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Integration of remote-sensing based metrics and econometric models to assess the socio-economic contributions of carbon sequestration in unmanaged tropical dry forests

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A B S T R A C T

Carbon sequestration by forests is one of the vital ecosystem services regulating the global climate. Equally important are the socio-economic co-benefits of carbon sequestration, given their implications for designing policies focused on conservation or restoration of tropical forests. Much debate has been around how to account for, and maximize, the co-benefits of carbon sequestration. Prior research suggests that a better understanding of the spatial relationship between carbon sequestration potential and forest types and dynamics - as a function of geographical context and time - is needed to better estimate their socio-economic benefits. Hence, this paper uses the Tropical Dry Forests of Central and South America to propose a new approach to quantify carbon sequestration of this biome, and its efficiency, using time series of the Terra-MODIS satellite. Our estimations of carbon sequestration are then coupled with a benefit transfer approach to infer carbon sequestration's monetary cost. Results reveal that these tropical forests sequester an annual average of 22.3 ± 3.3 tCO_2 ha^{-1} yr^{-1} or in total, 1.16 $GtCO_2$. The associated social cost of carbon, calculated using three econometric models, ranges from USD 489 ha^{-1} yr^{-1} to USD 2828 ha^{-1} yr^{-1}. These results can open new perspectives regarding the benefits of carbon sequestration against the costs of the negative impacts of climate change for national welfare accounts, their relevance for environmental policy-making, and the implementation or monitoring of carbon-based incentive programs (e.g., WAVES).

1. Introduction

Tropical forests store more carbon than any other terrestrial ecosystem in the biosphere (Gibbs et al., 2007). The reduction of atmospheric carbon dioxide (CO_2) by terrestrial ecosystems is an essential regulating service identified by the Millennium Ecosystem Assessment (MEA, 2005) since it plays a crucial role in regulating climate. Over the last decades, the increase of extreme climatic events, and the release of greenhouse gases due to deforestation and forest degradation, have drawn considerable attention to aboveground biomass estimates (Kumar and Mutanga, 2017). Carbon emissions resulting from deforestation and forest degradation are not well established at local, national, and continental scales, partly due to uncertainties related to estimates of aboveground biomass (Hill et al., 2013; Sheng, 2017). Measuring carbon sequestration over time, forecasting its losses from land use/cover change, and estimating the expected economic contributions or losses to national ecosystem services accounts has become the focus of global scientific efforts and initiatives (Costanza et al., 2017). Global initiatives, such as the post-Kyoto international negotiation process for the development of carbon credits for Reducing Emissions from Deforestation and Forest Degradation; the conservation, sustainable management and enhancement of forest carbon stocks (REDD+); the United Nation's Framework Convention on Climate Change (UNFCCC, 2011); the United Nations System of Environmental Accounting (SEEA, 2012); and the Wealth Accounting and the Valuation of Ecosystem Services (WAVES) of the World Bank global partnership, aim not just to include forest values into national accounts (West et al., 2020) but also to foster the involvement of social actors in community-based projects that can be sustainable in the long term (Bennet, 2015). Moreover, improving the understanding and control of carbon dynamics is an integral step towards achieving global commitments such as the Paris Agreement, and the U.N. Sustainable Development Goals (SDGs).

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Closely associated with aboveground biomass is carbon balance, a concept that addresses forests' carbon sequestration capability (Chertov et al., 2005). In turn, carbon sequestration refers to the conversion of carbon into oceanic, pedologic, biotic, and geologic strata (Lal, 2008). The reduction of atmospheric carbon dioxide from terrestrial ecosystems is fundamental for regulating climate (Bonan, 2016), and therefore, relevant to mitigate the effects of global climate change (Pan et al., 2011). Tracking carbon sequestration and carbon balance over time is, therefore, a promising way to better understand the actual contributions of forests to climate regulation, assess their health and status, and evaluate the success of forest conservation policies. A commonly used parameter to measure carbon balance is Net Primary Productivity (NPP), defined as the difference between gross primary productivity (GPP) and autotrophic losses associated with growth and maintenance (Waring and Running, 2010). Essentially, NPP is a measure of the net accumulation of carbon in live biomass and, therefore, of forests' capacity to remove carbon dioxide from the atmosphere (Bonan, 2016). A complementary parameter to quantify carbon storage is Carbon Use Efficiency (CUE), defined as the ratio of NPP to GPP (Gifford, 1994; Manzoni et al., 2012). NPP and CUE are two ways of measuring the same thing: when NPP establishes a fixed quantity of carbon stored in biomass, the CUE reveals this as a dimensionless ratio of how efficient the transfer of GPP to NPP is (DeLucia et al., 2007). High CUE values indicate growth, whereas low CUE values suggest that lesser amounts of carbon are converted to biomass (Manzoni et al., 2012). According to DeLucia et al. (2007), CUE is a robust integrator of the factors affecting GPP, autotrophic respiration, and NPP. Therefore, understanding the spatial CUE patterns can help resolve uncertainties about respiration regulation among forests of different types, ages, and management practices. Using the two parameters (NPP and CUE), instead of one, more comprehensive information can be obtained about carbon balance, its regulating components, and potential changes associated with carbon sequestration.

Furthermore, relating carbon sequestration measures to economic estimates such as the Social Cost of Carbon (SCC) —a metric of the expected economic damages from carbon dioxide emissions— (Tol, 2008; Hope, 2011; Nordhaus, 2017; Ricke et al., 2018), enable better tracking of benefits derived from maintaining forests and ecosystem functions (Pizer et al., 2014). Although previous studies agree on the significant gap between domestic and global values of the SCC, they provide limited agreement on the distribution of the SCC by region (Ricke et al., 2018) or biome; which represent a significant shortcoming for country-based monitoring and reporting of international initiatives related to climate change and sustainable development (e.g., Goal 15 of the UN Sustainable Development Goals, WAVES, the UN Decade on Ecosystems Restoration).

Hence, this paper introduces a methodology to provide information that can be used in reporting Aboveground Biomass (ABG) and the associated SCC using open access, high temporal and moderate spatial resolution remote sensing data, combined with econometric modeling. To this end, we use case studies located in Tropical Dry Forest (TDF) of Central and South America and: 1) calculate their total annual estimate of sequestered CO_2, 2) the associated CUE metric, and 3) the total monetary value of the sequestered carbon in each study area.

2. Materials and methods

2.1. Study sites

Tropical Dry Forests (TDFs) of the neotropics are an ecosystem dominated by deciduous trees where the mean annual temperature is 25 °C, and the total annual precipitation ranges between 700 and 2000 mm (Sánchez-Azofeifa et al., 2005a). Precipitation is strongly seasonal, with a 5–7 month long dry season (Borchert et al., 2004). TDFs perform a key social role by providing direct or indirect services to millions of people (César, 1992; Calvo-Rodriguez et al., 2017a). Furthermore, these forests provide a variety of environmental functions and services (Calvo-Rodriguez et al., 2017a) and are a hotspot of endemic and threatened species (Myers et al., 2000). Given the suitability of many of the TDF areas for agriculture and other human activities, TDFs are one of the most disturbed ecosystems in the Americas (Portillo-Quintero and Sánchez-Azofeifa, 2010).

Six sites (Fig. 1 and Table 1) fulfilling the criteria of being large fragments of TDF — and therefore avoiding potential effects associated with forest fragmentation such as edge effects (Portillo et al., 2013)— were selected in Mexico (the Chamela-Cuixmala Biosphere reserve (CHA) and the Yucatan Peninsula YU)), Costa Rica (the Santa Rosa National Park (SR)), Brazil (the Parque Estadual da Mata Seca, Minas Gerais (MA)) and Bolivia (the San Matias Natural Area (SM) and the Tucabaca Municipal Wildlife Reserve (TU)).

2.2. Methodology

A general workflow diagram on methods, variables, and outputs of the methodology is presented in Fig. 2, and the components described hereafter. Noteworthy is that outputs from the SCC estimations, along with the carbon sequestration values, and estimates of the CUE are hereby suggested to be used as a means of measuring and reporting the benefits that TDF ecosystems provide to people.

2.2.1. Biophysical quantification of carbon sequestration

Above ground living biomass of trees is a key indicator used to assess terrestrial carbon stocks (Chave et al., 2014). However, as pointed by Costanza et al. (2017) net primary productivity (NPP) is a more accurate indicator of ecosystem health and productivity than gross primary productivity (GPP), since it accounts for respiration losses. In practice, these values are calculated as monthly and annual averages at a selected site. As such, we selected NPP as the final indicator for measuring carbon sequestration per unit area at each study site. GPP values from the Multi-temporal calibrated Moderate Resolution Imaging Spectroradiometer (MODIS) were used as the main input, along with the MOD17 algorithm, for calculating monthly and annual NPP using the workflow described below and shown in Fig. 3. GPP values were consequently used for trend comparisons. R-squared was used as a statistical measure to evaluate the significance and variance of the trendline at each site (Moore and Fligner, 2015).

The first step of our analysis consisted in collecting MODIS GPP (MOD17A2H v.6) and MODIS Leaf Area Index (LAI) (MOD15A2H v.6) 8-day composites at 500 m pixel resolution, for each site, from the EarthExplorer (EE) user interface. Datasets from 2000 to 2015 (1472 images) were used to that end. The MODIS Quality layer was used to support the interpretation of the images, as well to select year 2000 as a starting point and the year 2015 as an endpoint. All images were processed in ENVI (Exelis Visual Information Solutions, Boulder, Colorado). The MOD17 NPP algorithm of Running (2004) was then applied and improved with local average temperature data for each site (see Table 1 for details). Since there is no field data available for the other biome attributes used in the algorithm, parameters from the MODIS Biome Property Look Up Tables (BPLUT), as detailed in appendix A (Running and Zhao, 2015), were used.

In the second step, MODIS GPP and LAI data were aggregated into monthly GPP and LAI values for the time interval of the study. Monthly NPP, following NPP MODIS algorithm (Fig. 2), was computed using equation (1) as follows:

$$NPP = GPP - Rm - Rg \tag{1}$$

where *Rm* is maintenance respiration of the vegetation also known as autotrophic respiration and *Rg* is the total carbon loss during growth respiration. Since the algorithm estimates *Rm* as a function of LAI, six parameters within the BLUT (Appendix A) were needed to calculate *Rm*. LAI aggregates were next used to calculate Leaf Mass (equation (2)).

