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INTEGRATING ARTIFICIAL INTELLIGENCE IN FORESTRY EDUCATION: A FRAMEWORK FOR GOVERNANCE, INSTITUTIONAL CAPACITY, AND CURRICULUM INNOVATION

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Abstract: Artificial intelligence is transforming forestry practice through applications in remote sensing, wildfire prediction, pest detection, and biomass estimation. Yet, the integration of AI into forestry higher education remains fragmented, shaped less by technology than by governance structures, institutional capacity, and curricular design. This study conducts a comparative analysis of five national models including China's centralized, the United States' decentralized, Germany's regionally collaborative, Australia's crisis responsive, and Brazil's community focused approaches to examine how policy frameworks influence educational outcomes. We hypothesize that governance models create trade-offs between scale, innovation, equity, and pedagogical depth. Using policy documents, institutional reports, and curricula, we develop two novel tools: a Forestry Specific AI Competence Framework and a Comparative Curriculum Taxonomy. Findings reveal that centralized systems achieve rapid scale but risk superficial depth, while decentralized systems foster innovation yet exacerbate inequality. Collaborative and mission driven models offer more balanced pathways. The study contributes an evidence based hybrid governance model that blends strategic coordination with localized innovation, providing actionable guidance for building an equitable, practice oriented global forestry workforce.
Keywords: Artificial Intelligence, Forestry Education, AI Competence Framework, Educational Equity, Sustainable Forestry

INTRODUCTION

Forests comprise essential ecosystems on Earth, supporting climate regulation, biodiversity preservation, water security, and the livelihoods of millions (Raman, Manalil et al. 2024). In response to rapid ecological deterioration and global climate change, the forestry sector is progressively leveraging digital technology, especially artificial intelligence (AI), to enhance monitoring, planning, and decision-making processes (Feng, Yang et al. 2024, Hegde, Clara Manasa et al. 2025) AI algorithms are now capable of categorizing tree species from satellite imagery, forecasting wildfire danger, identifying pests and diseases using UAV-acquired data, and assessing biomass with enhanced precision (Ahmad, Gilani et al. 2021, Wang, Zuo et al. 2025) These tools are fundamentally transforming the competencies required of forestry professionals, creating an urgent imperative for higher education to adapt its curricula (Waeber, Melnykovych et al. 2023). However, the systematic integration of AI into forestry higher education remains globally fragmented and poorly understood (Vettriselvan and Ramya 2025). While technological applications have been extensively studied, previous research has largely neglected a critical determinant of adoption: the profound influence of national governance structures, institutional capacity, and curriculum design (Damaševičius and Maskeliūnas 2025, Wang, Zhang et al. 2025).
The velocity, breadth, and quality of this integration are not merely a function of technical availability but are significantly shaped by divergent policy frameworks and economic priorities worldwide. This gap is particularly pressing as universities worldwide are expected to produce AI-literate graduates despite a lack of standardized models, trained faculty, and proven competency frameworks (Singh, Sinha et al. 2024, Dong, Zhang et al. 2025).
Five countries, including China, U.S., Germany, Brazil, and Australia, were chosen to represent a range of governance structures (centralized, decentralized, and regionally collaborative) and ecological environments in order to address this. Our study uses a comparative multiple-case analysis to accomplish this. We hypothesize that these different governance frameworks create particular trade-offs between scale, innovation, equality, and pedagogical depth, hence determining the nature of AI integration.
This study aims to fill these gaps by conducting a comparative analysis of AI integration in forestry higher education across the five selected countries. The specific objectives are to:
1. Examine the effects of governance frameworks and institutional capabilities on the incorporation of AI curricula.
2. Evaluate faculty readiness, resource distribution, and the potential for experiential learning.
3. Develop a forestry-specific AI Competence Framework and a comparative curricular taxonomy to guide the fair and practice-oriented use of AI in forestry education worldwide.
This paper contends that the development of effective global AI education strategies necessitates a detailed comprehension of these governance-driven pathways. This research makes three primary contributions by analyzing the

impact of national models on curriculum implementation, faculty readiness, and resource distribution. These contributions include an empirical, multi-level analysis of AI integration, a novel, forestry-specific AI Competence Framework, and a comparative curriculum taxonomy. Additionally, the study provides evidence-based guidelines for promoting equitable, practice-oriented AI education in forestry across diverse national systems.

LITERATURE REVIEW

Applications of Artificial Intelligence in Forestry Practice

Artificial intelligence has swiftly become a revolutionary influence in forestry, altering monitoring, prediction, and management methodologies globally. Remote sensing integrated with machine learning allows extensive categorization of tree species, calculation of canopy density, and detection of changes in forest cover (Brandt, Chave et al. 2025). Convolutional neural networks (CNNs) and other deep learning methodologies have been extensively used in unmanned aerial vehicle (UAV) imaging for rapid detection of disease and pest outbreaks, offering managers near real-time decision-making assistance (Shahi, Xu et al. 2023). Biomass estimate, formerly dependent on allometric equations and field inventories, has been markedly enhanced by AI-driven prediction models that use multispectral and hyperspectral satellite data. These advancements are particularly pertinent to carbon accounting systems, where precision is essential for climate policy and international reporting (Augoye, Muyiwa-Ajayi et al. 2024).

Another important use is wildfire forecasting. In advanced environments, such as the U.S., AI-augmented models based on recurrent neural networks (RNNs) and ensemble learning approaches are being integrated into state and federal early warning systems (Liu, Shu et al. 2025). However, in emerging regions like China, AI has been integrated into government "smart forestry" initiatives, where integrated systems oversee afforestation, reforestation, and ecological restoration endeavors (Wang, Zhang et al. 2025). Despite these advancements, obstacles endure: AI models need extensive, high-caliber datasets, which are inconsistently accessible across various forest kinds and geographies. The computational expense and restricted interpretability of "black box" models frequently delay their use in resource-limited environments (Waheed, Memon et al. 2025). These inequalities emphasize the need to examine how educational institutions prepare future forestry professionals to use AI-driven technology effectively and responsibly.

Artificial intelligence in Higher Education

Artificial intelligence is radically changing higher education. AI has been implemented into curricula, institutional efforts, and learning systems across several disciplines, including personalized learning analytics and data science training (Rahman, Ghazali et al. 2025). Global universities are progressively integrating AI classes into practical sciences, allowing students to develop computational skills in conjunction with their expertise in the field. In disciplines like engineering and medicine, AI literacy has become a necessary outcome for graduates; analogous changes are also occurring in forestry (Krishna, Zhang et al. 2025).

The concept of AI literacy emphasizes the significance of both technical knowledge, such as coding and algorithmic comprehension, as well as practical application and ethical awareness (Karakaya, Alpat et al. 2025). In forestry, AI literacy requires students to manage geographic data, analyze machine learning outputs, and critically evaluate the ecological and social significance of algorithmic decision-making. Competency-based education frameworks propose that student learning should be evaluated based on observable abilities and practical outcomes rather than only on course completion (Wang, Zuo et al. 2025). Nonetheless, the availability of established techniques for assessing AI performance in real domains remains limited. The lack of standards inhibits institutions' ability to evaluate outcomes and compare progress across programs (Khan, Ali et al. 2025).

