THE NEXT GREAT DIVERGENCE
WHY AI MAY WIDEN INEQUALITY BETWEEN COUNTRIES

People-Centric AI for Conserving Biodiversity

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Asia and the Pacific is one of the most biologically diverse places on Earth, but this richness is steadily being lost. To mitigate this loss, countries across AP are racing to better understand and monitor their existing biodiversity and take action to protect and rehabilitate ecosystems. AI has been shown to be a powerful tool in this pursuit, reducing the cost and expanding the scale of biodiversity monitoring and analysis. However, fully realizing this promise across the region will require a fundamental shift from technology-centric to people-centric design. AI systems must be carefully tailored to local user needs and capacities, ensuring that technological solutions benefit Indigenous Peoples and Local Communities (IP and LCs) and respond to ecological realities. This chapter offers a people-centered AI roadmap for biodiversity that aligns with regional development goals and empowers those most affected by environmental change.

Asia and the Pacific has seven of the world's 17 'megadiverse' countries that house the majority of the Earth's species – across many complex ecological interfaces including tropical forests, near-shore marine ecosystems, and mountain landscapes.[1,2] This diversity directly supports the livelihoods of many hundreds of millions of people and helps sustain sustainable food security. The value of this biodiversity to the region has been estimated at over $2.19 trillion, including ecosystem services, medical research potential, and economic gains from ecotourism.[3]

Biodiversity monitoring has traditionally been carried out by species inventories, field surveys, and manual habitat assessments – labor-intensive and expensive exercises that are often infeasible at large scales or in remote regions.[4] Relatively few countries have the necessary infrastructure, technological capacity, or funding to monitor the decline in biodiversity – especially Indigenous Peoples, who typically stand to lose the most.[5]

To address the accelerating decline of biodiversity, the world needs new tools and approaches.[6] AI can play an important part by processing vast quantities of data from multiple sources such as camera trap images, acoustic recordings and hyperspectral satellites – which can be used to monitor ecosystems, detect species, and track changes in land cover, deforestation, and habitat fragmentation with unprecedented precision.[7,8] AI image analysis can also monitor marine systems tracking reef health, for example, and bleaching events.[9]

Nevertheless, the intricate web of relationships between species, environmental conditions, and ecosystem dynamics often defies simple computational modelling. Existing machine learning algorithms struggle to capture the nuanced, often unpredictable nature of ecological relationships, with non-linear interactions and context-dependent behaviors.

Benefits of AI – remote sensing and analysis

AI can substantially reduce the time and costs of biodiversity surveys: human-walked transects through ecosystems can now be supplemented with data collected from sensors such as camera traps, passive acoustic sensors, drones and satellite imagery.[10] These are particularly valuable in remote or rugged environments where human access is limited. Unlike human observers, these sensors can operate continuously and across a broader area of ecosystems providing a finer-grained picture.

Using camera trap images, AI analysis can identify common species of wildlife as accurately as human experts.[11] AI can also classify audio recordings of animal calls which are particularly valuable for monitoring nocturnal species, or for 'cryptic' species that are otherwise difficult for human observers to distinguish.[12]

AI can also be used to prioritize policy enforce regulation, and provide early warning to mitigate human-wildlife conflict. AI can help identify areas where deforestation is likely to occur next,[13] and forecast species migration under climate and anthropogenic change. With sufficient bandwidth to send data to a central hub, or sufficient computational capacity on the sensors themselves, AI-enhanced acoustic monitoring systems can detect chainsaw noise in forests and alert rangers before illegal logging escalates, [14] or highlight the potential for human-wildlife conflict. In India, AI-enhanced camera traps detect the presence of tigers and alert nearby villagers of potential danger.[15] This real-time response capability can transform enforcement and adaptive management.[16]

Finally, AI-enabled technology can combine diverse data sources into unified platforms to enable more integrated analysis. This improves the understanding of complex ecological interactions, supports predictive modelling, and provides a basis for more strategic and proactive conservation planning.

Threats from AI – disruption and exclusion

Alongside these benefits, AI can also be disruptive and even misleading. One of the most pressing concerns is the potential for AI to introduce significant bias into monitoring systems. AI systems are only as good as the data they are trained on, and many existing biodiversity datasets are geographically skewed toward the Global North or certain charismatic species.[17] As a result, AI models may perform poorly in underrepresented areas, many of which are in Asia and the Pacific, leading them to misclassify species or fail to detect important ecological changes.[18]This imbalance in AI performance can reinforce or expand existing global power and resource imbalances.[19]

There are also risks of AI deployment related to surveillance and privacy. AI systems that monitor environmental sounds or track wildlife movement may inadvertently capture sensitive information about human activity – which could be used to monitor communities without their consent or criminalize traditional land uses.[20]

In addition, there are issues of sustainability. Advanced AI applications have high infrastructure and maintenance costs – for expensive sensors, high-throughput communication networks, and software and hardware upkeep. Deploying technical infrastructure and expertise often requires significant human oversight – for validating models, maintaining systems, and interpreting data. In these circumstances, countries without these resources remain dependent on foreign institutions to support their access to these technologies and may struggle to build AI systems specialized to work well within their own changing ecological contexts. In regions where technical capacity is low and capacity building is not prioritized, this over-dependence on external support makes sustaining such projects difficult. And when donor funding ends, such projects may be abandoned.[21]

Finally, technological innovation can sometimes overshadow, or divert funding from, fundamental non-technical conservation needs – community organizing, legal reform, or ecological restoration. This form of 'techno-solutionism' risks addressing symptoms without tackling root causes, such as land tenure insecurity, extractive industries, or weak governance.[22] And with AI only sporadically deployed the outputs of such systems, despite their local value, are less likely to be integrated into conservation policy.

