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Technical and Financial Feasibility of Space Technology for the Control and Monitoring of Cacao (Theobroma cacao L.) Crops: A Review and Techno-Economic Framework for Smallholder Agroforestry Systems

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ABSTRACT

Cacao (Theobroma cacao L.) is a strategic tree crop for the tropical economies of Latin America, and Ecuador ranks among the world's leading exporters of fine-flavour cocoa. Yet the sector is dominated by smallholders who cultivate shaded agroforestry plots of one to a few hectares, where yields are low, pest and disease pressure is high, and management decisions still rely largely on visual field inspection. Space technology—satellite Earth observation complemented by unmanned aerial vehicles (UAVs) and cloud-based geospatial processing—offers spatially explicit, repeatable and increasingly affordable information on crop extent, vigour, stress, yield and land-use change. This paper reviews the technical capabilities and constraints of space-based monitoring for cacao and develops an integrated techno-economic framework to assess whether adoption is convenient—that is, simultaneously technically feasible and financially justifiable—for Ecuadorian and comparable Latin American production systems. Drawing on sixty peer-reviewed studies, we synthesise evidence on Earth observation platforms and sensors, vegetation indices and radar backscatter, machine-learning classification of cocoa under complex canopies, crop-health and disease detection, and satellite yield estimation. We then structure the cost side (imagery, hardware, software, connectivity, skilled labour and validation) against benefit streams (input savings, yield protection, targeted scouting, deforestation-free regulatory compliance, certification premiums, carbon and index-insurance products) and illustrate feasibility through scenario analysis at farm, cooperative and landscape scales. The evidence indicates that open-access constellations such as Sentinel-1/2 and Landsat, processed on platforms like Google Earth Engine, make technical monitoring of cacao achievable at low marginal cost, while financial convenience is strongly scale-dependent: individual smallholders rarely justify dedicated systems, whereas cooperative and service-provider models spread fixed costs and unlock high-value benefits, particularly compliance with the European Union Deforestation Regulation. We conclude that space technology is best framed not as a farm-level gadget but as shared digital infrastructure, and we identify

the enabling conditions—cooperative aggregation, capacity building, hybrid satellite–UAV designs and public co-investment—required to convert technical potential into net economic value.

Highlights

- Open-access satellites, radar–optical fusion and machine learning can map and monitor cacao under complex agroforest canopies with 85–97% accuracy.
- Space-based imagery has near-zero marginal cost, but the capability to use it is a largely fixed cost, creating strong economies of scale.
- Financial convenience is scale-dependent: uneconomic for isolated smallholders, but favourable for cooperatives and supply chains.
- The EU Deforestation Regulation turns satellite monitoring into a near-condition of market access for EU-bound cocoa.
- Space technology for cacao is best deployed as shared digital infrastructure, supported by ground truth, capacity building and public co-investment.

1. Introduction

Cacao (Theobroma cacao L.) is one of the most economically and culturally significant tree crops of the humid tropics. Its beans are the raw material of the global chocolate industry, and its cultivation sustains the livelihoods of millions of predominantly smallholder families across West Africa, Latin America and Southeast Asia. In the Americas, and particularly in Ecuador—historically a producer of the prized fine-flavour or *cacao fino de aroma*—the crop is deeply woven into rural economies, export earnings and agrarian identity. Ecuador is the third largest cacao exporter in the world, and a substantial share of national output is grown by small producers who manage diversified, shaded agroforestry plots rather than intensive monocultures [4,5]. These systems combine cacao with timber, fruit and service trees, and they generate a spectrum of ecosystem services—carbon storage, microclimate regulation, biodiversity habitat and soil-health benefits—that increasingly attract policy and market attention [5,7,8,9].

Despite this importance, the productivity and economic performance of smallholder cacao remain fragile. Comparative economic analyses across Colombia, Ecuador and Peru show that only a fraction of production systems reach living-income thresholds, with profitability contingent on sufficient prices, adequate yields, timely diversification and low input costs [6]. In the Ecuadorian Amazon, average smallholder yields have been estimated at only a few hundred kilograms per hectare, and net margins are thin and volatile [5]. Field management is still largely reactive: producers detect pest and disease outbreaks, nutrient deficiencies or water stress by walking their plots, often after damage has already occurred. At the landscape scale, the expansion of cacao has been associated with encroachment into forests and protected areas in several producing regions, exposing the commodity to reputational and regulatory risk [16,17,54].

The Ecuadorian case sharpens these tensions. Cacao is cultivated across the coastal lowlands, the Andean foothills and the Amazon, under production styles ranging from traditional *Nacional* fine-flavour agroforests to intensively managed CCN-51 clonal plantings. In the Amazon alone, tens of thousands of hectares are devoted to cacao, more than four-fifths of it managed by smallholders farming fewer than ten hectares and relying heavily on unpaid family labour [5]. Life-cycle and cost–benefit analyses show that organic and agroecological management can match conventional systems in income while lowering environmental impact, yet profitability remains the sector's persistent weakness, constrained by low yields, price volatility, ageing plantations, disease and, increasingly, the presence of cadmium and climate stress [4,5]. Programmes promoting dynamic agroforestry and direct-trade relationships have improved prices and ecological outcomes for participating producers, demonstrating latent value that better information could help unlock [9,12,13]. These are precisely the conditions—many small, dispersed, information-poor plots embedded in a high-value but fragile value chain—under which spatial information technologies could, in principle, deliver disproportionate benefit, provided their economics can be made to work.

Against this backdrop, *space technology*—understood here as the constellation of satellite Earth observation (EO) systems, their derived data products, and the aerial and computational tools that extend and operationalise them—has emerged as a transformative instrument for agricultural monitoring. Satellite remote sensing enables synoptic, repeatable and increasingly fine-resolution observation of crop extent, canopy condition, phenology, biophysical status and land-use change over large areas at marginal cost [1,2,3]. The launch of open-access constellations, most notably the European Space Agency's Sentinel-1 (C-band synthetic aperture radar, SAR) and Sentinel-2 (multispectral) missions, alongside the long Landsat archive and coarse-resolution MODIS series, has dramatically lowered the barrier to entry for agricultural EO [3]. Unmanned aerial vehicles (UAVs, or drones) complement satellites at the sub-metre scale, delivering on-demand, ultra-high-resolution imagery for localised diagnosis [28,32]. Cloud-based geospatial platforms such as Google Earth Engine (GEE) remove the need for costly local infrastructure by co-locating petabyte-scale archives with planetary-scale computation [38,39,40].

For a perennial, shade-grown crop such as cacao, however, the promise of space technology confronts distinctive obstacles. Smallholder cacao parcels are small (often 1–2 ha), spatially fragmented and cultivated beneath a heterogeneous canopy that is spectrally similar to surrounding forest, which complicates detection with optical sensors [2,15]. The crop is concentrated in persistently cloudy equatorial regions, degrading the availability of clear optical acquisitions and motivating the use of cloud-penetrating radar [14,20,21]. Consequently, a rich but geographically uneven literature has developed—dominated by West African studies of Côte d'Ivoire and Ghana—demonstrating that cacao can be mapped and monitored, but only with careful sensor fusion, texture analysis and machine learning [16,19,20]. Whether these technical solutions are *financially convenient*, especially for resource-constrained smallholders, is a separate and under-examined question.

The economic literature on precision agriculture is instructive but ambivalent. A meta-analysis of eighty-five studies found that adopting precision agriculture technologies raised the average return

on investment by roughly 22% and net profit by roughly 19%, while cutting input use and emissions—yet these gains were markedly weaker and less stable on small farms and in developing countries [42]. Multiple reviews converge on the finding that benefits are strongly scale-dependent, with profitability thresholds frequently placed above 100–200 ha for information-intensive technologies, and with high capital costs, limited digital literacy and weak support services acting as persistent barriers for smallholders [43,44,45,46,47]. This tension—robust technical feasibility coupled with contingent, scale-sensitive financial returns—lies at the heart of the present paper.

The Spanish-language title of this work frames the central question as one of *conveniencia técnica financiera*: the joint technical and financial convenience of using space technology to control and monitor cacao crops. We interpret 'convenience' rigorously as the simultaneous satisfaction of two conditions: (i) technical feasibility—the ability of EO and allied technologies to deliver accurate, timely, decision-relevant information for cacao systems; and (ii) financial justification—a positive and defensible balance between the costs of acquiring that information and the value it creates. A technology may be technically dazzling yet financially unconvincing, or financially attractive only under particular organisational arrangements. Disentangling these dimensions is essential for producers, cooperatives, exporters and policymakers deciding whether and how to invest.

Accordingly, this paper pursues four objectives. First, it reviews the technical capabilities and limitations of space technology for cacao monitoring, integrating evidence on platforms, sensors, indices, classification methods, health and disease detection, and yield estimation. Second, it structures the cost architecture and the benefit streams of space-based monitoring for cacao production systems. Third, it develops an integrated techno-economic feasibility framework and illustrates it through scenario analysis at farm, cooperative and landscape scales. Fourth, it identifies the enabling conditions, barriers and research gaps that determine whether technical potential translates into net economic value. The novelty of the contribution lies in bridging two literatures that rarely meet—the remote-sensing literature on cacao and the economic literature on precision-agriculture adoption—within a single, decision-oriented framework tailored to smallholder agroforestry contexts.

The remainder of the paper is organised as follows. Section 2 describes the review approach and the analytical framework. Section 3 examines the technical dimension of space technology for cacao. Section 4 appraises the technical convenience—strengths and limitations—specific to cacao agroforestry. Section 5 analyses the financial and economic dimension. Section 6 integrates both into a feasibility framework and scenario analysis. Section 7 discusses barriers, enabling conditions and research gaps, and Section 8 concludes.

2. Materials and Methods

2.1. Review approach and scope

This study is a structured narrative review combined with a conceptual techno-economic synthesis. Because primary field data were not collected, the methodology is designed to maximise the transparency and reproducibility of the evidence base rather than to generate new empirical measurements. The literature was assembled through systematic searches of peer-reviewed

academic databases, prioritising indexed journal articles and privileging high-quartile (Q1) sources where available. Search themes were organised around five pillars aligned with the paper's objectives: (i) remote sensing and Earth observation for tree-crop and cacao monitoring; (ii) UAV and multispectral sensing for crop health, pest and disease detection; (iii) satellite-based crop yield estimation and cloud geospatial processing; (iv) the economics and adoption of precision-agriculture technologies, with emphasis on smallholders; and (v) cacao production systems, economics and land-use dynamics in Latin America and the major producing regions.

