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#SecureTree: pursuing new trajectories for risk assessment models in precision forestry

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The #SecureTree model presents a novel method for assessing tree risk through IoT-based sensors and analytics within a precision forestry context. Unlike conventional techniques that often depend on individual, subjective mechanical assessments, #SecureTree utilizes a network of minimally invasive sensors to continuously monitor key biophysical factors such as temperature, humidity, and branch movement. These data are processed to generate real-time risk assessment maps based on the analysis of trees' behavioral progression under varying environmental conditions. The primary innovation of the model lies in its capability to track multiple trees over extended periods, providing forest managers with objective, data-driven insights into tree stability and health. These insights make it possible to identify long-term risk patterns, allowing for proactive interventions and improved emergency management. By moving from isolated evaluations to a scalable, sensor-based approach, #SecureTree greatly enhances the accuracy of tree risk assessment and establishes a new benchmark in environmental management. This model allows for significant advancements in precision forestry, enabling more effective, real-time decision-making while promoting sustainable forest management practices aligned with digital innovation.

KEYWORDS
environmental modeling, IoT sensors, operational research, precision forestry, risk assessment

1 Introduction

Forestry management is undergoing a major transformation, shifting from manual assessments to digital, data-driven methodologies. This evolution, commonly referred to as Precision Forestry, leverages high-resolution sensor networks, AI-driven analytics, and cloud-based decision-making systems to enhance forest monitoring, risk evaluation, and ecosystem sustainability (Meena et al., 2018; Yachmeneva et al., 2020; Rahman et al., 2023). In the last decades, a paradigm shift has in fact occurred from highly manual/analog-based management systems for handling environmental resources to the deployment of high-resolution data to support site-specific tactical and operational decision-making.

Precision forestry, as a relatively new term within the major realm of Ecological Systems Theory (EST) (Bronfenbrenner, 2009), aims in other words to accomplish (i) tighter control of operations with improved data collection; (ii) increased selectivity of prescriptions to match site and needs; (iii) automation of operations; (iv) optimized decision making by means of advanced analytics; and (v) sustenance of forest-based ecosystem services (Esposito et al., 2023; Guan and Zhang, 2025). From EST also descends the Ecological Risk Assessment (ERA) Theory (Paustenbach, 2008). Current, well-known tree risk assessment methods, such as Visual Tree Assessment (VTA), Static Integrated Analysis (SIA), and Quantitative Tree Risk Assessment (QTRA), can be conceptually framed as domain-specific implementations of broader ERA paradigms. As such, they inherit many of the structural limitations that have been widely documented in ERA literature, particularly when applied to complex, dynamic biological systems. As they in fact rely on manual inspections and do not account for continuous changes in environmental conditions, they are also widely recognized as time-consuming, expert-dependent, and affected by high levels of uncertainty, particularly when dealing with dynamic systems and temporal risk evolution—see, e.g., Refs. Ostrom and Wilhelmsen (2019), Roman et al. (2021), Li et al. (2022). Conversely, in forestry management science, digital solutions often confront a system that still operates largely on the basis of sustainable forest management fundamentals (Paustenbach, 2008). In this regard, a widespread lack of expertise related to the adoption of the latest, sensor-based technologies in managing forests is witnessed in both the public and private sectors. This translates into little knowledge as to how to set up real use cases, which causes, in turn, a slow uptake by the end-user community (often inadequately trained on how technology can enhance and optimize their work), and, accordingly, relatively few practical examples are currently up and running.

As the technological landscape is rapidly evolving, many fields of potential applications are identified within the larger field of precision forestry, which span the full value chain, such as the mobile electronic devices—capable of giving supervisors constant access to forest information systems and planning tools—or the deployment of e-dashboards allows visualizing performance data, based on central, standardized, electronic data repository. Furthermore, (software-based) forest-planning models can support forest-management decisions, from the strategic to the tactical, to the operational sides. Eventually, the analysis of large amounts of data through advanced analytics can lead to solving complex problems, such as identifying critical constraints on tree growth at a micro-level and determining the most cost-effective interventions (Choudhry and O'Kelly, 2018; Kang et al., 2016; Thorn et al., 2020).

In this regard, it is a fact that every tree, regardless of size or location, poses a certain level of risk to surrounding people, buildings, and public facilities. Many risk mitigation strategies have been tailored for a twofold aim: (i) improving tree growth conditions to reduce the number of safety incidents involving trees; (ii) minimizing the impact of incidents when they occur. Furthermore, as assessing tree risks is a critical aspect for both forest and urban trees, the focus is not only on preserving their health and longevity, but also to allow communities that live alongside them to flourish, ensuring their safety and wellbeing (Li et al., 2022).

Still, inconsistencies persist in risk assessment that have yet to be addressed through the design of best management practices and training programs. In response to these challenges, leveraging the potential of Operational Research (OR)–based methods at both theoretical and applied levels (Weintraub and Romero, 2006; Rönnqvist et al., 2023), the objective of the present study is to introduce #SecureTree, an innovative tree risk assessment map model, i.e., a stack for assessing the risk levels of green subjects, that leverages IoT-based commercially available sensors to gather continuous data on critical biophysical parameters such as temperature, humidity, and acceleration.

#SecureTree is based on the elaboration of the so-called trees' progressions of behaviors, a novel concept of risk profile that, moving beyond static assessments, leads to a more dynamic, behavior-based framework. By analyzing how trees respond to varying environmental conditions, in particular mechanical responses to external forces such as wind, #SecureTree generates real-time risk assessment maps that provide actionable insights for forest management. This approach enables forest managers to (i) track trees' dynamic responses over time, providing a more accurate and comprehensive understanding of tree stability and associated risks; (ii) visualize risk levels spatially and allocate resources efficiently in the light of data-driven decision-making; and (iii) get deeper insights into how trees interact with their environment thanks to the deployment of a behavior-centric framework. The long-term goal is to design trajectories of risk evolution during time spans of increasing width, by means of (digital) functionalities capable of managing the complex web of human, animal, and environmental interconnections. Such advancements have broader implications in terms of governance of complex ecosystems, which encompass either forest management as well as eco-friendly agricultural practices, to enable the implementation of early-warning systems and improve emergency preparedness, ultimately promoting the maintenance of ecosystem services and ecological resilience, in view of an overall environmental sustainability (Benis et al., 2021; Tramontano et al., 2024).

The article is organized as follows: after the Introduction, an analysis of the literature is reported concerning urban green monitoring systems, and the dynamics related to risk assessment of urban greenery, with particular relation to smart cities. The technology deployed for monitoring activities and the IoT-based approach developed for mapping the risk assessment are then described, along with the field trial conducted (including some preliminary results). The discussion and conclusions are then shown in the final sections.

2 Related works

The study of the literature mainly focused on the following two aspects: analysis of urban green monitoring systems and evolution of risk assessment methods within the main context of environmental management.

2.1 Urban green monitoring systems

In the context of cities' transformation toward smarter and sustainable models, urban green space management plays a key role in improving life quality and managing environmental impacts. In this regard, the integration of advanced monitoring systems in the context of urban green is a significant step toward a higher rate of sustainability and resiliency. Several studies in the literature addressed this topic, showing how valuable support to urban planners and urban designers can be provided in innovative ways to promote greenery in urban areas, therefore helping to improve the quality of life and reduce environmental impacts.

The Normalized Difference Vegetation Index (NDVI) allows estimation of vegetation density and health using satellite images (Xu et al., 2022). Several ecosystem service evaluation methods are reported in the literature, which combine NDVI with correlation and regression analysis (Fan and Liu, 2017). Other methods allow analysis of the environmental benefits of urban forests by using tree inventories and tree data (Riondato et al., 2020), or involving modeling the impact of green spaces on urban climate (McPhearson et al., 2022).

A practical example of the application of advanced technologies in urban green management is provided by Matasov et al. (2020). This study focuses on the use of IoT technologies for monitoring trees in urban spaces in central Moscow. The use of TreeTalkers (TT+) devices allows immediate monitoring of data on ecophysiological indicators of trees. Through this device, authors achieved excellent results in the management and conservation of urban greenery. Similarly, an innovative method that uses integrated cameras installed on moving vehicles to monitor urban green in Melbourne, Australia has been introduced by Fuentes et al. (2021). This approach allows the collection of real-time data on plant health and growth, providing important information about monitoring urban green spaces.

In addition, Lu et al. (2023) conducted a review of the use of Street View (SV) images to evaluate urban green, thus highlighting its potential in supporting a wide range of urban green studies. Another study proposes a significant development in urban green monitoring, instead, showcasing an innovative system for evaluating the quality of green urban spaces through deep learning techniques (Xia et al., 2021). This system offers an automated and scalable approach to assessing urban greenery, providing efficient and accurate monitoring of the condition of roadside plants.

Eventually, in the work of Hui et al. (2023), a detailed survey of the integration of urban natural resources and smart city technologies to promote environmental sustainability is provided, with an overview of the challenges and opportunities related to the use of smart technologies in urban green management and natural resource optimization.

