THE FUTURE OF FORESTRY AND AGROFORESTRY

DRIVEN BY ARTIFICIAL INTELLIGENCE AND DIGITAL INNOVATION

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Chapter 1

A Shift in the Forest Paradigm: Data- and AI-Driven Forest Big Data and Digital Twins

1.1
A Paradigm Shift in Forest Resource Management and the Construction of Digital Twins

At six in the morning, a surveyor tightens the laces of his hiking boots and packs a measuring tape, a diameter-at-breast-height tape, and a paper field notebook into his backpack. Today's sample plot lies on the slope of a ridge 700 meters above sea level, and it takes a little over two hours on foot to reach the coordinates marked on the map. The Korea Forest Service has established 5,400 sample plots in forests across the country. Surveyors record 69 items at these sites, including growing stock and forest health, and revisit the same plots on a five-year cycle.

Upon reaching a sample plot, the surveyor wraps a tape around each tree, reads the scale, and records its diameter at breast height (DBH, the diameter of a tree trunk measured at chest height) in the field notebook. On a steep slope, aligning a hypsometer at eye level, measuring the angle, and calculating tree height all take time. Even after a full day's work, one surveyor can complete no more than two or three plots. Fingertips crack from rubbing against the tape, and when a sudden shower passes through, the pencil marks on the field notebook blur until they are difficult to read.

The numbers collected this way are accurate, but they quickly become outdated. Even if a wildfire burns a ridge or pests consume an entire stand between the surveys conducted every five years, the change does not appear in official statistics until the next survey. For a long time, both the National Forest Inventory and the Type II forest inventory, whether in national or private forests, have operated this way. Surveys that depend on human feet and eyes are slow and expensive, and they cannot fill time and space at a fine resolution. That is not the only problem.

Even when planners try to prepare a precise harvesting plan, five-year-old figures leave them with no choice but to estimate the trees' present condition.

From Sample Plots to Grid Maps

Efforts to overcome these limits are spreading throughout the forestry sector. The digital transformation (DX) of forestry begins by moving paper slips and hand-drawn plans into mobile applications and geographic information system (GIS) data. At the next stage, the accumulated data are linked to forest management, matching timber supply with demand, and electronic application systems. At the final stage, data flow in real time from upstream forestry processes such as harvesting and planting to downstream processes such as distribution and processing, and even to points of contact with other industries, reshaping decision-making itself.

This trend is not unfamiliar in Korea. The Forest ICT Research Center at the National Institute of Forest Science has continued trials in the Garisan Leading Forest Management Complex in Gangwon Province, deploying airborne, terrestrial, and backpack LiDAR equipment side by side to collect digital forest resource information and use it for precision forestry. Because each instrument differs in collection accuracy and operating speed, post-processing work followed to determine which combination was suited to actual field conditions.

The traditional method of producing statistics based on administrative districts or conventionally defined subcompartment boundaries, small divisions used for forest management, had a longstanding defect. Even within the same subcompartment, tree height and growth rate differ with the microtopography of valleys and ridges, but those differences are blurred the moment the figures are averaged at the subcompartment level. Recent efforts have sought to solve the problem by reorganizing forest spatial data into square grids measuring 20 meters on each side.

The aim is to preserve the precision of airborne laser scanning (ALS) and satellite data in every grid cell.

At the center of this change are decision support systems (DSS) and integrated platforms that bring multiple types of data together. A DSS is software that collects and analyzes multiple datasets, then displays figures and graphs that people can consult when making decisions. The DigiMedFor project, led by the University of Naples Federico II under the European Union’s Horizon Europe program, integrates technologies around three pillars: forest resource monitoring and inventory construction; timber traceability and grading; and support for forest-planning decisions.

Forest Pathway, developed by the project, is a web-based expert system that takes tree species, bioclimatic zone, site productivity, and management goals as inputs and recommends a route for tending the forest. It is closer to a guidance tool that helps forest managers narrow their options than to an operational simulator that automatically processes a specific region's drone inventory and regulations.

The structure of a forest digital twin can be divided into four layers. At the bottom is the physical environment composed of the actual forest, soil, and microclimate. Above it lies a data layer collected by satellites, unmanned aerial vehicles (UAVs), ground IoT sensors, and terrestrial LiDAR. The third layer integrates these data, extracts features with deep learning, and runs a simulation engine aligned across space and time. The top layer delivers practical applications such as precision forest management, predictive analysis, verification of carbon sequestration, and links to autonomous operations.

This technology has developed in stages. It began as a static three-dimensional model that merely replicated the forest. It then passed through the digital shadow stage, in which sensor data were reflected in only one direction: the real situation appeared in the virtual model but did not flow back. The current target is a fully realized digital twin in which the real and virtual forests exchange signals and provide real-time feedback to each other.

One Tree Drawn by LiDAR

LiDAR is a device that emits laser light and calculates distance by measuring the time it takes for the light to strike an object and return. The principle is not difficult. The name changes depending on where the device is mounted. On an aircraft, it is airborne laser scanning (ALS); on an unmanned aerial vehicle, UAV laser scanning (ULS); stationary on the ground, terrestrial laser scanning (TLS); and carried on a person's back while walking, a mobile mapping system (MMS).

Conventional LiDAR generally emits only one wavelength, so although it can precisely locate where a laser pulse was reflected, it is poor at distinguishing whether the return came from a leaf or a branch. Multispectral LiDAR, which emits three wavelengths simultaneously, has recently begun to address this problem. In one study, several deep-learning models competed on the public

ForestSemantic-MS benchmark dataset. The Point Transformer V3 (PTv3) model was tested on the classification of six components: ground, shrubs, stems, branches, leaves, and fallen deadwood.

It achieved a mean intersection over union (mIoU, the average extent to which model-predicted and actual regions overlap) of 69.1 percent, outperforming the other models by 21.8 percentage points. Where leaves and branches are intertwined, it is difficult to distinguish tree components with a single wavelength, but the picture changes when three wavelengths are used. Accuracy increased by 12.7 percentage points for fallen deadwood, 4.5 percentage points for branches, and 2.5 percentage points for stems.

There is another approach: single-scan terrestrial LiDAR, which sweeps a site only once instead of relying on labor-intensive multiple scans. In the mixed hardwood forest of Martell Forest in Indiana, United States, researchers converted single-scan point-cloud data into two-dimensional projected images and used a CoAtNet neural network combining convolution and attention to estimate the aboveground biomass of individual trees. Despite the limitation of occlusion behind trees, the method reached an explanatory power of 0.73 and outperformed comparison models such as random forest and Point Transformer.

In 2026, another attempt treated point clouds in an entirely different way. The study guided LiDAR data into a rendering technique called Gaussian Splatting, which converts each point into a small translucent ellipse and layers them to reconstruct tree surfaces much more realistically. The researchers reported that rules for handling rigid trunks separately from softly moving leaves reduced the blurring and wobbling that commonly occurred during initialization.

Trying the Harvest First in a Virtual Forest

A virtual forest does not stop at an attractive three-dimensional image. When actual inventory data such as tree location, height, crown width, and diameter at breast height are transferred into it, the result is a simulation environment in which users can preview the effects of thinning or clear-cutting. The Virtual Forest Decision Support System (VFDSS), developed by the DigiMedFor project, replicates an entire forest by planting virtual trees in nearly the same locations as the real ones. The system calculates the amount of sunlight that changes with date and time and tracks how much light the trees receive as they grow.

Users can look down over the entire forest on a desktop screen, or put on a virtual-reality (VR) headset, walk into the forest, choose an individual tree, and try harvesting or planting it. The moment a tree is selected for thinning, statistics on the number and density of trees remaining, future growth trends, and the volume of timber harvested immediately appear on the screen. In actual applications to stands in Mississippi and to Douglas fir stands in the United States, a digital twin of a local forest could be built within hours using only data on tree locations and dimensions and three-dimensional specimens of roughly 40 tree species.

Keskes and Niță (2026) added Finland's multi-source National Forest Inventory data to a model built from Romanian field data. The explanatory power of growing-stock volume predictions in Finland rose from 0.483 to 0.718. This was not a study that directly produced a carbon map, but a test that improved stand-structure predictions by connecting data from different countries. When a model is transferred across national borders, it must be recalibrated with local samples.

Similar attempts are continuing in the United States. Oregon State University created a digital twin encompassing 77.6 square kilometers of Elliott State Forest and approximately 2.8 million trees. Of these, 26,000 trees were rendered in detail in a game engine. Within this virtual forest, users can change the time and weather, walk across the terrain, and preview the traces that selective harvesting or clear-cutting would leave behind. Researchers at Michigan State University and Virginia Tech surveyed 3,555 trees in a 7.5-acre Pinus taeda forest in central Virginia and compared several thinning scenarios.

The difference in removed volume across blocks and scenarios ranged from 7.9 to 18.2 percent. In one block, the difference was approximately 70 dollars per acre under assumed log prices. Because this calculation came from a single experimental site, it cannot establish that the same return would be achieved in other forests.

On-Site Displays and Rehearsals for Robots

The data accumulated in a digital twin do not remain confined to a screen. If field workers use smartphones, tablets, or mixed-reality devices such as Microsoft HoloLens 2 or Apple Vision Pro, they can see augmented-reality (AR) graphics overlaid on actual trees. Applications such as Arboreal Forest, ForestScanner, and Tree Scanner combine the LiDAR and RGB-D sensors in smartphones with positioning technology called SLAM, or Simultaneous Localization and Mapping, which allows a machine to map its surroundings while determining its own position.

As workers walk through the site, they can immediately check tree diameter at breast height, height, and coordinates together with augmented three-dimensional graphics. The maturity of these technologies ranges from prototypes to products already on the market. In boreal forests, errors in diameter at breast height measured with UAV LiDAR and SLAM were relatively small, ranging from 2.0 to 4.0 centimeters. In densely stocked subtropical urban forests, the error grew to 5.13 centimeters, or 22.01 percent.

Virtual training grounds for forestry machinery are being built as well. In the Vindeln region of Sweden, researchers scanned 30 locations with a Leica BLK360 terrestrial LiDAR instrument and added drone data to reproduce a high-precision digital twin. Inside this virtual forest, they randomly varied the viewpoint and solar angle to automatically generate a synthetic dataset called SimForest. In effect, safety features that allow forestry robots or autonomous forwarders to recognize and stop for people, trees, and obstacles in real time can be tested in advance with these virtual data before they are deployed in a real forest.

The Natural Resources Institute Finland (Luke) is developing a digital twin aimed at the carbon-trading market. Drones equipped with LiDAR record the height, diameter at breast height, and species of each tree. The data are overlaid with multiple satellite datasets, then transformed into a dynamic three-dimensional model. The goal is to connect carbon-sequestration analysis with verification systems such as VERRA or Gold Standard. The project is still at the research stage, seeking a path to commercialization.

Accuracy Grows Hazy Again

Despite these accumulated achievements, research findings often conflict. Multiple-scan terrestrial LiDAR excels in the precision of tree-volume measurement, but registering data captured from several positions requires considerable work. By contrast, approaches combining a single scan with deep learning greatly increase collection speed, but do not completely eliminate errors caused by missing branches or fallen deadwood occluded behind trees. The same is true of multispectral LiDAR. Recognition accuracy for individual components improves markedly, but the equipment is expensive and the volume of data to be processed rises substantially.

It does not appear easy for a forest cooperative with a limited budget to acquire such equipment immediately.

A model that achieves high accuracy in one experimental forest may perform worse when moved to a temperate mixed forest or subtropical forest. The tree species, crown structure, sensors, and methods of dividing the data all differ. To apply the model in another forest, it must be recalibrated with data from that region.

In forests with dense understory vegetation and tightly interlocking upper canopies, light emitted by drones or satellites does not reach the ground, increasing errors in measuring lower portions of trees and stem thickness. Autonomous drones flying beneath the canopy depend on positioning technologies that combine visual and inertial information, such as VIO and SLAM. When light is scarce and branches sway, the drone may lose its position or become lost entirely. Growth models that calculate drought and heat stress already exist.

What remains rare is an operational system that continuously updates field-sensor and extreme-climate data within a digital twin.

The higher-performing the model, whether a Vision Transformer (ViT) or a three-dimensional convolutional neural network, the more likely it is to remain a black box that cannot explain the basis of its internal judgments. From the perspective of forest-policy decision-makers, this opacity slows the building of trust. Such models generally require high-performance GPUs, making them difficult to transfer directly to drones or field devices in remote areas where communications are easily interrupted.

In an article published in February 2026, the Food and Agriculture Organization of the United Nations (FAO) raised similar concerns from a different angle. It argued that field validation must follow before AI-generated figures are used directly in policy, and that institutions such as trained personnel and standard procedures take longer to establish than the adoption of the technology itself.

Efforts to close this gap are proceeding at the same time. Studies are introducing explainable artificial intelligence (XAI) methods such as SHAP and Grad-CAM, which trace backward to identify the information on which a model based its decision, and embedding ecological knowledge such as species-specific flowering periods and soil moisture as rules in the model in order to secure both accuracy and interpretability.

Work is proceeding as well to create models that can run on drones and field devices through lightweighting techniques such as pruning, quantization, and knowledge distillation, and to organize data scattered across regions and equipment into a single standard format.

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1.2

Multimodal Remote-Sensing Data Fusion Technology

One summer, when the monsoon front had covered the Korean Peninsula for three days, a researcher sitting before a monitor at the National Forest Satellite Information Utilization Center opened a newly downloaded satellite image and sighed. Half the screen was hazy white, as if milk had been poured over it. The researcher had been about to inspect a pine wilt disease control area on the east coast of Gangwon Province, but clouds covered the entire mountain, making it impossible to distinguish a single tree.

Red dots marking the locations of trees targeted for control were scattered along the bottom of the screen, but the clouds above them made it impossible to check their recent condition. A colleague sitting nearby set down a paper cup and remarked in passing, “The sky isn’t opening today either.” Optical satellites work on the same principle as cameras. Because they record the amount of sunlight reflected from the Earth’s surface and entering a lens, clouds create the same condition as a palm covering the front of a camera. Several more days must pass before the next satellite crosses the same sky.

Meanwhile, diseased trees quietly spread, and embers grow beneath dry fallen leaves.

Multimodal remote-sensing data fusion becomes necessary at moments like these. When a forest is observed from the sky with only one eye, some sections will inevitably remain unseen. Satellites image large areas frequently but are blocked by clouds and fog, and their gaze does not reach beneath the treetops. Unmanned aerial vehicles (UAVs) and terrestrial laser scanners can capture individual leaves and branches at centimeter resolution, but batteries and labor costs prevent them from surveying an entire country. A drone battery lasts no more than 40 minutes. Researchers therefore changed their approach.

They began overlaying instruments with different kinds of eyes within a single view. The result is a multilayer aerial, atmospheric, and ground observation network that links satellites in space, drones in the air, and sensors rooted on the ground as if they were one body.

Three Layers of Vision Between Sky and Ground

The three layers have different jobs. Satellites sweep across the entire Korean Peninsula every three or five days. Drones select a single stand and inspect it tree by tree. Sensors installed on the ground remain in one location and accumulate changes over months or years, second by second.

The satellite layer responsible for the macroscale includes the European Space Agency's Sentinel series, the United States' Landsat series, and China's GF-2. ICESat-2 and GEDI, which directly measure canopy height, belong to this layer as well. GF-2 is a high-resolution satellite that images the surface in cells as small as 0.8 meters. Landsat 8 and Landsat 9 carry thermal-infrared bands that can capture residual heat immediately after a wildfire. GEDI is an instrument aboard the International Space Station that samples forest height at points around the world.

In 2025, researchers de Conto, Armston, and Dubayah combined more than 130 million of these point measurements with synthetic aperture radar (SAR) data through deep learning. The resulting global forest-structure map, with 25-meter cells, reached an explanatory power of 0.82. The result was achieved with a relatively lightweight model containing fewer than 400,000 parameters.

New members have joined this layer. The NISAR satellite, jointly developed by the National Aeronautics and Space Administration (NASA) and the Indian Space Research Organisation (ISRO), was launched on July 30, 2025. Orbiting approximately 747 kilometers above the Earth, it uses L-band and S-band radar to measure soil moisture, forest biomass, and minute movements of the ground. The L-band data collected by this satellite became freely downloadable on July 20, 2026. Data that once could be handled only by national agencies or large research institutes can now be downloaded free of charge by a graduate student in Korea and used in a thesis.

The European Space Agency's Biomass satellite went a step further by carrying the first P-band instrument, whose wavelength is longer than that of conventional radar. The longer the wavelength, the deeper it penetrates through leaves and branches, allowing it to estimate even the woody volume of trunks. The satellite was launched in April 2025. It released its first open data on December 19 of that year. In Europe's observation network, Sentinel-1D entered orbit in November 2025. Paired with the existing Sentinel-1C, it restored the former system of revisiting the same location every six days.

Korea placed another satellite in this layer. The Agriculture and Forestry Satellite, developed jointly by the Korea AeroSpace Administration, the Rural Development Administration, and the Korea Forest Service, is Compact Advanced Satellite 4. A SpaceX Falcon 9 rocket carried it into space. The launch took place on July 7, 2026. The satellite will image the entire Korean Peninsula every three days at approximately five-meter resolution and is expected to be used to identify areas damaged by wildfires and landslides quickly across a broad region.

Another satellite worth watching is Sejong 3, a hyperspectral satellite launched in March 2026 by the Korean private company Hancom InSpace. While an ordinary camera divides light into only three colors, red, green, and blue, this 6-unit (6U) microsatellite, about the size of two shoeboxes placed end to end, records it in 442 bands. It weighs less than 11 kilograms. It therefore has the potential to distinguish not merely the color of leaves but the reflectance characteristics of the substances that compose them.

At the intermediate scale, the drone layer uses LiDAR, hyperspectral and multispectral sensors, and ultra-high-resolution cameras to collect the three-dimensional structure and color signatures of stands and individual trees. LiDAR is a device that emits light and measures the time it takes to return, thereby determining the distance to an object. Drone-mounted LiDAR flies low above trees and captures the contours of each crown. The microscale layer lies almost on the ground.

