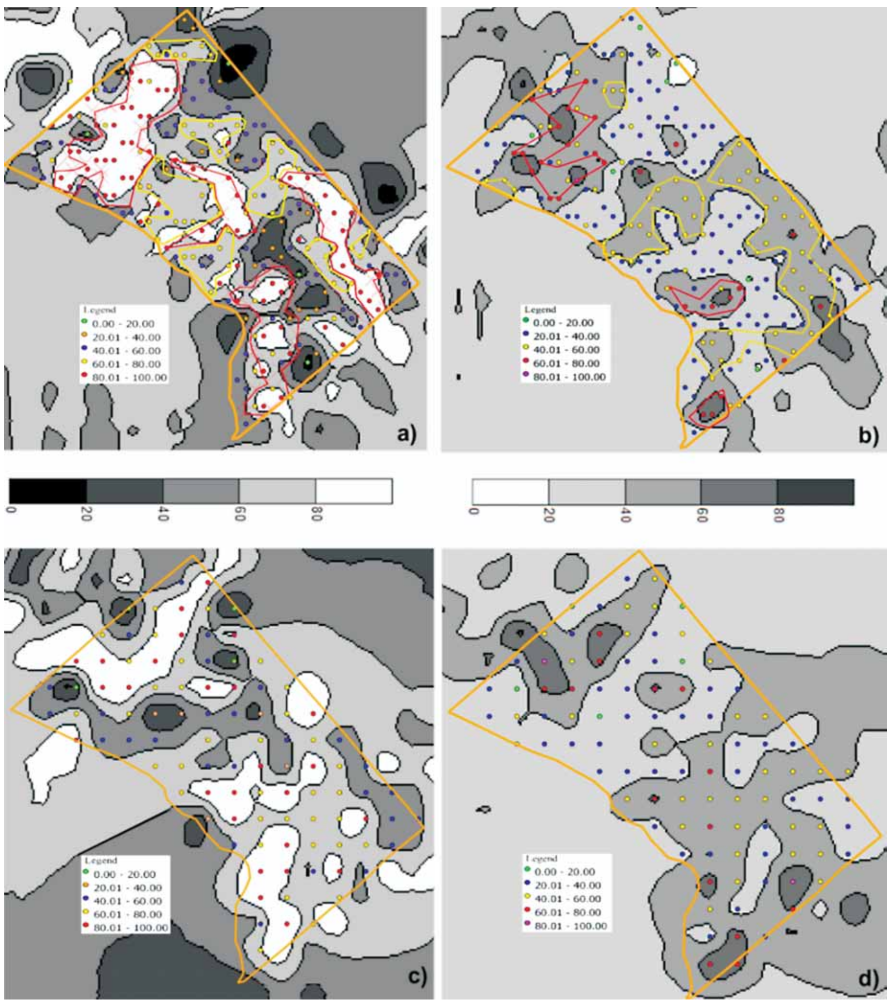

Figure 5. *Map of spatial index distribution of damage index (a – random sample, c – systematic sample) and mean damage (b – random sample, d – systematic sample).*

statistical indicators of forest damage) with vectorization (sample points), their continuous presentations and analyses are highly acceptable, as this enables the monitoring of local or regional (regions, management units) occurrence, development and trends in forest damage in space and time. According to Tikvic *et al. (38),* the map of spatial distribution of forest damage can be a good base for forest management planning in future, which should be adjustable to the condition and vitality of stands.

Damage indicator maps are the result of the following: data variability (random, partially regular or regular changes in the value of the observed variable in space), sampling intensity and method, form of experimental and theoretical semivariograms which were subsequently used to compute kriging matrices (the ordinary kriging method was selected for this research), method of selecting a particular semivariogram (since this procedure always involves uncertainty because the number of possible choices of semivariogram curves is practically infinite), assessment accuracy, the choice of interpolation methods (kriging, cokriging, stochastic simulation, inverse distance, etc.).

Despite the forest management activities aiming to regulate and improve the structure and quality of the stand, forest damage has been occurring intensely and continually over time. It does not have regular, but rather random spatial distribution and intensity. Monitoring the intensity and dynamics of tree damage in stands is one of the necessary ways to determine certain patterns of this phenomenon and to improve the management of forests with a disturbed stability *(38)*.

This is why the primary aim in identifying forest damage is to incorporate the whole area of interest into sampling. Sampling intensity should be adapted to the required accuracy and to time and funds at our disposal.

CONCLUSIONS

This research relied on the application of color infrared (CIR) aerial photographs and geostatistical tools (semivariogram surface maps, semivariograms, continuous maps of spatial distribution) in spatial analysis of forest damage. Continuous maps of damage indicators acquired with kriging provide a better insight into the spatial distribution of damage than do thematic maps obtained by interpreting CIR aerial imagery on the basis of a systematic sample (the raster method). The raster method does not take into account the impact of the values of adjacent points. In other words, it is difficult to assess the boundary between particular damage degrees because the result is related only to the surface value of a raster point, in this case to the area of 1 ha. Integration of interpretation results of CIR aerial images and geostatistical approach ensures a more precise distribution of damage indicators, and consequently, the possibility of better spatial analysis of the occurrence, trends and development of damage in the study area.

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