

Revealing the Widespread Mosaic of Shifting Cultivation Across the Tropics

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Revealing the Widespread Mosaic of Shifting Cultivation Across the Tropics

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Abstract

Shifting cultivation is often viewed as an agricultural system in decline, driven by policy interventions, agricultural intensification, market integration, land tenure changes, and other socioeconomic drivers. However, mapping its global extent remains challenging because of landscape heterogeneity and the technical barriers that hinder consistent detection. In this study, we combined deep learning with high-resolution satellite imagery to map the extent of shifting cultivation across the pantropics at 1-km resolution. We estimate shifting cultivation covers 211.7 ± 16.2 Mha across 76 countries in 2020, indicating that the system remains prevalent despite reported declines. Globally, 61.4% of shifting cultivation occurs in tropical rainforests, whereas in Africa more than half (55.1%) is found in savanna and open woodland biomes. Mapped areas are frequently located on gentle terrain (below 7° slope). Over 90% of shifting cultivation areas in Asia-Oceania and the Americas are located within 5 km of plantations, compared with 71% in Africa. This global assessment provides a foundation for understanding the persistence, spatial heterogeneity, and contemporary land-use context of shifting cultivation across the pantropics, including its association with agricultural intensification, plantation systems, and socioeconomic development.

29 Main

30 Shifting cultivation persists despite multiple announcements of its imminent demise¹. Also
31 known as swidden, or, ‘slash and burn’ agriculture, it is an ancient, multifaceted form of
32 agriculture involving the rotational clearing and burning, or in a few cases mulching, of woody
33 vegetation to temporarily enhance soil fertility². After cultivation, fields are left to regenerate,
34 allowing vegetation regrowth and when repeating the cycle, a landscape mosaic of cultivated
35 areas, fallow lands and natural forest or savanna is formed³. For millennia, this cycle has
36 supported millions of farmers, local communities and Indigenous people across the planet and
37 still does in many parts of the tropics^{4,5}. The agroecological balance of the system is regulated by
38 fallow length and the number of consecutive years of cultivation. Historically, intensification
39 was mainly due to population pressure resulting in land scarcity⁶, but in recent decades, the
40 system has been increasingly affected by other drivers such as expansion of commercial
41 plantations, conservation efforts, carbon farming, and market integration^{7,8}.

42 Shifting cultivation has frequently been portrayed as a major driver of forest loss⁹ and
43 greenhouse gas emissions (GHG)¹⁰. From the 1950s onwards, it was widely perceived as a low-
44 productivity agricultural practice and actively discouraged in favor of more intensified and
45 market-oriented forms of agriculture. However, this narrative often overlooks broader economic
46 forces, as the expansion of market-oriented commodity production, driven by increasing global
47 demand and profitability, has frequently contributed substantially to deforestation. In many
48 settings, integration into global markets has stimulated further agricultural expansion rather than
49 reducing forest loss. Examples include the global expansion of oil palm^{11,12}, and rubber in
50 Southeast Asia¹³, cocoa and coffee in Africa¹⁴, soybean¹⁵, and pasture in Latin America¹⁶.

51 Shifting cultivation has often been criticized for contributing to deforestation and land
52 degradation, particularly where systems have undergone intensification¹⁷. Shortened fallow
53 periods can constrain forest regeneration, leading to declines in biodiversity, carbon storage, and
54 ecosystem services. Such concerns have often supported transitions toward more permanent and
55 market-oriented forms of agriculture. However, these transitions do not automatically generate
56 environmental benefits. Indeed, recent studies suggest that shifting cultivation can store more
57 carbon than some tree-based or biofuel plantations, challenging simplified narratives of

environmental harm^{18,19}. The environmental consequences of transitioning away from shifting cultivation therefore depend critically on both the characteristics of the original system, particularly fallow length, and the land use that replaces it. Robust assessment of these trade-offs requires accurate knowledge of the current status of the spatial extent and distribution of shifting cultivation and its successor land-use systems. Yet substantial gaps remain in our knowledge and understanding of shifting cultivation systems.

In global agricultural assessments, shifting cultivation is frequently excluded from standardized land-use definitions and mapping processes²⁰. Current estimates rely heavily on literature-based compilations of case studies^{7,21}, which are constrained by spatial biases and limited scalability. Although satellite-based machine learning approaches have advanced global land-cover mapping, shifting cultivation has largely been mapped only at national scales²². The most comprehensive global dataset to date is derived from coarse-resolution (10 km) visual interpretation²³. This coarse resolution limits its utility for applications requiring spatial details and accuracy, such as carbon accounting, fallow monitoring, or tracking land-use transitions. Moreover, the absence of automated and operational mapping frameworks limits our ability to generate consistent updates over time. Such information is essential for both scientific understanding and policy making, especially when aiming to create informed land use policies and standardized methods for tracking changes in swidden systems.

Mapping shifting cultivation at a global scale remains challenging because of its spatial heterogeneity, temporal variability, and landscape diversity²⁴. Most existing remote sensing approaches rely on decision tree-based algorithms applied to time-series satellite data²². These rule-based methods are often tailored to specific regions and fail to generalize well across broader spatial scales, because land use patterns vary widely between different landscapes²⁵ (Extended Data Fig. S1). In recent years, deep learning has emerged as a transformative tool in remote sensing, offering new opportunities to address these limitations. Models based on convolutional neural networks (CNNs) and other advanced architectures provide a flexible and robust framework to learn directly from imagery²⁶. Unlike traditional spectral feature-based methods, deep learning can capture complex spatial and spectral patterns that are otherwise difficult to obtain.

Here, we reconceptualize the detection of shifting cultivation as a spatial-pattern recognition problem rather than a purely temporal classification task. Shifting cultivation landscapes form characteristic mosaics composed of active fields embedded within fallows at different stages of regrowth. The size and geometry of clearings are constrained by manual labor and local livelihood needs, typically producing a compact and recurrent landscape pattern configuration. We show that these mosaic signatures, although shaped by long-term shifting cycles, can be identified from single-time high-resolution imagery.

To achieve this, we use PlanetScope nano-satellite imagery via the Norway's International Climate and Forest Initiative (NICFI) programme, which offers near cloud-free mosaics at fine spatial detail (4.77 m resolution) for the global tropics by year 2020. Employing a deep learning framework, we identify and map shifting cultivation based on its spatial configuration, resulting in a globally consistent 1-km resolution dataset. This approach bridges a critical data gap in land-use monitoring and provides a foundation for evaluating the environmental and socioeconomic consequences of shifting cultivation in the context of sustainability governance.

Results

Pantropical extent and validation of shifting cultivation

We produced a pantropical land-use classification map at 1 km resolution consisting of five classes: shifting cultivation, high tree-cover woodland, conventional agriculture, mixed woody plantations, and other land cover. Agricultural systems were categorized into non-tree-based (e.g. permanent cropland and pasture systems) and tree-based types (e.g. monoculture plantations and agroforestry), distinct from shifting cultivation. The resulting map of shifting cultivation density is shown in Fig. 1a.

Model performance remained stable across spatial scaling from national to pantropical domains, with an overall multi-class accuracy exceeding 80%, indicating that mosaic landscape features characteristic of shifting cultivation is consistently learnable and transferable across regions. Independent map validation for the shifting cultivation class yielded an overall accuracy of 87.8% (see Methods for details), with producer's and user's accuracies of 84.7% and 81.7%, indicating balanced omission and commission errors at pantropical scale. Our map also shows strong agreement with the shifting cultivation occurrence map of Heinimann et al.²³. Within the

area covered by both maps, 98.9% of grid cells fell within one-level difference of occurrence (Extended Data Fig. S7). We also compared our map-based area estimates with previously published regional estimates (Extended Data Table S5), finding general agreement in area estimated extent, although differences remain due to variations in data sources, methodologies, and the timing of the imagery used.

Shifting cultivation is widespread through the tropics, occurring in 76 countries with at least 10 kha of mapped area. The total pantropical shifting cultivation extent in 2020 was estimated at 211.7 Mha (95% confidence interval: ± 16.2 Mha). Regionally, shifting cultivation is most widespread in Africa (113.6 ± 8.7 Mha), followed by Asia and Oceania (49.3 ± 3.8 Mha), and the Americas (48.9 ± 3.7 Mha). Despite its widespread occurrence, shifting cultivation is highly unevenly distributed, with 80% of the total area located in just 20 countries (Fig. 1c). The Democratic Republic of the Congo (DRC) ranks first in total extent (39.7 ± 3.0 Mha), followed by Brazil, Indonesia, Myanmar and Mozambique (Fig. 1d). In contrast, when expressed as a proportion of national land area, shifting cultivation is most prominent in smaller countries such as Sierra Leone and Liberia, where it constitutes a dominant component of the national landscape (Fig. 1f).

The relative importance of shifting cultivation within national agricultural systems varies substantially (Fig. 1e). In several countries, including the DRC, Liberia, and the Central African Republic, shifting cultivation represents the dominant agricultural system in 2020. In the DRC, shifting cultivation accounted for 56.6% of total agricultural land, exceeding conventional agriculture (36.8%), while plantations occupied only a minor share (6.5%). Similarly, in Liberia, shifting cultivation dominated national agriculture (75.1%), with conventional agriculture covering only about 1% of agricultural land. However, it should be noted that in Liberia, recently established cacao plantations can produce spatial patterns closely resembling shifting cultivation mosaics in high-resolution imagery, and some misclassification between these two systems is likely. Our shifting cultivation estimates for Western African countries featuring extensive cacao production should therefore be interpreted with caution. In contrast, countries such as Brazil and India exhibit large absolute extents of shifting cultivation but lower proportional importance due to the dominance of other agricultural systems. Other countries, including Mozambique, Zambia, Angola, Madagascar, Mexico, and Venezuela, are characterised by a greater share of

conventional agriculture, while plantation-dominated systems are observed in Indonesia, Côte d'Ivoire, and Colombia. In Laos and Papua New Guinea, shifting cultivation and plantation systems occupy nearly equal proportions.

