



AI-driven forest restoration: A governance framework for people and nature

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ABSTRACT

Forest restoration has become a key global environmental policy objective, underscoring the need for cost-effective approaches capable of operating at large scales. In this context, Artificial Intelligence (AI) is increasingly seen as a disruptive tool for forest restoration, offering new opportunities to enhance precision, efficiency, and scalability. However, its application entails substantial technical challenges, including uneven and incomplete data availability across regions, which often leads to simplified representations of ecosystem dynamics. Beyond these, governance-related risks, such as limited transparency of models, high entry costs, capacity barriers, and persistent power imbalances, may undermine both the effectiveness and legitimacy of outcomes. Here, we argue that the effectiveness of AI applications in restoration ultimately hinges on governance systems capable of addressing these challenges and delivering equitable benefit-sharing. To this end, we propose development of a governance framework built on three pillars: (1) participatory knowledge integration, embedding plural knowledge systems into AI design and use; (2) multi-scalar policy alignment, linking international commitments with national and local priorities; and (3) polycentric governance, promoting distributed stewardship and access to innovation across multiple centers of authority. This framework provides a basis for researchers, practitioners, and policymakers to critically assess and guide AI applications in forest restoration efforts.

1. Introduction

Forest restoration is gaining recognition as a necessary global response to halt biodiversity decline, combat climate change, and alleviate poverty (Toto et al., 2025). This endeavor is supported by many institutional commitments that aim to restore millions of hectares over the coming decades (Castro et al., 2021), such as the Bonn Challenge, the

UN Decade on Ecosystem Restoration, and the Global Biodiversity Framework Target 2. However, in practice, most targeted areas have yet to see restoration initiated (Bell-James, Watson, 2025)), and the finance gap remains significant, with estimates ranging from USD 600–800 billion annually (Deutz et al., 2020; Mirzabaev and Wuepper, 2023). To meet global restoration ambitions, cost-effective methods capable of operating at large scales must be developed, particularly in

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resource-limited priority regions where on-the-ground implementation will take place (Brancalion and Holl, 2025). Common forest restoration strategies, such as promotion of natural regeneration and tree planting, have been widely implemented but show highly variable outcomes across contexts (Rodríguez-Uña et al., 2020). Their scalability is often constrained by labor demands, high costs, and long-term maintenance requirements (Busch et al., 2024). In addition, reliance on manual operations and uncertainty about future climatic suitability further limit their effectiveness at larger scales (Barragán et al., 2023; Brancalion et al., 2019).

In this context, emerging strategies have begun integrating artificial intelligence (AI) to enhance restoration efforts (Nitowski et al., 2021; Raihan, 2023; Ullah et al., 2024; Yang et al., 2025; Hernandez-Montilla et al., 2026). AI refers to machine-based systems that, for explicit or implicit objectives, infer from inputs they receive how to generate outputs such as predictions, recommendations, content, or decisions that can influence physical or virtual environments (OECD, 2024). Application of AI-based methods enables the analysis of large and complex datasets to identify patterns and predict outcomes at unprecedented speed and scale compared with conventional approaches (Castro et al., 2024; Kulkarni, 2024; Russell and Norvig, 2020). This capacity can support restoration projects at different stages. For instance, in the planning phase, AI can integrate both climate projections and socio-economic data in ways that are not feasible using traditional rule-based forest models, allowing the prioritization of sites with the highest potential for long-term success (Wang et al., 2024). Moreover, during implementation, AI-driven drones can autonomously deploy seeds into targeted microhabitats, increasing seedling establishment in heterogeneous landscapes (Castro et al., 2024; Saldarriaga et al., 2025). In the monitoring phase, aerial imagery analyzed by AI models can be used to estimate tree density in regenerating sites with high accuracy (Fromm et al., 2019) and thereby estimating accumulated carbon (Zhang et al., 2024). Thus, this paradigm shift can support the implementation of more efficient restoration strategies and enable further scalability (Ullah et al., 2024).

This integrative power of AI holds potential to revolutionize how restoration projects are designed, implemented, and monitored (Yang et al., 2025). However, the integration of this cutting-edge technology brings new social and ecological challenges. Globally, the impacts of AI technologies have so far been very unevenly distributed: To date, they are mostly benefiting high economic return sectors and inadvertently favoring industrial-scale interventions over community-led efforts (Cerutti et al., 2025). This, in turn, calls into question the benefits of large-scale restoration (Adams et al., 2016). Additionally, models trained on limited or biased datasets may generate automated decisions that are ecologically inappropriate or socially unjust (Schiff et al., 2020), particularly if they fail to account for traditional ecological knowledge or local priorities (Fleishman et al., 2022; Rakova et al., 2021). In this context, restoration initiatives can reshape local institutions and social dynamics, ultimately influencing governance structures (Ullah, 2024). This can shift control away from traditional land stewards and widen the gap between decision-making spaces and the people affected by restoration interventions, perpetuating top-down approaches. Meanwhile, evidence indicates that the success of large-scale restoration depends strongly on community participation and appropriate local governance arrangements (Ullah et al., 2023). This highlights a major gap in the availability of governance frameworks in many countries, particularly in the Global South, where much of the world's biodiversity and bio-cultural diversity is concentrated (Jobin et al., 2019). Thus, whether AI strengthens or undermines restoration outcomes will depend on our governance capacity to address these challenges and promote fair benefit-sharing. Without this, AI-driven restoration efforts risk going astray, resulting in misguided interventions that fail both people and ecosystems.