2.2 Risk assessment

Risk Assessment plays a key role, especially in Smart Cities, as it allows for the identification, assessment, and management of risks associated with the complexity of urban infrastructures. This process not only provides for the prevention of disaster events but also ensures the safety of citizens and environmental sustainability. The use of advanced technologies such as IoT and AI allows for continuous monitoring of urban conditions, while Risk Assessment guides informed decisions in urban planning, contributing to an effective mitigation of potential risks to people, infrastructure, and the surrounding environment, thus promoting a better quality of life in smart cities.

Urban economic growth has led to a diffuse deterioration of the ecological environment of cities. According to Önder et al. (2017), concepts such as "garden city" and "green city" describe the balance between ecology and economy, focusing on the urban environment. As highlighted by Roman et al. (2021), urban trees play a crucial role in improving the ecosystem of cities. However, urban economic development causes problems such as "urban diseases" that cause trees' health to degrade. According to Sheng et al. (2018), trees can become dangerous due to problems such as aging, especially under extreme weather conditions. It is therefore essential to take measures to manage such risks, while Klein et al. (2023) proposed that tree risk assessment is an essential process for identifying and analyzing hazards, determining the level of risk. Furthermore, Coelho-Duarte et al. (2021) have been stating to a different extent about the importance of assessing the risk of trees in areas with a lot of human activity, also highlighting that tree risk management helps protect people and property in cities. Moreover, Linhares et al. (2021) underscore that the risk of accidents from falling trees is minimal compared to the benefits they provide in cities.

Regarding environmental management and urban greenery, Szalińska et al. (2021) provide a detailed methodological approach to addressing environmental hazards in cities, focusing on the protection of urban green spaces. In this research, an analysis of the relationships between urban natural resource integration, smart city technologies, and the promotion of sustainability was conducted. The methodology is based on the analysis of information to identify trends, patterns, and implications in the field of research. The objective was to identify key elements, challenges, and opportunities in the smart city context, providing practical tools to estimate the vulnerability of cities, planning mitigation and adaptation measures. This study integrates with the work of Rust and Stoinski (2022), where an innovative methodology is proposed based on general dynamic logic (GDL) to evaluate the risk associated with falling urban trees. The approach aims to standardize tree risk assessment by integrating measurable and unmeasurable parameters to increase the robustness and reliability of assessments. In addition, the study conducted by Jim and Zhang (2013) focused on a detailed assessment of the structural and health condition of historic trees in the city of Hong Kong provided important information to understand and mitigate the risks associated with urban trees, helping to guarantee the safety of citizens and the sustainability of cities.

In the field of sustainable construction, Nguyen and Macchion (2023) shift the focus to risk assessment in the building context. The study focuses on risk assessment in sustainable construction projects, using the Mean Scoring method and Fuzzy Synthetic Evaluation, allowing to evaluate risks in green construction projects by considering the probability of occurrence and manageability of risk, and showcasing a practical method for estimating risks in green construction projects.

3 Materials

Figure 1 shows the plot of land, belonging to private owners, placed within an urban landscape in Campania Region, Italy (40.866385, 14.210219), where a pilot study was conducted between March and June 2024. The choice was made since such land comprises four different areas—named from C1 to C4—each of which hosting trees of *Citrus Medica* [Scientific Name: *Citrus medica* L.; Family: Rutaceae (Rue or Citrus family); Genus: Citrus L.; Species: *C. medica.*], commonly known as *citron* (from here onwards), with similar features. Citron planting was in fact carried out, one area at a time, in subsequent moments in time from the 1960s to the 1990s. Accordingly, each of the four areas features citrons that look similar in terms of height, age, and tree stem size. Leveraging such homogeneity, despite the fact that approaches exist to assess multiple trees in a stand (Trouillier et al., 2019), in accordance with the domain experts involved in the study, it was decided to test the effectiveness of the proposed approach on a smaller scale before. A single tree was then chosen for each area to be representative of the entire population it belongs to. An extensive monitoring activity was conducted on the following parameters: (gravity) acceleration, temperature, humidity,

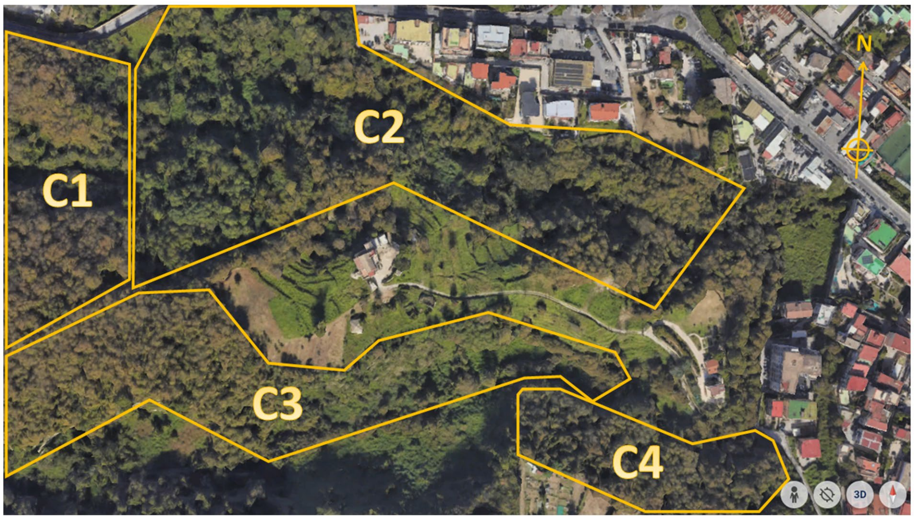

FIGURE 1
Aerial view of the four plots of land where the field work was conducted. Map data © 2024 Google.

TABLE 1 Characteristics of the four sample sites.

Characteristics	C1	C2	C3	C4
Species	*Citrus medica*			
Altitude (m)	≈340	≈340	≈310	≈325
Slope (°)	2–5	5–10	2	2
Aspect	W	N	S	SE
DAMS[a]	20	18	13	20
Age (years)	≈ 60	≈ 50	≈ 40	≈ 30
Average spacing (m)	3,8	3,5	5,6	3,3
Mean height (m)	≈ 8	≈ 8	≈ 7	≈ 5

[a]DAMS (Detailed Aspect Method of Scoring; Quine, 2000; Locatelli et al., 2017) is a measure of exposure. DAMS of 12 represents a sheltered site; DAMS of 20 represents an exposed site.

and wind speed. To this end, a Wireless Sensor Network was set up, embedding different kinds of IoT sensors, as described in the following sections.

The experimental sites are summarized in Table 1. Instrumentation, data processing, and the competition indices used are reported in subsequent sections.

3.1 Wireless sensor network

The WSN architecture was initially developed with the objectives of affordability, scalability, and ease of use. This architecture comprises two types of devices that work together: Gateway Stations (GSs) and sensors, placed on trees' branches. The latter are responsible for gathering data from the subjects (referred to as 'green subjects') under surveillance and transmitting these data as an encrypted radio signal, functioning as a radio beacon. For these reasons, the installation process was designed and guided by the domain experts, in order to prevent sensors from being wrongly placed at a defect such as a codominant stem with a bark inclusion, thereby avoiding, e.g., wind loading causing the branch union to respond differently than when a small branch is attached to a larger parent stem. On the other hand, the GSs receive these signals from the sensors, process them to extract the data from the payload, and forward it to a central server for storage and display. This tree network-based design is cost-effective and its cost does not directly correlate with the number of subjects monitored. In fact, to add more subjects to the monitoring site, it only takes to integrate more sensors, while the rest of the architecture remains unchanged. Regarding the scalability of the architecture, it is contingent on the number of GSs deployed in the monitoring operation. This design ensures that the solution remains affordable and scalable, regardless of the size or complexity of the monitoring task.

3.2 Sensors

The selection of sensors was a critical factor in achieving accurate and reliable tree risk assessment (Dhaka et al., 2023; Schiefer et al., 2024). The sensors selected for measuring temperature and humidity (TH) and acceleration of branches along the three axes X, Y, Z and (ACC) were picked from the existing market offerings, depending on their capacity to align with the overarching goals of the entire architecture. On the one hand, temperature and humidity modulate tree physiology and biomechanics, including turgor pressure, wood moisture content, and elastic modulus. These factors influence branch flexibility and damping, thereby affecting how trees respond to dynamic loads over time (Dahle et al., 2017). On the other hand, accelerometers capture the kinematic response of tree branches and stems to external loading, including wind dynamic forces. Branch and stem oscillation characteristics (i.e., natural frequency, damping ratios, and amplitude) are, in fact, altered by internal defects, decay, and structural weakness—effectively acting as proxies for mechanical integrity. This set of biomechanical signatures, which cannot be captured by visual inspection alone, has been correlated experimentally to failure risk under dynamic loading (James et al., 2014). The choice was also influenced by other critical factors, such as (1) to house large batteries to ensure a minimum of 6 months of continuous monitoring operations, (2) non-invasiveness, to avoid any possible harm to the plant life in the monitored areas, and (3) to be waterproof and dustproof, given their outdoor placement.

