SDG POLICY BRIEF SERIES NO. 14

Leveraging Digital Technologies for Sustainable Forest Management: Possible Applications in Low- and Middle-Income Countries

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Acknowledgement

This policy brief was developed by the United Nations Development Programme (UNDP) Seoul Policy Centre (USPC), in partnership with the OJEong Resilience Institute (OJERI).

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We would also like to thank the following staff from UNDP for their insightful contributions in reviewing the publication: Tim Scott (UNDP Nature Hub), and Reina Otsuka (UNDP Nature Hub).

The publication was based on the technical background paper prepared by Professor Woo-Kyun Lee (Director, OJERI, Korea University) and Dr. Minwoo Roh (Research Fellow, Korea University).

The production of this publication was made possible through the generous support of the Ministry of Foreign Affairs of the Republic of Korea.

Acronyms and abbreviations

AFoCO	Asian Forest Cooperation Organization
AFOLU	Agriculture, Forestry, and Other Land Use
AI	Artificial Intelligence
CCTV	Closed-Circuit Television
CLIMEX	Climate Matching and Ecological Modeling
CNN	Convolutional Neural Network
COOLR	Cooperative Open Online Landslide Repository
CSV	Comma-Separated Values
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
DSM	Digital Surface Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA	ECMWF ReAnalysis
ESA	European Space Agency
FAO	Food and Agriculture Organization of the United Nations
FAR	False Alarm Ratio
FIRMS	Fire Information for Resource Management System
GHG	Greenhouse Gas
GEE	Google Earth Engine
GIS	Geographic Information System
GPM	Global Precipitation Measurement
GPN	Global Policy Network
GPP	Gross Primary Productivity
HR	Hit Rate
HWSD	Harmonized World Soil Database
HWP	Harvested Wood Products
ICT	Information and Communication Technology
IoU	Intersection over Union
IPCC	Intergovernmental Panel on Climate Change
KAIST	Korea Advanced Institute of Science and Technology
KFS	Korea Forest Service
KIGAM	Korea Institute of Geoscience and Mineral Resources
KLES	Korean Landslide Early Warning System

KMA	Korea Meteorological Administration
K-NN	K-Nearest Neighbor
LDAPS	Local Data Assimilation and Prediction System
LiDAR	Light Detection and Ranging
LMICs	Low- and Middle-Income Countries
LSM	Landslide Susceptibility Map
LULUCF	Land Use, Land-Use Change and Forestry
MAP	Mean Average Precision
MODIS	Moderate Resolution Imaging Spectroradiometer
MRV	Measurement, Reporting, and Verification
NASA	National Aeronautics and Space Administration
NDC	Nationally Determined Contribution
NDVI	Normalized Difference Vegetation Index
NFDRS	National Forest Fire Danger Rating System
NFI	National Forest Inventory
NFC	Near Field Communication
NIFoS	National Institute of Forest Science
NPP	Net Primary Productivity
OJERI	OJEong Resilience Institute
PCF	Phenological Classification Framework
POWER	Prediction of Worldwide Energy Resources
PSI	Phenological Satellite Imagery
PWD	Pine Wilt Disease
R&D	Research and Development
RCP	Representative Concentration Pathway
REDD+	Reducing Emissions from Deforestation and forest Degradation in developing countries
RGB	Red, Green, Blue
RTK	Real-Time Kinematic
SAR	Synthetic Aperture Radar
SINMAP	Stability Index Mapping
SMI	Soil Moisture Index
SRTM	Shuttle Radar Topography Mission
SSTC	South-South Triangular Cooperation

TACCC	Transparency, Accuracy, Consistency, Completeness, and Comparability
TOPMODEL	Topographic Model
TRIGRS	Transient Rainfall Infiltration and Grid-based Regional Slope-Stability model
TTA	Test-time Augmentation
TWI	Topographic Wetness Index
UAV	Unmanned Aerial Vehicle
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
USPC	UNDP Seoul Policy Centre
VIIRS	Visible Infrared Imaging Radiometer Suite
VNIR	Visible and Near-Infrared
VTOL	Vertical Take-Off and Landing
VTCI	Vegetation Temperature Condition Index
WHO	World Health Organization
WWIS	World Weather Information Service
YOLO	You Only Look Once
YSGWF	Yonsei Ground-Water Flow

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Executive summary

The climate and biodiversity crises call for urgent action in the management of natural resources. The incidence of forest fires, pest outbreaks, and land degradation is closely linked to human activities, including unsustainable agricultural practices and the overexploitation of forests and other carbon sinks. These impacts disproportionately affect women, youth and vulnerable communities, underscoring the urgent need for more ambitious and inclusive solutions that engage society as a whole.

Driven by recent advances in artificial intelligence (AI), remote sensing, GIS technologies and the growing availability of open datasets, digital innovation presents opportunities for concrete and practical solutions on the ground. These can deliver direct benefits at the national and local levels while contributing to long-term and decisive solutions for biodiversity and climate.

Since the end of the Korean War, the Republic of Korea (hereafter, Korea) has achieved remarkable success in reforestation, transforming once barren and degraded landscapes into thriving vegetation. This impressive success is now sustained through a strong governance framework and digital platforms that ensure the effective management of natural environments.

Based on this experience, this paper presents the different digital tools and strategies that have been implemented in Korea for sustainable forest management. It provides an overview of the latest forestry research on AI and remote sensing, and highlights several models and innovative approaches to better anticipate and manage disasters such as fires, landslides and pest outbreaks.

1. Approaches for low- and middle-income countries on a case-by-case basis

Several adaptable and low-cost approaches drawing on AI, remote sensing and Geographic Information System (GIS) technologies can be applied by policymakers for low- and middle-income countries on a case-by-case basis. When tailored to national and local contexts, these approaches can improve forest management, support biodiversity conservation and help curb climate degradation.

2. Improving sustainable forest management with global datasets and mapping

Initial efforts can focus on leveraging freely available global datasets and open-access platforms to establish core functions such as basic forest monitoring, disaster risk assessment, and carbon accounting. As capacity increases, these foundational systems can be progressively enhanced through the integration of field data, machine learning-based mapping, and observation-driven activity data.

3. Governance frameworks and capacity development to support forest management technologies

At the same time, targeted investments in institutional coordination, human capacity development, and clear governance frameworks are essential to ensure that digital tools translate into concrete management actions and policy decisions. When pursued together, technology transfer and international cooperation can support practical, context-specific improvements in forest management and disaster response.

4. Boosting innovation that prioritizes usability and long-term sustainability

Overall, the promise of digital technologies in the forestry sector lies not in pursuing technologically sophisticated solutions in isolation, but in building integrated, context-sensitive systems that convert data and models into concrete management actions and policy decisions. Research and innovation efforts that prioritize usability, institutional fit, and long-term sustainability are most likely to deliver lasting impact in forest management and disaster risk reduction.

1. Introduction

1.1 Climate crisis and sustainable forest management

Climate change is causing more disturbances as extreme heat, wildfires, heavy flooding, and powerful storms become increasingly frequent, intense, and widespread. Current evidence shows that around 3.6 billion people live in areas highly vulnerable to climate-related risks.[1] Many of the world's climate hotspots, including large parts of Africa, South Asia, Central and South America, and Small Island Developing States (SIDS), are predominantly LMICs. [2] According to World Health Organization (WHO), climate change is projected to cause approximately 250,000 additional deaths every year between 2030 and 2050 due to undernutrition, malaria, diarrhoeal diseases, and heat-related impacts.[3]

As global temperatures rise closer to beyond the 1.5˚C threshold, the risks of severe and irreversible impacts on people and ecosystems grow substantially. According to the United Nations Environment Programme (UNEP) Emissions Gap Report 2025, global temperatures are likely to exceed 1.5°C above pre-industrial levels within the next decade, highlighting the need for stronger mitigation and adaptation efforts. Women, youth and vulnerable communities will be disproportionately affected by climate change.[4]

As natural carbon sinks, forests have long been recognized as essential mitigators of climate change. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report points out that resilient land and forest management systems not only provide multiple ecosystem services and biodiversity benefits, but also offer an effective mitigation potential.[5] While forests are part of the solution, it is also increasingly at risk as climate change continues to influence the frequency and intensity of extreme weather events affecting forests.[6] This trend is reinforced by unsustainable forest management and land-use driven by agriculture, overexploitation and various economic activities.[7] These pressures on natural environments contribute to rapid biodiversity loss, which is closely linked to the climate crisis.[8]

These pressures are already visible worldwide with extended fire seasons, expanding pest outbreaks, shifts in species distribution and widespread degradation. As a result, countries are under increasing pressure to manage forests more proactively and strategically. However,

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[1] IPCC (2023). Summary for Policymakers. *Climate Change 2022: Impacts, Adaptation, and Vulnerability,* 3-33. https://doi.org/10.1017/9781009325844.001.

[2] Ibid.

[3] WHO (2023, October). Climate change. https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health.

[4] UNFCCC (2022, June 10). New Report: Why climate change impacts women differently than men. https://unfccc.int/news/new-report-why-climate-change-impacts-women-differently-than-men?gad_source=1&gclid=CjwKCAiAxaCvBhBaEiwAvsLmWLazL6rBf3XyYmwxZhtUid4zUiv6u-E9FjNWbvOpDoh0AelVNKrIExoClgwQAvD_BwE.

UNEP (2025). Emissions Gap Report 2025: Off target - Continued collective inaction puts global temperature goal at risk. https://doi.org/10.59117/20.500.11822/48854.

[5] IPCC (2023). Agriculture, Forestry and Other Land Uses (AFOLU). *Climate Change 2022: Impacts, Adaptation, and Vulnerability*, 747–860. https://doi.org/10.1017/9781009157926.009.

[6] IPCC (2023). Technical Summary. *Climate Change 2022: Impacts, Adaptation, and Vulnerability,* 37–118. https://doi.org/10.1017/9781009325844.002.

[7] IPBES (2019). Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. https://files.ipbes.net/ipbes-web-prod-public-files/inline/files/ipbes_global_assessment_report_summary_for_policymakers.pdf.

[8] Ibid.

many LMICs continue to face challenges such as limited data, insufficient monitoring systems, and constrained budgets. These gaps reduce their ability to anticipate risks, prevent damage, and respond quickly when incidents occur. Strengthening sustainable forest management is therefore not only a climate priority but also a development strategy closely linked to livelihoods, biodiversity conservation, and community resilience.

1.2 Sharing Korea's experience: Leveraging digital technologies

Digital technologies play a crucial role in sustainable forest management. Korea's experience shows how investments in data, remote sensing, ICT systems, and digital platforms can transform the way forest agencies plan, monitor, and respond. Over several decades, Korea has developed digital tools that support day-to-day decision-making, ranging from integrated forest information systems and digital mapping tools to early-warning systems for forest fires, pests, and landslides. However, these systems were not built overnight. From the intensive reforestation efforts of the 1960s following the Japanese occupation and the Korean War to today's advanced technologies, they have evolved through long-term policy commitment, institutional coordination, and continuous improvements to data quality and technical capacity.

Korea's experience is relevant because many LMICs are now beginning to explore similar solutions, but often with limited resources of fragmented systems. While the contexts differ, Korea's journey offers practical lessons, where certain approaches can be replicated.

By sharing what has worked well in Korea, along with the challenges and conditions that enabled progress, this policy brief aims to support LMIC policymakers and practitioners who are seeking cost-effective and scalable digital tools for sustainable forest management. The goal is not to suggest a one-size-fits-all model, but to highlight realistic entry points and opportunities for adaptation based on LMIC priorities, capacities, and institutional realities.

At the global level, digital solutions can be used for direct applications that help improve sustainable forest management as demonstrated in this report and in UNDP initiatives such as the Climate Promise and Nature Pledge. Moreover, innovation in the digital sphere can also help provide new tools for governance and environmental services such as digital public goods (DPG) and digital public infrastructure (DPI) that can directly contribute to halt deforestation or fight climate degradation.[9] For example, by using geospatial AI information, an initiative funded by Korea has improved traceability for deforestation-free coffee or cacao in countries such as Costa Rica, Ecuador and Ethiopia.[10]

This brief draws from a technical background paper prepared by Professor Woo Kyun Lee, a leading expert in digital forestry and climate-resilient forest management at Korea University, together with his research team. Their analysis provides the evidence based on Korea's digital forest technologies and informs the recommendations presented here.

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[9] UNDP (2024, August). Designing digital systems for scale: Payments for Environmental Service. https://www.undp.org/publications/designing-digital-systems-scale-payments-environmental-services.

[10] UNDP (2025, December). How developing countries are taking action forward. https://climatepromise.undp.org/news-and-stories/how-developing-countries-are-taking-climate-action-forward.

1.3. UNDP Seoul Policy Centre: Leveraging solutions for sustainable development

The UNDP Seoul Policy Centre (USPC) fosters strategic knowledge exchange and policy innovation, leveraging Korea’s tested and proven development solutions to support sustainable development globally. Through its flagship SDG Partnerships programme, USPC facilitates the adaptation of Korean policy tools and models to diverse country contexts, enabling partner governments, and UNDP’s Global Policy Network (GPN), including Country Offices and Regional Bureaus, to co-create locally relevant solutions. USPC’s work spans critical areas such as green recovery and transition, governance and gender, development cooperation and private sector engagement and development, with a strong emphasis on South-South and Triangular Cooperation (SSTC). Through SDG Partnership projects on green recovery and transition, USPC has been supporting partner countries across Africa, Asia, Latin America and the Balkans to explore practical approaches to sustainable forest management and climate resilience by sharing Korea’s experience with digital technologies and early-warning systems for forest fire prevention and management.

As a thought contributor, USPC helps shape global development impact by incubating new approaches and fostering inclusive and evidence-based policies. Guided by its Theory of Change, USPC’s approach is operationalized through the Centre’s Project Document (2023–2026), which sets out "innovative and country-driven development solutions based on the Korean experience catalysed to support the achievement of the SDGs, leveraging UNDP's convening, policy, advisory and thought leadership role” as its outcome.[11]

Broader Context and Partnerships

USPC’s impact is amplified through close collaboration with other UNDP offices and a wide range of partners, including UN agencies and international institutions, government institutions, academia, civil society and the private sector. The Centre plays a critical role in identifying and pursuing strategic partnerships with Korean actors, drawing on its deep understanding of Korea’s policy ecosystem and institutional landscape. In partnership with UNDP’s Global Policy Network (GPN), including Regional Bureaus and UNDP Country Offices, this unique positioning allows USPC to act as a bridge between Korean expertise and global development needs, facilitating dynamic knowledge exchanges and joint initiatives that respond to emerging challenges such as climate change, digital transformation and inclusive governance. Through this role, USPC contributes to advancing the climate-biodiversity nexus as a core pillar of UNDP's Climate Promise and Nature Pledge flagship initiatives.[12]

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[11] UNDP Seoul Policy Centre (2022). USPC Project Document (2023-2026). https://open.undp.org/projects/00147276.

[12] UNDP Climate Promise (2025). Nature. https://climatepromise.undp.org/what-we-do/areas-of-work/nature.

2. Methodology

2.1 Background and rationale

Korea has approximately 63 percent of forest cover and features a complex landscape composed of high mountain ranges in the east and extensive forested areas with limited accessibility in the west.[13] These characteristics have long posed challenges for monitoring and responding to forest-related hazards such as forest fires, landslides, and forest pests.[14] They have also created uncertainties in forest management activities that require precise information on forest growth, ecosystem health, and carbon storage.[15] In recent years, climate change has intensified high temperature and dry conditions, the interface between urban areas and forests has expanded, and new pest species have emerged.[16] As a result, forest conditions are changing rapidly through the combined effects of intensified climatic stress, altered disturbance regimes, changing vegetation structure and increasing human influence, leading to more heterogeneous and less predictable forest environments.[17]

Because forests extend across large areas and often include remote and inaccessible regions, structural limitations persist in detecting hazards early and securing detailed management information.[18] These conditions have contributed to a growing need for digital approaches that include remote sensing for large-scale observation, ground-based sensor monitoring, GIS-based spatial analysis, automated large-volume data processing, and AI for predictive modelling. Such technologies improve the ability to accurately assess forest conditions in hard-to-reach areas, support early prediction of hazard risks, and enable more science-based decision-making for forest growth monitoring, species distribution analysis, and carbon sink assessment.[19]

Korea has accumulated decades of experience in forest restoration and management, and it has recently expanded this foundation by integrating digital technologies into its forest governance system. The purpose of this report is to introduce Korea's technical and

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[13] KFS (n.d.). Korean Forests at a Glance. https://english.forest.go.kr/kfsweb/kfi/kfs/cms/cmsView.do?cmsId=FC_001679&mn=UENG_01_03.

[14] KFS (n.d.). Forest Disaster Management Division. https://english.forest.go.kr/kfsweb/kfi/kfs/cms/cmsView.do?cmsId=FC_002120&mn=UEFR_04_01_02.

[15] KFS (2021). 제 6 차 산림기본계획(영문) [Korea's National Forest Plan (6th NFMP)]. https://www.forest.go.kr/kfs/file/%EC%A0%9C6%EC%B0%A8+%EC%82%B0%EB%A6%BC%EA%B8%B0%EB%B3%B8%EA%B3%84%ED%9A%8D.pdf.

[16] Kim, J. Y. et al. (2025, March). Spatial and temporal variability of forest fires in the Republic of Korea over 1991–2020. *Natural Hazards*, 1-21. https://link.springer.com/article/10.1007/s11069-025-07169-4.

Choi, W. et al. (2019). Changes in major insect pests of pine forests in Korea over the last 50 years. *Forests*, 10(8), 692. https://www.mdpi.com/1999-4907/10/8/692.

Lee, K. H. et al. (2024). Urban Expansion and Landslide Risk: Investigating the August 2022 Landslide Events in South Korea. *International Journal of Erosion Control Engineering*, 17(3), 35-41. https://www.jstage.jst.go.jp/article/ijece/17/3/17_35/_article/-char/ja/.

[17] Lim, J. et al. (2006, September). 기후변화에 따른 산림생태계 영향: 우리나라 연구현황과 과제(영문) [Climate change impacts on forest ecosystems: Research status and challenges in Korea]. *Korean Journal of Agricultural and Forest Meteorology*, 8(3), 199-207. https://www.kci.go.kr/kciportal/ci/sereArticleSearch/ciSereArtiView.kci?sereArticleSearchBean.artiId=ART001033745.

[18] Cui, F. (2020, February). Deployment and Integration of Smart Sensors with IoT Devices Detecting Fire Disasters in Huge Forest Environment. *Computer Communications*, 150, 818–827. https://doi.org/10.1016/j.comcom.2019.11.051.

[19] Walther, G. R. et al. (2002). Ecological responses to recent climate change. *Nature*, 416(6879), 389-395. https://www.nature.com/articles/416389a.

operational experiences and provide guidance for LMICs facing similar challenges as they design strategies for adopting digital technologies and building forest information systems.

2.2 Objectives and scope

This report provides a comprehensive analysis of the digital technologies applied in Korea's forestry sector. The scope includes both disaster response areas such as forest fires, landslides, and forest pests, as well as broader forest management domains including forest growth monitoring, ecosystem management, species distribution analysis, and carbon sink assessment. The analysis covers national and local-level operational systems and platforms, analytical techniques and predictive models developed in research and academic settings, and the data environments and research infrastructure that support their implementation.

The report also seeks to identify key considerations for countries planning to introduce digital technologies in the forestry sector. These considerations include the types of data required for operational application, the institutional and human-resource structures needed for system management, and options for designing phased implementation strategies that align with national environments and policy conditions. The goal is to support countries in developing realistic transition strategies that reflect their forest conditions, institutional frameworks, and technical capacities.

2.3 Structure of the paper

This report is structured to provide a comprehensive and policy-relevant understanding of digital technologies in Korea's forestry sector by focusing on two core thematic domains: sustainable forest management and forest disaster management. These two themes were selected because they represent the most critical and widely shared challenges faced by forest-dependent countries today—namely, the need to ensure long-term forest sustainability while simultaneously responding to increasing climate-driven risks such as forest fires, landslides, and forest pest outbreaks.

The first main section of the report (Section 3) focuses on digital technologies for sustainable forest management. This part examines technologies related to forest growth and management, forest mapping, species distribution analysis, and carbon sequestration. At the national level, it reviews operational systems such as the National Forest Inventory (NFI), forest type mapping, forest growth and carbon models, and legally embedded greenhouse gas inventory frameworks. At the academic and research level, it analyses advanced applications of remote sensing, Light Detection and Ranging (LiDAR), AI, and growth modelling that support high-resolution forest monitoring, carbon accounting, and scenario-based policy analysis. Together, these sections illustrate how digital technologies underpin long-term forest resource assessment, ecosystem health evaluation, and climate mitigation strategies.

The second main part of the report (Section 4) addresses digital technologies in forest disaster management, with a focus on forest fires, landslides, and forest pests and diseases. This part reviews national operational systems for risk forecasting, real-time monitoring, early warning, and response coordination, alongside academic and research efforts that apply AI-based modelling, numerical simulations, and remote sensing to analyse disaster occurrence, spread, and impacts. By examining both operational and research perspectives, this section highlights how digital technologies enhance preparedness, situational awareness, and decision-making under rapidly evolving hazard conditions.

Building on the analyses in Sections 3 and 4, Sub-Section 3.3 and Sub-Section 4.3 identify potential opportunities for LMICs, outlining scalable pathways for adopting digital forestry technologies using globally accessible data, open-source platforms, and IPCC-consistent methods. The final chapter synthesizes key findings across both thematic domains, discusses overarching policy implications, and presents recommendations for future technological development, research, and international cooperation. Through this structure, the report aims to offer a practical and transferable framework for countries seeking to design digital forestry strategies tailored to their environmental, institutional, and developmental contexts.

2.4 Methodology

This report is based on a desk review of Korea's forest policy documents, national operational systems managed by the Korea Forest Service (KFS) and the National Institute of Forest Science (NIFoS), as well as academic research and technical reports.

The analysis distinguishes between national operational systems and research- and development-oriented technologies, while examining how these two domains interact and complement each other in practice. Rather than focusing on detailed technical or operational prerequisites, the report examines on the types of information produced by digital technologies and evaluates how this information can be applied to forest management, disaster risk reduction, and policy decision-making.

To support countries considering the adoption of digital forestry technologies, the analysis further considers practical aspects such as data accessibility, the use of open-source or low-cost analytical tools, and the general feasibility of implementation under different institutional and technical conditions. The objective is to provide not only a technical overview of digital technologies, but also an integrated assessment of their informational value, practical usability, and relevance for policy and management applications.

3. Digital technologies for sustainable forest management

3.1 Forest growth and management

3.1.1 National level

3.1.1.1 Forest growth characteristics and management in the Republic of Korea

Korea has utilized species-specific stand yield tables for predicting forest growth and establishing forest management plans, and these tools are undergoing continuous refinement.[20] To achieve this, the NFI is essential, as it accurately reflects the actual structure and changing forests.

The NFI is a nationwide, sample-based monitoring system designed to provide statistically representative information on the extent, structure, condition and temporal dynamics of forest resources.[21] It is typically based on permanent or rotating field sample plots that enable repeated measurements of forest composition, age class, stand structure, growing stock, biomass, mortality, soil properties, and other ecological characteristics over time.[22] NFI data provide a fundamental evidence base for national forest policy formulation, sustainable forest management planning and the assessment of forest disturbances, and they also support greenhouse gas accounting under the Land Use, Land-Use Change and Forestry (LULUCF) framework.[23] In addition, NFI plot data serve as essential reference information for integrating field observations with airborne and satellite remote sensing, thereby supporting the production of national forest type maps, biomass estimates and forest carbon stock assessments.[24]

In Korea, the NFI is implemented as a nationwide survey based on permanent sample plots to quantitatively assess the structure, growth and changes of national forest resources.[25] The entire country is divided into a 4 km × 4 km grid, with sample points arranged using a probability sampling method. Each sample point consists of a single cluster plot composed of four sub-plots, including a central plot and three additional sub-plots located 50 m away at azimuths of

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[20] Park, J. H. et al. (2017, October). 임분밀도관리도를 이용한 소나무림의 적정 임분밀도 관리 기준 및 수확목표(영문) [The Production Objectives and Optimal Standard of Density Control Using Stand Density Management Diagram for Pinus densiflora Forests in Korea]. *Journal of Korean Society of Forest Science,* 106, 457-464. https://doi.org/10.14578/jkfs.2017.106.4.457.

[21] FAO (2013, September). Voluntary guidelines on national forest monitoring. https://www.fao.org/4/mi562e/mi562e.pdf.

[22] Kim, D. H. et al. (2008, December). Forest Resources of Korea Based on National Forest Inventory Data. *Journal of Forest Science*, 24(3), 159–164. https://www.kci.go.kr/kciportal/landing/article.kci?arti_id=ART001552939.

[23] IPCC (2019, May). Refinement to the 2006 IPCC guidelines for national gas inventories (vol. 4, Agriculture, forestry and other land use). https://www.ipcc-nggip.iges.or.jp/public/2019rf/vol4.html.

[24] Tomppo, E. et al. (2010, December). National forest inventories. *Pathways for Common Reporting*. European Science Foundation. 541-553. https://link.springer.com/book/10.1007/978-90-481-3233-1.

[25] KFS (2011). 제 6 차 국가산림자원조사 및 산림의 건강·활력도 조사(영문) [Guidelines for the 6th National Forest Inventory and Field Survey on Forest Health and Vitality]. https://www.forest.go.kr/newkfsweb/cmm/fms/BoardFileDown.do?atchFileId=FILE_000000000365943&fileSn=1&dwldHistYn=N&bbsId=BBSMSTR_1130.

0°, 120°, and 240°.[26] In island areas and selected metropolitan regions where the basic grid does not provide sufficient sampling density, additional auxiliary sample points may be installed at 2 km or 1 km intervals in accordance with national regulations. Based on this sampling framework, approximately 4,100 permanent sample plots are distributed nationwide.[27] The survey covers key aspects of forest structure, including stand characteristics, species composition, diameter at breast height (DBH), tree height and the status of saplings and dead wood.[28] During field surveys, original plot locations and marker trees are verified and markers are reinstalled or updated when necessary.

In particular, repeated surveys of permanent sample plots hold great significance as they allow for the systematic tracking of structural changes and growth patterns in forest ecosystems over time. By maintaining identical survey protocols at the same locations, it is possible to quantitatively compare changes in growth rates due to climate change, the impacts of disturbances such as forest fires, typhoons and diseases, and resilience following silvicultural operations (e.g., thinning, harvesting).[29] Furthermore, such long-term data serves as critical input data for the refinement of stand yield tables and growth models, standing as the most reliable national statistics that enable the construction of models based on actual forest conditions. Moreover, NFI data is utilized in various fields, including carbon sink management, biomass resource assessment and forest management certification.[30]

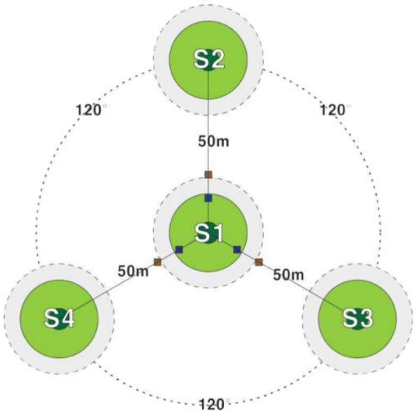

Figure 1 Structure of NFI cluster plot[31]

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[26] KFS et al. (2022, March). 제 8 차 국가산림자원조사 및 산림의 건강활력도 조사 지침서(영문) [Guidelines for the 8th National Forest Inventory and Field Survey on Forest Health and Vitality]. https://forest.go.kr/kfsweb/cop/bbs/selectBoardArticle.do;jsessionid=JjXOEaEYsBNHIrPo60GbhnbsBpHngzOoEumXdZ8R1sTqVqA6t1QV0iXq17oi4BNl.frswas02_servlet_engine5?nttId=3186970&bbsId=BBSMSTR_1016&pageIndex=2&pageUnit=10&searchtitle=title&searchcont=&searchkey=&searchwriter=&searchdept=&searchWrd=&ctgryLrcls=CTGRY447&ctgryMdcls=&ctgrySmcls=&ntcStartDt=&ntcEndDt=&orgId=&mn=NKFS_04_05_10&component=.