While existing literature has examined AI in environmental management (Ekeh et al., 2025; Korol and Korol, 2025; Lalrinmawia et al.,

2025) and forest restoration governance (Chazdon et al., 2021) separately, their interaction remains underexplored. Consequently, frameworks addressing the governance implications of AI in restoration are largely absent. This paper explores the role of AI in scaling up forest restoration, understood here as enabling restoration efforts to operate across large spatial extents through logistically feasible and cost-effective approaches, while accounting for sociocultural constraints (Brancalion and Holl, 2025). To this end, the paper is structured around three objectives:

- (1) Provide a summary of application and opportunities for AI use in the design, implementation, and monitoring of forest restoration.
- (2) Analyze the limitations and risks associated with its adoption.
- (3) Propose a governance framework for responsible AI use that addresses emerging risks and supports restoration outcomes at scale.

2. Application and opportunities of AI in forest restoration

Advances in AI have generated widespread public enthusiasm, and generative systems, particularly large language models (LLMs) such as ChatGPT, Gemini, and DeepSeek, are increasingly being integrated into everyday tasks. Similarly, core AI technologies, particularly deep learning (DL), offer substantial potential in forest restoration contexts for processing large ecological datasets, identifying spatial patterns, and supporting data-informed modeling (Ekeh et al., 2025; Eugenio et al., 2025). Moreover, DL models can be algorithmically trained to perform a wide range of tasks. For example, vision models are usually pre-trained to learn a vast number of rich features from image data based on either supervised learning or self-supervised learning (Jing and Tian, 2020). These models can then be fine-tuned with local data sources to address specific tasks or applications, such as estimating the growth of different tree species (Fromm et al., 2019), predicting animal distributions (Guirado et al., 2019), or assessing plant health (Yang et al., 2025).

In restoration, these AI applications provide a methodological foundation for automating complex tasks, reducing fieldwork demands, and lowering computational costs (Rana and Varshney, 2021), which is particularly valuable in remote and large-scale landscapes. However, while AI has been progressively adopted across multiple sectors, including healthcare (Jiang et al., 2017), security (Gill, 2019) and precision agriculture (Sanida et al., 2023), and has been explored in forest and natural resource management for several decades (Coulson et al., 1987), its application to forest restoration remains comparatively limited (Shivaprakash et al., 2022). This slower adoption is attributed to factors including limited digital infrastructure, high implementation costs, and institutional inertia within forestry organizations (Wang et al., 2025). These developments highlight the underutilization of AI in forest restoration, where these tools could enhance process precision, efficiency, and overall restoration outcomes (Castro et al., 2021).

Successful forest restoration depends on the ability to plan where and what to restore, implement appropriate interventions, and monitor outcomes over time (Holl and Aide, 2011). To identify where AI can most effectively contribute, it is necessary to examine how it supports the core stages of the restoration process (Table 1). AI can support each of these stages in several ways, for instance:

- Planning: AI integrated with satellite-based, and high-resolution aerial imagery can generate site-specific recommendations that would otherwise be prohibitively costly or inaccurate (Ullah et al., 2024). DL tools have also been applied to identify priority areas that maximize biodiversity and climate benefits, thereby supporting strategic planning and policymaking (Silvestro et al., 2025).
- Implementation: AI-driven tools can support operational decisions such as species or trait selection (Stanturf et al., 2024), inform intervention choices by anticipating site suitability and future ecological conditions (Yin et al., 2021), and optimize seeding

Table 1

Examples of major applied uses of AI that directly support forest restoration across the planning, implementation, and monitoring phases. The table is not exhaustive but provides a summary of relevant reference cases. SDMs: Species Distribution Models; RF: Random Forest; ANN: Artificial Neural Network; ML: Machine Learning; NB: Naive Bayes; RL: Reinforcement Learning; LCR: Least-Cost Route (or Least-Cost Path); CDSA: Circuit-theory / connectivity-based spatial analysis (acronym usage may vary by study); RGB: Red–Green–Blue; LiDAR: Light Detection and Ranging; SVM: Support Vector Machine; LULC: Land Use/Land Cover; NDVI: Normalized Difference Vegetation Index; CHM: Canopy Height Model; CH: Canopy Height; AGE: Forest/stand age; AGB: Above-Ground Biomass; GBM: Gradient Boosting Machine (or Gradient Boosting Model); GSD: Ground Sampling Distance.