Next, fine root mass was estimated (equation (3)) to calculate the maintenance respiration of the fine root mass (Froot_MR) (equation (4))

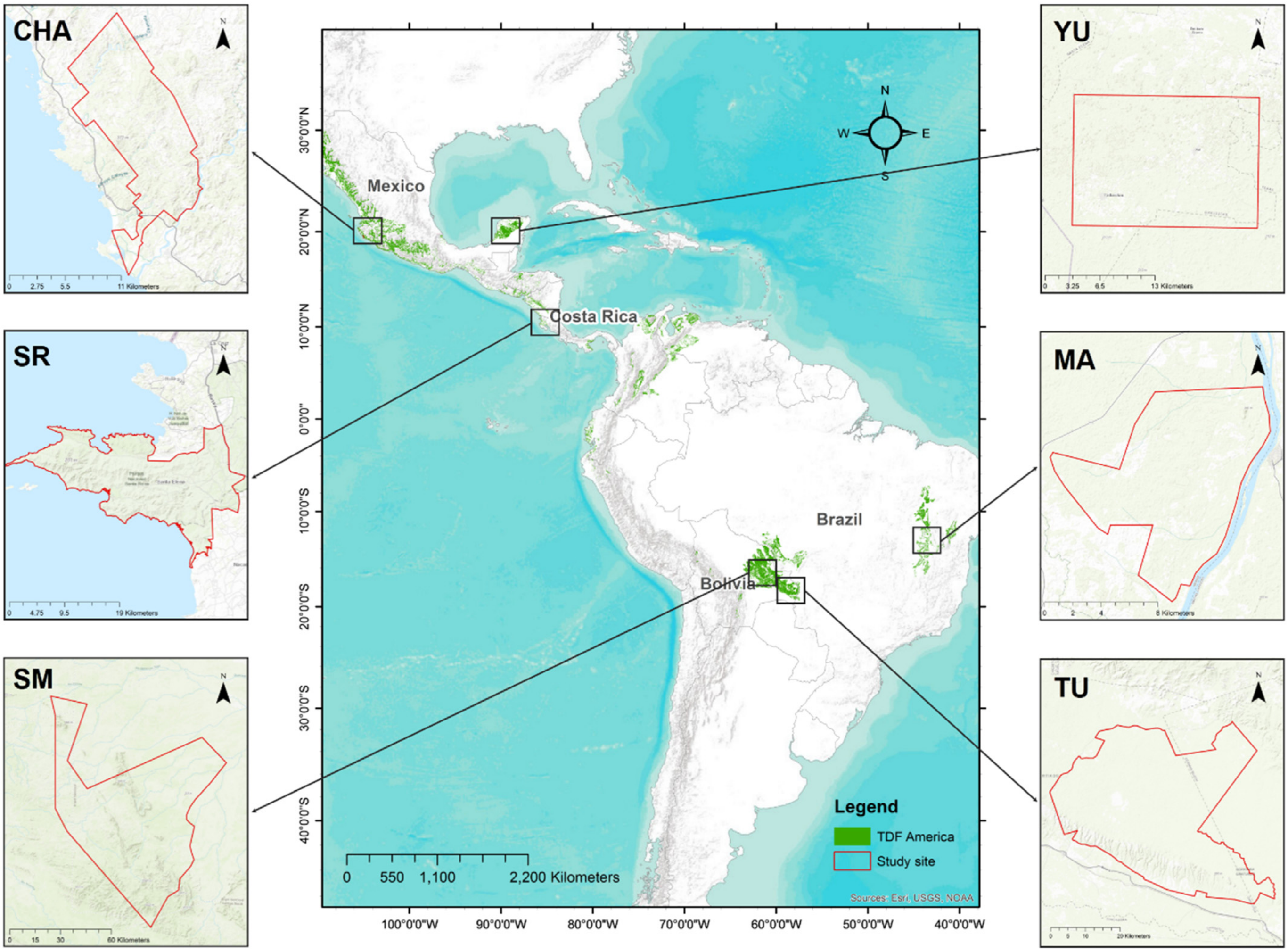

Fig. 1. Location of the study sites across the tropical dry forests (TDF) of Central and South America: Chamela (CHA) and Yucatan (YU) in Mexico, Santa Rosa (SR) in Costa Rica, Mata Seca (MA) in Brazil and San Matias (SM) and Tucabaca (TU) in Bolivia.

as follows:

$$\text{Leaf\_Mass} = \frac{LAI}{SLA} \tag{2}$$

$$\text{Fine\_Root\_Mass} = \text{Leaf\_mass} \times \text{froot\_leaf\_ratio} \tag{3}$$

$$\text{Froot\_MR} = \text{Fine\_Root\_Mass} \times \text{froot\_mr\_base} \times \text{Q10\_mr}^{\frac{Tavg-20}{10}} \tag{4}$$

where SLA is the Specific Leaf Area (Appendix A), and Q_{10}, the factor by which the rate of a measurement increases for every 10° rise in temperature (Bonan, 2016), was assigned a constant value of 2 for estimating fine root (equation (4)) and live wood (equation (8)). We used local average temperature data (*Tavg*) for each site to estimate an acclimated Q10 (equation (5)) which was then used to calculate leaf maintenance respiration (Leaf_MR) in equation (6). The latter follows recommendations of Tjoelker et al. (2001) of using a temperature corrected Q_{10} for leaf respiration to improve the accuracy of modeled respiratory CO_2 in plants.

$$Q_{10} = 3.22 - 0.046 \times Tavg \tag{5}$$

$$Leaf\_MR = Leaf\_Mass \times leaf\_mr\_base \times Q10\_mr^{\frac{Tavg-20}{10}} \tag{6}$$

Live wood maintenance respiration (Livewood_MR), calculated using equation (8), required prior calculation of the live wood mass (equation (7)):

$$Livewood\_mass = Leaf\_mass * livewood\_leaf\_ratio \tag{7}$$

where leaf mass will be used from equation (2) and livewood leaf ratio from the MODIS BPLUT as presented in Table 1SI.

$$Livewood\_MR = Livewood\_mass \times livewood\_mr\_base \times Q10\_mr^{\frac{Tavg-20}{10}} \tag{8}$$

In the third step, *Rg* was empirically parameterized as 25% of NPP following Cannell and Thornley (2000) recommendation. The components above were then used to estimate NPP in kg C m^2 (equation (9)):

$$NPP = 0.8 \times (GPP - \text{Leaf}_{\text{MR}} - \text{F\_root}_{\text{MR}} - \text{Livewood\_MR}) \tag{9}$$

Lastly, in order to demonstrate one single representative value for each selected site, monthly estimates of NPP were averaged spatially using the mean value of all values (pixels) of each site based on their geographical boundaries. The final annual NPP data is the aggregation (sum) of all monthly values for each year.

2.2.2. Total CO_2 calculation

Although carbon is a well-used metric for studying the carbon cycle, it is not an intuitive metric for reporting the social or economic values associated with carbon sequestration in forests. Moreover, carbon is usually reported in tonnes of carbon dioxide (tCO_2) when done in association with climate change, sustainable development, and societal carbon footprint, but the social cost of carbon (SCC) is usually reported in US

Table 1
Biophysical characteristics of the six study areas of selected Tropical Dry Forests in the Americas. Each study area relates to the administrative boundary of a protected area. Abbreviations: T = Annual mean temperature, P = Mean annual precipitation, Tmax = Annual maximum temperature, Tmin = Annual minimum temperature.

Study site	Geographic coordinates	Surface area (km^2)	Mean Altitude (m.a.s.l.)	Mean annual T (°C)	Mean annual Tmax (°C)	Mean annual Tmin (°C)	Mean annual P (mm)	Land cover characteristics	References
Chamela-Cuixmala Biosphere reserve (CHA), Mexico	19°22′1.6″N–19°35′8.9″N; 104°56′15.3″W–105°3′24.04″W	127	0–500	24.9	30	19.4	748	Tropical deciduous forests under different successional stages; early secondary growth to largely undisturbed forest. Dry season: November to June.	Lott et al. (1987) Kalacska et al. (2004) Balvanera and Aguirre (2006) Sánchez-Azofeifa et al. (2009) García-Oliva et al. (2002)
Yucatan Peninsula (YU), Mexico	20°01′1.3″N–20°09′46.6″N; 89°23′24.2″W–89°35′59.8″W	341	40–200	26.5	32.4	20.92	1190	Tropical dry semi-deciduous forest under current regrowth due to cropland abandonment.	Dupuy et al. (2012) Dai et al. (2015)
Santa Rosa National Park (SR), Costa Rica	10°44′7.2″N–10°57′16.4″N; 85°34′43.2″W–85°57′4.8″W	388	0–325	26.6	33	22.1	390.8	Seasonally dry (December to April) Neotropical forest covered by a mosaic of secondary forests under various stages of succession (early, intermediate and late).	Janzen (2000) Kalacska et al. (2004) Arroyo-Mora et al. (2005) Sánchez-Azofeifa et al. (2005a) Sánchez-Azofeifa et al. (2005b) Hilje et al. (2015)
Parque Estadual da Mata Seca (MA), Minas Gerais, Brazil	14°48′36″S–14°56′59″S; 44°04′12″W–43°55′23.9″W	116	452	24.9	32	19.8	871	Various successional stages (early, intermediate, and late) of natural regeneration. Dry season from May to October.	IEF (2000) Sánchez-Azofeifa et al. (2009) Calvo-Rodriguez et al. (2017b)
Area Natural de Manejo Integrado San Matias (SM), lowlands of Santa Cruz, Bolivia.	16°54′27.4″S–18°06′28.4″S; 58°43′2.4″W–59°37′9.4″W	5713	108–900	24.9	32.7	15	1488	Chiquitano tropical dry forest of Bolivia. A transition zone between the humid Evergreen forests of the Amazon and the deciduous thorn-scrub vegetation of the Gran Chaco. High diversity of fauna and flora that spreads across two fragile interconnected ecosystems: the Chiquitano dry forest and the Pantanal. Dry season from April to October.	Navarro and Maldonado (2004) GADSC (2017) SENAMHI (2020)
Tucabaca Municipal Wildlife Reserve (TU), lowlands of Santa Cruz, Bolivia	18°07′47.3″S–18°33′58.9″S; 58°57′33.2″W–59°32′43.8″W	1741	300–450	25.19	31.9	19.5	1143.3	Transitional zone of the semi-deciduous forest towards the Chaco and Bolivian-Tucuman bio-geographical provinces. Dry season from April to October.	Navarro and Maldonado (2004) SEARPI (2011) GADSC (2017) SENAMHI (2020)

dollars per ton of CO_2. Therefore, the total annual estimates of sequestered CO_2 were calculated using a conversion based on the relationship between the molecular mass of an existing amount of carbon in 1 mol of CO_2 and each kg of C. Here, a multiplication factor of 3.667, defined by Clark (1982), was used for this conversion. Final values were expressed in tons of CO_2 per hectare per year (t CO_2 ha^{-1} $year^{-1}$). Finally, CUE was used to characterize the capacity of TDF study areas to transfer carbon from the atmosphere to terrestrial biomass.