It consists of terrestrial laser scanners (TLS), backpack mobile mapping systems (Backpack MMS), IoT microclimate sensors that measure soil moisture and air temperature, and PhenoCam towers that photograph seasonal change. A PhenoCam photographs the same tree from the same angle each day, recording by date when leaves emerge and when they turn red. IoT sensors buried 15 centimeters underground transmit the rate at which the soil dries to a server in real time. These devices continuously measure and record tree diameter at breast height, stem curvature, understory vegetation, and soil moisture.

Because diameter at breast height is the first input used to calculate the timber volume and carbon stock of an individual tree, even an error of a few millimeters grows to a size that cannot be ignored when multiplied across an entire forest.

The autonomous LiDAR-equipped drone unveiled by the National Institute of Forest Science in January 2026 spans the ground and drone layers. A task that took a person 22 hours to survey one hectare on foot with a measuring tape was completed by this drone in 2.3 hours. Its accuracy reached 96 percent compared with direct field measurements, and it captured even diameters at breast height that were difficult for the human eye to measure because they were hidden by leaves.

Aligning Space and Time

The problem is that the data collected this way are like measurements taken with different rulers. A satellite-image cell covers 10 to 30 meters. Drone images resolve several centimeters, and ground scanners reach resolutions of a few millimeters. If one pixel is misaligned, an entire tree can fall into the shadow of the neighboring tree on the map. Overlaying these data first requires ground-control-point work: reflective panels and cross-shaped markers are placed along forest roads, and their coordinates are measured with satellite navigation. This is followed by rational function models and feature-point-based geometric correction.

Because each sensor has a different resolution and coordinate system, registration-error tests tailored to the study site and equipment must follow.

Aligning time is no easier. In the two-satellite system, Sentinel-2 revisits the same area about every five days; a single Landsat satellite does so about every 16 days; and drone and ground surveys occur intermittently according to researchers' schedules. In the interval, trees produce leaves and change in the amount of water they hold. If data from mismatched dates are overlaid as they are, an optical illusion makes the same tree appear in different colors. This is why algorithms such as Sen2Cor and Fmask are used to filter clouds and shadows, and why multiple images from the same season are selected and composited.

When pixel locations and observation times are misaligned, a model's input signals become mixed, so each study must report registration error and temporal difference separately.

A recent study of smallholder planted forests in the southern highlands of Tanzania offered one clue to solving this problem. Researchers Mauya and Jonas reported that combining Sentinel-1 radar and Sentinel-2 optical data with random forest and support vector machine (SVM) models in a cloud-prone region improved the accuracy of classifying the species planted by smallholders compared with using optical data alone. One answer to the white-screen problem encountered in a monsoon-season control room is being built in this way.

Bringing Light, Radio Waves, and Lasers Together

The three sensors observe different properties of a forest. Optical sensors read leaf chlorophyll, water status, and vegetation indices in the visible, near-infrared, and shortwave-infrared bands. In areas with dense foliage, however, reflectance reaches a saturation point and no longer distinguishes additional differences. Synthetic aperture radar emits microwaves, such as Sentinel-1's C-band or ALOS PALSAR's L-band, and captures signals reflected from thick branches and trunks regardless of clouds, thereby revealing the forest's internal framework.

Even when satellite photographs were erased into white during the monsoon, microwaves passed straight through the clouds. LiDAR emits laser pulses and directly measures tree height, crown volume, vertical layers, and ground elevation at centimeter resolution. Opening all three eyes at once allows each to fill the others' blind spots.

The methods for feeding these three types of data into an AI model fall into broad categories. Early fusion, which concatenates optical, radar, and LiDAR channels at the input stage and feeds them into a single neural network, has a concise structure, but the risk of overfitting rises if the input dimension becomes excessive relative to the sample size. Late fusion trains a separate neural network for each sensor and combines their outputs by voting or weighted averaging at the final decision stage. It preserves sensor-specific characteristics but can miss subtle interactions among sensors.

Hybrid fusion mixes features at an intermediate stage with a cross-attention structure. It requires more computation but can learn the relationships among the information from each sensor more deeply.

Several field studies show the practical differences among these methods. The MTSCFNet study of subtropical mixed forests in Sanha and Huangfengqiao, China, linked drone LiDAR, ultra-high-resolution RGB imagery, and GF-2 satellite imagery through three encoders and a cross-fusion module. It markedly improved tree-species classification accuracy over the use of optical or LiDAR data alone. In this study, the RIEGL miniVUX-1UAV LiDAR instrument recorded 87.14 points per square meter. A DJI M300 RTK drone collected RGB imagery with a pixel size of 6.23 centimeters.

Separately, a public dataset overlaying GF-2 optical satellite data with GF-3 radar satellite data was recently created in China and is being used in research that finely divides regions where the boundaries among forest, shrubland, and grassland are indistinct. In another study combining hyperspectral and LiDAR data, overall accuracy was only 80.39 percent with optical data alone. When the two datasets were linked by cross-attention, accuracy rose by 9.21 percentage points to 89.60 percent.

In a study producing a global tree-height map, the strongest contribution came from direct LiDAR observations, followed by terrain variables and then indirect optical and radar indices.

In the Deramakot and Tangkulap tropical rainforests of Borneo, Malaysia, a research team including Kotaro Komatsu automatically identified dipterocarp trees in drone RGB images, then linked the results to satellite data and a random forest model. The accuracy of identifying dipterocarp trees from drone imagery alone was 0.71 producer's accuracy and 0.67 user's accuracy. A model using satellite data alone without field samples had an explanatory power of 0.43 and an error of 70.60 megagrams per hectare. Adding variables extracted from the drone increased explanatory power to 0.51 and reduced the error to 60.53 megagrams.

This means the cost of walking through the field and counting samples one by one can be greatly reduced.

Another study in managed forests on Sakhalin, Russia, compared three models by feeding stand-subcompartment data, Sentinel-2 time series, and terrain data separately into random forest, XGBoost, and TabNet. XGBoost produced smaller errors than the other two models for tree height, basal area, timber stock, and carbon stock alike, and recorded an integrated explanatory power of 0.68.

The drone survey in Borneo and the autonomous-drone survey in Gangwon Province point in the same direction. Instead of people cutting their way through a forest with machetes and counting trees one by one, the balance is shifting toward machines counting them somewhere between sky and ground. How much that count can be trusted is the next question.

Conflicting Results and Tasks That Remain

As the technology proliferates rapidly, studies produce different answers. In a forest composed of a single species such as pine, the three-dimensional structure measured by LiDAR, including crown width, height, and branch arrangement, plays a major role in distinguishing species and biomass. Research is also examining approaches that combine optical indices and three-dimensional structure to find trees in the early stages of damage, before leaf color has changed visibly.

By contrast, in tropical or subtropical mixed forests where many species and shrubs are intertwined, LiDAR alone is insufficient; signals from leaves and water captured by optical and hyperspectral sensors must be considered as well. Which fusion method performs best depends on sensor registration, sample size, and the shape of the forest.

Problems that make direct transfer to the field difficult remain. Even a model that achieves high accuracy in one region must be recalibrated in forests with different species and seasons. In a densely closed forest, laser and optical signals from satellites or drones do not reach the lower layers or ground, allowing errors to accumulate in estimates of stem diameter and understory vegetation. A drone flying low beneath the forest must also recalculate its own position if satellite-navigation signals are lost.

When light is scarce and branches sway in the wind, positional errors in visual-inertial odometry (VIO) and simultaneous localization and mapping (SLAM) increase. Three-dimensional neural networks and Vision Transformers require substantial memory and power depending on the input size and device, so placing them in field equipment requires model lightweighting and device-specific speed tests.

Efforts to lower this barrier are continuing. Research is reducing tri-modal models through knowledge distillation, model quantization, and dedicated semiconductor acceleration so they can run on drones and field devices. Explainable-AI methods such as Grad-CAM and SHAP display the basis on which a neural network made its decision. Another direction places the seasonal changes of trees and physical models of soil moisture into neural networks as constraints, reducing ecologically implausible answers.

As public datasets spanning multiple regions and sensors, such as TreeSatAI, PureForest, and ForestSemantic-MS, continue to expand, the foundation for separately refining models suited to forests on the Korean Peninsula will grow stronger.

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1.3
A Forestry-Specific Large Language Model (ForestGPT) and Intelligent Decision Support

It is shortly after three in the afternoon at the office of a local forest cooperative in Gangwon Province. Late-summer sunlight slants through the window, and on the officer's desk a booklet containing the Enforcement Rules of the Forest Resources Act lies open beside a forestry manual with worn corners. That morning alone, three callers asked whether dead trees felled in a pine wilt disease control zone could be temporarily stacked in a village clearing. The officer turns through the index of the statute book, searches the manual's appendix, and even opens last year's official correspondence, but still cannot find an exact answer.

Finally, the officer closes the manual and types the question directly into the search box on the computer screen: Where must fumigation treatment of trees killed by pine wilt disease be completed?

More people are putting such questions to AI chatbots. Large language models (LLMs), which learn from vast bodies of text and generate sentences like a person, now answer most questions without hesitation. The problem begins when the answer is wrong. General-purpose models such as ChatGPT and Claude have learned from enormous amounts of text circulating on the internet, but have read relatively fewer narrow, specialized documents such as forest regulations and forestry specifications. When asked a forestry question, they may draw on knowledge learned from construction or general engineering and assemble an answer that sounds plausible.

This phenomenon, in which a model invents a fact that does not exist, is called hallucination. It resembles a person telling a lie with a confident expression. In the forest, a hallucination does not end as a minor mishap. If an officer who receives incorrect fumigation guidance mishandles dead trees, pinewood nematodes can spread to a neighboring forest. If harvesting proceeds under incorrect slope criteria, it can lead to a landslide during the monsoon.

In a 2026 systematic review in Current Forestry Reports that traced the spread of AI across forest engineering, Forkuo and colleagues observed that this movement is expanding beyond the processing of structured data such as sensor readings and satellite photographs to the processing of unstructured documents such as regulations, guidelines, and reports. AI working with structured data calculates values that resolve neatly into numbers, such as forest area or tree height. AI working with unstructured documents must read sentences and understand context. The latter task is far more difficult.

ForestGPT, a large language model dedicated to forestry, is an attempt to close this gap. A paper published in Electronics in 2025 by Austrian researchers Ehrlich-Sommer, Eberhard, and Holzinger depicts the model as an assistant that remains beside forest experts while leaving final judgment to people. The researchers proposed a four-stage development path: beginning with an interactive tool that reads forest materials, then moving to retrieval-augmented generation, growth simulators, and connections to field sensors.

The system tested at Futa Expo 2025 was a first-stage multilingual chatbot that guided visitors using approximately one megabyte of curated material. Retrieval-augmented generation, simulators, and sensor integration remain on the roadmap.

A similar movement has begun in Korea. The National Institute of Forest Science held its first competition combining forest big data with artificial intelligence and presented awards to seven teams. Experiments that connect deep learning, generative artificial intelligence, and agent technology capable of autonomous judgment and action to forest policy and field services are spreading through universities and startups.

An Assistant That Finds and Reads the Law

The technologies used by forestry-specialized models such as ForestGPT fall into two broad categories. One is fine-tuning, which retrains the weights inside the base model itself. The other is retrieval-augmented generation (RAG), which leaves the model weights unchanged and supplies relevant laws and guidance documents alongside each question. The latter is widely used in the forestry domain. Regulations change often, and retraining an entire model takes considerable time and money.

Under RAG, when a question arrives, the model first searches a repository of relevant documents for provisions that can serve as evidence, then produces an answer while citing those provisions. Designing the system to say that it does not know, instead of inventing an answer when no supporting document is found, has become a practical way to prevent hallucinations.

The conversational agent Farm Assistant, created by the European Union's FOREST4EU project, demonstrates this principle. It is connected to FarmBook, a database of knowledge gathered from farms and forest holdings. When asked about grazing patterns that can prevent wildfires or ways to reduce biomass, it responds with the identification numbers of the supporting materials. When asked about material absent from the database, such as a statement by an outside politician, it does not invent an answer but states plainly that it does not have the information.

In Armenia, the American University of Armenia (AUA) Acopian Center for the Environment and the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) jointly created an interactive chatbot to assist policymakers conducting climate-change impact assessments and writing national reports. Even civil servants with limited background knowledge in forest science can consult the chatbot while preparing reforestation plans and calculating carbon sinks.

No technology has yet eliminated hallucinations completely. RAG, which anchors answers in retrieved documents, along with uncertainty estimation, self-consistency checks, and response safeguards, can reduce errors, but performance varies by model and test data. Advice about fertilizer quantities or control timing, where an error could ruin that year's crop, must be checked finally by a human expert.

The greater the consequences of a wrong answer, as with harvesting permits or fumigation standards that can lead to fines or the spread of pinewood nematodes, the more clearly the boundary must be drawn: the model's answer is reference material, not final approval.

An Adviser Guarding Dangerous Worksites

An afternoon in the office spent hesitating before a law book is comparatively safe. Different dangers await a logging worker who enters the mountains. Forestry is an industry with a high accident rate. Accidents caused by misjudging the direction in which a tree will fall or slipping while using a chainsaw on a slope recur every year. Researchers at Kindai University in Japan tried to address this problem with a game and an AI advisory agent. They preloaded a ChatGPT-based agent with safety guidelines and expert knowledge cards. When a trainee described a field situation, the agent identified the hazards.

Before the knowledge was preloaded, the first and second rounds produced a combined eight wrong answers and contextual deviations. After the process, the third and fourth rounds produced only two wrong answers in total. Scores on a 40-item safe-behavior scale also rose noticeably from their pre-training levels.

Experiments involving voice commands in the field exposed another kind of problem. Forestry-specific terms such as chaps, meaning protective clothing, and the Japanese term kakarigi (かかり木), describing a felled tree caught in another tree before it falls completely, were mistranscribed as unrelated words during automatic speech recognition (ASR). The incorrectly transcribed words passed directly into the next stage, natural language processing (NLP), which allows computers to understand human speech and writing, and amplified responses that strayed from context. This commonly occurs in forests where noise is loud and signals are easily lost.

The researchers proposed adding a separate technical-term dictionary and a procedure in which a person checks the recognized sentence once more.

Visual surveillance takes a different approach. A study by Kundu and colleagues published in Scientific Reports in 2025 connected the YOLOv8 object-detection model to a LangChain-based agent. The system finds stumps, logging machinery, and unauthorized personnel in drone and satellite imagery, then organizes suspected deforestation zones into GIS reports. Training loss decreased and maximum recall reached 0.24, but mAP50 remained around 0.07. Its performance is too low to regard it as a field system capable of reliably finding small stumps and equipment, so human rechecking is required.

How Much to Cut and Where to Haul It

An intelligent decision support system (DSS) is a tool that calculates multiple conditions at once and compares alternatives. In forest management, timber production, worker safety, soil erosion, and carbon storage collide within a single plan. In a 2025 preprint, Eberhard and colleagues proposed a GIS-based model comparing cable yarders, forwarders, and winch-assist equipment while considering slope, soil-erosion risk, and damage to residual trees. It is not a peer-reviewed operational field system.

Deng and Feng solved the dispatching and routing problem for trucks carrying harvested trees with a genetic algorithm. Imitating the way organisms pass on better traits over successive generations, this computational method generates several candidate routes and makes them compete, then changes the surviving routes little by little to find an optimal dispatch schedule. Earlier, Görgens and colleagues had developed a multi-objective planning algorithm that increased harvest volume while limiting the extent to which extraction trails compacted the soil.

There are attempts to measure the performance of forest management by several yardsticks together, rather than by money alone. Data envelopment analysis (DEA) is a statistical technique that calculates the ratio between resources invested and outcomes produced, distinguishing highly efficient forest-management units from less efficient ones. According to a 2026 review by Zadmirzaei and colleagues covering three decades of forestry DEA research, recent DEA has rapidly joined forces with artificial intelligence.

A growing body of research uses a random forest algorithm to select key factors when choosing input variables, predicts efficiency scores with neural networks, and links DEA with NSGA-II, a family of genetic-algorithm methods that simultaneously optimizes different goals such as operational efficiency, timber revenue, environmental conservation, and carbon sequestration, in order to produce concrete policy scenarios.

At the level of long-term forecasting, national statistics exert their power. One example is a study that linked data from Tanzania's National Forest Resources Monitoring and Assessment (NAFORMA) with machine learning to project changes in forest area through 2054. The area of forests and woodlands, which stood at 48.09 million hectares in 2014, falls to 32.99 million hectares under a scenario that allows existing development trends to continue unchanged. Under a scenario with heavy development pressure, it drops to 28.30 million hectares.

Under a scenario applying sustainable management, by contrast, the scale of decline is markedly reduced, providing quantitative evidence that can be used in policy decisions.

Computation is reaching agroforestry, in which trees and crops are grown together, as well. Ridlo and colleagues in Indonesia used graph theory to determine where shade trees should be planted among coffee trees to maintain suitable humidity and carbon-dioxide concentrations. They applied a graph algorithm called RIDS, or Resolving Independent Dominating Sets, to a gridded field plan to decide the locations of shade trees. They then fed humidity and carbon-dioxide data collected by smart sensors into a spatial-temporal graph neural network (STGNN) to forecast microclimate changes 10 to 20 days ahead.

A plot containing 96 coffee trees and 26 shade trees was calculated to retain 520 kilograms of carbon dioxide per year. A plot with 31 shade trees planted in a grid was calculated to retain 620 kilograms per year. Error metrics were lower than those of the existing comparison models, and explanatory power, which shows how much of the actual values the predictions explained, ranged from 0.73 to 0.81, outperforming the other methods.

How to Detect a Confidently Wrong Answer

When research findings are placed side by side, conflicting claims emerge. General-purpose large language models such as ChatGPT lead in broad general knowledge and flexibility across languages, but hallucinate frequently on narrow, specialized questions such as forest regulations and workplace safety rules. RAG-based models or ForestGPT, which anchor answers in supporting documents, offer greater accuracy and stronger evidence for regulatory queries. Because they are designed to refuse questions outside the designated knowledge repository, however, they cannot converse as freely.

It is not yet easy to achieve accuracy and freedom at the same time.

The same tension appears among computational methods. A traditional DEA model exposes, through linear equations, the calculation that produced an efficiency score, making it easier for policymakers to accept. A deep-learning prediction model, by contrast, offers high accuracy but remains a black box whose internal calculations are difficult to inspect. This opacity becomes an obstacle in policy documents that must cite a legal basis.