Balancing the benefits and disruptions of AI requires a holistic approach. Tools must be evaluated not only for their technical performance but also for their social, ethical, and ecological impacts. Ensuring that AI contributes to, rather than detracts from, inclusive and sustainable conservation requires participatory design, transparent evaluation frameworks, and adaptive governance mechanisms.

The need for AI systems specific to Asia and the Pacific

Machine learning systems require "training" to perform well, via large, expert-curated, well-labelled datasets. Such data is lacking for many species and ecosystems in Asia and the Pacific, and models trained in one region or on certain species often underperform when transferred to new settings, a phenomenon known as 'domain shift'.[23] For example, models trained on North American camera trap images or European satellite imagery often fail in Asian landscapes which can have different lighting conditions, vegetation cover, or miss endemic species.[24] These problems are particularly acute in tropical forest and island ecosystems rich in species but from which there is little systematic data collection.[25]

We have seen examples where concentrated effort to build training data has led to significant benefits: in Canada, for example, the careful curation of a dataset including audio recordings for 317 Canadian bird species led to the development of the powerful, accurate HawkEars species recognition model, which is now deployed across Canadian national parks.[26] To see such benefits in Asia and the Pacific, a strategic, multi-country effort to curate AI-ready biodiversity datasets would significantly reduce current imbalances in AI performance relative to other parts of the world.

The value of local knowledge

Another significant challenge for AI systems is the integration of local ecological knowledge. Traditional ecological understanding has developed through generations of intimate environmental interaction and often contains subtle insights that elude quantitative technological approaches. Predictive modelling in these situations demands extraordinary complexity and will push current AI technologies to their conceptual and computational limits.

Developing models that can meaningfully represent ecological complexity requires a fundamental reimagining, where interactive, data-driven biodiversity monitoring and understanding systems can be a tool for local experts, where their knowledge can be introduced to expand and benefit ecosystem understanding.[27] At the same time, AI systems must continuously adapt to shifting baseline conditions, a task that requires sophisticated, flexible learning mechanisms that go beyond traditional computational approaches. Crucially, AI systems should respect ethical and legal frameworks that prioritize data sovereignty over local knowledge, ensuring that the communities and nations from which the biodiversity data originates retain control and authority over its use and distribution.

The dangers of deepening inequality

While AI can benefit biodiversity monitoring, its deployment risks deepening existing inequalities relating to who can access, influence, and benefit from AI technologies, and whose knowledge, data, and priorities are represented.

Within-country inequalities

Disparities are often most visible in the division between urban and rural areas, or between state institutions and Indigenous Peoples and local communities. In many parts of Asia and the Pacific, Indigenous Peoples are the primary stewards of biodiversity-rich landscapes but often marginalized in conservation technology development and policy, particularly at the regional or global levels. Conservationists from global NGOs or well-endowed research institutions often deploy drones, camera traps, or acoustic sensors in developing countries but bypass IP and LCs, failing to secure free, prior, and informed consent.[28] The prevalent data governance model remains extractive and non-transparent, with minimal benefit-sharing mechanisms that perpetuate historical patterns of technological and ecological marginalization.

This has multiple implications. First, it undermines trust in conservation institutions and technologies, especially when monitoring is perceived as surveillance. Second, it

can disrupt customary land management by introducing tools that are misaligned with local governance systems. Third, it misses opportunities: indigenous ecological knowledge, when integrated respectfully with scientific methods, can enhance the performance and relevance of AI systems.[29]

Between-country inequalities

There are also stark divides between countries. Richer countries with stronger scientific infrastructure, and deeper integration into global technology networks are much more likely to lead and benefit from AI innovation. In Asia and the Pacific, Australia, China, Japan and Singapore, for example, have active AI research communities, strong digital infrastructure, and greater access to competitive grant funding.[30] These are also the countries with the greatest capacity for AI model development and interpretation.[31] They benefit from centralized biodiversity databases, robust digital infrastructure, and well-funded research institutions. In Singapore, the National Biodiversity center has advanced camera trap systems and acoustic monitoring integrated into urban ecological networks.[32] Similarly, the Australian Acoustic Observatory uses cutting-edge approaches and is partnering with Google to search decades of passive acoustic monitoring data for observations of specific bird species.[33]

By contrast, remote Pacific island nations or poorer developing countries have far fewer resources and tend to rely on external NGOs and universities whose AI models may not be tailored to their ecological or institutional contexts.[34] Often these countries are also the ones lacking the technological capacity, data and computational infrastructure to develop targeted conservation strategies.[35] This systematically impedes conservation efforts. Technology transfer is further complicated by linguistic diversity combined with low digital literacy.[36] Their environmental protection agencies are often critically underfunded and lack the technical expertise to develop, deploy, and maintain sophisticated AI-driven conservation technologies.[37]

Unequal access to technology could also be exacerbated through a different channel. Countries, regions, or protected areas in the region with pre-existing relationships or partnerships with newly emerging leaders in AI (countries, companies, or academic institutions) often have readier access to their technology partnerships and platforms. While often beneficial in terms of rapid adoption, this can affect the type of technologies prioritized through these partnerships and the strategic interests they serve. For example, if the relationship is with a partner that has an interest in carbon offsets, the AI that is prioritized for deployment may focus on estimating carbon for global carbon markets but may not consider or prioritize local-held biodiversity or community land-use goals. These externally designed and built AI-enabled systems may lead to a shift in priorities in local or global conservation decisions downstream, driven by what environmental information is made readily available via AI. In contrast, countries and communities that have the capability to build their own AI systems can directly encode their local conservation priorities, cultural values, and land-use goals into the systems.

