Integrating Earth Observation and Ecological Modeling to Advance Sustainability Assessment of Cocoa Expansion

Shuntian Wang[1,2*], Yue Yu[1,*], Christie Walker[1], Jorge Perez[3], Wendy Francesconi[3], Jhon Tello[3], Louis Reymondin[3], Stephan Pfister[1,2]

[1]*Ecological Systems Design, Institute of Environmental Engineering, ETH Zurich*

[2] *Institute of Science, Technology and Policy, ETH Zurich*

[3] *Alliance of Bioversity International and CIAT*

*Contact of corresponding author: shuntian.wang@ifu.baug.ethz.ch, yueyuy@ethz.ch

SI Table of Contents

Supplementary Text

Text S1. Region of interest: Ucayali Agroecological Living Landscape (UALL), Peru

Text S2. Quantification of the loss of water purification services from cocoa-driven deforestation

Supplementary Figures

Figure S1. Location map of the Agroecological Living Landscape (UALL).

Figure S2. The workflow for mapping LULC by leveraging multi-source satellite imagery and machine learning for classification.

Supplementary Tables

Table S1. Assigned mean species abundance (MSA) values for animals and plants corresponding to different LULC classes used as input parameters in the GLOBIO4 model.

Table S2. The identification of nature land cover and human land use based on the LULC code.

Table S3. LULC-Specific Biophysical Parameters for NDR Modeling.

Table S4. The area of direct deforestation caused by cocoa cultivation in each district of UALL (measured in hectares).

Table S5. The area and rate of deforestation from 2000 to 2020 in each district (measured in hectares).

References

Text S1. Region of interest: Ucayali Agroecological Living Landscape (UALL), Peru

The Ucayali department lies in the central-eastern Peruvian Amazon, encompassing four provinces—Coronel Portillo, Padre Abad, Atalaya, and Purús—and spanning 102,400 km². Within this region, the Agroecological Living Landscape (UALL) for the CGIAR Agroecology Initiative includes the entirety of Padre Abad Province, along with the districts of Nueva Requena, Campoverde, Manantay, and Yarinacocha in Coronel Portillo Province (home to the regional capital, Pucallpa). Spanning 14,064 km², roughly 14% of Ucayali's total area, the UALL closely aligns with the regionally designated Agroecological Corridor, known as the Cuenca de Aguaytía (Pareja et al., 2023).

Ucayali features a warm-humid climate characteristic of the Amazonian bioclimatic region, with a departmental multi-year mean temperature of ~26 °C and rainfall of ~2,000 mm per year (2000–2015 baseline) (Castro et al., 2021; Pareja et al., 2023). The UALL encompasses two distinct sub-zones: a cooler, wetter sub-Andean western sector (min ~10 °C; max ~31 °C; 3,000–4,500 mm precipitation per year) and a drier, warmer Amazon plain that hosts the majority of agricultural activity (min ~19 °C; max ~32 °C; 1,200–3,000 mm precipitation per year). Predominantly shaped by the Aguaytía River basin—a major tributary of the Ucayali River—the UALL saw licensed consumptive water use in 2021 heavily dominated by agriculture (~94% of the granted volume), followed by domestic, industrial, and other uses.

The physiographic diversity of the UALL is striking, encompassing three major provinces: the Andean Mountain Range (sub-Andean zone), the Amazon sedimentary basin (Amazon plain), and the Sierra del Divisor. This mosaic results in a landscape dominated by mountains (~15%), hills (~40%), and plains/terraces (~43%), transitioning from rugged sub-Andean terrain in the Aguaytía headwaters to expansive alluvial lowlands at its confluence with the Ucayali River (Pareja et al., 2023). Land-use capacity assessments, grounded in Ecological Economic Zoning, reveal that 58% of the UALL is ideally suited for protection or sustainable forest production. Merely 33% is deemed appropriate for agricultural pursuits (albeit with notable limitations), while the remaining ~9% consists of zones with mixed agricultural potential embedded within protective forest areas.