Comparative Models of AI Integration in Forestry Education

The implementation of artificial intelligence in forestry higher education is significantly influenced by national governance and institutional frameworks. In the United States, the incorporation of AI exemplifies a decentralized and market-oriented higher education system. Universities function independently, and innovation frequently emerges from alliances with technological firms, business partnerships, and research funding (O'Dwyer, Filieri et al. 2023). Land-grant institutions in the United States have developed certification and master's programs that combine artificial intelligence with geospatial science, precision forestry, and wildfire analytics. This decentralized strategy creates unpredictability. While prominent schools provide sophisticated AI applications, smaller or teaching-focused universities may lack money and skilled instructors (O'Dwyer, Filieri et al. 2023, Partheepan, Sanati et al. 2024).

Similarly, China's higher education system is significantly influenced by centralized government policies. The Ministry of Education has released national action plans to incorporate AI across many disciplines, connecting digital innovation with the nation's ecological civilization objectives (Mikeladze, Meijer et al. 2024). Forestry universities have established "smart forestry" laboratories, interdisciplinary AI curriculum, and research institutes in accordance with national guidelines. This unified control facilitates swift expansion and curriculum coherence among schools. Nonetheless, obstacles persist in guaranteeing pedagogical depth, faculty proficiency, and equal access for provincial or under-resourced universities (Mncube, Ajani et al. 2023). Similarly, in Germany the DraAuf Drone-assisted automated reforestation project (by Kempten University of Applied Sciences) seeks to deploy drones with AI for autonomous planting of climate-resilient tree species in mountain forests (Han, Xiao et al. 2025).

Comparing the two scenarios reveals that they possess distinct strengths and limitations. The U.S. model supports localized innovation and strong relationships with industry; however, it has the potential to increase gaps among institutions. Conversely, the Chinese model guarantees uniformity and comprehensive coverage throughout the nation; however, it may prioritize immediate compliance over the development of sustainable capacity (Dong, Zhang et al. 2025). In combination, these contrasts emphasize the importance of comparative analysis between a developed and a developing context.

Identified Gaps

Despite promising advancements, the research reveals enduring limitations. Initially, there exists an inconsistency in curriculum practices. Numerous forestry students are introduced to AI via conventional computer science courses instead of through practical modules utilizing ecological datasets or field-based issues (Husain, Bloom et al. 2023). In the absence of project-based learning opportunities, students may have theoretical information without the capacity to use it practically. Secondly, faculty preparedness continues to be an limiting element. Surveys of forestry educators indicate a lack of confidence in instructing AI-related material, attributing this to insufficient technical training and institutional support (Simpson, Williams et al. 2017). In China, rapid policy-driven integration has outpaced faculty development, whereas in the U.S., professional development is inconsistent and sometimes centered in well-funded initiatives (Thangamani, Sathya et al. 2025). Third, there exist persistent gaps in resource allocation. Access to superior datasets, computing resources, and cloud-based platforms is centralized inside prestigious or research-focused organizations. This restricts practical learning possibilities for students in smaller programs, especially in developmental situations (Roberto, Grossi et al. 2025).

Ultimately, there exists a limitation in measuring. Although generic AI literacy frameworks are available, there are limited validated instruments that encompass the many competencies necessary in forestry, including technical, practical, and ethical aspects (Mikeladze, Meijer et al. 2024). The lack of tools blocks policymakers, organizations, and academics from assessing efficacy and directing reform. Addressing these deficiencies necessitates comprehensive comparative research that connects governance models, institutional practices, and student outcomes. This paper addresses the necessity by examining the integration of AI in forestry higher education in global countries particularly China, U.S., Germany, Brazil and Australia, extracting insights applicable to both developed and developing environments. However, existing studies remain fragmented and rarely connect policy-level reforms to actual pedagogical or competence-based outcomes. This study advances the field by integrating multi-level analysis (policy, institution, and curriculum) to produce a validated cross-national framework for AI competence in forestry.

THEORETICAL FRAMEWORK

The incorporation of artificial intelligence into forestry higher education should not be perceived only as a technological or curricular modification. It encompasses relationships between student outcomes, teacher competency, institutional capacities, and governance frameworks. Three complimentary theoretical frameworks competence-based education, diffusion of innovations, and socio-technical systems theory, are used in this study to thoroughly examine these dynamics. Collectively, they offer a multifaceted perspective for evaluating the integration of AI in forestry higher education across developed and developing contexts.

Socio-Technical Systems Theory

Socio-technical systems theory asserts that the adoption of technology is influenced by both the attributes of the technology and the institutional frameworks, cultural practices, and human agents it engages with (Dąbrowska, Almpanopoulou et al. 2022). In the framework of higher education, Socio-Technical Systems (STS) asserts that the incorporation of AI cannot be just equated to the addition of new courses or software applications. Alignment is necessary among technology infrastructure (datasets, computational resources), organizational routines (curriculum design, assessment methods), and human capability (faculty competence, student preparation). The STS viewpoint in forestry education emphasizes the necessity for alignment between novel AI-enabled technologies and established educational traditions. The implementation of UAV-based remote sensing modules is not only a curricular choice; it necessitates faculty training in geospatial analytics, sufficient laboratory facilities, and institutional regulations to facilitate field-based experimentation (Das, Anowar et al. 2024). In China, centralized regulations offer substantial system-level incentives for alignment; nonetheless, different institutional capacities result in certain colleges being unable to effectively implement state directions. The lack of centralized coordination in the United States fosters innovation at premier colleges, although many smaller schools grapple with effectively using AI (Rismawati, Junaid et al. 2025). STS, therefore, conceptualizes the integration of AI as an evolving negotiation among policy, infrastructure, and pedagogy.

Diffusion of Innovations

Diffusion of Innovations (DOI) offers a framework for examining the dissemination of innovative behaviors and technology within systems (Kaushalya, Thayaparan et al. 2024). Five stages of adoption are identified by the DOI: knowledge, persuasion, decision, implementation, and confirmation. It also discusses the impact of communication channels, opinion leaders, and innovation characteristics (compatibility, complexity, trialability, and observability) on the adoption of new technologies (Han, Xiao et al. 2025). In the United States, a decentralized higher education system implies that dissemination is typically led by instructors who are entrepreneurs, multidisciplinary centers, and collaborations with businesses. The standard for others to follow was established by early adopters, who are typically located at research-heavy land-grant institutions, who developed forestry courses that focused on AI. However, smaller

universities or colleges that concentrate on education are generally sluggish to implement new technologies due to their lack of resources and the absence of visible local supporters (Council, Affairs et al. 2012).
Dispersion is executed differently in China. Centralized mandates from the Ministry of Education establish system-level incentives that expedite adoption across institutions (Zhang, Song et al. 2025). Innovation is increasingly disseminated through hierarchical mandates, standardized curricula, and government-funded laboratories, rather than through individual opinion leaders. DOI warns that innovations that are disseminated through top-down mandates may encounter resistance or remain superficial if local institutional capacities are not adequately developed, even though this accelerates nationwide integration (Krishna, Zhang et al. 2025). This study is capable of elucidating the mechanisms through which integration occurs, as well as the varying tempo of adoption in China and the United States, through the application of DOI. Specifically, policy-driven diffusion in developing contexts and market and innovation-driven diffusion in developed contexts are contrasted.

