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Quantifying and mapping urban trees' decay severity using thermal and spatial indices: implications for tree hazard assessment and management

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Abstract. Wood decay, a crucial factor in tree stability, is an internal long-term interaction between fungi and tree that leads to the disruption of energy flow, temperature abnormalities on the tree's surface, and possible tree mortality, especially when the decay extent is close to the threshold of 33%. In this study, arboreal vegetation species' stability in two urban parks in the city of Mytilene, Greece, was evaluated, in accordance with the tree failure criterion, by measuring the trees' morphological traits along with their decay severity. Thermal indices were developed by analyzing tree trunks' temperature data, and strength loss equations associated with wood decay were applied for each tree. Temperature spatial dependence across each tree's trunk was estimated using Moran's I index, while statistically significant spatial clusters were assessed using local spatial autocorrelation statistics. Relationships between tree stability, thermal, and spatial indices, were established using linear and logistic regression models. Finally, the Getis-Ord Gi* statistic was used for the recognition of hazardous tree hotspots in the urban parks, and the kriging geostatistical procedure was applied for mapping their spatial extension. The results have shown that thermal and spatial indices can sufficiently explain decay severity, identify hazardous trees, and contribute to tree health assessment for specialized park management.

Keywords: Urban tree stress, infrared thermography, geospatial analysis

1. Introduction

Urban forests are complex dynamic ecosystems created by the interaction of anthropogenic and natural processes which generate critical benefits to both humankind as well as urban wildlife. They provide a wide range of ecosystem services; (a) provisioning, i.e. production of wood, fuel, and water supply, (b) regulating, i.e. recycling of nutrients, air quality regulation, controlling local microclimate, (c) supporting, i.e. circulation of elements, primary production, soil formation, habitat function, hydrological cycle, and (d) cultural, i.e. recreational activities and ecotourism. Moreover, as they age, they provide increasingly diverse wildlife habitats and microhabitats as a result of developing features, such as cavities and decaying wood. However, tree-related microhabitats, structural defects, and tree aging are crucial factors that may jeopardize their mechanical integrity and stability, with consequences for both wildlife and public safety. Therefore, tree health assessment is an essential task in supporting decision-making tree arborists, so that they will develop an effective management plan to protect and conserve the trees from possible failing issues. In parallel, identifying hazardous tree hotspots and evaluating their risk probability, are fundamental requirements for urban forest management. In this context, several (a) tools, classified according to their measurement speed, resolution and accuracy, and (b) methodologies, characterized as destructive and non-destructive, are presented in the international scientific literature (Vidal & Pitarma 2019). Infrared thermography is a fast-growing, non-contact, and non-invasive technique for monitoring, among others, plant species' health state, as it can estimate accurately vegetation disturbances that may compromise their resilience. Thermal data are non-invasive indicators, useful in obtaining reliable information without directly affecting the ecosystems and their enclosed species. They can be used to identify disturbances, assess the growth of plant species, and monitor plants' physiological status (Dragavtsev and Nartov 2015). In woody vegetation species, thermal imaging detects the trees' surface temperature distribution and indicates their structural defects and potential disturbances. Moreover, the homogeneous temperature distribution on stems and branches is considered a hallmark of their health state, as deterioration, voids, decay, and structural defects in general, which may occur within their trunks, interrupt the energy flow, and cause temperature abnormalities on their surface (Omran 2017). Wood decay, a crucial factor in tree stability, is an internal long-term interaction between fungi and tree that leads to the disruption of energy flow, temperature abnormalities on the tree's surface, and possible tree mortality, especially when the decay extent is close to a threshold value of 33% (Smiley & Fraedrich 1992). The main aim of this research was to quantify and map urban trees' decay severity using thermal and spatial indices along with the identification of hazardous tree hotspots.

2. Materials & Methods

In this research, 135 trees, concerning three dominant species of arboreal vegetation (*Robinia pseudoacacia*, *Morus alba*, *Melia azedarach*), in two urban parks in the city of Mytilene, Greece, were assessed using a non-destructive screening method: infrared thermography.