Phase	Location	Function	AI Method	Data	Scalability implications	Ref.
Planning	South Africa	Reforestation suitability (SDMs; climate scenarios)	LightGBM, RF, ANN	Climate, topo, RS/NDVI, LULC, ownership	Accurate, replicable	Buthelezi et al., (2024)
	Morocco	Suitability for <i>Quercus ilex</i>	ML classifiers	12 env. Vars, presence/absence	Strong performance, open-source	Manaouch et al., (2023)
	New Caledonia	Priority-area spatial optimization	Restoptr (R)	Habitat rasters, access layers	Open-source, flexible	Justeau-Allaire et al., (2023)
	Global	Budgeted carbon–biodiversity optimization	CAPTAIN (deep RL)	Simulated climate/ species /cost	Adaptable to regional real-world data	Silvestro et al., (2025)
	China	Corridors, risk, prioritization	Bayesian, connectivity	Land/ soil/ slope, socioecon. proxies	Flexible, urban policy support	Yin et al., (2021)
Implementation	Multi-region	Microsite detection for drone seeding	Faster/Mask R-CNN	RGB, LiDAR, labels	Generalizable across forest types	Castro et al., (2024)
Monitoring	Ecuador	Biodiversity monitoring (bird ID)	CNN (MobileNetV2)	Acoustics, metabarcoding	Cost-effective	Müller et al., (2023)
	Canada	Conifer seedling detection	CNN (R-CNN/SSD)	RGB drone imagery	Repeatable for linear projects	Fromm et al., (2019)
	Brazil	Tree crown delineation	Mask R-CNN	RGB, CHM, field plots	Transferable, low-cost, plugin ready	Albuquerque et al., (2022)
	Malawi	LULC, vegetation health	SVM	Landsat/GE, NDVI, field	Public imagery, participatory	Nyengere et al., (2025)
	China	Forest landscape types	U-Net (ResNet–50)	RGB, structure (CH/AGE/AGB)	Standard pipeline, adaptable	Wan et al., (2024)
	India	Explain plantation outcomes	Interpretable ML (GBM)	Forest cover, household surveys	Robust evaluation, policy insights	Rana et al., (2024)
	Romania	Tree-level inventory & management	VirtSilv (AI, 3D)	LiDAR, field validation	Accurate, time-efficient	Niță et al., (2021)
	Australia	Co-designed wetland monitoring	Healthy Country AI	Drone camera and Indigenous data	Replicable with ethical co-design	Robinson et al., (2022)

strategies, including drone-assisted deployment in heterogeneous and difficult-to-access landscapes (Castro et al., 2023, 2024).

- **Monitoring:** AI can process remote sensing data to detect habitat change with increased accuracy and temporal frequency (Lahoz-Monfort and Magrath, 2021). DL applied to soundscape data can also track biodiversity recovery over time (Müller et al., 2023).

Together, these applications enhance operational capacity across the restoration cycle, enabling forest restoration to be delivered at large scales more rapidly and efficiently than ever before.

3. Limitations and risks of AI integration in forest restoration

Despite the applications and opportunities offered by AI, its integration into forest restoration also entails significant potential for unintended negative outcomes (Reynolds et al., 2025). In particular, AI can reshape decision-making processes, redistribute authority, and influence which knowledge, values, and priorities are privileged in restoration (Urzedo et al., 2023; Woodrich and Pape, 2024). Anticipating and mitigating these limitations and risks requires understanding where and how harm may arise across the AI-driven restoration project cycle (Suresh and Guttag, 2021), particularly given the absence of clear ethical guidelines and regulatory oversight in many contexts (Mittelstadt, 2019; Pritchard et al., 2022). If left unaddressed, these shortcomings may undermine restoration effectiveness and exacerbate existing inequalities. Among the main challenges are (1) data availability varies across regions and communities, (2) models may oversimplify ecosystem dynamics and land-use practices, (3) limited transparency can restrict stakeholder access and trust, (4) initial high costs and limited capacity can restrict access to funding, and (5) power imbalances may marginalize certain regions and voices.

3.1. Data availability varies across regions

A notable obstacle is the dependence of AI systems on large volumes of high-quality ecological and socio-economic data for training, validation, and deployment (Adnan et al., 2024). In many regions targeted for restoration, especially in the Global South, such data are either unavailable, outdated, or incomplete (Raihan, 2023; Shukla et al., 2023). In particular, Africa has less consistent, available, and searchable data collected from its environments, leading to less accurate predictions (Rutenberg et al., 2020). In addition, many countries do not have real-time digital data acquisition systems, making it difficult to maintain the timeliness and accuracy needed for predictive modeling or adaptive planning (Holzinger et al., 2022). Although the amount of high-resolution, site-specific datasets are rapidly increasing (Holzinger et al., 2022), they often lack sufficient post-computational capacities, making these requirements difficult to meet for many countries. Additionally, spatial and institutional biases in existing datasets can also reduce model reliability. For instance, ImageNet, a widely used dataset, contains 1.2 million labelled images, 45% of which were taken in the United States, with most of the remainder coming from North America or Western Europe, whereas only 1% and 2.1% of the images originate from China and India, respectively (Deng et al., 2009). Studies have shown that such representational biases result in poorer image classification performance for underrepresented countries (Shankar et al., 2017), which is a concern given that much of the projected restoration areas are located in the Global South (Fagan et al., 2020).

