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VM0047 ARR

VM0047 Origination Sample Report for ARR Projects

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Executive Summary

Note: This sample report represents an example project created for demonstrative purposes only. It is created as if delivered in 2019 (as the project starts).

Space Intelligence was contracted by **Sample Client** to conduct a baselining (i.e. pre-commencement) assessment for **Project X** located in the Amazonas district of Brazil. The assessment follows Verra's VM0047 V1.0 methodology for Afforestation, Reforestation and Revegetation (ARR). The project area extends across 4,029 ha, with the project starting in 2019, and the project involved planting of the species *Schizolobium parahyba var. amazonicum*. The project will follow the area-based approach for ex-ante removals estimation.

Key findings

- **ALOS-2 PALSAR-2 HV polarization** (Horizontal transmit, Vertical receive) was selected as the best performing remote sensing stocking index. This was used to generate project and control plots for baselining.
- The ex-ante **performance benchmark** was estimated to be **0.0**, which suggests that there is no significant natural regrowth within the project area and the increase in vegetation is solely due to the implementation of project activities.
- The projected carbon dioxide removals predicted to be obtained by the project in the first five years from the project start date in 2019 was estimated to be **107,480 tCO2e.**

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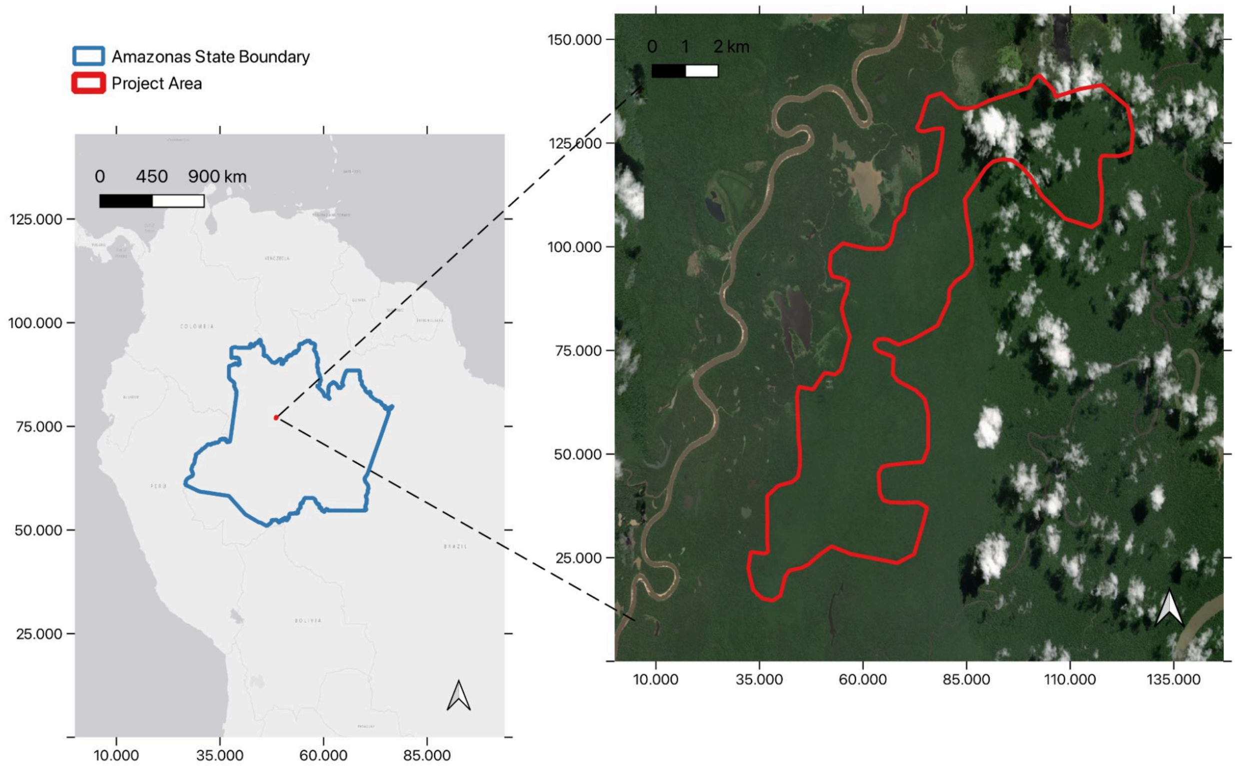
1. Project Background

This report showcases a comprehensive description of the baselining procedure for a sample afforestation, reforestation, and revegetation project named Project X. The project area spans **4,029 ha** and is located in the Amazonas district in Brazil (Figure 1). The project is established under Verra's VM0047 VCS methodology for Afforestation, Reforestation and Revegetation (ARR), and follows the area-based approach for removals quantification, with project activities commencing in the project area in **2019**. The historic reference period spans 10 years from **2009 to 2019,** the data from which is used during the project and control plot matching process.