[27] Ko, Y. et al. (2024, May). Generic Carbon Budget Model for Assessing National Carbon Dynamics toward Carbon Neutrality: A Case Study of Republic of Korea. *Forests*, 15(5), 877. https://doi.org/10.3390/f15050877.

[28] Wesely, N. et al. (2018, June). Structural Attributes of Old-Growth and Partially Harvested Northern White-Cedar Stands in Northeastern North America. *Forests*, 9(7), 376. https://doi.org/10.3390/f9070376.

[29] Dobrowolska, D. et al. (2022, March). Canopy Gap Characteristics and Regeneration Patterns in the Białowieża Forest Based on Remote Sensing Data and Field Measurements. *Forest Ecology and Management*, 511, 120123. https://doi.org/10.1016/j.foreco.2022.120123.

[30] National Forestry Cooperative Federation. (n.d.). 국가산림자원조사(5 차이후) - 8 차(영문) [The 8th National Forest Inventory(NFI) of Korea]. https://nfric.nfcf.or.kr/forest/user.tdf?a=common.HtmlApp&c=8011&d=nfric&page=/bizdiv/nfric/business0204.html&mc=MEM_NFC_BIZ0204.

[31] Ibid.

Figure 2 National NFI plot distribution[32]

3.1.1.2 Innovation in forest growth and management based on AI and ICT

Building on the long-term, field-based monitoring framework established through the NFI, recent advances in digital technologies are transforming how forest growth and management information is generated and applied. In particular, rapid developments in Information and Communication Technology (ICT) and AI technologies are enabling a more sophisticated national forest inventory system by improving data integration, spatial resolution, and temporal monitoring. As high-resolution spatial data such as drone imagery, aerial imagery, satellite remote sensing and Forest Satellite data are combined with growth models and AI analysis, it has become possible to precisely calculate various forest ecological indices, including stand structure, species distribution, growth rates, phenology, photosynthesis-based productivity, including Gross Primary Productivity (GPP) and Net Primary Productivity (NPP), water stress and forest vitality.[33]

Korea's forests require continuous monitoring due to their distinct phenological (i.e., seasonal changes in vegetation growth) characteristics and complex mountainous terrain. To address this, the KFS is pursuing the launch of Forest Satellite.[34] A remote sensing-based approach is not only essential for establishing a Measurement, Reporting, and Verification (MRV) system for greenhouse gas absorptions and emissions in the forest sector in response to the new climate regime, but also for enabling the production of accurate forest statistics such as forest area and growing stock, and the establishment of a history management system for forest management activities, including the selection of silvicultural treatment sites and post-monitoring.[35] These technologies complement the limitations of existing sampling survey methods and enhance the timeliness and consistency of national forest monitoring. Furthermore, accumulated time-series

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[32] Kim, M. et al. (2017, September). Assessing the impacts of topographic and climatic factors on radial growth of major forest forming tree species of South Korea. *Forest ecology and management,* 404, 269-279. https://www.sciencedirect.com/science/article/abs/pii/S0378112717308162.

[33] NIFoS (n.d.). Introduction to the Agricultural and Forestry Satellite. https://nifos.forest.go.kr/kfsweb/kfi/kfs/cms/cmsView.do?cmsId=FC_003753&mn=UKFR_02_07_01.

[34] Ibid.

[35] IPCC. (2019, May). Refinement to the 2006 IPCC guidelines for national greenhouse gas inventories (vol. 4, Agriculture, forestry and other land use). https://www.ipcc-nggip.iges.or.jp/public/2019rf/vol4.html.

data allow for the identification of long-term trends in forest ecosystem changes, thereby increasing the predictability of policy responses.[36] As a result, utility is expected to significantly increase across various policy and administrative fields, such as improving the accuracy of nationally approved forest statistics, strengthening the foundation for greenhouse gas inventory data supply, monitoring forest management activities, assessing climate vulnerability, and analysing ecosystem services. Moreover, this information production system serves as a foundation that significantly enhances the speed and precision of national-level decision-making.[37]

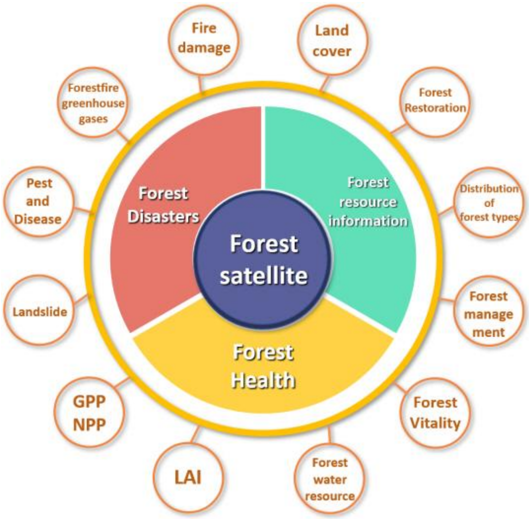

Figure 3 Diverse application of satellite imageries to the forestry sector[38]

Several opportunities are also brought by LiDAR technology. While satellite remote sensing provides broad spatial coverage, LiDAR technology is evaluated as a core tool that fundamentally changed the paradigm of forest inventory.[39] Terrestrial LiDAR is precise enough to measure tree height, DBH, canopy structure, and stand density at the individual tree level with centimetre-level error, while drone and aerial LiDAR can rapidly collect extensive forest information, including from inaccessible areas.[40] As a result, LiDAR provides 3D structural information that used to be difficult to capture with conventional field survey methods, significantly improving the performance and realistic applicability of growth models. Furthermore, with the advancement of automated processing technologies for LiDAR data, survey costs are being reduced while maintaining consistent survey quality. The application of such LiDAR-based data is rapidly expanding beyond simple surveys to include automatic measurement at harvesting sites, estimation of log diameter and volume, growing stock

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[36] Forest Assessment & Management and Conservation Division (2013). National forest monitoring systems: monitoring and measurement, reporting and verification (M & MRV) in the context of REDD+ activities. FAO. https://openknowledge.fao.org/items/676d7832-2833-4da4-961b-18f5232694a3.

[37] NIFoS (2020, May). 산림위성활용 기술개발 및 인프라구축 실행계획 (2020~2025)(영문) [Implementation Plan for Forest Satellite Utilization Technology Development and Infrastructure Establishment (2020–2025)]. https://book.nifos.go.kr/library/10110/contents/5815772.

[38] NIFoS (2020, May). 산림위성활용 기술개발 및 인프라구축 실행계획 (2020~2025)(영문) [Implementation Plan for Forest Satellite Utilization Technology Development and Infrastructure Establishment (2020–2025)]. https://book.nifos.go.kr/library/10110/contents/5815772.

[39] Lefsky, M. A. et al. (2002, January). Lidar Remote Sensing for Ecosystem Studies. *BioScience,* 52(1), 19-30. https://andrewsforest.oregonstate.edu/sites/default/files/lter/pubs/pdf/pub2813.pdf.

[40] Liang, X. et al. (2016). Terrestrial laser scanning in forest inventories. *ISPRS Journal of Photogrammetry and Remote Sensing*, 115, 63-77. https://www.sciencedirect.com/science/article/pii/S0924271616000204.

estimation, and carbon sequestration assessment, thereby accelerating the transition to a dynamic and integrated forest resource management system.[41] Consequently, LiDAR is expected to be a key technology determining the major trends of future forest policy and management.[42]

Figure 4 Field measurement using a terrestrial laser scanner for forest resource inventory conducted by NIFoS, Republic of Korea[43]

3.1.1.3 Growing stock change and forest carbon balance model

The Integrated Supply and Demand Model of the NIFoS is a comprehensive forecasting model established to project long-term changes in forest resources, forest products, and forest services within a single consistent framework.[44] By interconnecting various sub-models such as the Forest Land Area Change Model, Forest Type Change Model, Timber Market Model, Short-term Forest Products Market Model, Forest Water Balance Model, and Forest Welfare Demand Model, it integrally simulates the entire process, ranging from changes in forest area and forest types to timber production, timber demand, and carbon sequestration.[45]

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[41] Lefsky, M. A. et al. (2005). Combining lidar estimates of aboveground biomass and Landsat estimates of stand age for spatially extensive validation of modeled forest productivity. *Remote Sensing of Environment*, 95(4), 549-558. https://www.sciencedirect.com/science/article/pii/S0034425705000258.

White, J. C. et al. (2013). A best practices guide for generating forest inventory attributes from airborne laser scanning data using an area-based approach. *The Forestry Chronicle,* 89(6), 722-723. https://pubs.cif-ifc.org/doi/abs/10.5558/tfc2013-132.

[42] NIFoS (2019, October). NIFoS 산림정책이슈 제 132 호: 산림자원정보 탐색을 위한 라이다 기술의 활용 및 전망(영문) [NIFoS Forest Policy Issue No. 132: Application and Prospects of LiDAR Technology for Forest Resource Information Exploration]. https://book.nifos.go.kr/library/10110/contents/5816312.

[43] Lee, Y. G. (2016, August). 드론·지상스캐너 등 ICT 장비로 산림조사(영문) [Forest survey using ICT equipment such as drones and terrestrial scanners]. *에코타임스.* https://www.ecotiger.co.kr/news/articleView.html?idxno=18150.

[44] Jung, B. H. et al. (2021, December). Development and Application of Computation Program for Integrated Supply and Demand Model in Forest Sector. *Journal of Forest Economics Research*, 28(2), 61–71. https://doi.org/10.31541/KJFE.28.2.6.

[45] NIFoS (2023, June). 산림자원,임산물,산림서비스의 장기전망(영문) [Long-term Outlook for Forest Resources, Forest Products, and Forest Services]. https://book.nifos.go.kr/library/10110/contents/5849129.

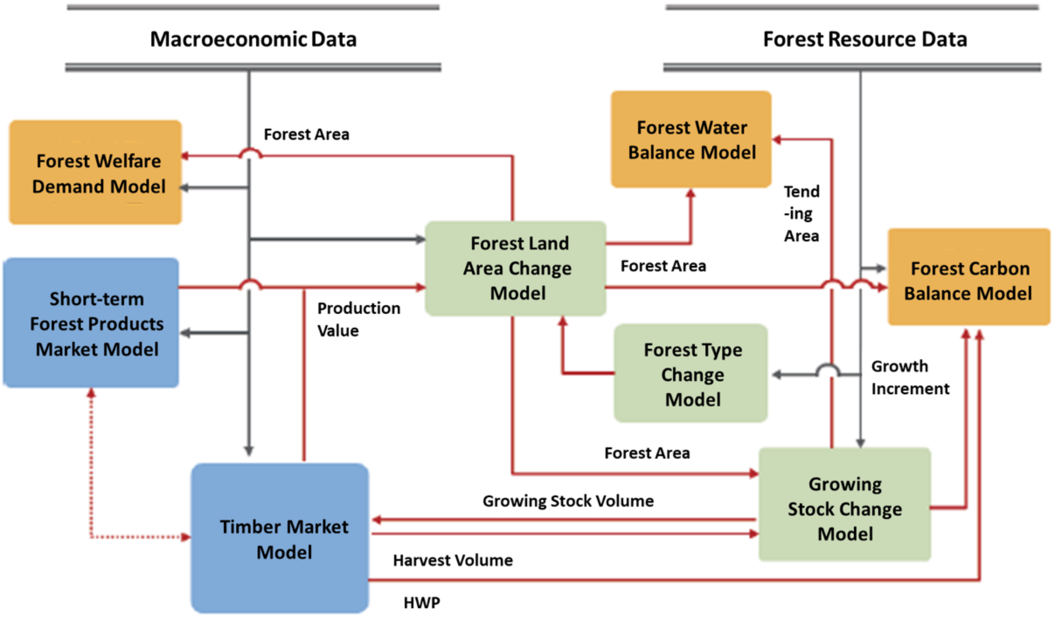

Figure 5 Integrated supply and demand model in the forest sector[46]

The Growing Stock Change Model (see Figure 5) is designed to quantitatively assess the growth processes and structural changes of forests based on the NFI. It estimates long-term changes in growing stock by reflecting growth characteristics according to ownership, land type, forest type, and age class. The model simulates how forest stands grow and decline through silvicultural activities such as planting, regeneration, thinning, and final felling. Results from the Forest Land Area Change Model, Forest Type Change Model, and Timber Market Model serve as exogenous variables, while factors like mortality, thinning, and final felling function as endogenous variables to calculate annual growth and decrease. By utilizing the 7th NFI data,[47] growth models for each forest type were developed using the Chapman-Richards equation (a mathematical function used to describe how biological variables such as tree height, biomass, or growing stock increase over time and approach a stable upper limit), thereby reflecting the biological patterns of forest growth.[48]

Simulation analysis revealed that Korea's forests, having passed a period of rapid growth, are gradually entering a mature stage where their growth rate is slowing down.[49] The timing of peak growth and subsequent decline varies by species, region, and age class. This indicates the necessity of seeking regional forest management strategies based on long-term forest growth predictions, considering silvicultural activities, increased mortality due to forest disasters, and reductions in forest area.

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[46] Jung, B. H. et al. (2021, December). Development and Application of Computation Program for Integrated Supply and Demand Model in Forest Sector. *Journal of Forest Economics Research*, 28(2), 61–71. https://doi.org/10.31541/KJFE.28.2.6.

[47] KFS (2020). 2020 한국의 산림자원(국가산림자원조사) 개정판 (영문) [2020 Assessment of Korea's Forest Resources Revised Edition]. https://kfss.forest.go.kr/stat/ptl/article/articleFileDown.do?fileSeq=3001&workSeq=2166.

[48] Hwang, B. et al. (2025, October). Enhancing Distance-Independent Forest Growth Models Using National-Scale Forest Inventory Data. *Forests*, 16, 1567. https://doi.org/10.3390/f16101567.

[49] Hwang, J. et al. (2025, May). Assessing the Impact of Urbanization and Forest Aging on Carbon Absorption in the Seoul Metropolitan Area of South Korea. *Urban Forestry & Urban Greening*, 97, 128420. https://doi.org/10.1016/j.ufug.2024.128420.

The Forest Carbon Model is directly linked to the Growing Stick Model to quantitatively estimate changes in carbon stock and sequestration based on forest growth.[50] The growing stock and reforestation area derived from the Growing Stick Model serve as key input values for analysing forest biomass carbon stock. Additionally, the new afforestation area from the Forest Land Area Model and timber production by use from the Timber Market Model are utilized for biomass carbon stock analysis and Harvested Wood Products (HWP) carbon stock analysis respectively.

The Forest Carbon Model consists of five sub-modules: forest biomass carbon stock, soil and litter carbon stock, harvest emissions, HWP carbon stock, and bioenergy substitution effects.[51] Through these, it integrally analyses the carbon flows occurring across the entire process of planting, growth, harvesting, timber utilization, and energy substitution. In particular, the forest biomass carbon stock module calculates carbon stock and sequestration by applying carbon conversion factors to the annual growing stock, establishing a carbon change analysis framework based on forest growth.[52] This structure reflects forest growth characteristics considering age class changes and is used to project long-term changes in carbon sequestration and stock under future policy scenarios such as expanded reforestation, planting of superior varieties, and increased timber utilization.[53]

3.1.2 Academic and research level

3.1.2.1 Remote sensing-based advanced forest growth and management technologies

Drone, aerial, and terrestrial LiDAR technologies play a key role in generating precise growth information at the individual tree level by complementing the limitations of conventional sample-based survey methods.[54] Aerial LiDAR data can estimate tree height and canopy structure with high accuracy after undergoing outlier removal and point cloud refinement processes, while terrestrial LiDAR is highly effective in precisely extracting stand structural characteristics such as DBH, tree height, and individual tree locations. Furthermore, drone-based Digital Surface Model (DSM) and orthomosaics[55] are suitable for identifying individual tree canopy areas, while deep learning-based species classification technology has demonstrated a high accuracy of approximately 95%, contributing to the understanding of species-specific growth characteristics, competition structures, and mortality patterns.[56] These technologies allow for the measurement of core growth elements such as diameter, height, and canopy structure, with greater precision and efficiency than existing survey methods, and can

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[50] Vangi, E. et al. (2023, November). Large-Scale High-Resolution Yearly Modeling of Forest Growing Stock Volume and Above-Ground Carbon Pool. *Remote Sensing of Environment*, 295, 113674. https://doi.org/10.1016/j.envsoft.2022.105580.

[51] Repo, A. et al. (2015). Sustainability of Forest Bioenergy in Europe: Land-Use-Related Carbon Dioxide Emissions of Forest Harvest Residues. *Global Change Biology Bioenergy,* 7(5), 877–887. https://doi.org/10.1111/gcbb.12179.

[52] Vande Walle, I. et al. (2005). Growing Stock-Based Assessment of the Carbon Stock in the Belgian Forest Biomass. *Annals of Forest Science*, 62(8), 853–864. https://doi.org/10.1051/forest:2005076.

[53] Jonsson, R. et al. (2018, April). Outlook of the European Forest-Based Sector: Forest Growth, Harvest Demand, Wood-Product Markets, and Forest Carbon Dynamics Implications. *Forest Policy and Economics*, 92, 1–8. https://doi.org/10.3832/ifor2636-011.

[54] Xu, D. et al. (2021, April). LiDAR Applications to Estimate Forest Biomass at Individual Tree Scale: Opportunities, Challenges and Future Perspectives. *Remote Sensing,* 13(9), 1742. https://www.mdpi.com/1999-4907/12/5/550.

[55] Images generated from aerial photographs that have been geometrically corrected (orthorectified) using camera parameters and terrain models so that the image has a uniform scale and can be used as a map.

[56] Caspersen, J. P. et al. (2011, December). How Stand Productivity Results from Size- and Competition-Dependent Growth and Mortality. *PLOS ONE*, 6(11), e28660. https://doi.org/10.1371/journal.pone.0028660.

serve as foundational data for constructing dynamic growth models and analysing growth changes.[57]

In forest management, the development of optimized thinning technologies combining LiDAR-based stand information with machine learning analysis techniques is emerging as a critical research field.[58] This technology defines variables necessary for selecting thinning targets such as individual tree age, diameter, grade, and vitality, and establishes a machine learning-based automatic selection algorithm utilizing these variables.[59] Furthermore, a path optimization model for thinning operations has been developed to enhance work efficiency and economic viability.[60] In the field, high-precision Global Positioning System (GPS)-based real-time tracking technology has been introduced to precisely locate equipment and workers.[61] A Smart Thinning System, combining LiDAR-based forest resource information with thinning optimization technology, has been established and its accuracy and economic feasibility were verified at a 2 ha demonstration site consisting of *Pinus koraiensis* and *Larix kaempferi*.[62] This series of technological developments promotes the automation, precision, and efficiency of forest management operations, enabling a transition to a digital-based forest management system.[63]

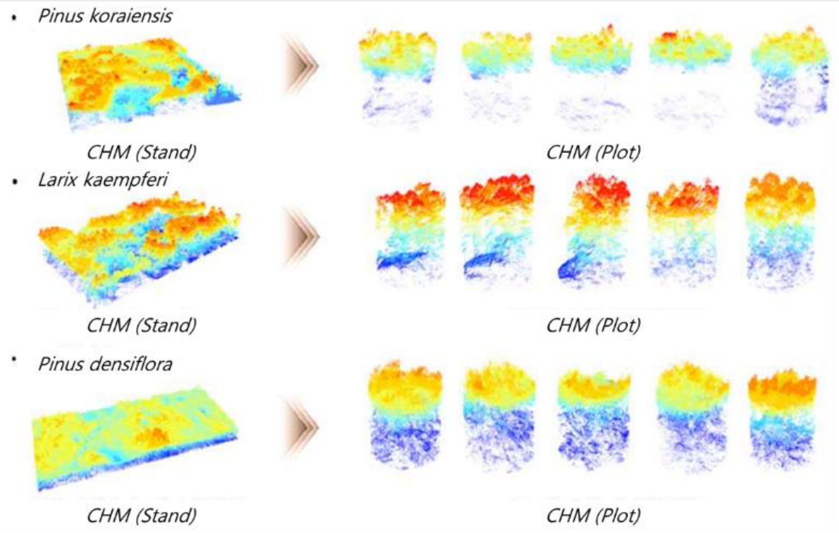

Figure 6 CHM results by species at stand and plot levels[64]

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[57] Lee, B. et al. (2022, September).원격탐사기반 임분고 추정 모델 개발 국내외 현황 고찰 및 제안(영문) [Review of remote sensing technology for forest canopy height estimation and suggestions for the advancement of Korea's nationwide canopy height map]. *Journal of Korean Society of Forest Science*, 111(3), 435-449. https://www.koreascience.kr/article/JAKO202227954652102.page.

[58] Lee, Y. et al. (2025, November). Development and Evaluation of a Thinning Tree Selection System Using Optimization Techniques Based on Multi-Platform LiDAR. *Forests*, 16, 235. https://doi.org/10.3390/f16121776.

[59] Lee, Y. et al. (2025, January). Selection of Trees for Thinning Using Machine Learning Algorithms and Competition Indices. *Forests*, 16, 312. https://doi.org/10.3390/f16010065.

[60] Moriguchi, K. (2020, August). Acceleration and Enhancement of Reliability of Simulated Annealing for Optimizing Thinning Schedule of a Forest Stand. *Journal of Forest Research,* 25(5), 301–309. https://doi.org/10.1016/j.compag.2020.105691.

[61] Cho, H. et al. (2022, December). Application of Real-Time Positioning Systems (RTPS) for Precision Forestry Operations. *Forests*, 13, 2105. https://doi.org/10.18494/SAM4214.

[62] Lee, Y. et al. (2025, November). Development and Evaluation of a Thinning Tree Selection System Using Optimization Techniques Based on Multi-Platform LiDAR. *Forests*, 16, 235. https://doi.org/10.3390/f16121776.

[63] KFS (2024, May). 드론 및 지상 LiDAR 기술을 이용한 정밀 산림자원 정보 구축 알고리즘 개발(영문) [Assessment of precision forest inventory using UAV and terrestrial LiDAR]. https://scienceon.kisti.re.kr/srch/selectPORSrchReport.do?cn=TRKO202400012507.

[64] Ibid.

3.1.2.2 Model-based forest growth and management simulation

While the NIFoS Integrated Supply and Demand Model projects long-term changes in forest resources at the national level, more detailed stand-level dynamics can be analysed using species-specific growth models. The Dynamic Forest Growth Model is a framework capable of predicting species-specific growth by incorporating the impact of climate change, comprising sub-models that simulate DBH, tree height, and stand density (number of trees). Among these, the DBH[65] and stand density models[66] are designed so that the growth and mortality processes of major domestic species respond sensitively to climate. First, the DBH growth model analyses tree-ring data of major species to identify which topographic and climatic factors influence growth. It was found that the environmental factors to which species respond sensitively vary, and that not only temperature and precipitation but also topographic factors such as slope and aspect act as major determinants of growth.[67]

Regarding changes in stand density, mortality rates were predicted using the maximum stand density and seasonal temperature information. If stand density becomes excessively high, competition-induced mortality increases. Meanwhile, seasonal temperature also acts as a significant factor affecting mortality. Based on these DBH and density models, the dynamic forest growth model estimates the growth of eight major Korean species, including tree height growth. The growth coefficients for each species are established by estimating species-specific growth curves from the plot data of the NFI.[68]

The base map, utilized as input data for running the model, represents the current state of Korean forests at a 100 m spatial resolution and consists of the Forest Cover Map, Korean Protected Area Map, Forest Soil Map, elevation, slope and watershed information. The Forest Cover Map provides information on species and age class, while the Korean Protected Area Map defines areas where forest management is restricted. Additionally, elevation, slope, and watershed information area used to identify areas where management activities, such as harvesting, are physically difficult.[69]

Forest management scenarios can apply simple thinning and final felling or construct more refined scenarios by species and age class to simulate conditions similar to actual field management. Thinning intensity is user-adjustable, and the harvest age is also designed to be adjustable from a given default value, allowing for the experimentation of various forest management strategies.[70] In this manner, the model can estimate future growth and changes

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[65] Kim, M. et al. (2017, September). Assessing the impacts of topographic and climatic factors on radial growth of major forest forming tree species of South Korea. *Forest ecology and management*, 404, 269-279. https://www.sciencedirect.com/science/article/abs/pii/S0378112717308162.

[66] Kim, M. et al. (2016, December). Modeling stand-level mortality based on maximum stem number and seasonal temperature. *Forest Ecology and management*, 386, 37-50. https://www.sciencedirect.com/science/article/pii/S0378112716311549.

[67] Kim, M. et al. (2017, September). Assessing the impacts of topographic and climatic factors on radial growth of major forest forming tree species of South Korea. *Forest ecology and management*, 404, 269-279. https://www.sciencedirect.com/science/article/abs/pii/S0378112717308162.

[68] Caspersen, J. P. et al. (2011, December). How Stand Productivity Results from Size- and Competition-Dependent Growth and Mortality. *PLOS ONE*, 6(11), e28660. https://doi.org/10.1371/journal.pone.0028660.

[69] Ko, Y. S. et al. (2024, December). 기초지자체의 공간기반 탄소흡수원관리를 위한 마을단위 산림탄소흡수지도 개발(영문) [Development of village-level forest carbon sink map for spatial carbon sink management of the local government]. *Journal of the Korean Society of Climate Change Research*, 15(6), 989–1000. https://www.kci.go.kr/kciportal/ci/sereArticleSearch/ciSereArtiView.kci?sereArticleSearchBean.artiId=ART003167282.

[70] Blanco, J. A. et al. (2005, March). Sustainability of Forest Management Practices: Evaluation through a Simulation Model of Nutrient Cycling. *Forest Ecology and Management*, 213(1–3), 209–228. https://doi.org/10.1016/j.foreco.2005.03.042.

in growing stock reflecting climate change, which can serve as foundational data for constructing a long-term forest carbon sequestration map.