Ucayali holds national significance for biodiversity conservation, containing approximately 9.21 million hectares of forests ("Resolución Ministerial N.° 179-2021-MINAM," n.d.) and 10 Protected Natural Areas (PNAs) that total ~2.26 million hectares, covering ~22% of the departmental area. The UALL itself includes four PNAs: Cordillera Azul National Park (~73,901 hectares) and three private conservation areas (~5,320 hectares total). Regional inventories document remarkable species richness, including ~1,600 plant species, >377 fish, 402 amphibians, 82 reptiles, 782 birds, and 257 mammals (J, 2022; Pareja et al., 2023). The dominant Selva Baja ecozone is characterized by high tree density (~458 individuals per hectare; DBH ≥10 cm) and contains the highest estimated carbon stock among all Peruvian ecozones, at ~138.84 Mg C per hectare (Silvestre, 2020).

Ucayali has experienced substantial historical forest loss, totaling ~1.03 million hectares, with approximately half of this loss occurring between 2001 and 2021. This deforestation is disproportionately concentrated within the UALL, which accounted for ~55% of the department's total forest loss during this period. By 2021, roughly 40% of the UALL's original

forest cover had been cleared (Pareja et al., 2023; “Resolución Ministerial N.° 179-2021-MINAM,” n.d.) The principal proximate drivers are agricultural expansion—for crops such as oil palm, cocoa, and pasture—and infrastructure development, particularly roads. These pressures are compounded by underlying factors including limited governance capacity, weak regulatory enforcement, poor inter-sectoral coordination, and corruption, all of which elevate forest conversion risk.

Ucayali is a key national producer of cocoa, ranking third in output with ~21,600 tons harvested in 2021 (Charry et al., 2023). Production has surged in the past decades, driven primarily by area expansion rather than yield intensification (mean ~977 kg per hectare in 2021). This production is highly concentrated in the UALL, which accounts for ~72% of departmental production and ~76% of the harvested area. Cocoa cultivation is dominated by small- to medium-scale farmers, with a mean agricultural unit size of ~23 hectares, of which ~2 hectares is dedicated to cocoa (Pareja et al., 2023). These farms are typically diversified, commonly integrating banana (~62%), cassava (~25%), and other subsistence and cash crops, alongside small-scale livestock. The field design for cocoa plantations typically employs a 3×3 m spacing (in square or triangular arrangements), corresponding to a density of approximately 1,100–1,300 plants per hectare (Goñas et al., 2022; Rojas-Briceño et al., 2022). For clones with low to medium vigor where higher densities are desired, a 3×2 m configuration (≈1,666 plants/ha) is also common. Shade cover is maintained at 30–50% during the first two years of plantation establishment and is gradually reduced to approximately 20% (typically 10–20%) as the cocoa canopy closes to ensure adequate ventilation and light penetration (Rajab et al., 2016). Pruning management begins with formation pruning after planting to define the trunk and select 3–4 primary branches ((Goñas et al., 2022; Rojas-Briceño et al., 2022)). This is followed by maintenance pruning approximately every 6 months to remove chupons (water sprouts), crossing, diseased, or dead branches, and basal suckers, with phytosanitary pruning performed as needed. During the productive phase, tree height is controlled at around 3–4 m to facilitate harvesting and mitigate disease risk (Goñas et al., 2022; Rojas-Briceño et al., 2022). This approach helps maintain robust yields and ecosystem services in a complex landscape where conventional and organic systems operate alongside high-carbon forests and sensitive hydrological systems. Market segmentation exists between conventional and certified organic producers, with the latter estimated to represent ~38% of the cocoa area (2020) (Pareja et al., 2023). The UALL thus represents a critical tropical agricultural landscape, where the expansion of smallholder cocoa mosaics directly interfaces with high-carbon, biodiversity-rich forests and water quality sensitive systems.