Competency-Based Education

Competency-based education (CBE) redirects the emphasis of higher education from inputs (course hours, credit accumulation) to outputs (what students can tangibly demonstrate with their knowledge) (Loureiro, Martins et al. 2023). This method is especially advantageous for the examination of AI integration, as success cannot be evaluated solely by course offerings; rather, it must also be evaluated by student proficiency. The competence of AI in the field of forestry is diverse. It encompasses technical skills (machine learning literacy, data management, and coding), applied capacity (utilizing AI for biomass estimation, insect detection, and wildfire prediction), and ethical competence (awareness of environmental sustainability, transparency, and bias) (Holzinger, Schweier et al. 2024). The conceptual foundation for evaluating these dimensions and designing validated instruments, such as the AI-Competence Scale for Forestry developed in this study, is provided by CBE.
CBE's significance is particularly evident in comparative research. Curriculum reforms in China frequently prioritize nationwide coverage and breadth, but they fail to assess students' proficiency in applied skills (Chen, Goncharova et al. 2024). Decentralized adoption in the United States has resulted in robust applied opportunities at top institutions, particularly through internships and project-based learning. However, there is a lack of standardization of competence criteria throughout the system (Lepsch-Cunha, Muraro et al. 2024). CBE enables this study to evaluate outcomes in a comparable manner, highlighting both strengths and deficits across developed and developing contexts.

Integrative Value of the Frameworks

Each framework offers unique perspectives, their integration enables a more thorough examination. The adoption of AI is positioned within the interplay of human intelligence, institutions, and policy in socio-technical systems theory. The mechanisms by which adoption spreads in centralized versus decentralized contexts are elucidated by the diffusion of innovations. Competency-based education provides a method for assessing student outcomes, ensuring that curricular reforms are evaluated not only on their existence but also on their impact.
The systemic, processual, and outcome-oriented dimensions of AI adoption in forestry higher education are illuminated by these frameworks when considered in conjunction. In addition, they facilitate a meaningful comparison between the global countries with governance, curriculum innovation and institutional capacity. Consequently, this multi-theoretical approach is indispensable for the analysis of both convergence and divergence in the integration of AI into forestry education, as well as for the formation of evidence-based recommendations for policy and practice in a variety of national contexts. Research on forestry education rarely uses this triangulation, which combines competency-based learning, diffusion of innovations, and socio-technical systems. It enables this study to establish a conceptual basis for the comparative analysis that follows by linking policy diffusion with quantifiable educational results.

METHODS

Research Design

This study employs a comparative multiple case study design to investigate AI integration in forestry higher education across five national contexts: China, U.S., Germany, Brazil, and Australia. This selection represents a spectrum of governance models (centralized, decentralized, regionally collaborative, biodiversity-focused) and economic development levels, allowing for a nuanced analysis of how diverse policy structures and institutional capacities shape educational adaptation to technological innovation (Brożek, Kożuch et al. 2025). A qualitative examination of secondary data, such as institutional reports, policy papers, and curricular materials, served as the foundation for the study. Access to data that represents both national strategic aims and local execution within higher education institutions is made feasible by this document-based method, which is suitable for cross-national comparison (Morozov, Panikar et al. 2024). By triangulating these diverse data sources, the study mitigates the potential biases associated with any single source and enables a systematic examination of the interactions between policy, institutional capacity, and curriculum on a global scale.

Data Sources

The research employs a variety of publicly available secondary data sources from all five sample countries to provide a multi-scalar, global perspective. We reviewed national and international policy documents. These included China's AI Innovation Action Plan, plans from the US Department of Education, Germany's Digital Education Strategy for Forestry, Brazil's National Forestry Policy with AI Mandates, and Australia's Bushfire Research and AI Funding Guidelines. Data were collected from the official websites and public documents of prominent forestry universities in each country, including Nanjing Forestry University, Oregon State University, the Technical University of Munich (TUM) (Parajuli, Chizmar et al. 2022), the University of São Paulo, the University of Melbourne (Loureiro, Martins et al. 2023), etc. We examined course catalogs, syllabi, program descriptions, institutional strategic plans, and yearly digital transformation reports to identify AI-related content and assess the institution's ability to manage it. In addition to these primary sources, we used academic literature, such as peer-reviewed publications and conference proceedings on AI in forestry and education, to provide a scholarly framework for our results, putting institutional practices in context with global trends and confirming our findings.

Units of Analysis

The analysis of this study is structured into three interrelated levels to offer a comprehensive understanding of the integration of AI in forestry higher education. At the global level, the integration of AI in higher education institutions is facilitated by governance structures, finance mechanisms, and regulatory frameworks. Universities and colleges that offer forestry programs are the focus of attention at the institutional level (Bullard, Walker et al. 2024). Comparisons are made among institutions based on resource availability, research intensity, and geographic location. Futhuremore, Through an analysis of AI-related content in courses, laboratory work, and practical learning opportunities, this study examines the extent to which national objectives and institutional strategies are embodied in pedagogical practice. This multi-tiered methodology allows for the analysis of interactions between macro-level policy frameworks, meso-level institutional reactions, and micro-level curricular design, thereby offering a comprehensive perspective on the evolution of AI adoption in both developed and developing environments (Mikeladze, Meijer et al. 2024).

Analytical Framework

The research incorporated two distinct methodologies to address both the overarching institutional dynamics and the specifics of the curriculum. In order to evaluate the degree of AI integration in forestry curricula, a seven-dimensional curriculum taxonomy was developed. This taxonomy assessed the integration of AI theory, foundational data science, remote sensing applications, UAV and other methodologies, computational lab intensity, ethics and governance, and industry or practicum involvement. The inter-rater reliability was achieved by achieving a Cohen's κ of 0.80 or higher, which ensured consistency in classification. Each dimension was assessed on a scale from 0, which denoted absence, to 3, which indicated substantial integration (Simpson, Williams et al. 2017). Thematic analysis was implemented in conjunction with this structured approach to institutional and policy documents. An inductive process was employed to identify recurring themes, including faculty availability, access to infrastructure, resource allocation, and pedagogical innovation. A deductive coding strategy was employed to guide interpretation, drawing on socio-technical systems theory and the diffusion of innovations. The analysis was able to capture the measurable extent of curricular integration and the contextual factors that shape institutional adoption as a result of this dual strategy, which anchored the study in a rigorous and theoretically informed framework (Aithal and Maiya 2023, Soomro, Soomro et al. 2024).

Global Case Selection Rationale

The five nations and their principal institutions were chosen using a theory-driven, purposive sampling technique to guarantee substantial diversity in three critical domains for this research. The cases encompass a broad spectrum of global governance to examine the impact of various policy frameworks. For instance, China's centralized state-led model, the U.S.'s decentralized market-driven approach, Germany's regionally coordinated framework within the EU, and Brazil's and Australia's federal systems are predicated on distinct national findings (Yu, Liu et al. 2025). Second, the instances were selected because they are significant to the ecosystem in their region. For example, in Brazil, Australia, China, U.S., and Germany, AI education is related to sustainability challenges such as biodiversity protection, wildfire management, carbon storage, and climate-smart forestry (Pimenow, Pimenowa et al. 2025). Third, the selection includes diverse institutional types from elite research universities to land-grant institutions and universities in emerging economies to analyze how resource disparities and institutional mission influence AI integration and address issues of educational equity (Zhao, Zhao et al. 2024). Subsequently, all of the selected examples contain a large amount of publicly accessible data, which is essential for transparency, accuracy, and comprehensive comparative analysis.