Historical data collection

These disparities are compounded by legacy issues in biodiversity data, which is a key component of successful AI development. Colonial-era specimen collection and unequal research funding historically prioritized accessible or economically significant species.[38] As a result, many global biodiversity databases – such as the Global Biodiversity Information Facility – are still heavily skewed toward species and ecosystems in the Global North. AI models trained on these datasets underperform when applied to data-poor regions, reinforcing cycles of invisibility and underinvestment.

There are also problems of data ownership.[39] In the developing world, many research repositories and comprehensive biodiversity datasets are collected, owned and managed by European or North American institutions. This may be the only practical way to fund

data collection and analysis, nevertheless, organizations from the Global North are capturing data from the Global South but the benefits of that collected information are not always realized in the communities and regions where the data was collected.[40]

Inequalities in access to existing systems

Some countries and communities are excluded by language barriers or lack of expertise. Much of the documentation, software, and training resources for AI are available only in English, creating additional hurdles for practitioners in non-Anglophone countries. Moreover, environmental science curricula may not include computer science or data ethics, making it harder for conservation professionals to engage meaningfully with AI systems.[41] Finally, existing databases, tools, and platforms may not be accessible to those without institutional connections, academic or otherwise, effectively marginalizing local communities acting to conserve species.

Regional variations in biodiversity value and support

In the Asia-Pacific region, some countries are richer in biodiversity but economically poorer. In Indonesia and the Philippines, for example, funding for conservation has to compete with priorities like economic growth and poverty alleviation.[42] Further disparities emerge between areas that receive priority because of their ecotourism potential and those that provide essential but less visible ecosystem services such as insect pollination or protecting watersheds.[43] Priority may also be given to areas where biodiversity objectives chime with livelihoods and disaster risk reduction, such as mangrove conservation for coastal protection and flood mitigation.[44]

External financing may also be attracted to areas with famous or charismatic species, such as tigers, while other regions with less charismatic but equally threatened forms of biodiversity struggle to secure comparable resources. Additionally, external funding for AI technology adoption often prioritizes high-visibility conservation projects with flagship species or ecotourism potential.[45]

Conservation efforts can thus be weakened by a misalignment between global interests, external funding mechanisms, and local priorities.[46] Addressing these intersecting inequalities effectively, requires multi-faceted and targeted interventions. These include:

- In-country data collection and processing infrastructure
- Training programs tailored to diverse user groups – such as policymakers, forest rangers, and indigenous monitors
- Platforms for cross-country collaboration.
- Open-source models and data-sharing agreements
- Participatory governance mechanisms
- Local data ownership, where national frameworks function primarily to support rather than supersede community-level decision-making.

To conclude, regional disparities are compounded by technological dependency on imported pre-trained models and contracts for foreign technical teams, creating systemic barriers to local technological sovereignty. This dependency compromises long-term sustainability, as ongoing system maintenance, updates, and troubleshooting remain contingent on continued external engagement and funding.

Inequality in the deployment and efficacy of AI tools for biodiversity conservation in Asia and the Pacific is deeply rooted in complex, multifaceted disparities that extend far beyond data limitations and technological capabilities.[47] These inequalities are fundamentally shaped by historical power dynamics, colonial legacies, and uneven development priorities that persist in contemporary conservation efforts,[48] inhibiting the development of local conservation capabilities – perpetuates a colonial approach to ecological research.[49]

Overcoming technical and institutional barriers

Addressing these profound inequalities demands a comprehensive, multi-faceted approach that transcends technological solutions. Key interventions include sustained investment in national and regional biodiversity data collection infrastructure, development of robust AI and technological education programs, and promotion of open-source technology. Critically, technological design must include local and indigenous communities to ensure solutions are contextually appropriate and culturally sensitive.

Local and regional computing infrastructure

Many AI applications require high-performance computing infrastructure, including GPUs, large-scale data storage, and stable internet connectivity – requirements which are difficult to meet in remote or resource-constrained areas – from highland forests in Nepal or outer island chains in the Pacific. One emerging solution is to process data locally on low-power 'edge'-devices that have embedded artificial intelligence.[50] For example, in India AI-enabled camera traps can identify endangered Sumatran tigers directly on the device, enabling alerts to be sent rapidly over limited networks without needing to send entire images.[51] However, widespread adoption remains constrained by high initial hardware costs, limited local technical expertise, the need for new machine learning models that often require sophisticated model compression and can accurately perform within the limitations of edge devices and in diverse and complex ecological environments.[52] Despite these challenges, edge AI shows promise for wildlife monitoring and conservation in the Asia-Pacific region – empowering local researchers and practitioners with advanced technological capabilities.[53]

Interdisciplinary collaboration and capacity building

Current educational systems are often poorly equipped to produce professionals with the interdisciplinary skills required for AI-driven or AI-enabled work.[54] AI for biodiversity will require breaking down institutional silos so as to foster meaningful and informed dialogue between conservation scientists, computer scientists, local practitioners, and policymakers.[55]

Curriculum redesign must occur from primary education through to advanced professional training, creating integrated learning pathways that break down traditional disciplinary boundaries. Universities, research institutions, and government agencies can develop sustained strategies that view interdisciplinary expertise as a core institutional value. This requires creating supportive ecosystems that reward complex, boundary-crossing research and professional practice.