The core project intervention involves the establishment of native trees (*Schizolobium parahyba var. amazonicum*), implemented as part of a structured afforestation effort aimed at restoring tree cover on historically deforested or degraded lands. The species is chosen here for their rapid growth and carbon sequestration, and availability of seedlings, in an area where rapid soil stabilisation and carbon capture were seen as the priority, as opposed to creating a biodiverse landscape.



↑ ***Figure 1.*** *The location of Project X within the Amazonas district in Brazil, alongside a zoomed in view of the project area, overlaid on an RGB satellite image. The CRS of the maps and layers displayed is EPSG:4326. Source: © Bing.*

2. Project Baseline

Under VM0047, the project must utilise a dynamic baseline. Dynamic baselining, as stipulated by the methodology, involves (i) selection of an appropriate remote sensing stocking index, (ii) matching of project plots and control plots, and (iii) ex-ante calculation of the performance benchmark based on this stocking index and the plots.

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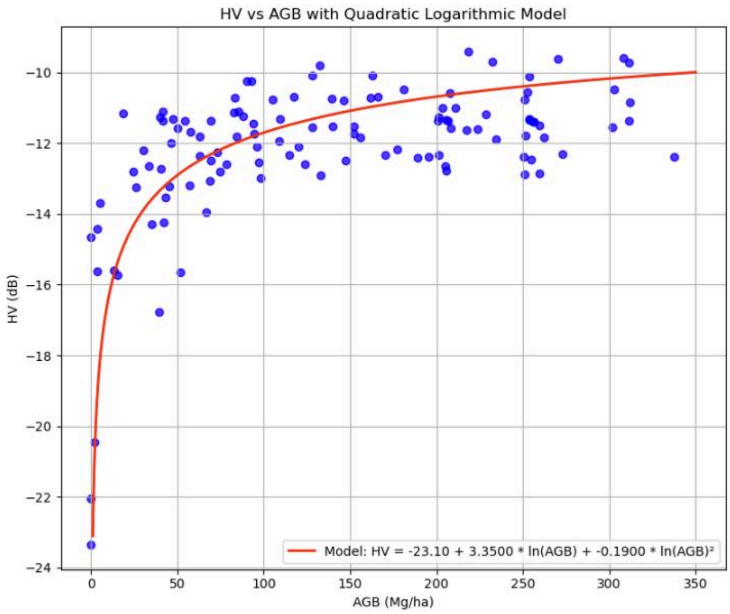
2.1 Project Stocking Index

Guided by scientific literature, we explored and tested a range of remote sensing metrics with respect to their ability to predict Above Ground Biomass (AGB) in forests near the project area. We used a synthetic set of 117 x 0.063 ha 'forest inventory plots', actual single pixels taken from our **CarbonMapper™** product run over the area, to simulate a set of forest inventory plots. The radiometric remote sensing variable **HV backscatter from ALOS-2 PALSAR-2** was chosen as the best performing stocking index against these field plots. The relationship between HV backscatter and AGB is visualised graphically in Figure 2.