The sensors chosen to be embedded into the architecture are shaped like parallelepipeds measuring 10 × 2.5 × 5 cm. They have an IP68 rating, making them resistant to dust, rain, or irrigation water. They are powered by a CR123 battery, which can extend their operational time to nearly a year. They also feature a Power Amplifier (PA) that can broadcast the radio signal up to approximately 200 meters in open air. The electronic components of the sensors are based on a Nordic Semiconductor nRF52820 system-on-a-chip (SoC), which handles physical sensor reading and data communication. The SoC of the sensors also hosts a lightweight customized firmware, allowing for adjustments to settings such as the PA's amplification, broadcast frequency, sampling rate, and password for settings change. The average price for each of the TH and ACC sensors is around 15€.

Wind (WND) is also a primary dynamic load in forested and urban environments, as it interacts with tree architecture, soil anchorage, and internal structural defects to amplify mechanical stress (Andreozzi et al., 2025). The sensor used for detecting this parameter is an IP68-rated anemometer that is directly connected to the GS. Given the limited extension of the monitoring site, it was decided to assume that wind gusts would be uniform across the four areas (Lawan et al., 2014; Pearre and Swan, 2018). Only one anemometer was then deployed and connected to the GS, which operates within a range of 0–1.4 V and can detect wind gusts up to 130 km/h. The average price for the single WND sensor is around 30€.

Sensors' main features are summarized in Table 2. Sensors' sampling rate was measured via Cycles per Minute (CPM (Nagahage et al., 2021).

3.3 Gateway stations

The research team assembled GSs that are used in the tree-shaped network. These are self-sustaining stations that incorporate an ESP32 microcontroller from Espressif, which executes the business logic for data collection. The ESP32 microcontroller is already widely used in Industry 4.0 applications due to its high versatility, cost-effectiveness, and low power consumption (Martikkala et al., 2021).

The GSs are equipped with a solar panel on the front side, capable of generating up to 30 W of power. The energy produced is stored in a 12 V 12 Ah Ni-Mh battery located within the main body. Although it would have been possible to power the GSs from a power line, the decision was made to opt for a self-sufficient solution to maximize the coverage area of each monitoring site and overcome any potential constraints related to the placement of the GSs. The ESP32 microcontroller runs specific software, designed by the research team using the C++ language. This software is responsible for detecting the iBeacon signals from the sensors deployed in the monitoring system, extracting sensor data from the iBeacon packet, writing this information to a file stored on an SD card, and periodically sending the sensor data from the file to a central server. The software decodes the iBeacon packets to obtain the identifications of the trees and the associated sensor readings. In addition to their gateway-related tasks, GSs also function as sensor nodes of the network. They are equipped with both internal and external TH sensors to assess the condition of the electronic equipment inside the box and the surrounding environmental conditions. The external temperature and humidity monitoring, along with the wind gusts information, contribute to this sensor node functionality. The overall aggregated cost is around 200€—as the raw sum of the single components. It has to be noted that, given the low number of GSs to be realized for an exploratory study, the authors performed all the requested assembling activities themselves, such as soldering, drilling, and metal cutting.

4 Methodology

The following section will illustrate, in order, the different steps of the #SecureTree methodology. Each subsection describes a single step to be applied, from data processing to pattern recognition, to get to the final structure of the risk assessment map. Data analysis was performed via in-house coding activity by means of R and Python.

4.1 Data (pre)processing

The different technical characteristics of the sensors used for the monitoring activities made it necessary, in the first place, to harmonize the frequencies of the observations coming from the devices deployed, to build up an internally consistent database to perform the next data processing steps onto.

The original database consisted of as many tuples as the observations of each sensor. With reference to Table 1, the sampling rate of the anemometer (1 CpM) was used as a benchmark. First, each WND observation value was associated with the average value of ACC, as assessed in the time frame spanning from 30 s before and 30 s after WND observation. Similarly, as temperature and humidity vary slowly over time, it was decided to associate the same value of TH for all the WND occurrences in the time frame spanning from 15 min before and 15 min after a given TH observation. As a result, each tuple of the

TABLE 2 Sampling rates for each type of sensors deployed.

Sensor type	Sampling rate (cycle per minute/CPM)	Application
Triaxial accelerometer (ACC)	3	Evaluating the inclination of masts' branches and trunks over time
Temperature and humidity sensor (TH)	1/30	Monitoring temperature and humidity of the masts at crown height and of the terrain close to the masts' roots
Anemometer (WND)	1	Retrieving information on the wind gusts within the monitoring site

extracted dataset contained values for either gravity acceleration, temperature, humidity, or wind speed.

After this, the first step of data processing consisted of calculating the trees' inclination values starting from the ACC occurrences gathered from the sensors. Using a fixed coordinate reference system, where the Z axis is perpendicular to the ground, the inclination value for each tree can be calculated with respect to the X axis (Pitch) and to the Y axis (Roll) by means of Equations 1, 2:

$$Pitch = \theta = \tan^{-1}\left(\frac{A_x}{\sqrt{A_y^2 + A_z^2}}\right) \quad (1)$$

$$Roll = \varphi = \tan^{-1}\left(\frac{A_y}{\sqrt{A_x^2 + A_z^2}}\right) \quad (2)$$

In order to assess the variation of the inclination over time from the initial position, a normalization of the time series of the inclination values was performed. To this end, the quantities θ_0 and φ_0 were calculated in the first place as the average values of θ_i and φ_i of the first N = 10 occurrences of t_i, as ordered by timestamp. For each following t_i, it was therefore possible to assess the variables $\Delta\theta_i$ and $\Delta\varphi_i$ as expressed in Equations 3, 4:

$$\Delta\theta_i = \theta_i - \theta_0 \quad (3)$$

$$\Delta\varphi_i = \varphi_i - \varphi_0 \quad (4)$$

4.2 SBfactor

Since branches' oscillations result from the combination of components lying on two orthogonal planes—one parallel to the ground, and another perpendicular—the ratio between the sum and difference of these components ($\Delta\varphi$ and $\Delta\theta$) was identified as a factor capable of effectively representing the overall movement of a branch (Hale et al., 2012). In other words, for each tree at each time point t_i, a coefficient called $SBfactor_i$ (a.k.a. Shaking Branches factor) was calculated as reported in Equation 5:

$$SBfactor_i = \frac{|\Delta\theta_i| + |\Delta\varphi_i|}{|\Delta\theta_i| - |\Delta\varphi_i|} \in R : \Delta\varphi_i \neq \Delta\theta_i \quad (5)$$

where:

- $\Delta\theta_i$ is the angular displacement (pitch) in one plane as resulting between two following time points;
- $\Delta\phi_i$ is the angular displacement (roll) in another orthogonal plane as resulting between two following time points;
- $|\Delta\theta_i| + |\Delta\phi_i|$ represents the total angular displacement in both planes combined;
- $|\Delta\theta_i| - |\Delta\phi_i|$ represents the differential movement between the two planes.

Equation 5 can be loosely related to the concept of natural frequencies and vibration modes of structures (such as branches) (Kovacic et al., 2018). From a physical perspective, the oscillations captured by $\Delta\theta_i$ and $\Delta\phi_i$ are linked to mechanical stress experienced by the branch. Larger angular displacements imply greater bending moments, which are related to the forces acting on the branch, e.g., wind. SBfactor, as a dimensionless, behavior-based indicator describing the dynamic oscillatory response of tree branches under environmental forcing, provides a proxy for how the intensity of wind is connected with the oscillations of branches on different, orthogonal planes. By using the sum and difference of these displacements, it indicates how the movement is distributed between the two planes, depending on the relative magnitudes of pitch and roll displacements. More specifically, SBfactor values are evaluated longitudinally and across wind intensity classes. Risk emerges from sustained deviations and behavioral progression over time, rather than from isolated SBfactor thresholds (Sellier and Fourcaud, 2009; Jackson et al., 2021; Ekeoma et al., 2024). In this regard, high positive SBfactor values indicate oscillation dominated by a single plane, which reflects a directionally coherent bending. From a biomechanical perspective, this behavior is associated with efficient load transfer, effective damping, and structural continuity of wood fibers. This response can be interpreted as a relative dynamic stability under the observed conditions, and is commonly observed in branches exhibiting intact mechanical integrity and adaptive growth.

Conversely, low or strongly negative SBfactor values arise when pitch and roll components contribute comparably to motion, producing multi-plane or torsional oscillations. Such complex oscillatory patterns reduce damping efficiency and increase internal strain heterogeneity under cyclic loading. Persistently, regimes of this kind are therefore interpreted as indicators of dynamic instability, potentially preceding fatigue accumulation or progressive structural weakening.