Ethical Considerations

The study utilized secondary data, therefore lacking direct engagement with human participants. Nonetheless, ethical issues were acknowledged. Institutional materials were employed solely when publicly available or with clear permission, and no secret or sensitive information was included (Tertulino, Antunes et al. 2024). To ensure cross-national comparability, attention was given to contextual variations in language and reporting processes. All data were securely saved and utilized solely for academic reasons. To ensure methodological rigor, cross-validation was applied among document coders (Cohen's $\kappa \geq 0.8$). Triangulation between data sources and theoretical lenses enhanced internal validity and reduced researcher bias.

Limitations

Numerous limitations are associated with the methodological approach. The utilization of secondary data may initially yield an imperfect depiction of specific facets of teaching practice, including informal pedagogical innovations or unreported faculty efforts (Boesdorfer, Del Carlo et al. 2022). Secondly, the comprehensiveness of accessible data may be limited by variations in language, accrediting frameworks, and institutional transparency, which must be considered in cross-national comparisons (Roberto, Grossi et al. 2025). The depth of understanding of life experiences is limited by the lack of direct viewpoints from students or staff. Nonetheless, the analysis prioritizes structural and institutional trends above individual judgments, and the breadth of data sources alleviates these limitations.

RESULTS

Curriculum Integration and National Governance

The analysis reveals that national governance models are the most important determinant of how artificial intelligence is combined into forestry curricula, resulting in a diverse range of adoption patterns across the five countries, as mentioned in Figure 1. At one end of the spectrum, China's centralized, state-led approach promotes uniform, top-down integration. National regulations, such as the AI Innovation Action Plan, require universities to systematically incorporate standardized modules in AI ethics (Zhu, Zhu et al. 2025), geospatial data analysis, and UAV-based monitoring, providing nearly universal curriculum coverage across their enormous higher education institutions (Hegde, Clara Manasa et al. 2025). Whereas the United States illustrates a decentralized, market-oriented strategy, leading to a significantly fragmented environment. While elite, research-focused institutions offer advanced AI programs for wildfire analytics and precision silviculture, smaller colleges, especially in rural areas, often lack the resources necessary for comprehensive AI training, leading to significant disparities in student access. Table 1 synthesizes these governance models and their primary outcomes as evidenced by the collected data.

Germany's forestry education, which occupies a middle ground, is influenced by a concept of regional cooperation within the framework of the European Union (Brożek, Kożuch et al. 2025). This fosters a strong, consistent emphasis on AI applications for carbon sequestration modeling and climate-smart forestry, with curricula often aligned with EU Green Deal objectives, ensuring a high standard of technical integration across its institutions. Similarly, Australia's approach is characterized by a coordinated national response to specific ecological crises, notably bushfires (Xu, Yu et al. 2023).

TABLE 1. Overview of How Different National Governance Models Shape the Integration of AI into Forestry Higher Education

Country	Governance Model	Advantage	Disadvantage	Reference
China	Centralized & State-Led	Fast, uniform rollout of AI courses across the country.	Low depth of teaching, big gap between top and ordinary universities.	(Chen, Maddi et al. 2025)
U.S.	Decentralized & Market-Driven	Top universities are highly innovative and industry-connected.	Highly unequal, many smaller colleges lack resources and trained staff.	(Consoni, Bermúdez-Rodríguez et al. 2025)
Germany	Regionally Collaborative	High, consistent quality and well-prepared teachers across institutions.	Can be less flexible and slow to adapt to new trends.	(Carter, Mehta et al. 2025)
Australia	Crisis-Responsive	Highly practical and focused education for urgent national problems (e.g., bushfires).	AI education can be too narrow, ignoring other important forestry topics.	(Farner, Rich et al. 2023)
Brazil	Community-Focused	Strong ethical focus and innovative projects with local communities.	Lacks funding and advanced technology, difficult to scale up successful projects.	(Hermann, Bonzanini Bossle et al. 2025)

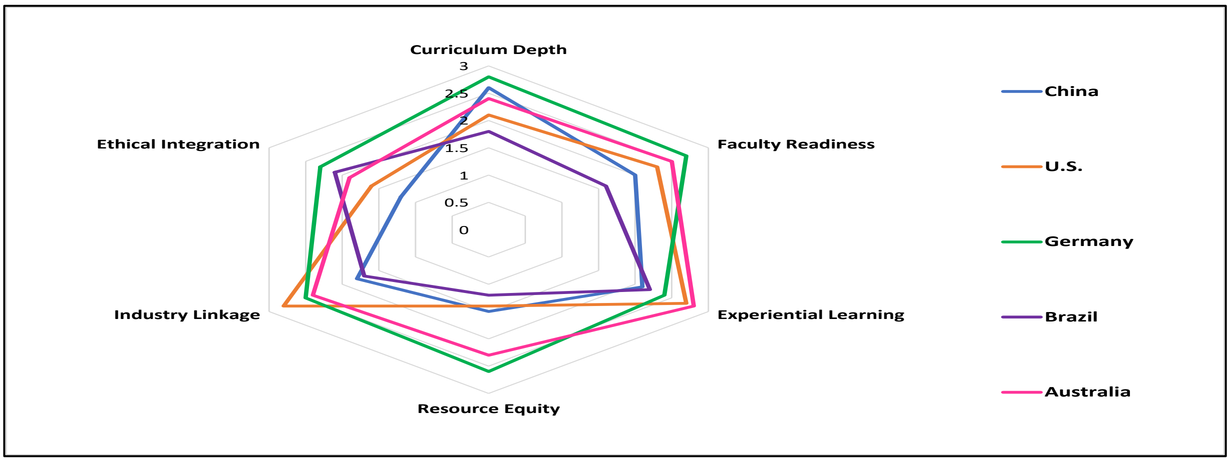

FIGURE 1. Five-country Profiles of AI Integration Dimensions

Note: A multi-dimensional profile for each country across key themes: Curriculum Depth, Faculty Readiness, Experiential Learning, Resource Equity, and Ethical Integration. This perfectly captures the unique "fingerprint" of each national model.

Federal funding and research guidelines have directly spurred the integration of AI and machine learning modules focused on fire prediction and risk assessment into relevant forestry programs. Meanwhile, Brazil presents a context where AI integration is strategically niche and problem-oriented (Gubarev, Biletska et al. 2024). Efforts are heavily focused on biodiversity conservation, with curricula often developed in collaboration with Indigenous groups and centered on using AI for tasks like mapping Amazonian medicinal plants and detecting illegal logging, reflecting a community-co-design model within a developing economy framework. However, the comparative scoring presented in the figure 2 reflects an approximate assessment of institutional research strength in forestry, environmental science, and sustainability-related fields. Values (1–5) were assigned based on each university's recognized research capacity, publication output, and thematic alignment with forestry, ecosystem management, and climate-focused studies. Higher scores indicate globally influential or nationally leading institutions (e.g., Nanjing Forestry University, Oregon State University, and the University of São Paulo), whereas lower values represent regional or rural universities with more limited research intensity. This scoring framework provides a contextual basis for interpreting institutional variation within the study.