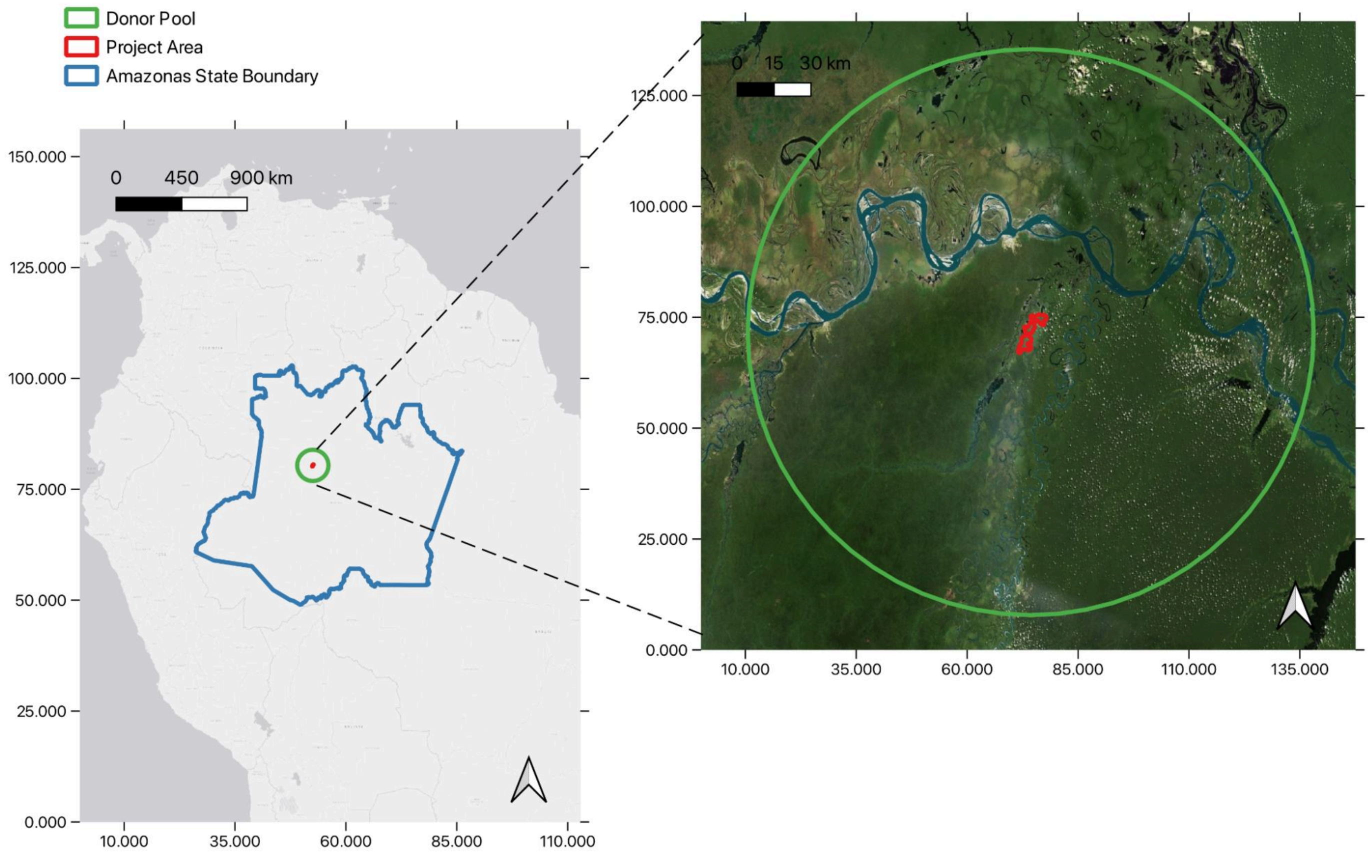


← ***Figure 2.*** *The relationship between HV backscatter (dB) and AGB (Mg/ha). The red line shows the fitted second degree (quadratic) logarithmic model.*

2.2 Project and Control Plots

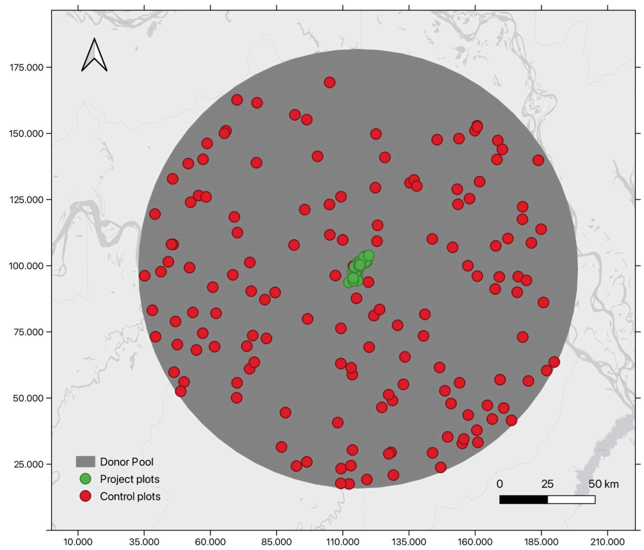
For the purpose of the sample project, the project forest inventory plots were chosen as **30** randomly sampled patches of 0.25 ha (50m x 50m) across the project area.

A donor pool was defined around the project area as the region within a 100 km radius that is similar to the project area with respect to categorial variables like jurisdictional boundary, ecoregion, presence of other AFOLU projects, etc. The donor pool for Project X is visualised along with the project area in Figure 3 below.



↑ ***Figure 3.*** *Donor pool, the area within a circle of radius 100 km and centred at the geometric centre of the project area, overlaid on an RGB satellite image. The CRS of the maps and layers displayed is EPSG:4326. Source: © Bing Satellite.*

For each project plot, **5** control plots (50m x 50m) were statistically matched based on how similar the control plots are to the project plot in terms of the stocking index value and its historical trend. A total of **150** control plots were selected, as shown in Figure 4. A step-by-step description of this approach is presented in Appendix 2.2.