To reflect the expected oscillatory changes based on the tree's age, it was possible to modify Equation 5 as follows in Equation 6:

$$SBfactor_{adj,i} = SBfactor_i * A_{adj} \quad (6)$$

In this case, A_{adj} is an age-based adjustment coefficient that modulates the SBfactor based on the tree's age. This factor would be derived from species-specific growth data and reflect expected changes in branch flexibility or mass distribution as the tree matures (Linares et al., 2013; Salehnia and Ahn, 2022). The A_{adj} coefficient can be figured out as follows in Equation 7:

$$A_{adj} = 1 + \alpha * (age_c - age_b) \quad (7)$$

where:

- α is a species-specific growth rate coefficient, representing the rate of change in oscillatory behavior with age. Based on the literature, its value is ≈ 1 for all the citron trees of the present study—and by extension, for the entire population the analyzed trees belong to—as (i) trees' ages are very close to each other, and (ii) they are relatively still young if compared to an average citron tree life, which can exceed 150 years;
- age_c means the current age of each tree;

- age_b is a reference age used as baseline—in this case, the trees from the C1 area, as it was the first where citrons' implantations took place.

That said:

- if $A_{adj} > 1$, the oscillation is greater than what would be expected for the age, possibly signaling structural or health issues;
- if $A_{adj} \approx 1$, the oscillation is within the expected range for a healthy tree of that age;
- if $A_{adj} < 1$, this means that oscillations are less than expected, which could indicate stiffness or structural limitations in older trees.

For simplicity, from here onwards, $SBfactors_{adj}$ will keep being referred to as SBfactor.

4.3 Behavior progression matrix

The extracted dataset was enriched, for each tuple, with the SBfactor. A matrix called M0 was figured out, which reported the values of wind speed (W) on the rows, and of the SBfactor (SB) on the columns. Both W and SB variables were divided into three intervals using the interquantile distance, as it better approximates the actual distribution of the values (Atwood and Shaik, 2020). The M0 matrix is drawn as shown in Figure 2a. Each cell of M0 was then populated with the number of tuples falling within the specific corresponding ranges W_i/SB_j. Each tuple was labeled from C1 to C4, as it was decided to consider one tree for each of the four areas of study.

In the next step, for each row of M0, the cell featuring the maximum number of occurrences of each label had to be detected. Each cell would then be relabeled C_i with accordingly. $i \in \{1,2,3,4\}$

As the number of labels (four, in our case) exceeds the number of columns (three), this implies that, for each row, one of the cells would necessarily feature two labels C_i. In addition, each cell was also assigned another label Q_i with $i \in \{1,2,3\}$: in particular, the cells of the SB1 column were labeled Q1, and so on for SB2 and SB3 columns. The M0 matrix, so organized, was renamed M1 (Figure 2b).

In M1, it is possible to figure out $3^3 = 27$ possible combinations of Q1, Q2, and Q3 column-wise, or, in other words, 27 possible triads/vectors in the form (Q_i, Q_j, Q_k) with $i, j, k \in \{1,2,3\}$ where Q_i belongs to the lowest row, Q_j to the middle one, and Q_k to the upper one. In this way, each vector points out a specific progression of the behavior of a tree, that is, the rate of oscillation as the wind increases from W1 to W3. For instance, the vector (Q1, Q1, Q2)—also referred to as (1,1,2)—means that when the wind speed falls within the W1 interval (W = W1), SB falls within the range of oscillation values defined by SB1 interval; for W = W2, SB remains in the SB1 range; for W = W3, the oscillation rate increases and shifts to the range identified as SB2. This means that the shaft movement only increases at high wind values.

It descends from this that (Q_i, Q_j, Q_k) = f(W1, W2, W3). Accordingly, M1 can also be renamed as the behavior progression Matrix, or BPM.

The #SecureTree risk assessment map is figured out and built on these progressions. To this end, from the $3^3 = 27$ overall combinations of Q1, Q2, and Q3 retrievable from the BPM, the only possible behavior progressions for a tree are 10: Q_is' trend must be, in fact, monotonic nondecreasing, as it is highly likely that the SBfactor does not decrease as the intensity of the wind increases.

4.4 Use of clustering techniques for pattern recognition

The #SecureTree risk assessment map is articulated in the following clusters, relatable to increasing levels of risk (Li et al., 2022; Tamburis et al., 2020):

1. LR = Low Risk;
2. MLR = Medium-Low Risk;
3. MR = Medium Risk;
4. MHR = Medium-High Risk;
5. HR = High Risk.

Each one of the 10 triads/vectors that describes a tree's behavior progression was associated with a specific cluster. In order to do that, starting from the components of each vector (Q_i, Q_j, Q_k), the Euclidean distance, the Manhattan distance, and the Hamming distance were calculated (Pandit and Gupta, 2011; Oyewole and Thopil, 2023). This made it possible to group the vectors into a series of clusters.

On the one hand, the vectors with the minimum value for any of the distances considered were assigned the label/risk level LR, as the increasing intensity of the wind does not affect their initial behavior—it was the case of the vectors (1,1,1), (2,2,2), (3,3,3). On the other hand,

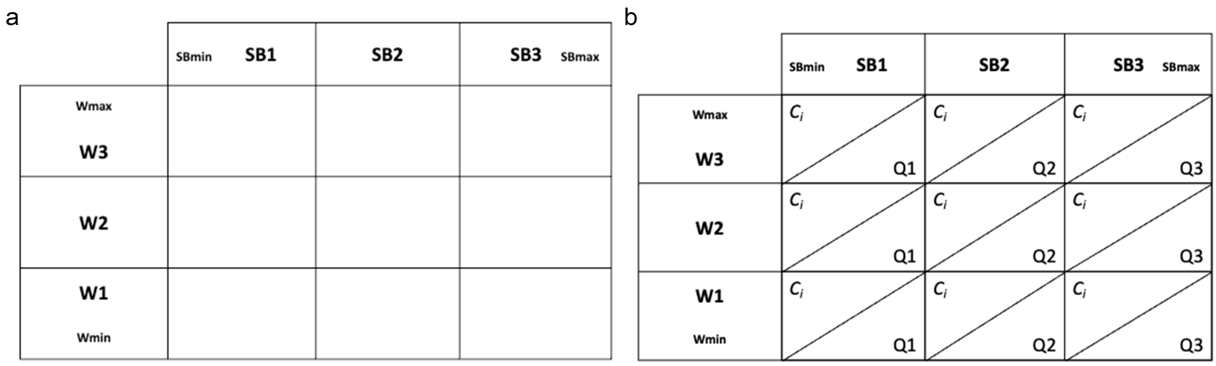

FIGURE 2
M0 Matrix (**a**, left); M1 Matrix, featuring C_i and Q_i labels (**b**, right). C_i parameters mean, for each cell, the tree with the maximum number of occurrences for that specific combination 'wind speed interval/SBfactor interval'; Q_i parameters relate to the components of the vector that specifies the tree's behavior progression under the increasing intensity of wind gusts.

the vectors featuring a value falling within the interval]1; 2] for any of the distances considered, were assigned the label/risk level HR—it is the case of the vector (1,2,3) that clearly points out how an increasing intensity of the wind turns into increasing rates of oscillations.

For what concerns the remaining in-between cases, the cluster analysis conducted was further honed via a confrontation with domain experts, along with an in-depth analysis of the literature (see, e.g., Mitchell et al., 2001; Alcasena et al., 2016; Boukhris et al., 2023). The fundamental principle codified was that the sooner the tree responds—i.e., oscillations—to an increase in wind gust intensity, the higher the overall risk level. It was then decided to classify the vectors based on the way the SBfactor overall changes, depending on the increasing intensity of wind. In this way, the MLR label was assigned to the vectors (1,1,2) and (2,2,3), as the SB interval shifts upward by one position when the intensity of the wind is high (W2 ➔ W3). The MR label was assigned to the vector (1,1,3) as the SB interval shifts upward by two positions when the intensity of the wind is high (W2 ➔ W3). Eventually, the MHR label was assigned to the vectors (1,2,2), (2,3,3) since the SB interval shifts upward by one position already at an average intensity of wind (W1 ➔ W2). The vector (1,3,3) was assigned the label MHR as well, because, similar to the previous vectors, the SB interval, after an initial shift (W1 ➔ W2)—although, in this case, of two positions—then remains constant (W2 ➔ W3).

Figure 3 summarizes the three single conditions—Q1, Q2, Q3—whose triadic combinations correspond to risk levels detected. Figures 3a–e shows the different tree behavior progressions after an increasing intensity of wind gusts.