3.2. Models may oversimplify ecosystem dynamics and land-use practices

The technological maturity and adaptability of AI tools in complex socio-ecological restoration settings remains a challenge. Landscape-level dynamics such as successional trajectories, species interactions, disturbance regimes, and feedback loops are often context-dependent

and computationally difficult to represent. As a result, the validity of automated classifications and predictions may be reduced (Liu et al., 2018; Alexandrov, 2025). Beyond ecological complexity, AI models may overlook socially embedded variables that structure restoration systems, such as actors, institutions, and land-use dynamics. This can omit locally salient drivers of restoration success or failure (Shelton et al., 2024). Even when models rely on quantifiable variables (e.g., land cover, accessibility, population density, or economic indicators), many factors remain difficult to formalize and are therefore underrepresented. These include relational values such as cultural meanings, sense of place, and identity (Woodrich and Pape, 2024). As a result, this abstraction can lead to technically optimized but socially misaligned restoration, potentially triggering displacement, conflict, or resistance (Sarkar and Chapman, 2021). Missing such factors may abstract the larger context into a simple model that provides inadequate decision-support (Holloway and Mengersen, 2018; Selbst et al., 2019).

3.3. Limited transparency can restrict stakeholder access and trust

Many DL systems operate as “black-box” systems, for which decision-making logic is difficult to interpret or audit (Sagar et al., 2024). For instance, in the case of LLMs, the built-in probabilistic generation processes produce inherently variable responses to identical queries. Moreover, LLMs are not designed to be aware of their own knowledge limitations and may fill these gaps by generating fabricated or unsupported causal relationships. This means that their responses can result in them providing confident but factually incorrect outputs, a phenomenon commonly referred to as ‘hallucination’ (Ji et al., 2023). Recent evaluations in biodiversity contexts show that such outputs can include for example the provision of non-existent species names, invented references, or inaccurate geographic distributions (Elliott and Fortes, 2024). Hallucinations pose a major risk of misleading ecological analyses and, in turn, poor decision-making by stakeholders, particularly when users are unaware of model limitations. Consequently, the opacity of these systems and the potential unreliability of their outputs can undermine trust among stakeholders and constrain opportunities for collaborative approaches (Rakova et al., 2021). Such unreliability underscores the need for integrating verification pipelines, transparency tools, and human oversight before LLM-generated information can be applied in restoration processes.

3.4. Initial high costs and limited capacity can restrict access to funding

High technical and financial costs create barriers to adoption and long-term viability of AI in forest restoration (COWLS et al., 2019). Developing, deploying, and maintaining AI systems may require computing infrastructure, specialized expertise, reliable connectivity, and stable energy systems. Overreliance on automation can also reduce local employment and livelihood co-benefits traditionally associated with restoration activities (Werden et al., 2024). Accordingly, investments in AI must be accompanied by sustained support for local technical training, infrastructure, and institutional capacity-building.

AI may also reshape restoration funding priorities. The growing attention to apply technological approaches, reflected in an increasing number of corporate-funded grants, may generate a polarizing effect on restoration funding and leadership (Gabrys, 2020). If AI-driven restoration comes to be perceived as a de-facto “gold standard”, financing streams may shift away from conventional experimentation and field-based practices, which already face chronic underfunding (Bosshard et al., 2021). Such dynamics may further privilege well-resourced actors while sidelining participatory approaches that are essential for creating community ownership and positive attitudes toward restoration (Woodrich and Pape, 2024). Funders must therefore adopt balanced portfolios that support a diversity of restoration approaches, ensuring that technological innovation complements field-based, community-led practices.

3.5. Power imbalances may marginalize certain regions and voices

Restoration frequently occurs in socially sensitive contexts, including Indigenous territories, community-managed lands, and biodiverse protected areas. In these settings, AI tools can reproduce extractive or colonial patterns if developed and deployed without meaningful local authority over data, model assumptions, and decision rules (Lewis et al., 2025; Rakova and Winter, 2020). AI-driven tools are frequently developed in centralized data hubs within elite institutions and technology companies, often located in the Global North, and then deployed to shape land-use decisions in the Global South (Latonero, 2018). This dynamic, often described as ‘algorithmic colonization’ (Birhane, 2020; Sarkar and Chapman, 2021), echoes historical patterns of technocratic governance, where knowledge and agency are abstracted from those most dependent on the land. In other words, decision-making power shifts from local actors to distant institutions that design or maintain AI models, externalizing governance and eroding local agency. Without appropriate ethical guardrails, the application of AI therefore risks exacerbating existing inequalities or legitimizing interventions misaligned with local socio-ecological realities (Schiff et al., 2020).

The opportunities and limitations outlined above underscore that integrating AI into forest restoration requires systems that actively mediate between technological capabilities and socio-ecological realities. AI use in forest restoration should be carefully analyzed and prioritized in contexts where its benefits demonstrably outweigh potential risks (Fig. 1). Therefore, emerging AI applications must be steered through appropriate governance to mitigate unintended consequences while unlocking their potential for forest restoration (Jobin et al., 2019). In the following section, we propose a governance framework designed to reduce risks and enable a responsible, context-sensitive use of AI in large-scale restoration.