Inclusion favoured studies that (a) addressed cacao directly, or (b) provided transferable methodological or economic evidence from analogous perennial and tree crops (coffee, oil palm, banana, arecanut, date palm, olive, apple) and from precision agriculture more broadly. Preference was given to recent work (predominantly 2018–2026) to reflect the rapid evolution of open-access constellations, deep-learning methods and cloud platforms, while retaining foundational earlier references. Sixty studies were retained for detailed synthesis. Their evidence was extracted along consistent dimensions—platform and sensor, spatial and temporal resolution, method, reported accuracy, crop and geography, and, where relevant, cost and economic outcome—to support comparative interpretation.

2.2. Analytical framework for techno-economic feasibility

To assess convenience, we adopt a two-axis framework. The **technical axis** evaluates whether space technology can deliver the information products cacao management requires—crop mapping and area estimation, vigour and stress monitoring, pest and disease early warning, yield forecasting, and land-use-change and deforestation verification—at the spatial, temporal and thematic accuracy needed for decisions. The **financial axis** evaluates whether the value created by those products exceeds their full economic cost, considering the level of aggregation (individual farm, cooperative, or landscape/supply chain) at which costs and benefits accrue. On the cost side we distinguish: (i) data acquisition (free open-access imagery versus commercial very-high-resolution (VHR) tasking, and UAV flights); (ii) capital equipment (drones, sensors, field devices); (iii) software and cloud computing; (iv) connectivity and data infrastructure; (v) skilled labour for processing and interpretation; and (vi) ground-truth collection and validation. On the benefit side we distinguish direct agronomic benefits (input savings through site-specific management, yield protection through early detection, and scouting-cost reduction) from value-added and risk-management benefits (regulatory compliance, certification and price premiums, carbon and payment-for-ecosystem-services revenues, and index-based insurance). Feasibility is then examined not as a single verdict but as a function of scale and organisational model, recognising that the same technology can be uneconomic for an isolated smallholder yet highly economic when its fixed costs are shared across a cooperative or embedded in a supply-chain service. This framing deliberately departs from the common practice of reporting a single average return on investment for a technology. Averages obscure the decisive heterogeneity in cacao—across farm size, organisational form, market destination and agro-ecological setting—that determines whether adoption pays. By making scale and benefit composition explicit variables rather than hidden assumptions, the framework yields conditional, decision-useful conclusions: it identifies not merely *whether* space technology can be

convenient for cacao, but *under what organisational and market conditions* it becomes so. This conditional logic is, we argue, the appropriate form for feasibility assessments of digital agriculture in smallholder-dominated tropical commodities, where the distribution of costs and benefits across actors is as important as their totals.

The scenario analysis in Section 6 is explicitly *illustrative and parametric*: its cost and benefit magnitudes are drawn from ranges reported in the cited literature and combined under stated assumptions to reveal the structure of feasibility, not to assert measured returns for any specific farm. All figures are presented as assumptions to be calibrated with local data, and the sensitivity of conclusions to key parameters is discussed.

2.3. Defining technical–financial convenience

We formalise 'convenience' to keep the assessment disciplined. A monitoring solution is deemed *technically convenient* for a given decision if it supplies information of sufficient accuracy, spatial detail, timeliness and interpretability to change that decision for the better relative to current practice. It is deemed *financially convenient* for a given actor if the present value of the incremental benefits it generates for that actor exceeds the present value of its full incremental costs over a relevant horizon—equivalently, if its benefit–cost ratio exceeds one and its net present value is positive under defensible assumptions and discounting. Overall convenience requires both conditions to hold *for the same decision-making unit*. This last qualifier is essential and frequently neglected: a solution can be technically convenient for a farmer's agronomic decisions yet financially convenient only for an exporter's compliance decisions, so the unit at which each condition is evaluated must be stated. The framework's task is to identify, for cacao, the decision-making units and organisational configurations at which both conditions are simultaneously met. Three parameters dominate the resulting assessment and are treated as explicit variables throughout: the *aggregated area* over which fixed costs are amortised; the *benefit composition*, meaning the mix of agronomic, regulatory, market and environmental-service value accessible to the actor; and the *sensor strategy*, meaning the chosen portfolio of free satellite, commercial VHR and UAV acquisition. Holding technology constant, these three parameters largely determine whether convenience is achieved, which is why the analysis emphasises organisational scale and design over any particular device or algorithm.

3. The Technical Dimension: Space Technology for Cacao Monitoring

3.1. Earth observation platforms and sensors

Space-based monitoring rests on a layered constellation of platforms whose spatial, spectral and temporal characteristics determine their suitability for cacao. Table 1 summarises the principal options. Open-access optical missions anchor most operational workflows. The Landsat programme provides a multi-decadal 30 m archive that is unmatched for historical land-use analysis, and it has been used to reconstruct decades of cocoa-plantation change—for instance documenting the expansion of cocoa area in Ondo State, Nigeria between 2000 and 2015 [18]. Sentinel-2, with 10–20 m bands, a red-edge capability and a five-day revisit from its twin platforms, has become the workhorse of agricultural EO, offering an unprecedented combination of spatial detail, spectral

richness and free access for crop mapping and stress detection [3]. The coarse-resolution MODIS series, though too coarse for individual smallholder plots, underpins regional yield modelling and time-series gap filling [38]. Because cacao is grown in persistently cloudy equatorial belts, optical data alone are often insufficient. Synthetic aperture radar (SAR), and especially the C-band Sentinel-1 mission, penetrates cloud and is sensitive to canopy structure, moisture and texture—properties that help separate cacao's complex agroforest canopy from surrounding forest [14,20,21]. For the finest detail, commercial VHR optical constellations (sub-metre to a few metres, e.g. PlanetScope's near-daily 3 m imagery) resolve individual crowns and small plots; PlanetScope combined with Sentinel-1 has been used to map cacao systems and their climatic response in northern Peru [23]. At the base of the pyramid, UAVs carry RGB, multispectral, hyperspectral, thermal and LiDAR payloads to deliver centimetre-scale, on-demand observation over single plots, bridging the gap between satellite synopsis and ground truth [25,28,32]. No single platform is optimal for cacao; each occupies a distinct niche in a resolution–cost–coverage trade-space. Coarse free optical data offer coverage and history at the expense of detail; fine commercial and UAV data offer detail at the expense of cost and coverage; and radar offers all-weather structural information that complements both. The design task is therefore to compose a portfolio rather than to select a single sensor—using free satellite data as the always-on backbone, radar to defeat cloud, and expensive high-resolution acquisition sparingly and purposefully where the decision value justifies it. This portfolio logic recurs throughout the paper and is central to keeping monitoring both accurate and affordable [28,32,49].

Platform / mission	Type	Spatial res.	Revisit	Access	Primary role for cacao
Landsat 7/8/9	Optical multispectral	30 m	16 days	Free	Historical land-use change; long-term plantation dynamics [18]
Sentinel-2 A/B	Optical + red-edge	10–20 m	~5 days	Free	Core vigour, stress and mapping workhorse [3,16]
Sentinel-1 A/B	C-band SAR	~10–20 m	6–12 days	Free	Cloud-penetrating canopy/texture; agroforest delineation [20,21]
MODIS (Terra/Aqua)	Optical, coarse	250–500 m	Daily	Free	Regional yield modelling; time-series compositing [38]
PlanetScope	Optical VHR	~3 m	~Daily	Commercial	Plot-scale mapping; crown-level detail [23]
UAV (drone)	RGB/MS/HS/thermal	0.5–10 cm	On demand	Owned/service	Localised diagnosis; disease scouting; calibration [25,28,32]

Table 1. Principal space-technology platforms and their roles in cacao monitoring. Resolutions and revisit intervals are nominal; effective optical revisit is reduced by cloud cover in equatorial cacao

regions, motivating optical–radar fusion. VHR = very high resolution; MS = multispectral; HS = hyperspectral; SAR = synthetic aperture radar.

3.2. Spectral indices, radar backscatter and biophysical variables

The information content of EO imagery is distilled into vegetation indices and biophysical variables that correlate with plant condition. The Normalized Difference Vegetation Index (NDVI), computed from red and near-infrared reflectance, remains the most widely used proxy for canopy greenness, biomass and photosynthetic activity, and it has been applied to delineate cacao and to flag stressed versus healthy plots from Sentinel-2 time series [16,22]. However, NDVI saturates over dense tree canopies and is not uniquely diagnostic; a broad family of complementary indices has therefore been mobilised. The Enhanced Vegetation Index (EVI) reduces saturation and atmospheric influence; the red-edge indices (NDRE, Chlorophyll Index red-edge, red-edge curve index) exploit the red-edge bands available on Sentinel-2 and modern UAV sensors and are particularly sensitive to chlorophyll and early stress; and soil-adjusted indices (SAVI, OSAVI) mitigate background effects in open canopies [3,4,32,37]. Comparative studies across crops repeatedly find that red-edge-based indices outperform standard NDVI for detecting disease and nutrient stress, because they respond earlier and more specifically to pigment changes [34,35,36]. For structural and moisture information, and to overcome cloud limitations, SAR backscatter and texture measures are decisive. Grey-level co-occurrence matrix (GLCM) texture features derived from multi-season Sentinel-1 imagery have been shown to discriminate cocoa agroforests from transition forest with overall accuracies approaching 89%, outperforming single-date optical classification in cloud-prone Cameroon [20]. Backscatter intensity and polarimetric ratios also capture canopy-gap variability and shade distribution relevant to agroforestry management [21]. Increasingly, the strongest results come from *fusion*: stacking multispectral and radar features, across seasons and polarisations, feeds machine-learning classifiers that leverage the complementary strengths of each source [14,15]. Table 2 summarises the indices and radar features most frequently mobilised for cacao and analogous tree crops, together with their principal diagnostic use.

Index / feature	Formulation basis	What it captures	Cacao-relevant use
NDVI	(NIR−Red)/(NIR+Red)	Greenness, biomass, cover	Mapping; stress zoning; saturates over dense canopy [16,22]
EVI	NIR, Red, Blue (soil/atm. adjusted)	Vigour with reduced saturation	Robust vigour in dense agroforest [15]
NDRE / CIre	Red-edge & NIR	Chlorophyll; early stress	Early disease/nutrient stress; outperforms NDVI [34,35]
SAVI / OSAVI	NIR, Red, soil factor	Vigour with soil-background control	Open or young plots [3,32]
GNDVI	Green & NIR	Chlorophyll / N status	Nutrient assessment [32,36]

Index / feature	Formulation basis	What it captures	Cacao-relevant use
SAR backscatter (VV/VH)	C-band σ°	Canopy structure, moisture	Cloud-free delineation; canopy gaps [20,21]
GLCM texture	Spatial co-occurrence stats	Canopy heterogeneity	Separates cacao from forest [19,20]

Table 2. Vegetation indices and radar/texture features used in cacao and analogous tree-crop remote sensing, with their diagnostic role. NIR = near-infrared; VV/VH = co-/cross-polarised backscatter; GLCM = grey-level co-occurrence matrix; N = nitrogen.