Operationalizing the above-described criteria, the following code in Python language was worked out, which allows assigning each 3-component vector to the corresponding risk assessment label:

ALGORITHM 1:
Assignment of risk assessment label

```
def calculate_category(Q_j, Q_i, Q_k):
    if abs(Q_j - Q_i) == 0 and abs(Q_k - Q_j) <= 1:
        return "MLR"
    elif Q_j - Q_i < 1 and Q_k - Q_j > 1:

        return "MR"
    elif Q_j - Q_i >= 1 and abs(Q_k - Q_j) == 0:
        return "MHR"
```

The final structure of the #SecureTree risk assessment map is reported in Figure 4. The model features as many levels as the levels of risk identified—from Low Risk (LR) to High Risk (HR). For each of them, the triads corresponding to the trees' behavior progressions are then reported.

The articulation of risk classes as described in Figure 3 is eventually to be coupled with practical management actions to be prioritized, to reduce risk to an acceptable level (Dunster et al., 2013; Esperon-Rodriguez et al., 2022; Klein et al., 2023):

1. LR = Low Risk: Carrying out standard, routine maintenance (e.g., regular inspections). No specific, immediate mitigation required;
2. MLR = Medium-Low Risk: Increasing monitoring frequency to check for changes in condition;
3. MR = Medium Risk: In addition to what was stated for MLR, further mitigation may be required if the target is high-value;
4. MHR = Medium-High Risk: Prompt mitigation—e.g., pruning to reduce weight, cabling to stabilize branches, or restricting access to the area—is required;
5. HR = High Risk: Immediate, urgent action is required to close the area or remove the tree/target to prevent injury or damage.

Among the key mitigation strategies, the following can be listed (Brundu et al., 2020; Szalińska et al., 2021):

1. Risk Removal/Reduction: Pruning, bracing, or cabling, or complete removal of the tree if structural failure is imminent;
2. Target Management: Access is restricted to the target area (e.g., closing a walking path or moving benches) to reduce the likelihood of impact.
3. Monitoring and Inspection: Implementing a systematic inspection program—particularly in high-traffic, urban landscapes, or public areas.
4 Site Improvement: Improving soil conditions or protecting root zones to enhance overall tree health.

5 Results

The original Database comprised over 6,3 Mln rows related to the observation data from the following monitoring sensors:

- Accelerometer (ACC).
- Temperature/Humidity (TH).
- Anemometer (WND).

Table 3 reports the distribution of the data across the sensors.

The main features of the variables analyzed for statistical purposes are described in Table 4.

From the mentioned process of harmonization of the different sensors' sampling rates, a dataset composed of 1.554.964 tuples was extracted. In the next step, all the tuples featuring a null value for the wind (approximately 33%) were deleted. The Dataset in its final form comprised 1.046.801 tuples.

A summary of the SBfactor variable is reported in Table 5. To ensure high accuracy, values have been rounded to the third decimal place.

The interquantile intervals calculated for W and SBfactor variables are reported in Table 6.

The resulting M0 Matrix populated with data is reported in Figure 5a. For each row of the M0 matrix, the citrons highlighted in green are those with the highest frequencies (expressed in %). Accordingly, the resulting M1/Behavior Progression Matrix is defined as depicted in Figure 5b.

It was, therefore, possible to set up the triads/vectors that underscore the progression of the behavior for each citron tree. By extension, the behaviors figured out can be applied to the trees in each area into which the investigated plot of land was divided. The final result was as follows:

- C1 = {Q3, Q3, Q3}
- C2 = {Q1, Q1, Q1}
- C3 = {Q2, Q2, Q2}
- C4 = {Q2, Q3, Q3}

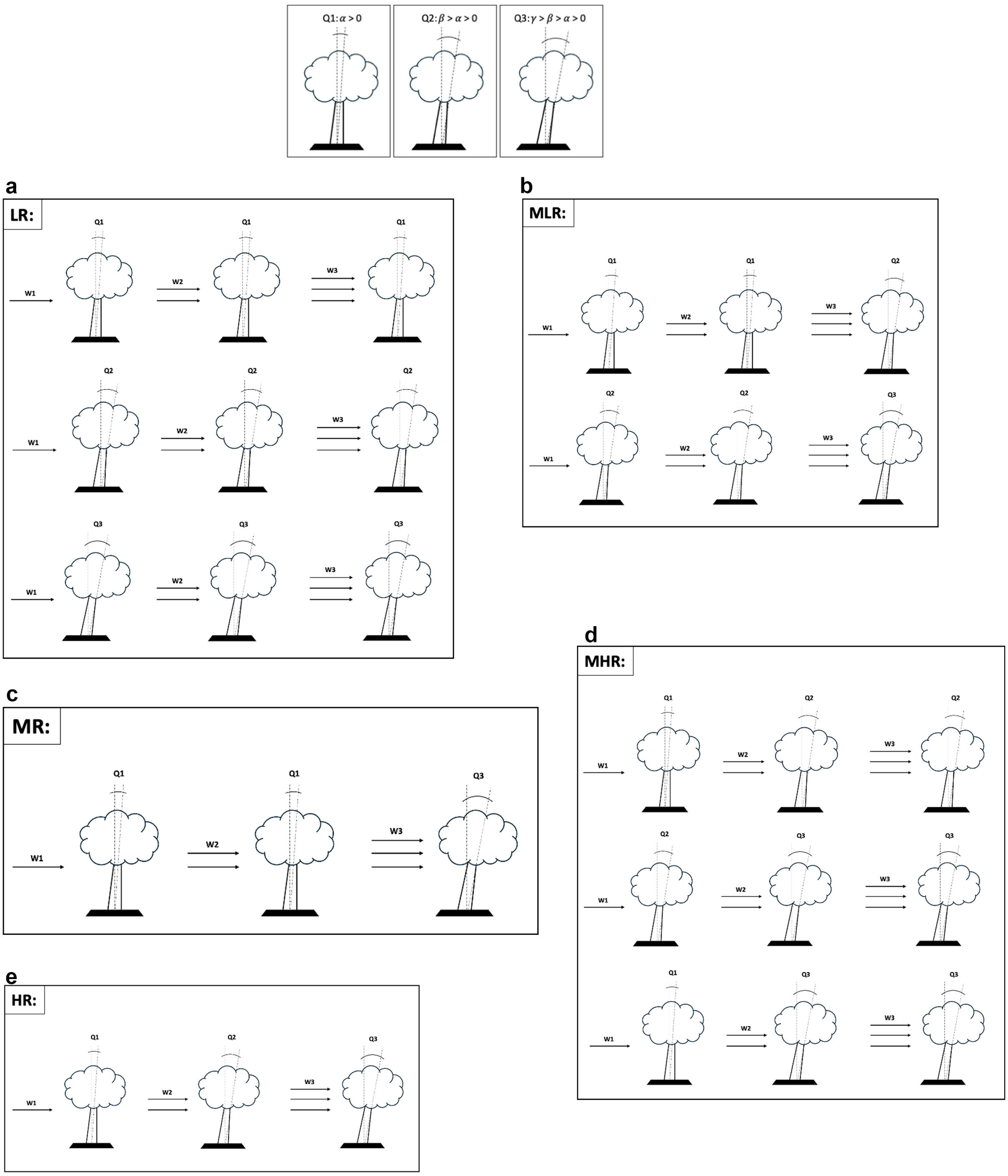

FIGURE 3
The three single conditions – Q1, Q2, Q3 – whose triadic combinations correspond to risk levels detected. **(a)** Triads/vectors that describe a tree's behavior progression for the Low Risk level. **(b)** Triads/vectors that describe a tree's behavior progression for the Medium-Low Risk level. **(c)** Triad/vector that describe a tree's behavior progression for the Medium Risk level. **(d)** Triads/vectors that describe a tree's behavior progression for the Medium-High Risk level. **(e)** Triad/vector that describe a tree's behavior progression for the High Risk level.

It has been observed that in three areas out of four—represented by C1, C2, and C3—a similar behavior was witnessed, i.e., the oscillation rate (SBfactor) did not vary as the wind speed increased. Some variation could only be appreciated for C4. As a consequence, Figure 6 shows the final implementation of the #SecureTree risk assessment map, where C1, C2, and C3 were assigned to the Low Risk (LR) level, while C4 was assigned to the Medium/High Risk (MHR) level. No behavior progression was found that matched the characteristics of the Medium/Low Risk (MLR), Medium Risk (MR), and High Risk (HR) levels.

The interpretation of the results emerging from the map allowed for the uncovering of valuable information, also corroborated by what was underscored by the domain experts.

During the field trial, wind gusts were registered mainly from the Tyrrhenian Sea (West of the study field), thus making the C1 area the most directly affected by the phenomena analyzed.

C2 area, even though at the same altitude as C1, was somewhat protected by the latter. In addition, C2 features a higher average slope than C1: for these reasons, the wind effect was further dampened.

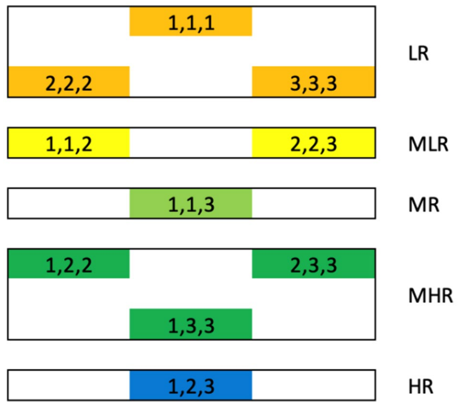

FIGURE 4
#SecureTree risk assessment map Model, featuring five classes of risk, each of which related to a specific type of tree's behavior progression.

