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Artificial Intelligence for Modelling Biophysical Elements of Forest Ecosystems: Opportunities and Challenges

Polina Lemenkova[1,*]

[1]Disaster and Emergency Management Department, Institute of Earthquake Engineering and Disaster Management, Istanbul Technical University, İTÜ Ayazağa, 34469, Maslak Kampüsü, İstanbul, Türkiye

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Review Article

Abstract − Biophysical elements of forests are essential for tree health, biodiversity, and ecosystem services, with their effects increasingly influenced by climate change and global environmental dynamics. Understanding the interactions between biotic and abiotic components of forest ecosystems poses challenges due to the large spatial extent, size, and inaccessibility of tree massifs, along with the often complex relationships among various factors, including soil, hydrology, relief, meteorological conditions, and other ecosystem components. This review serves as an introduction to the field of forest biophysical elements, outlining significant challenges such as multifactorial links, and the responses of roots and vascular systems to soil quality. It highlights emerging issues related to environmental dynamics that complicate the study of these interactions. Furthermore, the paper explores the application of artificial intelligence (AI) in modeling the connections between biotic and abiotic components of forest ecosystems. This involves the integration of advanced techniques such as remote sensing, imaging, geospatial data analysis, and cartographic methods, which are employed across various spatial and temporal scales to enhance our understanding of these complex ecological relationships. Lessons from silviculture systems highlight tools and pitfalls for forestry, emphasising the necessity for interpretable models backed by machine learning (ML), the integration of ecological context, and validation of various algorithms such as random forest (RF) and Support vector machines (SVM). We conclude that coordinated data infrastructures are essential for ensuring that AI provides actionable insights and scalable solutions for monitoring complex forest ecosystems.

Keywords − *Python, data modelling, data analysis, artificial intelligence, environmental monitoring*

Orman Ekosistemlerinin Biyofiziksel Unsurlarının Modellenmesinde Yapay Zekâ: Fırsatlar ve Zorluklar

Polina Lemenkova[1,*]

[1]İstanbul Teknik Üniversitesi (İTÜ), Deprem Mühendisliği ve Afet Yönetimi Enstitüsü, Afet ve Acil Durum Yönetimi Bölümü. İTÜ Ayazağa, 34469, Maslak Kampüsü, İstanbul, Türkiye

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Derleme Makalesi

Öz −Ormanların biyofiziksel unsurları, ağaç sağlığı, biyoçeşitlilik ve ekosistem hizmetleri için hayati öneme sahiptir ve etkileri iklim değişikliği ve küresel çevre dinamiklerinden giderek daha fazla etkilenmektedir. Orman ekosistemlerinin biyotik ve abiyotik bileşenleri arasındaki etkileşimleri anlamak, ağaç kütlelerinin geniş mekânsal yayılımı, büyüklüğü ve erişilemezliği ile birlikte, toprak, hidroloji, rölyef, meteorolojik koşullar ve diğer ekosistem bileşenleri de dahil olmak üzere çeşitli faktörler arasındaki genellikle karmaşık ilişkiler nedeniyle zorluklar ortaya koymaktadır. Bu inceleme, orman biyofiziksel unsurları alanına bir giriş niteliğindedir ve çok faktörlü bağlantılar ve köklerin ve vasküler sistemlerin toprak kalitesine verdiği tepkiler gibi önemli zorlukları özetlemektedir. Bu etkileşimlerin incelenmesini karmaşıklaştıran çevresel dinamiklerle ilgili ortaya çıkan sorunları vurgulamaktadır. Ayrıca, makale, orman ekosistemlerinin biyotik ve abiyotik bileşenleri arasındaki bağlantıları modellemede yapay zekanın (YZ) uygulamasını incelemektedir. Bu, bu karmaşık ekolojik ilişkileri daha iyi anlamamızı sağlamak için çeşitli mekânsal ve zamansal ölçeklerde kullanılan uzaktan algılama, görüntüleme, coğrafi veri analizi ve kartografik yöntemler gibi gelişmiş tekniklerin entegrasyonunu içermektedir. Ormancılık sistemlerinden alınan dersler, ormancılık için araçları ve tuzakları vurgulayarak, makine öğrenimi (ML) ile desteklenen yorumlanabilir modellerin, ekolojik bağlamın entegrasyonunun ve rastgele orman (RF) ve destek vektör makineleri (SVM) gibi çeşitli algoritmaların doğrulanmasının gerekliliğini ortaya koymaktadır. Yapay zekanın karmaşık orman ekosistemlerinin izlenmesi için uygulanabilir içgörüler ve ölçeklenebilir çözümler sağlamasını sağlamak için koordineli veri altyapılarının şart olduğu sonucuna varıyoruz.

Anahtar Kelimeler − *Python, veri modelleme, veri analizi, yapay zekâ, çevresel izleme*

1 lemenkova@itu.edu.tr
*Corresponding Author / Sorumlu Yazar

1. Introduction

The forest ecosystem is characterized by a high-dimensional matrix of biophysical elements, categorized into biotic nodes (taxonomic diversity across plants, animals, and microorganisms) and abiotic features (edaphic properties, hydrological regimes, and climatic forcings). These components are linked via stochastic physical processes and feedback loops that govern ecosystem architecture and metabolic functionality. Specifically, the land-atmosphere interface acts as a critical regulator of energy flux and moisture transport, illustrating a dynamic, non-linear interplay between biological agents and their geophysical environment.

Despite the transformative potential of Artificial Intelligence (AI) in environmental management, deploying predictive models within silvicultural contexts presents significant computational hurdles. The inherent complexity of forests-defined by extreme species heterogeneity, multi-decadal temporal scales, and vast spatial extents-introduces substantial "noise" into the data. This complicates feature extraction and the mapping of inter-element dependencies. Nevertheless, the evolution of high-level programming frameworks and open-source libraries has catalyzed the development of robust, AI-driven environmental models, enabling more precise quantification of complex ecological patterns (Niu et al., 2022; Lemenkova, 2019).

This research evaluates the current state of the art and the persistent bottlenecks in forest informatics, with a primary focus on environmental assessment under climatic non-stationarity. Central to this study is the integration of Machine Learning (ML) and Deep Learning (DL) architectures, which offer scalable alternatives to traditional frequentist statistics for multi-modal data analysis. Current methodological shifts emphasize the inversion of biophysical parameters through AI-enhanced workflows, moving toward a more predictive, data-centric paradigm for monitoring forest dynamics and system resilience

2. Problem formulation

The modeling of forest ecosystems is primarily constrained by their behavior as complex, self-regulating stochastic networks (Mansourian & Stephenson, 2023; Yasin et al., 2025). System functionality is governed by the non-linear interactions between biotic nodes (taxonomic hierarchies including arborescent flora, microbiota, and fauna) and abiotic covariates (edaphic properties, topographic relief, and solar irradiance). These multi-scalar interactions-stratified from the canopy to the rhizosphere-facilitate critical energy fluxes and biogeochemical cycling, providing the foundational stability required for habitat maintenance and hydrological buffering.

High-dimensional species heterogeneity introduces significant variance into the system architecture, complicating the derivation of generalized predictive models (Tong et al., 2026). While species richness is functionally correlated with climatic and topographic features, the spatial non-stationarity of these relationships across diverse landscapes necessitates advanced analytical frameworks (Ao et al., 2026; Zhang et al., 2026). Consequently, the shift toward AI-driven modeling-utilizing architectures tailored for high-dimensional ecological data-is essential for capturing these complex dependencies and optimizing forest management strategies under varying environmental stressors (Sasaki & Abe, 2025; Abreu-Dias et al., 2025).