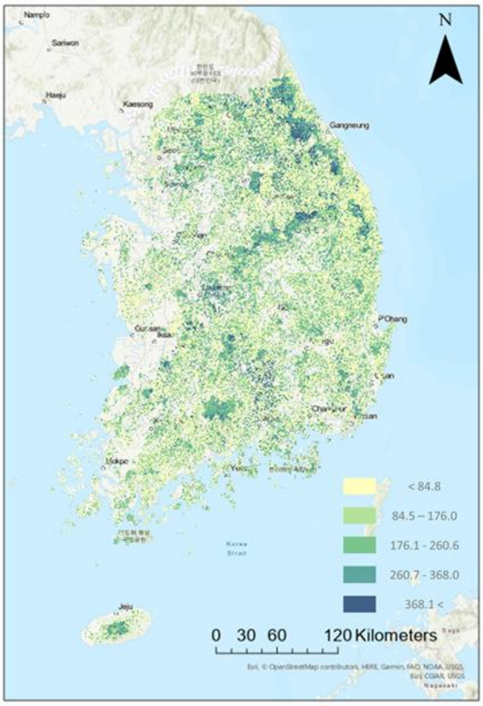

Figure 7 Growing stock in the Republic of Korea[71]

3.2 Forest mapping and carbon sequestration

3.2.1 National level

3.2.1.1 National forest distribution and four types of forests

Forests in Korea are classified into five primary types, which together form the basic framework for national forest resource management.[72] Coniferous forests, dominated by species such as pine, Japanese pine, Korean pine, and larch, occupy extensive areas because early national afforestation programmes focused heavily on establishing conifer plantations.[73] Broadleaved forests, consisting of species such as Mongolian oak, sawtooth oak, hornbeam, and zelkova, were historically reduced due to fuelwood harvesting and logging, but their extent has expanded through natural succession and regeneration following large-scale reforestation efforts.[74] Mixed forests contain a combination of coniferous and broadleaved species, and their structure varies depending on local mountain environments and successional stages. These forests are generally more resilient to climate impacts, pests, and forest fires than single-

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[71] KFS & FAO (2015). 세계 산림자원 평가 2015 – 대한민국 국가 보고서(영문) [Global Forest Resources Assessment 2015 – Country Report: Republic of Korea]. https://openknowledge.fao.org/handle/20.500.14283/az312e.

[72] KFS (2021, September). 2020 산림기본통계(영문) [2020 Forest Basic Statistics Revised Edition]. https://kfss.forest.go.kr/stat/ptl/article/articleFileDown.do?fileSeq=2494&workSeq=1902.

[73] KFS (2025, February). 제 6 차 산림기본계획 변경('18~'37)(영문) [6th Forest Basic Planning Revised Edition [2018~2037]]. https://www.forest.go.kr/kfsweb/kfi/kfs/cms/cmsView.do?mn=NKFS_02_13_01&cmsId=FC_000388.

[74] Lee, D. K. et al. (2004). Natural Restoration of Deforested Woodlots in South Korea. *Forest Ecology and Management*, 201(1), 23–33. https://doi.org/10.1016/j.foreco.2004.06.019.

species plantations, and they provide valuable habitat, landscape, and recreational functions, making them increasingly favoured in recent forest policy discussions.[75] Bamboo forests, although limited in distribution and concentrated mainly in the southern regions and valleys, play important roles in preventing soil erosion, shaping rural landscapes, and supporting local economic activities, and in some cases are managed as a distinct category due to their unique ecological characteristics.[76] Unstocked forests refer to areas with sparse or minimal tree cover that are difficult to classify as forest, including degraded sites, abandoned logging areas, grasslands, rocky terrain, and lands designated for future afforestation. Rather than being regarded simply as non-forest, these areas are considered potential targets for restoration, afforestation, and ecological recovery, and they hold management significance at the forest–non-forest boundary.[77] National forest type maps are produced based on the four major stocked forest categories, supplemented with additional attributes such as natural or planted forest status, age class, growing stock, and dominant tree species, and serve as essential spatial data for understanding national forest distribution and guiding forest planning.[78]

3.2.1.2 Forest distribution mapping system and national project infrastructure

Korea's forest distribution and mapping project has a multi-layered structure that combines the NFI, spatial information infrastructure, and remote sensing technology. First, the NFI uses a standardized, sampling-point survey system to assess stand structure, growing stock, tree species composition, forest health, and soil characteristics on a five-year cycle.[79] Because Korea's forests cover a large area, the NFI database is also refreshed annually by surveying a different section each year, so that updates accumulate continuously across the full cycle. As noted in Section 3.1, these NFI outputs provide statistically representative baseline data and are used as a foundation for forest distribution mapping and forest modelling. Recently, research was also being conducted to comprehensively analyse the ecological, climatic, and ecosystem service functions of natural and planted forests, as well as coniferous, broadleaf, and mixed forests, utilizing data from the 7th NFI.[80]

Second, the forest type map identifies forest types by visually interpreting high-resolution aerial photographs.[81] Beyond the four forest classification, the project further categorizes standing forests into natural and planted forests, which are then further categorized into 15 detailed forest types.[82] This forest type map serves as the top-level resource for the forestry section of national spatial data. Land cover maps and other data also use the forest type map as a

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[75] KFS (2020, June). 지속가능한 산림자원 관리지침(영문) [Guidelines for sustainable forest resource management] (Effective June 15, 2020; Korea Forest Service Administrative Rule No. 1454). https://www.law.go.kr/LSW//admRulInfoP.do?admRulSeq=2100000190248&chrClsCd=010201.

[76] Paudyal, K. et al. (2022). Ecosystem Services from Bamboo Forests: Key Findings, Lessons Learnt and Call for Actions from Global Synthesis. *Ambio*, 51, 1100–1113. https://doi.org/10.1007/s13280-021-01626-3.

[77] Yemshanov, D. et al. (2012, September). Mapping Forest Composition from the Canadian National Forest Inventory and Land Cover Classification Maps. *Environmental Monitoring and Assessment,* 184, 4655–4675. https://link.springer.com/article/10.1007/s10661-011-2293-2.

[78] Ibid.

[79] Kim, K. M. et al., (2008, December). 수치임상도 표준 메타데이터 설계 및 구현(영문) [Design and implementation of standard metadata for digital forest cover type map]. https://kiss.kstudy.com/Detail/Ar?key=2744602.

[80] KFS (2020). 2020 한국의 산림자원(국가산림자원조사) 개정판 (영문) [2020 Assessment of Korea's Forest Resources Revised Edition]. https://kfss.forest.go.kr/stat/ptl/article/articleFileDown.do?fileSeq=3001&workSeq=2166.

[81] Kim, K. M. et al. (2008, December). 수치임상도 표준 메타데이터 설계 및 구현(영문) [Design and implementation of standard metadata for digital forest cover type map]. https://kiss.kstudy.com/Detail/Ar?key=2744602.

[82] Carle, J. & Holmgren, P. (2003). Definitions Related to Planted Forests. *FAO Working Paper 79,* Food and Agriculture Organization of the United Nations. https://www.fao.org/forestry-fao/25853-0d4f50dd8626f4bd6248009fc68f892fb.pdf.

foundation for understanding forest types and distribution. In summary, Korea's forest distribution mapping project pursues a virtuous cycle of "survey-mapping-modelling-policy," which can serve as an operational model for LMICs to build forest information systems.

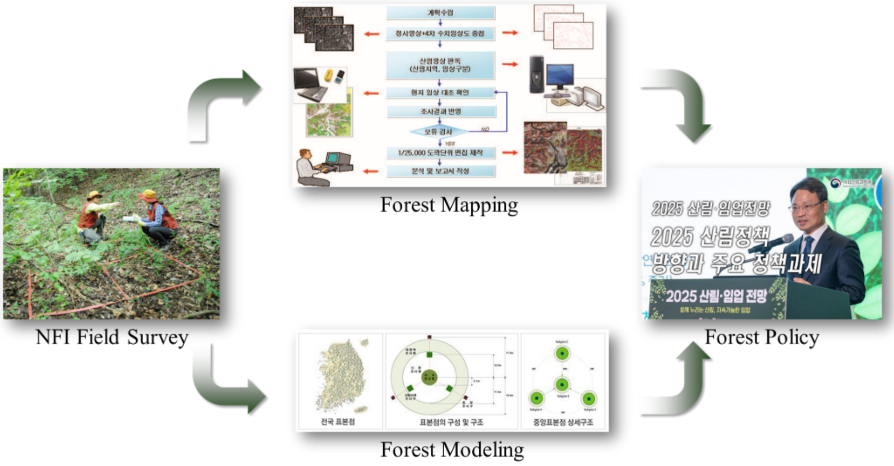

Figure 8 Survey-mapping-modelling-policy cycle of Korea[83]

3.2.1.3 Forest carbon sequestration and national greenhouse gas inventory

In Korea, forests are the largest carbon sink within the Agriculture, Forestry, and Other Land Use (AFOLU) category and are managed as a key area in the national greenhouse gas inventory to offset emissions from the energy and industrial sectors.[84] Consequently, forests are recognized not simply as objects of protection, but as strategic carbon infrastructure supporting the national carbon neutrality strategy. Korea legally and institutionally managed forest carbon sinks through the Framework Act on Carbon Neutrality and Green Growth for Climate Crisis Response and the Act on the Maintenance and Enhancement of Carbon Sinks (hereafter referred to as the Carbon Sinks Act). The Carbon Sinks Act legally defines forests, carbon sinks, forest carbon sequestration, LULUCF, and provides the basis for compiling forest sector greenhouse gas statistics, expanding carbon sinks, and operating the forest carbon offset system. Through this system, activities such as new forestry and reforestation, improved forest management, and restoration of degraded lands are recognized and managed as carbon sink enhancement projects within the institutional framework. In terms of estimation methodology, Korea complies with the IPCC's 2006 National Greenhouse Gas Inventory Guidelines and the 2019 revised guidelines.[85] Specifically, Korea utilizes data from the NFI and forest type maps to develop and apply country-specific emission and absorption factors by tree species and forest type. This allows Korea to build a more precise inventory that reflects Korea's forest structure and management characteristics compared to the IPCC default factors.

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[83] Park, E. S. (2025). 2025 산림·임업 전망 – 제 1 부 공통세션: 주제발표 1(영문) [2025 Forest and Forestry Outlook – Part 1: Plenary Session, Presentation 1]. 2025 Forest and Forestry Outlook Conference, Korea Forest Service. https://www.youtube.com/watch?v=zQQxPRpTy48.

[84] Lee, S. J. et al. (2018, October). Estimation of Forest Carbon Stocks for National Greenhouse Gas Inventory Reporting in South Korea. *Forests*, 9, 625. https://doi.org/10.3390/f9100625.

[85] IPCC (2019). 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. https://www.ipcc-nggip.iges.or.jp/public/2019rf/index.html.

3.2.2 Academic and research level

3.2.2.1 Remote sensing and deep learning for forest and land-cover mapping

Korean academia has developed an advanced research ecosystem that integrates remote sensing, deep learning, and forest science to improve land-cover and forest-type mapping.[86] A representative example is the development of the Phenological Classification Framework (PCF), which uses time-series satellite imagery to capture seasonal dynamics in vegetation reflectance and applies them to land-cover and forest classification.[87]

The PCF is a land-cover classification approach that utilizes seasonal vegetation dynamics derived from satellite image time series. By exploiting the repeatable annual cycle of vegetation reflectance, the PCF uses temporally ordered satellite observations to distinguish land-cover types based on their phenological patterns rather than relying on a single-date spectral signature. In many applications, time-series Sentinel-2 imagery is integrated with deep learning models such as U-Net to capture these seasonal trajectories and improve classification accuracy.[88]

The PCF exploits the fact that, in temperate regions such as the Korean Peninsula, vegetation follows a highly repeatable annual cycle. By constructing Phenological Satellite Imagery (PSI)—chronologically ordered composites of Sentinel-2 Visible and Near-Infrared (VNIR) bands at regular intervals—and feeding these into a U-Net deep learning model, Korean researchers have demonstrated that land-cover can be classified not only from spectral differences at a single date but also the full annual trajectory of vegetation change. This approach moves beyond conventional "snapshot" classifications and establishes a methodological foundation for operational, annually repeatable land-cover products aligned with IPCC activity data requirements.[89]

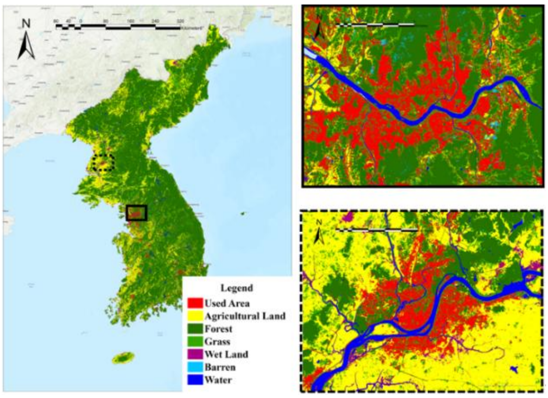

Figure 9 Phenological classification based landcover map[90]

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[86] Mitra, A. et al. (2024, July). Mapping Planted Forests in the Korean Peninsula Using Artificial Intelligence. *Remote Sensing*, 16, 1803. https://doi.org/10.3390/f15071216.

[87] Kim, J. et al. (2025, September). Advancing forest GHG inventory accuracy with a phenological classification framework: Toward an observation-based approach 3 in South Korea. *Ecological Informatics,* 103420. https://www.sciencedirect.com/science/article/pii/S1574954125004297.

[88] Kim, J. et al. (2024, March). Application of the Domain Adaptation Method Using a Phenological Classification Framework for the Land-Cover Classification of North Korea. *Ecological Informatics,* 81, 102576. https://doi.org/10.1016/j.ecoinf.2024.102576.

[89] Solórzano, J. V. et al. (2021, September). Land Use Land Cover Classification with U-Net: Advantages of Combining Sentinel-1 and Sentinel-2 Imagery. *Remote Sensing*, 13(18), 3600. https://doi.org/10.3390/rs13183600.

[90] Kim, J. et al. (2024, March). Application of the Domain Adaptation Method Using a Phenological Classification Framework for the Land-Cover Classification of North Korea. *Ecological Informatics,* 81, 102576. https://doi.org/10.1016/j.ecoinf.2024.102576.

As evidenced in the previous paragraphs, the approach featured not only uses state-of-the-art deep learning architectures (such as U-Net and Convolutional Neural Network (CNN)-based models) but also adapts them to the specific challenges of land-based climate policy, including activity data for AFOLU and monitoring of deforestation in politically or physically inaccessible regions. This approach is a testbed for methods that have the potential to later be transferred to LMICs.

3.2.2.2 Forest carbon sink modelling and high-resolution spatial products

Beyond land-cover mapping, Korean research institutions have also advanced the quantitative modelling and mapping of forest carbon sinks at multiple spatial scales. A key example is the development of village-level forest carbon sink maps to support carbon neutrality strategies of local governments.[91] A forest carbon sink mapping framework has been developed on the KO-G-Dynamics forest growth model, which incorporates forest type, stand age, site conditions, and climate scenarios (Representative Concentration Pathway (RCP) 8.5) to simulate forest growth and associated carbon sequestration.[92] Using national-scale input data such as forest cover maps, forest site environment maps, protected area maps, watershed boundaries, Digital Elevation Model (DEM), and the NFI, the model was driven at 1 ha spatial resolution, and the outputs were aggregated to administrative units (neighbourhood-village, city–county, etc.) relevant to local decision making.[93] The study estimated that Korean forests sequestered approximately 41.5 million tons of carbon in 2020,[94] and then downscaled this national figure to local government units using high-resolution forest characteristics and growth parameters.[95]

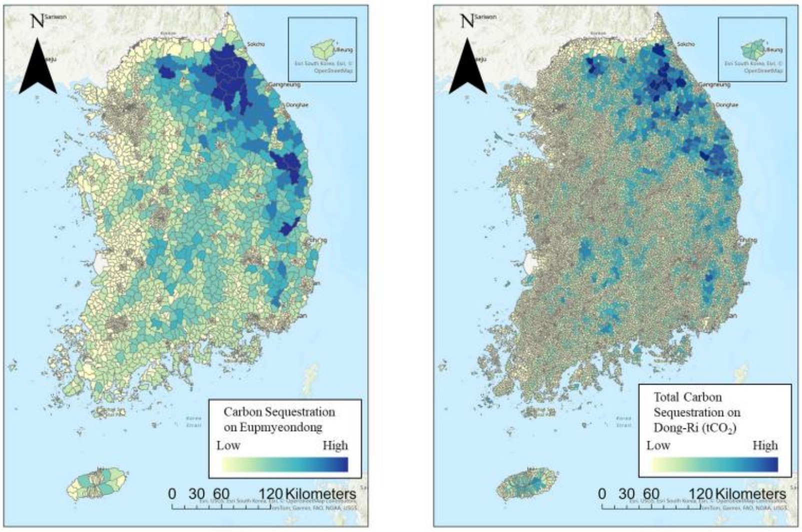

Figure 10 Carbon sink map according to local government scale[96]

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[91] Qin, J. et al. (2024). Forest Carbon Storage and Sink Estimates under Different Management Scenarios in China from 2020 to 2100. *Journal of Environmental Management,* 351, 119671. https://doi.org/10.1016/j.scitotenv.2024.172076.

[92] Ibid.

[93] Ibid.

[94] Ibid.

[95] Lee, S. J. et al. (2018, October). Estimation of Forest Carbon Stocks for National Greenhouse Gas Inventory Reporting in South Korea. *Forests*, 9, 625. https://doi.org/10.3390/f9100625.

[96] Lee, W. K. et al. (2024). 탄소수지 모델 개발 및 지자체 탄소중립 달성 가능성 분석 연구 – 전국 행정체계 단위 탄소배출지도 및 탄소수지지도(영문) [Development of a carbon balance model and analysis of local carbon neutrality potential – Carbon emission and carbon balance maps at the national administrative unit level]. OJeong Resilience Institute, Korea University. https://ojeri.korea.ac.kr/board/news_view.asp?idx=528&boardID=1.

This allowed to identify areas with particularly high carbon absorption—especially municipalities along the Baekdudaegan mountain range—and to highlight the paradox that many of these high sink areas coincide with regions experiencing population decline.[97] On this basis, targeted incentive schemes and differentiated policy support for rural and forest-village regions were proposed, linking carbon sink capacity to local socioeconomic challenges.[98] This is a significant step beyond traditional academic work and shows a strong orientation toward implementation.

3.2.2.3 Advancing IPCC-compliant forest GHG inventories with observation-based Approach 3

This issue is particularly relevant for LMICs, where limited statistical infrastructure and field-based monitoring capacity often constrain the development of spatially explicit land-use data for national GHG inventories.

A third pillar of Korea's academic capacity lies in the strong linkage between remote sensing research and the improvement of IPCC-compliant national GHG inventories, particularly in the forest sector under LULUCF. While the current national inventory mainly operates at Tier 2 and Approach 1—using country-specific emission and removal factors but relying largely on aggregated statistical area data—Korean researchers are actively working to support the transition toward Approach 3 by generating observation-based activity data derived from spatially explicit remote sensing sources such as satellite imagery, LiDAR, and Unmanned Aerial Vehicle (UAV) observations. In this context, Tier 2 refers to the use of country-specific emission or removal factors, Approach 1 estimates land-use areas using aggregated statistical data without tracking spatial transitions, and Approach 3 uses spatially explicit observation-based datasets to monitor land-use changes over time for national GHG inventories.

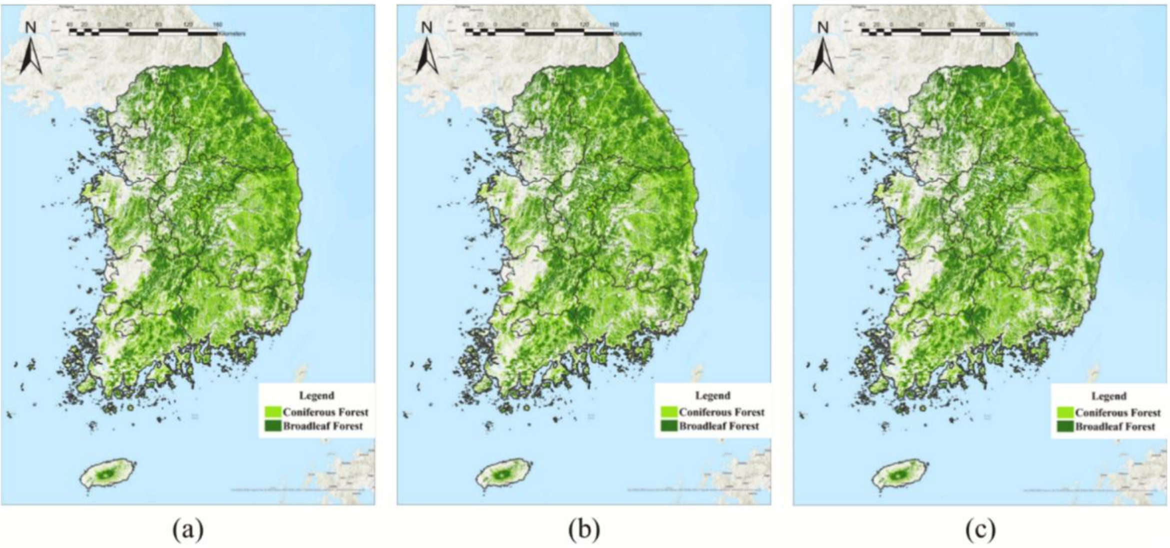

Figure 11 Remote sensing and deep learning-based forest type map in (a) 2019, (b) 2020, and (c) 2021[99]

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[97] Zhang, X. et al., (2023, February). Simulation of Spatial and Temporal Distribution of Forest Carbon Stocks in Long Time Series—Based on Remote Sensing and Deep Learning. *Forests,* 14(3), 483. https://www.mdpi.com/1999-4907/14/3/483.

[98] Griscom, B. W. et al. (2017, October). Natural climate solutions. *Proceedings of the National Academy of Sciences (PNAS)*, 114(44), 11645–11650. https://www.pnas.org/doi/abs/10.1073/pnas.1710465114.

[99] Kim, J. et al. (2025, September). Advancing forest GHG inventory accuracy with a phenological classification framework: Toward an observation-based approach 3 in South Korea. *Ecological Informatics*, 103420. https://www.sciencedirect.com/science/article/pii/S1574954125004297.

Kim et al. (2025)[100] applied the PCF that uses seasonal Sentinel-2 reflectance patterns and deep learning to classify coniferous and broadleaf forests for improved GHG inventory data specifically to forest-type mapping across Korea, focusing on the discrimination between coniferous and broadleaf forests using Sentinel-2 satellite's time series (10 m resolution). By generating phenological composites at two-month intervals (March–April through November–December) and stacking them into a 20-layer PSI, they developed a U-Net classifier with official forest-type maps as labels.[101] The resulting maps for 2019–2021 achieved an overall accuracy of 83.13%, [102] with clear, year-to-year separability in digital number distributions between coniferous and broadleaf classes.[103] Crucially, this work directly addresses a known limitation in the current national inventory: in mixed forests, Korea's Approach 1 method splits areas 50:50 between coniferous and broadleaf types, even though actual dominance can vary significantly by region.[104] Approximately 25% of Korea's forest area is officially classified as mixed forest, meaning that this thus undermines the TACCC principles (transparency, accuracy, consistency, completeness, and comparability) of the IPCC Guidelines.[105] Kim et al. (2025)[106] showed that the true conifer-broadleaf proportions depart systematically from the assumed 50:50 split, and that when these observation-based areas are propagated through the stock-difference method, the resulting carbon stock trajectories diverge meaningfully from those in the official inventory.

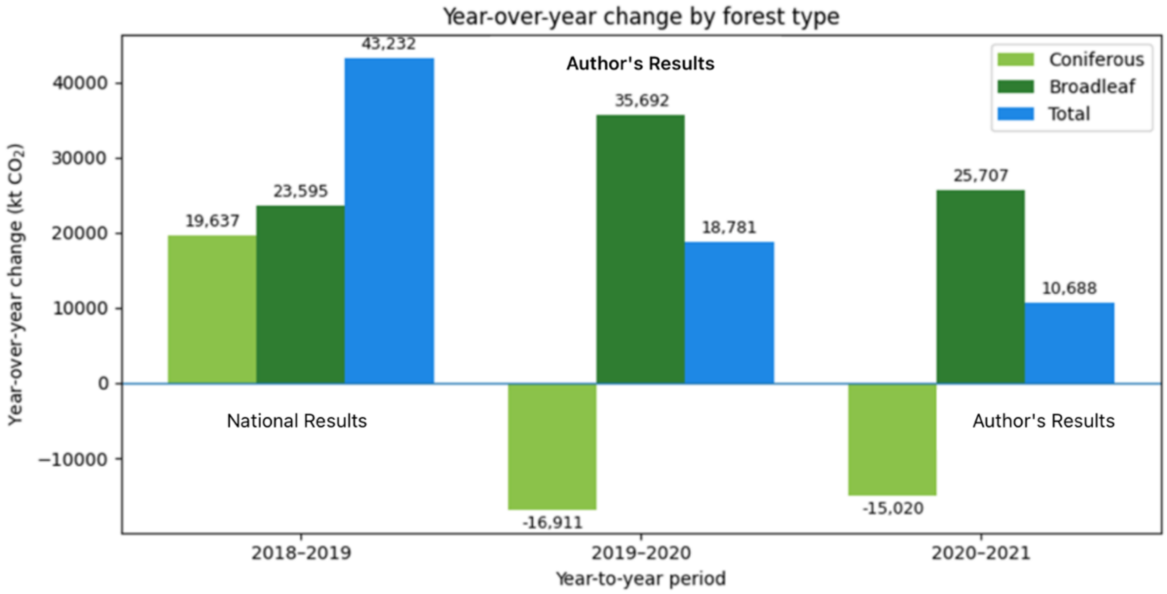


Figure 12 Year over year change by forest type for the periods 2018-2019, 2019-2020, and 2020-2021.

---

[100] Kim, J. et al. (2025, September). Advancing forest GHG inventory accuracy with a phenological classification framework: Toward an observation-based approach 3 in South Korea. *Ecological Informatics*, 103420. https://www.sciencedirect.com/science/article/pii/S1574954125004297.

[101] Ibid.

[102] $\kappa = 0.6755$.

[103] Ibid.

[104] Ibid.

[105] Ibid.

[106] Ibid.

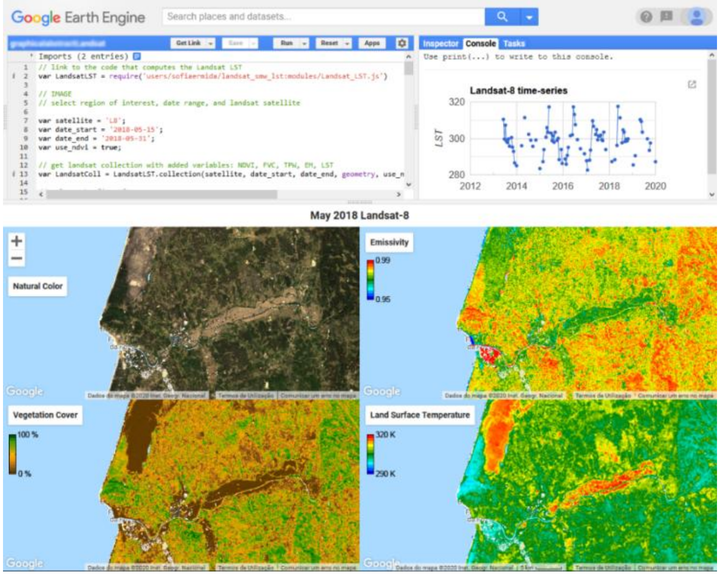
3.3 Potential opportunities

While Korea's experience reflects a relatively advanced stage of forest governance and research capacity, many of the underlying concepts and tools are transferable to LMICs at different stages of institutional and technical development. The combination of (1) a clear legal and institutional framing of forests as national assets and carbon sinks, and (2) a research ecosystem that links remote sensing, forest growth modelling, and IPCC-compliant inventories,[107] offers several potential entry points for international cooperation. This section outlines how LMICs could use the Korean experience and tools to progressively enhance their forest information systems and technical capacity.

