Assessing UAV direct-seeding for tropical forest restoration: carbon sequestration potential and cost efficiency

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GS, EC conceived the ideas and designed the methodology. GS led data analysis and writing, with support from MV and LKW for interpretation. JT contributed to manuscript revision. EC supervised writing, analysis, and review. All authors critically reviewed the drafts and approved the final version.

Abstract

Abstract

Introduction: Afforestation, Reforestation, and Revegetation (ARR) projects are key to global reforestation targets under frameworks like the Paris Agreement and the UN Decade on Ecosystem Restoration. However, manual planting remains labor-intensive and costly, limiting large-scale restoration. UAV-assisted direct seeding offers a scalable alternative, yet its carbon sequestration and cost-efficiency remain underexplored. **Objectives:** This study assesses UAV-assisted direct seeding as a cost-effective alternative to manual planting for tropical and subtropical reforestation. We compare early-stage

CO_2 sequestration, model long-term sequestration potential, and evaluate economic feasibility. **Methods:** Over 2.5 years, we measured CO_2 sequestration in trees established via UAV-assisted direct seeding and manual planting. A cost analysis compared implementation expenses, and long-term modeling projected carbon capture and financial feasibility. **Results:** From 18 months onward, CO_2 sequestration rates were comparable between UAV-assisted direct seeding and manual planting. Long-term modeling supports UAV-assisted direct seeding as a viable strategy for sustained carbon sequestration. Cost analysis indicates planting costs are 2.5 to 7.8 times lower than manual methods. **Conclusions:** UAV-assisted direct seeding achieves similar carbon sequestration benefits as manual planting while significantly reducing costs. This approach facilitates large-scale reforestation by improving financial feasibility. **Implications for Practice:** This study serves as a proof of concept demonstrating that UAV-assisted direct seeding is a viable alternative for carbon sequestration. By achieving comparable sequestration rates to manual planting at significantly lower costs, this approach enhances the financial feasibility of reforestation projects. Lower establishment costs not only improve accessibility to carbon financing but also increase the potential for generating more carbon credits per investment. This could make reforestation more attractive within the Voluntary Carbon Market (VCM), particularly for small-scale landowners and restoration practitioners. Additionally, UAV technology enables reforestation in degraded or remote areas where manual planting is impractical, expanding the range of viable restoration sites. By reducing cost barriers and increasing scalability, UAV-assisted direct seeding can support larger, more inclusive carbon sequestration efforts, reinforcing its role as an effective tool for climate mitigation and restoration at scale.

Introduction

Tropical forests are among the most biodiverse and productive ecosystems on Earth, serving as critical components of global carbon cycling, climate regulation, and biodiversity conservation (Artaxo et al. 2022). They house more than half of the world's terrestrial species and play a vital role in supporting millions of livelihoods (Saha 2020). Despite their ecological and economic importance, these ecosystems face unprecedented levels of deforestation and land degradation. Over the last decades, tropical deforestation has accounted for roughly 20% of global greenhouse gas emissions, leading to significant ecological and economic losses (Gibbs & Herold 2007). In response to these challenges, large-scale reforestation and afforestation projects have emerged as essential strategies to combat climate change and biodiversity loss (Bonan 2008). These efforts are increasingly supported by international political frameworks, such as the Convention on Biological Diversity (CBD) and the United Nations Framework Convention on Climate Change (UNFCCC), including its Paris Agreement. These frameworks emphasize forest restoration as a cornerstone for achieving global biodiversity and climate targets. Moreover, recent studies highlight the co-benefits of reforestation, including enhanced carbon sequestration, improved water regulation, and increased productivity through species diversity (Rosa & Marques 2022). However, the practical implementation of reforestation at scale is fraught with challenges. Traditional restoration techniques, such as manual planting, require intensive labor and incur high operational costs, particularly in remote or degraded areas (Khoza et al. 2024). Additionally, these methods often involve substantial resource investments, which can pose financial barriers for large-scale projects. To overcome these challenges, innovative and cost-effective approaches are crucial (Werden et al. 2024). Emerging technologies offer promising solutions to these barriers. Among these, UAV-based direct seeding has been proposed as an efficient method for remote-area reforestation, potentially reducing labor costs, enhancing seed-deposition rates, and facilitating post-planting monitoring through advanced sensing and machine-learning techniques (Stamatopoulos et al. 2024). However, although seed broadcasting by UAVs can lower the upfront cost of nursery facilities and manual planting, it also presents challenges such as seed predation and limited suitability to species with specific germination requirements (Andres et al. 2022). Beyond planting alone, drones offer substantial utility for restoration planning, implementation, and monitoring at scale, including habitat mapping, wildfire management, and high-resolution imaging to track seedling establishment and growth (Robinson et al. 2022). Yet critics caution that success rates are often overstated; seeds and young seedlings must still overcome plenty of biotic and abiotic obstacles, and systematic, large-scale evidence of drone-based restoration success remains scarce (Castro et al. 2023). In particular, researchers emphasize the need for precise seed placement tailored to microhabitats rather than "mass firing" approaches if drone seeding is to be genuinely effective. This study contributes new empirical data by experimentally comparing UAV-based seeding to traditional manual planting in tropical forest restoration, thereby offering insights into both the ecological and economic implications of adopting drone technologies. Building on these considerations, this study evaluates the cost-benefit dynamics of traditional manual planting versus UAV-based direct seeding in tropical reforestation projects in the northern Amazon forest. Conducted over a period of 30 months, the study compares key factors—mostly aboveground biomass accumulation quantified via ground based measurements —as well as economic outcomes derived from detailed cost analyses and projected revenue from carbon credits. One of the primary goals is to quantify the speed and efficiency with which these approaches produce carbon credits in an economically viable manner under current carbon market frameworks. In these markets, time is a critical factor; project developers must rapidly generate credits to offset costs and attract investment, making restoration strategies that balance ecological benefits with financial viability particularly valuable (Golub et al. 2021).

Materials and methods

Study areas

Direct-seeding study areas

This analysis focuses on comparing four direct-seeding reforestation projects to manual plantation projects. The direct-seeding projects were conducted on former mining sites in the northern Brazilian Amazon and French Guiana. According to the Köppen-Geiger classification (Beck et al. 2023), the sites in French Guiana fall under the Af (tropical rainforest) climate zone, which is characterized by high rainfall distributed throughout the year with a very short dry season. In contrast, the Brazilian site is classified as Am (tropical monsoon), featuring a distinct and longer dry season while maintaining high annual rainfall. All sites are located within broadleaf evergreen forests (Eva et al. 2002). Regional precipitation patterns and the key average ecological and soil characteristics are summarized in the Table S1.