← ***Figure 4.*** *The project and control plots over the donor pool. The CRS of the maps and layers displayed is EPSG:4326.*

2.3 Ex-ante Estimates

The ex-ante estimates of carbon stock change, the performance benchmark, and carbon dioxide removals are estimated from a growth model suitable for the project scenario, and discounted by the performance benchmark value. If the background growth of carbon, as assessed by the stocking index in the control plots, is similar to that within the project plots, then the performance benchmark would be ~1 and the project would generate almost no carbon credits. In contrast, if the stocking index growth is much greater in the project than control plots, then the performance benchmark is near zero and the project generates carbon credits equivalent to the growth model.

2.3.1 Carbon Stock Change from Growth Modelling

The increase in carbon stock as a result of project activities is forecast using a growth model for the native species that will be planted. A detailed description of the growth model is presented in Appendix 2.3. The carbon stock change calculated from the growth model for 5 years from the project start date is **126,448 tCO_2e.**

2.3.2 Performance Benchmark

The ex-ante performance benchmark is calculated as the ratio between change in stocking index in control plots derived from the historic reference period using a linear regression through time, to the change in stocking index in project plots calculated from the growth model for *Schizolobium parahyba var. amazonicum* using another linear regression through time. The ex-ante performance benchmark in this case was evaluated to be **0.0** (or **0.0%**) since the slope obtained from the linear regression, which is the stocking index change in the control plots, was deemed not significantly different from a 0 slope line. More details are provided in Appendix 2.4.

2.3.3 Baseline Carbon Dioxide Removals

For the purposes of this sample report, we will assume that the leakage associated with the project is 0. For a performance benchmark value of 0.0, an increase in carbon stock of 126,448 tCO_2e, and a 15% cumulative uncertainty attributed by the methodology, the total carbon dioxide removals that the project is expected to achieve is **107,480 tCO_2e** across the first 5 years from the project start date in 2019.

A positive value for carbon removals indicate that the project is expected to be **additional**.

Appendix 1. About Space Intelligence

Space Intelligence is a nature tech company based and registered in Edinburgh, UK. We provide world class nature data and insights to support the development, monitoring and independent due diligence of nature-based solution (NbS) projects worldwide. We provide our services to large corporations (e.g., Apple, Shell, Equinor), asset managers and NbS project developers and intermediaries (e.g., Climate Impact Partners, Everland). We also provide data to support the activities of NGOs (e.g., the Nature Conservancy, Wildlife Conservation Society, and the Biodiversity Consultancy), national governments and other agencies (e.g., Verra).

Our high accuracy nature mapping data provides greater confidence and certainty in decision-making in NbS project origination and investment. We achieve this level of accuracy by employing processes developed by our co-founders who have a combined 30+ years of experience in remote sensing. Our senior mapping team have published more than 100 peer-reviewed papers on the use of satellite data for land cover and biomass mapping and analysis.

Our remotely-sensed data and ecological expertise is used within our own machine learning framework, which is locally calibrated to capture regional factors such as national forests definitions, seasonality, cloud cover impact and more. We assess the accuracy of our maps and their uncertainty in a statistically rigorous way, following best practice as described in the scientific literature and international standards.

Appendix 2. Methodology

VM0047 introduced a dynamic baselining approach which involves reassessing the baseline at regular intervals of time to incorporate vegetative growth which would have occurred in the absence of the project. This is achieved through the use of a remote sensing metric, a **Stocking Index (SI)**, to derive the **performance benchmark.** The performance benchmark is the ratio of the change in the SI within the control plots to the change in SI within the project plots. The dynamic baselining approach involves the reassessment of the performance benchmark at regular intervals by monitoring the evolution of the SI within project and control plots.

A.2.1 Selection of a Remote Sensing Stocking Index

A Stocking Index (SI) is a remote sensing variable that can act as a proxy for AGB in forest stands. A good SI has a strong relationship with AGB in and around the project area. A poor SI will fail to accurately represent AGB, thereby increasing the risk of detrimentally affecting the project's crediting potential. VM0047 relies heavily on a good SI for its dynamic baselining procedure. An appropriate SI is selected based on extensive literature review and rigorous testing with the objective to explore the sensitivity and accuracy of the remote sensing variable to AGB in the project area.

For the selection of the SI for Project X, we investigated L-band radar datasets from satellite programs such as JAXA's PALSAR-2 ALOS-2,[1] and vegetation indices derived from optical satellite programs such as NASA's Landsat[2] and ESA's Sentinel-2,[3] such as NDVI and NDWI. The remote sensing variables obtained from these datasets that were considered in the SI selection process included radar variables such as L-band HH and HV, and indices derived from optical data such as NDVI and NDWI. While all of these variables demonstrate correlation with AGB, some are expected to be more suitable than others due to factors like the properties of the data variables themselves, the limitations posed by tropical forests such as extensive cloud coverage, confusion with grasses or shrubs, the forest type, and the project region.