TABLE 3 Data count per type of sensor.

Type of measure	Count
ACC	4,664,892
TH	51,832
WND	1,554,964
TOT	6,271,688

In the C3 area, a lesser mitigating effect from C1 was registered than in C2, partly because of the different altitude. Plants' behavior remained almost unchanged here, although set over slightly higher ranges of SB values than those recorded for C2.

The case for C4 area was eventually different: if for low wind values the behavior registered was similar to C3 (W = W1; SB = SB2), for higher levels of wind gusts (W = W2; W = W3) the oscillation rates registered for C4 were instead more similar to those registered for C1 (SB = SB3). A possible explanation, all other things being equal (e.g., DAMS, average spacing), can be found in the youngest age of C4 among all the subjects analyzed, which likely implies a lesser overall steadiness.

5.1 Validation process

The validation of the #SecureTree approach was designed to demonstrate that behavior-based risk indicators derived from continuous sensor data correspond to established risk assessment outcomes and, where possible, empirical observations. Standard validation principles in risk assessment emphasize the need to verify that a model (i) "measures what it is supposed to measure," (ii) produces consistent and reproducible results, and (iii) correlates with real-world failure indicators or benchmark methods (Klein et al., 2019).

Cohen's κ was applied to evaluate agreement between risk classes produced by two independent classification systems: on the one hand, the #SecureTree model; on the other hand, those obtained using established tree risk assessment methods, namely, ISA BMP and THREATS. The choice of the latter was mainly driven by the fact that both are qualitative methods based on a structured, numbered system to rate risks: a 4-class division for ISA (Low, Moderate, High, and Extreme) and a 7-class division (from Insignificant to Extreme) for THREATS (Matheny and Clark, 1994; Ferrini et al., 2017; Klein et al.,

TABLE 4 Reference values for the variables analyzed.

VarName	Min	Max	Mean
acc_x	−1.03 g	0.97 g	−0.26 g
acc_y	−0.88 g	1.03 g	0.18 g
acc_z	−0.77 g	0.71 g	0.18 g
theta	−179.91°	180.01°	−9.90°
phi	−76.85°	81.37°	14.60°
temp	−0.16 °C	38.10 °C	19.51 °C
humi	19.55%	99.64%	69.45%
wind	0.910 km/h	93.64 km/h	7.99 km/h

TABLE 5 Reference values for SBfactor variable.

Min	1st quartile	Median (2nd quartile)	Mean	3rd quartile	Max
−3,311	−2.626	0.421	−0.381	1.451	7,589

TABLE 6 Interquantile intervals for reference values for W and SBfactor variables.

W1	W2	W3
[0.910; 5.450]	[5.450; 13.640]	(13.640; 93.640]

SB1	SB2	SB3
[−3,311; −0.516]	[−0.516; 1.351]	[1.351; 7,589]

a

	SBmin SB1	SB2	SB3 SBmax
Wmax	C1 = 2186 (1.8%)	C1 = 12267 (10.12%)	C1 = 106755 (88.08%)
W3	C2 = 115569 (95.43%)	C2 = 2295 (1.9%)	C2 = 3238 (2.67%)
	C3 = 27214 (34,87%)	C3 = 36120 (46.29%)	C3 = 14700 (18.84%)
	C4 = 2232 (32.79%)	C4 = 2163 (31.78%)	C4 = 2411 (35.42%)
W2	C1 = 2214 (1.74%)	C1 = 14424 (11.31%)	C1 = 110890 (86.95%)
	C2 = 122345 (95.87%)	C2 = 2329 (1.82%)	C2 = 2943 (2.31%)
	C3 = 29627 (41.02%)	C3 = 39683 (54.94%)	C3 = 2916 (4.04%)
	C4 = 2264 (11.26%)	C4 = 2555 (12.71%)	C4 (15282 (76.03%)
W1	C1 = 2244 (1.63%)	C1 = 16635 (12.09%)	C1 = 118707 (86.28%)
	C2 = 131746 (95.71%)	C2 = 2344 (1.7%)	C2 = 3558 (2.58%)
	C3 = 31632 (35.09%)	C3 = 42491 (47.13%)	C3 = 167026 (17.78%)
Wmin	C4 = 2192 (32.25%)	C4 = 2378 (34.99%)	C4 = 2226 (32.75%)

b

	SBmin SB1	SB2	SB3 SBmax
Wmax W3	C2 Q1	C3 Q2	C1; C4 Q3
W2	C2 Q1	C3 Q2	C1;C4 Q3
W1 Wmin	C2 Q1	C3; C4 Q2	C1 Q3

FIGURE 5
M0 Matrix populated with the number of occurrences of 'wind speed interval/SBfactor interval' combinations for each tree (**a**, left); Resulting behavior progression Matrix (**b**, right). The Ci parameters reported for each cell related to the maximum amount of occurrences registered – and reported in green in (**a**, left).

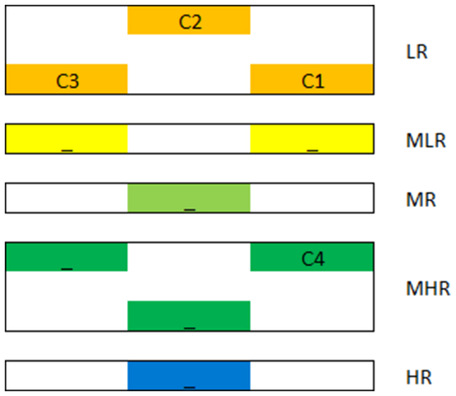

FIGURE 6
#SecureTree risk assessment map implementation, with the exact positioning of the trees analyzed in the study.

2019; Coelho-Duarte et al., 2021). An adaptation was then made to use the ISA BMP method as the so-called "traditional" one, for a two-fold reason: (i) as the #SecureTree is the approach to be validated, it appeared more appropriate to focus on a different, already existing, classification method, and (ii) the THREATS method, although similar in nature to the others, could become too dispersive.

Because of such non-trivial aspects, a weighted formulation of Cohen's κ was performed as well. Quadratic weights were used to assign partial credit to near agreements (e.g., low vs. medium risk) while strongly penalizing distant disagreements (e.g., low vs. high risk) (Warrens, 2011).

(Unweighted) Cohen's κ is expressed via the following Equation 8:

$$k = \frac{P_o - P_e}{1 - P_e} \tag{8}$$

where:

- P_o = Number of trees assigned to the same class by both methods/N
- P_e = Expected agreement by chance
- N = Total #trees = 4

The risk assignments of the two approaches are reported in Table 7.

It is worth noting that the Medium-High score for C4 in #SecureTree was mapped as Medium for κ computation, thus preserving ordinality.

According to what was stated before, $P_o = 2/4 = 0.5$.

For each risk class X, the probability that both methods independently assign that class is $P_A(X)$*$P_B(X)$, where P_A and P_B mean marginal probabilities, which describe how often each method assigns each class, independent of the other method.

Marginal probabilities are reported in Table 8.

There follows in Equation 9:

$$P_e = \sum_{X=L}^{H} P_A(X) * P_B(X) = 0.375 + 0.0625 + 0 + 0 = 0.4375 \tag{9}$$

The final value was therefore $\hat{e} \approx 0.11$.

(Weighted) Cohen's κ is expressed instead via the following Equation 10:

$$k = \frac{P_o^w - P_e^w}{1 - P_e^w} \tag{10}$$

where:

- P^w_o = Weighted observer agreement
- P^w_e = Expected weighted agreement by chance
- N = Total #trees = 4

The first step was to build an expected agreement matrix $E = \left[e_{ij}\right]$, where each cell e_{ij} represents the number of trees classified in the category i by #SecureTree and category j by the traditional, reference method (Table 9). Moreover, in this case, A means the #SecureTree approach, and B the reference one.

The next step was to build a weight matrix $W = \left[w_{ij}\right]$ to quantify the severity of disagreement between categories. Each cell w_{ij} is the result of the following Equation 11:

$$w_{ij} = 1 - \left(\frac{i - j}{N - 1}\right)^2 \tag{11}$$

TABLE 7 Risk assignments between #SecureTree and traditional (ISA BMP) methods.

Tree	#SecureTree approach (A)	Traditional method (B)
C1	Low	Low
C2	Low	Low
C3	Low	Moderate
C4	Moderate	High

TABLE 8 Marginal probabilities for unweighted Cohen's κ.

Risk rate	P_A	P_B
Low	P_A(Low) = ¾ = 0.75	0.50
Moderate	0.25	0.25
High	0	0.25
Extreme	0	0

TABLE 9 Expected agreement matrix for weighted Cohen's κ.