2.1. Tree hazard assessment

Arboreal vegetation species' stability was evaluated, in accordance with the tree failure criterion, by measuring the trees' morphological traits along with their decay severity. In particular, in order to identify hazardous trees, a variety of their traits (a) height (H), (b) diameter (D), (c) basal area (BA), (d) crown length (CL), and (e) crown ratio (CR), were measured. Moreover, traits related to their vitality: the number of external indications of rotten wood, missing bark, cavities, and hollows as well as their spreading over the tree (depth, height, diameter), were measured. To evaluate trees' mechanical integrity, structural defects were examined, decay proportion was estimated, and a strength loss equation (**Eq1.**) for each tree (Smiley & Fraedrich 1992) was applied:

Eq.1 $SL\% = d^3 + \left((R \times (D^3 - d^3)\right) * (100 \div D^3))$

where SL = Strength loss, d = cavity diameter, D = diameter of a healthy stem, and R = ratio of the opening of the cavity to stem circumference.

2.1. Infrared thermography

The surface of each tree trunk was photographed during suitable environmental conditions at a specific distance (2.0 m) and height (1.3 m) using a handheld thermal camera (Testo 875-1i, Testo SE & Co. KGaA), with a thermal resolution of < 0.08 °C and a thermal sensitivity of < 50 mK, which extracts images with infrared resolution of 160 x 120 pixels. The thermal camera was calibrated at the exact shooting moment in the field using ambient temperature, relative humidity, solar irradiance, and emissivity values (ε = 0.95) corrected for the tree species under investigation.

2.2 Analysis of infrared images

The infrared images were processed with Testo IR software (v.4.5) in order to discrete the areas of interest (tree trunks) from other objects included in the IR images. To develop thermal indices, tree temperature data were analyzed using ArcGIS software 10.2. Assessing the state of individual traits appearing on tree trunks, which are directly related to their stability (eg signs of decomposition) requires the study of extreme temperature values. Therefore, it was chosen to calculate the range of the temperature difference (T_{range}) of the surface of each tree. Moreover, several spatial statistical tools were implemented in order to examine their spatial clustering (Royle et al. 1981). In particular, to assess temperatures' spatial dependence, the overall degree of spatial autocorrelation across the trees' bark texture, was estimated using Moran's I index. To identify statistically significant spatial clusters of high and low values, two local indicators of the spatial association were used, the Getis-Ord Gi* and the Anselin Local Moran's I (**Figure 1).** Finally, the Getis-Ord Gi* spatial autocorrelation method was used to recognize hazardous tree hotspots in the study area (**Eq.2**) and kriging geostatistical procedure, as an interpolation technique, was applied for mapping the hotspots' spatial extension (**Figure 4**).

Eq.2 $Gi^* = \frac{\sum_{i=1}^{n} w_{ij} x_j}{\sum_{j=1}^{n} x_j}$

Where Gi* = the spatial autocorrelation of an event i over n events, xj = the magnitude of variable x at events j over all n, and wij = the weight value between the event i and j that represent their spatial interrelationship.

2.3. Statistical analysis

All statistical analyses were carried out using SPSS software. Data were expressed as means ± standard deviation (SD) and statistical significance was assumed at the 5% level. Data were evaluated for normality and homogeneity with graphical methods and the Kolmogorov-Smirnov test. Variables concerning trees' stability and vitality, were correlated with the exported thermal and spatial variables. The relevance of linear and logistic regression models was estimated for all the trees' stability and vitality traits along with the thermal variables.