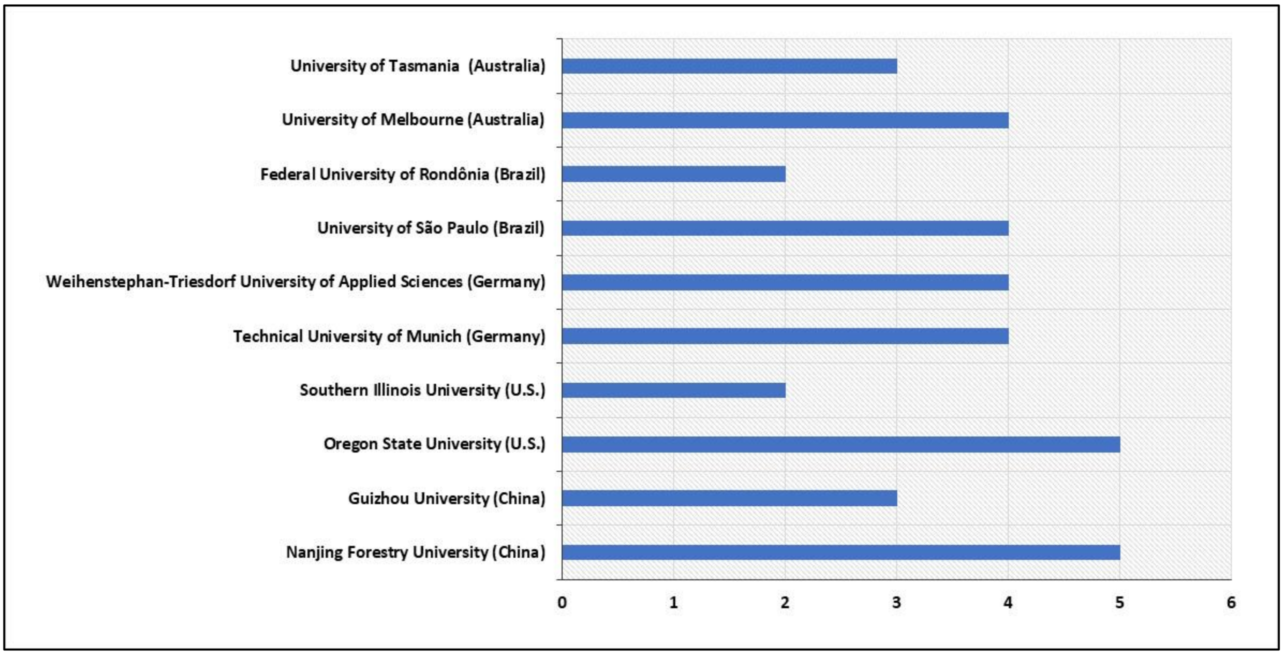

FIGURE 2. Comparative Research Strength of Selected Universities in Forestry, Environmental Science, and Sustainability Fields

Note: Values (1–5) represent an approximate assessment of each institution's research strength based on recognized outputs in forestry, environmental science, ecosystem management, and sustainability-related disciplines.

Faculty Readiness and Institutional Capacity

Faculty preparedness emerged as a critical mediator of successful AI integration, with pronounced variations evident across and within the five national contexts. In China, state-sponsored training initiatives have successfully established a broad baseline of AI literacy among forestry faculty, ensuring widespread curricular exposure (Council, Affairs et al. 2012). However, this top-down approach has struggled to cultivate deep technical expertise, particularly in computational modeling at provincial institutions, creating a gap between policy intent and pedagogical execution. The United States exhibits a high degree of internal variance. Faculty at leading research universities often possess advanced, interdisciplinary expertise and drive innovation, whereas instructors at smaller colleges frequently report low confidence and a lack of institutional support, severely limiting their ability to teach applied AI concepts.

Germany demonstrates a high level of faculty readiness, supported by structured national and EU projects (e.g., from DFG/BMBF) that ensure continuous professional development (Farner, Rich et al. 2023).This is complemented by a strong culture of interdisciplinary collaboration between forestry and computer science departments, boosting both confidence and pedagogical effectiveness. In Brazil, faculty are often highly motivated and engaged with national priorities, depicted in the form of a data score in Figure 3. But they face systemic challenges, including the limited reach of training programs from agencies like CAPES and EMBRAPA (Hakamada, Frosini de Barros Ferraz et al. 2023), and inadequate access to computational resources outside well-equipped hubs. Conversely, Australia benefits from continuous national teaching frameworks and well-funded AI hubs, which provide structured support and resources, resulting in generally high faculty confidence and a strong capacity for delivering practice-oriented AI education. Figure 3 presents an overview of institutional research strength across ten domains related to forestry, environmental science, and sustainability. Scores from 0.8 to 2.9 indicate different levels of emphasis, capacity, and specialization among institutions. Higher values appear in areas such as Forest Science & Natural Resources Research, Forestry & Forest-Engineering Research, and Environmental Systems & Climate Technology Research, while lower values are observed in Environmental Management & Extension-Based Research and Amazonian Ecology & Tropical Forest Research. The overall trend line shows a gradual decline across the categories, reflecting diverse research intensity shaped by each institution's focus and regional priorities.