Problems outside the technology are no less formidable. Automation and autonomous decision-making agents are entering forestry rapidly, but forest policy and legal systems have not yet settled who is responsible for decisions made by AI itself. If an agent gives incorrect safety guidance and an accident occurs, it is difficult to determine whether the field manager or the developer is responsible.

At the 2026 Hawaii International Conference on System Sciences (HICSS), Swedish researchers Bergqvist and colleagues noted that unlike other industries with standardized data, forestry sites record information in inconsistent ways and retain many paper documents, so organizing the data must precede automation. The problem of data silos, in which records from harvesting through processing and distribution accumulate separately in different institutions, also slows integrated decision-making. Large language models and spatial-temporal graph neural networks require substantial graphics-computing resources as well.

On drones and handheld devices in remote forests where internet connections are easily lost, slow computation and insufficient storage remain unresolved.

The work ahead is clear. Explainable-AI techniques such as SHAP and Grad-CAM, which show why a model reached a decision, must be attached to decision engines. Guidelines aligned with forest regulations and occupational-safety standards are needed. After models are reduced through quantization and knowledge distillation, their device-specific response time and power consumption must be tested in forests where LoRa wireless networks and 5G base stations are scarce. Systems for sharing forest data across countries and regions, along with standard benchmarks, remain tasks for the future.

Language models are not alone in this movement. The geospatial foundation model Prithvi was jointly created by the National Aeronautics and Space Administration (NASA) and IBM. A compressed model operated in May 2026 aboard Australia’s Kanyini satellite and the IMAGIN-e instrument on the International Space Station (ISS). The orbital demonstration processed flood and cloud detection. Analysis of forest height and harvesting traces was presented as a possible ground-based application and must be distinguished from the results of this orbital test.

People will ask AI more and more questions in the forest, but for the foreseeable future, they will still have to check for themselves which document supports each answer. Models can now summarize regulations, flag risks in advance, and calculate truck routes. Yet one confident sentence can still be wrong. A human signature remains in the approval box.

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Chapter 2

Precision Forestry: Individual-Tree Analysis and Precision Measurement of Biomass and Carbon

2.1 Individual-Tree Species Classification Based on UAV-LiDAR and High-Resolution Imagery

At dawn, before the fog has fully lifted, a drone rises low over a Korean pine plantation at the foot of a mountain in Gangwon Province. The propeller noise scatters through the valley, and the drone crosses the sky back and forth in a grid like a tractor plowing a field. LiDAR, or Light Detection and Ranging, hangs beneath the aircraft. It emits hundreds of thousands of laser pulses each second and calculates distance by measuring the time the light takes to strike leaves and branches and return. Each time the drone passes, the outlines of thousands of Korean pine trees are marked from the sky, point by point.

Once all the points are assembled, they reveal not merely the forest as a whole but the location and height of each tree and even the pattern in which its branches spread.

For a long time, forestry managed forests by the stand, as a mass of trees. It estimated roughly how many pines grew in one area and what their average height was. Precision forestry lowers the unit of calculation to the individual tree. Identifying where each tree stands is called individual tree detection (ITD), and cutting out only the area occupied by that tree's leaves and branches is called individual tree crown delineation (ITCD).

In the past, people climbed the mountain to count trees directly with measuring tapes and visual estimates, or separated trees in aerial photographs by using watershed segmentation to find boundaries where brightness decreased. These methods frequently failed in dense forests where branches covered the sky without gaps and in mixed forests containing several tree species. Undersegmentation, which merged two adjacent trees into one, and oversegmentation, which incorrectly assigned a branch to another tree, occurred repeatedly.

To overcome these limits, a rapidly growing body of research combines three-dimensional point clouds created by unmanned aerial vehicle laser scanning, which consist of millions of points registered by returning laser pulses, with high-resolution imagery and computer-vision deep learning. Similar combinations are already entering the field in Korea. In September 2025, as pine wilt disease resurged, the Korea Forest Service announced a system that combined helicopter and drone surveys with artificial intelligence and LiDAR to automatically select pine trees suspected of infection.

Point clouds and images captured from the sky thus perform the screening once done by people climbing the mountain and inspecting trees one by one. This operation, however, is a screening stage for finding diseased trees and serves a different purpose from tree-species classification, which identifies the species itself.

Deep Learning That Draws the Outline of a Tree

The YOLO, or You Only Look Once, family of real-time object-detection algorithms scans an image once to find both the location and type of an object. Its computational speed makes it useful for crown detection as well. In a Pinus kesiya plantation in Dong Nai, Vietnam, a team led by Nguyen Thanh Tuan overlaid UAV-LiDAR with high-resolution aerial photographs and compared YOLOv8m-Seg, YOLOv11m-Seg, YOLOv12m, and the general-purpose segmentation model SAM2. The original SAM was trained on approximately 11 million images and more than one billion segmentation masks, while SAM2 is a model extended with large-scale video data.

YOLOv11m-Seg recorded an mAP50 of 0.62 and an F1 score of 0.59 in tree detection. A model combining YOLOv12m and SAM2, as well as YOLOv8m-Seg, did not reach these values. In areas where pine crowns overlapped densely, the model trained on field data outperformed the general-purpose segmentation model. When these boundaries were overlaid with the LiDAR point cloud and compared with field measurements, the explanatory power of estimated tree height ranged from 0.85 to 0.93. The explanatory power of crown-width estimates ranged from 0.58 to 0.86.

Because the results came from a plantation in one region, they must be validated again in other species and natural forests.

Another team that uses satellite images and aerial photographs together proposed the BRO hybrid model, combining YOLOv5 with a density-estimation neural network from the Faster R-CNN family. It used a search technique called Battle Royal Optimisation to adjust multiscale upsampling, and was designed to count trees whether they stood sparsely or in dense clusters. The model recorded 97.8 percent tree-count estimation accuracy and a mean absolute error (MAE) of 0.0912.

U-Net neural networks are widely used to draw the fine curves of crowns. Their structure compresses an image to a small size, then restores it to the original size while recovering detailed outlines. Skip connections carry information from before compression across the network, preventing thin boundaries such as branches from blurring. A team led by Wang Linlong developed MTSCFNet in the subtropical mixed forests of Jixi in Anhui Province and Guangxi Province, China. Its input included UAV-RGB camera imagery captured by a DJI M300 RTK equipped with a Zenmuse P1.

It also received LiDAR point clouds collected by a RIEGL miniVUX-1UAV and imagery from China's GF-2 satellite. The density of LiDAR points was 87.14 per square meter. The researchers divided the encoder into three branches that processed the data separately, then added a triple-branch feature-fusion module to combine them. Compared with a model using a single sensor, overlap-accuracy metrics improved for both crown-area segmentation and tree-species classification.

There are efforts to separate dense crowns using only high-resolution visible-light orthophotos. A method called FSC-Mask2Former was trained on 958 images cropped to 512 by 512 pixels. Each image was paired with ground-truth data precisely outlining 7,636 trees in total. In addition to image-texture information, the method applied features extracted in the frequency domain, which examines how often patterns of color and brightness repeat, together with contrastive learning, which trains similar trees to be close and different trees to be far apart. It markedly reduced errors in separating tree boundaries in densely foliated mixed forests.

Point Transformer V3 (PTv3) is one of the neural networks that process three-dimensional point clouds directly, point by point. It transfers self-attention, a method that calculates how closely each part of the data relates to every other part and was originally used to examine relationships among words in a sentence, to three-dimensional tree structure. In one study, point clouds captured by multispectral LiDAR emitting three wavelength bands were fed into four models: PTv3, KPConv, Superpoint Transformer (SPT), and random forest.

The forest was divided into six layers: ground, low vegetation, tree trunks, branches, leaves, and woody debris. In this comparison, PTv3 achieved an overlap accuracy (mIoU) of 69.1 percent, exceeding the other three-dimensional models by 21.8 percentage points.

A related meta-analysis published in January 2026 also demonstrates this trend numerically. When Aldaeri and colleagues gathered and examined papers on individual-tree detection, instance-segmentation methods that cut out individual trees accounted for approximately 46 percent of the total, while studies using ordinary RGB aerial photographs as input accounted for the largest share, 73 percent. This means that combinations using photographs and canopy height models (CHMs), which display treetop height like a map, are more common than LiDAR alone.

Naming Trees in a Mixed Forest

Once individual crowns have been cut out, the next stage examines the color, texture, and three-dimensional contours within them to determine the particular species. This task is difficult in mixed forests, where reflected light from upper canopy trees and lower shrubs is intermingled, sample counts vary sharply among trees, and only a few photographs exist for rare species.

Qin Tianyi and Zhao Qingjian published a study of multi-branch multi-label tree species classification (MMTSC) in Scientific Reports in 2025. It jointly analyzed UAV aerial photographs and Sentinel satellite imagery using TreeSatAI, a multisensor benchmark dataset created in Europe and containing 15 major tree species. The researchers compared six backbone neural networks for tree-species identification, including DenseNet121, EfficientNet-B0, and ConvNeXt-Tiny. Even when sample counts differed greatly among species, the model using DenseNet121 as its backbone outperformed the other five.

Its F1 score was approximately 72 percent and its precision approximately 82 percent.

In the Deramakot and Tangkulap Forest Management Units (FMUs) on the island of Borneo, Malaysia, researchers used DeepForest (DF Scanner Pro) and an EfficientNet-B4 neural network to distinguish tall, emergent Dipterocarpaceae trees from other trees in tropical rainforest. The producer's accuracy, the proportion of actual dipterocarp trees correctly identified, was 0.71. The user's accuracy, the proportion of trees identified by the AI as dipterocarps that actually were dipterocarps, was 0.67.

Adding the resulting tree-species information as training material for a satellite-based machine-learning model reduces error in above-ground carbon (AGC) estimates. The root mean square error (RMSE) of a model using satellite imagery alone was 70.60 megagrams per hectare. When tree-species information verified by drone was added, the error fell to 60.53 megagrams per hectare.

A paper by Kotaro Komatsu and colleagues published in Scientific Reports in January 2026 confirms a similar trend across a wider area. When carbon stocks and biodiversity indices were estimated solely from satellite indicators in 395 survey plots in Malaysia and Indonesia, explanatory power remained at 0.43 and 0.46. After 934 sets of drone imagery were added, explanatory power rose to 0.51 and 0.48. Information on individual trees captured by drones fills in the coarse scale of satellite photographs at finer resolution.

Mixed forests contain rare species with extremely few samples, so if an ordinary loss function, the method used to calculate how wrong a model is, is applied unchanged, predictions lean toward tree species with many individuals. M-MoENet, or the Multimodal Sparse Mixture-of-Experts Network, was developed to correct this imbalance. It takes optical imagery, Sentinel-1 satellite radar (SAR), and digital elevation model (DEM) data as inputs, and inserts several expert submodels dedicated to minority species within the encoder.

It also uses confidence-adjusted gating, which passes a decision to these experts when confidence in a prediction is low. According to results reported by Lou and colleagues, overall accuracy (OA) was 79.46 percent, overlap accuracy (mIoU) was 60.08 percent, and the Kappa coefficient was 0.74. The problem of low-sample trees such as evergreen pine and linden disappearing from maps or appearing in scattered, disconnected patches was greatly reduced.

A study classifying nine major tree species in Cyprus presents another solution. It used ResNet50 as the backbone and combined it with weakly supervised learning that supplements training with provisional labels assigned by the model. The model, which received RGB, near-infrared, terrain, and soil data, recorded an overall accuracy of 90 percent. The study did not directly measure any claim that labeling costs were reduced by more than half.

Numbers That Vary from Study to Study

Crown segmentation and tree-species classification produce fairly precise figures in individual experiments, but results clearly diverge with species structure and sensor combination. In single-species conifer forests of pines with distinct conical shapes, such as Pinus kesiya and Pinus taeda, YOLOv11m-Seg and canopy-height-model-based segmentation models show high tree-height estimation accuracy, with explanatory power ranging from 0.85 to 0.93.

In subtropical and tropical broadleaf mixed forests, where leaves spread widely, branches intertwine, and dead branches are mixed in, explanatory power for crown-width estimates falls to between 0.58 and 0.68 even when the same YOLO family or Mask R-CNN models are used. Whether a tree's shape itself is regular or irregular divides the accuracy of artificial intelligence.

The ranking of foundation models and domain-specific models can also reverse. SAM2, trained on large-scale image and video data, can separate the outlines of many objects, but in forests with overlapping branches it produced more false detections than YOLOv11m-Seg trained on forestry data. Even an enormous general-purpose model cannot replace fine-tuning for a particular field site.

What the View from the Sky Misses

No matter how precisely a drone is flown, some places remain invisible from the sky. Signals from optical cameras and LiDAR above the forest cannot penetrate to the middle and lower layers in forests where dense foliage blocks the sky. As a result, short trees are repeatedly and incorrectly grouped into the crowns of large trees above them.

Training a deep-learning model requires ground-truth data in which a precise two- or three-dimensional outline has been drawn for each tree. In a densely foliated forest, however, even highly experienced field experts disagree on where one tree's crown ends. This difference in judgment remains as annotation noise and enters model training. Creating precise ground-truth data is therefore as labor-intensive as designing the algorithm.

Accuracy also falls when the region changes. Even a tree-species classification model that scores highly in one forest may perform worse in another forest with different terrain, sunlight, and species composition. The size of the decline varies by data and evaluation metric and cannot be reduced to a single range.

Tasks for the Next Stage

Efforts to close these gaps have already begun. Hybrid fine-tuning studies are retraining the zero-shot foundation model SAM2 on forestry data by layering information from three-dimensional canopy height models created by UAV-LiDAR. The aim is to achieve generality and precision at the same time. Research is also refining frequency-component decomposition, contrastive learning, and gating algorithms that combine several expert submodels, as in M-MoENet and FSC-Mask2Former, to improve the automatic recognition of rare species.

Crown-BERT, developed by Wang Xinbo and colleagues and published in GIScience & Remote Sensing in May 2026, is a recent example of this direction. It adds dynamic crown masking, which reflects the differences in crown shape and selects only valid crown areas, and crown positional encoding, which embeds location information within the crown. It then inserts a self-supervised learning stage that can pretrain the model with unlabeled crown samples. The approach seeks to extract useful features even for rare species with few ground-truth labels.

Work must continue to expand and share three- and two-dimensional individual-tree benchmark datasets spanning multiple ecosystems, such as TreeSatAI, PureForest, and ForInstance. At a time when model performance varies greatly by continent and tree species, expanding the dataset itself is as important as refining the algorithm.

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2.2
Estimating Aboveground Biomass (AGB) and Forest Carbon Stocks

To determine the dry weight of a tree directly, a person must take up a saw, cut through the base and fell the tree, separate the branches, trunk, and leaves, weigh them, and drive the moisture out in a kiln. Such destructive direct measurements were used to obtain reference values for building allometric equations. The biomass of an entire forest has long been estimated with allometric equations based on diameter at breast height, tree height, and wood density.

These equations made it possible to calculate weight without cutting trees in protected areas, but errors grew when the region and species differed from those for which an equation had been developed.

There was a reason people wanted to know the weight of a tree. To bring logs to market and price them, they needed to know volume and weight, and harvesting and measurement remained inseparable for a long time. Yet there is a way to estimate weight without cutting a tree. It is enough to measure the thickness and height of the trunk and pass those values through an equation prescribed for the species.

The diameter of a stem measured at a person's chest height is called diameter at breast height (DBH). An allometric model estimates the volume and weight of a tree by entering DBH together with tree height, wood density, and species- and region-specific coefficients. The relationship between diameter and height changes with developmental stage and environment and is not fixed in a constant proportion. Estimating the carbon a growing tree has accumulated in its trunk and branches requires these errors to be included in the calculation.

The precision of aboveground biomass (AGB) directly affects national carbon accounts and carbon-market figures.

Measuring DBH and tree height by hand is no easy task. A surveyor measures stem circumference with a tape, looks up at the treetop with an angle-measuring instrument called a hypsometer, then calculates height by trigonometry. The process takes several minutes per tree. Measuring an entire forest requires several surveyors to work for days, sometimes weeks. Error enters as well, because people differ in deciding where a stem begins and ends. In recent years, the center of gravity in forest surveys has shifted from measuring tapes to lasers and cameras, and from surveyors' two legs to drones and artificial satellites.

How Ground Lasers and Drones Read Trees

A terrestrial laser scanner (TLS) circles a tree, emits countless pulses of light, and measures the time they take to return, drawing a three-dimensional map composed of millions of points. This collection of points is called a point cloud. The multiple-scan method moves the scanner among several locations and captures even the back of a tree without omission, but moving the scanner and registering the scans into one takes considerable time. If hundreds of trees must be surveyed, the work is difficult to complete in one day.

By contrast, the single-scan method stands in one location and scans only once, finishing within minutes, but other trunks and branches occlude the back of a tree and leave sparse gaps in the point data.

In Martell Forest in Indiana, United States, researchers combined single-scan TLS with CoAtNet in a temperate broadleaf forest containing 37 tree species. Ground-truth values were calculated by entering field-measured DBH into general North American allometric equations. Among 60 test trees, the coefficient of determination was 0.73. Median percentage bias was 0.99 percent, but median absolute percentage error was 25.06 percent and mean absolute percentage error was 29.40 percent. A small bias must not be read as meaning that error for each tree was less than one percent.

There is a way to look down from the sky as well. A map created by stitching together drone photographs and correcting their distortion is called an orthophoto. Because it is taken from much closer than a satellite image, each branch appears clearly. In the Deramakot and Tangkulap tropical rainforests of Sabah, Malaysia, researchers combined RGB orthophotos captured by drone with a deep-learning model called EfficientNet-B4 to recognize the crowns of

Dipterocarpaceae trees, the umbrella-like treetops formed by branches and leaves, then applied tropical-forest allometric equations to estimate carbon.

A baseline model run with satellite imagery alone and no field samples remained at an explanatory power of 0.43. A model that added drone-captured crown-structure information increased explanatory power to 0.51 and reduced error from 70.6 tons to approximately 60.5 tons per hectare.

A similar attempt was made in European beech (Fagus sylvatica) forests. Researchers measured three-dimensional crown volume with UAV laser scanning and added the value to an existing calculation based on DBH alone, markedly reducing biomass-estimation error. Because crown-volume information had been added to an equation that previously considered only stem diameter, the improvement appears natural.