Brazil

The Brazilian study site is situated in the northeastern region of Pará, near Paragominas, at an elevation of 110 meters above sea level (see Figure 1). This area, a former bauxite mining site, has undergone significant soil degradation due to the removal of nutrient-rich topsoil during the extraction process, leaving behind clayey soils with poor chemical properties (Abdilla et al. 2023). The site is classified within *Dystrophic Yellow Oxisols*, characterized by high clay content and low nutrient availability (Bliss 2013). The water table lies approximately 20 meters below the surface (Crowther et al. 2022). The site receives an average annual precipitation of 1,800 mm and maintains a mean temperature of 25°C.

French Guiana

The French Guiana study includes three reforestation sites (see Figure 1), all located near riverbeds within former alluvial gold mining areas. These sites are classified as "riparian forests, lowlands, and wet valleys" (Guitet et al. 2015). Proximity to water bodies makes these areas susceptible to flooding, with water tables ranging between 0.77 and 5.5 meters (Fan et al. 2013). The soils are sandy and hydromorphic, typically low in iron and nitrogen but containing some available phosphorus. Mercury contamination from historical gold mining is also a common issue.

- The first site, located near Saint-Élie in western French Guiana, lies at 45 meters above sea level. This site experiences an average annual precipitation of 2,200 mm and a mean temperature of 26°C.
- The second site, also near Saint-Élie, is located at an elevation of 92 meters and features sandy terrain.
- The third site, near Regina in central French Guiana, is situated at 44 meters above sea level. This site experiences higher annual precipitation, averaging 3,600 mm, with a mean temperature of 25°C.

Restoration method

Restoration was conducted using UAV-assisted broadcast seeding at approximately 15 m above ground, enabling rapid seeding over large areas. Fertilization depended on terrain constraints: in Brazil, 15-15-15 NPK fertilizer was applied at 82 kg ha^{-1} to enhance plant establishment, whereas no fertilizer was used at two French Guiana sites due to accessibility issues. Species selection was tailored to local vegetation, and leguminous cover crops were planted simultaneously with native trees to foster favourable microhabitats. In Brazil, restoration efforts incorporated 30 native tree species and 4 herbaceous species to promote biodiversity and restore ecosystem functionality. The three French Guianese projects were implemented as such:

- The first project involved planting 29 native tree species and 3 herbaceous species, supported by an application of 100 kg ha^{-1} of 15-15-15 NPK fertilizer.
- The second project included 28 native tree species and 4 herbaceous agricultural species.
- The third project focused on 14 native tree species and 3 herbaceous species.

Depending on the seedling recruitment density, several rounds of plantations have been done (up to three in the first Guianese project)

CO2 sequestration data

Measurements from direct-seeding experimental sites were conducted to estimate above-ground biomass (AGB) and carbon sequestration during early growth stages. Data were collected across multiple sites using standardized methods to account for variability in recruit density, with height and diameter measurements forming the basis for biomass calculations. In parallel, biomass and carbon data for manually planted trees were sourced from Verra-certified Afforestation, Reforestation, and Revegetation (ARR) projects within the Amazon biome. These datasets enabled a comparative analysis of carbon sequestration potential between direct seeding and traditional manual reforestation approaches.

Seedling measurements and discrimination

Field measurements were conducted at different stages for each project, depending on their age. Monitoring took place at 4 months, 5 months, and 30 months after the initial seeding, with the specific timing varying across projects. Only direct-seeded seedlings that successfully recruited were included in the measurements. Sampling was performed within several 10 $\times$ 10 m plots, with the number of plots varying according to the area of each project. Plot installation followed a stratified random sampling approach, guided by drone imagery to account for differences in recruit density across the project area. To estimate above-ground biomass, both height and diameter measurements were conducted, as these are key variables for allometric models. For taller seedlings, defined as those with a trunk reaching at least breast height (1.3 m), diameter was measured at breast height using a diameter tape, and total height was measured with a laser rangefinder. For younger seedlings, which were smaller and did not yet reach breast height, height was measured by straightening the plant and measuring from the ground to the apical bud. Diameter for these younger seedlings was measured using a caliper, below the first true leaf node.

Seedling age determination

In projects involving multiple plantations, specimens were classified into *small* and *big* groups based on a simple cutoff at 400 cm in height. This straightforward approach was chosen as seedlings were measured only once, at 30 months, and the area had undergone two separate rounds of direct seed broadcasting. The classification aimed to account for these distinct planting events and provide a practical way to estimate the growth and age of the specimens.

Selection of allometric models

The allometric model for estimating above-ground biomass (AGB) was selected from a comprehensive set of 663 equations commonly used in Brazilian forestry (Calais et al. 2022). Filtering criteria included applicability to native, natural forests (496 equations), individual trees (492 equations), and dense ombrophilous forests (90 equations). Further narrowing considered relevance to the Amazon biome (56 equations), suitability for Pará (17 equations), compatibility with multiple species in diverse plantations (12 equations), and applicability to young trees with thin stems (2 equations). The final selection was based on minimizing the standard error to enhance the model's accuracy in estimating AGB, which lead to one unique general model, provided by Ducey et al. 2009. Although the filtering process emphasized relevance to Pará, this approach remains pertinent for French Guiana, as both regions fall within the same floristic domain of the Amazon forest (Silva-Souza & Souza 2020).