2.2.3. Socio-economic valuation of CO_2 sequestration

The SCC can be considered an indicator of the price of CO_2 emissions, and it can be used to weigh the benefits of sequestrating CO_2 against the costs of the negative impacts of climate change and global warming on national economies (Pizer et al., 2014). Hence, to determine the monetary value of sequestered CO_2 at our study sites, we used a range of economic values in US dollars based on the SCC and the selection of a benefit transfer method recommended by Saklaurs et al. (2016).

From a meta-analysis of more than 200 models for estimating the SCC (Tol, 2008), three primary econometric models (Table 2), were selected based on their relevance and use of variables to estimate reference SCC values: i) the Dynamic Integrated Climate-Economy – DICE 2016R (Nordhaus, 2017), ii) the Climate Framework for Uncertainty, Negotiation, and Distribution - FUND Meta-Analysis (Tol, 2008), and iii) the Policy Analysis of the Greenhouse Effect – PAGE09 (Hope, 2011).

The DICE 2016R model, called DICE from herein, is an updated version of the computer-based integrated carbon cycle model DICE of Nordhaus (1993a). DICE analyses economic growth, temperature sensitiveness, and increases of consumption as a function of population changes, and as such, is defined as a “social-welfare function model” (Nordhaus, 1993b). Conducting cost-benefit analyses, the model generates different scenarios based on a set of assumptions on the discount rates, carbon cycle, climate damage, warming projections, policies, and impacts/effects of other variables. A major highlight of the DICE model is that although it quantifies global SCC, it is also possible to use regional SCC values (Nordhaus, 2007).

FUND Meta-Analysis, called FUND from herein, is an integrated

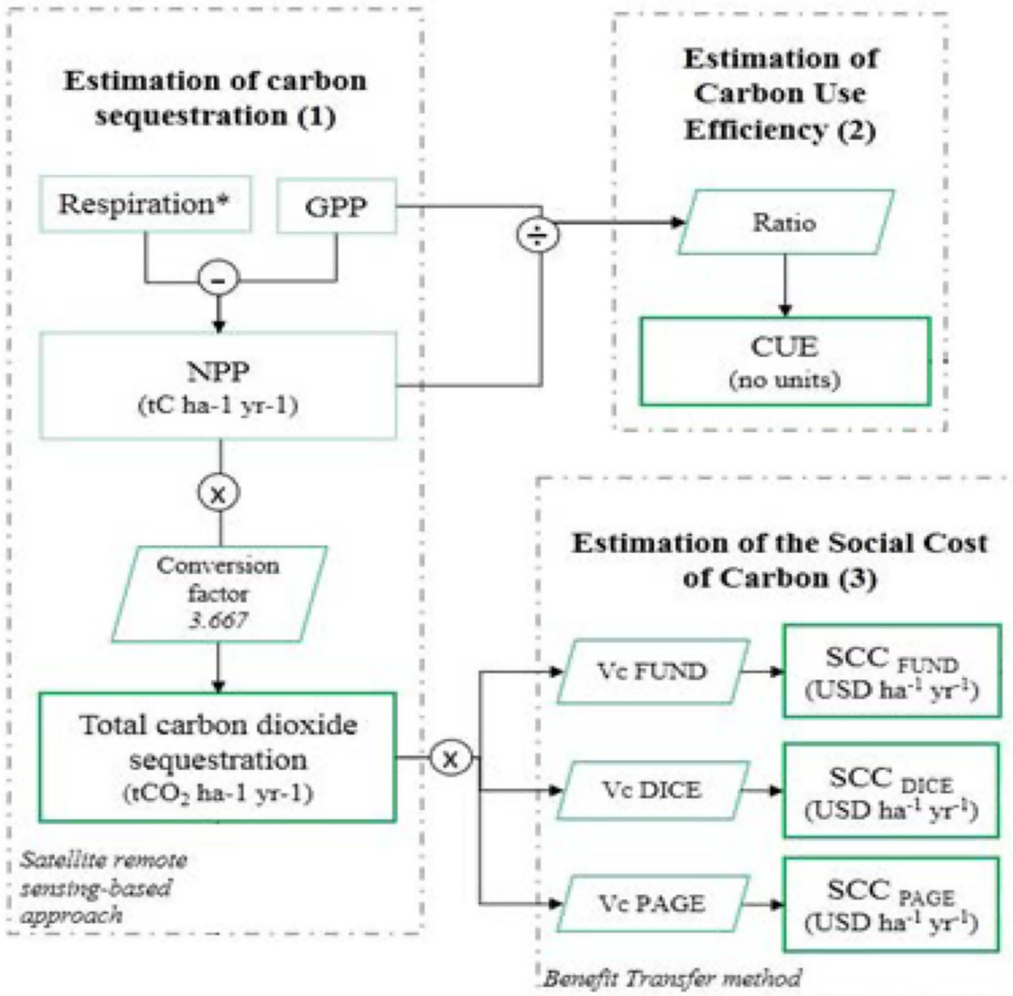

Fig. 2. Overview of the general workflow process describing the methodological framework used, as well as the variables, methods, and final outputs. Four main stages are displayed: (1) estimation of carbon sequestration using a satellite remote sensing-based approach, (2) estimation of carbon use efficiency as a health/status indicator, (3) socio-economic valuation of carbon sequestration based on the estimation of the social cost of carbon and three monetary reference values (Vc). For detailed explanations on the acronyms, see section 2.2.

assessment model originally designed to study the transference of international capitals to poorer and more vulnerable countries (Tol, 1995). Its use was eventually expanded to analyze the effectiveness of climate change policies and regulations (Marten et al., 2013), cost-benefit analysis of greenhouse gas emission reduction policies (Waldhoff et al., 2015), and to support research for international environmental agreements (Tol and Downing, 2004). The model describes plausible futures downscaled to 16 major world regions, based on data projections of population, carbon cycle, technology, economics, emissions, atmospheric chemistry, current climate, sea level, climate scenarios, and impacts (Tol, 2008). All these elements make FUND one of the most complex SCC models (Anthoff and Tol, 2013).

The PAGE09 model, called PAGE from herein, is an updated version of the PAGE2002 integrated assessment model (Hope, 2006), originally developed by Plambeck and Hope (1995) to evaluate the economic responses to climate change and the costs of policies for addressing adaptation to climate change. Described fully in Hope (2006) and Hope (2010), the last version of the model incorporates all data from the 4th assessment report of Intergovernmental Panel for Climate Change (IPCC) for CO_2 emissions, climate sensitivity, the effect of sulfates, carbon cycle feedback from increased temperatures, economic impacts on the gross domestic product, damage responses and pressures on non-economic impacts, among others. Although not as complex as FUND (Anthoff and Tol, 2013; Hope, 2010), outputs of the model cover two emission scenarios: business as usual and decreasing emissions for eight regions.

All three previously described models highlight climate sensitivity as the parameter with the most influence and were selected based on their specific characteristics. More specifically, DICE was chosen for its strength on parameterization, FUND for its regional SCC values, and PAGE for its complexity.

In this context, the calculation of the total monetary value of CO_2 sequestered is computed for each TDF site (EV_{CSi}) following equation (10):

$$EV_{CSi} = CS_i \times V_c \tag{10}$$

where $EVcs_i$ is the total economic value of carbon sequestration for a hectare of TDF in each site, *CSi* is the amount of carbon sequestered annually in a hectare of TDF (expressed in tCO_2 ha^{-1} $year^{-1}$), and V_c is the monetary value of one ton of carbon dioxide.

Table 2 contains the monetary reference values (V_c) of the three SCC models in the TDF sites, from the highest (PAGE) to the lowest (FUND). The SCC estimates are expressed in USD per tCO_2^{-1} of the year in which they were calculated. To achieve this, the initial values were updated by considering the annual inflation rates for a US dollar (World Bank, 2017) at each site, following the step by step guidance of Bassi and ten Brink

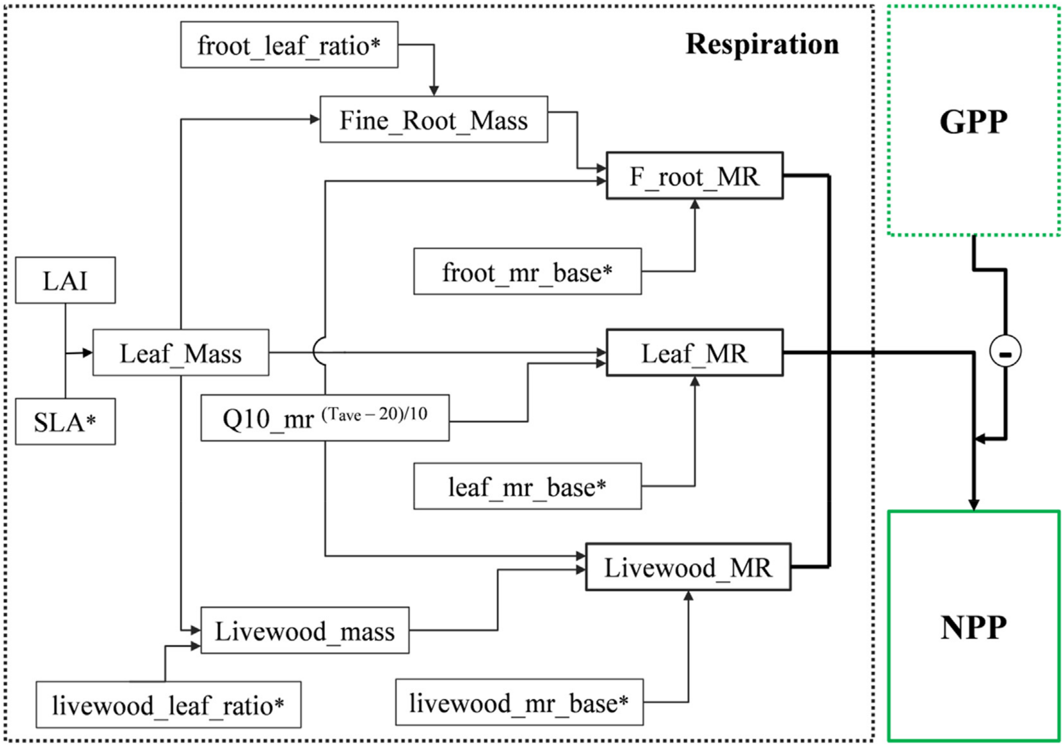

Fig. 3. Flowchart showing the calculations inherent to the Multi-temporal calibrated Moderate Resolution Imaging Spectroradiometer (MODIS) MOD17 algorithm for calculating monthly and annual Net Primary Productivity (NPP). Elements designated with an asterisk correspond to biome constant values of the Biome-Property-Look-Up-Table (BLUT) of MOD17 (after Running 2004). For detailed explanations on the parameters, see section 2.2.1 and Appendix A.