For 117 points spatially distributed across the project area, we sampled our audit-grade AGB maps created using Space Intelligence's **CarbonMapper™** technology for AGB values, and also rasters of the remote sensing variables mentioned above. The points were sampled such that a representative range of AGB values that is expected from within the project area was obtained. The relationship between AGB values and these remote sensing variables were then explored.

[1] https://www.eorc.jaxa.jp/ALOS-2/en/about/palsar2.htm
[2] https://landsat.gsfc.nasa.gov
[3] https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2

A quadratic logarithmic model that captures the relationship between the SI and AGB, chosen through experimentation and literature review[4], was used to select the stocking index by the evaluation of goodness-of-fit of the model to the data. The quadratic logarithmic model used is described below,

$$\sigma^0(HV) = a + b \cdot ln(AGB) + c(ln(AGB))^2, \qquad (1)$$

where σ^0 is the radar backscatter coefficient in decibels, AGB is the above ground biomass in Mg ha^{-1}, and a, b and c constants.

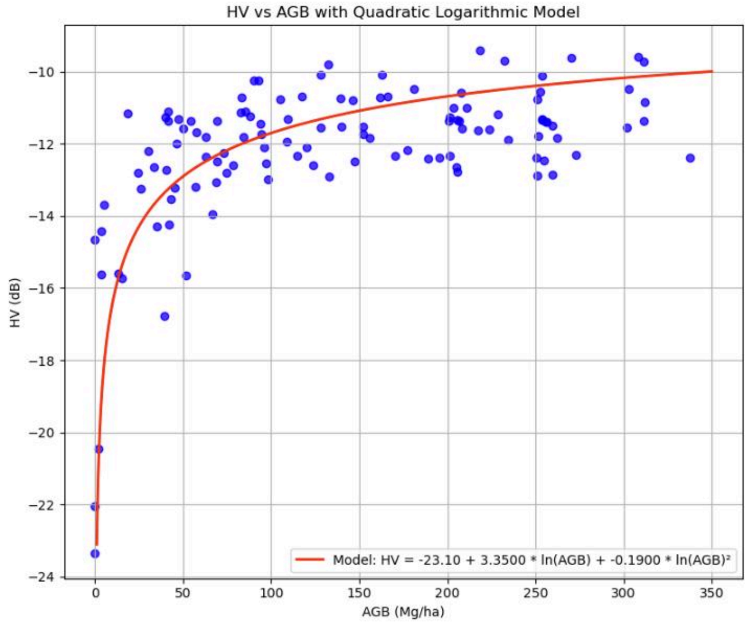
We selected the remote sensing variable that showed the best performance in terms of goodness-of-fit metrics such as MAE and RMSE calculated on the inverse of the model presented in equation (1). The inverse of the function described in equation (1) gives AGB values corresponding to SI values making the model easier to interpret. We also made sure to select the variable that showed the best performance against saturation at higher AGB values. Table A.2.1 below shows goodness-of-fit metrics for the various remote sensing variables considered in the SI selection process.

↓ ***Table A.2.1.*** *MAE and RMSE values for the different remote sensing variables considered in the SI selection process.*

Remote sensing variable	MAE (MG ha^{-1})	RMSE (Mh ha^{-1})
HV	60.34	82.63
HH	71.46	96.56
NDVI	74.45	97.23
NDWI	75.33	99.90
Sentinel-2 Green band	93.23	117.34

In this instance, cross-polarized L-band radar backscatter was the best performing metric tested with the least error associated with it in modelling AGB, with significant correlation with AGB also as proven in scientific literature,[5,6] HV backscatter values plotted against the AGB values along with the quadratic logarithmic model is shown in Figure A.2.1.

[4] Mitchard et al. (2009) Using satellite radar backscatter to predict above-ground woody biomass: A consistent relationship across four different African landscapes, *Geophysical Research Letters*, 12:6637-6653. https://doi.org/10.1029/2009GL040692.
[5] Bouvet et al. (2018) An above-ground biomass map of African savannahs and woodlands at 25m resolution derived from ALOS PALSAR, *Remote Sensing of Environment,* 206:156-173. https://doi.org/10.1016/j.rse.2017.12.030.
[6] Mitchard et al. (2012) Mapping tropical forest biomass with radar and spaceborne LiDAR in Lopé National Park, Gabon: Overcoming problems of high biomass and persistent cloud. *Biogeosciences* 9:179-191. https://doi.org/10.5194/bg-9-179-2012.



↑ ***Figure A.2.1.*** *HV backscatter values plotted against AGB values sampled from our carbon maps. The red line is the quadratic logarithmic model fitted for HV vs AGB.*

It is worth noting that the use of the audit-grade AGB map and the point-based sampling approach is exclusively for the sake of the example project described in this sample report. For an operational project, the AGB numbers on the X axis would come from field measurements submitted to us by the project developer as stipulated by the methodology, and not from Space Intelligence's audit grade carbon maps. We would then sample the remote sensing rasters for plots in the field data to obtain mean value for the remote sensing variable per plot corresponding to the carbon stock associated with the plot.

