ЛЕСОУСТРОЙСТВО, ЛЕСОУПРАВЛЕНИЕ, ИНФОРМАЦИОННЫЕ ТЕХНОЛОГИИ И ГИС В ЛЕСНОЙ ОТРАСЛИ

DOI:10/58168/FECC2025_68-74
UDC 630(510):004.8:519.7

ANALYSIS OF KEY CHALLENGES IN DEVELOPING ARTIFICIAL INTELLIGENCE - DRIVEN SOFTWARE SOLUTIONS FOR FOREST MANAGEMENT IN CHINA

D.V. Koleda
Faculty of Computational Mathematics and Cybernetics, Shenzhen MSU-BIT University, Shenzhen, China; Federal State Budgetary Educational Institution of Higher Education Lomonosov Moscow State University, Moscow, Russia; dk.china@yandex.ru.

Abstract: This study explores the main challenges in developing artificial intelligence (AI)-driven software solutions for forest management in China, focusing on two ecologically and economically distinct provinces: Heilongjiang and Fujian. Findings show that limited data, environmental complexity, and regional differences in climate and forest types hinder AI implementation. Comparing the provinces shows how local factors affect AI performance and design.

Keywords: forest management; Heilongjiang Province; Fujian Province; artificial intelligence (AI); climate and environmental challenges; wildfire detection; biodiversity monitoring.

АНАЛИЗ ОСНОВНЫХ ПРОБЛЕМ ВОЗНИКАЮЩИХ ПРИ РАЗРАБОТКЕ ПРОГРАММНЫХ РЕШЕНИЙ НА БАЗЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА ДЛЯ УПРАВЛЕНИЯ ЛЕСНЫМИ РЕСУРСАМИ В КИТАЕ

Д. В. Коледа
Факультет вычислительной математики и кибернетики, Университет МГУ-ППИ в Шэньчжэне, Шэньчжэнь, Китай; Федеральное государственное бюджетное образовательное учреждение высшего образования «Московский государственный университет имени М.В.Ломоносова», Москва, Россия; dk.china@yandex.ru

Аннотация: В данном исследовании рассматриваются основные проблемы, возникающие при разработке программных решений на базе искусственного интеллекта (ИИ) для управления лесными ресурсами в Китае с акцентом на два экологически и экономически различных региона — провинции Хэйлунцзян и Фуцзянь. Результаты показывают, что ограниченность данных, сложность окружающей среды и региональные различия в климате и типах лесов затрудняют внедрение ИИ. Сравнение провинций по этим показателям демонстрирует, как местные факторы влияют на эффективность и проектирование ИИ-систем.

Ключевые слова: управление лесными ресурсами; провинция Хэйлунцзян; провинция Фуцзянь; искусственный интеллект (ИИ); климатические и экологические вызовы; обнаружение лесных пожаров; мониторинг биоразнообразия.

1. Introduction:

In 1978, China started the 'Great Green Wall' project—also known as the Three-North Shelterbelt Forest Program [1]. The country has been putting considerable effort into forest management to increase the forest coverage of the country from 16.7% (~157.1 Mha) to roughly 23.8% (~223.7 Mha) in 2022 [2]. Most recently, in 2025, it has been estimated that China has 142.6 billion trees, roughly 100 trees per person. This project increased the country's wood production throughout the years and significantly increased carbon sequestration. With the rapid developments in the field of AI, forest management has become an easier task, as AI can help in tree species identification, forest inventory analysis, wildlife monitoring, biomass estimation, carbon sequestration, etc. However, with these benefits also come challenges such as limited data, environment complexity, and canopy layering interference.

2. Characteristics of objects:

This article will focus on two provinces, one from the north and one from the south of China, comparing AI technologies used, how they work, and what challenges they face. The two provinces chosen are Heilongjiang (North) and Fujian (South).