Targeted capacity-building programs can enhance technical skills within government agencies and local research institutions, while simultaneously developing AI tools that are contextually relevant and that align with specific regional conservation needs.[56] Examples are educational programs such as CV4Ecology,[57] and the AI for Science Masters program at the African Institute of Mathematical Sciences,[58] which are developing curricula that increase AI development capacity in the conservation and biodiversity communities. Around the world, a growing number of conservation technology programs are making practical use of technology and supporting decision-making,[59] but there are fewer such programs in Asia and the Pacific where open-source education tools can be hampered by language barriers. Successful adoption of these technologies will require significant investment in local and accessible AI and technology capacity building.

Impact assessments

AI deployment must be evidence-based and supported by informed and rigorous impact assessments. Information from pilot projects can show if projects are technically feasible, but few systematically assess whether they improve conservation outcomes, increase efficiency, or reduce costs. Without robust impact metrics, it is difficult to justify ongoing investments or to learn

from past successes and failures. Weak evaluation also makes it harder to identify unintended consequences, such as reinforcing data biases or displacing local knowledge systems.

Evaluation of technology should capture the regional and local value.[60] This will enable a fundamental reimagining of conservation technology governance and prioritization – shifting from top-down, globally-driven models to more inclusive, locally-empowered approaches that center on the knowledge, priorities, and capabilities of regional researchers and communities.

By prioritizing local agency, developing adaptive institutional capacities, and creating flexible technological infrastructures, the conservation sector can begin to develop AI solutions that are not just technologically sophisticated, but also broadly accessible and responsive to local ecological and social contexts.

People-centered AI for biodiversity

The UNDP 2024 Regional Human Development Report presents a transformative vision for development in Asia and the Pacific – one that is centered on people, prioritizes inclusion, and advances sustainability.[61] This requires re-evaluating current paradigms for design and deployment of AI for biodiversity monitoring – moving the conversation from purely technical performance to questions of equity, empowerment, and social outcomes.

People-centered development prioritizes human dignity, agency, and well-being. For biodiversity, this means recognizing the roles of local communities, indigenous peoples, and under-resourced governments not just as beneficiaries but as key actors whose participation, knowledge, and governance must shape AI tools.[62]

AI systems should be responsive to local values, and interpretable and usable without extensive technical expertise. A local ranger should be able to understand and act on the model's outputs, so the main priority should be useability rather than absolute prediction accuracy.

People-centered development must address the dangers of 'data deserts'. AI is notoriously data hungry, and struggles to learn concepts robustly if it has few examples to learn from.[63] Filling these voids requires investment in locally led data collection and human infrastructure. Community-based monitoring programs, when equipped with appropriate technology and training, can fill data gaps while building local ownership and capacity.[64]

In parallel, AI systems should be designed to operate in low-resource environments. Research is still needed to develop AI models that can robustly recognize species with limited training data. AI algorithms should optimize for energy and computational efficiency and be able to operate with limited bandwidth and less access to cloud computing or local access to GPUs. This also reduces the environmental footprint of AI itself – given the extensive carbon, energy, and water costs of training large models.[65]

Another critical aspect is skills. People-centered AI requires more than just awareness workshops; it demands sustained investments in education, mentorship, and institutional development. Local ecologists need to be trained in AI tools, while AI developers need to be sensitized to ecological principles and local contexts. Tool developers and end users should collaboratively define goals and metrics, bridge disciplinary divides, and build mutual understanding.[66]

It is also important to establish policy frameworks. National strategies should mandate inclusive stakeholder engagement in technology initiatives and create mechanisms for feedback, redress, and shared governance. Regional bodies like ASEAN and the Pacific Islands Forum can support alignment by promoting best practices, facilitating knowledge exchange, and providing member states with technical support. International donors, meanwhile, must reorient to long-term community-embedded approaches.

Finally, AI needs to be embedded in broader visions of sustainable development. Technological tools should not just be monitoring biodiversity but supporting human well-being, land rights and customary governance systems. Biodiversity data should therefore be linked with health, agriculture, and climate resilience indicators. AI-generated insights can also be used to guide conservation finance mechanisms such as payments for ecosystem services and more generally as a catalyst for inclusive environmental stewardship.

Policy implications and recommendations

The Asia-Pacific region is a critical nexus of biodiversity hotspots scattered across diverse ecological, social, and technological landscapes.[67] It also has complex socioeconomic challenges and widely differing technological capabilities. This demands a nuanced and people-centric approach that sees AI technology not as a solution, but as an opportunity for collaborative knowledge creation and environmental stewardship – moving beyond technological determinism to embrace a holistic vision centered on human and ecological well-being.[68]

Policymakers will need to collaborate with ecologists, computer scientists, and local communities, who together can develop AI technologies that are not only scientifically robust but also socially and contextually appropriate.[69] Country strategies should also be linked to regional collaborative mechanisms that foster knowledge sharing and collective technological development.

By prioritizing local agency, cultural sensitivity, and adaptive strategies, the Asia-Pacific region can emerge as a global leader in reimagining the relationship between technology, human communities, and the natural world.

Inclusive and sustainable digital infrastructure development

Governments can tailor digital infrastructure to the region's diverse geographical and socioeconomic conditions, building distributed computing networks and low-power and climate-resilient infrastructure. They can also work through regional bodies including ASEAN, the Pacific Islands Forum, and the South Asian Association for Regional Cooperation (SAARC) to create regional data-sharing platforms that uphold local data sovereignty.

