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Counting Green Wealth

Towards a Future-Ready People's Forest Economy in Himachal Pradesh

हिमाचल प्रदेश सरकार

ISB Bharti Institute of Public Policy

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We place on record our deep appreciation for the forest guards, range staff, and field functionaries of the Himachal Pradesh Forest Department whose dedication made this forest inventory effort possible. Working across difficult terrain, remote forest landscapes, and demanding field conditions, they brought extraordinary commitment, discipline, and sincerity to the data collection process. Their patient effort, local knowledge, and sense of duty form the true foundation of this work.

This report is, in many ways, a reflection of their quiet service and stzeadfast contribution. We extend our heartfelt thanks to every forest guard and ranger who invested time, energy, and care in generating the field evidence that underpins this exercise. Their contribution goes far beyond data collection; it strengthens the scientific understanding, stewardship, and future of Himachal Pradesh's forests.

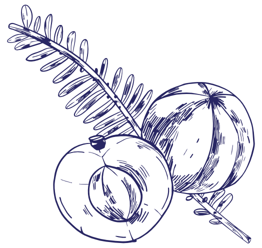
In Honour of Those Who Walked the Forests

Table of Contents

01

02

03



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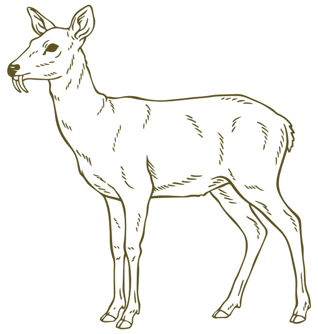


06

सुखविंदर सिंह सुक्खू
माननीय मुख्यमंत्री
हिमाचल प्रदेश

संदेश

हरित संपदा और जन-भागीदारी से समृद्ध होता हिमाचल

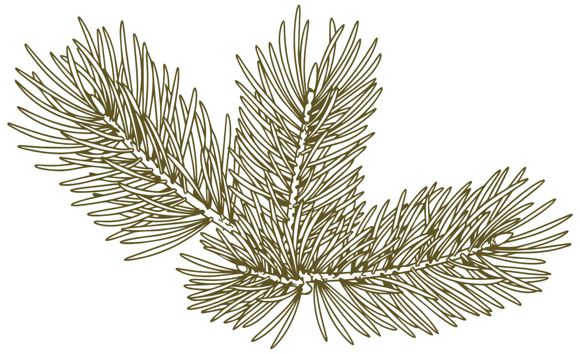
हिमाचल प्रदेश की देवतुल्य भूमि अपनी प्राकृतिक सुंदरता और समृद्ध वन संपदा के लिए विश्वविख्यात है। हमारे वन केवल पारिस्थितिक तंत्र का हिस्सा नहीं हैं, बल्कि ये प्रदेश की आर्थिकी और यहाँ के निवासियों, विशेषकर ग्रामीण समुदायों की जीवनरेखा हैं। हमारी सरकार का ध्येय 'हरित हिमाचल-समृद्ध हिमाचल' के संकल्प को धरातल पर उतारना है, जहाँ प्रकृति का संरक्षण और जनकल्याण साथ-साथ चलें।

मुझे यह जानकर अत्यंत हर्ष हो रहा है कि हिमाचल प्रदेश वन विभाग और भारती इंस्टीट्यूट ऑफ पब्लिक पॉलिसी, इंडियन स्कूल ऑफ बिज़नेस, हैदराबाद (BIPP–ISB) के संयुक्त प्रयासों से 'Counting Green Wealth: Towards a Future-Ready People's Forest Economy in Himachal Pradesh' रिपोर्ट तैयार की गई है। यह रिपोर्ट राज्य के वन संसाधनों के प्रबंधन में एक युगांतरकारी बदलाव का प्रतीक है। पहली बार, हमने पारंपरिक गणना से आगे बढ़कर अत्याधुनिक तकनीक और वैज्ञानिक पद्धतियों के माध्यम से प्रदेश के वनरक्षकों ने प्रमुख वृक्ष-प्रजातियों जिनमें चीड़, देवदार, बाँस, आँवला, खैर, साल और बुरांश सम्मिलित हैं, का जीवित वृक्ष-स्तरीय भू-संदर्भित सर्वेक्षण किया। इस डेटा को Artificial Intelligence और उपग्रह-चित्रण के साथ जोड़कर प्रजाति-वितरण मानचित्र और उपज-आकलन तैयार किए गए हैं। इसके साथ ही, रिपोर्ट में जोड़ा गया 'कार्बन स्टॉक मूल्यांकन' यह दर्शाता है कि हिमाचल प्रदेश जलवायु परिवर्तन की वैश्विक चुनौतियों का सामना करने के लिए पूरी तरह तैयार है।

भारत ने 2030 तक अतिरिक्त वन और वृक्ष आवरण (forest and tree cover) के माध्यम से 2.5 से 3 अरब टन CO_2 समतुल्य (CO_2 equivalent) का अतिरिक्त कार्बन सिंक बनाने की अपनी एनडीसी (NDC) प्रतिबद्धता व्यक्त की है, और हिमाचल प्रदेश इस लक्ष्य की प्राप्ति में एक अग्रणी योगदानकर्ता है।यह रिपोर्ट उस योगदान को पहली बार वैज्ञानिक आधार पर प्रमाणित करती है। यह दस्तावेज़ स्पष्ट करता है कि कैसे हम अपने वनों को एक 'जन-वन अर्थव्यवस्था' (People's Forest Economy) के रूप में विकसित कर सकते हैं, जहाँ स्थानीय समुदायों को वनों के संरक्षण के साथ-साथ स्थायी आजीविका के नए अवसर प्राप्त हों।

मैं इस वृहद और दूरदर्शी कार्य के लिए वन विभाग के अधिकारियों, BIPP-ISB के शोधकर्ताओं और विशेष रूप से हमारे कर्मठ वन रक्षकों को बधाई देता हूँ, जिन्होंने कठिन भौगोलिक परिस्थितियों में जाकर इस डेटा को संकलित किया। मुझे विश्वास है कि यह दस्तावेज वन विभाग के अधिकारियों, नीति-निर्माताओं, शोधकर्ताओं और समुदायों के लिए एक अमूल्य संदर्भ सिद्ध होगी।

(सुखविंदर सिंह सुक्खू)



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Foreword

Forests are among the most important public assets of Himachal Pradesh. They regulate water, stabilise slopes, support biodiversity, store carbon, shape rural livelihoods, and define the ecological identity of the Himalayan landscape. Yet, for too long, forests have been viewed either as protected ecological spaces or as sources of limited extractive value. This report invites us to move beyond that binary. It presents forests as dynamic socio-ecological and economic systems whose sustainable management requires the convergence of science, institutions, technology, and frontline knowledge.

The joint exercise undertaken by the Himachal Pradesh Forest Department and the Bharti Institute of Public Policy, Indian School of Business, represents an important step in that direction. At its core, this collaboration is not simply about producing maps or models. It is about building a new evidence infrastructure for forest governance. More than 500 forest guards, 9 DRFs and several frontline staff have contributed tree-level observations and species-tagged images from the field. These observations, when combined with remote sensing, artificial intelligence, machine learning, and ecological modelling, create a new generation of forest intelligence for the state.

This is significant because good forest policy begins with knowing what exists, where it exists, how it is changing, and what it can sustainably support. Species-level inventory and distribution mapping are essential for estimating standing biomass, assessing carbon stocks, planning silvicultural interventions, understanding climate vulnerability, and identifying forest-based livelihood opportunities. In a mountain state such as Himachal Pradesh, where elevation, aspect, moisture, species composition, and community dependence vary sharply over short distances, coarse forest-cover statistics are insufficient. The state requires spatially explicit, species-aware, and periodically updated information systems.

My own research has long been concerned with the relationship between institutions, forests, livelihoods, and development. Across landscapes, one lesson is clear: forests produce better social and ecological outcomes when people, rules, markets, and knowledge systems are aligned. The Initiative on the Forest Economy at BIPP–ISB builds on this insight. It seeks to make the forest economy visible, formal, sustainable, and beneficial to local communities, while protecting ecological integrity. The objective is not to commercialise forests in a narrow extractive sense, but to build institutions and value chains that recognise the true contribution of forests to prosperity, resilience, and climate action.

Himachal Pradesh offers a compelling setting for this approach. The state has a large legally recorded forest area, high ecological diversity, and a long tradition of scientific forest management through working plans and territorial forest administration. At the same time, it faces new pressures: climate change, changing snowfall and rainfall regimes, fire risk, rural livelihood transitions, and the need to align forest management with India's national and global climate commitments. These pressures demand a new kind of forest governance—one that is adaptive, data-rich, locally grounded, and capable of linking conservation with sustainable economic opportunity.

The HPFD–BIPP–ISB collaboration demonstrates how such governance can be built. Forest guards are not treated merely as implementers of instructions; they are recognised as knowledge holders and primary producers of high-quality ecological data. The Forest Department is not merely a custodian of land; it becomes the institutional platform through which data can inform working plans, restoration, climate adaptation, fire management, and forest-based enterprise planning. BIPP–ISB contributes scientific design, AI/ML modelling, validation systems, and policy translation. Together, this creates a model of co-production. A co-produced system creates capacity, tools, and institutional memory. The datasets, models, protocols, and dashboards emerging from this exercise can be updated, improved, and reused. They can support future working-plan revisions, carbon assessments, ecosystem-service valuation, bioeconomy planning, and climate finance readiness. They can also help Himachal Pradesh identify where biomass is increasing, where it is declining, which species require management attention, and where sustainable forest-based livelihoods can be strengthened without compromising ecological limits.

The broader promise of this work lies in connecting the forest economy with climate action. Forests are central to India's Nationally Determined Contribution, especially the goal of creating additional carbon sinks through forest and tree cover. But durable carbon sequestration depends not only on area under forest; it depends on species composition, regeneration, disturbance risk, and institutional stewardship. By linking species inventory, above-ground biomass assessment, and climate-sensitive modelling, this report provides a pathway for Himachal Pradesh to develop a scientifically credible and socially grounded carbon strategy.

The report also speaks directly to the Sustainable Development Goals. It contributes to SDG 15 through improved forest management and biodiversity conservation; SDG 13 through carbon monitoring and climate adaptation; SDG 8 through forest-based livelihoods and green enterprise; and SDG 12 through responsible and traceable use of biomass resources. In doing so, it shows that the forest economy is not peripheral to development. It is central to the future of mountain states.

I congratulate the Himachal Pradesh Forest Department, the forest guards and frontline staff who generated the field data, and the BIPP–ISB team for undertaking this ambitious and timely exercise. I hope this report becomes more than a technical document. It should serve as a foundation for a new compact between data, people, and the state—one in which forests are managed as living ecological systems, economic assets, carbon sinks, and sources of dignity and resilience for future generations.

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संदेश

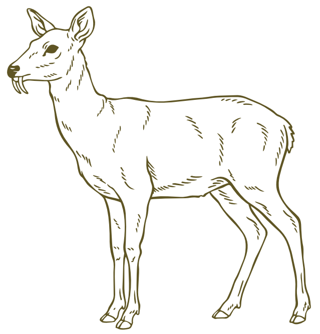
वन प्रशासन का डिजिटल रूपांतरण: एक संस्थागत यात्रा

हिमाचल प्रदेश वन विभाग दशकों से राज्य की वन संपदा का संरक्षक रहा है। इस भूमिका को और अधिक प्रभावी बनाने के लिए आवश्यक था कि हम पारंपरिक दशकीय कार्यशील योजनाओं की सीमाओं से आगे बढ़ें और एक ऐसे डेटा-आधारित ढाँचे की ओर अग्रसर हों जो वास्तविक समय में वन संसाधनों की स्थिति का आकलन कर सके। 'Counting Green Wealth' रिपोर्ट महज एक गणना नहीं है, बल्कि यह हमारे विभाग के लिए वन शासन (Forest Governance) को आधुनिक बनाने का एक ब्लूप्रिंट है।

हम अब उस दौर में हैं जहाँ वन प्रबंधन की पारंपरिक विधियों को अत्याधुनिक डेटा और वैज्ञानिक विश्लेषण के साथ जोड़ना अनिवार्य हो गया है। इस रिपोर्ट के माध्यम से हमने पहली बार 'हरित संपदा' का वास्तविक आकलन किया है। कार्बन स्टॉक मूल्यांकन यह स्पष्ट करता है कि हमारे वन वैश्विक कार्बन चक्र में कितनी महत्वपूर्ण भूमिका निभा रहे हैं। यह डेटा हमें उन क्षेत्रों की पहचान करने में मदद करेगा जहाँ वनीकरण की तत्काल आवश्यकता है और जहाँ वन-आधारित उद्यमों के प्रसंस्करण के माध्यम से महिलाओं और युवाओं के लिए रोजगार सृजित किये जा सकते हैं।

मैं इस कार्य में संलग्न भारती इंस्टीट्यूट ऑफ पब्लिक पॉलिसी, इंडियन स्कूल ऑफ बिज़नेस, हैदराबाद (BIPP–ISB) की टीम और वन विभाग के फील्ड स्टाफ की सराहना करता हूँ। उनके द्वारा एकत्रित किए गए साक्ष्य हमें एक ऐसी 'जन-वन अर्थव्यवस्था' की ओर ले जाएंगे जो पर्यावरण की रक्षा के साथ-साथ स्थानीय आर्थिकी को भी मजबूती प्रदान करेगी। यह प्रतिवेदन हिमाचल प्रदेश को एक विज्ञान-आधारित, जलवायु-संरेखित वन प्रशासन का राष्ट्रीय प्रतिमान बनाने की दिशा में एक ऐतिहासिक कदम है।

(कमलेश कुमार पंत)



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संदेश

वन, जलवायु एवं विकास का त्रिकोण: एक नई नीतिगत सोच

जलवायु परिवर्तन के इस दौर में हिमालयी राज्यों की भूमिका अत्यंत संवेदनशील है। पर्यावरण और विज्ञान विभाग के लिए यह अनिवार्य है कि हमारे पास ऐसे वैज्ञानिक उपकरण और डेटा हों, जिनसे हम पारिस्थितिक तंत्र में होने वाले परिवर्तनों को माप सकें। जलवायु परिवर्तन के इस संकटकाल में वन केवल पारिस्थितिक तंत्र नहीं, वे भारत की जलवायु प्रतिबद्धताओं के सबसे महत्त्वपूर्ण स्तंभ हैं। 'Counting Green Wealth: Towards a Future-Ready People's Forest Economy in Himachal Pradesh' रिपोर्ट और इसका 'Carbon Stock Assessment' अध्याय इसी दिशा में एक महत्वपूर्ण तकनीकी प्रगति है।

यह रिपोर्ट महज़ एक इन्वेंट्री नहीं है, बल्कि यह प्रदेश के लिए 'क्लाइमेट इंफ्रास्ट्रक्चर' के समान है। कार्बन स्टॉक का प्रजाति-वार और ऊँचाई-वार विश्लेषण हमें यह समझने में मदद करता है कि जलवायु परिवर्तन का हमारे वनों पर क्या प्रभाव पड़ रहा है और हम किस प्रकार अपनी रणनीतियों को इसके अनुकूल ढाल सकते हैं। भारती इंस्टीट्यूट ऑफ पब्लिक पॉलिसी, इंडियन स्कूल ऑफ बिज़नेस, हैदराबाद (BIPP–ISB) द्वारा प्रयुक्त AI/ML मॉडलिंग और रिमोट सेंसिंग तकनीकों ने इस रिपोर्ट की विश्वसनीयता को वैश्विक मानकों के समकक्ष ला खड़ा किया है। इस रिपोर्ट का कार्बन स्टॉक अध्याय जलवायु परिवर्तन विभाग की परिप्रेक्ष्य से विशेष महत्त्व रखता है। प्रजाति-वार बायोमास आकलन अब यह संभव बनाता है कि हम राज्य की ग्रीनहाउस गैस सूची को अधिक सटीक, गतिशील और विज्ञान-समर्थित बनाएँ।

मैं वन विभाग, BIPP–ISB और सभी सहभागियों को इस अंतर-विभागीय वैज्ञानिक पहल के लिए बधाई देता हूँ। मुझे विश्वास है कि यह रिपोर्ट हमारे पर्यावरण संरक्षण के लक्ष्यों को प्राप्त करने और सतत विकास की दिशा में मील का पत्थर साबित होगी।

(सुशील कुमार सिंगला)

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संदेश

वन-बुद्धिमत्ता परत: वनरक्षक से AI तक एक समन्वित ज्ञान-तंत्र

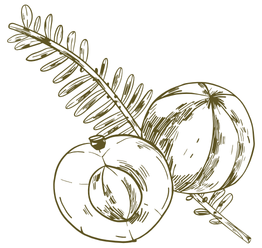
एक वन अधिकारी के रूप में, मुझे यह देखकर गर्व होता है कि हमारा विभाग तकनीक और डेटा के उपयोग में नई ऊंचाइयों को छू रहा है। 'Counting Green Wealth: Towards a Future-Ready People's Forest Economy in Himachal Pradesh' रिपोर्ट हमारे फील्ड अधिकारियों और वन रक्षकों की निष्ठा का परिणाम है, जिन्होंने कठिन रास्तों और प्रतिकूल मौसम की परवाह किए बिना धरातल पर जाकर डेटा एकत्र किया। यह रिपोर्ट उस विभागीय परिवर्तन का दस्तावेज़ है जिसकी परिकल्पना वर्षों से की जा रही थी, जब वन विभाग के जमीनी कर्मचारी केवल प्रहरी नहीं, बल्कि वन ज्ञान के सह-उत्पादक बन जाएँ। 500 से अधिक वनरक्षकों ने जो 2 लाख से अधिक वृक्ष-स्तरीय अभिलेख एकत्रित किए हैं, वह हिमाचल के वन इतिहास में एक अभूतपूर्व उपलब्धि है।

इस अभियान की विशिष्टता केवल इसके विशाल पैमाने में नहीं, बल्कि इसकी वैज्ञानिक परिपक्वता में भी है। प्रजाति-पहचान से लेकर GPS जियो-टैगिंग और बहुस्तरीय डेटा गुणवत्ता नियंत्रण तक, प्रत्येक चरण में हिमाचल प्रदेश वन विभाग और भारती इंस्टीट्यूट ऑफ पब्लिक पॉलिसी, इंडियन स्कूल ऑफ बिज़नेस, हैदराबाद (BIPP–ISB) के बीच सहयोगी सहनिर्माण मॉडल ने सुनिश्चित किया कि यह डेटा केवल एक शोध-अभ्यास नहीं, बल्कि विभाग की कार्यशील योजनाओं और प्रबंधन प्रक्रियाओं में सीधे उपयोगी हो।

यह रिपोर्ट वन प्रबंधन के पारंपरिक तरीकों और आधुनिक डेटा साइंस का एक सफल समन्वय है। कार्बन स्टॉक के मूल्यांकन को वन सूची (Forest Inventory) के साथ जोड़कर हमने यह प्रदर्शित किया है कि हमारे वन भविष्य की 'ग्रीन इकोनॉमी' के लिए कितने तैयार हैं। यह डेटा हमारे वर्किंग प्लान के नवीनीकरण, चरागाह प्रबंधन और स्थानीय समुदायों के साथ सह-प्रबंधन एवं उनकी आजीविका संवर्धन की नई रणनीतियों के कार्यान्वयन में अत्यंत सहायक होगा।

मैं इस अभियान में सहभागी प्रत्येक वनरक्षक, वनपाल, क्षेत्रीय वनाधिकारी और BIPP–ISB की टीम को हार्दिक बधाई देता हूँ। यह प्रतिवेदन हिमाचल वन विभाग को देश में विज्ञान-आधारित वन प्रशासन के अग्रदूत के रूप में स्थापित करता है।

(संजय सूद)



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हिमाचल प्रदेश

संदेश

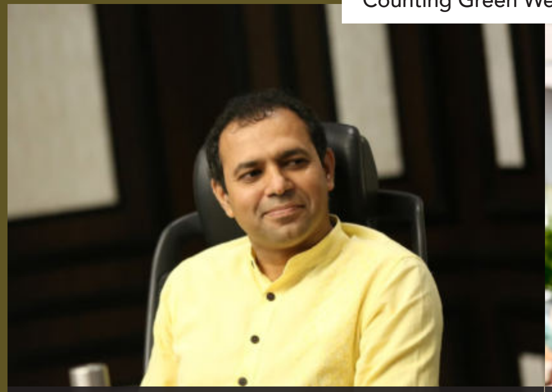
कार्बन लेखांकन से जलवायु वित्त तक: हिमाचल प्रदेश की वन-आधारित जलवायु रणनीति

जलवायु परिवर्तन की वैश्विक चुनौती के संदर्भ में यह प्रश्न अत्यंत महत्त्वपूर्ण हो गया है कि हम अपने वनों की जलवायु-भूमिका को किस प्रकार वैज्ञानिक रूप से मापें, दस्तावेज़ीकृत करें और नीति-निर्माण में समाहित करें। 'हरित संपदा की गणना 'Counting Green Wealth: Towards a Future-Ready People's Forest Economy in Himachal Pradesh' रिपोर्ट और उसका कार्बन स्टॉक मूल्यांकन इसी दिशा में एक महत्त्वपूर्ण कदम है।

इस रिपोर्ट की सबसे बड़ी विशेषता इसका व्यापक तकनीकी विश्लेषण है। पारंपरिक वन सर्वेक्षणों की सीमाओं को लांघते हुए, इस अभ्यास में अर्थ ऑब्जर्वेशन और रिमोट सेंसिंग के साथ-साथ प्रजाति-वितरण मॉडल (Species Distribution Models) का प्रभावी समन्वय किया गया है। वनों की सूची तैयार करने के लिए रिग्रेशन मॉडलिंग और एआई/एमएल (AI/ML) एल्गोरिदम का उपयोग किया गया है, जो न केवल प्रजातियों के भौगोलिक विस्तार को दर्शाता है, बल्कि उनकी घनत्व और स्वास्थ्य की स्थिति का भी सटीक चित्रण करता है। विशेष रूप से, 'कार्बन स्टॉक मूल्यांकन' तकनीकी नवाचार का उत्कृष्ट उदाहरण है, जो 'एबव ग्राउंड बायोमास' (Above Ground Biomass) में हुए परिवर्तनों का तुलनात्मक विश्लेषण किया गया है। बायोमास घनत्व (Biomass Density) और कार्बन पृथक्करण (Carbon Sequestration) की गतिशीलता को मापने के लिए स्पेशियल मॉडलिंग (Spatial Modelling) और पिक्सेल-स्तरीय विश्लेषण का प्रयोग किया गया है। यह विश्लेषण स्पष्ट करता है कि विभिन्न ऊँचाइयों (Altitudinal Gradients) और ढलानों (Aspects) पर वन प्रजातियाँ जलवायु तनाव के प्रति किस प्रकार प्रतिक्रिया दे रही हैं।

पर्यावरण विभाग के लिए यह डेटा केवल एक सांख्यिकीय रिकॉर्ड नहीं है, बल्कि यह राज्य के विभिन्न क्षेत्रों की पारिस्थितिक सेहत की नियमित निगरानी करने का एक व्यावहारिक वैज्ञानिक माध्यम है। इसके विश्लेषण से हमें यह समझने में मदद मिलेगी कि जलवायु परिवर्तन का विभिन्न ऊंचाइयों पर स्थित वन प्रजातियों और उनके बायोमास घनत्व पर क्या प्रभाव पड़ रहा है। यह साक्ष्य-आधारित सोच हमें 'क्लाइमेट रेजिलिएंट' भविष्य की योजना बनाने में सक्षम बनाएगा। मैं इस जटिल तकनीकी कार्य को सफलतापूर्वक संपन्न करने के लिए वन विभाग और भारती इंस्टीट्यूट ऑफ पब्लिक पॉलिसी, इंडियन स्कूल ऑफ बिज़नेस, हैदराबाद (BIPP–ISB) को इस अंतर-संस्थागत अनुसंधान के लिए बधाई देता हूँ । मुझे विश्वास है कि यह रिपोर्ट वैज्ञानिक वन प्रबंधन और पर्यावरणीय निगरानी के क्षेत्र में एक नए मानक स्थापित करेगी।

(पुष्पेंदर राणा)



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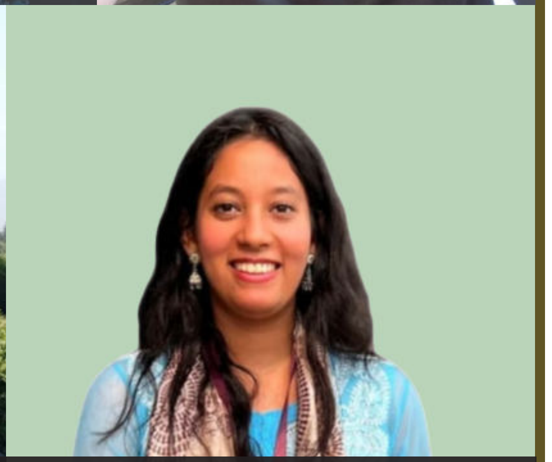

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Executive Summary

Himachal Pradesh is one of India's most forest-endowed Himalayan states. Approximately 68% of its geographical area is legally classified as area under forest, reflecting an unusually high concentration of natural capital within a relatively small mountain economy. This legal forest estate must be distinguished from satellite-observed forest cover: recent assessments based on Forest Survey of India data indicate that forest cover increased from about 14,353 km^2 in 2003 to approximately 15,580 km^2 in 2023, raising the share of forest cover from 25.7% to around 28% of the state's geographical area. Tree cover has also increased to about 855 km^2, or roughly 1.5% of the state's area. Forests in Himachal Pradesh store an estimated ~258 million tonnes of carbon across biomass and soil pools, making the state a significant contributor to India's terrestrial carbon sink and a critical actor in national climate mitigation.

The carbon significance of Himachal Pradesh's forests is especially important in the context of India's climate commitments. India's Nationally Determined Contribution commits the country to creating an additional carbon sink of 2.5–3.0 billion tonnes of CO_2 equivalent through additional forest and tree cover by 2030, alongside the long-term national commitment to achieve net-zero emissions by 2070. Himachal Pradesh's forest carbon stock, increasing forest and tree cover, and emerging climate-linked forest programmes—including the state-supported biochar initiative using pine needles, invasive lantana, bamboo and other biomass residues—position the state as a potential national demonstrator for climate-positive forest economy pathways. A scientifically credible carbon strategy, however, requires more than aggregate forest-cover statistics. It requires species-level inventories, above-ground biomass monitoring, spatially explicit carbon accounting, and uncertainty-informed systems for monitoring, reporting and verification.

Yet, despite expansion in forest and tree cover and the high carbon value of the state's forests, the economic value of forest provisioning services—timber and non-timber forest products—has declined by nearly 29% in real terms between 2010–11 and 2021–22, even as carbon retention services have increased. This divergence reveals a central structural challenge: Himachal Pradesh's forests are contributing increasingly to climate regulation and carbon retention, but the formal forest economy—defined as the sustainable, livelihood-enhancing and value-generating use of forest resources—remains under-realised and weakly integrated with state income accounts, local employment systems and industrial planning.

Natural capital accounting studies have already shown that many forest ecosystem services—hydrological regulation, erosion control, slope stabilisation, biodiversity support, cultural values and landscape-level climate regulation—are not fully captured in conventional Gross State Domestic Product estimates. This leads to systematic undervaluation of forests in planning and investment decisions. For a Himalayan state where forests regulate water flows, influence hydropower and horticulture, reduce disaster risk and sustain rural livelihoods, this accounting gap is not merely technical; it directly affects development strategy.

This report documents a joint institutional effort by the Himachal Pradesh Forest Department (HPFD) and the Bharti Institute of Public Policy, Indian School of Business (BIPP–ISB) to build the data and analytical infrastructure required to realise Himachal Pradesh's forest economy and climate potential. In a large field campaign, more than 500 forest guards across selected ranges collected approximately 200,000 tree-level location records and species-tagged images, following protocols and training modules designed by BIPP–ISB. These ground observations were integrated with high-resolution satellite imagery, Sentinel-derived covariates, topography, canopy-height information and other environmental layers to train artificial intelligence and machine-learning models for tree species distribution mapping, standing yield estimation and biomass-linked forest resource assessment. A central innovation of this work is the creation of a "forest intelligence layer" that can provide compartment-, range- and division-scale information on species composition, spatial distribution, stocking, yield potential and carbon-relevant biomass patterns, together with uncertainty estimates suitable for operational decision-making. This allows HPFD to move from periodic, coarse and labour-intensive forest assessments towards a dynamic, spatially explicit and repeatable system for evidence-based forest management.