Heilongjiang Province is in the northeast region of China, bordering Russia. The province's cities face cold winters, averaging at a low of around -23 degrees Celsius in January, and rainy but warm summers, with an average of 28 degrees Celsius in July [3, 4]. The highest average precipitation occurs in July, with a 120mm average throughout the province. In Heilongjiang Province, the mountainous regions are densely covered with forests, primarily consisting of conifers or a combination of coniferous and broad-leaved trees. Typical species include red and white pines, Manchurian ash, cork trees, and catalpas [5]. In Heilongjiang, AI applications directly support the province's forest management priorities—such as wildfire detection, carbon emission monitoring, and optimizing timber logistics in harsh climates.

Fujian Province is positioned right across Taiwan island and is southeast of China. Since the province is located just above the Tropic of Cancer, it has a subtropical climate, meaning mildly cold winters, with an average low of 8 degrees Celsius in January, and hot summers, with average highs of 33 degrees Celsius in July [6, 7]. The rainfalls are at an average of 195mm. In Fujian Province, most forests are subtropical and laurel-leafed, with deciduous trees, conifers, and flowering shrubs like rhododendrons being trees found higher up on mountains [8]. In this province, the main aims of forestry are bamboo and fast-growing plantations, biodiversity conservation, and carbon sequestration. In Fujian, AI helps monitor biodiversity, enhance carbon sequestration, and improve efficiency in bamboo and fast-growth plantations.

3. Methods:

To examine the main challenges in developing AI-driven software solutions for forest management in China, this study analyzes the use of neural network-based machine learning techniques, particularly deep learning models such as convolutional neural networks (CNNs). These models are commonly optimized via gradient-based learning methods to minimize error across training datasets composed of remote sensing imagery, forest inventory data, and environmental metrics. CNNs are particularly suited for analyzing spatial patterns from satellite data, such as Sentinel-1 SAR time series, which are widely used for tasks like forest harvesting detection and land cover classification [9]. Feature preprocessing methods, including normalization and dimensionality reduction, are also commonly applied to enhance model performance and generalization in these applications.

4. Results/Observations:

4.1. Heilongjiang Province:

4.1.1. Wildfire Detection and Predictions:

In the province of Heilongjiang, where winters are long and harsh, the spring and summer seasons tend to increase the risk of wildfires, some due to lightning strikes, others from agricultural fires, and many others - most of these fires happening in April [10]. Through the years, AI technologies such as convolutional neural networks (CNNs) models trained by satellite data, such as Sentinel-2 and Gaofen series imagery, have been incorporated into predicting and detecting wildfires. Over the years, these models have become significantly more effective in detecting changes in vegetation indices and thermal anomalies to identify the early stages of wildfires. Such visual fire-detecting systems as YOLOv5 and EfficientNet, which are based on deep learning, have proven to have accuracy levels between 85% and 96% in benchmark evaluations [11]. These are helpful during the season of high wildfire risks. Furthermore, AI-driven probability models have been developed to predict wildfire risks that integrate the following factors: forest dryness indices, human activity layers, and historical fire records. They have achieved high predictive performance across seasonal datasets [12].

The main challenge related to detecting and predicting wildfires is the lack of sufficient data. Publicly available wildfire datasets are limited, and this hinders the ability to train and validate high-performing AI models. Due to this deficiency in information/data, it has become common for researchers to either construct their own datasets or use small-scale ones that are available [11].

Another difficulty lies in detecting early or small fires. Since wildfires typically ignite at the forest floor and progress upward, initial flame activity often remains obscured beneath the canopy, making them hard to detect. Moreover, because these fires create minimal smoke and have a low thermal signature, these fires have a huge visual complexity. With such conditions, AI technologies would have a hard time differentiating the wildfires from other phenomena of the forest.

One more critical challenge in identifying and predicting wildfires is the harsh weather conditions. If the wildfire were to occur during the end of winter or early spring, the snow, cloud layers, or low solar angles could be a disturbance to the satellite in capturing images/videos of smoke and fire. Additionally, in mountainous areas the wind could be unpredictable, making it hard for AI-driven predicting modules to estimate where the fire is going to go based on past datasets.