It is particularly important to employ open-source tools, datasets, and commons-based digital public infrastructure.[70] Open access to AI tools can accelerate innovation across data-reliant sectors such as public health and ecosystems.[71] Policymakers can also help democratize the development and use of AI-enabled technologies by mandating open access to publicly funded research where ethical to do so.[72] This is especially critical for small island states, and other countries likely to be excluded from commercial AI ecosystems.[73]

Adaptive and contextual technology

AI technologies should be localized to specific ecologies and cultures. This requires bottom-up innovation that empowers local communities to develop and adapt solutions to their unique environmental challenges with support for small-scale, community-driven AI projects that demonstrate innovative approaches to biodiversity conservation. These initiatives should be viewed not as isolated technological interventions, but as part of a broader strategy of active ecological and social resilience.[74]

Capacity building and human capital development

Capacity building must be reimagined as a holistic, culturally embedded process that goes far beyond traditional training to create an ecosystem of knowledge and innovation that bridges technological expertise with deep ecological understanding.

Collaborative research networks across national boundaries will enable knowledge exchange and joint innovation. Regional centers of excellence in AI and biodiversity conservation can create interdisciplinary training programs that integrate indigenous ecological knowledge with advanced computational techniques

that can capture nuanced ecological insights with multilingual capabilities and local language processing technologies.[75] And to reflect the diversity of the region's ecological and cultural landscapes, fellowship and mentorship programs should support researchers from underrepresented communities.[76]

Diverse sources of funds

The costs of AI infrastructure for biodiversity monitoring can far exceed the budgetary capacities of many national environmental agencies in the region.[77] Support can come from a variety of sources. Multilateral development banks, for example, can provide targeted financial support for technological infrastructure. Governments can also leverage private sector expertise and capital. Public-private partnerships offer another promising avenue, along with regional collaborative funding pools. Companies and organizations can also establish nature-positive supply-chain certification that safeguards equity and ecological integrity.[78] Further funds can come from such mechanisms as green bonds, and carbon and biodiversity offset credits that directly support nature stewardship.

Participatory governance and ethical frameworks

Governance mechanisms must move on from top-down to participatory models of technological development deeply rooted in the region's diverse cultures and ecologies. Region-specific ethical AI guidelines should establish indigenous rights principles, local community consent mechanisms, and culturally sensitive data collection practices.

Legal frameworks must be developed to protect community data rights, ensure transparency in AI systems, and provide robust mechanisms for addressing potential technological harms. Policymakers should require that AI systems disclose their training data sources, model limitations, and decision criteria.[79] Countries can reduce the risks of misuse or bias and build public trust through independent audits, public reporting, and multi-stakeholder oversight bodies that include representatives from indigenous communities, ecological scientists, AI ethics experts, and local policymakers.[80] National AI strategies can include local adaptations of ethical AI standards – such as those developed by the EU, OECD, and UNESCO.[81]

Regional collaboration and knowledge sharing

An essential mechanism for building technological and ecological capacity is international collaboration based on equitable sharing of knowledge, ensuring that technological and ecological insights flow in multiple directions, not just from leading AI countries to less advanced ones.

Regional institutions such as ASEAN, the Pacific Islands Forum, and the UN Economic and Social Commission for Asia and the Pacific (ESCAP) should invest in collaborative platforms, harmonized policy frameworks, and regional AI observatories. Cross-border ecosystems – such as coral reefs, river basins, and migratory routes – require coordinated monitoring and management. The region can create shared AI biodiversity monitoring infrastructures based on common data standards and joint analysis.[82]

Promising initiatives are emerging. Regional collaboration mechanisms like the ASEAN center for Biodiversity and the Pacific Islands Roundtable for Nature Conservation offer potential frameworks for joint capacity building and shared data repositories. However, realizing their transformative potential requires sustained political commitment, financial support, and a genuine commitment to technological equity.[83]

Flexible and iterative innovation

Translating policy recommendations into effective, sustainable practices requires careful, nuanced navigation through multiple interconnected barriers. This involves a flexible, iterative approach with continuous evaluation, allowing for responsive adjustment based on real-world outcomes. Leadership will need to prioritize flexibility, interdisciplinary collaboration, and be willing to continuously reassess and reimagine

technological interventions. Institutions will need to embrace uncertainty, value experimentation, and view failure as an opportunity for refinement.

These recommendations converge on a central principle: AI for biodiversity must be designed and governed as a public good. Only by embedding values of equity, inclusivity, and sustainability can we ensure that the application of AI contributes to people-centered development and ecological resilience.

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Case Study 1 – Community- and institutionally driven coral reef monitoring

This case study compares two distinct approaches to coral reef monitoring: community maintenance of coral gardens in the Pacific Islands, and institutional projects by the King Abdullah University of Science and Technology and the Swiss Federal Institute of Technology Lausanne along the Red Sea coastlines.

GEOGRAPHIC AND DATA CONSTRAINTS

- The Pacific Islands reef systems are dispersed across vast oceanic expanses. As a result, monitoring has had to be distributed across countries and communities – and coverage has been determined by accessibility and local priorities.As a result, coverage has been patchy with significant temporal and spatial gaps. These could be partially filled by indigenous ecological knowledge though it can be difficult to combine these insights with AI integration.[85]
- Red Sea reefs form a more continuous system along linear coastlines, enabling systematic surveys supported by research vessels and permanent stations, with extensive temporal datasets for AI training.[86]

RESOURCE AND TECHNOLOGY

- Pacific Islands monitoring operates with limited resources, relying on community volunteers and basic machine learning with consumer-grade equipment.[87] Funding depends on short-term grants and volunteerism.[88]
- Red Sea initiatives benefit from specialized research teams, advanced equipment including remotely operated vehicles and hyperspectral imaging, substantial institutional funding, and high-performance computing capabilities.[89]