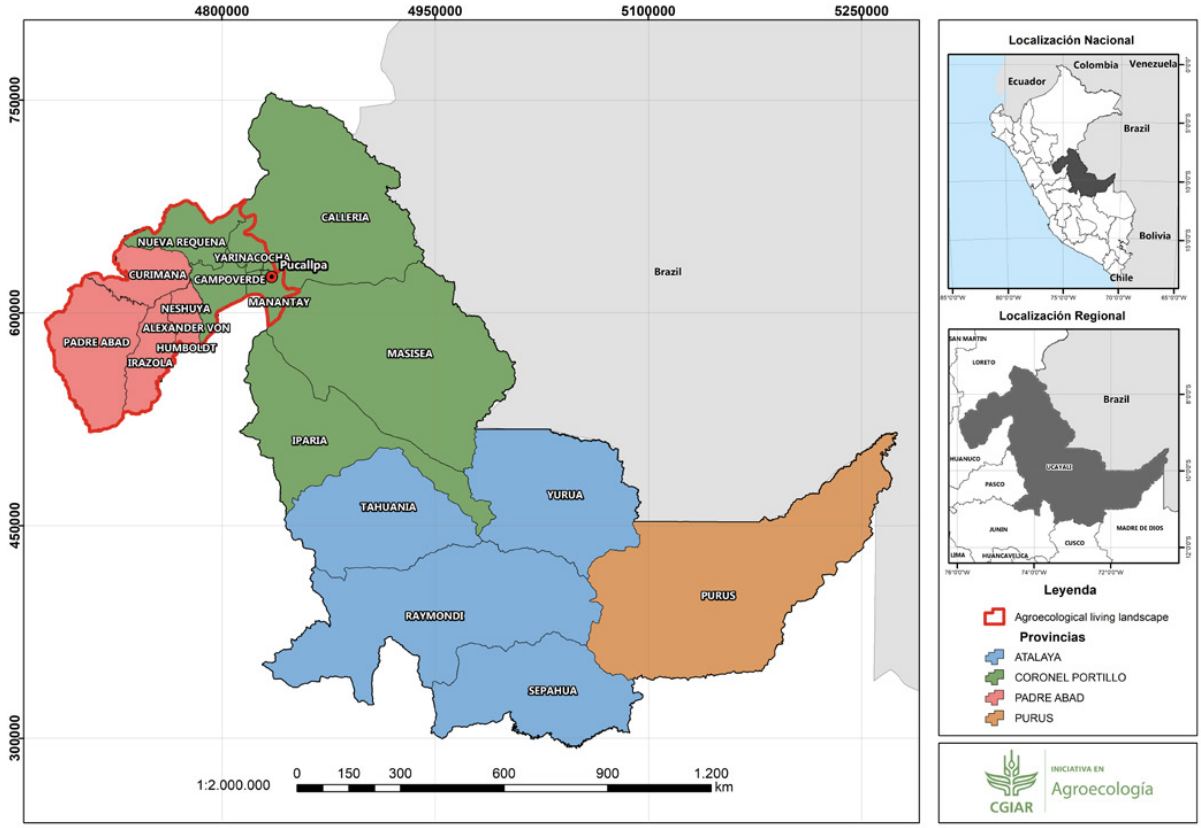

Figure S1. Location map of the Agroecological Living Landscape (UALL). The map displays the geographical location of the UALL within Peru, highlighting its position in the Ucayali region and showing the specific administrative districts included. Two inset maps provide context: the upper inset shows the location of the Ucayali region within Peru, while the lower inset details the regional boundaries. This map was directly referenced from "Analysis of the context and agroecological principles in Ucayali's ALL" by Piedad Pareja.

Text S2. Quantification of the loss of water purification services from cocoa-driven deforestation

To quantify the degradation of the water purification service, this study simulated the increase in nitrogen (N) export resulting from cocoa-driven deforestation. The assessment was conducted using the Nutrient Delivery Ratio (NDR) model, a component of the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) software suite developed by the Natural Capital Project (Natural Capital Project, 2024). The NDR model is specifically designed to map nutrient sources from watersheds and their transport to stream networks, providing a spatially explicit quantification of nutrient retention by natural vegetation. By simulating how LULC change affects nutrient runoff from non-point terrestrial sources, the model provides a powerful tool for assessing impacts on water quality. The primary objective of its application in this study was to quantify the change in nitrogen retention capacity of the landscape following the conversion of native forest to cocoa cultivation.

The InVEST NDR model is a spatially explicit, empirical model that estimates the long-term, steady-state export of nutrients from each pixel on a landscape to the adjacent stream network. Unlike more sophisticated, process-based biogeochemical models that require extensive and often unavailable input data, the NDR model leverages simplified empirical

relationships to simulate nutrient cycling and transport. This approach makes it exceptionally well-suited for regional-scale assessments in data-limited contexts, such as the agricultural landscapes of the Amazon basin. The model's logic is centered on two fundamental processes that are calculated for each grid cell in the landscape: (1) Nutrient Loading: This represents the gross amount of a nutrient generated on a given grid cell, which is primarily a function of its LULC type and local runoff potential. (2) Nutrient Delivery: This represents the proportion of the nutrient load from a pixel that is transported downslope and ultimately reaches the stream. This proportion is determined by the hydrological connectivity of the pixel to the stream and the nutrient retention capacity of the downslope flow path.