3.3.1 Building an entry-level forest information system with free satellite data

Korea's experience suggests that a robust forest information system does not have to start with expensive data or infrastructure. LMICs can take an important first step by using freely available satellite data and cloud-based platforms to establish a simple, but scalable, forest information system.

Platforms such as Google Earth Engine (GEE),[108] as shown in Figure 13, provide free access to long-term archives of Landsat series and Sentinel-2 imagery, together with powerful processing capabilities that do not require local high-performance computing. By leveraging these datasets, countries can generate basic but operational products such as forest and non-forest maps and a small set of forest types (for example, evergreen forest, deciduous forest,[109] mixed forest). This is conceptually similar to Korea's forest phase classification (coniferous, broadleaved, mixed, bamboo, and unstocked forest) but adapted to local ecological and policy conditions.



```
Imports (2 entries)
// link to the code that computes the Landsat LST
var LandsatLST = require('users/sofiaermida/landsat_smw_lst:modules/Landsat_LST.js')

// IMAGE
// select region of interest, date range, and landsat satellite

var satellite = 'L8';
var date_start = '2018-05-15';
var date_end = '2018-05-31';
var use_ndvi = true;

// get landsat collection with added variables: NDVI, FVC, TPW, EM, LST
var LandsatColl = LandsatLST.collection(satellite, date_start, date_end, geometry, use_n
```

```
Use print(...) to write to this console.
```

Figure 13 Google Earth Engine

---

[107] IPCC (2006, July). 2006 IPCC guidelines for national greenhouse gas inventories (vol. 4, Agriculture, forestry and other land use). https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html.

[108] Google Earth Engine (n.d.). https://earthengine.google.com.

[109] A forest dominated by trees that shed their leaves seasonally, typically in autumn or during a dry season.

An entry-level forest information system can be built in phases:

Phase 1 – Simple classification: using Landsat or Sentinel-2 on GEE to produce a forest and non-forest mask and 2 to 3 additional classes that reflect national priorities (e.g., plantations vs. natural forest).

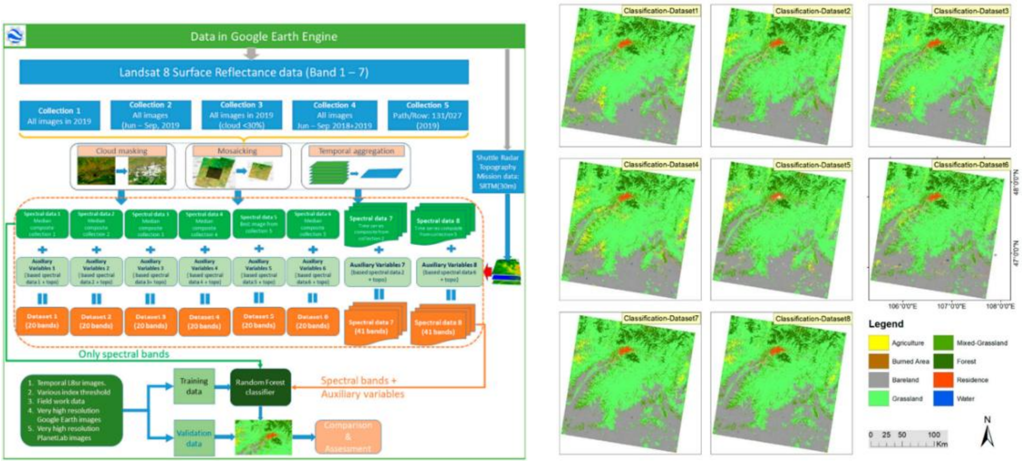


Figure 14 & 15 Examples of forest classification results using GEE[110]

Phase 2 – Institutional anchoring: designating a lead agency to maintain, update, and distribute these maps, and to ensure that they are linked to national forest programs, land-use planning, and disaster risk management.

Figure 16 An example of forest spatial information management through Korea's forest spatial information service[111]

Phase 3 – Progressive refinement: adding more detailed forest classes, temporal composites, or higher-resolution data as technical capacity and data availability improve.

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[110] Phan, T. et al. (2020, July). Land cover classification using Google Earth Engine and random forest classifier—The role of image composition. Remote Sensing, 12(15), 2411. https://www.mdpi.com/2072-4292/12/15/2411.

[111] KFS (n.d.). *Forest Geographic Information Service*. https://map.forest.go.kr/forest/.

This approach allows LMICs to enter the forest mapping arena with modest resources, while still using methods that are consistent with the logic of Korea's "survey-mapping-modelling-policy" cycle and that can be upgraded over time.

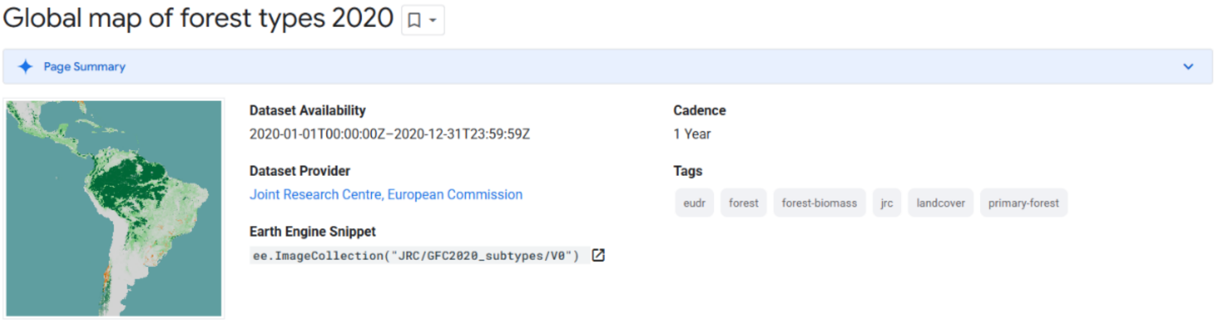
3.3.2 Strengthening forest carbon accounting with IPCC default coefficients

A second opportunity lies in strengthening forest carbon accounting even when country-specific data are limited. While Korea has already developed its own emission and removal factors by tree species and forest type, many LMICs are still at an earlier stage. For them, a practical pathway is to combine new forest maps with the default carbon coefficients provided by the IPCC.

The IPCC Guidelines Refinement[112] provides default emission and removal factors (biomass densities, carbon fractions, growth rates) for major forest types and climate regions. Using these default coefficients, countries can estimate forest carbon stocks and annual carbon sequestration (removals) for each forest class derived from Landsat or Sentinel-2 mapping, even before a full national forest inventory is in place. This corresponds to IPCC Tier 1 methods but already provides a transparent, internationally recognized starting point for AFOLU/LULUCF reporting.

In practice, a structured approach could take the following steps:

1. Use GEE and free satellite imagery to map forest area by basic forest type (e.g., evergreen, deciduous, plantations, degraded forest).



Global map of forest types 2020

Dataset Availability
2020-01-01T00:00:00Z–2020-12-31T23:59:59Z

Dataset Provider
Joint Research Centre, European Commission

Earth Engine Snippet
`ee.ImageCollection("JRC/GFC2020_subtypes/V0")`

Cadence
1 Year

Tags

Figure 17 Global map of forest types (2020) derived in GEE[113]

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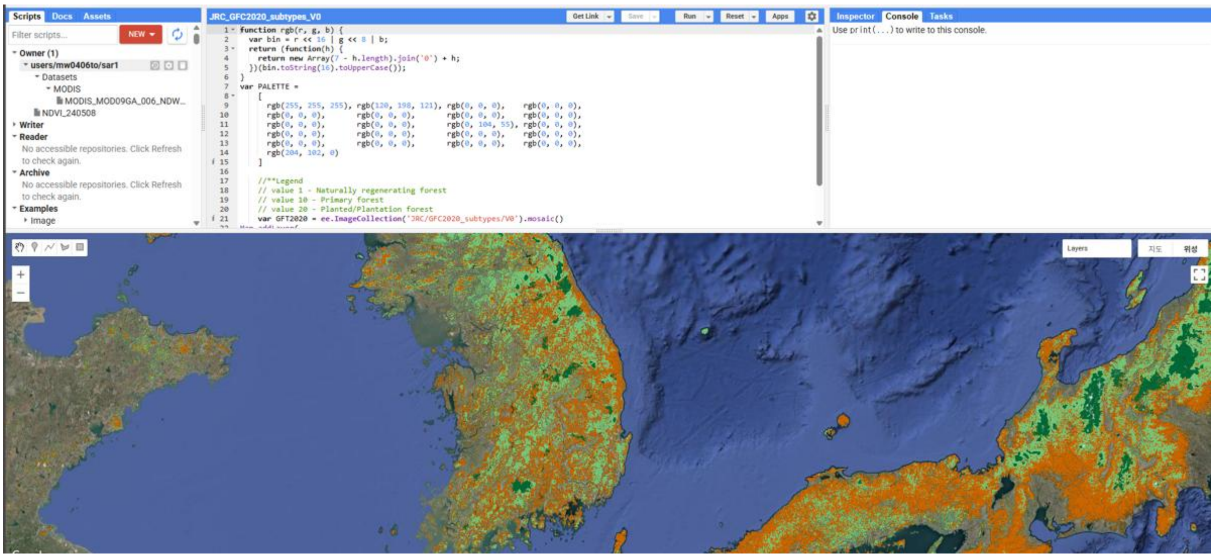
[112] IPCC (2006, July). 2006 IPCC guidelines for national greenhouse gas inventories (volume 4, Agriculture, forestry and other land use). https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html.

IPCC (2019, May). Refinement to the 2006 IPCC guidelines for national greenhouse gas inventories (vol. 4, Agriculture, forestry and other land use). https://www.ipcc-nggip.iges.or.jp/public/2019rf/vol4.html.

[113] Bourgoin, C, et al. (2024). Global map of forest types 2020. https://developers.google.com/earth-engine/datasets/catalog/JRC_GFC2020_subtypes_V0?_gl=1*1mglxsx*_up*MQ..*_ga*MTAzNjc0NzY5OS4xNzY3NjU4NTk5*_ga_SM8HXJ53K2*czE3Njc2NTg1OTgkbzEkZzAkdDE3Njc2NTg1OTgkajYwJGwwJGgw.



```
function rgb(r, g, b) {
  var bin = r << 16 | g << 8 | b;
  return (function(h) {
    return new Array(7 - h.length).join('0') + h;
  })(bin.toString(16).toUpperCase());
}
var PALETTE =
    [
      rgb(255, 255, 255), rgb(120, 198, 121), rgb(0, 0, 0),    rgb(0, 0, 0),
      rgb(0, 0, 0),       rgb(0, 0, 0),       rgb(0, 0, 0),    rgb(0, 0, 0),
      rgb(0, 0, 0),       rgb(0, 0, 0),       rgb(0, 104, 55), rgb(0, 0, 0),
      rgb(0, 0, 0),       rgb(0, 0, 0),       rgb(0, 0, 0),    rgb(0, 0, 0),
      rgb(0, 0, 0),       rgb(0, 0, 0),       rgb(0, 0, 0),    rgb(0, 0, 0),
      rgb(204, 102, 0)
    ]

    //**Legend
    // value 1 - Naturally regenerating forest
    // value 10 - Primary forest
    // value 20 - Planted/Plantation forest
    var GFT2020 = ee.ImageCollection('JRC/GFC2020_subtypes/V0').mosaic()
```

Use print(...) to write to this console.

Figure 18 Execution of global forest type mapping in GEE[114]

2. Assign each class to an appropriate IPCC climate zone and forest types and apply the corresponding default carbon coefficients to estimate above-ground and below-ground carbon stocks.

3. Combine these with simple assumptions on growth or transition between classes (e.g., deforestation, afforestation, degradation) to estimate annual carbon sequestration and emissions per class.

As national capacity grows, countries can gradually move towards IPCC Tier 2 and Tier 3 by establishing sample plots, conducting national forest inventories, and deriving country-specific emission/removal factors, following the trajectory already taken by Korea. However, even at the early stage, the combination of IPCC default coefficients and satellite-derived forest maps provides a credible foundation for Nationally Determined Contribution (NDC) reporting, Reducing Emissions from Deforestation and Forest Degradation (REDD+) strategies, and climate finance proposals.

3.3.3 Scaling up to machine-learning-based forest mapping and Approach 3 activity data

A third opportunity is to progressively adopt machine-learning–based forest classification methods to approximate the technical level demonstrated by Korean research. While Korea has developed advanced frameworks such as the PCF with deep learning models (e.g., U-Net), a wide range of machine learning algorithms—including Random Forests, Support Vector Machines,[115] gradient boosting,[116] and convolutional neural networks[117]—are now widely available and can be tailored to different climatic and ecological conditions.

---

[114] Google Earth Engine (n.d.). https://earthengine.google.com. Screenshot taken on 18 Dec 2025.

[115] A supervised learning method that finds an optimal boundary (hyperplane) to separate classes (or predict values) by maximizing the margin between data groups.

[116] An ensemble technique that builds a strong model by sequentially adding many weak learners (typically decision trees), where each new model corrects the errors of the previous ones.

[117] A deep learning architecture designed to learn patterns from grid-like data (e.g., images), using convolutional filters to capture local spatial features and hierarchical representations.

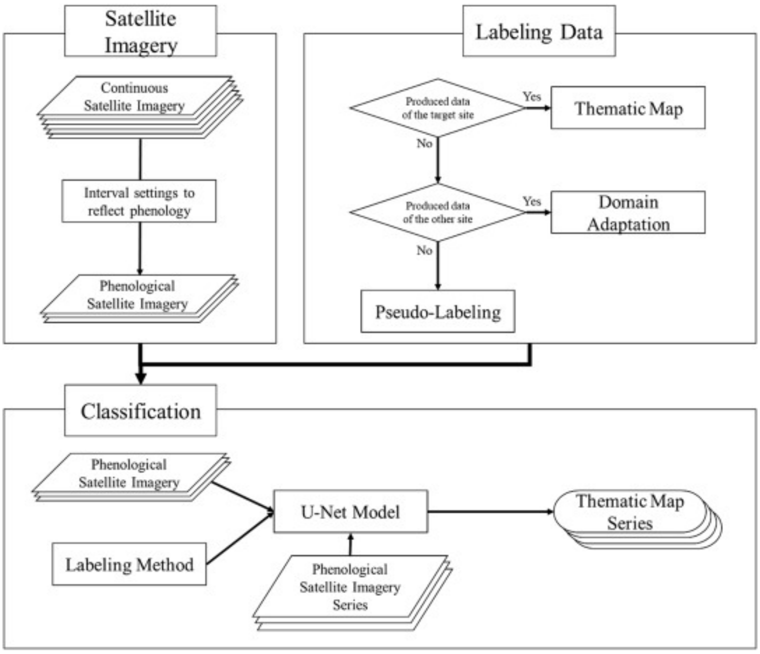


Figure 19 A reference structure of a phenological classification framework (conceptual workflow)[118]

By leveraging GEE and other open-source environments, LMICs can:

- Train Random Forest or other machine learning classifiers on Landsat/Sentinel-2 spectral bands, vegetation indices, and topographic variables to produce forest-type maps.

- Incorporate seasonal or phenological information (e.g., dry vs. wet season composites, multi-month time series) in regions where vegetation has strong annual cycles, similar in spirit to Korea's phenology-based approach.

- Design classification schemes that explicitly reflect the national climate and forest conditions (for example, moist vs. dry forest, montane vs. lowland, mangrove vs. inland forest), rather than copying another country's legend.

3.3.4 Summary of recommendations

To synthesize the key implications of Sections 3.3.1–3.3.3 and to provide a clear transition toward the next section, we highlight here how the proposed approach can be operationalized and progressively advanced. Because many of these algorithms are directly available in GEE, national agencies can experiment with multiple classifiers and select configurations that balance accuracy, robustness and operational simplicity. Over time, as training data, ground truth, and institutional experience accumulate, countries can move toward more advanced phenology-based deep learning approaches similar to those used in Korea, thereby generating observation-based activity data (Step 3) for their forest GHG inventories.

In summary, the Korean experience illustrates a scalable pathway for LMICs:

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[118] Kim, J. et al. (2024, March). Application of the Domain Adaptation Method Using a Phenological Classification Framework for the Land-Cover Classification of North Korea. Ecological Informatics, 81, 102576. https://doi.org/10.1016/j.ecoinf.2024.102576.

1. Start with free satellite data and GEE to build basic forest maps and simple forest typologies.

2. Use IPCC default coefficients to estimate forest carbon stocks and sequestration by class, establishing an initial and internationally consistent AFOLU/LULUCF inventory.

3. Gradually adopt machine-learning algorithms, adapted to national climate and forest conditions, to refine forest distribution mapping, and ultimately develop observation-based activity data comparable in concept to Korea's advanced phenology and deep-learning-based methods.

Through targeted technical cooperation and capacity building, this pathway can help LMICs rapidly elevate their technical level in forest mapping and carbon accounting, while staying fully aligned with IPCC guidance and making effective use of globally accessible data and tools.

4. Digital technologies in forest disaster management

4.1 Forest fire

4.1.1 National level

4.1.1.1 National forest fire risk forecasting and prevention system

Korea is experiencing increasing forest fire risks due to the expansion of hot and dry conditions driven by climate change and the accumulation of forest fuels.[119] In response, the country has continuously advanced its national, technology-based forest fire management systems.[120] Forest fire response in Korea integrates risk forecasting real-time monitoring, incident reporting, spread analysis, and suppression resource management under a centralized command structure.[121] Overall, the national response framework is divided into pre-fire and post-fire phases.[122]

In the pre-fire stage, the core technology is the National Forest Fire Danger Rating System (NFDRS) operated by the NIFoS.[123] This system integrates forecast information from the Korea Meteorological Administration (KMA) with real-time meteorological observations along with

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[119] Park, J. C. et al. (2025, September). Climatic and forest drivers of wildfires in South Korea (1980–2024): Trends, predictions, and the role of the wildland–urban interface. *Forests*, 16(9), 1476. https://doi.org/10.3390/f16091476.

[120] KFS (2025, March). 2026 년도 전국 산불방지 종합대책(영문) [Nationwide Comprehensive Plan for Forest Fire Prevention in 2026]. https://www.forest.go.kr/kfsweb/cop/bbs/selectBoardArticle.do?nttId=3205455&bbsId=BBSMSTR_1008&pageUnit=10&pageIndex=1&searchtitle=title&searchcont=&searchkey=&searchwriter=&searchWrd=&ctgryLrcls=&ctgryMdcls=&ctgrySmcls=&ntcStartDt=&ntcEndDt=&mn=NKFS_02_15_01.

[121] Ibid.

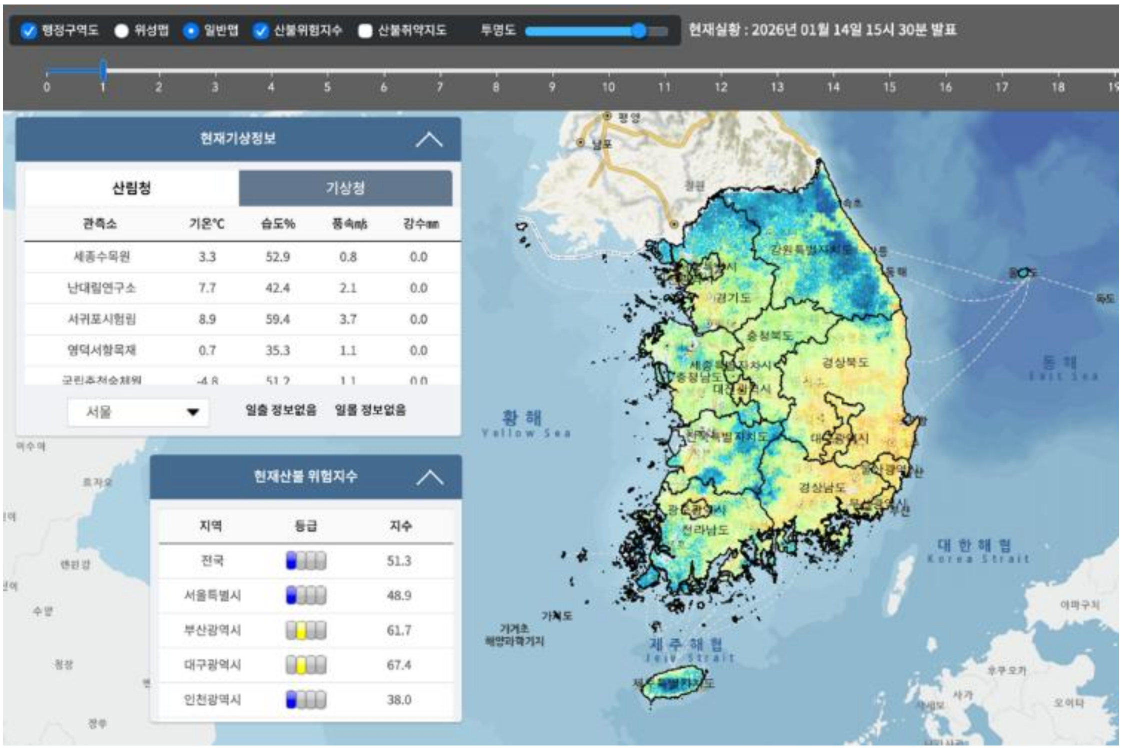
[122] Ibid.

[123] Ibid.

data on forest fuel conditions and topographic characteristics.[124] Through this combined analysis, it produces a forest fire danger index and risk levels for each region.[125] The resulting risk categories, ranging from low to very high, enable local governments to strengthen surveillance in vulnerable areas, reinforce restrictions on open burning, and adjust personnel and equipment deployment to support proactive fire prevention.[126] Long-term statistical data on forest fire occurrence and analyses of seasonal and spatial risk patterns also serve as important references for mid- to long-term fire prevention policies.[127]

4.1.1.2 Real-time forest fire monitoring and information sharing

During the monitoring stage, the Real-Time Forest Fire Information System operated by the KFS plays a central role. This platform compiles reports from fire watchers, Closed-Circuit



현재기상정보

산림청 | 기상청

관측소	기온℃	습도%	풍속m/s	강수mm
세종수목원	3.3	52.9	0.8	0.0
난대림연구소	7.7	42.4	2.1	0.0
서귀포시험림	8.9	59.4	3.7	0.0
영덕서향목재	0.7	35.3	1.1	0.0
국립춘천숲체원	-4.8	51.2	1.1	0.0

서울 ▼ 일출 정보없음 일몰 정보없음

현재산불 위험지수

지역	등급	지수
전국	🟦⬜⬜⬜	51.3
서울특별시	🟦⬜⬜⬜	48.9
부산광역시	⬜🟨⬜⬜	61.7
대구광역시	⬜🟨⬜⬜	67.4
인천광역시	🟦⬜⬜⬜	38.0

Figure 20 Real-Time Forest Fire Risk Index (NFDRS) in Korea[128]

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[124] KFS. (2014). 산림공간정보소개: 산불위험예보시스템. *산림공간정보서비스 (FGIS)*. https://www.forest.go.kr/newkfsweb/html/HtmlPage.do?pg=/fgis/UI_KFS_5002_030200.html&orgId=fgis&mn=KFS_02_04_03_05_02

[125] Ibid.

[126] Ibid.

[127] Won, M. S. et al. (2010, September). Development and application of a forest fire danger rating system in South Korea. *Journal of the Faculty of Agriculture*, Kyushu University, 55(2), 221–229. https://catalog.lib.kyushu-u.ac.jp/opac_download_md/18833/p221.pdf.

Lee, S. Y. & Won, M. S. (2005, February). 산불위험예보 실시간 웹서비스(영문) [Real-time web service for forest fire danger forecasting]. Article Index, National Institute of Forest Science, 10–11. https://book.nifos.go.kr/library/10110/contents/5818677?checkinId=1850269&articleId=1142524.

[128] NIFoS (n.d.). Forest Fire Information System. https://forestfire.nifos.go.kr/menu.action?menuNum=1. Screenshot taken on 14 January 2025.

Television (CCTV) surveillance streams, and incident reports from local governments, firefighting agencies, and the police, and visualizes forest fire incidents on a map in real time.[129] Through this system, both the public and relevant authorities can view fire locations, suppression progress, and estimated damage simultaneously. As a fire escalates and the response level is raised, spatial information on affected and threatened areas is provided to support rapid alerts and timely operational decisions. In recent years, some regions have adopted automated smoke and flame detection based on CCTV imagery, strengthening early detection capacity across extensive forested areas.[130]

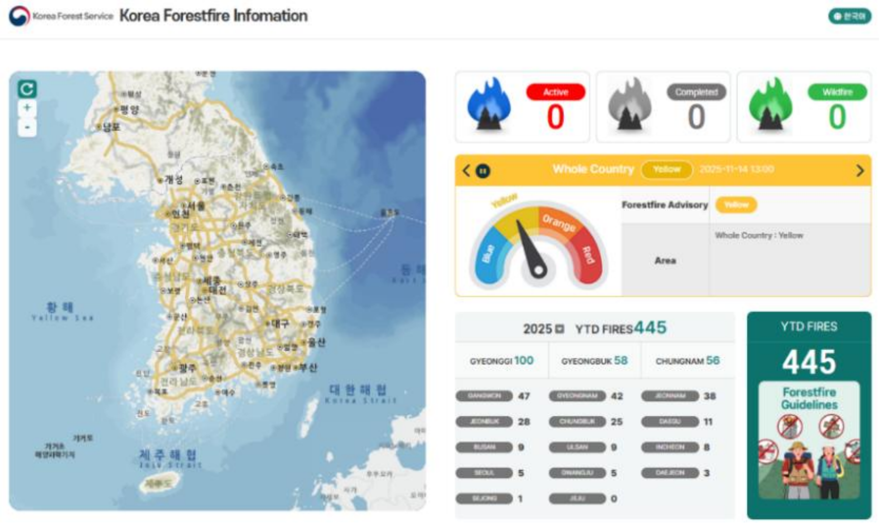

Figure 21 Korea forest fire information dashboard[131]

4.1.1.3 Forest fire spread prediction and operational decision support

Once a forest fire occurs in Korea, the Forest Fire Spread Prediction System becomes the central component of the response framework.[132] This system simulates potential spread direction and speed using real-time meteorological inputs—such as wind direction, wind speed, humidity, and temperature—together with geospatial variables including slope, aspect, and elevation, as well as detailed information on forest fuel conditions.[133] Based on these simulations, the system estimates the anticipated arrival time of the fire at villages, roads, and other critical infrastructure, identifies priority suppression areas, and determines where evacuation may be necessary.[134] These outputs directly support operational decision-making by field commanders.[135] Designed to update continuously as conditions evolve, the system

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[129] KFS (2025, March). 2026 년도 전국 산불방지 종합대책(영문) [Nationwide Comprehensive Plan for Forest Fire Prevention in 2026]. https://www.forest.go.kr/kfsweb/cop/bbs/selectBoardArticle.do?nttId=3205455&bbsId=BBSMSTR_1008&pageUnit=10&pageIndex=1&searchtitle=title&searchcont=&searchkey=&searchwriter=&searchWrd=&ctgryLrcls=&ctgryMdcls=&ctgrySmcls=&ntcStartDt=&ntcEndDt=&mn=NKFS_02_15_01.