GOVERNANCE AND STAKEHOLDER COMPLEXITY

- Pacific Island conservation operates across multiple national jurisdictions complicated by customary marine tenure systems, requiring engagement with village councils, traditional leaders, national governments, and international NGOs.[90]
- Red Sea initiatives feature fewer jurisdictions but have greater geopolitical tensions, with stakeholders dominated by research institutions and regulatory agencies, though recent efforts have expanded community engagement.[91]

ECONOMIC STAKES AND PRIORITIES

- Pacific Island reefs contribute 30-80 percent of household protein and support 50-90 percent of rural livelihoods, with coral loss potentially creating annual economic losses of 3-8 percent of GDP in countries like Kiribati.[92]
- Red Sea reef value predominantly derives from tourism – $7 billion annually along the coast of Egypt. These nations have greater financial resources and more diversified economies where coral degradation impacts a lower proportion of GDPs – 0.3-1.2 percent.[93]

IMPLICATIONS FOR PEOPLE- CENTERED AI DEVELOPMENT

- The Pacific Islands model demonstrates AI adaptation to resource-constrained environments through simplified interfaces, offline functionality, and community integration, while maintaining local control over data and knowledge systems.[94]

- The Red Sea approach showcases advanced technological capabilities generating high-resolution insights but risking dependencies on external expertise.

AI implementation is thus shaped by resource contexts, geography, governance, and economic realities. Neither model offers a complete solution but it is possible to combine elements of both, with AI systems incorporating both quantitative data and qualitative observations, and having tiered approaches with local and accessible tools but also advanced analysis at regional hubs.

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Case study 2 – Urban biodiversity monitoring in Singapore and Jakarta

Singapore and Jakarta are South-East Asian cities with different governance structures and levels of resources – with contrasting experiences in urban biodiversity monitoring.[96]

RESOURCES AND INFRASTRUCTURE

- Singapore benefits from robust resources including well-trained environmental scientists through academic institutions and the National Parks Board (NParks).[97] Around 80 percent of monitoring sites have automated systems. With significant governmental funding, the city-state has invested in remote sensing, AI-enabled camera traps and environmental DNA sampling.[98]

- Jakarta enjoys less funding divided among competing environmental priorities; its staff-to-monitoring-area ratio is one-eighth that of Singapore.[99] Infrastructure remains concentrated in a few urban parks, and sensor deployment is limited, relying primarily on conventional methods like manual species counts and basic camera trap networks.[100]

DATA LANDSCAPES AND HISTORICAL CONTEXT

- Singapore has comprehensive urban biodiversity datasets with systematic records dating back to the 1800s and continuous monitoring data spanning 60 years.[101] The Singapore Biodiversity center maintains records for an estimated 95 percent of known species, enhanced by citizen science initiatives through iNaturalist with nearly 800,000 species observations. [102]

- Jakarta's data sets involve more gaps. Systematic record-keeping was only standardized in the late 1990s, and rather than documenting ecosystems comprehensively it concentrates on economically significant species.[103] The Jakarta Green Open Space program has improved data collection since 2015, but integration with community programs remains somewhat incomplete.[104]

INTERNATIONAL PARTNERSHIPS AND STANDARDS

- Singapore leads regional biodiversity monitoring through the ASEAN center for Biodiversity initiatives and hosts the GBIF Southeast Asia node.[105] NParks collaborates with over 20 international institutions, and the Singapore Index on Cities' Biodiversity has been adopted as a standardized framework by over 70 cities worldwide.[106]

- Jakarta's international involvement is growing but more limited, participating in the Urban Biodiversity Hub network and partnerships with international NGOs. Jakarta joined Cities4Forests in 2018 and participated actively at COP16 in 2024, signaling increased commitment to international biodiversity monitoring practices.[107]

ECOSYSTEM SERVICES AND URBAN BENEFITS

- Singapore's monitoring system quantifies significant ecosystem services: urban forests reduce local temperatures by 3-5°C;[108] native pollinators contribute to 30 percent of urban food production;[109] and monitored waterway biodiversity supports natural filtration and reduced treatment costs.[110]

- Jakarta's assessments indicate the importance of ecosystems which provide flood protection and carbon sequestration.[111] Monitored green spaces show

particulate matter reductions of up to 24 percent.[112] Visitor surveys demonstrate the mental health benefits of urban parks.[113]

IMPLICATIONS FOR PEOPLE- CENTERED AI DEVELOPMENT

Singapore's resource advantages enable sophisticated technological implementation while, despite the constraints, Jakarta demonstrates progress through strategic partnerships and community engagement. Rather than applying a one-size-fits-all approach, AI tools must acknowledge differing contexts.[114] Overall, Singapore and Jakarta demonstrate four priorities for people- centered AI development for biodiversity in cities:

- Democratize access through lightweight mobile applications enabling broader community participation.[115]
- Integrate indigenous and local knowledge systems, ensuring that algorithms recognize locally significant species and ecosystem relationships.[116]
- Establish regional data-sharing protocols, allowing resource-constrained communities to benefit from innovations while contributing local insights.[117]
- Prioritize transparent AI systems that build community trust through collaborative approaches where participants can meaningfully engage with technological outputs.[118]

By centering on human needs, knowledge, and participation, cities throughout Asia and the Pacific can develop more resilient, inclusive, and effective conservation approaches benefiting both Nature and people.

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Case Study 3 – Biodiversity monitoring programs in India and Papua New Guinea

India and Papua New Guinea (PNG), are megadiverse but very different nations with distinct approaches to biodiversity monitoring.