Biomass computation and outlier removal

To estimate the biomass for each specimen in the Amazon biome, we applied a power function for Above Ground Biomass (AGB), based on the formula (Ducey et al. 2009):

$$\mathrm{AGB} = 0.0985 \times \mathrm{DBH}^{1.879} \times (\mathrm{Height})^{0.7355}$$

This formula estimates the above-ground biomass using the diameter at breast height (DBH) and total height of the tree. We compared results to the model proposed by Chave et al. 2014, and retained their approach systematically underestimates carbon accumulation in this context by excluding trees with stem diameter below 5 cm (see S. To account for below-ground biomass (BGB), we used the following equation derived from Clean Development Mechanism Executive Board 2013:

$$\text{BGB Factor} = \frac{\exp(-1.085 + 0.9256 \times \ln(\mathrm{AGB}))}{\mathrm{AGB}}$$

The BGB was then calculated as:

$$\mathrm{BGB} = \mathrm{AGB} \times \text{BGB Factor}$$

The belowground biomass (BGB) equation used in this study, originally developed for hectare-scale applications, was adapted for individual tree-level analysis to match the data provided for manual plantations. While practical for this context, this adaptation assumes uniformity in root development across sites and densities, potentially introducing scaling uncertainties (Zhou et al. 2017). The total biomass was the sum of AGB and BGB. To convert the biomass values into carbon dioxide (CO_2) equivalents, we assumed that 47% of the biomass was composed of carbon (Martin & Thomas 2011), which was then multiplied by the molecular weight ratio of CO_2 to carbon (44/12). The final CO_2 estimate for each specimen was calculated using the formula:

$$\mathrm{CO_2} = (\mathrm{AGB} + \mathrm{BGB}) \times 0.47 \times \frac{44}{12}$$

After calculating CO_2, the dataset was cleaned to ensure data integrity. Outliers were identified using z-scores, which were computed separately within each age group (in months). This intra-group computation accounts for potential differences in variance at different growth stages. 16 data points with z-scores exceeding ±3 were excluded, ensuring that extreme values did not distort the analysis. The z-scores were computed in R (version 4.3.3, 2024-02-29) using the `stats` package.

Traditional manual reforestation projects

Biomass data for traditional manual reforestation projects were sourced from the Verra Registry, an industry-leading platform for carbon credit projects Verra Registry 2024. Selection criteria were applied to identify relevant projects, starting with all projects in Brazil (283 projects). From these, 38 Afforestation, Reforestation, and Revegetation (ARR) projects were identified, of which 8 were located within the Amazon biome. Finally, 2 projects were included for analysis due to the availability of detailed tree plantation plans and precise CO_2 sequestration data. While the number of projects included is limited, this selection allows for a close comparison within the same biome, ensuring that external factors influencing biomass accumulation remain consistent. Additionally, by focusing solely on Verra-certified projects, this analysis allows for a practitioner-to-practitioner perspective.

Statistical modelling

To model the relationship between tree age and CO_2 sequestration, six statistical models were evaluated, each designed to capture biomass accumulation and carbon storage dynamics in tropical trees. The selection process prioritized models that aligned with biological growth patterns and provided a good fit to the data, leveraging established tree growth modelling approaches Salas-Eljatib et al. 2021. Log-transformed models were initially considered to normalize data distributions but were excluded due to their inability to reflect realistic growth trajectories. The remaining models were compared using the Akaike Information Criterion (AIC) and R^2 to balance goodness-of-fit and parsimony (see Table S2 for comparative metrics). The chosen model was a Chapman-Richards function, recognized for its ability to capture sigmoidal growth patterns in tropical species (Bukoski et al. 2022). This function relates tree age (in years) to CO_2 sequestration (in kilograms) and is expressed as:

$$\mathrm{CO}_2 = y_{\max} \cdot \left(1 - e^{-k \cdot \mathrm{Age}}\right)^{\frac{1}{1-m}},$$

where k is the growth rate parameter, m is the shape parameter, and $y_{\max} = 300$ kg is the fixed asymptotic maximum CO_2 sequestration per tree, based on Franklin Jr & Pindyck

2024. Fixing $y_{\max}$ reflects the dataset's limitation to early growth stages (up to 30 months), where estimating long-term maximum values would be unreliable. To ensure adherence to observed trends, the model was constrained to target a sequestration value of 124.98 kg at 10 years, informed by prior studies (Lefebvre et al. 2021). This constraint was implemented through a penalized residual sum of squares (RSS):

$$\mathrm{RSS}_{\text{penalized}} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \left(\hat{y}_{\text{target}} - y_{\text{target}}\right)^2,$$

where y_i are the observed CO_2 values, $\hat{y}_i$ are the model predictions, $\hat{y}_{\text{target}}$ is the predicted value at the target age, and $y_{\text{target}} = 124.98$ kg. The penalty weight λ was set to 100 to balance data fit and adherence to the constraint. Model parameters were estimated using the `optim` function in R with the L-BFGS-B method, which allowed bounds ($k \geq 0$, $m \geq 0$). The estimated parameters were $k = 0.0997$ and $m = 0.4723$. To account for uncertainty due to the limited dataset, bootstrapping with 1,000 iterations was performed. In each iteration, the dataset was resampled with replacement, and the constrained Chapman-Richards model was refitted, generating parameter distributions and predicted CO_2 sequestration over time. Confidence intervals (CIs) were constructed by taking the 1st and 99th percentiles of the bootstrapped predictions at each time point, yielding a 98% CI that reflects the uncertainty inherent in the small sample size. Due to the limited availability of long-term data, a constrained model was employed to project aboveground biomass (AGB) trends using data from manual plantations. This approach focuses on the critical establishment phase, during which direct seeding must perform comparably to manual planting to justify further exploration. The analysis was conducted at the individual tree level to account for differences in tree density between datasets.

Plantation costs

Direct seeding

Plantation costs per hectare for direct seeding implementation were analyzed based on data from two MORFO projects in Brazil and French Guiana. These costs were categorized by key project stages, including pre-plantation activities (diagnostic, planning), initial plantings, follow-up plantings, and monitoring phases. Within each stage, costs were itemized into categories such as field labor, office support, seeds, ecosystem services, equipment, freight, and data management. Among these, field labor, seeds, and equipment accounted for the largest expenditures. To enable a fair comparison between plantation methods, monitoring costs were excluded from the analysis. This exclusion reflects the variability in monitoring methods across projects (Cole et al. 2024), which are not directly correlated with the chosen plantation method.

Manual planting

Costs for manual planting were sourced from a recent study (Cole et al. 2024) that analyzed restoration expenses across Latin America. This study provided aggregated costs for site preparation, tree planting, and maintenance up to the point of seedling establishment, typically spanning 1–3 years. To refine the estimates, restoration costs specific to Brazil were derived from Brancalion et al. 2019, offering a more localized and lower-cost perspective. Brazil was selected as the primary source for manual planting costs because it holds the largest potential for restoration globally, making it a key reference point for large-scale restoration initiatives (Williams et al. 2024).