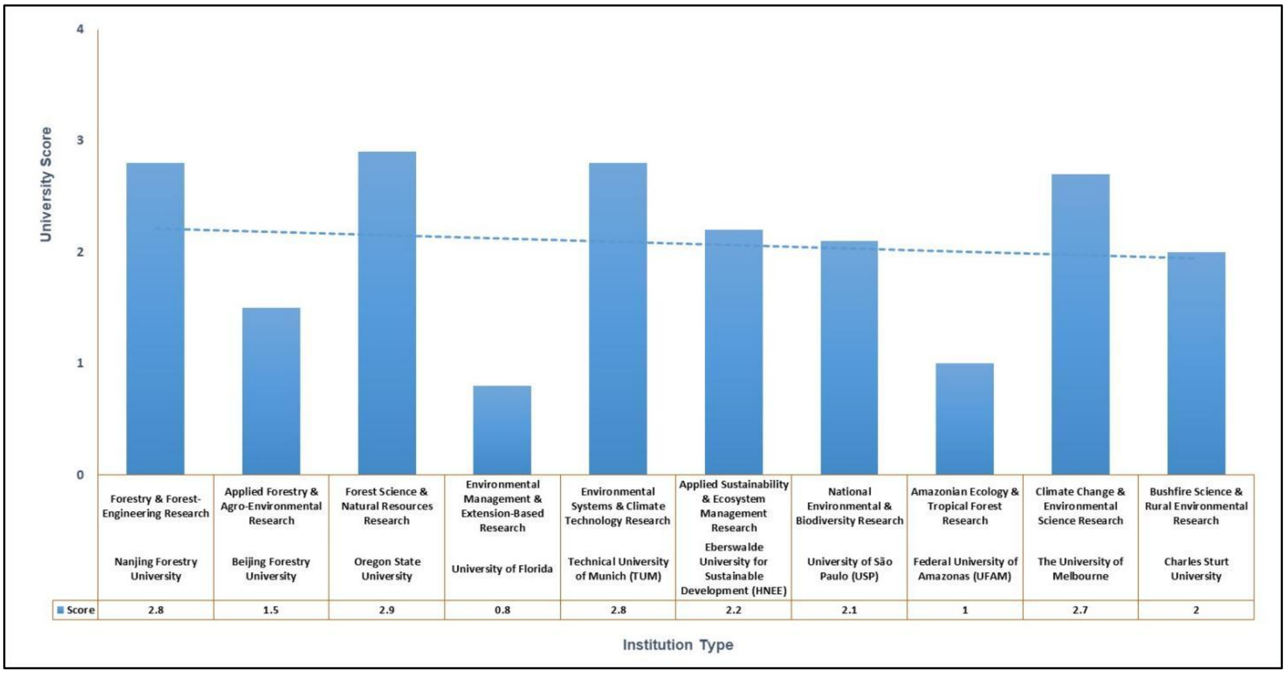

FIGURE 3. AI Theory Integration Scores by Institution Type

Experiential Learning and Student Competence

The development of student competence is most directly linked to the availability and quality of experiential learning opportunities, which themselves are a function of national priorities and institutional partnerships. In China, experiential learning is often channelled through large-scale, government-funded projects, such as national afforestation campaigns or provincial UAV monitoring programs. Students at universities with strong government ties gain invaluable experience by applying AI to real-world datasets (Wang, Zhang et al. 2025), though access to these premium opportunities is stratified. The United States leverages its robust industry and federal agency network (e.g., with the USDA and private tech firms) to provide high-quality internships and capstone projects. These experiences, focused on issues like wildfire prediction and carbon accounting, are highly effective but are disproportionately available to students at well-connected, research-intensive universities. Additionally, Scores were derived from a comparative assessment of AI-related courses, research initiatives, and institutional strategies documented in official university curricula and policy reports. Values are normalized on a 0–3 scale, where 3 indicates high integration and 0 indicates minimal or no integration, depicted in Figure 4 according to the institutional levels between China and the U.S. the distribution of university performance scores across forestry and environmental science institutions in China and the United States. Chinese universities including Beijing Forestry University, Nanjing Forestry University, and Northeast Forestry University show consistently high scores, each reaching a value of 3. Fujian Agriculture & Forestry University also performs strongly with a score of 2.8. Among U.S. institutions, the University of Washington (2.7) and Oregon State University (2.5) demonstrate strong research capacity, while Mississippi State University (1.8) and Northern Arizona University (1.5) show more moderate levels of activity. Overall, the chart highlights notable variation in institutional strengths, reflecting differences in national priorities, research funding, and academic focus within the forestry and environmental sciences sector.

Germany's approach is characterized by its integration within EU-wide and national research projects (Morozov, Panikar et al. 2024). Students frequently engage in hands-on learning through university-industry collaborations focused on technical challenges like carbon sequestration modeling, ensuring that applied competence is closely tied to both regional policy and industrial practice. In Brazil, experiential learning is uniquely community-engaged; students often work alongside Indigenous groups to co-design AI models for biodiversity monitoring (Caldeira, Sekinairai et al. 2025), fostering a strong sense of ethical application and context-specific problem-solving, albeit within resource constraints. Australia's model is crisis-driven; experiential learning is heavily centered on bushfire management, with students often working with state-of-the-art prediction tools and data from recent fire events, directly linking their education to immediate national environmental security needs.

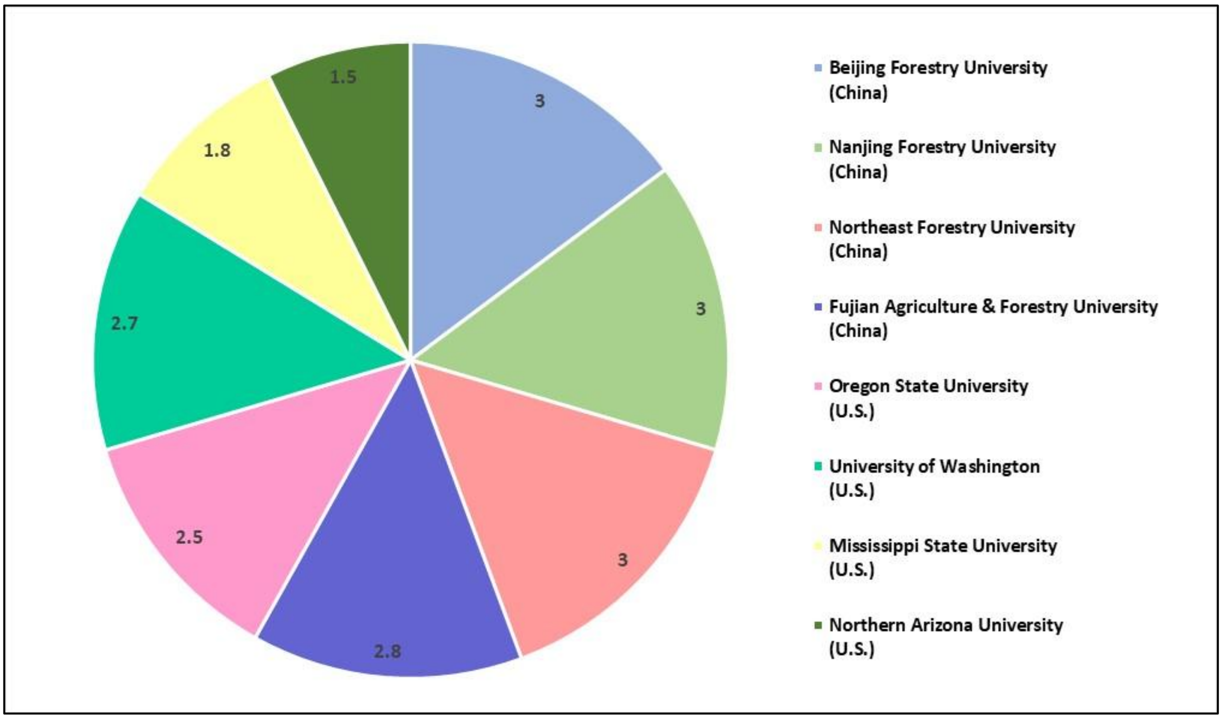

FIGURE 4. University Performance Scores in Forestry and Environmental Science Programs Across China and the United States

Note: Higher values indicate stronger overall performance. Chinese institutions generally exhibit higher and more consistent scores, while U.S. universities show greater variability across programs.

Resource Inequality and Infrastructure

A persistent theme across all five countries is the challenge of resource inequality, though its nature varies with the governance model. In China, disparities are stark between the generously funded "Double First-Class" universities, which boast advanced computing labs and UAV fleets, and provincial institutions that struggle with outdated infrastructure, creating a two-tiered system of educational quality (Krishna, Zhang et al. 2025). Similarly, the United States exhibits a sharp divide between resource-rich, research-intensive universities and smaller, often rural, colleges that lack access to cloud computing platforms and high-quality annotated datasets, forcing students to rely on simulations rather than real-world data (Lang, Füreder et al. 2024).