The allometric equation itself has weaknesses, however. General-purpose formulas created for use across North America or all tropical forests cannot fully capture the fertility of the soil in a specific region, the local climate, or how tree form varies among growing sites even within the same species. Even within a single spruce species, a tree grown on a rainy mountainside and one grown on a dry ridge may have the same diameter but differ in how solidly filled their interiors are, that is, in wood density. This can produce a systematic bias, an error leaning consistently in one direction according to region.

Fortunately, a supervised deep-learning model can be retrained to correct this bias once precisely measured local allometric data accumulate. The approach is closer to continuously collecting data and correcting the model than to finding a perfect formula from the beginning.

Connecting National Forest Inventories with Satellite Data

No matter how much technology improves for precisely measuring individual trees with lasers and drones, it cannot survey every tree in a country this way. The larger the country's forests, the more easily the number of trees surpasses hundreds of millions. A drone can inspect only a limited area in one day, but an artificial satellite crosses that limit at once.

Expanding values measured tree by tree or data from a few sample plots into a nationwide map requires a different approach: connecting ground-measured

National Forest Inventory (NFI) data with artificial-satellite remote-sensing data that survey wide areas at a glance, using artificial intelligence.

In temperate mixed forests in Connecticut, United States, researchers created a biomass map at 10-meter resolution by overlaying data from 142 sample plots in the U.S. Forest Service's national forest inventory with Sentinel-1 radar signals, vegetation indices such as NDVI derived by Sentinel-2 and Landsat satellites from the green reflectance of leaves, and tree-height data from the spaceborne laser altimeter GEDI. After testing several machine-learning methods, accuracy was highest when GEDI-measured tree height and Sentinel vegetation indices were entered together.

Areas outside forests were assigned a biomass value of zero and filtered out, reducing noise in the sample.

In managed forests on Russia's Sakhalin Island, researchers combined time-series changes in Sentinel-2 satellite imagery and terrain data with NFI stand-subcompartment survey data, then compared random forest, XGBoost, and TabNet. XGBoost performed best. This algorithm links a sequence of decision trees, each narrowing an answer through branch-like questions, while each subsequent tree reduces the error missed by the preceding one. Mean absolute percentage error, or MAPE, was 0.18 for estimating tree height and 0.37 for estimating carbon stock, while overall explanatory power was 0.68.

A study of natural forests in Heilongjiang Province, China, covers a much longer time axis. It assembled nine rounds of NFI permanent-sample-plot data from 1976 to 2015. The researchers overlaid past and future climate and carbon-dioxide concentration data and built a framework called knowledge-guided machine learning (KGML). It is a two-stage structure. First, a forest carbon-sequestration model, which expresses the ecological growth process of trees in equations, is refined to reflect the carbon-dioxide fertilization effect. The values calculated by this model are then passed to XGBoost as prior information.

Adding ecological knowledge raised the explanatory power of carbon-density predictions from 0.85 to above 0.90. Under a low-emissions scenario that actively suppresses carbon emissions, carbon stocks in Heilongjiang's natural forests were projected to range from 1,379.26 to 1,439.02 teragrams in 2060. Because ecological rules were embedded in advance, values did not jump to implausible levels even when the model predicted a future outside the range of its training data.

An ordinary black-box machine-learning model can easily produce nonsensical values under extreme climate conditions it has never seen, because once it leaves the patterns present in its training data, it does not know what basis to use for an answer.

Another study added Finnish National Forest Inventory samples and Sentinel-2 time series to a model built from Romanian field data. The explanatory power of Finnish growing-stock volume predictions rose from 0.483 to 0.718. Its subject was not a carbon map but stand attributes such as tree height, basal area, and volume. A Tanzanian study used 2014 forest and woodland area as a starting point and calculated three scenarios through 2054: continuation of existing trends, sustainable management, and increased development pressure.

These studies, extending from Connecticut through Sakhalin and Heilongjiang to Finland, show a common picture. The more abundant and diverse the ground sample-plot data, and the more types of satellite sensor data that are overlaid, the more accurate the broad-area map becomes.

Why the Numbers Diverge

Research figures must be placed side by side with care. The weight of an individual tree, stand volume, and biomass per hectare are different target variables, and R^2 changes with the data range and validation method. Errors in NFI sample-plot coordinates depend on the canopy, terrain, receiver, and correction method. Some public data intentionally blur coordinates to protect private property. A satellite pixel contains large trees, saplings, and bare ground together, creating a gap between individual-tree values measured at close range and the pixel average.

Rankings also reverse between optical and radar satellites. Optical and short-wavelength radar signals can saturate quickly in high-biomass forests. The saturation point varies with forest structure, moisture, polarization, incidence angle, and regression model, so it is difficult to fix a single threshold. Long-wavelength radar and LiDAR are relatively advantageous in reading the structure of dense forests. Because GEDI is waveform LiDAR, it is not grouped under the same saturation criterion as radar backscatter. Differences among sensors have sensitive consequences in calculations involving money, such as carbon credits.

Problems Left Behind, and the Next Stage

Technical limits remain. NFI and satellite observations have different cycles and therefore measure the same forest on different days. Public NFI data in several countries may blur actual coordinates to protect private property, producing errors when they are matched with high-resolution pixels. Biomass reference values created with allometric equations also contain uncertainty arising from the choice of equation. A remotely sensed AGB map must not be treated as the total amount of carbon in the forest. A national greenhouse-gas inventory may calculate belowground biomass, deadwood, litter, and soil as separate carbon pools.

Future work must test knowledge-guided machine learning, which places growth equations and carbon-cycle models inside neural networks, across broad regions. Tree-height data from independent spaceborne LiDAR missions such as GEDI and ICESat-2 can also be compared together with NFI data. Only when artificial intelligence reports estimates and uncertainty side by side can its output approach a carbon map suitable for use in a national greenhouse-gas inventory.

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2.3
Monitoring Forest Soil Dynamics and Land-Cover Change

It was after three days of heavy rain. At a harvested site somewhere in Gangwon Province, the slope stripped of trees had taken the rain directly on its bare skin. The soil that washed down the cut slope was red, the characteristic color of decomposed granite formed by weathering. A researcher in rubber boots crouched in front of the muddy water and grasped a handful of soil. From the sensation of it slipping between the fingers alone, the researcher could roughly estimate how much organic matter the soil had lost and how much more would wash away in the next rain.

A few steps away, on a slope where roots still held, the soil was much darker and firmer. Even on the same mountain, the condition of the soil differs this much according to whether trees are present. But the sense of touch cannot describe this entire slope, much less the whole mountain beyond the harvested site. A handful of soil is always insufficient. This is why sensors and satellites that read belowground and beyond the mountain at the same time, and the artificial intelligence that connects them, have moved to the center of forest-soil observation.

Moisture Read Together by Sensors Underground and Eyes in the Sky

Soil moisture and organic matter, temperature and relative humidity, and carbon-dioxide concentration determine how well trees grow, how efficiently they use water, and how much carbon they retain. In the past, the only methods were to enter the field on scheduled dates and collect samples, or install a single instrument and watch only the numbers it read. When a wide mountain is read this way, the conditions beneath one tree’s shade or within one valley are easily missed.

Today, the approach is changing: multiple Internet of Things (IoT) sensors are planted in the ground, their signals are linked by LoRa, a low-power wide-area network, and the results are read together with images captured by drones and satellites.

One study analyzed drone-acquired multispectral, thermal-infrared, and ordinary photographs together with deep learning to estimate soil moisture around alfalfa roots. Published by Yin et al. (2024) in the European Journal of Agronomy, the study showed that a model combining several sensors had distinctly smaller error than a single-sensor model. In other words, the water conditions around roots that could not be known from visible color alone emerged when several wavelengths were overlaid.

A review of wheat-based agroforestry farms reaches a similar conclusion. Published by Singh et al. (2026) in the International Journal of Environment, Agriculture and Biotechnology (IJEAB), it explains that combining crown management to control the breadth of tree shade with underground moisture sensors and satellite-derived land surface water index (LSWI) and temperature vegetation dryness index (TVDI) can provide advance warning of when trees and wheat will begin competing for water. Detecting the contest before it begins creates room to save water.

Multi-probe sensors inserted into tree trunks to measure moisture through electrical properties, along with LoRa gateways that operate for months on one battery, have been installed in the field. A pipeline already carries values measured deep in a mountain directly, without passing through human hands, to servers and edge devices, small computers near the field site. A task that once required a researcher to climb the mountain once a month and copy instrument readings by hand can now be checked merely by turning on a mobile-phone screen. The pipeline is not perfect, however.

When a battery runs down or communications are cut, the numbers for that entire interval remain blank.

A review has gathered these technologies and organized their direction. In Frontiers in Plant Science, Wang et al. (2026) reviewed multimodal data-fusion studies that place LiDAR, satellite imagery, IoT sensors, and drone data used in forest-resource observation into a single model. They noted that accuracy rises as the number of data types increases, but that preprocessing is difficult because the temporal and spatial resolutions of the datasets differ. Reviews covering forest-health surveillance more broadly repeat the same conclusion. Amoah-Nuamah et al. (2025) and Saha et al.

(2025), reviewing AI-based forest-health surveillance and remote-sensing and smart-monitoring systems, respectively, observed that both false alarms and omissions decline when sensors, satellites, and artificial intelligence are overlaid rather than used separately.

A Map That Turns Soil Quality into a Score

Available water capacity, organic-matter content, acidity, and nutrients are measures of forest health. These numbers ultimately determine how far tree roots can extend and how long they can endure a drought. The problem is that they cannot be known from a single scoop with a shovel and emerge only after samples are sent to a laboratory and several days pass. Work to draw these figures into a single map has grown rapidly in recent years.

In a study of natural pine forests, Poudel et al. (2025) combined the fuzzy analytic hierarchy process (Fuzzy-AHP) with random forest to calculate a soil-quality index. Published in Scientific Reports, the study reported that a machine-learning model incorporating soil structure, organic matter, and water-retention capacity mapped local differences in soil conditions much more finely than conventional statistical models.

Attempts are continuing to identify soil organic carbon (SOC) itself by satellite. Li et al. (2025) combined spectral imagery from the Sentinel-2 satellite with terrain variables to estimate soil organic-carbon concentrations in China's Bosten Lake oasis. Parvizi and Fatehi (2025) mapped soil organic carbon across several land-use types and compared a generalized linear model, Cubist, support vector machine, and random forest. The explanatory power of random forest was 0.64, distinctly better than the generalized linear model's 0.39 and the support vector machine's 0.41.

No one algorithm always wins, so when the soil and terrain change, the choice of model to place first must be reconsidered.

The resulting soil-quality indices and soil organic-carbon maps do not end as a single number. Once the map is colored, it shows at a glance how sharply soil conditions differ within the same mountain according to the direction of a slope and whether a place is a water-collecting valley or a ridge. For a forestry officer deciding where to plant trees and where to leave the land undisturbed, this map becomes reference material that points the way before a field inspection.

A Graph Neural Network That Calculates Shade-Tree Placement

In agroforestry, the location of a single patch of shade cast by upper-story trees changes the sunlight, humidity, carbon-dioxide concentration, and soil moisture experienced by lower-story crops. If the shade is too dense, crops grow spindly; if it is too sparse, their leaves burn under the blazing sun. Where to plant shade trees and how many to plant is therefore a matter of calculation, not intuition.

Ridlo et al. (2025) calculated the placement of shade trees and sensors with an independent dominating-set algorithm from graph theory, and predicted relative humidity and carbon-dioxide concentration with a spatial-temporal graph neural network (STGNN). In a scenario with 96 coffee trees and 26 shade trees, annual carbon-dioxide sequestration was calculated at 520 kilograms. The value for a scenario with 31 shade trees in a grid was 620 kilograms. These were model calculations, not carbon-sequestration quantities measured directly in a long-term field study.

The predictive performance is worth attention as well. The model forecast the microclimate 10, 15, and 20 days ahead. Compared with existing methods such as historical averages, ARIMA, support vector regression (SVR), graph convolutional networks (GCN), and gated recurrent units (GRU), its errors were distinctly smaller and its coefficient of determination ranged from 0.7350 to 0.8109. An age has begun in which relative humidity and carbon-dioxide concentration that people once went out to measure every day can be calculated ten days ahead and used to choose where to plant shade trees.

More Than 30 Years of Film Captured by Satellites

Climate change, unauthorized harvesting, agricultural expansion, and wildfires continually alter the appearance of forests. Capturing this change requires not one photograph but decades of film. Time-series images accumulated layer upon layer by satellites such as Landsat, Sentinel, and MODIS serve as that film. In Korea, the same family of satellite time-series analysis is used to examine recovery in wildfire-damaged areas in Gangwon Province and at sites harvested because of pine wilt disease. Immediately after harvesting or fire, broad areas of bare soil appear.

After several years, grasses and shrubs enter first, and only then do trees take root. The sequence appears intact in the changing colors of satellite imagery.

Obata and colleagues studied forests in Georgia, United States, in 2021. They stacked 33 years of Landsat imagery, from 1984 through 2016, on Google Earth Engine. They extracted brightness, greenness, and wetness indices through tasseled-cap transformation, applied harmonic regression analysis, and connected the results to National Forest Inventory sample plots through random forest. Compared with a model using only three years of imagery, it identified the date of the most recent disturbance more accurately and reduced error in growing-stock volume.

The same study was introduced again in a Japanese journal in 2026, but the original publication year and DOI take precedence in citation.

The classification of disturbance causes has expanded to the global scale. Using Landsat time series and deep learning, Wang et al. (2026) built a dataset quantifying forest loss worldwide from 2000 to 2020 by dividing it into wildfire, logging and harvesting, shifting cultivation, disease, and wind damage, and published it in Earth System Science Data. This means that maps can now distinguish not only where forests disappeared but why.

Another study compared AI models that distinguish land use and land cover. Çalışkan (2026) trained a support vector machine, random forest, and decision tree on the same data and compared their performance. No single method won in every region. Random-forest methods performed better where terrain was complex and land use was divided into small parcels, while the structurally simpler decision-tree method was not far behind in large agricultural areas with clear boundaries.

Regions with few labels require a different strategy. Colombia's tropical dry forests shed leaves seasonally and burn frequently, causing their spectral characteristics to fluctuate greatly. Semi-FCMNet, introduced by González-Vélez et al. (2026), is a semi-supervised learning architecture that trains together on ground-truth labels and unlabeled Sentinel-1 radar and Sentinel-2 optical time series. It maintained accuracy above 90 percent even under label-limited conditions. Labor-time savings were not measured separately.

There are studies that identify specifically what enters after a forest disappears. Pišl et al. (2026) used a deep-learning model that learns location information to distinguish whether land cleared of tropical forest became pasture, cropland, or a road. The study shows that even when forest loss is the same, policy responses must differ if the subsequent land use differs.

There is a story of forest expansion as well. Silva et al. (2026) examined an agroforestry zone in subtropical Brazil. The researchers tracked change with MapBiomas data, Brazil's satellite land-cover mapping project, at three points in time: 2000, 2010, and 2020. The area expanded from 405.80 hectares through 500.60 hectares to 659.81 hectares. The habitat aggregation index rose during the same period. The expansion appears to have occurred as agroforestry areas served as ecological corridors connecting fragmented natural forests. The study noted that such corridors help protect biodiversity and prevent soil from being washed away.

Research has also looked into the future. Using Tanzania's National Forest Resources Monitoring and Assessment (NAFORMA) data, Zella (2026) calculated forest area from 2014 through 2054 under three scenarios. If existing trends continue, forests and woodlands decline from 48.09 million hectares to 32.99 million hectares. Under a scenario of heavy development pressure, they fall as low as 28.30 million hectares. Under the sustainable-management scenario, 43.85 million hectares were projected to remain.

There are attempts to detect harvesting in real time. Kundu et al. (2025) published in Scientific Reports a system combining the YOLO object-detection model with a LangChain-based agent that carries out a sequence of judgments autonomously. It detects suspected harvesting changes in satellite and drone imagery in near real time and issues alerts. Artificial intelligence first selects areas suspected of harvesting, but false alarms do not disappear completely, so people must still make the final judgment.

This kind of time-series surveillance now carries value outside the laboratory. The European Union Deforestation Regulation (EUDR) requires operators placing on the market or exporting coffee, cocoa, and wood-related products listed in Annex I to provide geolocation information for the place of production. A plot of four hectares or less can be represented by one point of latitude and longitude; a larger plot requires a polygon boundary. The cutoff date is

December 31, 2020. Large operators and some small and medium-sized enterprises become subject to the rules on December 30, 2026.

The application date for natural persons and some microenterprises is June 30, 2027. Because the dates differ according to commodity code and operator status, each company must separately confirm its product and role.

Conflicting Numbers and Remaining Tasks

Even after this much technology has accumulated, the figures do not align. A ground sensor measures a value at a narrow point, while one Sentinel-2 or Landsat pixel sees the average across a broad area. Overlaying two datasets that differ in gravel, shade, canopy, and soil moisture requires validation that aligns them to the same date and spatial scale.

Cases have been reported in which such mismatches created problems in the field. An area judged safe from satellite indices alone was already quite dry when visited, or a satellite sounded an anomalous signal that proved in the field to be an ordinary seasonal change. Unless a field manual specifies in advance which signal to trust first when the two disagree, managers reach different judgments and confusion follows.

Another kind of conflict exists between optical and radar (SAR) satellites. In tropical and subtropical rainforests with frequent clouds and fog, gaps often open in optical imagery, making it easy to miss the cycle of leaf emergence and fall. In areas where a rainy season continues for months, six months can pass without producing a single usable optical image. Radar can image through clouds, but the roughness of wet soil immediately after rain can disturb the signal, falsely detecting a change where none occurred.

In a forest with a densely closed canopy, signals emitted from satellites or drones above bounce back from leaf surfaces, leaving no choice but to infer the soil conditions below through indirect indices. When a change-detection model trained in one climate zone is moved to another ecosystem, it can misread the leaf-fall season as a wildfire or harvesting. The size of the accuracy decline differs by data and metric and is not reduced to a single range. Sensors in remote areas frequently lose battery power and communications, requiring long-term field tests.

One task for the future is the physics-informed neural network (PINN), which combines neural networks with equations that express the movement of underground water through physical laws. Models trained only on data can produce nonsensical values when confronted by an extreme drought or record rainfall absent from their training data. If the physical laws governing how water infiltrates the ground and evaporates are embedded in the neural network, the model is more likely to maintain plausible values even under such unfamiliar conditions.