3.3. Detecting and mapping cacao under complex canopies

Accurately mapping where cacao is grown is the foundation of every downstream product—area statistics, compliance verification, yield aggregation and targeted advisory. This is technically the hardest task for cacao because shaded plots are spectrally confusable with forest and are small and fragmented.

The literature demonstrates that the problem is nonetheless tractable with modern methods. Random forest classifiers trained on combined Sentinel-1 and Sentinel-2 features, including NDVI and second-order texture, mapped cocoa across Côte d'Ivoire and Ghana and revealed that a fifth of detected plantations lay inside protected areas [16]. Fusing GLCM texture with vegetation indices from Sentinel data achieved 97% overall accuracy in distinguishing smallholder cocoa–coconut systems from other cover in an e-agriculture planning tool for Papua New Guinea, with red band, red-edge curve index and NIR entropy among the most important variables [15].

Deep learning has pushed performance further. A convolutional-neural-network semantic-segmentation approach that integrated Sentinel-1 SAR and Sentinel-2 multispectral imagery over a 100×100 km area of Ghana, trained on nearly 90,000 ground-truth polygons, reached an F1 score of 86.6%, with the addition of temporal SAR improving predictions—an explicit demonstration that texture, moisture and canopy characteristics carry decisive information for cocoa detection [14]. At national scale, a deep-learning framework applied to public satellite imagery produced high-resolution cocoa maps for Côte d'Ivoire and Ghana, showing that official statistics underestimated planted area by up to 40% and that cocoa underlay a large share of protected-area forest loss [17]. Studies in Peru using PlanetScope and Sentinel-1 in GEE mapped cacao monocultures and agroforestry systems with thematic accuracy of 0.85 and a kappa of 0.81 [23].

Critically for operational use, uncertainty is itself mappable: Shannon-entropy analysis of classification probabilities delineates where cocoa predictions are reliable and where they are not, informing risk-aware decisions [19]. Table 3 consolidates representative cacao and closely analogous tree-crop studies, indicating the data, method and reported accuracy that together define the current technical state of the art.

Study / region	Data	Method	Task	Reported accuracy
Therias et al., Ghana [14]	Sentinel-1 + Sentinel-2	CNN semantic segmentation	Cocoa detection	F1 = 86.6%
Abu et al., CIV & Ghana [16]	Sentinel-1 + Sentinel-2	Random forest, texture+NDVI	Cocoa mapping	82.9% prod. acc.
Singh et al., PNG [15]	Sentinel-1 + Sentinel-2	RF, GLCM + indices	Cocoa–coconut mapping	97% overall
Kalischek et al., CIV & Ghana [17]	Public satellite imagery	Deep learning	National cocoa map	Validated in situ
Numbisi et al., Cameroon [20]	Multi-season Sentinel-1	RF, GLCM texture	Agroforest vs forest	88.8% overall
Atalaya-Marin et al., Peru [23]	PlanetScope + Sentinel-1	RF in GEE	Cocoa systems mapping	0.85 acc.; κ = 0.81
Anyimah et al., Ghana [22]	Sentinel-2 NDVI series	Thresholding / zoning	Stress detection	Stress maps
Ye et al., banana [34]	UAV multispectral	BLR, red-edge indices	Fusarium wilt	80–92% overall
Lei et al., arecanut [35]	UAV multispectral	BPNN / SVM	Disease severity	86.6% (BPNN)

Table 3. Representative cacao and analogous tree-crop remote-sensing studies. Accuracy metrics are as reported by the original authors and are not directly comparable across differing validation designs. CIV = Côte d'Ivoire; PNG = Papua New Guinea; RF = random forest; CNN = convolutional neural network; BLR = binary logistic regression; BPNN = back-propagation neural network; SVM = support vector machine; κ = kappa; GEE = Google Earth Engine.

3.4. Crop health, stress, pest and disease monitoring

Beyond mapping, EO supports the surveillance of crop condition that cacao management most urgently needs. Multitemporal NDVI from Sentinel-2 has been used to classify cocoa plots into stressed and healthy classes month by month, producing spatial stress maps and suitability layers that direct scarce scouting and remediation resources to the worst-affected areas [22]. The general principle—that vegetation indices track the physiological decline caused by biotic and abiotic stress before it is obvious on the ground—is well established across tree crops and transfers to cacao [2,3].

The most operationally mature disease-detection evidence comes from UAV multispectral and hyperspectral sensing, where centimetre resolution resolves individual affected trees. Reviews document a rapidly maturing field in which drones equipped with multispectral, hyperspectral and thermal sensors, coupled with machine-learning and deep-learning classifiers, detect plant disease early and at scale, cutting pesticide use and crop loss [29,30,31,33]. Concrete analogues for cacao's pathosystems are instructive: banana Fusarium wilt was identified from UAV multispectral imagery using red-edge chlorophyll indices with overall accuracies above 80–90%, with red-edge bands and

resolutions finer than 2 m proving essential [34]; the severity of arecanut yellow-leaf disease was quantified per tree by combining several vegetation indices with machine-learning models [35]; and multispectral UAV indices discriminated maize disease severity levels statistically [and other reviews confirm the pattern] [33]. For cacao specifically, high-resolution UAV multispectral datasets over ten agroforestry typologies in Côte d'Ivoire have been released precisely to enable tree-level characterisation of structure, abundance and health, signalling the direction of travel [25]. Thermal and structural (LiDAR) payloads extend detection to water stress and canopy-volume change associated with infestation [28]. Comparative sensor studies caution, however, that calibration and processing choices materially affect the accuracy of derived indices, so operational reliability depends on disciplined workflows [36].

The economic stakes of disease detection in cacao are exceptionally high, which sharpens the relevance of these methods. Cacao's principal pathogens—frosty pod rot (Moniliophthora roreri), black pod (Phytophthora spp.) and, in parts of the Americas, witches' broom (Moniliophthora perniciosa)—can individually destroy a large fraction of a harvest and, in severe outbreaks, render cultivation uneconomic. Because these diseases attack pods and spread rapidly under humid conditions, the window for effective intervention is short and the payoff to early, spatially targeted detection is large. Two features of the problem shape how EO can help. First, several key symptoms manifest on pods beneath the canopy and are not directly visible from above, so remote sensing detects disease indirectly—through the canopy-level physiological decline, defoliation and vigour loss that accompany heavy infection—rather than by imaging the lesions themselves; this favours multitemporal red-edge and thermal approaches sensitive to early stress over single-date greenness [2,34]. Second, the fine spatial scale of infection foci within small plots pushes detection toward UAV resolution for confirmation, while satellites provide the wall-to-wall screening that flags candidate areas for inspection [28,32]. The strong performance of red-edge indices against structurally analogous pod- and canopy-affecting diseases in banana, arecanut and date palm [13,34,35] indicates that operational cacao disease surveillance is technically within reach; what is largely missing is cacao-validated field data and locally trained models, a gap identified in Section 7.

3.5. Yield estimation and forecasting

Timely, spatially explicit yield information underpins procurement, logistics, financing and food-security planning. A large body of work demonstrates that satellite time series, combined with weather and soil data and machine learning, can predict crop yields months before harvest with useful accuracy. Foundational work introduced a scalable satellite-based crop-yield mapper that trained statistical models on crop-model simulations and applied them within GEE, capturing a meaningful fraction of field-level maize and soybean variation across the US Midwest without ground calibration [38]. Subsequent studies at county and field scale integrated climate, satellite, soil and spatial data in GEE using random forests and deep learning (DNN, CNN, LSTM), reaching coefficients of determination frequently between 0.75 and 0.90 for staple crops one to two months before harvest [39]. Field-scale mappers such as GYMEE estimate yield and evapotranspiration globally from Landsat and gridded weather within GEE, with relative errors on the order of ±15% across contrasting sites [40]. A recent review confirms a methodological shift from simple regressions to machine-

learning and multi-sensor fusion frameworks, with Sentinel-2, Landsat and MODIS dominating and radar gaining ground [41].

Most of this evidence concerns annual field crops; cacao yield estimation from space is comparatively nascent, reflecting the difficulty of relating a multispectral canopy signal to below-canopy pod production in a mixed agroforest. Nevertheless, analogues in perennial and tree crops are encouraging: satellite-and-machine-learning frameworks have predicted olive and apple yields early in the season with operationally useful accuracy [olive and apple studies] [and reviews document the transferability of the approach] [41]. Integrating remote sensing with in-situ climate data has already been used to relate rainfall anomalies to cacao yield in Peru, quantifying the climatic drivers of production at landscape scale [23]. The realistic near-term expectation for cacao is therefore relative, trend- and anomaly-oriented yield intelligence—identifying under-performing zones and seasons—rather than precise absolute tonnage, with accuracy improving as ground-truth networks and canopy models mature.

3.6. Cloud computing, data platforms and workflow integration

The operational feasibility of all the above rests on the computational layer. Cloud geospatial platforms, above all Google Earth Engine, co-locate multi-petabyte satellite archives with elastic computation, allowing analysts to process national or landscape extents without downloading imagery or maintaining servers—an especially decisive advantage where local infrastructure and connectivity are weak [39,40]. GEE has become the default environment for cocoa mapping in Peru [23], for scalable yield modelling [38,39], and for time-series gap-filling that repairs cloud-corrupted optical sequences before analysis [various GEE workflows] [40]. The temporal and data-continuity dimension also matters. The Landsat programme's uninterrupted multi-decadal record and the guaranteed continuity of the Copernicus Sentinel missions give planners confidence that monitoring built today will be sustainable and comparable over the plantation lifetimes—decades—that perennial cacao demands [3,18]. Emerging and forthcoming capabilities, including hyperspectral spaceborne missions, improved SAR constellations and commercial daily VHR, promise to relax current spectral and spatial constraints, while gap-filling and harmonisation techniques already reconstruct usable optical time series from cloud-corrupted sequences [40,41]. This trajectory means that the technical ceiling for cacao monitoring is rising even as the cost of access falls—an important consideration when appraising an investment intended to serve for many seasons. Spatial decision-support systems (S-DSS) translate these analytics into end-user tools: a near-real-time, web-based S-DSS co-designed with sugarcane cooperatives in Costa Rica delivered harvest-progress monitoring and early-warning alerts that agronomic advisors judged fit for daily use, illustrating a replicable template for cacao cooperatives [27]. The technical stack for cacao monitoring is thus essentially assembled; the binding constraints are data quality under cloud, ground-truth availability, and—crucially—the economics of deploying and sustaining these tools, to which we now turn.