The carbon brief emerging from this work is clear: species distribution is the missing bridge between forest inventory, carbon accounting and climate adaptation. Forests do not store carbon uniformly. Carbon accumulation and permanence depend on species identity, canopy structure, elevation, aspect, disturbance exposure, regeneration status and management history. By linking species-level maps with above-ground biomass datasets and field observations, the HPFD–BIPP–ISB framework enables the state to identify where biomass is increasing, where it is declining, which species groups are contributing most to carbon storage, and where climate or disturbance risks may threaten future carbon stability. This is essential for state-level climate action, carbon-finance readiness, restoration planning and climate-resilient silviculture.

The approach embodies a data–people–state convergence. Frontline forest staff and local ecological knowledge systems generate the primary observations; BIPP–ISB contributes study design, training, AI/ML pipelines, validation protocols and analytical frameworks; and HPFD provides the institutional mandate to embed these tools into working plans, fire management, restoration strategies, climate adaptation planning and forest-based enterprise development. This vertically integrated architecture transforms dispersed field observations into actionable evidence for policy.

The resulting evidence base can support multiple policy functions: identifying species-wise resource clusters for wood-based industries and bioeconomy pathways; prioritising restoration and assisted natural regeneration; designing climate-resilient silvicultural systems; estimating sustainable biomass availability; strengthening carbon monitoring and reporting; and developing forest-based livelihoods without compromising ecological integrity. It also creates a foundation for future carbon-finance mechanisms, including improved measurement of carbon co-benefits from restoration, biochar, bamboo management, fire-risk reduction and sustainable forest management.

By explicitly linking forest resource assessment to livelihoods, industry, carbon mitigation and climate adaptation, the HPFD–BIPP–ISB collaboration advances multiple Sustainable Development Goals: SDG 15 through sustainable forest management and biodiversity conservation; SDG 13 through enhanced carbon sinks and climate-risk reduction; SDG 1 and SDG 8 through forest-based livelihoods and decent work; and SDG 12 through responsible, traceable and sustainable biomass use.

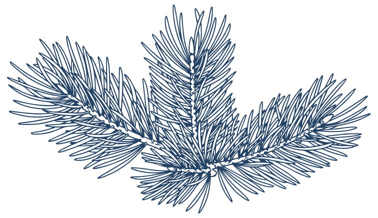
Himachal Pradesh's experience demonstrates how a Himalayan state with a high forest endowment can move beyond passive protection towards a scientifically managed, climate-aligned forest economy. Emerging technologies are not a substitute for people and institutions; they are a multiplier of institutional capacity, frontline knowledge and evidence-based governance.

This executive summary sets the stage for the detailed analysis that follows: quantifying Himachal Pradesh's forest resource base, evaluating its current and potential economic contributions, assessing species-wise biomass and carbon dynamics, and outlining a roadmap for technology-enabled forest economy planning that is ecologically sound, socially just and aligned with India's national and global climate and development commitments.

Highlights

Massive Economic Potential (₹22,600 Crore)

The report identifies an untapped state-wide potential of ₹22,600 crore from five primary forest bio-resources: pine needles (₹5,500 crore), Amla (₹8,700 crore), wild mangoes (₹4,800 crore), Sal seeds (₹2,400 crore), and Rhododendron flowers (₹1,200 crore). This aggregate value more than doubles the current recorded value of all forest provisioning services in the state.



AI-Enabled "Forest Intelligence" Layer

A sophisticated two-stream AI/ML modeling pipeline integrates multispecies Deep Neural Networks (DNN) and Random Forest models with high-resolution canopy height maps. This system transforms over 200,000 tree-level field records into a dynamic intelligence layer for precision forest management.

High-Frequency and High-Resolution Monitoring

Addressing the traditional 10-year gap in divisional working plans, the current framework utilizes 10m high-resolution spatial layers and high-frequency satellite data capable of generating ecological alerts every month. This ensures that harvesting activities are monitored in near real-time.

Monetizing Restoration and Risk

The report highlights a paradigm shift by converting ecological hazards into assets. For instance, the 11 lakh tonne annual yield of inflammable pine needles—which costs the biodiversity sector ₹6 crore annually in fire losses—is monetized into a ₹5,500 crore bio-industrial sector providing 50,000 person-days of income.

Closing the Provisioning-Carbon Paradox

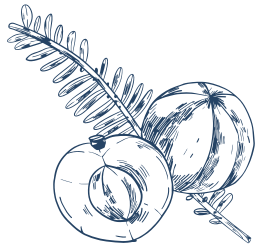
Despite a net increase in forest cover, the state witnessed a 29% decline in provisioning value between 2010 and 2022. The report provides a technological roadmap to reverse this trend by unlocking under-realized industrial value chains for species like bamboo and wild fruit giants.

Precision Sustainability through "Yield Sweet Spots"

The modeling adopts non-linear yield logic to map the "yield sweet spot" for each species. This ensures that economic extraction is restricted to specific maturation windows based on canopy height, preventing the over-exploitation of young stands and the ecological stagnation of over-mature ones.

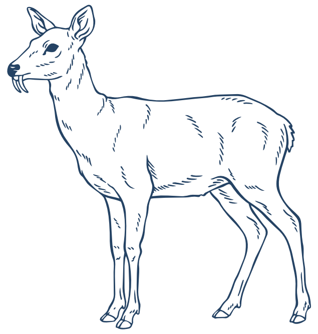
Circular Industrial Value Chains

The framework promotes "Industry 5.0" applications, moving beyond traditional extraction to high-value composites, bio-ethanol, and pharmaceutical-grade nutraceuticals. This transition retention of economic value within local community clusters.



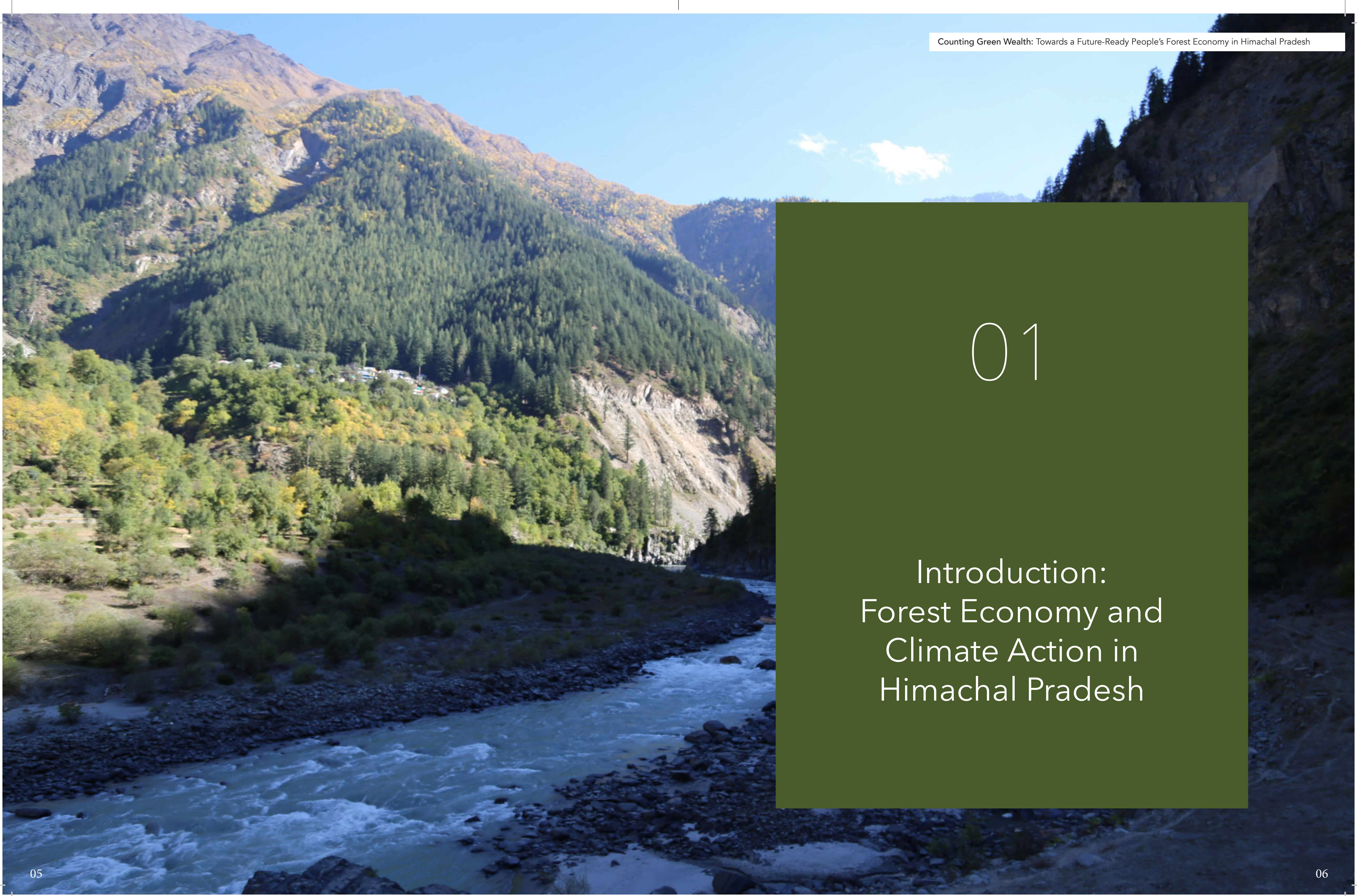
"Data-People-State" Co-Production

The report institutionalizes an unprecedented collaborative architecture where more than 500 forest guards function as data co-producers. Their localized taxonomic knowledge, embedded into high-resolution AI layers, ensures long-term institutional ownership and scientific precision in forest administration.



Alignment with Global Climate Goals

By linking resource assessments directly to India's Nationally Determined Contributions (NDC) and net-zero targets, the strategy projects the generation of massive carbon credits over time through climate-positive industrial pathways.



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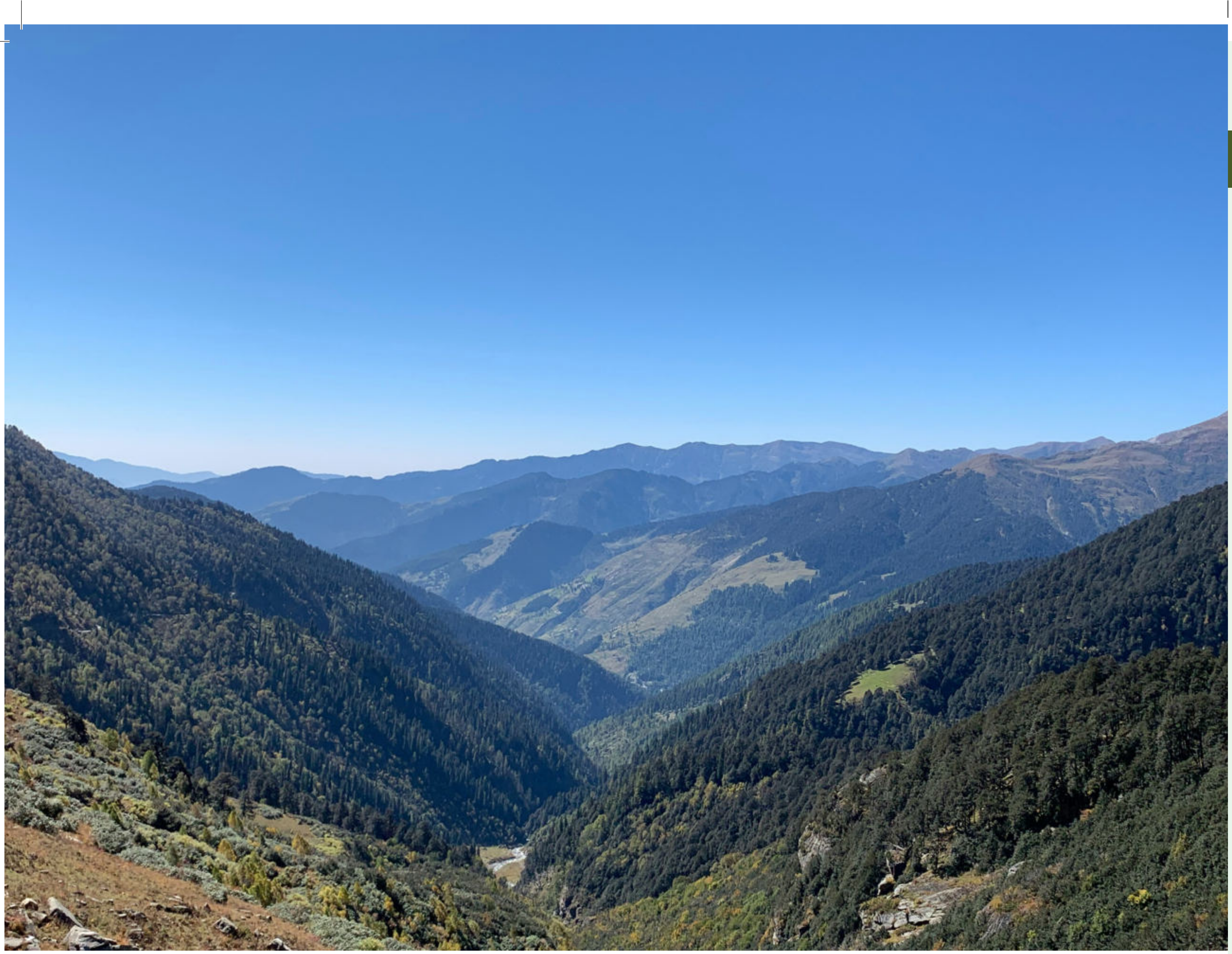
Introduction: Forest Economy and Climate Action in Himachal Pradesh



1.1 Himachal Pradesh in India's forest and climate landscape

Himachal Pradesh is a small mountain state in the western Himalaya with a geographical area of 55,673 km^2 and a predominantly rural population of 6.86 million, nearly 90% of whom live in villages. Its terrain spans Shivalik foothills (<1,500 m), a middle Himalayan belt (1,500–3,000 m), and the higher Himadri zone (>3,000 m), with roughly one-third of the area under permanent snow, glaciers and cold desert.

Himachal Pradesh General Studies

Forests and tree cover form the ecological backbone of this landscape. Based on Forest Survey of India (FSI) assessments, the state's forest cover increased from 14,353 km^2 in 2003 to about 15,580.4 km^2 in 2023, rising from 25.73% to approximately 28% of the state's geographical area; tree cover also increased from 491 km^2 to 855.07 km^2 over the same period. Recorded Forest Area (RFA) is 37,033 km^2—about 66.5% of the state's area—comprising reserved, protected and unclassed forests.

Ecologically, Himachal's forests are highly diverse. Under the Champion and Seth classification, the state hosts eight major forest-type groups and 39 forest types, ranging from dry scrub and mixed deciduous forests at lower elevations to chir pine, oak, deodar, kail, fir–spruce, bamboo, and alpine pastures at higher elevations. More than 3,000 plant species, of which around 95% are endemic to the state, have been recorded.From a climate perspective, these forests represent a significant carbon asset. FSI estimates that Himachal's forests (including larger patches of trees outside forests) store approximately 252.36 million tonnes of carbon, equivalent to about 925.32 million tonnes of CO_2, accounting for around 3.54% of India's total forest carbon stock—substantially higher than the state's share in India's land area. This carbon stock underpins the role of Himachal Pradesh in India's strategy to meet its Nationally Determined Contribution (NDC) and long-term climate goals.

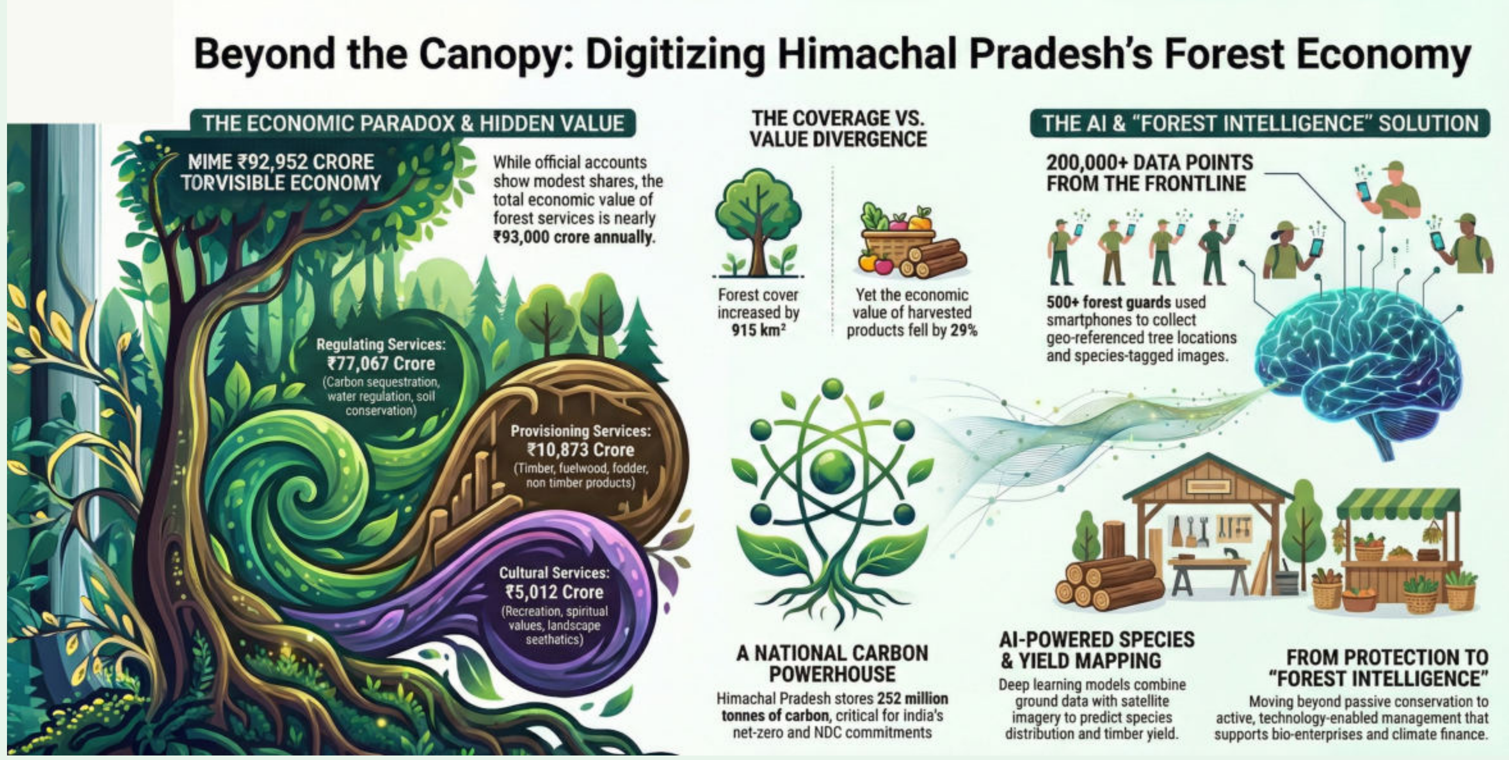
1.2 Forests and the state economy

Although conventional national accounts attribute a relatively modest share of Gross State Domestic Product (GSDP) to forestry and logging (about 4–5% in earlier planning periods), forest ecosystem services underpin a far larger portion of Himachal's economy. A forest ecosystem services valuation commissioned by the Himachal Pradesh Forest Department and carried out by the Indian Institute of Forest Management used the Millennium Ecosystem Assessment framework to estimate the Total Economic Value (TEV) of the state's forests. The study found that:

- Provisioning services (timber, fuelwood, fodder, non-timber forest products, etc.) were valued at approximately ₹ 10,873 crore per year;
- Regulating services (carbon sequestration, hydrological regulation, soil conservation, etc.) at about ₹77,067 crore; and
- Cultural services (recreation, spiritual and aesthetic values) at about ₹5,012 crore.

The combined value of these selected services was estimated at roughly ₹92,952 crore, with indirect benefits (largely regulating and supporting services) dominating the total. A related natural resource accounting exercise for land and forestry suggested that direct forest benefits were about ₹1,129 crore annually, while indirect benefits approached ₹98,475 crore. These figures highlight two core features of Himachal's forest economy:

1. Forests are economically central but under-recorded. Standard GSDP measures capture only a narrow band of market-based provisioning services, underestimating the contribution of forests to hydropower, irrigation, tourism, and climate regulation.
2. Regulating and cultural services dominate economic value. The state's hydropower, horticulture, and tourism sectors all rely on stable forested catchments, reduced sedimentation, and the maintenance of landscape quality—services that do not appear as "forestry" in the accounts but are essential for long-term growth.



Recent analyses of forest accounting across northern states underscore a paradox: between 2010–11 and 2021–22, Himachal Pradesh recorded a net increase of about 915 km^2 in forest cover, yet the economic value of provisioning services from forests declined by nearly 29%, even as carbon retention services and associated economic values rose. This divergence—more forest on paper, but weaker market flows from provisioning services—reinforces the need for a broader "forest economy" perspective that integrates ecosystem services, livelihood benefits, and climate co-benefits rather than focusing narrowly on timber or non-timber outputs.

1.3 Forest-dependent livelihoods and social systems

At the national scale, forests are central to rural livelihoods. World Bank and Government of India assessments estimate that roughly 275 million people in rural India depend on forests for at least part of their subsistence and cash income. The FSI's India State of Forest Report notes that India's forests support the livelihoods of a large share of the global rural population and a significant proportion of the world's livestock, underscoring their importance for fuel, fodder, and grazing. Himachal Pradesh reflects and amplifies these patterns. Around 90% of the state's population is rural, and livestock density is high relative to population, creating strong dependence on forests for fodder, fuelwood and grazing.

FSI's forest dependence assessments, which quantify fuelwood, fodder, small timber and bamboo harvested by forest-fringe communities, report substantial annual offtake for Himachal Pradesh, confirming the significance of subsistence use in the state. Empirical studies along elevation gradients in the Giri catchment, for example, show that households derive a considerable share of their energy and fodder from forests, with consumption patterns strongly shaped by altitude, accessibility, and species composition. Other work on forest-based livelihoods in the north-western Himalaya highlights the importance of non-timber forest products (NTFPs)—such as medicinal plants, wild fruits, and resin—for cash income, especially among tribal communities.

Institutionally, Himachal's forest-dependent communities interact with multiple governance regimes: state forest departments, joint forest management committees, village forest management societies, and traditional community arrangements. Comparative research in the Indian Himalaya shows that differences in access rules, benefit sharing, and participation across these regimes shape who gains from forest benefits and under what conditions. For Himachal, designing a forest economy strategy therefore requires not only quantifying flows of biomass and services, but also understanding how rules, norms, and power relations distribute those benefits across social groups, including women, Scheduled Tribes, and marginal households.

1.4 Forests, SDGs and India's climate commitments

Forests are integral to the 2030 Agenda for Sustainable Development. SDG 15 ("Life on Land") explicitly calls for the protection, restoration and sustainable use of terrestrial ecosystems and sustainable forest management, while SDG 13 ("Climate Action") emphasises mitigation, adaptation, and climate-resilient development. Forests contribute directly to SDG 15 and indirectly to a wide range of goals—poverty reduction (SDG 1), food security (SDG 2), clean water (SDG 6), and decent work (SDG 8).

India's updated first Nationally Determined Contribution (NDC) under the Paris Agreement commits to:

- reducing the emissions intensity of GDP compared with 2005 levels,
- increasing the share of non-fossil fuel-based energy capacity, and
- creating an additional carbon sink of 2.5–3 billion tonnes of CO_2 equivalent through additional forest and tree cover by 2030.

By 2021, national estimates suggest that land-use, land-use change and forestry (LULUCF) had already created an additional carbon sink of about 2.29 billion tonnes of CO_2 equivalent compared to 2005, positioning India on track towards this NDC target. Within this national picture, Himachal Pradesh plays a disproportionate role because of its large forest carbon stock relative to area and its historically positive forest cover trend. State-level greenhouse gas inventories indicate that, for the reference years analysed, Himachal Pradesh's LULUCF sector functions as a net carbon sink, sequestering on the order of 1.6–1.7 million tonnes of CO_2. The state's climate policy framework—including its State Action Plan on Climate Change and subsequent sectoral plans—explicitly recognises forests as central to both mitigation and adaptation, with forestry, land use, agriculture and water as key sectors through which SDG and NDC linkages are to be operationalised.

In parallel, the Himachal Pradesh Forest Ecosystem Services (HP-FES) project, implemented by HPFD and GIZ between 2016 and 2020, introduced a Forest Ecosystem Services (FES) approach into divisional working plans, piloted Payment for Ecosystem Services (PES) mechanisms, and developed a long-term ecological monitoring framework. The project is explicitly linked to SDG 15 targets on sustainable forest management and mountain ecosystems, and provides an important institutional precedent for this report's forest-economy framing.
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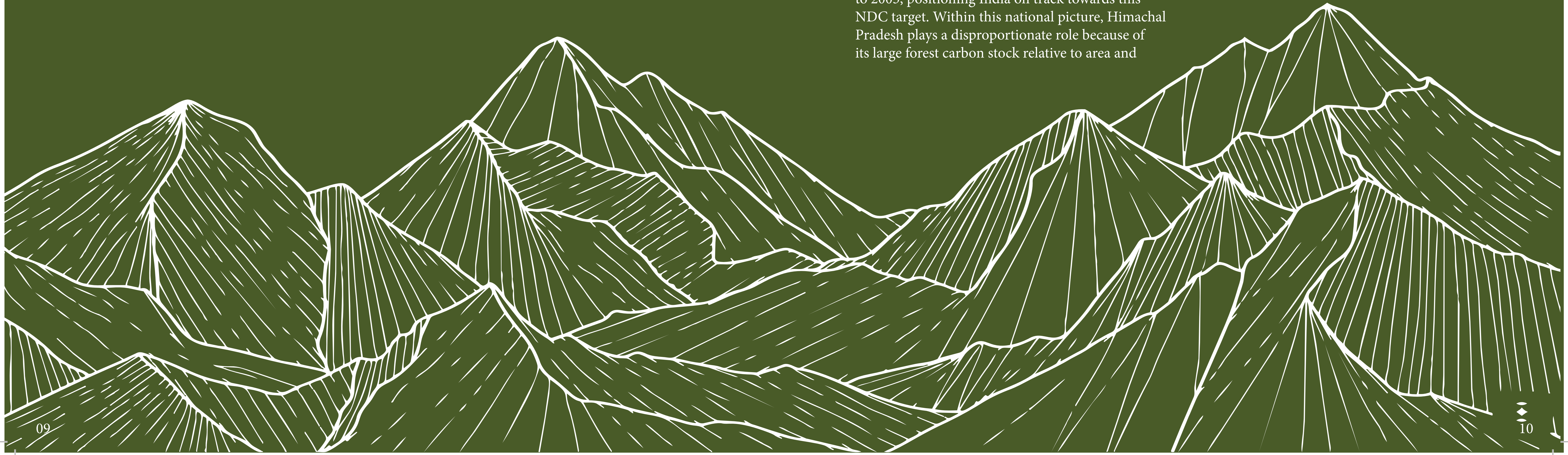
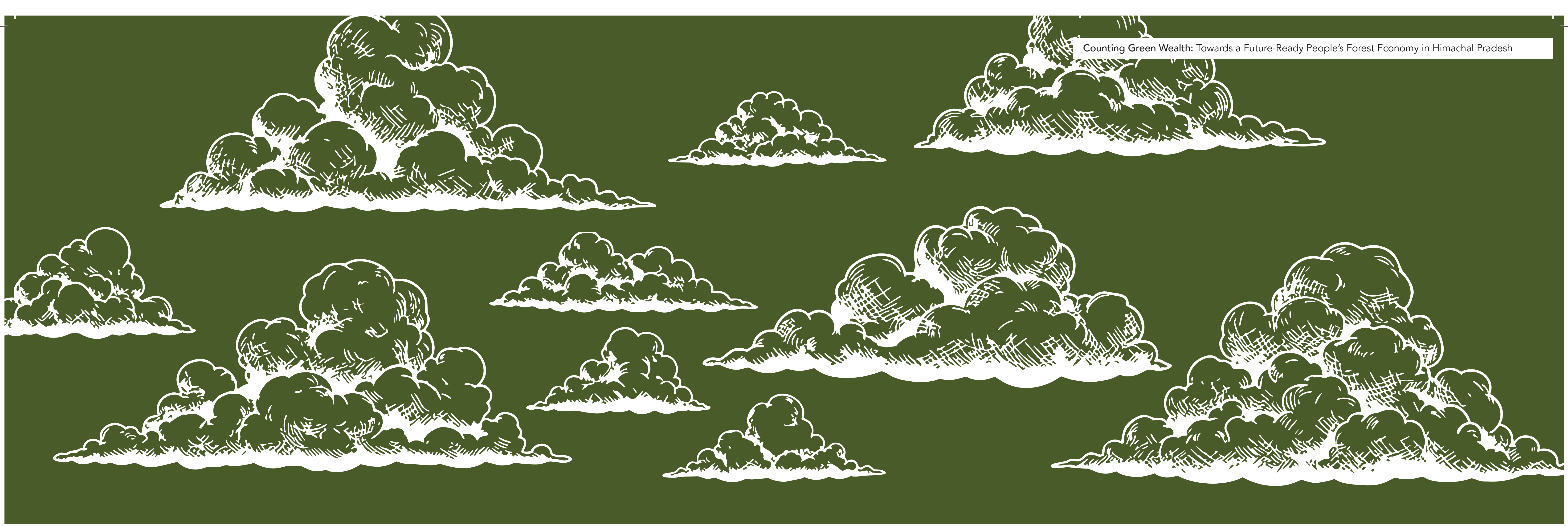




1.5 Climate risk in the Himalayan context

The Hindu Kush–Himalaya (HKH) region, of which Himachal Pradesh is a part, is globally recognised as highly climate-sensitive. The HKH Assessment and subsequent analyses show that even if global warming is limited to 1.5°C, warming in the HKH is expected to be higher—by at least 0.3°C on average and up to 0.7°C higher in the north-western Himalaya and Karakoram—leading to significant glacier and snowpack loss and altered hydrology. Recent peer-reviewed work reports intensified occurrences of "snow droughts"—periods of unusually low snowfall or early melt—across the HKH, with measurable declines in snow-covered days in key basins, including those feeding the Indus and Ganga. Complementary assessments emphasise that high mountain regions are warming faster than the global average, with implications for cryosphere stability, river flow regimes, sedimentation, and the frequency of extreme events downstream.