Carbon credits

Carbon credit price is highly variable in the Verified Carbon Market (VCM), because it is influenced by factors such as project scope, certification standards, and buyer preferences. To have a reliable basis, the average prices of VCM credits for Afforestation, Reforestation, and Revegetation (ARR) projects were obtained from Procton 2024 for the years 2022 and 2023.

Economic evaluation

The economic evaluation considered three scenarios based on establishment density: high density (1,300 seedlings/ha) requiring one planting round, medium density (550 seedlings/ha) requiring two planting rounds, and low density (350 seedlings/ha) requiring three planting rounds. For manual plantations, only one planting round was assumed, as maintenance costs are included in the total plantation cost, based on the average density observed in manual plantation project (1104 seedlings/ha) (Cole et al. 2024). The total value (V_{total}) was defined as the product of the total CO_2 absorbed at a given time and the carbon credit price:

$$V_{\text{total}} = CO_2 \text{ absorbed at year } y \times \text{Carbon credit price}$$

Using this definition, the Return on Investment (ROI) was calculated as:

$$\text{ROI} = \frac{V_{\text{total}}\ (\text{at 25 years}) - \text{Total cost}}{\text{Total cost}}$$

Payback time (PT) was determined as the minimum year (y) where the total value exceeded the total cost:

$$\text{PT: } \min y \,\text{such that } V_{\text{total}} > \text{Total cost}$$

Results

Early-stage comparison

Direct-seeding projects were monitored for up to 2.5 years, offering a valuable opportunity to compare early growth trends with those observed in manually planted projects. A total of 2,392 seedlings and young trees were measured over the different direct-seeding project sites. Data for manually planted trees were obtained from VERRA-certified projects at comparable developmental stages, allowing us to examine early carbon sequestration dynamics. For example, during the initial 1.5 years, direct-seeded plants exhibited lower carbon absorption than manually planted trees (see Table 1). This lag is primarily due to the biological time required for seed germination and seedling establishment inherent in direct seeding (Grossnickle & Ivetić 2017). Despite this initial lag, direct-seeded trees displayed rapid growth after establishment, catching up with, and in some cases surpassing, manually planted trees by the end of the second year, as shown in Figure 2.

Table 1 highlights high standard deviations (SD) and relatively low standard errors (SE) for direct-seeded trees at later growth stages, reflecting variability in individual performance while ensuring the statistical reliability of median CO_2 sequestration estimates. These findings underscore the capacity of direct-seeded trees to close the gap and potentially outperform manually planted trees.

Later-stage comparison

Long-term projections from the direct-seeding model provide valuable insights into the carbon sequestration potential of individual trees. According to the Chapman-Richards growth model, a single tree is estimated to sequester approximately 17.11 kg of CO_2 by 30 months, increasing to 125.38 kg at 10 years (120 months), 227.35 kg at 20 years (240 months), and reaching 254.74 kg by 25 years (300 months). These estimates are consistent with the growth and maturation patterns typically observed in manual reforestation projects. By the 25-year mark, the direct-seeding model converges to an estimated 254.74 kg of CO_2 sequestered per tree, a value comparable to that achieved through traditional manual Afforestation, Reforestation, and Revegetation (ARR) projects. This convergence highlights that, over the long term, carbon sequestration rates are largely similar between direct-seeding and manual plantation methods. However, for the remainder of this analysis, only data from manual plantation projects were considered. This approach was adopted to ensure a conservative estimate of carbon sequestration potential.

Costs comparison

Revegetation per hectare

Three planting scenarios were evaluated to compare the cost-efficiency of direct seeding (DS) with manual plantation methods. These scenarios involved one, two, or three planting rounds, each designed to achieve the desired tree density per hectare. The analysis revealed a clear cost advantage for direct seeding (DS), with low-cost estimates for DS being consistently less expensive than manual plantation methods. Specifically, DS costs were between 2.51 and 7.87 times lower than manual methods, as detailed in Table 2. Even under a worst-case scenario—where DS incurs high costs and low establishment density, necessitating up to three rounds of planting—the total cost-effectiveness remained comparable to that of manual plantations (Figure 4). Additionally, DS demonstrated a significant scalability advantage, enabling implementation over larger areas within the same budget (Pérez et al. 2019).

Potential for the VCM market

Under current Voluntary Carbon Market (VCM) conditions, the financial viability of direct seeding and manual plantation methods differs across scenarios. Manual plantations, whether evaluated under low- or high-cost estimations, generally exhibit higher break-even carbon credit prices, which may pose challenges for profitability at prevailing market rates. Specifically, for the projects analyzed here, the break-even carbon credit price for manual plantations is at least 17.7 USD per tCO_2, exceeding the 2023 average carbon credit value for Afforestation, Reforestation, and Revegetation (ARR) projects in the VCM (15.74 USD) Procton 2024. However, carbon credit prices fluctuate significantly between projects, and many are sold above this average, meaning that manual plantations remain financially viable in various contexts. Direct seeding, in contrast, demonstrates strong potential for achieving profitability, particularly under favourable cost and establishment conditions. In the lowest-cost estimation, direct seeding is consistently profitable across all scenarios, achieving a return on investment (ROI) as high as 464.73% in Scenario 1. Under the high-cost estimation, profitability varies by scenario: positive ROI is observed in Scenario 1 (80.02%) and Scenario 2 (0.50%), while Scenario 3 results in a negative ROI of -30.6%. In this case, a carbon credit price of 22.7 USD per unit would be required to break even. The payback time (PT) (see Table 3) for direct seeding further highlights its financial viability, ranging from 7 to 25 years depending on the scenario and cost estimation. Under favourable conditions, returns can be achieved within 7 years, making direct seeding attractive for projects aiming to combine ecological restoration with financial sustainability. At a carbon credit value of 50 USD, all methods—including manual planting and direct seeding—become profitable. Under this condition, direct seeding achieves payback times between 5 and 10 years, depending on the scenario. This shorter payback period enhances its appeal for investors seeking quicker returns while maintaining scalability and cost-efficiency. Figure 5 illustrates the profitability trends for both methods at different carbon credit prices.