Germany stands out for its relatively equitable distribution of high-quality research infrastructure, a benefit of its federal model and sustained public investment, which mitigates extreme disparities between institutions. In addition, Brazil faces significant regional inequality, with advanced computational resources and datasets concentrated in agencies like EMBRAPA and a few flagship universities, while many other forestry programs operate with minimal digital infrastructure . Australia presents a more balanced picture due to consistent public funding aimed at maintaining regional university capacity; however, a concentration of the most advanced digital tools and partnerships still occurs within the leading metropolitan research hubs.

Comparative Synthesis

This five-country analysis reveals a complex global context in which the route of AI integration in forestry education is influenced primarily by economic development but also by governance systems, ecological priorities, and institutional capability. China's centralized model achieves uniformity and scale, but it fails in quality, equity, and complexity. The decentralized model of the United States excels in fostering innovation at the top tier, but at the cost of systemic fragmentation and access inequality (Geppert, Krachunova et al. 2024). Germany's regionally collaborative, well-resourced approach ensures high-quality, standardized integration with a strong technical focus (Helmi, Bastidas et al. 2024). Australia's nationally coordinated, crisis-responsive model effectively directs educational resources toward pressing environmental challenges. Brazil's context-driven, community-involved approach demonstrates how AI can be harnessed for specific conservation goals even within resource constraints, though it faces significant scalability and equity issues. A critical convergence across all contexts is the indispensable role of faculty readiness and experiential learning. Regardless of the national model, the translation of AI curricula into tangible student competence fails without qualified instructors and opportunities for practical application. Furthermore, while the sources of disparity differ elite vs. provincial in China, research vs. teaching in the U.S., and regional in Brazil, the challenge of equitable resource distribution is a universal barrier to building a uniformly capable, AI-literate forestry workforce. These findings collectively underscore that there is no single optimal model; each governance approach presents a distinct set of trade-offs between scale, innovation, quality, and equity in the race to modernize forestry education for the 21st century.

DISCUSSION

This study provides the first comprehensive, cross-national analysis of how artificial intelligence is being integrated into forestry higher education across five distinct governance contexts. The findings reveal a global landscape characterized not by a uniform technological transition but by distinct pathways shaped by deeply embedded governance structures, economic priorities, and ecological contexts (Miörner, Binz et al. 2021). The data demonstrates that the success of AI adoption is less a function of technological availability and more a complex negotiation between policy directives, institutional capacity, and pedagogical practice, as illuminated by our integrated theoretical frameworks (Jin, Yan et al. 2025) .

A central finding is that a country's economic wealth is not the sole determinant of successful integration. Figure 3 provides powerful empirical evidence for this claim, illustrating the decisive role of resource distribution, which is itself a function of governance. The scatter plot demonstrates that while institutional resources are a strong predictor of AI integration success (as shown by the general upward trend), the distribution of that success varies dramatically by governance model. The tight clustering of German and Australian institutions in the high-resource, high-integration quadrant reflects their coordinated models, which promote equity and consistent outcomes. In stark contrast, the wide dispersion of U.S. and Chinese institutions reveals the internal inequalities generated by their respective systems: the U.S. due to its decentralized, market-driven approach that concentrates resources, and China due to its centralized but stratified system that creates a sharp divide between elite and provincial universities. Brazil's position further underscores that mission-driven innovation can achieve moderate integration even with limited resources, but it also highlights the challenge of scaling such success without greater investment (Kaushalya, Thayaparan et al. 2024). This visualization underscores that governance models fundamentally mediate the relationship between resources and educational outcomes, making equity a deliberate policy choice rather than an accidental byproduct.

The socio-technical systems perspective clarifies why the mere insertion of technology into curricula often fails. Our results show that even in China, where top-down mandates ensure the most consistent technical integration of AI, the socio components, specifically, uneven faculty depth and stark resource inequity between elite and provincial institutions, create a system-wide gap between policy ambition and classroom reality (Xu and Gao 2024, Ali, Rahman et al. 2025). Conversely, the United States' decentralized model excels at creating pockets of socio-technical excellence where research infrastructure, industry partnerships (Lang, Füreder et al. 2024), Faculty expertise aligns in top-tier universities also provides a clear relationship between institutional resource allocation Vs. AI integration score. However, this model systematically fails to marshal these components at less-resourced institutions, resulting in a highly fragmented and inequitable system (Chtena, Alperin et al. 2025). Germany and Australia emerge as cases where a more balanced socio-technical alignment is achieved. Germany's regionally collaborative model, supported by sustained public investment, ensures high-quality infrastructure and faculty readiness are widely distributed (Morozov, Panikar et al. 2024). Australia's crisis-responsive approach effectively channels resources and curriculum development toward the nationally unifying priority of bushfire management, ensuring relevance and coordination (Rismawati, Junaid et al. 2025). Brazil's context underscores that even with limited technical infrastructure, a strong socio-cultural alignment with community needs and conservation goals can foster innovative, ethically-grounded pedagogical models, though scalability remains a challenge (Consoni, Bermúdez-Rodríguez et al. 2025). Figure 5, shows how different universities from China, the United States, Germany, and Brazil score in terms of AI integration and the resources they have to support it. Each dot represents one university. Most schools fall around similar AI integration levels, while their resource scores vary more widely. Several universities especially those in China, the U.S., and Germany appear in the higher range of resource scores (2.6–2.9), suggesting they have stronger support systems in place for using AI. In contrast, some universities show lower resource scores, indicating more limited support.