4.1.2. Carbon Emissions Monitoring and Prediction:

Beyond wildfire detection, AI technologies have also been applied in Heilongjiang for carbon emissions monitoring and prediction, particularly in line with China's "Dual-Carbon" strategy [13]. Machine learning models have been used to analyze the temporal and spatial evolution of carbon emissions across the province's major sectors, including forestry, agriculture, industry, and energy. To simulate future carbon emission scenarios and predict peak emission timelines, land use classifications, economic activity layers, and forest carbon stock estimates are being used. AI tools have proven especially valuable in detecting regional disparities in emissions and identifying potential pathways to accelerate carbon reduction.

However, several challenges persist. One limitation arises from variations in data detail and the absence of uniform standards across different regions of Heilongjiang, especially in rural or heavily forested areas. Additionally, dynamic economic and environmental factors, such as fluctuations in timber harvesting or industrial development, make it difficult to make stable long-term predictions. It is also becoming increasingly important to integrate real-time forest carbon sequestration data, which is often challenging to acquire consistently due to seasonal weather conditions and limitations in current remote sensing infrastructure. Nonetheless, AI-assisted carbon forecasting models will continue to help shape provincial policies and assist Heilongjiang in making their province more sustainable.

4.2. Fujian Province:

4.2.1. Monitoring Biodiversity:

In Fujian Province, AI is increasingly being adopted to enhance biodiversity monitoring within forest ecosystems, particularly in protected mountainous regions. Projects such as the PRISM AI-powered biodiversity monitoring initiative leverage machine learning algorithms in combination with sensor data, satellite imagery, and acoustic monitoring to detect the presence of various species and track ecosystem changes over time [14]. These systems can automatically identify animal calls, detect changes in canopy cover, and flag anomalies in species distribution that might indicate ecological disruption.

While this technology dramatically increases the spatial and temporal resolution of biodiversity assessments, challenges remain. Implementation gaps—such as inconsistent field data collection, limited AI literacy among forest rangers, and administrative fragmentation—undermine the full effectiveness of these systems in Fujian [15]. In many protected areas, conservation plans are not always enforced as intended, resulting in discrepancies between AI-detected trends and actual on-the-ground outcomes. Additionally, dense subtropical forests and complex mountainous terrain in Fujian introduce environmental noise that can reduce the accuracy of AI classification models, especially when using acoustic or visual sensors.

4.2.2. Improving Efficiency in Bamboo and Fast-growth Plantations:

AI is also being progressively utilized to enhance the efficiency of bamboo and fast-growing plantations in Fujian, which aligns with the goals of sustainable forestry. One notable example of this is ZHUART, a bamboo enterprise based in Jianyang, which has integrated AI and automation into its production processes. ZHUART has developed intelligent robotic systems for bamboo strand processing, bundling, and transportation, collaborating with Fuzhou University and Nanjing Forestry University. These innovations have significantly improved production efficiency by reducing labor requirements and energy use while also emphasizing eco-friendly practices and the production of biodegradable bamboo goods [16].

AI is also used in mapping and monitoring Moso bamboo forests through methods like hyperspectral imaging and satellite time series, which help track forest health and productivity for better management planning [17, 18].

Despite these advancements, challenges remain. Implementing AI systems requires considerable investment and technical expertise, which may be limited in rural or under-resourced areas. Furthermore, the effectiveness of AI applications depends heavily on high-quality, consistent data, which is often difficult to collect due to environmental conditions and resource constraints.