Discussion

Direct-seeding projects initially lagged behind manual plantations in CO_2 sequestration during the first 1.5 years due to the time required for seed germination and establishment. However, direct-seeded trees demonstrated rapid growth thereafter, closing the gap with manual plantations by the second year. Long-term projections indicate comparable carbon sequestration potential between the two methods, with direct-seeding trees estimated to sequester approximately 255 kg CO_2 per tree over 25 years. Cost analysis highlights direct seeding as significantly more economical, achieving cost-effectiveness ratios up to 7.85 times higher than manual plantations. These findings emphasize direct seeding as a scalable and financially viable strategy for large-scale reforestation. The operational differences between these methods are notable. Direct seeding offers lower establishment costs and greater scalability, making it particularly advantageous for large-scale reforestation initiatives constrained by limited budgets. By enabling restoration over larger areas within the same financial framework, direct seeding aligns with global restoration targets. Furthermore, its lower costs make large-scale monitoring more feasible, a critical component for ensuring long-term project success (Lindenmayer 2020). Emerging technologies, such as UAV-based monitoring and remote sensing, can further enhance cost-efficiency and data accuracy, supporting carbon credit-based funding models (Almeida et al. 2020; Stamatopoulos et al. 2024). Variability in carbon credit prices significantly influences the financial feasibility of restoration projects. Direct seeding achieves profitability under most scenarios at the current average carbon credit price of 15.74 USD per tCO_2, while manual planting seems to require higher prices to break even. Direct-seeding projects emphasizing biodiversity, native species, and community involvement could qualify for premium carbon credit prices, further improving financial outcomes (Pande 2024). This scalability and financial viability make direct seeding a promising approach for achieving restoration targets within pressing timelines. UAV-assisted reforestation complements direct seeding by fostering job creation across the production chain, from drone manufacturing to deployment and post-planting monitoring. These roles, including seed collection, sorting, and preparation, provide direct opportunities for farmers, indigenous communities, and local cooperatives to supply high-quality seeds suited to native ecosystems. Such efforts empower local communities while advancing restoration goals, aligning ecological and socio-economic objectives. However, equitable transitions require targeted policies to support workforce development and community participation (Anam et al. 2024; International Labour Organization (ILO) 2020. Several limitations must be acknowledged. Tree density was held constant across datasets to ensure comparability, yet density is a critical factor for achieving sufficient carbon stocks and ecosystem functionality. Additionally, the study spans distinct climates and soil types, with northern Brazil's tropical monsoon climate and French Guiana's tropical rainforest climate influencing early tree development. French Guiana's higher rainfall and phosphorus availability may have enhanced tree performance, suggesting that these findings may not directly apply to other biomes or severely degraded sites such as former mining areas. Long-term monitoring across diverse environmental and land-use contexts is essential to refine projections and evaluate broader restoration co-benefits, including biodiversity conservation and socio-economic development. This study provides valuable insights into the economic and ecological feasibility of direct seeding as a reforestation strategy. By addressing scalability and cost-effectiveness, it highlights the potential for direct seeding to meet restoration goals while advancing socio-economic and environmental objectives. However, future research should prioritize long-term monitoring, density-dependent analyses, and the development of site-specific strategies to ensure sustained success across diverse ecosystems.

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Conflict of interest statement

Some authors are affiliated with a private sector company specializing in direct seeding for tropical reforestation. However, this affiliation did not influence the study's design, analysis, or interpretation. No conflicts of interest exist regarding the publication of this work.

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Figures

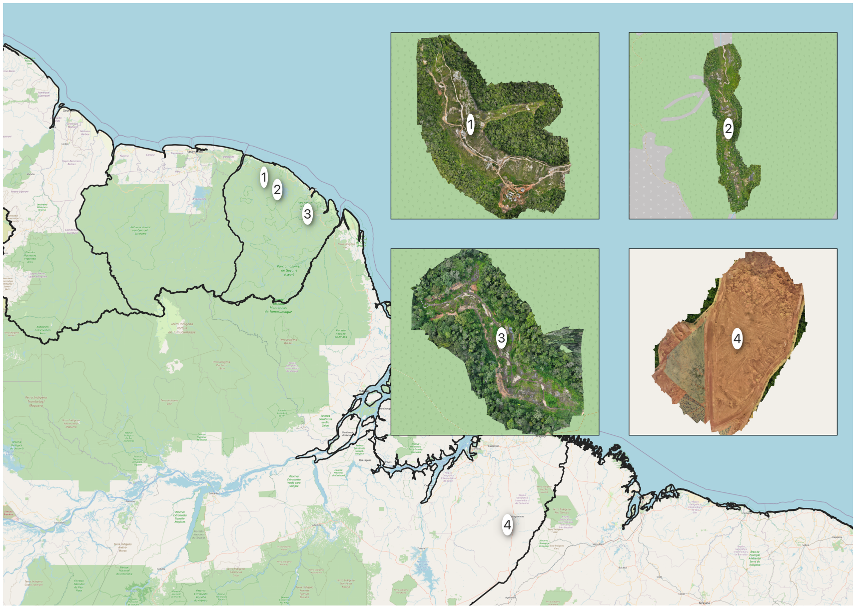


Figure 1: Location and orthophotos of the four different reforestation projects, spanning across northern Brazil and French Guiana.