[130] KFS (2022, May). Cutting-Edge Forest Fire Response System (WFC). https://english.forest.go.kr/kfsweb/cop/bbs/selectBoardArticle.do;jsessionid=c1JMFpDnLKoj0IGaehxScFePB0MuxD10pghProRDIVsQ52zptOMMJ8uXvSnx3M5g.frswas01_servlet_engine5?nttId=3170699&bbsId=BBSMSTR_1055&pageUnit=10&pageIndex=7&searchtitle=title&searchcont=&searchkey=&searchwriter=&searchWrd=&ctgryLrcls=&ctgryMdcls=&ctgrySmcls=&ntcStartDt=&ntcEndDt=&mn=UENG_04_01&orgId=.

[131] KFS (n.d.). Forest Fire Analysis System (FFAS) – English version. https://fd.forest.go.kr/ffas/gis/english.do. Accessed on 14 November 2025.

[132] NIFoS (2025). 2025 년 산불 제대로 알기(영문) [Understanding 2025 Forest Fires properly (Research Publication No. 1156)]. https://book.nifos.go.kr/library/10212/contents/7148854.

[133] Ibid.

[134] Ibid.

[135] Ibid.

provides consistent analytical support from the ignition stage through final suppression.[136] Efforts to improve computational efficiency and model accuracy are ongoing, and discussions continue expanding the set of input data to enhance predictive performance.[137]

All major information produced before and during a forest fire—including risk forecasts, real-time monitoring data, fire locations and status, spread prediction outputs, and suppression resource movements—is integrated at the National Forest Disaster Management Headquarters.[138] Using the Forest Fire Situation Management System, the headquarters monitors nationwide fire conditions, surveillance footage, weather information, and resource deployments in real time. Based on this information, it issues evacuation advisories, disseminates emergency alerts, and directs helicopter and ground-crew operations as part of national-level decision-making.[139] This integrated platform minimizes information gaps during response operations and strengthens coordination among all actors, thereby improving both efficiency and accuracy.

Overall, the forest fire response system of Korea has evolved to strengthen prevention capacity through early risk forecasting, support rapid initial action through real-time monitoring and information sharing, and enhance operational precision through scientific spread prediction and centralized incident management.[140] These components offer a practical reference model for countries facing rising forest fire risks. The danger forecasting system, in particular, represents a scalable and resource-efficient approach that can be adopted even where infrastructure is limited. Likewise, data-driven spread prediction tools and centralized management frameworks provide a structural pathway for gradual system expansion in countries with limited experience in forest fire management.

This relevance is already reflected in ongoing regional cooperation in the Mekong region.[141] For example, Asian Forest Cooperation Organization (AFoCO)-supported projects in Cambodia and Viet Nam are demonstrating ICT-based forest fire management systems based on Korean experience and best practices, including fire risk assessment, GIS-based monitoring, and institutional capacity-building for government agencies and stakeholders. In Cambodia, related

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[136] Ibid.

[137] Lee, M. B. et al. (2010, August). IT 를 활용한 산림재해 관리(영문) [IT-based forest disaster management]. *Forest Science Bulletin*, NIFoS. 7. https://book.nifos.go.kr/library/10110/contents/5803541.

[138] Ibid.

[139] Global Delivery Initiative (2021, February). Smart Forest Fire Management in the Republic of Korea: Creating a DataDriven and User-Oriented Wildfire Prediction and Monitoring System. https://www.effectivecooperation.org/sites/default/files/documents/gdi_case_study_smart_forest_fire_management_in_korea_0.pdf.

[140] Jeong, K. & Kim, D. (2022). A Study on the Improvement of Safety Management by Analyzing the Current Status and Response System of Forest Fire Accidents. *Journal of the Society of Disaster Information*, 18(3), 457-469. https://doi.org/10.15683/kosdi.2022.9.30.457.

Joo, Y. K. et al. (2022). A Study on the Problems and Improvement by Analyzing the Disastrous Large-scale Forest Fire Response System: Focusing on Simultaneous Forest Fires along the East Coast of Gangwon-do Province. *Journal of Safety and Crisis Management 12*, no.5. http://doi.org/10.14251/jscm.2022.5.21.

NIFoS (2025, March). 2025년 산불 제대로 알기(수정본)(영문) [Understanding Wildfires Properly 2025 (Revised Edition)]. https://book.nifos.go.kr/library/10110/contents/7148854.

[141] Asian Forest Cooperation Organization (2023). Information and communication technology (ICT) for adaptation to climate change and forest fire management in the Mekong region (Project Brief 037). https://afocosec.org/publication/project-brief-afoco-037-2023/.

pilot activities have also been accompanied by hands-on training for forestry officials to support the local use of these systems.[142]

The integrated technological and operational architectures demonstrated in Korea can support capacity-building efforts in low- and middle-income countries and provides a valuable foundation for international cooperation to address increasing forest fire risks under a changing climate.

4.1.2 Academic and Research Level

4.1.2.1 AI-based forest fire occurrence risk modelling

In Korea, a wide range of national Research and Development (R&D) programs and academic research initiatives are being conducted in parallel with the national forest fire response system to quantitatively analyse forest fire occurrence, spread, and damage.[143] In the past years, studies have incorporated diverse environmental datasets, including remote sensing products and socioeconomic variables, in additional to traditional meteorological and topographic information, in order to examine the spatial characteristics of forest fires.[144] With the rapid advancement of AI and machine learning technologies, these analytical approaches are increasingly being applied to forest fire prediction models.[145] These research efforts complement national forecasting and monitoring systems by addressing fine-scale local conditions that are difficult to capture within operational structures, and they provide essential groundwork for exploring potential future directions in the development of national forest fire management technologies.

In the field of forest fire occurrence risk analysis, various studies have used environmental inputs such as meteorological conditions, terrain, forest fuel characteristics, and human-related factors including roads, population, and agricultural areas to estimate the spatial likelihood of ignition. A common approach is to combine satellite-based vegetation and dryness indices, such as Normalized Difference Vegetation Index (NDVI) and Vegetation Temperature Condition Index (VTCI), with indicators of human exposure, and to use AI-based modelling techniques to simulate ignition conditions. Roh et al. (2024)[146] introduced a diagnostic model that incorporates surface, dryness, fuel moisture indices, forest structural attributes, and anthropogenic variables to estimate ignition conditions for specific regions and periods.[147] In

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[142] Vireak, C. (2025, February). Building Up Capacity of Cambodia's Forestry Administration on the ICT-Based Forest Fire Management System. *Asian Forest Cooperation Organization*. https://afocosec.org/newsroom/news/building-up-capacity-of-cambodias-forestry-administration-on-the-ict-based-forest-fire-management-system/.

[143] Ibid.

[126] Choi, J. et al. (2025, May). Forest Fire Risk Prediction in South Korea Using Google Earth Engine: Comparison of Machine Learning Models. *Land*, 14(6), 1155. https://doi.org/10.3390/land14061155.

Lee, C. J. et al. (2025, August). Year-round daily wildfire prediction and key factor analysis using machine learning: a case study of Gangwon State, South Korea. *Scientific Reports*, 15(1), 29910. https://doi.org/10.1038/s41598-025-15508-5.

Piao, Y. et al. (2022). Forest fire susceptibility assessment using google earth engine in Gangwon-do, Republic of Korea. Geomatics, *Natural Hazards and Risk*, 13(1), 432-450. https://doi.org/10.1080/19475705.2022.2030808.

[145] Jo, H. W. et al. (2023, March). Modeling historical and future forest fires in South Korea: The FLAM optimization approach. *Remote Sensing*. 15(5). 1446. https://www.mdpi.com/2072-4292/15/5/1446.

Choi, S. et al. (2024, November). A forest fire prediction model based on meteorological factors and the multi-model ensemble method. *Forests,* 15(11), 1981. https://www.mdpi.com/1999-4907/15/11/1981.

[146] Roh, M. et al. (2024, June). Development of a forest fire diagnostic model based on machine learning techniques. *Forests*, 15(7), 1103. https://www.mdpi.com/1999-4907/15/7/1103.

[147] Jeong, K. & Kim, D. (2022). A Study on the Improvement of Safety Management by Analyzing the Current Status and Response System of Forest Fire Accidents. *Journal of the Society of Disaster Information*, 18(3), 457-469. https://doi.org/10.15683/kosdi.2022.9.30.457.

addition, a dedicated operational forecasting system has been separately established by OJEong Resilience Institute (OJERI) to apply this model in practice, providing wildfire risk forecasts.[148] This type of research demonstrates how diverse datasets can be integrated to analyse the conditions under which forest fires occur.[149] If such models are incorporated into national operational systems in the future, they may support higher-resolution identification of vulnerable areas and inform proactive management policies, including strategies for deploying prevention personnel.

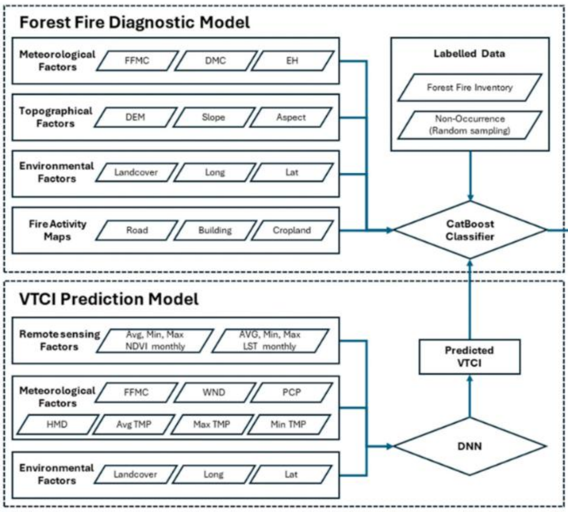
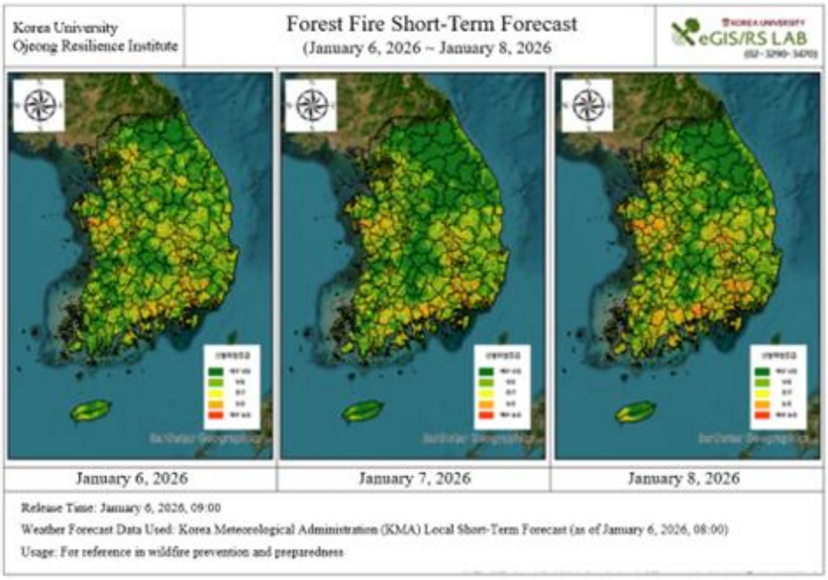


Figure 22 Workflow of the forest fire diagnostic model[150]



Release Time: January 6, 2026, 09:00

Weather Forecast Data Used: Korea Meteorological Administration (KMA) Local Short-Term Forecast (as of January 6, 2026, 08:00)

Usage: For reference in wildfire prevention and preparedness

Figure 23 OJERI forest fire forecast results for 6-8 Jan 2026[151]

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[148] Ibid.

[149] Ibid.

[150] Ibid.

[151] OJERI (2026, January). 2026 Short-Term Wildfire Risk Forecast Map (January 6–January 8), as of 8:00 AM on January 6, 2026. https://ojeri.korea.ac.kr/board/news_view.asp?mode=mod&restring=%252Fboard%252Fnews%252Easp%253Fxsearch%253D0%253D%253Dxrow%253D5%253D%253DBoardID%253D4%253D%253Dpage%253D1&idx=1127&page=1&BoardID=4&xsearch=1&cn_search=.

4.1.2.2 Numerical simulation models for forest fire spread

Research on forest fire spread prediction increasingly utilizes numerical simulation models to understand how meteorological conditions, fuel characteristics, and topographic features influence fire behaviour.[152] Physics-based models such as FARSITE are commonly applied to estimate potential spread patterns and assess how different suppression or management strategies might alter fire progression.[153] By comparing simulated outcomes under various scenarios, these models help identify high-risk areas, evaluate the effectiveness of containment or suppression tactics, and support evidence-based planning for forest fire response. Overall, numerical spread-prediction modelling serves as a critical tool for improving situational awareness and informing strategic decision-making in forest fire management.[154]

4.1.2.3 Remote sensing and AI-based burned area mapping

Research on burned area classification in Korea has primarily utilized satellite imagery such as Sentinel-2 and Landsat to delineate fire-affected areas.[155] While studies have applied spectral indices to detect burned pixels and distinguish them from unburned vegetation, more recent publications have incorporated machine learning and deep learning methods using multi-band satellite inputs, topographic data, or vegetation characteristics to improve classification accuracy in complex Korean forest environments.[156] These approaches provide reliable burned-area maps that support rapid post-fire assessment and inform subsequent restoration planning efforts.

In summary, academic institutions and research organizations in Korea continue to develop quantitative approaches for analysing forest fire occurrence risk, spread patterns, and damage intensity using diverse datasets and AI-driven methodologies. This body of work provides important insights into the types of data and model structures that are needed to understand the spatiotemporal characteristics of forest fires. The findings also offer valuable references for future efforts to enhance national forecasting and warning systems and to develop response technologies that reflect local environmental conditions. These contributions support both policy-oriented and technological advancement in forest fire management.

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[152] Holsinger, L et al. (2016, August). Weather, fuels, and topography impede wildland fire spread in western US landscapes. *Forest Ecology and Management*, 380, 59–69. https://www.sciencedirect.com/science/article/pii/S0378112716304583.

[153] Finney, M. A. (1998). FARSITE: Fire Area Simulator-model development and evaluation (No. 4). Res. Pap. RMRS-RP-4, Revised 2004, Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. https://doi.org/10.2737/RMRS-RP-4.

[154] Kim, N. G. et al. (2024, May). 산불확산 예측 시뮬레이션을 통한 산불 진화선 구축 방향 고찰 - 2022 울진–삼척 산불 사례 -(영문) [Exploring directions for establishing forest fire containment lines through forest fire spread prediction simulations: A case study of 2022 Uljin–Samcheok wildfire]. *Crisisonomy*. 20(5). 73–84. https://www.earticle.net/Article/A453206.

[155] Roy, D. P. et al. (2019, July). Landsat-8 and Sentinel-2 burned area mapping – A combined sensor multi-temporal change detection approach. *Remote Sensing of Environment*, 231, 111254. https://doi.org/10.1016/j.rse.2019.111254.

[156] Lee, C. H. et al. (2022). Machine learning-based forest burned area detection with various input variables: A case study of South Korea. Applied Sciences, 12(19), 10077. https://www.mdpi.com/2076-3417/12/19/10077.

Chae, H. et al. (2024). Sentinel-2 위성영상과 U-Net 을 이용한 산불 피해지 추출 방법 연구(영문) [Wildfire-affected area extraction method using Sentinel-2 imagery and U-Net: A case study for wildfires in Korea]. Journal of the Korean Geographical Society, 59(2), 283–294. https://journal.kgeography.or.kr/media/sites/geo/2024-059-02/N013590212/N013590212.pdf.

4.2 Landslide

4.2.1 National level

Landslide mitigation strategies can be categorized into structural and non-structural strategies. Structural strategies primarily include engineering construction such as erosion control work, while non-structural strategies involve approaches such as the operation of early warning systems.[157] With recent advances in AI and computational processing capacity, non-structural strategies have rapidly evolved, particularly through the enhancement of landslide detection and prediction models that form the core of early-warning systems.

In Korea, two major national systems support landslide risk management: the Landslide Information System operated by the KFS, and the Landslide Monitoring System operated by the Korea Institute of Geoscience and Mineral Resources (KIGAM).[158] The KFS provides real-time landslide risk information, forecasts, and warnings for forested areas nationwide based on rainfall conditions, while KIGAM provides landslide and debris-flow risk information for national parks.

Landslide risks alerts are issued by the KFS under the *Forest Protection Act*,[159] based on the agency's landslide prediction information. The KFS operates several landslide prediction and susceptibility models and provides three main categories of landslide information.[160] However, some of these products are accessible only to government officials, which restricts access to the public.

4.2.1.1 Korean Landslide Early Warning System (KLES)

The KLES is based on landslide prediction information.[161] This prediction information is generated using the TANK model, with input data consisting of rainfall data provided by the KMA and nationwide geological distribution data.[162] The rainfall data from KMA are provided on a 5 km grid and include hourly forecasts extending up to three days ahead.

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[157] Sultana, N. et al. (2021, June). Landslide mitigation strategies in southeast Bangladesh: Lessons learned from the institutional responses. *International Journal of Disaster Risk Reduction*, 62, 102402. https://www.sciencedirect.com/science/article/pii/S2212420921003630.

[158] NIFoS (2025, May). 2025 년 산사태 제대로 알기(영문) [Understanding landslides in 2025]. https://book.nifos.go.kr/library/10110/contents/7478416.

KIGAM (2019, December). 기후변화 적응 산사태 조기경보기술 및 지질환경재해 리스크 제어기술 개발(영문) [Landslide early warning and risk control technology of geo-environmental hazards for climate change adaptation (GP2017-017-2019)]. https://scienceon.kisti.re.kr/srch/selectPORSrchReport.do?cn=TRKO202000005450.

[159] Ministry of Government Legislation (2012). 산림보호법(영문) [Forest Protection Act]. https://www.law.go.kr/lsInfoP.do?lsiSeq=123358.

[160] Eu, S. et al. (2024, December). Nonstructural landslide mitigation of the Republic of Korea. *Landslides*, 22(3), 763–772. https://link.springer.com/article/10.1007/s10346-024-02445-z.

[161] Lee, S. J. et al. (2025, April). Machine learning-based rainfall-induced landslide susceptibility model and short-term early warning assessment in South Korea. *Landslides*, 22, 2809–2827. https://link.springer.com/article/10.1007/s10346-025-02513-y.

[162] Lee, C. W. et al. (2009, June). Tank Model 을 이용한 산지토사재해 경계피난 기준우량 산정법 개발 및 검토(영문) [Development and verifying of calculation method of standard rainfall on warning and evacuation for forest soil sediment disaster in mountainous area by using TANK model]. *Journal of Korean Society of Forest Science*, 98(3), 272-278. https://koreascience.kr/article/JAKO200910103423104.page.

For landslide prediction, the entire country is divided into 11 regions.[163] The classification is based on the spatial distribution of mean rainfall during July to September, which divides the country into four rainfall-based zones, and on geological characteristics, which classify areas into three lithological groups: igneous, metamorphic, and sedimentary rocks.[164] Although this produces 12 theoretical combinations, two regions with similar geological characteristics are merged, resulting in a final total of 11 regions.[165]

Rainfall distribution values for each region serve as input variables to the TANK model. Through linkage with weather forecasts, the model produces the Soil Moisture Index (SMI), which represents the amount of water stored in the soil.[166] A “landslide caution” message is issued when regional soil moisture reaches 80 percent, while a “landslide alert” is issued when it reaches 100 percent.

The KLES has been evaluated using Hit Rate (HR) and False Alarm Ratio (FAR) from 2013 to 2023.[167] During this period, the HR is approximately 90 percent, whereas the FAR remains high at around 85 percent. This to indicate that a large number of cautions and alerts has been issued, which leads to unnecessary administrative burdens. To address this, the KFS plans to fine-tune the KLES by adjusting the threshold values for issuing cautions and alerts based on actual landslide occurrence records.

When first developed in 2014, the KLES provided forecasts only up to one hour ahead, which was insufficient for evacuation. The system now produces forecasts 12 hours and up to 48 hours into the future.[168] However, due to high uncertainty in weather forecasts beyond 12 hours, long-range forecasts are provided as advisory information to support preparedness rather than immediate response.

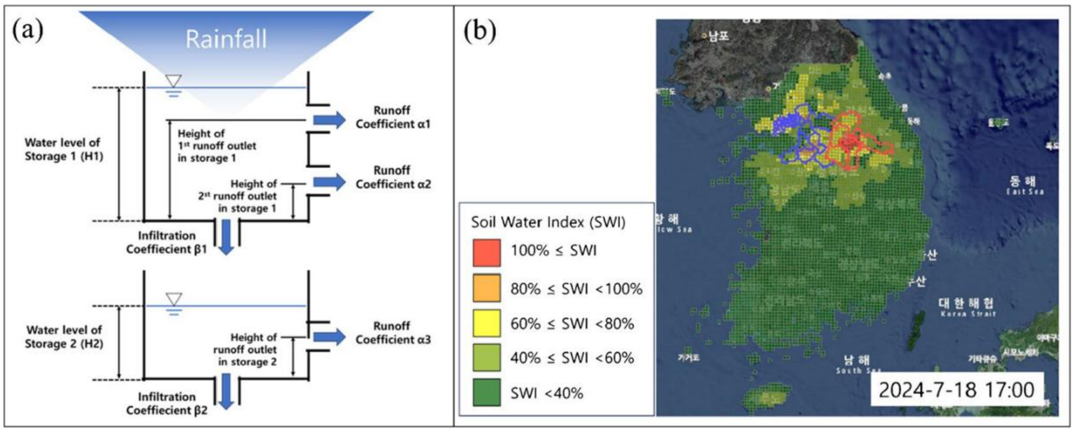

Figure 24 (a) Structure of the two-level TANK model; (b) KLES interface from the landslide information system[169]

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[163] Lee, C. W. et al. (2015, December). 토양함수지수를 이용한 국가 산사태 예보체계 구축 및 운영(영문) [Construction and operation of the national landslide forecast system using soil water index in Republic of Korea]. *Journal of the Korean Society of Hazard Mitigation*, 15(6), 213–221. https://www.j-kosham.or.kr/journal/view.php?number=7696.

[164] Ibid.

[165] Ibid.

[166] Lee, C. W. et al. (2015, December). 토양함수지수를 이용한 국가 산사태 예보체계 구축 및 운영(영문) [Construction and operation of the national landslide forecast system using soil water index in Republic of Korea]. *Journal of the Korean Society of Hazard Mitigation*, 15(6), 213–221. https://www.j-kosham.or.kr/journal/view.php?number=7696.

[167] Eu, S. et al. (2024, December). Nonstructural landslide mitigation of the Republic of Korea. *Landslides*, 22(3), 763–772. https://link.springer.com/article/10.1007/s10346-024-02445-z.

[168] Ibid.

[169] Ibid.

4.2.1.2 Landslide Susceptibility Map (LSM)

The LSM was first developed in 2014 and provides a 10 m × 10 m grid-based assessment of susceptibility across forested areas nationwide.[170] The susceptibility levels are categorized into five classes, ranging from "very low" to "very high." The LSM is produced using nine key landslide-related factors, specifically forest type, forest density, slope degree, aspect, slope length, curvature, parent rock, soil depth, and Topographic Wetness Index (TWI).[171] In other words, the model relies solely on terrain, forest, soil, and geological information, and employs a logistic regression algorithm.

The LSM evaluates the spatial likelihood of landslide occurrence based on terrain, forest, soil, and geological factors. In Korea, the LSM was developed using logistic regression and provides a 10 m × 10 m grid-based susceptibility assessment across forested areas, classified into five levels from very low to very high susceptibility.[172]

Approximately 2,000 historical landslide records from 2005 to 2011 were used to train the logistic regression model.[173] When the input datasets are updated, the pre-trained model is reapplied to generate an updated LSM. Although the map provides detailed spatial resolution, it remains a static product because it does not incorporate rainfall information, which is a primary landslide-triggering factor.[174] As a result, the LSM reflects only inherent susceptibility derived from terrain and soil characteristics.

Model validation was conducted using landslide occurrences from 2012 and 2013, yielding an accuracy of approximately 76%.[175] Recently, the KFS has begun incorporating anthropogenic land cover changes into the LSM by applying correction factors for roads, buildings, forest roads, solar power facilities, and burned areas.[176] As of 2025, the current LSM incorporates information from the large-scale forest fire-affected areas in North Gyeongsang Province in February 2025.[177]

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[170] Woo, C. et al. (2014, December). 로지스틱 회귀모형을 이용한 전국 산사태 발생위험 예측지도 개발(영문) [Landslide hazard prediction map based on logistic regression model for application to the whole country of South Korea]. https://www.j-kosham.or.kr/journal/view.php?number=7316.

[171] Woo, C. et al. (2014, December). 로지스틱 회귀모형을 이용한 전국 산사태 발생위험 예측지도 개발(영문) [Landslide hazard prediction map based on logistic regression model for application to the whole country of South Korea]. https://www.j-kosham.or.kr/journal/view.php?number=7316.

[172] Shang, H. et al. (2023, October). Spatial prediction of landslide susceptibility using logistic regression (LR), functional trees (FTs), and random subspace functional trees (RSFTs) for Pengyang County, China. *Remote Sensing*, 15, 4952. https://doi.org/10.3390/rs15204952.

[173] Ibid.

[174] Reichenbach, P. et al. (2018, March). A review of statistically-based landslide susceptibility models. *Earth-Science Reviews*, 180, 60–91. https://www.sciencedirect.com/science/article/pii/S0012825217305652.

[175] Lee, S. J. et al. (2025, April). Machine learning-based rainfall-induced landslide susceptibility model and short-term early warning assessment in South Korea. *Landslides*, 22, 2809–2827. https://link.springer.com/article/10.1007/s10346-025-02513-y.

[176] Ibid.

[177] KFS et al. (2025, May). 2025 년 산사태 제대로 알기(영문) [Understanding landslides in 2025]. https://book.nifos.go.kr/library/10110/contents/7478416.

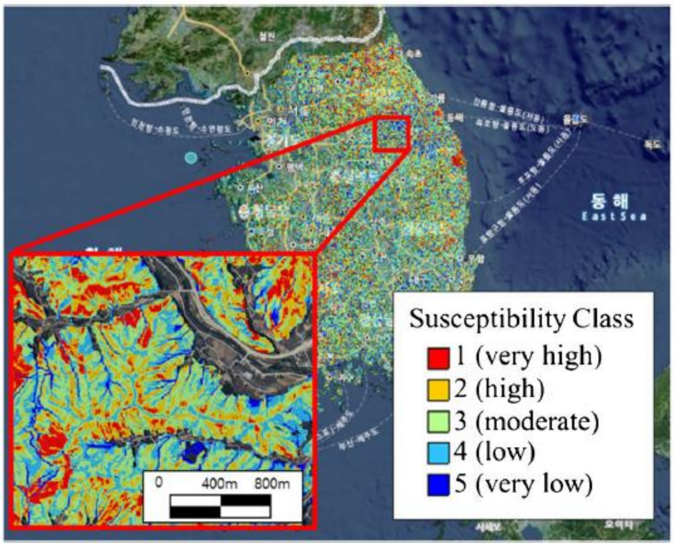

Figure 25 Latest nationwide grid-based landslide susceptibility map (2024)[178]

4.2.1.3 The Dynamic Landslide Hazard Map

The Dynamic Landslide Hazard Map was developed to complement the static nature of the LSM and the coarse spatial resolution and rainfall-based information of the KLES by integrating both datasets.[179] In essence, this map provides real-time landslide hazard levels for administrative districts and watersheds by combining the static susceptibility information from the LSM with real-time rainfall conditions.