Table 2
Reference values of the social cost of carbon (SCC) used for the economic assessment of CO_2 sequestration in tropical dry forests. All values are express in US Dollars (USD) and were updated in December 2017.

SCC Initial value (USD per tCO_2^{-1})	SCC Updated value (USD per tCO_2^{-1})	Author	Model
13,62	21.88	Tol (2008)	FUND Meta-Analysis
31	34,54	Nordhaus (2017)	DICE – 2016R
50–100	63,3–126,6	Hope (2011)	PAGE 09

(2013); this was done for the evaluation period from 2001 to 2015. The last update of the average SCC value estimated by Tol (2008) for the FUND model, and by Nordhaus (2017) for the DICE model were established as the lower limit. The upper limit of the PAGE model was established using the updated estimates by Hope (2011).

3. Results

3.1. Biophysical quantification of carbon sequestration

A comparison of annual GPP trends across the sites (Fig. 4, Appendix B and Appendix C) indicates that from 2001 throughout 2015 the sites at the most Northern latitudes (CHA, YU and SR) accumulated a higher GPP than those of Southern latitudes (SM and TU). Despite its Southern location, MA is an exception by showing high GPP values. Although trends are not statistically significant, they show great variability among seasons with higher and lower peaks. SM and TU show a positive trend (R^2 = 0.19 and 0.16 respectively) although small, while the others remain neutral. Among the sites with the highest GPP values, SR comes first with an annual average GPP of 12.9 tC ha^{-1} $year^{-1}$, and an annual carbon loss for respiration of 3.2 tC ha^{-1} $year^{-1}$.

This generates an annual NPP average of 9.6 tC ha^{-1} $year^{-1}$, and a CUE of 0.75 (i.e. 75% of the total GPP; Appendix C). The second highest Primary Productivity corresponds to MA that has an average GPP of 10.9 tC ha^{-1} $year^{-1}$, and a total NPP of 8.1 tC ha^{-1} $year^{-1}$. This corresponds to a CUE of 0.74. CHA and YU present similar values of forest productivity (Appendix 3): their average GPP values are 9.9 tC ha^{-1} $year^{-1}$ and 9.0 tC ha^{-1} $year^{-1}$, respectively. CHA shows a relatively efficient CUE of approximately 0.71, whereas in Yucatan it is just 0.62. The southern TDFs sites of Bolivia (SM and TU) present the lowest primary productivity rates; SM records an annual average GPP of 5.3 tC ha^{-1} $year^{-1}$, with a capability to convert only 59% of total GPP as NPP, followed by Tucabaca with a capacity to convert approximately 58% of all incoming GPP (estimated at 4.9 tC ha^{-1} $year^{-1}$) to NPP. Fig. 5 presents the results of annual NPP and respiration rates for all TDFs sites. An average CUE of 0.66 across all sites is presented in detail for each site in Fig. 6.

3.2. Total CO_2 calculation

When averaged across our study sites, the mean annual carbon sequestration value of the six TDF study areas is 22.34 ± 3.2 tCO_2 ha^{-1} yr^{-1} (Fig. 7). The highest carbon sequestration values can be found in SR (35.3 ± 2.9 tCO_2 ha^{-1} yr^{-1}), MS (29.7 ± 3.3 tCO_2 ha^{-1} yr^{-1}), CHA (25.8 ± 2.5 tCO_2 ha^{-1} yr^{-1}) and YU (20.5 ± 1.5 tCO_2 ha^{-1} yr^{-1}). The lowest carbon sequestration rates per hectare correspond to the study sites in Bolivia, with 11.8 ± 5.0 tCO_2 ha^{-1} yr^{-1} for SM and 10.8 ± 4.1 tCO_2 ha^{-1} yr^{-1} for TU. Historical trends (Table 3 and Fig. 4) suggest similar patterns of consistent annual behavior, low variation, and no significant differences in carbon sequestration for SR, CHA, YU, and the MA. Contrary to this, increasing CO_2 sequestration trends are observed in SM and TU.

3.3. Socio-economic valuation of CO_2 sequestration

The mean annual value of carbon sequestration for a hectare of TDF computed using all the sites ranges from 489 USD ha^{-1} yr^{-1} (FUND model)

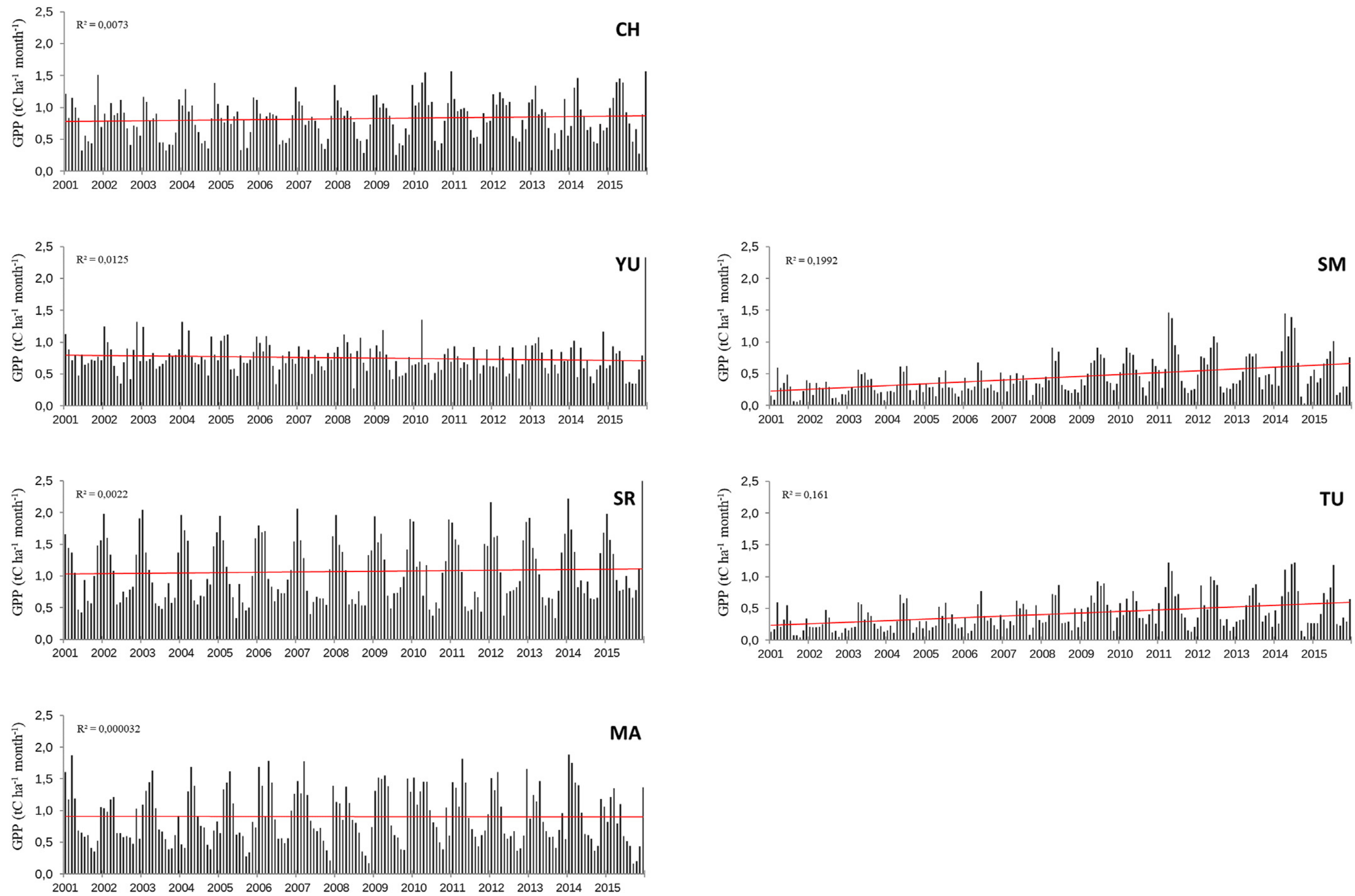

Fig. 4. Total monthly values of MODIS GPP for all TDFs sites from the years 2001–2015. Units are expressed in tC ha^{-1} month^{-1} and site information is displayed from North to South as follows: Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU).

to 772 USD ha^{-1} yr^{-1} (DICE model) and between 1414 USD and 2828 USD ha^{-1} yr^{-1} (PAGE model).

The SR study site provides the maximum economic value per hectare (Table 4), followed by MA, CHA, YU, SM, and TU. However, it should be noted that all values correspond to one single hectare on each study site; and hence the total estimates for each site will change as a function of the area covered. For example, adopting the DICE model as the median and latest updated reference value of the SCC, given in Table 2, and considering the total area occupied by each study site, given in Table 1, the SM site in Bolivia sequesters carbon for an economic value that is almost five times higher than the Santa Rosa study site (i.e. USD 233.7 million versus USD 47.3 million). Thus, the differences in the carbon sequestration ability of the sites, and thereby, their economic value in this respect, partially varies as a function of the surface area.