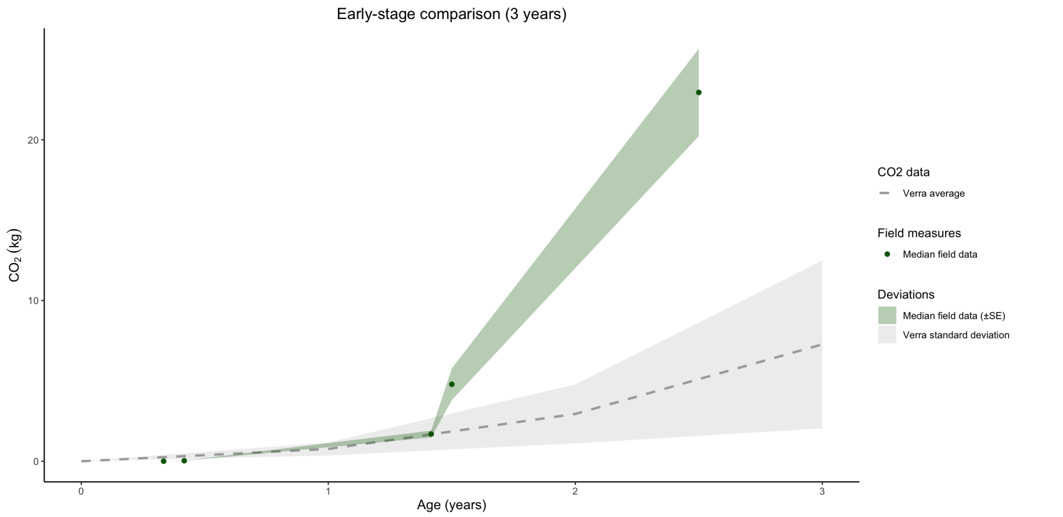


Figure 2: Comparison of measured median CO_2 sequestration in direct-seeding field data and average manual plantation data during the first 30 months of monitoring. The graph illustrates observed CO_2 sequestration data from direct-seeding field measurements (green points) along with associated standard error (green ribbon). The grey ribbon and line correspond to the average and variability (mean $\pm$ SD) of CO_2 sequestration for manual plantation projects, coming from the Verra data. This visualization highlights early-stage performance differences between direct seeding and manual plantations, showing the variability and uncertainty of both approaches.

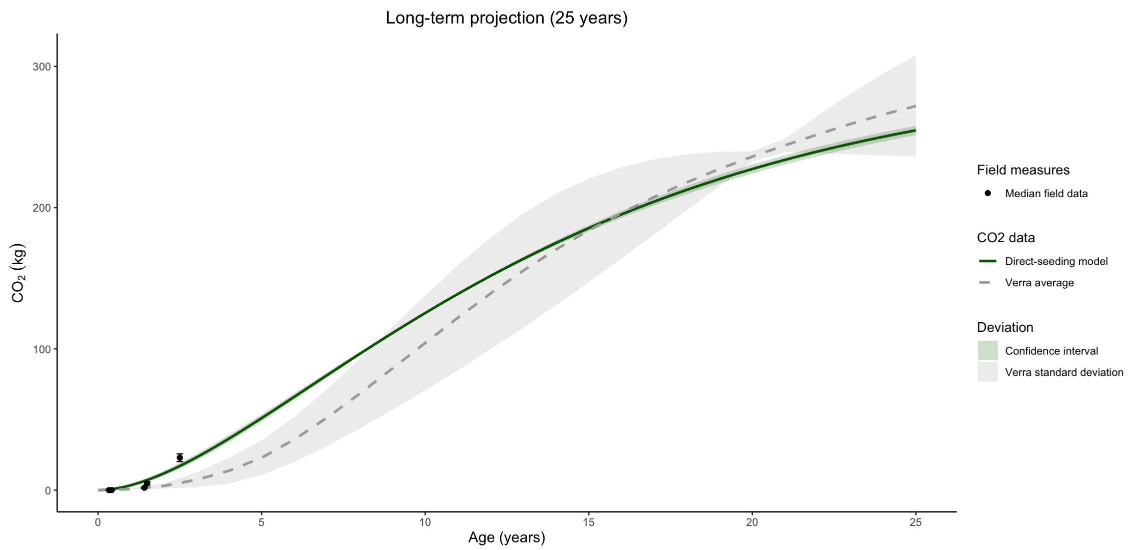


Figure 3: Comparison of median CO_2 sequestration between direct-seeding field data and average manual plantation data over a 25-year project monitoring period. The green curve represents the constrained Chapman-Richards model predictions with uncertainty (green ribbon), while the grey curve depicts average manual plantation data with standard deviation (grey ribbon).

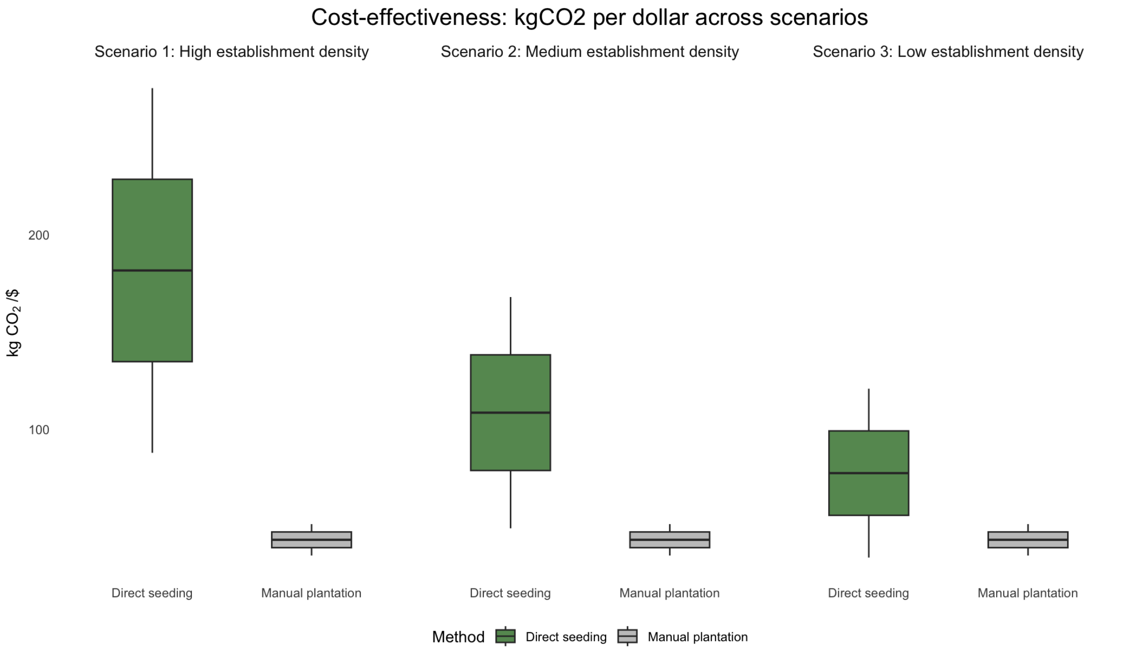


Figure 4: Cost-effectiveness per hectare over the 25 years of the project, assuming both methods sequester the same amount of carbon. This figures indicates the amount of CO2 generated per USD injected in the project, over three establishement density scenarios.