A.2.2 Selection of Control Plots

Once the project plots are selected, the selection of control plots (50m x 50m squares) can be broken down into three main steps.

Step 1: Defining the Donor Pool

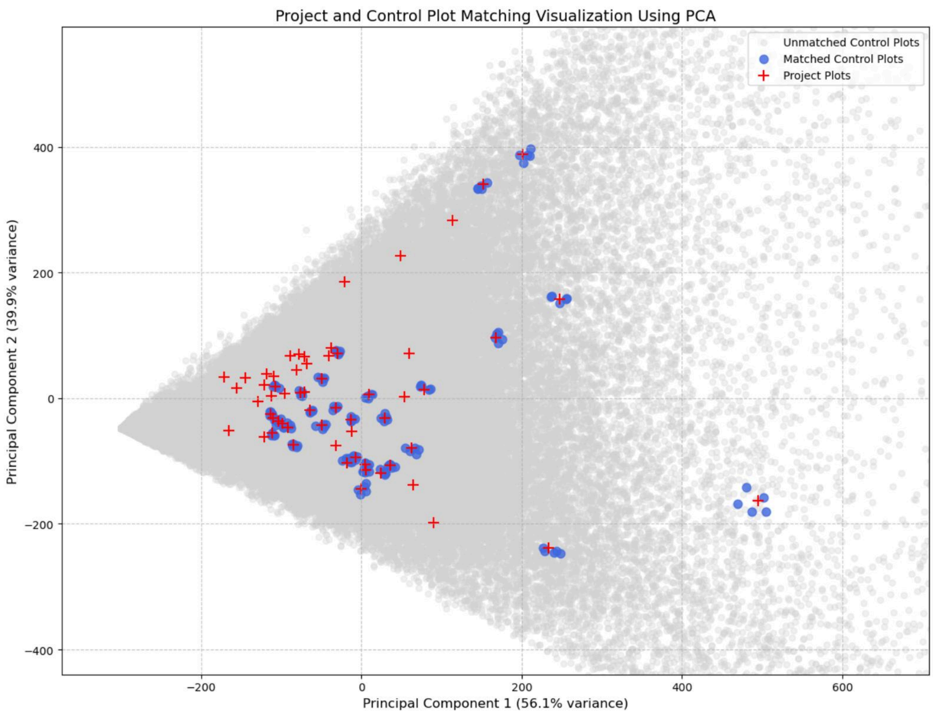
We define the donor pool as the area within a circle centred at the geometric centre of the project area and of radius 100 km. It is essential to ensure that the donor pool does not intersect with protected areas or pre-existing VCS projects, as required by the methodology. In cases where we are unable to match sufficient number of control plots from the donor pool defined in the first instance, we are allowed, as instructed by the methodology, to expand the donor pool in 100 km radius increments, given the donor pool stays within the project ecoregion. In practice, additional factors may be considered when defining the donor pool.

Step 2. Defining Matching Parameters for Pixel Matching

We select a set of variables that includes the SI and variables derived from the SI as parameters to match control and project plots. For Project X, we included the SI values from three time points within the historic reference period as matching parameters. The temporal trend of the SI across the historic reference period is captured using linear regression performed on the SI values across time. The slope, intercept, and R-value from the regression are included as matching parameters.

Step 3. Selecting Control Plots

We run an iterative algorithm per project plot to select control plots. For every project plot, we perform a systematic search across every pixel in the donor pool outside the project area to choose k=5 control plots that are closest to the project plot in terms of the multivariate Euclidean distance between the project plot and the control plots in the space of the parameters described in Step 2. We then statistically evaluate the match quality using the statistical metric Standardized Differences of Means (SDM) between the project and control plots matching parameters. As recommended in the methodology, we control that the calculated SDM is less than 0.25 between all project plots and their respective control plots to ensure the quality of the matching. Figure A.2.2 visualises the goodness of project and control plot matching using Principal Component Analysis.



↑ ***Figure A.2.2.*** *Using Principal Component Analysis, we visualised the relationship between project and control plots in the feature space. Closer points represent similar plots with respect to the parameters used for matching.*

A.2.3 Growth Modelling

A literature review was performed by Space Intelligence's ecology team in order to select a growth model suitable for the project scenario. The dummy Project X assumes that the project activity involves planting of *Schizolobium parahyba var. amazonicum*. The growth model chosen is a generalised logistic model,[7] which can be applied uniformly across all plant species. It is characterised by a sigmoidal growth curve, defined by an intrinsic growth rate, a carrying capacity and curve shape parameter, which together represent the limitation of resources and competition over time, capturing the essential growth dynamics of any plant species. In this instance, it allows for the calibration of *S. parahyba* growth trajectory based on literature-derived estimates.[8]

In particular, the **carrying capacity** reflects the upper limit of stand volume that the site can support over time, given constraints such as soil fertility, water availability, stand density, and competition for light and nutrients. It is not a fixed biological limit, but it can be chosen according to the species of interest, as the value chosen represents the result of the interaction between species-specific growth potential and site-specific environmental conditions and constraints.