Vast spatial extent of forest ecosystems poses significant challenges for effective monitoring. Forests cover millions of hectares, often located in remote areas that are topographically challenging and hard to access. Such complexity requires substantial logistical and analytical efforts to monitor these landscapes efficiently. Remote sensing (RS) has advanced to facilitate forest mapping through enhanced resolution and expanded coverage. New approaches in modelling biophysical structure of forest rely on such tools using the following data types:

- Airborne Laser Scanning (ALS) data (Gobakken et al., 2015; Kimothi et al., 2009; Ørka et al., 2012),

- Unmanned aerial vehicles (UAVs) (Marques et al., 2025; Kang et al., 2025; Zhang et al., 2019; Naseri & Shataee Jouibary, 2024),
- Light Detection and Ranging (LiDAR) technologies (Koetz et al., 2006; He & Wei, 2013),
- InSAR (Interferometric Synthetic Aperture Radar) data (Wang et al., 2023),
- Multispectral imagery (Huang et al., 2025; Ahmed et al., 2016).

These innovations improve management of forest ecosystems. Despite these benefits, RS generate large quantities of diverse data, leading to significant challenges in their processing, interpretation, and integration into decision-making frameworks. AI is highly effective in analysing diverse, large RS datasets, including high-resolution aerial imagery for sustainable forest management (Espíndola et al., 2025; Li et al., 2022). AI is highly effective in analysing diverse, large datasets of forest biophysical parameters, including high-resolution aerial imagery and fieldwork-collected data.

In contrast to the traditional statistical methods that depend on predefined linear assumptions, AI algorithms can uncover intricate, nonlinear relationships within forestry data (Nunes, 2025). This ability poses AI as a key asset for understanding complex interactions in forest-related environmental, vegetation and climate datasets (Hyyppä et al., 2020). Additionally, emerging technologies that integrate AI with RS contribute to the development of the smart forestry management, Figure 1.

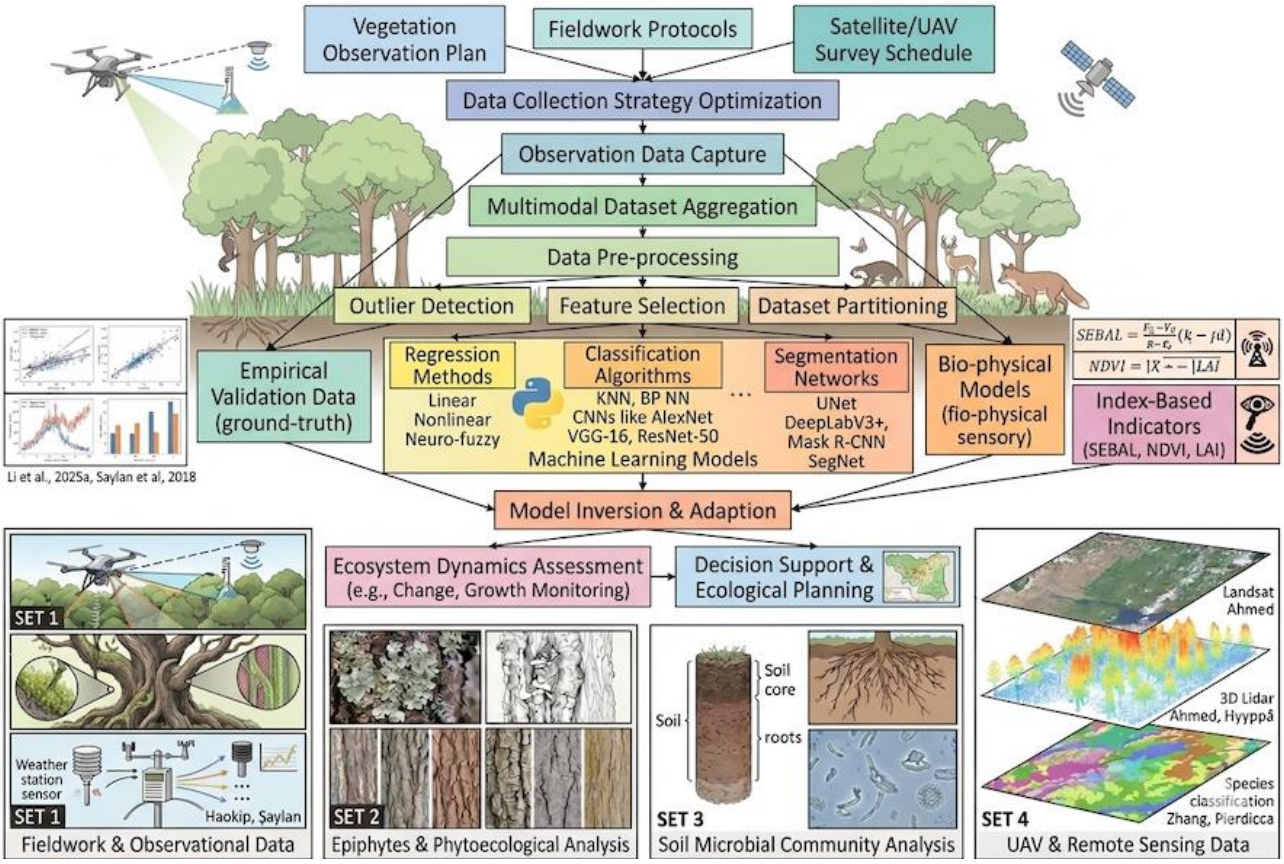

Figure 1. Methodological framework for AI-driven forest monitoring: integrating multimodal data streams, machine learning architectures, and multi-scale ecological observations. Diagram source: author.

To decode these high-dimensional interactions in forest ecosystem, modern forest ecology increasingly relies on AI-driven modeling and machine learning (ML) architectures. By treating the ecosystem as a graph-based data structure, Graph Neural Networks (GNNs) can be deployed to model the non-linear dependencies between canopy health and soil microbial diversity. Furthermore, the integration of Computer Vision (CV) via Deep Learning (DL) models-such as CNNs and Vision Transformers (ViTs)-enables the automated extraction of biophysical parameters from multi-source remote sensing data (e.g., LiDAR, hyperspectral, and RGB). These AI frameworks allow for the transition from static observations to predictive analytics, facilitating the detection of early-warning signals for forest decline and the simulation of carbon sequestration capacity under varying climate scenarios. By synergizing Transfer Learning and Reinforcement Learning, researchers can optimize forest management strategies, transforming raw environmental data into actionable intelligence for ecosystem resilience.

3. Objectives and goals

In response to the increasing complexity in modeling, mapping, and processing the biophysical structures of forests, influenced by a range of biotic and abiotic factors including climatic and anthropogenic effects, this review examines the recent advancements in AI, ML, and DL methodologies for data analysis in forestry. Artificial intelligence (AI) is the replication of human intelligence in machines designed to think, learn, and solve problems independently. These AI systems excel in analysing extensive datasets, discerning patterns, and making informed decisions or predictions, frequently surpassing conventional approaches across various scientific domains. In the realm of forest biophysical modelling, the applications of AI are primarily categorised into three main types:

1. machine learning, which employs algorithms for data analysis, prediction and forecasting;
2. computer vision, which utilises RS imagery from drones or satellites to assess tree health;
3. natural language processing (NLP), which facilitates the extraction of valuable insights from scientific literature and field reports to identify or recognise emerging environmental risks to forests.

This review addresses the essential field of 3 types of AI in forest ecosystem modelling, highlighting significant challenges such as the complex interplay between multifactorial ecosystem structures, including both biotic and abiotic components. It explores the potential application of AI in understanding and modelling these interactions by integrating diverse data sources such as RS, imaging, genomics, and ecological datasets across various spatial and temporal scales. Furthermore, it draws parallels with agricultural systems to identify potential tools and recognise pitfalls relevant to forestry practices.