3.7. Integrating Earth observation with ancillary and in-situ data

The accuracy and value of space-based products rise sharply when EO is fused with complementary data streams rather than used in isolation. Yield and stress models consistently improve when

satellite indices are combined with meteorological variables (rainfall, temperature, evapotranspiration) and soil properties, which together explain far more of the variation in crop performance than spectral data alone [39,41]. For cacao specifically, integrating remote sensing with in-situ climate records enabled the quantification of rainfall anomalies' impact on yield in northern Peru, revealing the climatic drivers behind good and poor seasons [23]. Ground-based proximal sensors, hand-held spectral devices and increasingly dense networks of low-cost Internet-of-Things (IoT) stations can calibrate and validate satellite retrievals, tightening the link between the orbital signal and conditions beneath the canopy [1]. Farmer-supplied observations and crowdsourced ground truth address the reference-data bottleneck that reviews identify as central to reliable monitoring, while also fostering the participation that underpins adoption [1]. The practical implication is that the most robust and defensible cacao monitoring systems are *multi-source by design*, layering free satellite synopsis, targeted aerial detail, environmental covariates and field knowledge—an architecture whose incremental data cost is modest but whose accuracy dividend is substantial.

3.8. Accuracy assessment, uncertainty and operational reliability

A recurring theme across the reviewed studies is that headline accuracy figures must be interpreted with care, because they depend heavily on validation design, class definitions and reference-data quality. Overall accuracy, producer's and user's accuracy, F1 score and the kappa coefficient each emphasise different error types, and a single summary statistic can mask systematic confusion between spectrally similar classes such as cacao and forest [16,20]. For operational decisions—especially regulatory ones—what matters is not only average accuracy but the spatial distribution and consequences of error. The mapping of classification uncertainty via Shannon entropy demonstrated for cocoa agroforests is therefore methodologically important: it converts a global accuracy figure into a spatially explicit reliability layer, allowing users to treat high-confidence and low-confidence areas differently and to prioritise field verification where predictions are ambiguous [19]. This uncertainty-aware posture is increasingly regarded as best practice and is essential where a misclassification can wrongly exclude a compliant producer or admit a non-compliant one [57]. Operational reliability further depends on disciplined pre-processing—atmospheric correction, cloud masking, radiometric calibration and temporal compositing—whose quality materially affects derived indices and downstream classification, as demonstrated by sensor-comparison studies in which calibration method determined index accuracy [36]. Cloud contamination remains the central practical obstacle for optical monitoring of cacao, and gap-filling, smoothing and multi-sensor harmonisation are now standard steps to reconstruct usable time series before analysis [40]. The maturation of these workflows within reproducible, cloud-based pipelines means that reliability is increasingly a matter of adopting established good practice rather than of unsolved science—again shifting the binding constraint from technical possibility toward the cost and capacity required to apply that practice consistently.

4. Technical Convenience: Strengths and Limitations for Cacao Systems

Synthesising Section 3, the technical convenience of space technology for cacao is high in principle but conditional in practice. On the strengths side, EO offers wall-to-wall spatial coverage that no field

survey can match, high revisit frequency for change detection, a deep free archive for baselines and trends, and a modular sensor hierarchy—from free 10 m Sentinel to centimetre UAV—that can be matched to the decision at hand [1,3,28]. Machine learning and sensor fusion have repeatedly overcome cacao's canopy-confusion problem, delivering classification accuracies of 85–97% in multiple countries [14,15,16,20]. Radar circumvents the cloud barrier that would otherwise cripple optical monitoring in equatorial belts [20,21]. Cloud platforms remove the infrastructure barrier and make national-scale processing accessible from a laptop [39,40]. Table 4 organises the principal EO products against cacao management decisions and their maturity.

Information product	Cacao decision supported	Primary data / method	Maturity for cacao
Crop extent & area map	Compliance, aggregation, targeting advisory	S1+S2 fusion, RF/CNN [14,15,16,17]	High (demonstrated 85–97%)
Vigour / stress zoning	Prioritised scouting, input targeting	S2 NDVI/red-edge time series [22]	Moderate–High
Pest / disease early warning	Timely, localised intervention	UAV MS/HS + ML; red-edge [29,30,34,35]	Moderate (crop analogues strong)
Yield / anomaly forecast	Procurement, finance, food security	Satellite + weather + ML in GEE [38,39,41]	Emerging for cacao
Land-use / deforestation change	EUDR due diligence, sustainability	S2 change detection, forest baselines [54,56,57]	High (operational tools exist)
Shade / canopy structure	Agroforestry & carbon management	S1 backscatter; UAV LiDAR [21,25]	Moderate

Table 4. Earth observation information products mapped to cacao management decisions, with indicative technical maturity. RF = random forest; CNN = convolutional neural network; MS = multispectral; HS = hyperspectral; S1/S2 = Sentinel-1/Sentinel-2.

It is worth stressing that these accuracies, while impressive, are achieved under specific and often data-rich conditions, and that transferability to new regions is not guaranteed. Classifiers trained in Ghana or Côte d'Ivoire encode the spectral, structural and phenological signatures of West African cocoa systems and may not generalise to Ecuadorian *Nacional* agroforests or Amazonian mixed systems without local retraining and validation [16,19]. The dominant lesson of the technical literature is therefore conditional: cacao monitoring is feasible *where appropriate data, methods and ground truth are assembled*, and the effort required to assemble them is itself a determinant of convenience. This reinforces the argument that technical and financial feasibility cannot be assessed independently—the cost of achieving a given accuracy is part of the accuracy's meaning for decision-making.

On the limitations side, four constraints recur. First, *spatial mismatch*: many smallholder cacao plots are near or below the effective resolution of free optical sensors, so 10–30 m pixels blend cacao, shade trees and neighbours, capping accuracy and pushing users toward costlier VHR or UAV data [2,15]. Second, *spectral confusion and cloud*: cacao's forest-like canopy and the cloudiness of its habitat degrade optical separability and acquisition frequency, a problem only partly solved by radar and fusion [14,20]. Third, *ground-truth dependence*: every classifier and yield model requires field reference data for training and validation, and reviews identify ground-data accessibility as a central bottleneck for reliable crop monitoring [1]; the strongest cacao results rest on tens of thousands of ground polygons that most producing regions lack [14]. Fourth, *interpretation and workflow risk*: index accuracy is sensitive to calibration and processing, and misclassification can have real consequences—for example, agroforestry wrongly mapped as forest under deforestation regulations [36,57]. These limitations do not negate technical convenience, but they define the conditions—appropriate sensor choice, radar-optical fusion, investment in ground truth, and disciplined workflows—under which it is realised, and they carry direct cost implications that shape the financial analysis.

5. The Financial and Economic Dimension

5.1. The cost architecture of space-based monitoring

The financial appraisal of space technology begins with a clear cost architecture. A useful distinction separates the *marginal cost of information* from the *fixed cost of capability*. The marginal cost of an additional satellite observation from open-access constellations is effectively zero: Sentinel and Landsat imagery are free, and their systematic, repeated acquisition means that the incremental cost of monitoring one more hectare or one more date is negligible once a workflow exists [3]. This is the single most important economic fact about modern EO and the foundation of its potential convenience. The fixed cost of building and sustaining the *capability* to turn that imagery into decisions, however, is substantial and largely independent of area: it comprises skilled labour for processing and interpretation, software and cloud computing, connectivity, and—above all for cacao—ground-truth collection and validation.

UAVs invert this structure. They entail meaningful capital outlay and per-flight operating costs but deliver on-demand, ultra-high-resolution data that satellites cannot. Systematic evidence from smallholder contexts quantifies the trade-off: RGB drone systems achieve roughly 89% detection accuracy at about US$16.5 per percentage point of accuracy, whereas hyperspectral systems reach roughly 94% but at about US$132 per point—a 25-fold cost differential—so sensor choice is fundamentally an economic decision [49]. The same analysis finds that UAV capital requirements can equal 0.8–3.1 times annual smallholder income, an unaffordable barrier for individuals but a tractable one for cooperatives or service providers serving 20–50 farmers [49]. Table 5 organises the cost components and their scaling behaviour.

Cost component	Nature	Scaling behaviour	Mitigation / sharing
Open-access imagery (S1/S2, Landsat)	Recurrent	~Zero marginal cost per ha [3]	Inherently shareable
Commercial VHR tasking	Recurrent	Scales with area & frequency	Pool orders; target hotspots
UAV hardware & sensors	Capital	Fixed; high per-farm if owned [49]	Cooperative ownership; drone-as-service
Cloud computing (e.g. GEE)	Recurrent/low	Largely fixed; free tiers exist [39,40]	Shared processing pipelines
Skilled labour / analytics	Recurrent	Fixed capability cost	Shared analyst; service provider
Ground truth & validation	Recurrent	Scales with rigour required [1,14]	Crowdsource; cooperative field teams
Connectivity & devices	Capital/recurrent	Fixed per site	Public rural-broadband investment

Table 5. Cost architecture of space-based cacao monitoring. The decisive feature is that most costs are fixed 'capability' costs largely independent of monitored area, whereas open-access imagery imposes near-zero marginal cost—together implying strong economies of scale and a central role for cost-sharing.

5.2. Benefit streams and evidence from precision agriculture

Against these costs stand several benefit streams. The first is *direct agronomic value*—input savings and yield protection from site-specific, information-guided management. The precision-agriculture meta-analytic evidence is broadly positive: adoption raised average return on investment by about 22% and net profit by about 19%, while improving nitrogen-use efficiency by 15%, cutting pesticide application by 13% and reducing emissions [42]. Systematic reviews report input savings of roughly 8–20% and yield gains of 2–6%, with reported ROI commonly in the 5–15% range [53], and case evidence of double-digit percentage increases in economic benefit as digital-technology adoption intensity rises [52]. For a low-input, disease-vulnerable crop such as cacao—where frosty pod rot, black pod, witches' broom and pests can destroy large yield fractions—the value of *early, localised detection* that concentrates scouting and treatment where they are needed is potentially large, plausibly exceeding the modest input-optimisation gains seen in fertiliser-intensive field crops [22,29].