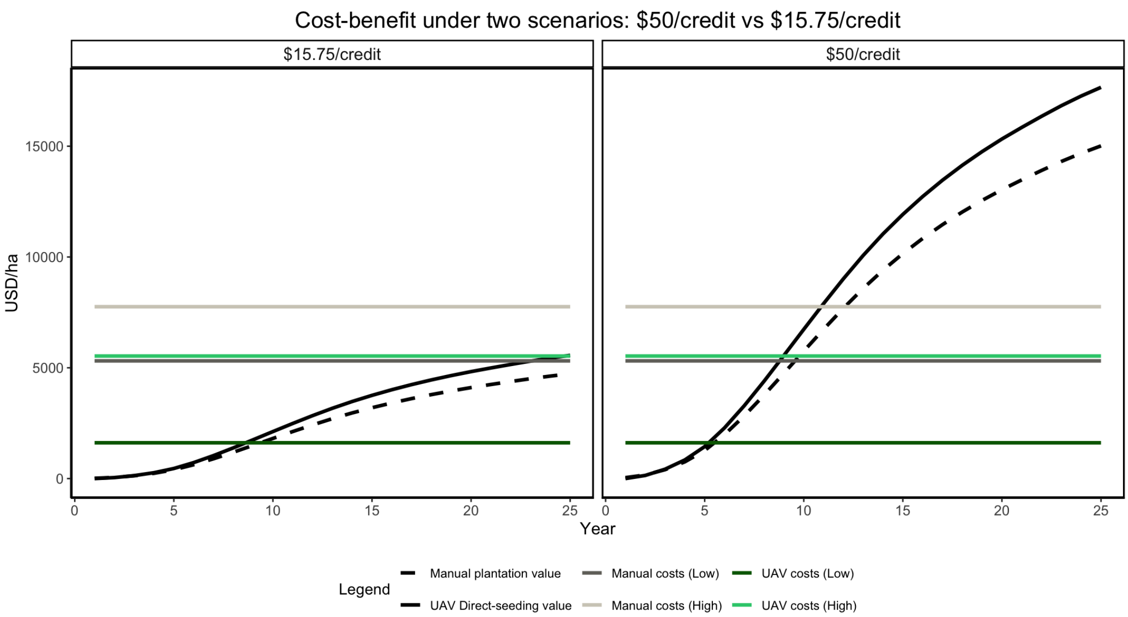


Figure 5: Profitability and payback times for manual plantation and direct seeding methods at current and potential future carbon credit prices.

Tables

Table 1: Tree growth and CO_2 sequestration at various growth stages across Amazonian sites. DS : direct-seeding

Age (months)	Manual CO_2 (kg)	Height (cm)	Diameter (cm)	DS CO_2 (kg)	SE	SD
4	0.255	11	0.241	0.00348	0.000562	0.0154
5	0.319	32	0.580	0.0339	0.00826	0.0503
17	1.67	190	2.290	1.69	0.211	3.26
18	1.86	260	3.180	4.79	0.982	5.73
30	5.11	500	6.480	22.9	2.72	18.8

Table 2: Cost ratios: Direct-seeding compared to manual plantations. Abbreviations: Low = Low costs, High = High costs.

Scenario	Method	vs Manual (high)	vs Manual (low)
Scenario 1:	DS low	7.87	5.39
	DS high	2.51	1.72
Scenario 2:	DS low	4.80	3.29
	DS high	1.40	0.96
Scenario 3:	DS low	3.45	2.37
	DS high	0.97	0.67

Table 3: Payback Time (PT) and Return on Investment (ROI) for Different Scenarios (Carbon credit at 15.74 USD). Abbreviations: DS = Direct Seeding, M = Manual, Low = Low Costs, High = High Costs.

Scenario	Method	PT (years)	ROI (%)
Scenario 1	DS Low	7	464.73
	DS High	13	80.02
Scenario 2	DS Low	9	244.32
	DS High	25	0.50
Scenario 3	DS Low	11	146.50
	DS High	NA	-30.61
Manual	Low	NA	-11.02
	High	NA	-39.06

Appendix

Soil analysis

Table S1: Soil properties and nutrient measurements in Brazil.

Loc	Sand	Silt	Clay	qCO_2	pH	P	K	Ca	Mg	Al	H+Al	CEC Eff	CEC pH7	Al Sat	OM
Brazil	0.18	0.14	0.69	0.18	4.84	0.45	23.67	0.69	0.22	0.35	3.46	1.26	4.36	39.03	2.09
French Guiana	0.71	0.19	0.10	0.29	4.98	1.81	12.28	0.11	0.63	0.62	2.60	0.98	2.95	15.85	1.21

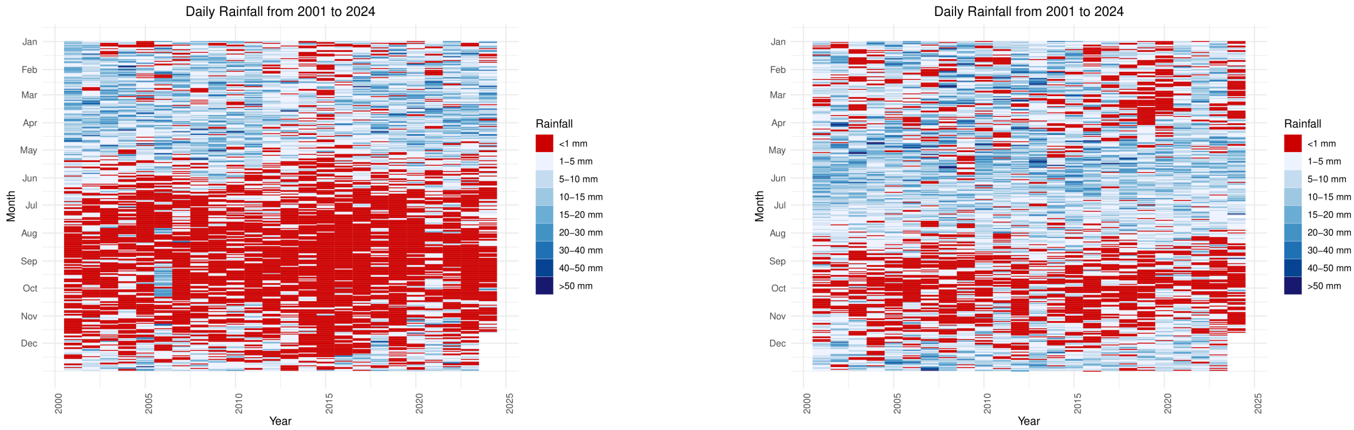
Model fit analysis and comparison

Table S2: Comparison of model performance metrics for original and log-transformed data.