Specifically, the system utilizes ultra-short-range observed weather data, LSM, KLES, and forest watershed information as input datasets.[180] Using a matrix-based combination of these inputs, it produces hazard information classified into four levels.[181]

Although the Landslide Information System currently provides the Dynamic Landslide Hazard Map, internal evaluation is still underway to determine its suitability for operational decision-making. As a result, the map is currently offered only as advisory information rather than for official use.[182]

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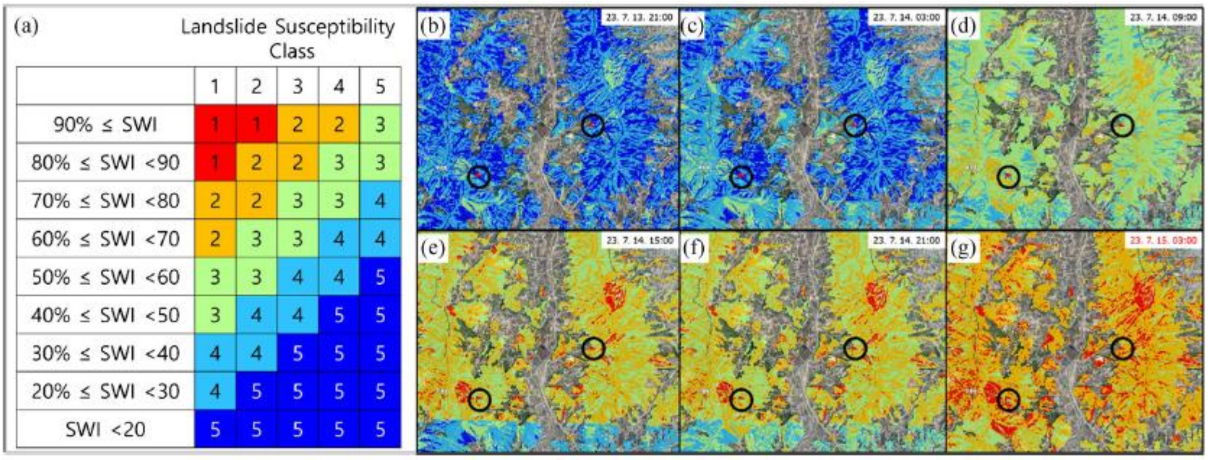
[178] Eu, S. et al. (2024, December). Nonstructural landslide mitigation of the Republic of Korea. *Landslides*, 22(3), 763–772. https://link.springer.com/article/10.1007/s10346-024-02445-z.

[179] Kim, K. D. et al. (2020, September). 매트릭스 기법을 활용한 동적 산사태위험도 평가기법 개발 및 적용성 분석(영문) [Assessment and applicability analysis of dynamic landslide hazard using matrix approach]. https://journal.kci.go.kr/cemtp/archive/articleView?artiId=ART002636820.

[180] Lee, J. J. et al. (2022, October). Dynamic landslide susceptibility analysis that combines rainfall period, accumulated rainfall, and geospatial information. *Scientific Reports*, 12, 18429. https://doi.org/10.1038/s41598-022-21795-z.

[181] Ibid.

[182] Eu, S. et al. (2024, December). Nonstructural landslide mitigation of the Republic of Korea. *Landslides*, 22(3), 763–772. https://link.springer.com/article/10.1007/s10346-024-02445-z.



	Landslide Susceptibility Class				
	1	2	3	4	5
90% ≤ SWI	1	1	2	2	3
80% ≤ SWI <90	1	2	2	3	3
70% ≤ SWI <80	2	2	3	3	4
60% ≤ SWI <70	2	3	3	4	4
50% ≤ SWI <60	3	3	4	4	5
40% ≤ SWI <50	3	4	4	5	5
30% ≤ SWI <40	4	4	5	5	5
20% ≤ SWI <30	4	5	5	5	5
SWI <20	5	5	5	5	5

Figure 26 (a) Matrix combination structure of the dynamic landslide hazard map; (b-g) Dynamic hazard maps showing temporal changes during a rainfall event. Hazard classes range from Class 1 (very high) to Class 5 (very low)[183]

4.2.2 Academic and research level

Landslide modelling approaches can be categorized into qualitative and quantitative methods.[184] Qualitative methods involve expert-based designation of areas susceptible or vulnerable to landslides. Quantitative methods, on the other hand, can incorporate modern technologies such as AI and are generally divided into data-driven and physically-based approaches.

Data-driven approaches utilize historical landslide occurrence records along with meteorological, topographic, and surface information, and can incorporate machine learning, deep learning, and spatiotemporal analytical techniques. Physically-based approaches also rely on landslide occurrence records and meteorological data but additionally require geotechnical information.[185] At national scales, however, geotechnical data often contain substantial uncertainties.[186] To address this limitation, new research applies statistical back-analysis techniques to infinite-slope stability models, supported by high-performance computing that enables large-scale simulations.[187]

Currently, data-driven approaches are being applied by OJERI at Korea University, while physically-based approaches are utilized by the KIGAM, Yonsei University, and the Korea Advanced Institute of Science and Technology (KAIST).

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[183] Ibid.

[184] Fell, R. et al. (2008, December). Guidelines for landslide susceptibility, hazard and risk zoning for land use planning. *Engineering Geology*, 102(3–4), 85–98. https://www.sciencedirect.com/science/article/abs/pii/S0013795208001762?via%3Dihub.

[185] Song, Y. S. et al. (2022, December). 기후변화 대응 산사태 조기경보시스템 개발 및 운영 현황(영문) [State-of-the-art on development and operation of landslide early warning system for climate change response]. *Journal of the Geological Society of Korea*, 58(4), 509-525. https://doi.org/10.14770/jgsk.2022.58.4.509.

[186] Hwang, I. T. et al. (2023, October). Probabilistic back analysis for improving landslide susceptibility assessment using Markov Chain Monte Carlo simulation. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4614291.

[187] Ibid.

4.2.2.1 Regional-scale landslide diagnostic information

The OJERI at Korea University has developed a landslide diagnostic model that has provided short- and long-term landslide risk forecasts since 2023.[188] The service is delivered through a web-based platform and currently offers nationwide risk levels classified into five categories.[189] For long-term forecasting, the model utilizes three-month seasonal prediction data.[190] Seasonal forecasts offer predicted anomalies of monthly precipitation, which are downscaled to daily precipitation using a semi-parametric statistical downscaling technique. Specifically, Markov Chain and K-Nearest Neighbors (K-NN)[191] algorithms are applied to the precipitation patterns of the seasonal forecasts to generate hindcasts[192] based on historical meteorological records that match similar patterns.

For short-term forecasting, the model uses short-range forecasting data and ultra-short-range observed data provided by the KMA.[193] Short-range forecasts provide hourly precipitation information up to three days ahead, while ultra-short-range observations offer real-time hourly rainfall measurements.[194] OJERI integrates these two datasets into daily precipitation inputs to produce landslide risk forecasts up to three days in advance. Both long- and short-term forecasts are generated using the same algorithmic framework. [195]

Since 2023, the OJERI has adopted a data-driven approach, with the core algorithm implemented using Random Forest. Random Forest is a machine learning method that makes predictions by combining the results of many decision trees. However, the data-driven approach was found to be highly sensitive to precipitation variability. As of 2025, the OJERI now incorporates physically-based methods alongside data-driven techniques to improve the robustness of its landslide risk forecasts.[196]

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[188] Lee, S. J. et al. (2025, April). Machine learning-based rainfall-induced landslide susceptibility model and short-term early warning assessment in South Korea. *Landslides*, 22, 2809–2827. https://link.springer.com/article/10.1007/s10346-025-02513-y.

[189] Ibid.

[190] Ibid.

[191] Heuvelink, G. B. M. & Webster, R. (2001, February). Modelling soil variation: past, present, and future. *Geoderma*, 100(3–4), 269–301. https://www.sciencedirect.com/science/article/pii/S0016706101000258.

[192] Hindcasts are model simulations that use historical data to reproduce or predict past events in order to evaluate model performance.

[193] Kim, Y. et al. (2022). Very Short-Term Rainfall Prediction Using Ground Radar Observations and Conditional Generative Adversarial Networks. *IEEE Transactions on Geoscience and Remote Sensing*, 60. https://doi.org/10.1109/TGRS.2021.3108812.

[194] Ibid.

[195] Ibid.

[196] Lee, S. J. (2025, August). Development of an AI-based landslide prediction model and its application to an early warning framework. Doctoral dissertation, Korea University. https://dc.korea.ac.kr/srch/srchDetail/000000305759?localeParam=.

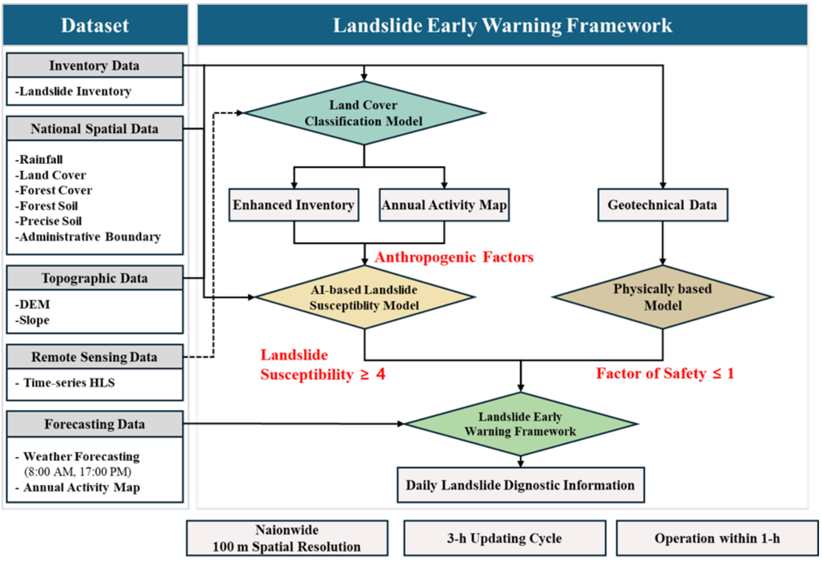

Figure 27 OJERI landslide diagnostic framework results[197]

The data-driven approach uses 4,408 historical landslide records from 2017 to 2023 that were generated through the OJERI's proprietary landslide detection algorithm.[198] A total of 19 input variables are used, including meteorological information, terrain attributes, environmental data, and activity maps.[199] The activity maps represent annual land cover changes derived from satellite imagery, which allows the model to incorporate surface changes such as forest fire-affected areas and development zones.

Meteorological variables include daily rainfall, 3-day cumulative rainfall, and 5-day cumulative rainfall.[200] Terrain and environmental information such as national forest type maps and forest soil maps are processed into 100 m × 100 m grid datasets.[201] After evaluating several machine learning and deep learning algorithms, CatBoost was selected as the core model for the data-driven approach. CatBoost is a machine learning algorithm that learns patterns from data to make predictions, particularly when working with diverse datasets.

The physically-based model uses Stability Index Mapping (SINMAP). For model applications, nationwide geotechnical datasets were generated using national spatial data, including forest soil maps and precise soil maps.[202] The model combines daily rainfall information with outputs from the deterministic SINMAP framework. SINMAP integrates the infinite-slope stability concept with the hydrological Topographic Model (TOPMODEL), which simulates soil moisture and runoff based on topography, and produces a stability index classified into six levels.[203]

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[197] OJERI (2023). 2023 Short-Term Landslide Hazard Forecast Map (July 14-16), as of 5:00 PM on July 13, 2026. https://ojeri.korea.ac.kr/board/news_view.asp?mode=mod&restring=%252Fboard%252Fnews%252Easp%253Fxsearch%253D0%253D%253Dxrow%253D5%253D%253DBoardID%253D1%253D%253Dpage%253D57&idx=448&page=57&BoardID=1&xsearch=1&cn_search=.

[198] Lee, S. J. (2025, August). Development of an AI-based landslide prediction model and its application to an early warning framework. Doctoral dissertation, Korea University. https://dc.korea.ac.kr/srch/srchDetail/000000305759?localeParam=.

[199] Ibid.

[200] Ibid.

[201] Ibid.

[202] Ibid.

[203] Ibid.

Integration of the data-driven and physically-based models is carried out using flow-direction information. The final output is a daily landslide hazard map with a 100 m × 100 m resolution, classified into five levels, and is provided through the OJERI website.[204] The OJERI conducts annual validation and refinement of the model, and in 2026 the system will incorporate early detection of winter season land surface condition changes.

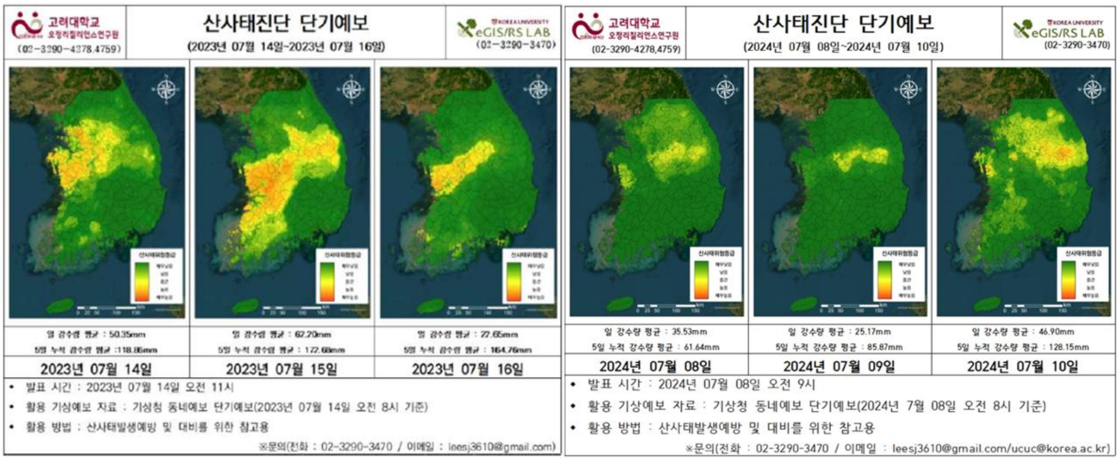

Figure 28 OJERI landslide early warning results[205]

4.2.2.2 Local-scale landslide prediction system

The KIGAM has developed its own Landslide Monitoring System, which integrates a physically-based prediction model for unsaturated slope failure under rainfall conditions with a pre-event meteorological analysis and forecasting system using weather radar data.[206] The core algorithm is a physically-based model that includes surface runoff analysis, infiltration flow analysis, and unsaturated infinite-slope stability analysis that incorporates suction stress.[207]

For pre-event meteorological analysis and forecasting, the system uses Local Data Assimilation and Prediction System (LDAPS) rainfall forecasts provided by the KMA along with weather radar data from Japan.[208] These datasets allow the system to acquire pre-event rainfall information in real time, up to one day before potential landslide occurrence. The current application area includes Mt. Jiri, located in the southern region of Korea, and surrounding national parks, where the system enables one-day-ahead landslide early warning services.[209] Although the system is

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[204] Ibid.

[205] OJERI (2023). 2023 Short-Term Landslide Hazard Forecast Map (July 14-16), as of 5:00 PM on July 13, 2026. https://ojeri.korea.ac.kr/board/news_view.asp?mode=mod&restring=%252Fboard%252Fnews%252Easp%253Fxsearch%253D0%253D%253Dxrow%253D5%253D%253DBoardID%253D1%253D%253Dpage%253D57&idx=448&page=57&BoardID=1&xsearch=1&cn_search=.

[206] Song, Y. S. et al. (2022, December). 기후변화 대응 산사태 조기경보시스템 개발 및 운영 현황(영문) [State-of-the-art on development and operation of landslide early warning system for climate change response]. *Journal of the Geological Society of Korea*, 58(4), 509-525. https://doi.org/10.14770/jgsk.2022.58.4.509.

KIGAM (2019, December). 기후변화 적응 산사태 조기경보기술 및 지질환경재해 리스크 제어기술 개발(영문) [Landslide early warning and risk control technology of geo-environmental hazards for climate change adaptation (GP2017-017-2019)]. https://scienceon.kisti.re.kr/srch/selectPORSrchReport.do?cn=TRKO202000005450.

[207] Lu, N. & Godt, J. W. (2008). Infinite slope stability under steady unsaturated seepage conditions. *Water Resources Research*, 44(11). https://doi.org/10.1029/2008WR006976.

[208] Song, H. et al. (2019). Evaluation of Rainfall Forecasts with Heavy Rain Types in the High-Resolution Unified Model over South Korea. *Weather and Forecasting*, 34, 1277-1293. 10.1175/WAF-D-18-0140.1. https://doi.org/10.1175/WAF-D-18-0140.1.

209 KIGAM (2023, October). 인공지능 기반 산불 예측 모델 개발(영문) [Development of an Artificial Intelligence-Based Forest Fire Prediction Model]. https://www.kigam.re.kr/gallery.es?mid=a20204000000&bid=0034&list_no=2804&act=view.

provided as a web-based service, access is restricted to responsible personnel and government officials, which limits public availability.

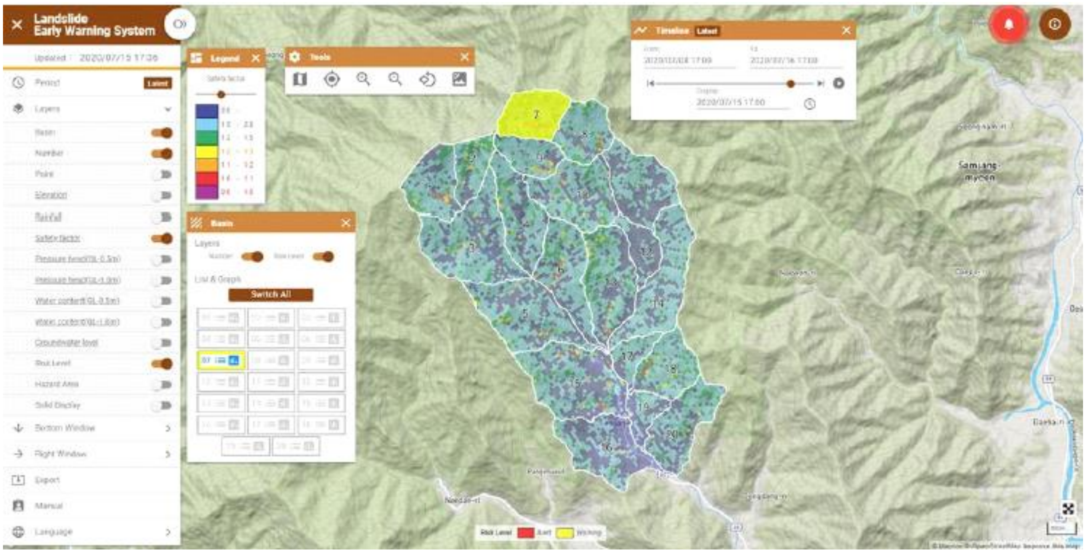

Figure 29 Landslide early warning system of Korea Institute of Geoscience and Mineral Resources[210]

4.2.2.3 Fine-scale landslide prediction model

Another landslide model, the YS-SLOPE Model developed by the research team at Yonsei University combines the hydrological rainfall infiltration and groundwater flow model YSGWF (Yonsei Ground-Water Flow) with an infinite-slope failure model.[211] To incorporate unsaturated soil properties, the model applies a modified Green-Ampt approach and uses Darcy's law along with GIS-based slope and flow-direction information for groundwater flow calculations. The Green–Ampt approach estimates the rate at which rainfall infiltrates into soil, while Darcy's law describes the movement of water through porous media such as soil or rock. Comparative analyses conducted at selected study sites have shown that the YS-SLOPE Model provides more accurate predictions than the Transient Rainfall Infiltration and Grid-based Regional Slope-Stability model (TRIGRS) framework because it accounts for both groundwater flow and wetness distribution simultaneously.[212] However, due to its detailed consideration of infiltration and saturation processes, the model is suitable mainly for local-scale applications. The prediction outputs are not provided through any web-based service.

Furthermore, the CRCritical Model developed by the research team at KAIST is a physically-based landslide evaluation framework designed to assess shallow landslides triggered by short-duration extreme rainfall events.[213] This model focuses on shallow failures occurring in areas with soil depths of less than 1 m and is based on the infinite-slope stability concept. Shallow failures refer to landslides that occur within shallow soil layers, typically less than 1-2 m

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[210] Song, Y. S. et al. (2022, December). 기후변화 대응 산사태 조기경보시스템 개발 및 운영 현황(영문) [State-of-the-art on development and operation of landslide early warning system for climate change response]. *Journal of the Geological Society of Korea*, 58(4), 509-525. https://doi.org/10.14770/jgsk.2022.58.4.509.

[211] Kim, J. H. et al. (2014, November). GIS-based prediction method of landslide susceptibility using a rainfall infiltration-groundwater flow model. *Engineering Geology*, 182, 63–78. https://doi.org/10.1016/j.enggeo.2014.09.001.

[212] Baum, R. L. et al. (2008, June). TRIGRS: A Fortran program for transient rainfall infiltration and grid-based regional slope-stability analysis, version 2.0. U.S. *Geological Survey Open-File Report*, 2008-1159, 75 p. https://pubs.usgs.gov/of/2008/1159/.

[213] Park, J. Y. et al. (2019, October). A regional-scale landslide early warning methodology applying statistical and physically based approaches in sequence. *Engineering Geology*, 260(3), 105193. https://www.sciencedirect.com/science/article/abs/pii/S0013795218318283.

deep. It calculates the factor of safety for forested slopes and simulates temporal variations in suction stress.[214] Although the CRCritical Model offers detailed physical assessments, its prediction outputs are not publicly available through a web service.

4.3 Forest pest and disease

4.3.1 National level

Driven by global warming and associated climate degradation, as well as increasingly active international trade, forest pests and diseases including invasive alien species have been on the rise. In response, the KFS is promoting research to identify and predict patterns of introduction, establishment, and spread of non-native forest pests, while also implementing continuous monitoring and control measures to manage forest health. As a result of these efforts, most forest pests other than pine wilt disease have shown a generally declining trend. However, several pest outbreaks have emerged in recent years, including the gypsy moth (*Lymantria dispar)* in 2020, stick insects (*Baculum elongatum*) in 2021, and the fall webworm (*Hyphantria cunea*) in 2022, with additional cases of overseas introduction being reported.[215]

Forest insect pests are defined based on their adverse impacts on humans and the benefits expected from forests, but they also play ecological roles as components of forest ecosystems.[216] Accordingly, control measures are selectively applied only when pest-induced damage exceeds a certain threshold. For other pest species, the KFS adopts a strategy of monitoring fluctuations in occurrence while guiding management in a way that maintains ecological balance.

To date, more than 1,500 species of forest insects have been identified in Korea.[217] Among these, only about ten species such as the pine needle gall midge (*Thecodiplosis japonensis*) are classified as major pests, while the remainder are considered potential or non-economic pests. Recently, the number of alien pests introduced from abroad has been increasing in tandem with expanding international trade, and climate change is further heightening the likelihood of these species establishing viable populations.[218] Among them, pine wilt disease, which affects pine species such as Pinus densiflora, P. koraiensis, and P. thunbergii, is of particular concern. Once infected, trees wilt and die within a short period. There is no curative treatment, and mortality reaches nearly 100%, making it the most critical forest pest issue Korea is currently facing.

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[214] Ibid.

[215] KFS (2024, September). Monthly forest pest information (No. 6, September 2024). https://www.forest.go.kr/kfsweb/cop/bbs/selectBoardArticle.do;jsessionid=C7eaS3aag92D0prBCD5s76N3j6rxX4hh9xE0epvaJUbOf8BKzjElaEYrk6SKdGDh.frswas02_servlet_engine5?nttId=3199695&bbsId=BBSMSTR_1069&pageIndex=1&pageUnit=10&searchtitle=title&searchcont=&searchkey=&searchwriter=&searchdept=&searchWrd=&ctgryLrcls=&ctgryMdcls=&ctgrySmcls=&ntcStartDt=&ntcEndDt=&orgId=&mn=NKFS_06_09_01&component=.

[216] Boyd, I. L et al. (2013, November). The consequence of tree pests and diseases for ecosystem services. *Science*, 342(6160), 1235773 https://www.science.org/doi/full/10.1126/science.1235773.

[217] Lee, J. W. et al. (2019, November). Insect fauna of Korea, Volume 13: Pteromalinae (Hymenoptera: Pteromalidae). *National Institute of Biological Resources*, Ministry of Environment, Korea. https://www.nibr.go.kr/aiibook/catImage/156/Insect%20Fauna%20of%20Korea%2013_12E.pdf.

[218] KFS (2025). Definition and classification of forest pests and diseases. https://www.forest.go.kr/kfsweb/kfi/kfs/cms/cmsView.do?cmsId=FC_001163&mn=AR04_02_01_02.

Since pine wilt disease was first detected in Busan in 1988, the number of infected trees surged to 2,180,000 in 2014.[219] Intensive control measures subsequently reduced the damage for several years, but from 2022 onward the disease has again entered a phase of nationwide expansion. According to recent KFS statistics, the number of infected pine trees over the past five years (2021–2025) was 307,919 in 2021 and 378,079 in 2022, before sharply increasing to 1,065,967 in 2023.[220] The figure then declined to 899,017 in 2024 but surged again to 1,486,338 in 2025, resulting in a cumulative total of 4,137,320 infected trees over the five-year period.[221] An analysis of the causes of newly infected and recurrently infected areas during this period revealed that 22 out of 30 cases were attributable to anthropogenic spread.[222]

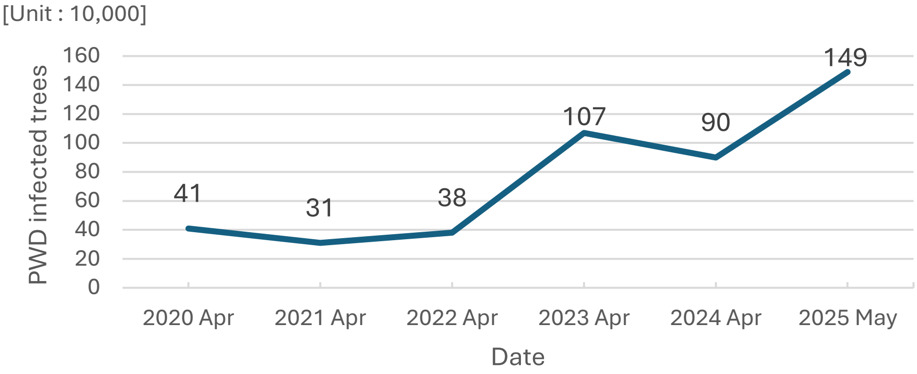

Figure 30 Annual trend of pine wilt disease damage in Korea[223]

Korea's forests are characterized by steep slopes and high-elevation terrain, where access by ground crews is often difficult. Given limited manpower and budgets, surveillance and control efforts must therefore be prioritized and spatially focused. To contain the spread of pine wilt disease, the KFS establishes differentiated regional strategies based on the severity and location of damage.[224] Areas where infections have occurred and adjacent zones at risk of spread are designated as "frontline zones," where intensive surveillance is conducted to prevent further expansion. In already affected areas, infected trees are felled, collected, and chipped or fumigated, and ecological restoration activities are carried out in parallel.[225] To minimize undetected gaps in surveillance, the KFS has introduced advanced technologies including drones, AI, and Near Field Communication (NFC) to complement conventional ground-based monitoring and to operate a year-round, continuous monitoring system.[226]

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[219] Shin, S. C., & Han, H. R. (1998, June). Pine wilt disease in Korea. *Plant Disease*, 82(6), 675–676 https://link.springer.com/chapter/10.1007/978-4-431-75655-2_5.