The second stream is *scouting and labour efficiency*. Smallholder cacao management is labour-intensive and depends heavily on unpaid family labour [5]. Remote stress zoning that directs field visits to the most affected plots converts blanket, calendar-based scouting into targeted, condition-based scouting, saving labour or redeploying it more productively [22,27]. The third and increasingly decisive stream is *regulatory and market value*, examined next. The fourth comprises *risk-management and environmental-service revenues*—carbon and payments for ecosystem services, and satellite-enabled index insurance—that monetise the very agroforestry attributes cacao systems already possess [12,60]. Two cautions from the economics literature must temper any optimism. First, benefits are strongly *scale-dependent*: profitability thresholds for information-intensive precision technologies frequently sit above 100–200 ha, and gains on small farms and in developing countries are weaker and less stable [42,43,53]. Second, adoption is shaped as much by *social, informational and institutional* factors—awareness, digital literacy, trust, access to credit and support services—as by raw economics, and high capital cost is a recurring but not solitary barrier [44,46,47,50,51]. These findings imply that the financial case for cacao rarely closes at the level of the isolated smallholder and must be constructed at the level of the cooperative, the service provider or the supply chain. Table 7 organises the benefit streams, the mechanism through which each creates value for cacao systems, the evidence basis, and the scale at which each is most readily captured. The pattern is clear: the modest, farm-capturable agronomic benefits sit alongside much larger value-added and risk-management benefits that require aggregation, market linkage or regulatory exposure to realise. This distribution of benefits across scales is the crux of the feasibility question and directly motivates the framework of Section 6.

Benefit stream	Value-creation mechanism	Evidence basis	Capture scale
Input savings	Site-specific fertiliser/agrochemical targeting	PA ROI +22%, input −8–20% [42,53]	Farm+
Yield protection	Early stress & disease detection averts loss	UAV/red-edge disease detection [29,34,35]	Farm+
Scouting efficiency	Condition-based, targeted field visits	NDVI stress zoning [22,27]	Farm / coop
Regulatory market access	EUDR-compliant traceability & alerts	Sentinel-2 due diligence >90% [55,56]	Coop / chain
Certification premium	Verified sustainability lowers audit cost	Direct-trade premiums [12,13]	Coop / chain
Carbon & PES	Quantified C stocks & land-cover change	Profitable PES projects, B/C>1 [12,60]	Coop / landscape
Index insurance	Satellite-based drought/yield triggers	Climate–yield links quantified [6,23]	Coop / chain

Table 7. Benefit streams of space technology for cacao, their value-creation mechanism, evidence basis and the organisational scale at which each is most readily captured. PA = precision agriculture;

ROI = return on investment; PES = payments for ecosystem services; B/C = benefit–cost ratio; C = carbon.

5.3. Value-added: regulatory compliance, certification, carbon and insurance

The benefit stream most likely to make space technology financially convenient for cacao is regulatory compliance, driven by the European Union Deforestation Regulation (EUDR). The EUDR requires that cocoa (among other commodities) placed on the EU market be traceable to plot-level geolocation and verified as deforestation-free after the end-2020 cut-off, using satellite-based due diligence [55]. Because Europe consumes a large share of world cocoa, the regulation's impact on the crop is expected to be among the greatest of any commodity [55]. Compliance is costly and is expected to restructure supply chains in favour of larger, better-documented, traceable operations—precisely the actors able to invest in EO capability—while compliant supplies earn a premium [55]. Satellite monitoring is the enabling technology: operational systems already combine Sentinel-2 imagery, forest baselines and machine learning to produce farm-scale deforestation alerts and due-diligence reports with user accuracies above 90% [56], and remote sensing is central to traceability and accountability across cocoa and other forest-risk supply chains [54,58].

The magnitude and distribution of EUDR effects sharpen this point. Analyses of the regulation anticipate that compliance costs, while potentially significant in aggregate, are small relative to the trade value at stake, and that they will restructure supply chains by favouring larger farms and international traders able to bear traceability burdens, with compliant supplies commanding a price premium and non-compliant producers risking exclusion from the lucrative EU market [55]. Studies across producer countries—Côte d'Ivoire, Peru, Brazil and others—document the practical challenges of plot geolocation, legality verification and country-risk benchmarking, and warn that costs and administrative burdens could disadvantage the smallholders and Indigenous communities who grow much of the world's fine cocoa under agroforestry [54,55,59]. The unifying implication is that satellite monitoring is simultaneously the tool that makes compliance achievable and the tool that, if built on inaccurate maps, could inflict unjust exclusion. This dual character elevates accurate, regionally calibrated cacao mapping from a technical nicety to an instrument of economic justice, and it places a premium on the very capabilities reviewed in Section 3.

This regulatory driver transforms the economics. For an exporter or cooperative, EO-based compliance shifts from a discretionary efficiency investment to a *condition of market access*, so its benefit is not a marginal yield gain but the retention of the entire EU revenue stream and any deforestation-free premium. At the same time, the literature warns of a critical downside risk that is itself a technical-economic problem: global forest maps frequently misclassify shaded agroforestry as forest, which could wrongly exclude compliant smallholders and inflict 'collateral' economic damage unless regionally calibrated, commodity-specific datasets are built [54,57,59]. Accurate cacao mapping (Section 3.3) is therefore not merely useful but economically protective for producers.

Two further value-added streams reinforce the case. Certification and direct-trade relationships already deliver price premiums and better terms to Ecuadorian fine-flavour producers, and EO-based verification can lower the audit cost and raise the credibility of such schemes [12,13]. Carbon and

payment-for-ecosystem-services revenues monetise cacao agroforestry's storage and biodiversity benefits; remote sensing quantifies carbon stocks and land-cover change to support these markets [12], and economic analyses in Peru show that environmental-service projects on cacao farms can be profitable (benefit–cost ratios well above one) [60]. Finally, satellite-derived vegetation and weather data underpin index-based insurance that can protect cacao incomes against drought and climate shocks, addressing the volatility that undermines smallholder viability [6,23]. Together, these streams shift the benefit side from thin agronomic margins toward substantial, market- and policy-driven value.

5.4. Climate resilience and the temporal value of monitoring

A benefit dimension easily overlooked in static cost–benefit accounting is the *temporal* value of information under climate variability. Cacao is climate-sensitive: rainfall anomalies, heat and drought materially depress yields, and cacao agroforestry is promoted partly for its role in buffering temperature extremes and mitigating climate change through carbon storage [7,23]. In this setting, monitoring delivers value not only as an average annual efficiency gain but as an *option and insurance* value—the ability to detect an emerging drought-stress signature, a disease outbreak or an anomalous season early enough to act, and to document conditions for insurance and relief. The multi-dimensional meta-analysis of cocoa agroforestry versus monoculture found that agroforestry stores about 2.5 times more carbon and lowers and buffers temperatures, while achieving comparable profitability through diversified total-system yields [7]; EO can quantify and verify precisely these attributes at scale, turning them into monetisable and reportable assets. Because the value of early warning is convex—small, timely interventions avert large, late losses—the expected benefit of continuous monitoring rises with the frequency and severity of climate shocks. As those shocks intensify, the financial case for maintaining a standing monitoring capability strengthens correspondingly, a dynamic that conventional single-year ROI calculations understate.

5.5. Adoption barriers as economic costs

A complete financial appraisal must internalise the barriers that adoption studies identify, because these are not merely sociological footnotes but real economic costs and risks that shift the net-benefit calculus. Systematic reviews of precision-agriculture adoption among small-scale farmers converge on a consistent set of determinants: high initial investment and uncertain returns, limited digital literacy and technical support, weak infrastructure and connectivity, small and fragmented landholdings, and—frequently dominant—social and informational factors such as awareness, trust and cultural norms [46,47,50]. Qualitative work with small commercial family farms shows openness to precision technologies coexisting with reluctance driven by cost uncertainty and the absence of affordable, small-scale-appropriate applications and reliable service provision [50]. Meta-analytic and modelling evidence indicates that learning costs, subsidy levels and the availability of low-cost, modular technologies strongly condition the minimum viable farm size, and that machinery cooperatives, service providers and targeted (rather than blanket) support are more effective than generic subsidies at raising uptake [44,52]. Each of these barriers has a monetary shadow: training and extension time, the risk premium producers attach to uncertain returns, the cost of connectivity and devices, and the transaction costs of coordination. Incorporating them explains why nominally

positive agronomic returns often fail to materialise at the farm level and reinforces the paper's central conclusion that the binding constraints on cacao EO are organisational and institutional as much as technological. It also identifies the levers—cost-sharing, capacity building, service models and appropriate low-cost sensor strategies—through which these costs can be reduced enough for net benefits to emerge [44,46,49].

6. Integrated Techno-Economic Feasibility Framework and Scenario Analysis

6.1. A scale-dependent feasibility logic

Combining the technical and financial dimensions yields a central proposition: for cacao, *technical feasibility is largely scale-invariant while financial convenience is strongly scale-dependent*. The same open-access imagery and cloud-processed algorithms that map or monitor one plot can map an entire region at near-zero marginal cost; what changes with scale is the denominator over which the fixed capability costs are spread and the range of high-value benefits that become accessible. This logic organises feasibility into three archetypes—individual farm, cooperative, and landscape/supply chain—summarised in Table 6 and illustrated in Figure 1.

Scale / model	Cost exposure	Accessible benefits	Feasibility verdict
Individual smallholder (1–3 ha)	Full fixed capability cost on tiny area; UAV = 0.8–3.1× income [49]	Input/scouting savings only; limited	Rarely convenient alone
Cooperative (dozens–hundreds of members)	Fixed costs shared; UAV-as-service; shared analyst [49,27]	Agronomic + certification + aggregated compliance	Frequently convenient
Landscape / supply chain / exporter	Capability embedded in operations	Full stack incl. EUDR market access & premiums [55,56]	Convenient / near-mandatory

Table 6. Scale-dependent feasibility archetypes for space technology in cacao. The decisive economic lever is aggregation, which both dilutes fixed costs and unlocks high-value regulatory, certification and environmental-service benefits unavailable to isolated farms.

6.2. Illustrative scenario analysis

To make the logic concrete, we present an illustrative, parametric scenario analysis. We stress that the values below are *assumptions synthesised from the cited ranges*, not measured results; they are intended to expose the structure of feasibility and should be recalibrated with local data. Consider a Sentinel-based monitoring service (open imagery, GEE processing, one shared analyst, periodic UAV scouting of hotspots, and cooperative field validation). We assume an annual fixed capability cost in the order of US$8,000–20,000 for a functioning service, drawing on reported precision-agriculture investment ranges and UAV cost evidence [45,49,53]. We assume the service yields, per hectare, a

conservative blend of input and scouting savings and yield-loss avoidance worth on the order of US$30–90 per ha per year (consistent with 5–15% improvements on the thin margins reported for Amazonian cacao, where net margins average a few hundred dollars per hectare [5,6]), plus—where the EU market is in play—the protection of export revenue and any deforestation-free premium.