4. Discussion

Although carbon storage and carbon sequestration are a subject of extensive scientific research aimed to quantify the value of ecosystem services (ES, Costanza et al., 2017), current research efforts are still commonly missing an integrated approach. For example, previous studies in TDFs have either focused on exploring particular components of the biophysical (Balvanera and Aguirre, 2006; Vargas et al., 2008; Dai et al., 2015; Mora et al., 2017) or economical (Pfaff et al., 2007; Pagiola, 2008) dimensions of carbon sequestration. This was emphasized by Calvo-Rodriguez et al. (2017a) on their evaluation of ES research for TDFs.

This study provided an integral example of calculating the total carbon sequestration and the associated social cost of carbon using six TDF study sites across the Americas. Our results reveal that between 2000 and 2015, the TDFs had a yearly average sequestration rate of 22.3 ± 3.2 tCO_2 ha^{-1} yr^{-1}, which equals to an economic value of 489 USD ha^{-1} yr^{-1} to 2828 USD ha^{-1} yr^{-1}, depending on the econometric model used. These values represent a sequestration of approximately 1.16 gigatons of CO_2 per year for the 519,597 km^2 of the TDFs in the Americas. This has an equivalent economic value that ranges between USD 25 billion (lowest estimate) to USD 146 billion (highest estimate). Below, we analyze the significance of our results.

4.1. The significance of carbon sequestration and the CUE differences between the study sites

The carbon sequestration estimates of our study appear to be larger at Northern latitudes (CH, YU and SR) than at Southern latitudes (SM and TU). However, our time series analysis results show a small but positive increase of carbon sequestration in Bolivia (SM and TU). We acknowledge the importance of relating such carbon sequestration estimates to deforestation/reforestation dynamics and suggest it for future research using the methodology provided in this paper.

According to Zhang et al. (2009), global terrestrial ecosystems have an average CUE of 0.52. Furthermore, DeLucia et al. (2007) explored variability in CUE values for different forest types, identifying values in a range of 0.23–0.83. Similar ranges (0.326–0.875) were presented by Ito (2011), in a historical meta-analysis of global land NPP and CUE. According to our results, the CUE values of the sites range from 0.74 in Santa Rosa to 0.58 in Bolivia. As such, the CUE values of our study are higher than what has been previously estimated, for example, in tropical *terra firme* sites of the Amazonia (CUE: 0.32; Chambers et al., 2004).

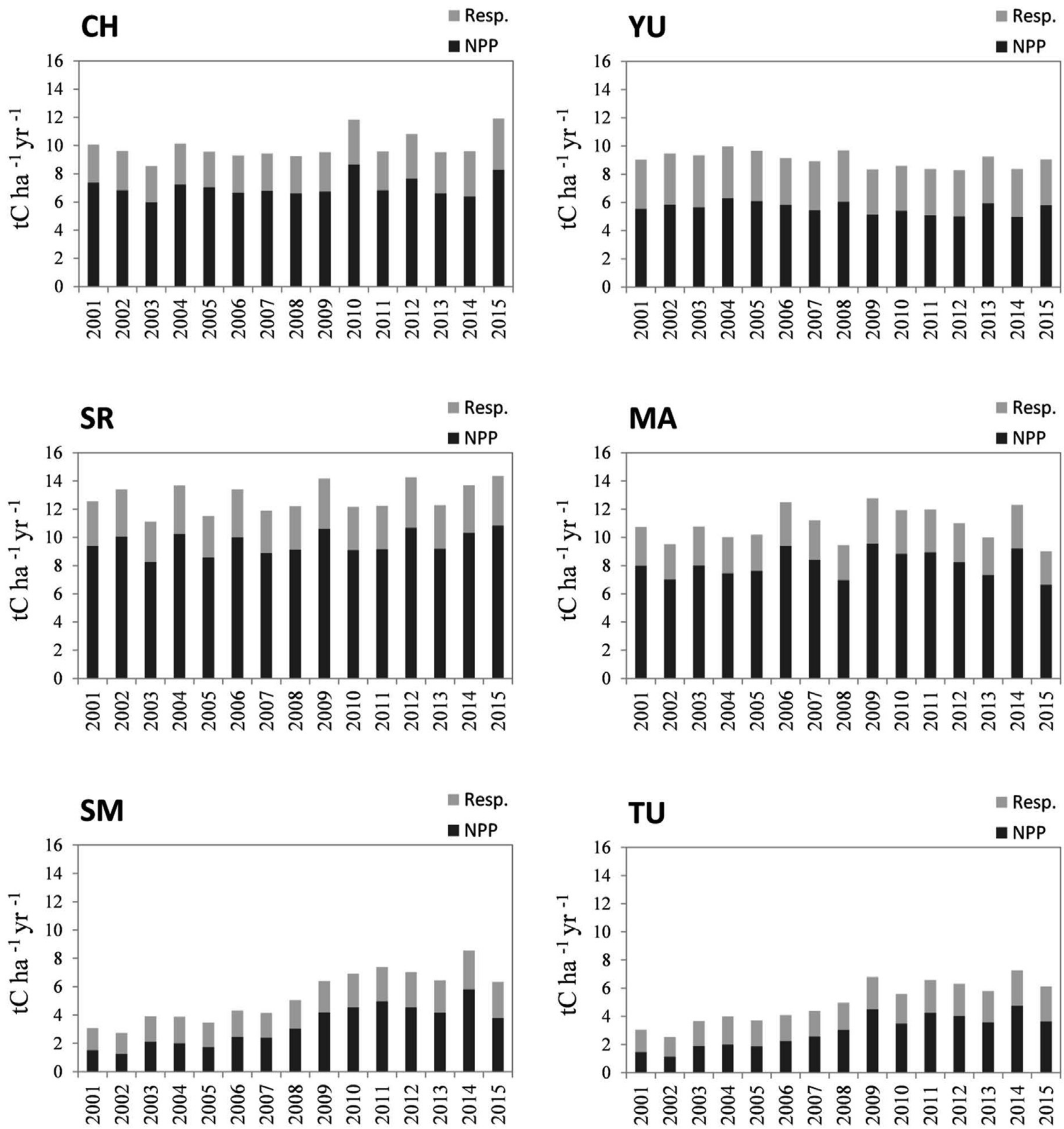

Fig. 5. Total annual Net Primary Productivity (NPP) and respiration (Resp.) rates between years 2001 and 2015 of Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU).

Chambers et al. (2004), suggest that the generally low CUE value of tropical forests result from their higher respiratory demands, potentially combined with a high amount of wastage respiration associated with more carbon fixation than what can be consumed (Chambers et al., 2004). Kwon and Larsen (2012) reported that MODIS band saturation could result in underestimation of GPP values in warm and humid regions, which would lead to an overestimation of CUE values in low latitudes (Kwon and Larsen, 2013). Also using MODIS NPP/GPP data products, Letchov (2018) reported that under stress conditions forest biomes can exhibit the lowest and the highest CUE variance, highlighting the complexity of factors that can affect the carbon sequestration capacity of forests. In general, the CUE values of TDFs are poorly established and more research is needed to better understand them.

The biological processes that regulate carbon sequestration are sensitive to environmental conditions, including temperature, precipitation, soil fertility, forest type, species composition, age, leaf mass-to-total mass and CO_2 availability (DeLucia et al., 2007; Zhang et al., 2009; Manzoni et al., 2012, Doughty et al., 2018), but also to geographic factors such as latitude and longitude (Zhang et al., 2009; Chen and Yu, 2019). As detailed in Table 1, the sites with the lowest CUE values (San Matias and Tucabaca) record the highest rainfall. According to Zhang et al. (2009), areas of wet and warm low-elevation environments have lower CUE values than areas that are drier, colder, or at a higher elevation. Furthermore, Ise et al. (2010) described the relation between temperature sensitivity and autotrophic respiration, and its effect on lower CUE for some regions. The rise of temperatures in the dry forests of Bolivia, resulting from climate change (Seiler et al., 2015), might thus also contribute to the observed decrease of the CUE values between 2001 and 2015 (Table 4). We attribute the observed geographic differences and time-series trends in the CUE values of the study sites predominantly to environmental factors such as changes in the mean annual precipitation and temperature.

In this context, it is pertinent to highlight the use of carbon sequestration, whether expressed as CUE or totals, as a metric to better model

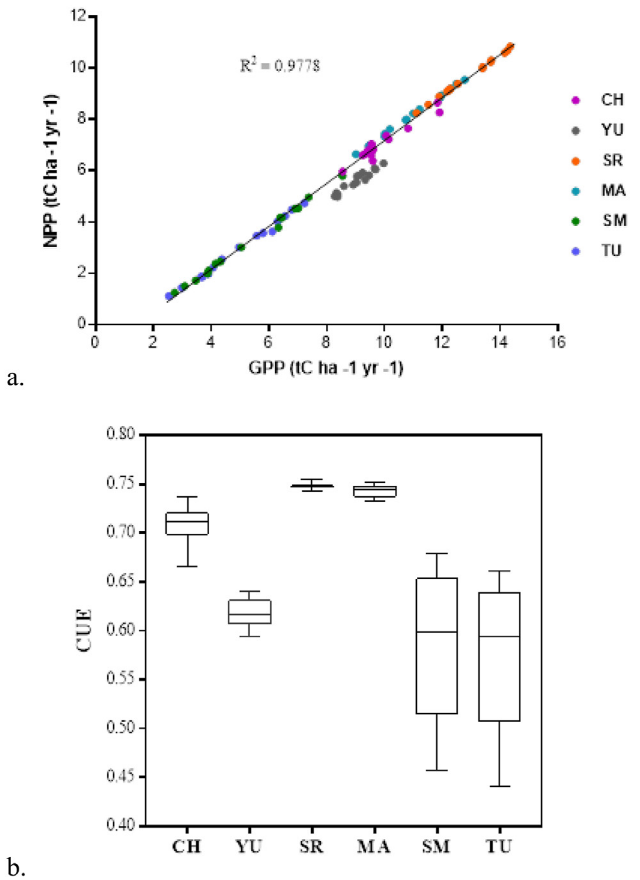

Fig. 6. a) Ratio of NPP to GPP for Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU). b) Distribution of CUE values for all TDFs sites. Higher values indicate more efficiency and NPP accumulation.