The total nutrient export from a pixel is calculated as the product of its nutrient load and its NDR. The model accounts for two primary nutrient transport pathways: surface runoff and subsurface flow. This distinction is particularly important for nitrogen, a portion of which is highly mobile as dissolved nitrate in groundwater. The model partitions the total load on a pixel into surface and subsurface components based on a user-defined parameter, proportion_subsurface_n, which quantifies the ratio of dissolved nutrients to the total nutrient amount. The NDR for a pixel is a critical component that reflects its position in the landscape and the filtering capacity of downslope ecosystems. It is calculated as a function of several factors, most notably the Index of Connectivity (IC) and the retention efficiency of LULC types along the flow path. The IC is a topographic index derived from the Digital Elevation Model (DEM) that represents the hydrological connectivity, or the likelihood that a nutrient on a pixel will reach the stream. The model calculates the proportion of nutrients that are not retained by downslope pixels, considering their LULC-specific retention efficiencies and a characteristic retention length. The final NDR value integrates these factors to estimate what fraction of the nutrient load from the pixel will be delivered to the stream.

The selection of the InVEST NDR model for this analysis was a strategic decision that balanced the need for quantitative, spatially explicit outputs with the practical constraints of data availability in the study region. The UALL is a dynamic agricultural landscape, a context often characterized by a scarcity of the detailed, long-term data required by more complex hydrological models (e.g., SWAT). Such models typically demand extensive parameterization, including detailed soil physics, daily meteorological data, and precise fertilizer and manure application rates, which are not available at the scale of this analysis. The InVEST NDR model is designed precisely for these conditions. It provides robust, quantitative estimates of nutrient export in physical units (kg/year), which is essential for assessing ecosystem service loss, without imposing prohibitive data requirements. The model's primary strength, and a key reason for its selection, lies in its application for scenario comparison. By running the model for a baseline (pre-deforestation) scenario and a current (post-deforestation) scenario while holding all other inputs constant, the analysis can robustly quantify the change in nutrient export attributable solely to LULC change.

The NDR model requires a suite of geospatial data layers to simulate nutrient transport across the landscape. Each dataset was carefully selected and pre-processed to ensure consistency in spatial resolution, projection, and extent, thereby guaranteeing the analytical integrity of the model runs.

A high-quality Digital Elevation Model (DEM) is the foundational dataset for the NDR model, as it is used to derive all topographic and hydrological characteristics of the landscape. The analysis utilized the Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global digital elevation model. Specifically, the void-filled Version 3 product (SRTMGL1 v003), provided by the NASA Jet Propulsion Laboratory (JPL) (NASA Jet Propulsion Laboratory and NASA, 2013), was selected. This dataset has a spatial resolution of approximately 30 m at the equator and was generated from data collected by the Space Shuttle Endeavour in February 2000. Data tiles covering the study region were acquired through the U.S. Geological Survey (USGS) EarthExplorer portal. Individual SRTM tiles were mosaicked to create a single, continuous elevation raster covering the entire UALL study area. The mosaicked DEM was then projected to the appropriate Universal Transverse Mercator (UTM) zone for the central Peruvian Amazon to ensure that all distance and area calculations performed by the model were accurate. No manual hydrological conditioning (e.g., sink filling or stream burning) was performed on the DEM, as the InVEST software suite includes robust internal algorithms to pre-process the elevation data and derive hydrologically consistent flow paths. The DEM is used by the model to compute flow direction, flow accumulation, slope gradients, and the critical Index of connectivity that governs the simulated pathways of nutrient transport from land to water.

The LULC maps serve as the primary drivers of spatial heterogeneity in the model, defining both the location and magnitude of nutrient sources and retention sinks across the landscape. To specifically isolate the impact of cocoa-driven deforestation, two distinct LULC maps were prepared. The Baseline scenario represents a hypothetical landscape in 2020 without cocoa-driven deforestation, where pixels classified as cocoa in 2020 were reassigned to their original forest or other pre-cocoa land cover from the year 2000. The Current Scenario represents the actual contemporary landscape of 2020, explicitly reflecting cocoa-driven deforestation that occurred between 2000 and 2020. Both LULC maps were prepared as raster datasets with the same spatial resolution (~10 m), coordinate projection (UTM), and DEM to ensure precise cell-by-cell alignment. Integer codes (lucode) assigned to each land cover class in these rasters were matched with corresponding codes in the biophysical input table (see Table S3). The LULC map thus acts as the core variable in this analysis, as the model relies on the lucode of each grid cell to assign its nitrogen load and retention efficiency parameters. Given that the LULC map was the only parameter altered between these two model simulations, any differences in nitrogen export can be directly attributed to cocoa-driven deforestation.