A\B	L	M	H	E
Low (L)	$P_A(L)*P_B(L) = 0.75*0.50 = 0.375$	$P_A(L)*P_B(M) = 0.75*0.25 = 0.1875$	0.1875	0
Moderate (M)	$P_A(M)*P_B(L) = 0.25*0.50 = 0.125$	0.0625	0.0625	0
High (H)	0	0	0	0
Extreme (E)	0	0	0	0

TABLE 10 Weight matrix for weighted Cohen's κ.

A\B	L	M	H	E
Low (L)	1.00	0.75	0.25	0
Moderate (M)	0.75	1.00	0.75	0.25
High (H)	0.25	0.75	1.00	0.25
Extreme (E)	0	0.25	0.75	1.00

where:

- o $w_{ii} = 1$ ➔ perfect agreement

  w_{ij} ➔ 0 as $|i-j|$ increases

- o N = Total #trees = 4

The (symmetrical) weight Matrix is reported in Table 10.
There follows in Equations 12, 13:

$$P_e^w = \sum_{i=1}^{N}\sum_{j=1}^{N} e_{ij} * w_{ij} \approx 0.766 \qquad (12)$$

$$P_o^w = {\sum_{i=1}^{j} w_{ij}} \Big/ N \approx 2.188 \qquad (13)$$

The final value was therefore is ≈ 6.01.
Usually, for both cases:

- o $\kappa \approx 0$: no meaningful agreement beyond chance;
- o $0.4 \le \kappa < 0.6$: moderate agreement;
- o $\kappa \ge 0.6$: substantial agreement.

In the present case, while unweighted κ appears modest, mainly due to strict penalization in a very small sample, weighted κ reveals substantial ordinal agreement, showing that disagreements are minor boundary shifts, not structural divergences.

6 Discussion

Systematic tree risk assessment methods encompass codified processes and protocols for (i) identifying, analyzing, and determining tree risks to detect those before safety incidents occur, and (ii) determining the level of risk and possible impact based on the surrounding environment (Smiley et al., 2012; Li et al., 2022). Specific measures are to be performed, as often as necessary, for both the aspects of risk reduction/mitigation and risk management. Such methods are mainly characterized by a qualitative analysis approach that makes it difficult, to a certain extent, to address uncertainties in the perception of tree hazards—which means, in other words, assigning a risk to a tree without likely managing to explain why that tree is at risk (Brundu et al., 2020).

Although the inputs of a tree risk evaluation are typically left to the judgment of the assessor, research from a tree mechanics perspective has shown the capability to lead to findings reliable enough to originate valid recommendations for those subjects—such as property managers, urban foresters, or homeowners—called to make the final decisions (Klein et al., 2019; Dunster et al., 2013). It is the case of, e.g., the visual tree assessment (VTA), which focused on the external manifestations of internal defects (Zevgolis et al., 2022); the static integrated analysis (SIA), where the rupture strength of hollow trees is the result of the assessment of factors such as tree height, wood strength, and crown shape (Mattheck et al., 2008); or the Wessolly method, whose nodal point to determine the strength and stability of a tree is working out how it assumes loads (for instance, gusts of wind) and transfers them to the ground via its internal stresses (Gardiner et al., 2016). The latter aspect, which was revealed as of particular importance in our case, has been coped with through specific methods and models centered on how to address the consequences of wind loads to different extents by means of, e.g., wind tunnel tests (Manickathan et al., 2018), tree dynamics analysis (mainly focusing on the physics of branches) (Ciftci et al., 2013), or controlled pulling to reduce dynamic factors to their static primitives (Giadrossich et al., 2017). In any case, tests like those previously mentioned are often time-consuming, since they are usually performed separately, on one tree at a time, in specific moments of time (Paine, 1971). Finding out trends and/or evolutionary paths for risk determination demands, therefore, repeating invasive activities on the same subject, not to mention the eventual difficulties in scaling such activities on forest-like scenarios. Related, but not identical to the concept of risk assessment, is the health status of the tree. This is a necessary condition to deal with for determining the mentioned risk, by means of an effective control of the complex mechanical challenges a plant encounters as it grows and develops—the so-called mechanosensitive control—from without and within, especially from turgor and wind pressure (Kouhen et al., 2023). Moreover, in general, forestry decision-making requires methods and tools to gather information about biological risks, to tackle and overcome uncertainty on an extended time horizon (Zhang et al., 2011). Notably, it is critical to find out a common denominator underlying the issues related to monitoring trees' health status, assessing the probability of tree failure (never possible; possible; likely to happen soon), as well as the probability of influencing the target (from very low; low; medium to high).

Risk analysis theory has been used since the 1970s in many fields, from underground mining to automotive plants to military operations, introducing and codifying the concept of a quantifiable risk as a combination of the probability and severity of an accident (Özfirat et al., 2017). For environmental sciences, the risk rating matrix introduced within ISA's BMP Method (Best Management Practices for Tree Risk Assessment) takes into account all the mentioned issues, incorporating them in a way to assess the likelihood that a tree will fall and impact the target (Ferrini et al., 2017; Klein et al., 2019). Along with this, worth mentioning are similar approaches like the QTRA (quantitative tree risk assessment) system, which is based on the concept of probabilistic quantification of tree risk (Ellison, 2005); or the THREATS (Tree Hazard: Risk Evaluation and Treatment System) methodology, in which a dedicated algorithm is performed to underline the subtle interaction between the three components of tree risk: defect, target, and impact (Matheny and Clark, 1994; Coelho-Duarte et al., 2021). Although these systems claim to be largely based on quantitative assessments, mapping and/or categorizing "frequency" and "severity" ratings to detect corresponding risk priority levels and sort of predetermine the extent of reasonable or acceptable risk, it still depends on a subjective interpretation, which could even lead to assigning identical ratings to quantitatively very different risks ("range compression") (Cox, 2008; Pascarella et al., 2021). An important aspect of risk assessment relates to the overall amount of uncertainty that the parameters used generate, which impacts the reliability of the results. Comparing the results of the application of different methods is critical, as it sheds light on the possibility to identify the one/s featuring the better applicability to local conditions, as well as an adequate level of reliability and repeatability (Schiefer et al., 2024).

In this scenario, the deployment of non-invasive, IoT paradigm-based sensors already available on the market (consumer electronics) allows for the #SecureTree approach to be implemented on multiple trees in wide areas, thus providing a far more reliable risk assessment than current practices. Moreover, the data flow originating from the continuous monitoring of biophysical parameters of green subjects makes it possible to meet the requirements of both tree risk assessment and risk management activities, along with the possibility to set up longitudinal studies for tracking down trees' health and structural integrity—as in the present case, where data gathered span over an entire season. The very last aspect turned out as critical to pursue the actual innovation the proposed approach stands on, that is a radical change of the point of view by replacing the classic dyad "entity/probability of damage"—inevitably affected by the aforementioned uncertainty and highly subjective interpretation of result - with the idea of "tree's progression of behavior" under varying environmental conditions. This means that for each unit, the #SecureTree risk assessment map is no longer a value but a type of behavior, as it evolves depending on external factors.

On such a basis, and also based on the results of the validation process, a structured comparison is shown in Table 11 between #SecureTree and the mentioned three major existing tree risk assessment methodologies.

The most critical aspects to be highlighted are where #SecureTree, integrating IoT sensors and a behavior progression framework, introduces key improvements, related to:

- *Shift from static to dynamic Risk Assessment*: traditional methods (e.g., ISA's BMP) rely on one-time visual inspections, offering only a snapshot of tree health. QTRA introduces probability models but still lacks continuous tracking. #SecureTree's capacity to continuously monitor tree behavior allows for the generation of (more properly) real-time risk assessment maps that enable, in turn, the modeling of evolving risks and enable proactive management accordingly;
- *Enhanced Predictive Power*: unlike static evaluations, #SecureTree tracks tree behavior progression under changing environmental conditions, recognizing early signals of instability (e.g., abnormal oscillations). The other methodologies analyzed lack this capability, only inferring the risk from visible defects or statistical averages;
- *Scalability and Cost-Efficiency*: the extent of automation introduced by #SecureTree, which leverages consumer-grade IoT sensors and a wireless network, reduces labor while expanding coverage, posing therefore as ideal for large-scale urban and forest ecosystems. In this regard, the scalability to more complex urban environments does not represent an issue in the first instance, as

TABLE 11 Key innovations of #SecureTree compared to existing methods.