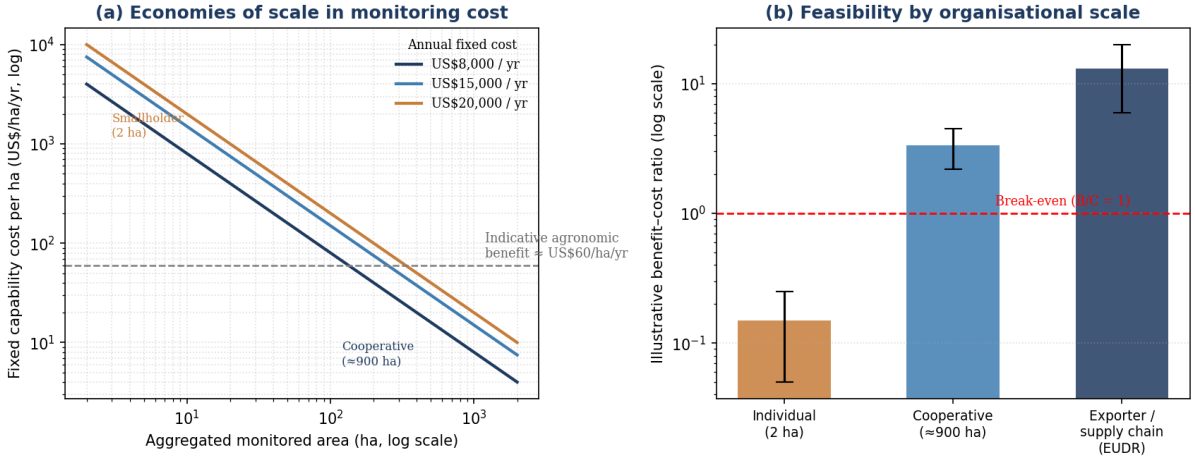

Figure 1. Illustrative techno-economic structure of space-based cacao monitoring. **(a)** Because most costs are fixed and largely independent of area, the fixed capability cost per hectare falls steeply as the monitored area is aggregated (log–log axes); the dashed line marks an indicative agronomic benefit of about US$60 ha^{-1} yr^{-1}, so a service crosses into profitability on agronomic grounds alone once a few hundred hectares are pooled. **(b)** Illustrative benefit–cost ratios by organisational archetype (log scale): individual smallholders fall below break-even (B/C = 1), cooperatives rise comfortably above it, and exporters facing EUDR obtain the highest ratios because monitoring protects entire market-access revenue. Values are parametric assumptions synthesised from cited ranges [5,6,42,45,49,53,55], not measured results, and are intended to reveal structure rather than to predict returns for any specific farm.

Under these assumptions the arithmetic is illuminating. For an **individual 2 ha farm**, agronomic benefits of perhaps US$60–180 per year cannot support a dedicated capability costing thousands, confirming that stand-alone adoption is uneconomic [43,49]. For a **cooperative of 300 members averaging 3 ha (≈900 ha)**, the same fixed cost of, say, US$15,000 per year equates to under US$20 per ha, comfortably below even conservative agronomic benefits, before any certification or compliance value is counted—yielding a favourable benefit–cost ratio and positive net present value once multi-year horizons and discounting are applied [45,53,60]. For an **exporter facing EUDR**, the benefit denominator is not marginal agronomic gain but continued access to the EU market for the entire sourced volume; here the compliance-monitoring cost is small relative to the revenue it protects, and investment is effectively obligatory [55,56]. The pattern mirrors the wider precision-agriculture finding that returns turn positive above particular size thresholds and with public or collective support [42,44,53].

Sensitivity analysis reinforces three levers. First, *aggregated area* is the dominant driver: because most costs are fixed, feasibility improves almost linearly with the hectares over which they are spread. Second, *benefit composition* matters more than benefit level: adding regulatory-access and

premium value changes the verdict far more than tuning agronomic savings, which is why EUDR and certification are pivotal for cacao. Third, *sensor strategy* is a cost dial: defaulting to free Sentinel data and reserving expensive UAV or VHR acquisition for validated hotspots keeps costs low without sacrificing decision quality [49,32]. The framework thus does not deliver a single yes/no answer but a conditional map: space technology is financially convenient for cacao when—and largely because—it is deployed as shared infrastructure at cooperative or supply-chain scale and oriented toward the high-value benefit streams that scale unlocks.

6.3. Organisational models that realise value

The framework points to specific organisational designs. *Cooperative ownership and drone-as-a-service* models spread capital and analytic costs and have been shown to raise UAV adoption far above isolated approaches in smallholder systems [49]. *Shared spatial decision-support systems*, co-designed with end users as in the Costa Rican sugarcane case, embed analytics in tools that advisors actually use, avoiding the common failure in which technically sound systems go unadopted [27]. *Supply-chain and exporter-led deployment* internalises EO capability where the EUDR benefit accrues, then extends services back to suppliers. *Public and donor co-investment*—in rural connectivity, ground-truth networks, capacity building and targeted subsidy—addresses the market failures that keep otherwise beneficial technology from smallholders, an intervention repeatedly recommended in the adoption literature [43,44,47]. In each design, the recurring principle is that value is captured collectively, not individually.

These models are mutually reinforcing rather than exclusive, and a realistic implementation pathway sequences them. An initial phase might establish a shared, cloud-based mapping and alert service over a cooperative's members using free Sentinel imagery, financed jointly and staffed by one trained analyst, delivering plot geolocation, extent maps and stress zoning at very low cost per hectare. A second phase would add periodic UAV scouting of flagged hotspots, funded on a fee-for-service or shared-ownership basis, to confirm and localise disease and stress. A third phase would integrate the resulting geospatial record into supply-chain due-diligence systems for EUDR compliance and certification, converting the monitoring apparatus from a cost centre into a market-access and premium-generating asset. Each phase is individually justifiable and progressively unlocks higher-value benefits, allowing investment and capability to grow with demonstrated returns rather than requiring a large, risky, up-front commitment—an incremental design well suited to the risk tolerance and financing constraints of smallholder-based sectors [44,46,49].

7. Discussion

7.1. Reconciling technical potential with economic reality

The analysis resolves the apparent paradox in the sector's discourse—between enthusiastic technical demonstrations and sluggish real-world uptake—by locating feasibility at the level of organisation rather than technology. Technically, the reviewed evidence leaves little doubt that cacao can be mapped, its condition monitored, its diseases detected and its land-use change verified from space and air, with accuracies that are operationally useful and improving [14,16,20,34,56]. Economically, the same evidence, read alongside the precision-agriculture literature, shows that these capabilities

do not pay for themselves on a two-hectare plot but do so readily when their near-fixed costs are shared and when they are directed at the high-value benefits—market access, premiums, environmental-service revenue—that only aggregation and regulation make available [42,49,55]. The 'conveniencia' of the title is therefore real but conditional, and the conditions are principally institutional.

This reconciliation also clarifies why so many pilot projects in digital agriculture fail to scale. Pilots are typically evaluated on technical performance—accuracy, resolution, timeliness—which cacao EO can readily satisfy, and are frequently funded as one-off, externally subsidised interventions whose true capability costs are hidden. When the subsidy ends and costs become visible, an intervention validated on technical grounds collapses on financial ones, because it was never structured at a scale or with a benefit mix that could sustain it. The framework advanced here guards against this failure mode by insisting that feasibility be assessed on both axes simultaneously and at the correct decision-making unit from the outset. Applied prospectively, it would steer investment away from technically impressive but financially orphaned farm-level pilots and toward the aggregated, benefit-rich, institutionally embedded deployments that the evidence indicates can endure. In this sense the paper's contribution is not only analytical but practical: a lens through which producers, cooperatives, exporters and policymakers can appraise proposed cacao monitoring initiatives before committing resources, asking of each not merely 'does it work?' but 'for whom, at what scale, and against which benefits does it pay?'

7.2. Barriers and enabling conditions

Several barriers must be managed for value to be realised. *Ground-truth scarcity* is the pre-eminent technical-economic constraint: reliable classification and yield models demand field reference data that Latin American cacao regions largely lack, and building this public good is a prerequisite investment [1,14]. *Digital literacy and human capital* are limiting; the adoption literature consistently finds social and knowledge factors as influential as cost [46,47,50]. *Connectivity and infrastructure* deficits in rural cacao zones impede cloud-based workflows and device use [49,51]. *Data-governance and equity* concerns—who owns farm geolocation data, and how misclassification risk is borne—are acute under EUDR, where a mapping error can exclude a compliant farmer [54,57,59]. Enabling conditions mirror these barriers: cooperative aggregation, regionally calibrated and commodity-specific datasets, capacity building, appropriate low-cost sensor strategies, co-designed decision-support tools, and public or supply-chain co-investment [27,44,49,54].

7.3. Comparison with conventional alternatives

Space technology should be judged against the status quo of visual field inspection and blanket management, not against perfection. Conventional scouting is labour-intensive, spatially limited, historically blind and unable to deliver the plot-level geolocation now demanded by buyers and regulators [22,55]. EO complements rather than replaces field knowledge: it directs limited human attention to where it is most needed and provides the auditable spatial record that certification and compliance require. The most robust designs are explicitly *hybrid*—free satellite synopsis for wall-to-wall screening, UAV precision for validated hotspots, and field expertise for interpretation and action

[28,32,49]. Framed this way, the relevant question is not whether space technology outperforms every alternative in isolation but whether adding a shared EO layer improves the decisions and market position of a cacao production system at acceptable cost; for aggregated systems, the evidence says it does. Table 8 contrasts the principal monitoring approaches across the criteria that matter for cacao decisions and compliance.

Criterion	Field inspection	Satellite (open)	UAV	Hybrid (recommended)
Spatial coverage	Low	Very high	Medium	Very high
Resolution	Very high (local)	10–30 m	cm-scale	Multi-scale
Revisit / timeliness	Irregular	Days (cloud-limited)	On demand	High
Historical baseline	None	Decades [18]	None	Decades
Plot geolocation record	Manual	Yes	Yes	Yes
Marginal cost / ha	High (labour)	≈Zero [3]	Medium [49]	Low–medium
EUDR readiness	Weak	Strong [56]	Supporting	Strong

Table 8. Comparison of cacao monitoring approaches across decision-relevant criteria. The hybrid model—free satellite synopsis for wall-to-wall screening, UAV precision for validated hotspots, and field expertise for interpretation—dominates on the combined criteria most relevant to smallholder cacao systems and regulatory compliance.