For Himachal Pradesh, these changes intersect directly with forest governance and the forest economy.

- Hydropower: The state has substantial, but not fully tapped, hydropower potential, and depends on forested catchments for moderated flow, reduced sediment load, and slope stability.
- Tourism: Nature-based tourism and ecotourism—landscape aesthetics, snow-dependent recreation, and cultural landscapes—rely on both stable mountain ecosystems and well-managed forests.
- Local livelihoods: Climate-induced shifts in species composition, fire regimes, and water availability will directly affect the availability of fodder, fuelwood, NTFPs, and ecosystem services on which rural livelihoods depend.

In short, forests in Himachal Pradesh are not only a mitigation asset but also a frontline adaptation system. A forest economy strategy must therefore be designed with explicit attention to climate risk and resilience, not only to static stocks of biomass or carbon.

1.6 The case for a "forest economy" perspective

Taken together, the evidence suggests three reasons for adopting an explicit "forest economy" framing for Himachal Pradesh:

Scale and composition of value. Natural capital accounting shows that the economic value of regulating and cultural services from forests far exceeds the recorded value of harvested products, yet these services are often invisible in planning decisions.

Changing patterns of benefits. Despite increases in forest cover and carbon retention, the economic contribution of timber and NTFPs to the state economy has declined, reflecting shifts in policy, markets, labour, and household energy transitions.

Distribution and institutions. Access to forest benefits is mediated by complex institutional arrangements—state-managed forests, joint forest management, community institutions and emerging PES schemes—producing differentiated outcomes for various social groups.

A forest economy lens moves beyond narrow sectoral budgeting for "forestry" to ask:

- How do forests support hydropower, horticulture, agriculture, tourism, and rural enterprises in Himachal Pradesh?
- How are these benefits distributed, and how can policies and investments enhance equity and inclusion, particularly for forest-dependent and tribal communities?
- How can forest management and investment decisions be aligned with India's NDC and the SDGs, while maintaining ecological integrity and intergenerational equity?

This report positions Himachal Pradesh as a test case for answering these questions using a combination of classical forest economics, environmental–economic accounting (SEEA), and new data-driven techniques.

1.7 Data, emerging technologies, and the HPFD–BIPP-ISB collaboration

Conventional forest inventories in India rely on periodic sample plots, working plan records, and ad hoc field surveys. While robust for certain purposes, these methods are often:

- labour- and time-intensive, limiting their temporal frequency;
- coarsely resolved, making it difficult to monitor fine-scale changes in species composition, stand structure, or degradation; and
- weakly integrated with socio-economic and market data needed for forest-economy analysis.

Over the last decade, advances in remote sensing, artificial intelligence (AI), and machine learning (ML) have opened new possibilities for forest monitoring and planning. Recent reviews show rapid growth in the use of deep learning and ML for tasks such as tree-species classification, canopy cover mapping, biomass and carbon estimation, and detection of forest damage, using data from satellites, UAVs, ground-based images, and other sensors. For example, state-of-the-art deep-learning models applied to UAV or satellite imagery have substantially improved accuracy in forest cover classification and tree species recognition relative to earlier methods, demonstrating the potential of AI for operational forest monitoring. At the same time, emerging platforms such as OpenForest and related data catalogues illustrate how curated datasets can accelerate innovation in ML-based forest monitoring.

Against this backdrop, the joint collaboration between the Himachal Pradesh Forest Department (HPFD) and the Bharti Institute of Public Policy, Indian School of Business (BIPP-ISB) responds to following complementary needs:

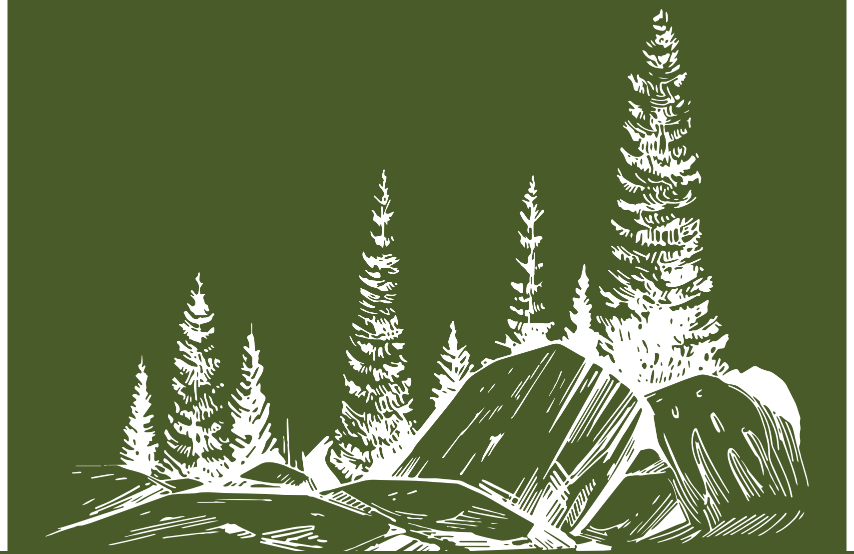
- Strengthen and extend the state's forest data infrastructure.
- HPFD forest guards, with technical training from BIPP-ISB, collected geo-referenced tree location data and high-resolution images of key tree species across representative forest types.
- These data are linked to existing forest inventory information and working plan boundaries, creating a rich, spatially explicit dataset for analysis.
- Leverage AI/ML for species distribution and yield estimation.

The ground data are used to train and validate machine-learning models that predict tree species distribution and estimate yield (e.g., timber volume or species-specific biomass) across heterogeneous terrain. The modelling framework is designed to be integrated with satellite-based layers and administrative boundaries, so that HPFD can use AI outputs within existing decision-making processes—such as working-plan revisions, fire-risk management, and planning for NTFP-based enterprises.

This approach aligns with global trends in AI-enabled sustainable forest management, but is distinctive in two respects:

- it is embedded in a state-led institutional partnership, rather than a standalone research exercise; and
- it treats forest data as a bridge between people, markets and the state, not only as a technical monitoring tool.

In parallel, Himachal Pradesh has begun experimenting with other innovative instruments at the forest–climate–livelihood interface. The state-supported biochar programme, launched as India's first such initiative, aims to convert pine needles and other biomass into biochar for agricultural and industrial use, generating an estimated 28,800 carbon credits over a decade and about 50,000 person-days of employment annually, while contributing to forest fire mitigation. Together with PES pilots under HP-FES, this signals a policy environment that is receptive to new ways of linking forest management, livelihoods, and climate finance.



1.8 Objectives and structure of the report

Building on this context, the overarching objective of the report is to characterise the forest economy of Himachal Pradesh using an integrated, evidence-based framework that combines field data, remote sensing, AI/ML models, and environmental–economic accounting, in order to inform state-level policy and investments aligned with India's SDGs and NDC.

More specifically, the report aims to:

1. Describe the ecological and economic structure of Himachal's forests, including forest types, carbon stocks, ecosystem service flows, and their linkages to key sectors such as hydropower, horticulture, agriculture, and tourism.
2. Quantify and interpret forest-dependent livelihoods and value chains, with particular attention to NTFPs, fuelwood, fodder, and emerging community-based enterprises, and to distributional issues across gender, caste, and geography.
3. Demonstrate the application of AI and ML tools—trained on the HPFD–BIPP-ISB tree-location and image dataset—for mapping tree species distribution and estimating yields, and assess how these tools can be operationalised within HPFD's planning and monitoring systems.
4. Develop policy-relevant indicators and scenarios for a sustainable forest economy, including options for PES, climate finance (such as carbon credits and nature-based solutions), and institutional innovations that enhance community participation, resilience, and accountability.

Throughout, the report treats forests not simply as a land-use category, but as dynamic socio-ecological systems whose sustainable management is central to Himachal Pradesh's development strategy, India's national climate commitments, and global progress towards the SDGs.

02

Institutional and Operational Context

2.1 Mandate and evolving functions of the Himachal Pradesh Forest Department

The Himachal Pradesh Forest Department (HPFD) is the primary state agency responsible for the conservation, management and sustainable use of forests and forest land, which together cover roughly two-thirds of the state's geographical area. In line with national legislation—the Indian Forest Act, 1927, the Forest (Conservation) Act, 1980, and the Wildlife (Protection) Act, 1972—as well as state-specific regulations, HPFD's mandate spans protection of recorded forest area, regulation of forest-based extraction, biodiversity conservation, soil and water conservation, and support to community-based forestry initiatives.

The department's own manuals emphasise that, beyond the traditional role of "regulator and protector," HPFD is increasingly required to undertake emerging functions related to ecosystem services, climate change mitigation and adaptation, and livelihood support. This expanded mandate is reflected in: integration of forest ecosystem services (FES) into divisional working plans and long-term ecological monitoring, as under the Himachal Pradesh Forest Ecosystem Services (HP-FES) project implemented with GIZ; participation in multi-sectoral programmes such as the Mid-Himalayan Watershed Development Project (MHWDP) and associated bio-carbon reforestation initiatives, which position HPFD as a nodal actor for watershed restoration, afforestation and community-based resource management; adoption of digital tools for forest land diversion, fire risk mapping, encroachment monitoring (e.g., the MoFEES system), and GIS-based administrative decision-support.

Within this institutional setting, the HPFD–BIPP–ISB collaboration on AI-enabled forest resource assessment builds on an administration that is not only a guardian of forest land but a manager of natural capital and a key implementing agency for state climate and development policy. Due to massive technology adoption initiatives of HPFD, administrative boundaries are increasingly underpinned by a spatial data infrastructure. HPFD has prepared GIS layers up to the beat level for all territorial divisions, enabling spatially explicit planning and monitoring of forest operations, fires, encroachment and plantations. This pre-existing GIS framework is a critical foundation for integrating AI/ML outputs from the HPFD–BIPP–ISB collaboration into routine decision-making, because model outputs can be produced and visualised at familiar administrative units—circles, divisions, ranges and beats.

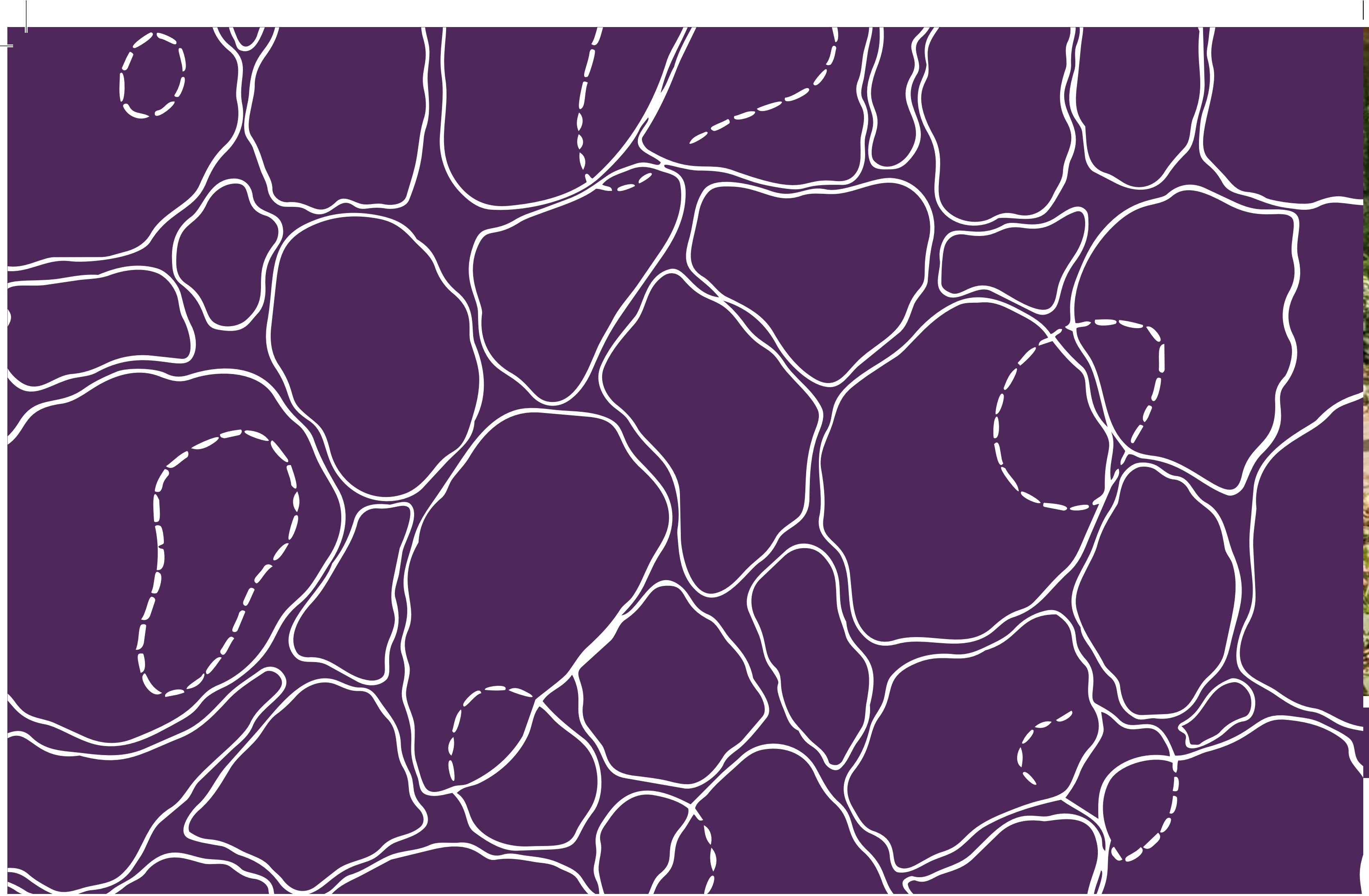
2.2 Working plans as the core planning instrument

In India, the working plan is the primary instrument for scientific forest management. The National Working Plan Code (NWPC) 2014—recently updated in 2023—sets out a standardised framework for the preparation, implementation and periodic revision of working plans across all states. The Code emphasises that forest management planning must address ecological, economic and social dimensions in an integrated manner, with explicit consideration of biodiversity conservation, climate change and the livelihood needs of forest-dependent communities. In Himachal Pradesh, working plans are prepared at the division level, which functions as the basic unit for management. An assessment of tree species composition in the Kullu Forest Circle, based on HPFD working plans and compartment history files, notes that a working plan is a "written scheme of management that aims to ensure continuity of policy action and controlled treatment of a forest," with the division as the fundamental planning unit used to evaluate the status of forests and biodiversity resources.

Over the last decade, HPFD has been at the forefront of integrating ecosystem service and climate considerations into working plans. Under the HP-FES project, the department has:

- piloted FES-based divisional working plans that explicitly prioritise selected ecosystem services (e.g., water regulation, timber availability, ecotourism);
- developed and institutionalised a Long-Term Ecological Monitoring (LTEM) framework to track forest biodiversity and ecosystem services; and
- experimented with Payment for Ecosystem Services (PES) mechanisms at catchment and community levels.

These innovations are directly relevant to this report: AI-derived species and yield maps can be embedded into working plans as spatially explicit evidence for defining working circles, prescribing silvicultural treatments, prioritising restoration and setting sustainable harvest levels.



2.3 Silvicultural systems in Himachal Pradesh

Silvicultural practice in Himachal Pradesh reflects both the state's ecological diversity and the historical evolution of forest management in the western Himalaya. Working plans across multiple divisions refer to a mix of selection systems, shelterwood systems and species-specific silvicultural regimes. For example: In the Dalhousie Forest Division, a revised working plan notes a shift "from earlier selection system to [the] Indian irregular shelterwood system," with the explicit objective of achieving more regulated and sustainable yields.

In the Shimla Forest Division, deodar and kail forests assigned to the "Deodar Shelterwood Working Circle" are reported as being managed under the Punjab Shelterwood System, a form of uniform shelterwood tailored to coniferous forests of the north-west Himalaya. In the Jogindernagar Forest Division, one working circle is described as being "worked under Punjab shelterwood system with fixed periodic blocks with provisions of selection," illustrating hybridisation of selection and shelterwood features in practice. In the Nachan Forest Division, the prescribed silvicultural method is the selection system, described as the most conservative method among available systems for the exploitation of forests, with emphasis on retaining continuous forest cover while periodically removing selected trees. Silvicultural fellings in chir pine (Pinus roxburghii) forests have been the subject of specific regulatory scrutiny, including litigation before the National Green Tribunal regarding the conditions under which silvicultural fellings may proceed. These debates underline the need for robust, spatially explicit data on stand density, regeneration status and species composition when designing or revising silvicultural regimes in fragile Himalayan landscapes.

The HPFD–BIPP–ISB collaboration contributes directly to this requirement. By providing high-resolution information on species distribution and standing yield, the AI/ML framework can support silvicultural zoning, estimation of growing stock within working circles, and the design of species-specific treatments that account for both productivity and resilience under changing climate conditions.

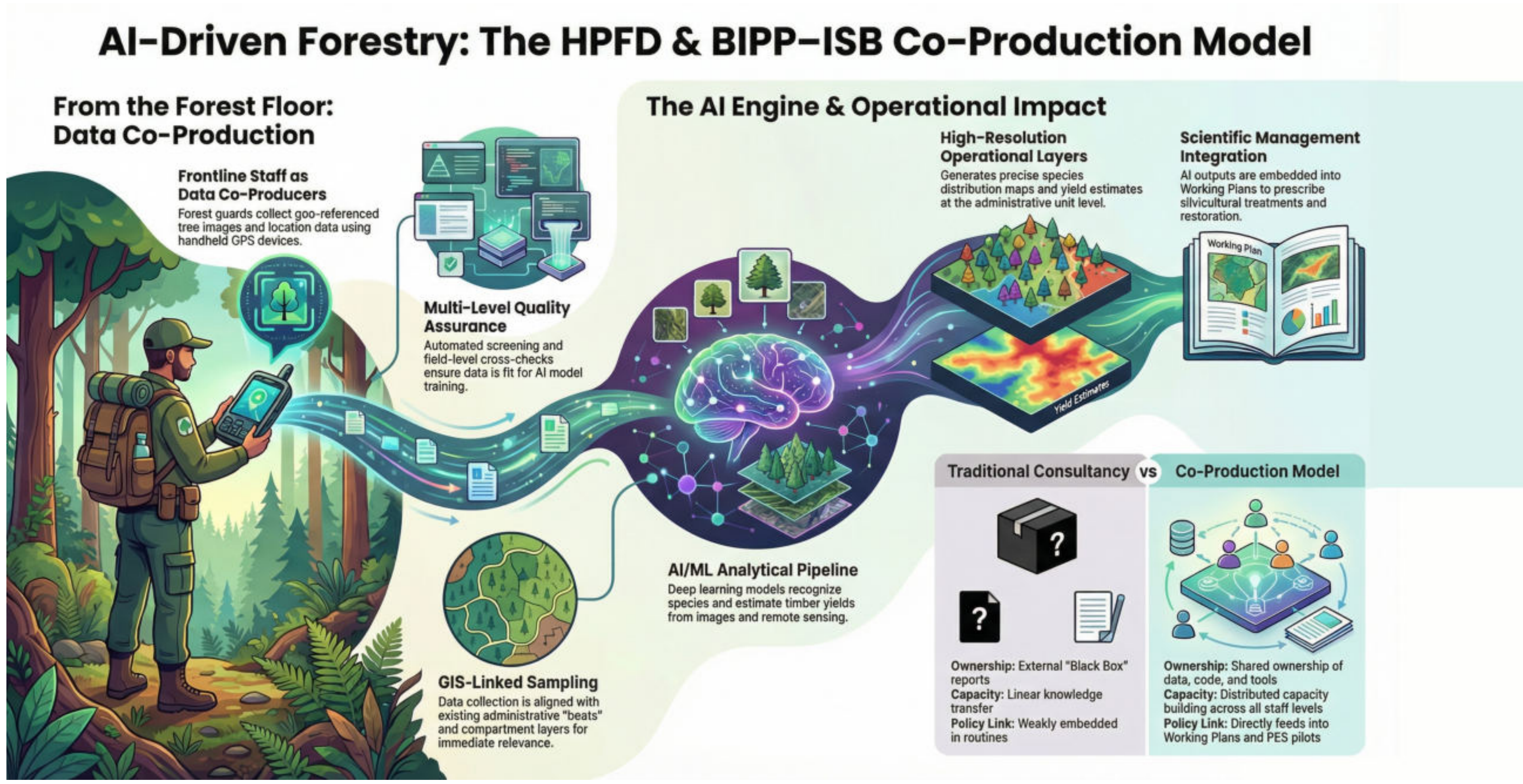
2.4 Forest guards and frontline staff: from protection to data co-production

India's forestry literature consistently identifies frontline staff—rangers, foresters and forest guards—as the backbone of the forestry sector, responsible for implementing a wide range of functions at the "cutting edge" of forest administration. Empirical accounts and policy analyses on forest policing in India highlight that frontline staff routinely face difficult terrain, resource constraints and personal risk—ranging from encounters with illegal loggers and wildlife crime to exposure to fires and extreme weather—while performing these duties. At the same time, national training policies and sectoral guidance stress the importance of upgrading frontline capacity in areas such as GIS, GPS use, conflict resolution, biodiversity conservation and climate change.

Within this context, the HPFD–BIPP–ISB collaboration explicitly recognises forest guards and frontline staff as co-producers of data and knowledge, not merely as implementers of centrally designed schemes. In the present project:

- Forest guards are responsible for collecting geo-referenced tree location data and species-tagged images within their beats, using handheld GPS-enabled devices or mobile applications aligned with HPFD's GIS infrastructure.
- Foresters and Range Forest Officers provide first-line supervision, ensuring adherence to sampling protocols, resolving species identification doubts in the field and verifying the completeness of data submissions.
- BIPP–ISB experts, scientists and HPFD's officers jointly review incoming data to identify gaps or inconsistencies, which are then communicated back to field staff through feedback loops and refresher guidance.

This design is consistent with broader evidence that participatory and co-produced monitoring systems can improve both data quality and institutional ownership of monitoring outputs, particularly in complex socio-ecological systems.



AI-Driven Forestry: The HPFD & BIPP–ISB Co-Production Model

From the Forest Floor: Data Co-Production

Frontline Staff as Data Co-Producers
Forest guards collect goo-referenced tree images and location data using handheld GPS devices.

Multi-Level Quality Assurance
Automated screening and field-level cross-checks ensure data is fit for AI model training.

GIS-Linked Sampling
Data collection is aligned with existing administrative "beats" and compartment layers for immediate relevance.

The AI Engine & Operational Impact

AI/ML Analytical Pipeline
Deep learning models recognize species and estimate timber yields from images and remote sensing.

High-Resolution Operational Layers
Generates precise species distribution maps and yield estimates at the administrative unit level.

Scientific Management Integration
AI outputs are embedded into Working Plans to prescribe silvicultural treatments and restoration.

Traditional Consultancy	Co-Production Model
Ownership: External "Black Box" reports	**Ownership:** Shared ownership of data, code, and tools
Capacity: Linear knowledge transfer	**Capacity:** Distributed capacity building across all staff levels
Policy Link: Weakly embedded in routines	**Policy Link:** Directly feeds into Working Plans and PES pilots

2.5 BIPP–ISB's role in the collaboration

2.5.1 Study design

BIPP–ISB's role begins with the design of the empirical study that underpins AI/ML model development. In close consultation with HPFD, the team:

- defined the sampling frame in terms of divisions, ranges and beats, ensuring representation of major forest types, altitudinal zones and management regimes;
- specified plot and tree-level variables to be recorded (species, approximate size class, condition, location, image set, and basic site descriptors), balancing scientific needs with the time and capacity constraints of frontline staff; and
- aligned data collection with existing working plan compartments and GIS layers, so that derived products would be directly usable within HPFD's planning processes.

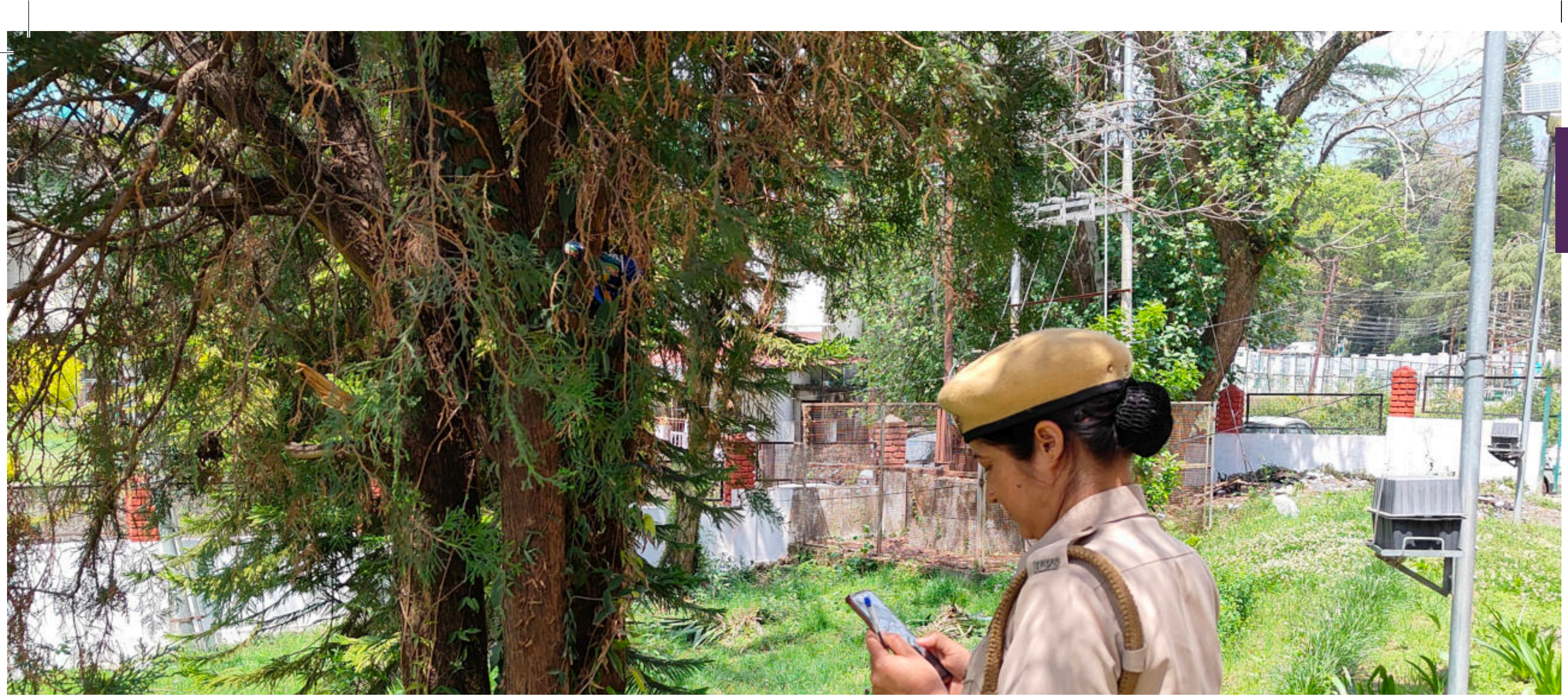
In designing this framework, BIPP–ISB draws on contemporary scholarship on forest inventories and environmental monitoring, which emphasises the importance of integrating ground plots, remote sensing and statistical models in a coherent design to support both carbon accounting and forest management decisions.