Methodology	#SecureTree	ISA's BMP	QTRA	Threats
Risk assessment approach	Data-driven, behavior progression-based, using IoT sensors.	Visual, qualitative assessment with a risk matrix.	Probabilistic model, quantifying failure likelihood.	Algorithm-based analysis of defects and impacts.
Data collection	Continuous monitoring via wireless sensors.	Manual periodic inspection by experts.	Field observations combined with probability models.	Visual inspection and structural analysis.
Risk output	Real-time risk maps showing behavioral progression.	Low, moderate, and high risk categories.	Numeric probability of failure and consequence.	Risk rating from low to high.
Scalability	Multi-tree monitoring, scalable to large areas.	Single-tree evaluations, slow scaling.	Single-tree assessments are labor-intensive for scaling.	Limited scalability, single-tree focus.
Time sensitivity	Real-time, continuous assessment.	Snapshot assessments during inspections.	Relies on periodically updated probability data.	One-time assessment; periodic follow-up needed.
Predictive capability	Tracks behavior over time to anticipate failure.	No predictive capability — current-state focused.	Predicts failure probability, but lacks behavior tracking.	Limited predictive insights.
Automation level	High-automated data collection and mapping.	Fully manual.	Manual input, statistical model analysis.	Manual assessments, algorithm-supported analysis.
Environmental adaptability	Adjusts for wind, humidity, and branch behavior.	No dynamic adaptability to the environment.	Considers environmental factors probabilistically.	Limited adaptation to environmental changes.
Cost and resource efficiency	IoT sensors reduce costs; automation lowers manpower needs.	Labor-intensive, requires skilled experts.	Time-consuming analysis by experienced arborists.	Requires trained assessors for reliable analysis.
Error sensitivity	Built-in data redundancy minimizes errors.	Subjective visual interpretation.	Data accuracy depends on observation quality.	Risk of bias from visual evaluations.
Key innovation	Tracks behavior progression, focusing on cause-and-effect dynamics.	Visual inspection framework.	Probabilistic failure quantification.	Algorithm-based analysis of defects and impacts.

the well-known aspects related to interoperability, energy efficiency, security, and coverage are an integral part of the design process of the WSN (Jamshed et al., 2022), as reported in Sections 3.1 and 3.2;

- *Environmental Adaptability*: the existing methods rarely account for environmental variability in a dynamic way (e.g., QTRA includes probabilistic weather factors, but lacks live adaptation to sudden environmental changes), where #SecureTree adapts to real-time environmental shifts that affect tree stability;
- *Minimizing Subjectivity and Error*: ISA's BMP and THREATS are driven by human interpretation, thus risking inconsistency. QTRA relies on statistical data but still depends on human assessments. #SecureTree minimizes subjectivity through automated data collection and real-time analysis, ensuring consistent, objective risk evaluations.

#SecureTree allows for damage-based methodologies to be therefore replaced with a reliable and more effective, "cause/effect"-related one. It is still possible to see this under a classic point of view and state that the assessment units of the map originate in some way from the concept of damage assessment, meaning that each assessment unit is a sort of classic-like (mini)matrix. However, the proposed methodology allows for the intrinsic cited limits of risk rating to be overcome: altering the point of view causes in fact the shift of the assessment objective from a qualitative element (the damage) external to the tree, to another one intrinsic to it (the behavior expressed as a result of the action of external factors, and from which quantitative measures can be derived). To a certain extent, it is possible to refer back to the parallelism between the Mercalli and the Richter scales for assessing the effects of an earthquake: whereas the former provides a qualitative evaluation (the damages caused by an earthquake), the latter turns the focus on an intrinsic feature of the phenomenon (the magnitude of an earthquake, as registered by seismographs), thus allowing for a quantitative evaluation of the phenomenon itself (Yew et al., 2019; Aptikaev et al., 2021).

Furthermore, the very nature of the behavior-based ecological risk model for the #SecureTree framework, along with its peculiar working dynamics, points clearly to its ability to operationalize variables that are observable, measurable, and reproducible, towards a sustainable and significant management of tree risk assessment (Gentile and Harwell, 1998; Harwell et al., 2019). The analysis of trees' progressions of behaviors relies on the assessment of time series of environmental parameters gathered via reliable systems (IoT devices), which allow a continuous observation of the state and the shape of the many parts the trees are composed of, such as the tree crown, branches, and roots. In this regard, (i) the use of kinematic response variables and environmental covariates is consistent with ecological risk modeling literature, where dynamic response, rather than static descriptors alone, is informative of structural condition (James et al., 2006; Ekeoma et al., 2024; Zanotto et al., 2024); (ii) aspects related to trees' structural history—e.g., age-related conditions, evolutions, pruning, defects, and damage—are often qualitative, inconsistently recorded, observer-dependent, and rarely available at scale. The way the model was designed and set up aims at not ignoring them, as those are anyway implicitly encoded in long-term oscillatory patterns, and detectable through variance, persistence, and response asymmetry.

Following these premises, multiple successive assessment units over time (i.e., time series of assessment units over consecutive time periods) are meant to constitute pathways of evolution of risk level for either the individual tree and/or group of trees. The deployment of data analysis techniques to analyze these data-driven pathways will eventually make it possible to obtain a highly replicable, scalable, and configurable monitoring tool for predicting forest machine behavior (Melander, 2021). This will make it, therefore, possible to (i) plan (and realize) reliable long-term actions to handle disruptive events, and (ii) set up digitally focused strategies for emergency management (Vocaturo et al., 2023; Di Mauro et al., 2024). Such a complex scenario that clearly encompasses the human and animal dimensions as well, shall be tackled under an overarching and multidisciplinary One (Digital) Health vision (Benis et al., 2023b).

6.1 Limitations of the study

As the present study aims at introducing the #SecureTree approach in its first, proof-of-concept iteration, room for improvement is to be considered for many aspects. The main limitation that can be found is that the proposed methodology was tested and deployed on a plot of land only featuring one species of trees. An integration (where necessary) of the #SecureTree approach is therefore expected when scaling up the pilot study described in the present study, with more forest-based characteristics such as species composition, degree of stand density, and forest type (Bruchwald et al., 2018), as well as taking into account peculiar, urban-related ecosystems such as aquatic urban ones (Gawne, 2020). Similarly, the model was mainly designed taking into account the geographical and geophysical characteristics of the plot of land analyzed, with the specific objective of proving a sound shift from (theoretical) efficacy to (practical) effectiveness. This means that it was not dimensioned to address issues related to, e.g., extreme weather conditions, or specific age-related issues. Moreover, in this case, the original structure of the model is meant to be further refined, including features and parameters for which data may become available when moving to other, larger-scale case studies. In addition to this, as the whole approach also depends on aspects like the availability of nodes, sensors' coverage, and connectivity, malfunctioning in the WSN may lead to significant data loss. To reduce such risk, algorithms for continuous sensors' polling may be implemented to raise alarms whenever a sensor is not reachable (Siddiqui et al., 2018).

7 Conclusion and future prospects

In the present study, a tree risk assessment method called #SecureTree is proposed, which provides a continuous monitoring of the biophysical parameters of green subjects through the use of consumer electronics, meaning in this case non-invasive, IoT paradigm-based sensors already on the market. The real innovation #SecureTree stands upon is the shift from the well-known categorization of "frequency" and "severity" ratings of the damage to detect corresponding risk priority levels, to the concept of trees' progressions of behaviors, as a result of the combined variation over time of the environmental parameters affecting them.

In order to verify the reliability and applicability of the proposed approach, a wireless sensor network was set up on the citron trees (*Citrus Medica*) hosted in a given plot of land in the Campania Region, South Italy. A specific tree age-dependent variable called SBfactor that accounts for branch oscillation was worked out, and its relation was calculated with the range of intensity of wind. This made it possible to detect and map a class of data-driven levels of risk, mainly based on a "cause/effect"-like principle. As the continuous monitoring activity provided by the sensors installed allows for getting trees' health status data in real-time, long-term goals can be pursued, notably designing trajectories of risk evolution during time spans of increasing width.

Steps forward are planned to further improve the solution in an ever-increasing precision forestry perspective. In addition to testing the proposed approach on different kinds of ecosystems, likely hosting different species of trees, plans are in progress to figure out how to deploy techniques like (probabilistic) Petri Nets for analyzing the paths of risk evolution, in order to build up the necessary set of requirements for designing "early warnings" Decision Support Systems. Such long-term longitudinal deployments are meant to allow evaluation of whether persistent deviations in behavior-based indicators would precede documented structural degradation, pruning interventions, or hazard mitigation actions. This will make it possible to further improve interventions of environmental governance by improving the capability of managing the complex web of human, animal, and environmental interconnections (Benis et al., 2023a).

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

OT: Data curation, Supervision, Conceptualization, Software, Writing – review & editing, Writing – original draft, Investigation, Methodology, Resources, Visualization, Funding acquisition, Project administration, Formal analysis, Validation. MM: Project administration, Supervision, Visualization, Writing – review & editing. VM: Methodology, Formal analysis, Writing – review & editing, Data curation, Investigation, Visualization, Validation. GP: Data curation, Formal analysis, Visualization, Investigation, Writing – review & editing. AT: Investigation, Conceptualization, Resources, Writing – original draft, Writing – review & editing, Visualization, Methodology, Validation, Data curation, Formal analysis, Supervision. EV:

Visualization, Data curation, Software, Supervision, Formal analysis, Resources, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

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