We further ranked the share of shifting cultivation within total agricultural land (Extended Data Fig. S6a). Among the top 20 countries, 11 of them are in Africa, led by Liberia, Equatorial Guinea, and Sierra Leone. We compared our shifting cultivation area with the Potapov et al.²⁰ cropland dataset, which maps annual croplands excluding shifting cultivation. We estimated the proportion of shifting cultivation of the combined crop production area that includes both shifting cultivation and annual cropland as two distinct, non-overlapping categories. The analysis shows that in 38 countries (excluding French Guiana), shifting cultivation constitutes more than 50% of the crop production area (Extended Data Fig. S6b). This highlights its continued importance in agricultural land use across tropical regions, despite being absent from global cropland statistics.

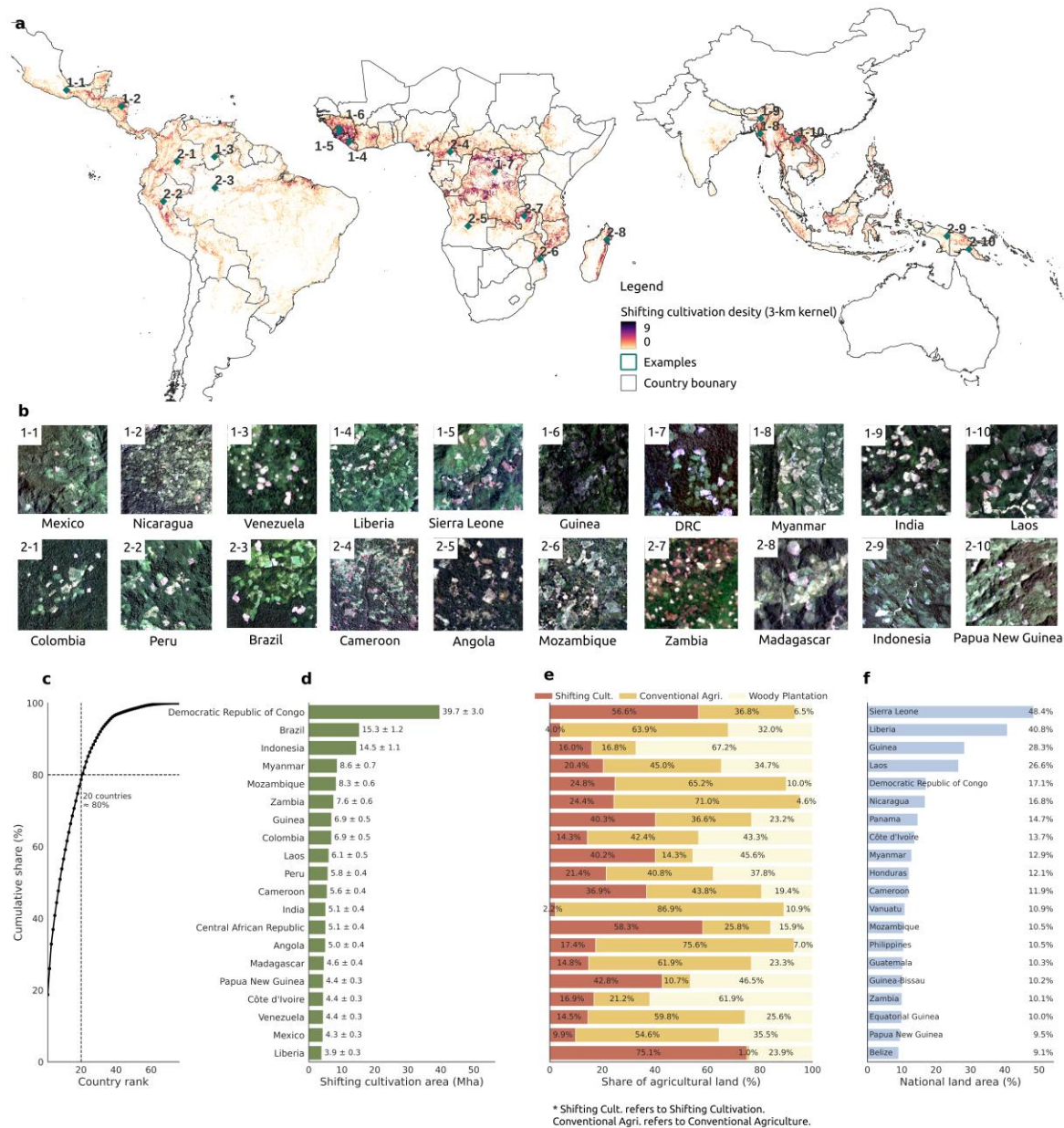


Fig. 1 | Shifting cultivation extent and spatial patterns across countries. a, Global distribution of shifting cultivation shown as a kernel density map (3-km radius). Numbered boxes indicate the locations of landscape examples shown in panel b. b, Twenty representative examples of mapped shifting cultivation landscape mosaics illustrating cross-regional variability in mosaic landscape structure (imagery from PlanetScope; RGB bands 3-2-1). c, Cumulative distribution curve showing the total share of shifting cultivation extent accounted for by individual countries ranked from largest to smallest

extent. d, Top 20 countries by total shifting cultivation extent. e, The share of agricultural land under different production systems (shifting cultivation, conventional agriculture and mixed woody plantation within the top 20 countries ranked by shifting cultivation. f, Top 20 countries ranked by the percentage of national land area under shifting cultivation.

Biogeographic and topographic distribution

Shifting cultivation showed strong continental differences in biomes and topographic distribution based on spatial overlays with the World Wildlife Fund (WWF) Terrestrial Ecoregions classification and Shuttle Radar Topography Mission (SRTM) elevation data (Methods). In the Americas and Asia-Oceania, shifting cultivation was primarily associated with tropical rainforest biomes (Fig. 2d), accounting for 77.6% and 90.4% of the mapped area, respectively. In Latin America, mapped areas were concentrated along riparian corridors of the lowland Amazon basin, with additional hotspots in Andean montane forest zones. In central America, occurrences were mainly located at the foothills of the montane moist forest (Fig. 2a). Asia and Oceania share a similar rainforest-foothill association, with a larger share located in lower montane zones, particularly in Myanmar, Laos, and Papua New Guinea (Fig. 2c). In contrast, shifting cultivation in Africa shows a broader distribution across biomes. Although the Congo Basin rainforest forms a major core area, a substantial fraction of shifting cultivation occurs in savanna and woodland systems (55.1%) (Fig. 2d). Prominent clusters are found across the miombo woodlands of southern and eastern Africa, the West African forest-savanna mosaic, the Guinean lowland forests and parts of Madagascar's lowland forest regions (Fig. 2b), with additional smaller clusters in coastal tree-covered landscapes.

Topography (derived from SRTM elevation and slope layers) influences ecology, accessibility, land-use pressure, and socio-economic systems, all of which influence where and how shifting cultivation occurs. Across all continents, shifting cultivation shows a consistent pattern of occurrence in low- to mid-elevation areas with relatively gentle terrain. Median elevations are 521 m in Africa, 231 m in the Americas, and 389 m in Asia-Oceania, with over 75% of mapped areas occurring below approximately 800 m.

Similarly, shifting cultivation is predominantly located on low slopes, with median slope values below 1° in Africa, around 1° in the Americas, and about 4° in Asia-Oceania. More than 75% of

196 mapped areas are located on slopes below 1.5° in Africa and below 7° in other regions. This
197 consistent cross-continental pattern indicates that shifting cultivation is commonly associated
198 with relatively low-elevation and gently sloping landscapes.