4. A governance framework to enable responsible AI-driven forest restoration

A broad body of literature shows that the success of land-use interventions depends strongly on local socioeconomic contexts, including governance systems, power relations, and value systems (Chhatre and Agrawal, 2009; Elias et al., 2021; Erbaugh et al., 2020; Fischer et al., 2023; Jobin et al., 2019; Klein et al., 2015; Nagendra and Ostrom, 2012; Reyers et al., 2018; Wells et al., 2020). Accordingly, understanding these contexts is essential to ensure that restoration efforts move beyond technical efficiency and promote responsible and equitable outcomes. In this context, growing attention to the socio-ecological implications of AI has spurred the development of various governance frameworks that seek to promote transparency, fairness, accountability, and other principles associated with responsible use of AI (Floridi et al., 2018; Latonero, 2018; Papagiannidis et al., 2025; Rakova et al., 2021; Rana and Varshney, 2021; Ulnicane 2025). However, these approaches remain largely sector-agnostic, and, to our knowledge, no framework has yet been developed to explicitly address how AI reshapes governance in forest restoration contexts. Building on these insights, we propose a three-pillar governance framework for the use of AI in forest restoration, designed to mitigate risks while enhancing the benefits of large-scale restoration. The framework is operationalized through three complementary governance pillars: (1) participatory knowledge integration, (2) multi-scalar policy alignment, and (3) polycentric governance (Fig. 2).

4.1. Participatory knowledge integration

Forest restoration involves an increasingly diverse constellation of stakeholders as initiatives scale from local projects to national and global programs (Löfqvist et al., 2023; Mansourian et al., 2025). Public agencies, private companies, civil society, NGOs and academia both shape and are shaped by restoration interventions. In this context,

Use of AI in upscaling forest restoration

Applications & Opportunities

- ▲ Process large datasets beyond manual capacity.
 - ▲ Automate restoration operations.
 - ▲ Support integrated decision-making and cross-sector innovation.
-
- ▲ Enhances site-specific planning improving ecological fit.
 - ▲ Enable real-time monitoring and adaptive management.
 - ▲ Detect risks early (pests, fire, invasives).
 - ▲ Aids in predicting future ecological conditions
-
- ▲ Can empower communities through accessible, participatory tools.
 - ▲ Enables the integration of Indigenous and local knowledge into planning.
 - ▲ Can reduce labor burden and improve safety in remote or hazardous restoration tasks.
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- ▲ Reduce costs through automation and prioritization.
 - ▲ Supports efficient resource allocation, minimizing waste in inputs like seedlings or labor.
 - ▲ Facilitates access to restoration funding through better measurement and verification.
-
- ▲ Strengthen evidence-based policy and scenario planning.
 - ▲ Improve monitoring, reporting, and accountability.
 - ▲ Enable cross-sector and multi-level coordination.
 - ▲ Offers tools for more transparent, accountable governance when paired with inclusive design and oversight mechanisms.

Technological

Ecological

Social

Economical

Governance

Limitations & Risks

- ▼ Low transparency and limited interpretability.
 - ▼ Limited robustness under changing conditions or incomplete data environments.
 - ▼ Dependence on large, high-quality datasets.
-
- ▼ Lack of high-resolution, site-specific environmental data, particularly in the Global South.
 - ▼ Poor ecological fit from biased data or oversimplified models.
 - ▼ Environmental heterogeneity reduces model transferability.
-
- ▼ Marginalization of local and Indigenous communities in AI design.
 - ▼ Can undermine data sovereignty and participation.
 - ▼ Exclude actors due to low capacity or infrastructure.
 - ▼ Can prioritize industrial over community-led efforts.
-
- ▼ High upfront costs limit access for low-resource initiatives.
 - ▼ Dependence on specialized infrastructure and skills.
 - ▼ Concentration of benefits in wealthy institutions.
-
- ▼ Weak national and international frameworks for AI ethics and accountability.
 - ▼ Centralized, top-down decision-making.
 - ▼ Absence of inclusive governance structures that embed AI into participatory restoration.
 - ▼ Data blind spots can exclude relational, cultural, and Indigenous dimensions

Fig. 1. Applications and opportunities versus limitations and risks of AI use in forest restoration across key dimensions.

meaningful participation of stakeholders becomes a prerequisite for representing diverse perspectives and values while reconciling competing interests (Woodrich and Pape, 2024). Restoration decisions should therefore integrate place-based knowledge held by local communities and Indigenous peoples, alongside scientific evidence and practitioner expertise to enable effective AI-driven restoration (Ullah et al., 2023). For instance, Rakova and Winter (2020) show how traditional ecological knowledge systems, such as the Maya Milpa or the Chagga Kihamba forest gardens, offer detailed insights that can inform machine learning (ML)-driven restoration and ensure bioculturally relevant outcomes. Such participatory mechanisms are particularly important for marginalized actors, who are often excluded from technological decision-making despite holding essential ecological knowledge (Haq et al., 2023). Participation also helps identify biases, contextual blind spots, and implausible AI-generated outputs. In this way, the inequities in stakeholder access and participation discussed in the previous section can be mitigated through the integration of plural forms of knowledge into AI systems (Santos and Carvalho, 2025).