Model	AIC	BIC	RMSE	R^2	Residual Std. Dev.	Shapiro p
Weibull - Original	5410.18	5425.70	1.9187	0.7063	1.9193	0
Exponential - Original	5437.75	5453.27	1.9390	0.7001	1.9343	0
Logistic - Original	5436.14	5451.66	1.9378	0.7004	1.9333	0
Weibull - Log-Transformed	5283.23	5298.75	1.8276	0.6615	1.8283	0
Exponential - Log-Transformed	5261.30	5276.82	1.8123	0.6672	1.8130	0
Logistic - Log-Transformed	5255.99	5271.52	1.8086	0.6685	1.8093	0

Supplementary Information

Climate



(a) Pluviometry in Northern Brazil.

(b) Pluviometry in French Guiana.

Figure i: Pluviometry at the experimental sites: Northern Brazil and French Guiana, during the 2001-2024 period.

Soil analysis

Table i: Units for soil properties and nutrient measurements.

Abbreviation	**Unit**
Sand	g/kg
Silt	g/kg
Clay	g/kg
qCO_2	/
pH	pH (H_2O)
P	mg/dm^3
K	mg/dm^3
Ca	cmolc/dm^3
Mg	cmolc/dm^3
Al	cmolc/dm^3
H+Al	cmolc/dm^3
CEC Eff (CEC Effective)	cmolc/dm^3
CEC pH7	cmolc/dm^3
Al Sat (Aluminum Saturation)	%
OM (Organic Matter)	dag/kg

Table ii: Soil type, precipitation, temperature, and water table depth at the experimental sites.

Project	**Soil Type**	**Precipitation (mm/year)**	**Temperature (°C)**	**Water Table Depth (m)**
Brazil	Clayey, Dystrophic Yellow Oxisols	1,800	25	20
French Guiana (Site 1)	Sandy, hydromorphic	2,200	26	0.77
French Guiana (Site 2)	Sandy, hydromorphic	2,500	25	3.8
French Guiana (Site 3)	Sandy, hydromorphic	3,600	25	5.5

Allometric models

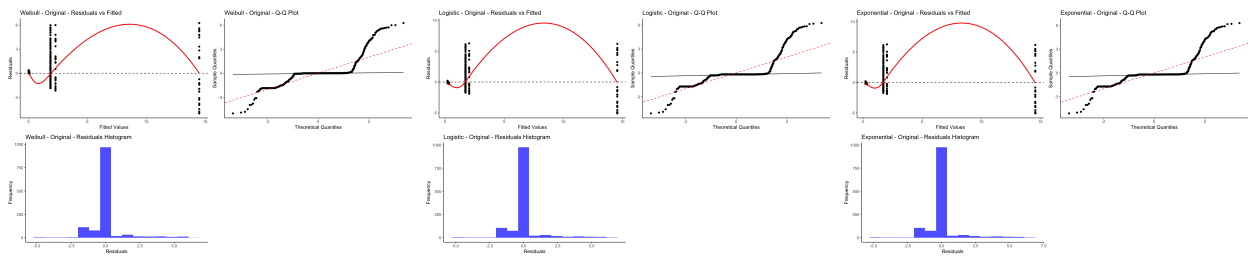
Table iii: Results of a t-test comparing the median values of Ducey et al and Chave et al equations. Significant differences (p-value < 0.05) are indicated for all rows.

Age (months)	Median kgCO2 (Ducey et al)	Median kgCO2 (Chave et al)	p-value
4	0.005	0.001	< 0.05
5	0.0243	0.009	< 0.05
17	1.131	0.470	< 0.05
18	3.043	1.862	< 0.05
30	12.530	6.637	< 0.05

Carbon data

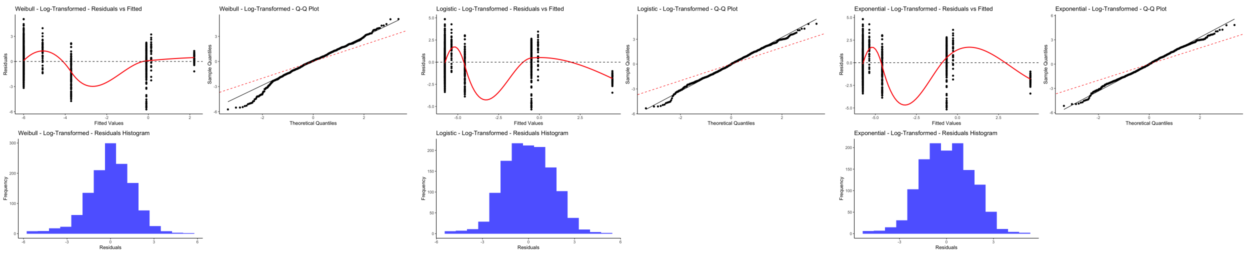
Table iv: Yearly sequestration data for Manual and UAV ($kgCO_2$/tree). UAV data is derived from the Chapman-Richards growth model.

Year	Manual	UAV
0	0.000	0.000 1
0.765	3.459	
2	2.180	8.275
3	4.325	11.377
4	6.430	13.360
5	9.240	14.535
6	12.970	15.120
7	15.420	15.271
8	16.990	15.106
9	17.855	14.714
10	18.040	14.165
11	17.835	13.510
12	17.220	12.789
13	16.210	12.033
14	14.915	11.265
15	13.510	10.500
16	12.385	9.752
17	11.315	9.030
18	10.355	8.340
19	9.480	7.684
20	8.740	6.486
21	8.020	5.944
22	7.705	5.441
23	7.365	4.974
24	6.705	4.542
25	6.025	6.025



(a) Weibull (Normal) (b) Logistic (Normal) (c) Exponential (Normal)

Figure ii: Model analysis for normal data.



(a) Weibull (Log Transformed) (b) Logistic (Log Transformed) (c) Exponential (Log Transformed)

Figure iii: Model analysis for log-transformed data.

Density and costs data

Table v: Densities and costs data for Manual and UAV.

Parameter	**Value**	**Unit**
Density		
Density Manual	1104	-
Density UAV Low	350	-
Density UAV Medium	544	-
Density UAV High	1302	-
Costs Manual		
Low	5312	$
High	7756	$
Costs UAV		
Low	2245.54 - 7973.68	$
Medium	1615.46 - 5530.69	$
High	985.38 - 3087.70	$