Response to Comments from the Public Consultation on the Guidelines for the Use of Models in Baseline Carbon Quantification in the Land-Use Sector

Version 1.0

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Dear participants,

Cercarbono extends its sincere gratitude for your participation in our public consultation on the ***Guidelines for the Use of Models in Baseline Carbon Quantification in the Land-Use Sector***, version 1.0, conducted electronically from 07.07.2025 to 13.08.2025.

These valuable comments will allow us to generate a more complete and robust Guidelines document so that holders and developers of GHG removal initiatives may develop programs or projects across different land-use sectors and participate in Cercarbono's voluntary carbon certification program.

In the attached table, a compilation of the different comments received is included, as well as the respective clarifications and responses prepared by our technical team. This document will remain publicly available on our website, under the section: Consultations.

We once again express our gratitude for the time dedicated to the review and for your valuable contribution.

Sincerely,

Alex Saer
Chief Executive Officer Cercarbono

No.	Comment	Section	Answer
1	Why is a minimum sampling percentage applied to all quantification methods (conventional field-based, inclusion of spectral indices derived from satellite imagery, and methods including LiDAR), despite the fact that each presents significantly different technical requirements, operational scales, and costs? When methods such as LiDAR or conventional field sampling are implemented, monitoring between 1% and 3% of the eligible area becomes technically, logistically, and economically unfeasible. In such cases, it is more appropriate to apply a statistical sampling approach based on a sampling intensity that ensures a sampling error within acceptable limits[1]), guaranteeing representativeness and reliability without compromising project feasibility. In this regard, it is suggested to introduce a flexible and adaptive approach for the design of calibration plots. Furthermore, clarification is requested on whether the internal and external plots are primarily intended for periodic monitoring of carbon quantification throughout the life of the project, or whether their function is limited solely to the estimation of the baseline scenario. 1. The suggested sampling error should be around 10-15%, as established by the IDEAM (Yepes A.P., Navarrete D.A., Duque A.J., Phillips J.F., Cabrera K.R., Álvarez, E., García, M.C., Ordoñez, M.F. 2011. *Protocolo para la estimación nacional y subnacional de biomasa - carbono en Colombia. Instituto de Hidrología, Meteorología, y Estudios Ambientales* [IDEAM]. Bogotá D.C., Colombia.).	**Section 5.1** General requirements for establishing internal and external plots	The guidelines establish mandatory minimum sampling percentages (between 1% and 3% of the eligible area of the CCMP) in order to guarantee a homogeneous level of spatial representativeness for model calibration, regardless of the quantification method used (field-based, spectral indices, or LiDAR). These percentages constitute a minimum regulatory requirement aimed at ensuring the traceability, permanence, and verifiability of the plots throughout the entire implementation period of the project. However, Cercarbono's methodological framework is consistent with international tools such as AR-Tool 13 of the Clean Development Mechanism, which allows determining the number of plots based on statistical criteria such as population variance, confidence level, and allowable sampling error. In this regard, the developer may use AR-Tool 13 as a technical optimization tool for sampling design, provided that, in all cases, compliance with the minimum percentage established by Cercarbono's methodology is ensured. Accordingly, the developer may estimate the statistical representativeness of the calibration plots through a sampling design that demonstrates a 95% confidence level, a relative sampling error ≤ 10%, and a total uncertainty ≤ ±20% at 95% confidence, as complementary statistical quality criteria, without these replacing the mandatory minimum regulatory percentage. Additionally, the developer may apply complementary statistical techniques such as early stopping of sampling, whereby the collection of additional plots may be suspended when the marginal variation of the estimation error is no longer significant.