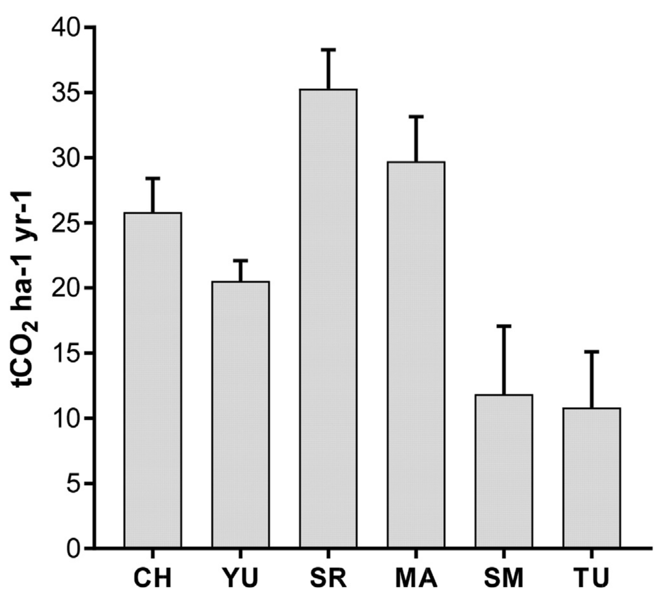

Fig. 7. Total mean annual estimates of CO_2 sequestration from years 2001–2015 Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU). Values are expressed in tCO_2 ha^{-1} yr^{-1}. Bar size represents the mean across all years and whiskers above represent the standard deviation.

Table 3
Total annual CO_2 sequestration rates from 2001 to 2015. The values are expressed in t CO_2 ha^{-1} yr^{-1} for the study sites of Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU). Total annual averages and standard deviations across all TDFs are also included.

Year	CH	YU	SR	MA	SM	TU	Annual average
2001	27.0	20.3	34.4	29.3	5.5	5.3	20.3
2002	25.0	21.4	36.9	25.7	4.6	4.1	19.6
2003	21.9	20.7	30.3	29.4	7.7	6.8	19.5
2004	26.5	23.1	37.6	27.3	7.3	7.3	21.5
2005	25.8	22.3	31.4	27.9	6.3	6.8	20.1
2006	24.4	21.4	36.7	34.5	9.0	8.2	22.3
2007	24.9	20.0	32.6	30.8	8.8	9.4	21.1
2008	24.2	22.2	33.5	25.6	11.1	11.1	21.3
2009	24.7	18.8	38.9	35.0	15.3	16.5	24.9
2010	31.7	19.8	33.3	32.4	16.6	12.7	24.4
2011	25.0	18.6	33.6	32.8	18.2	15.5	24.0
2012	28.1	18.3	39.2	30.2	16.7	14.8	24.5
2013	24.2	21.7	33.7	26.9	15.3	13.1	22.5

Table 4
Estimated monetary values of CO_2 sequestration between 2001 and 2015 for Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU). The results are obtained using FUND, DICE, and PAGE, the three-social cost of carbon -models of this study. Values in brackets are the economic value of CO_2 sequestration for the entire site. Abbreviations: USD=US dollar. M = million.

Study site	FUND	DICE	PAGE
	USD ha^{-1}	USD ha^{-1}	USD ha^{-1}
CH	564,9 [7.2 M]	891,8 [11.3 M]	1634.3–3268.6 [20.8–41.5 M]
YU	449,5 [15.3 M]	709,6 [24.2 M]	1300.4–2600.9 [44.3–88.7 M]
SR	772,5 [29.9 M]	1219,5 [47.3 M]	2234.8–4469.7 [86.7–173.4 M]
MA	650 [7.5 M]	1026,5 [11.9 M]	1881 - 3762 [21.8–43.6 M]
SM	259 [148 M]	409 [233.7 M]	749,7–1499 [428.3–856.4 M]
TU	236,8 [41.3 M]	373,8 [65.1 M]	685–1370 [119.3–238.5 M]

and understand ecosystem functions. As shown in Table 4, carbon sequestration and CUE trends are not always identical. Although variations in CUE and NPP allocation are rarely quantified, evidence of declining productivity in dry forests with compensatory shifts in CUE has been previously identified by Malhi et al. (2015). They found that seasonal water deficit gradients, mortality rates and specific carbon allocation dynamics might have an incidence on low biomass accumulation and high CUE responses. Furthermore, CUE may also change with disturbance and soil fertility (Aragão et al., 2009). Zanotelli et al. (2015) also suggest that multiple factors regarding autotrophic respiration and all components of NPP allocation (wood, canopy and fine roots) need to be analyzed to understand such variations. Therefore, a combined analysis of carbon sequestration and CUE can help understand biomass growth and carbon metabolism processes and facilitate carbon tracking over time.

4.2. Considerations on the social cost of carbon (SCC)

TDFs possess a value that goes beyond the extraction of raw materials, such as timber and other non-forest products. Since ecosystem services can be quantified (Costanza et al., 2017), our study identified the economic contributions (using the SCC) of a hectare of TDF (in $USD) and using well-known reference values (Tol, 2008; Hope, 2011; and Nordhaus, 2017).

Costa Rica is the only country that has developed a local carbon market with incentives for forest conservation, reforestation lands, and agroforestry systems (Sanchez-Azofeifa et al., 2007; Pagiola, 2008). Currently, the Fondo Nacional de Financiamiento Forestal (FONAFIFO), the authorized entity for the trade of carbon compensation units in Costa Rica, has determined a payment of USD 7.5 per ton of CO_2

(Sánchez-Chaves and Navarrete-Chacón, 2017) which, given our biophysical estimates, corresponds to a value of 264.5 USD ha^{-1}. This value falls under our estimates for Costa Rica but is higher than the ones expressed by Kalacska et al. (2008) who estimated values in a range of \$14.6 to USD 43.9 ha^{-1}.

Mexico, Brazil, and Bolivia, based on a review of Reducing Emissions from Deforestation and forest Degradation (REDD) initiatives in Latin America, pledge costs in a range of USD 2 to USD 10 per ton of CO_2 (Bastos-Lima et al., 2017), which represent lower estimates than the ones calculated in this study. However, REDD reference values are currently being debated given the low competitiveness of forest preservation against other land uses, such as agriculture and cattle ranching (Hall, 2012). Furthermore, new forest and conservation policies, such as Law 300 in Bolivia aim to set aside carbon markets and pledge for more integral and sustainable ways of managing forests, especially those inhabited by local peasants and indigenous peoples.

Our results also show that the estimated values for 1 ha of TDF could consequently be used to calculate the total revenue of a specific area; such as the protected area or a reclaimed land. This can change the perspective of the decision-makers and the general public on the overall value of a particular site. We have shown that by multiplying the unitary value for the total area of each site, forests such as those in Tucabaca and San Matias have the largest economic value. An important fact, considering that Bolivia protects 10,609 km^2 of dry forests followed only by Brazil (Portillo-Quintero and Sanchez-Azofeifa, 2010).

One of the benefits of the methodology of our study is its ability to be applied to forested areas irrespective of their potential land use changes. For future research, we suggest calculating the SCC generated by the monetary loss due to deforestation for all the TDF sites in Central and South America. This would provide an enhanced economic framework on the monetary benefits of halting deforestation and promoting afforestation, land management initiatives advocated by current UN initiatives such as the UN Decade on Ecosystem Restoration (Aronson et al., 2020) and the Land Degradation Neutrality (Cowie et al., 2018). We foresee that in general, increasing local and national-level understanding of the SCC can lead to positive outcomes in terms of willingness to preserve and sustainably manage forest resources.

4.3. Carbon sequestration in global policy objectives

Multiple international policy objectives and commitments aim to preserving the ecological integrity of forest ecosystems, support long-term economic growth and improving human wellbeing without putting on risk the sustainability of the planet, e.g. the Sustainable Development Goals (SDGs), the Convention of Biological Diversity (CBD) Aichi Targets, the Paris Agreement and the Nationally Determined Contributions (NDCs) of all countries to the UNFCCC. Evaluating progress towards any of the objectives relies on supporting metrics that along with official indicators, can make complex information understandable to the civil society (Metternicht et al., 2019; Kavvada et al., 2020).

Following the current reporting practices of the United Nations for the SDG dashboard traffic light framework (Sachs et al., 2020), we performed a qualitative analysis to portray a visual representation of how our carbon sequestration metrics (NPP and CUE) can be reported in a global policy objective context with a 5 years rate of change (Appendix D). Negative loss rates ($<$0.96) are represented as red-colored symbols, small change rates (0.97–1.01) as yellow circles, and stable and positive rates ($>$1.01) as green symbols. Positive (SR, YU, and TU) and negative (CH, MA, SM) rates of change for carbon sequestration can be compared with the CUE performance (positive for CH, YU, SR and MA; and negative for TU and SM) in a simple and visual display of results. Reporting and monitoring of C-dynamics, and management of policy instruments related to global international policies would greatly benefit from the incorporation of our proposed metrics, especially for developing countries that lack of resources for the implementation of robust monitoring systems. Also beneficial to detect trends and trade-offs with other ecosystem services (Geijzendorffer et al., 2017), and the integration with monitoring the progress towards their goals and national assessments.

4.4. Associated uncertainties

A key challenge in any process is imperfect information (Costanza et al., 2017). The process of transferring values from one ecological context to a social context is also likely to have uncertainties. However, to start acting towards promoting and achieving sustainable development and conservation policies, it is better to act on reasonable estimates, than to act on no estimate at all (Ackerman and Stanton, 2012).

In applying our approach to the development of our ecological base indicator, there were several related uncertainties worth noting. First, because the estimation of CUE and SCC relies entirely on biophysical quantities of CO_2, limitations on the biophysical estimation method might also be transferred to the related indicators. Second, even if a remote sensing-based approach, coupled with a benefit transfer method, is useful for avoiding the costs and time of fieldwork, it has uncertainties related to the selection of the remote sensing products. The MODIS MOD17A3 NPP vegetation product is one of the most highly used data sources for ecological studies associated to the global carbon cycle (Turner et al., 2006; Zhang et al., 2009; Ise et al., 2010; Guo et al., 2012; He et al., 2018), although prior studies (Zhao et al., 2005; Pan et al., 2006) indicate the necessity to adjust MODIS -based estimates to regional or local scales. For example, overestimation of NPP at low productivity areas or underestimation at high productivity areas has been reported for tropical forest studies (Turner et al., 2005). Nevertheless, a consistent relation between MODIS NPP and field measurements has also been reported for a period of five years in Turkey (Gulbeyaz et al., 2018), suggesting no overall bias when using MODIS NPP and GPP products in mid-latitudes. Third, scientific uncertainties related to the reference values of the SCC models (FUND, PAGE, and DICE) of this study could affect our results. To mitigate uncertainties related to any given model, we provided SCC estimates using three independent models.