A spatially explicit proxy for runoff potential is required by the model to weight nutrient generation across the landscape. Mean annual precipitation was used as the runoff proxy. Data were from the PISCOp (Peruvian Interpolated data of the SENAMHI's Climatological and hydrological Observations) V2.1 dataset (Aybar et al., 2019). PISCOp is a high-resolution gridded precipitation product developed specifically for Peru. It is generated by blending quality-controlled in-situ rain gauge data from the extensive network of the Peruvian National Meteorology and Hydrology Service with satellite-based precipitation estimates. This blending process results in a robust, locally calibrated product that is highly valuable for hydrological applications in Peru. The dataset has a native resolution of 0.1 degrees (approximately 10 km) and provides data from 1981 to the present. To create a long-term average, monthly PISCOp

data for the period 2000–2020 were aggregated to calculate a mean annual precipitation raster. This coarse-resolution raster was then resampled to the 10 m resolution of the LULC using a bilinear interpolation method. This step produced a smooth, continuous surface of precipitation values that reflects regional climate patterns. In the model, this raster acts as a weighting factor; areas with higher mean annual precipitation are assumed to have greater surface runoff, leading to a higher potential for nutrient mobilization and transport. The decision to use the PISCOp dataset instead of a more readily available global precipitation product (e.g., GPCP) significantly enhances the regional accuracy of this analysis. The study area spans a sharp environmental gradient, which creates complex orographic effects and steep precipitation gradients. Coarse-resolution global datasets often fail to capture this fine-scale variability. Because PISCOp is specifically calibrated for Peru and incorporates thousands of local rain gauge observations, it provides a much more realistic representation of these precipitation patterns. This commitment to using the best available, locally-validated data improves the reliability of the runoff proxy and, by extension, the entire nutrient export simulation.

Watershed boundaries were defined using the HydroBASINS dataset (Lehner, 2014). HydroBASINS provides a globally consistent, multi-level suite of hierarchically nested watershed polygons, which is itself based on SRTM DEM data. The dataset employs the Pfafstetter coding system, a topological scheme that allows for the delineation of nested sub-basins from continental scale (Level 1) to very fine scales (Level 12). For this regional-scale analysis, Pfafstetter Level 9 basins were selected as the aggregation unit. The global HydroBASINS shapefile for South America was obtained and clipped to the spatial extent of the study area.

Threshold flow accumulation defines the minimum number of upslope pixels that must drain into a given pixel for it to be classified as part of a stream network. It is derived directly from the DEM and strongly influences the delineation of hydrologic connectivity and subsequent nutrient export estimates. When a flow path intersects a stream, nutrient retention processes cease, and any nutrients reaching the stream channel are assumed to be exported to the catchment outlet. Therefore, selecting an appropriate threshold is critical to ensure that modeled stream networks closely match actual stream conditions. After extensive validation against observed stream data, we chose a threshold value of 3000.

The biophysical table is a critical input that parameterizes the model by linking each LULC class to its associated nutrient loading and retention characteristics. The parameters used in this study were compiled based on a review of relevant literature for tropical agriculture and forestry systems, and are presented in Table S3. This table provides the core assumptions driving the model's simulation of nutrient dynamics.

Nitrogen Load (load_n): This parameter represents the gross amount of nitrogen generated on-site per hectare per year for each LULC class, before accounting for landscape retention. The parameterization of load_n directly encodes the central hypothesis of the study. The value for intact forest is set at a low baseline of 0.9 kg/hectare/year, representing background nitrogen cycling in a natural ecosystem. In stark contrast, the values for intensive agricultural systems like Cocoa (15.0 kg/hectare/year) and Oil Palm (25.0 kg/hectare/year) are orders of

magnitude higher. These elevated values reflect external nutrient inputs from synthetic fertilizers, the rapid mineralization of soil organic matter following land clearing, and increased soil erosion. This differential ensures that the model simulates a substantial increase in nitrogen loading on any pixel converted from forest to agriculture.