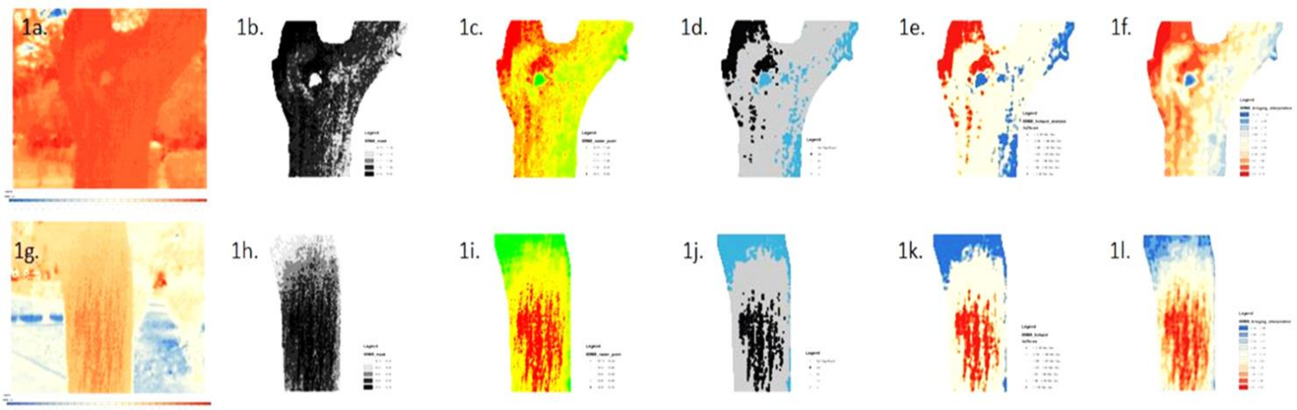

Figure 1. Sample of two *Robinia pseudoacacia* individuals with a wood decay (1a -1f) and without decay (1g - 1l): (1a, 1g) the initial infrared image as a file with .txt extension (feature class was created based on coordinates given in a text file); (1b, 1h) conversion of

the txt. file to a raster dataset; (1c, 1i) conversion of a raster dataset to point features; (1d, 1j) Cluster and Outlier Analysis (Anselin Local Moran's I) and spatial autocorrelation report based on feature locations and attribute values using the Global Moran's I (GMI) statistic; (1e, 1k) Hot Spot Analysis (Getis-Ord Gi*); (1f, 1l) Kriging geostatistical procedure that generates an estimated surface from a scattered set of points with z-values.

3. Results and Discussion

The microclimate on the study area, during the field study, displayed an average temperature of 16.72 °C (SD 1.76), relative humidity 65.2 % (SD 4.04), solar intensity of 325.35 W/m^2 (SD 105.66) and North East wind intensity of 6.23 km/h (SD 1.87). The tree stability, vitality, thermal, and spatial variables are presented in **Table 1**.

Table 1. Descriptive Statistics for urban trees' variables (N = 135)

Variables	Mean	SD
Stability		
Height (cm)	695.70	279.92
Diameter (cm)	38.24	12.02
Basal Area (m^2)	.12	.07
Crown length (cm)	501.40	250.14
Crown ratio	.68	.12
Vitality		
Wood decay (n)	1.54	3.18
Decay height (cm)	36.70	45.17
Decay diameter (cm)	12.82	12.98
Decay depth (cm)	12.78	13.98
Decay proportion	.19	.24
Strength loss (%)	25.54	35.22
Thermal & Spatial		
T_{range} (°C)	1.56	1.17
GMI	.71	.13

3.1. Relationships between tree stability, thermal, and spatial indices

Scatterplots evaluation between T_{range} and Global Moran's Index, as well as T_{range} and trees' morphological characteristics, provided a visual representation of their relationship and indicated linear associations among specific plotted variables related to trees' wood decay; diameter, height, depth, proportion, and strength loss (**Figure 3**). The analysis that was couched from the coefficient of linear correlation, revealed significant associations among the examined variables (**Figure 2**).

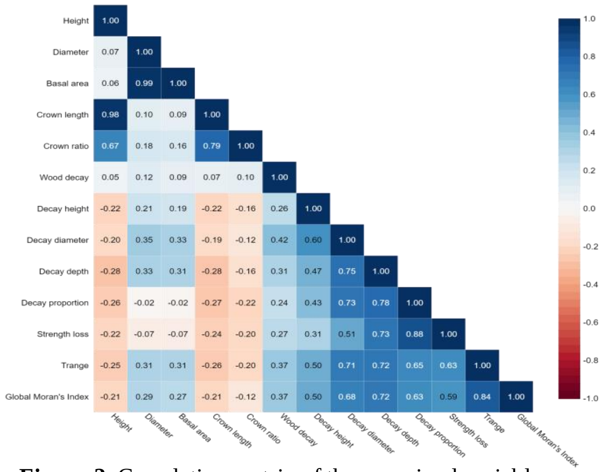

Figure 2. Correlation matrix of the examined variables.