5. Conclusions

TDFs are important ecosystems for the regulation of climate through the sequestration of CO_2, a benefit of great value for local and global well-being. This study reported the carbon sequestration, CUE and the associated economic value of six TDF sites in Central and South America. We argue on the advantages of an explicit remote sensing-based approach to estimate the capacity and efficiency of specific forest ecosystems to sequestrate carbon. Coupling the output to conventional models of carbon costing, promoting biodiversity conservation and incorporating ecosystem services into decision-making processes offers a viable means for countries to better estimate and report the social and economic dimensions of sustainable forest management.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

6. Acknowledgments

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Appendix A. Values of Biome-Property-Look-Up-Table (BLUT) for MODIS NPP algorithm calculation (Running and Zhao, 2015)

Parameter	Value	Units	Description
SLA	21.8	(m^2 kg C^{-1})	Projected leaf area per unit mass of leaf carbon.
froot_leaf_ratio	1.1	None	Ratio of fine root carbon to leaf carbon.
leaf_mr_base	0.00778	(kg C kg C^{-1} day^{-1})	Maintenance respiration per unit leaf carbon per day at 20 °C.
froot_mr_base	0.00519	(kg C kg C^{-1} day^{-1})	Maintenance respiration per unit root carbon per day at 20 °C.
livewood_leaf_ratio	0.203	None	Ratio of live wood carbon to annual maximum leaf carbon.
livewood_mr_base	0.00371	(kg C kg C^{-1} day^{-1})	Maintenance respiration per unit live wood carbon per day at 20 °C.

Appendix B. Database of all monthly GPP values expressed in tC ha^{-1}, processed from MODIS17A from the year 2001–2015 for all TDFs sites

CHAMELA												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2001	1.21	0.84	1.15	1.00	0.84	0.32	0.56	0.47	0.43	1.04	1.51	0.70
2002	0.90	0.79	1.07	0.87	0.91	1.12	0.92	0.67	0.41	0.72	0.69	0.56
2003	1.16	1.09	0.79	0.83	0.90	0.45	0.45	0.32	0.42	0.41	0.61	1.12
2004	1.03	1.29	0.94	1.03	0.72	0.61	0.44	0.47	0.35	0.83	1.38	1.05
2005	0.84	0.77	1.03	0.74	0.86	0.93	0.33	0.82	0.36	0.61	1.16	1.12
2006	0.90	0.80	0.86	0.92	0.89	0.87	0.42	0.49	0.44	0.52	0.88	1.32
2007	1.10	1.03	0.72	0.79	0.85	0.79	0.67	0.43	0.35	0.51	0.87	1.35
2008	1.11	1.00	0.87	0.95	0.86	0.78	0.51	0.47	0.28	0.50	0.73	1.19
2009	1.20	1.00	1.06	0.99	0.87	0.73	0.25	0.44	0.41	0.67	0.58	1.35
2010	1.03	1.08	1.39	1.55	1.03	1.09	0.47	0.33	0.43	0.79	1.07	1.57
2011	1.14	0.94	0.97	0.99	0.94	0.64	0.52	0.54	0.43	0.91	0.77	0.79
2012	1.21	1.05	1.24	1.14	1.04	1.09	0.54	0.51	0.46	0.81	0.66	1.08
2013	1.13	1.34	0.89	0.97	0.93	0.68	0.33	0.59	0.35	0.64	1.13	0.56
2014	0.71	1.31	1.46	0.96	0.87	0.64	0.69	0.46	0.43	0.74	0.63	0.68
2015	0.99	1.15	1.40	1.46	1.39	0.93	0.75	0.46	0.66	0.28	0.89	1.57
YUCATAN												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2001	1.13	0.89	0.72	0.80	0.48	0.80	0.64	0.67	0.72	0.71	0.77	0.72
2002	1.25	1.00	0.88	0.63	0.47	0.35	0.68	0.90	0.42	0.88	1.32	0.70
2003	1.24	0.70	0.73	0.83	0.58	0.62	0.66	0.71	0.82	0.77	0.80	0.88
2004	1.32	0.81	1.18	0.77	0.68	0.65	0.77	0.73	0.47	1.09	0.81	0.71
2005	1.02	1.10	1.11	0.57	0.58	0.47	0.79	0.68	0.67	0.73	0.84	1.08
2006	0.99	0.85	1.09	0.95	0.63	0.34	0.57	0.79	0.66	0.86	0.73	0.66
2007	0.93	0.77	0.77	0.88	0.50	0.80	0.71	0.62	0.55	0.83	0.72	0.84
2008	0.92	0.75	1.12	1.00	0.82	0.28	0.86	1.07	0.68	0.55	0.90	0.75
2009	0.95	0.85	1.19	0.80	0.56	0.42	0.70	0.46	0.48	0.52	0.76	0.64
2010	0.66	0.68	1.35	0.64	0.68	0.41	0.52	0.69	0.56	0.82	0.90	0.69
2011	0.94	0.78	0.60	0.68	0.65	0.40	0.93	0.74	0.51	0.64	0.89	0.62
2012	0.62	0.60	0.94	0.75	0.46	0.51	0.92	0.72	0.43	0.66	0.95	0.73
2013	0.95	0.98	1.08	0.83	0.60	0.51	0.88	0.65	0.51	0.85	0.70	0.71
2014	0.92	1.02	0.45	0.91	0.59	0.71	0.46	0.36	0.57	0.64	1.17	0.59
2015	0.64	0.93	0.82	0.86	0.71	0.35	0.37	0.35	0.35	0.57	0.79	2.33
SANTA ROSA												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2001	1.66	1.44	1.37	1.05	0.47	0.42	0.93	0.61	0.57	1.00	1.48	1.56
2002	1.98	1.60	1.34	1.08	0.55	0.58	0.75	0.66	0.78	0.83	1.34	1.90
2003	2.04	1.37	1.09	0.90	0.57	0.52	0.48	0.67	0.89	0.57	0.66	1.37
2004	1.96	1.72	1.55	0.94	0.62	0.55	0.69	0.68	0.95	0.86	1.47	1.69
2005	1.94	1.56	1.15	0.87	0.67	0.34	0.87	0.58	0.46	0.51	1.00	1.59
2006	1.80	1.69	1.71	0.95	0.83	0.60	0.79	0.72	0.73	0.94	1.09	1.54
2007	2.06	1.56	1.28	0.77	0.40	0.59	0.67	0.65	0.65	0.54	1.10	1.63
2008	1.96	1.49	1.38	1.09	0.55	0.63	0.56	0.76	0.54	0.53	1.33	1.41
2009	1.94	1.53	1.67	1.26	0.69	0.48	0.73	0.74	0.83	0.98	1.42	1.90
2010	1.86	1.14	1.23	0.68	1.17	0.47	0.37	0.58	0.49	1.05	1.23	1.89
2011	1.84	1.57	1.49	1.06	0.52	0.45	0.47	0.75	0.66	0.44	1.50	1.47
2012	2.16	1.61	1.64	1.06	0.38	0.73	0.76	0.77	0.83	0.92	1.56	1.85
2013	1.91	1.45	1.28	1.02	0.66	0.53	0.65	0.64	0.33	0.77	1.37	1.66
2014	2.22	1.73	1.38	0.82	0.92	0.73	0.91	0.65	0.63	0.66	1.37	1.68
2015	1.98	1.57	1.35	0.94	0.77	0.78	1.00	0.80	0.66	0.78	1.12	2.62
MATA SECA												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2001	1.61	1.17	1.88	1.19	0.69	0.65	0.59	0.61	0.41	0.36	0.53	1.06
2002	1.04	0.99	1.18	1.22	0.64	0.64	0.58	0.60	0.57	0.47	1.03	0.56
2003	1.09	1.31	1.45	1.63	1.04	0.70	0.67	0.55	0.39	0.40	0.61	0.92
2004	0.47	0.41	1.30	1.69	1.39	0.91	0.76	0.73	0.46	0.39	0.68	0.83

(continued on next column)

(*continued*)