Nitrogen Retention Efficiency (eff_n): This parameter defines the proportion of nutrients that are retained, removed, or uptaken as they flow over a pixel of a given LULC type. It quantifies the landscape's natural filtration capacity. The values assigned to this parameter represent the secondary impact of deforestation: the degradation of the landscape's ability to regulate nutrient flows. Forest is assigned a very high retention efficiency (0.80), reflecting the capacity of its dense multi-layered canopy, complex root systems, and thick organic soil horizons to trap and assimilate nutrients. Conversely, agricultural lands (e.g., Cocoa at 0.60, Pastures at 0.35) and especially Urban areas (0.05) are assigned much lower efficiencies. This reflects their simplified vegetation structure, compacted soils, and more impervious surfaces, which facilitate rapid runoff rather than filtration. Therefore, deforestation not only increases the source of nitrogen pollution but also simultaneously reduces the landscape's inherent ability to mitigate its transport to waterways.

Proportion of Subsurface Flow (proportion_subsurface_n): This parameter determines the fraction of the total nitrogen load that is transported via subsurface pathways as dissolved nutrients. Forest is assigned a high value (0.60), reflecting the high infiltration rates and soil porosity characteristic of undisturbed forest soils. Agricultural and urban lands, which often have more compacted soils and higher rates of surface runoff, are assigned lower values.

Retention Length (crit_len_n): This parameter defines the distance (in meters) over which a given LULC type is assumed to reach its maximum retention efficiency. In the absence of specific empirical data for the diverse LULC types in the study region, this parameter was held constant at 200 meters for all classes. This is a common and practical approach in regional-scale InVEST applications and ensures that the relative differences in retention capacity between LULC types are driven by the more sensitive eff_n parameter. Other parameters in the model use InVEST NDR's default settings.

We quantified the degradation of water purification services as the net change in annual nitrogen export between the two scenarios. On the resulting map, positive values indicate degradation of this service. The resulting metric enables the direct identification and ranking of regions with the greatest service degradation. This approach explicitly links landscape-scale deforestation patterns to their cumulative downstream hydrological consequences. Ultimately, the aggregated map serves as a decision-support tool for prioritizing conservation, restoration, and management efforts in watersheds most impacted by agricultural expansion.