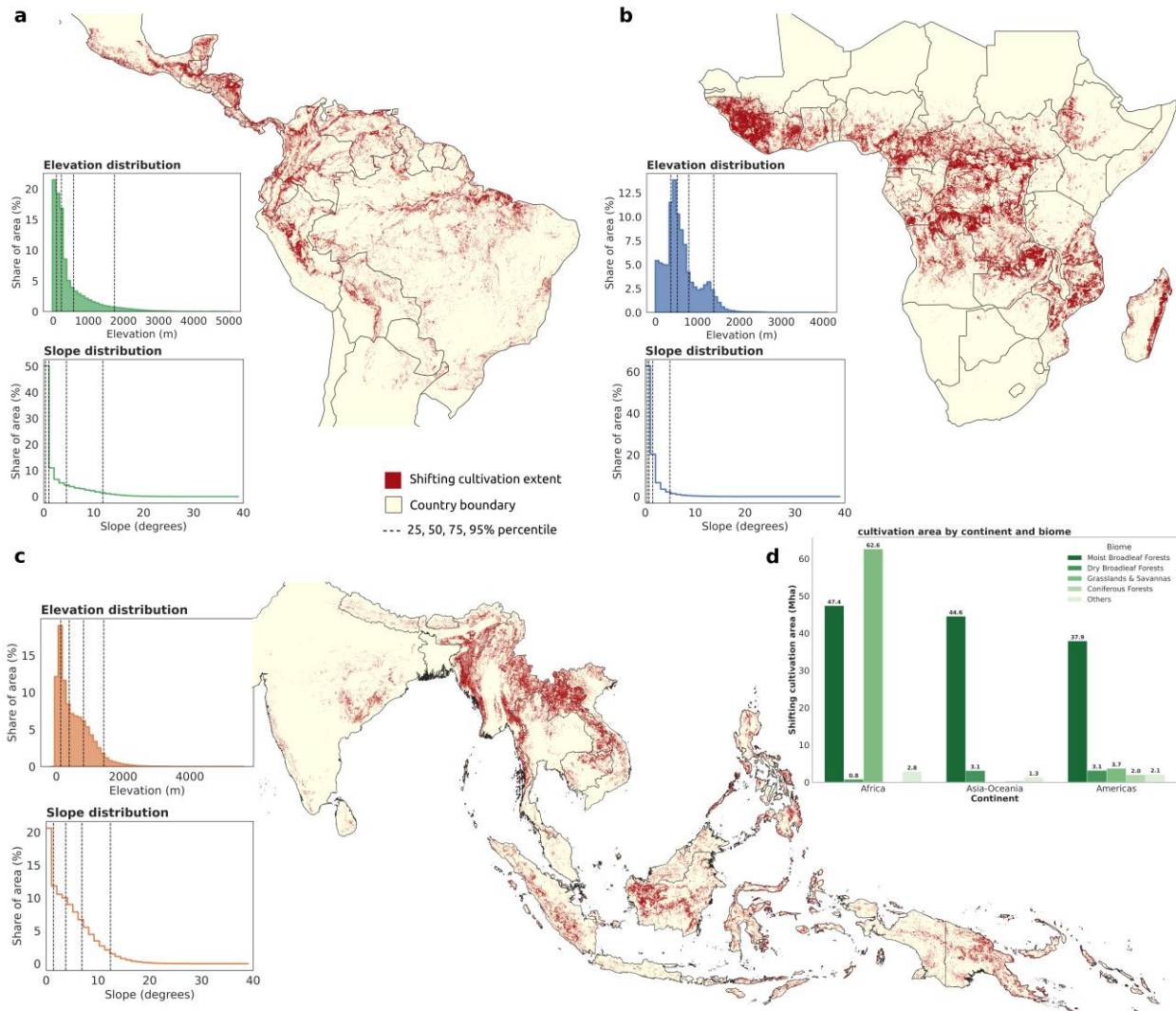


Fig. 2 | Distribution of shifting cultivation in relation to biome classes and topography across the pantropics. a–c, Distribution of mapped shifting cultivation across the Americas (a), Africa (b) and Asia-Oceania (c). Inset histograms show the elevation and slope distributions of shifting cultivation pixels within each region, expressed as a percentage of total regional shifting cultivation area. Dashed vertical lines indicate the 25th, 50th, 75th, and 95th percentiles of each distribution. Elevation and slope derived from the Shuttle Radar Topography Mission (SRTM) 30-m digital elevation model. d, Distribution of shifting cultivation extent across biome classes derived from the World Wildlife Fund (WWF) Terrestrial Ecoregions classification.

Shifting cultivation and land use transitions

Shifting cultivation is consistently embedded with other agricultural systems rather than randomly distributed across tropical landscapes. At the pantropical scale, it frequently occurs in spatial association with plantation systems and conventional agriculture (Fig. 3a). We quantified spatial proximity to these land-use systems to assess the context in which land-use transitions may occur (Methods).

The strength of spatial association between shifting cultivation and plantation systems varies markedly across regions. Proximity to plantations was particularly high in Asia-Oceania and the Americas, where 79.5% and 72.0% of shifting cultivation areas occurred within 2 km of plantations, increasing to 97.8% and 92.8% within 5 km, respectively. In Africa, proximity to plantations was lower, with 38.2% of shifting cultivation areas located within 2 km and 71.1% within 5 km (Extended Data Fig. S8). Distances to conventional agriculture were generally larger across all regions: only 37.1% of shifting cultivation areas in Africa, 30.6% in the Americas, and 17.0% in Asia-Oceania occurred within 2 km of conventional agriculture areas. Within 5 km, these proportions increased to 67.2% in Africa, 65.3% in the Americas, and 48.0% in Asia-Oceania (Extended Data Fig. S9).

Because spatial associations with plantation systems were generally stronger, regional examples of plantation landscapes illustrate the diverse contexts in which land-use transitions may occur (Fig. 3b–f). In Latin America, shifting cultivation in core Amazon regions remains comparatively distant from large plantation systems, whereas foothill and montane transition zones along the Andes show more frequent spatial co-occurrence with perennial crops and plantations (Fig. 3b). In Southeast Asia, shifting cultivation landscapes are commonly interspersed with or adjacent to large, contiguous plantation systems (Fig. 3d, e). Africa, which contains the largest total area of shifting cultivation, shows heterogeneous patterns: West African hotspots frequently occur near both industrial and smallholder plantation zones (Fig. 3c), while Central African regions, including parts of the Congo Basin, show greater spatial separation, with only scattered plantation presence within predominantly forested landscapes (Fig. 3f). However, spatial proximity alone does not establish whether plantation expansion directly replaces shifting cultivation or reflects independent deforestation trajectories.

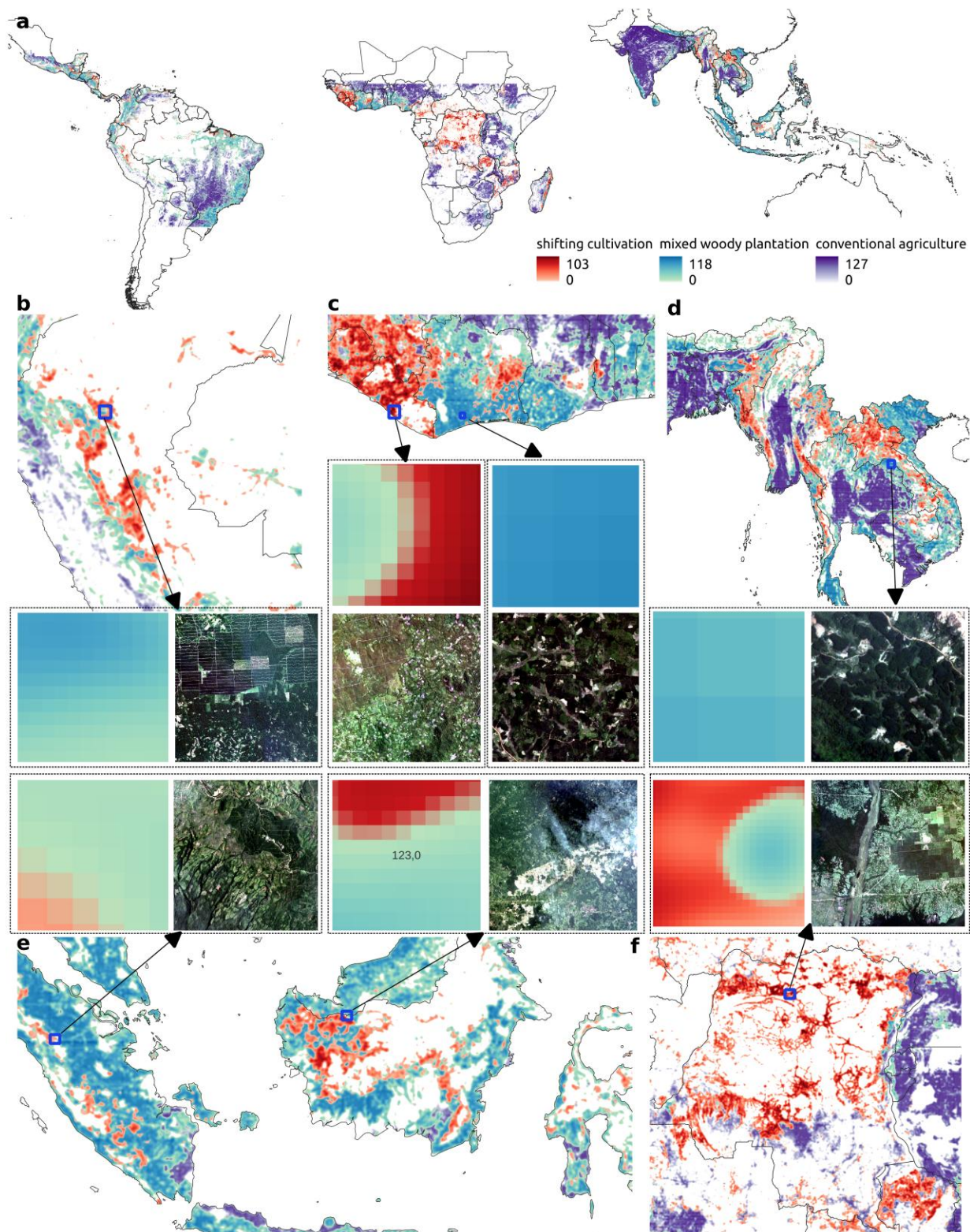


Fig. 3 | Shifting cultivation hotspots and the spatial association with other land use. a, Density of shifting cultivation, conventional agriculture (permanent cropland or pasture)

and mixed woody plantations (perennial plantations or agroforestry systems without clear shifting fields) at $0.1^\circ \times 0.1^\circ$ resolution. Country boundaries data are from GADM (<https://gadm.org>). b, Zoom-in example in Peru showing an industrial oil palm plantation adjacent to shifting cultivation. c, West Africa: industrial plantation in Liberia (left) and smallholder plantations in Ghana (right). d, Large-scale rubber plantation in Laos. e, Shifting cultivation and plantation landscapes in Indonesia (left) and Borneo (right). f, Plantations in the central DRC rainforest.

Clearing intensity and socioeconomic gradients of shifting cultivation

Clearing is a key component of shifting cultivation systems. Recent clearing intensity was characterised using the Hansen et al.^{27,28} tree cover loss data aggregated over 2015-2020 within mapped shifting cultivation landscapes, as a proxy for land-use intensity across rotational systems.

Clearing activity is highly heterogeneous across these landscapes (Fig. 4a). When the mapped 1-km areas were ranked by the sum of tree cover loss within it, the top 10% of those 1-km areas accounted for 37.2% of total tree cover loss over 2015-2020, indicating a strong spatial concentration of recent clearing activity. By contrast, 14% of areas showed no detectable tree-loss events during this period (Fig. 4c). These low-activity areas include woody savannas that fall below the forest definition (tree cover < 10% and height < 5 m) of the Hansen dataset, areas where no new clearing of forested land was detected within the observation window, and areas where shifting cultivation may be misclassified. Tree cover loss records only the first loss event per pixel since 2001. Consequently, repeated clearing within rotational systems following earlier disturbance may not be captured.