MATA SECA												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2005	0.64	1.33	1.44	1.62	1.11	0.62	0.65	0.60	0.28	0.34	0.82	0.73
2006	1.69	1.39	0.91	1.78	1.44	0.86	0.55	0.56	0.49	0.56	1.00	1.26
2007	1.47	1.27	1.78	1.25	0.83	0.72	0.68	0.73	0.52	0.37	0.21	1.39
2008	1.13	1.11	0.85	1.38	1.12	0.86	0.80	0.65	0.35	0.29	0.17	0.74
2009	1.31	1.52	1.50	1.55	1.38	0.76	0.61	0.57	0.39	0.38	1.50	1.30
2010	1.52	1.09	1.30	1.46	1.45	1.01	0.81	0.74	0.50	0.39	1.05	0.60
2011	1.45	1.36	1.06	1.82	1.44	0.89	0.71	0.59	0.43	0.61	0.69	0.94
2012	1.51	1.32	1.61	1.06	0.64	0.55	0.59	0.68	0.37	0.41	0.61	1.65
2013	0.87	1.25	1.14	1.47	0.82	0.68	0.58	0.59	0.41	0.69	0.96	0.55
2014	1.88	1.75	1.44	1.40	0.97	0.63	0.61	0.56	0.37	0.45	1.19	1.06
2015	0.82	1.22	1.35	0.80	1.10	0.59	0.52	0.44	0.16	0.20	0.44	1.37
SAN MATIAS												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2001	0.15	0.09	0.59	0.28	0.36	0.49	0.30	0.07	0.06	0.08	0.23	0.39
2002	0.36	0.17	0.35	0.28	0.28	0.37	0.29	0.11	0.12	0.05	0.18	0.18
2003	0.24	0.29	0.26	0.57	0.49	0.52	0.41	0.42	0.25	0.19	0.21	0.08
2004	0.22	0.23	0.21	0.32	0.61	0.53	0.62	0.25	0.08	0.24	0.35	0.21
2005	0.34	0.28	0.29	0.14	0.45	0.28	0.55	0.29	0.28	0.19	0.14	0.24
2006	0.43	0.27	0.25	0.30	0.68	0.55	0.27	0.28	0.33	0.23	0.21	0.52
2007	0.42	0.22	0.48	0.34	0.50	0.39	0.48	0.39	0.08	0.16	0.35	0.34
2008	0.28	0.45	0.40	0.91	0.70	0.85	0.32	0.25	0.24	0.20	0.25	0.21
2009	0.41	0.31	0.50	0.67	0.71	0.91	0.81	0.75	0.38	0.36	0.24	0.34
2010	0.52	0.66	0.91	0.83	0.80	0.56	0.46	0.29	0.15	0.38	0.74	0.62
2011	0.56	0.28	0.57	1.46	1.37	0.95	0.81	0.39	0.28	0.20	0.25	0.26
2012	0.48	0.78	0.75	0.64	0.91	1.08	0.99	0.30	0.21	0.27	0.26	0.35
2013	0.34	0.40	0.53	0.77	0.82	0.77	0.81	0.44	0.25	0.48	0.49	0.33
2014	0.60	0.30	0.86	1.45	1.08	1.39	1.22	0.67	0.14	0.04	0.34	0.46
2015	0.56	0.37	0.43	0.66	0.73	0.85	1.01	0.16	0.20	0.30	0.30	0.76
TUCABACA												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2001	0.13	0.17	0.60	0.21	0.32	0.55	0.31	0.07	0.08	0.04	0.15	0.34
2002	0.21	0.21	0.20	0.21	0.25	0.47	0.35	0.12	0.14	0.05	0.12	0.19
2003	0.15	0.20	0.21	0.60	0.56	0.32	0.44	0.38	0.26	0.18	0.22	0.14
2004	0.16	0.23	0.12	0.30	0.72	0.58	0.66	0.34	0.12	0.21	0.30	0.19
2005	0.30	0.16	0.20	0.23	0.52	0.38	0.59	0.27	0.41	0.25	0.19	0.20
2006	0.36	0.11	0.15	0.26	0.57	0.77	0.38	0.31	0.35	0.24	0.17	0.40
2007	0.33	0.18	0.30	0.24	0.62	0.50	0.57	0.48	0.08	0.20	0.55	0.32
2008	0.28	0.28	0.39	0.72	0.71	0.87	0.27	0.28	0.29	0.16	0.50	0.21
2009	0.50	0.29	0.52	0.70	0.59	0.93	0.85	0.89	0.56	0.47	0.15	0.35
2010	0.58	0.39	0.65	0.46	0.77	0.61	0.35	0.35	0.25	0.40	0.49	0.26
2011	0.58	0.14	0.84	1.22	1.09	0.69	0.73	0.42	0.36	0.16	0.13	0.21
2012	0.35	0.86	0.55	0.48	1.00	0.94	0.87	0.33	0.23	0.33	0.15	0.21
2013	0.30	0.32	0.33	0.55	0.70	0.82	0.88	0.59	0.29	0.39	0.42	0.21
2014	0.47	0.26	0.69	1.11	0.76	1.20	1.23	0.77	0.15	0.06	0.28	0.27
2015	0.27	0.27	0.41	0.74	0.64	0.83	1.19	0.26	0.23	0.36	0.29	0.65

Appendix C. Annual average values of GPP (in tC ha^{-1}), NPP (in tC ha^{-1}), RA (in tC ha^{-1}), and CUE of the selected study sites Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU) from 2001 to 2015

	CHA				YU				SR				MA				SM				TU			
YEAR	GPP	NPP	RA	CUE	GPP	NPP	RA	CUE	GPP	NPP	RA	CUE	GPP	NPP	RA	CUE	GPP	NPP	RA	CUE	GPP	NPP	RA	CUE
2001	10.07	7.37	2.70	0.73	9.03	5.55	3.49	0.61	12.55	9.39	3.16	0.75	10.74	7.98	2.76	0.74	3.09	1.51	1.57	0.49	2.98	1.45	1.60	0.49
2002	9.61	6.83	2.78	0.71	9.48	5.83	3.64	0.62	13.40	10.05	3.35	0.75	9.52	7.01	2.51	0.74	2.74	1.25	1.49	0.46	2.53	1.12	1.42	0.44
2003	8.55	5.98	2.58	0.70	9.34	5.65	3.69	0.61	11.12	8.26	2.86	0.74	10.77	8.00	2.77	0.74	3.91	2.11	1.80	0.54	3.65	1.87	1.80	0.51
2004	10.15	7.23	2.92	0.71	9.98	6.29	3.69	0.63	13.69	10.24	3.44	0.75	10.02	7.45	2.57	0.74	3.87	2.00	1.88	0.52	3.91	1.98	2.01	0.51
2005	9.56	7.04	2.52	0.74	9.66	6.09	3.56	0.63	11.53	8.57	2.95	0.74	10.19	7.62	2.57	0.75	3.47	1.73	1.74	0.50	3.69	1.86	1.84	0.50
2006	9.30	6.65	2.66	0.71	9.14	5.83	3.31	0.64	13.40	10.00	3.40	0.75	12.49	9.40	3.10	0.75	4.31	2.46	1.85	0.57	4.06	2.24	1.85	0.55
2007	9.44	6.80	2.64	0.72	8.93	5.45	3.48	0.61	11.90	8.89	3.01	0.75	11.22	8.40	2.82	0.75	4.15	2.39	1.76	0.58	4.38	2.56	1.81	0.59
2008	9.25	6.60	2.65	0.71	9.70	6.05	3.65	0.62	12.21	9.13	3.08	0.75	9.46	6.97	2.49	0.74	5.06	3.03	2.03	0.60	4.97	3.03	1.94	0.61
2009	9.54	6.73	2.81	0.71	8.34	5.13	3.21	0.62	14.16	10.60	3.56	0.75	12.78	9.54	3.24	0.75	6.40	4.18	2.22	0.65	6.79	4.49	2.30	0.66
2010	11.84	8.66	3.18	0.73	8.60	5.40	3.20	0.63	12.17	9.09	3.08	0.75	11.93	8.84	3.09	0.74	6.92	4.53	2.38	0.66	5.58	3.47	2.12	0.62
2011	9.59	6.82	2.77	0.71	8.38	5.08	3.29	0.61	12.24	9.16	3.08	0.75	11.98	8.94	3.04	0.75	7.38	4.97	2.42	0.67	6.56	4.24	2.35	0.65
2012	10.82	7.65	3.17	0.71	8.29	5.00	3.29	0.60	14.27	10.69	3.58	0.75	11.00	8.24	2.76	0.75	7.03	4.54	2.48	0.65	6.30	4.03	2.28	0.64
2013	9.54	6.61	2.93	0.69	9.25	5.92	3.32	0.64	12.29	9.19	3.10	0.75	10.00	7.33	2.67	0.73	6.44	4.16	2.28	0.65	5.79	3.57	2.22	0.62
2014	9.60	6.39	3.21	0.67	8.38	4.98	3.40	0.59	13.70	10.31	3.39	0.75	12.30	9.20	3.10	0.75	8.55	5.80	2.75	0.68	7.24	4.74	2.53	0.65
2015	11.92	8.28	3.64	0.69	9.06	5.79	3.27	0.64	14.36	10.84	3.52	0.75	9.02	6.64	2.38	0.74	6.33	3.79	2.55	0.60	6.12	3.63	2.49	0.59
Mean Ave.	9.92	7.04	2.88	0.71	9.04	5.60	3.43	0.62	12.87	9.63	3.24	0.75	10.89	8.10	2.79	0.74	5.31	3.23	2.08	0.59	4.97	2.95	2.04	0.58
Standard Dev.	0.90	0.68	0.29	0.02	0.53	0.40	0.17	0.01	1.01	0.78	0.23	0.003	1.16	0.90	0.26	0.01	1.74	1.38	0.37	0.07	1.43	1.13	0.31	0.07

Appendix D. Dashboard Analysis of carbon sequestration (a) and carbon use efficiency (CUE) (b) for the study sites of Chamela (CH), Yucatan (YU), Santa Rosa (SR), Mata Seca (MA), San Matias (SM) and Tucabaca (TU). Average annual values for carbon sequestration, calculated as 5-year averages, are expressed in tCO_2 per ha, and CUE in %. Values in brackets equate the rate of change (r) for every site according to the traffic light analysis. Red color means a negative loss rate, yellow means no or small change rate, and green means a stable or positive rate

a) Carbon sequestration

Site	2001	2005		2011		2015	
CH	27	▼	25.8 [r:0.96]	▲	31.7 [r: 1.23]	▼	30.3 [r:0.96]
YU	20.3	▲	22.3 [r: 1.10]	▼	19.8 [r: 0.89]	▲	21.2 [r: 1.07]
SR	34.4	▼	31.4 [r: 0.91]	▲	33.3 [r: 1.06]	▲	39.7 [r: 1.19]
MA	29.3	▼	27.9 [r: 0.95]	▲	32.4 [r: 1.16]	▼	24.3 [r: 0.75]
SM	5.5	▲	6.3 [r: 1.15]	▲	16.6 [r: 2.63]	▼	13.9 [r: 0.84]
TU	5.3	▲	6.8 [r: 1.28]	▲	12.7 [r: 1.87]	▲	13.3 [r: 1.05]

b) CUE

Site	2001	2005		2011		2015	
CH	73.2	●	73.6 [r: 1.01]	●	73.1 [r: 0.99]	▼	69.5 [r: 0.95]
YU	61.4	▲	63.1 [r: 1.03]	●	62.8 [r: 0.99]	▲	63.9 [r: 1.02]
SR	74.8	●	74.4 [r: 0.99]	●	74.7 [r: 1.00]	●	75.5 [r: 1.01]
MA	74.3	●	74.8 [r: 1.01]	●	74.1 [r: 0.99]	●	73.6 [r: 0.99]
SM	49	▲	49.8 [r: 1.02]	▲	65.5 [r: 1.32]	▼	59.8 [r: 0.91]
TU	48.6	▲	50.4 [r: 1.04]	▲	62.1 [r: 1.23]	▼	59.3 [r: 0.96]

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