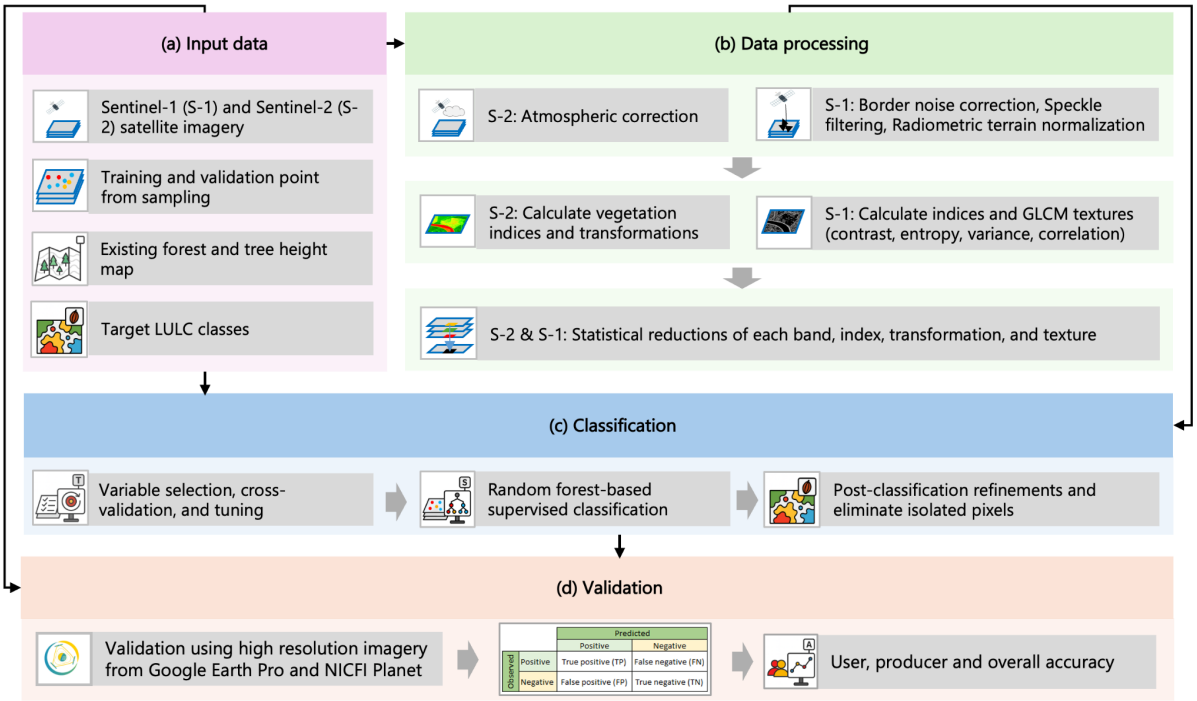

Figure S2: The workflow for mapping LULC by leveraging multi-source satellite imagery and machine learning for classification. (a) Input data: Acquisition of Sentinel-1 radar and Sentinel-2 optical satellite imagery, supplemented by training and validation points, an existing forest map, and tree height data, as well as the definitions of 10 target land cover classes. (b) Data processing: Atmospheric correction applied to Sentinel-2 data, followed by calculation of vegetation indices, transformations, and statistics; for Sentinel-1 data, border noise removal, speckle filtering, and radiometric terrain normalization; derivation of GLCM textures (contrast, entropy, variance, correlation) with a small window, with statistical reductions (mean, median, standard deviation, maximum, minimum) to create normalized multiband compositions. (c) Classification: Training and validation, followed by feature selection, cross-validation, hyperparameter tuning, and supervised classification with a random forest algorithm; post-classification refinements include application of overlapping masks and a majority filter to eliminate isolated pixels and mitigate noise. (d) Validation results: Accuracy assessment using high-resolution imagery from Google Earth Pro and NICFI Planet, incorporating a confusion matrix to compute user accuracy, producer accuracy, and overall accuracy, under a stratified random sampling design. Arrows indicate sequential data processing flows between stages.

Table S1. Assigned mean species abundance (MSA) values for animals and plants corresponding to different LULC classes used as input parameters in the GLOBIO4 model.

LULC code	LULC description	MSA vertebrates	MSA plants
1	Agriculture	0.452	0.156
2	Urban	0.264	0.361
3	Bare soil	1	1
4	Forest	1	1
5	Water	0	0
6	Pasture	0.401	0.149
7	Secondary vegetation	0.621	0.568
8	Oil palm	0.452	0.156
9	Other plantations	0.621	0.568
10	Cocoa	0.452	0.156

Table S2. The identification of nature land cover and human land use based on the LULC code.

LULC description	GLOBIO 4 Category
Nature land cover	Forest, Secondary vegetation, Bare soil
Human land use	Agriculture, Urban, Pasture, Oil palm, Other plantations, Cocoa

Table S3. LULC-Specific Biophysical Parameters for NDR Modeling

lucode	LULC Description	Nitrogen Load (kg/ha/yr)	Nitrogen Retention Efficiency (eff_n)	Proportion of Subsurface Flow (proportion_subsurface_n)	Retention Length (crit_len_n) (m)
1	Agriculture	12.0	0.25	0.30	200
2	Urban	16.4	0.05	0.05	200
3	Bare soil	9.0	0.00	0.05	200
4	Forest	0.9	0.80	0.60	200
5	Water	0.0	0.00	0.00	200
6	Pasture	5.5	0.35	0.40	200
7	Secondary vegetation	2.5	0.70	0.50	200
8	Oil palm	25.0	0.55	0.50	200
9	Other plantations	4.0	0.60	0.40	200
10	Cocoa	15.0	0.60	0.40	200

Table S4. The area of direct deforestation caused by cocoa cultivation in each district of UALL (measured in hectares).

Year/ District	Alexander von Humboldt	Irazola	Neshuya	Padre Abad	Curimana	Nueva Requena	Campoverde	Yarinacocha	Manantay	Total
2000	46	93	109	0	99	13	64	4	1	429
2001	54	39	100	0	77	10	93	14	2	389
2002	74	206	165	6	114	0	22	8	1	597
2003	20	87	118	5	31	2	71	9	0	344
2004	56	120	177	12	0	22	174	28	3	591
2005	9	2	15	9	0	0	116	7	0	158
2006	98	320	261	210	142	0	109	10	1	1151
2007	46	117	128	49	106	0	182	23	4	655
2008	71	283	185	107	251	0	132	8	1	1038
2009	47	306	138	155	284	1	96	9	1	1037
2010	51	168	60	65	126	0	96	5	8	579
2011	21	157	63	120	154	0	125	4	8	652
2012	59	412	153	234	402	42	135	2	5	1445
2013	54	376	94	112	208	33	113	2	0	992
2014	106	504	179	161	263	71	144	7	1	1436
2015	71	389	135	151	161	100	114	10	1	1134
2016	51	503	142	191	322	97	109	7	2	1424
2017	28	96	42	97	78	74	40	6	0	462
2018	53	434	90	207	304	234	51	7	0	1379
2019	61	264	108	183	338	378	220	8	0	1560

Table S5. The area and rate of deforestation from 2000 to 2020 in each district (measured in hectares).