NATIONAL PRIORITIZATION AND APPROACHES

- India has demonstrated strong institutional commitment through flagship initiatives like Project Tiger, which expanded from 9 to 53 reserves covering 75,000 km^2.[119] The Wildlife Institute of India is a premier research institution, and the country combines species-centric programs with ecosystem-level planning, incorporating satellite imagery, camera traps, and AI-based tools for species identification.[120]
- PNG has 7 percent of global biodiversity in less than 1 percent of global land area. Over 97 percent of land is under customary ownership.[121] PNG's approach to indigenous stewardship integrates traditional ecological knowledge with scientific monitoring through initiatives like the Tenkile Conservation Alliance. The Conservation and Environment Protection Authority (CEPA) coordinates monitoring but has limited resources.

DATA SOVEREIGNTY FRAMEWORKS

- India has developed robust national governance through the Biological Diversity Act (2002) and the National Biodiversity Authority, asserting sovereign rights over biological resources and associated knowledge. The Indian Biodiversity Information System provides centralized data management with clear protocols, maintaining stringent controls on bioprospecting and requiring benefit-sharing arrangements.[122]
- PNG approaches data sovereignty through community-level ownership reflecting customary land tenure. The 2014 National Strategy for Responsible Sustainable Development recognizes traditional knowledge as integral to conservation and asserts community rights to control information about their biological resources. This decentralized approach creates national monitoring challenges but aligns with local data sovereignty.[123]

TECHNOLOGICAL CAPACITY AND AI DEVELOPMENT

- India possesses substantial technological infrastructure through its robust IT sector, extensive scientific institutions, and Digital India initiatives. The National Mission on Biodiversity includes provisions for emerging technologies, through the Indian Biodiversity Portal and the Wildlife Institute of India's automated species identification systems. Challenges remain, however, in bridging digital divides and incorporating diverse knowledge systems.[124]

- PNG faces funding constraints, sparse technological expertise and limited digital infrastructure – internet penetration is only 15 percent. CEPA relies on international partnerships and donor funding, collaborating for technological solutions with organizations like the Wildlife Conservation Society. [125] Externally developed systems may not, however, reflect local contexts and can be difficult to sustain.[126]

DATA INFRASTRUCTURE AND COLLECTION

- India operates multi-scale infrastructure. The National Biodiversity Authority coordinates with the Zoological and Botanical Surveys and research institutions. Long-Term Ecological Observatories have established systematic data collection across ecosystems, though it can be difficult to harmonize different methodologies and timeframes.[127]

- PNG's infrastructure is more fragmented, according to some. Data collection occurs primarily through time-bound projects, and coverage by the PNG Biological Records Database is less complete. Community-based monitoring provides valuable local data but can employ inconsistent methodologies, while limited rural digital infrastructure might necessitate hybrid approaches to data collection.[128]

POLICY FRAMEWORKS

- India's comprehensive framework centers on the Biological Diversity Act and National Biodiversity Action Plan (revised 2019), with strong centralized planning and state-level implementation. The 2020 National Mission on Biodiversity explicitly recognizes the role of emerging technologies, though there are difficulties in balancing conservation with development pressures.[129]

- PNG's framework emphasizes the Protected Areas Policy (2017) and community-based conservation areas as primary protection mechanisms. The policy acknowledges that biodiversity conservation is inseparable from indigenous practices and land rights, though there are capacity and funding constraints and limited provisions for digital tools.[130]

RECOMMENDATIONS FOR PEOPLE- CENTERED AI DEVELOPMENT.

Five key recommendations emerge:

1. Develop tiered technological solutions functioning across different infrastructure levels, enabling resource-constrained regions to benefit from appropriate AI applications.

2. Institutionalize collaborative design processes, meaningfully engaging local communities and indigenous knowledge holders throughout development.

3. Establish regional technology transfer mechanisms enabling poorer developing countries to benefit from innovations developed in technologically advanced countries like India.

4. Create flexible data sovereignty frameworks protecting indigenous knowledge while enabling scientific collaboration.

5. Invest in local capacity building, ensuring AI tools can be locally maintained, adapted, and governed. People-centered AI development must build upon existing capacities while respecting local interests.

Integrating elements of India's centralized, technology-intensive approach with PNG's decentralized, community-centered model can help Asia-Pacific countries develop AI technologies that enhance biodiversity monitoring while respecting diverse knowledge systems, governance

structures, and technological capacities. Such hybrid approaches ensure technological advances empower rather than marginalize communities at conservation's frontlines.

END NOTES

1. (Russel A Mittermeier, 1988)
2. (Mora et al., 2011)
3. (Ha Van, Lichang and Dang Thanh Quoc, 2024; Campaign for Nature, no date)
4. (Pimm et al., 2015; Schmeller et al., 2018; Stephenson, 2020)
5. (Brubacher et al., 2024)
6. (IPBES, 2019)
7. (Ngcamu, 2023)
8. (Christin, Hervet, and Lecomte, 2019; Tuia et al., 2022)
9. (David Obura, Mishal Gudka, and Suraj Bacha Gian, 2017)
10. (Norouzzadeh et al., 2018; Christin, Hervet, and Lecomte, 2019)
11. (Norouzzadeh et al., 2018; Gadot et al., 2024)
12. (Wrege et al., 2017; Sethi et al., 2023)
13. (Jetz, McPherson and Guralnick, 2012)
14. (Prasetyo, Mutiara and Handayani, 2018)
15. (Dertien et al., 2023a)
16. (Cash and Moser, 2000)
17. (Sullivan et al., 2009; Farley et al., 2018; Gibb et al., 2019)
18. (Bevan et al., 2025)
19. (Stevens, 2024)
20. (Sandbrook, Luque-Lora and Adams, 2018)
21. (Danielsen, Burgess, Jensen and Pirhofer-Walzl, 2010)
22. (Morozov, 2013)
23. (Jetz, McPherson and Guralnick, 2012; Horn and Perona, 2017)
24. (Beery, Van Horn and Perona, 2018; Sethi et al., 2018)
25. (La Salle, Williams and Moritz, 2016)
26. (Huus et al., 2025)
27. (Reynolds et al., 2025)
28. (Whakatane, 2019)
29. (Danielsen, Burgess, Jensen and Pirhofer-Walzl, 2010)
30. (Jenkins, 2022)
31. (Kidangoor, 2024; Kyodo News, 2024; Sharon, 2024)