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			When statistical criteria cannot be demonstrated, calibration plots must be established using the minimum percentage of the eligible area of the CCMP, in accordance with the following scale: • CCMP up to 500 ha: minimum 3%. • CCMP between 500 and 2,000 ha: minimum 2%. • CCMP between 2,000 and 10,000 ha: minimum 1.5%. • CCMP greater than 10,000 ha: minimum 1%. Furthermore, it is clarified that internal and external plots have as their primary objective the calibration and validation of the models implemented in the Baseline Scenario, and are not defined as a direct instrument for periodic monitoring of removals during the life of the project—this function corresponds to the project's MRV system.
2	The governance conditions, land-use practices, applicable public policies, road infrastructure, access to markets, land tenure, and local socioeconomic dynamics are important factors that influence the development of a CCMP in the reforestation sector. However, this information is usually qualitative in nature and is complex to structure and translate into quantifiable variables for its direct inclusion in the models. Additionally, the level of disaggregation available for these variables is limited in Colombia, especially at the village, municipal, or regional levels, which restricts their effective integration into modeling processes. Considering the above, do socioeconomic variables mainly serve a descriptive and contextual function within the design and analysis of CCMP projects, with their inclusion in predictive or machine learning models being optional and dependent on the	**Section 3.2.2** Socioeconomic Dimensions **Section 6.2.4** Collection of Socioeconomic Variables	Socioeconomic variables do not serve solely a descriptive function. In accordance with Cercarbono's guidelines, these variables must be quantifiable and may be incorporated into both classical statistical models and machine learning models, either as explanatory variables or as input variables in predictive algorithms. Their inclusion is particularly relevant in the context of REDD+ projects, as it enables the characterization of anthropogenic drivers of land-use change, strengthens the construction of the baseline scenario, and enhances the analysis of leakage risk, in coherence with reference approaches for avoided deforestation and degradation. However, the incorporation of socioeconomic variables into predictive models will depend on the availability, quality, level of disaggregation, traceability, and temporal

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	availability, quality, and level of disaggregation of the data, as well as on the specific objectives of the modeling?		consistency of the data, as well as on the specific objectives of the modeling. In all cases, these variables must be transformed into verifiable numerical indicators that guarantee their replicability and technical validity.
3	The use of spectral indices such as NDVI for detecting changes in vegetation cover must be considered with caution, since these indices were not originally designed for discriminating types of land cover, but rather for estimating the vigor and physiological condition of vegetation. NDVI (Normalized Difference Vegetation Index) was created specifically to quantify the amount, quality, and vigor of green biomass. Its use has become popular mainly for monitoring crop health, estimating primary productivity, and analyzing the seasonal dynamics of vegetation. However, NDVI presents limitations for discriminating changes between different types of cover, especially in heterogeneous landscapes where various cover types (for example, crops, grasslands, shrubs, or secondary forests) may share similar NDVI ranges due to comparable levels of vegetation vigor, cover density, or phenology. This may lead to confusion, false positives, or false negatives in detecting land-use changes, which affects the accuracy and reliability of baseline analysis. **Illustrative example – NDVI saturation in dense forests:** Sometimes forests show lower NDVI values than other vegetative covers, a phenomenon documented in scientific literature known as NDVI saturation. NDVI becomes saturated when the Leaf Area Index (LAI) exceeds 2 m^2/m^2, a typical condition in mature and dense forests. Under these conditions: • Multiple vegetation layers fully absorb red radiation • The closed canopy generates shadows that reduce overall reflectance • Multiple internal reflections occur that alter the spectral response	**Section 6.2.3 Image** Analysis and Spectral Index Generation *"Generation of spectral indices, such as NDVI, EVI, and NBR, through the processing of multispectral bands from remote sensors."*	Although NDVI was initially developed to estimate the amount, vigor, and green biomass, its use has been widely extended in the scientific literature and in operational applications for detecting changes in vegetation cover and analyzing land-use dynamics. Cercarbono's guidelines explicitly recognize the use of NDVI, as well as other spectral indices such as EVI and NBR, which have proven to be valid tools for differentiating land-cover types and detecting disturbances. In particular, EVI improves sensitivity in areas of dense vegetation and reduces saturation problems and soil effects, while NBR is especially useful for identifying abrupt biomass losses associated with fires, deforestation, degradation, or severe vegetation stress. However, it is acknowledged that these indices present limitations when applied to highly heterogeneous landscapes or to cover types that share similar spectral ranges, which may generate classification errors in the absence of adequate calibration with field plots. In this regard, the guidelines explicitly keep open the possibility of incorporating other spectral indices, multispectral analyses, or more advanced classification techniques, provided that they: • Are properly documented in the scientific literature, • Are calibrated with representative field data,