We defined high-intensity areas as those exceeding the 75th percentile of total tree cover loss. Across countries with mapped shifting cultivation, the proportion of high-intensity areas was correlated with total shifting cultivation extent (Spearman $\rho = 0.56$, $P < 0.001$; Fig. 4d), indicating that countries with larger shifting cultivation areas tend to exhibit a higher share of active clearing.

In absolute terms, high-intensity clearing is concentrated in Africa (59.2% of global high-intensity cells), reflecting its larger shifting cultivation extent. When normalized by mapped shifting cultivation area, Africa still shows the highest share of high-intensity clearing (28.1%), followed by Asia-Oceania (23.4%) and the Americas (20.2%), though the regional differences are modest. Prominent clusters occur in West Africa (e.g. Sierra Leone, Liberia and Guinea), as well as in the DRC, Laos and Madagascar (Fig. 4b).

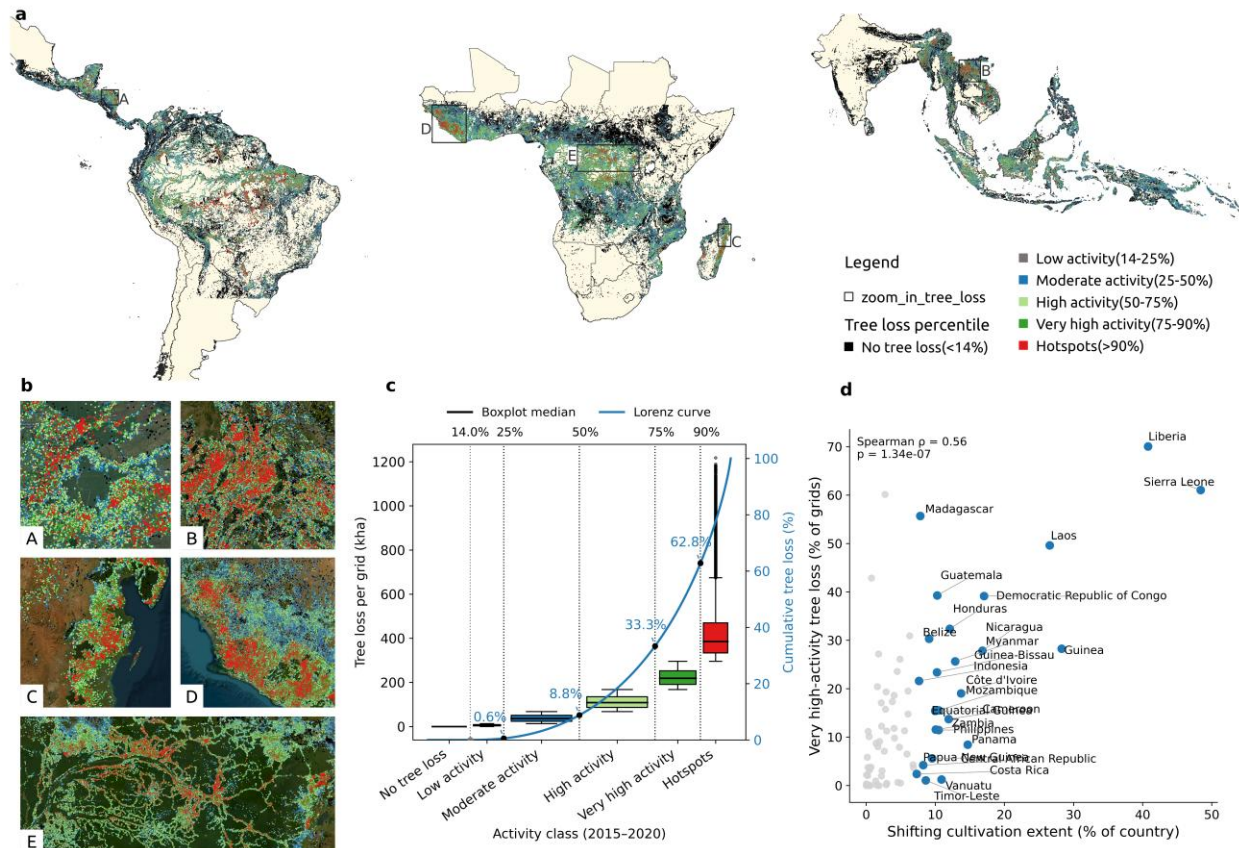


Fig. 4 | Spatial distribution and intensity of tree loss in shifting cultivation landscapes.

a, Global distribution of first-detected tree cover loss within shifting cultivation landscapes between 2015 and 2020, aggregated to 1-km grid cells and classified into six activity classes based on percentile thresholds of total tree cover loss. Boxes indicate regions shown in panel b. b, Close-up examples of high-intensity tree cover loss in five representative regions: A, Central America; B, Southeast Asia; C, Madagascar; D, West Africa; E, Democratic Republic of the Congo. c, Distribution of tree cover loss per grid cell (kha) across activity classes (boxplots), with the Lorenz curve (right axis) showing the

cumulative proportion of total tree cover loss. Percentile boundaries and cumulative loss shares are annotated. d, Relationship between national shifting cultivation extent (% of country area) and the proportion of grid cells exceeding the 75th percentile of total tree cover loss (very high activity and hotspots). Each point represents a country; blue points indicate the 25 countries with the highest shifting cultivation share. Spearman $\rho = 0.56$, $P < 0.001$.

Beyond spatial patterns of clearing activity, the relative importance of shifting cultivation also varies systematically with economic development. We examined this relationship among countries where shifting cultivation areas exceed permanent cropland area, using the ratio of shifting cultivation to cropland as an indicator of relative agricultural prominence. This ratio was negatively correlated with total GDP (Spearman $\rho = -0.36$, $P = 0.032$; $n = 37$), indicating that countries with larger total GDP tend to have lower relative shares of shifting cultivation (Extended Data Fig. S12). By contrast, no significant relationship was observed with GDP per capita ($\rho = 0.07$, $P = 0.67$; $n = 36$; Extended Data Fig. S13). This suggests that total national GDP, rather than GDP per capita, is more closely associated with the relative prominence of shifting cultivation within agricultural systems.

At the subnational level, clear patterns emerge along gradients of human development as defined by the Human Development Index (HDI)²⁹. The share of shifting cultivation declines consistently with increasing HDI, both relative to total land area (Fig. 5a) and to tree-dominated landscapes (Fig. 5c). Low-HDI regions, predominantly in Africa, show the highest shares and greatest variability, whereas very high HDI regions show uniformly low shifting cultivation shares. Intermediate-HDI regions retain substantial variability, indicating that land-use systems are at varying stages of change across these regions.

In contrast, mixed woody plantation cover is higher in regions with greater human development, both as a share of total land area (10.5% at Low HDI rising to 25.2% at High HDI) and as a share of tree-covered area (34.2% rising to 55.4%), indicating that plantation systems are more prevalent in higher-development contexts (Fig. 5b, d). At Very high HDI levels, plantation cover as a share of tree-covered area declines (50.4%), despite remaining elevated in absolute terms (24.6% of land area). This divergence may reflect a greater extent of natural or protected forest

314 cover in the highest-development regions, which is consistent with forest transition patterns
315 observed in high-income countries, though causal attribution is beyond the scope of this analysis.

316 Together with the decline in shifting cultivation, these patterns are consistent with an association
317 between increasing human development and the relative prevalence of permanent, tree-based
318 production systems, although this cross-sectional analysis cannot determine whether
319 development drives these differences or reflects broader structural and regional factors. Regional
320 variation remains pronounced. Plantation-dominated landscapes are more common in Asia-
321 Oceania and the Americas, whereas African regions generally exhibit limited plantation
322 expansion.