2.5.2 Training modules for forest guards

Based on the identified variables and protocols, BIPP–ISB developed training modules for forest guards, foresters and range staff. Informed by national guidance on training frontline forest staff and the documented gaps in existing training provision, the modules typically cover:

- Conceptual foundations – why tree-level data and images matter for forest management, climate policy and the forest economy;
- Species identification and coding – field identification of key tree species, use of standard species codes, and handling of ambiguous or mixed-species cases;
- Geospatial skills – use of GPS-enabled devices or mobile apps for recording coordinates, linking points to compartments, and basic map reading;
- Image capture protocols – number and angle of images per tree, distance from stem, lighting considerations, and file naming or automatic metadata capture;
- Data entry and transmission – step-by-step workflows for entering, checking and uploading data, with attention to offline conditions and error handling;
- Ethics and safeguards – do-no-harm principles, avoidance of sensitive personal information, and awareness of safety protocols during fieldwork.

Training is delivered in a blended format, combining classroom sessions, field demonstrations and hands-on exercises using the actual devices and forms that guards will employ. This approach is consistent with best practices identified in the training literature, which recommends context-specific, practice-oriented modules that address both technical and behavioural aspects of frontline work.



2.5.3 Data quality protocols

To ensure that ground data are fit for AI/ML training and operational use, BIPP–ISB and HPFD jointly establish data quality protocols that operate at three levels:

- Instrument and form design – mandatory fields, drop-down lists for species codes, built-in date/time stamps and automatic capture of GPS coordinates reduce the scope for missing or inconsistent entries.
- Field-level checks – foresters and range officers periodically re-measure a subset of trees or revisit plots to cross-check species identification, coordinates and images, creating an internal validation dataset.
- Centralised screening and feedback – BIPP–ISB analysts perform automated checks for outliers (e.g., improbable coordinates, duplicate entries, implausible combinations of species and elevation) and generate feedback reports that are discussed with HPFD counterparts and communicated back to field staff.

This multi-level quality assurance is aligned with recognised principles for designing monitoring systems that support high-stakes applications such as biomass estimation, carbon accounting and silvicultural planning.

2.5.4 AI/ML model development and validation

On the analytical side, BIPP–ISB leads the design and implementation of AI/ML pipelines for:

tree species recognition from images, building on state-of-the-art deep learning architectures that have been successfully applied to tree species classification using aerial, terrestrial and hyperspectral imagery;

species distribution modelling, combining ground observations with multi-source remote sensing data (e.g., Sentinel-1/2, DEM, land cover) to predict the probability of occurrence or relative abundance of key species across the landscape;

yield estimation, in which species-specific peer-reviewed yield tables are used to derive per-tree production volume from modelled and observed attributes such as total tree height (and diameter, where available), with aspect and related topographic indices incorporated as proxies for site quality and age–productivity conditions.

Model validation uses held-out ground data, cross-validation across ecological zones, and comparison with existing working plan estimates where available. HPFD officers are involved in reviewing validation outputs—particularly residual patterns that may correspond to known data gaps or atypical stands—ensuring that model refinement reflects both statistical performance and field realities.

The end products are operational layers—species probability surfaces, stand-level yield estimates, uncertainty bands—that can be ingested into HPFD's GIS and planning systems and visualised at the administrative units familiar to field and managerial staff.

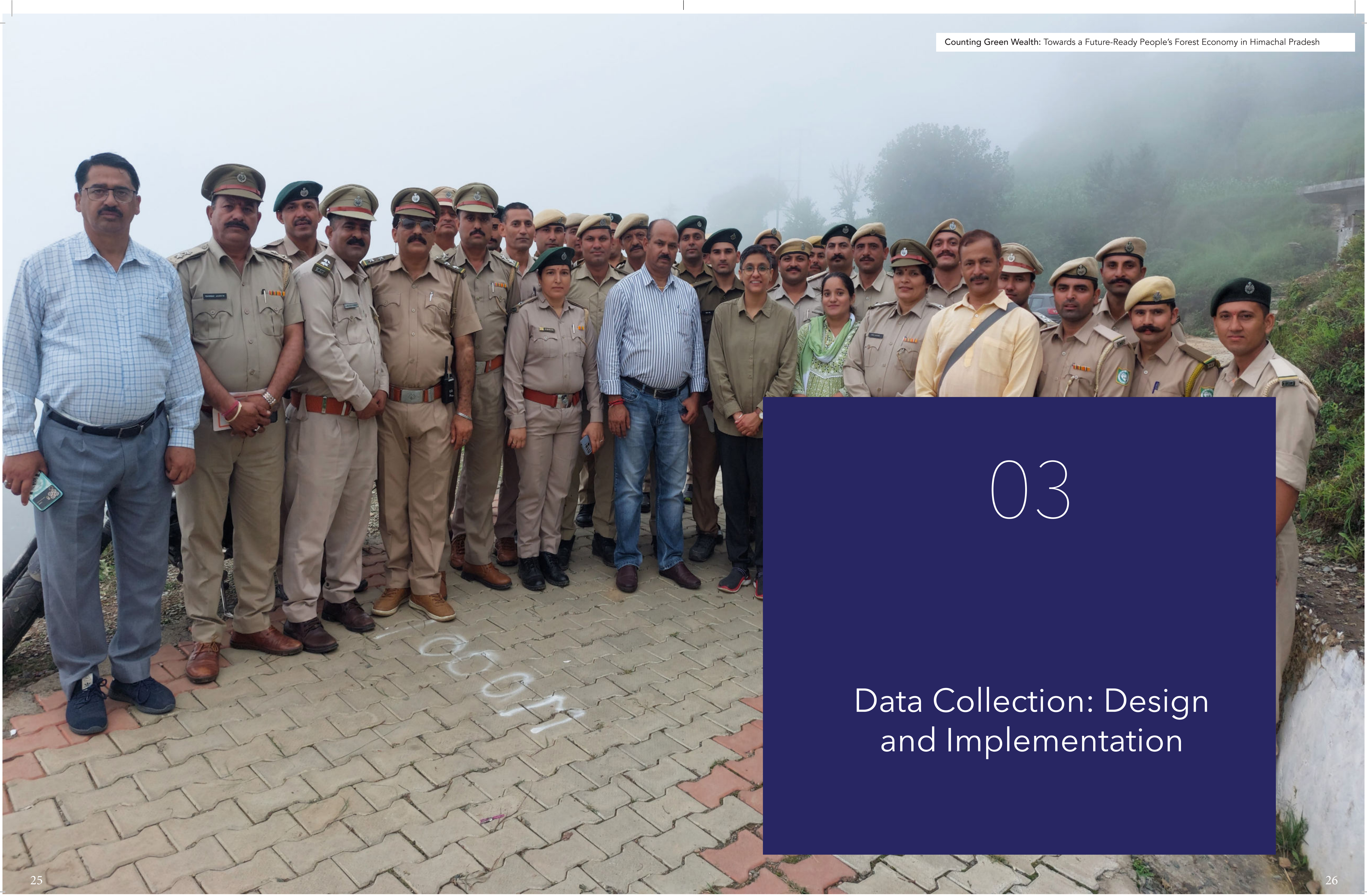
2.6 From consultancy to co-production: distinctive features of the HPFD–BIPP–ISB partnership

Many externally supported exercises in forest inventory, modelling or valuation function as time-bound consultancies, where external experts generate analyses and reports that are only weakly embedded in departmental routines. Comparative work on the science–policy interface and knowledge co-production shows that such linear "knowledge transfer" models often limit the uptake and long-term use of scientific outputs in policy and management. The HPFD–BIPP–ISB collaboration has been deliberately structured to move towards a co-production model, with several distinguishing features:

- Joint problem framing and study design
  The core questions—how to generate operational species and yield maps, and how to link them to forest economy planning—have been defined jointly by HPFD and BIPP–ISB, rather than imposed externally. The sampling frame, variables and data structures are aligned with existing working plans, GIS layers and administrative boundaries, ensuring immediate relevance for HPFD workflows.
- Shared ownership of data and tools
  Data collected by forest guards are stored within BIPP-ISB's systems as per standard DPDP and NSDI guidelines , with BIPP–ISB providing analytical support and documentation so that models can be retrained or adapted in future. AI/ML code, model configurations and documentation are developed with a view to reusability and eventual internalisation by HPFD's technical units, rather than as a "black box" service.
- Capacity building across levels
  Training efforts are targeted not only at frontline forest guards but also at foresters, range officers and selected divisional staff, building a distributed capacity for data collection, interpretation and use. This approach is consistent with evidence that co-produced knowledge is most effective when multiple levels of an organisation are involved in iterative cycles of problem definition, data collection and interpretation.
- Integration with existing and emerging policy instruments
  The collaboration is explicitly designed to feed into working plans, FES-based management plans, PES pilots, and climate-related programmes such as biochar and afforestation initiatives, rather than standing apart as a research-only exercise.
- Longer-term perspective and learning

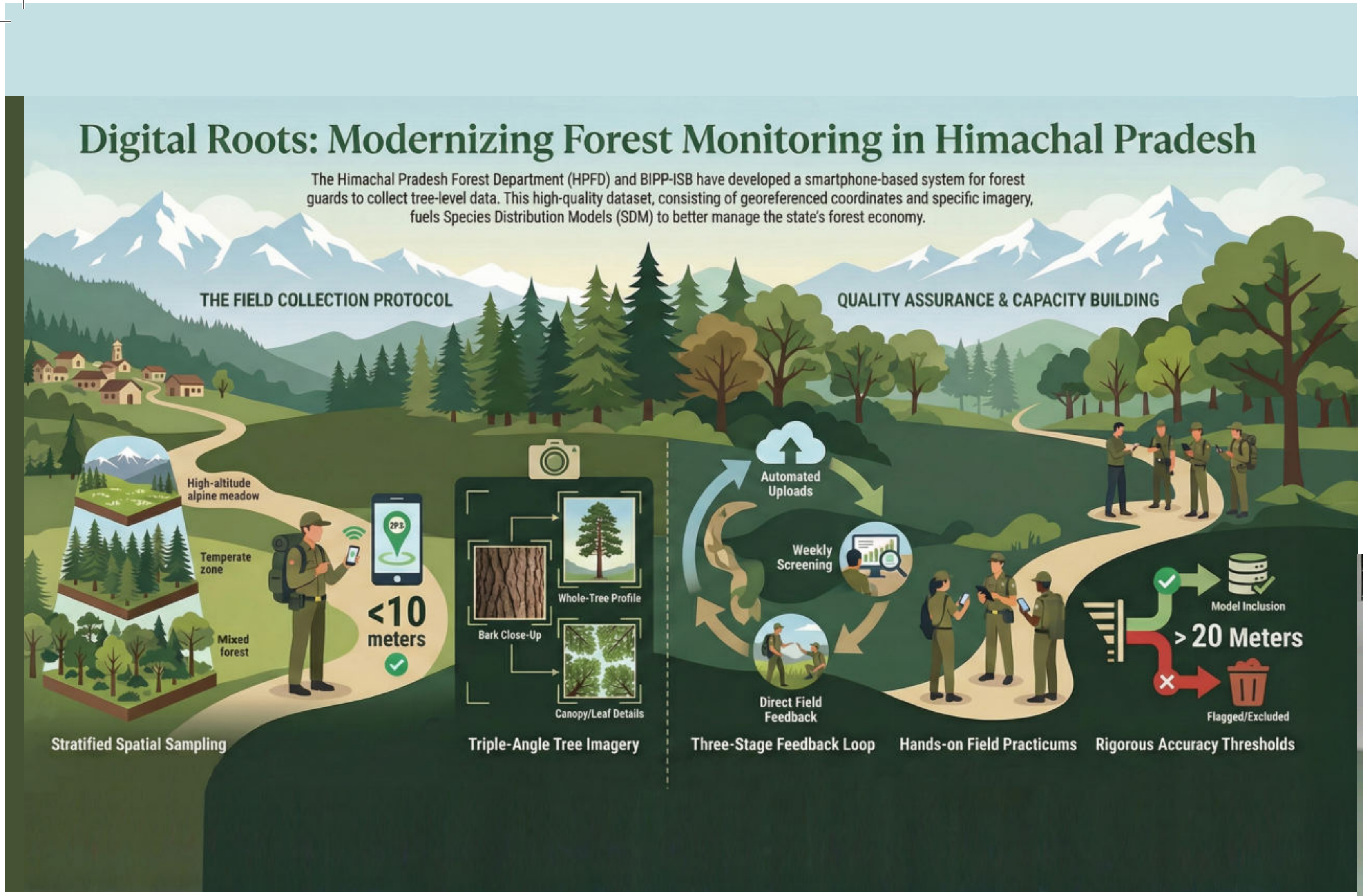
  The focus on reusable tools, documentation and shared capacity creates the conditions for adaptive learning, where HPFD can iteratively improve data collection protocols, retrain models, and refine forest economy strategies as new evidence and technologies emerge.

In sum, the institutional and operational context in Himachal Pradesh—an experienced forest department with a strong working plan tradition, expanding ecosystem service and climate mandates, and a frontline workforce capable of co-producing data—provides a fertile setting for the HPFD–BIPP–ISB partnership. The next chapters build on this foundation to show how AI-enabled forest intelligence can support a scientifically grounded, climate-aligned forest economy for the state.



03

Data Collection: Design and Implementation



Digital Roots: Modernizing Forest Monitoring in Himachal Pradesh

The Himachal Pradesh Forest Department (HPFD) and BIPP-ISB have developed a smartphone-based system for forest guards to collect tree-level data. This high-quality dataset, consisting of georeferenced coordinates and specific imagery, fuels Species Distribution Models (SDM) to better manage the state's forest economy.

3.1 Overview

This chapter describes the empirical foundation of the HPFD–BIPP–ISB collaboration: a tree-level, presence-only dataset consisting of georeferenced tree locations and associated photographs, collected by forest guards and frontline staff and designed primarily to support species distribution modelling (SDM) and related AI/ML applications. The design draws on established principles from national forest inventory practice, geospatial best-practice for plot georeferencing, and recent work on smartphone-based forest data collection. The core idea is simple but powerful: each observed tree, when accurately located and reliably identified, becomes a presence record that can be linked to environmental covariates (topography, climate, land cover, remote-sensing indices) and used to infer the spatial distribution of species and stand characteristics through SDMs and machine-learning models.

3.2 Sampling strategy

3.2.1 Spatial stratification and selection of ranges/compartments

The sampling design was developed jointly by HPFD and BIPP–ISB to ensure that the dataset:

- Represents the main ecological gradients in Himachal Pradesh (elevation, aspect, forest type, moisture regime);
- Aligns with existing management units, including working-plan divisions, ranges and compartments; and
- Is operationally feasible for forest guards to implement within routine patrolling and fieldwork.

The state's territorial divisions were first grouped into strata defined by combinations of:

- dominant forest type groups (e.g., coniferous, broadleaf, mixed), based on HPFD working plans and FSI classifications;
- elevation bands (e.g., <1,500 m, 1,500–2,500 m, >2,500 m); and
- broad management regimes (e.g., protection-oriented vs. production-oriented working circles).

Within these strata, pilot ranges were selected through consultation with DFOs and Range Forest Officers to ensure coverage of:

- typical, well-studied areas (for calibration);
- under-documented or ecologically sensitive areas (for improved representation); and
- areas with existing GIS and working plan datasets of sufficient quality.

Inside each selected range, compartments and, where relevant, sub-compartments or beats were chosen to maximise variation in forest structure and composition while limiting travel costs for frontline staff. This stratified cluster design is consistent with contemporary recommendations to use auxiliary spatial data and operational constraints to rationalise smartphone-based forest sampling.

3.2.2 Tree-level location-only data and photographs for SDM

Within a selected compartment or beat, forest guards were instructed to record tree-level presence-only information for pre-identified target species (e.g., key commercial, ecological or indicator species), rather than conducting full plot-based inventories. For each target tree, the following minimum information was collected:

- a single point location (geographic coordinates);
- pecies identity (field identification using agreed codes);
- one or more photographs following a standard protocol; and
- basic contextual metadata (e.g., elevation from mobile GNSS sensor, date, time and observer ID).

This choice of presence-only sampling reflects both the primary objective—species distribution modelling—and field realities: presence-only data, when combined with well-characterised environmental covariates and appropriate modelling approaches, have been shown to perform well for SDM, especially when sampling effort and bias are explicitly considered.

3.3 Field protocols

3.3.1 Georeferencing tree locations

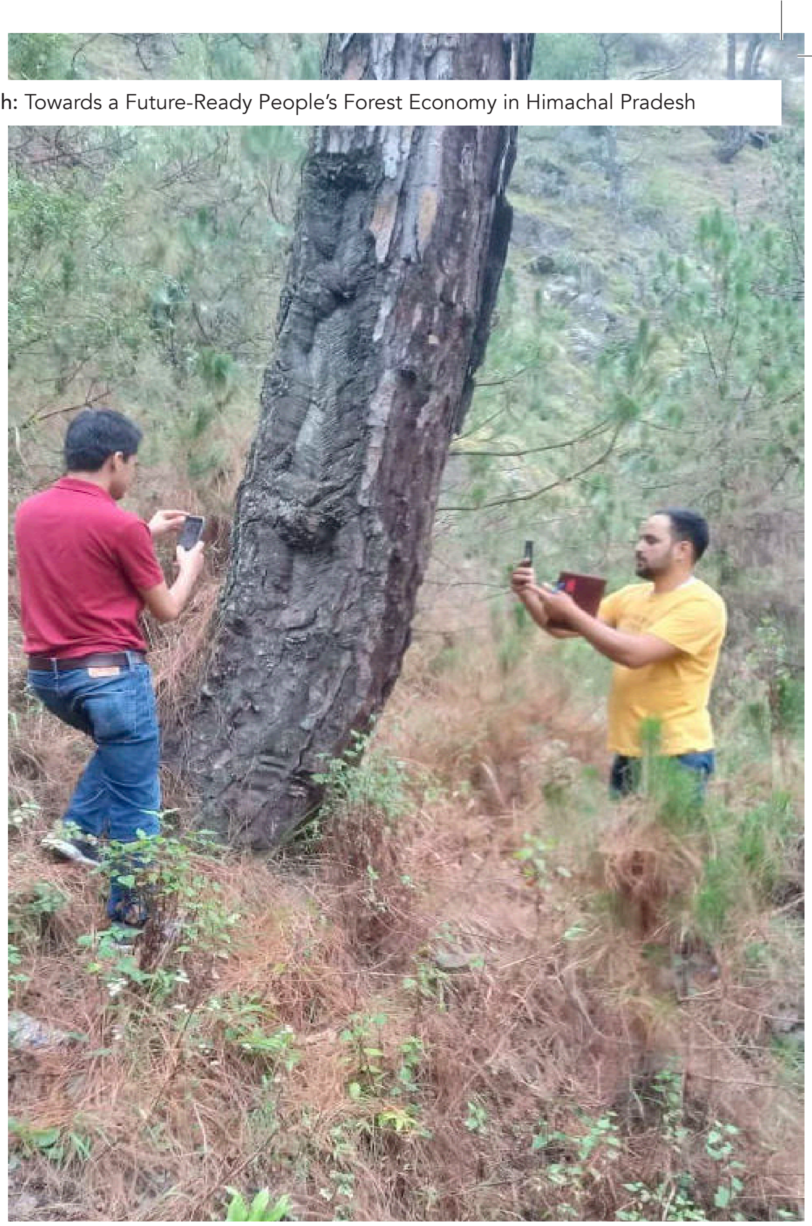
All tree locations were recorded using GNSS-enabled smartphones carried by forest guards. The protocol was informed by:

- the National Forest Inventory field manual, which requires the use of handheld GPS to reach and record sample plot centres;
- best-practice guidelines for georeferencing biodiversity and vegetation records (point–radius methods, explicit uncertainty estimates); and
- empirical studies of GNSS accuracy in forest environments, which show that smartphone devices typically achieve horizontal root mean square errors of ~6–10 m under open sky and ~8–15 m under forest canopies, with performance dependent on canopy closure, device model, and acquisition time.

Key steps in the protocol were:

At each target tree, the guard held the device at chest height and waited for positional stabilisation (minimum of 15–30 seconds), observing the on-screen estimated position accuracy. If the estimated accuracy exceeded a pre-defined threshold (typically 5-10 m), the guard either waited longer. Coordinates, once below the pre-defined accuracy threshold, were stored automatically by the mobile application application, which also recorded date–time and, an estimate of horizontal accuracy or dilution of precision (DOP).

In dense canopy or steep terrain where GNSS performance was poor, additional qualitative location descriptors were derived from secondary data sources, allowing later refinement of coordinates following recognised georeferencing best practices.



3.3.2 Species identification and handling ambiguity

Species identification was carried out in the field by forest guards, foresters and range staff, who possess substantial local taxonomic knowledge.

To standardise observations:

HPFD and BIPP–ISB prepared a species list for each division, aligned with working-plan records and FSI classifications, and assigned unique species codes (e.g., for deodar, kail, chir pine, oak species, broadleaf groups). Photographs and visual aids (leaf, bark, branching patterns, cones/fruits) were provided to support consistent identification.

The photograph protocol (Section 3.3.3) was deliberately designed to support post-hoc taxonomic checks by BIPP–ISB and HPFD technical staff, and—where appropriate—to train image-based classification models that can further reduce identification errors over time. This approach mirrors established practice in smartphone-driven biodiversity and forest monitoring where in-field identifications are refined with expert review and machine learning.

3.3.3 Image capture: angle, distance, number of images and metadata

For each target tree, guards captured a minimum of three photographs using the smartphone camera:

Bark/stem close-up at approximately 1.3–1.5 m above ground (breast height), filling most of the frame;

Whole-tree profile, showing crown shape and branching structure, from a distance sufficient to view the entire tree where possible;

Canopy/leaf detail, zoomed in on leaves, needles or small branches.

Where terrain or vegetation prevented whole-tree images, guards prioritised bark and foliage photographs, which are particularly informative for image-based classification. Experimental work in forest inventory using smartphone imagery and low-cost sensors has shown that such targeted views can substantially improve automatic extraction of species and structural variables.

Basic guidelines were provided to minimise variability and blur:

- maintain a consistent distance for bark photos (roughly 1–1.5 m from the stem);
- avoid strong backlighting where possible;
- keep the camera perpendicular to the trunk for bark close-ups; and
- ensure that at least one image includes distinctive features (e.g., cones, fruits, exfoliating bark) where present.

In all the data collection exercise, the geotagging was enabled so that each photograph carried embedded EXIF metadata, including coordinates and time. Studies of smartphone photo geolocation show that, when GNSS has been allowed to stabilise, such metadata typically achieve sub-10 m accuracy under open conditions and comparable performance to direct GNSS readings in many forest settings, subject to canopy and device constraints.

3.4 Training provided by BIPP–ISB

3.4.1 Curriculum for forest guards and frontline staff

BIPP–ISB developed a structured training curriculum and video instructions tailored to the roles and existing skill profiles of forest guards, foresters, and range officers, drawing on national training needs assessments for frontline forestry personnel. The curriculum covered three broad domains:

Conceptual foundations

- Forests as natural capital and their role in Himachal's forest economy and climate commitments;
- Basics of SDM and AI/ML in forest monitoring, explained in operational terms (e.g., why many accurate points matter more than a few very detailed plots);
- The importance of georeferencing accuracy, consistent species identification, and high-quality images for reliable modelling.

Technical skills

- Use of smartphones for navigation and georeferencing (waypoints, track logs, reading and interpreting accuracy indicators);
- Species identification refreshers, focusing on frequently confused taxa and use of field keys;
- Camera handling for consistent image capture and geotagging;
- Step-by-step walkthrough of the data-collection app and forms.

Operational and ethical aspects

- Planning data-collection routes to integrate with routine patrolling and other duties;
- Safety considerations in steep terrain and remote areas;
- Basic data protection and privacy principles (no identifiable images of people, no sensitive information).

Training was delivered as division-level workshops combining classroom modules with field practicums, consistent with best practice for adult professional training in natural resource agencies.

3.4.2 Practical sessions and mock data collection

Each training event included mock data-collection exercises:

In a nearby forest patch or plantation, trainees were organised in small groups (typically 3–5 persons) and asked to simulate a data-collection round, including navigation to pre-selected trees, recording coordinates, species codes, and images. Trainers (BIPP–ISB and HPFD technical staff) conducted direct observation and spot checks, pointing out common errors (e.g., failing to let GNSS stabilise, mis-labelling species, poor framing of images). Selected records from the mock exercise were downloaded and projected during the debrief session to show how data appear in the central system and how errors manifest in maps and tables. This hands-on design reflects evidence that practice-based, iterative training significantly improves field data quality and staff confidence, particularly when introducing digital tools to frontline personnel.

3.4.3 Data entry, error checking and feedback loops

Where mobile connectivity allowed, forest guards synchronised records daily from the smartphone application to a central server managed by HPFD with analytical support from BIPP–ISB. In low-connectivity areas, data were stored locally and uploaded on return to range or divisional headquarters where mobile network connectivity is available.

A three-stage feedback loop was implemented:

- Automated checks at upload – the application flagged missing mandatory fields, implausible coordinates (outside state/division boundaries), or obviously corrupted images.
- Weekly screening by analysts – BIPP–ISB generated summary statistics and maps (e.g., point density by beat, proportion of records by species, distribution of GNSS accuracies) to identify anomalies or gaps.
- Structured feedback to field staff – brief feedback notes and annotated maps were shared with Range Officers and, where necessary, discussed in short online or in-person briefings to clarify issues and adjust field practices.

This iterative system mirrors recognised principles of adaptive monitoring, where data collection protocols are refined over time in response to observed error patterns and operational constraints.

3.5 Data quality control

3.5.1 GPS accuracy thresholds and spatial uncertainty

To safeguard the usefulness of observations for SDM and remote-sensing model training, HPFD and BIPP–ISB adopted explicit positional accuracy thresholds informed by empirical studies of GNSS performance in forests and by the spatial resolution of key environmental covariates (e.g., 10–30 m satellite imagery). Records with estimated horizontal accuracy ≤ 10 m (where such an estimate was available) were classified as high-confidence and used without restriction. Records with estimated accuracy between 10 and 20 m were retained but flagged, and sensitivity analyses in modelling were planned to test the effect of including or excluding these points. Records with estimated accuracy > 20 m, or with clear spatial inconsistencies (e.g., points falling in non-forest land-use types contrary to field notes), were either corrected using auxiliary information (e.g., proximity to mapped boundaries, trails) or excluded from the core modelling dataset.

For observations lacking device-reported accuracy estimates, a default uncertainty radius (e.g., 20 m) was assigned, consistent with georeferencing best practice; this uncertainty was retained as a metadata field and can be propagated in later analyses if required.