7.4. Research gaps and future directions

Four gaps stand out. First, *cacao-specific yield modelling* from EO remains immature; relating canopy signals to below-canopy pod production in mixed agroforests is an open problem requiring dedicated ground networks and canopy models [23,41]. Second, *disease-specific detection* for cacao's key pathogens (frosty pod rot, black pod, witches' broom) has strong crop analogues but few cacao-validated operational systems, a priority given the diseases' economic weight [29,34,35]. Third, *rigorous, farm-level techno-economic studies* for cacao EO are almost absent; the field needs primary cost–benefit and adoption research analogous to that available for grain crops, ideally in Ecuadorian and Andean-Amazonian settings [42,53]. Fourth, *equity-preserving compliance datasets*—regionally calibrated forest/agroforest maps that do not misclassify shaded cacao—are urgently required to prevent EUDR from harming the smallholders it should not target [54,57,59]. Beyond these, three cross-cutting directions merit attention. First, the integration of EO with emerging artificial-

intelligence methods—including foundation models for Earth observation and large vision models now entering agricultural remote sensing—may reduce the ground-truth burden through transfer learning and self-supervision, directly addressing the reference-data bottleneck that constrains cacao mapping [29,41]. Second, participatory and low-cost monitoring designs that place smartphones and simple protocols in producers' hands can simultaneously generate validation data, build digital literacy and strengthen the trust on which adoption depends, converting a technical need into a capacity-building opportunity [1,50]. Third, interoperable, standardised geospatial workflows and reference datasets—developed jointly by regulators, data providers and producer organisations—are needed to make compliance verification auditable, comparable and fair across the sector, avoiding both fraud and the wrongful exclusion of smallholders [57,58]. Progress on these fronts would move space technology for cacao from demonstrated potential to routine, equitable and demonstrably profitable practice.

7.5. Implications for Ecuador and Andean-Amazonian cacao

For Ecuador specifically, several implications follow. The country's dependence on the EU market for fine-flavour cocoa makes EUDR compliance a strategic priority, and the misclassification risk to shaded agroforests is acute given the prevalence of *Nacional* systems that resemble forest to global maps [55,57]. Investing early in nationally calibrated, cacao-specific reference datasets and plot geolocation is therefore both a compliance necessity and a protection against the wrongful exclusion of legitimate smallholders [54,57,59]. Ecuador's relatively strong cooperative and association structures—exemplified by producer unions transitioning members to dynamic agroforestry—provide ready vehicles for the aggregated, shared-infrastructure model that the feasibility analysis identifies as economically viable [9,12]. The premium attached to fine-flavour and certified cocoa raises the value of EO-based verification above that in bulk-cocoa economies, improving the benefit side of the ledger [13]. Finally, the environmental attributes of Ecuadorian cacao agroforestry—carbon storage, biodiversity, watershed protection—are assets that satellite monitoring can quantify for carbon and payment-for-ecosystem-services markets, diversifying producer income in a manner already shown to be profitable in comparable Andean-Amazonian settings [12,60]. Public agencies and development partners have a clear role in funding the shared datasets, connectivity and capacity that individual smallholders cannot, converting a collectively beneficial technology into an accessible one.

7.6. Limitations of this study

This work is a review and conceptual synthesis, not a primary empirical study, and its scenario analysis is illustrative and parametric rather than measured; its magnitudes should be calibrated with local data before informing investment. The cacao-specific remote-sensing evidence base is geographically skewed toward West Africa, so some inferences for Ecuador rest on transfer from analogous systems and crops. Finally, the fast-moving nature of sensors, algorithms, data costs and regulation means that specific cost and accuracy figures will date; the framework, however, is designed to remain valid as parameters change, because its conclusions follow from the cost *structure*—near-zero marginal imagery cost against largely fixed capability cost—rather than from any single price or accuracy value.

8. Conclusions

This paper asked whether the use of space technology for the control and monitoring of cacao crops is *convenient*—technically feasible and financially justified—for Ecuadorian and comparable Latin American production systems, and it answered by distinguishing the two dimensions and locating their intersection. Technically, the evidence is affirmative: open-access satellite constellations, radar–optical fusion, machine learning, UAVs and cloud platforms can map cacao under complex canopies, monitor vigour and stress, detect disease at tree level, forecast yield anomalies and verify land-use change, with accuracies that are operationally useful and rising [14,16,20,34,38,56]. The technical stack for cacao monitoring is, in essence, already assembled.

Financially, convenience is real but conditional and scale-dependent. Because the marginal cost of open-access imagery is effectively zero while the cost of capability is largely fixed, space technology exhibits pronounced economies of scale: it seldom pays for an isolated smallholder yet becomes readily and often compellingly economic when deployed as shared infrastructure at cooperative or supply-chain scale, and when directed at the high-value benefit streams—EUDR market access, certification premiums, carbon and index insurance—that aggregation and regulation unlock [42,49,55,60]. The European Union Deforestation Regulation, in particular, converts satellite monitoring from an optional efficiency tool into a near-condition of market access for EU-bound cocoa, decisively strengthening the economic case for aggregated actors while creating an equity risk for smallholders that accurate, regionally calibrated mapping must mitigate [55,57].

More broadly, the cacao case exemplifies a general principle for digital agriculture in the Global South: the economics of information technologies are governed less by their unit performance than by the architecture of their costs and the scale of their deployment. When a technology's core input is free and abundant while its enabling capability is fixed and lumpy, the efficient and equitable response is collective provision—pooling demand, sharing infrastructure and distributing benefits—rather than individual acquisition. Cooperatives, service providers, exporters and public agencies are therefore not peripheral to the adoption of space technology in cacao but constitutive of its feasibility. Recognising this reframes the policy question from 'how do we get drones and dashboards onto farms?' to 'how do we build the shared institutions and datasets that make orbital and aerial information a public good for the cacao sector?'

The central recommendation follows directly: space technology for cacao should be conceived and financed not as a farm-level gadget but as *shared digital infrastructure*—owned by cooperatives, delivered as a service, embedded in supply chains, and co-invested in by the public sector—supported by ground-truth networks, capacity building, hybrid satellite–UAV designs and equity-preserving datasets. Under these organisational conditions, the technical potential documented throughout this review translates into net economic value, sustainability gains and enhanced resilience for the smallholder cacao systems on which Ecuador's fine-flavour reputation and rural livelihoods depend. Realising that potential is now less a question of technology than of institutions, investment and inclusive design.

For Ecuador and its Andean-Amazonian neighbours, the stakes of getting this right are considerable. A fine-flavour cocoa sector built on dispersed smallholders confronts, simultaneously, the opportunity of premium and certified markets and the threat of exclusion under tightening deforestation regulation. Space technology, deployed collectively, offers a coherent response to both: it can verify the deforestation-free, agroforestry-based provenance that these markets and regulations reward and require, quantify the carbon and biodiversity assets that diversify producer income, and direct scarce agronomic effort to where disease and stress most threaten yields. The alternative—leaving smallholders without the spatial evidence base that buyers and regulators increasingly demand—risks consolidating the sector toward larger, better-documented operations and marginalising the very producers whose agroforestry systems underpin Ecuador's cocoa distinctiveness. Framed as shared infrastructure and supported by inclusive institutions, space technology can help ensure that the future of cacao monitoring is not only technically capable and financially sound, but also equitable. That triple objective—capable, convenient and inclusive—should guide the investments and policies that follow from this analysis.

Author Contributions

Conceptualisation, A.M.R.-B. and G.H.P.-B.; methodology, A.M.R.-B., H.P.S.-J. and O.M.B.-S.; formal analysis, R.E.C., E.G.F.-T. and V.S.-O.; investigation, all authors; writing—original draft preparation, A.M.R.-B., H.P.S.-J. and G.F.G.-G.; writing—review and editing, all authors; supervision, A.M.R.-B. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Wu, B.; Zhang, M.; Zeng, H.; Tian, F.; Potgieter, A.B.; Qin, X.; et al. Challenges and opportunities in remote sensing-based crop monitoring: a review. National Science Review 2022, 10, nwac290.
[2] Bégué, A.; Arvor, D.; Bellón, B.; Betbeder, J.; de Abelleyra, D.; Ferraz, R.P.D.; et al. Remote Sensing and Cropping Practices: A Review. Remote Sensing 2018, 10, 99.
[3] Segarra, J.; Buchaillot, M.L.; Araus, J.L.; Kefauver, S.C. Remote Sensing for Precision Agriculture: Sentinel-2 Improved Features and Applications. Agronomy 2020, 10, 641.
[4] Vargas, C.A.; Bottani-Claros, R.; et al. Assessment of the environmental impact and economic performance of cacao agroforestry systems in the Ecuadorian Amazon region: An LCA approach. Science of the Total Environment 2022, 838, 156454.
[5] Vargas, C.A.; et al. Agroecology as a means to improve energy metabolism and economic management in smallholder cocoa farmers in the Ecuadorian Amazon. Sustainable Production and Consumption 2023, 39, 302–316.
[6] Charry, A.; Enciso, K.; Díaz, M.F.; et al. The bittersweet economics of different cacao production systems in Colombia, Ecuador and Peru. Agricultural Systems 2025, 223, 104200.
[7] Niether, W.; Jacobi, J.; Blaser, W.J.; Andres, C.; Armengot, L. Cocoa agroforestry systems versus monocultures: a multi-dimensional meta-analysis. Environmental Research Letters 2020, 15, 104085.

[8] Tinoco-Jaramillo, L.; Vargas-Tierras, Y.; et al. Agroforestry Systems of Cocoa (Theobroma cacao L.) in the Ecuadorian Amazon. Forests 2024, 15, 195.

[9] Allen, S.L.; et al. Productivity, Soil Health, and Tree Diversity in Dynamic Cacao Agroforestry Systems in Ecuador. Land 2024, 13, 1810.

[10] Castañeda-Ccori, J.; Bilbao-Núñez, A.; et al. Unveiling Cacao Agroforestry Sustainability through the Socio-Ecological Systems Diagnostic Framework: The Case of Four Amazonian Rural Communities in Ecuador. Sustainability 2020, 12, 5934.

[11] Blare, T.; Useche, P. Competing objectives of smallholder producers in developing countries: examining cacao production in Northern Ecuador. Environmental Economics 2017, 8, 78–86.

[12] Middendorp, R.S.; Foley, E.; Kessler, A.; et al. Improving smallholder livelihoods and ecosystems through direct trade relations: High-quality cocoa producers in Ecuador. Business Strategy & Development 2020, 3, 322–338.