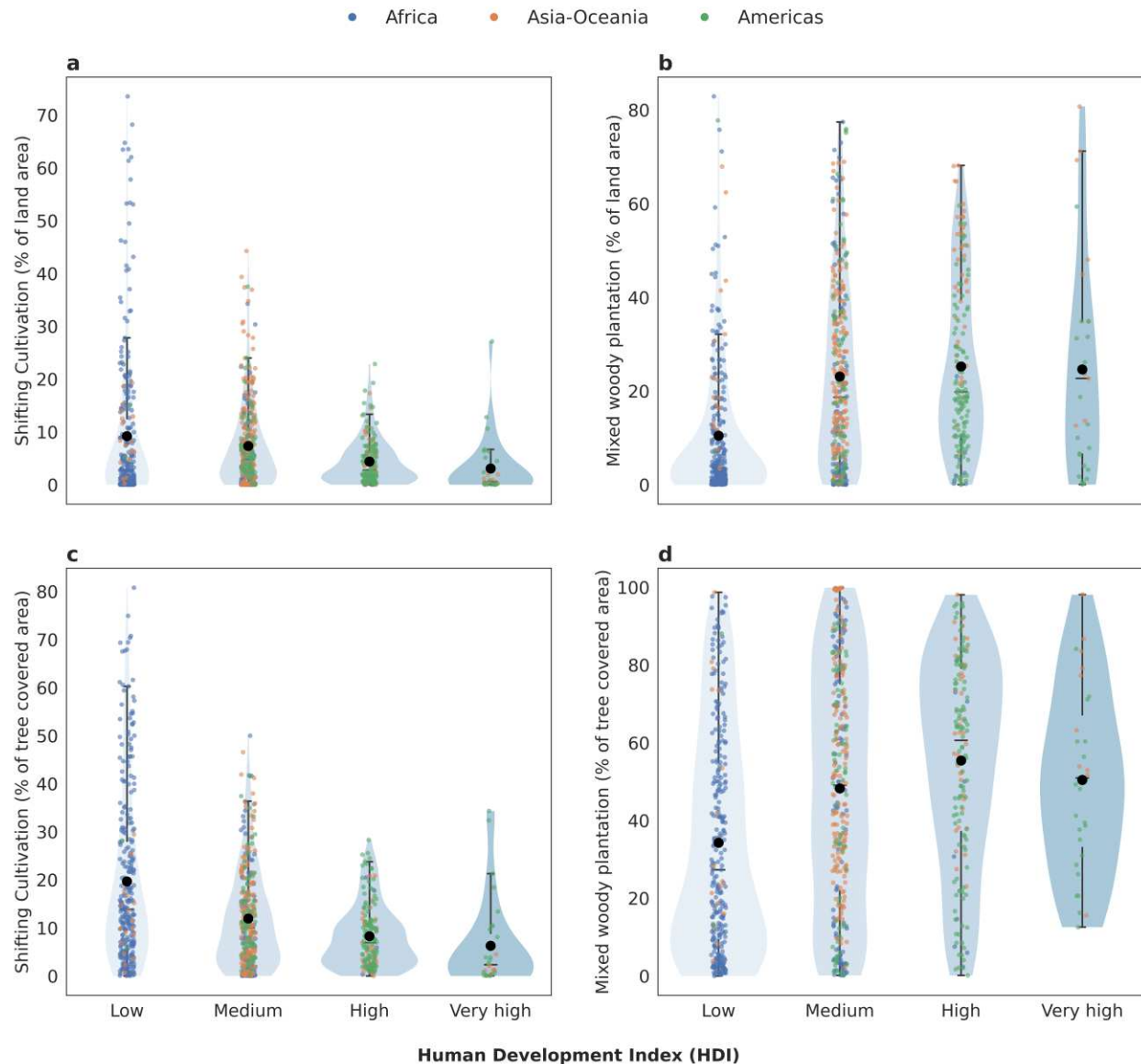


Fig. 5 | Distribution of shifting cultivation and mixed woody plantation across Human Development Index (HDI) classes. Violin plots show the subnational distribution of shifting cultivation (panels a, c) and mixed woody plantation (panels b, d) across four HDI categories (Low, Medium, High, Very high), with points represent the individual sub-administration unit colored by continent. Black dots indicate group means. HDI classes follow the United Nations Development Programme (UNDP) classification. a, Shifting cultivation as a percentage of total land area. b, Mixed woody plantation as a percentage of total land area. c, Shifting cultivation as a percentage of tree-covered area (high tree-cover

woodland, mixed woody plantation, and shifting cultivation). d, Mixed woody plantation as a percentage of tree-covered area.

Discussion

Shifting cultivation remains one of the most spatially extensive yet least mapped agricultural systems in the tropics. Mapping it at large spatial scales has traditionally relied on time-series trajectory analysis using decision tree-based algorithms, often constrained by coarse spatio-temporal resolution, persistent cloud cover, landscape heterogeneity, and limited transferability. Here, we demonstrate a complementary approach based on recognizing characteristic mosaic landscape patterns using high-resolution PlanetScope mosaics and deep learning. By reframing detection from temporal trajectories to spatial configuration signatures (Extended Data Fig. S3), we show that shifting cultivation can be robustly identified at 1 km resolution across the pantropics, with consistent performance from national to continental scales (Extended Data Table. S2, S5).

The presence of shifting cultivation across rainforest, woodland, and forest-savanna mosaic biomes confirms that the system is not confined to a single biome but occurs across diverse ecological settings³⁰. Topographic analyses show that contemporary shifting cultivation is concentrated in low- to mid-elevation, low-relief environments across the tropics, with regional differences in rainforest versus woodland dominance. Across continents, most mapped areas occur below moderate elevation thresholds and on gentle slopes, indicating that accessibility and terrain constraints remain key spatial controls. This contrasts with the traditional view of shifting cultivation as primarily a ‘hill practice’^{31,32}, where sloping terrain limits more intensive land uses such as irrigated paddy farming.

Distance-based analysis reveals that shifting cultivation landscapes are frequently located near plantation systems and permanent cropland, although the strength of these spatial associations varies substantially across regions. A large share of shifting cultivation occurs within short distances of plantations in Asia-Oceania and the Americas, whereas shifting cultivation in Africa is more commonly associated with permanent cropland. These gradients indicate heterogeneous transition pathways and suggest that mosaic systems are now often embedded within mixed agricultural frontiers rather than following a single uniform trajectory.

The observed proximity between plantation systems and shifting cultivation likely reflects multiple, regionally specific processes of agrarian change. In some settings, plantation expansion may directly convert or progressively replace shifting cultivation landscapes. In others, transitional coexistence may emerge during periods of land-use change, while plantation employment and rising cash incomes can reduce dependence on subsistence farming and shift food consumption toward purchased goods. Elsewhere, smallholder cultivation systems may persist alongside plantations to supply local markets or maintain livelihood diversity. Spatial proximity alone cannot distinguish among these mechanisms, but it provides measurable evidence that contemporary shifting cultivation transitions are closely linked to broader processes of commercialization, labour reallocation, and rural transformation.

We estimated that areas of shifting cultivation cover approximately 211.7 Mha across the pantropics. This estimate is considerably lower than the 400 Mha reported by the Food and Agriculture Organization (FAO) of the United Nations in the early 1980s, which was based on reports from 90 tropical countries, and lower than the more recent estimate of 280 Mha by Heinimann et al²³. This likely reflects both methodological differences and genuine land-use transitions over recent decades. Transitions away from shifting cultivation have been widely documented across Asian countries^{7,8,33}, whereas low population density in the Amazon has kept shifting cultivation active, where it represents the predominant agricultural system in riverine areas³⁴. Africa remains the largest contemporary hotspot, with shifting cultivation being widespread in both rainforest and open woodlands systems. This pattern is projected to persist or intensify through mid-century, especially for Central Africa²³. However, transitions from shifting cultivation are also emerging in Africa due to socio-economic change, infrastructure expansion, and policy interventions.

A persistent narrative within the poverty-environment nexus portrays shifting cultivation as inherently linked to rural poverty and environmental degradation³⁵, while transitions towards more permanent and intensive agriculture are often assumed to deliver a double dividend of poverty reduction and forest conservation. In practice, these outcomes are far from guaranteed and assessments of the socio-ecological impacts of shifting cultivation should be compared to counterfactual land uses. For instance, the designation of shifting cultivation areas as protected forest is assumed to reduce tree loss and improve ecological function and forest structure over

time, if strong forest governance is in place. In settings with weak forest governance, tree loss can continue or even accelerate, as profitable commodity crop or plantation expansion can accelerate permanent deforestation, while increases in average income may coincide with rising inequality, disputed tenure rights, and losses in autonomy, justice, and other non-material dimensions of well-being. More broadly, agricultural intensification does not automatically spare forests. Yield gains may also increase land rents and stimulate expansion (rebound/Jevons paradox)³⁶, meaning that environmental outcomes depend fundamentally on governance quality³⁷, tenure security, and market incentives³⁸. Evidence from the Amazon and broader syntheses further shows that legally recognized Indigenous and community land rights are often associated with lower deforestation, underscoring tenure as a critical moderator of land-use change³⁹. The continued presence of shifting cultivation is likewise context-dependent⁴⁰, reflecting either adaptive livelihood strategies or a lack of viable alternatives. Where land access is constrained, shortened fallow cycles and more frequent cultivation may reinforce poverty traps and further constrain land management options through declining soil fertility and reduced yields⁴¹.

As education, health services, infrastructure, and non-farm employment expand, reliance on extensive rotational systems like shifting cultivation often declines⁴². In several countries, transitions away from swidden have also been actively driven by land allocation, sedentarization, and forest zoning policies, which were often framed as ‘eradication’ or ‘stabilization’⁴³. Yet shifting cultivation functions as a rotational agroforestry system, and policies that rigidly separate ‘forest’ from ‘agriculture’ may undermine both ecological processes and livelihood resilience while displacing pressures elsewhere⁴⁴.

Our results show that countries with larger extents of shifting cultivation often coincide with more active land-use dynamics, reflected in concentrated tree-loss hotspots. However, the interpretation of tree loss within shifting cultivation landscapes depends on the counterfactual baseline. Within stable rotational systems, localized clearing may be offset by regrowth elsewhere, maintaining mosaic tree cover through time. Relative to permanent annual cropping systems, shifting cultivation often retains substantially more woody cover. However, compared with intact or protected forests, it generally exhibits lower forest quality, biodiversity value, and

carbon storage. Where the fallow period is shortened or repeated clearing intensifies, shifting cultivation may also contribute to net forest loss and ecological decline.

These distinctions cannot be resolved using static tree-loss indicators or single-date land-cover maps alone. A deeper understanding of its environmental and socio-ecological impacts requires more detailed land-use histories derived from dense satellite time series coupled with local institutional and livelihood data. Time-resolved observations would enable quantification of fallow duration, regrowth trajectories, and transitions to permanent land uses. This could allow clearer separation between stable rotational systems, intensified short-fallow practices, and permanent land conversion. Such temporal depth is essential for linking shifting cultivation to tree loss and vegetation recovery in a process-based way rather than through static spatial framework. This will become increasingly achievable as high-resolution satellite data records lengthen.

In this study, tree cover loss is interpreted as an indicator of clearing activity within landscapes mapped as shifting cultivation, rather than being attributed directly to shifting cultivation as the causal driver of individual loss events. This captures broader associations between shifting cultivation extent and active land-use change while avoiding unsupported assumptions about the cause of individual tree-loss events. Because land-use systems transition over time, pixels currently mapped as plantation or mixed agriculture may previously have been under shifting cultivation, or vice versa. A one-to-one attribution framework would therefore risk overstating causal relationships between present land cover and observed forest loss.