For *S. parahyba* a carrying capacity of **340.40 m^3/ha** is used. This value reflects the expected maximum volume under moderately productive plantation conditions typical of fast-growing S. parahyba stands in temperate or subtropical climates.

The **intrinsic growth rate** determines how quickly the volume increases from its initial condition. Higher values of this parameter reflect more rapid accumulation of biomass, particularly in the early growth phase. For *S. parahyba*, a value of **12.40** is selected to represent the species' capacity for fast juvenile growth and early stand closure, particularly under managed conditions with minimal competition and optimal spacing.

Finally, the **shape parameter** determines how sharply the growth curve transitions from its initial slow phase to the rapid growth stage, and eventually towards saturation. It controls the position of the inflection point - the time at which growth rate is maximised - and the curve's symmetry. Lower values result in a more gradual, extended growth phase, while higher values produce a sharper rise and earlier plateau. For *S. parahyba*, a shape parameter of **0.0661** is used, reflecting a relatively fast transition from exponential to asymptotic growth, consistent with the species' rapid early development and earlier onset of density-dependent constraints.

[7] Silva et al. (2021). Scientific paper giving growth rates - detail redacted here. Brazilian Journal of Biometrics, 39(1).
[8] Castro et al. (2019). Scientific paper giving growth rates - detail redacted here, 43(1), Journal of Forestry, 22.

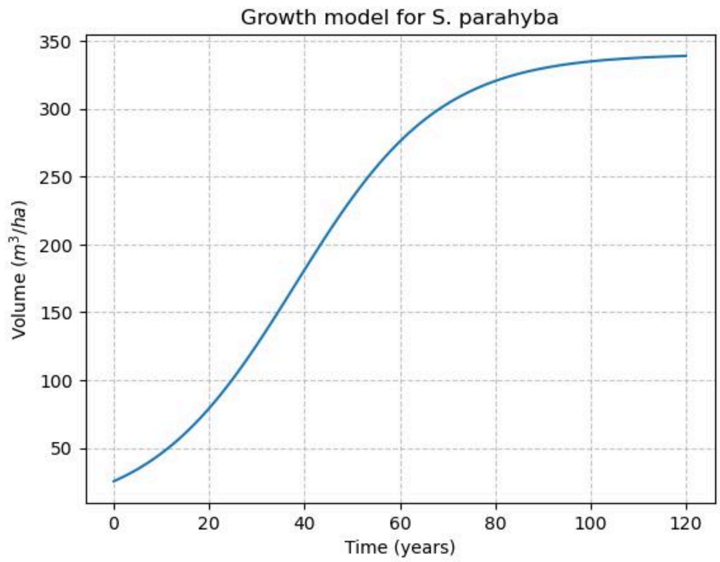
The generalised equation for the growth model is as follows,

$$V(t) = \frac{\alpha}{1 + k * e^{(-\beta * t)}}, \qquad (2)$$

where:

V(t) = The predicted volume of tree stems per hectare (m^3/ha) at time t,
α = The asymptotic maximum volume, or carrying capacity, under assumed environmental conditions (m^3/ha),
κ = The intrinsic growth rate coefficient,
β = The shape of the curve parameter.

The values specific to *S. parahyba* are applied to the equation, and the species-specific growth curve is represented in Figure A.2.3.



↑ ***Figure A.2.3.*** *Predicted stand volume accumulation (m^3/ha) over time for S. parahyba, using a generalised logistic model. The curve illustrates a typical sigmoidal growth pattern, with rapid biomass accumulation during the mid-growth phase and eventual saturation as the site approaches its carrying capacity.*

Conversion of stem volume to tCO_2e units

Once the projection for stem volume growth over time is calculated for *S. parahyba* at 5 years of growth (projecting 5 years forward from the project start date, which is the typical length of a monitoring period), the result is converted to tCO_2e with the following formula,

$$tCO_2e = V(t) * \rho * 0.47 * \frac{44}{12} * BEF * (1 + RS) * A, \quad (3)$$

where:

tCO_2e = carbon dioxide equivalent (tonnes),
V(t) = the predicted volume of tree stems per hectare (m^3/ha) at time t,
ρ = wood density (Mg/m^3),
0.47 = Carbon Fraction (CF) of dry biomass (IPCC)[9],
$\frac{44}{12}$ = ratio of molecular weight of carbon dioxide (CO_2),
BEF = Biomass Expansion Factor from stem to total Above Ground Biomass,
RS = Root-to-Shoot ratio, used to calculate Below Ground Biomass (BGB),
A = total project area (ha).