This integration can be operationalized through the adaptation of generic models using locally sourced data, allowing experts and knowledge holders to shape model behavior (Holzinger et al., 2024), or through agent-based architectures that combine ecological, socio-cultural, and policy knowledge within integrated decision-support systems. For example, the CAPTAIN project (Silvestro et al., 2025) employs reinforcement learning to prioritize restoration areas by integrating multiple ecological and socio-environmental variables into decision-support scenarios. Although still nascent, these approaches accommodate heterogeneous knowledge while enabling participation and deliberation. Therefore, active stakeholder participation improves both restoration legitimacy and model quality by enabling stakeholders to challenge, refine, or reject AI-generated recommendations (Mansourian et al., 2025; Yadav Uprety et al., 2012). Without such participatory integration, restoration efforts risk resistance and the marginalization of stakeholders, particularly those with the least decision-making power (Chazdon et al., 2021; Schultz et al., 2022).

Such participation should be facilitated through user-friendly

interfaces that lower barriers to engagement, accommodate diverse technical capacities, and provide transparent explanations of algorithmic outputs (Doshi-Velez and Kim, 2017). Examples include co-design workshops during model development, participatory validation of model outputs before implementation, and iterative ground-truthing. Establishing these governance arrangements helps translate experiential knowledge into forms that can guide or complement responsible AI systems while allocating meaningful decision-making authority to local actors (Papagiannidis et al., 2025; Ruiz et al., 2023). For instance, in Australia's Kakadu National Park, Traditional Owners collaborated with researchers through co-production processes to develop a decision-support tool integrating drone imagery, ecological models, and Indigenous management practices (Robinson et al., 2022). This example illustrates how AI can complement rather than replace local knowledge when governance arrangements explicitly prioritize co-production.

Finally, not all relevant knowledge can or should be digitized. Customary land-use practices, cultural values, and tacit ecological understanding are often embedded in lived experience and risk being “averaged out” when AI models rely predominantly on global datasets (Tella et al., 2025). Consequently, participation must extend beyond consultation to incorporate meaningful influence over decisions (Fischer et al., 2025). This includes authority over how AI tools are used, adapted, and embedded within existing governance systems, while safeguarding data sovereignty and privacy (Rana and Varshney, 2021). Participatory governance should therefore ensure that stakeholders influence not only how AI is used, but also whether its use is appropriate in a given restoration context. Where AI risks outweigh benefits, local knowledge and conventional approaches may be preferable. Technological adoption should therefore be guided by demonstrated need rather than novelty or external pressure. Ultimately, building inclusive governance coalitions is essential if AI is to democratize restoration governance rather than reinforce existing inequalities (Schiff et al., 2020).