[220] KFS (2024). 최근 5 년(2020~2024 년)간 소나무재선충병 발생 현황(영문) [Status of Pine Wilt Disease Occurrence over the Past Five Years (2020–2024)]. Unpublished data provided to the Agriculture, Food, Rural Affairs, Oceans & Fisheries Committee.

[221] Bae, S. Y. (2025, September 10). 전국 곳곳 소나무재선충병 급속 확산 비상(영문) [Nationwide emergency as pine wilt disease spreads rapidly across the country]. *Segye Ilbo*. https://www.segye.com/newsView/20250909514750.

[222] Ibid.

[223] Bae, S. Y. (2025, September). 전국 곳곳 소나무재선충병 급속 확산 비상(영문) [Nationwide emergency as pine wilt disease spreads rapidly across the country]. *Segye Ilbo*. https://www.segye.com/newsView/20250909514750.

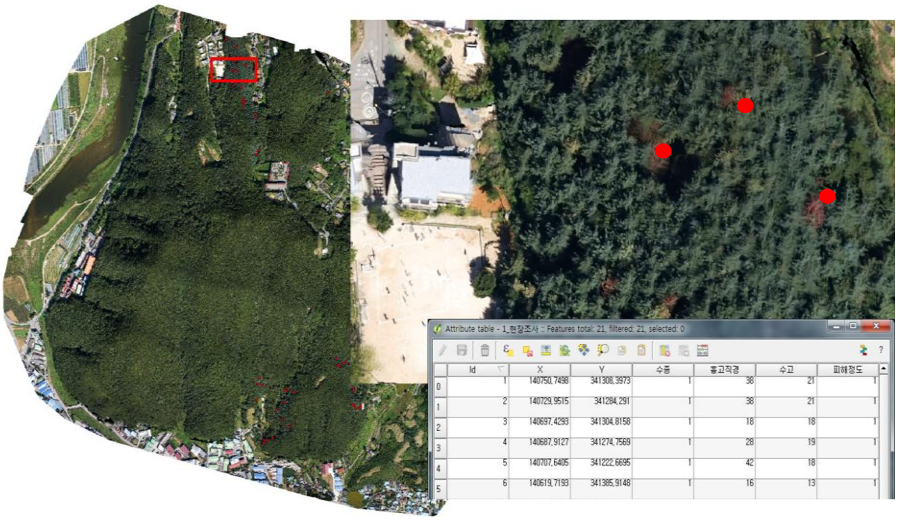
[224] Kwon, T. S. et al. (2011, December). Management of pine wilt disease in Korea through preventative silvicultural control. *Forest Ecology and Management*, 261(3), 562–569. https://www.sciencedirect.com/science/article/pii/S0378112710006675.

[225] Ibid.

[226] Ibid.

4.3.1.1 Drone-based monitoring

Frontline zones function as national-level defensive lines to prevent further spread of the disease. Because these areas are of high priority for control and management, comprehensive and gap-free surveillance is essential.[227] To this end, the KFS combines helicopter-based aerial monitoring with drone-based image acquisition. UAV imagery is processed into orthomosaics and spatially referenced, after which visual interpretation is used to identify dead and suspected trees.[228] The resulting information is provided to local governments in the form of maps and geospatial data layers, supporting their control operations. [229] Drone-based monitoring reduces the manpower and time required for frontline surveillance, lowers overall resource needs such as budget, and also serves as an important evidence base for local governments in assessing damage, planning control operations, and overseeing implementation.[230]



Attribute table - 1_현장조사 :: Features total: 21, filtered: 21, selected: 0

	Id	X	Y	수종	흉고직경	수고	피해정도
0	1	140750,7498	341308,3973	1	38	21	1
1	2	140729,9515	341284,291	1	38	21	1
2	3	140697,4293	341304,8158	1	18	18	1
3	4	140687,9127	341274,7569	1	28	19	1
4	5	140707,6405	341222,6695	1	42	18	1
5	6	140619,7193	341385,9148	1	16	13	1

Figure 31 Utilizing drones to produce orthophotos and detect dead trees

4.3.1.2 NFC-based electronic monitoring boxes

Human-based monitoring and patrols remain indispensable for forest pest management, particularly to prevent anthropogenic spread. Efficient deployment of personnel is also critical for field activities such as sampling to determine the causes of tree mortality. To support systematic and science-based integrated surveillance at the national level, the KFS performs optimal location analyses based on factors such as past occurrence locations and special protection areas and installs NFC-based electronic monitoring boxes at key access points and vantage points within each region.[231] Dedicated monitoring staff are assigned to these units, with patrol routes and inspection frequencies predefined and managed within the system.[232]

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[227] Syifa, M. et al. (2020, July). Detection of the Pine Wilt Disease Tree Candidates for Drone Remote Sensing Using Artificial Intelligence Techniques. *Engineering*, 6(8), 919–926. https://www.sciencedirect.com/science/article/pii/S2095809920301727.

[228] Ibid.

[229] Ibid.

[230] Ibid.

[231] Lee, K. W. (2017, July). 북부지방산림청, 'NFC 전자예찰함' 설치... 정밀예찰 실시(영문) [Northern Forest Service has installed an NFC Electron Surveillance box and is conducting precise Surveillance]. *Gangwon News*. https://www.gwnews.org/news/articleView.html?idxno=108223.

[232] Ibid.

Figure 32 Use of NFC electronic monitoring boxes and human-based surveillance[233]

4.3.1.3 Drone-based control operations

Among conventional control strategies, aerial application of insecticides using helicopters has been employed to kill insect vectors directly. However, this method has led to various issues, including complaints from nearby residents related to pesticide drift, attribution of honeybee mortality to aerial spraying, and reduced efficacy due to broad, non-target dispersion of chemicals.[234] To address these problems, the KFS has been phasing out helicopter-based aerial spraying and replacing it with drone-based control operations implemented by local governments nationwide. Drone-based control allows chemicals to be applied from low altitude and only within affected areas, thereby reducing the causes of public complaints and enabling highly targeted, intensive treatment of infestation sites. In addition, by employing DSM to support automated flight path planning, drones can maintain a constant height above the canopy and apply only the minimum amount of pesticide required for effective control, thereby improving overall efficiency.[235]

Figure 33 Comparison of helicopter-based aerial spraying and drone-based control operations[236]

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[233] Ibid.

[234] Kwon, T. S. et al. (2005, November). Effects of aerial insecticide sprays on ant communities to control pine wilt disease in Korean pine forests. *Applied Entomology and Zoology*, 40(4), 563–574. https://www.jstage.jst.go.jp/article/aez/40/4/40_4_563/_article.

[235] Kwon, T. S. et al. (2005, November). Effects of aerial insecticide sprays on ant communities to control pine wilt disease in Korean pine forests. *Applied Entomology and Zoology*, 40(4), 563–574. https://www.jstage.jst.go.jp/article/aez/40/4/40_4_563/_article.

[236] Kim, D. H. (2023, February 22). 산림청, 소나무재선충병 항공방제 중지. . ."위해성 우려. . .드론 · 지상 방제 전환"(영문) [Korea Forest Service Suspends Aerial Control of Pine Wilt Disease… “Concerns Over Potential Risks… Transition to Drone and Ground-Based Control.”]. 한국농어촌방송. https://www.newskr.kr/news/articleView.html?idxno=87382.

4.3.2 Academic and research level

4.3.2.1 Integration of UAV and satellite remote sensing with AI-based image analysis

Unmanned aerial vehicles (UAVs, drones) and satellite remote sensing have become key tools for monitoring and detecting forest pest damage across extensive forested areas in both space and time. Over the past six years, their use in Korean forest pest research has expanded rapidly.[237] These technologies alleviate the limitations of traditional ground, vehicle, and helicopter surveys in terms of accessibility, time, and cost, while providing high-resolution data that can capture pest damage at individual tree and stand scales.

You et al. (2020)[238] demonstrated that Red, Green, Blue (RGB) values and spectral vegetation indices derived from low-altitude UAV imagery can be used to distinguish pine trees damaged by pine wilt disease from healthy trees. RGB imagery refers to images composed of three visible light bands, red, green, and blue, which correspond to the wavelengths detectable by the human eye. Park et al. (2021)[239] summarized how advances in UAV imaging technology have eased challenges associated with large-area data collection and have begun to be applied in earnest to forest pest monitoring, including the interpretation of pine wilt damage. This marks a turning point in Korea, where the use of UAV imagery has expanded from basic mapping to dedicated pest surveillance.

UAV platforms allow flexible design of flight paths, altitudes, and revisit intervals, enabling repeated collection of remote sensing data at high spatial and temporal resolution.[240]

In Korean forest pest research, RGB visible imagery and multispectral imagery are most commonly used. Multispectral data, which include specific spectral bands such as near-infrared and red-edge (a narrow spectral region between red and near-infrared wavelengths where vegetation reflectance changes rapidly) that are sensitive to vegetation condition, are particularly advantageous for capturing early signs of pest infestation that are difficult to discern through visual observation alone.

The resulting high-resolution imagery is analysed using AI-based image processing techniques, including machine learning and deep learning. Random forest classifiers and CNNs, among other deep learning models, are frequently employed for UAV image analysis in forest health applications.[241]

Lim (2021)[242] investigated deep learning-based detection of pine wilt damage using UAV imagery and showed that deep learning models can improve both the efficiency and

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[237] Kang, D. (2021, October). Recent research trends of UAV-based forest pests and disease detection. *Journal of Next-generation Convergence Information Services Technology*, 10(5), 583–591. https://doi.org/10.29056/jncist.2021.10.10.

[238] You, J. H. et al. (2020, November). Detection of pine wilt disease using RGB-based low-altitude images and spectral vegetation indices from a drone. *Journal of Agricultural and Life Science*, 54(6), 21–27. https://www.kci.go.kr/kciportal/ci/sereArticleSearch/ciSereArtiView.kci?sereArticleSearchBean.artiId=ART002658646.

[239] Park, J. I. et al. (2021, August). Analysis of trees damaged by pine wilt nematodes using unmanned aerial images. *Journal of the Korean Cadastre Information Association*, 23(2), 78–86. https://doi.org/10.46416/JKCIA.2021.08.23.2.78.

[240] Zhang, Z. & Zhu, L. (2023, June). A Review on Unmanned Aerial Vehicle Remote Sensing: Platforms, Sensors, Data Processing Methods, and Applications. *Drones*, 7(6), 398. https://doi.org/10.3390/drones7060398.

[241] Kang, D. (2021, October). Recent research trends of UAV-based forest pests and disease detection. *Journal of Next-generation Convergence Information Services Technology*, 10(5), 583–591. https://doi.org/10.29056/jncist.2021.10.10 .

[242] Lim, E. T. et al. (2021, June). Pine wilt disease detection based on deep learning using an unmanned aerial vehicle. *KSCE Journal of Civil and Environmental Engineering Research*, 41(3), 317–325. https://koreascience.kr/article/JAKO202117563202992.page.

consistency of detection compared to human visual interpretation. Byun and Kang (2020)[243] reported that analysis of UAV-derived orthomosaics achieved an accuracy of over 70% in identifying trees suspected of pine wilt infection, demonstrating the potential of UAV imagery to complement and enhance conventional pest survey results.

Lee et al. (2023)[244] proposed a workflow for forest pest surveillance and automated control based on Real-Time Kinematic (RTK)-equipped Vertical Take-Off and Landing (VTOL) drone photogrammetry. In their study, infected tree polygons delineated from UAV imagery were used to generate automated control plans, establishing a spatially explicit process that links detection and operational control.

Overall, research integrating UAV/remote sensing with AI-based image analysis in Korea has focused primarily on specific host–pest systems, such as pine wilt disease in pine forests. This indicates potential for extension to other tree species, insect pests, and disease complexes.

4.3.2.2 AI-based prediction using meteorological, environmental, and outbreak history data

Early prediction and warning systems for forest pest outbreaks are essential for minimizing damage and improving the efficiency of control measures.[245] Meteorological, climatic, environmental, and historical pest occurrence data have been recently integrated to develop AI-based predictive models that estimate future probabilities of pest occurrence.[246]

In addition to regression- and classification-based machine learning approaches, spatial analysis methods that simulate spatio-temporal spread are also employed in pest occurrence prediction.

Lee et al. (2021)[247] developed Random Forest and MaxEnt models to predict the occurrence of Pine Wilt Disease (PWD) in Korea using geographic, meteorological, and land-use variables. Both models showed strong predictive performance, with elevation and distance to roads identified as key determinants of disease occurrence. The ensemble model, which integrates the two algorithms, further improved prediction accuracy and produced a national-scale PWD risk map. Under future climate scenarios, the study projected a substantial expansion of high-risk areas across the country.

Ha et al. (2023)[248] used MaxEnt to predict the potential distribution of pine wilt disease in Jinju City by incorporating a suite of environmental variables. MaxEnt, a regression-based probabilistic model, requires multiple layers of environmental covariates to estimate the

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[243] Byun, S. et al. (2020, March). Operation model for forest-UAV for detection of forest disease. *Journal of Platform Technology*, 8(1), 3–9. https://scienceon.kisti.re.kr/commons/util/originalView.do?cn=JAKO202022349952786&oCn=JAKO202022349952786&dbt=JAKO&journal=570784.

[244] Lee, D. K. et al. (2023, September). Process establishment of forest pest prediction and auto pest control based on RTK-VTOL drone photogrammetry. *Journal of Korean Society for Geospatial Information Science*, 31(3), 79–90. https://doi.org/10.7319/kogsis.2023.31.3.079.

[245] Wu, Q. et al. (2022, March). Research and Application of Crop Pest Monitoring and Early Warning Technology in China. *Frontiers of Agricultural Science and Engineering*, 9(1), 19–36. https://doi.org/10.15302/J-FASE-2021411.

[246] Wang, J., & Zhang, D. (2024, May). Intelligent pest forecasting with meteorological data: An explainable deep learning approach. *Expert Systems with Applications*, 252, 124137. https://doi.org/10.1016/j.eswa.2024.124137.

[247] Lee, D. S. et al. (2021, July). Predicting potential occurrence of pine wilt disease based on environmental factors in South Korea using machine learning algorithms. *Ecological Informatics*, 64, 101378. https://doi.org/10.1016/j.ecoinf.2021.101378.

[248] Ha, U. R. et al. (2023, December). Predicting potential distribution of the pine wilt disease using MaxEnt model in Jinju-si. *Journal of Agriculture & Life Science*, 57(6), 93–104. https://www.dbpia.co.kr/pdf/cpViewer?nodeId=NODE11778816.

likelihood of species occurrence. In that study, key input variables included climate data (e.g., temperature and precipitation), topographic indices (elevation, slope), soil properties, vegetation type, and distance to roads—all factors known to influence pest occurrence and spread.[249] These variables were compiled in a GIS environment and combined with observed pine wilt occurrence records for model training.[250] The resulting model outputs, visualized as maps of high-probability areas, demonstrated that such tools can support science-based decision-making by guiding the allocation of limited control resources to priority areas, emphasizing the importance of shifting from purely reactive control to proactive, prediction-based strategies.

Yoon et al. (2023)[251] simultaneously considered the potential spatial distribution of pine wilt disease and the climatic suitability of its insect vectors to evaluate current and future risk zones and to identify priority management areas for monitoring and control. Using pine wilt occurrence records from 2016–2020 and associated climatic and environmental variables, they constructed a MaxEnt model to estimate spatial variation in disease occurrence probability.[252] For the vector species, they applied the Climate Matching and Ecological Modeling (CLIMEX) model to derive climate suitability indices. By combining the two models in an ensemble framework, they delineated composite risk zones under both current and projected 2050 climate conditions.[253] Their results provide a robust scientific basis for designating priority monitoring areas, determining resource allocation strategies, and formulating climate change adaption measures, while also underscoring the need for higher-resolution climate and environmental data to further refine model performance.

4.3.2.3 Deep learning-based classification and object detection of suspected infected trees

Traditional labour-intensive surveillance approaches for forest pests demand considerable time and effort, which frequently leads to gaps in monitoring coverage in hard-to-access areas.[254] Although drone-based monitoring now allows large areas to be imaged rapidly, the identification and classification of dead or suspected infected trees in the imagery remain heavily dependent on expert visual interpretation. Applying such manual interpretation consistently across extensive forest landscapes at the provincial or national scale poses fundamental constraints in terms of labour, time, and consistency. To address these limitations, an increasingly combined high-resolution UAV imagery with deep learning and computer vision techniques can automatically detect and classify suspected infected trees (including dead and dying trees).

Studies have employed a range of data types, including RGB, multispectral, and time-series imagery, together with various deep learning architectures such as You Only Look Once (YOLO), a real-time object detection framework, CNN–based object detectors, and U-Net–type

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[249] Phillips, S. J. et al. (2006, July). Maximum Entropy Modeling of Species Geographic Distributions. *Ecological Modelling*, 190(3–4), 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026.

[250] Ibid.

[251] Yoon, S. et al. (2023, November). Ensemble evaluation of the spatial distribution of pine wilt disease mediated by insect vectors in South Korea. *Forest Ecology and Management*, 529, 120677. https://doi.org/10.1016/j.foreco.2022.120677.

[252] Ibid.

[253] Ibid.

[254] Ecke, S. et al. (2022, July). UAV-Based Forest Health Monitoring: A Systematic Review. *Remote Sensing*, 14(13), 3205. https://doi.org/10.3390/rs14133205.

semantic segmentation models. This line of research has emerged as a central direction for advancing national-scale forest pest surveillance.[255]

Among these, UAV RGB-based studies are the most active. Lim et al. (2022)[256] developed a YOLOv3-based detection model using 10 cm UAV imagery and DSMs to identify pine wilt-induced dead trees. Their model successfully detected 321 dead trees with a very high accuracy, demonstrating strong potential for practical field application. You et al. (2022)[257] used a large RGB dataset collected from 32 cities and 167 areas across the country and incorporated hard negative mining, extensive data augmentation, and test-time augmentation (TTA) to improve model generalization. In validation using full orthomosaic images, their model detected 711 out of 730 suspected infection points, indicating that data-driven detection technologies can feasibly support national-level operations.

Multispectral UAV studies are being conducted in parallel, contributing to improved detection of subtle early-stage discoloration and structural changes associated with infestation. Park et al. (2021)[258] constructed a multichannel object detection model that integrates spectral bands such as red-edge and near-infrared, achieving a mean Average Precision (mAP), a standard metric for evaluating object detection accuracy, of 86.63% and an Intersection over Union (IoU), which measures the overlap between predicted and ground-truth bounding boxes, of 71.47%.

Research focusing on deep learning-based semantic segmentation has also emerged, targeting more precise classification and spatial delineation of infected trees. Lee et al. (2023)[259] compared several segmentation models—including U-Net, SegNet, and DeepLabV3+ using time-series UAV imagery, and found that DeepLabV3+ delivered the highest performance.

Their findings demonstrate the feasibility of segmenting suspected infected trees as spatially explicit objects (e.g., pixel-level masks or tree-level polygons generated from segmentation outputs) rather than simple point features, thereby enabling more detailed analysis of stand-level conditions and temporal change.

Jung et al. (2024)[260] analysed performance differences among multiple object detection models under varying conditions, providing guidance on the stability and suitable application contexts of deep learning-based automatic detection systems.

More recently, researchers have begun to link detection outputs with spatial distribution modelling to enhance the practical utility of these technologies. Ha et al. (2025)[261] proposed a

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[255] Duarte, A. et al. (2022, June). Recent Advances in Forest Insect Pests and Diseases Monitoring Using UAV-Based Data: A Systematic Review. *Forests*, 13(6), 911. https://doi.org/10.3390/f13060911.

[256] Lim, W. et al. (2022). Efficient dead pine tree detecting method in the forest damaged by pine wood nematode (Bursaphelenchus xylophilus) through utilizing unmanned aerial vehicles and deep learning-based object detection techniques. *Forest Science and Technology*, 18(1), 36–43. https://doi.org/10.1080/21580103.2022.2048900.

[257] You, J. et al. (2022, March). A deep learning-based generalized system for detecting pine wilt disease using RGB-based UAV images. *Remote Sensing*, 14(1), 150. https://doi.org/10.3390/rs14010150.

[258] Park, H. G. et al. (2021, August). Multichannel object detection for detecting suspected trees with pine wilt disease using multispectral drone imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*,14, 8350–8358. https://ieeexplore.ieee.org/document/9507079.

[259] Lee, M. G. et al. (2023, August). Detection of pine wilt disease using time series UAV imagery and deep learning semantic segmentation. *Forests*, 14(8), 1576. https://doi.org/10.3390/f14081576.

[260] Jung, Y. et al. (2024, February). Harnessing synthetic data for enhanced detection of pine wilt disease: An image classification approach. *Computers and Electronics in Agriculture*, 218, 108690. https://doi.org/10.1016/j.compag.2024.108690.

[261] Ha, U. et al. (2025, September). Enhanced pine wilt disease outbreak prediction: Integrating deep learning-detected infected trees with species distribution modeling. *Ecological Informatics*,103421. https://doi.org/10.1016/j.ecoinf.2025.103421.

framework that integrates deep learning-based segmentation of infected trees with MaxEnt-based species distribution modelling. By incorporating time-series detection results and distance between infection sites as predictors, they demonstrated that variables representing actual spread dynamics can significantly improve model performance.[262] This work suggests that UAV-based deep learning detection can evolve beyond stand-alone monitoring to serve as an integral component of prediction, decision support, and risk zoning within broader forest health management systems.

Overall, Korean research on deep learning-based detection of suspected infected trees is advancing along several interconnected trajectories: the enhancement of UAV high-resolution image-based automatic detection; expansion of data types from RGB to multispectral and time-series imagery; evolution from simple detection to semantic segmentation and fine-scale object classification; and increasing integration of detection outputs with predictive and distribution models. Collectively, these efforts provide a foundation for automatically detecting suspected infected trees across large forested areas, quantifying the spatio-temporal dynamics of pest outbreaks, and designing scientifically grounded strategies for resource allocation and control. The convergence of UAV and deep learning technologies is expected to play a central role in the digital transformation of national forest pest surveillance, diagnosis, and early warning systems.

4.4 Potential opportunities

4.4.1 Global open data as entry points for forest disaster prediction

In many LMICs, the primary constraint in establishing forest disaster prediction systems is not the absence of advanced algorithms or computing capacity, but rather the limited availability of reliable baseline data and the lack of institutional frameworks to systematically utilize such information.[263] In recent years, however, a growing number of international organizations and space agencies have made disaster inventories, meteorological records, topographic data, and environmental datasets openly and globally accessible.[264]

These global open-access datasets provide a critical opportunity for countries where national disaster information systems are still under development to initiate basic diagnostic and predictive analyses. Rather than serving as complete solutions, they offer practical entry points for building foundational understanding of disaster occurrence patterns and risk drivers. This section introduces key globally available datasets relevant to forest disasters and discusses how they can be used as initial building blocks for progressively developing national-level forest disaster prediction and management systems.

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[262] Ibid.

[263] Gosling, J. et al. (2024, March). Lessons Learned from Health System Rehabilitation Preparedness and Response for Disasters in LMICs: A Scoping Review. *BMC Public Health*, 24, 806. https://doi.org/10.1186/s12889-024-17992-2.

[264] Olbrich, P. (2018, October). Open Space: The Global Effort for Open Access to Environmental Satellite Data. *Astropolitics*, 16(3), 230–236. https://doi.org/10.1080/14777622.2018.1534470.

4.4.2 Disaster inventory data

A systematic record of past disaster events, including their locations, timing, and magnitude, is a fundamental foundation for building predictive disaster models.[265] However, many low- and middle-income countries lack well-structured inventory systems, and their available records are often inconsistent or incomplete, making them difficult to use directly for modelling.[266] To help overcome these gaps, various international organizations provide global open-access disaster inventory datasets that can serve as a starting point for developing basic predictive models even in environments where national systems are not fully established.

In the case of forest fires, globally accessible data sources are particularly well developed. National Aeronautics and Space Administration (NASA) Fire Information for Resource Management System (FIRMS) provides real-time and near-real-time fire detections from Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS), as well as historical fire occurrence data.[267] These datasets can support analyses such as fire frequency assessment and the identification of spatial fire patterns.