Improving temporally explicit mapping of shifting cultivation would also increase its visibility in land-use statistics and policy frameworks. Because shifting cultivation is often poorly represented or misclassified in existing land-cover products, it is frequently misrepresented or generalized in policy narratives and grouped with generalized deforestation drivers. More detailed and time-resolved datasets would support more context-sensitive policies by distinguishing rotational agroforestry systems from permanent conversion and large-scale plantation expansion.

Persistent cloud cover remains a major obstacle in tropical land-use mapping. We reduced this constraint by combining two independent PlanetScope composite mosaics and integrating prediction probabilities across dates, thereby lowering omission errors in persistently cloudy

regions. Classification uncertainty is primarily associated with boundaries between shifting cultivation and mixed woody plantation systems. The plantation class in our framework intentionally aggregates a wide range of plantation development stages (Extended Data Fig. S14), from early establishment to closed-canopy dominance, to ensure a conservative delineation of shifting cultivation extent. Consequently, it may omit transitional mosaics where plantation and fallow components coexist. Additional uncertainty occurs along forest-agriculture frontiers, where pasture expansion and short-fallow rotations can produce similar spatial patterns (Extended Data Fig. S15). These ambiguities reflect both landscape similarity and the limitations of single-date pattern recognition.

In summary, shifting cultivation remains a major but rapidly transforming tropical land-use system. Understanding where it persists, how it changes, and under which governance conditions transitions can support both rural livelihoods and forest conservation will be central to future tropical sustainability strategies.

Methods

We developed a deep learning-based framework to map shifting cultivation landscapes across the pantropics for the year 2020 using high-resolution PlanetScope satellite imagery. The method exploits the fact that shifting cultivation produces a characteristic mosaic-like landscape pattern through repeated cycles of clearing, cultivation, abandonment, and vegetation regrowth within a defined area. These cycles create heterogeneous spatial textures composed of newly cleared fields, fallows at multiple successional stages, and remnant forest patches.

Previous national-scale mapping approaches have primarily relied on long-term medium-resolution time series and decision tree-based algorithms to detect disturbance and regrowth trajectories. However, cloud contamination, data gaps, coarse spatial resolution, and strong regional heterogeneity (Extended Data Fig. S1) limit their applicability to consistent pantropical mapping. In contrast, high-resolution imagery captures fine-scale spatial mosaics directly, enabling landscape-pattern recognition without requiring long temporal image stacks. We therefore use high-resolution imagery in combination with a patch-based classifier that captures local spatial context to identify shifting cultivation based on its characteristic mosaic landscape patterns, rather than relying on temporal disturbance trajectories.

A detailed description of class definitions, satellite data, sampling methods, modelling, validation, and spatial analyses is provided below.

Class definitions

Shifting cultivation encompasses mosaic landscapes formed by cyclical clearing, cropping, abandonment, and regrowth, typically consisting of irregular patches of cleared land, fallows at multiple stages, and forest remnants. In addition to shifting cultivation, we introduced four other classes to help identify a clear shifting cultivation extent. *High tree cover woodland* encompasses dense forest and open-canopy woodland systems with predominantly continuous tree cover. *Conventional agriculture* includes permanent croplands and pasture systems characterised by continuous cultivation for food crop and livestock production. *Mixed Woody Plantation* represents land under structured plantation or agroforestry management, characterised by a mixture of woody perennial species. Unlike shifting cultivation systems, these areas do not exhibit spatial patterns of recent clearing, fallowing, or rotational field dynamics. The class therefore reflects more continuous and stable tree-based land management, often associated with long-term production systems. *Background* includes non-agricultural land uses including urban areas, water bodies, bare land, savannas, and shrublands with minimal human land-use signals. Visual examples of the five classes are provided in Extended Data Fig. S2.

Satellite image

We used PlanetScope nano-satellite imagery for both training sample generation and pantropical prediction. PlanetScope imagery is acquired from a constellation of small satellites (“Doves”) with near-daily global revisit frequency. This high temporal frequency, combined with 4.77m spatial resolution, enables detailed observation of fine-scale landscape structure, which is particularly important for mapping tropical forest ecosystems subject to persistent cloud cover.

Mosaic basemaps were accessed through the Norway’s International Climate and Forest Initiative (NICFI) Satellite Data Program⁴⁵. The dataset is provided as biannual composites, covering December–May and June–November periods. However, for 2020, Planet Labs released only a June–August composite for the second period. In this study, we used the December 2019–May 2020 mosaic for model development. To reduce cloud-related artefacts and improve prediction consistency, we additionally incorporated the June–August 2020 mosaic. Although

this does not correspond to the standard biannual composite, it provides complementary observations under different atmospheric conditions, reducing omission errors in persistently cloudy regions. All the satellite data were downloaded as customised one-degree grid tiles, which also served as the spatial unit for model inference and prediction mosaicking.

Study area

The study covers tropical regions between approximately 30°N–30°S across Africa, Asia-Oceania, and the Americas, where NICFI high-resolution mosaics are available, and shifting cultivation is known to occur. The spatial extent was further constrained using the occurrence dataset of Heinimann et al.²³ to guide the definition of the study region. The final study extent is illustrated in Extended Data Fig. S4. China was excluded due to lack of consistent PlanetScope mosaic coverage and limited present-day occurrence, despite historical localized practices⁴⁶

Calibration data

Mapping shifting cultivation is challenging due to strong spatial heterogeneity in landscape patterns across regions. To address this, we adopted a phased and scalable sampling strategy.

Model development was initiated in the Democratic Republic of the Congo (DRC), where shifting cultivation is particularly extensive and well-documented, providing a tractable starting point for establishing the sampling framework. After a prototyping phase on DRC, the training data were subsequently expanded to the African continental scale using stratified sampling to ensure balanced representation of land-use classes across diverse landscapes. Stratification was guided by the one-degree shifting cultivation occurrence dataset of Heinimann et al.²³. The sampling was then extended to the pantropical domain. At each stage, independent test datasets were withheld to evaluate model generalization.

Initial evaluation of the pantropical model revealed residual cloud-related artefacts, which introduced false positives in the prediction map. To improve classification robustness under varying cloud and seasonal conditions, we trained the final model using samples derived from two independent PlanetScope mosaics from 2020, a six-month composite (December 2019-May 2020) and a shorter-period composite (June-August 2020). This dual-mosaic approach provides complementary observations under different atmospheric conditions, thereby improving

classification consistency in persistently cloudy regions. Qualitative assessment of prediction maps confirms that the dual-mosaic approach substantially reduces cloud-related false positives (Extended Data Fig. S5).

In total, 84,016 samples were used for the final model. Sample sizes for each stage are reported in Extended Data Table S1. Sample distribution can be viewed in Extended Data Fig. S3. All sampling was conducted in QGIS (version 3.22).

Model

We used an EfficientNet-B1 convolutional neural network with a modified input layer and classification head for land-cover classification. The input convolutional layer was adapted to accept four-channel imagery (R, G, B, NIR). The classification head consisted of fully connected layers with dimensions 640, 320, 64, and 5, corresponding to the five target land-cover classes. Dropout ($p = 0.2$) was applied between layers to reduce overfitting.

The model was initialized with pre-trained weights from the ImageNet-1K dataset⁴⁷. Training was performed using the Adam optimizer with a learning rate of 5×10^{-5} and a multi-class cross-entropy loss function. A batch size of 15 was used. To improve generalization, data augmentation was applied, including horizontal and vertical flips, random rotations, downscaling, brightness and contrast adjustments, and Gaussian blur. Augmentation probabilities were assigned per sample to account for class imbalance.

The training and validation sets were split at an 8:2 ratio. Training was stopped when validation F1 score stabilized. The model checkpoint achieving the highest F1 score on the validation set was selected for inference. All training and prediction were performed on an NVIDIA GeForce RTX 3090 GPU.

Model and product accuracy assessment

Model performance was evaluated using independent hold-out test sets constructed at each stage of model development (DRC, Africa and global). For the DRC and Africa-scale models, 20% of samples were reserved for testing. For the global model, 10% were reserved to maximize the number of training samples. Model accuracy was assessed using precision, recall, overall

accuracy and F1 score. Confusion matrices for each geographic scale are provided in Extended Data Table S2.

We applied a stratified random sampling strategy⁴⁸ for map validation. Strata were defined by combining the predicted shifting cultivation prediction, the associated class probability (confidence) layer and an independent global forest loss driver dataset⁴⁹. Because strata were partly derived from the model's own outputs, the validation sample is not fully independent of the prediction map. However, purely random sampling would require a prohibitively large number of points to capture sufficient shifting cultivation observations at pantropical scale, and no independent pantropical reference dataset exists at this resolution. Four strata were defined to target the agreement, disagreement, and uncertainty between datasets. Stratum definitions and area proportions are summarized in Extended Data Table S3, and their spatial distribution is shown in Extended Data Fig. S10.

We randomly selected 100 sample locations from each stratum (Extended Data Fig. S11). Each sample location was spatially linked to its corresponding 1-km prediction grid cell derived from the original prediction tiles. The full 1-km grid cell was served as the validation unit. Land use within each validation unit was interpreted using high-resolution satellite imagery in Google Earth Pro. When 2020 imagery was unavailable, PlanetScope data and the nearest available subsequent imagery were used to support interpretation.

All validation units were interpreted across the five land-use classes, allowing accuracy estimates for all classes, though the stratification was designed to better capture areas of agreement and disagreement in shifting cultivation mapping. Each validation unit was assigned to one of the five land-use classes according to our class definitions. A unit was classified as shifting cultivation when evidence of rotational cropping was present without signs of plantation establishment. Units with visible plantation development were assigned to the woody plantation class (Extended Data Fig. S14). Conventional agriculture was assigned where agricultural land use was present without evidence of old-growth forests. For units located at forest edges, shifting cultivation was assigned when rotational patterns were evident, regardless of proportional area, whereas for conventional agriculture and plantations, the dominant land-use class within the grid cell determined the final label.