Governance framework for AI-driven forest restoration

Multi-level goals integration

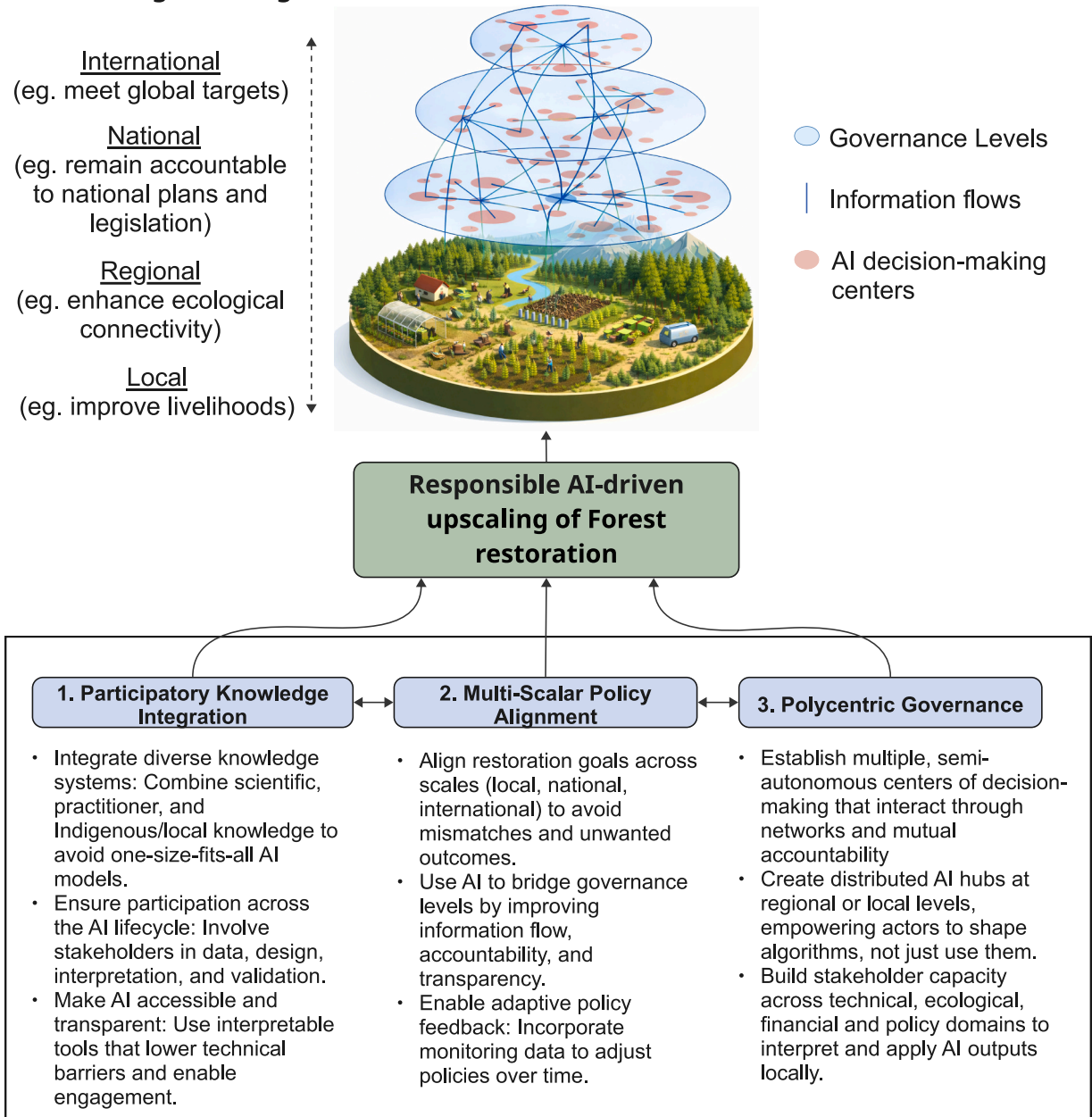


Fig. 2. Three-pillar governance framework for enabling responsible AI use in large-scale forest restoration.

4.2. Multi-scalar policy alignment

Forest restoration inherently operates across multiple spatial and institutional scales, involving actors ranging from local land stewards to national governments and international conservation coalitions (Chazdon et al., 2021). While international initiatives such as the Bonn Challenge or national reforestation programs provide essential political momentum and mobilize resources, they often struggle to translate broad commitments into effective, locally relevant outcomes (Bell-James, Watson, 2025; Coleman et al., 2021; Stanturf and Mansourian, 2020). Evidence from large-scale restoration programs shows that misalignment across governance levels is a major cause of implementation failure and a frequent source of social contestation (Sayles, 2018). Therefore, responsible AI governance in restoration requires a

clear division of responsibilities across governance levels. International initiatives should establish broad principles for transparency and accountability; national governments should translate these principles into regulatory frameworks and funding criteria; local actors should retain authority over implementation decisions and contextual adaptation (Wiegant et al., 2022). At the same time, decentralization alone is insufficient. Studies show that transferring responsibilities to local actors without adequate support, accountability, or fiscal autonomy can generate new bottlenecks (Wiegant et al., 2022). In Vietnam, for instance, the national government allocated funding to city councils, which in turn directed resources toward monoculture plantings. These had low ecological value and were misaligned with local communities' land-use priorities (Dang et al., 2019).

The integration of responsible AI within multi-level governance

systems introduces both risks and opportunities. On one hand, AI risks reinforcing top-down paradigms by concentrating analytical and predictive power in centralized agencies; ML models trained on satellite imagery may, for example, identify “priority” restoration areas without accounting for local socio-political land claims or local indigenous land rights (Schiff et al., 2020). On the other hand, successful implementation tends to bridge gaps across multiple levels of governance (Wiegant et al., 2022). By facilitating both bottom-up and top-down information flows, AI operationalizes these linkages by connecting knowledge with decision-making across governance levels. For instance, bottom-up data collection using DL-processed drone imagery can support local reporting of carbon stocks to national monitoring systems (Reiersen et al., 2022). Similarly, cheap devices such as camera traps and smartphone-based applications are increasingly being used for automated species identification and restoration monitoring. Applications such as *Merlin*, *Google Lens*, *PlantNet*, or *iNaturalist* combine advances in computer vision with large, community-validated datasets, often achieving high accuracy for well-represented taxa (Atsumi et al., 2024; Coşkunserçe, 2024; Goëau et al., 2013; Jones, 2020; Van Horn et al., 2018). These tools can cost-effectively generate extensive ecological information from the ground that can be aggregated to inform governance priorities, track restoration progress, and support compliance with international restoration goals. At the other end of the scale, global monitoring initiatives such as *Global Forest Watch*, leverage AI and satellite-based analytics to improve comparability across local projects and support international restoration commitments (World Resources Institute, 2026). Together, these applications show how AI can connect actors across governance levels, facilitating accountability and helping prevent contradictions across governance scales that often hinder restoration efforts (Wiegant et al., 2022). In doing so, this pillar helps address previously identified risks such as limited transparency while coordinating global restoration efforts that remain responsive to local contexts.

4.3. Polycentric governance

As AI becomes embedded in restoration practice, it starts to influence not only what decisions are made, but how and by whom they are made. Consequently, it reshapes power relations, with the potential to deepen existing asymmetries, or to support more inclusive and distributed forms of governance (Woodrich and Pape, 2024). When AI systems are developed and interpreted within closed technical silos, they risk reinforcing fragmented, top-down governance structures. In such contexts, decisions may be shaped by opaque, remotely designed models that are misaligned with local knowledge, values, or land-use rights (Schiff et al., 2020). As a result, this concentration of technical control can create epistemic gatekeeping, limiting stakeholders' ability to question or contest AI outputs.