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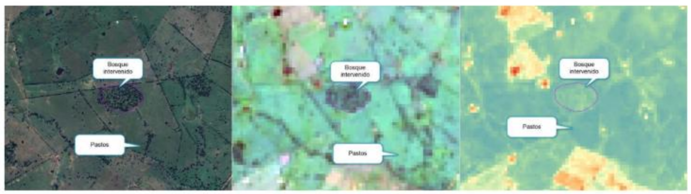
	NDVI stops increasing proportionally with vegetation density and may show lower values than less dense vegetation (grasslands, shrubs). This behavior is commonly reported in remote sensing studies and does not indicate forest degradation, but rather an inherent limitation of NDVI in very dense vegetation.  a) Imagen de Google Earth b) Landsat (RGB) c) Landsat (NDVI) For these reasons, it is requested to leave open the possibility of using other indices, multispectral analyses, or more advanced classification techniques that allow for better discrimination between land-cover types, as suggested by international best practices and methodologies.		• Are validated through objective performance and uncertainty metrics, and • Have full methodological traceability. In this way, it is ensured that land-cover change analysis does not depend on a single index, but rather on a flexible, robust, and scientifically verifiable approach, aligned with international best practices.
4	The document mentions some commonly used algorithms, such as multiple regressions, Random Forest, and neural networks. However, there are other machine learning models that may also be applicable, depending on the characteristics of the project and the performance they offer in terms of fit and accuracy. For this reason, the methodological document should explicitly leave open the possibility of using other predictive models, provided that they meet criteria of statistical rigor.	**Section 6.2.6.2** Procedures for the Use of Models (Classical or Advanced Predictive Models)	The guidelines do not restrict the use of predictive models to a closed set of algorithms. Although the document mentions regression models, Random Forest, and neural networks as examples, these should be understood as methodological references and not as a technical limitation. Consequently, the CCMP developer may implement any statistical or machine learning model that is suitable for the characteristics of the project and the nature of the available data, provided that such model: • Is calibrated using valid field plots (internal or external), • Incorporates formal validation procedures (e.g., cross-validation, bootstrap, or others),

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			• Explicitly quantifies the error and uncertainty associated with the estimates, • Presents objective performance metrics (e.g., RMSE, MAE, R^2), • And has verifiable methodological traceability, replicability, and technical documentation. In this way, the guidelines ensure a flexible framework for innovation in modeling, without sacrificing the principles of statistical rigor, conservativeness, transparency, and information quality required by the standard.
5	Our concern relates to the requirement to measure in the field a fixed minimum percentage of the project area for calibration purposes. Best practices in carbon project development link the intensity of field sampling to the target levels of statistical uncertainty in biomass estimates, not to a fixed percentage of the project area. The approach proposed in the *Guidelines for using Models in Baseline Carbon Quantification in the Land Use Sector* is based on a fixed percentage, which does not consider key variables such as the heterogeneity of the project area, which is often an important factor in the design of sampling plans. To illustrate the impact: we are working with a developer whose project covers just under 300 hectares and who has already measured 89 field plots, each of 400 m². This represents 3.56 hectares of measurements, or approximately 1.2% of the project area. Under the new guidelines, this project would need more than double the number of plots to reach the 3% threshold. This would considerably increase costs and logistical burdens, which in turn would discourage the use of models. The objective of incorporating models should be to enable project developers to increase transparency, improve	Undetermined	This concern corresponds to the same technical and regulatory basis addressed in Response 1, regarding the mandatory nature of the minimum sampling percentage (1%–3%) established by Cercarbono's guidelines for model calibration in baseline estimation. Accordingly, although it is recognized that from the standpoint of operational efficiency and cost reduction it is desirable to link sampling intensity solely to statistical uncertainty objectives, under the current regulatory framework these approaches do not replace compliance with the minimum area threshold required by the guidelines, which must be met for purposes of validation, registration, and verification of the CCMP.

No.	Comment	Section	Answer
	monitoring coverage, optimize efficiency, save costs in field campaigns, and reduce uncertainty through scalable remote sensing models calibrated with available field data. A fixed-percentage requirement undermines these benefits. Therefore, we recommend, as an alternative, that the guidelines maintain flexibility by basing field sampling requirements on achieving an acceptable uncertainty threshold, instead of a fixed percentage of the project area. This would allow adaptive, statistically robust, and cost-effective monitoring designs that improve transparency and expand access to high-quality data for project developers. We would be pleased to discuss this recommendation further and share our knowledge and experience on how modeling can strengthen monitoring and make project development more accessible under the Cercarbono standard.		