By integrating prior and current literature on AI-enhanced forest ecosystem modelling from the over 100 reference sources indexed in Scopus and/or Web of Sciences (WoS) bibliographic databases, the review seeks to outline the advancements made recently in forest research. Alongside methodological developments, it also proposes directions for future investigation and application within the domain of forestry and silviculture investigated through AI, ML and DL algorithms. This paper discusses on future directions for the field, stressing the importance of developing interpretable models, embedding ecological context, validating models across different species, and creating coordinated data infrastructures to ensure that AI can provide actionable and scalable solutions to the complexities present in forest ecosystems.

4. Biotic elements in biophysical elements of forest

System stability is increasingly modulated by anthropogenic climate change, where shifts in thermic and precipitation variables act as primary stressors on the network. These perturbations induce non-linear responses in Net Primary Productivity (NPP), alter species distribution patterns, and increase the frequency of stochastic disturbances like wildfire propagation and insect outbreaks. The resulting impacts on forest health directly influence the delivery of critical ecosystem services, encompassing provisioning (resource extraction), regulating (carbon sequestration), supporting (pedogenesis), and cultural dimensions, all of which require robust stakeholder-led policy frameworks for sustainable management.

Forest ecosystem is conceptualized as a multi-layered, complex network of interacting biotic and abiotic nodes, as synthesized in Figure 2. The system architecture is defined by the spatial stratification of biotic components-ranging from arborescent canopy taxa to soil microbiota-and their functional integration with abiotic covariates such as solar irradiance, hydrological regimes, and edaphic properties. This structural topology facilitates autonomous biogeochemical cycling and energy flux, maintaining the forest as a self-sustaining unit.

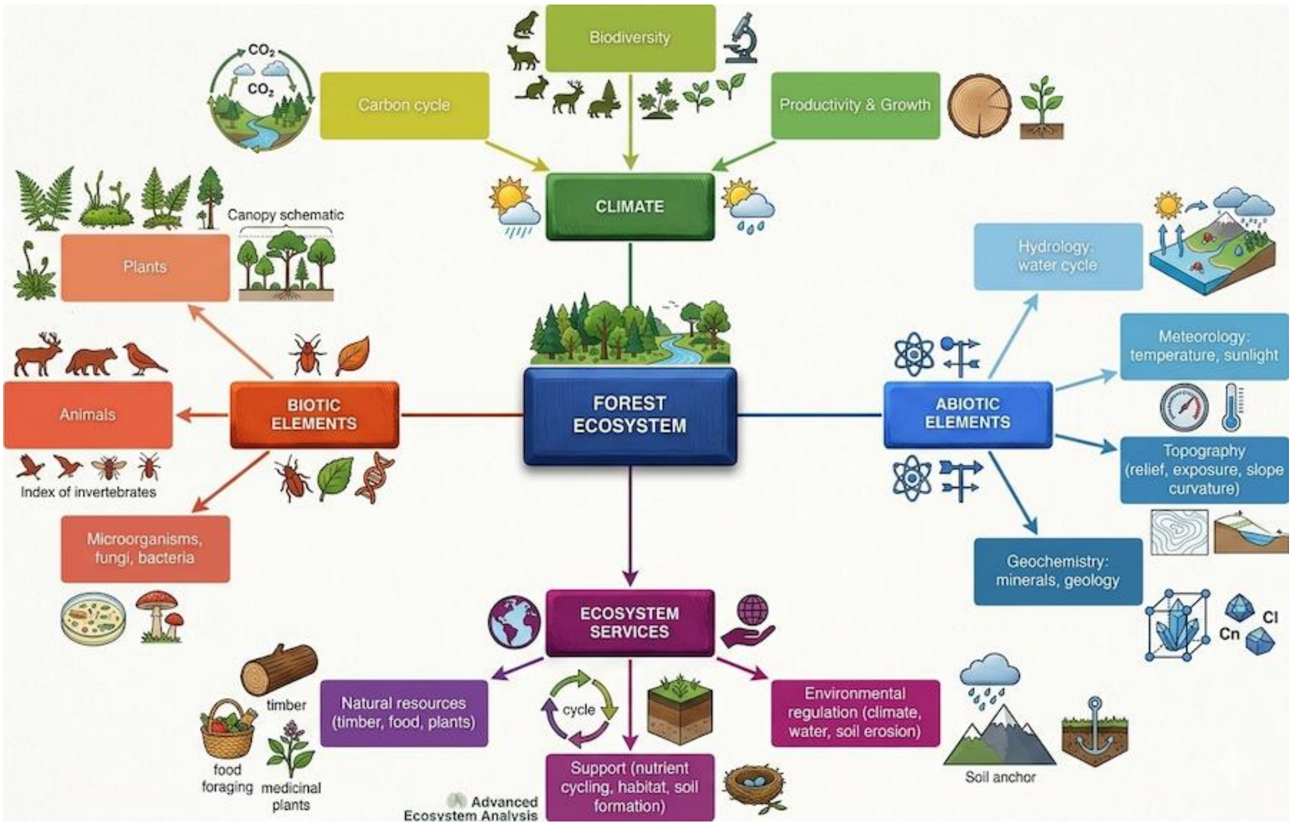

Figure 2. Structure, functions, services, units and types of forest ecosystem. Diagram source: author.

5. Plants and biomass

Canopy evapotranspiration and tree transpiration depends on leaf characteristics and the overall canopy structure through Leaf Area Index (LAI) (Wu et al., 2025). Forest plant biomass is typically partitioned into various components to facilitate measurement and analysis into the Aboveground Biomass (AGB) and Belowground Biomass (BGB) as drivers of net primary productivity (NPP) (Cui et al., 2025). The Aboveground Biomass (AGB) encompasses all living matter above the soil: trunk (stem), branches, crown, and leaves which serve as the primary sites for photosynthesis and gas exchange (Lu et al., 2016; Njomaba et al., 2026). The BGB includes roots, which absorb water and nutrients and understory vegetation under the main canopy that includes other plants: shrubs, grass, and bryophytes (Lei et al., 2026).

The interplay between canopy evapotranspiration, tree transpiration, and major abiotic stressors such as precipitation and temperature forms a complex system in forest ecology. This interaction results in varying moisture regimes, ranging from extremely dry to highly saturated conditions. To address these complexities, the integrative approaches use the AI-supported climate-hydrological modeling combined with the detection and prediction of moisture levels in forest ecosystems (Haokip et al., 2025).

The deployment of Artificial Intelligence (AI) architectures to model the high-dimensional complexity of forest biotic components facilitates the decryption of non-linear ecological interactions. By integrating multi-modal data streams-encompassing Remote Sensing (RS), hyperspectral imaging, genomics, and longitudinal ecological datasets-AI-driven frameworks can quantify the synergistic effects of abiotic stressors and phytopathogenic decline across heterogeneous spatio-temporal scales (Hessenauer, 2025).

This transition from frequentist statistics to deep learning (DL) allows for the processing of unstructured data to identify early-warning signals of ecosystem instability. For instance, the classification of complex forest structures has evolved through the application of diverse supervised learning algorithms. Zhang et al. (2020) demonstrated the efficacy of both traditional and deep architectures, including K-Nearest Neighbor (KNN) and Backpropagation Neural Networks (BP NN), alongside advanced Convolutional Neural Networks (CNNs) such as AlexNet, VGG-16, and ResNet-50. Utilizing RGB optical imagery, these AI-driven models are benchmarked for the automated segmentation and species-level identification of tree canopies within mixed urban stands, Figure 3. Such workflows leverage feature extraction layers to isolate morphological "fingerprints" of various taxa, significantly reducing the error rates associated with manual silvicultural assessments and enabling large-scale, automated monitoring of biomass distribution and forest health.