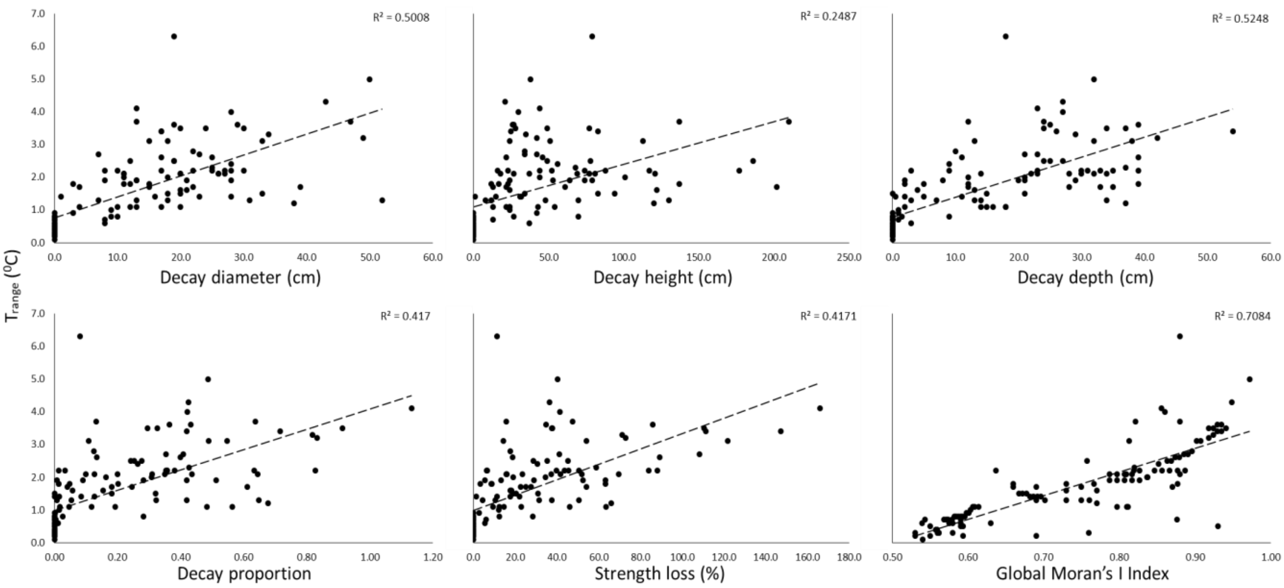

Figure 3. Characteristic scatterplots concerning the linear relationship of urban trees' vitality and spatial variables with T_{range}.

3.2. Logistic regression models for hazardous trees classification

Binary logistic regression models (BLR) were used to examine the probability of thermal and spatial indices to explain the presence or the absence of hazardous trees (trees were designated as hazardous if their strength loss was more than 33%). Regarding T_{range}, the BLR model identified it as the one important factor which best separates hazardous and non-hazardous trees ($p < .0001$; **Table 2**), with a predicted classification accuracy of 88.1% for hazardous and 76.3% for non-hazardous. The area under the ROC curve (AUC = .898; S.E. =.027, 95% CI .846-.950; $p < .0001$), correctly classified hazardous and non-hazardous trees at 89.8% of the time. The Nagelkerke R^2 value indicates that the model explains 47.9% of the total variance of the dependent variable, and the Hosmer - Lemeshow test result reported a chi-square value of 8.076 ($p = .326$) which estimates that the model fits the data at an acceptable level.

Table 2. Logistic regression model log(p/1-p) = 3.540 + (- 1.55 x T_{range}), where B = logistic coefficient; S.E. = standard error of estimate; Wald = Wald chi-square; df = degree of freedom; sig. = significance.