5. Discussion:

As observed, the two provinces of Heilongjiang and Fujian employ distinct AI models tailored to their unique forest management needs. Heilongjiang primarily focuses on wildfire detection and carbon emission monitoring, while Fujian's AI applications center around biodiversity tracking and enhancing the efficiency of bamboo plantations. Given the differences in their objectives, the AI tools deployed in these provinces are vastly different, making direct comparisons of performance challenging. This disparity highlights a key issue in the development of AI-driven solutions for forest management: the difficulty of creating a universal AI tool that works effectively across diverse regions. Factors such as climatic conditions, forest composition, and economic priorities play a significant role in shaping the design and application of AI technologies. As a result, AI models must be specifically tailored to regional contexts to optimize their effectiveness. Additionally, the case studies from both provinces reveal that one of the most persistent challenges AI models face is data inconsistency or insufficiency. While this issue is expected to diminish over time as more data becomes available, overcoming it will require continued investment in data collection infrastructure and increased efforts in training personnel and securing funding to ensure proper implementation and long-term sustainability of AI systems.

5.1. How do regional factors influence AI implementation?

5.1.1. Climate:

Cold climates and harsh winters, like in Heilongjiang Province, pose challenges to real-time sensing and image clarity. As a result, AI models should be built and adapted to seasonal variations.

On the other hand, the humid subtropical climates of Fujian Province also create difficulties for AI models. Due to high rainfall, dense vegetation layers must be processed, and frequent cloud cover in satellite imagery must be dealt with.

5.1.2. Forest type:

In northern coniferous or mixed forests, AI is needed to, for example, detect and predict wildfires and timber logistics. Whereas in southern subtropical forests and bamboo plantations, such problems don't exist, they are more concerned with biodiversity monitoring, species classification, etc.

5.1.3. Economic focus:

Heilongjiang's focus is on timber production, forest conservation, as well as wildfire prevention. Hence, AI is invested in surveillance systems, early warning, and sustainable harvesting. In contrast, Fujian has an economic reliance on its bamboo products, biodiversity-rich reserves, and tourism, making the province more interested in resource efficiency, biodiversity tracking, and AI-enhanced conservation policies.

6. Conclusion:

This study has shown that AI technologies, such as Convolutional Neural Networks (CNNs) for wildfire detection and ZHUART for biodiversity monitoring, are being integrated into forest management in provinces like Heilongjiang and Fujian, respectively. As AI continues to advance globally, it has become an essential tool in many different fields, including forestry. AI-driven solutions are crucial in helping China achieve its goals of improving sustainability and carbon sequestration in the rapidly growing forest industry.

However, as demonstrated in Heilongjiang and Fujian, it is important to consider many different factors such as climate, forest composition, and economic priorities when developing these AI tools. Despite the promising results, challenges such as limited datasets, environmental complexities, and the need to make a universal model remain significant barriers.

For future improvements, efforts should be put into collecting more data and improving the AI model interpretability for decision-making and policy adoption.

With the rapid growth and development of AI technologies, the future of China's forestry looks promising, offering new opportunities for more efficient and sustainable environmental stewardship.

References

1. Chinese scientists use laser drones to count the country's trees — all 142.6 billion of them // Live Science. – URL: https://www.livescience.com/planet-earth/plants/chinese-scientists-use-laser-drones-to-count-the-countrys-trees-all-142-6-billion-of-them (accessed: 31.05.2025).

2. China – Forest Monitoring Dashboard // Global Forest Watch. – URL: https://www.globalforestwatch.org/dashboards/country/CHN/ (accessed: 31.05.2025).

3. Weather in Heilongjiang // ChinaDiscover.net. – URL: http://www.chinadiscover.net/heilongjiang-tourism/heilongjiang-weather.htm (accessed: 31.05.2025).

4. Climate of Harbin, China // Weather Atlas. – URL: https://www.weather-atlas.com/en/china/harbin-climate (accessed: 31.05.2025).

5. Heilongjiang // Encyclopaedia Britannica. – URL: https://www.britannica.com/place/Heilongjiang (accessed: 31.05.2025).

6. Average Weather in Fuzhou, China – Year Round // WeatherSpark. – URL: https://weatherspark.com/y/133373/Average-Weather-in-Fuzhou-China-Year-Round (accessed: 31.05.2025).