3.5.2 Species verification

Species identity is critical for SDM and any downstream forest-economy analysis. Data quality measures included:

Internal consistency checks – cross-tabulating species codes against elevation, broad forest type and division to flag improbable combinations (e.g., a low-elevation species recorded in a known high-elevation conifer belt);

Image-based verification – random subsamples of records for each species were reviewed by HPFD and BIPP–ISB experts using the associated photographs, with corrections recorded and used to refine training and identification aids;

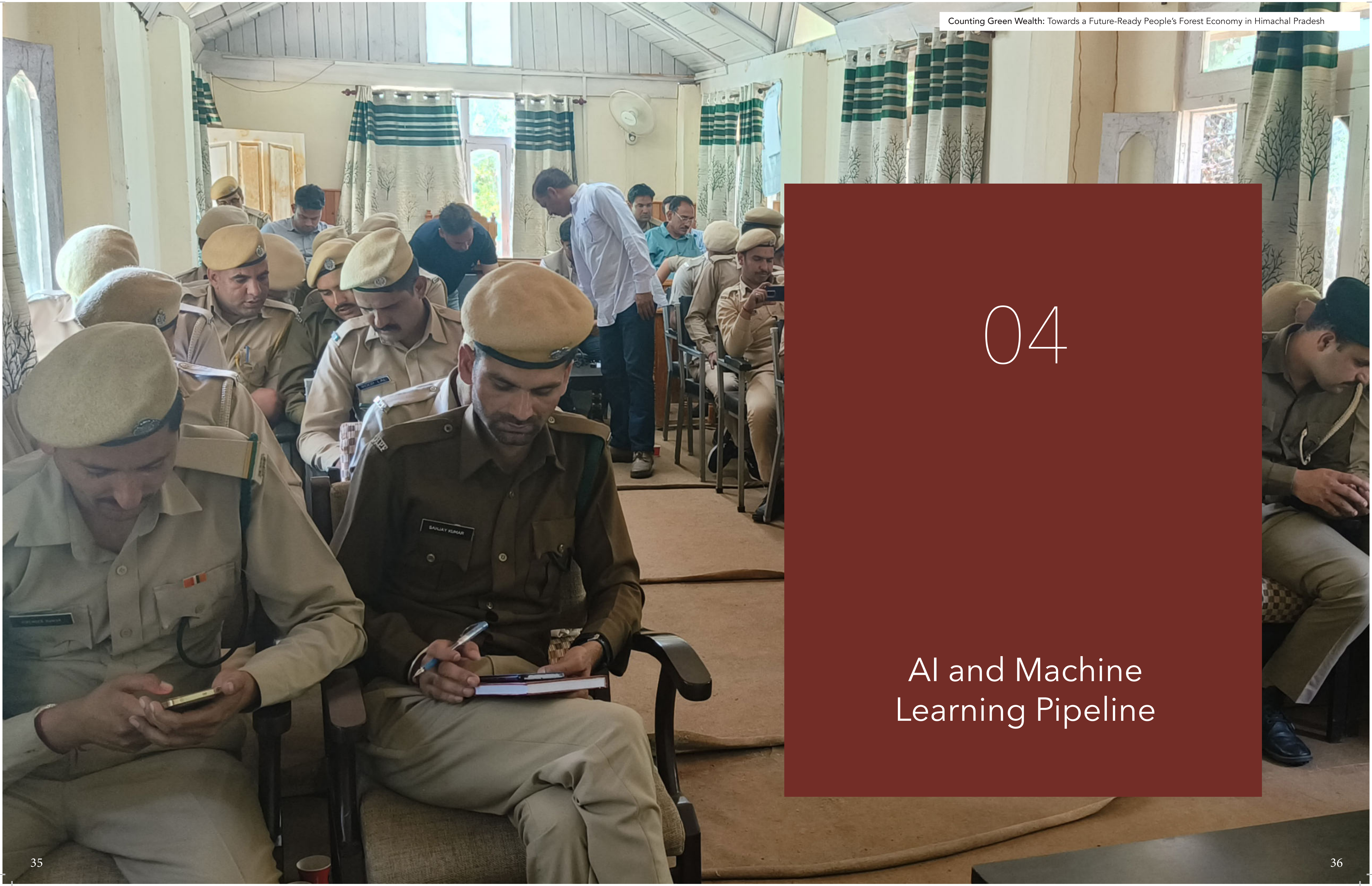
These steps are consistent with evolving practice in smartphone-based biodiversity monitoring, where expert review and machine-learning tools are increasingly used to validate and refine field identifications.

3.5.3 Handling missing and inconsistent records

A set of rules for missing and inconsistent data was agreed in advance to ensure transparency:

- Records missing coordinates were excluded from SDM datasets but retained in auxiliary tables if species information was considered useful for qualitative assessments.
- Records lacking species codes but having valid coordinates and images were stored in a "to be resolved" queue; where feasible, species were later inferred by expert review of images.
- Duplicate records (same species, same coordinates, same timestamp) were collapsed to single entries; near-duplicates were checked manually where they could reflect multi-tree clusters or genuine repeated visits.
- Inconsistent combinations (e.g., coordinate suggesting a non-forest land use while field notes indicated "dense forest") were flagged for targeted follow-up during subsequent field visits.

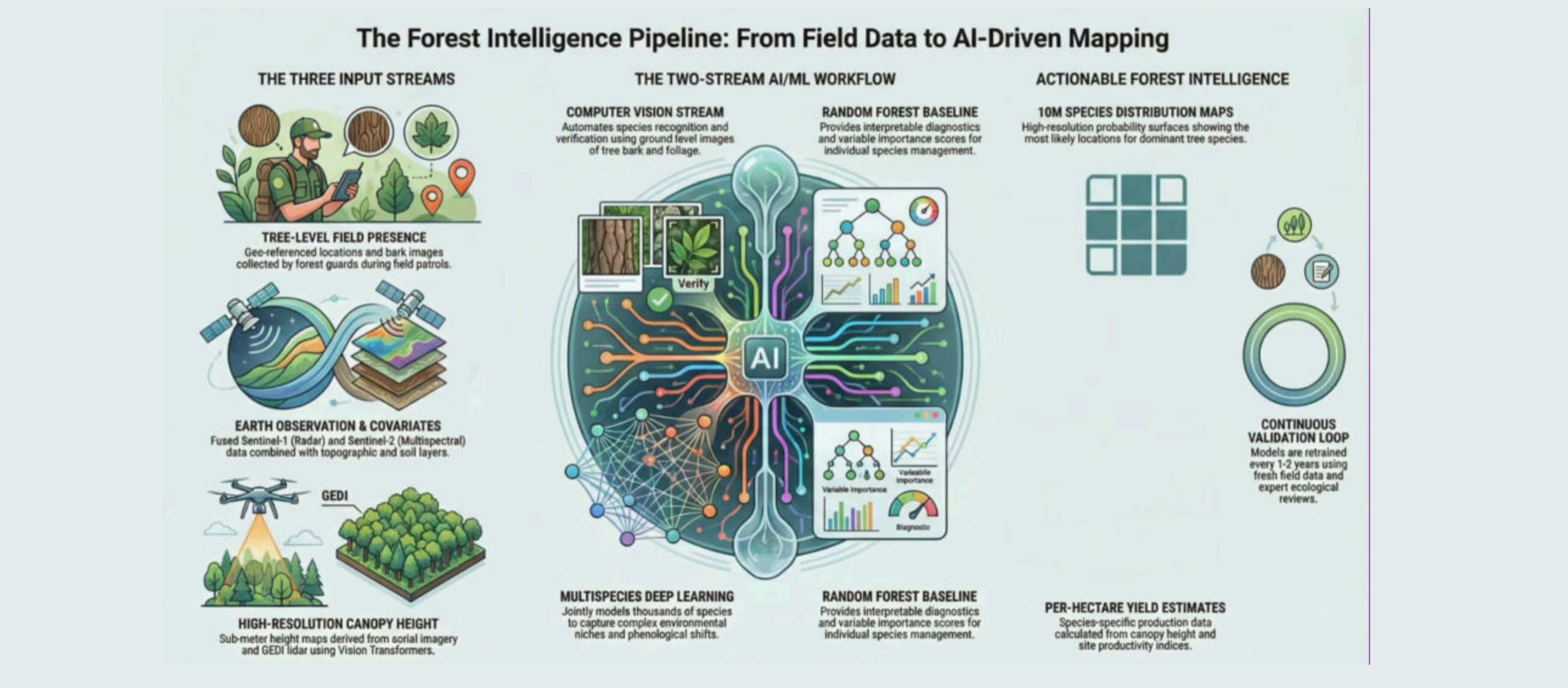
All modifications (e.g., corrections, exclusions) were logged in a change history so that analysts can reconstruct original data if needed and evaluate the effect of different cleaning choices on model outputs—an important practice for transparency and reproducibility in environmental monitoring. Collectively, this sampling strategy and field implementation created a large, spatially explicit, quality-controlled dataset of tree-level presence records and associated imagery, tightly integrated with HPFD's administrative geography and working-plan framework. The following chapter will describe how these data are combined with remote sensing and environmental covariates and used within AI/ML pipelines to generate species distribution and yield estimates that can inform Himachal Pradesh's evolving forest economy strategy.



04

AI and Machine Learning Pipeline

Deep learning and Random Forest (RF) together provide the core technological backbone for forest resource mapping: multispecies deep neural networks ingest dense stacks of environmental predictors—Sentinel-1/2 time series, canopy height, topography, climate and soils—to jointly learn complex, non-linear relationships between habitat conditions and the occurrence of many tree species, building on recent advances that show such models outperform classical stacked SDMs for plant and tree communities at high resolution. In parallel, Random Forest models are used as species-specific SDMs and yield estimators, leveraging their strong performance on high-dimensional ecological data, inherent handling of interactions, and ability to provide variable-importance and partial-dependence diagnostics that are easily interpretable by forest managers. Together, these methods allow the conversion of tree-level observations and Earth-observation covariates into high-resolution maps of species distribution and per-hectare production estimates, with associated uncertainty, forming an operational "forest intelligence" layer for planning, working-plan revision and climate-aligned forest-economy decisions.



The Forest Intelligence Pipeline: From Field Data to AI-Driven Mapping

THE THREE INPUT STREAMS

TREE-LEVEL FIELD PRESENCE
Geo-referenced locations and bark images collected by forest guards during field patrols.

EARTH OBSERVATION & COVARIATES
Fused Sentinel-1 (Radar) and Sentinel-2 (Multispectral) data combined with topographic and soil layers.

HIGH-RESOLUTION CANOPY HEIGHT
Sub-meter height maps derived from aerial imagery and GEDI lidar using Vision Transformers.

THE TWO-STREAM AI/ML WORKFLOW

COMPUTER VISION STREAM
Automates species recognition and verification using ground level images of tree bark and foliage.

RANDOM FOREST BASELINE
Provides interpretable diagnostics and variable importance scores for individual species management.

MULTISPECIES DEEP LEARNING
Jointly models thousands of species to capture complex environmental niches and phenological shifts.

RANDOM FOREST BASELINE
Provides interpretable diagnostics and variable importance scores for individual species management.

ACTIONABLE FOREST INTELLIGENCE

10M SPECIES DISTRIBUTION MAPS
High-resolution probability surfaces showing the most likely locations for dominant tree species.

CONTINUOUS VALIDATION LOOP
Models are retrained every 1-2 years using fresh field data and expert ecological reviews.

PER-HECTARE YIELD ESTIMATES
Species-specific production data calculated from canopy height and site productivity indices.

4.1 Overview of the modelling architecture

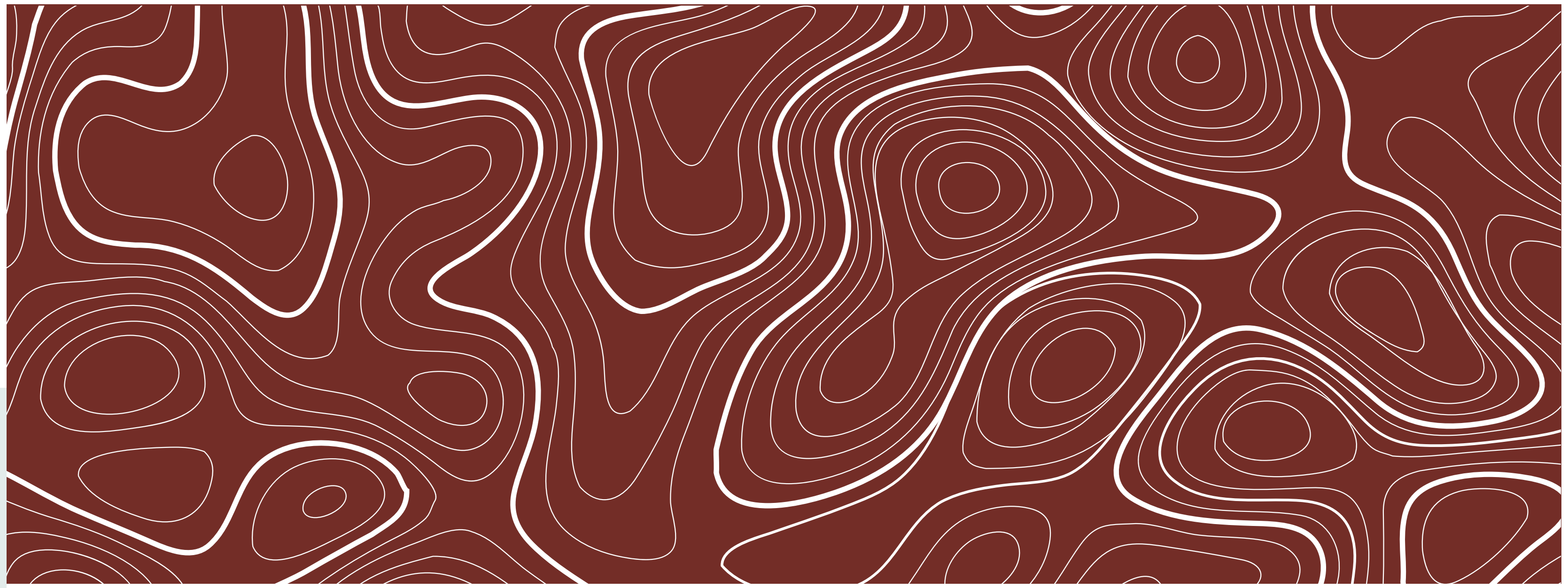
The HPFD–BIPP–ISB AI/ML workflow is organised as a two-stream pipeline:

- A computer-vision stream that uses ground-level tree bark images to support species recognition, verification and future automation of identification; and
- A spatial modelling stream that combines tree-level presence data with multi-source geospatial covariates to produce species distribution maps, canopy-height-informed yield estimates, and associated uncertainty layers.
- Conceptually, the pipeline transforms three classes of inputs into operational forest intelligence products:
- Tree presence data: geo-referenced tree locations and species labels collected by forest guards (Chapter 3).
- Earth observation and environmental covariates: Sentinel-1 C-band SAR backscatter, Sentinel-2 multispectral reflectance, derived vegetation and texture indices, a digital elevation model (DEM), slope, aspect and related topographic metrics, soils and climate layers.
- High-resolution canopy height: a global ~1 m canopy height map derived from aerial imagery and GEDI lidar using a self-supervised vision transformer framework, further cross-validated against other recent global canopy height products.

The outputs are:

- Species distribution maps (probability-of-occurrence surfaces at 10 m resolution);
- Per-hectare yield estimates by species; and
- Uncertainty estimates, derived from model ensembles and cross-validation diagnostics, presented as confidence intervals or coefficient of variation maps.

These products are generated in a way that allows direct integration with HPFD's GIS layers (beats, ranges, divisions) and working-plan framework.



4.2 Input data and feature engineering

4.2.1 Tree-level presence data

The core biological inputs are the tree presence records described in Chapter 3:

geographic coordinates (with quantified spatial uncertainty),

field-identified species or species groups, and

vertically-structured image sets (bark, crown, foliage).

For SDM, these records are treated as presence-only data, a format widely used in contemporary species distribution modelling, particularly when absence information is not reliably available.

4.2.2 Sentinel-1 and Sentinel-2 data

The pipeline exploits the complementary strengths of Sentinel-1 (C-band SAR) and Sentinel-2 (multispectral optical) data, following approaches that have been shown to substantially improve forest structure and biomass estimation in diverse regions.

Sentinel-2: Level-2A surface reflectance is used at 10–20 m resolution. From these bands, the workflow derives:

vegetation indices (e.g., NDVI, NDMI, red-edge indices, EVI);

short-wave infrared indices sensitive to moisture and lignin–cellulose content;

texture metrics (e.g., GLCM-based) in selected bands and indices.

Sentinel-1: dual-polarisation VV and VH backscatter (and their ratios) are used, along with temporal statistics (median, percentile composites) to capture canopy structure and moisture patterns. Numerous studies show that fusing Sentinel-1 and Sentinel-2 features in machine learning models improves above-ground biomass and canopy height estimation relative to single-sensor approaches. Sentinel features are extracted at each tree point and on a regular prediction grid, ensuring that training and mapping use a consistent feature space.

4.2.3 Ancillary environmental layers

To represent environmental controls on species distributions and productivity, the pipeline incorporates:

Topography: DEM-derived elevation, slope, aspect, curvature, and compound indices such as topographic position index (TPI) and terrain ruggedness. Aspect is transformed into solar-radiation-related indices (e.g., TRASP), following established methods, to better capture insolation differences between slopes.

Soils: categorical soil type and selected continuous properties (texture class, depth, organic carbon) from harmonised soil databases, resampled to the Sentinel grid.

Climate: long-term mean and seasonal variables (temperature, precipitation, moisture indices) from high-resolution climatologies such as WorldClim/CHELSA, which are standard inputs in SDM.

These variables are known to jointly influence forest species composition and productivity through their effects on water balance, nutrient status and disturbance regimes.

4.2.4 High-resolution canopy height

For yield estimation, the pipeline taps into a sub-metre canopy height map generated using self-supervised learning and a vision transformer trained on aerial RGB imagery and GEDI lidar footprints, which provides tree canopy height estimates at ∼1 m resolution globally for 2009–2020, with most data concentrated between 2018–2020. In addition, the pipeline can ingest regional canopy height / AGB products at 10–30 m resolution produced by fusing ICESat-2 or GEDI with Sentinel-1/2 data, which have demonstrated strong performance in mapping forest structure and biomass. These canopy height layers are co-registered with the species probability maps to support species-specific height–yield modelling.

4.3 Computer vision component: image-based species recognition

4.3.1 Purpose and design

The computer vision (CV) component has three main roles:

Species verification – checking and refining field-identification labels from tree images;

Assisted labelling – providing model-based suggestions for ambiguous cases; and

Future automation – laying the groundwork for semi-automatic species recognition from guard-captured images.

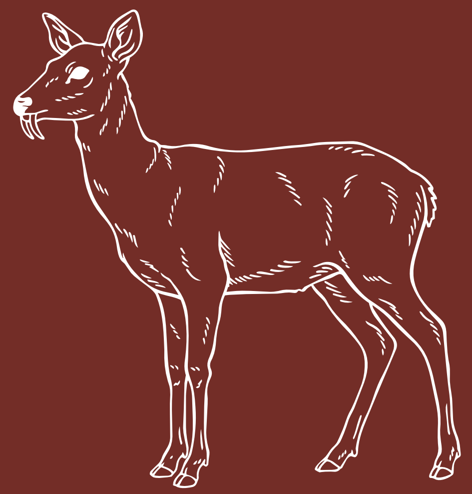
4.3.2 Model families and training strategy

The CV pipeline follows current best practice in tree-species image classification, where convolutional neural networks (CNNs) and more recently vision transformers (ViTs) outperform traditional machine learning models across a variety of remote-sensing and ground-level datasets.

The workflow is as follows (high-level, non-implementation-specific):

Images associated with each tree are pre-processed and standardised (colour normalisation, resizing, cropping to focus on bark). A training dataset is created by selecting trees with high-confidence species labels (after expert review) and splitting them into training, validation, and test sets at the tree—not image—level to avoid leakage.

Several architectures are evaluated, including: CNN backbones (e.g., ResNet, EfficientNet-style), hybrid CNN–attention networks, and light-weight ViTs suitable for deployment on modest hardware. Training uses cross-entropy loss, with no data augmentation. Performance is assessed using overall accuracy, per-class F1 score and confusion matrices, focusing particularly on species that are ecologically important or difficult to distinguish visually. Peer-reviewed work on UAV-based and ground-level tree species classification indicates that such architectures can achieve high (>80%) accuracy when trained on sufficient examples and careful augmentation, including for complex mixed forests.



4.4 Spatial modelling: from tree points to species distribution maps

Multispecies deep learning model for tree-species distributions and community composition

To exploit the full information content of the Himachal Pradesh tree-point dataset, the core species distribution engine is structured as a multispecies deep neural network (DNN) that models many tree species jointly across the state. This design is explicitly inspired by the multispecies DNN framework developed for vascular plants in Switzerland by Brun et al. (2024).

4.4.1 Problem formulation and predictors

Each ground observation by forest guards (tree location + species identity + timestamp where available) is treated as a single-positive, multi-label record: at any given forest location, multiple species may be present, but only one is recorded per tree. This is analogous to citizen-science biodiversity datasets where only a subset of the species present at a site is reported.

For each tree point, the model ingests a vector of environmental predictors, assembled on a regular grid:

Vegetation structure: 1 m global canopy height maps (Meta–WRI) aggregated to the working resolution of 10m; metrics such as maximum height and height percentiles provide proxies for stand structure and potential biomass.

Spectral and phenological indices: multi-year statistics of Sentinel-1 and Sentinel-2 NDVI/EVI (e.g. seasonal means and differences).

Topography: elevation, slope, aspect, terrain ruggedness, and wetness indices derived from high-resolution DEMs, following standard SDM practice and the Swiss plant modelling work.

Climate: downscaled temperature and precipitation climatologies (annual and seasonal), and derived indices such as growing degree days and frost frequency, (CHELSA-based predictors).

Soils and land cover: categorical and continuous soil proxies (pH, moisture, nutrients) and land-cover classes encoded as one-hot vectors (vector embeddings).

Seasonality (where dates are available): sine–cosine transformation of day-of-year to allow the model to learn phenological shifts in observation probability along altitudinal and aspect gradients.

These predictors are collated for all grid cells across Himachal Pradesh, allowing the DNN to estimate relative observation probabilities for each species at each location and (if used) time of year.

4.4.2 Network architecture and training

The multispecies DNN follows the general design in Brun et al. (2024): a fully connected deep network with residual blocks and a multi-output layer, where each output neuron corresponds to one tree species (or species group).

- Input layer: one node per environmental feature (topography, climate, vegetation structure, spectral indices, and seasonality where applicable).
- Hidden layers: several residual blocks, each comprising dense layers with rectified linear units (ReLU) and dropout, to capture nonlinear interactions and reduce overfitting.
- Output layer: one node per species, returning scores that are transformed into relative observation probabilities or ranks for all modeled species at each grid cell.
- Two cost-function formulations are particularly relevant:
- Cross-entropy loss (CEL): widely used in multi-class classification and previously applied in multispecies SDMs; it tends to learn well-calibrated conditional probabilities but implicitly assumes that unobserved species are absent.
- Normalized Discounted Cumulative Gain (NDCG)–based ranking loss: as implemented by Brun et al., this cost function treats the task as a ranking problem—finding the most relevant species for a given environment—without assuming absences for unreported species.

Brun et al. show that multispecies DNNs trained with either CEL or NDCG can effectively exploit millions of opportunistic plant observations (4.6–6.7 million records of 2477 taxa) and achieve high predictive accuracy at both 100 m and 25 m resolution.

We adopt this paradigm for Himachal Pradesh, with the key difference that presence data are systematically collected by forest guards rather than opportunistic citizen scientists.

4.4.3 Advantages for a mountainous forest landscape

Three properties make the multispecies DNN especially suitable for Himachal Pradesh:

Joint modelling of many species

By learning shared representations across species, multispecies DNNs can leverage common ecological responses to topography, climate, and forest structure, while still capturing species-specific niche differences. This joint modelling reduces susceptibility to spatial sampling bias because biases that are shared across species cancel out in relative probability estimates.

Use of the full dataset without aggressive thinning

Classical SDMs often rely on spatial thinning and pseudo-absence strategies in complex terrain to manage sampling bias, at the cost of discarding information. By contrast, multispecies DNNs can use all filtered observations, which is critical for capturing fine-scale elevational and aspect-related patterns characteristic of Himalayan forests.

Phenology and potential dominance

Brun et al. demonstrate that multispecies DNNs can model seasonal variation ($_{\text{tpmax}}$) and potential dominance of canopy-forming tree species with high accuracy, achieving species-level AUC ≈ 0.945 and community AUC ≈ 0.976 for high-resolution models.

The same approach in Himachal Pradesh allows us to:

- Map likely dominant and co-dominant species along elevation and aspect gradients, and
- Explore phenological shifts under climate change, once sufficient temporal data are available.

4.4.4 Empirical performance benchmark

In Brun et al. (2024), the DNN ensemble consistently outperformed stacked SDMs (SSDMs) built from classical algorithms (GLM, GAM, gradient boosting, Random Forest, and MaxEnt) across several metrics:

- Median rank of observed species in predictions improved from ~169 for SSDMs to ~71–73 for DNNs and ~41 for the best high-resolution DNN ensemble.
- Species-wise AUC increased from ~0.937 for SSDMs to 0.942–0.945 for DNNs, and
-
- Site-wise community AUC increased from ~0.964 to 0.974–0.979 for DNN ensembles.

These benchmarks provide a quantitative justification for prioritising multispecies DNNs as the primary modelling engine in Himachal Pradesh, while still maintaining classical SDMs as complementary tools.

4.5 Random Forest–based species distribution models (SDMs)

Alongside the multispecies DNN, we implement Random Forest (RF)–based SDMs as a complementary, more interpretable baseline for individual species. RFs are widely used in ecology and have been shown to perform competitively in SDM tasks, particularly when sample sizes are moderate and relationships are complex and nonlinear.

4.5.1 Model setup

For each tree species with sufficient occurrences, we construct a single-species SDM using RF, closely following the ensemble SDM setup used in Brun et al. (2024):

Presence data: thinned to at most one observation per grid cell (100 × 100 m) to reduce local clustering and overfitting.

Absences: multiple sets of absence/background points generated with geographically and environmentally stratified strategies, ensuring coverage of the state's environmental space.

Predictors: a subset of the environmental covariates used in the DNN (topography, climate, canopy height, spectral indices, soils) selected via a variable-selection routine that enforces low pairwise collinearity ($|r| < 0.7$) and a minimum presence-to-predictor ratio (~10:1).

Each RF SDM consists of an ensemble of decision trees (e.g. hundreds to thousands), trained on bootstrapped samples with random feature subsets at each split. This design reduces variance and captures nonlinear interactions and threshold effects common in ecological responses.

4.5.2 Outputs and interpretation

RF SDMs provide, for each species: Per-cell habitat suitability or occurrence probability estimates across Himachal Pradesh; Variable importance scores, indicating which environmental gradients (e.g. elevation, canopy height, moisture indices) most strongly constrain that species; Partial response curves that help interpret ecological niches and test hypotheses about climatic and topographic limits. Because RF SDMs are fit separately for each species and do not require modelling thousands of species jointly, they are computationally lighter and can be easily retrained as new data become available.

4.5.3 Role in the overall pipeline

In the HPFD–BIPP-ISB pipeline, Random Forest SDMs serve three complementary purposes:

- Baseline comparison: They provide a classical SDM benchmark against which the performance of the multispecies DNN can be quantitatively evaluated for selected species.
- Interpretability and communication: Variable importance and partial dependence plots are easily communicated to managers and working-plan authors, supporting transparent discussion of drivers of species distribution.
- Fallback for data-poor taxa: For species with moderate data, RF can sometimes be calibrated more reliably than deep networks, and ensemble "small models" strategies used in Brun et al. can be combined with RF to handle very rare species.

4.6 Comparative assessment: multispecies deep learning vs Random Forest SDMs

A scientifically grounded comparison of multispecies DNNs and RF-based SDMs is important for justifying modelling choices.

4.6.1 Predictive performance and community-level realism

The most direct comparison comes from Brun et al. (2024), who contrasted multispecies DNNs with stacked SDMs (SSDMs) built from an ensemble of GLM, GAM, gradient boosting, Random Forest, and MaxEnt algorithms for 2477 plant taxa.

Their key findings are:

- DNNs substantially improved rank-based metrics for left-out observations (median rank ~71 vs ~169 for SSDMs).
- DNNs achieved higher AUC scores for both individual species and community composition; best DNN ensembles reached species-level AUC ~0.944 and site-level AUC ~0.969.
- DNNs uniquely produced detailed maps of potentially dominant canopy-forming species and phenological timing, which are difficult to obtain from species-by-species RF models alone.

Independent studies using CNN-based deep SDMs reinforce these conclusions:

Deneu et al. (2021) show that CNN-SDMs leveraging spatial environmental tensors outperform Random Forest and other classical "punctual" models, particularly for species with few occurrences, by capturing neighbourhood-scale habitat structure. Estopinan et al. (2022) demonstrate that deep SDMs using Sentinel-2 time series yield higher predictive performance than baselines, especially for occurrence-poor species and diversity-rich regions, highlighting the added value of temporal information that RF models using static covariates cannot easily capture. Together, this evidence indicates that multispecies DNNs generally provide superior predictive performance and richer ecological information than classical RF SDMs when high-volume occurrence data and rich environmental predictors are available.

4.6.2 Robustness to sampling bias and presence-only data

Both the Swiss and French deep-SDM studies treat presence-only data without explicit pseudo-absences by reframing the task as conditional species ranking, which substantially reduces dependence on pseudo-absence selection and background sampling choices that can strongly influence RF-based SDMs. Multispecies DNNs further mitigate spatial sampling bias because they exploit shared patterns of observer effort across species; biases that affect all species similarly have a smaller effect on relative observation probabilities. RF SDMs calibrated with pseudo-absences remain more sensitive to how background points are chosen, especially in rugged mountain terrain where environmental gradients are steep and access biases are strong. For Himachal Pradesh, where observation density varies strongly with accessibility and patrolling effort, this robustness is a major argument for prioritising the multispecies DNN as the main modelling framework.