District	Deforested Area (hectares)	Percentage of Total (%)	Forest Area in 2000 (hectares)	Deforestation Rate (%)
Irazola	4876	28	168678	2.89
Curimana	3463	20	176499	1.96
Neshuya	2463	14	41433	5.94
Campoverde	2206	13	63594	3.47
Padre Abad	2073	12	433763	0.48
Nueva Requena	1078	6	181790	0.59
Alexander von Humboldt	1075	6	9335	11.52
Yarinacocha	177	1	23210	0.76
Manantay	40	0	28769	0.14

References

Aybar, C., Fernández, C., Huerta, A., Lavado, W., Vega, F., Felipe-Obando, O., 2019. Construction of a high-resolution gridded rainfall dataset for Peru from 1981 to the present day. Hydrological Sciences Journal 65, 770–785. https://doi.org/10.1080/02626667.2019.1649411

Castro, A., Dávila, C., Laura, W., Cubas Saucedo, F., Ávalos, G., López, C., Villena, D., Valdez, M., Urbiola, J., Trebejo, I., Menis, L., Marín, D., 2021. Climas del Perú: mapa de clasificación climática nacional, in: Climas del Perú: mapa de clasificación climática nacional. pp. 70–70.

Charry, A., Torres, N., Fonseca, C., Narjes, M., 2023. The cocoa value chain in Ucayali: Analysis to identify business models with agroecological potential.

Goñas, M., Rubio, K.B., Briceño, N.B.R., Pariente-Mondragón, E., Oliva-Cruz, M., 2022. Tree diversity in agroforestry systems of native fine-aroma cacao, Amazonas, Peru. PLOS ONE 17, e0275994. https://doi.org/10.1371/journal.pone.0275994

J, R., C.,. Alberdi, I.,. Bahamondez, C.,. Freitas, 2022. National Forest Inventories of Latin America and the Caribbean: Towards the harmonization of forest information. Food & Agriculture Org.

Lehner, B., 2014. HydroBASINS: Global watershed boundaries and sub-basin delineations derived from HydroSHEDS.

NASA Jet Propulsion Laboratory, NASA, 2013. NASA Shuttle Radar Topography Mission Global 1 arc second (SRTMGL1) v003. https://doi.org/10.5067/MEASURES/SRTM/SRTMGL1.003

Natural Capital Project, 2024. NDR: Nutrient Delivery Ratio — InVEST User Guide [WWW Document]. URL https://storage.googleapis.com/releases.naturalcapitalproject.org/invest-userguide/latest/en/ndr.html

Pareja, P., Arce, A., Sánchez Choy, J.G., Velasquez, J.S., 2023. Context document (Peru): Analysis of the context and agroecological principles in Ucayali's ALL.

Rajab, Y.A., Leuschner, C., Barus, H., Tjoa, A., Hertel, D., 2016. Cacao Cultivation under Diverse Shade Tree Cover Allows High Carbon Storage and Sequestration without Yield Losses. PLOS ONE 11, e0149949. https://doi.org/10.1371/journal.pone.0149949

Resolución Ministerial N.° 179-2021-MINAM [WWW Document], n.d. URL https://www.gob.pe/institucion/minam/normas-legales/2188100-179-2021-minam (accessed 7.17.25).

Rojas-Briceño, N.B., García, L., Cotrina-Sánchez, A., Goñas, M., Salas López, R., Silva López, J.O., Oliva-Cruz, M., 2022. Land Suitability for Cocoa Cultivation in Peru: AHP and MaxEnt Modeling in a GIS Environment. Agronomy 12, 2930. https://doi.org/10.3390/agronomy12122930

Silvestre, S.N.F. y de F., 2020. Inventario Nacional Forestal y de Fauna Silvestre, Informe de resultados Panel 1. Servicio Nacional Forestal y de Fauna Silvestre.