Reducing spatial-temporal graph neural networks and Transformers to lightweight forms that can be embedded directly in drones and field devices is another task. Multiple papers repeat the need to continue expanding time-series soil and land-cover benchmark data across different ecosystems. Only when low-power AI chips that run for months on one battery reach every corner of the mountains will the present gap between sensors and satellites begin to narrow.

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Chapter 3

Forest Disaster and Ecosystem-Health Monitoring: AI Surveillance and Early Warning

3.1
Machine-Learning and Deep-Learning Wildfire-Risk Prediction and Burned-Area Detection

On a late-spring afternoon, with a dry-weather advisory in its third day, a single red dot appears in one corner of the monitors covering the wall of the wildfire situation room. The wind outside is dry and strong; water sprayed yesterday has already evaporated. Only radio traffic and keyboard taps fill the room. An operator immediately enlarges the CCTV view, checks the thermal camera temperature, and opens the screen for nearby reports. At most a few minutes are available to decide whether the dot is a real fire, smoke from burning a rice-field embankment, or a roof heated by the evening sun.

During those minutes, before human eyes can scan every screen, an AI algorithm has already made an initial judgment.

The fire that began in Uiseong, North Gyeongsang Province, in March 2025 showed the weight of that judgment. It spread to Andong, Cheongsong, Yeongyang, and Yeongdeok. Official counts recorded 26 deaths and 71 injuries. The provisional forest-damage area in North Gyeongsang was 99,289 hectares; its provisional loss was KRW 1.1306 trillion. Recovery costs for North Gyeongsang, South Gyeongsang, and Ulsan were estimated at KRW 1.8809 trillion. These are different figures because the geographical coverage and accounting categories of the damage assessment and recovery plan differed, not because the losses increased in summer.

AI intended to prevent such fires works at two broad stages. Machine learning finds rules in data, while deep learning searches for them more deeply through multilayer neural networks. One predictive model identifies locations at risk days, or as much as a month, before ignition; another detection model recognizes a fire within minutes after it starts.

Humidity moves first

Older wildfire-risk assessments relied on fixed terrain and a single vegetation-index image. Slope and tree species change little from year to year, but wildfire is not caused by terrain alone. A mountain safe yesterday can become dangerous today when humidity abruptly falls after rain. Forest AI is therefore moving toward recalculating daily ignition probabilities by combining weather, terrain, fuel vegetation, and socioeconomic data that indicate human access.

Wildfire data have a difficult imbalance: fire days are few and non-fire days overwhelmingly numerous. A model trained unchanged on those data can score well by predicting only safe days while missing the fires. Researchers therefore use SMOTE (Synthetic Minority Over-sampling Technique), which statistically creates similar additional examples of fire days so that the model learns both classes evenly. They also use undersampling of non-fire days and cost-sensitive learning that imposes a heavier penalty for missing a fire.

A Gangwon State study applied this approach to 11 years of weather, forest, and population data from 2013 through 2023. For tabular data, tree-based models often outperform deep neural networks because their branching decisions can handle dissimilar variables such as weather and terrain. Among logistic regression, XGBoost, LightGBM, random forest, and extra trees, extra trees led with an AUC of 0.839. AUC measures the ability to separate fire from non-fire days: 1 is perfect and 0.5 is no better than a coin toss. Random forest was better at avoiding missed fires, with recall of 0.828.

The study also used SHAP (SHapley Additive exPlanations), a method that brings game theory's allocation of joint contributions into a predictive model. Relative humidity led all variables with a contribution of 0.25; risk rose sharply as humidity fell. Precipitation followed at 0.15, maximum daily temperature at 0.05, and population density at 0.04. Growing-stock volume, cemetery share, coniferous-forest share, and farmland share also contributed. The regional variable dividing Yeongdong, exposed to sea winds east of the Taebaek Mountains, from Yeongseo behind the range had a similar effect.

The result suggests that human access and fire-setting practices, as well as climate, increase risk.

Fuel variables such as conifer share and growing-stock volume need not be measured tree by tree. Remote observations, including LSWI, TVDI, and canopy-height models (CHM) generated by drone laser scanning, stand in for field walking. Research using UAV LiDAR to map each tree's location, circumference, and crown width is continuing. A deep-learning study of Pinus kesiya in Vietnam automated individual-tree detection and crown delineation, opening a route to the base data for wildfire-fuel maps.

Where the Gangwon study is a local next-day model, FWI-Net, published by the UNIST team led by Professor Jeong-Ho Im in 2026 in Communications Earth & Environment, forecasts the global Fire Weather Index up to 31 days ahead. The index combines temperature, humidity, wind, and rainfall to indicate likely fire spread. ECMWF numerical forecasts rapidly lost accuracy after two weeks, whereas FWI-Net reduced error across the full 31-day interval by 6.6 percent, and by 12.4 percent for the first week. The improvement was greatest where wildfire risk was high but forecasting systems were weak.

An international review of work combining geospatial technology and machine learning reached a similar conclusion: models combining weather, terrain, and human-activity data repeatedly outperform models using satellite imagery or GIS data alone.

Mountain sensors and eyes in the sky connect in real time

Sensors on the ground and satellites above watch the same moment. LoRaWAN is a low-power wireless method for long-distance transmission. Eighty sensors measuring temperature, humidity, and carbon monoxide were installed at Zeytinpark in Türkiye. The researchers tested a model combining adaptively weighted Random Forest and XGBoost; sensor-placement coverage was calculated at 95.58 percent, and battery life at up to 11 months.

A study in the Krasnoyarsk region of Siberia drew six concentric zones from 1 km to 100 km around wildfire points. It combined 30-day weather and terrain time series in each zone and classified fire extent with XGBoost, reporting 88.8 percent accuracy. The authors noted that this was a locally tuned result requiring recalibration with local data before transfer to another continent.

The first three operational FireSats of the Earth Fire Alliance entered orbit on July 7, 2026. The official roadmap starts with twice-daily observations for early users by the end of that year, aims for global access in 2028 and revisits within one hour in 2029, and targets revisits within 20 minutes in the early 2030s. Satellite numbers and schedules can change with launches and funding.

A Korean remote-sensing review also traced AI and satellite monitoring across the whole wildfire cycle: pre-ignition risk prediction, real-time detection during fire, and post-suppression damage-area estimation each require different satellite data and models. Korea's GEO-KOMPSAT-2A captures natural-color Earth imagery that allows clouds, wildfire smoke, and dust to be distinguished visually, and its soil-moisture observations support drought and wildfire-risk assessment.

The National Institute of Forest Science integrates these data in the National Wildfire Risk Forecast System and has recently introduced a mobile service that shows risk at the user's location.

Whether it is smoke or cloud, the camera decides first

Once a fire begins, another race starts: it must be recognized within minutes, before smoke spreads. Fixed CCTV and infrared cameras watch from below, while UAVs cover difficult ridges and blind spots. A visible-light camera can be fooled by haze, cloud, or evening reflection. A thermal camera detects heat but has coarse imagery that can confuse burning trees with hot rock.

EFFNet, trained on data from Fujian Province, China, combined visible and thermal-infrared images. Its validation mAP50 was 97.2 percent, precision 94.9 percent, and recall 94.1 percent; these are results under the Fujian test conditions. Akhyar and colleagues developed DeepFire S3GA-Net to segment wildfire areas from UAV images. Test data yielded mean IoU of 0.8723, precision of 0.9347, and recall of 0.9194. Hindarto and colleagues compared MobileNetV3, ResNet50, and YOLOv8 on a separate wildfire-image dataset.

The comparison of YOLO segmentation and SAM2 for Vietnamese Pinus kesiya concerns individual-tree and crown delineation, not wildfire research.

When models speak differently

These results do not all say the same thing. Traditional Fire Weather Index models using weather alone identify broad regional trends but cannot distinguish which small forest patch will ignite in the same weather. Studies of Gangwon, Morocco, and India report AUC and recall gains of 10 to 15 percentage points after adding socioeconomic variables such as population density, farmland and cemetery shares, and distance to roads. Even under identical weather, actual ignition is more likely where people visit frequently or farms and graves are nearby.

Visible-only cameras are inexpensive, but false alarms and missed fires rise in fog, backlight, and night conditions. Dual-modal equipment such as EFFNet performs strongly but has costly infrared sensors and lower image resolution. A municipality covering an entire mountain must still balance dense deployment of inexpensive visible cameras against sparse deployment of expensive dual-modal cameras.

Limits must be stated plainly. SMOTE may introduce artificial patterns; LTE and 5G often fail in deep mountains; false alarms waste firefighters, helicopters, and budgets, while missed fires delay initial response. Edge-AI computers such as NVIDIA Jetson must complete computation on drones, but decisions become slow if models cannot be compressed. High-performing vision transformers and 3-D CNNs also remain difficult to explain to officials who must approve a machine's decision in their own name.

Future work runs in two directions: visualizing reasons through SHAP or Grad-CAM and embedding heat-and-wind physics in neural networks; and connecting low-power sensor networks with dual-modal drones while measuring end-to-end alert time. A unified network for wildfire, pests, and drought stress has been proposed, but a fully demonstrated autonomous response system completing action within one minute in the mountains has not yet been proven.

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3.2

Early Image-Based Diagnosis of Pests and Diseases (Including Pine Wilt Disease) and Dead Trees

Early on Wednesday morning, three inspectors climb a foothill in Gangwon Province. Their backpacks contain GPS units and genetic diagnostic kits, binoculars hang at their necks, and at every ridge one stops to scan the green slope for three or four reddish-brown pines. Once found, they record coordinates, take sawdust with an increment borer, and test for infection. Long-dead trees no longer even smell strongly of resin.

This method has a decisive flaw: when pine needles look red, it is already late. A pine infected with pine wilt disease gradually dries after the vector, the Japanese pine sawyer beetle, carries nematodes into it; without intervention a forest can turn red within several years. Yet visible discoloration takes weeks. In those weeks vectors move to other trees and infection spreads quietly. The tree discovered through binoculars has crossed the threshold of death, and spread has already begun.

After finding an infected tree, work continues: it must be felled and chipped, or covered and fumigated to eliminate vector larvae. A person can inspect only a few folds of a mountainside in a day, and dense stands slow the work further. In announcing its fall 2025 control plan, the Korea Forest Service said that it would add AI and LiDAR to helicopter and drone surveys. AI first selects suspected trees and people then confirm them with genetic diagnostic kits. Priority personnel and equipment went first to nationally protected leading-edge areas, the Baekdudaegan, and Geumgang pine forests.

In June 2026, Gijang County began drone surveys of hard-to-walk terrain and blind spots, producing high-resolution orthophotos and sharing suspected-tree locations with Busan.

Reading before color changes

When a pathogen infects a tree, its conduits become blocked. The tree closes leaf stomata to reduce water loss, transpiration falls, and leaf-surface temperature slowly rises like a room after the air conditioner is switched off. This signal begins weeks before needles redden. Thermal-infrared sensors on UAVs can detect it when canopy temperature, vegetation indices such as NDVI and SAVI, and weather data are combined. Accuracy depends on species, time of imaging, shadow, and water status.

Repeated morning, noon, and evening imaging helps separate false shade signals from physiological stress; the signal cannot by itself confirm a pathogen, so field sample tests must follow.

This difference of days or weeks is decisive. If infected trees are found only after discoloration, vectors may already have laid eggs in several neighboring trees. If detected before color change, removing one tree may stop spread. That time window is the target of early diagnosis.

Another approach measures composition rather than color. Chlorophyll, moisture, and pigment ratios change before reddening, producing red-edge and shortwave-infrared signals. In a U.S. Forest Service and University of Minnesota oak experiment, drought stress was distinguished up to 27 days early and oak-wilt responses up to 24 days early. A Spanish 2021 study examined oak decline associated with Phytophthora cinnamomi infection and water stress by hyperspectral and thermal imagery. Oak wilt and oak decline have different pathogens and pathology.

The same approach is being attempted for pine wilt disease. A 2025 Remote Sensing study combined pigment and moisture-content indices in UAV hyperspectral imagery to follow biochemical stress early in infection. A 2024 study combined monthly UAV time series with deep learning to estimate infection stage and monthly spread distance. A managed poplar-seedling experiment using ResNet18, CBAM, and LSTM reported 99.69 percent accuracy for cultivar and drought-stress classification, a striking figure that should not be read as a field result across unmanaged forests.

A 2026 Frontiers in Plant Science review describes the wider pattern: satellite remote sensing for broad coverage, UAV hyperspectral sensing for intermediate coverage, and ground sensors for close precision are being layered together for species classification, forest-disaster monitoring, and tree-health assessment.

Eyes that count trees already dead

Trees that escape early diagnosis turn red to their trunks, lose all needles, and dry gray. Such standing dead trees remain difficult to count and map. A 2026 review by Chowdhury and thirteen colleagues found YOLO-family models strong where dead trees are scattered. LDS-YOLO, published in 2022, was designed not to miss small dead trees in shelter forests with complex backgrounds. When a tree occupies only a few image pixels, heavy models can erase it as background noise. A 2025 dual-path feature-fusion study reduced false positives in dense dead-tree patches.

Where crowns overlap, rectangular object detection is less suitable than segmentation that labels each pixel as live or dead. Germany's 2021 Silvi-Net runs two CNNs together for tree-species classification and dead-tree judgment. The Chowdhury review also covers newer models such as FSC-Mask2Former and ADA-Net; precision values from different datasets must be read with imaging conditions and evaluation metrics.

An important change is the way data are accumulated. deadtrees.earth, introduced in Remote Sensing of Environment in 2026 by Mosig, Kattenborn, and colleagues, is an open database combining thousands of centimeter-resolution aerial images from across the world. It covers more than one million hectares, and humans have labeled live and dead trees in more than 58,000 hectares. Users can upload drone images, receive an AI classification, correct it, and feed that correction back to the model.

It is an attempt to address models that work in one forest but fail elsewhere; as the shared database grows, the labor of retraining models from European spruce to Korean pine may decline.

A 2025 experiment illustrates the importance of resolution. It detected pine-wilt-infected trees with U-Net in UAV imagery at 7 cm resolution and Chinese BJ3N and BJ3A satellite imagery at 30 cm and 50 cm. UAV imagery scored F1 89.1 percent and multispectral fused 30 cm satellite imagery 88.9 percent. Using uncorrected 1.2 m and 2 m imagery reduced scores to 66.6 percent and 58 percent. When a pixel is larger than a tree, AI vision becomes blurred as well.

Mapping the route of spread

Diagnosing one tree and mapping where disease will spread are different tasks. Monthly repeated UAV imaging can connect time series to estimate infection stage and monthly spread distance. Stacked multispectral and thermal images of the same stand can map the advancing edge of disease and guide where control should begin next, even allowing a preventive line along the still-healthy forest edge. Sharing Gijang County results with Busan serves the same purpose: a spread map becomes more useful when it crosses administrative boundaries.

Control is not the end. After aerial chemicals, trunk injection, or felling and fumigation, imaging the same place every two or three weeks and comparing spectral indices and canopy temperature with healthy reference plots can measure the effect. Sevinç's 2025 Scientific Reports study used artificial neural networks to assess mechanical, chemical, and biological control methods against industrial wood production and forest health. Chemical control alone burdens soil and nearby streams; biological control alone can be slower than spread, so numerical records of results help select the next season's integrated pest-management strategy.

Two Chinese Agricultural Science papers published in 2026 likewise review UAV remote sensing for forest-resource surveys and pest control, and intelligent technology for pest control and fine management.

Comparable work concerns bark beetles. A July 2026 Remote Sensing paper combined weekly Sentinel-2 imagery with fixed information such as tree age and terrain in XGBoost and reported improved early detection over satellite-only, fixed-data-only, and earlier approaches. A Czech spruce study found 81 percent accuracy for separating healthy, infected, and dead trees with UAV hyperspectral imagery, compared with 73 percent from manned aircraft. The common limitation is that the period from beetle entry to adult emergence may be shorter than the time required for satellites or drones to notice canopy change.

Conflicting results and remaining tasks

Hyperspectral sensors detect invisible spectral shifts well before discoloration but are expensive and slow to process. RGB and multispectral YOLO or U-Net systems are cheaper and cover large areas quickly, but tend to detect trees well only after needles have reddened. Choice also depends on forest structure: YOLO is efficient for scattered dead trees in remote mountains, whereas U-Net or Mask R-CNN segmentation can lead in dense mixed stands where overlapping boxes increase false positives.

Even excellent drones and satellites cannot see every tree. In forests with dense upper canopies, optical and thermal signals mostly return from the top layer and hide early infection below. A model accurate in one ecosystem can lose performance in terrain or species elsewhere; the decline varies by data and metric. Human variation in drawing dead-crown boundaries also changes validation results. Temperate-conifer models can falter in subtropical broadleaf forests because leaf thickness, wax, stand density, and soil moisture differ from their learned conditions.

The next stage has two directions: self-supervised learning on unlabeled imagery combined with global databases such as deadtrees.earth, and UAVs that carry thermal, hyperspectral, and LiDAR sensors and compute on board so that a suspected infection can alert the field within one minute. If the inspectors' binoculars are ever fully replaced by drones and AI, intervention may already have begun before trees turn red.

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3.3

Illegal-Logging Acoustic Detection and IoT/Blockchain Forest-Protection Networks

High in a tropical-rainforest tree hangs a small device with a solar panel and microphone. It is Guardian, from the U.S. nonprofit Rainforest Connection. It analyzes forest sound at the device and sends an alert when it detects signs of human intrusion, such as chainsaws or vehicles. The organization says its acoustic-monitoring program has helped protect more than 726,000 hectares. Because publicly reported cumulative figures use different project periods and criteria, device numbers, recording hours, and verified species cannot be compared as one bundle of outcomes.

The same recording contains birds, frogs, and insects: a microphone installed for intrusion alerts may also become an ear for biodiversity.

Satellite photographs show tree removal only after it happens, and clouds can hide even that. Foot patrols cannot scan an entire forest daily. To stop felling, someone must know in the few minutes between starting a chainsaw and dropping a tree. This need has spread networks that combine microphones and sensors mounted on trees, low-power communications, and AI that judges sound immediately.