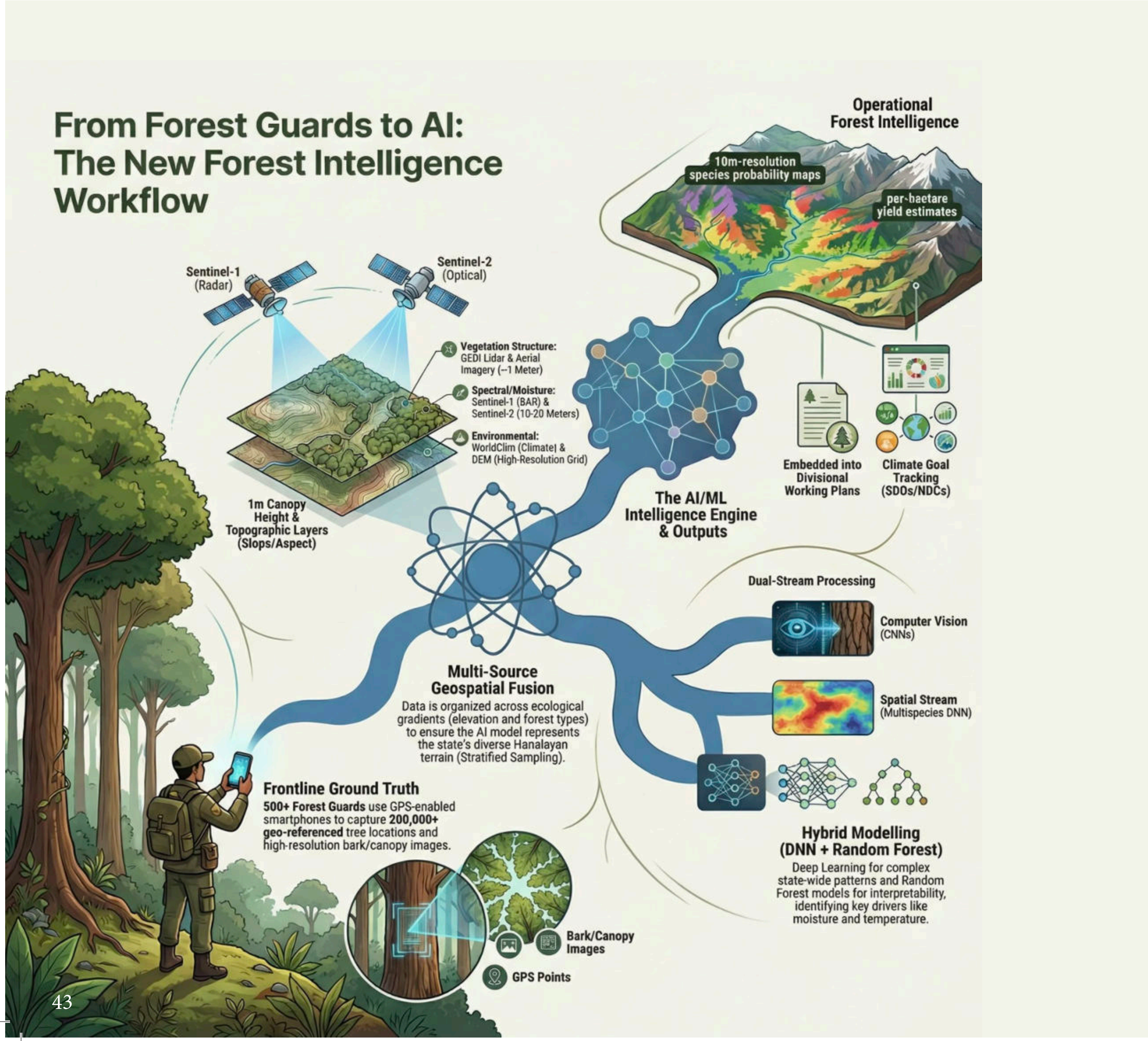
4.6.3 Interpretability, data requirements, and operational considerations

However, RF SDMs retain several practical advantages:

- Interpretability: RF provides straightforward variable importance measures and partial dependence plots, which are easier to interpret and communicate to working-plan officers than the internal representations of a deep network.
- Lower data and compute requirements: RF models can be trained with smaller datasets and modest computing resources, whereas DNNs benefit from large sample sizes (hundreds of thousands to millions of observations) and GPU acceleration to avoid overfitting and to converge efficiently.
- Stable behaviour under extrapolation: Classical RF SDMs are not designed for extrapolation in space or climate, but their behaviour under moderate extrapolation is better characterised than that of deep networks, which can produce poorly constrained predictions outside the training domain if not carefully regularised.

In the HPFD–BIPP-ISB pipeline, this suggests a hybrid strategy:

Using multispecies DNNs as the primary engine for generating state-wide maps of tree-species distributions, potential dominance patterns, and (eventually) phenological metrics relevant for climate-change assessments.



From Forest Guards to AI: The New Forest Intelligence Workflow

Data is organized across ecological gradients (elevation and forest types) to ensure the AI model represents the state's diverse Hanalayan terrain (Stratified Sampling).

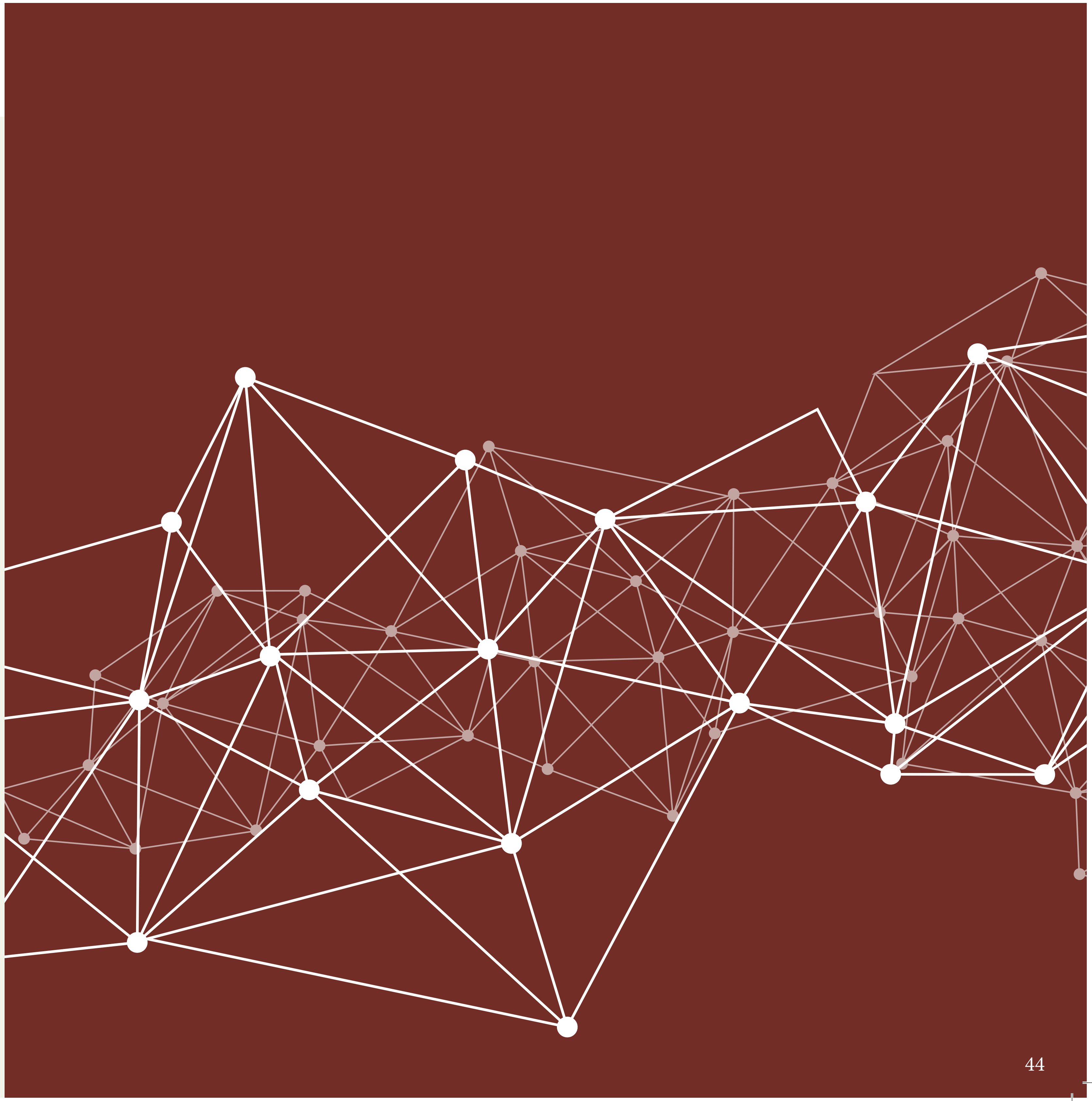
500+ Forest Guards use GPS-enabled smartphones to capture **200,000+ geo-referenced** tree locations and high-resolution bark/canopy images.

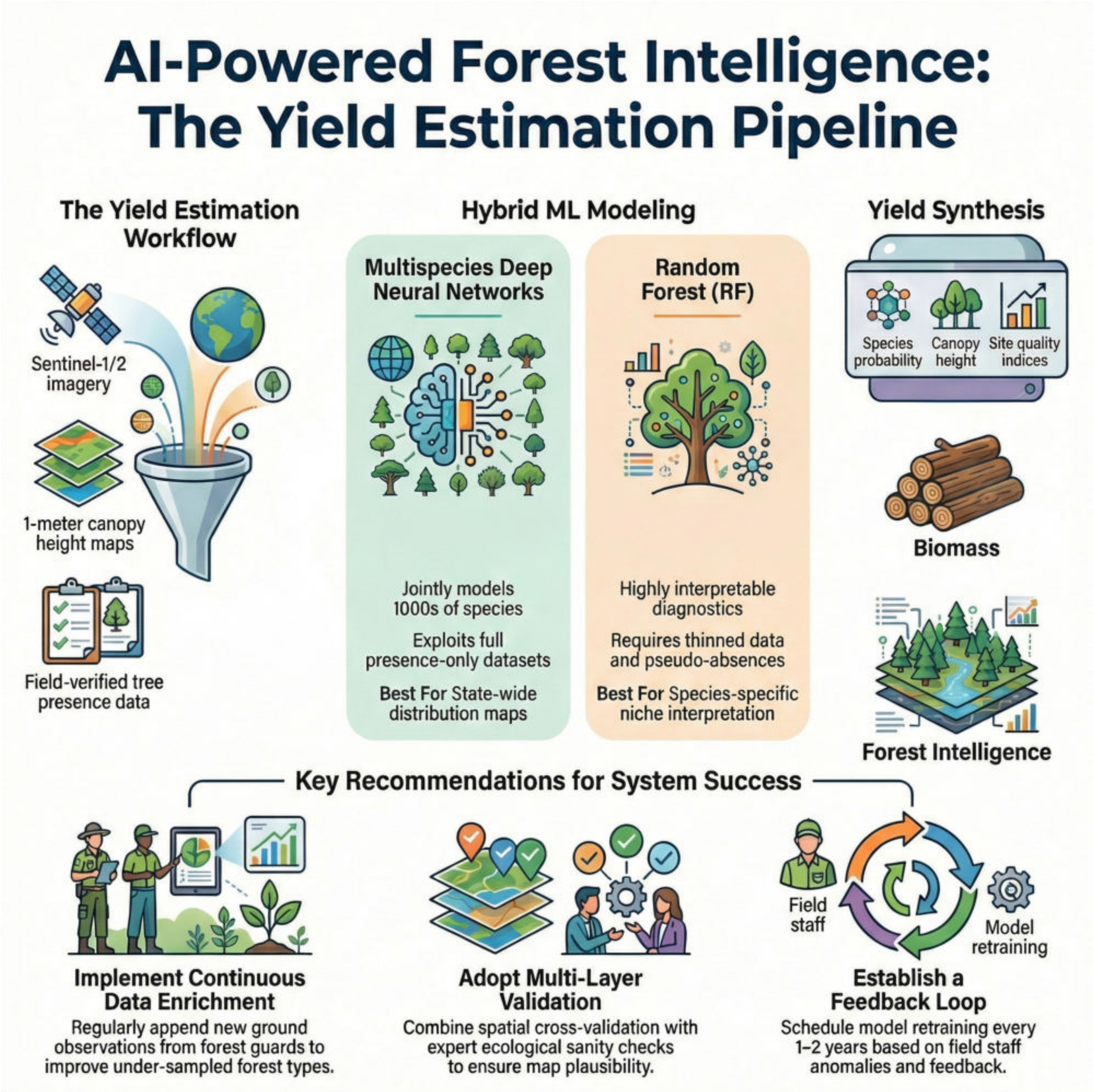
Deep Learning for complex state-wide patterns and Random Forest models for interpretability, identifying key drivers like moisture and temperature.

Using Random Forest SDMs as complementary tools for:

- Species-specific niche interpretation,
- Sensitivity analyses and uncertainty communication, and
- Rapid prototyping in data-poor or operational conexts where deep learning infrastructure is not yet available.

This combined approach leverages the predictive power and bias-robustness of modern deep learning, while retaining the interpretability and operational reliability of Random Forest SDMs, and is consistent with the direction of current macroecological and remote-sensing research on species distribution modelling.





4.7 Yield estimation: canopy height, site conditions and stocking

4.7.1 Using canopy height and aspect as proxies for productivity

Yield estimation builds on the integration of species-specific occurrence probabilities, canopy height, and site conditions (e.g., slope, aspect, elevation). Global and regional studies have shown that combining canopy height maps derived from lidar with Sentinel-1/2 and topographic data substantially improves above-ground biomass and canopy structure estimates. At the same time, forestry research consistently finds that elevation, slope and aspect significantly influence forest productivity and site index, often through their effects on solar radiation, water availability and competition.

Within this framework, the HPFD–BIPP–ISB pipeline:

- Extracts species probability and canopy height at each grid cell;
- Transforms aspect into a solar-radiation-related index and combines it with elevation and slope as a proxy for site quality;
- Uses published productivity information from peer-reviewed sources and HPFD timber volume table—with parameters derived from long-term studies—to relate height to per-tree volume or biomass.

In other words, yield estimation uses species-specific peer-reviewed yield tables to derive per-tree production (volume/biomass) from canopy height and site conditions, with aspect and related topographic indices incorporated as proxies for age–productivity and microclimatic conditions.

4.8 Validation and uncertainty assessment

4.8.1 Validation with held-out field data

For both SDM and yield components, validation follows a multi-layered strategy:

Cross-validation: spatially blocked k-fold cross-validation is used during model fitting to obtain robust estimates of predictive performance (AUC, TSS, RMSE for yield).

Independent test sets: where possible, subsets of tree presence data from different compartments or ranges are held out entirely during training and used exclusively for testing. Predicted locations were further validated by forest guards by visiting the locations.

This approach mirrors best practice in forest remote-sensing and SDM, where rigorous spatial cross-validation is needed to avoid overestimation of model performance.

4.8.2 Cross-comparison with working plan estimates

Where divisional working plans provide compartment-level or working-circle-level estimates of growing stock and allowable cut, the pipeline compares:

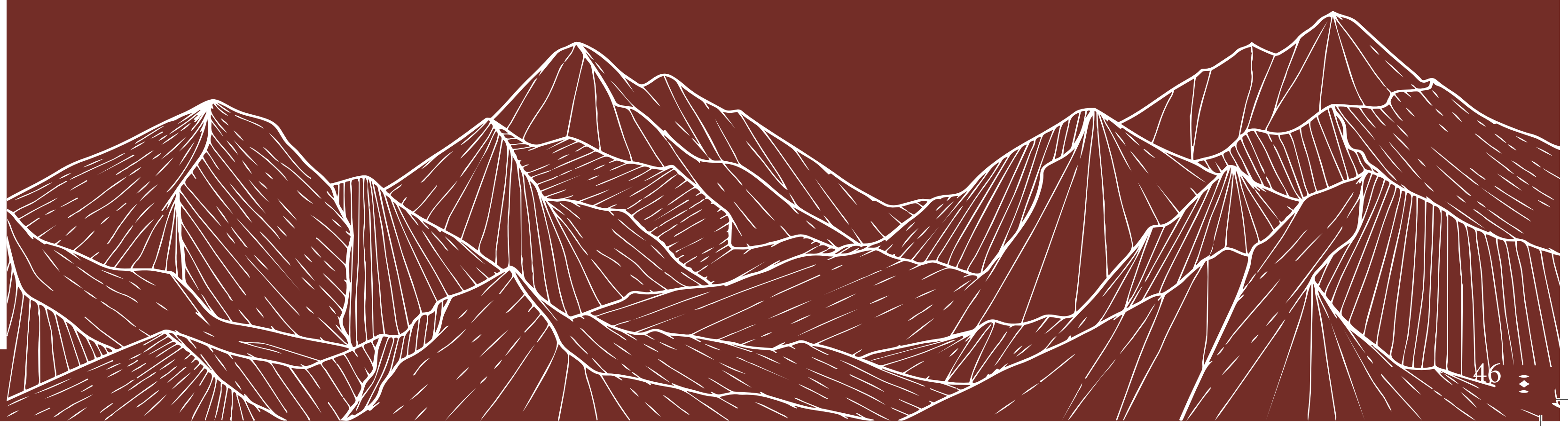
Predicted yield (summed or averaged over compartments) with Working-plan estimates derived from traditional inventory and volume tables. Discrepancies are analysed jointly by HPFD and BIPP–ISB to account for and update genuine under- or overestimation in historical inventories and modelled output. Such triangulation between new AI-derived estimates and established planning figures is critical for building institutional trust and for prioritising where to invest in additional field verification.

4.8.3 Ecological sanity checks and expert review

Beyond statistical metrics, ecological plausibility checks are performed:

- verifying that species' predicted elevational ranges and aspect preferences align with known ecology and published site-index studies;
- ensuring that high-yield predictions correspond to combinations of appropriate forest types, canopy heights and site qualities, and not to artefacts such as snow, rock or built-up areas misclassified in remote-sensing inputs;
- examining spatial patterns of residuals (under-/over-prediction) for clustering that may indicate missing covariates or unmodelled disturbance.

This expert review—drawing on HPFD officers' field experience and BIPP–ISB's quantitative diagnostics—forms a key part of the uncertainty assessment.



4.9 Model maintenance, retraining and institutional learning

The AI/ML pipeline is explicitly designed as a living system, not a one-time analytical exercise. Its sustainability rests on three pillars:

Incremental data enrichment

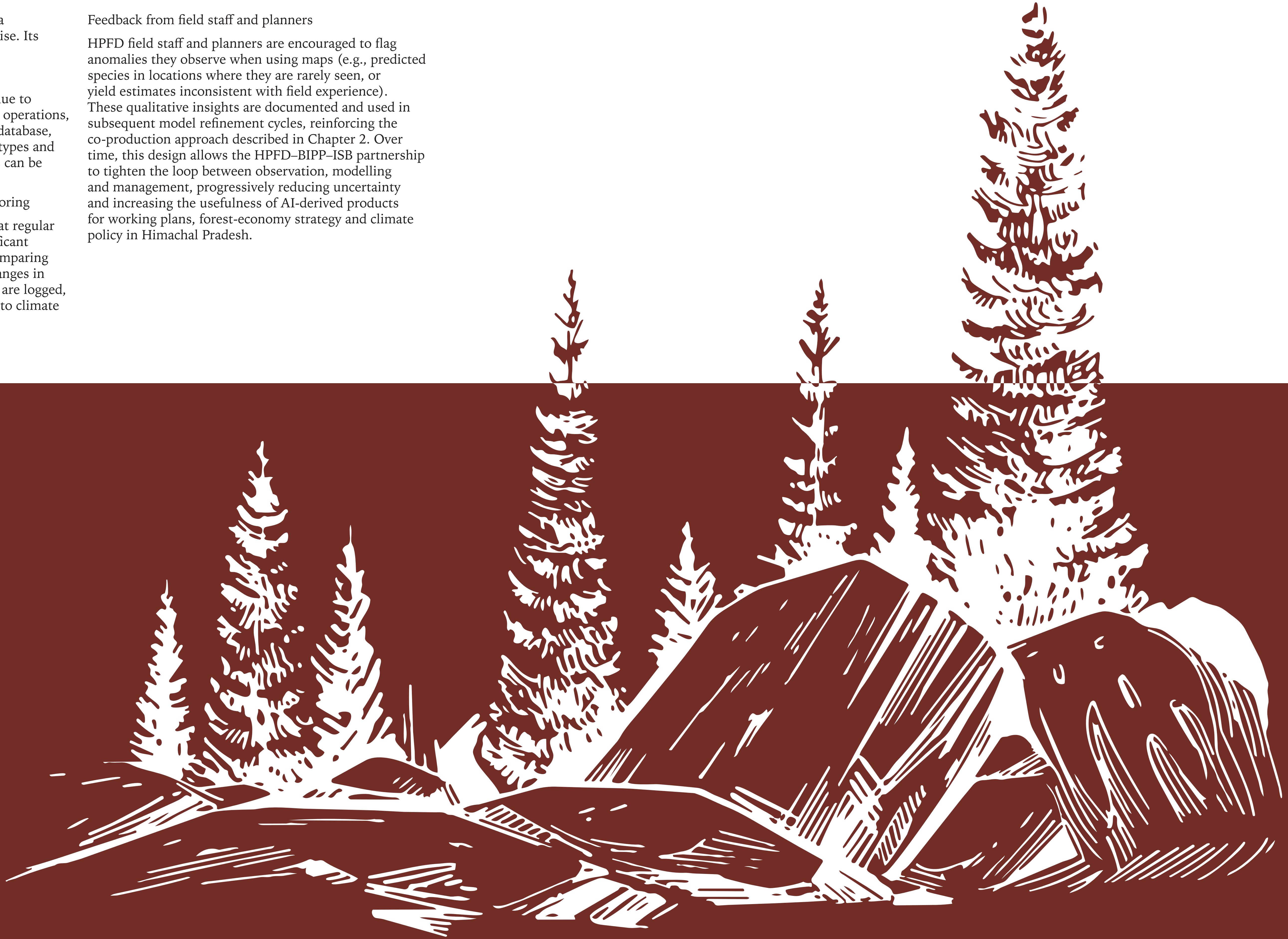
As forest guards and other HPFD staff continue to collect tree points and images during routine operations, these new observations are appended to the database, improving coverage in under-sampled forest types and ranges. New ground plots or biomass studies can be incorporated to refine yield components.

Scheduled retraining and performance monitoring

The SDM and yield models will be retrained at regular intervals (e.g., every 1–2 years, or after significant additions of data), with automated scripts comparing performance to previous model versions. Changes in performance or spatial patterns of prediction are logged, enabling diagnosis of concept drift (e.g., due to climate or management changes).

Feedback from field staff and planners

HPFD field staff and planners are encouraged to flag anomalies they observe when using maps (e.g., predicted species in locations where they are rarely seen, or yield estimates inconsistent with field experience). These qualitative insights are documented and used in subsequent model refinement cycles, reinforcing the co-production approach described in Chapter 2. Over time, this design allows the HPFD–BIPP–ISB partnership to tighten the loop between observation, modelling and management, progressively reducing uncertainty and increasing the usefulness of AI-derived products for working plans, forest-economy strategy and climate policy in Himachal Pradesh.



05

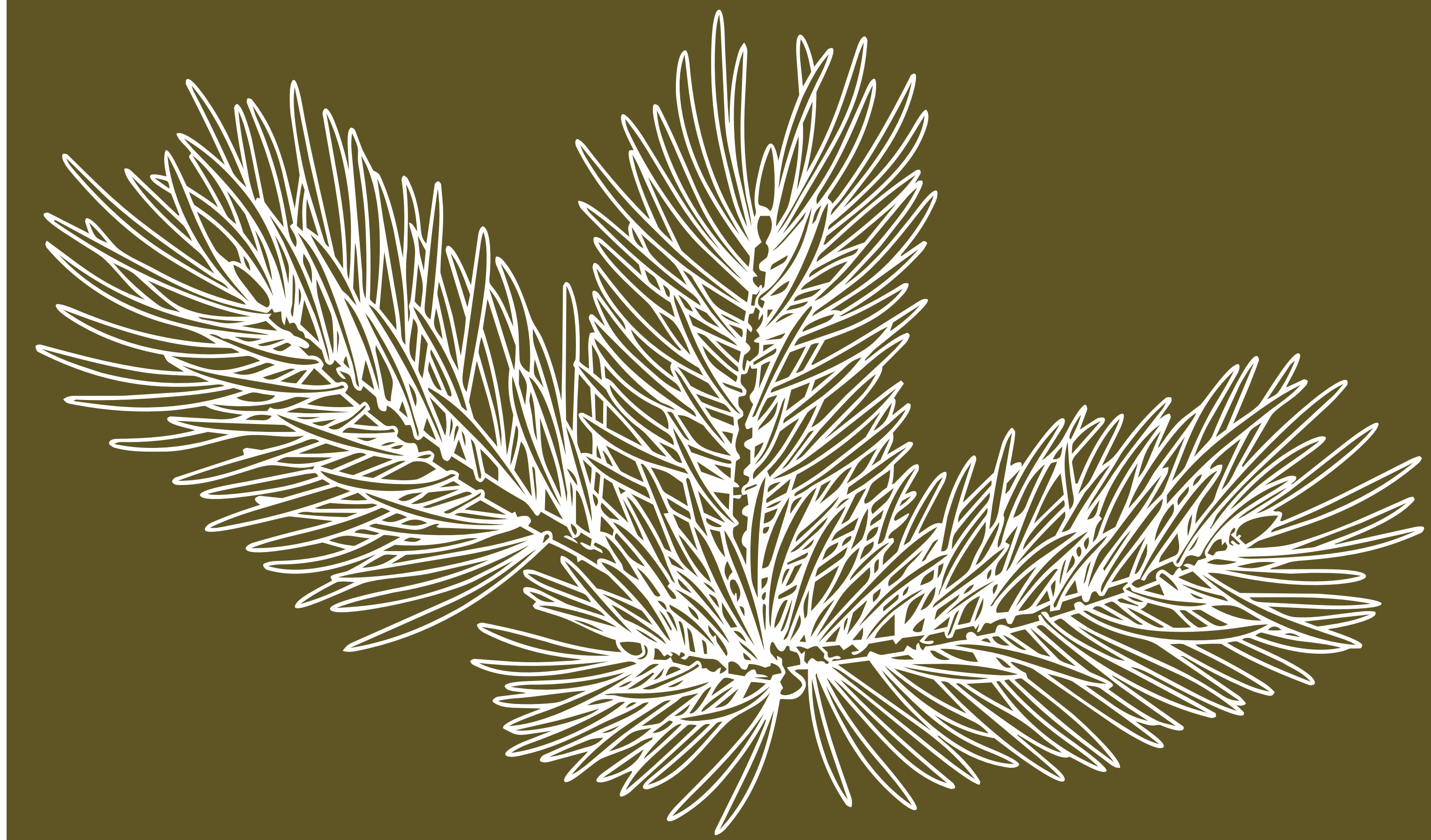
Species Distribution and Yield

5. Results, Discussion and Conclusion

The convergence of advanced geospatial intelligence and localized forest management frameworks marks a significant evolution in the governance of natural capital within the Western Himalayas. This report details the synthesized results and economic implications derived from a state-wide assessment involving more than 500 forest guards and the collection of 200,000 tree-level georeferenced records across Himachal Pradesh. By integrating multispecies deep neural networks and high-resolution canopy height models, the study transitions from static inventory methods to a dynamic "forest intelligence" layer capable of informing sustainable livelihoods and national climate commitments.

5.1. Results: AI-Enabled Species Distribution and Yield Stratification

The interpretation of species distribution and yield maps follows a rigorous analytical pipeline that correlates presence-only data with environmental covariates including topography, moisture regimes, and spectral indices. The following results represent the application of non-linear yield logic, categorizing forest stands into early-stage, peak "yield sweet spot," and over-mature stabilization phases based on canopy height as a proxy for structural maturity.