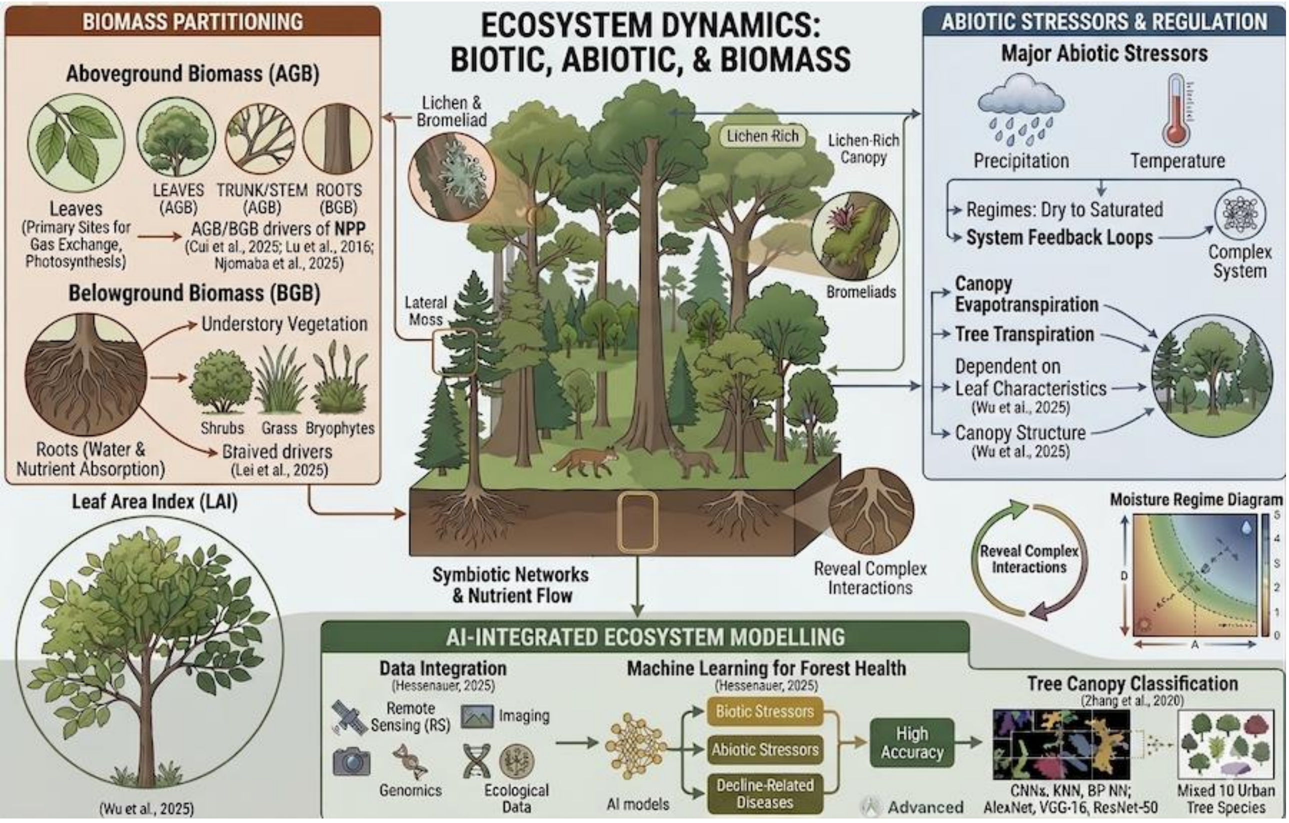

Figure 3. Scheme of forest ecosystem dynamics: Synergizing biotic, abiotic, and biomass interactions with methods of modelling and prediction

6. Microbes and epiphytes and their role in forest functioning

The integration of microbial and epiphytic communities into forest modeling necessitates treating these taxa as high-dimensional biotic nodes within a complex stochastic network. These organisms function as primary biological drivers of biogeochemical cycling, where their metabolic pathways can be modeled as discrete inputs for soil edaphic health and nutrient fertility. By quantifying processes such as organic matter decomposition and symbiotic nitrogen fixation, researchers can deploy predictive analytics to map soil productivity gradients. Beyond chemical regulation, these microorganisms significantly augment hydrological stability; by modulating soil porosity and canopy moisture regimes, they function as critical variables in evapotranspiration (ET) inversion models and water retention simulations.

The presence and diversity of these taxa provide specialized micro-habitats that bolster trophic complexity, which can be analyzed through Multi-Source Feature Fusion. By synergizing genomics data with high-resolution Remote Sensing (RS) and UAV-based imagery, AI architectures-such as Graph Neural Networks (GNNs)-can establish the structural interdependencies required for ecosystem resilience. These models treat microbes and epiphytes not as isolated variables, but as integral components of a Self-Regulating System, allowing for the detection of non-linear feedback loops between biodiversity and forest stability (Figure 4).