7. Average Weather in Longyan, China – Year Round // WeatherSpark. – URL: https://weatherspark.com/y/131370/Average-Weather-in-Longyan-China-Year-Round (accessed: 31.05.2025).

8. Fujian // Encyclopaedia Britannica. – URL: https://www.britannica.com/place/Fujian (accessed: 31.05.2025).

9. Ting Y., Li J., Ma L., Zhou J., Wang R., Eichhorn M. P., Zhang H. Status, advancements and prospects of deep learning methods applied in forest studies // International Journal of Applied Earth Observation and Geoinformation. – 2024. – Vol. 131. – Article 103938. – URL: https://doi.org/10.1016/j.jag.2024.103938 (accessed: 31.05.2025).

10. Jiao Q., Fan M., Tao J., Wang W., Liu D., Wang P. Forest fire patterns and lightning-caused forest fire detection in Heilongjiang Province of China using satellite data // Fire. – 2023. – Vol. 6. – Article 166. – URL: https://doi.org/10.3390/fire6040166 (accessed: 31.05.2025).

11. Cheng G., Chen X., Wang C., Li X., Xian B., Yu H. Visual fire detection using deep learning: A survey // Neurocomputing. – 2024. – Vol. 596. – Article 127975. – URL: https://doi.org/10.1016/j.neucom.2024.127975 (accessed: 31.05.2025).

12. Wu Z., Li M., Wang B., Quan Y., Liu J. Using Artificial Intelligence to Estimate the Probability of Forest Fires in Heilongjiang, Northeast China // Remote Sensing. – 2021. – Vol. 13, Article 1813. – URL: https://doi.org/10.3390/rs13091813 (accessed: 31.05.2025).

13. Yu Z., Zhang M., Zhan Y., Guo Y., Zhang Y., Liang X., Wang C., Fan Y., Shan M., Guo H., Zhou W. Analysis of Temporal and Spatial Evolution Characteristics and Peak Predic tion of Carbon Emissions in China Under the Dual-Carbon Target: A Case Study of Heilongjiang Province // Agriculture. – 2025. – Vol. 15, Article 1126. – URL: https://doi.org/10.3390/agriculture15111126 (accessed: 31.05.2025).

14. AI-powered biodiversity monitoring in forest ecosystems // PRISM – Sustainability Directory. – URL: https://prism.sustainability-directory.com/scenario/ai-powered-biodiversity-monitoring-in-forest-ecosystems/ (accessed: 31.05.2025).

15. Wang W., Zhai D., Huang B. Implementation gaps affecting the quality of biodiversity conservation management: An ethnographic study of protected areas in Fujian Province, China // Forest Policy and Economics. – 2023. – Vol. 152. – Article 102933. – URL: https://doi.org/10.1016/j.forpol.2023.102933 (accessed: 31.05.2025).

16. ZHUART: Pioneering Innovation to Drive Bamboo Industry Growth // ZhuArt Bamboo. – URL: https://zhuartbamboo.com/zhuart-pioneering-innovation-to-drive-bamboo-industry-growth/ (accessed: 31.05.2025).

17. Qi S., Song B., Liu C., Gong P., Luo J., Zhang M., Xiong T. Bamboo Forest Mapping in China Using the Dense Landsat 8 Image Archive and Google Earth Engine // Remote Sensing. – 2022. – Vol. 14, Article 762. – URL: https://doi.org/10.3390/rs14030762 (accessed: 31.05.2025).

18. He A., Xu Z., Li Y., Li B., Huang X., Zhang H., Guo X., Li Z. Monitoring Moso bamboo (Phyllostachys pubescens) forests damage caused by Pantana phyllostachysae Chao considering phenological differences between on-year and off-year using UAV hyperspectral images // Geo-spatial Information Science. – 2025. – Published online: 04.02.2025. – URL: https://doi.org/10.1080/10095020.2025.2454521 (accessed: 31.05.2025).