At midnight a microphone may catch a waveform broken into two beats, the rhythm of an engine when a person repeatedly pulls and releases the trigger. A small chip scans it in seconds, distinguishes it from breaking branches or a passing motorcycle, and assigns a confidence score. From that point, sound-recognizing AI, on-site computing and communications, and a ledger that follows felled timber begin to work together.

The forest ear that recognizes a chainsaw

The engine sound of powered equipment is a clue to logging. Ultra-low-power acoustic IoT sensors attached to a trunk or support receive ambient sound and analyze it in a small computer. Andreadis et al. (2021) tested a prototype placing a CNN that extracts sound features on an ultra-low-power device and sending alerts over LoRa. The paper reported classification accuracy of 85 percent from restricted experimental data. The same accuracy cannot be assumed where forest type, season, or equipment changes.

Training is harder than it looks. Motorcycles and small generators have rotational frequencies similar to chainsaws, and distant naturally breaking trees and thunder also confuse early models. Researchers collected months of sound from real logging sites and ordinary forests and taught the model such cases. Coverage also varies with terrain and tree density; protecting a large reserve requires scores or hundreds of grid-like nodes, prioritized at access routes and historically logged areas.

Sound can be insufficient in dense rainforest because it disperses before traveling far. Prasetyo et al. (2018) built a sensor that detects both chainsaw sound and the fine vibration transmitted through a trunk when it is cut. The combination substantially reduced false alerts: where one signal weakens, the other can support the decision.

Battery-powered decisions and drone dispatch

In remote forest it is difficult to send continuous original recordings to a server. Placing the model on the device and transmitting only coordinates and a decision when chainsaw probability is high reduces traffic and power consumption. LoRaWAN is fundamentally a star-of-stars network in which sensors communicate directly with gateways, not a mesh in which neighboring sensors relay signals. Valleys outside radio coverage require extra gateways or separate relays.

Sharma et al.'s (2022) LoED proposed a forest-monitoring architecture combining LoRa and edge computing; it did not provide field validation permitting a general claim of sub-minute alerts or 40-percent traffic reduction in every forest. Battery life varies with panel size, shade, transmission frequency, and computational load.

At the control center, all this computation appears as a point on a map with coordinates, confidence, and distance to the nearest patrol route. Staff decide whether to dispatch; recurring false alarms can lead them to lower local model sensitivity. A drone sent to an alert coordinate can add video confirmation. Ramadan et al. (2024) proposed an acoustic-sensor/UAV structure. Kundu et al. (2025) tested YOLOv8 and agentic AI on separate imagery, with maximum recall around 0.24 and mAP50 around 0.07. These studies do not demonstrate a deployed automatic-dispatch system; for now, a person must confirm images after an acoustic alert.

Digital traces from stump to display shelf

Enforcement in the forest cannot stop timber already carrying apparently legal documents from entering the market. The EU Deforestation Regulation, EUDR (Regulation 2023/1115), requires operators making Annex I commodities, including timber, available on or exporting from the EU market to provide geolocation and exercise due diligence. A plot of four hectares or less may be represented by a single latitude-longitude point; a larger plot needs a boundary polygon. Not every timber product and every small plot is subject to polygon submission.

Blockchain is a distributed-ledger technology in which participants hold copies of the same ledger. It makes later alteration of agreed records easier to detect, but false origin or species information entered initially remains false. Stopfer et al. (2024) and Düdder and Ross (2017) considered its potential to share wood-supply-chain records and reduce due-diligence costs. There is no field evidence that blockchain alone prevents mixing legal and illegal timber or guarantees a history for every tree. RESET.org's ForestGuard is an open-source prototype for deforestation-free coffee, not a timber-supply-chain project.

Diagrams show harvesters recording coordinates and diameter and transport and milling measurements continuing in one ledger. In practice, data formats differ among manufacturers and firms, and the link weakens when logs are split into boards or mixed with other wood. Proof of origin may be necessary for customs and trade but does not itself guarantee a high sale price. Sensors, verification, physical marking, and field audits must be combined to narrow the gap between ledger and wood.

Barcodes, QR codes, and RFID remain necessary physical links, but a system combining automatic harvester marking, sawmill LiDAR, tree-ring fingerprints, and blockchain has not been validated. Triplat et al. (2026) classify logs by market-value grade in separate photographs; that is not a timber-traceability or three-dimensional fingerprinting test.

Korean firms participating in supply chains that place Annex I goods on, or export them from, the EU market may be affected. Product names such as furniture or plywood alone do not decide coverage; customs codes, the firm's role, and raw-material route must be checked together.

Conflicting choices and unresolved work

Acoustic sensors respond within seconds and are relatively inexpensive, but can raise false alarms from thunder, breaking branches, or leaves. SAR satellite or drone imagery can map actual clearing area but responds later because of acquisition cycles and cloud, and costs more to install and run. No approach yet supplies both immediate response and broad confirmation. Repeated false alerts can make patrols slow to answer real alerts, so precision is also a matter of preserving field staff trust.

Public blockchains such as Ethereum are transparent but process few transactions per second and can be expensive. During peak harvesting, hundreds of logs may reach a sawmill scale each hour, creating a bottleneck. Many wood-supply-chain studies therefore favor private or consortium chains such as Hyperledger Fabric, accessible only to particular mills and public bodies; restricting participants reduces the openness the system sought to protect.

Tags can fall off or fail in rain, mud, and rough mountain transport, and processing logs into lumber or chips can erase the mark. Remote acoustic sensors lose accuracy in wind, rain, and wildlife noise, and their solar batteries require continuing energy management. Entering harvest records in unfamiliar apps has a very different barrier for a small private forest owner than for a large company with dedicated staff. Maintenance over years, including replacement batteries and panels, repaired nodes, and retrained sound models, can cost more than initial installation.

The EU repeatedly adjusted EUDR timing. Under the current timetable, general operators are covered from December 30, 2026. Natural-person micro and small enterprises established on or before December 31, 2024 are separately deferred to June 30, 2027; this does not mean every small business receives the same deferral. Legal form and establishment date must be checked. DNA and stable-isotope analysis instead compares genetic or chemical traces in wood tissue with reference materials to estimate species or origin. It can work after a tag is lost but has limited reference coverage and requires time and money.

Field systems must combine acoustic alerts, geospatial information, physical tags, document checks, and sample testing. StanForD is a production-and-operation data-exchange standard for forest machinery, not an international timber-trade form, and no single blockchain linking national due-diligence records and customs systems is yet an accepted operating standard.

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Chapter 4

Smart Forest Operations and Robotics: Work Safety, Autonomous Driving, and Forest-Road-Network Optimization

4.1
Automatic Extraction of Forest Roads and Skid Trails and Terrain-Fitted Harvest Planning

On the map, a green line crossed the mountainside smoothly and a truck navigation system said the landing lay 400 meters ahead. Around the bend, no road remained. Summer downpour had carried half the roadbed into the valley, and arm-thick brush stood head-high on the other half. The loaded log truck stopped. Radio signals failed between mountains, so someone had to walk up, measure the collapsed section and slope by eye, sketch it in a notebook, and return. Two following trucks idled behind it. The map was three years old; the forest had changed.

This is familiar in Korea. Forest roads are built and collapse each year. The Korea Forest Service set its 2026 budget at KRW 3.026 trillion, 15.6 percent, or KRW 409.1 billion, higher than the prior year; building and repairing robust roads for extreme weather is among its priorities. Parliament passed the Forest Road Installation Act, bringing planning, installation, operation, and maintenance within one legal framework. Yet truck movement still stops when maps no longer match ground reality. Hence the growing use of airborne data to redraw roads automatically.

Redrawing roads from the sky

Traditional surveys depended on people walking or driving roads, inspecting surfaces and updating maps by hand. Under dense canopy, minor terrain changes, surface damage, and new tracks often remained absent until the next survey. Airborne laser scanning closes this gap. LiDAR on aircraft or drones can select returns reaching the ground and create a digital terrain model (DTM), alongside canopy-height models (CHM) and slope maps. Roads leave traces: a band of gentle, smooth, and consistently wide surface.

AI learns these traces, draws a line, analyzes cross-sections for usable width and surface condition, and updates the existing network file with broken, eroded, and vegetation-invaded segments. The output is typically a GIS-ready vector file.

Roussel and colleagues' 2022 ALSroads system extracted seven indicators including road width, slope, and curvature from point clouds and combined them with pathfinding to correct old road maps. Buján et al. had earlier used a hybrid rule-based classification combining slope, curvature, and reflectance. CNN and U-Net models similarly distinguish the flat, smooth road form in DTMs from surrounding terrain, including beneath closed canopy.

For broad-area work, Morley et al. updated northern road networks in 2024 using single-photon LiDAR. Winiwarter et al. applied CNNs to 3 m PlanetScope CubeSat imagery; they chose cloud- and smoke-free mosaics, so places without clean imagery remained gaps. This is not optical satellite observation through cloud. Siafali et al. combined airborne LiDAR, mobile SLAM LiDAR, and iPhone LiDAR to reconstruct mountain-road surfaces. Broad observation and close-range precision solve different problems.

Width a truck can actually pass

A mapped line does not prove that a large timber truck can pass. Karjalainen and Waga showed how ground-surface cross-sections perpendicular to the road can be analyzed with machine learning. Even under branches that prevent direct overhead width measurement, profiles show passable width, erosion, cracking, blocked ditches, and roadside vegetation. A clear profile has a flat compacted center, gentle drainage slopes at both sides, and the original mountain slope beyond; blurred profiles or a collapsed side signal maintenance needs.

Hrůza et al. (2025) combined UAV and airborne LiDAR to locate rocks, uncut stumps, and fallen dead trees that obstruct road construction, and to simulate routes to landings before ground disturbance. Tanaka et al. (2025) demonstrated a Japanese algorithm that ranks forest-operation-road construction using LiDAR analysis alone, deriving slope, microclimate, standing timber, and suitable landing locations from one dataset. It can be useful to small associations or firms unable to fund separate surveying teams.

Measuring wheel traces

Where a forest road is a formal truck road, a skid trail is a temporary route made by harvesters, forwarders, and skidders. Repeated heavy passes compact soil and deepen wheel ruts. Compacted soil loses pores for air and water; runoff increases, remaining roots grow more slowly, and damage can contribute to landslides and muddy streams. Abdi et al. (2022) used high-density airborne LiDAR and U-Net to segment trails partly hidden by understory. Latterini et al. compared UAV LiDAR before and after harvest at five Mediterranean sites using hillshading, local-relief models, relative-density models, and SkidRoad_Finder.

The relative-density model led, with about 73 percent accuracy and 66 percent sensitivity, and also estimated rut depth, volume, and compaction risk. Usui (2021) addressed scarce trail images with GAN-generated augmentation.

Calculating a route that avoids damage first

Measuring damage after trail construction identifies an existing problem. To reduce damage, routes must be selected before felling. Görgens et al. (2020) combined LiDAR-derived tree locations and volumes, terrain slope, and soil-wetness indices with genetic algorithms, dynamic programming, and linear programming. The model reduces log travel while avoiding high-compaction-risk and steep areas. Picchio et al. (2018) created a GIS decision-support model for Italian mountains that considers slope, erosion sensitivity, damage to retained trees, and whether to use cable yarders, forwarders, or winch support. Eberhard et al.

extended a related model to steep terrain in 2025. On gentle ground forwarders operate; on steeper slopes cable yarders suspend logs. Output routes can be delivered on paper or tablet.

Between theory and field remains a gap. Single-photon LiDAR and CubeSat imagery cover major networks cheaply but cannot resolve narrow trails and wheel ruts. Drone LiDAR, ground SLAM, and phone LiDAR reach centimeter scale but cover little area and take longer to process. The theoretical optimum from Görgens may not coincide with actual driver trails observed by Abdi because daily weather, obstacles, and driver behavior are not fully captured.

Dense summer foliage and understory reduce ground returns, high-density point clouds are computationally demanding, and transfer to forests with different terrain and species requires local verification.

Snow introduces another issue. Podolskaia and Sinitsina's 2026 Krasnoyarsk winter-road dataset records roads visible only in winter and disappearing at thaw, showing that algorithms must be relearned across seasons and latitudes. Gao et al. improved DeepLabv3+ on multi-temporal satellite imagery in 2026 to identify forest-road access for wildfire responders. All these models require labeled training data, which are slow to obtain for regionally varied roads and trails. Future work includes interfaces that show technicians the slopes and surface undulations behind an AI passability decision.

StanForD can be considered as a production-data link when plans are passed to machinery, but it does not itself establish safe navigation; path data, machine control, and safety rules need separate validation.

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4.2
Remote-Controlled Harvesters, Autonomous Forwarders, and Forestry Robotics

The operator sits in an office chair, with carpet underfoot, cold coffee on the desk, a parking lot outside the window, six monitors ahead, and a game-controller-like joystick in hand. A few years ago, this person would have been in a vibrating cab on a steep slope, cutting trees amid engine noise. Now, a small joystick movement makes a robot arm hundreds of meters away grip a tree. One screen shows the grapple angle at the butt, another the machine's tilt, and another video checking for people and equipment nearby. Angles once invisible from the cab are visible together from the office; only tiny finger movements remain.

This is no longer science fiction. In fall 2025, a newly built Komatsu forwarder equipped for remote operation arrived at the Troëdsson Forestry Teleoperation Lab in Jälla near Uppsala, Sweden. Researchers working with Umeå University are extracting data for AI models that will train robots to make decisions. Their objective is forestry in which neither people nor trees are injured and operations remain sustainable.

Korea has started comparable work. In August 2025, the National Institute of Forest Science announced driving tests of an intelligent forestry-work robot that combines GNSS and INS and runs camera-trained AI directly inside its body. It recognized a forest road, found its centerline, and followed it. Because computation is onboard, it does not stop when communications are weak or lost, an approach suited to deep Korean forests where even mobile signals are unreliable.

The reason for sending machines first into dangerous places is clear: chainsaw felling and extraction combine steep slopes, falling rocks, machine rollover, and musculoskeletal strain. Some experiments classify work posture or work stage from video and inertial sensors with high accuracy, but those values came from small test sets or restricted activity categories; they do not show that every forest posture and fatigue condition can be recognized equally well.

In Bonghwa County, North Gyeongsang, the Korea Forest Service's Yeongju National Forest Management Office will operate a dedicated depot from August 2026 to store and service high-performance equipment including harvesters, forwarders, and mulchers. Building the infrastructure to buy, operate, and repair robots advances alongside robot development.

Machines on 45-degree slopes

Winch-assist equipment adds continuous pulling force from a strong cable anchored to a sturdy uphill tree or dedicated anchor machine and connected to the harvester below. The cable can keep a machine attached to the ground on slopes from 30 degrees to above 45 degrees when wheels or tracks would otherwise slip. Before such equipment, people walked through these slopes carrying chainsaws. A machine placed on steep terrain without a cable can spin its wheels, tear soil, and overturn.

Japan Forest Machinery Association demonstrations divide methods clearly by slope. On moderate slopes, remote-controlled harvesters cut trees and autonomous forwarders transport them, allowing two people to undertake work that once involved five or six. On far steeper slopes, hand-carried chainsaw work is replaced by remote-controlled, winch-assisted harvesters, while cable grapples or tower yarders extract the wood. People stay at screens and machines climb the dangerous slope. European research published in 2025 supports this with GIS decision-support models combining slope, erosion risk, and protection of retained trees.

One zone may be firm enough for winch assistance, another may require cable extraction that leaves no wheel tracks; map values, not intuition, select the answer.

Where trees block satellite signals

Deep in forest, the sky disappears. Dense canopy can cut GNSS signals or mix reflected signals into erroneous positions. A remotely operated or autonomous machine cannot rely on human vision and feel, so it needs SLAM, which constructs a position and surrounding map simultaneously from ground-mounted sensors. In 2025, Yao and colleagues adapted Hector SLAM for forestry machinery moving in dense forest. They filtered LiDAR points reflected from leaves and small branches, fused IMU measurements to correct scan distortion over uneven ground, and estimated movement by matching LiDAR points rather than relying on wheel rotation that can slip.

Compared with baseline Hector SLAM, error fell 47.65 percent. Mean mapping error was 4.78 cm; maximum error stayed below 8.7 cm. Mean position error while stopped was 9.9 cm. Across three speed settings, horizontal error remained within 7.9 cm and heading error below 36.5 degrees. On narrow forest roads, a few centimeters can decide whether wheels leave the road or damage retained-tree roots. NIFoS road tests and Yao's forest-interior tests serve different targets, but together suggest that autonomous movement through GNSS-denied forest is an international problem.

Four-legged robots and load-carrying robots

Forest floors are deeply unstructured: boulders, decaying deadwood, knee-high shrubs, and sinkholes hinder both wheeled and tracked machines. The EU DigiMedFor project addressed this with Boston Dynamics' quadruped Spot, carrying 3-D LiDAR, high-resolution cameras, a small computer, optical filters, GPS, and tilt sensors. It crossed gravel, shrubs, and slopes, collected point clouds and imagery, and updated a digital twin containing information for individual trees. Where wheels would spin and stop, it adjusted one leg at a time.

Swedish work instead examined autonomous forwarders with a technology-organization-environment (TOE) framework. Unlike a factory floor or city road, forest conditions change in weather, soil moisture, and tree form. Researchers therefore proposed collaboration rather than full autonomy: an experienced driver judges the broad plan and the robot handles limited navigation, obstacle avoidance, and clearance from retained trees. This changes work as well as machinery: operators move to remote stations and maintenance staff need training for autonomous equipment.

To avoid damaging machines and forest while testing emergency braking and perception, Lapland University of Applied Sciences and Sweden's RISE created a virtual forest. Their Vindeln digital twin uses site material including drone imagery and high-resolution laser scans. In it, changing viewpoints, solar angles, and tree positions generate SimForest, a synthetic RGB-D instance-segmentation dataset. Scenarios such as a worker suddenly entering the machine's path or thick fog can be repeated hundreds of times, allowing testing without real danger.

Automation not yet mature

Walking robots move reliably over tangled ground and scan understory precisely but carry only tens of kilograms and cannot fell or haul trees. Autonomous forwarders and remote-controlled harvesters handle tonnes of logs but can bog down or compact soil in rough, dense terrain. No single body suits all forest; machines with different bodies must be deployed according to terrain. Results in virtual forest also leave a gap from real forest: fog, rain, lens dust, moving branches, and backlight degrade camera and LiDAR decisions, and the size of performance loss depends on sensor, weather, and test data.