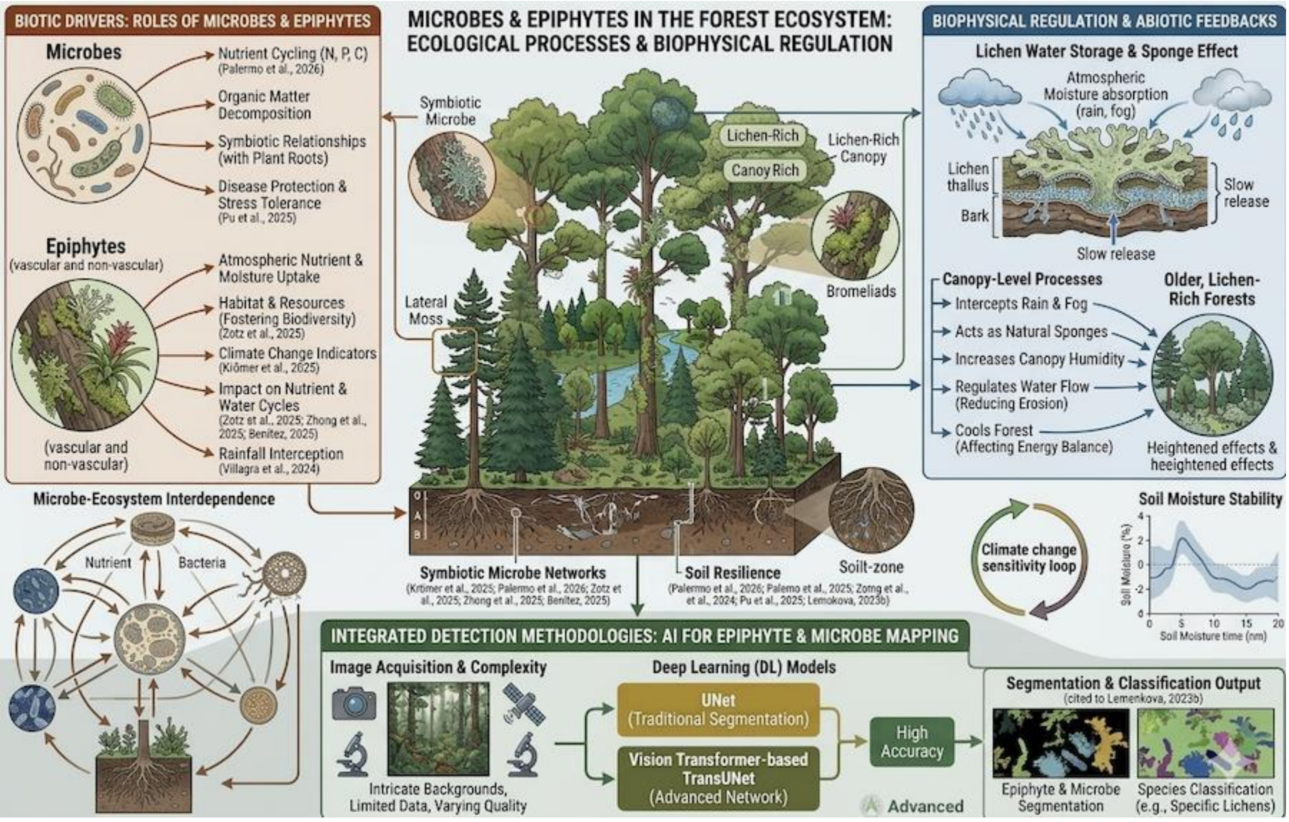

Figure 4. Microbe-epiphyte interactions in forest ecosystem: Biogeochemical cycling, biophysical regulation and methods of analysis. Diagram source: author.

Water storage capacity of lichens is crucial for forest biophysical regulation. It acts similar to the activities of natural sponges that absorb and slowly release moisture which further interacts with environmental setting. Such processes increase canopy humidity, regulate water flow through reducing erosion, and influence forest energy balance through cooling effect. Besides, lichens affect the overall water cycle by intercepting rainfall and fog, which is vital for forest health and climate, especially in older, lichen-rich forests.

Epiphytes are special plants that grow on the lateral surfaces and sides of trees, deriving their nutrients and moisture from the atmosphere. They are crucial for understanding the impacts of climate change in forests, as serve as primary indicators of such changes (Krömer et al., 2025). Beyond their role as climate indicators, epiphytes significantly influence water and nutrient cycles within montane tropical forests, a fact supported by numerous studies (Zotz et al., 2025; Zhong et al., 2025; Benítez, 2025). In particular, Villagra et al. (2024) highlighted the vital contribution of epiphytes to total rainfall interception in montane forests. These findings underline the ecological significance of epiphytes and highlight the urgent need for their conservation and protection within these ecosystems.

Microbes play a crucial role in forest ecosystems by driving nutrient cycles, supporting plant health through symbiotic relationships, enhancing carbon sequestration, and influencing plant-herbivore interactions (Palermo et al., 2026). They decompose complex organic matter, make essential nutrients available, provide disease protection, and help plants withstand stress, thus contributing significantly to forest resilience and its overall functionality (Pu et al., 2025).

Deep Learning (DL) models have demonstrated strong benefits for detecting epiphytes and microbes. Specifically, DL is useful for high level of accuracy in images analysis characterised by complex backgrounds, even when the training dataset is limited and the image quality varies. These models can leverage different methodologies for segmentation, including traditional image segmentation techniques as well as advanced DL-based segmentation networks (Lemenkova, 2023b). Prominent among these networks are the UNet and the Vision Transformer-based TransUNet, both of which can effectively discern and classify epiphytes within intricate visual contexts.

7. Abiotic factors in biophysical elements of forest

Climate stressors, including drought and temperature, are principal abiotic agents that affect forest stands and can accumulate and intensify due to climate change (Yuan et al., 2026). This combination can lead to significant forest diebacks on a large scale (Bent et al., 2025)

8. Soil and hydrology

Soil and hydrology play essential roles in the functioning of forest ecosystems. Soil serves multiple purposes, acting as a sponge, filter, and source of nutrients. On the other hand, forest crown type, stem characteristics and hydrology determine water flows in the ecosystem, impacting soil pH (Sarıyıldız & Küçük, 2011). Key components within this system include trees, particularly their root systems and leaf litter, as well as the structure of the soil, which consists of attributes like porosity and organic matter. These elements together manage important processes like water infiltration, runoff, and groundwater recharge. This intricate interplay establishes a crucial feedback loop that ensures the health and stability of the ecosystem.

Integrated approach facilitates modelling of water cycle in forest ecosystems where functionality of Python plays an essential role. The functionality of Python supports modelling of the meteorological features and environmental composition of precipitation, evapotranspiration, temperature and other parameters (Evcen and Yağcı, 2022; Hanbay Tiryaki and Balaman, 2021; Lemenkova, 2022b; Li and Gao, 2021). In such studies, the relation between precipitation type and these three meteorological drivers are used to predict the occurrence of fog and mixed precipitation during fieldwork period and compared with retrospective data. These predictions were also compared to environmental forests observations. The methodology of biophysical modelling was based on the comprehensive analysis of the existing studies reported in previous studies on forests (Alataş et al., 2019, 2023; Unan et al., 2024).

9. Meteorological conditions: Precipitation and fog

Precipitation and fog play a crucial role in the health and sustainability of forest ecosystems. They act as primary sources of moisture, which is essential for the survival of various plant and animal species. These elements not only provide water but also significantly affect the microclimates within forests, creating unique environmental conditions that support biodiversity. Furthermore, precipitation and fog are integral to nutrient cycling, enhancing the availability of essential elements for plant growth. Conversely, forests themselves have a reciprocal relationship with these weather phenomena by influencing their frequency and effects. Thus, the interplay between rainfall, fog, and forest ecosystems is essential for maintaining ecological balance and resilience.

Environmental modelling of meteorological setting is a key aspect in many ecological studies (Li et al., 2025a, 2025b; Lemenkova, 2022a, 2023a; Sahibzada et al., 2025). Evaluating these models in simulated eco-hydrological behaviours shows the relationships between the climate and environmental variables. Python libraries estimate eco-hydrological parameters through advanced modelling tools and compositions by statistical algorithms with user-defined variables. Such workflow includes dataset preprocessing, outlier detection, statistical analysis, climate-environmental feature selection, model validation and calibration and data post-processing. Python-based modelling supports understanding of the role of fog and age of trees in water balance of forests.

Obtaining climate-environmental information and reference from environmental observations requires data modelling, which depends on the software functionality, dataset formats and the variability of parameters (Sharma et al., 2025; Lemenkova, 2025a; Polat et al., 2024; Kalkan and Özkazanç, 2024; Abba Kyari and Agajo, 2021). Using advanced computing tools enables to perform required spatiotemporal analysis of eco-hydrological and geophysical characteristics, as also shown in previous studies (Karaogul et al., 2025; Lemenkova, 2025c; Rahimi et al., 2025). In a more complex model, the set of hydrological and meteorological parameters is represented by a large dataset collected within an annual period, and seasonal climatic changes are estimated from the fieldwork data collected using Eddy covariance techniques used in many studies (Chen et al., 2025; Şaylan et al., 2018; Liu et al., 2024; Yağcı, 2023; Xue et al., 2024). Such interactions are illustrated on scheme in Figure 5.