We followed the stratified estimation framework of Olofsson et al.⁵⁰, which corrects for unequal strata representation. Using the interpreted reference labels and the predicted map classes within the validation units, we computed an area-adjusted error matrix (Extended Data Table S4), and calculated user's accuracy, producer's accuracy and overall accuracy for all five classes.

Country-level statistics

We computed the area of each predicted grid cell using the equation for a rectangular area in geographic coordinates on a WGS84 reference ellipsoid⁴⁸. National boundaries polygons from the Global Data Lab (<https://globaldatalab.org/mygdl/downloads/shapefiles/>) were rasterized at 0.01° resolution, and each predicted pixel was assigned to the country in which its centroid falls. Country-level areas were computed by summing the pixel areas within each national boundary area, for each of the five land-cover classes. Countries with a mapped shifting cultivation area below 10 kha were excluded from the area estimation but are listed separately in the Supplementary Materials. The global shifting cultivation area was estimated as the sum of country-level areas across all countries exceeding the 10 kha threshold.

Uncertainty estimation

The validation sampling design was optimized to capture variation in shifting cultivation occurrence and uncertainty rather than proportional representation of all land-use classes. The user's and producer's accuracies for the shifting cultivation class (84.7% and 81.7%, respectively) indicate limited systematic bias between commission and omission errors. Mapped areas were therefore not adjusted using a full confusion-matrix-based area estimator.

Instead, uncertainty was estimated using user's accuracy (UA) under a binomial approximation. The standard error of the estimated area was calculated as:

$$SE(\hat{A}) = \hat{A} \sqrt{\frac{1 - UA}{n}}$$

Where $\hat{A}$ is the mapped area and n is the number of validation samples for the class. 95% confidence intervals were computed as ± 1.96 standard errors. These bounds reflect uncertainty associated with commission error and sampling variability but do not explicitly account for omission error and should therefore be interpreted as a lower bound on total mapping uncertainty.

One degree analysis

To enable comparison with the visual interpretation-based occurrence map of Heinimann et al.²³, we computed shifting cultivation occurrence within each of their 1-degree grid cells. For each grid cell, the occurrence percentage was calculated as the ratio of the summed shifting cultivation area to the total geodesic area of the cell, computed using the same WGS84 ellipsoidal zone formula mentioned in the section “Country-level statistics”. The resulting percentages were then classified into five occurrence levels following the original thresholds of Heinimann et al.²³: <1%, 1–9%, 10–19%, 20–39%, and ≥40%.

Agreement between our occurrence classification and that of Heinimann et al.²³ was assessed by comparing the occurrence level assigned to each overlapping one-degree grid cell. Cells where both maps assigned the same occurrence level were classified as high agreement. Cells differing by one level were classified as moderate agreement, and cells differing by two or more levels were classified as low agreement (Extended Data Fig. S7).

Biome statistics

Terrestrial ecoregion polygons from the World Wildlife Fund (WWF) dataset were rasterized at 0.01° resolution, and each predicted pixel was assigned to the biome in which its centroid falls. We retained four biome categories: Tropical & Subtropical Moist Broadleaf Forests (code 1), Tropical & Subtropical Dry Broadleaf Forests (code 2), Tropical & Subtropical Coniferous Forests (code 3), and Tropical & Subtropical Grasslands, Savannas & Shrublands (code 7). All remaining codes were merged into a single 'Other biomes' category. Biome codes, definitions and the grouping scheme are provided in Extended Data Table S6.

Topographic statistics

Topographic statistics were derived from the NASA Shuttle Radar Topography Mission (SRTM) 30-m digital elevation model (DEM), processed in Google Earth Engine (GEE). Slope were computed from the DEM, and mean elevation and mean slope values were extracted for each prediction pixel footprint.

Land-use proximity and spatial pattern analysis

To characterise spatial relationships between shifting cultivation and other agricultural land uses, we computed distances from each shifting cultivation pixel to the nearest conventional

agriculture and mixed woody plantation pixel from the prediction map. Pixel centroids pixels were used as source points. Distances were calculated using nearest-feature analysis in Equal Earth Greenwich coordinate system (EPSG:8857) to ensure metric accuracy. Results were summarized globally and by continent, and the proportion of shifting cultivation pixels within specified thresholds (2 km, 5 km and 10 km) were calculated.

Land use intensity proxy based on tree cover loss

Land-use intensity within shifting cultivation landscapes was approximated using tree cover loss as a proxy for recent clearing activity. Tree cover loss dynamics were quantified using the Global Forest Change dataset from Hansen et al.^{27,28}, which provides annual maps of tree-cover loss at 30 m resolution. We aggregated tree-loss pixels within 1-km shifting cultivation grid cells to calculate the total area of tree cover loss per grid between 2015 and 2020 using GEE. Tree-loss data prior to 2015 were excluded, as early-year layers underrepresent shifting cultivation dynamics in parts of Asia and the Americas due to omission of small-scale and rotational clearing events.

We calculated the proportion of grid cells recording no tree loss during 2015-2020, and derived percentile thresholds (25th, 50th, 75th, and 90th) from the distribution of total tree cover loss area per 1-km grid cell. These percentiles therefore represent relative thresholds of tree-loss magnitude across grid cells, rather than proportions of area or number of grids. Based on these thresholds, grid cells were classified into six activity categories: no tree loss, low activity (<25th percentile), moderate activity (25–50th percentile), high activity (50–75th percentile), very high activity (75–90th percentile) and hotspots (>90th percentile). The distribution of tree-loss intensity across grid cells was visualized using boxplots. To assess the concentration of clearing activity, we constructed a Lorenz curve relating the ranked proportion of grid cells to their cumulative share of total tree cover loss.

For country-level analysis, high-intensity areas were defined as grid cells exceeding the 75th percentile of the tree-loss distribution (combining very high activity and hotspot classes). The proportion of such grid cells within each country was used as an indicator of relative clearing intensity within shifting cultivation systems. This indicator was then compared with the national share of shifting cultivation (% of country area) using Spearman rank correlation.

677 **GDP analysis**

678 To examine whether shifting cultivation extent is associated with national economic
679 development, we combined country-level estimates of shifting cultivation extent with cropland
680 statistics and economic indicators. Shifting cultivation area per country was derived from the
681 prediction map with the approach described in the Country-level statistics section.

682 Cropland area statistics were obtained from Peter Potapov et al.²⁰, which maps annual and
683 perennial herbaceous crops and explicitly excludes shifting cultivation, woody plantations and
684 long-fallow systems. Total gross domestic product (GDP) and GDP per capita, were obtained
685 from the World Bank⁵¹.

686 For each country, we calculated the ratio of shifting cultivation area to cropland area as an
687 indicator of the relative importance of shifting cultivation within agricultural systems. The
688 analysis was restricted to countries where shifting cultivation area exceeded cropland area,
689 focusing on systems where shifting cultivation represents a dominant land-use component.

690 The relationship between the shifting cultivation-to-cropland ratio and economic indicators (total
691 GDP and GDP per capita) was assessed using Spearman rank correlation.

692 **HDI spatial analysis**

693 Subnational socioeconomic associations were assessed using the Human Development Index
694 (HDI) data²⁹. Subnational units were classified into four categories: Low, Medium, High and
695 Very High. For each subnational unit, we calculated the proportion of land under shifting
696 cultivation and mixed woody plantations relative to (1) area of national land (2) area of tree-
697 dominated land. Tree-dominated land was defined as the sum area of shifting cultivation, high
698 tree-cover woodland and mixed woody plantation classes derived from the prediction map.

Code Availability statement

An interactive map viewer of the pantropical shifting cultivation map is available at <https://ee-wanting.projects.earthengine.app/view/pantropicalshiftingcultivationmap>. All codes used for model training, inference, and accuracy assessment are available at <https://github.com/ywant/sc-mapping>. Trained model weights and example data are deposited on Zenodo at <https://doi.org/10.5281/zenodo.20392308>.

Data Availability

PlanetScope imagery was accessed through the Norway's International Climate and Forest Initiative (NICFI) Satellite Data Program for non-commercial research use. Although the public access programme has ended, data remain commercially available through Planet's Tropical Forest Observatory platform <https://www.planet.com/tropical-forest-observatory/>. The global cropland dataset is available from the Global Land Analysis and Discovery (GLAD) laboratory, <https://glad.umd.edu/dataset/croplands>. The World Wildlife Fund (WWF) Terrestrial Ecoregions dataset is available from the WWF website, <https://wwf.panda.org>. Shuttle Radar Topography Mission (SRTM) elevation data are available through Google Earth Engine https://developers.google.com/earth-engine/datasets/catalog/USGS_SRTMGL1_003. The Global Forest Change dataset is available at <https://storage.googleapis.com/earthenginepartners-hansen/GFC-2025-v1.13/download.html>. Human Development Index (HDI) data are available from the United Nations Development Programme <https://hdr.undp.org/data-center/human-development-index#/indicies/HDI>. Gross domestic product (GDP) statistics are available from the World Bank World Development Indicators database <https://databank.worldbank.org/source/world-development-indicators>.