Models trained on synthetic data need separate real-forest evaluation.

Spot-like electric walkers may exhaust batteries in one or two hours outdoors, unsuitable for long remote missions. SLAM can lose loop closure during long travel through dense forest, accumulating position error until a screen shows the machine on the road while it has actually drifted between trees. High initial costs are difficult for small forest owners, and responsibility for malfunction remains unsettled: manufacturer, forestry company, or distant joystick operator may each be implicated after a failure to recognize a person. Distributed multi-robot control, such as that proposed by Chen et al.

(2025), could link drones that inspect roads, walking robots that survey terrain, and forwarders that transport timber, but forestry deployment must jointly verify intermittent communications, on-site computation, collision avoidance, and emergency stops. StanForD supports record exchange, not robot safety. Stopping time must be set from speed, braking distance, sensing range, and worker separation. The institutional work of legal safety interlocks and international data standards may take longer than redesigning the robot itself.

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4.3
Worker-Safety Surveillance Based on Computer Vision and Wearable Sensors

At 6 a.m. at a logging site in Inje, Gangwon Province, a worker tightens a helmet strap twice. Inside the brim is a fingernail-sized gray inertial measurement unit (IMU), measuring body tilt and walking speed. The company issued the helmet three months earlier; the worker chiefly remembers that it became about 20 grams heavier. When the chainsaw starts, birds fall silent and engine noise fills the valley. Three trees are scheduled for felling, on a steeper slope than yesterday.

In March 2026, the Ministry of Employment and Labor reported 18 accident deaths in the combined forestry-and-fishing category in 2025, 11 more than the year before. The statistics do not separate forestry, but the category was identified, alongside wholesale and retail, as one of small establishments with weak safety-management systems. Fatalities from falling trees, slips on slopes, and crushing by equipment recur.

Article 24 of the Enforcement Decree of the Occupational Safety and Health Act groups forestry with manufacturing and wastewater/waste industries; establishments with 20 to fewer than 50 regular workers must designate at least a safety-and-health management officer. Designating a person cannot give that person real-time sight of the posture of someone alone with a chainsaw on a steep slope. Forestry workers are aging, while many continue climbing steep mountains with bodies less resilient than before.

Forestry combines irregular slopes, heavy logs, and high-risk powered machinery. U.S. BLS data for 2023 put logging-worker fatality at 98.9 per 100,000, about 28 times the overall worker average of 3.5. Felling, limbing, and cross-cutting require sustained bending, twisting, and leaning, contributing to work-related musculoskeletal disorders (WMSDs). OWAS scores back, arms, legs, and load into four risk levels: level 1 needs no change, while level 4 calls for immediate correction. RULA and REBA are related systems, but traditionally all required people to inspect video frame by frame.

Computer vision and wearables have emerged to automate a task too large for continuous human observation of all forest workers.

How cameras read posture

Human-pose estimation tracks joint points such as shoulders, elbows, and knees in video. Forkuo and colleagues trained ResNet-50 using images and skeletal connection lines. On 252 balanced test images, OWAS accuracy and F1 were 99.8 percent. This is a small balanced test set and does not establish identical performance across real forests with occlusion and changing light. A 2025 paper by the same group found the model 19 to 53 times faster than human assessment; Fleiss' kappa among human raters was 0.28 to 0.49.

These figures describe speed and disagreement among people, not proof that the model is more accurate or robust to changed camera angles.

Their work using image embeddings with Inception V3 and SqueezeNet achieved 84 and 89 percent during development, but roughly 49 to 60 percent on unseen data. The paper did not demonstrate smartphone field deployment. A small model and stable operation on a mountain phone are different claims.

Sensors worn on the body and sound

Cameras fail when a body cannot be seen beneath canopy, leaves, and branches. Wearables fill that blind spot. Three-axis accelerometers and gyroscopes in phones or watches, plus noise dosimeters on bodies or equipment, can measure movement and vibration without a camera. Chainsaw-hand tremor, shoulder tilt, and unstable gait become numbers regardless of shade or fog. Borz and colleagues tested seven models with accelerometers and dosimeters attached to worker and chainsaw during cross-cutting. A single back accelerometer achieved 63 percent accuracy; some settings combining chainsaw acceleration and noise reached 99.8 percent.

The study separated activity states such as work, rest, and movement; it did not diagnose excessive joint flexion or fatigue at the same accuracy. Performance must be retested as sensor position and behavioral categories change.

Korea has introduced sensor-equipped helmets. A May 21, 2025 report said Asgard's construction-worker smart helmet TUGU includes impact and temperature-humidity sensors, a camera, and radio functions. It is a manufacturer account, not independent field validation, and is not forestry-specific. The Korea Forest Service demonstrated wearable robots and intelligent-helmet prototypes for wildfire crews at the National Chilgok Forest Experience Center in October 2020, but no evidence was located that these became standard equipment at logging sites nationwide.

Wearables also face detachment through sweat and rough work, batteries that do not last a full day, and workers who decline to wear them.

When the helmet speaks

Separate work evaluates whether large language models can support forestry-safety consultation. Arimizu Kengo (2026) assessed model answers to forestry accident scenarios and specialist questions; it is not a deployed, complete field system that automatically judges risk from past incident reports and photos. Context-sensitive hazards such as hung-up trees should be checked by experienced practitioners, not handled by the model alone.

Hayashi and colleagues' 2025-2026 work attached a ChatGPT-based conversational agent as adviser to a forestry-safety card game. Each card presents a plausible felling-site situation and question, and the agent reviews the participant's answer. Before-and-after comparisons among students and novices showed statistically significant gains in all five domains, including safety communication and personal safety, on a 40-item workplace-safety scale. Early generic-model answers, however, gave eight irrelevant mechanical-engineering responses to forestry-specific questions such as fuel-container materials and chainsaw sharpening.

A custom model using in-context learning with forestry-safety knowledge cards reduced them to two. Automatic speech recognition also mistranscribed terms such as chaps and kakarigi (a hung-up tree), leading to a proposed standard confirmation procedure.

ForestGPT, introduced in 2025 by Ehrlich-Sommer and colleagues, is a conversational prototype that answered visitors' questions at Austria's Pötta Expo from about 1 MB of event material. Retrieval-augmented generation, forest-growth simulation, and integration with sensor, drone, and machine data are later development steps; the present prototype is not a complete field model with all those functions.

The feeling of being watched

In an imagined field deployment, real-time risk levels for several loggers appear on an office monitor and an alert goes to a manager's phone when level 4 is reached. This is welcome for safety management but different for the person wearing the helmet. Cameras require nothing on the body but miss workers behind branches; wearables work through occlusion but impose sweat, battery, and acceptance burdens. General language models converse flexibly in many languages but can hallucinate shallow forestry knowledge. Custom models with supplied knowledge reduce errors but may say they have no information when questions fall outside their cards.

Neither precision nor flexible conversation alone is sufficient.

A fundamental gap remains between laboratory classification and emergency braking in the field. Complete validation that links posture judgment or person recognition to machine control in forests with interrupted communications is still rare. Real logging sites must test mud, cold, network loss, and machine-specific braking distances together.

Continuous cameras also raise data-governance questions: who owns data sent from helmet sensors to company servers, how long they are stored, and whether they are used beyond accidents? The literature has not clearly resolved these questions. AI-surveillance debate in office work repeatedly notes safety data being quietly reused for other assessments. In May 2026, the Ministry of Land, Infrastructure and Transport and the Korea Authority of Land & Infrastructure Safety revised guidance for smart safety equipment, reorganizing worker-protection equipment including wearable cameras into three major and seven middle categories.

It is construction guidance; a forestry-specific counterpart had not appeared by August 2026.

Most enterprises expected to pay monthly camera, sensor, and server fees are very small logging businesses. Some postpone adoption because it is unaffordable; others can afford it but dispute data use with workers. Remote harvesters and autonomous forwarders may remove people from hazardous slopes, yet people holding chainsaws will remain. Safety-surveillance technologies ultimately concern those remaining workers. Next-stage proposals include explainable-AI dashboards using Grad-CAM and SHAP to show the body regions behind risk judgments, and knowledge distillation to fit smaller models on disconnected mountain terminals.

Papers already propose an integrated camera, wearable, and language-model pipeline to prevent WMSDs and catch accidents early. The date when such systems become standard logging equipment, and the rules deciding who retains recorded images and signals for how long, have not yet arrived. Risk ratings and alerts are becoming more sophisticated faster than rules for entrusting their results to anyone.

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Chapter 5

Sustainable Agroforestry and Timber Supply-Chain DX

5.1

Water-Use Efficiency (WUE) and Ecosystem-Service Optimization in Agroforestry Systems

In Punjab in northern India, when the sun reaches a wheat field early in the morning, the shadows of a row of poplars standing through its middle begin to move slowly. The row of trees, each more than 20 metres tall, covers the furrows on the west side of the field in the morning; at noon the shadow retreats to the trees' feet, and in the evening it covers the furrows on the opposite side again. Heat rising from the soil trembles like a mirage, and wheat heads repeatedly bow low and rise in the early-summer wind.

Any farmer who has spent years in that field knows that the wheat has subtly different colours where tree shade has passed and where it has not. To the farmer, these trees are neighbours with two faces. Their roots run deep and draw water that the wheat must drink, but their trunks and leaves block hot winds and hold moisture in the soil. Looking alone cannot answer whether the trees are thieves that take water or sentries that protect it. These poplars do not stand merely to cast shade. Once their trunks thicken, they are timber sold for matchsticks, plywood, or paper, so wheat farming and tree farming take place in the same field.

The answer requires measuring, in numbers, what happens beneath the roots and how much water each leaf releases.

The practice of raising trees and crops, and sometimes livestock, together on the same land is called agroforestry. Tree roots can compete with crops for water while reducing evaporation and soil loss through shade and leaf litter. Water-use efficiency, calculated by dividing yield by actual evapotranspiration, is an indicator of the result of these two effects. In statistics widely used by the Food and Agriculture Organization of the United Nations, agriculture accounts for more than 70 percent of global freshwater withdrawals. “Eighty percent of consumption” and “more than 70 percent of withdrawals” are not the same indicator.

In South Korea, the legal land category and eligibility for public-interest direct payments when trees are planted on farmland are determined by the state of the land, the cultivation method, and the requirements of the relevant programme. Planting a tree does not automatically turn farmland into forest land or cause the farmer to lose payment eligibility. Farmers considering adoption should first confirm the requirements for the relevant parcel with the local government and the National Agricultural Products Quality Management Service.

The arithmetic beneath the roots

Agronomists use two broad approaches for this calculation. One is to put their hands in the ground and measure directly. When time-domain reflectometry (TDR) and frequency-domain reflectometry (FDR) probes are inserted into soil near the roots, they determine moisture content from how quickly water between soil particles transmits an electrical signal. To obtain those values, a researcher must wear boots from dawn and move around the field inserting probes. Because the signal varies with soil condition, even the same location must be measured repeatedly over several days to yield a reliable value.

Adding neutron probes and automatic weather stations makes it possible to record, hour by hour, how much water tree roots and crop roots share in the same soil layer. According to a 2026 systematic review of wheat-based agroforestry, researchers feed these field measurements into crop and soil-moisture modelling programmes such as CROPWAT, AquaCrop, and APSIM to simulate how water moves through each root layer.

Such hands-on work cannot cover an entire field, so satellites take on that task. Values such as the Normalized Difference Water Index (NDWI, an index that infers moisture by analysing the wavelengths of light reflected by plant leaves) and land-surface temperature can be extracted from imagery taken by satellites such as Sentinel and Landsat. When those values are fed into evapotranspiration models such as SEBAL or METRIC, they can map which parts of a field are dry and which are wet.

Add algorithms such as random forest, a machine-learning method in which many decision-tree models each give an answer and the final answer is determined by majority vote, as well as support-vector machines, artificial neural networks, and XGBoost, and a model can learn soil condition, irrigation schedules, and the degree of tree shade together to predict water-use efficiency. The review found that pruning branches and adjusting shade spacing alone can markedly improve the water efficiency of the whole system by reducing water lost from the surface of understory crops and increasing the share of irrigation water that infiltrates the ground.

The reason this calculation matters to farmers is clear. Shifting the timing or amount of irrigation by a day or two can sharply affect that year's harvest. In an era of more frequent droughts, the value of a single drop of water is not what it was.

An agroforestry map drawn by satellites

Along India's western coast, in Goa, there is a traditional farming system called kulagar. Areca palms are planted with pepper, cacao, or bananas so that shade and humidity are shared. Enter a kulagar plot and there is a roof made by palm leaves overhead; below it pepper vines wind up palm trunks, while bananas and spice crops stand at one's feet. Different plants at each layer share water and sunlight at different heights. It may seem difficult to distinguish this field, an adjacent pure palm plantation, and natural forest from satellite images alone.

Uthappa and colleagues tackled that distinction by running three machine-learning models, random forest, gradient boosting, and support-vector machines, on Sentinel satellite imagery. Ordinary vegetation indices show only how green leaves are, and can therefore confuse a well-irrigated agroforestry plot with a natural forest just after the rainy season. That is why a separate moisture-responsive index is used. The result was clear. NDWI2, a water index that directly reflects moisture in tree and crop leaves, emerged as the key variable determining field-classification accuracy in all three models.

The gradient-boosting model recorded an accuracy of 0.86 and a kappa coefficient, which filters out agreement due to chance, of 0.83, making its classification the most stable of the three models.

The ability of satellites to read a field where crops and trees are intermingled gives policymakers seeking to expand agroforestry a useful tool. They can map each year how extensively agroforestry has spread in a given area without visiting every field by eye. Korea's annual Forestry Management Survey deals with similar statistics, but it relies heavily on farm questionnaires and field surveys and does not yet appear to have reached a system automatically updated by satellite maps.

The precise calculation of coffee-tree shade

In Indonesian coffee fields, the question is posed somewhat differently: where, and how many, shade trees should be planted in the upper layer to protect coffee trees from direct sunlight and water stress? Ridlo and colleagues addressed this placement problem with the RIDS algorithm, drawn from graph theory. Put simply, it treats the field as a network of points connected to points and calculates where trees should be planted so that shade does not become excessive yet reaches every corner of the field evenly.

Ridlo and colleagues calculated shade-tree and sensor positions as a graph. In a scenario with 96 coffee trees and 26 shade trees, annual carbon-dioxide sequestration was calculated at 520 kilograms. The figure was 620 kilograms in a scenario with 31 shade trees arranged in a grid. These are model calculations, not carbon quantities measured in the field over a long period.

The researchers used a spatiotemporal graph neural network to predict relative humidity and carbon-dioxide concentration 10 to 20 days ahead. Explanatory power ranged from 0.73 to 0.81 depending on the setting. These results were obtained from model comparisons. They are not a long-term field trial showing that coffee farmers used the system for actual irrigation schedules and improved yield or water use.

Ecosystem services beyond water

Ecosystem services are the benefits that nature provides without human intervention, as forests, wetlands, and tidal flats do. Filtering clean water, slowing floods, and keeping bees and birds alive to help pollinate the next generation of crops all fall within the term. The benefits of agroforestry do not end with yield and water efficiency. Tree roots prevent soil from being washed away by rain, while leaf litter and shade provide shelter for birds and insects.

A satellite time-series analysis by Silva and colleagues, who observed subtropical southern Brazil for 20 years, puts numbers on this value. Around 2000, the habitat area occupied by agroforestry was a little more than 400 hectares. By 2020, it had risen to nearly 660 hectares. Over the same period, the habitat-aggregation index connecting scattered natural forests also increased.

Natural forests that had been scattered like fragments among paddies and fields had begun to reconnect along agroforestry belts.

This does not mean that agroforestry can fully replace natural forest. Doherty and Häger (2026) compared Costa Rican natural forest with coffee and pasture agroforestry using remote sensing and field data. Above-ground carbon storage and tree-species diversity differed by land type. In natural forest, the spatial overlap between carbon-rich places and places with high tree-species diversity was 25.5 percent. Agroforestry can increase trees and connectivity in cultivated land, but it does not guarantee the carbon and biodiversity values of natural forest.

Jemal (2026) released version 1 of a systematic review in F1000Research that organised research trends in remote sensing and deep learning for Ethiopian agroforestry. It is not an experimental paper that directly compares convolutional neural networks, U-Net, and vision transformers at the same site. In Ghana, the World Resources Institute published research using transfer learning to distinguish natural forest, monoculture plantations, and agroforestry. If classification results are to be used in policy, field samples and misclassification maps for each class should be disclosed together.

In India, an experiment by Chavan and colleagues planting soybean beneath Indian gooseberry trees showed that adjusting shade intensity alone can change soybean physiology and yield even in degraded soils. Jinger and colleagues demonstrated an experiment in which a silvo-aromatic system, combining medicinal and aromatic trees with soil-moisture-conservation techniques, restored soil structure on degraded land and sequestered carbon dioxide. Before medicinal and aromatic trees take root, degraded land commonly sheds muddy water in channels when rain falls and raises only dust in the dry season.

After trees and water-management structures were installed together, the same land lost less soil and rainwater had more time to infiltrate between the roots. These studies, conducted in different countries and with different trees, point in the same direction: land planted with both trees and crops can hold soil, conserve water, and store carbon. A 2022 review brought such individual cases together under the framework of soil health and described agroforestry as one of the few farming systems that can restore soil fertility without relying on chemical fertilisers.

What the numbers miss

Even with the same satellite image, models sometimes give different answers. In the Goa kulagar study, random forest and gradient-boosting models estimated a larger agroforestry area than the support-vector machine. The first two models read the complex boundary of fields where trees and crops are densely mixed more generously and nonlinearly, while the support-vector machine tends to draw a conservative boundary. A model that looks only at one satellite water index can quickly calculate drought conditions across a wide area, but cannot capture how soil moisture changes at each crop-growth stage.

Conversely, models combining Internet-of-Things sensors and neural networks are precise, but carry the corresponding cost of installing and maintaining sensors.

Satellite and drone imagery mixes tree canopies, crops, and bare-soil reflectance into a single pixel measuring 10 to 30 metres. Imagine a single satellite-image cell containing the top of a tree, the shade below it, soil, and crops: the light reflected from it is no different from paint in which several colours have already been mixed. Asking a computer to separate the crop signal from this blended colour is much like trying to recover the original colours from paint that has already been mixed.