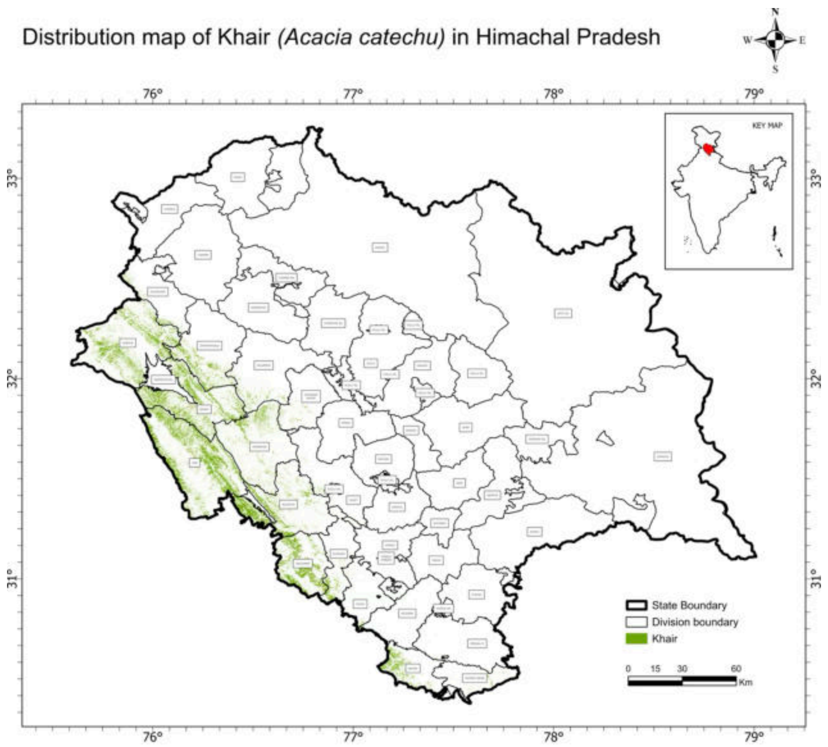


5.1.1. Khair (Acacia catechu): Heartwood Accumulation and Industrial Value Chains

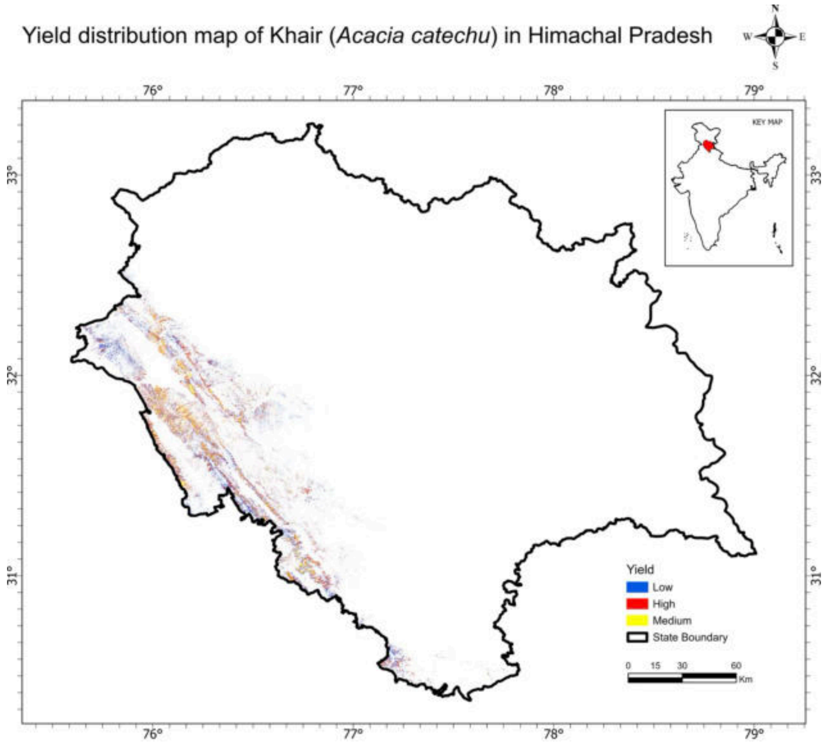
The distribution of Acacia catechu (Khair) is predominantly restricted to the subtropical Shivalik foothills, specifically in regions below 1,300 meters in elevation. The AI distribution mapping identifies high-probability clusters in the districts of Una, Kangra, Bilaspur, and Hamirpur, where the species dominates Northern Dry Mixed Deciduous and Dry Riverine forests.[2] The economic value of Khair is inherently tied to its heartwood, from which katha and cutch are extracted for medicinal and industrial use, particularly the booming pan masala industry which grows at a rate of 4.6% annually.

The non-linear yield logic for Khair demonstrates a critical threshold where heartwood formation becomes economically viable. While trees may be harvested as early as 15 years, peak heartwood recovery is achieved between 20 and 30 years of age. The following table stratifies the yield potential based on the AI-derived canopy height and diameter classes. The total estimated yield of heartwood is 2.5 million cubic meter. Assuming an average bulk price of roughly ₹20,000 per cubic meter for large-scale procurement, the cost for 2.5 million cubic meter is roughly ₹5,000 Crores.

The results indicate that heartwood formation is negligible in trees with a diameter at breast height (DBH) below 5 cm. For trees in the "yield sweet spot," the root heartwood accounts for approximately 24% of the total heartwood weight, suggesting that sustainable but intensive harvesting requires the excavation of the root system to prevent a significant loss in economic returns. Provenance variation studies in Himachal Pradesh highlight that above-ground biomass can vary significantly (20.20 kg to 54.49 kg per tree), with a high heritability for height (98%), indicating that site selection and genetic material significantly influence the final katha output.



Distribution map of Khair (*Acacia catechu*) in Himachal Pradesh



Yield distribution map of Khair (*Acacia catechu*) in Himachal Pradesh

Growth Phase	Canopy Height (m)	DBH Class (cm)	Total Heartwood (kg/tree)	Economic Status and Recovery Potential
Early-Stage	< 9.0	0 – 15	0.07 – 40.25	Sub-economic; high sapwood percentage (41-67%) limits katha yield.[4]
Yield Sweet Spot	9.0 – 15.0	15 – 30	40.30 – 303.4	Peak commercial maturity; heartwood represents ~45-47% of total tree weight.[4]
Stabilization	> 15.0	> 30	> 303.4	Structural stabilization; increased risk of heartwood rot in over-mature individuals.[3]

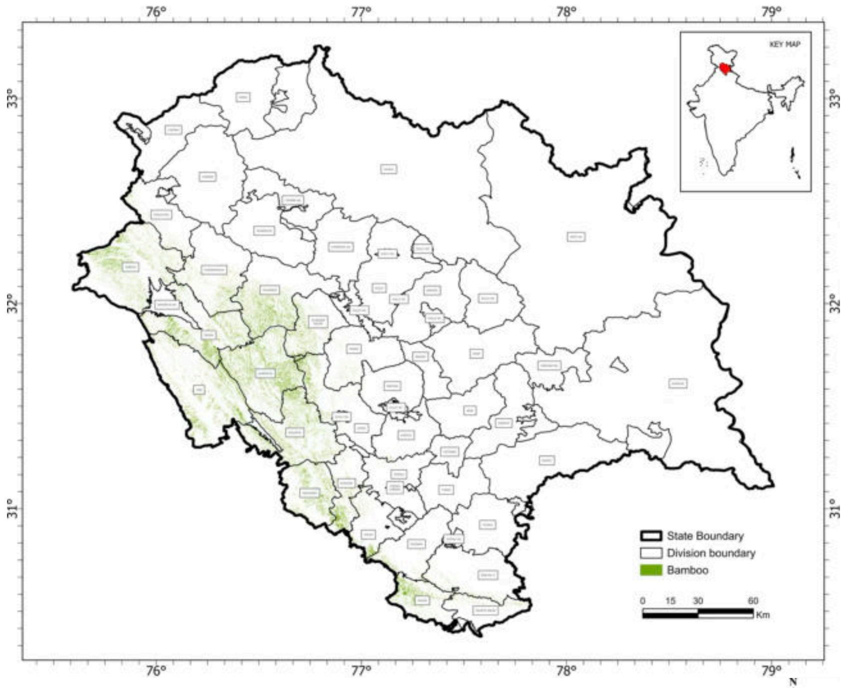
5.1.2. Bamboo (Dendrocalamus strictus and others): Biomass Productivity and the Biochar Frontier

Dendrocalamus strictus (Iron Bamboo) is extensively distributed across the Shivalik foothills and lower Himalayan tracts up to 1,200 meters, with dense clusters identified in the Kangra and Hamirpur districts. As a high-yield, rapidly renewable resource, bamboo serves as a strategic bioresource for Himachal Pradesh's transition toward a circular industrial economy. Its rapid renewability allows for multiple harvests, sequestering up to 259 tonnes per hectare and positioning it as a cornerstone of the state's climate-aligned industrial strategy.

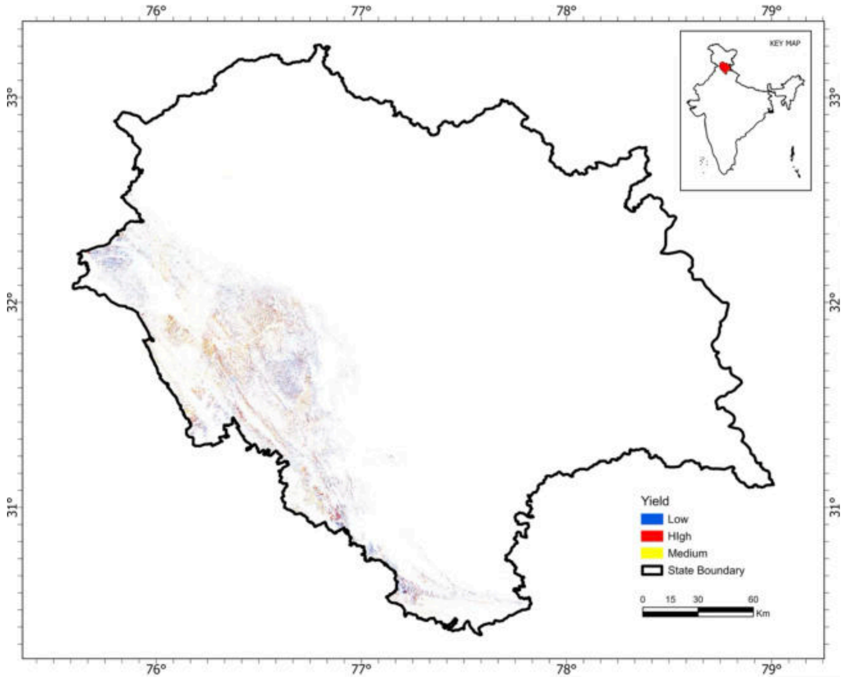
The assessment reveals that Himachal Pradesh's bamboo resources can underpin a multimillion-dollar economy through high-value industrial processing. The yield model suggests approximately 19 lakh tonnes of bamboo resource. Assuming an average bulk price of roughly ₹4000 per tonne, the present non-specialized bamboo economy amounts to ₹760 crores. As a "green gold" resource, bamboo is a primary feedstock for the emerging bio-energy sector, capable of producing bio-ethanol and bio-gas as sustainable alternatives to fossil fuels. The state's biochar initiative at Neri utilizes bamboo residues alongside pine needles to produce coal replacements, generating 28,800 carbon credits over a decade and providing a $1 million USD phased investment in localized pyrolysis technology.

Beyond energy, the circular value chain for bamboo includes advanced materials such as engineered composites and textiles, which are increasingly demanded in the global market—a sector valued at over USD 41 billion. By shifting from traditional use to "Industry 5.0" applications, Himachal Pradesh can leverage its 15.69 million hectares of national bamboo cultivation potential to create a resilient, climate-positive industrial base that integrates bio-ethanol production and activated carbon manufacturing with carbon-credit monetization.

Distribution map of Bamboo (*Dendrocalamus strictus* and others) in Himachal Pradesh



Yield distribution map of Bamboo (*Dendrocalamus strictus* & others) in Himachal Pradesh



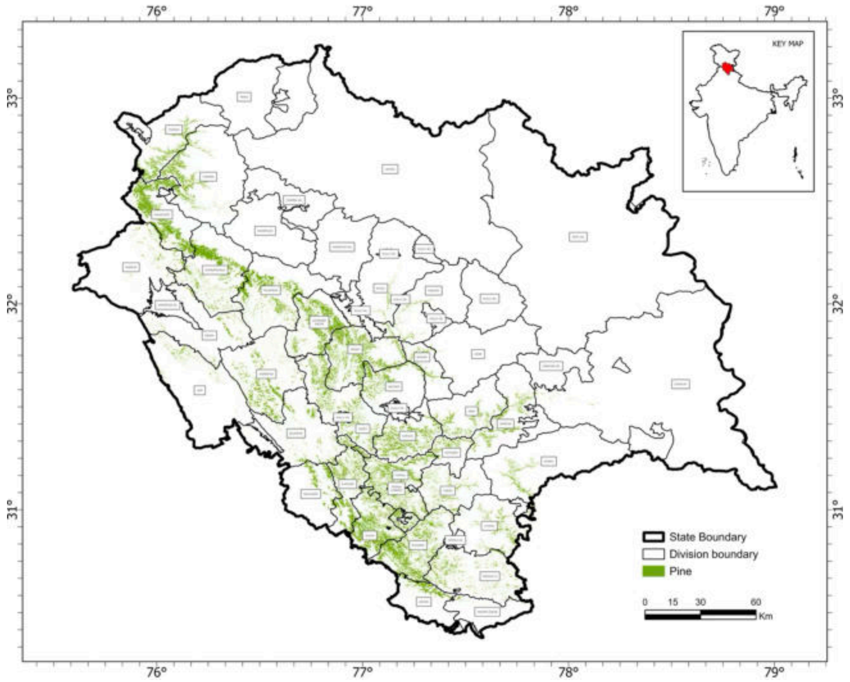
5.1.3. Chir Pine (Pinus roxburghii): Monetizing the ₹ 5,500 Crore Pine Needle Economy

Pinus roxburghii (Chir Pine) is the dominant coniferous species in Himachal Pradesh, covering approximately 6,77,813 hectares. While historically valued for resin and timber, the AI/ML modeling pipeline shifts focus to the species' most abundant and problematic byproduct: fallen pine needles (Chillaru). Traditionally viewed as a primary fuel for forest fires, pine needles now represent the state's largest untapped "green" asset.

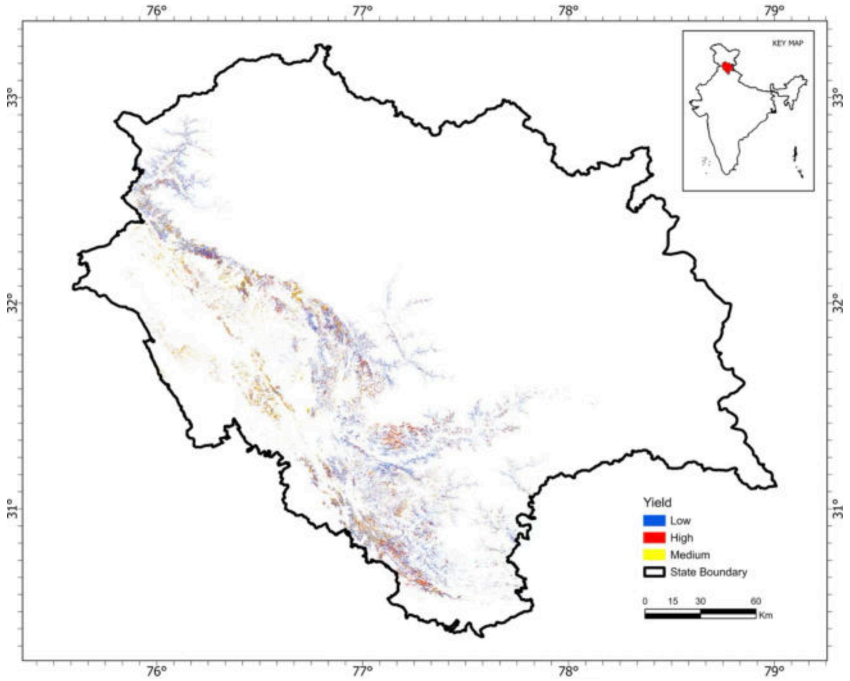
The yield model estimates a staggering annual yield of 11 lakh (1.1 million) tonnes of pine needles across the state's forests. At a current market cost of ₹50 per kg, the pine needle economy in Himachal Pradesh is valued at ₹5,500 crore. This valuation establishes pine needles as a cornerstone of the Western Himalayan bio-economy, capable of transforming the state's fiscal health and rural employment landscape.

The state's biochar programme at Neri (Hamirpur) acts as a proof-of-concept for this multi-crore industry, utilizing pyrolysis to convert needles into coal replacements. Scaled across the 11 lakh tonne yield, this initiative is projected to generate massive person-days of income through a decentralized collection network, where collectors can earn significant daily wages. Beyond energy, the conversion of this 1.1 million tonne biomass avoids carbon emissions from forest fires, effectively monetizing the entire life cycle of the Chir Pine stands.

Distribution map of Pine (*Pinus roxburghii*) in Himachal Pradesh



Yield distribution map of Pine (*Pinus roxburghii*) in Himachal Pradesh



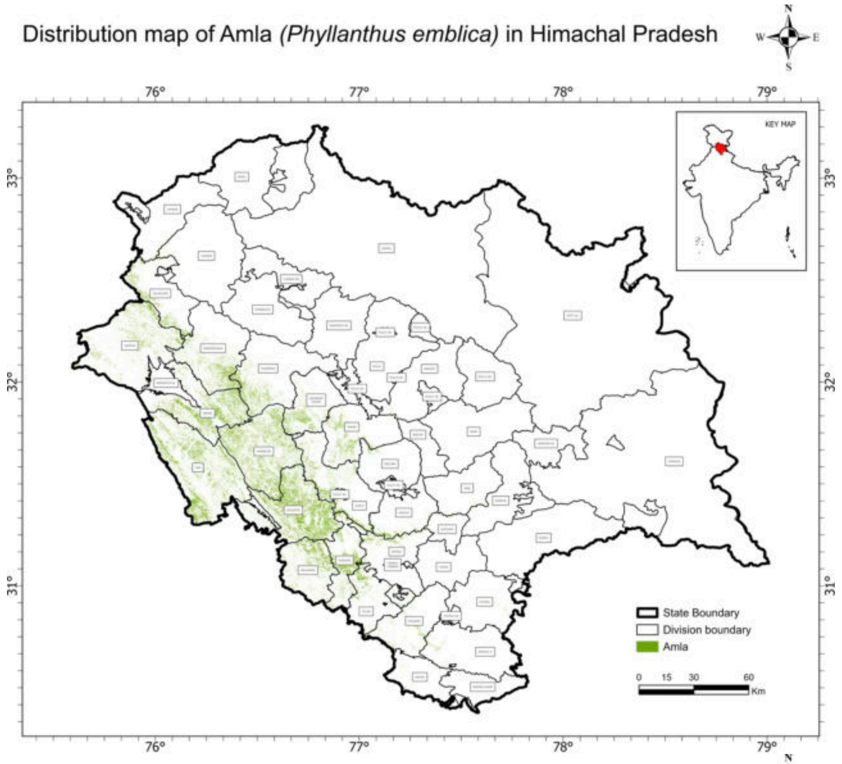
Maturity Phase	Height (m)	DBH (cm)	Volume / Service Output
Early Growth	< 15	< 30	Carbon sequestration; needle litter accumulation.
Peak Economic Yield	15 – 35	30 – 60	Commercial resin tapping; timber for rafters and sleepers.
Over-mature	> 35	> 60	Maximum carbon storage; high fire hazard due to resinous needles.

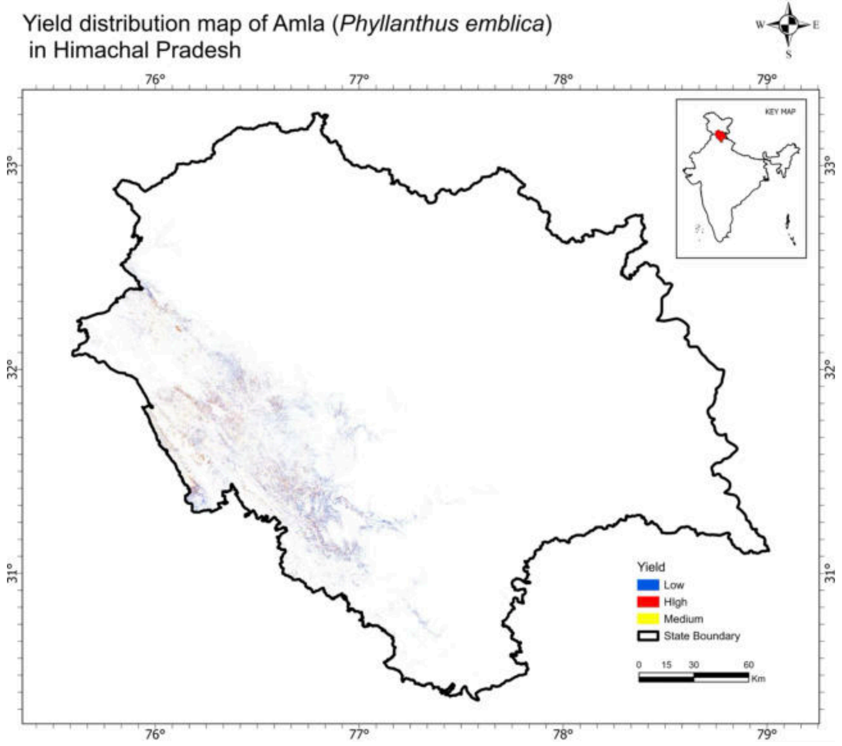
5.1.4. Amla (Phyllanthus emblica): Productivity Trends and Value Chain Optimization

Phyllanthus emblica (Amla) is a slow-growing deciduous species widely distributed in sub-humid subtropical and tropical climates of the state, primarily between 800 and 1,500 meters. The AI distribution mapping shows significant populations in Mandi, Hamirpur, and Kangra. Amla is highly valued as a Non-Timber Forest Produce (NTFP) due to its medicinal properties and high vitamin C content (700 mg per 100g).

The AI resource model estimates an aggregate annual fruit yield of 29 lakh (2.9 million) tonnes distributed across resource clusters in Mandi, Hamirpur, and Kangra districts. Utilizing a current market cost of ₹30,000 per tonne, the Amla fruit economy in Himachal Pradesh is valued at ₹8,700 crore. This valuation positions Amla as a transformative pillar of the state's forest-based income streams.

The results indicate that the "yield sweet spot" for Amla fruit production occurs between 5 and 12 meters, where stand maturity coincides with maximum reproductive output. By formalizing this 29 lakh tonne annual yield through the "Van Samridhi Jan Samridhi" scheme, the state can bridge the gap between collectors and the industrial market, where Amla is increasingly demanded as a "superfood" in the pharmaceutical and nutraceutical sectors.


Distribution map of Amla (*Phyllanthus emblica*) in Himachal Pradesh


Yield distribution map of Amla (*Phyllanthus emblica*) in Himachal Pradesh

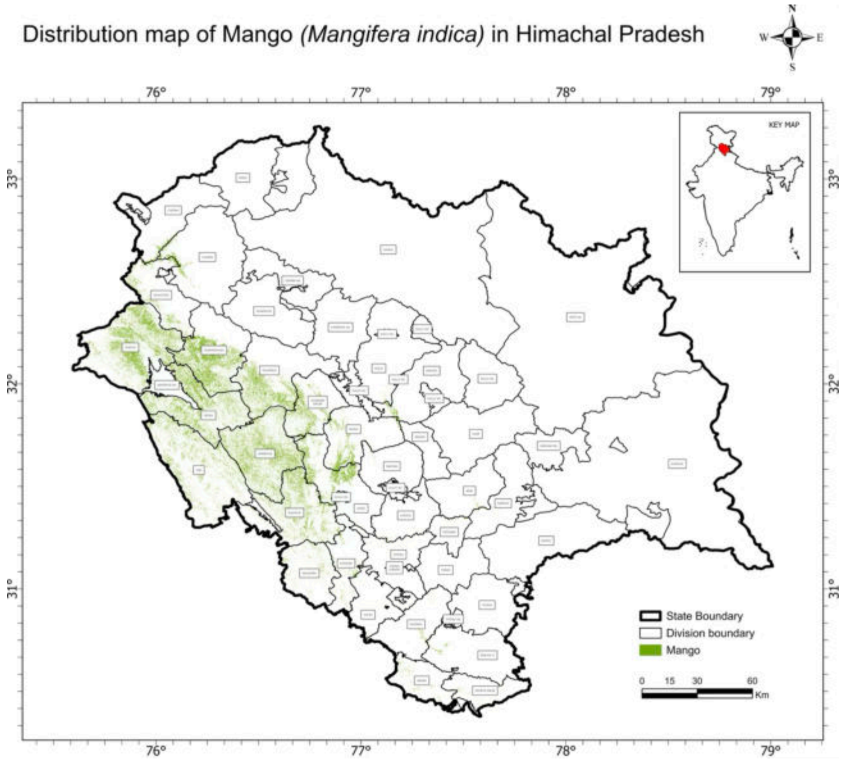
Stand Phase	Height (m)	Maturity (Years)	Fruit Yield (kg/tree/year)
Juvenile	< 5	0 – 8	0 – 5 kg; slow establishing period from seed.
Peak Yield Sweet Spot	5 – 12	10 – 40	100 – 150 kg; heavy cropping years can reach 300 kg.
Stabilization	> 12	> 50	10 – 30 kg; fruit size often decreases in over-mature trees.

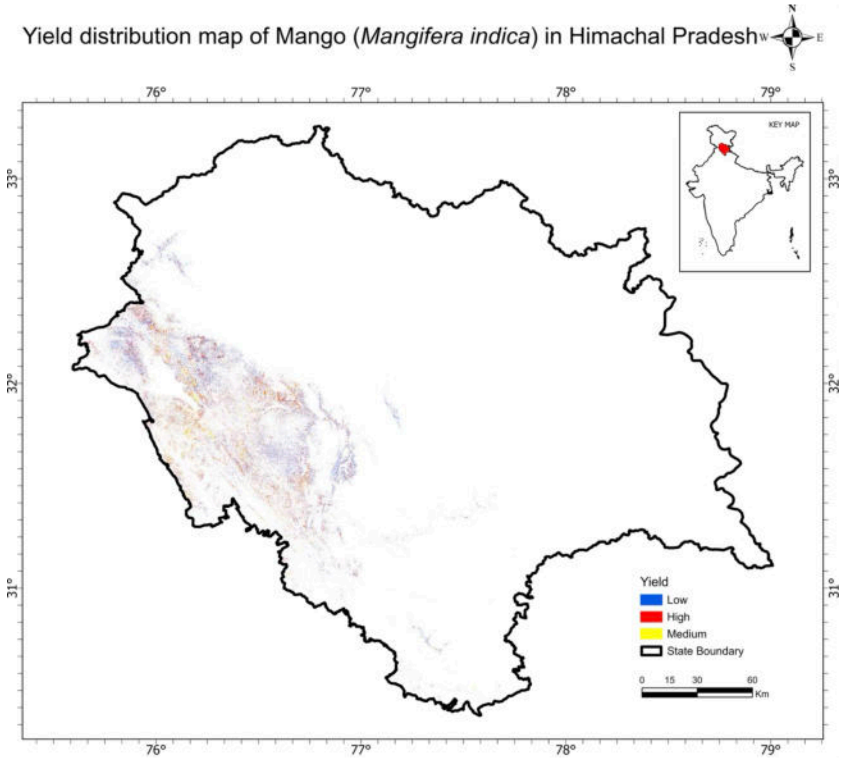
5.1.5. Mango (Mangifera indica): Valuing the Wild Seedling Fruit Economy

The distribution of Mangifera indica within Himachal Pradesh's forest areas focuses on wild "seedling mangoes" found in the subtropical tracts of the lower hills. Unlike cultivated varieties, these forest-grown trees are large, evergreen giants that can reach heights of 15 to 45 meters. The AI-enabled resource model identifies these wild stands as a major provisioning asset, focusing entirely on their fruit yield potential.

The AI resource model estimates a staggering annual fruit yield of 12 lakh (1.2 million) tonnes from wild seedling mango trees distributed across districts like Kangra, Hamirpur, Bilaspur, and Mandi. At a current market cost of ₹40 per kg, the forest-based mango fruit economy in Himachal Pradesh is valued at ₹4,800 crores.This valuation highlights the massive economic potential of wild-harvested forest produce in the state.

Several past studies identifies that forest seedling mangoes possess unique quality characteristics, with edible contents exceeding 88% in locations like Gopalpur (Mandi). The "yield sweet spot" for these forest giants occurs as they reach the 15–30 meter height class, where their canopy expands to support maximum flowering and fruit retention. Monetizing this 1.2 million tonne annual harvest through centralized processing and branding under the "Van Samridhi Jan Samridhi" scheme can provide a resilient income stream for forest-fringe communities, transforming a seasonal resource into a multimillion-dollar industrial asset.