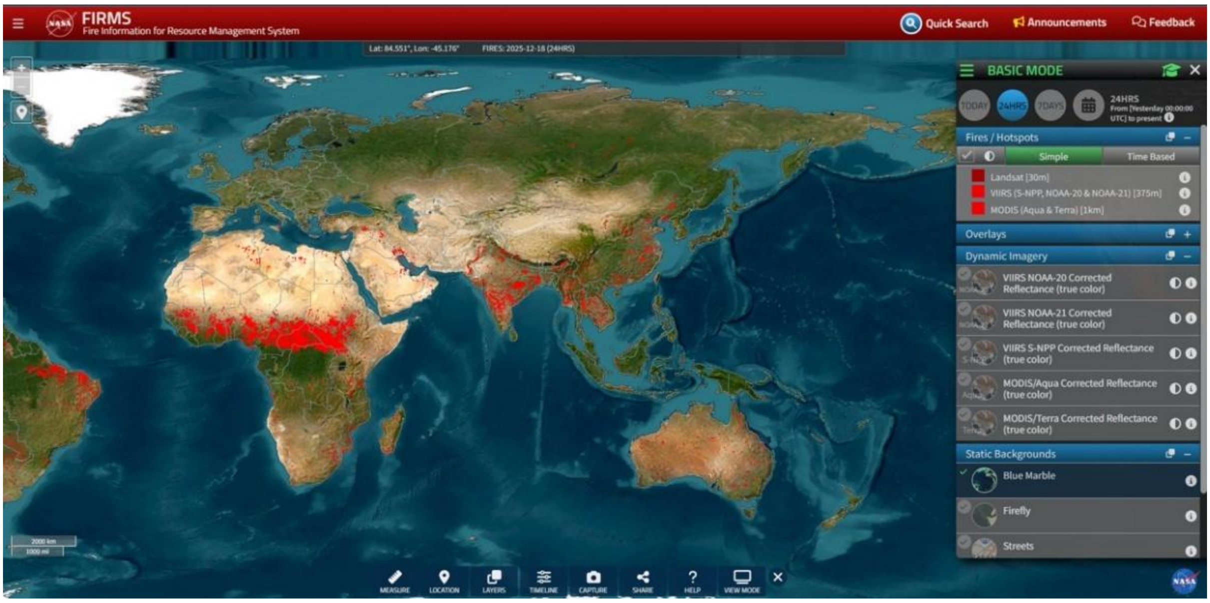

Figure 34 NASA FIRMS[268]

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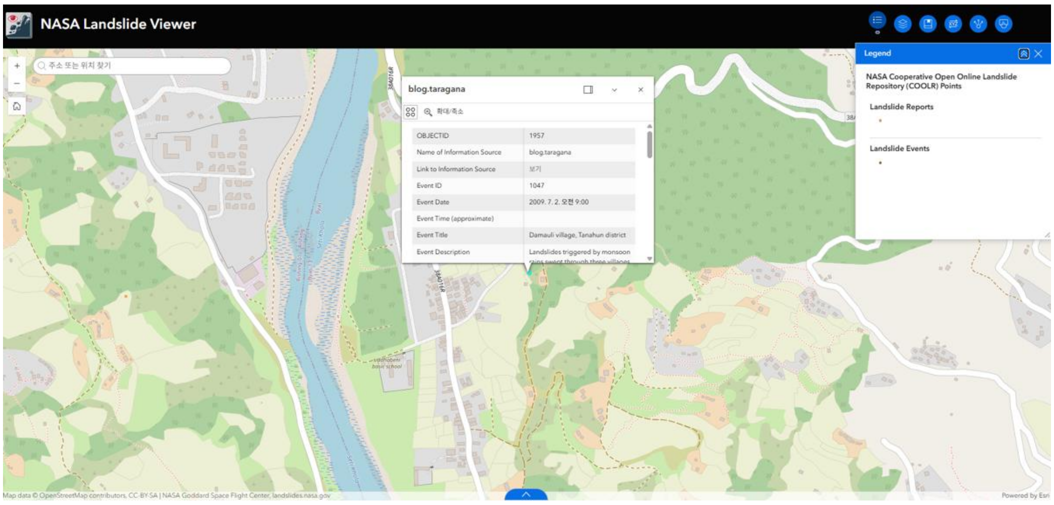
[265] Mazhin, S. A. et al. (2021, September). Worldwide Disaster Loss and Damage Databases: A Systematic Review. *Journal of Education and Health Promotion*, 10, 329. https://doi.org/10.4103/jehp.jehp_1525_20.

[266] Ibid.

[267] Davies, D. K et al. (2009, January). Fire Information for Resource Management System: Archiving and Distributing MODIS Active Fire Data. *IEEE Transactions on Geoscience and Remote Sensing*, 47(1), 72–79. https://doi.org/10.1109/TGRS.2008.2002076.

[268] NASA FIRMS (n.d.). Fire Information for Resource Management System (FIRMS). Screenshot taken on 18 December 2025.. https://firms.modaps.eosdis.nasa.gov/map/.

For landslides, NASA's Cooperative Open Online Landslide Repository (COOLR) is a representative global open-access dataset.[269] It provides information on landslide locations, dates, and triggering mechanisms such as rainfall or earthquakes. The data can be downloaded in several standard geospatial formats, including CSV (comma-separated values for tabular data), Shapefile (a widely used vector format for geographic features), and Geodatabase (a spatial database format for storing and managing geospatial datasets), which allows direct use in model development. When additional event information is required, satellite imagery, including optical and Synthetic Aperture Radar (SAR) data, as well as aerial photographs, can be used.[270] By comparing pre- and post-event imagery with reported damage information, detailed landslide inventories can be constructed.



OBJECTID	1957
Name of Information Source	blog.taragana
Link to Information Source	보기
Event ID	1047
Event Date	2009. 7. 2. 오전 9:00
Event Time (approximate)	
Event Title	Damauli village, Tanahun district
Event Description	Landslides triggered by monsoon

Figure 35 NASA COOLR viewer and an example of a landslide inventory in Nepal with detailed information[271]

4.4.3 Meteorological data

Meteorological variables such as precipitation, rainfall intensity, humidity, temperature, and wind speed serve as essential inputs for disaster prediction models. In countries where observational networks are limited, basic meteorological information can be obtained from the World Meteorological Organization's World Weather Information Service (WWIS).[272] For applications requiring higher resolution or more detailed analyses, global reanalysis or satellite-based datasets such as European Centre for Medium-Range Weather Forecasts (ECMWF) ReAnalysis (ERA5), NASA Prediction of Worldwide Energy Resources (POWER), and the Global Precipitation Measurement (GPM) mission can be used. Since precipitation measurement methods vary across institutions, selecting datasets that are appropriate for national disaster characteristics is important. These sources can be applied to estimating event likelihood, generating hazard indices, and conducting time-series assessments.

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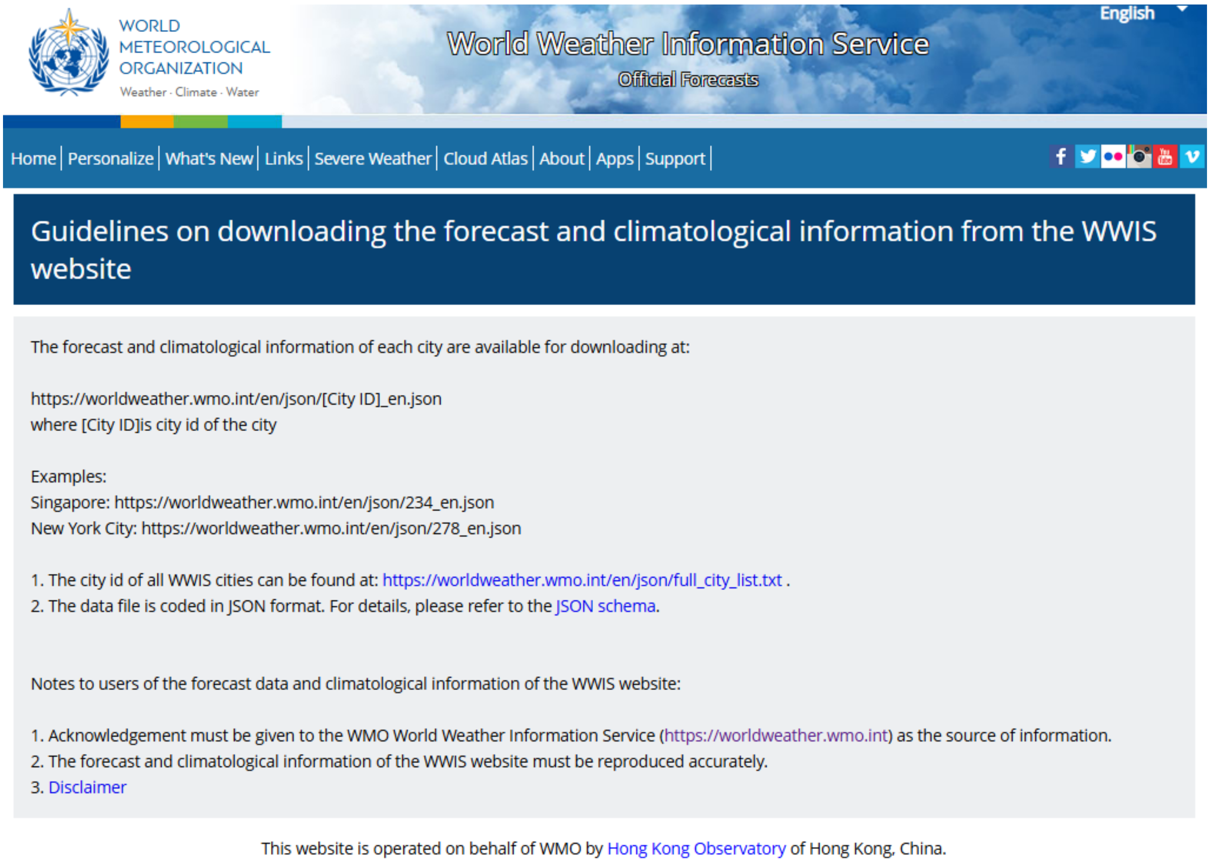
[269] NASA GPM (n.d.). Global Landslide Catalog. https://gpm.nasa.gov/landslides/index.html.

[270] Scaioni, M et al. (2014, October). Remote Sensing for Landslide Investigations: An Overview of Recent Achievements and Perspectives. *Remote Sensing*, 6(10), 9600–9652. https://doi.org/10.3390/rs6109600.

[271] NASA (n.d.). *NASA Landslide Viewer*. Screenshot taken on 18 December 2025. https://landslides.nasa.gov/viewer/.

[272] World Meteorological Organization (n.d.). World Weather Information Service data guide. https://worldweather.wmo.int/en/dataguide.html.



Guidelines on downloading the forecast and climatological information from the WWIS website

The forecast and climatological information of each city are available for downloading at:

https://worldweather.wmo.int/en/json/[City ID]_en.json
where [City ID]is city id of the city

Examples:
Singapore: https://worldweather.wmo.int/en/json/234_en.json
New York City: https://worldweather.wmo.int/en/json/278_en.json

1. The city id of all WWIS cities can be found at: https://worldweather.wmo.int/en/json/full_city_list.txt .
2. The data file is coded in JSON format. For details, please refer to the JSON schema.

Notes to users of the forecast data and climatological information of the WWIS website:

1. Acknowledgement must be given to the WMO World Weather Information Service (https://worldweather.wmo.int) as the source of information.
2. The forecast and climatological information of the WWIS website must be reproduced accurately.
3. Disclaimer

This website is operated on behalf of WMO by Hong Kong Observatory of Hong Kong, China.

Figure 36 WWIS guidelines on downloading the forecast and climatological information[273]

4.4.4 Topographic data

Korea provides high-resolution 5 m Digital Elevation Models (DEM) through its National Geographic Information Institute. In low- and middle-income countries, global elevation datasets such as NASA Shuttle Radar Topography Mission (SRTM) (30 m) and the Copernicus DEM are free available alternatives.[274] Google Earth Engine makes it possible to download or analyse DEMs for specific countries or regions through straightforward JavaScript-based workflows. Additionally, open-source GIS platforms such as QGIS can be used to derive topographic parameters including slope, aspect and curvature.[275]

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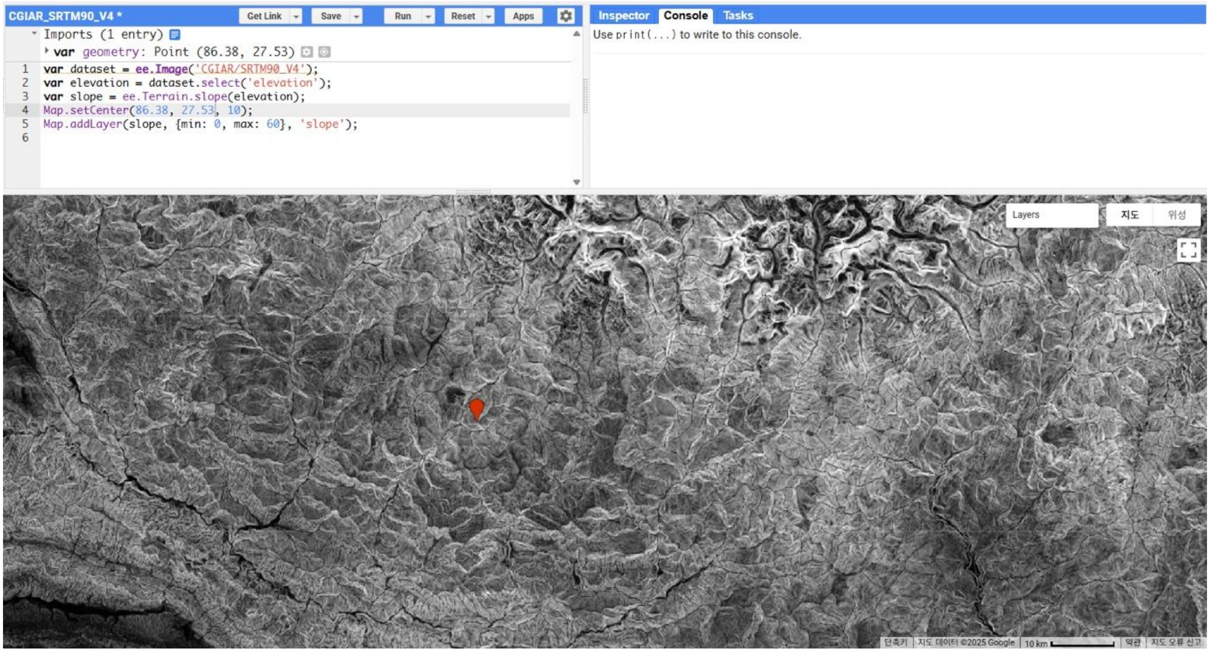
[273] WMO (n.d.). *World Weather Information Service*. Screenshot taken on 18 December 2025. https://worldweather.wmo.int/.

[274] Farr, T. G. et al. (2007, May). The Shuttle Radar Topography Mission. *Reviews of Geophysics*, 45(2), RG2004. https://doi.org/10.1029/2005RG000183.

Airbus Defence and Space (2022, November). Copernicus Digital Elevation Model Product Handbook. https://dataspace.copernicus.eu/sites/default/files/media/files/2024-06/geo1988-copernicusdem-spe-002_producthandbook_i5.0.pdf.

[275] Mattivi, P. et al. (2019, June). TWI Computation: A Comparison of Different Open Source GISs. *Open Geospatial Data, Software and Standards*, 4, 6. https://doi.org/10.1186/s40965-019-0066-y.



```
Imports (1 entry)
  var geometry: Point (86.38, 27.53)
var dataset = ee.Image('CGIAR/SRTM90_V4');
var elevation = dataset.select('elevation');
var slope = ee.Terrain.slope(elevation);
Map.setCenter(86.38, 27.53, 10);
Map.addLayer(slope, {min: 0, max: 60}, 'slope');
```

Use print(...) to write to this console.

Figure 37 Example of NASA Shuttle Radar Topography Mission (SRTM) digital elevation data in a mid-latitude mountainous region in Nepal (centered at approximately 86.38°E, 27.53°N)[276]

4.4.5 Environmental data

Environmental information, including land cover, soil properties and human-built features, plays an important role in identifying areas with higher disaster susceptibility. For land cover, widely used global datasets include European Space Agency (ESA) WorldCover (Sentinel-2 based, 10 m resolution) and the Copernicus Global Land Service.[277] Currently, the platform provides ESA WorldCover data together with Sentinel-1 and Sentinel-2 observations, allowing simultaneous access to land-cover and satellite-based environmental information. The WorldCover dataset consists of Version 1 and Version 2, where Version 1 represents land-cover conditions in 2020 and Version 2 provides information for 2021.[278] These datasets classify land cover into 11 categories, and Version 2 has been reported to achieve a global overall accuracy of 76.7%.[279] Sentinel-1 and Sentinel-2 data available through the platform are limited to observations acquired in 2020 and 2021. These datasets can be applied directly to analyses related to fuel characteristics for forest fires or susceptibility assessments for landslides. When higher-resolution information is required, Google Earth Engine can be used to develop customized classification models and generate localized land-cover maps.

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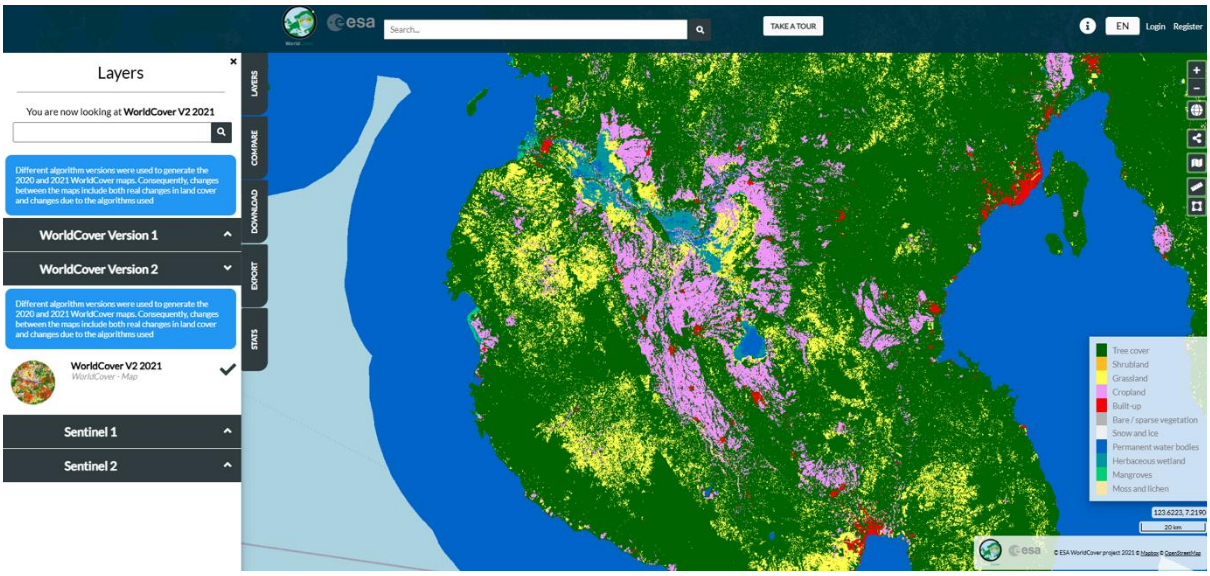
[276] SRTM DEM using Google Earth Engine. https://earthengine.google.com/. (Screenshot taken on 18 December 2025.)

[277] European Space Agency (n.d.). ESA WorldCover data access. https://esa-worldcover.org/en/data-access.

[278] Ibid.

[279] Zanaga, D. et al. (2021). ESA WorldCover 10 m 2020 v100. Zenodo. https://doi.org/10.5281/zenodo.5571936.



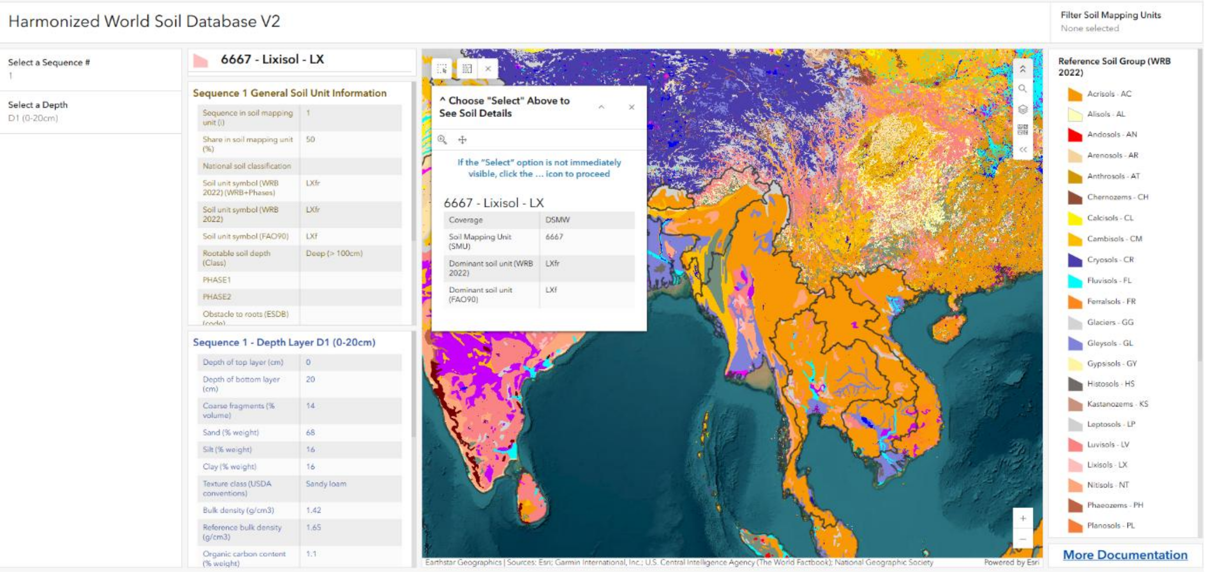
You are now looking at **WorldCover V2 2021**

Different algorithm versions were used to generate the 2020 and 2021 WorldCover maps. Consequently, changes between the maps include both real changes in land cover and changes due to the algorithms used

Different algorithm versions were used to generate the 2020 and 2021 WorldCover maps. Consequently, changes between the maps include both real changes in land cover and changes due to the algorithms used

Figure 38 An example of ESA WorldCover data for Southeast Asia[280]

Soil information is available through Harmonized World Soil Database (HWSD) developed by Food and Agriculture Organization of the United Nations (FAO). HWSD includes attributes such as soil depth, drainage class, and texture.[281] Because its spatial resolution is approximately 1 km, it may require refinement or supplementation when used in detailed modelling.



Select a Sequence #
1

Select a Depth
D1 (0-20cm)

6667 - Lixisol - LX

Sequence 1 General Soil Unit Information

Sequence in soil mapping unit (i)	1
Share in soil mapping unit (%)	50
National soil classification	
Soil unit symbol (WRB 2022) (WRB+Phases)	LXfr
Soil unit symbol (WRB 2022)	LXfr
Soil unit symbol (FAO90)	LXf
Rootable soil depth (Class)	Deep (> 100cm)
PHASE1	
PHASE2	
Obstacle to roots (ESDB)	

Sequence 1 - Depth Layer D1 (0-20cm)

Depth of top layer (cm)	0
Depth of bottom layer (cm)	20
Coarse fragments (% volume)	14
Sand (% weight)	68
Silt (% weight)	16
Clay (% weight)	16
Texture class (USDA conventions)	Sandy loam
Bulk density (g/cm3)	1.42
Reference bulk density (g/cm3)	1.65
Organic carbon content (% weight)	1.1

^ Choose "Select" Above to See Soil Details

If the "Select" option is not immediately visible, click the ... icon to proceed

6667 - Lixisol - LX

Coverage	DSMW
Soil Mapping Unit (SMU)	6667
Dominant soil unit (WRB 2022)	LXfr
Dominant soil unit (FAO90)	LXf

Figure 39 An example of FAO HWSD data for Southeast Asia[282]

At the global level, the UN Biodiversity Lab provides user-friendly access to geospatial datasets.[283] Designed for nonexpert users, it offers more than 400 datasets and a platform for

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[280] European Space Agency (n.d.). WorldCover Viewer. Screenshot taken on 18 December 2025. https://worldcover2021.esa.int/.

[281] FAO & IIASA (2023). Harmonized World Soil Database version 2.0. https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v20/en/.

[282] FAO (n.d.). Harmonized World Soil Database v1.2. FAO Soils Portal. Screenshot taken on 18 December 2025.

[283] UN Biodiversity Lab (2023). Why spatial data? https://unbiodiversitylab.org/wp-content/uploads/2023/07/UNBL-brochure_English.pdf.

data visualization, metadata access, and secure workspaces that enable users to explore and work with existing data repositories.[284]

4.4.6 Building capacity through stepwise data integration

The global datasets presented in this section should not be viewed merely as reference materials, but as practical foundations for the stepwise development of forest disaster prediction systems. In the initial phase, combining global disaster inventories with meteorological, topographic, and environmental data enables basic diagnostic modelling, such as identifying areas of recurrent hazard occurrence and assessing broad spatial patterns of vulnerability. These analyses can support the prioritization of high-risk regions and inform early-stage decision-making.

As national or sub-national observational data, field surveys, and administrative records become available, these global data-based models can be progressively calibrated and refined. This transition allows countries to move from raw diagnostic assessments toward more accurate short-term forecasting and early warning applications. Over time, accumulated experience in data integration and model operation can facilitate the development of context-specific forest disaster prediction systems that reflect local forest conditions, climatic characteristics and human activity patterns.

Accordingly, the datasets introduced in this section should be understood not as end products, but as starting points for strengthening forest disaster management capacity. Their effective use ultimately depends on parallel investments in institutional arrangements, technical capacity building, and operational workflows that enable data-driven decision-making to be sustained and scaled.

5. Conclusions and implications

5.1 Summary of key findings

Satellite-based monitoring real-time information-sharing platforms, and AI-based prediction tools are increasingly utilized in the areas of forest fires, landslides, and forest pests and disease control. In the management domain, technologies that support precise spatial analysis play a central role in assessing forest growth, monitoring species composition changes, and estimating carbon sequestration. These technological advancements strengthen the operational capacity of national systems while providing a foundation for more sophisticated model development within the research and academic sectors.

5.2 Policy implications

Korea’s experience demonstrates that the effective use of digital technologies in the forestry sector relies less on the technologies themselves and more on the systems that support them. Robust data production and management structures, mechanisms for inter-agency information sharing, professional workforce development, and legal and institutional support are essential

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[284] UN Biodiversity Lab (2023). Why spatial data? https://unbiodiversitylab.org/wp-content/uploads/2023/07/UNBL-brochure_English.pdf.

for ensuring that technologies function effectively in practice. When introducing new technologies, it is therefore critical to move beyond the acquisition of tools or software and to establish a clear strategy that identifies priority problems, responsible implementing bodies, and the institutional arrangements required for sustained operation.

For LMICs, the findings of Sections 3 and 4 suggest that digital forestry strategies can be pursued through a phased and scalable approach. Initial efforts can focus on the use of freely available global datasets and open platforms to establish basic forest monitoring, disaster risk assessment, and carbon accounting functions. As capacity increases, these foundational systems can be progressively enhanced through the integration of national field data, machine-learning-based mapping, and observation-based activity data. At the same time, investments in institutional coordination, human capacity building, and clear governance frameworks are essential to ensure that digital tools translate into concrete management actions and policy decisions. When these elements are addressed in combination, technology transfer and international cooperation can support practical, context-specific improvements in forest management and disaster response.

5.3 Research and innovation outlook

The analysis presented in this report indicates that future research and innovation in digital forestry should focus not merely on the adoption of new technologies, but on improving how existing data, models, and operational systems are integrated and applied. In particular, the cases reviewed in Sections 3 and 4 demonstrate that the greatest gains are achieved when remote sensing, field-based inventories, and analytical models are combined rather than used as stand-alone tools.

From a research perspective, priority areas include the development of observation-based forest information products that can directly support management and reporting needs, such as high-resolution forest type maps, biomass and carbon stock estimates, and spatially explicit risk indicators for forest fires, landslides, and pest outbreaks. Advancing methods that link time-series satellite data with national forest inventories will be important for improving consistency, transparency, and scalability across different spatial and institutional contexts. In this regard, machine-learning-based approaches may provide useful tools for analysing large volumes of satellite data, particularly as cloud-based platforms and open-source software increasingly lower technical and computational barriers for countries with limited resources.

From an innovation and implementation perspective, future efforts should emphasize operationalization: this includes designing systems that can be updated regularly with new data, are interpretable by non-specialist users, while being embedded within existing administrative and decision-making processes. For countries with limited technical capacity, the strategic use of open-source tools, cloud-based platforms, and modular system architectures offers a realistic pathway to incremental improvement, allowing national systems to evolve as data availability and institutional capacity grow.

Overall, the outlook for digital technologies in the forestry sector lies not in pursuing technologically sophisticated solutions in isolation, but in building integrated, context-sensitive systems that translate data and models into concrete management actions and policy decisions. Research and innovation efforts that prioritize usability, institutional fit, and long-term sustainability will deliver more impact on forest management and disaster risk reduction.

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