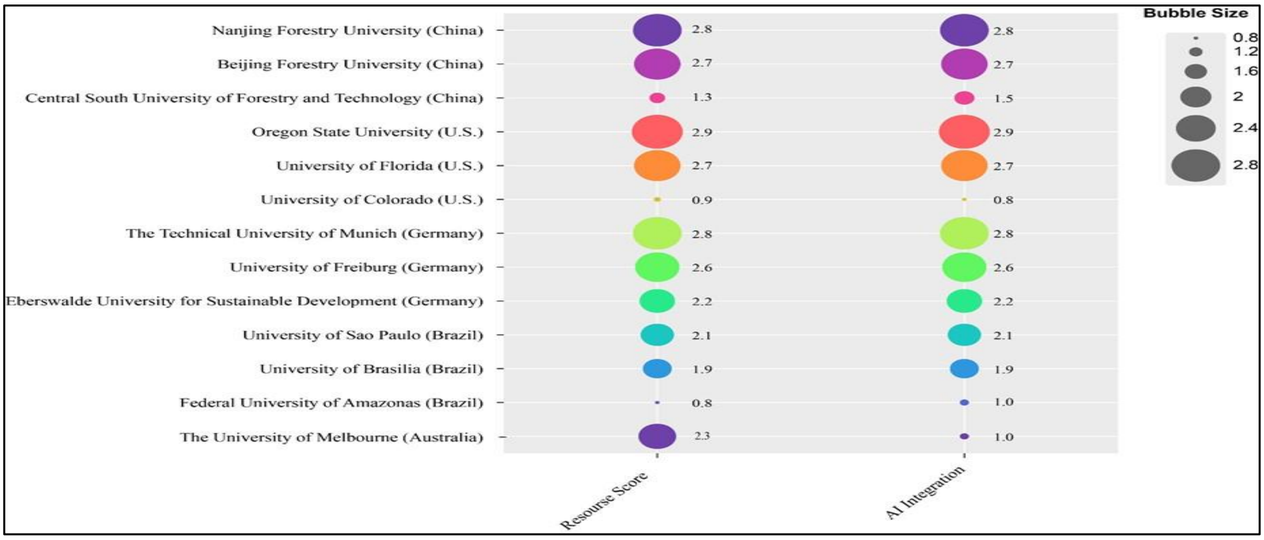

FIGURE 5. AI Integration Scores and Resource Scores of Forestry Universities

Note: This figure illustrates the relationship between institutional resource scores and AI integration outcomes across universities from various countries. higher range of resource scores (2.6–2.9), suggesting they have stronger support systems in place for using AI. In contrast, some universities show lower resource scores, indicating more limited support.

The Diffusion of Innovations (DOI) theory elucidates the mechanisms behind these patterns. China exemplifies a top-down, centralized diffusion that prioritizes speed and scale, achieving rapid curricular presence but often at the cost of depth and authentic adoption at the instructor level (Lou, Sun et al. 2023). The U.S. represents a classic decentralized diffusion, where innovation is championed by early adopters at elite institutions but spreads unevenly, hindered by the absence of coordinating mechanisms (Manica, Damásio et al. 2025). The trajectories of Germany (regionally collaborative) and Australia (crisis-responsive) suggest the emergence of hybrid diffusion models. These models leverage the coordination of centralized approaches through EU frameworks or national funding priorities while retaining the flexibility and relevance of localized, need-driven adoption, effectively balancing the breadth of China with the depth of the U.S.'s best examples (Kushwaha and Chandwani 2025, Roberto, Grossi et al. 2025).
Ultimately, the Competency-Based Education (CBE) framework provides the most critical lens for evaluating outcomes that students can actually perform (Chen, Kleppinger et al. 2024). The data consistently shows that, regardless of the national model, student competence is most strongly predicted by experiential learning. This finding cuts across all contexts from the government-led projects in China and the industry internships in the U.S., to the EU research collaborations in Germany, the community co-design in Brazil, and the bushfire simulation projects in Australia (Munoz Rivas, Davis et al. 2025). This universal principle reinforces that curricular checkboxes are insufficient; the translation of AI knowledge into professional forestry skill requires immersive, problem-based application (Pater, Denni et al. , Obae, Koscielniak et al. 2024). However, the underdevelopment of AI ethics in most curricula, as highlighted in our radar chart (Figure 1), represents a critical CBE deficit (O'Dwyer, Filieri et al. 2023). This leaves graduates potentially skilled in algorithmic tools but unprepared to navigate the profound ethical implications for forest governance, environmental justice, and algorithmic bias.

TABLE 2. A Competency Framework for AI in Forestry, Outlining Core Domains, Descriptions, and Learning Outcomes

Competence Domain	**Data Management**	**Results**	**Reference**
AI Applications in Forestry	Deployment of AI to enhance forest monitoring, prediction, and management.	Tree-species classification Wildfire and pest-risk modeling Biomass and carbon estimation	(Wang, Chai et al. 2025)
Research and Development Institutions	Advancement of AI methodologies and datasets for forestry science.	Development of remote-sensing AI models Creation of open geospatial datasets	(Kazanskiy, Khabibullin et al. 2025)
Governmental and Policy Agencies	Utilization of AI for national forest assessment, planning, and policy processes.	Wildfire early-warning systems AI-supported land-cover and conservation analysis	(Gacu, Monjardin et al. 2025)
Commercial and Industrial Sectors	Integration of AI into operational forestry workflows and decision systems.	Drone-based forest monitoring tools AI for inventory and supply-chain optimization	(Ali, Mijwil et al. 2025)
International and Conservation Bodies	Application of AI to support global forest governance and sustainability.	AI-driven deforestation monitoring Biomass modeling for carbon-accounting programs	(Oladeji and Mousavi 2023)

A central finding is that a country's economic wealth is not the sole determinant of successful integration also mentions some of the competency framework for AI in forestry, outlining core domains, descriptions, and learning outcomes in Table 2. While resources are crucial, Germany's and Australia's ability to temporarily achieve strong, equitable integration through strategic coordination rivals that of the more economically powerful but fragmented U.S. system (Raman, Manalil et al. 2024). Meanwhile, Brazil demonstrates that strategic, context-specific innovation can thrive despite broader resource constraints. This suggests that the strategic orchestration of resources through effective governance and clear priorities is as important as the volume of resources themselves.

CONCLUSION

This research concludes that the global integration of AI into forestry higher education is not converging on a single model but is instead diversifying into distinct, context-dependent pathways. Each of the five governance models presents a unique set of trade-offs. The centralized model (China) achieves scale and uniformity at the risk of pedagogical depth and equity (Masters-Waage, Spitzmueller et al. 2024). The decentralized model (U.S.) drives peak innovation and industry relevance but exacerbates systemic inequality and fragmentation (Fakhar, Lamrabet et al. 2024). The regionally collaborative model (Germany) demonstrates how sustained investment and coordination can balance high standards with equity (Morozov, Panikar et al. 2024). The crisis-responsive model (Australia) ensures national relevance and focused resource allocation. The community-focused model (Brazil) pioneers ethical, contextual application, proving that innovation can be driven by mission as well as by resources (de Queiroz Brunelli 2021, Rismawati, Junaid et al. 2025). The key implication for global educators and policymakers is that there is no universal "best" model. Instead, the strategic goal should be to identify and mitigate the inherent weaknesses of one's own system by learning from the strengths of others. Centralized systems must invest in faculty depth and foster grassroots pedagogical innovation to move beyond compliance (Elfert and Ydesen 2023, Abbaspour, Hosseingholizadeh et al. 2024). Decentralized systems require mechanisms, such as national consortia or targeted funding, to ensure equitable access and reduce fragmentation. All systems must universally prioritize the expansion of high-quality experiential learning and the rigorous, cross-curricular integration of AI ethics (Obae, Koscielniak et al. 2024). For practice, we recommend establishing international consortia for sharing open-access forestry datasets, developing joint curriculum modules on AI ethics, and creating faculty exchange programs focused on pedagogical innovation in AI (Shahi, Xu et al. 2023). Future research must move beyond the document-based analysis presented here to gather primary data on student learning outcomes and faculty experiences through surveys and longitudinal studies tracking the career impact of AI-enabled forestry education.

By embracing a hybrid approach that combines the strategic coordination seen in Germany and Australia with the localized innovation of the U.S. and the ethical engagement of Brazil, the global forestry education community can ensure that the AI revolution equips a new generation of professionals with the technical competence, ethical foresight, and practical ingenuity needed to steward the world's forests through an uncertain and challenging future (Hakamada, Frosini de Barros Ferraz et al. 2023).

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DATA SHARING AGREEMENT

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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