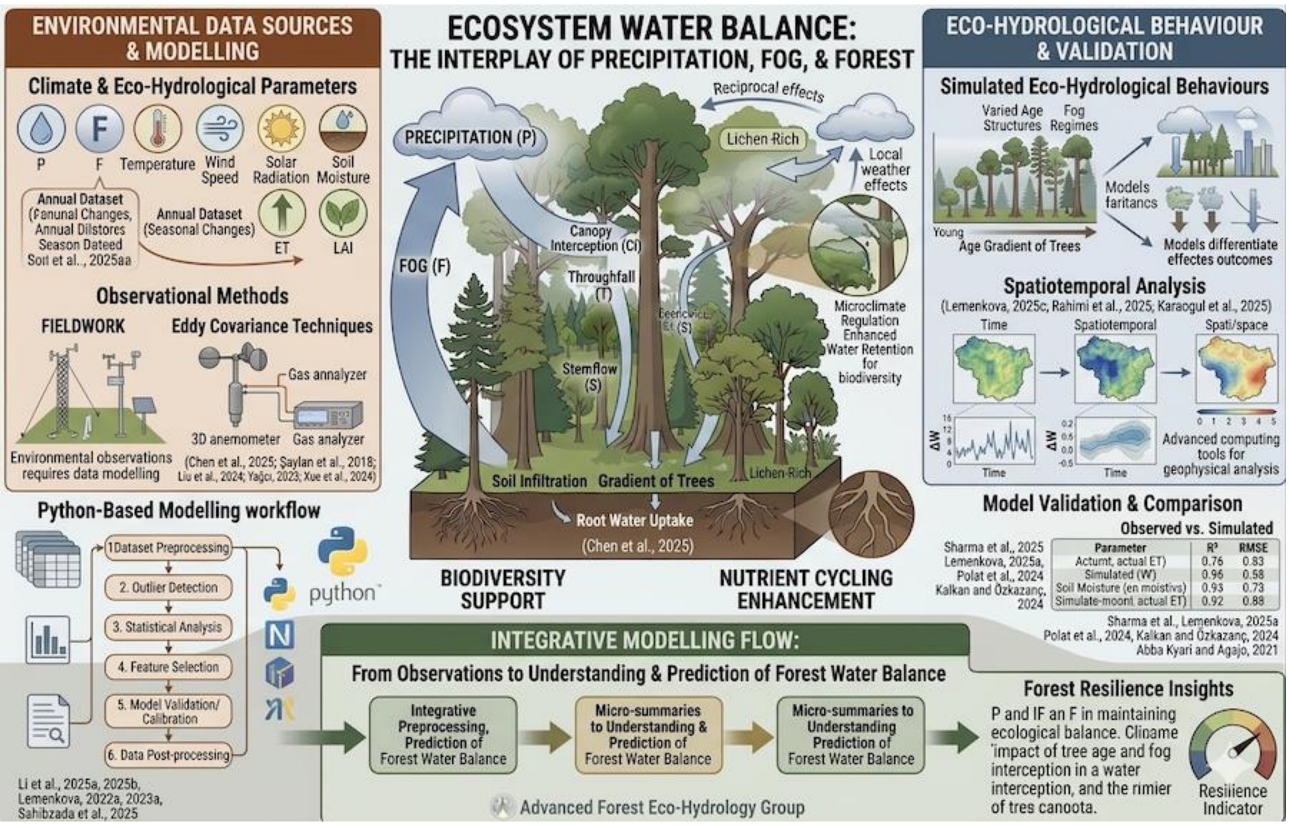

Figure 5. Eco-hydrological modelling framework: quantifying the reciprocal interactions between precipitation, fog, and forest water balance via Python-based analytical workflows. Diagram source: author.

10. Water partitioning and balance at catchment level

Forest ecosystems play a critical role in the water balance of a catchment by strongly influencing how precipitation is partitioned into different hydrological flows, primarily increasing evapotranspiration (ET) and reducing surface runoff compared to non-forested landscapes (Jiang et al., 2026; Hernández-Rodríguez et al., 2021). Forest ecosystems are essential in regulating the water balance within a catchment area, significantly affecting the distribution of precipitation into various hydrological processes.

A crucial aspect of this regulation is the enhancement of evapotranspiration (ET), which is considerably higher in forested areas compared to non-forested landscapes, leading to decreased surface runoff. Evapotranspiration, a key component in forest hydrology, involves the loss of water to the atmosphere through both the evaporation of intercepted rainfall from foliage and the transpiration process occurring in leaves. In tropical rainforests of Amazon, forests yield ET rates include major part of total precipitation (Justino et al., 2025). Additionally, interception loss (IC) plays a significant role in the hydrological cycle, where precipitation that lands on the forest canopy is lost back to the atmosphere via evaporation before it can reach the ground, constituting roughly 20% of global total evaporation rates. Overall, forest ecosystems thus exert a profound influence on hydrological dynamics, affecting water cycles.

Different ML methods can be used to estimate ET and IC data (Rueda Cadavid et al., 2026). Examples include methods of multiple linear regression (Kim et al., 2022), fuzzy modelling (Laaboudi & Slama, 2020), and convolutional neural networks (CNN) (Zhu et al., 2025). Technically, primary Python's libraries include such tools as Scikit-learn, Statsmodels, TensorFlow, and Keras.

Transpiration (T) refers to the process where water absorbed by plant roots is released as vapour through stomata, primarily occurring during photosynthesis. In boreal forests, the contributions of transpiration and interception can account for major part of the total ET during growing season (Hadiwijaya et al., 2020; Wang & Zhu, 2025). This highlights the significant role that these processes play in the water balance and overall ecosystem function of forest.

Runoff (R) refers to the water that either flows across the surface of the land or infiltrates into the soil, contributing to the replenishment of soil moisture, subsurface water movement, and overall streamflow. In regions where deforestation has occurred, the impact on these hydrological processes is notable; such areas typically experience increased drainage and higher rates of runoff. This is likely due to the removal of vegetation that otherwise promotes water absorption and retention in the soil, thereby altering the natural water cycle and increasing surface water flow.

Machine learning (ML) is transforming the analysis of runoff and soil infiltration through the development of highly accurate predictive models. Techniques utilizing algorithms such as Random Forest (Rodrigo-Comino et al., 2025), XGBoost (Elhallaoui Oueldkaddour et al., 2025), and Support Vector Machines (SVM) are employed frequently in conjunction with physical hydrological principles to create hybrid models (Asadollahi et al., 2024). These models forecast various aspects of water management, including the movement of water, water quality, and flood risks. By harnessing the complex interrelationships between soil properties-like texture and slope-and rainfall patterns, ML reduces dependence on expensive field measurements. This data-driven approach enhances the accuracy of flood predictions and water resource management strategies, thus facilitating the design of more effective stormwater systems through the identification of critical factors and refinement of simulation precision.

11. Applications of AI in modelling forest ecosystem

This section provides insights into the diverse applications of artificial intelligence (AI) within the field of forest ecosystem modelling. It highlights specific examples that demonstrate how AI technology is being used to enhance the understanding and management of forest ecosystems. A summary of the principal cases addressed in this discussion can be found in Table 1, which organises and presents these examples for clarity and reference. Key issues in forest ecosystems are addressed, emphasising biophysical elements where AI creates significant advancements. It assesses current AI applications via case studies, draws lessons from ecological science, and discusses future opportunities and challenges to consider.

Biotic part in forest ecosystems include a variety of elements such as plants, animals, fungi, microorganisms, and organic matter like dead leaves and wood. These elements are critical in forest ecosystems, where monitoring and analysis are increasingly conducted using artificial intelligence (AI). AI tools are employed for detecting and surveilling biotic elements, as well as predicting their dynamics and changes, including land cover alterations and tree coverage shifts.