Predictor	B	S.E.	Wald's χ^2	df	Sig.
T_{range}	-1.55	.27	31.49	1	≤.001
Constant	3.540	.568	38.89	1	≤.001

In terms of the spatial index, the BLR model (**Table 3**) presented a classification accuracy of 85.7% for hazardous and 80.6% for non-hazardous, the AUC was .884 (S.E. =.028, 95% CI .829-.938; $p < .0001$), the Nagelkerke $R^2 = .527$, and the Hosmer - Lemeshow test was 5.923 ($p = .656$).

Table 3. Logistic regression model log(p/1-p) = 3.540 + (- 1.55 x Global Moran's Index), where B = logistic coefficient; S.E. = standard error of estimate; Wald = Wald chi-square; df = degree of freedom; sig. = significance.

Predictor	B	S.E.	Wald's χ^2	df	Sig.
GMI	-14.53	2.53	32.86	1	≤.001
Constant	11.91	2.04	33.78	1	≤.001

3.3. Hazardous tree hotspots

The hazardous tree hotspots and coldspots are presented in **Figure 4**. The Gi* statistic, Z-score represented by the red dot (hotspots) indicates the statistical significance of clusters. A score of > 1.96 indicates a statistically-significant cluster ($p < .05$); scores lower than 1.96 (coldspots) are not significant ($p > .05$). The output of Getis-Ord Gi* tool provides a GIZScore map that indicates the hot and cold spots in the urban parks. This tool, named GiZScore which generates a z-score value for each feature, helps in indicating the statistical significance of feature clusters and eventually the hot and cold spots. Kriging geostatistical procedure was applied to the hotspot map which was generated using Getis-Ord Gi* analysis for visualizing of hotspots. It creates a smooth continuous surface on the hazardous tree hotspots which are distributed across the urban parks. The continuous smooth surface is classified into nine different classes of hotspots. The results showed that thermal and spatial indices can provide precise information on hazardous trees and can sufficiently explain the presence of cavities or decaying wood. In terms of species and individual trees, thermal imaging can help in detecting and mapping various types of defects, providing important data for specialized management concerning urban forests. Furthermore, identifying hazardous tree hotspots as well as tree risk zones across the urban forests, may offer significant data for more focused conservation strategies regarding arboreal vegetation management.

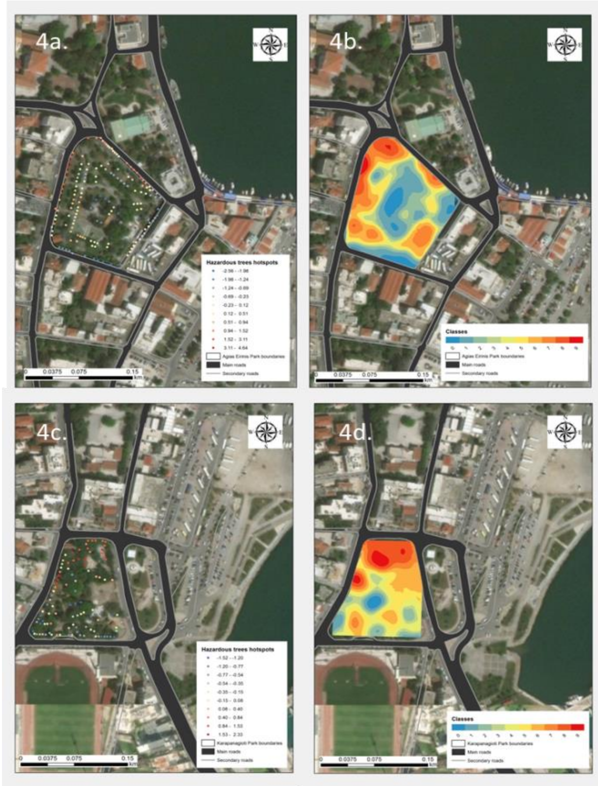

Figure 4. Locations of hotspots and coldspots in the two urban parks, Mytilene, Greece.

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