Reference

1. Padoch, C. *et al.* The Demise of Swidden in Southeast Asia ? Local Realities and Regional Ambiguities. **7223**, (2014).
2. Mertz, O. *et al.* Swidden change in southeast Asia: Understanding causes and consequences. *Human Ecology* vol. 37 259–264 Preprint at <https://doi.org/10.1007/s10745-009-9245-2> (2009).
3. Bruun, T. B. & Hepp, C. M. Carbon footprint of shifting cultivation landscapes: current knowledge, assumptions and data gaps. *Carbon Footprints* <https://doi.org/10.20517/cf.2023.06> (2023) doi:10.20517/cf.2023.06.
4. UNFCCC. *Shifting Cultivation and Climate Change*. (2009).
5. Mertz, O. *et al.* Who counts? Demography of swidden cultivators in southeast asia. *Hum. Ecol.* **37**, 281–289 (2009).
6. Boserup, E. The conditions of agricultural growth: The economics of agrarian change under population pressure. *The Conditions of Agricultural Growth: The Economics of Agrarian Change Under Population Pressure* 1–124 (1965) doi:10.4324/9781315016320.
7. van Vliet, N. *et al.* Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: A global assessment. *Global Environmental Change* **22**, 418–429 (2012).
8. Martin, D. A. *et al.* Drivers and consequences of archetypical shifting cultivation transitions. *People and Nature* **5**, 529–541 (2023).
9. Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A. & Hansen, M. C. Classifying drivers of global forest loss. *Science* (1979). **361**, 1108–1111 (2018).
10. Silva, J. M. N., Carreiras, J. M. B., Rosa, I. & Pereira, J. M. C. Greenhouse gas emissions from shifting cultivation in the tropics, including uncertainty and sensitivity analysis. *Journal of Geophysical Research Atmospheres* **116**, 1–21 (2011).
11. Descals, A., Gaveau, D. L. A., Wich, S., Szantoi, Z. & Meijaard, E. Global mapping of oil palm planting year from 1990 to 2021. *Earth Syst. Sci. Data* **16**, 5111–5129 (2024).
12. Descals, A. *et al.* High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth Syst. Sci. Data* **13**, 1211–1231 (2021).
13. Wang, Y. *et al.* High-resolution maps show that rubber causes substantial deforestation. *Nature* **623**, 340–346 (2023).

- 754 14. Parra-Paitan, C., Meyfroidt, P., Verburg, P. H. & zu Ermgassen, E. K. H. J. Deforestation
755 and climate risk hotspots in the global cocoa value chain. *Environ. Sci. Policy* **158**, 103796
756 (2024).
- 757 15. Song, X. P. *et al.* Massive soybean expansion in South America since 2000 and
758 implications for conservation. *Nat. Sustain.* **4**, 784–792 (2021).
- 759 16. Picoli, M. C. A. *et al.* Big earth observation time series analysis for monitoring Brazilian
760 agriculture. *ISPRS Journal of Photogrammetry and Remote Sensing* **145**, 328–339 (2018).
- 761 17. Villa, P. M. *et al.* Reducing intensification by shifting cultivation through sustainable
762 climate-smart practices in tropical forests: A review in the context of UN Decade on
763 Ecosystem Restoration. *Current Research in Environmental Sustainability* **3**, (2021).
- 764 18. Dressler, W. H. *et al.* The impact of swidden decline on livelihoods and ecosystem
765 services in Southeast Asia: A review of the evidence from 1990 to 2015. *Ambio* **46**, 291–
766 310 (2017).
- 767 19. Bruun, T. B. *et al.* Long rotation swidden systems maintain higher carbon stocks than
768 rubber plantations. *Agric. Ecosyst. Environ.* **256**, 239–249 (2018).
- 769 20. Potapov, P. *et al.* Global maps of cropland extent and change show accelerated cropland
770 expansion in the twenty-first century. *Nat. Food* **3**, 19–28 (2022).
- 771 21. Magliocca, N. R. *et al.* Synthesis in land change science: methodological patterns,
772 challenges, and guidelines. *Reg. Environ. Change* **15**, 211–226 (2015).
- 773 22. Chen, S., Olofsson, P., Saphangthong, T. & Woodcock, C. E. Monitoring shifting cultivation
774 in Laos with Landsat time series. *Remote Sens. Environ.* **288**, 113507 (2023).
- 775 23. Heinimann, A. *et al.* A global view of shifting cultivation: Recent, current, and future
776 extent. *PLoS One* **12**, 1–21 (2017).
- 777 24. Rufin, P., Bey, A., Picoli, M. & Meyfroidt, P. Large-area mapping of active cropland and
778 short-term fallows in smallholder landscapes using PlanetScope data. *International*
779 *Journal of Applied Earth Observation and Geoinformation* **112**, (2022).
- 780 25. Jiang, N., Li, P. & Feng, Z. Remote sensing of swidden agriculture in the tropics: A review.
781 *International Journal of Applied Earth Observation and Geoinformation* **112**, 102876
782 (2022).
- 783 26. Tuia, D. *et al.* Artificial Intelligence to Advance Earth Observation: A review of models,
784 recent trends, and pathways forward. *IEEE Geosci. Remote Sens. Mag.* 2–25 (2024)
785 doi:10.1109/mgrs.2024.3425961.

- 786 27. Potapov, P. *et al.* The Global 2000-2020 Land Cover and Land Use Change Dataset
787 Derived From the Landsat Archive: First Results. *Frontiers in Remote Sensing* **3**, (2022).
- 788 28. Hansen, M. C. *et al.* High-Resolution Global Maps of 21st-Century Forest Cover Change.
789 *Science* (1979). **342**, 850–853 (2013).
- 790 29. Smits, J. & Permanyer, I. Data descriptor: The subnational human development database.
791 *Sci. Data* **6**, 1–15 (2019).
- 792 30. Browder, J., Hecht, S. & Thrupp, L. A. *The Diversity and Dynamics of Shifting Cultivation:
793 Myths, Realities, and Human Dimensions.* (1995).
- 794 31. Kurien, A. J., Lele, S. & Nagendra, H. Farms or Forests? Understanding and mapping
795 shifting cultivation using the case study of West Garo hills, India. *Land (Basel)*. **8**, (2019).
- 796 32. Arman, A. A. H., Khatun, R. & Masum, K. M. Transformation of Jhum (Shifting Cultivation)
797 to Forest Plantation: Effect on Soil Properties in the Hill Tracts of Bangladesh. *Forestist*
798 **74**, 333–341 (2024).
- 799 33. Padoch, C. *et al.* The demise of Swidden in Southeast Asia? Local realities and regional
800 ambiguities. *Geografisk Tidsskrift* **107**, 29–41 (2007).
- 801 34. van Vliet, N., Adams, C., Vieira, I. C. G. & Mertz, O. ‘Slash and Burn’ and ‘Shifting’
802 Cultivation Systems in Forest Agriculture Frontiers from the Brazilian Amazon. *Soc. Nat.
803 Resour.* **26**, 1454–1467 (2013).
- 804 35. Takasaki, Y. Economic Models of Shifting Cultivation: A Review. *Deforestation Around the
805 World* <https://doi.org/10.5772/35745> (2012) doi:10.5772/35745.
- 806 36. Goulart, F. F., Chappell, M. J., Mertens, F. & Soares-Filho, B. Sparing or expanding? The
807 effects of agricultural yields on farm expansion and deforestation in the tropics.
808 *Biodivers. Conserv.* **32**, 1089–1104 (2023).
- 809 37. Benzeev, R. *et al.* What’s governance got to do with it? Examining the relationship
810 between governance and deforestation in the Brazilian Amazon. *PLoS One* **17**, 1–25
811 (2022).
- 812 38. Abman, R. & Lundberg, C. Contracting, market access and deforestation. *J. Dev. Econ.*
813 **168**, 103269 (2024).
- 814 39. Pacheco, A. & Meyer, C. Land tenure drives Brazil’s deforestation rates across socio-
815 environmental contexts. *Nat. Commun.* **13**, 1–10 (2022).

- 816 40. Mukul, S. A. & Herbohn, J. The impacts of shifting cultivation on secondary forests
817 dynamics in tropics: A synthesis of the key findings and spatio temporal distribution of
818 research. *Environ. Sci. Policy* **55**, 167–177 (2016).
- 819 41. Coomes, O. T., Takasaki, Y. & Rhemtulla, J. M. Land-use poverty traps identified in
820 shifting cultivation systems shape long-term tropical forest cover. *Proc. Natl. Acad. Sci. U.*
821 *S. A.* **108**, 13925–13930 (2011).
- 822 42. Dawson, N. M. *et al.* Environmental justice research shows the importance of social
823 feedbacks in ecosystem service trade-offs. *Ecology and Society* **22**, (2017).
- 824 43. Vongvisouk, T., Mertz, O., Thongmanivong, S., Heinimann, A. & Phanvilay, K. Shifting
825 cultivation stability and change : Contrasting pathways of land use and livelihood change
826 in Laos. *Applied Geography* **46**, 1–10 (2014).
- 827 44. Castella, J. C. *et al.* Effects of Landscape Segregation on Livelihood Vulnerability: Moving
828 From Extensive Shifting Cultivation to Rotational Agriculture and Natural Forests in
829 Northern Laos. *Hum. Ecol.* **41**, 63–76 (2013).
- 830 45. Planet. NICFI (Norway’s International Climate and Forest Initiative) Satellite Data
831 Program. (2025).
- 832 46. Yin, L., Zachary, M., Zheng, Y., Zhang, X. & Sakwa, A. Traditional Ecological Knowledge of
833 Shifting Agriculture of Bulang People in Yunnan, China. *American Journal of*
834 *Environmental Protection* **9**, 56 (2020).
- 835 47. Deng, J. *et al.* ImageNet: A Large-Scale Hierarchical Image Database. in *2009 IEEE*
836 *Conference on Computer Vision and Pattern Recognition, CVPR 2009* 248–255 (IEEE
837 Computer Society, 2009). doi:10.1109/CVPR.2009.5206848.
- 838 48. Tyukavina, A., Stehman, S. V., Pickens, A. H., Potapov, P. & Hansen, M. C. Practical global
839 sampling methods for estimating area and map accuracy of land cover and change.
840 *Remote Sens. Environ.* **324**, 114714 (2025).
- 841 49. Sims, M. J. *et al.* Global drivers of forest loss at 1 km resolution. *Environmental Research*
842 *Letters* **20**, (2025).
- 843 50. Olofsson, P. *et al.* Good practices for estimating area and assessing accuracy of land
844 change. *Remote Sens. Environ.* **148**, 42–57 (2014).
- 845 51. World Bank. *World Development Indicators (WDI)*. (2024).
- 846

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