Table 1

Summary of AI applications utilised in modeling forest ecosystems through various approaches aimed at monitoring forest health, identifying biotic and abiotic interactions, detecting deforestation and reforestation, and predicting the decline of forest stands due to climate change

Nr	Tree species	Region	Objective	AI / ML method	Reference
1	Mixed-conifer forest: Jeffrey pine (*Pinus jeffreyi*), lodgepole pine (*Pinus contorta*), red fir (*Abies magnifica*), white fir (*Abies concolor*)	USA: Southern Sierra Nevada Mountains, CA	identifying dominant trees species and dead standing trees	Convolutional neural network classifier (CNN), LiDAR	Fricker et al., 2019
2	Boreal mixed forests: pine (*Pinus sylvestris*), spruce (*Picea abies*), birch (*Betula pendula*) and larch (*Larix sibirica*)	Finland: Municipality of Padasjoki in southern	UAV-based photogrammetry and hyperspectral imaging for individual tree detection and tree species classification	Random Forest (RF) and Multilayer Perceptron (MLP), unmanned aerial vehicle (UAV), RS data	Nevalainen et al., 2017
3	Mountainous woods of downy oak (*Quercus pubescens*) and chestnut (*Castanea sativa*), Italian maple (*Acer opalus)*	Italy: Ascoli Piceno (Monte Ascensione), Ancona	Classification of tree images obtained from UAVs.	UAV4Tree DL, ResNet, DenseNet, InceptionV3, and Vision Transformer	Pierdicca et al., 2023
4	Species *Hymenolobium petraeum*, *G. glabra, Bowdichia nítida, Astronium lecointei, Hymenolobium petraeum* and *Dipteryx odorata*	Brazil: Nova Maringá, Feliz Natal, and Cotriguaçu, in the state of Mato Grosso	Improving the accuracy of forest species identification in timber inventories under Sustainable Forest Management (SFM)	CNN (ResNet50, VGG16, InceptionV3, MobileNetV2). Classifiers: SVM, ANN, RF, and LDA	Gama et al., 2025
5	Species *Ferula assa-foetida* L. (asafoetida)	India: Plant Tissue Culture Laboratory, CSIR-IHBT, Palampur, Himachal Pradesh	ML-based identification of the most suitable combinations of plant growth regulators (PGRs) for forest developmental processes.	ML, DL, CNN: approaches, RF, SVM, k-NN, DT, XG Boost, naïve bayes, regression, MobileNet	Kumari et al., 2025
6	Simao pine (*Pinus kesiya var. langbianensis*), rubber (*Hevea brasiliensis*), eucalyptus (*Eucalyptus robusta)*, Yunnan pine (*Pinus yunnanensis*), oak (*Quercus* L.), fir (*Cunninghamia lanceolata* (Lamb.) Hook.), birch (*Betula*), and alder (*Alnus cremastogyne Burk.*)	China: Kunming, Yunnan Province, Lincang, Xishuangbann, Puer	Evaluation of the potential of fusing freely available multi-modal data and ML/DL algorithms for accurately mapping tree species in Chinese forest.	ML algorithms RF, SVM and XGBoost applied for radar (SAR) imagery, Sentinel-1 and 2 through GEE.	Zheng et al., 2023
8	Species of tropical forests, *Shorea balangeran* and *Shorea teysmanniana*	Indonesia: Katingan Mentaya Project, in Central Kalimantan	Estimating canopy tree height via model, RS data, SAR and LiDAR, Sentinel and PlanetScope	ML algorithms MLR, RF, and CNN. ~Tools: R and Python (Keras, Tensorflow)	Pickstone et al., 2025
9	*Metrosideros excelsa* (pōhutukawa)-a culturally important New Zealand tree and is under threat from the invasive pathogen *Austropuccinia psidii* (myrtle rust).	New Zealand: within the coastal city of Tauranga	Develop a DL model to identify *Metrosideros excelsa* (pōhutukawa) through the distinctive visual characteristics of the canopies	tree-based models (XGBoost) that used spectral and textural metrics.	Pearse et al., 2021
10	Munessa natural forest, *Syzygium guineense - Croton macrostachyus,* family Fabaceae (*Calpurnia aurea),* family Podocarpaceae *(Podocarpus falcatus).*	Ethiopia: Munessa-Shashemene Natural Forest, Oromia Regional State, Arsi Zone	Estimating the structure, composition and diversity of tree species and their regeneration status in Munessa natural forest.	Correlation coefficients, vegetation classification, frequency, Shannon diversity index, Shannon evenness, by R software	Ahmedin & Eliasb, 2020

Table 1 (continued)

11	black spruce (*Picea mariana*), balsam fir (*Abies balsamea*), trembling aspen (*Populus tremuloides*), balsam poplar (*Populus balsamifera*), tamarack (*Larix laricina*), white spruce (*Picea glauca*), eastern white cedar (*Thuja occidentalis*)	Canada: Ontario, the Abitibi River Forest (ARF), southern boreal biome, along the Mattagami River	Identification of the location of tree species within naturally forested areas	ML Random Forest (RF) and support vector machines (SVMs) algorithms	Pittman & Hu, 2023
12	The chayote (*Sechium edule*) crop	Japan: the coastal eastern prefectures of Kantō, Chūbu, Kinki, Chūgoku, Kyūshū, and Shikoku regions	Location of the potential distribution of *S. edule* in Japan supported on ML models, to determine bioclimatic variables influencing its distribution geographically	Maximum entropy model (Maxent) model, generalized linear model (GLM) obtained the best true skills statistics (TSS); SVM	Iñiguez et al., 2024
13	Common saltmarshes species, salt couch grass (*Sporobolus virginicus*).	Australia:	Assessing large scale plant productivity of coastal marshes to estimate biomass	ML models of RF and SVM for the biomass prediction model; NDVI; Cross-validation for SVM	Rasel et al., 2021; Lemenkova, 2024a
14	Mixed forests with Alder (*Alnus glutinosa*), Oaks (*Quercus robur*), Ash (*Fraxinus excelsior*), Willows (*Salix species*), and Poplars (*Populus species*), with Elms (*Ulmus*), Hornbeams (*Carpinus betulus*), and Limes (*Tilia*)	France: Rennes, Bretagne region	Estimation of features derived from ALS data for describing trees genera from a riparian deciduous forest; classification using ML algorithms.	Quadratic Discriminant Analysis (sQDA), SVM RF methods.	Ba et al., 2020
17	Tropical rainforests in Berkelah Forest in Peninsular Malaysia, Dipterocarpaceae family trees (*Hopea, Shorea*)	Malaysia: Berkelah, Pahang, region of Kuantan City	Object-based segmentation method to extract feature changes in tropical rainforest cover using Landsat image and airborne LiDAR (ALS).	ML: Nearest Neighbor (NN), RF and SVM. Computation of NDVI.	Rozali et al., 2022; Nik Effendi et al., 2022
18	Land Use Land Cover (LULC) defined categories: cropland, grassland, forest, shrubland, wetland, water, impervious surface, bare land	South Africa: eThekwini Municipality, KwaZulu-Natal Province	Monitoring and providing accurate land use and land cover (LULC) change information	ML methods: RF, SVM, and Extreme Gradient Boosting (XGBoost)	Buthelezi et al., 2024; Lemenkova, 2024b

The integration of AI with remote sensing (RS) is enhancing forest ecosystem surveillance, enabling scalable detection of deforestation, quantification of spatial fragmentation, and assessment of ecological dynamics with high accuracy, Figure 6. Research indicates that different imaging technologies, including unmanned aerial vehicles (UAVs), airborne sensors, and satellites, can be combined with machine learning (ML) classification and computer vision to provide valuable insights for forest health monitoring. UAVs and multispectral sensors have been particularly effective in detecting the structure of the foliar canopy at both local and regional scales.