Distribution map of Mango (*Mangifera indica*) in Himachal Pradesh


Yield distribution map of Mango (*Mangifera indica*) in Himachal Pradesh

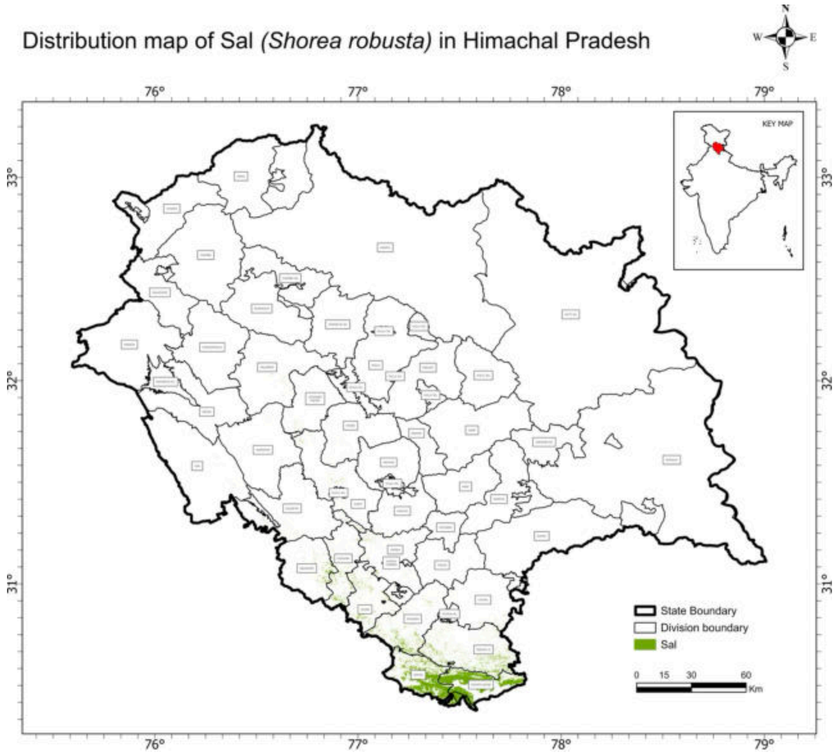
Maturity Phase	Canopy Height (m)	Canopy Logic	Fruit Yield Potential
Early Growth	< 15	Conical; rapid vertical expansion	Minimal fruit bearing (0–10 kg/tree).
Yield Sweet Spot	15 – 30	Spreading dome; umbrella-like	Peak reproductive output (up to 300 kg in heavy years).
Stabilization	> 30	High branching; forest giant	Stabilized or irregular bearing (average 7 t/ha).

5.1.6. Sal (Shorea robusta): Industrial Potential of the ₹2,400 Crore Seed Economy

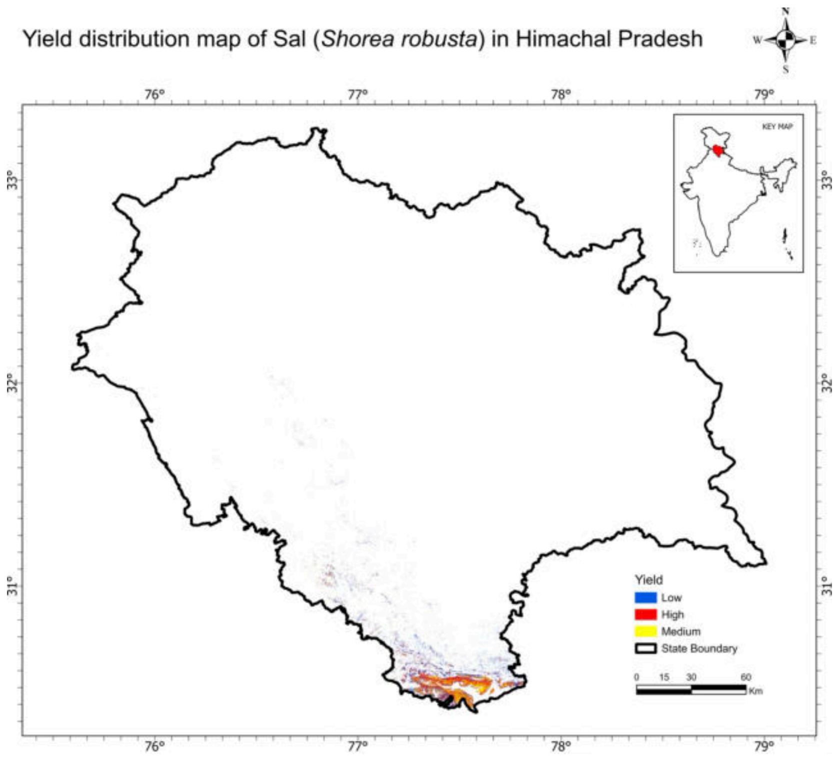
Sal (Shorea robusta) represents a climax species restricted mostly to the Paonta valley and Andreta villages, covering about 306.97 square kilometres. While historically managed for its high-value timber, the yield model focuses on the species' significant non-timber output: Sal seeds. Sal seeds yield a valuable fat known as Sal butter, which is a major ingredient in the global cosmetic and confectionery industries as a substitute for cocoa butter. The model estimates an annual seed yield of 8 lakh (0.8 million) tonnes from the state's Sal forests. At a current market cost of ₹30 per kg, the Sal seed economy in Himachal Pradesh is valued at ₹2,400 crore. This valuation positions Sal seeds as a critical driver for tribal economies and decentralized industrial development.

The results indicate that the "yield sweet spot" for seed collection occurs at middle elevations (900 m), where germination and dispersal rates are maximized. By formalizing the seed collection value chain and community user groups, the state can leverage India's position as a global exporter of Sal derivatives. This industrial pivot addresses the "carbon sink paradox" by creating value from forest litter (seeds and fallen leaves) without impacting the carbon retention of the primary timber bole.

Distribution map of Sal *(Shorea robusta)* in Himachal Pradesh



Yield distribution map of Sal (*Shorea robusta*) in Himachal Pradesh



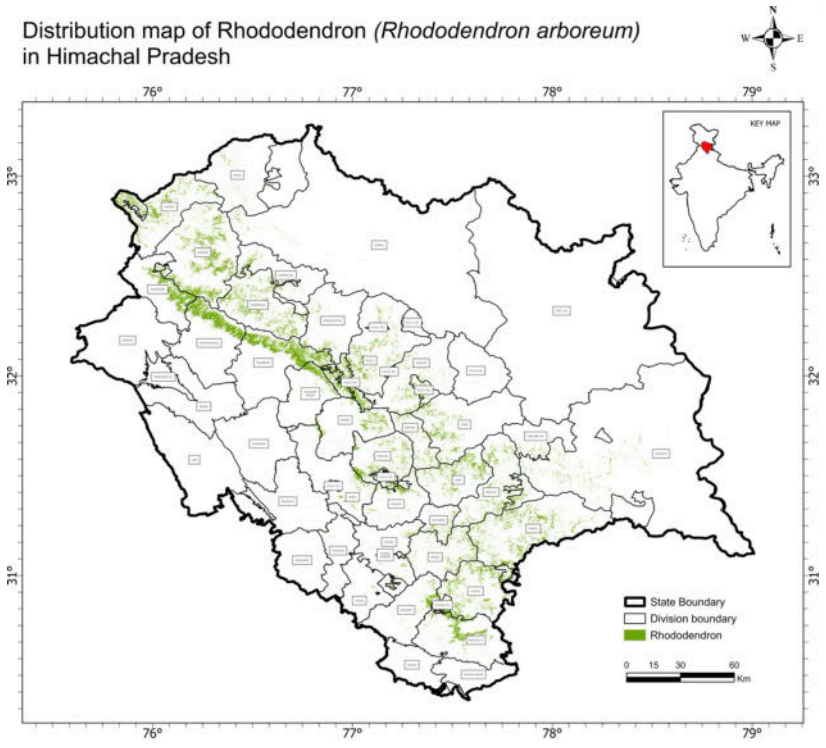
Vertical Strata	Height (m)	DBH (cm)	Management Context
Seedling/Sapling	< 2.0	< 5	High recruitment in Assisted Natural Regeneration (ANR).
Peak Maturation	18 – 32	50 – 135	Dominant canopy; Importance Value Index (IVI) up to 156.59.
Over-mature	> 35	> 135	Structural giants; potential for decline in regeneration if light is blocked.

5.1.7. Rhododendron (Rhododendron arboreum): Flower Yield and Economic Resilience

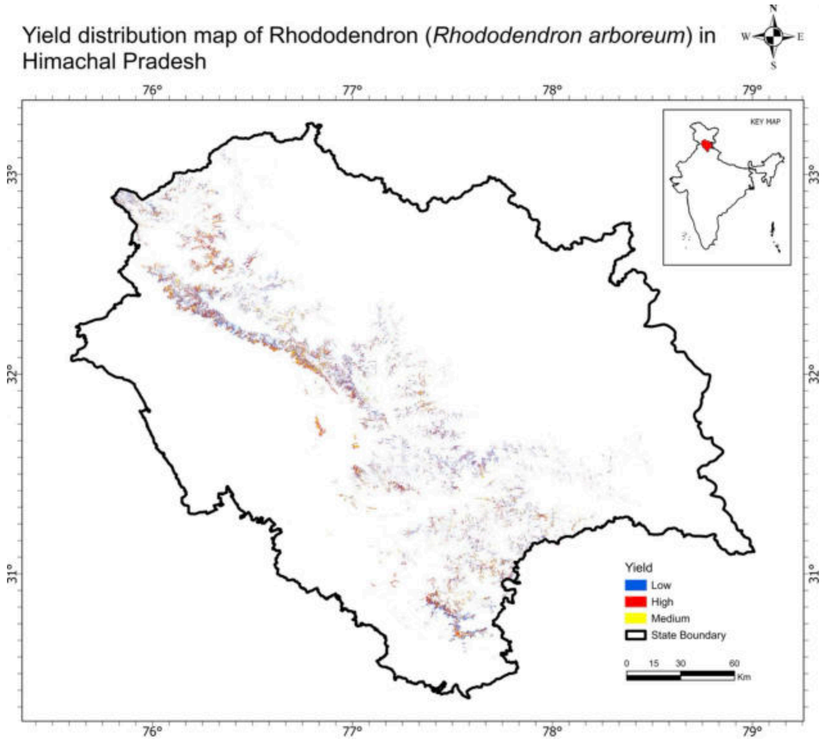
Rhododendron arboreum, the state flower, is an ecologically and aesthetically significant species found between 1,200 and 4,000 meters. It is a slow-growing tree, with mature individuals reaching heights of 7 to 14 meters. The economic potential of Rhododendron is primarily derived from its flowers, which are used to produce squashes, jams, and medicinal preparations. The model estimates an annual flower yield of 3 lakh (0.3 million) tonnes from the state's forests. At a current market cost of ₹40 per kg, the Sal seed economy in Himachal Pradesh is valued at ₹1,200 crore.

The past studies demonstrated a positive significant correlation between flower yield and tree circumference. The models accounts for the fact that the flower yield is maximized in the middle age classes (26-55 cm CBH), particularly in mixed Quercus leucotrichophora forest ecotones.

Distribution map of Rhododendron *(Rhododendron arboreum)* in Himachal Pradesh



Yield distribution map of Rhododendron (*Rhododendron arboreum*) in Himachal Pradesh



Circumference (CBH)	Height (m)	Flower Yield (kg/ha)	Economic Impact
5 – 25 cm (Young)	< 4.0	40.78	Aesthetic value; baseline phytochemical production.[48]
26 – 55 cm (Sweet Spot)	4.0 – 7.0	65.39 – 75.49	Peak commercial harvest; high antioxidant value.[48]
> 66 cm (Over-mature)	~7.0 (stable)	24.62	Structural stabilization; low flower-bearing frequency.[48]

5.2. Discussion: Synthesizing the Forest Economy Transition

The interpretation of the current modeling results within the broader ecological and economic context of Himachal Pradesh reveals three pivotal trends: the divergence between physical forest growth and provisioning value, the emergence of climate-aligned "green" industries, and the institutional shift toward data-driven co-production. It also reveals a paradigm-shifting opportunity: the transition from a passive conservation model to a state-wide, technology-enabled bio-economy.

5.2.1. Unlocking a ₹22,600 Crore Sustainable Asset

The most profound finding is the massive divergence between the currently recorded GSDP share of forestry (4–5%) and the potential state-wide potential of forest bio-resources. By aggregating the potential values—₹5,500 crore from pine needles, ₹8,700 crore from Amla fruit, ₹4,800 crore from wild mangoes, ₹2,400 crore from Sal seeds, and ₹1,200 crore from Rhododendron flowers—the total state-wide potential of these primary resources reaches ₹22,600 crore. This valuation more than doubles the previous recorded value of all forest provisioning services in the state (₹10,873 crore) and provides a definitive solution to the 29% decline in provisioning value observed over the last decade.

Ensuring Sustainability through High-Resolution AI Layers

The critical barrier to unlocking this economy has historically been the risk of over-extraction and environmental degradation. The current modeling exercise removes this risk by providing a high-resolution (10m) and high-frequency monitoring AI layer that serves as an operational "forest intelligence" system.

Unlike traditional decadal inventories, this AI-driven framework allows the HPFD to:

- Identify the "Yield Sweet Spot" in Real-Time: Using multispecies deep neural networks (DNN), the state can pinpoint specific compartments and beats where stands have reached peak maturation for fruit, seed, or residue collection without harming the core timber stock.
- Implement Adaptive Management: The system can detect changes in areas as small as 10-30 meters, generating alerts every 2–3 days to prevent illegal felling or unintended habitat loss during collection seasons.
- Monetize Restoration: By utilizing over-mature residues like pine needles —monitored via satellite and ground-truthing—the state transforms fire hazards into carbon-credit-generating assets.

Technology as a Economic Multiplier

This transition represents a shift from "extraction-based" to "data-driven co-production." The partnership between more than 500 forest guards and the AI modeling pipeline ensures that local taxonomic knowledge is embedded in the digital layer. This vertically integrated architecture allows Range Officers to identify species-wise resource clusters for localized industrial hubs, generating up to 50,000 person-days of employment annually while ensuring that the "Data-People-State" partnership remains equitable and sustainable.

5.3. Conclusion: A Roadmap for the Himalayan Bio-Economy

The forest economy of Himachal Pradesh stands at a historical threshold where natural capital can be unlocked through scientific precision. The results of the AI/ML resource assessment provide the spatially and quantitatively robust foundation for a sustainable economic transformation.

Key Conclusions

- Massive Untapped Potential: The state's primary forest bio-resources hold a cumulative annual value of ₹22,600 crore. This natural capital can revitalize the state's fiscal health and rural employment landscape while adhering to national climate commitments.
- AI-Guaranteed Sustainability: High-resolution and high-frequency AI monitoring layers provide the necessary infrastructure to ensure that economic unlocking does not lead to ecological degradation. This allows for precise, compartment-specific harvest triggers based on non-linear growth trajectories.
- Restoration-Led Growth: The success of the biochar and biofuel initiatives proves that problematic biomass can be converted into high-value industrial feedstocks, meeting India's 2030 NDC targets and multiple SDGs.
- Institutionalized Data co-production: The successful campaign proves that frontline forest staff are critical co-producers of the state's intelligence layer, ensuring long-term institutional ownership and adaptive learning.

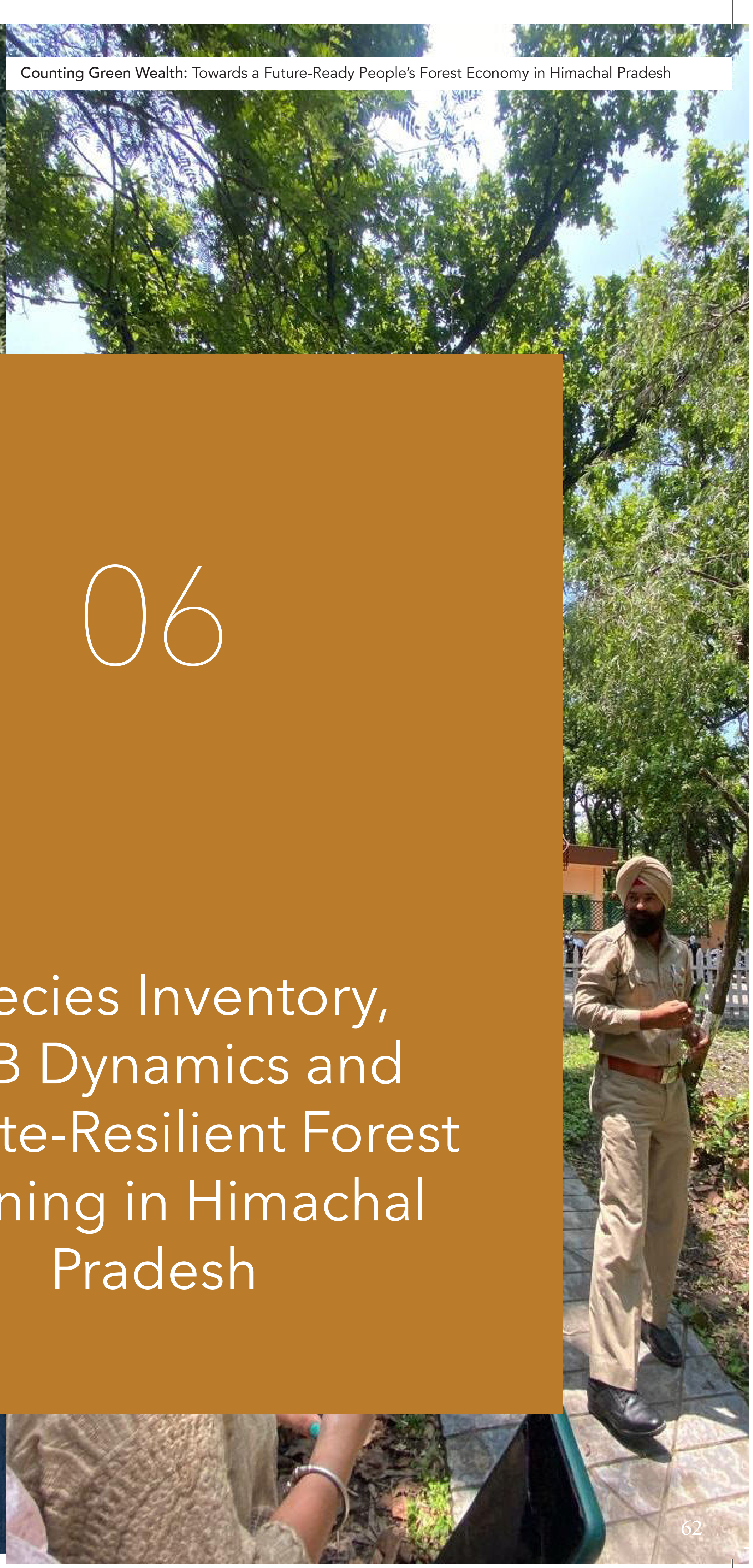
Policy Roadmap

- Scale the Forest Bio-Industrial Network: Expand the Neri biochar model and bio-ethanol processing frameworks to all districts, utilizing the 29 lakh tonne Amla yield and 11 lakh tonne pine needle yield as primary feedstocks.
- Operationalize the AI Intelligence Layer: Integrate 10m species probability and yield maps directly into divisional working plans to prescribe harvest triggers and identify resource clusters for community user groups (CUGs).
- Formalize the "Green Gold" Supply Chain: Establish decentralized hubs for grading, drying, and primary processing of Sal seeds, forest mangoes, and Rhododendron flowers to ensure the retention of economic value within the state.
- Institutionalize High-Frequency Monitoring: Maintain the partnership between HPFD and BIPP-ISB to refine AI models with multi-year temporal data, enabling real-time detection of phenological shifts and ensuring a truly climate-resilient forest economy.

By bridging the gap between natural capital and industrial value through high-resolution intelligence, Himachal Pradesh serves as a national demonstrator for a scientifically managed, equitable, and multimillion-dollar forest-based economy.

06

Species Inventory, AGB Dynamics and Climate-Resilient Forest Planning in Himachal Pradesh



6.1. Forest species information as climate infrastructure

For Himachal Pradesh, a scientifically grounded forest economy cannot be separated from carbon management and climate adaptation. Forests are not homogeneous carbon surfaces: their biomass accumulation, carbon persistence, vulnerability to disturbance, hydrological function and regeneration potential are all mediated by species composition, stand structure, elevation, aspect, soil moisture and management history. Recent studies in the north-western Himalaya show that carbon stock varies strongly across forest communities and altitudinal gradients, with tree density, diameter structure, dominant species and habitat type acting as major determinants of biomass and carbon storage. This makes species-level inventory and distribution mapping central to climate policy. A map that only shows "forest" is insufficient for adaptation planning; HPFD requires maps that show which species occur where, how much biomass they hold, how that biomass is changing, and where carbon-storing forests are vulnerable to climate or anthropogenic stress.

This is particularly important in the western Himalaya, where climate change is already interacting with topographic complexity, water stress, fire risk, snowline shifts and changing livelihood systems. A systematic review of Himalayan forests concluded that climate change and anthropogenic pressures jointly threaten forest ecosystems, and that long-term knowledge of changing forest distributions is essential for forest management and adaptation planning. A peer-reviewed climate vulnerability assessment for Kullu district also notes that mountain ecosystems are among the most climate-sensitive systems globally, and reports observed signals in Himachal Pradesh such as rising annual maximum temperature, changing rainfall patterns, reduced snowfall and shifts in climate-sensitive livelihood systems. In this context, the HPFD–BIPP–ISB species inventory and AI-enabled mapping effort should be understood not merely as a digital forest inventory, but as a climate intelligence system for the state.

6.2. AGB change analysis using ESA CCI biomass data

To quantify biomass change, this report analysed Above-Ground Biomass (AGB) for 2010 and 2022 using the ESA Climate Change Initiative Global Forest Above-Ground Biomass product. The ESA CCI Biomass dataset provides global AGB estimates for 2007, 2010 and annually from 2015 to 2022 at 100 m spatial resolution, with AGB reported in Mg/ha and uncertainty provided as per-pixel standard deviation. ESA defines AGB as the oven-dry mass of woody above-ground tree components, excluding stumps and roots; the product is derived from multi-sensor Earth observation, including Sentinel-1, Envisat ASAR, ALOS/ALOS-2 PALSAR and spaceborne lidar observations. The scientific basis of the 2010 global biomass product has been peer-reviewed, with Santoro et al. reporting a 1 ha global AGB dataset generated from satellite SAR observations and validated against 110,897 field AGB measurements.

In this analysis, the 100 m ESA CCI biomass layer was aligned with 10 m species distribution layers to estimate species-wise AGB change. For strict unit consistency, the correct interpretation is that Mg/ha is a biomass-density measure. Therefore, when a 100 m × 100 m pixel, equivalent to 1 hectare, has an AGB value of 20 Mg/ha, it represents 20 Mg of AGB in that pixel. If this pixel is subdivided into 100 cells of 10 m × 10 m, each 10 m cell represents 0.01 ha and therefore carries 0.2 Mg of biomass mass, while the original density remains 20 Mg/ha. In other words, the downscaling is mass-conserving when the pixel-level biomass mass is distributed across finer cells; it should not be described as changing the density from 20 Mg/ha to 0.2 Mg/ha. This distinction is important for carbon accounting and avoids unit inconsistency in downstream estimates.

Using this mass-conserving overlay, species-wise total AGB was computed by summing the 10 m biomass mass values within each species distribution mask for 2010 and 2022. Based on the followed method for data analysis , the major results are as follows, with percentage change recalculated against the 2010 baseline:

Species / species group	AGB 2010 (Mg)	AGB 2022 (Mg)	Change (Mg)	Change from 2010
Rhododendron	20,819,835	18,088,669	−2,731,166	−13.1%
Sal	7,919,972	8,210,466	+290,494	+3.7%
Mango	10,204,595	12,501,215	+2,296,620	+22.5%
Amla	6,365,374	6,920,589	+555,215	+8.7%
Pine	21,926,660	17,950,502	−3,976,158	−18.1%
Khair	11,034,139	11,470,312	+436,173	+4.0%
Bamboo	5,037,986	5,987,515	+949,529	+18.8%

Across the seven mapped tree species, total AGB declined from approximately 83.31 million Mg in 2010 to 81.13 million Mg in 2022, a net reduction of about 2.18 million Mg, or 2.6% relative to the 2010 baseline. This aggregate figure should be interpreted carefully because species distribution layers may represent modelled suitable areas or overlapping species masks rather than mutually exclusive forest classes. Nevertheless, the species-specific direction of change is policy-relevant: pine and rhododendron show substantial biomass decline within their mapped distributions, while bamboo, mango, amla, khair and sal show gains.

Using the IPCC default carbon fraction of 0.47 for above-ground forest biomass, the observed net AGB decline across the analysed classes corresponds approximately to 1.02 million Mg of carbon, or 3.76 million Mg CO_2 equivalent, when converted using the molecular weight ratio 44/12. This should be treated as an indicative estimate because it does not include below-ground biomass, deadwood, litter, soil organic carbon or uncertainty propagation from the ESA CCI product and species distribution models.

6.3. Interpreting species-wise AGB change for climate mitigation

The AGB results demonstrate why species inventory is essential for climate mitigation. If forest policy were based only on total green cover, the decline in biomass associated with pine and rhododendron-dominated areas could be masked by increases in other species groups. Conversely, gains in bamboo, amla, khair, mango and sal indicate areas where restoration, regeneration or landscape conditions may be supporting biomass accumulation. The implication is not that one species should automatically be prioritised over another, but that carbon outcomes are species- and site-specific.

This finding aligns with broader ecological evidence. Recent Himalayan biomass studies show that conifer, broadleaf and mixed communities differ significantly in biomass and carbon stocks, and that forest community composition, tree density, basal area and altitude jointly influence carbon storage. Global biodiversity–carbon research also Shows that biodiversity loss can reduce terrestrial carbon storage and produce feedbacks that amplify climate change. For Himachal Pradesh, this means that carbon strategy must not become a narrow plantation or carbon-credit exercise. It must be grounded in species composition, native forest structure, ecological suitability and long-term resilience.

The state climate policy relevance is direct. Himachal Pradesh's State Action Plan on Climate Change identifies the land-use, land-use change and forestry sector as a net carbon sink, with forest land sequestering CO_2while also experiencing emissions from deforestation, developmental activities and unsustainable fuelwood extraction. A species-wise AGB monitoring system can therefore strengthen the evidence base for state greenhouse-gas accounting, compensatory afforestation planning, restoration prioritisation and future carbon-finance mechanisms.

6.4. Species distribution as the bridge between mitigation and adaptation

Climate mitigation asks how much carbon forests store and sequester. Climate adaptation asks whether those forests will remain functional under future stress. Species distribution maps connect these two questions. A high-carbon forest that is climatically vulnerable may become a future emission source through mortality, fire, pest outbreaks or regeneration failure. Conversely, a moderately stocked but ecologically resilient mixed forest may provide more durable long-term carbon storage and better hydrological and livelihood co-benefits.

Forest resilience literature consistently emphasises that biodiversity enhances adaptive capacity. The Convention on Biological Diversity's synthesis on forest resilience notes that increasing biodiversity in planted and semi-natural forests can improve resilience and often productivity, including carbon storage. The Himachal Pradesh inventory therefore offers three adaptation-relevant benefits. First, it allows HPFD to identify species-climate mismatches, such as populations occurring near their lower or upper elevational limits. Second, it supports climate-smart silviculture, where regeneration, assisted natural regeneration and enrichment planting can be tailored to species-site suitability. Third, it enables risk-sensitive carbon planning, where high-biomass areas can be evaluated alongside fire exposure, slope instability, water stress and anthropogenic pressure.

6.5. Policy implications for Himachal Pradesh

The final policy message is that Himachal Pradesh should treat its forest species inventory, SDM layers and AGB change maps as a unified decision-support system. The system can support at least five climate-relevant functions:

Carbon accounting and MRV: Species-wise AGB change can strengthen monitoring, reporting and verification for state-level climate action, restoration programmes and potential carbon-finance projects.

Working-plan revision: Biomass trends and species distribution probabilities can be incorporated into working-circle prescriptions, regeneration planning and silvicultural treatment decisions.

Adaptation targeting: Areas showing declining biomass in climate-sensitive or disturbance-prone species can be prioritised for field verification, assisted regeneration, fire prevention or moisture-conservation interventions.

Restoration design: Plantation and restoration should prioritise ecologically suitable native and mixed-species systems rather than single-species carbon-maximisation, because durable carbon storage depends on ecological resilience.

Forest economy alignment: Species-wise biomass information can help identify sustainable biomass availability, NTFP potential, bamboo and medicinal species zones, and areas where livelihood-linked forest enterprises can be developed without compromising carbon and biodiversity objectives.

6.6. Concluding synthesis

The Himachal Pradesh forest economy report demonstrates that the future of forest management in mountain states lies in integrating species inventory, Earth observation, AI/ML modelling, carbon accounting and frontline institutional knowledge. The AGB change analysis from 2010 to 2022 provides a significant quantitative bridge between species distribution and climate outcomes. It shows that biomass gains and losses are not uniform across species groups, and that carbon-relevant planning must be spatially explicit, species-aware and uncertainty-informed.

For HPFD and BIPP–ISB, the next step is to convert this analytical framework into an operational monitoring cycle: periodically update species observations, retrain species distribution models, refresh biomass overlays, compare model outputs with field inventories and working-plan records, and translate the results into adaptive forest management. In doing so, Himachal Pradesh can position itself as a national leader in science-based, climate-aligned forest governance, where forests are managed simultaneously as biodiversity systems, carbon sinks, livelihood assets and critical infrastructure for adaptation in the western Himalaya.