Agroforestry water balances and changes in soil carbon require at least 10 years of observation before a pattern is visible, yet most current deep-learning studies rely on short datasets lasting only a few years, making it difficult to fully test resilience to climate change. The more remote the farm in a developing country, the more likely it is to lack both the money for Internet-of-Things sensors and a wireless network, so intelligent water-management technology often fails to reach the fields that need it most.

The question raised in the wheat field, whether trees take water or protect it, returned in calculations by the European Centre for Medium-Range Weather Forecasts. In a 2026 study, a scenario that strategically selected planting locations reduced evapotranspiration by as much as 60 percent and increased groundwater storage by as much as threefold. This result is a model scenario, not a guaranteed value for every farmed field.

Researchers are preparing the next step: joining physical laws to artificial neural networks. Efforts are under way to place the constraints of existing models based on physical equations, such as CROPWAT and APSIM, wholesale inside a deep-learning architecture called a physics-informed neural network (PINN), so that microclimate and moisture can be calculated together while reducing error from mixed satellite pixels. There is also discussion of building open datasets spanning dry regions, subtropics, and the tropics, and loading lightweight AI models trained on those data onto farmers' phones to provide real-time irrigation timing.

This lightweight model on a farmer's phone is envisioned as something that could send a single morning message saying how much water to apply to that day's field and when. In mountain villages where internet connections frequently fail, the calculation finishes on the phone, eliminating the time required to send and receive signals from a server. Still, this vision remains closer to a proposal in laboratory papers; there are few cases validated over many years in real fields.

The Food and Agriculture Organization of the United Nations explains that India's farm-forestry and agroforestry systems supply about 93 percent of annual timber demand. The figure refers to annual timber demand, not domestic consumption of all wood products. Expanding smallholders' tree production requires attention to seedlings, technology, market access, and rights to land and harvest together.

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5.2
ICT-Based Timber Traceability (QR/Electronic Tags) and Automated Timber Quality Assessment

Nakazawa and colleagues' system diagram shows a line carrying log information measured by a harvester to a server. The harvesting machine measures diameter and length and leaves operational data in StanForD format. Connecting physical tags and transport and sawmilling records to this data can provide a design for a log-traceability system. The cited source, however, does not depict a sawmill where QR codes or RFID tags are automatically attached to every log.

Electronic records can quickly share harvesting locations and measurements. Keeping the record connected to the actual log all the way through is a separate problem. The link may break when a tag falls off or a log is split into boards.

QR codes and RFID are only keys that call up records; they do not themselves guarantee a log's identity. Supply-chain traceability works only when harvesting records, physical markings, transport handovers, bundle management after sawing, and field audits are all in place.

Timber distribution once depended on paper slips and handwritten field sheets. Figures entered by people can contain errors, and illegally logged wood mixed among legal logs is difficult to filter out. The Korea Forest Service operated its Legal Timber Trade Promotion System on a one-year trial basis. The full implementation date was October 1, 2019. Businesses importing covered timber and timber products must prove, before customs clearance, that the wood was legally harvested in its country of origin. The Korea Forest Service distributes country-specific standard guidelines.

Harvester sensors, electronic tags, and AI are auxiliary means of reducing gaps in documentary review.

The second name carved into a log

A smart harvester entering a harvesting site writes data at the same time that it fells a tree and processes it into prescribed lengths. Sensors attached to the cutting head measure, second by second, the log's diameter and length and the extent to which the tree has grown crooked, while a satellite-navigation device records the exact harvesting location. In the brief instant in which the machine cuts a tree, it completes calculations that people once made by eye.

Nakazawa and colleagues developed, on the basis of StanForD, a system for sharing a harvester's log measurements and quality judgments. Its research scope is the connection of production and operational data from forest machinery; it does not cover a trading and settlement system for all of Japan.

Harvester data alone cannot follow a tree to the end. It is possible to design a process in which a barcode or RFID tag is attached to a log and the next business receives it. An operating system that combines automatic tag application by harvesting machinery, three-dimensional fingerprints of end-grain growth rings, and blockchain comparison has not yet been validated.

RFID can read an identification number without contact, but it requires tag cost and durability, labour for attachment, and bundle management after processing. A tag alone cannot guarantee the origin or legality of a log.

How to count trees loaded onto a truck

Measuring the volume of log piles at a landing or logs loaded on a transport truck was long a task done directly by hand. People measured the diameter of each log with a tape and estimated the total pile volume. In recent years, the work has shifted to smartphone cameras and LiDAR sensors built into iPads. LiDAR measures distance to an object by emitting light and timing its return, and it uses that principle to render the contours of a log pile as a dense point cloud.

The 2025 prototype study by Elias and colleagues, the Turkish trial by Ucar and colleagues, and the comparative study by Purfürst and colleagues estimated log-pile volume with smartphone photographs and LiDAR. Image-based measurement may reduce time in the field, but error varies by tree species, loading configuration, and camera angle.

There are empty spaces between logs in a truck bed. Niță and colleagues assessed an algorithm that estimates the outer form of the load and wood volume from LiDAR point clouds. It is not a study that fixes actual wood volume without error or automates settlement at a scaling station.

To use LiDAR estimates in transactions, stakeholders must compare them repeatedly with reference measurements to set allowable error, and establish sensor calibration and objection procedures. Test performance of an algorithm does not automatically establish a legal standard for payment settlement.

The moment a camera finds a knot

The value of logs and boards entering a sawmill is ultimately determined by defects. The same tree receives different grades depending on how many knots it contains, whether it has splits, and whether its colour has faded. For a long time, this judgment was entrusted to the eye of a grader. Even a skilled person's judgment can waver after looking at boards all day, and slightly different standards from one person to another can yield different grades for the same board. It was not rare for graders who inspected the same log in the morning and afternoon to write different grade sheets.

According to the 2024 literature review by Sandvik and colleagues, methods for log scaling and grading shifted rapidly toward deep learning around 2018, displacing other machine-learning approaches.

Qiu and colleagues introduced a wood-surface-defect-detection model called PADDL-YOLO in 2026. On test data, precision was 91.5 percent and recall 91.4 percent. mAP@0.5 was 95.0 percent. Computational load was 25.6 percent lower than for the baseline model. Lightening a model increases the prospect of deploying it on field equipment, but this is not evidence that it has operated for a long period at commercial speed on a sawmill conveyor.

Many studies pursue the same goal by different paths. He and colleagues located internal wood defects with a fully convolutional neural network, while Hwang and colleagues applied transfer learning to the ResNet-34 neural network widely used in image recognition to distinguish knot types. Urbonas and colleagues used Faster R-CNN to find defects on veneer surfaces. Longuetaud and colleagues used an improved YOLOv5s, and Zhang and Zhao used YOLOv7, to detect in real time defects in boards passing along conveyor belts.

Ozkan and colleagues trained a Mask R-CNN-family neural network on 2,972 beech lamella pieces to find defects and reached an accuracy of 90.90 percent. Hwang and colleagues chose a somewhat different approach, extracting texture and local-shape information from knot surfaces and feeding it into an artificial neural network to distinguish sound, rotten, and missing knots. Their approaches differ, but the goal is one: use cameras and neural networks to multiply the amount of board material that human eyes can inspect in a day.

The boards that graders once watched all day now pass before a camera, and people recheck only the few boards the machine has marked as ambiguous. Some boards on the screen are outlined in yellow. These are boards the neural network is not confident about and has passed to a person. The grader can now concentrate on these filtered boards rather than the entire conveyor. It is not that the work has disappeared; the place where the person stands has moved from in front of the conveyor to in front of a monitor.

Why a single photograph cannot price timber

Finding defects and assigning market-value grades are different tasks. In 2026, Triplat and colleagues compared market-value-grade classification models using 5,549 photographs from a Slovenian log auction. Several models exceeded 90 percent overall accuracy, but performance for lower-value grades was relatively weak. High overall accuracy alone can conceal misclassification of rare grades.

Image classification learns the photographed surface and the grade labels in the dataset. It cannot directly judge factors absent from the photograph, such as internal defects, moisture, and strength. Grades that are rare in training data are more strongly affected by a lack of samples.

Market-value judgments can also include inspections and transaction conditions beyond the photograph. Image models should therefore be used to assist screening, while low-confidence and rare grades should be checked again by people.

When a grade is assigned wrongly at auction, money moves immediately. If a high-grade log is wrongly classified as low-grade, the forest owner does not receive its proper value; conversely, if a low-grade log is passed off as high-grade, the sawmill that bought it may discover its loss only after sawing it into boards. This is why a human final check remains in automated appraisal systems.

PADDL-YOLO's mAP@0.5 and the classification accuracy in Triplat's study come from different data and tasks. They should not be compared directly. Surface-defect detection, market-value classification, and assessment of internal strength must be validated separately.

What rain erases and price prevents

Physical markings at a harvesting site can become unreadable or fall off because of mud, rain, impacts, and bark loss. RFID can likewise be damaged depending on how it is attached and on transport impacts. Three-dimensional fingerprints of growth rings have not become a validated operating system that solves this problem. Durability tests of markings, handover records, and sample audits are all needed.

The limitations of two-dimensional cameras remain. Surface images cannot capture decay progressing inside a tree or hidden internal cracks, so unexpected defects may appear only after sawing. The cost of acquiring all this equipment is a considerable burden for small sawmills and forest owners. Installing high-performance LiDAR scanners, X-ray CT equipment, and field AI computers at once requires substantial initial investment, and the threshold is harder to cross for smaller operations.

An institution with a research budget, such as the National Institute of Forest Science, may introduce this equipment on a trial basis, but it remains out of reach for a small forest owner with a mountain to manage or a neighbourhood sawmill. Where technology exists but cannot be afforded, the old practice of measuring by hand and grading by eye continues. A 2026 review by Forkuo and Borz of AI applications across forest operations also identified timber traceability and quality assessment as one of the fastest-growing areas after harvesting mechanisation.

X-ray CT and acoustic testing are supplementary tools for identifying internal defects a photograph cannot see. Nocetti and colleagues applied photogrammetry and acoustic surveys side by side to oak logs. Blockchain research proposes ways for several businesses to share the same record and check later changes. It cannot eliminate false initial entries, tag replacement, or a break between a real log and its record. Compliance with the EUDR requires geolocation information, due diligence, risk assessment, and document retention together.

Operational-data standards such as StanForD and blockchain are only tools that assist compliance evidence; they do not guarantee compliance.

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5.3
The Circular Bioeconomy and Forest Carbon Credits

Branches, bark, and stumps remain on a slope after harvesting ends. Whether to leave them in place to return to the soil or chip them and move them as fuel or material feedstock must be decided by considering wildfire risk, nutrient cycling, transport distance, and processing demand together. High moisture increases transport weight but can lower the calorific value of fuel. Pricing by weight alone can misalign quality and energy efficiency.

Lignin and cellulose can be extracted from woody residues to make materials, and logs meeting specifications can become engineered wood. Not every branch and root is an economically viable feedstock. The calculation must deduct the energy required for collection, drying, transport, and processing, as well as the amount of organic matter that must remain in the forest. Carbon credits, too, are issued only after a project passes registration, additionality, baseline, and verification requirements.

From residues to new materials

Trees consist largely of three substances: cellulose, which forms their fibres; hemicellulose, which fills the spaces between them; and lignin, which holds a tree upright and rigid. For a long time, paper and pulp mills regarded lignin as a nuisance. It was no more than a by-product mixed into the black liquor left after pulp extraction, then burned or discarded. Materials released by Japan's Forestry and Forest Products Research Institute (FFPRI) and Ministry of the Environment in 2025 and 2026 show that modified lignin technology, which reconfigures lignin's chemical structure, is changing this situation.

Modified lignin whose structure has been altered to withstand heat and resist breakage is used for automotive parts, electronic-product casings, and biodegradable-resin feedstock. Cellulose nanofiber (CNF), which disentangles wood fibre to nanometre thickness, is also increasingly being used in place of petroleum-based plastic. Parts made with modified lignin are first appearing in places such as automotive interior trim and electronic-product casings, where touch alone makes it hard to tell wood from plastic.

It cannot be assumed in advance that wood-based materials emit fewer greenhouse gases than petroleum-based materials. Feedstock origin, processing heat sources, chemicals, product life, reuse, and disposal must be compared through life-cycle assessment. The circular bioeconomy is a framework that seeks to use renewable biological resources for a long time and circulate them again. Wang and colleagues organised climate-smart forestry as an approach connecting AI-enabled forest management with climate adaptation and mitigation.

A forest planted in the city

One way to keep carbon in wood for a long time is to build with that wood. Engineered timber such as cross-laminated timber (CLT), made by bonding boards in layers with alternating grain, and glulam, used for columns and beams, is strong enough to raise a considerable number of stories even when used in place of concrete or structural steel. Mid- and high-rise buildings constructed from this thick wood are called mass-timber buildings. Japan’s Forestry Agency and Ministry of the Environment are advancing a policy called “a forest nation, a city of wood” to replace urban reinforced-concrete structures with wooden ones.

Visit a timber-construction site and its atmosphere differs from a concrete pour from the outset. Instead of ready-mix-concrete noise and dust, cranes lift pre-cut timber panels from the factory and workers tighten bolts. Carbon dioxide emitted by firing concrete and melting steel is reduced at the outset, while the completed building holds within its frame the carbon the trees absorbed for decades or centuries. Trees that stood in the mountains have moved to the middle of the city to become a second forest that stores carbon.

The climate benefit of wood construction arises when timber is supplied from legal and sustainably managed forests, forest carbon recovers after harvest, and the product actually substitutes for a higher-emitting material. Increased construction demand does not automatically bring reforestation and forest investment with it. Supply-chain certification and forest-management rules must create those conditions.

Elite trees and rotational harvesting

Tree age and carbon accumulation cannot be settled in a single sentence. Global data show that large individual trees can add more carbon each year even as they age. Net production per unit of stand area can decline with age, but it varies with species, soil, disturbance, and management history. There is no universal “peak between 30 and 40 years” for all forests. Breeding and genomic selection can shorten the time needed to select for growth or wood traits, but the magnitude of growth improvement also varies by species and trial conditions.

Whether harvesting benefits carbon cannot be judged by a fixed rotation age alone. Carbon remaining in the forest, emissions from harvesting and transport, the duration of storage in wood products, substitution effects for concrete and steel, and the success of reforestation must be placed in the same life-cycle assessment. The choice to conserve old natural forest and the choice to manage production forest on a rotation have different answers depending on forest functions and local conditions. When fast-growing varieties are planted broadly, risks from pests and diseases and genetic uniformity must be calculated too.

Eyes that count carbon: satellites and artificial intelligence

Whether a cycle of harvesting trees for materials and replanting them helps carbon neutrality must be verified with numbers. The procedure of measuring changes in forest carbon, reporting them, and having a third party confirm them is called MRV. Korea’s Forest Carbon Offset Scheme includes project types such as new afforestation and reforestation, forest management, use of wood products, and forest-biomass energy use. The fact that a project type is named in the scheme does not turn a pile of small branches into an emission-reduction result immediately.

It must pass the registered methodology, baseline, additionality, monitoring, and verification requirements.

Ground samples and remote sensing are used together to measure removals. GEDI leaves samples from waveform LiDAR along its orbit; the two-satellite Sentinel-2 system revisits the same place about every five days near the equator. A single Landsat satellite has a revisit interval of about 16 days. Cloud cover makes the interval between optical images that can actually be used longer.

Ground samples are the anchor for calibrating a model, and satellites and LiDAR are the eyes that estimate the space between them.

Geng et al. (2026) combined long-term survey data from natural forests in Heilongjiang Province, ecological models, and climate scenarios with knowledge-guided machine learning. Under a low-emissions scenario, carbon stock in 2060 was projected to range from 1,379.26 teragrams to 1,439.02 teragrams. This is a model projection, not an observed future.

Keskes and Niță (2026) added Finnish multi-source national forest-inventory data to a model built from Romanian field data. The subject was not a carbon map but prediction of Finnish standing timber volume. Explanatory power rose from 0.483 to 0.718. Lamahewage and colleagues' study of mixed forests in the United States shows that combining several remote-sensing datasets can improve above-ground-biomass estimation. Because the target variable and validation area differ by study, a number from one model must not be transferred to another country's carbon map.

Inflated numbers and the problem of trust

Swinfield et al. (2026) compared about 45 percent of REDD+ projects that had issued credits by 2020 with the results of six independent evaluations. The relevant set contained 44 projects. The aggregate over-crediting ratio across all issuance was 10.7 times, a figure raised by several large projects. The median level for a typical project was 4.1 times. Results finding that many projects reduced deforestation and results finding that baselines were inflated appeared together. "The project failed" and "the project issued more credits than its performance justified" are not the same statement.

Verra's VM0048 provides a framework for allocating baselines using jurisdictional deforestation-risk data. The methodology's 10 years are a historical reference period, and its six years are the period for baseline application. It did not reduce the same recalculation cycle from 10 years to six years. Digital MRV can help data collection and auditing, but it does not automatically resolve baseline selection or conflicts of interest.

Where publicly released coordinates of National Forest Inventory sample plots have been displaced for security reasons, matching them directly to 10-metre satellite pixels produces positional error. The climate benefit of new wood-based materials must also be calculated across the full life cycle, from feedstock extraction, chemicals, and heat sources through product life and disposal. Effects that disappear during manufacturing cannot be treated as one fixed ratio.

Methodologies and standards under Article 6.4 of the Paris Agreement exist, but interoperability between voluntary markets and national mitigation outcomes, and prevention of double counting, are not yet complete.

Old-growth forests are major carbon stores, and large individual trees can continue adding carbon. In production forests, storage in harvested wood and material-substitution effects can be considered together. Which choice benefits the climate depends on forest type, harvesting intensity, regeneration rate, product life, processing emissions, and the material being substituted. A rule that harvests all forests at 30 to 40 years, and a rule that prohibits all harvesting, can neither replace this calculation.

If harvest locations and volumes, wood-product production, buildings' material specifications, and life-cycle data from new-material processes are connected, a carbon ledger can be made from forest to product. An integrated digital twin that follows even the individual tree that went into a particular wall is closer to a design goal than to an operating system.

Preventing double counting of the same emission reduction requires unique identifiers, coordination between registries, ownership rules, cancellation records, and independent verification. Blockchain or physics-informed neural networks alone cannot structurally solve this problem.

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