Conversely, successful implementations tend to embed AI systems within a polycentric governance structure, facilitating interactions among diverse actors and helping enhance knowledge exchange (Korol and Korol, 2025). Polycentric governance refers to systems in which multiple centers of authority across different scales interact semi-autonomously, yet are interconnected through networks, negotiated rule-making, and mutual accountability (Ostrom, 2009). Across successful cases, three governance mechanisms consistently emerge: (i) local authority over implementation decisions, (ii) coordination and knowledge exchange across governance levels, and (iii) equitable access to shared data and technical infrastructure. Thus, rather than centralizing authority, such governance arrangements enable distributed power among actors with different forms of knowledge and responsibility. Existing restoration initiatives illustrate these principles. The Atlantic Forest Restoration Pact, a 1-million-hectare initiative involving over 300 institutions across scales, demonstrates how restoration legitimacy improved through stakeholder participation and knowledge co-production (Toto et al., 2025). Integrating responsible AI into such existing polycentric structures can enhance coordination and

decision making. Similarly, global digital platforms such as *Restor* facilitate data exchange and transparency across geographically dispersed restoration projects, creating shared infrastructures that support collaboration while preserving local autonomy (Restor, 2024). Together, these examples suggest that responsible AI can strengthen a polycentric restoration governance approach by acting as an enabler of distributed decision-making rather than a centralizing force.

However, realizing this potential requires deliberate institutional design. Recent work on decentralized AI infrastructures argues that this vision requires geographically distributed hubs of AI innovation embedded within the regions where restoration takes place (Cihon et al., 2020). In such arrangements, rather than relying on centralized AI platforms, local institutions retain authority over data, contextual interpretation, and implementation decisions, while higher-level organizations provide technical support, infrastructure, and opportunities for cross-site learning (Sarkar and Chapman, 2021). To operationalize this vision, open-source approaches can help enhance transparency and adaptability, but their effectiveness ultimately depends on systematic investment in capacity development and AI literacy (Bogina et al., 2022). Therefore, this shift requires moving away from passive models of technology transfer toward building capacities to access, interpret, and apply AI outputs locally (Santos and Carvalho, 2025). Empirical studies by Chisika and Yeom (2024) in Kenya illustrate how integrating AI into polycentric forest governance can enhance data sovereignty and strengthen local decision-making processes. By leveraging AI tools built on existing resources, the initiative improved efficiency and transparency while reducing errors, with 90% of participants expressing confidence in AI adoption. However, the study also underscored the importance of sustained community engagement and locally adapted AI policies, emphasizing the need for governance frameworks that keep AI responsive to community contexts.

Collectively, the three pillars suggest that responsible AI integration in forest restoration depends not on maximizing automation, but on embedding AI within participatory, accountable, and distributed governance systems. Across all pillars, successful implementation requires maintaining human oversight, and preserving the authority of local actors to adapt, contest, or reject AI-generated recommendations when necessary.

5. Conclusion

In this perspective, we argue that the role of AI in forest restoration success is not only technical but fundamentally governance-related, and we propose a framework to guide its responsible use. Building on this framework, we derive three governance priorities: First, participatory approaches should be prioritized to ensure that AI systems incorporate local knowledge, values, and priorities, avoiding the exclusion of stakeholders from decision-making processes. Second, multi-scalar alignment is needed to connect AI applications with existing policy frameworks, reducing inconsistencies across governance levels and improving coordination. Third, polycentric governance structures should be strengthened to enable distributed decision-making and more context-responsive restoration strategies. These recommendations have direct implications for practice. For researchers, this includes facilitating the enabling conditions for stakeholder interaction around the interpretation of algorithms and creating capacities in adjacent communities. For policymakers, it involves shaping the institutional conditions under which responsible AI is developed and deployed, including support for open infrastructures, capacity development, and mechanisms that safeguard transparency. For practitioners, it involves adopting AI in ways that complement, rather than replace, local knowledge systems and existing restoration practices. Especially in contexts where financial and technical resources are limited, AI holds promise for “doing more with less,” but efforts must ensure that it delivers ecologically sound and socially grounded decision support. To this end, future research should focus on identifying the conditions under which AI improves restoration

outcomes across different socio-ecological contexts. This includes examining how governance arrangements influence the distribution of benefits and risks associated with AI use.

As Latour (2005) reminds us, tools are never neutral; they alter the very goals they are designed to serve. In restoration ecology, where values are contested, dynamic, and difficult to quantify, this is particularly relevant as the use of AI exerts governance power by encoding knowledge, mediating access, and determining who participates and on what terms. Therefore, if AI is to improve large-scale restoration, it must be judged not only based on the technical or ecological outcomes, but also by how it transforms the governance of restoration itself.

CRediT authorship contribution statement

Harry W. Fischer: Writing – review & editing, Conceptualization. **Maganizo Kruger Nyasulu:** Writing – review & editing, Investigation, Conceptualization. **Ingo Fetzer:** Writing – review & editing, Conceptualization. **Domingo Alcaraz-Segura:** Writing – review & editing. **Siham Tabik:** Writing – review & editing. **Jorge Castro:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Fernando Morales-Rueda:** Writing – review & editing, Writing – original draft, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used ChatGPT solely to support language editing and clarity improvements. All scientific content, interpretations, and conclusions were developed by the authors, who reviewed and approved the final version and take full responsibility for the published work.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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