The parameters used to convert stem volume to carbon dioxide equivalent for S. parahyba is derived from the literature. The wood density chosen is **0.5 Mg/m^3**, consistent with values reported for 5-year-old individuals[10]. The BEF of 1.015 accounts for the additional AGB components beyond the stem, such as branches and foliage, following standard practices in biomass estimation for fast-growing S. parahyba. A RS ratio of 0.052 is then used to estimate the BGB based on conservative values reported for young stands under moderate site conditions. Both parameters are sourced from the minimum values reported for 8-year-old plantations[11] and are thus considered reasonable proxies for the 5-year-old stands assessed here, as the change in value between these ages is minimal.

These parameters allow for the calculation of total biomass (AGB + BGB), which is then converted to carbon using the IPCC default CF of **0.47**, and finally to carbon dioxide equivalent (tCO_2e) using the molecular weight ratio of $\frac{44}{12}$.

[9] IPCC (2006) 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use. Chapter 4: Forest Land. Prepared by the National Greenhouse Gas Inventories Programme, Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T. and Tanabe, K. (eds). Hayama, Japan: Institute for Global Environmental Strategies (IGES). http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html.
[10] Bonfatti Júnior et al. (2023). Basic wood density, fiber dimensions, and wood chemical composition of [redated]. Revista Árvore, pp xx-yy
[11] Dalla Corte et al. (2015). Fator de expansão de biomassa, razão de raízes-parte aérea e modelos para carbono para [redacted]. Enciclopédia Biosfera, [redacted]

The total project area (A) of **4,092 ha** is then used to scale the per-hectare estimates to site-level carbon removal estimates. The estimated total biomass (AGB + BGB) for 5-year-old *S. parahyba* is around **18 Mg/ha**, which is consistent with values reported in the literature.[12,13]

A.2.4 Performance Benchmark

The ex-ante performance benchmark is calculated as the ratio of the stocking index change in the control plots to the stocking index change in the project plots by means of linear regressions, subject to the P-values associated with the slopes of the regressions.

The stocking index change within the control plots is calculated as the slope of the linear regression performed across time on stocking index values within the control plots obtained from the historic reference period. There are 10 time points in the historic reference period from 2009 to 2019 for Project X and the mean stocking index value across all the control plots from all 10 time points is used in the linear regression. Table A.2.2. presents the full summary of the linear regression. The summary shows that the slope, which is the change in stocking index within control plots, is not significantly different from a 0 slope line. This means that there is no significant trend observed in the stocking index within control plots over the baseline period.

↓ ***Table A.2.2.*** *Summary of the linear regression performed in order to calculate change in SI within control plots. The change in Si within control plots is the slope of the regression line or the coefficient of SI.*

	coeff	**std err**	**t**	**P>|t|**	$q_{0.025}$	$q_{0.975}$
intercept	192.47	6.72	28.64	0.000	177.27	207.67
SI	1.765	1.134	1.55	0.155	-0.804	4.335

The stocking index change within project plots is obtained from the growth model for *S. parahyba* discussed in section A.2.3. We use the growth model to project the stocking index 5 years into the future from the project start year of 2019. Carbon stock values for the years 2019, 2020, 2021, 2022, and 2023 are therefore calculated. A linear regression is then performed on this set of values to derive the change in stocking index within project plots. Table A.2.3. presents the full summary of the linear regression. The change in SI thus obtained within project plots is **1.79** and is highly significant.

[12] Ferraz Filho et al. (2018). Thinning regimes and initial spacing for [redacted]. Anais da Academia Brasileira de Ciências, 90, pp.255-265.
[13] Viera, M. and Rodríguez-Soalleiro, R. (2019). A complete assessment of carbon stocks in above and belowground biomass components of a [redacted] plantation Forests.

↓ ***Table A.2.3.*** *Summary of the linear regression performed in order to estimate change in SI within project plots. The change in Si within project plots is the slope of the regression line or the coefficient of SI.*

	coeff	**std err**	**t**	**P>|t|**	$q_{0.025}$	$q_{0.975}$
intercept	226.62	0.108	2097.66	0.000	226.32	226.92
SI	1.793	0.036	50.259	0.000	1.694	1.892

Since the change in stocking index within the controls is not significant, the ex-ante performance benchmark is stipulated by the methodology to be set to **0**. This means that the increase in vegetation within the project area is produced by the implementation of project activities alone and not through any natural regrowth.