12. Perspectives and opportunities

AI tools have become increasingly prevalent in the monitoring and management of forest ecosystems. Alongside the DL models, we highlighted the most well-known algorithms, such as random forest (RF), support vector machine (SVM), k-nearest neighbours (kNN), decision tree (DT), region-based convolutional neural network (RCNN), extreme gradient boosting (XG Boost), Naïve Bayes, and logistic regression, with reported case studies. Their applications extend beyond merely detecting and surveilling forest stands; these technologies are also pivotal in forecasting the progression and dynamics of changes affecting biophysical elements within ecosystems. This dual utility underscores the transformative potential of AI in enhancing modelling of forest landscapes. Such approaches leverage the latest progress in ML/DL to enhance the efficiency of forest mapping. Environmental data modelling has emerged as critical target for understanding the role of fog in the hydrological balance of subalpine forest. Designed modelling libraries of Python programming language have high accuracy, precision, and flexibility and hence present attractive tool of data analysis in silviculture, forest and land management.

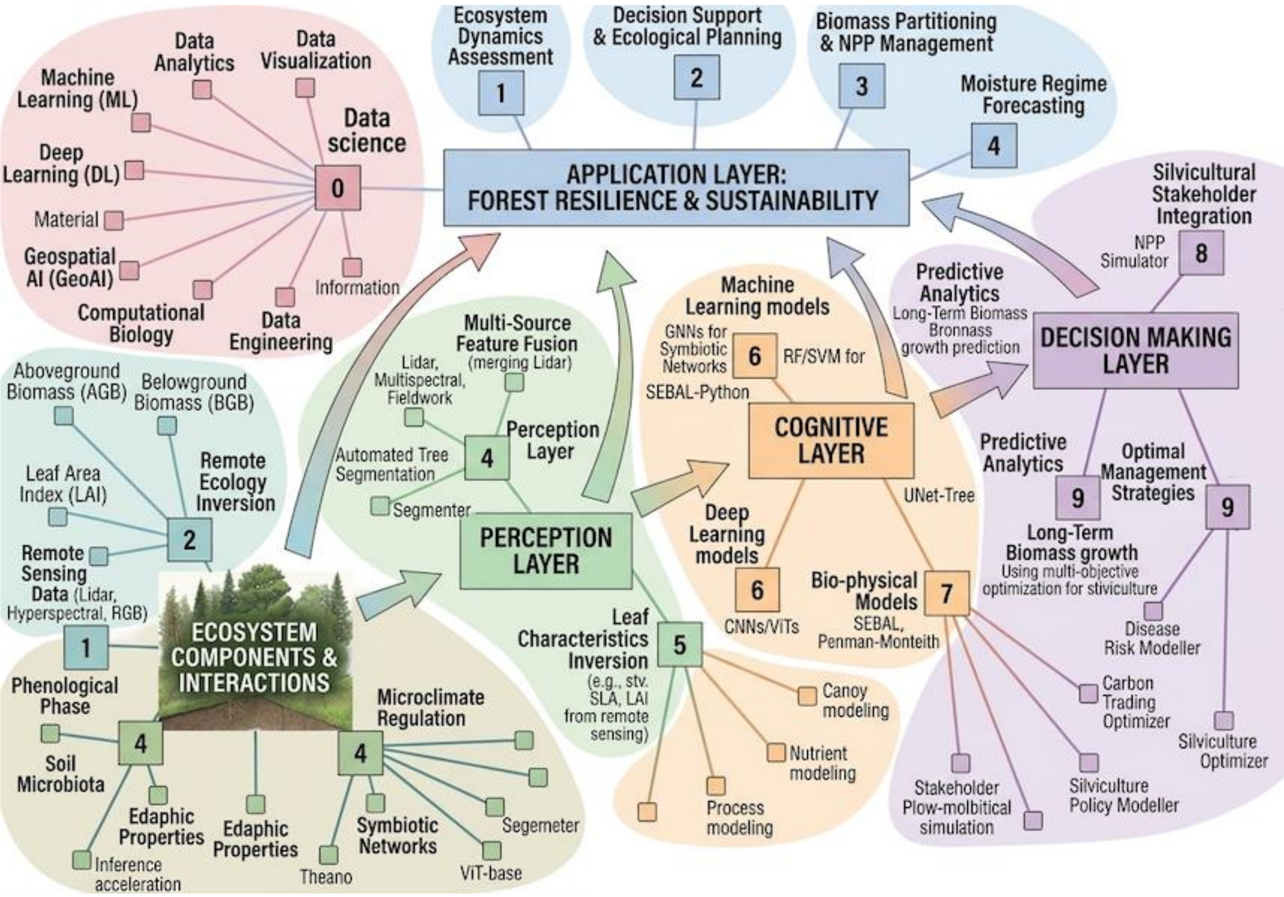

Figure 6. Advanced forest ecosystem dynamics AI-driven framework. Diagram source: author.

13. Future Outlook

For future studies, it is recommended to consider the novel AI tools for processing large datasets. In cases with high dataset complexities, as common in silviculture, the selection of AI modelling software can be supported by shortening the speed of each modelling and proceeding with the same time window. Likewise, it is also possible to widen the time period of fieldwork observations and use data integration methods, provided weather conditions approve additional observations campaigns. To include more input data in modelling, the different dataset (environmental, geological and climate variables) may be integrated into a single model (Öztürk et al., 2023; Baltacı and Yıldırım, 2020). Another important aspect to consider is the sensitivity of the models to environmental anomalies and outliers in the input dataset. This becomes more visible when the data are scarce due to the constraints in the direct fieldwork observations, for instance, because of the meteorological conditions during foggy days. In these cases, data handling techniques can be extended to data filling to decrease the sensitivity of Python models. Nevertheless, discrepancy in datasets must be considered during results interpretation and validation.

In essence, AI offers an open-source foundation for environmental studies that ensure reproducible research in climate-environmental works in silviculture. An open-source programming tool, such as Python, is useful for AI-supported environmental modelling of forest ecosystems. Through diverse libraries, dedicated to data modelling, visualization and statistical analysis, it considers the variability of the climate and environmental features that potentially affect water balance in coniferous forests. The analysed features may include the meteorological measurements, climatic parameters, temperatures, characteristics of tree stands (canopy and age) and variables derived from the re-analysis. Finally, application of AI for modelling large datasets is essential for big data analysis in environmental studies.

14. Conclusion

Understanding water balance in mountain regions is of essential importance for hydrological modelling as water provision has an impact extending far wider than their actual range. AI-enhanced data analysis in eco-hydrological studies simplifies and optimises modelling environmental characteristics and parameters (Lemenkova, 2025b). This enables to support decision maker solution for forest protection with past and projected warming exceeding the global average (Klaučo et al., 2013, 2017).

Vegetation of mountainous regions with coniferous forests is affected by climate change. In such regions, distribution of forest stands is driven by the climatic change that influence soil conditions along elevation gradients (Petronic et al., 2015; Outourakhte et al., 2025). Besides, it is also influenced by complex mountainous topography, which is an important, but often neglected factor in the mountain water balance. In the high-latitude mountains, the elevation belt is mostly covered by forests dominated by conifers (Khan et al., 2020; Güzel et al., 2023). As a result, mountain forests have a high capacity to influence the water balance by intercepting water through the canopy and releasing it back to the atmosphere as vapour. These processes and interrelation of factors maintain water cycle, as we demonstrated in this study by modelling. Additionally, mountain forests reduce runoff and increase infiltration.

Models and maps obtained using Python and R applications enable to highlight processes in ecosystems. These and previous studies are used as an example of protected areas with scarce and heterogeneous data that require advanced modelling methods. Choosing the right set of data processing methods and defining a suitable dataset of parameters for each approach (geospatial mapping and environmental modelling), considering the available computation power and time, is always demanding. In this case, we demonstrated the use of integrated data analysis support by Python and R for statistical analysis of forest hydrology.

Conflicts of Interest

The author declares no conflict of interest.

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