[13] Tscharntke, T.; Ocampo-Ariza, C.; Vansynghel, J.; et al. Socio-ecological benefits of fine-flavor cacao in its center of origin. Conservation Letters 2022, 15, e12936.

[14] Therias, A.; et al. Integrating radar and multi-spectral data to detect cocoa crops: a deep learning approach. Remote Sensing Applications: Society and Environment 2025, 37, 101430.

[15] Singh, K.; Gnanaharan, R.; et al. E-Agriculture Planning Tool for Supporting Smallholder Cocoa Intensification Using Remotely Sensed Data. Remote Sensing 2023, 15, 2113.

[16] Abu, I.-O.; Szantoi, Z.; Brink, A.; Robuchon, M.; Thiel, M. Detecting cocoa plantations in Côte d'Ivoire and Ghana and their implications on protected areas. Ecological Indicators 2021, 129, 107863.

[17] Kalischek, N.; Lang, N.; Renier, C.; Daudt, R.C.; et al. Cocoa plantations are associated with deforestation in Côte d'Ivoire and Ghana. Nature Food 2023, 4, 384–393.

[18] Dada, E.A.; Ogunkoya, O.O.; et al. Application of satellite remote sensing to observe and analyse temporal changes of cocoa plantation in Ondo State, Nigeria. GeoJournal 2020, 85, 1191–1204.

[19] Kanmegne Tamga, D.; Latifi, H.; Ullmann, T.; Baumhauer, R.; et al. Modelling the spatial distribution of the classification error of remote sensing data in cocoa agroforestry systems. Agroforestry Systems 2022, 96, 749–761.

[20] Numbisi, F.N.; Van Coillie, F.M.B.; De Wulf, R. Delineation of Cocoa Agroforests Using Multiseason Sentinel-1 SAR Images: A Low Grey Level Range Reduces Uncertainties in GLCM Texture-Based Mapping. ISPRS International Journal of Geo-Information 2019, 8, 179.

[21] Numbisi, F.N.; Van Coillie, F. Does Sentinel-1A Backscatter Capture the Spatial Variability in Canopy Gaps of Tropical Agroforests? A Proof-of-Concept in Cocoa Landscapes in Cameroon. Remote Sensing 2020, 12, 4163.

[22] Anyimah, F.O.; Anornu, G.K.; et al. Detection of stress areas in cocoa farms using GIS and remote sensing: A case study of Offinso Municipal and Offinso North District, Ghana. 2021.

[23] Atalaya-Marin, N.; Injante, P.; et al. Integrating remote sensing and in-situ data to determine climate diversity and variability in cocoa systems in the provinces of Jaén and San Ignacio, Cajamarca (NW Perú). Trees, Forests and People 2024, 16, 100566.

[24] Colli-Silva, M.; Pérez-Escobar, O.A.; et al. Human influence on the distribution of cacao: insights from remote sensing and biogeography. Biodiversity and Conservation 2024, 33, 1969–1988.

[25] Lammoglia, S.-K.; et al. High-resolution multispectral and RGB dataset from UAV surveys of ten cocoa agroforestry typologies in Côte d'Ivoire. Data in Brief 2024, 54, 110402.

[26] Som-ard, J.; Atzberger, C.; Izquierdo-Verdiguier, E.; Vuolo, F.; Immitzer, M. Remote Sensing Applications in Sugarcane Cultivation: A Review. Remote Sensing 2021, 13, 4040.

[27] Alemán-Montes, B.; et al. A Near Real-Time Spatial Decision Support System for improving Sugarcane Monitoring Through a Satellite Mapping Web Browser. Smart Agricultural Technology 2025, 10, 100745.

[28] Maes, W.H.; Steppe, K. Perspectives for Remote Sensing with Unmanned Aerial Vehicles in Precision Agriculture. Trends in Plant Science 2019, 24, 152–164.

[29] Zhu, H.; Lin, C.; Liu, G.; Wang, D.; Qin, S.; Li, A.; et al. Intelligent agriculture: deep learning in UAV-based remote sensing imagery for crop diseases and pests detection. Frontiers in Plant Science 2024, 15, 1435016.

[30] Kouadio, L.; El Jarroudi, M.; Belabess, Z.; et al. A Review on UAV-Based Applications for Plant Disease Detection and Monitoring. Remote Sensing 2023, 15, 4273.

[31] Shahi, T.B.; Xu, C.-Y.; Neupane, A.; Guo, W. Recent Advances in Crop Disease Detection Using UAV and Deep Learning Techniques. Remote Sensing 2023, 15, 2450.
[32] Zhang, S.; et al. A Review of the Application of UAV Multispectral Remote Sensing Technology in Precision Agriculture. Smart Agricultural Technology 2025, 10, 100812.
[33] Abbas, A.; Zhang, Z.; Zheng, H.; et al. Drones in Plant Disease Assessment, Efficient Monitoring, and Detection: A Way Forward to Smart Agriculture. Agronomy 2023, 13, 1524.
[34] Ye, H.; Huang, W.; Huang, S.; Cui, B.; Dong, Y.; Guo, A.; et al. Recognition of Banana Fusarium Wilt Based on UAV Remote Sensing. Remote Sensing 2020, 12, 938.
[35] Lei, S.; Luo, J.; Tao, X.; Qiu, Z. Remote Sensing Detecting of Yellow Leaf Disease of Arecanut Based on UAV Multisource Sensors. Remote Sensing 2021, 13, 4562.
[36] Deng, L.; Mao, Z.; Li, X.; Hu, Z.; Duan, F.; Yan, Y. UAV-based multispectral remote sensing for precision agriculture: A comparison between different cameras. ISPRS Journal of Photogrammetry and Remote Sensing 2018, 146, 124–136.
[37] Peticilă, A.; et al. Vegetation Indices from UAV Imagery: Emerging Tools for Precision Agriculture and Forest Management. AgriEngineering 2025, 7, 89.
[38] Lobell, D.B.; Thau, D.; Seifert, C.; Engle, E.; Little, B. A scalable satellite-based crop yield mapper. Remote Sensing of Environment 2015, 164, 324–333.
[39] Cao, J.; Zhang, Z.; Tao, F.; Zhang, L.; Luo, Y.; et al. Wheat yield predictions at a county and field scale with deep learning, machine learning, and Google Earth Engine. European Journal of Agronomy 2021, 123, 126204.
[40] Jaafar, H.H.; Mourad, R. GYMEE: A Global Field-Scale Crop Yield and ET Mapper in Google Earth Engine Based on Landsat, Weather, and Soil Data. Remote Sensing 2021, 13, 773.
[41] Radočaj, D.; Jurišić, M.; et al. Satellite Remote Sensing for Crop Yield Prediction: A Review. Agriculture 2026, 16, 12.
[42] Lan, J.; et al. The Farm-Level Economic and Environmental Benefits of Precision Agriculture Technology Adoption: A Meta-Analysis of Global Evidence. Sustainability 2025, 17, 3247.
[43] Barnes, A.P.; Soto, I.; Eory, V.; Beck, B.; Balafoutis, A.; Sánchez, B.; et al. Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. Land Use Policy 2019, 80, 163–174.
[44] Munz, J.; Gindele, N.; Doluschitz, R. Influencing the Success of Precision Farming Technology Adoption—A Model-Based Investigation of Economic Success Factors in Small-Scale Agriculture. Agriculture 2022, 12, 1773.
[45] Sanyaolu, M.; Sadowski, A. The Role of Precision Agriculture Technologies in Enhancing Sustainable Agriculture. Sustainability 2024, 16, 6668.
[46] Mizik, T. How can precision farming work on a small scale? A systematic literature review. Precision Agriculture 2022, 24, 384–406.
[47] John, D.; Newton, P.; et al. A systematic review on the factors governing precision agriculture adoption among small-scale farmers. Outlook on Agriculture 2023, 52, 469–485.
[48] Onyango, C.M.; Nyaga, J.M.; Wetterlind, J.; Söderström, M.; Piikki, K. Precision Agriculture for Resource Use Efficiency in Smallholder Farming Systems in Sub-Saharan Africa: A Systematic Review. Sustainability 2021, 13, 1158.
[49] Ahmed, W.A.; et al. UAV Technologies for Precision Agriculture: Capabilities, Constraints, and Deployment Models for Smallholder Systems in Sub-Saharan Africa. Drones 2026, 10, 15.
[50] Kendall, H.; Naughton, P.; Clark, B.; Taylor, J.; Li, Z.; et al. Precision agriculture technology adoption: a qualitative study of small-scale commercial 'family farms' located in the North China Plain. Precision Agriculture 2021, 22, 200–226.
[51] Dhillon, R.; Moncur, Q. Small-Scale Farming: A Review of Challenges and Potential Opportunities Offered by Technological Advancements. Sustainability 2023, 15, 15478.
[52] Geng, W.; et al. Digital Technologies Adoption and Economic Benefits in Agriculture: A Mixed-Methods Approach. Sustainability 2024, 16, 4431.
[53] Kovács, E.; et al. Economic Aspects of Precision Crop Production: A Systematic Literature Review. Agriculture 2026, 16, 5.
[54] Renier, C.; Vandromme, M.; Meyfroidt, P.; Ribeiro, V.; Kalischek, N.; zu Ermgassen, E.K.H.J. Transparency, traceability and deforestation in the Ivorian cocoa supply chain. Environmental Research Letters 2023, 18, 024030.
[55] Gilbert, C.L. The EU Deforestation Regulation. EuroChoices 2024, 23, 44–51.

[56] Reading, I.; et al. Due Diligence for Deforestation-Free Supply Chains with Copernicus Sentinel-2 Imagery and Machine Learning. Forests 2024, 15, 1552.

[57] van Noordwijk, M.; et al. Beyond imperfect maps: Evidence for EUDR-compliant agroforestry. People and Nature 2025, 7, 812–830.

[58] Heldt, L.; Beske-Janssen, P. Solutions from space? A dynamic capabilities perspective on the growing use of satellite technology for managing sustainability in multi-tier supply chains. International Journal of Production Economics 2023, 260, 108864.

[59] Solar, J.; Pokorny, B.; et al. Human Rights and Environmental Due Diligence Regulations for Deforestation-Free Value Chains? Exploring the Implementation of the EU Regulation on Deforestation-Free Products in the Cocoa and Coffee Sectors of Peru. Global Policy 2025, 16, 112–128.

[60] Goñas, M.; Rojas-Briceño, N.B.; et al. Economic Profitability of Carbon Sequestration of Fine-Aroma Cacao Agroforestry Systems in Amazonas, Peru. Forests 2024, 15, 866.