32. (Corlett, 2022; Sharon, 2024)
33. (A20Search, 2025)
34. (Speaker et al., 2022)
35. (Speaker et al., 2022)
36. (UNEP-WCMC, 2025)
37. (Díaz et al., 2019a)
38. (Amano, González-Varo and Sutherland, 2016; Meyer, Weigelt and Kreft, 2016)
39. (Seth, 2009; Ricaurte, 2019; Pritchard et al., 2022)
40. (Sterling et al., 2017a; Baker, Eichhorn and Griffiths, 2019; San Martín, 2021)
41. (Cole et al., 2023)
42. (UNESCAP, 2022)
43. (Raymond et al., 2017)
44. (Seddon et al., 2021)
45. (Chaplin-Kramer et al., 2023)
46. (Díaz et al., 2019b)
47. (Rintelen, Arida and Häuser, 2017)
48. (Navarro et al., 2017; Fletcher, 2019)
49. (San Martín, 2021; Baker, Eichhorn, and Griffiths, 2019)
50. (Biegajewski, 2023; Berenguer-Agullo et al., 2024)
51. (Dertien et al., 2023b)
52. (Beery, Van Horn and Perona, 2018; Wang et al., 2020)
53. (Elias et al., 2017; Arshad et al., 2020; Zualkernan et al., 2022)
54. (UNESCO, 2024)
55. (Amano, González-Varo and Sutherland, 2016)
56. (Speaker et al., 2022)
57. (Cole et al., 2023)
58. (AISM, 2025)
59. (De Klerk and Buchanan, 2017; WILDLABS, 2024)
60. (Rolf et al., 2024)
61. (UNDP, 2024b)
62. (UNDP, 2025c)
63. (Horn and Perona, 2017)
64. (Danielsen, Burgess, Jensen and Pirhofer-Walzl, 2010)
65. (Strubell, Ganesh and McCallum, 2019)
66. (Reed et al., 2009)
67. (Morand, Lajaunie and Satrawaha, 2018)
68. (Debnath, Tkachenko and Bhattacharyya, 2025)
69. (Christin, Hervet, and Lecomte, 2019; Tuia et al., 2022)
70. (Santos, Zaytseva and Serrano, 2025; UNDP, 2025c)
71. (Pollock et al., 2025)

72. (Chan, 2018; Reynolds et al., 2025)
73. (OECD, 2025b)
74. (Cash and Moser, 2000)
75. (Amano, González-Varo and Sutherland, 2016)
76. (Powles and Nissenbaum, 2018)
77. (GPAI, 2025)
78. (Nobre and Nobre, 2019; Dasgupta, 2021; Nepa, Phoumin and Khatri, 2021; Klusak, 2023; Grabbe and Moffat, 2024)
79. (Mitchell et al., 2019)
80. (Armitage et al., 2020; Vignieri, 2023)
81. (Madiega, 2019; Carter, 2020; UNESCO, 2021)
82. (DeSantis et al., 2025; Freitas and Gouveia, 2025)
83. (Sajise, 2015)
84. (Burns et al., 2024)
85. (Alexander et al., 2019)
86. (Berumen et al., 2019)
87. (Roelfsema et al., 2018)
88. (Bennett et al., 2021)
89. (Berumen et al., 2019; Mills et al., 2023)
90. (Jupiter et al., 2017; Burns et al., 2024)
91. (Burt, 2024)
92. (Laurans et al., 2013)
93. (Hilmi et al., 2019)
94. (Sterling et al., 2017b)
95. (Villon et al., 2018; Alexander et al., 2019)
96. (IPBES, 2018)
97. (Davison et al., 1018)
98. (WWF, 2024)
99. (Lechner et al., 2024)
100. (Sumarga et al., 2023)
101. (Centre for Liveable Cities, Singapore, 2015)
102. (iNaturalist, 2025)
103. (Darajati, 2016)
104. (Lechner et al., 2024)
105. (Webb, Slik and Triono, 2010)
106. (CBD Secretariat, 2021)
107. (Tanahair, 2024)
108. (Tan, Lau and Ng, 2016)
109. (Diehl et al., 2020)
110. (Khoo and Chew, 2017)

111. (Sumarga et al., 2023)
112. (Lechner et al., 2024)
113. (MD Alwi, 2020)
114. (Rajappan et al., 1 AD)
115. (Turner et al., 1994)
116. (IPBES, 2018)
117. (Lechner et al., 2024)
118. (Chisom et al., 2024)
119. (NTCA, 2025)
120. (Shivaprakash et al., 2022)
121. (van Helden, 2005)
122. (Morgera, Tsioumani and Buck, 2015)
123. (van Helden, 2005)
124. (Shivaprakash et al., 2022)
125. (Ferreira et al., 2025)
126. (Choquez-Millan et al., 2024)
127. (Turnhout and Boonman-Berson, 2011)
128. (Parsch et al., 2025)
129. (Bawa et al., 2021)
130. (Leverington, Peterson and Peterson, 2017)

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